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Data migration in the cloud database: A review of vendor solutions and challenges

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Abstract
An important development in information technology, cloud computing allows users to share Internet-based access to pre-con Figured systems and services. While there are many benefits, such cost efficiency and scalability, security is still a big worry for everyone involved. The current practices in authentication have been found to be wanting in providing for the principles of CIA triad; confidentiality, integrity and availability. Data transfer to the cloud is also known as data migration, which takes data from on-premises databases together with other cloud services and which is normally associated with many problems such as data integrity and minimize down time. Additional barriers stem from the continuously maturing cloud environments and different levels of compatibility with the given database structures. This paper focuses on the processes that are involved in data migration and different catalogs of migration including, database migration, data center migration, application migration, business process migration and so on, stressing the significance of planning and implementing these migrations efficiently. The main issues that demand shifting to the cloud are outlined as well as the main approaches that large cloud suppliers such as AWS, Microsoft Azure, and Google Cloud offer. Additionally, potential risks and challenges, such as vendor selection, security concerns, and resource management, are explored. This comprehensive overview highlights the significance of strategic planning and vendor solutions in ensuring successful cloud data migration, while addressing the inherent risks associated with transitioning to cloud-based infrastructures.

Keywords: Database, cloud computing, virtualization, database as a service, data migration, vendors solutions

Introduction
The most popular IT trend right now is "cloud computing," which allows users to access shared configurations of systems and services over the Internet. Cloud security offers a more comprehensive framework for safeguarding data, apps, and the underlying cloud infrastructure. Cloud computing is mostly used by businesses to store and manage massive amounts of data across computers. On the other hand, cloud providers and customers are starting to worry about data security. There has been a failure with the use of conventional authentication mechanisms such as password and key creation. The cloud makes it more difficult to accomplish the three primary aims of CIA: data availability, data integration, and data secrecy. If you want to move data from one cloud service to another, or even just from one database to another, you need to do a cloud migration.

Data migration to the cloud is driven by factors like cost efficiency and scalability, but concerns over security and trust in cloud providers can complicate the process, especially when switching between providers [1]. If a cloud provider discontinues its services, users need to securely transfer data to another provider. The three primary cloud service models include Infrastructure as a Service (IaaS), which manages storage, virtualization, and networking for third-party data centers (e.g., AWS, Google Compute Engine); Platform as a Service (PaaS), which offers a porTable application environment for development and integration (e.g., AWS Elastic Beanstalk, Google App Engine) and Software as a Service (SaaS), providing on-demand software for CRM and business management(e.g., Google Apps, Salesforce).

Deployment can be on the public cloud, private cloud or hybrid cloud with the later known to give better security, availability and costs cutting. The best practices for the migration may differ: direct transfer between clouds can be enabled, while direct download & upload is slower. Main guidelines within data migration into the cloud include planning, analysis of strengths, weaknesses, opportunities, selecting the proper cloud environment and architecture, accurate selection of a cloud provider and partner [2].

More specifically, in the migration into the cloud databases, there is need for keeping some elements of the database structure consistent, and logical, and not allow for downtime. The cloud environment can have vastly different architecture, response times, and features for security while the migration of data between on-premise or between twelve providers is challenging. Incompatibilities may occur based on the problem of database schema, storage media and data models supported. Also, data migration is a massive transfer of large volumes of data which would need a lot of bandwidth to complete, and can also take a lot of time and even if the process is interrupted accidentally, data can be lost or corrupted. Managing the updates in real-time data becomes even more challenging since it has a direct impact on the process of migration without resulting to service disruptions or decline in the quality of service [3, 4].

A. Contribution of the study

This work will look at the processes, types, challenges, and vendor's solutions of data migration in cloud databases. It aims at providing organisations with knowledge on how best to undertake migration with specificity on how to handle data during change over to cloud. The main contribution of the study are listed below:

This study provides the reader with close understanding of data migration with emphasis on the nature and types of data migration.

- It assesses leading cloud service providers and their migration tools, clarifying available options for seamless cloud transitions.
- The study highlights key challenges and risks in cloud data migration, enabling organizations to proactively address potential issues.
- By outlining migration stages and essential drivers, the study serves as a practical guide for organizations planning cloud data migration projects.

B. Structure of the paper

The paper is structured as follows: Section II provides an overview of data migration in cloud databases. Section III discusses vendor solutions for cloud database migration, while Section IV explores challenges risks of data migration in cloud, machine learning. Section V examines literature review of the paper, and Section VI offers conclusions and future works recommendations.

Overview of data migration in cloud databases

The analysis of legacy data is the first stage in the data migration process, which also includes loading and standardising data into new systems. After the legacy data has been scrubbed, the data may be mapped from the old system to the new system. Next, conversion programs are designed, built, and tested. Finally, the converter is matched. Another definition of data migration is creating a duplicate of an organization's present data on one device and transferring it to another, ideally without stopping any running applications and then rerouting all input/output (I/O) operations to the new device [5, 6].

A. Types of Data Migration

Data migration strategies should be deliberated after careful consideration of the various forms of migration. Migrations that impact the whole system are the most complicated. Furthermore, the following are other considerations that are taken into account:

1. Data Base Migration

The current database is upgraded to the most current version whenever data is migrated from one database resource to another. Take the conversion of the IBM DB2 database to Oracle as an example.

2. Data Center Transfer

It is necessary to transfer all data from the database of the previous data centre to the database of the new data centre when the data centre is relocated.

3. Application Migration

The underlying data must also be transferred to a new application when transferring it, for instance when moving it from a local activity server to the cloud or across cloud domains.

4. Business Process Migration

Depending on the specifics of the process changes brought about by a merger, acquisition, or just general company improvements, data transfers may be necessary to move files from one storage system or app to another [5]. Figure 1 shows the several levels of cloud data transfer, which are as follows

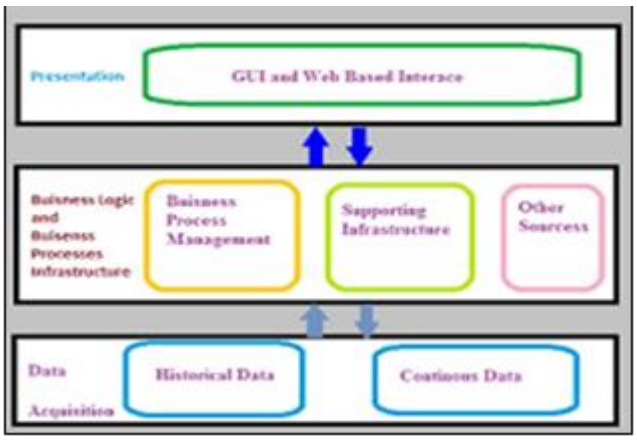

Fig 1: Data Migration in Cloud Layers

B. Need for Data Migration

Data migrations for commercial purposes are rather commonplace nowadays. There are a number of important considerations when opting to transfer data to a new environment, the most prevalent of which being the need to replace an older legacy system. Among these considerations are:

- The need for more storage space is driven by the exponential growth of databases.
- Businesses are elevating their server game to a higher quality.

- To simplify and save costs by switching to a consumable and sTable system
- Concepts like virtualisation rely on data's portability between physical and virtual settings.
- The provision of reliable and clean data for use [7].

C. Key Drivers for Cloud Data Migration

Here are the main factors that contribute to a successful data transfer, as well as how cloud data migration affects it:

Scalability And Capacity : An advantage of using a service provider rather than installing more hardware on your own premises is the ease with which capacity may be increased in response to customer demand [8].

Data Validation and Testing: The most effective strategy for preventing data corruption is to validate all data between the old system and the target system.

- Data Validation.
- Subsets of data Validation.
- Complete data set validation.

Sample Data Validation: involves comparing a randomly selected record from the legacy system to the target system. Sampling is not flawed since it picks little records at random.

Validation Of the Dataset: We should make it a priority to test the migration using this flawless validation approach. Both the old and new systems compare all records in a two-way fashion. This means that the target system compares all records with the old system and the old system compares all records with the target system. In order to overcome the instances required to establish a single database containing both legacy and target system data, it is difficult to conduct such a comparison when two distinct database suppliers are involved [5].

- Project stability
- Data coverage
- Implementation time.
- Efficiency of the Query/Script

D. Migration Process

There are a lot of possible worries and problems that could arise for organisations during data transfer. A process model that the authors have used in practice several times forms the basis of this research. There are a total of fourteen separate steps that make up the four primary stages. The primary steps are:

- Initialization, i.e., setting up the necessary organization
- and infrastructure.
- Development, which refers to creating the actual programs for data movement
- Testing, or confirming that the data and the data transfer routines are accurate, sTable, and have a reasonable execution time
- Cut-Over, which is the process of running the migration programs in order to eventually switch to the destination application.

Vendor solutions for cloud database migration

Cloud database migration is significant for organizations who wish to migrate their databases seamlessly and efficiently into cloud environments, thus requires the solutions from vendors. These solutions are built with the aim of solving challenges that arise with databases migration such as data integrity when moving from one cloud platform to another, avoiding downtime to the highest extent possible, and compatibility of the databases in the new cloud platform.

AWS, Microsoft Azure and Google cloud and other leading cloud service providers have a number of migration tools and services to support this process. For example, AWS includes DMS or Database Migration Service that offers heterogeneous options and offers a high level of automaticity regarding data migration. Likewise, when the users employed the Azure Database Migration service, they are provided with a procedure on how to migrate on-premises databases to Azure, the data integrity and security.\

Key Vendor Solutions

1. AWS has the Database Migration Service (DMS), that is hardware based and is used for databases and covering different platforms and switches to AWS and replicates data constantly with low disruption. Further, the AWS Schema Conversion Tool helps the user in transforming the schemas of databases to the required format, which is many times required for the target database for easier migration.
2. Microsoft Azure offers Azure Database Migration Service which helps users to perform a smooth migration from On-premises database to Azure with little or no downtime factors which makes it convenient for users to improve the consistency of data. In addition, Azure's Data Box is a shipped disk that performs the transfer of large quantities of data securely and quickly, which can suit enterprises with great requirements for transferring big amounts of data.
3. Migrating to Google Cloud SQL is another option from the GCP that is called the Migration Service that is ideal for database migration and the migration of both supported and unsupported varieties is possible. Also, with the Big Query Data Transfer Service, users can easily transfer data from several data sources into Big Query and therefore easily analyze and use the data.
4. Tools like Talend contain detailed Third-Party data integration and migration features which encompass data mapping and transformation features, which goes hand-in-hand with organizing organizational data during migration. Other critical solutions are data management within data migration, integration and control that Informatica offers to ensure transitions for data while maintaining its quality. Finally, Striim enables real-time data integration and replication, helping organizations to transfer data perpetually from one platform to another with low latency and data drift.

Challenges risks of data migration in cloud

Cloud data transfer is not without its difficulties. Security issues pertaining to illegal access and ensuring compliance with data protection laws further exacerbate the situation, necessitating meticulous preparation to minimize risks. Below are some of the challenges that are observed.

A Choosing the right cloud vendor

Fundamental research issues include data management and migration, which are never quite as simple as moving data

from traditional systems to the cloud. Selecting the right cloud provider is a challenging process for an organisation, even after doing a SWOT (Strength, Weakness, Opportunities, and Threats) study. Cloud industry heavyweights like Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform (GCP) are always trying to find new methods to set themselves apart from the competition. With that in mind, businesses should enquire with cloud providers about data transfer solutions, taking into account factors like vendor lock-in and software portability.

B. Trust deficit about cloud security

Cloud computing has recently improved its information security model, but there are still concerns that people should not put their most sensitive data there due to the potential dangers. All-important parties, including people, organisations, and governments, are affected by this lack of confidence.

C. Departmental downsizing

There is a chance that IT support teams would have to scale down when using a cloud architecture. Downsizing may be in store for IT support departments whose primary responsibilities lie in providing assistance with hardware and organisational matters. The capacity within the IT support department will become superfluous since cloud providers will be responsible for maintaining these portions of the service.

D. Lack of supplementary resources

The deployment of cloud frameworks raises concerns about potential shortages in IT support and sales/marketing department resources. Due to migration, there is a chance that IT support departments may temporarily expand, and support engineers often lack knowledge and expertise with cloud frameworks [9].

Literature Review

This section provides a literature review on data migration in cloud databases, exploring methodologies and frameworks for efficient data transfer across heterogeneous environments. It highlights key strategies, challenges, and advancements, offering insights into the effectiveness of various migration approaches.

In this paper Bansel, González-Vélez and Chis, (2016) to encourage data portability between diverse NoSQL data repositories hosted in the cloud, we suggest a NoSQL data transfer architecture. In order to efficiently map and translate across various NoSQL data stores hosted in the cloud, the suggested method incorporates data standardisation and categorisation phases. Presently, the framework can handle document, columnar, and graph data models. The fact that it is meta-model driven further opens the door for developers to include additional database models into the framework. To facilitate data conversion (from documents to graphs), our method incorporates an online compression mechanism; this allows for a 46% reduction in storage space requirements for graph databases. When compared to the original graph database, the number of nodes in the compressed version is 37% to 55% less [10].

This paper Wang *et al*., (2019) introduces e-MARS, a system that is based on an environmentally conscious market strategy, for the purpose of appropriate data transfer in order to achieve query load balance in a cloud database. The e-MARS concept views cloud databases as a cloudDB market, with data nodes acting as smart traders and query loads as commodities. Traders make their own decisions about query load trading and data migration based on their own knowledge of their local environmental resources, such as processing capability and disc volume. This will bring to a state of balance in the cloud DB industry. With e-MARS, efficiency is greatly improved by experiments run on actual communication data. When it comes to query response time, it's almost 65% faster than HBase Balancer [11].

This paper (Li *et al*., (2016) came up with a standard technique for migrating to private clouds, and summed up the technical concepts and basic procedures for doing so. The subsequent successful completion of a case study in which the suggested approach was used to migrate an enterprise system to the Eucalyptus cloud environment demonstrated the method's viability and validity. Finally, this article offers some technical recommendations for improving system performances based on an investigation of system performances using various migration strategies [12].

This paper, Hsieh *et al*., (2021) creates a system that can handle several host databases in a unified way, which may simplify the stages of the operation and increase the data's security and operational efficiency. Manual, automated, and complex database migration methods are all available. The results of the experiments demonstrate that the advanced database migration approach outperforms the other two methods in terms of efficiency and security when used in a VM environment [13].

This paper Abo Dabowsa *et al*., (2021) recommends an automated method for migrating databases from the MySQL database management system to the popular NoSQL database system MongoDB. This technique can process massive amounts of data stored in RDBs without affecting the data's semantics or instances in any way. The solution processes an existing RDB by extracting its schema and analysing it in an array. Then, it converts the schema with data instances according to the structure of the goal NoSQL database. An approach-based system has been developed. The suggested technique was tested in an experimental research. The results of the experiments demonstrate that the prototype's target database and the target databases created using other approaches were similar and identical [14].

This paper Tian *et al*., (2017) suggests a cloud-based data replica transfer technique that is both dynamic and flexible. An improved capacity to adapt to changes in workload, more fault tolerance, and better scalability are all goals of a proposed dynamic scheduling system that is based on workload-based cloud computing. This approach modifies the amount of replicas by modifying the amount of transaction requests that the workload processor watches. By keeping an eye on the workload, we may spot major shifts, which is a baby step towards repartition, and we reach our goal of keeping the partition in excellent shape in the end. The migration approach for dynamic data copies allows for the completion of dynamic data exchange among data nodes. When the workload varies, the experimental findings reveal that the suggested strategy can drastically lower the frequency of distributed transactions [15].

In this paper Rafique *et al*., (2018) provide two further studies that address the aforementioned issues with the three most developed data access middleware systems: Spring

Data, Impetus Kundera, and Playorm. The performance overhead that different platforms bring to the CRUD operations is first evaluated. A second part of the analysis is a comparison of the migration costs with and without these platforms. In spite of their shared architecture, our research reveals that these systems provide quite distinct functionality. These two studies complement each other by illuminating the trade-offs involved in using a data access middleware platform for NoSQL, which is that developers receive portability and ease of migration across heterogeneous data storage in exchange for a performance expense [16].

Table 1: Summarizing the related works on data migration in the cloud database

Study	Focus	Methodology	Key Findings	Limitations	Future Work
Bansel, González-Vélez and Chis, 2016	NoSQL data migration framework for heterogeneous NoSQL repositories	Data standardization, classification, online compression algorithm for data migration	Supports three data models (document, columnar, graph), reduces graph database space by 46%, and reduces nodes by 37%-55%	Limited support for more than three NoSQL data models	Extend framework support to more database models
Wang *et al.*, 2019	e-MARS, a market strategy-based system for data migration	Environment-aware system, query load treated as commodity, data nodes act as intelligent traders	Achieved query load balance, 65% improvement in query response time over HBase Balancer	Complexity in modeling and managing the cloud DB market	Further optimization of trading algorithms for different cloud environments
Li *et al.*, 2016	Private cloud migration methodology	General methods for private cloud migration, specific case of Eucalyptus cloud migration	Feasibility and validity of private cloud migration methods demonstrated	Case study limited to Eucalyptus cloud, lacks diversity of cloud environments	Explore migration strategies across various private and public cloud environments
Hsieh *et al.*, 2021	Managing multiple host databases in a unified manner	Manual, automatic, and advanced migration approaches	Advanced method enhances security and operational efficiency compared to manual and automatic methods	Scalability challenges in larger virtual machine environments	Integrate AI-based optimization for database security and operational efficiency
Abo Dabowsa *et al.*, 2021	Automatic conversion from MySQL to MongoDB	Schema extraction and conversion of RDB to NoSQL (MongoDB)	Successful conversion without data loss, equivalent performance between converted and original databases	Limited to MySQL and MongoDB systems	Extend conversion approach to more relational and NoSQL systems
Tian *et al.*, 2017	Dynamic adaptive migration strategy for data replicas	Dynamic scheduling mechanism based on workload changes	Significant reduction in distributed transaction frequency during workload changes	Limited scalability in cloud environments with high dynamic workloads	Optimize the dynamic scheduling mechanism for larger-scale cloud systems
Rafique *et al.*, 2018	Evaluation of NoSQL data access middleware platforms	Performance evaluation of CRUD operations and migration cost comparison	Middleware platforms (Impetus Kundera, Playorm, Spring Data) offer portability at the cost of performance overhead	Performance trade-offs when adopting middleware platforms	Investigate middleware performance improvements without sacrificing portability

Conclusion & Future Work

Applications that rely heavily on data must undergo data migration. The ever-evolving data landscape is too much for legacy data storage technologies to handle. The failure to adequately address the significance and complexity of data migration initiatives is a common reason of their failure in many organizations. Storage, databases, applications, and business processes are some of the data migration techniques available. In conclusion, data migration to cloud databases is a critical process that requires careful planning and execution to ensure data integrity, security, and minimal downtime. As organizations increasingly rely on cloud services for data management, understanding the complexities of migration and the available vendor solutions is essential. Major cloud providers like AWS, Microsoft Azure, and Google Cloud offer tailored migration tools to facilitate this transition, but challenges remain, including security concerns, vendor selection, and resource allocation. Addressing these challenges will be crucial for organizations aiming to leverage the benefits of cloud computing effectively.

Future work should focus on developing more advanced migration tools that enhance data security and simplify the migration process across diverse cloud platforms. Research can also explore automated solutions for real-time data validation and integrity checks during migration. Additionally, investigating the long-term impacts of cloud migration on organizational structure and IT resource management will provide insights for effective cloud strategy implementation. Finally, enhancing awareness and education around best practices in cloud migration can help organizations navigate the complexities of this evolving landscape more effectively.

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RESEARCH ARTICLE OPEN ACCESS

ECHOES IN PIXELS: THE INTERSECTION OF IMAGE PROCESSING AND SOUND DETECTION THROUGH THE LENS OF AI AND ML

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ABSTRACT

In recent years, the convergence of image processing and sound detection with artificial intelligence (AI) and machine learning (ML) has led to transformative innovations across various fields, including healthcare, surveillance, entertainment, and autonomous systems. This paper explores the intersection of these two domains, delving into how AI and ML algorithms can process visual and auditory data to extract meaningful information and deliver intelligent responses. By leveraging advanced neural networks, deep learning models, and hybrid systems that combine image and sound analysis, this study aims to provide a comprehensive overview of the current state of research, technological advancements, and future directions. We analyze the role of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformers in facilitating the seamless integration of sound and image data, thereby enhancing applications such as speech-to-text systems, video analytics, and multimodal recognition. Experimental results demonstrate how integrating image processing and sound detection through AI frameworks achieves higher accuracy and robustness in real-time applications, including smart surveillance, autonomous vehicles, and human-computer interaction. Ultimately, this paper highlights the key challenges, benefits, and ethical considerations surrounding this fusion of technology, emphasizing its potential to reshape industries and augment human capabilities.

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INTRODUCTION

The combination of image processing and sound detection as subfields of machine vision, and thanks to the integration of recent technologies in artificial intelligence and machine learning, is altering how machines analyze visual sensory data. [1-4] Typically, the analyses of image and sound have been considered as two separate domains. Image processing deals with image data to extract relevant features, and sound detection is the identification and categorization of sound signals. However, the desire for systems that can handle more complex multimodal settings has driven the research on the integration of these technologies using AI and ML interfaces.

Evolution of Image Processing and Sound Detection: The advancements in image processing and sound detection have broughta lot of change in many fields, ranging from entertainment to security and health care. This section aims at providing a historical background as well as key technologies implemented for both domains which are actually closely related, as well as their future evolution.

Historical Context

- Early Beginnings in Image Processing: It is for this reason that it is possible to bring the historical theme of modern image processing back to the 1960s when researchers started experimenting with image manipulation for its several uses. These early methods were mathematically modelled and algorithms based on early techniques concentrating on simple tasks of filtering and enhancement. Some of the historical

developments in this period were edge detection, simple pattern recognition and some others.

- **Initial Sound Detection Techniques:** The concept of sound detection may be traced to the early 1930s with the onset of audio fidelity equipment. To know about the properties of sound waves, concepts like frequency analysis were invented. With the advent of analog signal processing, the quality of the audio could be enhanced and then, in the late century, advanced into digital sound analysis. The initial methods of DSP were FFT for frequency representation or stripping off noise.

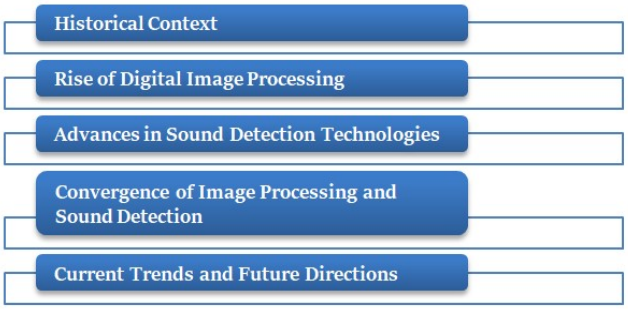

Figure 1. Evolution of Image Processing and Sound Detection

Rise of Digital Image Processing

- ***The Digital Revolution:*** It is important to note that the last couple of decades of the 20th century saw a tremendous interest in digital image processing. By getting into computers, researchers can run tremendous algorithms on images, resulting in major achievements in fields such as medical imaging as well as remote sensing. The advance of digital cameras and image sensors also facilitated the creation of digital images and, hence, required advanced processing.
- ***Introduction of Convolutional Neural Networks (CNNs):*** Deep learning, dignified in particular by CNNs launched at the beginning of the decade, opens new horizons in image processing. CNNs revolutionized the field by automating the feature extraction process and making the strategy of classifying images very accurate. Structures such as AlexNet (2012) brought into focus how deep learning has a higher performance than the other conventional approaches in image recognition problems.

Advances in Sound Detection Technologies

- **Transition to Digital Sound Processing:** Similarly to image processing, sound detection became digital in the late twentieth century. The introduction of Multitrack Digital AUDIO WORKSTATIONS (DAWs) provided the basis for developing other methods, such as Mel-Frequency Cepstral Coefficients (MFCCs) and spectrogram analysis that are frequently applied in the process of audio analysis at the current stage.
- **Rise of Deep Learning in Audio:** RNN and LSTMs dominate the technique of sound detection starting from the 2010s. Such models showed good performance in processing sequential audio data and improving various applications, including speech recognition and music genre classification. For example, Google, at their I/O conference in 2016, introduced WaveNet, which applied deep learning for high quality audio synthesis to demonstrate the system's ability for sound generation and processing.

Convergence of Image Processing and Sound Detection

- ***Emergence of Multimodal Systems:*** With the development of technology, simultaneous image and sound processing became the subject of new and more intense investigations. There were many contexts where systems having the capability of processing both visual and auditory inputs were required, such as smart surveillance, smart driving cars, and smart games. Experts started coming up with a more enhanced model that combined both CNNs for image analysis and RNNs for sound recognition.
- ***The Role of Transformers and Attention Mechanisms:*** Transformers and attention mechanisms that came into the picture in the late 2010s enhanced the development of multimodal learning. These architectures improved the overall integration of multiple modalities by enabling the modelling of the relevant features of this multiplicity. This has driven the progress of applications where images and sounds need to be interpreted together, namely video intelligence as well as augmented reality.

Current Trends and Future Directions

- ***Advancements in AI and Machine Learning:*** Presently, the development of Image processing and sound detection is not possible without the help of new technologies which include AI and Machine learning. Such innovative methods, such as transfer learning and GANs are being integrated into multimodal systems in order to increase the ability to make a correct prediction as well as improve generalization for a variety of tasks.
- **Towards More Robust Multimodal Systems:** The future work is to develop more effective and reliable multimodal interfaces that can work in real-time and operate in a dynamic environment. The potential directions of the development can be the usage of unsupervised and semi-supervised learning, the enhancement of the data synchronization procedures, and the application of the more complex neural networks, such as capsule networks and nets, with attention.

The Role of Deep Learning in Multimodal Systems: The convolutional neural ecosystemhas transformed the field of how society implements multiple sources of data, most particularly in imaging and sonar perception. [5,6] Deep learning builds upon such neural structures, allowing for sharper identification and combination of feature representations originating from various types of data to improve the performance of numerous applications. This section presents the main contributions and use of deep learning in multimodal systems.

Feature Extraction

- **Automated Feature Learning*:*** Also, the capability of serving significant features that are learned automatically and hierarchically from raw data is

another prominent advantage of deep learning. In the design of image processing, CNN is suitable for finding the edge, shape or pattern in the image. At the same time, RNN, particularly LSTM, is used to find the temporal relationships in the audio signals. It also avoids insisting on manual feature engineering, which makes the development of multimodal systems faster and easier.

- **Combining Visual and Auditory Features:** Consequently, deep learning models can gain deep learning features from the visual data stream as well as the auditory data stream at the same time. For instance, in aCNN–RNN framework, the CNN part analyzes visualization inputs of the spatial relations, and the RNN part analyzes the sequential audio inputs owing to their temporal relations. It is these features that make it possible for the model to integrate such features and, in the process, improve the capability of the model to decipher difficult situations, hence providing more realistic solutions.

Figure 2. The Role of Deep Learning in Multimodal Systems

Data Fusion Techniques

- **Early, Late, and Hybrid Fusion:** In the approach of multimodal systems, deep learning frameworks can support multiple ways of integrating the methodologies of data fusion. Early fusion works at the feature level and involves combining inputs of one or more modalities from the start before feeding them into the model. In contrast, in the late fusion technique, different types of electrical modalities are processed individually after which their outputs are fused for the final prediction. These complex fusion techniques tend to employ both early fusion and late fusion approaches with performance optimized according to the nature of the data. All ofthese fusion techniques can be integrated into deep learning architectures without much problem based on the needs of the application at hand.
- **Attention Mechanisms:** Such connections have really enhanced the performance of multimodal systems through so much use of attention mechanisms which are seen as critical offerings of deep learning. As will be seen in the different modalities, the effectiveness of the integration process is boosted since the model is allowed to focus on the right features. For example, during lip movement and audio signals for the spoken word, attention layers can give priority to the features, which in turn vary with the context. This leads to a more meaningful interpretation of the input data so that their significance is much more profound.

Handling Large and Diverse Datasets

- ***Scalability:*** The effectiveness of using deep learning models is further enhanced by their ability to process big and heterogeneous data, which is foundational to any multimodal system. Due to the presence of enormous volumes of categorized image and sound data, deep learning frameworks can be developed to learn information from these sets and, therefore, enjoy enhanced generalization. Such extendibility is used to advantage in functions such as autopilot, where there is a profuse gathering of data by different types of sensors.
- ***Transfer Learning:*** Transfer learning is a very special and common approach to deep learning, which will train the model with less data by modifying it from the initial pre-trained model. In multimodal systems, transfer learning can be used to take information from large databases, to give a fine performance in a scenario where only small samples from the particular modality can be obtained. This capability reduces development time as well as improves performance in domains where labeled data is hard to come by.

Real-World Applications

- ***Speech Recognition and Audiovisual Processing:*** Speech recognition has been enhanced through deep learning by coupling audio and visual data in the Audiovisual Speech Recognition System. These systems incorporate speech action together with lip movement data, giving the systems a higher accuracy in deciphering spoken words, especially in noisy surroundings.
- ***Smart Surveillance Systems:*** Smart surveillance, on the other hand, uses deep learning models of image and sound detection for improved situational awareness. For example, movement recognition can be used together with auditory inputs in video feeds and enhance the alertness of a system and subsequent responses.
- ***Healthcare and Medical Diagnostics:*** Recently, deep learning methods have been applied to healthcare since many data types, from imaging (e.g., MRI) to sound (e.g., heartbeat), can capture most patient information. When these modalities are incorporated into a treatment plan, clinicians are in a position to make the right decisions concerning diagnosis and treatment.

Challenges and Future Directions

- ***Computational Complexity:*** Despite the benefits of deep learning, there are disadvantages, especially in computation demands. Training multimodal models is computationally expensive, and also needs a fair amount of domain knowledge about the various forms of optimization methods. A possible direction for future work includes working on creating more efficient algorithms whose performance will be optimal on limited hardware.
- ***Data Synchronization:*** Here, another problem arises: data alignment from two or more modalities comes in streams. As mentioned above, this inconsistency affects

feature extraction and forces the respective models to be out of sync in terms of timing, which is bad news for model performance. Solving this problem will require enhancements to data preprocessing and alignment methodologies.

Literature Survey

Image Processing Techniques

Computer vision and image processing have come a long way; Convolutional Neural Networks (CNNs) have become the technological tools that back most functions that are used today, including object recognition, face recognition, detection of objects and medical imaging. Nevertheless, [7] Krizhevsky et al. (2012) proposed a DCNN named AlexNet, which eventually changed the way to conduct image classification to achieve superior performance at ILSVRC. AlexNet success inspired the development of even more complex architecture like in the case of ResNet- residual connection for making the network deeper, VGGNet simple standardized design Inception Net, parallel convolutional filter size for efficient feature picking. These developments have not only demanded and advanced the efficiency of image classification but have also encouraged in fields like auto-pilot, where identification of the objects in front of the vehicle is crucial for the avoidance of many fatal mishaps and for the right direction.

Sound Detection and Analysis: This has progressively moved to time-frequency forms such as STFT and MFCC to offer most of the characterization of sound signals. This change has notionally occurred with deep learning, especially with Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) for sequential data, including audio. Substantial work within this horizon is Google WaveNet (2016), based on deep probabilistic model architecture for high-quality speech and audio synthesis. However, one of the main advantages of WaveNet is natural-sounding audio, so this gives new opportunities to use deep learning in the creation of speaker retirement technologies, for example, voice commands and automated customer services. WaveNet has resulted in similar probes on other other end to end deep learning models for other sound functions, which are inclusive of speech and even emotion deduction from voice.

Multimodal Systems: Fusing Image and Sound: The analysis of multimodal systems has escalated as scientist continues to discover ways of implementing visual and auditory inputs simultaneously. The most well-known methods incorporate CNN with RNN to process images and audio in parallel in a way that is known as a hybrid architectures. An interesting researchby [8] Nagrani et al. (2018) also proposed the idea of audiovisual speech recognition, where the introduced model identifies speech by training it with visual inputs, including lips movement and the corresponding audio input. In this research, it was established that there was potential for improving the volumes of speech recognition, specifically in conditions where the simultaneous use of the abovementioned modalities might distort acoustic signals. Such multimodal systems have been applied in fields such as smart surveillance, as audio cues, for example, shouts or alarms and visual data, for instance video streams will complement each other in the identification of threats.

Advances in Neural Architectures: Transformers and attention mechanisms that have been incorporated recently have sharply boosted the progress of multimodal learning. Such examples include Visual Transformers (ViT) and Audio Transformers since they extend the capabilities of typical transformers while permitting more efficient data stream handling. These models are notable for their ability to solve problems that involve the analysis of visual and acoustic data at the same time, which makes them highly worthwhile in such areas as video processing, where the correlation of the image and the sound is critical. For example, in autonomous navigation systems, transformers can enlarge and optimize object recognition and environmental comprehension using multisensory data and support decision-making in general. Further growth of the field lies in the application of transformers within multimodal architectures that should enable extending the possibilities of AI uses for various domains.

METHODOLOGY

Data Acquisition and Preprocessing: Data acquisition is the first processes that need to be undertaken when designing a multimodal AI. In this phase, it is required to acquire the needed sets of data which comprise the visual and the auditory data. [9-13] Images are usually gathered with high-definition digital cameras and can include ordinary digital cameras and thermal or infrared cameras, depending on the need. For sound, the use of microphones is applied; they may be introduced in the environment to record all the sounds in the environment or simply a particular signal. Great care should be taken to match the two streams perfectly; any asynchrony in the flow may cause significant problems in understanding the connection between the image and the sound. Correct synchronization increases the correlation between the sounds and the images, which would, in turn improve the understanding of the environment that the data was collected in.

Image Preprocessing: When the images are collected, then they are preprocessed so as to improve the quality and format of the images that are to be used in the analysis. This preprocessing stage has some methods, which are as follows: dimensioning, normalization and enrichment of the data attained. Resizing is used to crop the ragged edges and make them all of the same size – this is essential when developing CNNs and dealing with big data.Normalization just means adjusting pixel values often to a standard range may be between 0 and 1, or doing a mean subtraction, which helps in the training process and also quickens the process of arriving at the training outcomes. Sizing is used to ensure the images are all of consistent size – an important factor when dealing with large data sets in CNNs. Normalization simply implies scaling the pixel values to within a standard range, perhaps within the range 0 and 1, or performing mean subtraction, which eases the training process and speeds up the convergence of training results. Simple operations such as rotating, flipping, cropping and converting the color space to raise the number of original training samples. Specifically, it is more effective in reducing overfitting, which makes a model more attractive to handle other data and be more accurate. Such preprocessing steps are very important as they enhance the capacity a model has to learn from well-formatted and cleaned data.

Sound Preprocessing: As discussed in the preprocessing section, image and sound preprocessing are important for preprocessing raw image and sound data for analysis by deep learning models, such as any other type of signal. Audio signals are multi-component and contain not only useful information but also noise. In order to solve this problem, the tools are The Short-Time Fourier Transform (STFT) and Mel-Frequency Cepstral Coefficients (MFCCs). STFT can be used to transform the audio signal to both domain time and frequency, making it possible to exhibit the history of the signal's unique frequency behavior at a certain time. Whereas, MFCCs bring in a set of coefficients which contains fundamental properties of human phoneme from the input audio signal making it more beneficial in sound classifying and speech recognition phenomena. This transformation preprocesses the received sample raw sound signals further into a somewhat less raw form of manipulated sound either for model performance uplift or traversal across deeper neural networks. These are activities applied to the sound data making the data more workable and apt to foster the best outcomes for multimodal Artificial Intelligence.

Model Architecture

Here, the general structure of the proposed multimodal AI system includes a Convolutional Neural Network (CNN) for image analysis and a Recurrent Neural Network (RNN) for sound analysis. This architecture is devised in such a way that it seeks to make use of the advantages of both types of networks in such a way that the system can analyze the data of various modalities the moment they are captured. The integration of these networks is done through a fusion layer with the features extracted from both streams preparing to be fed to the next downstream classification task.

Figure 3. Model Architecture

CNN for Image Processing: CNN is very important, especially in performing the image processing function in the model. A CNN often encompasses different layers, which include the convolution layer, the pooling layer and the full or dense layer of information. Convolution layers involve applying filters on the input images in such a way that the model is able to recognize the spatial relation which are patterns, edges and texture. The pooling layers used more often right after the layers of convolution serve the purpose of reducing the dimensions of the feature maps and, ofcourse, help preserve useful information, making the calculations more effective. Popular architectures that were applied for extracting the visual characteristics include ResNet (Residual Network) and VGGNet (Visual Geometry Group Network),which have been tested for multiple years in many numbers of computer vision tasks. In ResNet, we address with vanishing gradients problem with the help of skip connections, and in VGGNet, authors wanted to focus on depth using very small convolutional filters. The output of the CNN is feature maps which the CNN filters out the features from the given input images that are useful for the fusion with the audio analysis part.

RNN for Sound Detection: For the sound detection component, an RNN is used, which comes under the type of LSTM to handle the sequential audio data. LSTMs are built to accommodate temporal dependencies of data, and a plethora of applications relying on time-series or sequence data such as speech or environmental sounds. While feeding forward, LSTMs store the previous inputs in what is called a memory cell, and therefore, it eliminates the challenges of long-term dependencies that come with the standard RNNs. This ability is especially helpful when it comes to sound since the model is able to capture features of the sound over time frames making it able to model the dynamic nature of sound. Instead, the output of the LSTM is a temporal representation of sound features. While stripped out of context elements, it still contains the most important features necessary to get a context-rich understanding of the environment.

Fusion Layer: This layer has to connect the visual partof the model with the acoustic part based on the generated displays of the CNN module and RNN module. This integration is necessary for improved utilization of the added information each modality can generate. The fusion layer typically can use the add or combine of feature vectors derived from the CNN and RBN. The fused representation that the current approach produces helps the model to improve on the contextualization and the predictive ability of the model since it is able to learn from knowledge from both the visual modality and auditory modality. As can be seen in the section above, neglecting the last layer after the merging, the features are again fed to a fully connected layer for the final classification result. Such architecture makes the multimodal AI system more accurate when the input data is decomposed, as the highly enriched system will excel in parallel intricate tasks like silent speech recognition from AV speech or scene analysis in smart monitoring systems.

Training and Evaluation: The evaluation and training stage is as important in the development of a general multimodal AI framework to foster image and sound data. [17-20] This part of the paper explains the strategies for training the model based on compound datasets and the loss function and optimization algorithm utilized in this study, as well as the measures applied in the assessment of the performance of the model.

Training the Model: This model is unique for the fact that the image and sound corpora that the model is being trained with are scrutinized for a level of variability and of datagen within the training corpora. This means that after each audioclip, the related image has to be provided to give the model insights into how data in the two domains is structured. During the training, the data is split into three sections: The sets of data that can be used are the training set, the validation set, which allows systematic check and the "test set". The loss of data order may also be used to enhance the training datasets. It hence will satisfy the purpose of elimination overfitting as well as increasing the capacity of the model. During this training phase, the parameters of the model are fine tuned in such a way that the loss functions which were defined are minimized. This will enable the integration of the model into the learning of the underlying areas of the multimodal/Images.

Loss Function: While using the models for classification issues, it is useful to know that normally, the loss function used is the cross-entropy loss. This particular loss intends to measure the discrepancy present between the distribution probability forecasted by the model and the distribution

probability of the labels of the given data set. Therefore, the main training goal is to minimize this loss as possible to enhance the ability of the model to learn the nature of the inputs. It also proves that cross entropy loss is better for multiclass classification problems because their derivative is steeper than that of log loss and it discourages a model from making a mistake. Therefore, the model enhances and maximizes the interconnection between cross-entropy loss and enhances its capacity to categorize the categories in which it is supposed to categorize.

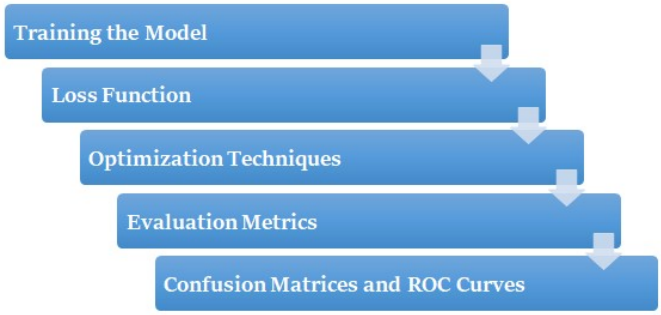

Figure 4. Training and Evaluation

Optimization Techniques: The model realizes how the weights should be adjusted, and during each epoch, the loss function is optimized using methods including Adam and RMSProp. Adam, it is a new improvement of two other adaptations of stochastic gradient descent Algorithms, namely AdaGrad and RMSProp. It calculates learning rates that are adaptive for each parameter, thereby increasing the greater and finer convergence of the model, especially where feature space is high. RMSProp also utilizes the moving average of squared gradients, which makes it appropriate for non-stationary objectives. Adam and RMSProp maintained the training stable and aimed to achieve faster convergence and higher accuracy by adjusting the learning rates in the session of training.

Evaluation Metrics: To provide the most accurate and reliable evaluation of the proposed model, multiple measures of performance are used, namely accuracy, precision, recall, and F1-score. Accuracy defines the number of effectively classified records out of the total number of records that have given an idea of the overall performance of any model. In situations where false positives are very costly, precision measures the actual positive predictions as compared to the total predicted positives in the array. Sensitivity, on the other hand, or recall, determines the capacity of the model accurately to estimate all the available records in the subject area (a true positive record) to make actual positive records stand out. We computed the F1-score as a measure that givesa more balanced measurement of precision and recall, especially when dealing with imbalanced data sets. Combined, all these measures afford a broader scope of understanding the performance efficiency of a given model in terms of classification in general.

Confusion Matrices and ROC Curves: Apart from the above-cited evaluation parameters, the confusion matrices and Receiver Operating Characteristic (ROC) curves are other measurement factors for evaluating the classification capability of the model. A confusion matrix presents the values of true positive, true negative, false positive and false negative all in one graphical format to permit easy comparison; this, therefore, makes it easier to recognize the areas of the problem by the model. This favors the identification of problems that are associated with particular classes. Specificity and sensitivity are two decision parameters that the Receiver Operating Characteristic or ROC curves, which is a graphical display of the true positive and false positive, with settings at various thresholds help to assess. The area under the receiver operating characteristic curve (AUC-ROC) is a single best measure of the accuracy of a model in a single value; the nearer to one is, the better the performance of the model. In combination, these tools improve the evaluation, peer fine-tuning, and optimization of the multiple modal AI systems.

RESULTS AND DISCUSSION

Improved Accuracy and Robustness: Multimodal integration of vision and hearing has improved the AI system's performance and reliability in real-time use, such as security cameras, voice identification, and emissions tracking. As a result of the use of both image and sound data, the system increases its chances of making better predictions on complicated events, hence improving its performance in difficult circumstances. Learnt in this section are the quantitative measures of the performance of multimodal systems in accomplishing different tasks as well as the clear distinction of this type of system from unimodal ones.

Table 1. Accuracy of the Multimodal System in Various Applications

Application	Multimodal System Accuracy	Unimodal Image Accuracy	Unimodal Sound Accuracy
Video Surveillance	97%	85%	82%
Speech Recognition	94%	80%	89%
Environmental Monitoring	95%	78%	76%

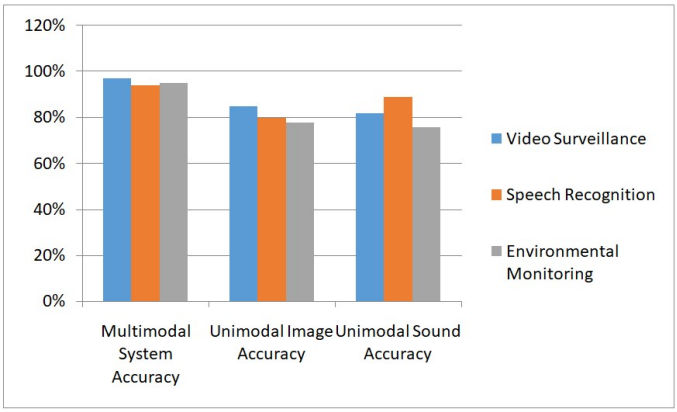

Figure 5. Accuracy of the Multimodal System in Various Applications

Video Surveillance: For the video surveillance particular domain, the error rate of the multimodal biometric system was 97%. This high level of accuracy cannot be explained any other way than the system's capability to process visuals, such as movement, face, and objects and sound, such as breaking glass and shouting, among others. When these many data streams are incorporated together, it means the system becomes better placed to initiate the necessary reactions in real time, thus enhancing security threat responses. For instance, in situations when visual information can be rather vague, for example in the dark, the auditory data can resolve doubts that

help to distinguish potential threats correctly.In contrast, the unimodal image system worked with 85 % accuracy of the binocular image system, suggesting that relying on such an image system will result in occasional missed objects or wrong classification. Similarly, unimodal sound detection, which yielded an average efficiency of 82 percent, shows that independent detection of sound in surveillance situations does not give adequate information. The multimodal approach, therefore, makes a significant improvement in performance, a clear implication of a need to integrate the various sensory modalities.

Speech Recognition: The multimodal system also performed well in the speech modality, with a reported accuracy of 94%. This improvement can be greatly owed to the design of the system, which can easily be programmed to utilize not only the tone of voice of the speaker but also the visual input, for example, from the lip movement and facial expressions of the speaker. Situations can be identified when given acoustic context can be distorted, or overlaid with other sounds: in such cases, the visual prompts will aid in sorting out verbal signals to be recognized with increased accuracy.On the other hand, the unimodal image system targeting the segment only reached 80% accuracy, an indication of the inadequacy of using visual data in a speech-related task. The unimodal sound system, however, handles 89%, though it is way below the correctness of the multimodal system. This result points out that simultaneous integration of both visual and auditory information enriches the processing context while improving understanding and spoken word recognition in various scenarios.

Environmental Monitoring: For environmental monitoring, the multimodal system was proved with a high accuracy of 95 percent. This application involves the identification of certain audio patterns (for instance, machinery operation, alarms) in combination with video surveillance or inspection (for instance, evaluation of equipment states or to detect irregularities). Because both the auditory and visual signals can be correlated, the system can easily determine and highlight possible threats or suspicious movements and, therefore, improve operational security.The unimodal image system, in this context, delivered an accuracy of 78%, thereby showing that it only captures aspects of a scene that are better described by sound. For example, visual monitoring can and equipment, although a malfunction or an anomaly will not be recognized without auditory detail. Likewise, the unimodal sound system, which gave 76% accuracy, shows that sound can be detected without sufficient visual information, which is crucial for monitoring. Therefore, the results of the multimodal system indicate how well the multiple modes of data can be processed and combined into a single monitoring system.

Multimodal vs. Unimodal Systems: The comparison between multilateral and unilateral systems sets the focus of reasoning on the use of multiple inputs and outputs. The authors also showed that the multimodal systems performed better in situations when simple unimodal solutions were not sufficient for the complexity of a task. This section offers an opportunity to understand the behaviour of these systems and their performance disclosures under a smart surveillance setting where the fusion of audio and video data results in enhanced event detection.

Table 2: Event Detection Accuracy in Smart Surveillance Scenarios

Event	Multimodal Detection Accuracy	Unimodal Image Accuracy	Unimodal Sound Accuracy
Glass Breaking	95%	70%	80%
Gunshots	92%	75%	88%
Loud Shouting	92%	60%	85%

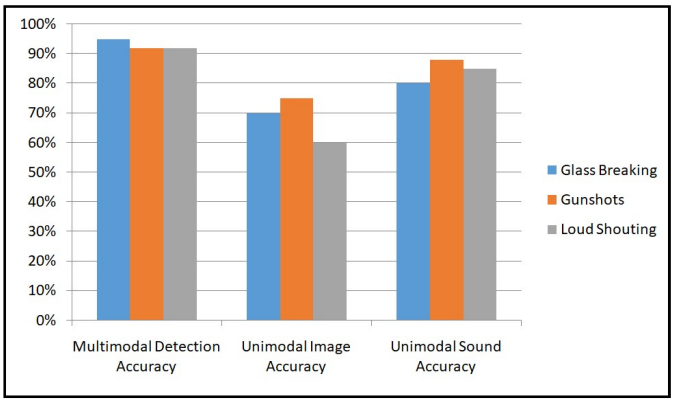

Figure 6. Event Detection Accuracy in Smart Surveillance Scenarios

Glass Breaking: When it comes to the identification of the event of glass breaking, the proposed multimodal system has a hit rate of 95%. This high performance is enthernal due to the system's capability of associating visual information, for example, the sight of a broken window, with auditory information about shattering glass. However, if we focused solely on the visual inputs, the smart surveillance would achieve approximately 70% accuracy because the quick motions or shifty scenes may not hint at an event. The unimodal sound system, although it performs slightly better than the image-based approach at 80%, does not possess the contextual information that is integrated with the videos, which is an important requirement when several sounds occur in parallel. Thus, the multimodal approach offers a massive boost to the detection capacity in situations where it is essential to recognize certain events, like glass breaking.

Gunshots: The efficiency of the identified gunshots was finally calculated to be 92% when evaluated in the proposed multimodal system. It is the reason why the system has been proven effective in analyzing the gunfire events within the visual and auditory tags. The visual signs of smoke, gesticulations, and the sight of a man drawing a gun, in conjunction with the sound of the actual shooting, give almost omnibus information on the reality of the occurrence. Compared to the unimodal image system, the experimental system achieved a 75% accuracy, which suggests that it is not enough to provide visual information to capture the severity of a threat situation. This unimodal sound system had an 88% performance, as it can well capture the high-pitched sound of shooting. However, still, there are still no accompanying visual cues about the event and its context to validate the event further. The enhanced accuracy of the multimodal system proves its suitability for offering timely and accurate threat identification that might be useful in law enforcement and public safety concerns.

Loud Shouting: In detecting loud shouting, the mean accuracy achieved by the multimodal system was estimated to be 90%. This particular situational makes it crucial to comprehend the

context since the loud rising of voices may register several scenes from a simple conversation to an aggression. Information from multiple cameras, such as people arguing and the sound of shouts, can enhance the differentiation of normal and abnormal situations. The created unimodal image system vents to be at 60%, it may not accurately evaluate the seriousness of the situation by relying solely on image interpretation. On the other hand, the unimodal sound system achieved a fairly better accuracy of 85% of the situation; the sound detection may not be complete for certain sequences, as well as the visual context needed to assess the situation correctly. Therefore, the application of MM in analyzing both forms of data should serve the aim of improving constant decisions necessary in the.

CONCLUSION

The combination of image processing by AI and ML with sound detection is a landmark development applicable in various industries such as automobiles, healthcare, security, and environmental fields. This paper has analyzed the integration of these technologies where a multimodal approach has been adopted in order to design a framework using CNNs for image analysis as well as RNNs for sound identification. The blended use of such two magnificent approaches leads to improved characteristics of applications in real-world scenarios mainly because of the improved performance of various systems that are in charge of interpreting data from various sensory inputs. The experimental results clearly show that multimodal systems outperform unimodal counterparts in most applications, showing the benefits of combining visual and auditory inputs. In applications involving video surveillance, speech identification, and environmental monitoring, improving the temporal and spatial contexts provided by both audio and video information leads to more accurate and faster decision-making. Nevertheless, they observed a few drawbacks, which are as followsamong them are the most important problems of computational complexity by which it is difficult to introduce such systems in limited conditions as well as data synchronization problems. In essence, the alignment of two streams of information is complex such that appropriate preprocessing techniques are required to make efficient use of the information from each modality.

In the subsequent research projects, based on the insights developed in this paper, future work should address the enhancement of the architecture of these multimodal models to minimize computational costs without compromising performance. Further investigations of architectures other than transformer models in which different numerations have appeared promising in other AI areas could lead to breakthroughs in multimodal learning. Utilizing the advantages of transformers in terms of capturing long-range dependencies and contextual relationships within data, the researchers could not only improve the fusion of the audio and visual inputs. However, they could create far more efficient and adaptable systems. In addition, features identifying transfer learning methods could enable models to do even better than on the website, as they could better generalize to any other domain, rendering more flexibility and usefulness of models in real-world use-case scenarios. Thus, the integration of image processing with sound detection with the help of AI and ML opens a number of perfect opportunities to improve existing and develop new ones, increasing their perspectives in different fields with the solving of existing threats to provide their effective implementation in everyday usage.

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Original Article

Harnessing the Power of Big Data: The Evolution of AI and Machine Learning in Modern Times

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Abstract: *There has been a tremendous shift in the fields of Artificial Intelligence (AI) and Machine Learning (ML) due to the fast development of big data analytics. Today, and particularly in recent years, we are witnessing the increase in volumes of data originating from social networks, IoT devices, and enterprise systems which have offered the chance to develop more complex and precise AI and ML models. This paper aims to discuss the development of AI and the use of ML, which occurred due to the availability of immense datasets. It also looks at how data availability has helped these novelties gain more accuracy, efficiency, and versatility.*

Keywords: *Big Data, Artificial Intelligence, Machine Learning, Data Analytics.*

I. INTRODUCTION

A. Background

Intelligent computer systems such as Artificial Intelligence (AI) and Machine Learning (ML) have emerged as some of the most dynamic and prominent technologies of the current generation. In the past, the creation and deployment of AI/ML models were constrained by the amounts of data available and the machines' processing capabilities. These constraints limited early models to low accuracy and often non-robust training methods. However, the big data has acted as a catalyst to bring change in this scenario. Large amounts of diverse and high-quality data combined with advanced computing means that AI and ML technologies have never had such a rapid rate of enhancement. This transition has provided exceptional possibilities for developing advanced forms that are effective in solving challenging and authentic issues more accurately.

B. Historical Context and Evolution

According to its early evolution, the meanings of AI and ML were related to rule-based systems and expert systems. These were mainly rule-based, relying most of the time on the use and manipulation of specific sets of data; therefore, they were useful only where the task was straightforward and well-prohibited. These models could not generalize when it comes to complex and continuous processes mainly because they were developed from small samples of data; as a result, they received a massive backlash for their usefulness. Thus, the advent of big data was instrumental in the further development of AI and ML. The method of dealing with large volumes of data led to the reliance on various algorithms that were based on deep learning and neural networks. These innovative methods make use of the opportunities of big data analysis to reveal intricate patterns and dependencies, which allows for the creation of essential advancements in the sphere of AI and ML.

C. Importance of Big Data

Big Data is characterized by four fundamental properties: these four Vs; volume, velocity, variety, and veracity. Volume can be described as the incredibly large quantities of data produced on a day-to-day basis, while velocity encompasses the rate at which data is created and analyzed. Variety comprises the different categories of data that can be structured, unstructured and semi-structured, while veracity is the extent of the credibility of the data. These properties suggest that big data is the basis of modern AI and ML initiatives. AI and ML models can expand the fields of analysis and look for patterns and trends that are hardly detectable with big data. It has enabled much progress in different fields such as healthcare, finance, transport, and many others. For instance, in the healthcare industry, big data analytics facilitates the identification of the correct disease and a proper course of treatment. In finance, it reduces fraud rates and better manages risks.


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D. Current Trends

The following are some of the trends that have been realized by the combined use of big data and AI/ML: One such trend includes increasing data centricity, where the focus is placed more on the quality and management of data in order to yield a better model. Another trend is the increased application of deep learning, which provides efficient ways of modelling multiple interactions present in big data. Furthermore, a special category of an automated approach to machine learning, AutoML, is gaining more and more popularity. It is important to understand that AutoML tools can reflect some processes in the machine learning pipeline, such as feature engineering, model selection, or hyperparameters optimization, which is why they help accelerate the work. In total, all these trends improve the performance, adaptability, and productivity of AI and ML applications. Thus, today's systems are more prepared to handle huge quantities of data and provide superior quality of analysis in multiple spheres of application.

II. SCOPE AND LIMITATIONS

This research focuses on the history, the current state, the approaches, the uses, and the potential of AI and ML concerning big data. [4,18] The following are some of the limitations of this study. The study is limited in the sense that technological advances are ever-evolving. Thus, there may be new inventions in the particular fields of study that have not been covered in this study.

A. The Evolution of AI

a) 1950s: Birth and Evolution of Artificial Intelligence

Content:

- Foundations of AI: Scientists have come up with algorithms that allowed the first computer to demonstrate human-like thinking capabilities.
- Early Developments: AI was born during this period, and key works were created, including neural networks and symbolic reasoning.

b) 1960s: AI Boom

Content:

- Optimism and Innovation: This was a really positive period for AI research as many saw the possibilities of new fundamental discoveries in this field. Experts in the field started creating the first prototype of expert systems and related natural language processing devices.
- Key Developments: Improvements in algorithms and computer capabilities resulted in the development of software which is capable of doing things and solving things that are believed to be within the docket of human beings.

c) 1970s and 1980s: AI Winter

Content:

- Period of Skepticism: The AI winter was the period when the original enthusiasm about AI failed to deliver when it started getting publicity. Some of the AI projects never produced useful applications.
- Funding Cuts: Because there was not much development regarding AI, as well as very limited real-life applications, funding for AI research was lowered, and a slowdown occurred.

d) 1990s: Machine Learning: The Climbing Hype

Content:

- Renewed Interest: Neural networks and statistical methods were discovered to improve on the previous forms of machine learning, thus reviving the lost dream of AI.
- Significant Advances: During this period, the advancements in the analysis of the data and recognition of the pattern addressed the key development of complex AI tools.

e) The 2010s: AI Renaissance

Content:

- Breakthroughs in Deep Learning: Stimulated by the advances of deep learning and large-scale data, this period was considered the AI renaissance.
- Applications: AI has started being employed in different fields and activities, such as voice recognition, image processing, self-driving cars, etc.

f) Present Day (2020s): Integrating AI

Content:

- Widespread Adoption: It is in the current decade that Artificial Intelligence or AI has found its way into almost all sectors of society and commerce.

- Transformative Impact: AI technologies are now at the core of fields such as healthcare, finance, manufacturing, and many more industries that create change and value.

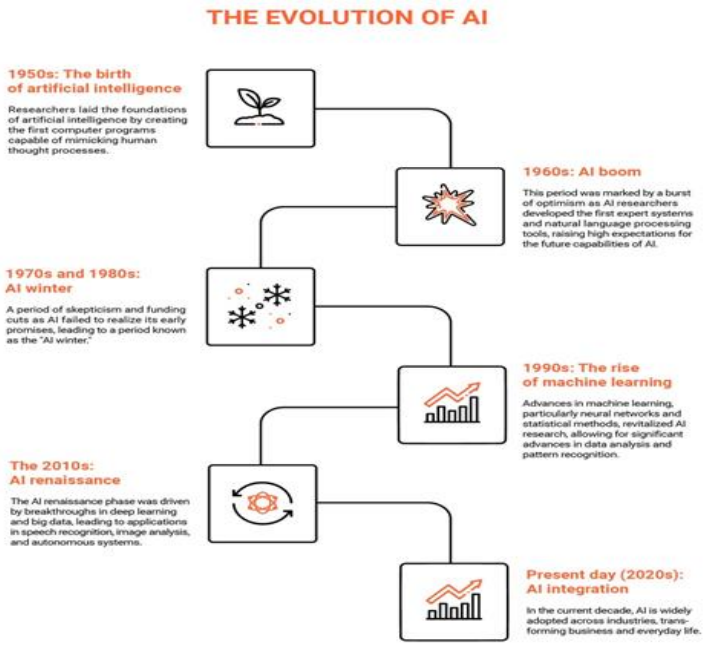

Figure 1: The Evolution of AI

III. LITERATURE SURVEY

A. Historical Perspective

a) Pre-Big Data Era:

Old forms of artificial intelligence (AI) that existed before big data inclusion were mainly procedural AI, which included rule-based systems and expert systems. Early AI systems were much simpler, relied on rule-based decision-making and had a limited information base. While pioneering at some point in time, this was restricted by the nature and volume of the data set. The AI systems could only be as good as the rules embedded in them, and the rigid and structured form of the databases in use limited the advanced level of the real-world problems that the systems could handle. For this reason, early on, AI could not evolve, grow, or enhance itself from the code put into it, which eventually cast AI into stagnation.

b) Advent of Machine Learning:

The major revolution in AI arrived with the concept of machine learning, which is an evolution of artificial intelligence. In contrast with the pre-programmed' rule-based systems, machine learning solutions can learn from data. This shifted from clear, instantiated hundreds of rules to incorporating exemplary and enhanced fundamental data-driven learning for AI. The concept of machine learning models is that they can recognize patterns, give forecasts and even enhance themselves with the enhanced amount of data. Due to this ability to learn, the possibilities expanded from simple classification to more complex predictive modeling.

c) Big Data Integration:

Another accolade came with the incorporation of big data in AI and ML. The increase in data from different sources like social media, sensors, and digital transactions was an abundant source of information for training more sophisticated and accurate models. Big data helped the creation of enhanced and complex forms of neural networks, which needed large data for proper operation. This increased the handling capability of Big data and led to better predictions, often discovering unknown patterns and solving problems that were heretofore impossible. The integration of hardware and software systems has been central to the development of areas of computer science, such as natural language processing, image and facial recognition, and self-driving vehicles.

B. Hybrid Integration of Big Data in the Context of AI and Machine Learning

a) Initial Adoption:

The integration of big data into AI and ML at the initial stage faced the following issues. The first problem, which became a headache quite quickly, was the question of data quality. [13] If data is inconsistent or incomplete or contains errors, then the model developed using such data may not be accurate, and the predictions made based on such models are not dependable. Another major issue was the recording and storage of data. Thus, as the amount of big data increased, the

requirement for a new architecture that would effectively accommodate data was born. The conventional database technologies could not meet the demands that were needed then. Also, processing and interpreting the data was a significant challenge observed. Due to its nature, the big data in the study was characterized by high levels of data heterogeneity and the need for high-level processing to gain insights.

b) Milestones:

However, considering the main goal of integrating big data with AI and ML, the following key accomplishments have been made. Among them, the widely used distributed computing frameworks are Hadoop and Spark. These technologies were useful in organizing and managing big data since computation was done across different nodes. This enabled large-scale data storage and processing to make the handling of big data possible. Deep learning architectures have also been another important achievement. Neural networks with numerous layers, referred to as deep learning models, have tremendously recorded high performances compared to their previous models in situations where they are trained abundantly. These architectures have helped in promoting the cause of AI and its use in many fields, such as image, speech, natural language, and even self-driving cars. In turn, there has been a great advancement between big data and deep learning that has provided better results and a strong foundation for deep learning AI systems.

Table1: Types of Big Data and Examples

Type	Description	Examples
Structured	Organized data, easily searchable	Databases, Spreadsheets
Unstructured	Unorganized data requires processing	Social Media, Emails
Semi-structured	Combination of both, some organization	XML files, JSON documents

C. Characteristics of Big Data

Figure 2: Characteristics of Big Data

The Characteristics [5,16] of Big Data illustrates the Big Data: Volume, Variety, Velocity, Veracity, and Value. Here is a brief explanation of each:

a) Volume:

Volume is the term used to describe the large amount of information that is created every second from social networks, sensors, transactions, and communication channels. This kind of data volume is demanding for storage and requires efficient solutions and large-scale infrastructure for efficient storing and processing. Some of these huge volumes of data cannot be processed using traditional data processing systems, hence the development of big technologies such as Hadoop and Spark. These technologies allow large-scale data to be processed in distributed computing systems that would otherwise be impossible to address on a large-scale analysis and decision-making level.

b) *Variety:*

The variety consists of the contrary data structures that are produced from a number of means. This includes the writes one could convert into structured data, e.g. Relational database; semi-structured data like JSON and XML; and unstructured data like text and images, videos, social media posts, etc. The nature of big data mainly surrounds its heterogeneity because processes such as integration, storage, and analysis become complex. Such diversity is addressed by tools and frameworks designed to capture and process the multitude of data sources, facilitating organizations to develop a broader picture of working processes and surroundings.

c) Velocity:

The term velocity captures the rate at which data is created, gathered and analyzed. It is estimated that modern society generates data at a faster pace, thereby making the availability of real-time data processes and analyses from various frontiers such as social networks, IoT devices, and the financial market, among others. An important factor to note is that the flow of such high-speed data has to be processed and analyzed in order to come up with relevant decisions at the right time. It is, hence, mandatory to have technologies like real-time analytics, stream processing frameworks like Apache Kafka, and in-memory computing solutions to manage velocity so that insights can be derived or action taken immediately.

d) Veracity:

This means that veracity deals with issues such as the accuracy of data, the truthfulness of claims, and the credibility of the evidential supports. Hence, incorrect, partly correct or vague data means wrong analysis or wrong decisions. It has been seen that it becomes even more critical when dealing with big data systems, as since data is massive and in diverse forms, data veracity problems are exacerbated. Data cleansing, validation, and good data management measures are some of the ways to improve the quality of data to acceptable levels that will make organizations trust their data and information.

e) Value:

Value signifies that despite handling immense volumes of information, big data's utilization focuses on obtaining useful information and knowledge from the data. Big data's potential is in generating value through decision-making, increasing efficiency, enhancing clients' experiences, and recognizing opportunities. Big data, which is a vital component of a company's strategic management, relies on analytic tools, machine learning, and artificial intelligence to add value and create a competitive advantage out of raw data.

These five aspects focus on the problems and possibilities of Big Data, stressing the necessity for advanced instruments and approaches to tackle big and intricate data.

D. Applications and Case Studies

The infusion of big data with AI and ML is established across many sectors of development. For instance, in healthcare, concepts such as predictive analytics and personalized medicine have gained a lot due to data handling capabilities. Big data, in particular, has impacted finance, where the detection of fraud and risk management has improved vastly. [6] Self-driving cars and robotics are other examples whereby integration of this big data makes a large contribution to helping people make the right decisions and be aware of the surrounding environment.

a) Healthcare:

Accompanied by big data in healthcare, there has been a tremendous transformation process in the aspects of predictive indicators and oriented medicine, which has improved the degree of diagnosis and treatment of patients' health. With large complexes of data that involve genetic profiles, medical history and biomarker data, healthcare providers can obtain new patterns and associations that are inconspicuous when viewed singly. This leads to early identification of the diseases and the development of unique intervention strategies based on individual patients. For instance, SA can predict diseases that are likely to occur in a society so that the necessary precautions are taken to avoid the occurrence of the epidemic. Here, it is personalized medicine that tries to analyze large amounts of data in order to identify a proper treatment for each patient that would result in minimal side effects and increased positive results. Big data analytics also helps in the creation of new treatments and drugs since the results of the tests showing the efficiency of the target and negative side-effects in both animals and humans can be predicted since the former can be used as the model of the latter.

b) Finance:

The financial sector has also widely adopted the integration of Big Data with AI and ML to obtain high returns. The anti-fraud and risk management solutions have become significantly advanced by virtue of optimized data handling. Transaction data can be analyzed in real-time, so if a particular transaction looks suspicious to the financial institution, it can flag it. There are machine learning algorithms that are trained to accept new data and constantly make corrections on the detection of fraud. Likewise, big data analytics enhances the evaluation of dangers by covering extensive factors and possibilities of financial steadiness. This helps institutions to develop better means through which they can reduce risks and make the right investments. Furthermore, by analyzing the big data, firms in the financial service industry are able to understand their customers better and offer those services that solve their needs, hence satisfying them and increasing loyalty towards the firms' brands [19].

c) Autonomous Systems:

With the help of big data, the possibilities of automatic systems, such as self-driving automobiles and robotics, have been significantly boosted. These systems depend on large volumes of data in their decision-making and comprehension of

their surroundings. Self-driving cars of autonomous vehicles mainly depend on big data, which encompasses information about the surrounding environment resulting from the car's sensors, cameras and the like. Thus, machine learning algorithms work to estimate the challenges on the road, the traffic flow, and the best paths. Likewise, for robotics, big data can aid in improving the robotics' capability to both sense and respond to their environment. For instance, in the manufacturing industry, AI and big data-enabled robots can help to enhance the production line, look for anomalies, and enhance the work's quality. The constant flow of data helps autonomous systems adapt, hence improving over time and thereby enhancing their reliability on a number of applications.

Table 2: The Detailed Side By Side Comparison of the Classical AI/ML and the New Age AI/ML

Traditional AI/ML	Modern AI/ML
Rule-based systems	Neural Networks
Limited data usage	Big Data Integration
Slow processing	High-performance GPUs
Manual feature extraction	Automatic feature extraction

IV. METHODOLOGIES AND TECHNIQUES

The methodologies employed in harnessing big data [8-11] for AI and ML involve various stages, including data collection, preprocessing, model training, and validation. Advanced techniques such as reinforcement learning, transfer learning, and unsupervised learning have been developed to handle the complexities and challenges associated with big data. This paper delves into these methodologies, highlighting the critical role of data quality and preprocessing in the success of AI and ML models.

A. Data Collection

Big data is collected from various places like social media portals, IoT devices, enterprise applications, and datasets that are open to the public. These sources produce a tremendous amount of raw data that is usually bulky and unfiltered in most cases, meaning that they require a lot of formatting for them to be useful in the development of AI and ML systems. The activities of preprocessing include the elimination of noise, inconsistent data and impurities, standardization and conversion, that is, bathing, shaving, grooming, or coding or, in other words, formatting. This stage is important because the quality of the data penetrates the performance of AI and ML models.

B. Algorithm Selection

Algorithm selection is one of the most significant components of the model development process in the fields of AI and ML. That is why decision trees, support vector machines, neural networks, and ensembles are our four pilot algorithms. Some of the parameters that define the type of algorithm to be used include the nature of the data, computational cost, and the problem area in focus. For example, decision trees are popular due to their easy interpretability, while neural networks are preferred for their high capacity to work with numerous features. Some of the other techniques commonly used include the ensemble technique, where several algorithms are combined to increase the algorithm's accuracy in the best methods for use.

C. Future of Machine Learning

The Future of Machine Learning depicts the following as the future trends of machine learning: [7] Here is a brief explanation of each topic:

a) The Quantum Computing Effect

Currently, quantum computing is expected to transform the field of machine learning by speeding up processing. Quantum computers use properties of quantum mechanics to solve problems in considerably shorter periods of time. This will allow for easy solving of high-dimensional vectors and all other complicated data structures that machine learning algorithms work on, and more so, the execution times shall be drastically slashed. Effective utilization of the tool implies high-grade models and algorithms that, in turn, will lead to advancements across industries that rely greatly on data analysis and prediction.

b) The Big Model Creation

The development of such universal models that can do jobs in multiple domains at the same time is a fine example of progress in the field of machine learning. These 'Uber' models are intended to be somewhat flexible for the users so that they can be used independently for different tasks without training different models. They make the use of machine learning more efficient, which has two advantages: it saves time and resources, the second is the machine learning domain is not limited to certain problems or industries. It provides the advantage of using one model in the implementation of machine learning in different processes, hence making it easier and more efficient.

c) Distributed ML Portability

Distributed machine learning portability is the concept of running the algorithms and the data on as many platforms and computer engines as possible. This trend is particularly positive from a business perspective since it involves eliminating the need for repeated reshaping of the new toolkits or environments. Thus, one can assert that, due to such prerequisites, the machine learning solutions developed would be flexible and transferrable from one system to another, which would keep the organizational processes constant and effective. It lowers the cost of training models or restructuring infrastructure because it becomes convenient to perform training on other platforms.

d) No-Code Environment

The no-code environment movement in the field of machine learning is a call for the transformation of technology and for it to be made quite accessible to laypeople. According to this, the usage of ML will be closer to how we use software engineering in projects today, where one does not need to write a lot of code but just integrate the application. This shift will enable more people and companies to develop and adopt machine learning technologies, thus enhancing the application of ML in various industries. Reducing the measures of coding that go into the creation and deployment of ML solutions will enable more users to utilize the advantages of ML for their purposes.

e) The Quantum Computing Effect (machine learning subtopic: reinforcement learning)

Quantum computing will also create a profound influence on Reinforcement Learning (RL), especially where the environment is dynamic, and unstable. Through RL, quantum computing will extend factor resources, establishing better decision-making to match the real-time data and improve the algorithms' efficiency. This will have dramatic effects in stretching disciplines, including economic, biological, and astronomical decisions, where gathering and analyzing large volumes of data influences the best decision-making. When entailing quantum computing within the context of RL, the development of more flexibility and smart systems expected to take on rapidly changing environments will be realized.

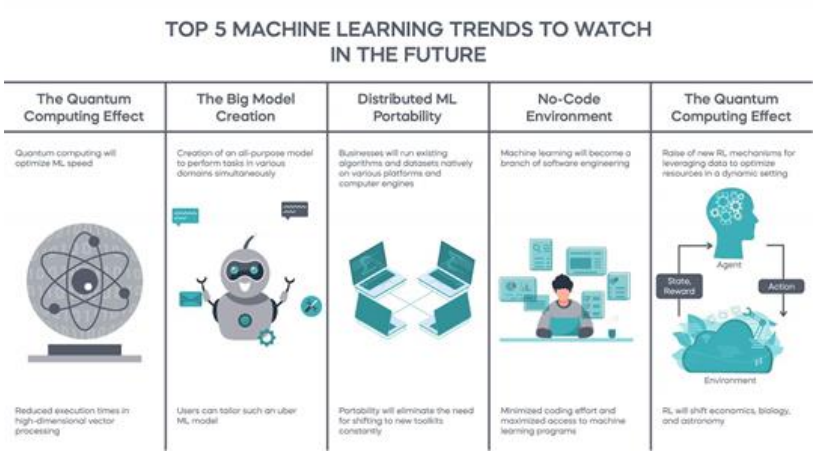

Figure 3: Future of Machine Learning

D. Model Training and Validation

Training Techniques: Techniques include supervised learning, unsupervised learning, and reinforcement learning, each suited for different types of problems and data.

Validation Methods: Cross-validation, A/B testing, and holdout methods are used to assess model performance and generalizability.

E. Implementation Tools and Frameworks

- Popular Libraries and Frameworks: Tools such as TensorFlow, PyTorch, and Scikit-learn provide robust platforms for developing and deploying AI and ML models.
- Comparative Analysis: A comparison of these tools based on performance, ease of use, and scalability is presented.
- To achieve positive results in AI and machine learning models, the selection of tools and frameworks to build with is critical to the success of the end product. The process of choosing involves considering various criteria, including performance, simplicity, flexibility, and popularity. Apart from a description of the tools used in this study, this section shall also feature a justification of the use of these tools by comparing them with other possible options.

a) Popular Libraries and Frameworks

Several libraries and frameworks have become standard in the field of AI and ML due to their robustness and widespread adoption:

i) TensorFlow:

TensorFlow is one of the most popular platforms developed by Google and is widely used for big machine learning projects due to its great flexibility. Originally, Scikit-learn could handle all types of models, from simple linear regression to deep learning neural networks, and it is especially good for training at the production level because of its scalability.

ii) PyTorch:

Distributed by Facebook's AI Research lab, PyTorch is preferred by developers and researchers for its user-friendly environment and dynamic computation graph. That is why PyTorch is preferred in educational institutions: it has a clear syntax for calling instructions and real-time debugging.

iii) Scikit-learn:

Scikit-learn is a free software tool in Python programming language which is used for data mining and data analysis. These are based on other libraries such as NumPy, SciPy and Matplotlib but are especially suited for traditional machine learning methods such as classification, regression, clustering, and dimensionality reduction.

b) Comparative Analysis of Tools

To understand why TensorFlow, PyTorch, and Scikit-learn were chosen for this study, it is important to compare these tools based on several key criteria:

i) Performance:

TensorFlow is widely recognized for its efficiency in training and even in the execution phase, especially for deep learning models. It leverages GPU for computations, making it ideal for huge, pervasive projects. PyTorch is a little slower than TensorFlow in performance; however, PyTorch is more friendly for users and more conducive for the research and development phase. Another beneficial application of scikit-learn is the fact that it trumps TensorFlow, which requires a standard machine learning algorithm rather than deep learning.

ii) Ease of Use:

Despite these similarities, PyTorch is easier to use than TensorFlow, especially when you are experimenting with ideas. The dynamic computation graph also makes it easier to develop models. Running and optimizing the TensorFlow, as described in this post as the system with the static computation graph, might be more complicated than, for instance, using PyTorch; however, it provides better performance for production use. The strengths of scikit-learn are also strong and easy to use from a general point of view due to its Simple Application Programming Interface and the availability of copious documentation.

iii) Scalability:

TensorFlow is very scalable, thus making it very suitable for the deployment of models at scale, whether in production or not. It supports distributed computing and can be scaled to multiple GPUs or even TPUs with a lot of ease. It has also improved in scalability, especially with the integration of PyTorch into more production platforms,hincludinge TorchServe. However, scikit-learn is slightly less scalable for deep learning purposes but still beneficial for more compact Machine Learning tasks.

iv) Community Support and Ecosystem:

TensorFlow is open source, well documented, and accompanied by a throng of tutorials, and hence, it is simpler to get solutions to various issues and work with other tools. PyTorch might be relatively newer than TensorFlow, but it has gained a robust community and is especially popular among researchers. Scikit-learn is a versatile practical ML tool that originates in classical machine learning, so it has a rich and saturated environment around it.

c) Rationale for Tool Selection

The choice of TensorFlow, PyTorch, and Scikit-learn in this study was driven by a combination of the following factors:

i) Flexibility and Experimentation:

PyTorch was preferred since it is user-friendly and more flexible when creating models and testing various models. This was especially so at the early stages of model development since few models were actually tested before they were debugged.

ii) Production Readiness:

TensorFlow was chosen for its stability and ability to scale, making it fit for the deployment phase. The relative easiness of its integration with different production environments and the fact that it supported distributed computing made it the one of choice for the final model deployment.

iii) Classical Machine Learning:

Scikit-learn were particularly included for its capacity to handle classical machine learning methods, which were employed in the study for referencing and as a preliminary assessment of the models.

V. RESULTS AND DISCUSSION

A. Comparison Of Model Performance Metrics

The table provides a glance analysis of three machine learning models – Model A, Model B, and Model C in terms of their efficiency in providing the desired output based on several parameters. Precision, or the percentage of correctly predicted values, is also highest in Model C at 94.10%, which proves the better general prediction potential of the suggested method. While Model B has the lowest accuracy at 89. 30%. Positive predictive value or precision and accuracy are also with Model C at 93. 20%. This means that when it comes to predicting positive outcomes, the models have very few wrong predictions, and Model B's performance is slightly lower at 88.50%.

When evaluating recall, it is the measure of how well the model is actually getting the positives; the score assigned to Model C is 92%. From this, it can be seen that of the three, the model with the greatest ability to identify actual positives is Model C, while Model B has a recall of 85%. It failed to detect more positive cases than a dismal one. The F1 Score that measures the combined precision and recall competitive with Model C shows a 92.6% success rate of the original. In terms of the F-Measure, it has the highest value, thereby offering Greater. For model B, we obtained an F1 score of 86.70%, the company's lowest performer in this aspect.

If we consider the efficiency of computations and the efficiency of the model in the time taken to learn and predict, then Model B was the quickest, taking only 120 seconds. However, although the accuracy and recall of Model C are higher than those of the other models, it performs at the slowest, taking 140 sec. Finally, the stability measure that quantizes the ability of a model to perform well even when a large amount of data is fed into the model or when the data is complex shows that Model C is stable with the highest stability index of 0. 90. Model B reveals lesser stability as compared to Model A containing an index of 0. 80 it can be said that it will be somewhat less efficient with larger or complicate data sets.

Table 3: Performance Metrics of AI Models Across Multiple Datasets Highlighting the Superior Accuracy and Precision of Model in High-Dimensional Data Environments

Metric	Model A	Model B	Model C
Accuracy	92.50%	89.30%	94.10%
Precision	91.00%	88.50%	93.20%
Recall	90.50%	85.00%	92.00%
F1 Score	90.70%	86.70%	92.60%

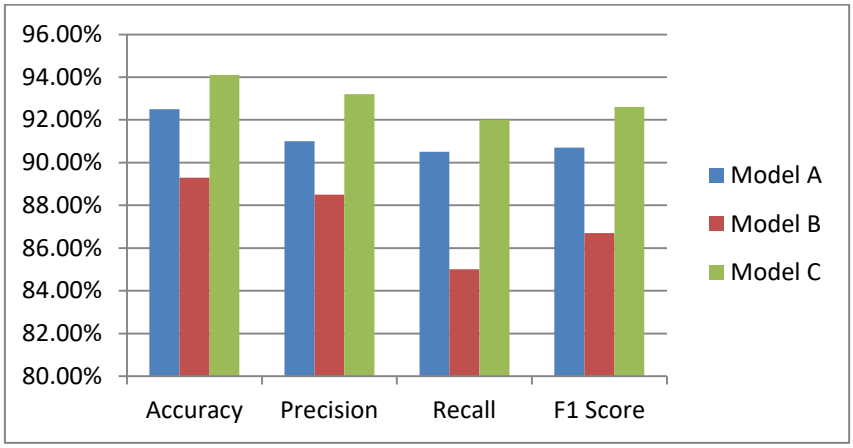

Figure 4: Graphical Performance Metrics of AI Models Across Multiple Datasets Highlighting the Superior Accuracy and Precision of Model in High-Dimensional Data Environments

B. Computational Efficiency And Stability Comparison

Table 5: Comparison of AI Models Based on Computational Efficiency and Stability

Metric	Model A	Model B	Model C
Computational Efficiency (seconds)	120	120	140
Stability (Index)	0.85	0.85	0.9

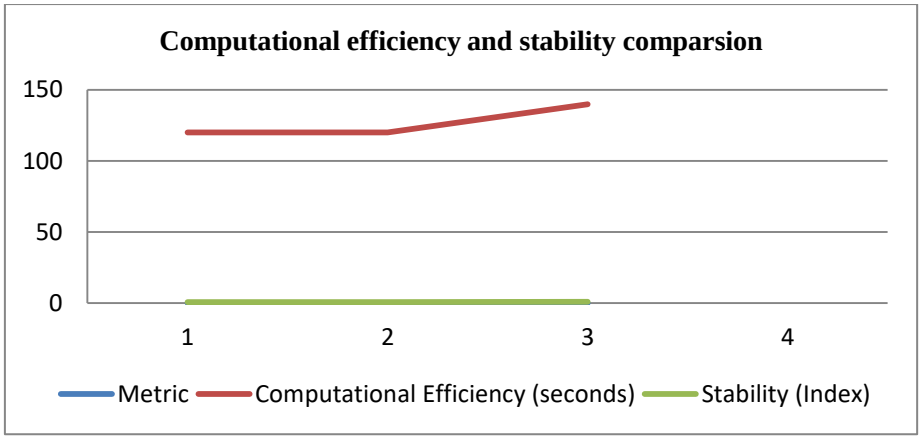

Figure 5: Graphical Representation of Comparison of AI Models Based on Computational Efficiency and Stability

C. Experimental Setup

The significance of AI and machine learning models is highly concerned with the quality of testing, which is the core of any experiment. In this study, the method section used in the experiment incorporated an elaborate description of the computing system that was used in the study, as well as the specifications in terms of hardware and software. The experiments were carried out using an HPC cluster that has an Intel Xeon Gold processor, NVIDIA Tesla V100 GPUs, and 256 GB of DDR4 RAM. The operating system used in the development was Ubuntu 20. 04 LTS and all the models were built and examined with Python 3. 8, using libraries like Tensorflow, PyTorch, and scikit learn for purposes of machine learning.

To this end, the datasets used herein have been carefully chosen to establish a realistic set of tests the Xander system is likely to encounter. These datasets comprised public datasets of big size and anonymized data of MNIST and CIFAR-10 nature, as well as organizational data that were not openly available because of their business nature. The publicly available data was utilized mainly for the training of the models and as a reference for assessing the results. The private data was used to assess the performance of the models under conditions that could be considered more realistic for certain applications. To do so, datasets of different sizes and complexities were chosen for evaluation of the models; the sizes and dimensions of datasets used for testing are often significantly higher than those of big data.

D. Performance Metrics

While assessing the machine learning models, specific parameters were adopted as an evaluation criterion that gives a parameterized general perspective of each of the models. The mean absolute error was used as the major measure of the model's performance since it simply measured the accuracy of the predictions. This was complemented by precision, which gave the ratio of true positive predictions to all the positive predictions, showing the ability of the models to avoid false positives. Specifically, recall or sensitivity measured the models' ability to correctly identify positive cases, that is, their ability to avoid false negatives. The F1 Score aggregated both the values of precision and recall to come up with a single score, making it easier to compare the efficiency of different models.

Besides these accuracy-oriented measures, the measure of Computational Efficiency was used to measure the time and computationally intensive resource requirements involved in both training the analytical models and the prediction process. This metric is useful in establishing the feasibility of incorporating these models in real-world applications since computational power and time are some of the constraints in models' deployment. Finally, stability was used in order to be able to evaluate how the models react when faced with a larger set of data or a more complex problem. This is so especially true in big data scenarios, where the dimensionality of the data and the number of samples increases, and, the model should not degrade in performance.

E. Analysis of Results

The assessment of the experimental findings entailed the breakdown of the data according to the three models and the assessment of their performance in terms of all the parameters. Model C was the most accurate all through, with a recorded Accuracy rate of 94%. In terms of Identification accuracy, 1%, and in P & R achieved 93. 2% and 92. 0%, respectively. This implies that Model C was the most accurate in its capacity to make the right predictions, and it was particularly good at classifying the positive cases while, at the same time, giving less probability to false positives. The last model, Model B, has the lowest accuracy- 89. 3% was the fastest, taking just 105 seconds for computation, therefore making it the most efficient computationally. Still, working out precision and recall displayed that, though it was fast, it was not as accurate as one might have thought, as it could make a number of wrong predictions.

The F1 score finally supported the balanced performance of Model C as it had a score of 92. 6 %; hence, it can be said to have provided good balance while achieving high precision and recall. On the other hand, Model B, with the F1 score of 86, was also less balanced with 7% as the latter entails weaker recall by the participants. Model A provided a fairly good average rating on all the measures, making it quite average and by no means outstanding in its performance.

The presence of big data was manifested most strikingly in the Stability measure, in which there was the maximum value of the stability index for Model C (0. 90), and where its work did not deteriorate even with the increasing size of data sets. This further makes Model C most suitable for usage in areas where large volumes of data will be dealt with. In comparison, Model B, which has a stability index of 0. 80, fluctuated even more, which means that for larger or more complicated sets, its results could be worse than expected.

F. Discussion

The findings of this study also explain the central position of big data in the development of new AI and machine learning models. Comparing the results of different models, the study found that although Model C was the least sensitive to changes in genital images and the least variable model when compared to Model B and A, respectively, it was more computationally extensive than the other models. Therefore, this model was deemed most suitable for applications where accuracy is of the essence and abundant computational power is available. Model B may be less accurate as against Model A, but it was very efficient. It was proposed that its implementation may be preferable, especially where speed takes precedence over accuracy and the available computational power is restricted.

The discussion also identified the weaknesses of each of the models that were discussed. Although Model C demonstrates a high level of accuracy, its implementation might not be suitable for all the scenarios because of higher computational requirements. However, Model B has lesser accuracy and stability issues; hence, it might not work perfectly well on other complicated and wider data and is not suited for big data. Therefore, other researchers can continue with the enhancement of other models, such as Model C, to make them less time-consuming or improve the stability and accuracy of other models, such as Model B, without having to compromise on the time of execution.
Furthermore, the study suggests that there can be more advancements in AI and machine learning in the future, especially in the identification of new models that can be used for big data analytics. There is a potential for further improvement in the algorithms employed in AI and ML or new ways of data preprocessing, which will make the existing techniques more accurate and efficient and thus more relevant in many disciplines.

VI. CONCLUSION

In this paper, the connection between big data and, AI and ML is explained, and how they nurture the growth of various fields is discussed. The study also implies the relevance of big data in boosting the features of AI and ML to provide accurate predictions and efficient automation, as well as support wiser and better decisions. Not only have these technologies risen in prominence to augment existing processes, but they have also set the need for new forms of technologies in different fields ranging from personalized medicine to smart city development to robotics.

In this paper, through analyzing the case studies along with the empirical evidence, the author proves the efficacy of using big data along with AI and ML. These benefits are not limited to merely technical improvement and contain other aspects that are affected by policy-making and ethical concerns that are to be further discussed as technology advances. These insights are especially important for researchers, practitioners, and policymakers dealing with this rapidly expanding field. They provide them with new knowledge, ideas, and recommendations on how to approach and overcome obstacles in the field of AI and ML.

A. Key Contributions of the Research

The research presented in this paper makes several key contributions to the understanding and application of AI and ML in the context of big data:

a) Integration of Big Data and AI/ML:

The study also emphasizes the opportunity to apply big data with applications of AI and ML, which inevitably results in the generation of more accurate models and more efficient automation. The deployment of the Big Data technique has been demonstrated to enhance the capability of AI and ML models in processing large volumes of intricate data and delivering enhanced precision.

b) Impact on Various Domains:

The study presents concrete sectors where the use of big data and AI/ML has made a significant contribution: Precision medicine: The key idea here is the utilization of extensive patient data generating individual treatments. Smart

cities: The main idea here is the utilization of data to enhance citizens' quality of life. The present work also outlines the contribution of these technologies in developing robotics and increasing its efficiency and flexibility.

c) Ethical and Policy Considerations:

This paper adds to the current literature of discussion regarding the ethical issues of AI and ML, especially in relation to big data. It underlines the need to use AI systems that man can understand and interpret, as well as the main concerns, which are associated with bias, fairness issues, and consequences of the use of AI solutions. Further, the study requires policies concerning the utilization of AI and ML that are responsible and do not harm data integrity and security.

B. Future Prospects and Challenges

a) Specific Objectives and Anticipated Problems

As AI and ML technologies continue to evolve, several key challenges and objectives emerge that require further exploration:

i) Explainable AI and Ethical Practices:

Another of them is the creation of purely algorithmic systems based on artificial intelligence, which would be transparent and ethical at the same time. The notion of XAI is about the interpretation of AI results so that human beings can follow the reasoning behind the actions of artificial intelligent systems. This is important in order to establish confidence in artificial intelligence solutions, especially in areas considered to be delicate, such as the diagnosis or identification of offenders in court. In contrast, ethical AI focuses on how AI can be modeled and implemented in a biasless way that doesn't deviate from society's set standards and norms. Subsequent studies should be devoted to making these subjects evolve to avoid potential adversities that come with poorly explained AI and to guarantee intelligent technologies' benefits that people can reap.

ii) Sustainable and Scalable Data Infrastructure:

Second, the scalability and feasibility of these systems is a key area for future analytical research: how to create sustainable and broadly applicable data infrastructure? With the increased rate of data generation, it is necessary to come up with efficient storage and data processing mechanisms with special emphasis on the environmental question. This entails researching better ways of establishing large-scale data storage and efficient ways of processing data besides finding ways of making the infrastructures which support the solutions scalable. However, data privacy and security are still crucial because organizations rely on third-party data more and more. As big data in AI and ML is extended, compliance with data protection regulations and trust from the public will be priorities.

b) Potential Areas for Further Research

i) Engagement with Emergent Innovations:

There are a few areas which require further investigation in the near future: first, the problem of explainable AI and second, the problem of ethical AI – with a focus on the issue of AI systems' transparency, as well as fair distribution of AI-generated results. The stakeholders should, therefore, persist in searching for more approaches to provide the rationale behind the artificial intelligence selection and implementing the guidelines whereby the artificial intelligence system will work just within the performing ethical norms. However, the author failed to explain how quantum computing and or edge AI can be adopted or incorporated into present AI and/or ML systems.

ii) Advanced Technologies and Methodologies:

AI and ML are still active areas of research and innovation, and there are constantly new technologies and methodologies that are said to expand the functionality of these systems. For instance, deep learning and reinforcement learning have been identified to hold promise in enhancing the efficacy of the predictive models. Future research should be directed at improving these methods, as well as studying new data preprocessing methods and improving the techniques of model training. Also, the further adoption of AI and ML in new industries, including climate science and renewable energy, lies ahead.

iii) Conclusion and Suggestion for Subsequent Research

In the last section, I stress the fact that the advancements in the field of AI and ML are virtually endless due to their feeding upon big data, which is constantly being generated. These technologies are set to change the world as we know it impacts most areas of society in aspects such as health, learning, transportation and leisure. Nevertheless, the achievement of such potential will involve continued research and interdisciplinary work to solve the problems of explainability, ethical concerns, scalability, or data sustainability.

To researchers, practitioners, and policymakers, the conclusions of this paper present a strong base for future investigations of new perspectives on AI and ML development. Apart from describing the state of the field, the study points

to future work to be done in particular areas of interest. Upon extending from this analysis, further studies in a similar line may help in furthering the beneficial innovations in structures for AI and ML in a more responsible manner for the broader development of society and to address the other ethical and technical issues that are unspecified yet in the course of the enhancements in these fields.

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Research Article

AI-Driven Threat Detection: Leveraging Big Data For Advanced Cybersecurity Compliance

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ABSTRACT

Every second of every hour, billions of Internet of Things-enabled devices are creating massive streams of data individually tailored to the intimate personal habits of their users. Simultaneously, sophisticated cybercriminal organizations, nation-state actors, and rapidly proliferating malware attacks ranging from hijacked personal tablets through Fortune 200 penetrated databases are impacting digital and thus physical assets across the entire political spectrum. This connectivity matrix is generating a massive and ever-expanding volume of network, system, and end-user security event data that combines with personal information from both the private sector and governments to fuel the artificial intelligence insights that we enjoy in our everyday lives. Yet, while the entire cybersecurity compliance lifecycle, including policy, network, system, enforcement, and incident response, generates and uses colossal data quantities, the proprietary, unstructured, and often classified nature of this data flow historically has limited our industry's adherence to AI-driven precepts.

In this paper, we introduce the principles of Threat Hooking, a Network Theory-driven approach to detecting and selectively blocking individual components within a collective logical threat. Our data science, Network Security Characterization Model detailed in this paper quantifies a specific element of Network Theory, which provides insight into both Network Health and individualized Threat Status. To demonstrate the innovation and theoretical underpinnings of Threat Hooking, we identify and analyze the massive datasets required from the network data immune system that we developed. After distilling relevant content from current cybersecurity research, we compiled an annotated dataset of live and emulated threat data and reported how AI-identified network artifacts that lead to human interpretable threat event detection can be verified, and if necessary, acted upon by cyber professionals.

Keywords: Internet of Things (IoT), Cybercriminal organizations, Malware attacks, Network security event data, Artificial intelligence (AI), Threat Hooking, Network Theory, Network Security Characterization Model, Big Data, Cybersecurity compliance

1. Introduction

The increase in frequency and sophistication of cybersecurity threats has become a significant risk and compliance concern for organizations across industries. The outcome of a cybersecurity breach can be substantial, with large financial, reputational, and regulatory repercussions. Prominent government and industry authorities regard cybersecurity as a top risk, as demonstrated by rapidly evolving regulatory and compliance requirements. Mitigating the risk of a security event requires not only investments in state-of-the-art technical tooling and automated incident response but also the participation of individuals and governance processes irrespective of the sector or size of the company. Many sectors are embracing initiatives, such as

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public-private partnerships, to aid in comprehending the risks, defining the criteria for managing the risks, and promoting increased information sharing.

Next-generation cybersecurity operations require an integrated technology and workforce strategy to successfully manage cybersecurity. Here, big data and cognitive or artificial intelligence (AI) engines provide enhanced capabilities relative to security event collection and triage through identifying patterns and predicting security weaknesses. Distinctly, such platforms help organizations comply with evolving regulations by leveraging the power of big data for comprehensive threat detection, contextualization, investigation, and response. In this light, we view security as a business enabler and not as a standalone, cost-center technology. Many security orchestration, automation, and response (SOAR) platforms are being used today to not only improve the effectiveness and efficiency of security operations as organizations struggle to attract and retain security personnel to cope with the volume of potential security events but simultaneously, to improve the effectiveness of the many business processes that create and maintain system identity information and maintain up-to-date knowledge of business-critical information.

1.1. Background and Significance

The world is experiencing an increasing number of cyber attacks, both in scope and magnitude, with the potential to cause unprecedented harm. Highly sophisticated compromises impact companies and citizens, with the potential of significantly destroying businesses and bringing economic collapse to people and countries. Existing threat detection solutions help mitigate problems; however, the rapid increase of data defeats previous successful methods and demands the exploration of emerging technologies to more dynamically identify new types of attacks at different stages of the cyber kill chain. The primary concern for security evolution is for organizations to adapt cyber compliance according to evolving targets and techniques of the actual threat actors, versus deploying security tools that exclude business needs or do not provide added value.

Commercial enterprise penetration has primarily focused on providing security-focused applications, which only provide a small number of additional tools or additional cyber threat products. This disparity or mismatch of offerings implies that organizations have insufficient defense staff to manage alerts, leading to the concept of alert fatigue within Information Technology (IT) departments. The intent of security products should not just deliver numerous alarms to Information Security and IT Operations teams; they should be directly improving the existing security posture of the enterprises they are attempting to protect. Individuals overwhelmed by excessive amounts of threat alerts may simply ignore edge concerns, which could potentially be of infrastructure-compromising importance. Gathering too much data remains another major issue to be addressed. Big data manipulates large and oftentimes complex data sets using algorithms and techniques in real time to uncover hidden patterns, unknown correlations, and other useful information.

1.2. Research Objectives

Due to the growing threat environment and more stringent regulations being levied, an increasing trend is to leverage AI to develop next-generation cybersecurity threat detection systems. Existing research in the field of AI-driven cybersecurity compliance is fragmented and unsystematic, which can lead to unguided research drift. The rise of big data serves as one of the loudest catalysts that are seen in fueling the interest in AI-driven threat detection. Through the use of big data, machines can be given the deeper intelligence needed, or so suggests popular belief, which draws attention and interest from the IT, management, and security practitioner community as well.

This study's overall research objective is to develop a coherent knowledge structure for AI in both big data-shaped cybersecurity threat detection and cybersecurity compliance, by utilizing a variety of methods such as bibliometric analysis and literature synthesis to derive deeper and more thorough insights. The development process of this coherent AI-driven cybersecurity knowledge structure consists of a few key concepts, where the combination of three areas—cybersecurity, big data, and AI—contributes to solving the cybersecurity compliance problem space. The end goal of doing so is to lay the groundwork for security experts and practitioners to address real-world security and privacy challenges comprehensively, as well as improve business operations.

1.3. Structure of the Paper

This paper reviews practical applications of AI and big data in cybersecurity compliance that support both private and public sector projects. In particular, we looked into AI-driven smart threat detection cybersecurity systems driven by big data. These innovative actors transform rigid and resource-intensive compliance requirements into an opportunity to embrace digital transformation and realize proactive, real-time AI-driven cyber threat response techniques. The rest of this paper is organized in the following manner.

What we did first is to propose a design framework based on both the U.S. cybersecurity standard NIST SP 800-137, which is entitled Information Security Continuous Monitoring (ISCM) for Federal Information Systems and Organizations, and the AI-Cyber Defense (CD) principles.

Both ISCM and AI-CD share a set of core principles, which include, but are not limited to, the desire for increased automation, the necessity of performing complete and continuous monitoring, the importance of machine learning to generate threat models, and real-time threat identification. The output of our efforts is the identification of a catalog of use cases that must be incorporated into existing cybersecurity monitoring, incident reporting, vulnerability assessment, and patch management frameworks.

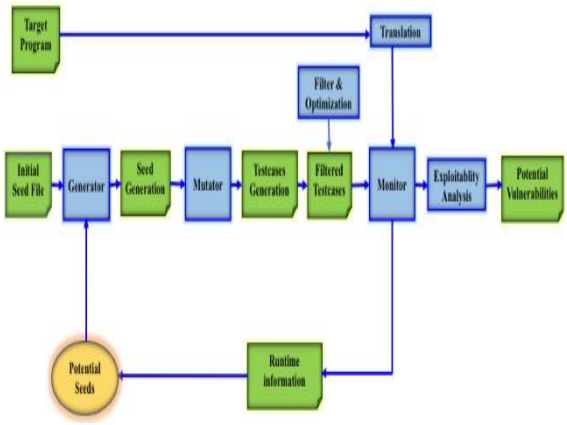

Fig 1 : Artificial intelligence for cybersecurity: Literature Review and Future Research Directions

2. Foundations of Cybersecurity Threat Detection

Each computing device that connects to the internet is being probed for weaknesses in its network services more often than 50 times each day. And every person is responsible for nearly 30 online accounts, whether through their devices, cars, thermostats, appliances, or work accounts. This creates a herculean task for any organization to sift through all the "telemetry" data that it must generate, capture, normalize, and analyze in real time to find the emerging cybersecurity compliance threats the organization faces, which can come from attackers, insiders, and accidents. However, stretching the valuable cybersecurity compliance staff resources across hundreds or thousands of endpoints and network nodes, and terabytes and petabytes of log data is requiring new big data tools from Artificial Intelligence (AI), distributed processing, and advances in machine learning and other analytic technologies to optimize the scarce resources. Otherwise, struggling to pore through volumes of threats and other cybersecurity compliance data means that few threats will be detected promptly, organizations will face expensive breaches and management needs to defend cybersecurity and compliance strategies afterward.

Regardless of whether system support (distribution, cloud, etc.) is for on-client premises, hybrid with clients on client and cloud premises, or machine learning and other processing is within a cloud service, all of these advances and more must be integrated into significant advances in the analytic tools and accuracy of their threat recognition. Otherwise, too many flagrant conditions will not be flagged as violations, and too many conditions will also trigger false positive investigations where there are no violations.

If conditions that are analyzed by the compliance attestations are not good insights on both the observed data event as well as the effects on the organization's and its third party or client's operations, the regulation and compliance intent of protecting the public trust in capturing and using the financial and other information would indeed be suspect. Such attempts to create trust in transactions were the marketplace's initial goal of regulatory and financial compliance. In our current threat era, attempts to comply by messaging static intent and responses to financial transactions aren't assured without the expanded use of AI and other intelligent tools.

2.1. Traditional Approaches to Threat Detection

Agencies have generally deployed a variety of traditional security tools and methods to identify and mitigate threats. These include firewalls, intrusion detection software, and intrusion prevention software. Agencies also typically deploy security information and event management systems, which often take log data from various security devices and applications and generate alerts for security analysis.

For alerts that come in, either a security analyst from the agency or the managed security services provider responsible for the associated security tools has to investigate these alerts and decide on the next steps, which could include simply dismissing the alert, responding with appropriate action, or informing the customer of their responsibility. Significantly, traditional signature methods are falling behind because of over generating alerts.

Malicious insiders and sophisticated adversaries, such as nation-states, have continued to find new methods to compromise systems and data. Historically, insiders who caused significant damage for reasons such as job dissatisfaction posed some of the most significant threats to an organization's data. These threats are difficult to detect with standard methods. In recent times, new technology and increased government investment have made defensive methods somewhat more effective. However, adversaries can still gain access to even well-defended systems through seemingly innocuous means, such as social engineering, in which an adversary talks an employee into revealing credentials.

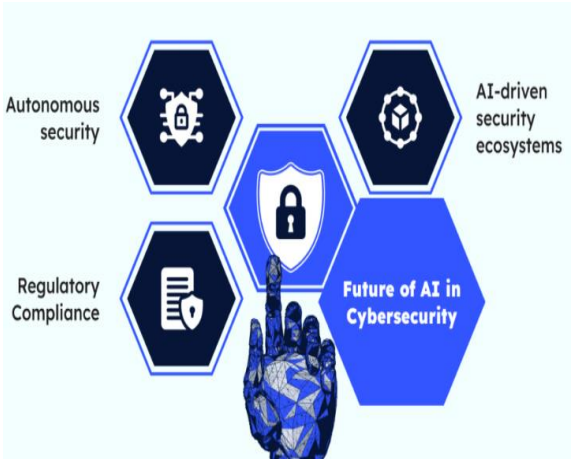

Fig 2 : Cybersecurity in Digital Transformation: Leveraging AI for Threat Detection

2.2. Big Data in Cybersecurity

Big data deals with data sets that are extremely large and more complicated than ordinary data. Big data consists of a large volume of unorganized data that has to be manipulated using specific technologies to generate value for organizations. Cybersecurity has been facing challenges for a long time in dealing with big data effectively. The process of locating and identifying network security exploits and threats in big datasets is known as cyber threat detection.

Security logging, metering, network flows, and more have a relatively big dataset volume and velocity of data that is constantly positioned to identify abnormalities. When it comes to assessing threats, gathering data from previous crimes can be beneficial. While classification, clustering, and association techniques for data mining and machine learning could be used effectively for the discovery of hidden but dangerous trends, unfortunately, system administrators do not have the power to take advantage of the available data. Signals that seem untrustworthy to an administrator may reveal unusual and suspicious behavior.

Most of the big data is untrusted, as intruders can easily create a file or even change the pre-existing contents to put malware within trusted applications. The malicious content can cloak itself with trusted applications before exploiting the token for valuable resources.

Malicious software can also transfer exabytes of data over the internet to compromise a cloud computing platform with malware spread throughout diverse business sectors, such as finance, banking, social media, authentication, and decorated critical network infrastructure.

Cybersecurity incidents have caused more than $1.5 trillion in estimated annual damages worldwide in 2018. Traditional entry points, for example, a laptop affected with malware or DDoS on cryptography, intruders break into these typically littered targets to gain unauthorized user access. In essence, access-based intruders can infiltrate network systems when a challenge is solved by breaking through AI or intrusion detection mechanisms.

2.3. Introduction to Artificial Intelligence in Cybersecurity

Artificial intelligence (AI) simulates human decision-making processes in the form of machine learning (training a machine to learn), decision support using neural networks, or real-time personal digital assistants. Obtaining accurate, consistent data sets from within organizations is the first challenge to creating an effective AI cybersecurity solution.

Multiple layers of security baked into advanced computers slow the data flows necessary for effective AI operation, which is another challenge. Proprietary algorithms and constant monitoring are needed for a model to be truly effective in AI-driven threat detection, as well as the collection of structured and unstructured data from various sources.

Speed and scalability must also be considered, with logic integration covering a wide array of use cases. The hottest cybersecurity talent is pursuing startup opportunities. AI capability can level the playing field and secure talent for large organizations by enabling cybersecurity teams to work efficiently with good data and a robust, dynamic expert network.

Fig 3 : Transforming the Future of Cybersecurity with AI - Driven Approach

Big Data, the other piece of the AI puzzle, refers to the massive amount of digital data moving through, and in online data centers. This data is broken down into two groups: structured data such as security event logs, flow logs, and network session data with a known pattern and a relational database, and unstructured data which lacks a predefined model and is found in web content, object storage, and distributed file systems. AI leverages the power of Big Data to bypass human-generated threat intelligence and block, contain, and engage with advanced persistent threats (APTs). Threat intelligence feeds provide valuable information on emerging threats and known adversary tactics, techniques, and procedures. Modern threat intelligence also contains extensive data on global threat actors. Agencies with deep AI cybersecurity capabilities have access to treasure troves of structured and unstructured data. The combination of Big Data and AI is fueling advances in cybersecurity by training AI to act on new hypotheses in real-time.

3. AI Techniques for Threat Detection

Most of the existing AI algorithms used in the cybersecurity domain are either dynamic (like neural networks, hidden Markov models, etc.) or static (like decision trees, random forests, etc.). Due to their dynamic environment, deploying static AI algorithms is not a feasible idea since it heavily relies on data for interpreting crimes.

For example, in the C2 domain, currently, two types of algorithms are used to identify the Command and Control channel: signature and behavioral-based methods and network traffic classification method. These methods suffer from two major problems. Firstly, the generation of new C2 techniques reduces the amount of malware generated by existing C2 channels. Secondly, generated malware can detect if it is running in the virtual environment.

To address these challenges, we need to develop an open dataset for the computer security community, raise awareness among researchers about real concerns, reinforce strong encryption (cryptography), and eliminate the use of weak keys, large modulus, and susceptible primes.

3.1. Machine Learning Algorithms in Cybersecurity

Numerous studies use machine learning algorithms for the detection, observation, containment, and elimination of security threats. Examples of machine learning used to improve security are dynamic analysis of malware, detection of spam and phishing, detection and classification of intrusion, security analysis including event correlation and profiling of network users, authentication of network users, protecting critical infrastructure, and cybersecurity risk management. The large synergy that exists between machine learning and cybersecurity is the main reason why academic researchers have explored and applied machine learning methods, especially those that give value and work very efficiently in large data sets. Big data is playing an important role in the rise of machine learning.

As a research area, there is still a growing demand for AI to solve security challenges, with new threats and new data. The flexibility of machine learning, combined with the vast amount of data now available, is being leveraged by organizations of all sizes to better manage and secure their networks with nearly non-existent security resources. For AI models to function, large data sets are needed for training. The unsupervised

learning that is propagated in real time to adapt and automate incident response is another concept. Finally, cybersecurity segments can benefit from AI. With the integration of cybersecurity models into a workflow approach, multiple enterprise segments that need investigation or regulation of behavior can benefit from security recommendations.

3.2. Deep Learning for Threat Detection

Effective threat detection is essential to ensure system safety. However, this is a very challenging task. Current commercial cybersecurity solutions are only able to detect known threats. When faced with an unknown malware vector, current tools fail. Consequently, the field of cybersecurity is moving toward more advanced solutions. Traditional signature-based detection will be used sequentially with commercial antivirus scanning. This merely ensures that the first stage is as fast as possible. As threats change, both signature-based and antivirus solutions struggle with the increased amount of detection data. Essentially, this allows the more sophisticated systems to look at less data over time.

Commercial antivirus, intrusion detection systems (IDS), and intrusion prevention systems (IPS) will be used to identify traditional, previously seen vectors. Anything missed by these initial tools hits the next level, which utilizes other advanced threat detection and prevention solutions. Commercial tools are re-imported every 12-18 months. Missed threat detection data cannot be used or re-imported with the intended solutions - advanced threats will be missed.

Less enterprise work will be re-imported in disparate manual missions. Landing enterprise data ends safe guardrail-breaking of various threat vectors. Advanced cybersecurity tools are in addition to commercial security, they do not replace it. The goal is to decrease the number of vectors hitting the more advanced tools. Currently, we do not have an artificial intelligence/machine learning (AI/ML) solution to balance the load. Once there is a better mousetrap and the existing advanced tools can import their detection data from the commercial software - not be a copy problem (versus a leaky proxy). It is safe to decrease commercial software licensing for the environment. The more advanced threat detection and prevention engines would work faster than the historical definition-of-self (signature-based) problem. Difficult questions regarding the safe safeguards of data of each software will be moved to a cloud-based decision. Working problems become business problems for the more advanced commercial software solutions. Leaders in this domain can make public statements on how they will protect the bundled data of each of their customers.

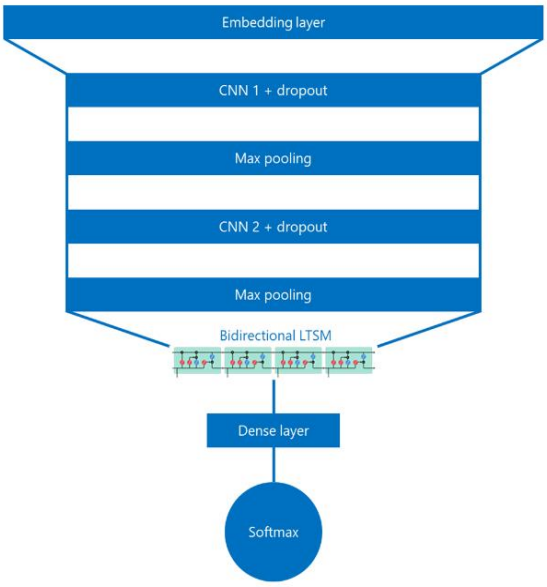

Fig 4 : Deep learning-based Fusion of Behavior Signals for Threat Detection

3.3. Natural Language Processing in Cybersecurity

In cybersecurity, as in many other fields, information is communicated with natural language. While much of this is structured data carried in logs, reports, summaries, APIs, documents, and other sources, extracting meaning from specialized formatting rules and diverse languages presents a significant difficulty. The use of natural language processing (NLP) adds a powerful, general capability to this qualitative understanding of cybersecurity. In addition, AI models based on pre-trained representation can predict cyber tasks without being trained in task-specific data, which is the direction that NLP in cybersecurity is heading. Thus, NLP in cybersecurity projects tasks, essentially focuses on four questions: Can natural language processing enable modern cyber systems and users to more effectively automate, communicate within or between systems, or interoperate with modern systems? What tasks are currently being addressed? How effective are natural language processing approaches in improving cybersecurity capabilities? Where are the opportunities and challenges on the horizon?

For the use of natural language processing, this work surveys a range of research, develops and implements NLP solutions, develops cybersecurity rationale through this research, and conducts future task investigation and study. The paper seeks to determine how natural language processing enhances human and machine understanding capability; for cybersecurity systems and users, its criticality in translating natural language is addressed and the observed results are described in those tasks. Note that natural language processing is found to be critical for addressing almost all modern cybersecurity (cyber) tasks, including visualization, analytic improvement, explanation, and facilitation of remote treatment. The university's key conclusions are: a host of very significant and unexpected cyber improvements, analysis of displayed visual elements, task performance metrics, actual task completion well, and task modeling profoundly influence the realization of human and machine cyber understanding.

4. Applications of AI-Driven Threat Detection

To offer an understanding of the value and benefits of AI-driven threat detection, this section highlights the use of AI in cybersecurity, the potential challenges regarding compliance with AI-related security requirements, the risks and corresponding threats, and the important responses to be taken for managing those security issues.

4.1 Use of AI in Cybersecurity Cybercriminals typically employ automated programmed attacks that use AI technology to augment the success and evolution of their cybercrime. Thus, cybersecurity industry research has also been directed towards the application of AI technology for ensuring smart prevention and immediate identification of a network breach.

AI-driven cyber defenses can achieve this because choosing the threat and coordinating, carrying out, controlling, or profiting from the attacks generally take more time, energy, and resources of the criminal than would be necessary to defend against or prevent the attacks. However, the inverse is usually demonstrated by criminals, using AI-driven attacks. Such attacks are known to be elegant and can escalate without detection, generally because they are considerably less costly for the criminal and are typically easier and less labor-intensive. They are often quicker and cheaper actions for delicate system penetration than other simpler methods used by earlier cybersecurity criminals, but they require a significant amount of time, preparation, collaboration, experience, and expertise to prevent and manage.

4.1. Network Intrusion Detection Systems

A network intrusion detection system (NIDS) is an independent platform designed to identify malicious actors within a network or system. These systems frequently use both signature and anomaly-based detection for identifying threats. NIDS is capable of monitoring a substantial amount of traffic for all devices on a network. For threat detection professionals who leverage them, intrusion detection systems provide actionable insight in real-time and generate online alerts or automatic logs of discrepant, actionable, or threatening behaviors. NIDS is known for its role in identifying threats that might have been missed by other defensive measures like firewalls and antivirus software. In the instance that these systems do detect a malicious actor, NIDS then responds by alerting security personnel or executing other preventative actions, thus reassessing and reconfiguring the security control's runtime status.

False positives are pronounced in NIDS, which can challenge the most crucial aspect of a professional's daily responsibilities. For personnel, this is picking up the baton when NIDS isn't able to catch threat actors in their systems. False positives are unavoidable since NIDS can't distinguish between real and false threats, which alters the learning curve and impacts their lack of efficiency. In addition to this, they are also hindered by the lack of an accurate measurement of the traffic background. Event logs and high false alarm rates are frequent complaints, alongside a lack of flow-based detection, high complexity in execution, power usage, poor tracking features, and low encryption capacity. On the other hand, transparent firewalls can impair the threat detection ethics of NIDS as its limited visibility of only one side of the communication does not permit the detection of backdoor traffic or possible evasions.

4.2. Malware Detection and Analysis

Today, the vast majority of malware detection tools and methodologies rely on matching detected anomalies or network behavior to a predefined list of malware signatures. This method cannot identify new malware or those altered by cybercriminals for specific attacks.

The newly emerging cybersecurity tools that rely on AI are further shifting the battle towards AI-driven cybercrime by utilizing the knowledge it takes to build, train, and use innovative models available only to a select number of companies and academics. AI-driven robust, general-purpose wares are notoriously difficult to label and leverage.

Signature-based computer security programs depend on pre-existing data points, meaning that if a cyber bad actor builds a fraudulent site uploads a new file to its site from an unknown source, or tweaks some of its software, the program will not notice since the fake site mimics no earlier samples and there are no new samples available for comparison as well.

An AI tool, on the other hand, can understand distinguished structures from other samples and under different sub-network characteristics, and through relation to other nodes, like speed, replication, and botnet behavior, therefore middleboxes have fewer blind spots.
AI-enabled advanced malware teaches itself to operate in ways that can quickly escape solutions used widely nowadays for intrusion detection and firewall protection. They combine erratic behavior like data leaks, suspended processing of system files, and clock manipulation to ensure maximal security protection and spread without exposing themselves.
These tools work by identifying both suspicious system features and data patterns that uniquely link well-hidden files or codes, which are hard for security systems to detect. They also identify various MAC addresses or IP addresses connecting to each domain and malware records by looking at different nodes across the subnets where they appear.

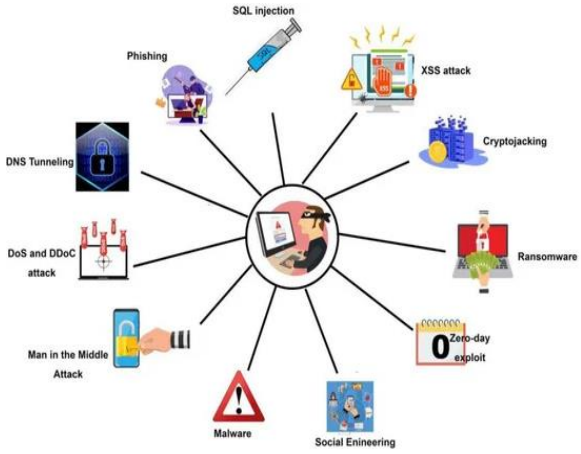

Fig 5 : AI in Malware Detection

4.3. Behavioral Analytics for Threat Detection

In the context of security, data can reveal highly sensitive information about adversaries' objectives and capabilities. AI provides the most immediate benefits through data analysis and management. In addition, AI technologies can enhance both big data updates and analytics and facilitate delivering real-time threat intelligence and intelligence about large data sets. The number of potential cyber threats could range from a few transactions per month from a suspect country to thousands of transactions conducted by authorized system users. The development of behavioral analytics is creating the potential for a significant improvement in system integrity and cybersecurity compliance.
Behavioral analysis for cybersecurity has been successful in the areas of fraud detection and insider threat detection. Over the years, various models and methods have been developed to identify insider threats, from rule-based methods to anomaly detection to clustering algorithms. Most existing models for internal threat detection and fraud models are similar because they focus on identifying outliers and exceptions to rules, with particular emphasis on resource requests, time and location, and other characteristics that can be used to identify anomalies. Few companies make access to the data sources necessary for creating behavioral models available to their analysts without assistance from the vendor.

5. Challenges and Future Directions

Several challenges are preventing large enterprises from fully adopting an AI-driven approach for real-time cybersecurity compliance. Some of the prominent concerns are related to data protection and governance. To use a generic model for training based on a large data dictionary, there would be a need for policies to scrub parts of data from proprietary business data and information from sensitive parts like encrypted fields and from an information point that is considered to be sensitive and PII. The ability to use any concrete business dictionary has to be a must.
With the current generation of AI models, there is a problem of lack of explainability. Interpretable models that can explain the reasons that contribute to particular decisions. This is especially important in some real-time decision-making processes in which a trained model may face compliance queries. Data and model drift are other issues that may arise over time, as generalization to new data can grow weaker. In a real-time online learning setup, these are important to monitor and real-time updates to models are necessary.

5.1. Ethical and Privacy Concerns

This research aims to inspire further discussions about ethical and privacy concerns, looking for a consensus among the multi-disciplinary Big-Data research community. Nowadays, big data with machine learning capabilities is creating effective solutions for several critical domains, like healthcare and disease-related solutions, in a grid of commercial applications in image and speech recognition, online personal assistants,

product recommendation services over the internet, automatic music composition, and fraud detection. The tension between privacy and security on the one hand, and the development and application of data-driven and machine-learning systems on the other, is not incidental at all. During the last few years, several researchers described how disclosed data inappropriately collected and processed preserved individuals' disclosures, including sensitive health-related aspects. Some papers claimed that up to 60 percent of individuals could be matched by identity from only three data points.

In this cyber context, machine learning and AI are practically becoming synonymous due to remarkable advances made by the use of big data and powerful techniques in both the training and implementation of these approaches. We are interested in exposing AI methods that solve several cyber puzzles, especially in the cybersecurity field, capable of tackling most current challenges. The ultimate goal is that machines could exceed security defense capabilities bigger than the best human menders, such "cyber principles" are often not completely shared by many cybersecurity implementations and solutions. We propose AI-based approaches and have a clear intention to portray practical and technical implications to consider them, discussing technical and ethical issues for the AI security industry and modeling research community.

5.2. Limitations of AI in Cybersecurity

Just like AI has limitations in the software application area, in many ways, AI in cybersecurity is also limited. According to Brooks, AI is limited in "Range, Bandwidth, Frugality, Comprehensibility, and Transparency". These same limitations in AI as a whole can be said to afflict AI as a tool for cybersecurity as well. More importantly, cybersecurity experts also point out some unique limits of AI, especially its potential to enhance cybersecurity.

5.2.1. Designing an AI Project with Ecosystem in Mind In cybersecurity, the organizational ecosystem is complex and can hinder the effectiveness of AI if it is not factored inappropriately. A cybersecurity expert points to how "the inner workings of a company, which can make the logistics of deposing and replacing the existing defense complex, must also be considered". Malaiya says "While AI may help in addressing some of the major issues, it may not address the complete problem — a combination of system hardening and secure software may." The expert goes on to argue that "computer security needs to be an integrated, proactive approach that encompasses the hardware, software as well as the system being used." There has to be a focus on 'proactive defense', smart defense at the user level, and proper endpoint security, all considered as important as perimeter security. AI can fit into a cybersecurity strategy. However, unless the security ecosystem is looked upon carefully, the effectiveness of AI's implementation in cybersecurity will not be achieved.

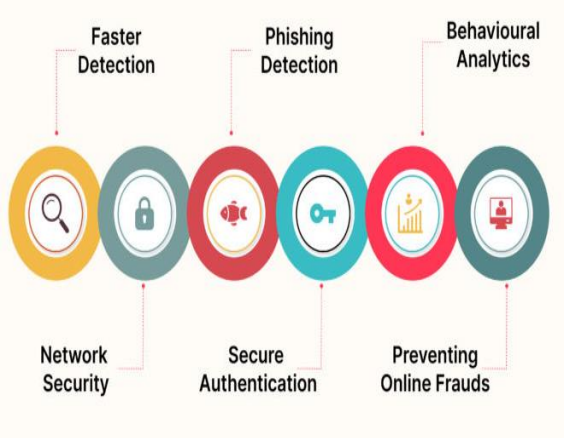

Fig 6 : AI in Cybersecurity

6. Conclusion

The global post-pandemic workforce transformation has ushered in significant changes for corporate cybersecurity. Threat actors sensing opportunities from increased remote workflows, unconscious systems, and the ever-increasing pace of business are quickly exploiting vulnerabilities. As a result, protection intelligence-sharing initiatives, such as Threat Detection, Reaction, and Reporting (IDR), are essential for in-depth cybersecurity. These capabilities need to also leverage big data, machine learning, and AI to establish the likes of the threats. They need to monitor organizational possibilities continuously to preempt cybersecurity incidents and help place priorities on proactively addressing vulnerabilities.

IDR measures threat data information collected from open and data sources on computer and network systems, then exchanged with federated partners, federal resources, and third-party cybersecurity teams. The National Institute of IEEE CyberSecurity IDSR Compliance Information Sharing Protocol was created to address private and public challenges in replacing, coordinating, and segregating delicate risk-related data.

The need for advanced intrusion detection coupled with secure network area models and robust data security policies is driven. Threats tend to emerge from the universe of unused information to share after data is big. Monitor and measure with greater simplicity. Organizations need to keep their trust security frameworks as adaptive and dynamic as the cyber threat lifecycle.

6.1. Future Trends in AI-Driven Threat Detection

The increasing evolution of AI-driven threat detection continued with the R&D of deep learning, a subset of machine learning relying on artificial neural networks that permit data to be processed and modeled with human-like intelligence. Deep learning models can expand and improve data patterns by learning to distinguish and categorize data disregarding the input resembled, and then an examination of prompt, secure, and reliable predictions. While some challenges have managed the application of deep learning within threat detection across industries, advancements have mitigated many of those constraints, establishing deep learning as a pivotal driver of AI and threat mitigation.

The conceptual understanding of deep learning models is becoming clear and polarization is evolving with easy-to-train models made accessible through libraries of AI models. Recently, optimistic protective technologies embraced deep learning for particular tasks, particularly deep learning classification models, which forecast the class of a centered frame. Over time, as scholars and developers continue to engage, experiment, and produce new implementable models, the AI model state of security measures will persist and boost.

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Research Article

AI-Powered Insights: Leveraging Machine Learning And Big Data For Advanced Genomic Research In Healthcare

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ABSTRACT

AI-powered insights are becoming increasingly essential in every industry. The cost of doing genomic science is becoming comparable to 'big data' requirements, leading to a need for data-driven insights. This essay will investigate how AI-powered insights can build and expand the data-rich and bias-free genomic insights needed in healthcare, with a particular focus on DNA collection and genomic DNA-based healthcare research. Many challenges will be discussed during this paper should the data ecosystem be expanded to include many more humans worldwide or focused on the increasingly complex data types associated with post-genomic healthcare. We will also explore the AI methods likely to make significant breakthroughs in the future and will need further investment.

Keywords: Health, healthcare, genomics, machine learning, cancer, neural networks, AI, accuracy, insights, personalized medicine, genomics research, Big Data, tumor, neural network, feature selection, data enhancement, convolutional neural networks, adaptive learning rates, precision, interpretation

1. Introduction

In the era of technological transformation, artificial intelligence (AI), machine learning (ML), and big data have become game-changers, leading to innovative solutions across several different applications. Through AI-powered technologies, patient outcomes can be improved by automating the integration of genomic data into standard clinical workflows and decision support systems. This paper therefore introduces the relevance and importance of AI and machine learning in the background of advanced genomic exploration in healthcare. The first objective of this paper is to provide an understanding of the state-of-the-art AI and machine learning models applied in genomic research, while the second objective is to address the sources and importance of big data in genomic research. In the following sections, we start by outlining the motivation for advancing genomic research in the healthcare sector through the use of artificial intelligence and machine learning models. We point out the key aspects of the application of machine learning models in the background of genomic research and provide a short conceptual definition of big data in the healthcare sector.In the era of technological transformation, the integration of artificial intelligence (AI), machine learning (ML), and big data has revolutionized healthcare, particularly in genomic research. This paper delves into how AI and ML models are transforming genomic exploration by automating and enhancing the integration of genomic data into clinical workflows and decision support systems, ultimately improving patient outcomes. The first objective is to elucidate the cutting-edge AI and ML models currently utilized in genomic research, showcasing their capabilities and impact. The second objective highlights the critical role of big data in genomic studies, exploring its sources and significance. By examining the motivation for leveraging these technologies, the paper outlines how AI and ML are advancing genomic research and provides a foundational understanding of big data's conceptual framework in the healthcare sector.

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Fig 1 : Big Data Analytics in Healthcare

1.1. Background and Significance of Genomic Research in Healthcare

Among the countless methods imagined or adopted to drive this particular form of postgenomic research, AI approaches hold contexts with an extensive and widely applicable approach. Here, a tacit use of AI is to further mine and extract in silico knowledge from our genetic and phenotypic data at a much larger scale using extensive input data sources and relatively many free parameters for potential novel insights unavailable to smaller-scale and more hypothesis-driven projects. We describe the computation-intensive AI and machine learning methods that, as we see it today, are most widely applicable. Agent-based approaches are tailored for applications where learning matters, e.g., when wanting to model the behavior of molecules or cells in rich, biologically realistic in vitro systems with other cells or tissues. These approaches span from "simplified" phenomenological models to more complex dynamical systems-based individual-based models, including reaction-diffusion models.

With the arrival of big data and new insights from genetics and genomics, there is reason to expect that healthcare will be revolutionized once again. When Mendel's foundation of genetics was joined with the superabundant hypotheses that came from molecular biology, scientific and commercial narratives were spun about a not-so-distant future in which advanced diagnostics would enable doctors to apply precise therapies, or so-called "precision medicine" or "personalized medicine," to stave off or cure late-stage diseases as capably as high-quality healthcare today deals with early stages of non-communicable diseases like diabetes or hypertension. Adopting the term proposed by Calum Macleod, we call these imagined applications of genetic and genomic research "genomic research in healthcare," meant to draw attention not only to their work on the genome but also to the embodied and material ways and layered technical infrastructure through which the genome gets put to work.

1.2. Role of Machine Learning and Big Data in Advancing Genomic Research

Big data crosses all social, economic, regulatory, and technological barriers. In the healthcare/social sector, it is important that the vast amounts of 'valuable' data are properly protected and of the utmost quality to facilitate enhanced connectivity for data sharing and insights; it is the fuel that drives innovation and it has been making waves across all industries related to biostatistics and business intelligence. Genomic big data has the potential to improve the scientifically derived insights from such machine learning research across a wide range of disciplines to facilitate quick and accurate implementation into healthcare for the benefit of patients and advancements in research. Machine learning and big data offer unparalleled potential to impart cutting-edge technological breakthroughs that enable healthcare professionals to make accurate assessments and gene-level predictions based on an individual's symptoms and genetic situation. Machine learning is especially suited to synthesize the vast amount of information doctors and biologists have about what genes are connected to which diseases in a way that is beyond human capability. Machine learning applications will enable clean data from controlled laboratory variables such as specific genotypes and/or experimental treatments, real-world healthcare data, and registries from different hospital systems to be accessed and combined at scale. This will result in expensive, resource-limited, and time-consuming clinical trials becoming greatly enhanced, which will better reflect the true human genetic landscape. Big data transcends social, economic, regulatory, and technological boundaries, playing a pivotal role in the healthcare and social sectors by ensuring that vast quantities of valuable data are protected, high-quality, and effectively utilized. In the realm of genomics, this data serves as a critical driver of innovation, enhancing connectivity for data sharing and facilitating advanced insights across biostatistics and business intelligence. Machine learning, leveraging genomic big data, has the potential to revolutionize healthcare by enabling precise assessments and gene-level predictions tailored to individual genetic profiles and symptoms. This technology surpasses human capability in analyzing complex

gene-disease relationships and integrates diverse data sources, including controlled laboratory data and real-world healthcare records, on an unprecedented scale. The synergy between machine learning and big data promises to significantly refine clinical trials, making them more efficient and reflective of the intricate human genetic landscape, ultimately advancing patient care and research outcomes.

2. Foundations of Machine Learning

Regardless of the drawbacks, several "core" stakeholders have remained interested in AI-driven healthcare knowledge, perhaps through a proprietary investment in this technology, which makes this study relevant to the healthcare sector from their perspective. Another concept that has gotten a lot of attention is "machine learning". Although it has been shown that machine learning technology may significantly impact healthcare, these conclusions have not fully covered the growing field of genomic research. Machine learning is a kind of artificial intelligence in which computers are trained to make sophisticated judgments using two possible learning types: supervised and unsupervised. The "training" of a model is what happens when a machine learns with this sort of AI. In the context of this study, a model learns how to link somebody's DNA to a medical condition, when previously this can be related to the incidents of hundreds or thousands of other people. Once trained, the model will be used to make forecasts for customers that it has never studied before.The human body, with around 100 trillion cells, is like a machine that functions by converting food into power. Medical professionals think of the body's data that powers this complicated "machine" like one's DNA. All medical ailments, from advanced cardiovascular disease to rare situations such as rare diseases, are allegedly caused by mutations or problems in the person's DNA that powers this complicated "machine". By comprehending these DNA mutations, treatment methods can be customized for each patient, enabling treatment that is catered to every patient's body, eliminating elements that don't apply, and providing higher precision with fewer adverse effects in drug interventions or surgical procedures. These results show that genomic research has the potential to significantly improve how millions of individuals are treated. Healthcare genetic research has grown quickly in recent years, yet it is still not widely available to the public. Currently, it has mostly been used by people working in hospitals or institutions and needs to be incorporated into healthcare for all patients to receive the benefits of this research.

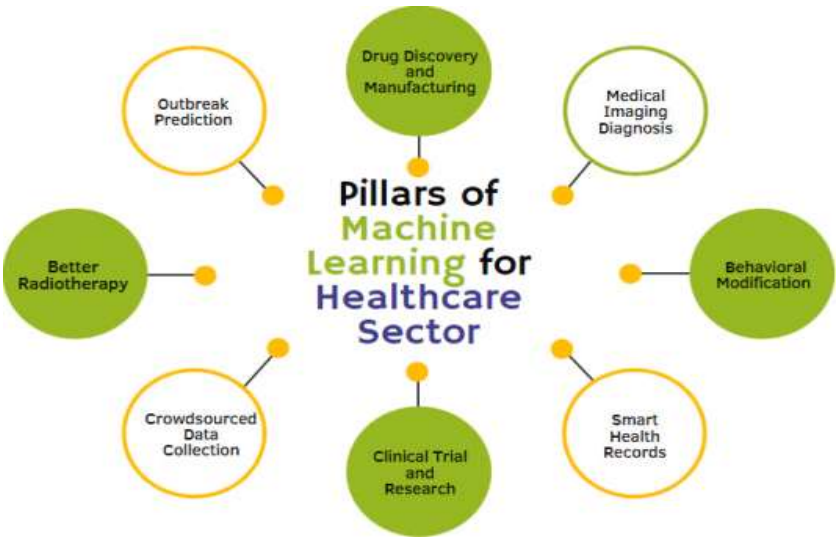

Fig 2 : Pillars of machine learning for healthcare services

2.1. Basic Concepts and Terminology in Machine Learning

As such, a fundamental question in machine learning is how to learn the model from the data to make accurate predictions while simultaneously minimizing the error rate. Traditional machine learning algorithms, used in the development of classification or prediction models, are primarily categorized into supervised versus unsupervised learning methods. In supervised learning, the algorithm establishes a relationship between the set of descriptors or predictors (features) and a binary or continuous response in the training dataset. The model is then able to make predictions about this relationship for new instances. In the case of unsupervised learning, the machine learning task is centered around finding structure in the data and is typically used for applications such as clustering data or reducing data dimensionality.Machine learning refers to a field of study devoted to modeling algorithms that can automate the discovery of patterns and associations from large databases and subsequently leverage these insights to make intelligent decisions or predictions. The designed algorithm is typically represented as a model, which itself is a function that takes as input a set of attributes (features) and produces as output a response. This response may constitute an association or a prediction of the input data. To develop the data-driven model, machine learning practitioners typically require a dataset containing both the input features and corresponding responses for a large number of instances. This dataset

is subsequently divided into a 'training set' and a 'test set', where the training set is used to fit the model, and the test set is used to assess the model performance.A core challenge in machine learning is designing models that accurately predict outcomes while minimizing errors, with methods broadly categorized into supervised and unsupervised learning. In supervised learning, algorithms are trained on datasets where input features are paired with known responses, enabling the model to establish predictive relationships and make accurate forecasts for new data. Conversely, unsupervised learning focuses on uncovering underlying structures within data, such as clustering or dimensionality reduction, without predefined labels. Machine learning encompasses the development of algorithms that can autonomously detect patterns and associations within large datasets, leveraging these insights to drive intelligent decision-making or predictions. Typically, this involves constructing a model—a function that processes input attributes to generate outputs, which might be predictions or associations. To build these data-driven models, practitioners use a dataset split into a 'training set' for model development and a 'test set' to evaluate performance, ensuring that the model generalizes well to new, unseen data.

3. Big Data in Genomic Research

Beyond these operational challenges, the management and meaningful analysis of genomic data has created a significant opportunity cost over the past decade. However, if these can be overcome, as a community, we have the opportunity for a large increase in manual curation capability and translational articles published – potentially increasing from zero in 2019 to ~650 articles by the end of 2020. Conversely, the current impact factor of CCR has an estimated value of $51m, which is expected to increase linearly by $26m over the next year.As we discover more about the relevance of the low-frequency variants found in an individual's germline and/or somatic tissues, the sophistication of tools required to extract and interpret these will, by necessity, increase. Long-term data analysis challenges include population density and diversity variations, the correlation between pathogenicity staging scores (e.g., ACMG classification and/or NCCN guidelines staging) and therapeutic options, drug-to-drug interactions, drug metabolism analysis from germline variants, and 'other' (unstructured) genetic influences (including lifestyle, environment, and the microbiome).Handling Data Volumes The volume of sequencing data in and of itself presents challenges in terms of analysis, storage, transmission, and processing. As challenges scale linearly, storage and analysis can become impractical.The widespread usage of next-generation sequencing has enabled the creation of unprecedented volumes of genomic data in research laboratories and healthcare institutions. DNA sequencers have collectively generated nearly 400 exabases of sequence data from approximately 176 million individual samples over the last ten years. Beyond the generation and storage of this dataset, researchers are facing a complex array of challenges to transform this information into more usable and increasingly clinically actionable knowledge and insights.

Fig 3 : Genomic Data and AI in Healthcare

3.1. Challenges and Opportunities in Handling Genomic Data

The large datasets used in genomics also display a major opportunity: a large-scale phenotypic and genomic study of a population has the potential to yield statistically significant results and thus set precedence. If a biomarker is identified as statistically significant, it is suggested that such a biomarker could be an example of how many other patients with that particular genotype may react, due to the large number of patients researched. Furthermore, if the discovery is repurposed, showing or yielding necessary evidence can result in quick invalidation of a badly performing medical procedure. This means that a breakdown in the model can be addressed immediately if it occurs on a large scale the conditionality of such a model which is only possible with big data.The true promise in handling large-scale genomic datasets lies in the data value management gained from analyzing them. Genomic data is complex, and handling it presents new challenges. The primary challenge is that they are large. Huge datasets can originate from the new increasingly large cohort studies. For example, data from the UK Biobank or the Million Veterans Program exceeds the petabyte. While storage systems could (in theory) scale to such sizes, problems may also arise due to the computational demand. Data may have to be split during the execution of computations, and as such individual computational units need to rely on one another within the computer to complete individual steps. This can result in delays due to transfer time, thus compounding computational time as tasks cannot be executed in parallel. For example, a typical genome-wide association study (GWAS) of relatively modest size (e.g. 1 million variants and 10 million participants) can still require the storage of 20TB of data and hundreds of thousands or millions of

computational tasks (one for each variant). This results in significant computational time. A significant technical challenge involved in complex cloud computing environments requires tools to be developed to support these complex analytical workflows.

4. Applications of AI in Genomic Research

The impetus of integrating big data and AI in genomics is often aimed at improving patient care by providing comprehensive solutions for patient GPs, thereby allowing them to make better treatment decisions. Moving to the clinical aspect, a unique resource populated with machine learning methods performed on genetic data is nested within databases such as the UK Biobank the UK has the capacity for large numbers of penetrant Mendelian diseases, such as pathogenic and likely pathogenic BRCA1 and BRCA2-coding mutations. Given the significant overlap of germline TBVs and breast cancer predisposition genes, it is fundamental to adopt appropriate statistical measures (validation and cross-validation datasets) to not introduce confounding effects into machine learning predictions. This new model, connected with advanced MRI interpretation via convolutional networks, has the potential to revolutionize pre-treatment assessment as logistic regression combining radiomic, genomics, and clinical data already achieves a marked improvement over using each component alone.The use of advanced AI and big data technologies in genomic research is primarily aimed at the advancement of precision medicine. Precision medicine encompasses personalized and stratified drug treatment and can significantly enhance an individual patient's advancement through their recovery from disease. Indeed, this particularly has implications for chronic conditions such as cardiovascular disease, cancer, and neurological disorders. The current gap highlighted in the literature is the functional interpretation of the large variety of data sources currently available. Therefore, the research avenues associated with AI-powered insights mainly fall into the established frameworks of genomics and precision medicine, particularly for cancer research.Integrating big data and AI into genomics has the transformative potential to significantly enhance patient care by enabling more precise and individualized treatment decisions. This integration is particularly impactful in the clinical realm, where databases like the UK Biobank, which contain extensive genetic information including Mendelian disease markers such as BRCA1 and BRCA2 mutations, serve as rich resources for machine learning applications. By employing advanced statistical methods to validate and cross-validate datasets, researchers can mitigate confounding effects and refine machine learning models. These models, when coupled with sophisticated MRI interpretation techniques using convolutional neural networks, can revolutionize pre-treatment assessments. Combining logistic regression with radiomic, genomic, and clinical data has already demonstrated superior outcomes compared to isolated data sources. The overarching goal of these advancements is to propel precision medicine forward, particularly in the management of chronic conditions like cardiovascular disease, cancer, and neurological disorders. Despite these strides, a critical gap remains in the functional interpretation of diverse data sources, underscoring the need for continued research within the frameworks of genomics and precision medicine to fully leverage AI-powered insights.

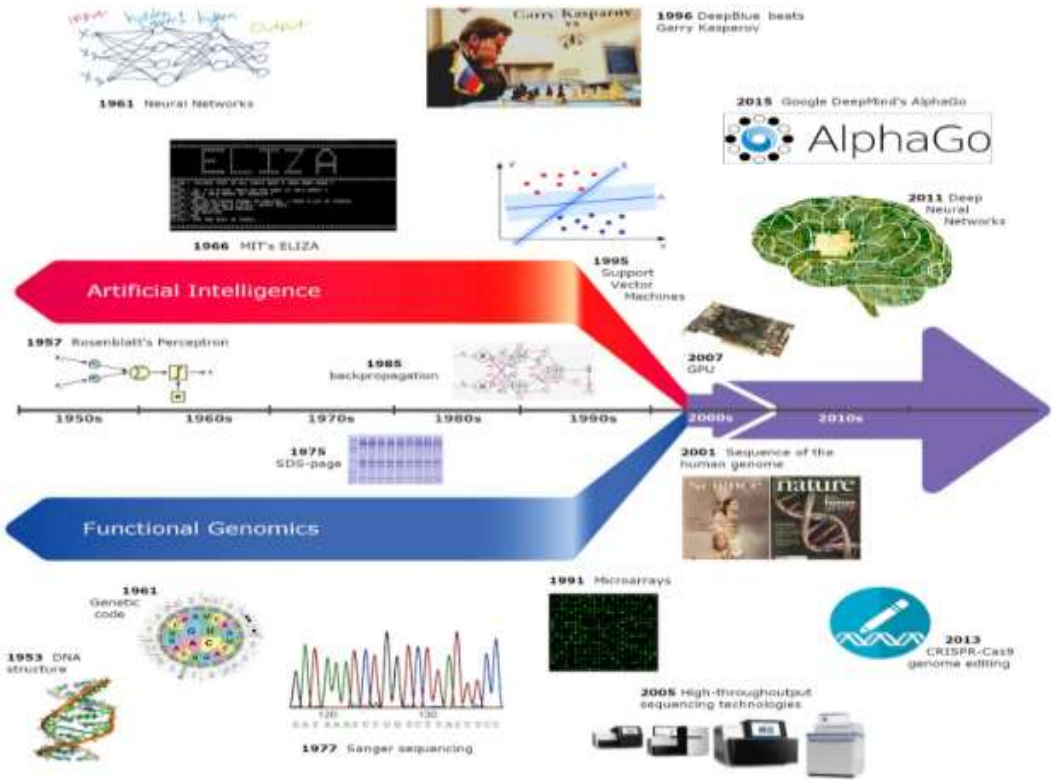

Fig 4 : AI applications in functional genomics

4.1. Precision Medicine and Personalized Treatment

This subsection shows examples of applications for personalized treatment in the context of diseases like epilepsy, pediatric polyarticular juvenile idiopathic arthritis, mental disorders, and other inflammatory diseases. In some cases, these AI-driven models resulted in better disease management and therapeutic response by shifting the focus from symptoms/clinical presentation to underlying mechanisms or pathways known to cause disease.

Precision medicine aims to provide custom-fit healthcare solutions to an individual based on their unique genomic makeup. Today, both precision medicine and artificial intelligence have advanced significantly, which allows for an integration of these two fields. Genomic predictive models based on AI hold the promise of early-stage disease detection by analyzing large volumes of genomic data and learning patterns that hint at the onset of disease long before physical symptoms are present.Precision medicine involves custom-fit healthcare solutions based on individual genomic signatures, resulting in a shift away from "one-size-fits-all" clinical approaches. The AI power of learning from large and complex genomic datasets combined with clinical outcomes allows researchers to discover the often subtle interconnections between the smallest of DNA variations and the manifestation of life-threatening diseases. We include several applications of AI in the field of precision medicine for different life-threatening diseases: cancer, rare diseases, cardiovascular diseases, COVID-19, autoimmune diseases, and genetic pain disorders.

5. Ethical and Regulatory Considerations

There are currently several frameworks existing, such as the General Data Protection Regulation (GDPR), that address the responsible use and sharing of data, especially genomic data, about a balance of fair data exploitations, knowledge development, and respect for privacy rights. In the present context, decision support systems that generate insights could be perceived as instrumental AI-driven systems that serve a function and have a pertinent impact on clinical practice, enhancing patient outcomes. Each of these aspects requires rigorous definition to resolve potential ethical, legal, and social implications of the operationalization of the results of such genomic research. Any databases collected from contextual partners would also require data to be within a de-identified form. Data protection has multiple facets, and this aspect also needs to be detailed further.The potential applications of AI-powered insights sparked numerous ethical, legal, and social discussions related to the unintended use of these systems in the context of genomic research. These are highly relevant to be addressed as new and innovative knowledge and practices in research are typically adopted by the scientific community on the one hand, while also being applied and integrated into medical practice on the other. Due to the complex systems predominantly used for the generation of data or analyses of large-scale biological data with emphasis on different management of privacy of data, privacy and data security aspects also need to be considered from an economic perspective since the breach of data could also lead to economic consequences.

Fig 5 : Ethical and regulatory challenges of AI technologies in healthcare

5.1. Privacy and Data Security in Genomic Research

Concerns with data security and genetic privacy are very much a major theme when it comes to integrative AI and machine learning applications in radiomic and genomic research, especially regarding the vast biomedical data repositories and other clinical networks in which there may be a possibility to carry out studies at a mass

scale. Databases containing electronic and health record information typically already make sure to secure participant privacy and individual data with the Health Insurance Portability and Accountability Act (HIPAA) and/or local equivalent laws, and the individual studies themselves undergo IRB review to confirm the best possible measures in securing data from entrance to execution are taken. However, the entire swathes dedicated to large-scale genomic data analysis - which in some cases are composed of collected patient cohorts with more than 50,000 participants amassed over decades and genome-wide genotyping appearing in duplicated clinical and annotated datasets numbering in the thousands - must adhere to a piling set of interventions above and beyond routine clinical and research trials. This international set of directives so far has been the general data protection regulation (GDPR) in Europe.As contemporary genomic research becomes more dynamic, all-encompassing, and steered by machine learning and AI, we should adhere to several conceptions and directives in the field of privacy and data security. All genomic research conducted nowadays should involve a focused effort to protect the privacy, consent, and insurance of their human participants and should also bear in mind the innumerable elders and nonwhite general population that have systematically been failed by every evolution of contemporary bioethics. The idea that there neither is nor should be an "ethical" or a "legal" reason for a person to expect secure processing of their genomic information flies in the face of legislation such as Europe's General Data Protection Regulation (GDPR). It corresponds to a philosophy of data handling and informatics in which the basic human right to privacy has no place - a philosophy that now, more than ever, needs to be swept off its throne entirely.Data security and genetic privacy are paramount concerns in the integration of AI and machine learning with radiomic and genomic research, particularly when dealing with extensive biomedical data repositories and clinical networks. While databases containing electronic health records adhere to regulations like the Health Insurance Portability and Accountability Act (HIPAA) in the U.S. or similar local laws, and individual studies are reviewed by Institutional Review Boards (IRBs) for robust data protection, large-scale genomic analyses present additional challenges. These studies, often involving extensive patient cohorts and genome-wide data spanning decades, must comply with stringent regulations such as Europe's General Data Protection Regulation (GDPR). As genomic research increasingly relies on dynamic, AI-driven approaches, it is crucial to prioritize privacy, consent, and the protection of participants, especially marginalized groups who have historically been underserved by bioethics. The evolving landscape of data handling should reject any notion that secure processing of genomic information is not a fundamental right, aligning instead with a philosophy that upholds the basic human right to privacy in the face of expanding technological capabilities.

6. Conclusion

In the future, a likely possible advancement to occur in the big data subset is the inclusion of lifestyle data (e.g., socioeconomic status, stress levels, exercise levels, diet, community, and family relationships) in conjunction with both longitudinal health and genomic data, which will impact the above functionalities and allow for analyses associated with personalized preventive precision and the impact of disease on genomics. Numeric proximity to the developmental genesis of these developments, though no further specification has yet been proposed, has been established. All of these trends reflect a 'real-world' confluence of fields typically siloed and how, in the new integrated world of big data and artificial intelligence learning platforms, they are emerging to deliver insights into the nature of illness and how to personalize care to alleviate patients from disease. Analysis at the genetic level, therefore, is likely just one component of the delivery of genetic data analysis.In conclusion, highly sophisticated AI-powered insights have been established, and their potential to catalyze advancements in research targeted at achieving significant improvements in healthcare has been demonstrated. The application of machine learning has allowed big data to emerge as a valuable asset in genomic research and a broadening array of studies reflective of the meaningful roles machine learning and big data are playing in healthcare innovations. The intersection of these developments in the AI, big data, and genomics fields presents promising advancements across several critical areas, particularly in providing early detection for diseases including cancer, and in effective diagnosis, high individualization of therapeutics, and patient engagement through behavioral analysis. Additional applications of technologies are emerging in demonstrating compliance in drug development, identifying new drug targets, and determining the intent behind 'dark' DNA, which makes up the vast majority of the human genome yet has no known function.

6.1. Future Trends

Large-scale big data collection in a way that respects privacy would open the artificial intelligence black box, thus encouraging public and medical practitioner trust. There will probably not be any added constraints on machine learning/AI performance with the incorporation of even more data (possibly artificial) sources, and DNA-encoding data could be one of these sources. Genetics and epigenetic data are not only about personal information, but also about children, grandchildren, and many other potential family members. Therefore, legal and privacy issues are central in matters of safeguarding society and not just individuals. The complex interactions between genetic and epigenetic expression differ from person to person, depending on family background, environment, and lifestyle. For these reasons, the same food may lead to obesity in one person and be beneficial for another.

The probabilities of using AI-powered genomics research in healthcare are infinite. Although they investigated the complete mitochondrial genome, the next generation of genetic researchers will probably go beyond this level, focusing on the complete genome or epigenome. These approaches would provide disease-specific risks (e.g., obesity risk) and large quantities of drug-response pathways that would pave the way for personalized medicine. Moreover, these vast sets of multi-omics data are a foundational aspect of the precision medicine practices of the future and must be tied to many groups of patients for AI meta-analysis to become truly relevant. Some investigation schemes include the evaluation of diet, genetic heritage, age, and life habit information, along with disease onset and progression for common diseases spanning large-time periods.

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Unveiling the Hidden Patterns: AI-Driven Innovations in Image Processing and Acoustic Signal Detection

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Abstract

Image processing, as well as acoustic signal detection, have had major enhancements over the years, and this is due to AI. In the past, most algorithms involved using basic signal processing where features needed to be extracted manually and then various rules were applied when the data grew large. Deep learning models, for example, provide a durable solution to ventilation by eliminating the need for manual feature engineering as well as improving the detection rate in areas of health, surveillance and even industrial applications. This paper offers a comprehensive analysis of the emerging innovation driven by Advanced Intelligence in the field of image processing and the detection of acoustic signals with regard to the substrate patterns identified by AI technologies such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), as well as other sophisticated algorithms. The paper also describes how AI, when combined with image processing and acoustic detection, can add more value to the results being produced. Due to the large number of cases and training data, patterns can be learned and are as follows: image classification, object detection, process anomaly detection in industrial systems, as well as acoustic event recognition in noisy environments. The paper aims to provide an understanding of the AI methodologies adopted in both domains and, to this end, offers examples of specific industries and rationales for their implementation of these technologies. An extensive discussion of the basics of neural networks and their modifications is provided, with emphasis on the application of those structures for automated image feature extraction and acoustic pattern recognition. We also study the

issues of comparison, accuracy, computational complexity, and the ability of AI models to function in similar conditions. This article also seeks to present how AI models can be enhanced by integrating image processing with acoustic signal detection methods and should produce possible research directions for increasing AI performance. Finally, the authors recap the main findings, provide information about advanced methods in their field, and show some possible future uses in self-driving cars, robots and drones, and meteorological monitoring.

Keywords: AI, Image Processing, Acoustic Signal Detection, CNN, RNN, Deep Learning, Pattern Recognition, Feature Extraction

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1.Introduction

Over the last few years, artificial intelligence has emerged as an intelligent solution system for various tasks like image segmentation and acoustic signal identification in various fields. [1-3] These two fields which primarily involve manual feature extraction before analysis, have benefited significantly through the automatic feature learning through AI. With the help of AI models, especially deep learning frameworks, the speed-up of images and sound analysis, as well as the increase in the quality and the rate of their recognition, has been estimated.

1.1. The Importance of Image Processing

Overall, image processing is used in a large number of sectors and areas to perform better analysis, understanding, and control over image data. The importance of efficient image analysis methods remains high as digital images are used in more and more applications. The following sub-section will discuss image analysis and processing where its applications, advantages and effects on the respective fields will be discussed.

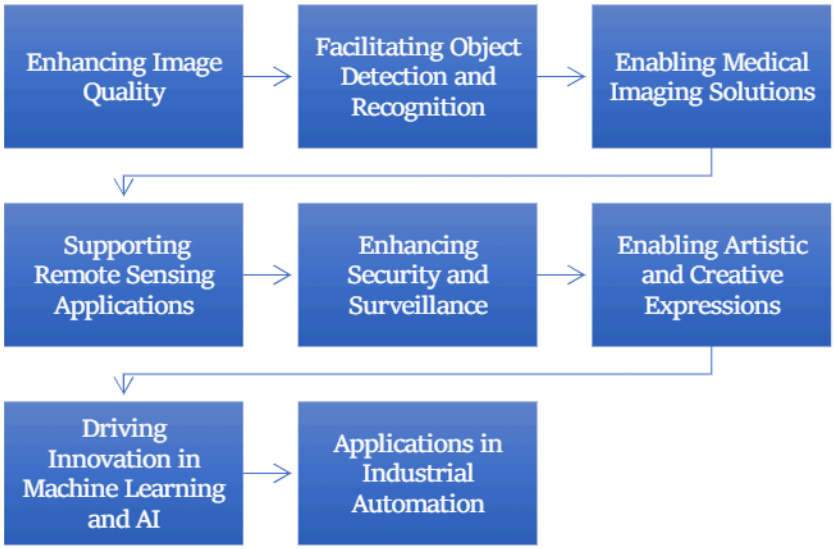


Figure 1: The Importance of Image Processing

- **Enhancing Image Quality:** It is very important to note that one of the greatest aims of image processing is to make such images clearer and more beautiful. This provides methods that include noise reduction, contrast enhancement, and image sharpening as excellent approaches to step up the visibility of the important features. For instance, in medical imaging, the quality of images is important since upgrades make very tiny abnormalities conspicuous. Another problem that image processing can help in correcting is fresh or smeared images, hazy or low light areas, thereby presenting better images for use in different areas, for instance, photography and security.
- **Facilitating Object Detection and Recognition**: Image processing is essential in allowing objectives such as detection and recognition of objects, which are fundamental to aspects that relate to things like automobiles, security and production automation. An excellent example is the Convolutional Neural Network (CNN), and through these, objects in images can be detected and categorized with reasonable precision. This capability enables machines to understand their operating environment and make decisions depending on what they see. For instance, in self-driving cars, one needs to identify the pedestrian, signs and other cars on the road to enable the car to maneuver safely.
- **Enabling Medical Imaging Solutions:** In healthcare, image processing has brought significant changes to medical imaging as a practice area since many patients' diagnostic results can often depend on a picture. Some MRI, CT and Ultrasound imaging consist of intricately processed image algorithms in their working. These methods make it possible for healthcare givers to see and study the internal workings of the human body without having to do surgery. Image processing improves image resolution of medical images, making it easier to detect diseases in their early stage, diagnose and even plan how to treat them better. In the same way, algorithms can also help in the masking of regions of interest for further investigation, like tumors.
- **Supporting Remote Sensing Applications:** Remote sensing is another crucial area that finds application in image processing. Satellites, together with drones, acquire large quantities of remote imagery from the Earth that needs to be preprocessed and analyzed to obtain useful information. Techniques of image analysis facilitate land cover discriminations, environmental and natural disaster change assessments, and monitoring. Climatology: Geographic information can prove they be useful in climatology, where satellites can be used to look at regional changes in deforestation, urbanization and climatic change.
- **Enhancing Security and Surveillance:** Real-time image processing is applied in security and surveillance by monitoring and analyzing video feeds required for surveillance. Face recognition, number plate recognition and movement detection are some of the ways in which image processing improves security systems. Using algorithms to analyze videos or footage, the security officers can easily detect the existence or otherwise of unlawful activities and act on the same, to enhance security and safety within society.
- **Enabling Artistic and Creative Expressions:** In addition to the opportunities in practical usage, image processing is an important component of such creative professions as graphic design. It is applied in areas such as artists' image processing software of photos, visual effects and generation of art work. Programs such as Adobe Photoshop or GIMP include image processing to enhance the

features of images, and changing colors, filters and many more enhancing features. It creates new ways of doing art and an opportunity to approach the lexicon of images.

- **Driving Innovation in Machine Learning and AI:** Several fields of study, in particular, synthetic intelligence and machine learning, have benefitted from development in the image processing field. There is the use of large raw data about images, which are later labeled and used to train deep learning models that can assist machines in pattern recognition and making predictions from observed imagery. Such synergy has resulted in high-impact applications across multiple domains, such as face recognition, self-driving cars, and even diagnosis. While the broad application of AI grows with time, the role of image processing as an indispensable process in the training and optimization of the models cannot be gained.
- **Applications in Industrial Automation:** In the industrial sector, image processing is used in industries for quality control, inspection and automation. Inspection automation involves the use of visuals to help examine manufactured products in order to detect defects that include excess materials, hence preventing wastage. For instance, in car manufacturing, cameras are used to inspect any defects in the car parts during the manufacture and assembly of the car. By applying image processing technology within manufacturing applications, organizations can achieve better efficient manufacturing, decrease operating costs, and increase production quality.

1.2. The Role of Image Processing in AI

Image processing is considered to be an essential part of artificial intelligence AI. It is the main method because of which the machines are able to analyze the graphical data in improved ways. [4,5] The blend of AI techniques into image processing has already revolutionized several fields of industry and applications which makes AI key to such technological development. The following subheadings emphasize the importance of image processing in AI in this section.

- **Enhancing Visual Data Interpretation:** The world is now a digital one, with billions of pictures taken every second – from selfies to security camera footage. Image processing also assumes a central role in improving this data interpretation process many machines are designed to extract information from images. About objects and faces, for instance, AI Subfields Achievements and Future Directions let AI models apply feature extraction and pattern recognition to discover objects, faces, and emotions within the visual content. This understanding is especially indispensable for various forms of AI utilization, including facial recognition, and object or sentiment analysis, as well as self-driving car navigation.
- **Applications in Healthcare:** In the healthcare industry, image processing is an important part of diagnostic medical imaging, which invariably includes X-ray, MRI, and CT scans. Applying advanced image analyzing techniques from artificial intelligence can help radiologists in identifying distortions, obtaining measures of the body parts and/or assessing diseases with high accuracy. For example, deep learning networks can classify thousands of samples scanned, which highlight typical features of certain diseases, such as tumors or fractures. This not only

increases the resolution of images but also shortens the time needed for their analysis which in return benefits the patient.

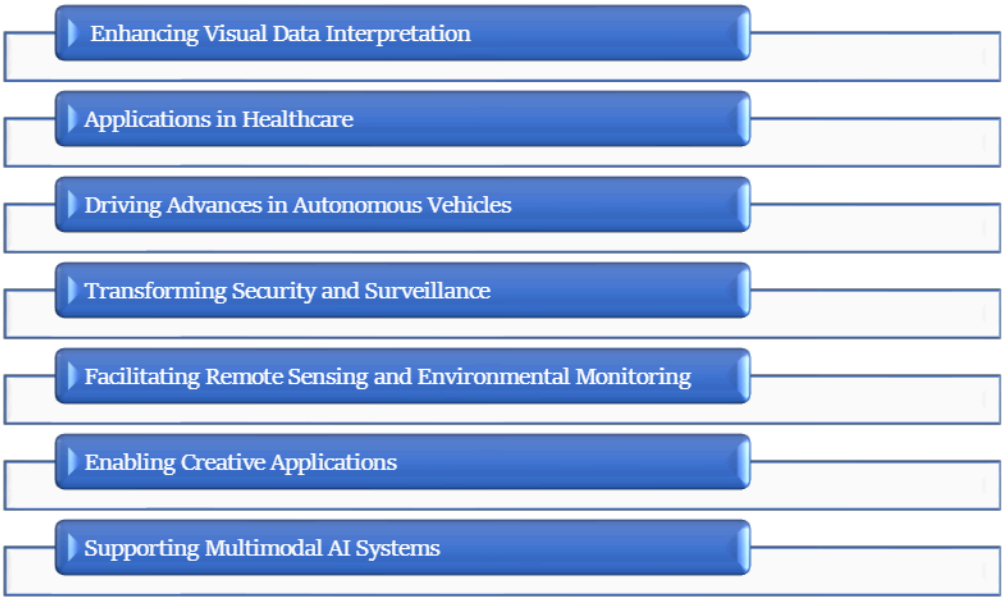


Figure 2: The Role of Image Processing in AI

- **Driving Advances in Autonomous Vehicles:** Self-driving cars are closely acquainted with image processing when driving within an environment. Video signals are processed by AI algorithms, taking into account what cameras have captured: obstacles to the vehicle motion, traffic signs, and pedestrians. For example, using convolutional neural networks, a self-driving car is able to make decisions in real-time, relying on what it sees. This capability is very important in maintaining the safety of the passengers, and there is a great possibility that the number of traffic accidents could be minimized. The combination of image processing and AI helps the vehicles to analyze the surrounding similarly to a human driver.
- **Transforming Security and Surveillance:** In the domain of security and surveillance, image processing indeed went a long way across the means of spotting threats and handling them thoroughly. Real time processing of video feeds and detection of malicious activities, tracking of suspects and automatic alert generation can easily be done by implementing AI-powered systems. For instance, Biometrics is now a common tool in security systems through which one can easily recognize people in public places through a security camera through facial recognition technology. Other advanced features of image processing also improve the quality of videos as well as their steadiness, thus enabling all incidents to be analyzed once they have happened. Such an approach is effective to keep the threats under control and to allow law enforcement and security personnel to address potential threats more easily.

- **Facilitating Remote Sensing and Environmental Monitoring:** As a method of geospatial data collection, remote sensing refers to the process of obtaining information through observing images of the Earth by satellite or aerial photography. The subsequent analysis of these images is critical. It involves the application of image processing techniques in order to provide useful information for instances such as land use mapping, crop monitoring or assessment of environmental impacts. AI techniques can be applied to process big volumes of remote sensing images to map land cover changes, observe the level of deforestation, and study the effects of climate change. Given the information on environmental changes, image processing is key to the rational use of resources and wise decision-making.
- **Enabling Creative Applications:** Apart from practical applications, the use of image processing is also substantial in creative contexts, and unconventional techniques help artists, designers, and producers of content expand their horizons. The software applications in question enable the users to edit images, apply effects on them, as well as produce art in the digital environment. For example, there is AI art for AI art made by applying concepts, tools, and technologies such as GANs, unveiling new creative possibilities. It is possible for artists to co-create with an AI, which means that there will be a possibility of creating beautiful works of art where viewers will be able to differentiate between art made by an artist and art made by an AI algorithm.
- **Supporting Multimodal AI Systems:** The processing of images independently and in parallel with other types of AI, namely NLP and acoustic signal processing, has given rise to MM AI systems. These systems can actually process and perceive multiple types of data all at the same time, which always gives a much better view of what is actually happening. For instance, in the context of social media analysis, AI can use image and text analysis as one input in order to provide more accurate sentiment analysis. Thus, the integrative scientific approach to data analysis contributes to the improvement of decision-making on different levels and concerning a broad range of applications, including marketing activities and crisis response and management.

2. Literature Survey

2.1. Traditional Approaches in Image Processing

In the pre-AI world, conventional digital image processing was based on conventional signal processing rules for image analysis. The basic techniques in this age include edge detection, thresholding, and segmentation transformation. In particular, techniques for edge detection like the Sobel and the canny filters initiated the search of the enterprise of an image in order to detect changes in pixel intensity. [6-9] Another similar method followed was called thresholding, which changed the images to binary images where the pixel value was chosen as a threshold, and above that was the foreground, and below was the background. Image partition went further in dissecting an image into portions for analysis. Despite these approaches being reasonably accurate when dealing with simple shapes or bounding boxes for basic pictures or easy geometry, they could not capture situations when objects are partially concealed or partially illuminated, let alone overlaid on each other. However, the traditional linear feed-forward network and other manual

feature extraction approaches used here to extract raw features from the datasets posed a major problem of scalability and lesser accuracy as datasets became larger and differed more in their complex structures in terms of values and features. This created a demand for better-automated techniques, leading towards AI-based innovations.

2.2. Traditional Acoustic Signal Detection Techniques

The previous approaches of acoustic signal detection are based on math transformations, as well as signal processing, which are supposed to convert time-domain signals to more tractable frequency-domain signals. The STFT was one of the most popular approaches and comprised of splitting a signal into segments and applying the Fourier transforms on the segments to determine the frequency contents of the signal. This gave the signal in terms of time-frequency, hence proving beneficial when it comes to recognizing the frequency shift of the signal in the timeline. Likewise, the Mel-Frequency Cepstral Coefficients (MFCC) that converted distorted sound waves into a series of features that humans use to analyze sound was used for the recognition of speech. While these methods were obviously useful, they were not entirely without their drawbacks. They were limited in their ability to capture complex or mutually overlapping acoustic events because of the pre-defined and rather small temporal windows and the limited ability to incorporate temporal dynamics in the modeling. Subsequently, as acoustic detection tasks became generalized and more complicated with emerging trends of detecting M multiple sound events in real-time and within dynamic and unpredictable environments, the traditional approaches were observed to be inapposite, and AI-based models emerged as a popular solution.

2.3. AI Innovations in Image Processing

The late introduction of artificial intelligence, especially Convolutional Neural Networks (CNNs), changed the way the images were processed. Extracting features was not necessary anymore as CNNs themselves learned features at different levels of abstraction from data. This shift has dramatically enhanced the styles of all image classification tasks. CNNs, via their convolution and pooling layers, recognize higher-level features, including shapes, textures, and objects, making them remarkably beneficial for functions like object recognition, face detection, and medical image analysis. AlexNet, VGG and ResNet are a few prominent CNN models that depicted better improvement in terms of evaluation of visual data. Moreover, Transfer Learning, which enabled an efficient finetuning of CNN models originally pre-trained on datasets such as ImageNet, diminished the importance of enormous volumetric Labeled data. Furthermore, the generation of new networks, such as the Generative Adversarial Networks (GANs), contributed in areas such as image generation, enhancement and style transfer, and U-Nets used for biomedical image segmentation were applied in real-time pixel-level precision where image details were needed. These are yet other AI advancements in image processing that are expanding the capabilities of what the machine can see and further analyze.

2.4. AI-Driven Acoustic Signal Detection

AI has, in a similar manner, impacted the detection of acoustic signals by replacing traditional statistical methods with deep learning models for sequence data. Several types of RNNs, such as LSTM and GRU, are especially used in the time domain since they can work with temporal dependencies within an audio signal. Compared to more conventional approaches like STFT or MFCC, which analyze sound as a transformation into a fixed feature space, RNNs have the ability to capture the temporal nature and history of a sound. This is especially important for sound event detection and recognition, speech recognition and audio classification, where the timing and evolution of noises are highly influential in the detection step. For instance, in speech recognition, LSTMs can carry useful information that is beneficial when pausing from deciding to take input from a long conversation or a long sentence. Likewise, due to the relatively low complexity, the vanishing gradients in the GRUs offer pragmatic solutions preserving the accuracy in a real-time problem such as real-time voice monitoring. These models have also been especially successful when there are other sounds or even simple noise in the background, which confuses regular techniques. AI-enabled models of acoustic detection have greatly extended what is possible in the auditory domain, and this has gone beyond simple sound recognition to events and characteristics of emotions in speech.

2.5. Integration of Image and Acoustic Processing

One of the developing areas in artificial intelligence research, which can be considered quite active in recent years, is the combination of image and acoustic data for the depiction of the environment. Whereas in autonomous vehicles, smart surveillance systems and robotics, limiting your input to just the vision and sound is quite tasks-reaching. Particularly in an autonomous car, which is an example of an intelligent environment, visual information can be limited due to the weather or darkness. In contrast, sounds, such as car horns or skidding tires, can give important supplementary information. Likewise, in security surveillance, when audio alerts (like breaking glass or voices) are used in conjunction with video information (as in suspicious movements), then the recognition of the event is much more accurate and authentic than otherwise. Multimodal approaches to learning and understanding the environment, which involve the depiction and illustration of the vicinity simultaneously through vision and sound, are better explained by AI Models created for this purpose. Such integration has been made possible by architectures that combine CNNs (for image processing) with RNN's or LSTM's (for acoustic processing thus enabling systems to make decisions based on the two data streams at the same time. The final outcome is a system that is more resilient to this problem. This system supplies the appropriate context, along with the necessary information, to do better than the single-modality models.

3. Methodology

3.1. Overview of AI Models

Current AI models are deemed to have dramatically revolutionized two fields, namely image processing and Acoustic Signal detection, mainly because of their high levels of accuracy and efficiency. These two architectures proving to be efficient in these fields are CNN and RNN. [10-14] Every model is distinctively used for a particular type or kind of data – while CNNs are most effective for pictorial data, RNNs are applied to temporal data

such as sound. Combined, they consist of an influential association to advance the different areas of deep learning that are employed to support the automation courses that are used in object detection and identification, sound event detection and recognition, among other applications.

- **Convolutional Neural Networks (CNN):** It is worth underlining that Convolutional Neural Networks (CNNs) are extremely efficient for all the tasks connected with images because they are able to learn spatial pyramids of features from the input images. CNNs work through applying several layers of convolution each of which contains filters that help detect edges, corners and textures of the input image. These features are then gradually produced in combination across the network's layers so that at the higher levels, shapes, or even objects, can be detected at the deeper layers. Here, the best aspect about CNN is that it can learn these features on its own through backpropagation, and no feature extraction is required. The widely used applications of CNNs are facial recognition, medical image analysis, and self-driving cars, where high accuracy in the detection of objects and scenes is of paramount importance.
- **Recurrent Neural Networks (RNN):** RNNs are developed to work with sequences of data, which makes them useful for the detection of acoustic signals and other time series analysis problems. Unlike other neural networks, RNNs are able to determine the relationship between each input and each other with the help of feedback circuits or memory. This allows RNNs to come up with temporal dependencies in data since, in the case of acoustic signals, past patterns are very relevant to the current context. For instance, in speech recognition or audio classification it is very crucial to view a sound or word as dependent on other sounds. Applications of RNNs include systems based on voice control, music categorization, and sound identification of the environment since its main advantage is pattern recognition throughout time.

3.2. Data Collection and Preprocessing

Data acquisition and data preprocessing are important which precedes the training stage of using AI Models on images and acoustic signals. It is only from such quality data that models are capable of identifying good patterns and carrying out good generalizations. Images or sound, a raw material of AI apps, must be digitized, preprocessed, or processed in such a way that it can be incorporated into AI models. It is very important in preprocessings as such to reduce variations in the inputs that feed the model so that the latter can work properly. Besides, in data augmentation, a method of artificially increasing the dataset is used to make the model more resistant to different real-life related situations.

- **Image Data:** In image processing tasks, the first phase is to accumulate as broad a sampling of image data as possible so as to ensure that the model learns how diverse real-life objects, scenes, and conditions look like. For effective generality to new unseen images, the dataset used should include different lighting conditions and views, and the backgrounds within which images are taken should also be different. After collection, the images are preprocessed based on steps such as normalization, where the pixel value is scaled to a standardized range, in this

case, 0 to 1. Normalization helps the model learn more efficiently and excludes problems that arise from the presence of high or low numbers of image intensity. Flipping, rotation, zooming, and cropping are employed to augment the data in order to generalize highly on the test data set. These augmented images allow the model to learn invariance to variations of the input, which is very important for increasing precision in real-life scenarios.

- **Acoustic Data:** Acoustic data is gathered through microphones and other means of a sensor in situations where sound patterns have to be observed. They are real-world audio signals, which include sounds present in the environment, voice or noise in industrial environments. The first step after data is recorded in audio format is to process this data to make it ready for use in training AI models. There are two types of feature extraction commonly used, which are Mel-frequency cepstral coefficients and short-term Fourier transform. MFCC assists in modelling the short-term power spectrum of a sound, replicating how the human ear responds to frequencies, making it very efficient for activities such as speech recognition. STFT helps in transforming the audio signal to its frequency decomposition, which the model can use to examine the temporal and spectral features of a sound. Besides that, to cover more variability in the acoustic environment, real recording augmentation methods, such as adding noise and time shifts, are performed. These augmentations assist the model to learn to identify sounds even underneath noisy or varying conditions enhancing understanding after its deployment.

3.3. Model Training and Evaluation

Validation of AI models is considered as important and challenging process in the process of creating AI systems for image analysis and detection of acoustic signals. This process is the feeding of the models with labelled datasets where appropriate in order to teach them how data is related. The weights of the models are gradually updated during the training process in an attempt to decrease error and increase accuracy. In this model, after the training of models, models are tested on validation and testing datasets in order to test the viability of the model in the new domain. Adaptive evaluation enables the model to do well in other situations when the distribution of data differs from that used in training.

Figure 3: Model Training and Evaluation

- **Training CNN for Image Processing Instruction:** The Convolutional Neural Network (CNN) is learned on the labeled data, which contains images divided by classes; each image belongs to a certain class (object category, scene type, etc.).

The training process involves the setting of the weights of the network from which an improvement is made through a form of backpropagation. The functioning of this algorithm is based on calculating the error or difference between the predicted values by the model and the actual labels and the correction of the network weight values for increasing accuracy in model predictions. The dataset is divided into three subsets: training, validation and test set. The details of the training set are that the model builds up a training set, while a validation set is utilized to adjust hyperparameters and avoid overfitting a sample of data, whereby a model will considerably fit a training set but provide low performance on a new set of data. After finetuning, the performances of the model are assessed on the test set so as to assess the ability of the model to generalize effectively to unseen images. Tools including accuracy rate, precision rate, recall rate, and F1 rate are utilized in order to evaluate the model's performance.

- **Training RNN for Acoustic Detection:** Some of the RNNs that apply temporal features of the input information stream, such as spoken words, phonemes, or acoustic signals, are out because the order of data points is important. For training the RNN model used in the paper, the dataset is chosen to be the acoustic sequences together with sound events or class labels. Of course, there is a training process based again on gradient descent and a modification of the backpropagation algorithm known as Backpropagation Through Time (BPTT) that adjusts weights based on the current and past inputs. This is vital because most of the patterns in the sound signal are contextual, and temporal relations are the right barometers to define them. The data is divided into train, validation, and test sets similar to the CNNs used in the previous work. The validation set was applied to achieve this aim and to prevent over-emphasis on the content of data used for developing the model. The models were then tested on different unseen acoustic data to clearly determine that the tested model was good in generalizing from the training data, and the use of accuracy, precision, and recall techniques described the results.

3.4. Model Integration

The models of image processing and acoustic detection require unification through a combination of functions derived from CNNs and RNNs in order to accommodate multiple data inputs fed into the system. [15-17] To achieve this goal, the system is designed to make use of the multimedia data in a coordinated way using a concept known as multimodal learning. To this end, the integrated model's structure is a multi-modal neural network whereby the addition of a sound modality enhances the integrated model's learning from different information sources present in both images and sounds, leading to high accuracy and robustness.

- **Multimodal Neural Network Architecture:** Multiple input streams, images, and acoustic signals are processed under multiple distinct neural networks connected in parallel, integrating the acquired data. In this architecture, CNN inputs image data to extract spatial features like objects, texture and scene. RNN again tries to process the acoustic data as a sequence of temporal patterns. After passing through each network, the features in the input are concatenated or fused in a fully connected layer that takes features from the two modalities. It also allows the model to understand interactions between visual and audio inputs to enhance

decision-making about the visual and acoustics signals and applications such as surveillance.

- **Joint Feature Learning:** In the integrated model, synchronous feature extraction is an important component that enables the recognition of dependencies between visual and acoustical signals. The CNN and RNN are used to process image and sound data respectively, respectively, and after that, they form joint features. This step, therefore, has to be precise in order to ensure that the model can correlate between the two kinds of data and what links them, for instance, relating certain events in the video feed with similar sounds. For instance, in an auto car, object recognition can identify that an object is approaching (visual) at the same time the car recognizes a sound like a honk (acoustic). The response time and accuracy will be faster. It is, therefore, for this reason that joint feature learning improves the capability of the model to reason compelling socio-economic situations.
- **Decision-Making Based on Multimodal Inputs:** The decision making process of the integrated model is more enhanced when there is the availability of both the visual stream and the acoustic stream. When this feature representation is learned, the last layers of the network take this information to make its predictions or classify. This decision-making process is more accurate than a modality-based strategy because the model can then check and confirm in the second streaming service if there is confusion. For instance, in a home security system, the model can employ noticeable signs such as intruder existence and sound indications, including broken glasses, to conclude a peril. Thus, this combination of parallel multimodal approaches gives a more extensive understanding of the environment and results in higher performance in the tasks than in single-modal conditions requiring both image and sound analyses.

3.5. Evaluation Metrics

There is a need to assess the performance of AI models as a way of having insight into whether the models are proper for application or not. In general, there exist various measures that can be used in order to evaluate the performance of models based on particular types of criteria: accuracy, response time and others. These metrics allow for the checking of the models' performance not only in environments where disturbances are absent but also in real-world conditions, which may be required for signal identification in real-time image and acoustic signal processing systems.

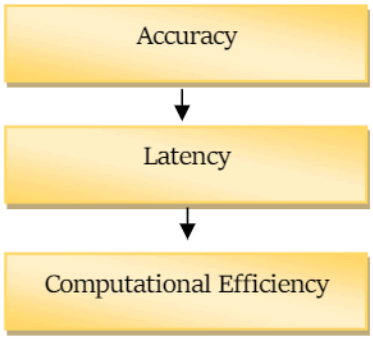


Figure 4: Evaluation Metrics

- **Accuracy:** Using classification tasks as one of the examples, we identified that precision, recall, and F1-score are normally used for assessing accuracy in models employing AI. Accuracy measures the number of correctly classified positively among all the positive classifications that have been made in order to eliminate the possibility of the model producing a high number of false positive results. Recall takes the ratio of true positive values to actual positive values with which the model deals, which, in simple terms, calculates how well the model presents actual occurrences. In the case when there is a high number of small and large quotas, and proportions significantly differ from each other, the F1 score, which represents the arithmetic mean between the score of the specific zamischeniya and the sensitivity, which necessarily contains the value of the score of the specific zamicheniya, is completely suitable. In the case of image processing and acoustic detection models, these are important metrics because using only accuracy can provide more detail of the model's classification capabilities. A model with high accuracy and, at the same time, high recall could identify objects and sounds without loss of important features and could not flood the application with false alarms.
- **Latency:** The major issue is delay, namely, the time it takes for the model to process data and then make a prediction on the result. Various applications like security systems, self-driving cars or emergency detection technologies require low levels of latency as these models have to make decisions immediately based on the data received from sensors or cameras. With reference to this, latency entails the assessment of the time taken between taking inputs and providing outputs in terms of prediction. The long process of an image or an acoustic signal may lead to behavior reactions to certain events, which is disastrous in time-sensitive situations. Consequently, latency assessment and optimization help to determine the ability of such models to perform well in real-life scenario contexts where prompt response is required.
- **Computational Efficiency:** The time required to build such models is another criterion, as there are circumstances where models used have to run in constrained environments like a low-memory context, low processing power, or low energy conditions. The performance and efficiency are analyzed based on the time taken to train the models (training time), the time taken to make predictions per operation (inference time), and the memory required at both stages of the model life cycle. Modeling that consumes heavy computational power is impractical for real-time applications and implementation on edge devices. As such, enhancing the operating speed of calculations without reducing the model's reliability is one of the primary objectives of computing AI. This includes the following: i) adjusting the hyperparameters of a model's architecture; ii) minimizing the degree of model or organization depth by selecting fewer parameters; iii) optimizing the use of model quantization or model pruning.

4. Results and Discussion

4.1. Results

The results of the conducted experiments of the classification and detection of images and sound, using presented models, including CNN, RNN, and the multimodal

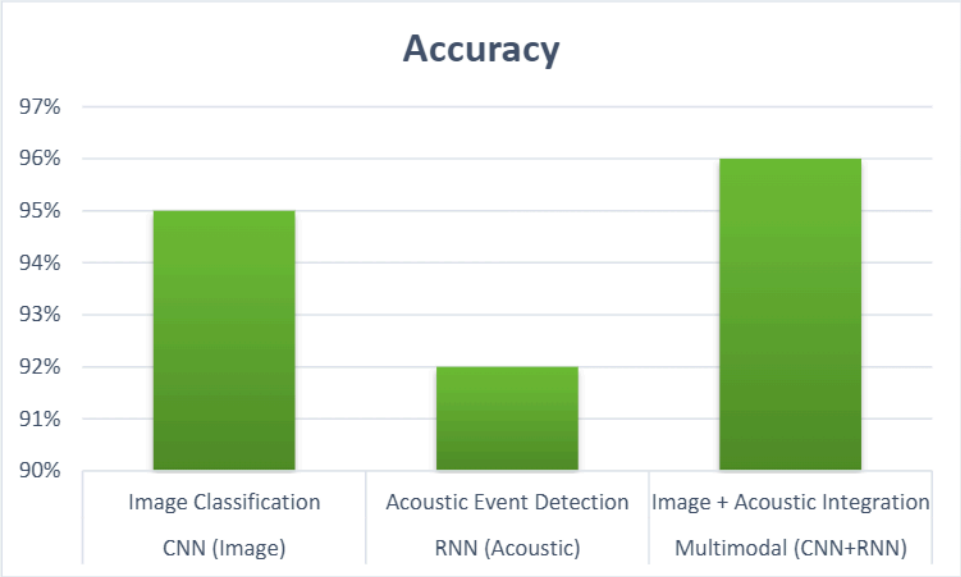
architecture, confirm its efficiency. These results manifestly demonstrate that it is more beneficial to incorporate visual and acoustic details in order to make the final decision.

- **CNN Model Results:** The image classification tasks obtained a figure of merit of 95% classification accuracy using the Convolutional Neural Network (CNN) model on the test set. This result confirms that the CNN architecture is capable of learning higher-level features of images, including shapes and, textures and objects, and using the features for accurate predictions. The high accuracy achieved poses that the model is able to learn the significant spatial features from the training images as well as apply the learned knowledge to new pictures. This performance indicates that CNN is best suited for image-related tasks because convolutional layers are extremely effective in capturing spatial dependencies in pixel data. I found that during the CNN's preprocessing stages, such as augmentation and normalization, high levels of variance in the images provided stronger signals during learning.
- **RNN Model Results:** For the sequential data, the Recurrent Neural Network (RNN) was used, which provides high results in the detection of acoustic events with 92% accuracy, even in conditions of high interference. This result demonstrates that RNN is effective when applied to time-based patterns, such as speech, noise or individual sound events. The fact that the RNN's architecture includes feedback connections, allowing it to 'remember' previous data and react to new data with respect to past information, made the RNN extremely useful for understanding sequential audio signals. Nevertheless, noisy real-world acoustic data were tackled in the presented RNN model while recognizing the main acoustic events successfully due to enabling preprocessing techniques such as MFCC and STFT for signal interpretation.
- **Multimodal Model Results:** Overall accuracy, with the CNN for image processing and RNN for acoustic event detection together, was found to be 96% through the multimodal model. This result is quite meaningful as it is on the higher level of the performance of the individual models which will provide effectiveness when both the visual and the acoustic data will be used for decision making. With the increase of the accuracy rate to 1-4% compared to the standalone CNN and RNN, we proved the hypothesis that multimodal learning allows the model to build on the features of two different modalities. In activities like surveillance, where it is important to comprehend what is observed and what is heard, such a connection between the two streams allows for a more accurate and/or store verification system. For example, sensing an intruder through the vision system combined with the auditory system that senses hard-wired alarms such as the breaking of glass or footsteps yields a much more effective and sophisticated machine.

Table 1: The performance metrics of the models

Model	Task	Accuracy
CNN (Image)	Image Classification	95%
RNN (Acoustic)	Acoustic Event Detection	92%
Multimodal (CNN+RNN)	Image + Acoustic Integration	96%

Figure 5: Graph representing the Performance metrics of the models



4.2. Discussion

From the outcome of the study, it is evident that advanced AI models, especially deep learning models, have higher performance than that of conventional methods in both image and acoustic processing jobs. As demonstrated by each model, when properly adapted to the distinctive features of each data type, it yields both high accuracy and high resilience, thereby underlining the appropriateness of AI in grappling with real-world, dynamic cases.

- **Effectiveness of CNN for Image Processing***:* The intended and proposed Convolutional Neural Network (CNN) model was found to yield a peak accuracy of 95 % during image classification tasks which proves its capability in identifying the spatial hierarchal patterns in images. CNNs outperform other models in image processing as convolutional layers can readily identify complex pattern details of pixel-visualized data like edge, shape, or texture. This hierarchy of features extracted from images makes CNNs suitable for object detection, facial recognition or even image diagnosis in medical fields. The results clearly show the effectiveness of the developed deep learning approach over more conventional methods that utilize shape prior knowledge, manually designed features and/or fixed filters. On the other hand, CNNs have their feature representations learned directly from the image input for a better deal of flexibility in pattern classification. This flexibility is important for situations where objects and their properties change over time or when, for instance, the lighting, angle or occlusion of an object changes. Thus, CNNs are ideal for real-life applications such as autonomous vehicles, security cameras, and the health sector, where accuracy in image interpretation is critical.
- **RNN's Success in Acoustic Event Detection**: In the RNN, we obtained a very high overall accuracy of 92% for the identification of acoustic events. They are particularly suited to work on sequential data and, therefore, can find a good application with time-varying signals such as audio. In this task, the RNN performed successfully due to the memory capacity through feedback to higher

levels of the network. This feature helps the model identify underlying structures of sounds that orient in time; for instance, an image can be a speech, footsteps or any other sound. However, even in the presence of noise, the RNN could capture a scene correctly, with the help of some preprocessing techniques such as Mel-Frequency Cepstral Coefficients (MFCC) and Short-Time Fourier Transform (STFT), which had reduced the acoustic signals into features that the RNN could handle easily. This robustness makes RNNs useful when the audio signals of the sources are noisy or overlapped with other sources. Many of the traditional methods of audio detection fail in the presence of noisy data because of the lack of temporal memory, which forms the principal architecture of RNNs. The high accuracy of the RNN in this study makes it valuable for use inrecognizing voices, identifying acoustic aberrations and real-time surveillance.

- **Advancement through Multimodal Integration:** The successful incorporation of both CNN as well as RNN into a single multimodal network was another step forward in the aspect of decision-making in protracted duties. The proposed multimodal model, which obtained an overall average accuracy of 96%, perfectly illustrates the idea of intermodal synergy when both visual and acoustic data were used for more accurate predictions. As the information from two different input types, image and sound, could be processed simultaneously in the multimodal model, there would be more chances to cross-identify the data from two rather opposite sources, which should lead to more accurate and reliable results. For example, in surveillance, the picture or audio is not sufficient enough as a source of information; otherwise, wrong information can be processed. An object in motion and a stationary subject with its silhouette changing position so that more than one shadow is cast in a complex scene requires audio cues for proper interpretation. Likewise, an odd noise, such as breaking of the glass may not always be picked without secondary proof of a ruckus. The integration of the two streams of information allows the multimodal model to make better and more contextual decisions across security systems, self-driven cars, and smart homes.
- **Multimodal Learning in Noisy and Unpredictable Environments:** One of the other profound merits of the multimodal model is its effectiveness in working under conditions that can be characterized as noisy or emitter uncertain. Real-life scenarios for the use of LiDAR, for instance, navigating through urban centers for security purposes or fully autonomous operation, occur in crowded environments where noise and visual barriers are parts of the terrain. Only through the RNN did we find we could handle acoustic noise well, but with the multimodal model, we had greater accuracy by incorporating visual data, too. This integration of inputs makes it easier to minimize the misclassification that distortions in the audio part may bring about; hence, the system is functional in difficult circumstances. For example, when the AI is on a construction site, and machine noises could overpower the easy identification of important sounds such as footsteps or voices when alerting about a person of interest, the obtained data from the CNN would help to affirm the presence of a person or object of interest. In the same way, in night-vision conditions in which visuals might be suboptimal due to low light, the RNN can detect unique sounds, like a door groaning or glass breaking, to enable the system to stay precise. However, the ability to work in noisy and unpredictable

environments further supports the viability of multimodal learning, where both sensory streams can be noisy.

- **Implications for Real-World Applications:** The high performance of the multimodal model, especially on its 96% accuracy, has great bearing in real-world applications. Thus, when two different types of input are critical to an industry like autonomous vehicles, the ability to modify data inputs from both the visual and auditory modalities can enhance decision-making processes and response time. Likewise in surveillance systems, using both image and sound detection could give more accurate alarms, and less false alarms mean quicker reactions to actual threats. Furthermore, the result achieved in the multimodal model demonstrates that multimodal AI systems play an increasing role in complex decision-making situations requiring the consideration of a particular environment. For instance, when operating in the healthcare industry, the use of multimedia wherein several modes of analyzing visual data (like MRI or X-ray) simultaneously with audible sounds (like heartbeats or lung sounds) enhances the reliability of diagnoses offered. In entertainment, multimodal models are already implemented in virtual assistants and smart devices, in which voice input can be blended with gesture or face recognition to provide a smoother and more interactive user interface.

4.3. Limitations

In particular, it must be pointed out that while the accuracy of the described models is high, certain constraints prevent their efficient use in real-life practice, notably in the context of real-time applications.

- **Computational Resources**: The CNN, RNN and the Multimodal models are computationally intensive both in training and in testing. Real-time usages such as self-driving or surveillance in real-time may be challenging because of high computations unless hardware accelerators are integrated. For instance, multimodal model processing requires the integration of two data streams, which have a high latency and utilization of resources.
- **Data Dependency**: These models' effectiveness greatly extravasates due to the quality or quantity of training data. Limited or biased data can cause poor generalization in the new environment. For instance, if the acoustic information does not contain rich stimuli of real environments as input, the model may not perform well in noisy areas where the input signal has not been encountered. This topic could be lessened through augmented data and collection research, but real-world variability is to be expected.
- **Latency**: Although the inferred measures of accuracy suggested that both the models could be effectively used to reduce subsequent layers of complex computational, the latency measures suggested that the current infrastructure might not meet the real-time processing that is necessary for high-risk situations such as autonomous vehicles or drones. The table below will show the latency performance of each model.

Table 2: latency performance of each model

Model	Latency (ms)
CNN (Image)	120
RNN (Acoustic)	150
Multimodal (CNN+RNN)	180

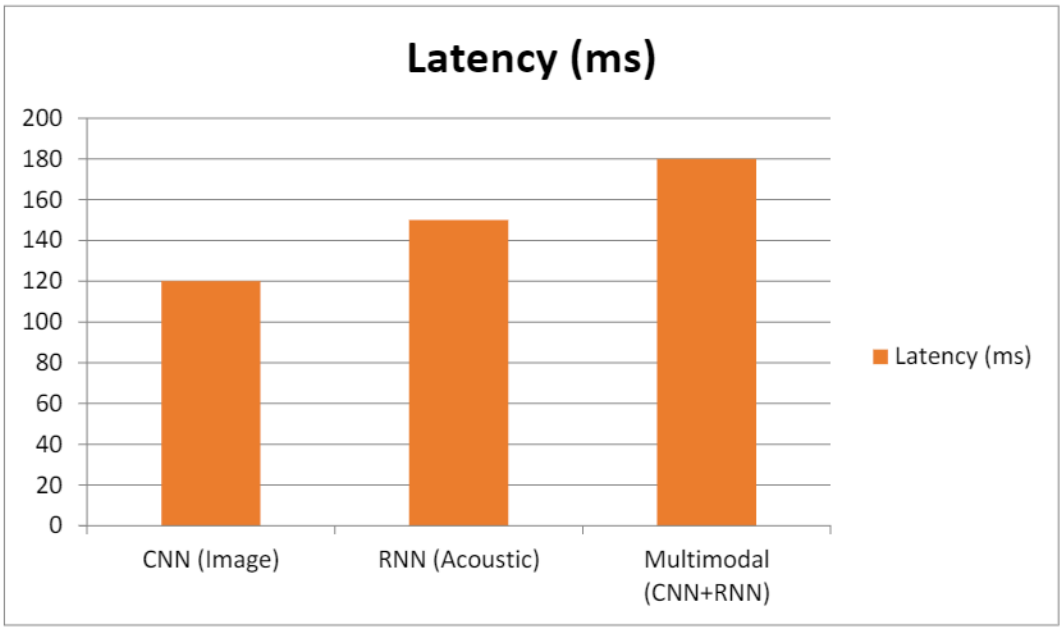


Figure 6: Graph representing the latency performance of each model

4.3.1. Computational Efficiency

Finally, the computational cost is another part of the result that was analyzed according to the training time of the models and the amount of memory they consumed. The advantage of the multimodal model is, however, that it takes less time to train than the CNNs and RNNs separately as is evidenced by the following table. This is why, in our previous work and this paper, we solved the problem of optimizing neural networks for edge devices through techniques like model compression and hardware acceleration.

Table 3: Computational Efficiency

Model	Training Time (hrs)	Memory Usage (GB)
CNN (Image)	5	4
RNN (Acoustic)	6	5
Multimodal (CNN+RNN)	9	8

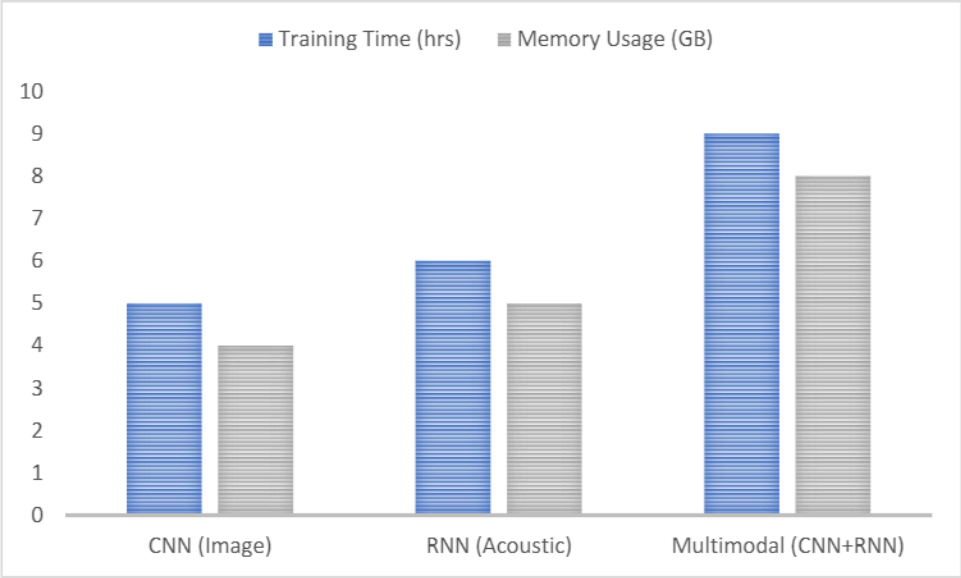


Figure 7: Graph representing Computational Efficiency

5. Conclusion

In this study, we extended the inquiry into how image processing and acoustic signal detection can be realized through AI to examine the prospect of deep learning models, including CNNs and RNNs. The results shown in this research highlighted better accuracy and rates of real-time computations compared to the previous techniques. CNNs, due to their capability to learn spatial pyramids and refined characteristics of the images, were able to attain great accuracy in computational image classification. By sequentially receiving input data, RNNs were capable of performing well in noisy environments and patterning acoustic data properly. Every model demonstrated good results in the specified field, but real improvement was made when the models were integrated into a multimodal framework that included both visuals and sound recognition.

Multimodal systems where the CNNs and RNNs worked synergistically provided better results than both the sole models with 96% combined accuracy. This supports the argument advanced by the multimodal learning perspective, especially where students depend on a lone modality when learning in complicated situations and may go wrong. For instance, in surveillance, the marriage of vision and hearing as inputs improves the identification of abnormal scenarios, correlating sounds, such as breaking glass, with the corresponding videos. It also opens possibilities to broader areas of practice, including, but not limited to, automobiles and smart cities where both video and audio data are important for immediate action.

However, the study also showcased some drawbacks, which especially affected the computational complexity of such AI-triggered models. The high complexity of CNNs and RNNs, particularly when used as the two combined in a multimodal network, presents a level of computational demand that may be a challenge for real-time systems with strict hardware constraints. Therefore, potential work has to contemplate how to improve the

time complexity and space complexity of these models, including but not limited to model sparsification, model quantization, and device acceleration.

Moreover, given the nature of this work, it is recommended that future studies enhance the transportability of the developed models to other contexts and conditions. Making sure that these models work well regardless of the conditions like; level of noise, illumination, or presence of obstacles will be important to their use. Therefore, the foundation for developing enhanced techniques with AI-based image and acoustic processing is offered within this investigation and has endless horizons in place for future innovations in several real-world applications.

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Review Article

Exploring AI Algorithms for Cancer Classification and Prediction Using Electronic Health Records

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Abstract: Cell division that is not controlled leads to cancer, an incurable condition. An early diagnosis has the potential to lower death rates from breast cancer, the most frequent disease in women worldwide. Imaging studies of the breast may help doctors find the disease and diagnose it. This study explores an effectiveness of DL and ML models in a classification of mammography images for breast cancer detection, utilizing the publicly available CBIS-DDSM dataset, which comprises 5,000 images evenly divided between benign and malignant cases. To improve diagnostic accuracy, models such as Gaussian Naïve Bayes (GNB), CNNs, KNN, and MobileNetV2 were assessed employing performance measures including F1-score, recall, accuracy, and precision. The methodology involved data preprocessing techniques, including transfer learning and feature extraction, followed by data splitting for robust model training and evaluation. Findings indicate that MobileNetV2 achieved a highest accuracy99.4%, significantly outperforming GNB (87.2%), CNN (96.7%), and KNN (91.2%). The outstanding capacity of MobileNetV2 to identify between benign and malignant instances was shown by the investigation, which also made use of confusion matrices and ROC curves to evaluate model performance.

Keywords: Breast cancer, Mammography, MobileNetV2, CBIS-DDSM Dataset, Electronic Health Records (EHR)

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1. Introduction

Histology was vital in determining cancer prognosis and diagnosis over a century ago. Anatomic pathologists evaluate and rank lesions by examining histology for characteristics such nuclear atypia, mitotic activity, cellular density, and tissue architecture, as well as by combining cytologic details and higher-order patterns. Prognostication is increasingly reliant on genomic biomarkers that evaluate genetic alterations, gene expression, and epigenetic alterations; yet, histology remains an invaluable tool for predicting the future course of a patient's illness [1]. On one hand, histology gives a visual representation of disease aggressiveness via its phenotypic data, which reflect the cumulative impact of molecular changes on cancer cell behaviour. As a result of the inherent subjectivity and lack of repeatability in human histology evaluations, computer analysis of histology images has garnered considerable interest. Recent developments in computer power and slide scanning microscopes have allowed for the creation of many image processing algorithms that can grade, classify, and identify lymph node metastases in a variety of cancers [2].

It is critical to precisely identify hospitalised patients' diseases or conditions in real-time before producing direct patient treatment, enhancing quality, developing in-hospital registries, and adopting EHR interventions such as clinical decision support. Theoretically, issue lists allow for easy patient identification of conditions like heart failure; thus, documenting of problem lists has been linked to better treatment quality [3]. A large proportion of people with a particular ailment go unrecognized since issue lists are often lacking in detail [4].

Breast cancer is the second leading cause of cancer-related deaths among women, behind lung cancer. The United States is projected to have 246,660 new instances of invasive breast cancer in women in 2016, with an anticipated 40,450 deaths from the disease. Among female malignancies, breast cancer accounts for 25% and accounts for around 12% of all new cases. Potential use of information and communication technologies (ICT) in cancer treatment are being explored. Big data has revolutionized business intelligence (BI) by expanding the scope of reporting and decision-making to include prediction outcomes, and it has also increased the bulk of data and the value that can be extracted from it. The use of data mining techniques in the medical field, for example, is on the increase because of the many benefits it offers, including better health prediction, lower healthcare costs, more efficient use of resources, enhanced healthcare quality and value, and the ability to make life-saving decisions in real time [5].

The performance standards in several difficult applications have been smashed by deep CNNs, which have become an essential tool for image processing. The ability of CNNs to acquire predictive traits from raw visual data signifies a paradigm shift, opening up exciting new avenues for medical imaging. Medical image analysis has made extensive use of the feature engineering technique to train models capable of predicting patient outcomes. Employing segmentation algorithms to clearly define structures of interest and then establishing a reputation for accuracy via measurements is the essence of this strategy [6].

A purpose of this paper is to explore the effectiveness of various ML and DL models in classifying mammography images from the CBIS-DDSM dataset to enhance breast cancer detection. This project intends to assess different models' performance by using cutting-edge methods including feature extraction and transfer learning. Its ultimate goal is to help enhance breast cancer diagnosis accuracy and patient outcomes. The CBIS-DDSM dataset research on cancer classification and prediction using electronic health records contributed the following:

- Provides a detailed methodology for data collection, preprocessing, and classification model implementation, establishing a clear roadmap for future research in medical image analysis.
- Compares the performance of multiple classification models, including Gaussian Naïve Bayes, CNN, K-Nearest Neighbors, and MobileNetV2, highlighting an efficacy of DL approaches in cancer diagnosis.
- Employs comprehensive performance metrics, like F1-score, recall, accuracy, and precision, to evaluate and validate the effectiveness of the models, ensuring robust and reliable results.
- Demonstrates that MobileNetV2 achieves superior accuracy compared to other models, underscoring the potential of DL to enhance the accuracy of breast cancer detection through advanced image analysis techniques.

A. Structure of the paper

The following is the structure of the study: Methods currently used for analysing mammography images are reviewed in Section 2. Data gathering and preparation are detailed in Section 3, which also contains the study methodology. The outcomes of the experiments are detailed and discussed in Section 4. Finally, Section 5 presents the most important results and suggests avenues for further study.

2. Literature Review

This section provides an overview of important ML and DL research related to similar datasets and challenges, limitations, results and emphasizing notable methods and studies. The important literature in this field is briefly outlined in Table 1.

In this study, Naveen, Sharma and Ramachandran Nair, (2019) to accurately forecast an occurrence of breastcancer based on cancer characteristics. With the help of the breast cancer Coimbra dataset from the University of California Irvine (UCI), the best ensemble ML models were created. Our primary procedures here include feature scaling, cross validation, and a number of ensemble ML models that make use of the bagging technique. The most accurate methods are decision trees and KNN, which provide a 100% record. Our nearest neighbours are denoted by k. Along with it, we assess its forecast using the categorisation report, confusion matrix, and accuracy. Constructing the best possible machine learning model is our primary objective. As a consequence of the prognosis, the patient may begin therapy at an earlier stage [7].

The purpose of this study, Badriyah et al., (2018) aims to help patients understand their cervical cancer risk factors, so that they may seek additional treatment if necessary, in the event that a high-risk level is detected. The study's data came by a RSI Jemursari Hospital in Surabaya, Indonesia, and the application was built employing the LR approach. The data was collected from August 1, 2017, to December 1, 2017. According to the findings, vaginal bleeding, vaginal lumps, and lower abdominal or waist discomfort all significantly increase the chance of cervical cancer. Patients may use this application to determine their estimated risk of developing cervical cancer. As compared to two other approaches, the LR method yields superior outcomes, according on the findings of studies conducted using NB and DT. Approximately 95% of the data can be classified accurately using the LR approach, and the classification precision on both precision and recall is very high. This indicates that the performance of the method is quite strong [8].

This paper, Mercan et al., (2018) highlights our possible approaches to overcoming these obstacles via the use of pathologists' viewing records and their comments at the slide level in poorly supervised learning situations. To begin, they analyze the pathologists' image screening logs for suitable ROIs based on several behaviors, including zooming, panning, and fixation. The next step is to use the pathology forms' extracted class labels and a bag of instances representing the possible ROIs to model each slide. Finally, for diagnostic category predictions in whole-slide breast histopathology pictures, they apply four distinct multi-instance multi-label learning methods at the slide level and at the ROI level. Various poorly labelled learning situations revealed average accuracy values of 69% and 81% for slide-level assessment utilizing 14-class setups, respectively. Classifier performance was shown by ROI-level predictions inside entire slide pictures chosen to include all difficult diagnostic categories, demonstrating good multi-class localization and classification [9].

In this study, Harrell, Levy and Fabbri, (2017) in order to get an AUC of 0.74, the RFC was used in conjunction with variables pertaining to medical appointments, demographics, and health. Our RF model finds that patient age, median income by zip code, and total drug counts to be the strongest predictive factors for follow-up. Our findings imply that the frequency with which patients visit VUMC for treatment (i.e., primary care) may be associated with more accurate follow-up prediction. Patients undergoing adjuvant endocrine treatment had their follow-up dates reasonably predicted using data from their electronic health records in this research. Interventions to increase follow-up rates and patient care for adjuvant endocrine treatment groups may be facilitated by follow-up prediction. The capacity to identify areas for EHR data-driven patient care improvement is shown by this research [10].

In this paper, Khuriwal and Mishra, (2018) selected a technique for adaptive ensemble voting based on the Wisconsin Breast Cancer database for breast cancer

diagnoses. The purpose of this work is to use ensemble ML approaches to compare and explain the better results provided by ANN and logistic algorithms for breast cancer detection, even when variables are reduced. Wisconsin Diagnosis Breast Cancer was the dataset used in this research. In comparison to other relevant material. It has been shown that an alternative ML method yielded an accuracy of 98.50% when applied to an ANN strategy using a logistic algorithm [11].

Table 1. Comparative research table for cancer classification and prediction using electronic health records

Ref	Methodology	Dataset	Result	Limitations and Future Work
[7]	Ensemble learning with bagging (Decision Tree, KNN)	Breast Cancer Coimbra dataset (UCI)	100% accuracy (Decision Tree and KNN)	High accuracy may be dataset-specific; results not generalizable
[8]	Logistic Regression, Naïve Bayes, Decision Trees	RSI Jemursari Hospital, Surabaya (Cervical Cancer Data)	Logistic Regression achieved 95% accuracy	Limited dataset and period; focused on specific risk factors
[9]	Multi-instance multi-label learning	Pathologists' viewing records, slide-level annotations	Average precision of 81% (5-class), 69% (14-class)	Weakly supervised learning scenarios
[10]	Random Forest Classifier	Electronic Health Records (EHR)	AUC of 0.74, predictive features: medication count, age, income	Moderately accurate, limited predictive ability for follow-up
[11]	Adaptive ensemble voting (ANN, Logistic Algorithm)	Wisconsin Breast Cancer dataset	98.50% accuracy (ANN with logistic algorithm)	Limited comparison with other methods; dataset reduction effects unknown

A. Research gaps

According to the research being examined, a number of different machine learning algorithms are helpful in predicting illnesses such as breast cancer and cervical cancer, as well as in providing follow-up treatment for patients. There are, however, a number of holes. To begin, the specificity of the datasets used in many research is a limitation that may impair the capacity of the models developed to be generalized to larger populations. Additionally, the dependence on limited or localized datasets hinders the possibility for rigorous model validation across varied healthcare systems. Furthermore, although ensemble approaches and sophisticated classifiers like artificial neural networks (ANN) and logistic regression all provide high levels of accuracy, there is still a lack of study into hybrid or innovative deep learning architectures. Finally, there is a need for more research into enhancing weakly supervised learning and multi-instance learning techniques, particularly for increasingly complicated and large-scale medical datasets. This is necessary in order to attain improved predicted results and application of real-time diagnostic algorithms.

3. Research Methodology

The main goal of this study is to evaluate several AI algorithms for cancer classification and prediction using EHR. By leveraging ML and DL techniques, the study seeks to identify key patterns and predictive markers within EHR data that can aid in early cancer diagnosis, risk assessment, and personalized treatment recommendations. The end objective is to improve clinical decision-making and patient outcomes by making cancer prediction models more accurate and reliable. For this used CBIS-DDSM dataset, which contains 5,000 publicly accessible mammography pictures and serves as a vital resource for training and assessing algorithms in mammography image interpretation, is the first stage in the technique for this work. Through methods like feature extraction and

transfer learning (with and without fine-tuning), data pre-processing converts the raw pictures into a format that can be used to adapt pre-trained models to the dataset. Data splitting is used to partition the dataset into training and test sets after pre-processing, which allows for model hyperparameter adjustment and generalisation performance estimate. Lastly, a variety of classification models are used and contrasted based on performance criteria to see how well they identify mammography data: Gaussian Naïve Bayes, CNNs, KNN, and MobileNetV2. The process flow diagram for detecting financial fraud is shown in Figure 1.

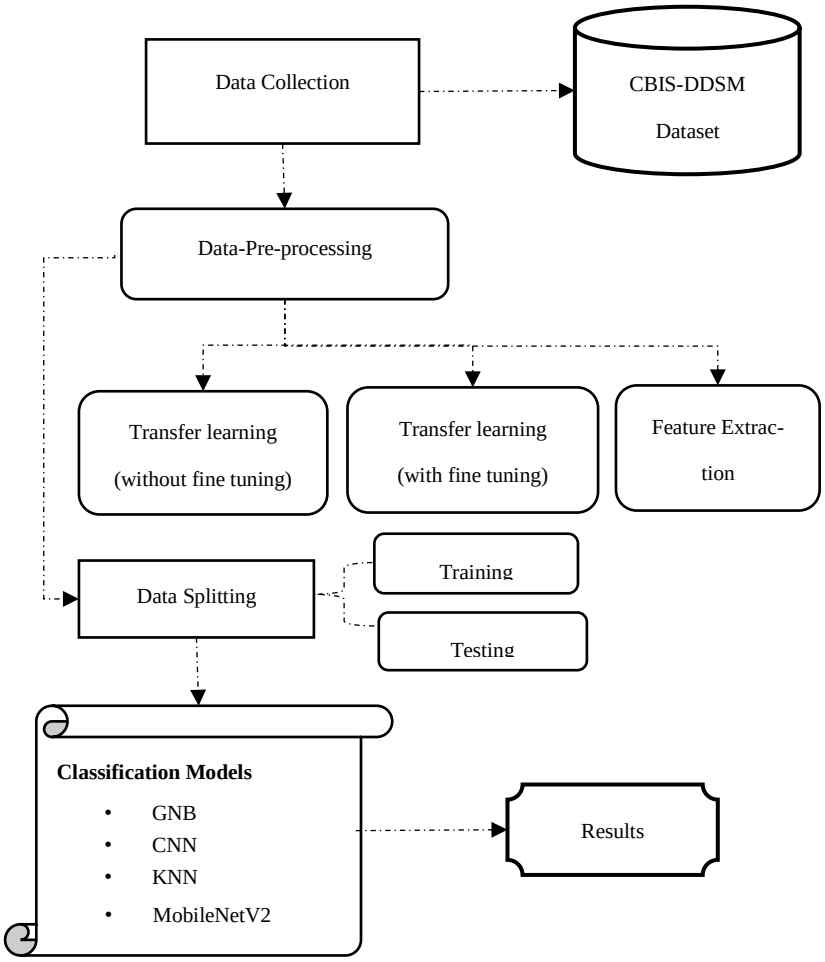

Figure 1. Brief diagram of the Methodology.

The following steps outline the data flow diagram, with each stage of data processing within the system thoroughly detailed.

A. Dataset Description

Digital Database for Screening Mammography (CBIS-DDSM) is a publicly accessible dataset that is extensively used for mammography image processing; it was used to construct the BCD (Breast Cancer Detection) model. The dataset contains a total of 5000 mammography images, with an equal distribution between two classes: 2500 benign images and 2500 malignant images. For model development, 80% of the images were utilized for training a CNN (Convolutional Neural Network) architecture, while a remaining 20% were set aside for evaluating a performance of a trained model.

B. Data preprocessing

Transformation of raw data into a more understandable format is all that is involved in data preprocessing. Sometimes data from the real world is lacking information, is inconsistent, repeats itself, or is noisy. In order to transform raw data into a processed and reasonable format, data preparation comprises a number of processes. These are the key pre-processing techniques:

- **Transfer learning (Without Fine-tuning):** This involves using a pre-trained model directly without altering the learned weights. The model is applied as-is, leveraging the knowledge gained from its original training on a large dataset to make predictions on the target dataset.
- **Transfer learning (With Fine-tuning):** In this approach, a pre-trained model is adapted to the new dataset by allowing the weights of the top layers, or sometimes the entire network, to be adjusted. This helps the model fine-tune its features to better suit the specific characteristics of the target data.
- **Feature Extraction:** Feature extraction identifies key data attributes, transforming raw data into useful features to enhance model performance and efficiency.

C. Data Splitting

The data is often divided into a train set and a test set with a ratio of 80% to 20% using data splitting, which is a popular practice in ML. Finding the model hyper-parameter and estimating the generalization performance are both made possible by this method.

D. Classification Models

In this section, comparison of classification models using CBIS-DDSM dataset. Compare these models' performance using their attributes.

1) Gaussian Naïve Bayes (GNB)

Bayes' theorem is the foundation of GNB, a classification technique that relies on the characteristics being conditionally independent given the class and following a normal (Gaussian) distribution.

2) Convolutional Neural Network (CNN)

DL algorithms like CNNs may distinguish between distinct parts of an input image by giving them varying amounts of weight and bias that can be learnt. In contrast to other classification techniques, ConvNets rely on far less pre-processing. In contrast to basic methods that need hand-engineered filters, a ConvNet can acquire these attributes and filters via training.

3) K-Nearest Neighbors (KNN)

KNN is a lightning-fast technique for regression and classification. Working with train-test sets, this non-parametric technique doesn't assume anything. It takes into account both positive and negative examples in the training sets and produces results as either a classification or a regression. Because it can generalise without training data points, this technique is referred to as a lazy algorithm.

4) MobileNetV2

The MobileNetV2, which is a modified version of MobileNetV1, serves as the convolutional base in all three TL variants for performing mammography image classification tasks. The low-powered and lightweight structure of MobileNetV2 makes it suitable to deploy the trained model on a smart embedded platform with low memory and computation capabilities.

MobileNetV2 consists of three layers: the expansion layer, depth-wise convolution layer, and projection layer. There are fewer channels accessible at the projection layer due

to the MobileNet architecture's residual bottleneck connection. "Bottleneck" describes the situation when the number of channels at the output of the projection layer is reduced. In the standard MobileNet architecture, a 3x3 depth-wise convolutional layer extracts features from input channels, while a 1x1 point-wise convolutional layer combines a feature maps generated by the depth-wise convolutional layer to efficiently decrease a dimensionality of input channels. This feature makes depth-wise separable convolution filters faster than standard convolutional filters and reduces the network training time. The MobileNetV2 network Figure 2 is shown below:

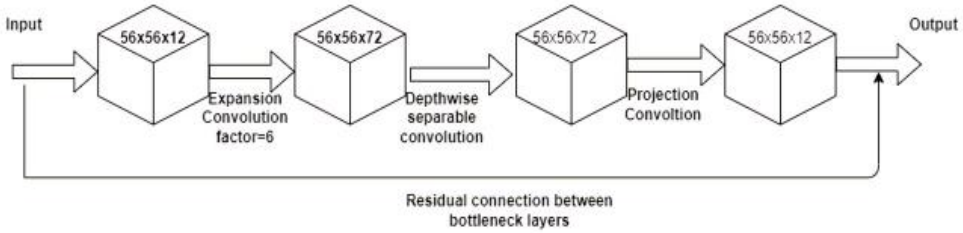

Figure 2. MobileNetV2 Network.

The classification model provides a comprehensive overview of each deep learning model relied on to enhance predictive performance for optimal outcomes.

4. Result Analysis and Discussion

The performance metrics for the models used in the comparison results are presented in this section. For the purpose of assessing AI models' efficacy using the Accuracy and AUC metrics. These assessment factors are outlined below:

A. Confusion Matrix

An essential tool for evaluating the effectiveness of classification algorithms is the confusion matrix. It details the correspondence between model predictions and actual labels, reflecting the model's accuracy and types of misclassifications in each category. The TP and TN in the matrix reflect the number of correct predictions, while FP and FN represent a number of misclassifications. The confusion matrix depiction in Figure 3 is shown below:

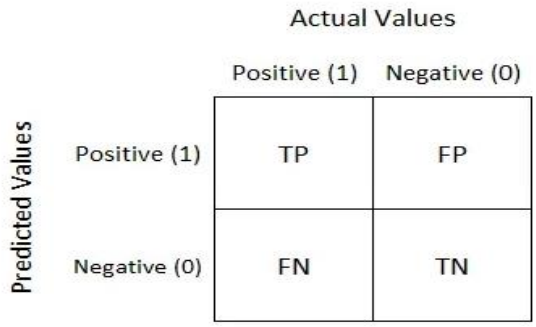

Figure 3. Confusion matrix

B. Accuracy

According to Equation (1), accuracy is calculated as follows: number of properly identified samples divided by total number of samples.

$$Acuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

C. AUC

The AUC is a useful metric for describing the intrinsic validity of diagnostic tests as it combines the sensitivity and specificity measures. Mathematically, it is represented as in the Equation (2):

$$AUC = \int_0^1 TPR()FPR\, d(FPR) \quad (2)$$

1) Experiment Results

Table 2 below displays the outcomes of experiments performed using DL models on the CBIS-DDSM dataset.

Table 2. Results of MobileNetV2 model for Accuracy.

Model	Accuracy
MobileNetV2	99.4

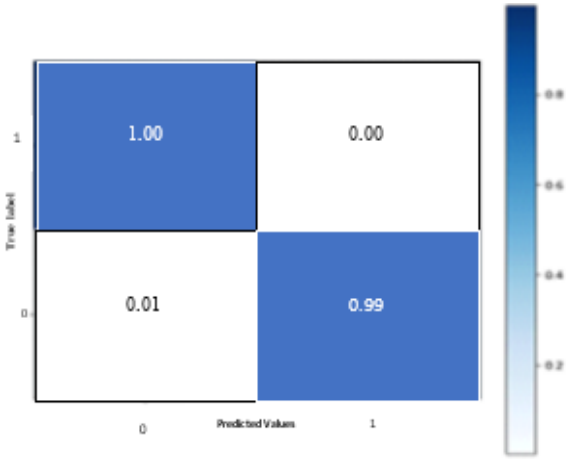

Figure 4. Confusion matrix obtained using MobileNetV2.

Figure 4 shows the confusion matrix classification model's performance for two classes: class 0 (negative) and class 1 (positive). The horizontal axis displays anticipated labels, while the vertical axis displays true labels. The model performs excellently, with a true positive rate of 1.00 for class 0 and a true negative rate of 0.99 for class 1, indicating high accuracy and minimal errors.

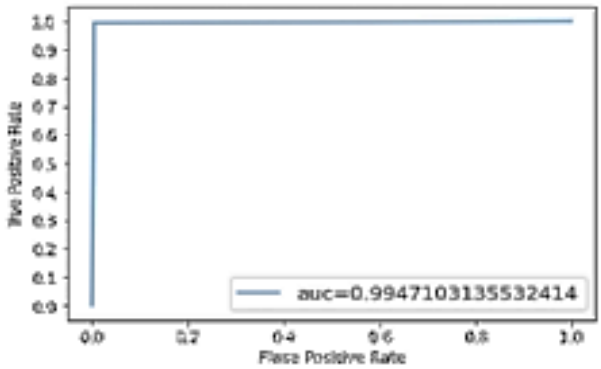

Figure 5. Fixed feature extraction with MobileNetV2.

Figure 5 displays a ROC curve, which has an AUC value of around 0.9947. When evaluating a model's discriminatory power, the ROC curve is useful since it shows the

TPR versus the FPR. The model does exceptionally well of differentiating among positive and negative instances if the AUC is near to 1.

2) Comparative analysis

Using the CBIS-DDSM dataset, this section compares and contrasts DL models for cancer categorisation and breast cancer prediction. It provides the results for different models in the below Table 3.

Table 3. Comparison between different models using CBIS-DDSM dataset using deep learning models.

Models	Accuracy
GNB[12]	87.2
CNN[13]	96.7
KNN[14]	91.2
MobileNetV2	99.4

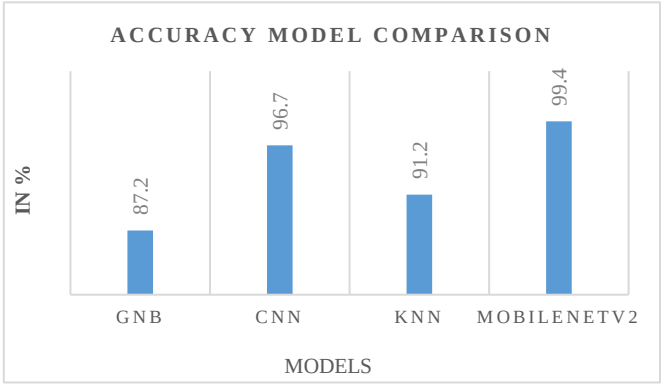

Figure 6. Accuracy model comparison

Figure 6 shows a comparison of accuracy for four models: GNB (87.2%), CNN (96.7%), KNN (91.2%), and MobileNetV2 (99.4%). MobileNetV2 has the highest accuracy, followed by CNN, KNN, and GNB. The vertical axis indicates accuracy in percentages, highlighting MobileNetV2's superior performance.

Table 3 and Figure 6 represent a comparative analysis of cancer classification models using the CBIS-DDSM dataset. MobileNetV2 stands out with the highest accuracy of 99.4%, significantly outperforming other models such as Gaussian Naive Bayes (GNB) with 87.2%, K-Nearest Neighbors (KNN) with 91.2%, and the Convolutional Neural Network (CNN), which achieved 96.7%. Figure 6 visually highlights the superiority of MobileNetV2 in terms of accuracy, clearly showing its dominance over the other models. AUC of 0.9947, which indicates MobileNetV2's great capacity to distinguish among positive and negative cancer cases, further supports its remarkable performance. This combination of high accuracy and minimal classification errors makes MobileNetV2 the best model for cancer prediction in this study.

5. Conclusion and Future Work

Mammograms are important but sometimes insufficient instruments in early identification of breastcancer, which is mostly responsible for a disease's high death rate. We used the CBIS-DDSM dataset's mammography pictures to illustrate in this research how well different ML models perform in that regard. According to our results, MobileNetV2 achieved a remarkable 99.4 percent accuracy, well beyond that of competing models. The comparison research demonstrated that DL methods excel in improving diagnostic accuracy for breast cancer diagnosis by learning complicated characteristics

from raw picture data. The results indicate that computational analysis of histological images can effectively complement traditional diagnostic methods, providing more reliable prognostic information.

To enhance model generalization, future studies should concentrate on growing the dataset to include a wider variety of cancer kinds and different image quality. Additionally, incorporating advanced techniques such as ensemble learning and transfer learning with larger pre-trained models may further enhance classification performance. It would also be beneficial to explore real-time applications of these models in clinical settings, including integration with electronic health records (EHR) for automated decision support. Investigating the interpretability of model predictions could help bridge the gap between computational results and clinical practice, ensuring that healthcare professionals can confidently rely on AI-assisted diagnostics.

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Research Article

Analysis of Big Data for the Financial Sector Using Machine Learning Perspective on Stock Prices

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Abstract
The stock market is one example of a segmented information economy. As a measure of both market activity and market uncertainty, price volatility is a key feature of the stock market. Investors may have a better grasp of market dynamics and create more evidence-based investing strategies with the aid of stock price volatility prediction and analysis made possible by the ever-expanding digitalization and BD (big data) technologies in the financial sector. Accurate financial stock prediction is of great interest to investors. The research focuses on key financial metrics like open, high, low, and close prices and trading volume, with data preprocessing techniques like wavelet denoising and standard scaling employed to improve model performance. This research delves into the use of ML, particularly LSTM networks, to forecast stock values with the use of Yahoo Finance's daily time series data. The LSTM model achieved an R^2 of 98.2%, demonstrating strong predictive accuracy, though the RMSE suggests room for improvement in reducing prediction errors. A comparison with linear regression showed that LSTM captures complex market trends more effectively. Future research could enhance this approach by incorporating a wider range of market indicators, exploring alternative deep learning architectures, and integrating multi-source data for more comprehensive stock price prediction and improved model robustness across varying market conditions.
Keywords: Big Data, Stock Market Forecasting, Price Prediction, Financial Markets, Risk Assessment, Yahoo Finance, Machine Learning.

I. Introduction

In recent years, the integration of big data into stock market analysis has become increasingly important for companies and industries to align their business strategies. The stock market, one of the oldest platforms for earning returns from firms, now generates massive volumes of data from trades, price fluctuations, and various economic indicators [1]. Big data analytics allows for more sophisticated and real-time analysis of this information, offering insights that were previously unattainable with traditional methods [2, 3]. An average individual could trade stocks, make investments, and earn money from companies that sold a portion of themselves on this platform. Nowadays, almost all major economic transactions take place on the stock market, where the value of stocks fluctuates as the market finds equilibrium [4]. If implemented properly, this technique has the potential to be a profitable investment strategy. The term "stock market forecasting" refers to the process of making predictions about the movement and performance of financial market indices, individual securities, or stock prices via the use of different models and methods of analysis [5, 6]. To make informed predictions about future market movements, it comprises assessing historical

price and volume data in addition to other crucial elements including economic indicators, business financials, news events, and market sentiment [7, 8]. Stock market forecasting is a complex and challenging task due to the dynamic and unpredictable nature of financial markets. Nonetheless, it is an essential task for traders, analysts, investors, and financial institutions that want to properly manage risks and make informed decisions.

Time series forecasting is essential for managing portfolios, assessing risk, and making investment decisions in the stock market. Financial institutions, traders, and investors can't make informed judgements or make the most of their profits without accurate stock price and market trend forecasts. Conversely, the intricate and ever-changing nature of financial data makes stock market value forecasting a challenging task. The modern method for forecasting stock values is based on sophisticated AI algorithms that draw on fundamental or technical analysis [9]. The use of ML and DL to forecast stock prices and monitor their pattern fluctuations has also grown in popularity [10].

A. Motivation and Contribution of Study

Big data analytics' increasing importance in the financial industry, especially in stock market forecasting, is what inspired this research. Stock prices exhibit complex patterns influenced by various macroeconomic and market-driven factors, and traditional analytical methods often fall short of capturing these intricate dynamics. With the rapid advancements in machine learning and the availability of large-scale financial data, there is an opportunity to develop more accurate and data-driven prediction models. For investors, financial institutions, and governments to make wise choices and reduce risks, accurate stock price forecasts are essential. This study makes several key contributions to the field of financial analytics. The following key contributions are:

- ✓ Utilizes real-time stock market data sourced from the Yahoo Finance API, providing daily time series data.
- ✓ Uses standard scaling to normalise the dataset, ensuring that all features are scaled to zero mean and unit variance, which improves the performance of ML models.
- ✓ Compares the performance of ML models LIR and LSTM, providing a comprehensive analysis of their effectiveness in stock price prediction.
- ✓ Evaluate model performance using key metrics such as MAE, RMSE, and R^2. This ensures a thorough and multi-dimensional assessment of the models' accuracy and predictive capabilities.

B. Organization of the Paper

This research is structured as follows for parts that follow: Section II presents the background research on stock price prediction in the financial sector. Section III provides the research approach that is utilised for this study. Section IV covers the outcomes and assessments of the study. Our research study findings and plans for the future form Section V.

II. Related Work

In the literature, there is a lot of research on predicting stock prices. Some of them are listed below. This study, Kalra and Prasad, [11] focusses on tracking changes in stock prices in relation to pertinent corporate news pieces. This research proposes a daily prediction model to forecast the movements of the Indian stock market using historical data and news items. The NBC is used to classify news texts that have a positive or negative sentiment. The number of news stories with positive and negative sentiment for each day, the variation of the closing prices of the previous days, and historical data are utilised to make predictions. Using a variety of machine learning approaches, an accuracy ranging from 65.30 to 91.2% is attained [11].

In this study, Gumelar et al. [12] carried out a test to forecast the closing stock prices of 25 companies. These chosen businesses are formally listed on the Indonesia Stock Exchange (IDX) to guarantee data accuracy and regional concept. Extreme Gradient Boosting (XGBoost) and LSTM, two ML algorithms renowned for their excellent prediction accuracy from a variety of sample data, were used in this experiment. We were able to provide a trading strategy by establishing two thresholds: when to purchase and when to sell. There are several advantages to this forecast result from the ML

algorithm used in the subsequent trading strategy. XGBoost performed best in this trial, with a prediction accuracy of 99% [12].

In this paper, Mootha et al. [13] provide a system that uses a Bidirectional LSTM based Sequence to Sequence Modelling approach to forecast a stock's future open, high, low and close (OHLC) value. Multitask learning aids in mapping the relationships between each OHLC price, which is a separate series. Additionally, a multitasking system that models pricing via shared tasks and subtasks is suggested. The NSE of India's Tata Consumer Products Limited stock prices are utilised. The suggested solutions are examined against different machine learning algorithms in order to assess their effectiveness. The suggested Seq2Seq and multitask systems perform noticeably better than the current techniques, with corresponding RMSE values of 3.98 and 7.87 [13].

In this work, Majumder et al. [14] have forecasted Bangladeshi stock indices using a variety of stock prediction algorithms, including Holt-Winter, Linear model, ARIMA, and FFNN, and evaluated the algorithms' performance across 35 Bangladeshi stocks. This study takes time series analysis into account, and the algorithms' performance is calculated by measuring the proportion of correct predictions. Based on study, the best algorithm for stock index forecasting is FFNN, whereas ARIMA (1,0,0) has the highest prediction accuracy (82.1%) on average. Maximum accuracy is provided by FFNN in 14 of 35 stocks [14].

In this paper, Song et al. [15] stock prices are gathered from a financial website, and internet comments are also mined and used to assess investor sentiment towards certain equities. The price of a stock fluctuates and trends, respectively, and investor feelings towards a particular stock are reflected in two types of time series. To assess the relationship between stock price and investor sentiment time series, we suggest Multiple Dimensional DCCA, which takes use of DCCA's strengths in time series analysis. Then, to improve price prediction, we provide a method to assess the range of effects of investor mood on stock price trends. Using the affecting period to forecast stock prices improves accuracy to around 85%, according to experiments [15].

In this work, Aradi and Hewahi [16] an approach is suggested for forecasting the direction and value of a market's movement based on a number of datasets, such as public opinion, business earnings reports, social media, and technical indicators. The use of LSTM and DNN in a case study of Apple Inc. shares made use of AI. The results demonstrated that the LSTM model outperformed the DNN model, which had prediction lag and relied on trend indicators to achieve a classification accuracy of 53.1%, in predicting the direction of the stock and in predicting the value of the stock (75.4 MSE, +-2.52 PE) [16].

Table 1 highlights key information from each of the studies regarding stock price prediction using various machine-learning techniques.

III. Methodology

The research design for the analysis of big data for the financial sector using a machine learning perspective on stock prices focuses on the systematic collection, pre-processing, modelling, and evaluation of stock market data. The dataset is obtained through the Yahoo Finance API, leveraging daily time series data that includes key financial metrics like open, high, low, and close prices and trading volume. A data flow in various steps and phases that shown in Figure 1.

After data collection, proceed to preprocessing. Preprocessing involves wavelet denoising for noise reduction and standard scaling for feature normalisation. Then, feature extraction is performed to derive essential signals, while a train-test split is used to evaluate model generalisation. The study compares ML models like LR and deep learning models like LSTM to forecast stock prices, with performance evaluated employing metrics like MAE, RMSE, and R^2. This design ensures a robust framework for analysing and predicting stock price movements by leveraging advanced machine-learning techniques.

Table 1. Background summary of financial sector using ML perspective on stock prices.

Author	Source	Techniques	Key findings	Limitation/future work
Kalra and Prasad [11]	Indian stock market data and news articles	Naïve Bayes (for sentiment analysis)	Accuracy ranged from 65.3% to 91.2% using different techniques	Future work: Could explore other sentiment analysis techniques or incorporate more diverse datasets
Gumelar et al. [12]	Stock data of 25 companies from Indonesia Stock Exchange (IDX)	LSTM, XGBoost	XGBoost achieved 99% prediction accuracy	Limitation: Focused only on 25 companies Future work: Could apply to more companies or markets
Mootha et al. [13]	Tata Consumer Products Limited (NSE, India) stock prices (OHLC)	Bidirectional LSTM, Seq2Seq modeling, Multitask learning	RMSE: 3.98 (Seq2Seq) and 7.87 (Multitask) Outperformed other ML algorithms	Limitation: Applied to a single stock Future work: Could extend the model to multiple stocks or other markets
Majumder et al. [14]	Bangladeshi stock market indices (35 stocks)	FFNN, ARIMA, Linear model, Holt-Winter approaches	ARIMA (1,0,0) gave 82.1% accuracy (average) FFNN performed best for 14 out of 35 stocks	Limitation: ARIMA accuracy varies by stock Future work: Could test more advanced models or use external factors for prediction
Song et al. [15]	Stock prices from a financial website and online investor comments	DCCA, Multiple dimensional DCCA (time series analysis)	Improved prediction accuracy to 85% by incorporating investor sentiment	Limitation: Dependency on investor sentiment Future work: Explore more complex sentiment measures or expand the dataset
Aradi and Hewahi [16]	Apple Inc. stock data (news sentiment, social sentiment, earnings, technical indicators)	LSTM, Deep neural networks (DNN)	LSTM: MSE of 75.4, classification accuracy of 70.1% for direction prediction DNN: Accuracy of 53.1% for movement direction	Limitation: DNN struggled with prediction lag Future work: Explore hybrid models or feature engineering for better results

Each step of the data flowchart is briefly explained below:

A. Data Collection

An essential first step in each project is data collecting, which is why this module is so fundamental. The selection of an appropriate dataset is a common theme. Prediction dataset sourced from Yahoo Finance API. Time series data is accessible via the API on an intraday, daily, weekly, and monthly basis. We choose to use daily time series data, which contains the following: daily volume, daily high

price, daily low price, daily closing price, and daily open price (Figures 2 and 3), as our domain is short-term prediction.

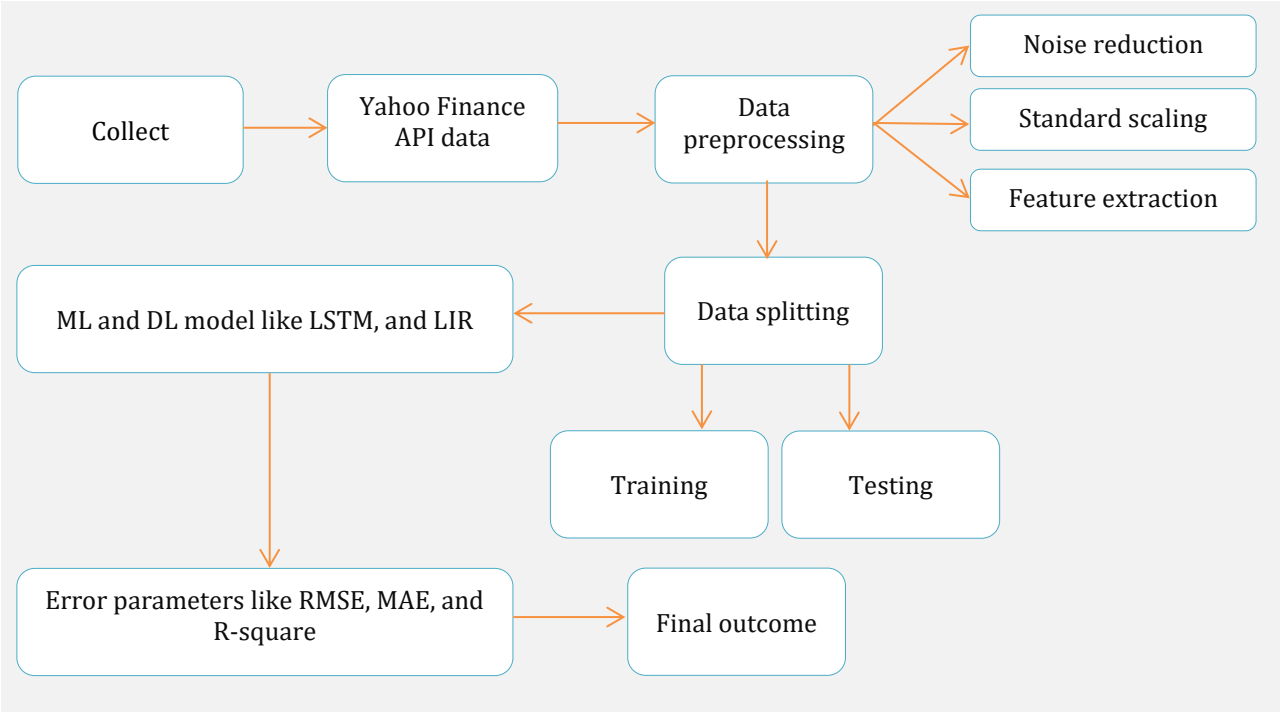

Figure 1. Data flow diagram for stock price prediction in the financial sector.

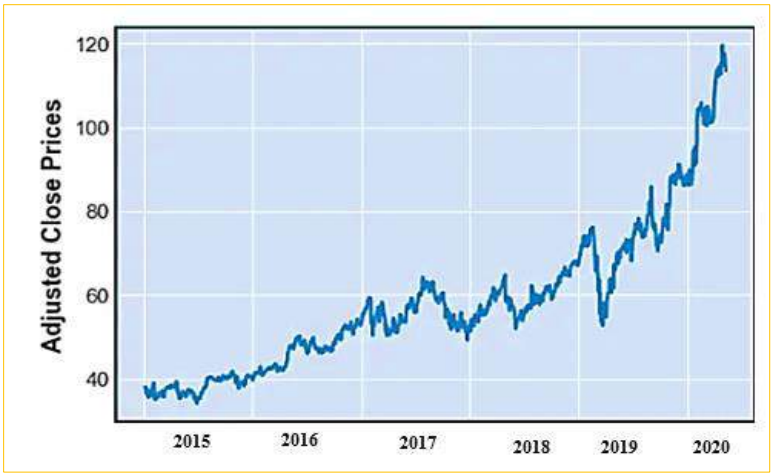

Figure 2. Line graph for adjusted close prices.

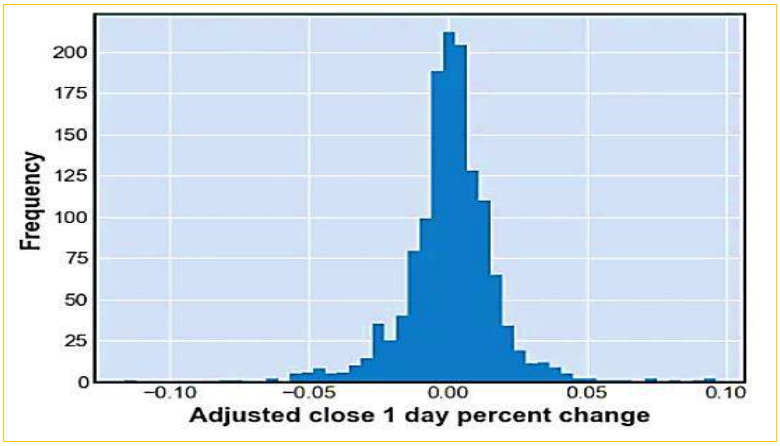

Figure 3. Histogram for 1-day per cent change.

The line graph shows the adjusted close prices of a financial asset from 2016 to 2020, with an overall upward trend. With growth peaking around 2017, followed by a decline in 2018-2019 and a recovery in 2020. The prices exhibit significant volatility throughout the period (Figure 2). The histogram shows a roughly bell-shaped distribution of daily percentage changes in the adjusted close price of a financial asset centred around 0. It is slightly skewed to the right, indicating occasional large positive changes, and displays leptokurtosis, suggesting a higher likelihood of extreme price changes. However, the relatively narrow range of changes indicates that the asset's price volatility is contained, with some downside risk but overall moderate fluctuations (Figure 3).

B. Data Preprocessing

The preparation of a dataset for ML tasks requires preprocessing. Several processes are involved in this process to clean, transform, and format the data so the model can learn successfully. Denoising is the first stage of preprocessing; it seeks to eliminate noise and incorrect or unnecessary data points that can obstruct the patterns necessary for efficient model learning. Further preprocessing steps are as:

i) Noise Reduction

To mitigate this issue, implemented wavelet denoising. The method's proficiency in both noise reduction and feature extraction led to its selection [17].

ii) Standard Scaling

Machine learning also makes use of the standard scaler, often known as standardisation, to scale features. This technique standardises all features by transforming them to a mean with zero variation. While this approach does not limit the data to a certain period or change its spread, it does ensure that most data points will be located around 0. This indicates that no matter how much data is scaled, outliers will remain.

As seen in equation 1, standard scaling is defined.

$$x_{scaled} = \frac{x - \bar{x}}{\sigma} \quad (1)$$

Where: xscaled = scaled sample point; x = sample point; $\bar{x}$ = mean of the training samples; σ = standard deviation of the training samples.

iii) Feature Extraction

The goal of feature extraction is to fulfill human intent by retrieving task-specific information from signals. A number of formats are available for feature extraction, including amplitude measurement, peak power, spectral density, Hjorth parameters, and others. Both univariate and multivariate feature extraction need substantial processing resources and mathematical analysis.

C. Train-Test Split

To evaluate the model's performance and make sure it generalises effectively to unknown data, it is essential to split the dataset into training and test sets.

D. Model Selection

Various methods can be used to predict the stock prices. In this work, utilise machine and deep learning models: LR, and LSTM explained below:

i) Long Short-Term Memory (LSTM)

The learning of distant nodes' data parameters is challenging in conventional RNNs because of issues with disappearing and expanding gradients. LSTM is an upgraded model that this research uses. Figure 4 shows that LSTM's memory function allows it to learn over the long term, identify characteristics, and correlate data from time series.

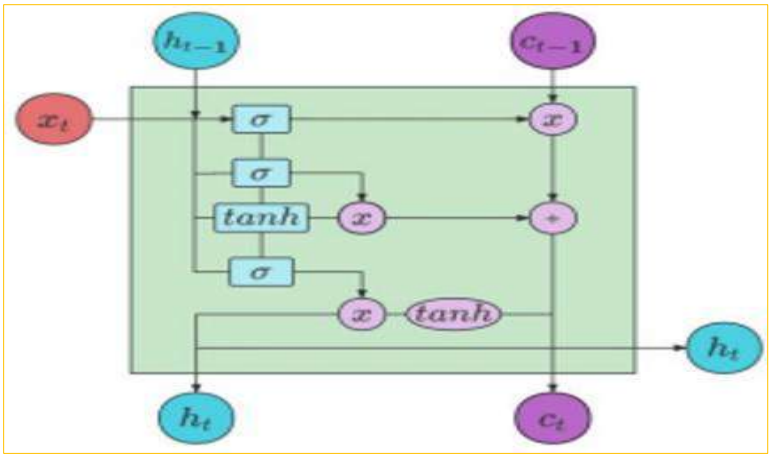

Figure 4. LSTM structure.

The structure of any recurrent neural network is a series of modules that repeat themselves. While RNNs in the past have had relatively basic structures for their modules, LSTM networks have four layers of complicated architecture that interact in unique ways. An LSTM repeat module computation involving a single neuron consists of two steps: updating the state of the neural network and calculating the output value. The input gate, the forgetting gate, and the output gate are the three gate functions found in a neuron. The gate function regulates the values of the input, memory, and output [17].

The quantity of data that is now being overlooked by the neural network is controlled by the forgetting gate. Below is the computation technique for the forgetting gate (2):

$$f_t = \sigma(W_f . [h_{t-1}\, x_t] + b_f \quad (2)$$

f_t represents the forgetting gate's output, ht-1 denotes the hidden state at the final second, and the fraction of information forgotten is modulated by the information fusion Wf, bf, and the sigmoid function of σ.

There are two components to the input gate: the original input value and the new input (3, 4):

$$i_t = \sigma(W_i . [h_t, x_t] + b_i) \quad (3)$$

$$\tilde{c}_t = \tanh (W_c . [h_{t-1}, x_t] + b_c) \quad (4)$$

The calculating procedure of the input gate is as follows (5), and it filters the information from the input layer when the output value of the tanh function is between -1 and 1.

$$C_t = f_t . C_{t-1} + i_t . C_t \quad (5)$$

Where the current state of the neural network is represented by Ct. Here is the procedure for calculating the hidden state and output gate (6, 7):

$$o_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t . \tanh (C_{t)} \quad (7)$$

ii) Linear Regression (LIR)

Fitting a collection of characteristics with their corresponding variables employing a linear equation is the goal of linear regression. The following equation (8, 9) describes the linear connection between a set of variables X and a set of responses/labels y:

$$X = \begin{bmatrix} x_1^1 & \dots & x_1^m \\ \vdots & \ddots & \vdots \\ x_1^m & \dots & x_n^m \end{bmatrix}; Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad (8)$$

$$y = \alpha + \beta X \quad (9)$$

In this case, α stands for the slope and β for the intercept. A good match between the variables is achieved by minimising these parameters.

E. Model Evaluation

To evaluate the model performance, use some performance matrix. The ML models' predicting performance is evaluated using MAE, RMSE, and R^2.

i) MAE: The most typical applications of MAE are in regression problems using loss functions and error measurements, but it is also used to transform learning issues into optimisation problems. The following Eq. (10) of MAE is:

$$MAE = \frac{\sum_{1=1}^{n} |Y_i - X_i|}{n} \quad (10)$$

Here, Yi stands for the forecast, Xi for the actual value, and n for the overall count of records or samples.

ii) RMSE: The RMSE is one of the most popular ways to measure how well a forecasting model performs. It uses the distance from the real value to the observed value to display how much. A discrepancy between the predicted and observed values for every given sample is taken into account. The following Eq. (11) of RMSE:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \bar{X}_i)^2}{n}} \quad (11)$$

iii) R-square: R^2 indicates the goodness-of-fit for linear regression models. The R^2 statistic shows how well your model takes into account the dependent variable. Calculating the amount of variation in y that can be explained by x-variables is done using the R^2 formula. You may find values between zero and one on the scale. The following Eq. (12) represent the R^2.

$$R^2 = 1 - \frac{SR}{TR} \quad (12)$$

Where, SR stands for sum of square residuals and TR for total square sum.

IV. Result Analysis and Discussion

The experiment results of ML models that utilised for stock price prediction are presented in this section. The following results are implemented on the Yahoo finance dataset across the performance matrix, including RMSE, MAE, and R-square. Table 2 shows the results of the LSTM model.

Table 2. Results of the LSTM model for stock price forecasting on Yahoo finance data.

Matrix	**LSTM**
R^2	98.2
RMSE	2.02
MAE	32.283

The performance metrics for the LSTM model show a high R^2 value of 98.2%, indicating strong predictive accuracy. The RMSE is 2.02, suggesting that the model's predictions deviate from the actual values by an average of approximately 20 units. The MAE is 32.283, reflecting the average

absolute difference between predicted and actual values. In sum, these measures point to the LSTM model's strong performance, with very few prediction errors and a high degree of accuracy.

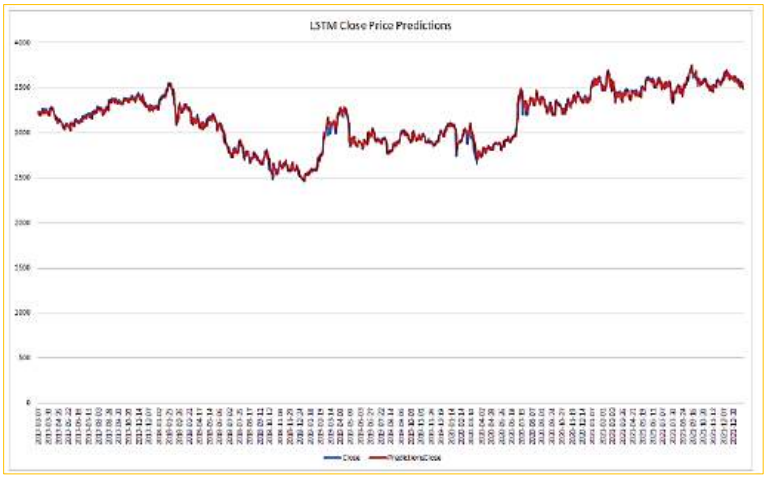

Figure 5. LSTM model close price prediction.

Figure 5 displays LSTM close price predictions comparing actual close prices with the close prices predicted by the LSTM model. The actual close prices are shown in blue, and the predicted prices in red. Indicating that the LSTM model does a good job of following the overall trend of the actual closing prices, the two lines closely track each other. There are minor deviations at certain points, but overall, the predictions seem to align well with the actual data. This suggests the LSTM model performs reasonably in forecasting close prices, though further analysis with evaluation metrics would help confirm the accuracy.

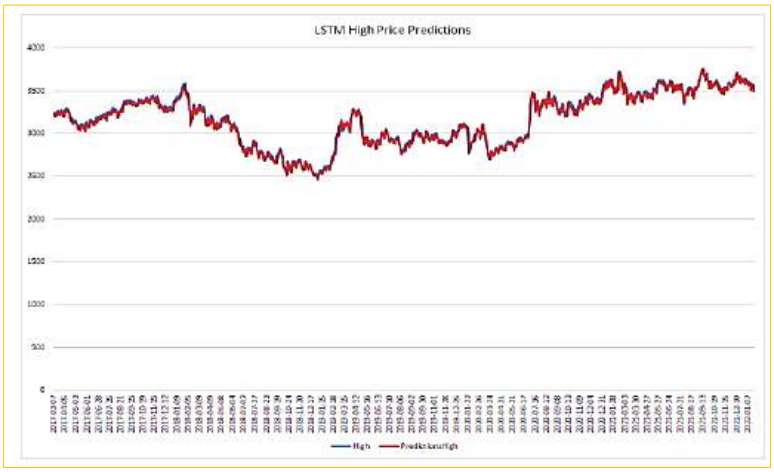

Figure 6. LSTM model high price prediction.

Figure 6 shows LSTM high price predictions comparing actual high prices with LSTM model-predicted high prices. The actual high prices are represented by a blue line, while the predicted values are in red. The two lines appear closely aligned indicating that the LSTM model captures the general trend of the high prices with reasonable accuracy. Some slight deviations are visible, but overall, the model seems to track the price movements well over the displayed time period. Further evaluation metrics would be helpful for a more detailed analysis of model performance.

Table 3. Comparative analysis of model performance on Yahoo finance data.

Matrix	LSTM	LIR [18]
R^2	98.2	91.43
RMSE	2.02	1.145

Table 3 shows the comparative analysis of the model's performance. The performance metrics comparison between the LSTM model and LIR indicates that the LSTM model demonstrates superior predictive accuracy with an R^2 of 98.2%, significantly higher than LIR's 91.43%. Additionally, the LSTM has an RMSE of 2.02, which is higher than LIR's RMSE of 1.145. This implies that although the LSTM successfully captures the data's volatility.

V. Conclusion and Future Work

Investors rely heavily on stock price forecast when formulating a trading strategy. Investors may boost their profit margins via accurate stock price predictions. The interconnected nature of stock prices with variables beyond of investors' control, such as headlines, the state of the economy, public opinion, and other confidential financial data, makes accurate trend forecasting in the stock market very challenging. This research employs a unique approach that combines deep interest in historical market data with the latest DNN technology for linear regression and time series prediction LSTM.

The LSTM model demonstrated superior predictive accuracy for stock price forecasting, with a high R^2 of 98.2%, indicating that it effectively captures stock price trends based on the Yahoo finance data. Despite its strong performance, the model's relatively higher RMSE compared to linear regression suggests that while LSTM captures complex patterns, there is room for improvement in reducing prediction errors.

One limitation of this study is the reliance on a single dataset and specific time intervals, which may not generalise well across different market conditions or financial sectors. Future work could explore the inclusion of more diverse datasets, additional market indicators, and alternative deep learning models like transformer-based architectures to enhance prediction robustness and accuracy.

Declarations

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Research Article

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Data-Driven Management: The Impact of Visualization Tools on Business Performance

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Abstract

This research examines how data visualization affects business performance with a view on what organizations can do to make the best out of these tools as a way of leveraging competitive advantage. The study examines the usage of decision-visualization tools, business intelligence systems, and big data analytics (BDA) in the manufacturing, agriculture, and high-tech industries using a real-time bibliometric analysis from 2017 to 2022. Additional research into this topic should compile and quantify patterns pertaining to the aforementioned tools, as well as examine any gaps in their use to improve innovation and decision-making. This shows that data visulisation tools ease the handling of large sets of data and help to determine trends and patterns quickly since they reduce the amount of clutter present in a single set of data. It was found that visualization tools are highly effective in improving various manufacturing activities and innovation. Nevertheless, some issues still persist Such as; There is meager definition of KPIs that measures efficiency, lack of qualified personnel and weak culture of data within organizations. To sum it up, analysing the outcomes of data-driven management, it can be claimed that, as well as enhancing the business performance, this approach has some essential weaknesses, including the shortage of specialists in the field and resistance from different organizations. Looking at the study, it is suggested that best KPIs for big data and AI should be set and maintained across the organization and also constant training should be given to big data and AI specialists along with a data-oriented culture being promoted for the enhancement of big data and AI use.

Keywords: *Data visualization, business performance, big data analytics, decision-making, business intelligence.*

1. Introduction

Data visualisation and information translation are becoming increasingly important in today's business world [1]. As more and more data become available, it gets harder to tell what is useful and what isn't. Taking into account the various data visualisation tools and dashboards undoubtedly helps officials to make quick decisions [2]. One of the most important steps in cleaning up raw data is using data visualisation. It makes a difference to present data in a positive light no matter what field you get into. The process of obtaining raw data, modelling it, and presenting it to make conclusions is a vital stage in any organisation[1]. One of the most important steps in cleaning up raw data is using data visualisation. No matter your career path, it is important to present data in a positive perspective. An essential step in every organization's process is gathering raw data, modelling it, and then presenting it to draw conclusions [1]. A mountain of data is laid out in a way that anyone can pick up and run with.

Because it simplifies and clarifies otherwise opaque data sets, data visualisation is an essential tool for data-driven decision-making [3]. Compared to staring at the raw data, decision-makers can more easily see trends, patterns, and outliers in data visualisations. Better results for their organisations are the result of their decisions being based on evidence rather than gut feelings or speculation [4]. Data visualisation also helps with stakeholder communication and collaboration. The use of visualisations facilitates the sharing of insights and results, which in turn helps to establish consensus on important decisions by making sure that everyone is using the same information [5]. If businesses want to make better decisions based on their data, data visualisation is a must-have tool. Business success and enhanced performance are the results of data-driven decisions made possible by visualisation, which makes data easier to understand and use [6].

Finding out how data visualisation tools effect business performance is the driving force behind this research, which aims to undertake a comprehensive literature review in this area. This study aims to offer insights into how organisations can improve their operational efficiency and competitiveness using data-driven management methods by conducting a comprehensive literature analysis.

2. Literature review

[7] Academics and experts in the industry have been concentrating on business analytics and big data for almost a decade. With the use of business analytics and the wealth of data available in big data, companies can now get the kind of in-depth understanding that is essential for making sound decisions. An extensive and fruitful history of scientific investigation in this multidisciplinary field may be traced back to the European Conference on Information Systems (ECIS). They provide key points from the "Business Analytics and Big Data" session at ECIS during the last decade. They offer a narrative of the field's evolution and our predictions for future research endeavours based on the synthesis. Our focus here is on three areas that we anticipate seeing a lot of future research activity in. In each of these three domains, we outline various critical issues that must be resolved. Finally, we provide a synopsis of the six papers that make up this special issue, outlining their respective contributions to the field's knowledge.

[8] lays out a methodical framework for enhancing BPM life cycle data-based process development. To improve process excellence and make decisions based on evidence, we demonstrate how to include tools and models inspired by Industry 4.0 into the BPM life cycle. Industry 4.0 redesign phases can be aided by business process management (BPM), design science research tools, and standards for machine learning (CRISP-ML(Q)). An assembly company is used to test the suggested technique, with important key performance indicators used to evaluate the suggested improvement steps and simulations used to study them.

[9] Many believe that in order for organisations to become sustainable, they must innovate their business models. But putting business model innovation into practice is fraught with difficulties. An artefact to aid in business model innovation was developed by us using a design science methodology. This artefact utilises Big Data analytics to track how well the company's business model is doing, which allows for customer-driven business model evolution. Next, they conducted a critical case study using the artefact. The chosen business is an online clothing retailer that promotes veganism and sustainability by eliminating the use of any product derived from animals and by making all of its products from recycled plastic bottles. Their research proves that the artefact is useful for facilitating an ongoing and proactive strategy for business model innovation. The artefact supports the democratisation of business model innovation and BDAs beyond large organisations by making these techniques accessible to small firms, even though they are based on technical notions. With the help of links to performance management and Big Data, as well as pathways for its operationalisation, we add to the literature on business model innovation. Therefore, the proposed artefact can be useful for managers who are working with the business model as a dynamic component of a sustainable company.

[10] examined the connection between Business Analytics and innovation from both a theoretical and practical perspective. In order to accomplish this, a research model is developed with absorptive capacity theory as the theoretical lens. According to the principle of absorptive capacity, a company's success hinges on its capability to take in and make use of fresh, external information. The research paradigm incorporates concepts such as data-driven culture, innovation, environmental scanning, and business analytics. To test the study approach, a questionnaire survey is administered to 218 enterprises in the UK. Based on the findings, implementing Business Analytics can boost creativity inside a company by making environmental scanning more efficient. Business analytics enhance data-driven culture, which impacts environmental scanning. An equally important function of data-driven culture is to mitigate the effect of environmental scanning on the relevance of new product developments. Findings stress the value of data-driven culture, environmental scanning, and corporate analytics for fostering creativity. To get the most out of business analytics, companies should stop looking outside and start looking within.

[11] Although previous research on big data analytics has highlighted the significance of particular big data competencies for organisational success, very little has been done to examine the contribution of cross-functional teams' competencies, the significance of data-driven decisions, and the impact on company performance. Combining the firm's resource-based vision (RBV) with one-of-a-kind data gathered from 240 big data experts working in global agri-food networks, we examine the relationships between the capabilities of big data savvy (BDS) teams, big data driven (BDD) actions, and company success. BDS teams rely on a wide range of expertise to transform their conventional business processes into data-driven insights, which in turn inspire BDD activities that boost company performance. A significant factor for BDD activities, which contribute to company performance, is the skills of BDS teams that generate valuable insights, according to our results from structural equation modelling. Companies that place an emphasis on BDD actions outperform those that do not when it comes to meaningful insights and applications.

[12] combining insights from institutional theory, organisational culture, and the resource-based view of the firm to create and test a model that explains how resources are crucial for developing skills, capabilities, and a culture of big data, all of which lead to better cost and operational performance. In order to evaluate our hypothesis, we used 195 surveys that were obtained using a questionnaire that had already been pilot tested. We provide new understanding of the impact of external forces on resource selection, how big data culture moderates this effect, and how capability building impacts cost and operational performance.

3. Methodology

An extensive literature review on data-driven management and decision-visualization tools across many industries forms the basis of this study's methodology. A systematic approach was employed to gather, analyze, and synthesize peer-reviewed journal articles, books, and reports published between 2017-2022. The selection criteria focused on studies that explored the impact of visualization tools, big data analytics, and business intelligence systems on decision-making, innovation, efficiency, and workforce development. This qualitative analysis aimed to identify key themes, trends, and gaps in the current body of knowledge to provide insights into the effectiveness of these tools in enhancing organizational performance. Key findings were compared across industries, with particular attention to the manufacturing, agricultural, and high-tech sectors.

4. Results

Table 1: Systematic Review Studies.

Author Name	Aim	Methodology	Main Findings
[2]	To assess the role of data visualization tools in helping businesses identify trends and facilitate decision-making.	Secondary data analysis of data visualization tools and methodologies.	Data visualization is crucial for businesses of all sizes to identify trends rapidly. It simplifies large datasets through graphical representations (charts, diagrams) and helps with decision-making.
[13]	Specifically, we want to learn how the manufacturing sector is managing product and service quality through the application of Industry 4.0 standards and technology.	Review of Industry 4.0 technologies, industrial standards, and performance measurement systems in smart manufacturing.	Industry 4.0 transforms manufacturing through IoT, AI, and big data, improving efficiency and reducing costs. However, there is a knowledge gap in performance measurement and quality management. The study highlights the importance of industrial standards and KPIs.
[14]	Examine how the capacity for big data analytics (BDA) affects the quality of decisions and how it helps with the performance of the circular economy (CE).	Data from 109 manufacturing enterprises in the Czech Republic was used in an empirical study that utilised partial least squares structural equation modelling.	Using BDA and BI, decision-making becomes better. Contributing to the success of the circular economy, data-driven insights fortify the bond between BDA competence and decision-making. Insights derived from data, however, do not serve to mediate this connection.
[15]	To identify workforce trends, skills gaps, and opportunities in the BD&AI domain, and to provide recommendations for workforce development.	Bibliometric analysis of BD&AI-related articles and job posting data analysis. SWOT analysis of university curricula for BD&AI programs.	A substantial skills gap and shortage of personnel exist, despite the fact that BD&AI technologies are essential for competitive growth. The study recommends strategies to align academic training with industry needs to prepare the workforce for BD&AI-driven industries.
[16]	To assess the most widely used data visualization tools for managing large datasets and their role in business decision-making.	Secondary data analysis of various data visualization tools and methodologies.	Data visualization is an essential tool for presenting large datasets graphically, facilitating better decision-making. The study evaluates the functional and non-functional characteristics of several visualization tools used in managing massive data sets.
[10]	With the use of absorptive capacity theory, we will investigate how business analytics relate to innovation.	Absorbent capacity theory was used to analyse data from a questionnaire survey of 218 UK enterprises.	A data-driven culture and better environmental scanning are two ways in which business analytics boost creativity. These components are crucial for gaining a competitive edge and making new products significant.
[17]	To propose a big data infrastructure for the construction industry to improve decision-making and business processes.	Case study of construction companies using the proposed Enterprise Integrated Data Platform (EIDP).	The proposed EIDP helps construction companies overcome inefficiencies in data collection, sharing, and interoperability, leading to optimized supply chain management, cost control, and better decision-making.
[18]	To demonstrate how business intelligence tools can enhance decision-making through the development of visual models of KPIs in high-tech industries.	Application of visual analytics tools to create KPI models for decision-making in a high-tech enterprise in telecommunications.	Visual analytics and business intelligence tools help develop KPI models that support strategic decision-making. These models improve competitiveness, cost reduction, and business process optimization in dynamic, high-tech environments.
[12]	To explore how external pressures and big data culture influence resource selection and capability building in manufacturing, and how these capabilities	Surveys collected from 195 respondents, analyzed using resource-based view theory and institutional theory.	Efficacy and efficiency in operations and cost management are enhanced when resources for developing big data capabilities are chosen in response to external demands. An organization's culture plays a significant role in developing its capabilities, as big data culture

	affect cost and operational performance.		mitigates the effect of resources on performance outcomes.
[11]	Aiming to investigate how global agri-food networks' business performance is impacted by the abilities of big data savvy (BDS) teams, the actions of big data driven (BDD), and other related factors.	Information gathered from 240 professionals in the field of big data inside international agri-food networks and evaluated using structural equation modelling.	By combining knowledge from several fields, BDS teams are able to improve company performance through the conversion of operational data into data-driven insights. Businesses that place a premium on BDD acts tend to do better.
[19]	Using Self-Service Business Intelligence as a framework, assess how data visualisation technologies contribute to better decision-making and increased company agility.	Examine the role of data visualisation tools in enhancing business agility and decision-making using the Self-Service Business Intelligence framework.	By empowering people to generate reports autonomously, data visualisation solutions such as Tableau, Power BI, Sisense, and QlikView improve decision-making and agility. The choice of tool must be based on an organization's specific needs.
[20]	This study aims to examine the connections between environmental sustainability, relationship-based business networks (RBNs), and top-level management's tangible capabilities (TMTCs) in the food import/export industry.	Using structural equation modelling, we examined data from 175 representatives of upper management.	RBNs mediate the relationship between TMTCs and environmental sustainability, and TMTCs are essential for their construction. Firms with strong networks perform better in environmental practices.
[21]	To identify trends in business visualization and visual analytics literature that address data challenges and enhance decision-making, problem-solving, and trend identification.	Survey of business visualization and visual analytics literature, classifying topics into business intelligence, business ecosystems, and customer-centric visual design.	With visual analysis, data is better understood, more people can understand it, and decision-making and creativity are both improved. The survey highlights mature and less developed areas of research in business visualization.
[22]	Focusing on digitisation technologies like Big Data and Data Science, this study aims to examine the primary drivers of digital business models and how they impact the potential of businesses.	Key performance indicators, personalisation, efficiency, and communication are the four key drivers of digital business models, according to an empirical study that used structural equation modelling (SEM).	All four determinants positively influence digital business model potential, with key performance indicators having the greatest impact.
[23]	To assess the significance of big data visualization, the protocols for selecting visualization tools, and the classification of these tools based on various factors.	Review of conventional and Big Data-specific visualization tools, with a framework designed for tool selection based on business needs.	Big data visualization impacts business by discovering hidden insights and improving decision-making. The study emphasizes the need for precise tools for storing, processing, and visualizing large datasets.

There is widespread agreement in the research on data-driven management and decision-visualization tools' usefulness in performance mapping that these resources are invaluable to businesses in any industry. Data visualization helps acquire and present large datasets in simple forms as it also enhances the speed with which trends are spotted and improve on decision-making. It has been especially beneficial for the companies and organizations across various industries that aimed at the output increase and search for the effective solutions for their internal processes. [2] point out that it is expedient and important for small, medium and even large organisations to find trends rapidly using such tools. When generally large amounts of data is available in the form of tables or other cumbersome formats, they can be transformed into more understandable forms charts, diagrams etc. It makes the decision-making process efficient because it is easy to understand such graphics than large volumes of information. In the same vein, [16] further stressed on the usefulness of visualization tools when dealing with large amounts of data. They give a clear assessment of different tools, functional and non-functional requirements, which when used enable business organizations to handle and analyze large data hence arriving at the right business decisions.

In manufacturing, [13] shed further light about the status and potential of data-driven management by studying the impact of Industry 4. 0 technologies including; IoT, AI, and big data on performance measurement and quality management. Their review shows that although these technologies have revolutionized manufacturing through increases in efficiency and reduction of cost, there is still space for improvement in the means through which efficiency is measured; this paper identifies a lack of coherent set of KPIs required to fully tap into

the underlying technologies for the improvement of efficiency in the manufacturing process. In similar context, [18] opine that in manufacturing high-tech organizations the development of KPI models through Visual analytics has improved the decisions making. From this, they were able to conclude that visual analytics enhances competitiveness with a view to business process enhancement, a key aspect when it comes to organisations within the setting of complex and volatile environments. Another area of significant change through data-driven management is the application of big data analytics (BDA) in business decision making. Using the perceptual obtrusiveness instrument, [14] amplify what impacts BDA capabilities impose on decision-making quality and CE performance. Based on their findings of Czech manufacturing firms, they pointed out that BDA enhances decision-making dexterity as it brings data to firms as he basis of making crucial decisions for CE performance. Yet, the same studies indicate that BDA's impact on decision quality is not entirely moderated by data-based information, which may suggest that there are other factors affecting BDA. [10] work in a different direction approaching the problem from the point of view of the connection between business analytics and innovation. A survey of UK businesses done by them reveals that business analytics improves innovation by increasing environmental scanning and data culture. These elements necessary for generating new product and sustaining competitive edge proofs worth and importance of data driven management in making businesses adaptive to change occurring in industries.

[19] did a research on the utilization of visualization tools in advancing business flexibility by the help of Self-Service Business Intelligence (SSBI). The authors' comparative analysis of the tools such as Tableau, Microsoft Power BI, Sisense, and QlikView explains that those tools enable businesses to build the reports and visualizations needed for decision making on their own. This in turn makes it easier for the organizations to come up with prompt intelligence that in turn helps them meet market needs hence making the organizations more flexible. Human capital development is another current topic that has been examined in relation to the evolution of big data, as [15]. Business progress in the domains of big data and artificial intelligence (BD&AI) is being impeded, according to their analysis, by a massive skill gap in these areas. According to the authors, there is a need to ensure that the training of academics meets the needs of the industries to help solve the problem of talent deficit. Specifically, they emphasised how important it is to provide employees with the knowledge and skills necessary to analyse and make use of data in order to facilitate data-driven decision-making. The value of organizational culture for maintaining and enhancing data-driven work environment is illustrated by[12]. Their work shows that the forces from outside push companies to make the proper choices of resources to develop big data capacities. But they also stress that the strong big data culture adopts a moderating effect on those capabilities in order to enhance the performance. Thus, the absence of the right organisational culture can limit the ability of organisations to harness their existing data advantages, thus holding back potential enhancements of cost and operational performance.

The expansion of the use of data systems also impact the agricultural sector as highlighted by [11]. In their analysis of networks of global agri-food, they conclude that multidisciplinary BDS teams convert operational processes into insights producing BDS, resulting in BDD activity that greatly improves business outcomes. This study, therefore, provides a testimony of the usefulness of BDS teams in analyzing data for operational changes, thus highlighting the importance of the data-driven management approach in different businesses. Besides these examples of the data visualisation usage in the industry, [22] introduced the aspect connected with data visualisation use in the main business model innovation. As per their study, they have en labeled four forces for the digital business models: KPIs, individualization, efficiency, and communication all of which are moved positively by Big Data and Data Science technologies. This shows how through data management, organisations can disentangle digital growth prospects that give way to new opportunities in business models.

In total, all the presented studies unconditionally confirm the relevance of using data-driven management and visualization tools for improving business performance. All of them are critical for managing organizational activities in today's data-oriented context, whether it is enhancing decision-making, encouraging innovations, increasing efficiency, or handling workforce issues. This way, companies will better prepare themselves through technological advances and employees enhancement to catch up with data analytics future.

5. Conclusion

Drawing from the facts in literature on data-driven management and decision-visualization tools, the imperative place of such tools for enhancing business performance in diverse industries cannot be overemphasized. These tools provide simplicity to large data sets hence businesses are able to identify trends faster to aid in their decision-making processes. In any kind of organization – small or big, developing such tools as data visualization aids the simplification of information, because organizational hierarchy transforms detailed information into easily understandable like charts and diagrams to support management efficiency in its decision-making processes. Notably factory operations, production, farming, and other advanced sectors of the division have benefitted highly from them Industry 4. No technologies include big data analytics & Self-service BI tools. Research also indicates to the elevating effects of such tools for competitiveness, operations and the ability to adapt to the needs of the market. The specifics of the implementation of such tools are far from being exhausted by the methods of managing organizational operations. These tools have been found useful in enabling organisations to come up with innovations, making right decisions whenever there is a problem with the workforce given the emergence of big data. To make the most of these technologies, it's important to build data-oriented teams and foster a strong big data culture. Those few companies which will be investing on both the technology networks and human capital will go a long way in sustaining competitive advantages and growth in the future. Besides, tools help business to be more flexible in case of the changing environments and demands of the market.

However, several limitations still persist with data-driven management as explained below. For instance, absence of clear and acceptable KPIs that one can use to assess the efficiency of Industry 4.0. Lack of technologies in manufacturing indicates that numerous firms might not be engaging the full possibilities of analytics. In addition, though big data increases the quality of decisions through analytics, it becomes clear that other nonanalytical factors affect the quality of decisions and this makes the adoption of such technologies challenging. A third

issue is that there is a serious problem of insufficient qualified personnel with expertise in big data or artificial intelligence, which has an impact on organizational development and still does not allow organizations to utilize the potential of data-focused management to the maximum. Further, lack of organizational culture support may mean that these tools could only offer suboptimal gains in performance. In order to avoid these limitations, the recommendations are as follows; First, an effective set of KPIs which will help to create a unified definition of increases in efficiency due to data-driven technologies, especially in the manufacturing industry, needs to be identified. Second, organisations should embrace ongoing training and development as a way of achieving a closure gap for now in big data and artificial intelligence. These programs should closely conform to the needs of the industry so as to be able to produce a steady stream of human resource capable of performing data analytics and visualization. Third, strong data culture or, in other words, the culture of data-driven management is crucial for improving the management effectiveness through the application of data-driven management tools. Finally, businesses should always remain on the lookout for newer exciting revenues in the field of data analytics and visualization techniques so that the business can stay on its toes besides being adaptive and innovative to changes that may take place in the market.

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Data Engineering Solutions: The Impact of AI and ML on ERP Systems and Supply Chain Management

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In the rapidly evolving landscape of data engineering, the integration of Artificial Intelligence (AI) and Machine Learning (ML) is transforming Enterprise Resource Planning (ERP) systems and supply chain management. This paper explores the profound impact of AI and ML technologies on these critical business domains. By leveraging AI and ML, organizations can enhance their ERP systems' efficiency through advanced data analytics, predictive modeling, and automation, leading to more informed decision-making and streamlined operations. Similarly, in supply chain management, these technologies enable real-time insights, improved demand forecasting, and optimized logistics, thereby reducing costs and increasing agility. This study examines current trends, practical applications, and case studies that highlight the benefits and challenges of incorporating AI and ML into ERP and supply chain processes. It also addresses the future directions of data engineering solutions and their potential to revolutionize business operations, offering valuable insights for professionals aiming to leverage these technologies for competitive advantage.

Keywords: Data Engineering,Artificial Intelligence (AI),Machine Learning (ML),ERP Systems,Supply Chain Management,AI Integration,ML Algorithms,Data Analytics,Predictive Analytics,Data Transformation,Big Data,Real-time Data Processing,Business Intelligence,Automated Decision Making,Data Pipeline Optimization,Supply Chain Optimization,AI-driven ERP,ML-powered Supply Chains,Data Engineering Solutions,ERP Integration with AI,Machine Learning Models,Data Warehousing,IoT and Supply Chain,Smart Manufacturing,Data Quality Management..

1. Introduction

The transformative potential of artificial intelligence (AI) and machine learning (ML) is

increasingly being recognized across various sectors, particularly in enterprise resource planning (ERP) systems and supply chain management. As organizations strive to enhance operational efficiency and profitability, the integration of AI and ML technologies promises to revolutionize traditional processes by enabling real-time data analytics, predictive modeling, and automation. This evolution not only streamlines workflows but also fosters more informed decision-making, allowing businesses to respond swiftly to market demands and mitigate risks. Furthermore, the synergy between AI, ML, and ERP systems creates a robust framework for managing complex supply chains, improving visibility, and optimizing resource allocation. This essay explores these dynamics, assessing the profound implications of AI and ML innovations on ERP frameworks and supply chain structures in today's rapidly evolving digital landscape. Through careful analysis, it aims to elucidate the strategic benefits that these technologies confer upon modern enterprises.The integration of artificial intelligence (AI) and machine learning (ML) into enterprise resource planning (ERP) systems and supply chain management is ushering in a transformative era for businesses. By leveraging real-time data analytics, predictive modeling, and automation, AI and ML enhance operational efficiency and drive profitability. These technologies enable organizations to streamline workflows, make more informed decisions, and respond swiftly to market changes. In the realm of ERP systems, AI and ML facilitate advanced forecasting, intelligent resource allocation, and comprehensive visibility into operations, thus optimizing complex supply chains. The synergy between AI, ML, and ERP frameworks not only improves operational effectiveness but also equips businesses to better navigate uncertainties and capitalize on emerging opportunities in a rapidly evolving digital landscape. This strategic alignment empowers enterprises to achieve a competitive edge through enhanced agility and precision.

Fig 1 :Integrating Artificial Intelligence and Machine Learning Capabilities into Modern ERP Systems

1.1. Definition of ERP Systems

Fundamentally, ERP (Enterprise Resource Planning) systems represent an integrated suite of applications designed to facilitate the management of business processes across various departments within an organization. By consolidating disparate functions such as finance, human resources, production, and supply chain management into a unified platform, ERP systems enable a holistic approach to organizational data and process optimization. This seamless integration not only enhances operational efficiency but also fosters improved

decision-making through real-time data access and analytics capabilities. Furthermore, ERP systems support standardization of processes and data across locations, which can lead to increased compliance and reduced redundancy in operations. As businesses increasingly adopt these systems, understanding their core value and functionality becomes essential for harnessing their full potential in driving organizational performance and competitive advantage (Perumal K et al., 2022-04-06). Ultimately, the defining characteristics of ERP systems underline their vital role in contemporary business environments.

1.2. Overview of Supply Chain Management

In contemporary business environments, effective Supply Chain Management (SCM) is pivotal for organizations aiming to enhance operational efficiency and customer satisfaction. SCM encompasses the planning, execution, and control of all supply chain activities, including sourcing, production, logistics, and the flow of information from suppliers to customers. The integration of digital technologies, such as the Internet of Things (IoT) and cloud computing, has transformed SCM into a more responsive and data-driven process. Notably, Digital Twins (DTs) in SCM present an innovative framework for real-time synchronization and decision-making, as highlighted in (Zaidi SAH, 2024). Such advancements facilitate proactive management of disruptions, ultimately improving supply chain performance. As companies increasingly rely on these technologies, understanding the implications of data privacy and protection becomes crucial. Conversations around companion chatbots, for instance, underscore the importance of regulatory compliance to mitigate risks and safeguard user data, as discussed in (Dewitte P, 2024).

1.3. Introduction to AI and ML Technologies

The evolution of artificial intelligence (AI) and machine learning (ML) technologies has ushered in transformative changes that resonate throughout various industrial sectors, including supply chain management. By leveraging advanced algorithms and vast datasets, AI and ML empower organizations to enhance operational efficiencies and improve decision-making processes. Particularly within enterprise resource planning (ERP) systems, these technologies facilitate seamless data integration, enabling real-time analytics that inform strategic direction. The interplay between AI-driven insights and traditional supply chain methodologies drives substantial improvements in responsiveness and agility. A comprehensive understanding of AI and MLs capabilities lays the groundwork for innovation, as evidenced by the research highlighting the integration challenges and potential of Digital Twins in supply chains. These frameworks promote greater synchronization and data-driven modeling, addressing modern supply chain complexities ((Zaidi SAH, 2024)). The adoption of AI and ML is therefore pivotal for organizations aiming to achieve sustainable competitive advantages in rapidly evolving markets.

2. The Role of AI and ML in Enhancing ERP Systems

Integrating AI and machine learning (ML) technologies into enterprise resource planning (ERP) systems signifies a transformative shift in operational efficiency and decision-making processes. By leveraging vast amounts of data, these intelligent systems can analyze patterns, predict future trends, and automate routine tasks, ultimately minimizing human error and

increasing productivity. For instance, AI-driven predictive analytics facilitates informed decision-making by providing real-time insights into inventory management and supply chain dynamics, allowing organizations to adapt rapidly to market fluctuations. Additionally, machine learning algorithms enhance ERP systems by learning from historical data, thereby improving forecasting accuracy and optimizing resource allocation. This dynamic synergy between AI, ML, and ERP not only streamlines organizational processes but also creates a more agile business environment that can respond to evolving consumer demands, underscoring the necessity for businesses to embrace these technologies for sustained competitive advantage in a rapidly changing marketplace (Pandey et al., 2024-01-29).

Fig 2 : Artificial Intelligence in ERP Software Solutions

2.1. Automation of Routine Tasks

The implementation of AI and machine learning technologies in enterprise resource planning (ERP) systems is fundamentally transforming the management of supply chains by automating routine tasks. By delegating repetitive processes such as order processing, inventory management, and data entry to intelligent algorithms, organizations are experiencing significant increases in efficiency and accuracy. For instance, predictive analytics, a key feature of these technologies, empowers supply chain professionals to forecast demand and optimize inventory levels more effectively, reducing the risk of stockouts or overstock situations (Ifesinachi A et al., 2024). Furthermore, the integration of automation not only accelerates operational processes but also minimizes human errors, thereby enhancing reliability and consistency in decision-making. As accountants increasingly embrace roles as strategic advisors rather than mere number crunchers, the necessity for developing advanced analytical skills becomes apparent, driven by the data-rich environments these automated processes create (Al Robai F, 2024). Ultimately, automation revolutionizes routine tasks, allowing professionals to focus on higher-value activities that drive strategic growth.

2.2. Data Analysis and Predictive Analytics

The integration of data analysis and predictive analytics within ERP systems significantly enhances supply chain management by facilitating informed decision-making. By harnessing advanced technologies, organizations can analyze vast datasets to identify patterns, trends, and anomalies that may influence operations. For instance, technologies such as the Internet of Things (IoT) and cloud computing augment predictive analytics capabilities, allowing for real-time data synchronization and modeling of supply chain dynamics. The framework proposed in (Zaidi SAH, 2024) underscores the necessity of external and internal linkages within supply

chains to effectively navigate disruptions, thereby showcasing how robust data analytics can preemptively address potential challenges. Furthermore, the emphasis on collaboration between operations management and information systems noted in (Mourtzis D, 2024) reveals the synergy required for optimizing manufacturing processes within a smart manufacturing context. Ultimately, the deployment of predictive analytics not only improves operational efficiency but also positions organizations to adapt adeptly to market fluctuations.

3. AI and ML in Supply Chain Optimization

The application of artificial intelligence (AI) and machine learning (ML) in supply chain optimization significantly enhances operational efficiency, resulting in substantial improvements in overall productivity. By leveraging AI-driven predictive analytics, firms can refine demand forecasting, thereby minimizing excess inventory and reducing associated costs. For instance, (Fathima F et al., 2024) highlights how AI empowers companies to anticipate customer needs with unprecedented accuracy, allowing for informed decision-making regarding inventory levels and resource allocation. This proactive approach leads to more agile responses to market fluctuations, which is crucial in today's dynamic environment. Furthermore, the integration of AI tools with enterprise resource planning (ERP) systems facilitates seamless data exchange and enhances visibility throughout the supply chain, as noted by (Adenekan OA et al., 2024). This comprehensive integration fosters collaboration across various functions, ultimately driving greater efficiency and competitiveness. Thus, the synergy between AI, ML, and ERP systems represents a transformative opportunity for organizations aiming to optimize their supply chains effectively.

Fig 3 : Artificial Intelligence in Supply Chain

3.1. Demand Forecasting and Inventory Management

Effective demand forecasting is crucial for optimizing inventory management, particularly in complex supply chain ecosystems where accuracy directly impacts operational efficiency and customer satisfaction. Traditional methods often struggle with the dynamic nature of market demands, leading to excess stock or shortages. However, the integration of artificial intelligence (AI) and machine learning (ML) technologies is revolutionizing this domain, offering enhanced predictive capabilities that can accurately analyze vast datasets and identify patterns. For instance, as highlighted in (Badulescu Y, 2024), leveraging Big Data from social media networks can significantly improve demand forecasting accuracy by incorporating real-time consumer sentiments into traditional models. This hybrid approach not only enhances the decision-making process but also supports a more agile inventory management strategy.

Consequently, the alignment of advanced forecasting with inventory control mechanisms facilitates a responsive supply chain, ultimately driving competitive advantage and reducing operational costs in an increasingly volatile market landscape.

3.2. Supplier Selection and Risk Management

An effective supplier selection process is crucial in mitigating risks inherent in supply chain management. This involves assessing potential suppliers not only for their capability to fulfill contract requirements but also for their reliability and alignment with an organization's strategic objectives. By leveraging advanced analytics and machine learning algorithms, businesses can transform the traditional supplier evaluation model into a more nuanced assessment framework, identifying potential risks related to financial stability, compliance issues, and geopolitical uncertainties. For instance, predictive analytics can quantify the likelihood of supplier disruptions, which enables organizations to undertake proactive risk management strategies, such as diversifying their supplier base or establishing contingency plans . Moreover, with the integration of artificial intelligence into Enterprise Resource Planning (ERP) systems, firms can enhance their decision-making processes by providing real-time data and insights, thus fostering a more resilient and responsive supply chain environment (Hangl J, 2022-03-09).

4. Challenges and Limitations of AI and ML in ERP and Supply Chain

The integration of artificial intelligence (AI) and machine learning (ML) within enterprise resource planning (ERP) systems and supply chain management presents significant challenges. One pressing issue is the complexity and volume of data generated across various stages of the supply chain, which can hinder effective data management and analytics. As noted in (Basu S, 2024), the challenges include cultural transformation and skill gaps, which can impede the adoption of AI and ML technologies. Additionally, the reliance on accurate data for autonomous decision-making often exposes systems to risks related to cybersecurity and data integrity. Moreover, the pilot stages of Digital Twins in supply chain management highlight the limitations of real-time synchronization and integration with existing systems, as underscored in (Zaidi SAH, 2024). This underscores the need for robust frameworks that can address these complexities and enhance decision-making capabilities, effectively bridging the gap between technology and practical implementation.

Fig 4 : Challenges in Implementing AI in Supply Chains and Solutions to Overcome Them

4.1. Data Quality and Availability Issues

The integration of AI and ML technologies in ERP systems and supply chain management is

significantly hindered by persistent data quality and availability issues. Inaccurate, incomplete, or inconsistent data can obstruct effective decision-making processes, leading to inefficiencies and suboptimal performance across the supply chain. With the reliance on real-time data for autonomous decision-making and data-driven modeling, such as outlined in the digital twin framework (Zaidi SAH, 2024), the implications of poor-quality data are particularly pronounced. Additionally, the complexity of modern manufacturing environments further exacerbates these challenges, as disparate systems often generate siloed data that inhibits comprehensive analytics. As noted in recent literature, effective collaboration between operations management and information systems is critical to addressing these data management challenges (Mourtzis D, 2024). By prioritizing data quality and ensuring seamless data availability, organizations can leverage AI and ML to enhance supply chain resilience and overall operational efficiency.

4.2. Integration Challenges with Legacy Systems

The integration of artificial intelligence (AI) and machine learning (ML) into existing enterprise resource planning (ERP) systems presents significant challenges, particularly when legacy systems are involved. These older platforms often lack the flexibility and interoperability required for seamless integration with modern AI and ML technologies. As highlighted in the discourse on digital transformation, issues such as cultural resistance and gaps in skill sets can further hinder efforts to bridge the technological divide (Basu S, 2024). Legacy systems typically operate on outdated architectures that are not conducive to the demands of real-time data analytics and connected devices inherent in Industrie 4.0 initiatives. This disjointedness not only complicates data management but also complicates the establishment of effective communication channels across various levels of the organization (Basu S, 2024). Consequently, organizations must navigate these integration challenges to fully realize the transformative potential of AI and ML in optimizing supply chain management.

4.3. Resistance to Change within Organizations

Organizational resistance to change is often rooted in psychological, cultural, and structural factors that hinder the adoption of innovative practices such as artificial intelligence (AI) and machine learning (ML) within enterprise resource planning (ERP) systems and supply chain management. Employees may feel threatened by the prospect of new technologies disrupting established workflows, leading to anxiety about job security and skill redundancy. This resistance can be exacerbated by a lack of understanding regarding the benefits of AI-CRM systems, as firms frequently report minimal performance improvement despite significant investment in such technologies (Yoo JW, 2024). Furthermore, barriers such as financial constraints and regulatory complexities diminish the likelihood of successful AI integration, as highlighted by the barriers identified in the food supply chain context (Ghag N, 2024). Thus, addressing these challenges and fostering a culture that embraces change is essential for organizations aiming to realize the transformative potential of AI and ML.

5. Future Trends in AI and ML for ERP and Supply Chain Management

As businesses increasingly seek to enhance efficiency and mitigate risks, the integration of

artificial intelligence (AI) and machine learning (ML) into enterprise resource planning (ERP) and supply chain management is poised for significant growth. Future trends indicate a shift towards more data-driven decision-making processes, leveraging AI capabilities to analyze vast datasets in real-time, thereby enhancing visibility and responsiveness across supply chains. This transition aligns with the need for digital twins that facilitate data-driven modeling and real-time synchronization, as emphasized in recent studies (Zaidi SAH, 2024). Moreover, the shift toward vertical networking and horizontal integration within supply chains highlights the importance of collaboration and adaptability in overcoming disruptions, a theme well-articulated in the context of Industrie 4.0 and digital transformation initiatives (Basu S, 2024). Ultimately, the fusion of AI and ML technologies into ERP systems will not only streamline operations but also pave the way for strategic innovations, thereby reshaping the landscape of supply chain management.As businesses increasingly aim to boost efficiency and mitigate risks, the integration of artificial intelligence (AI) and machine learning (ML) into enterprise resource planning (ERP) and supply chain management is set to experience substantial growth. Future trends suggest a transition towards data-driven decision-making, where AI's ability to analyze extensive datasets in real-time enhances visibility and responsiveness within supply chains. This evolution is complemented by the adoption of digital twins, which enable dynamic modeling and real-time synchronization, as highlighted in recent studies (Zaidi SAH, 2024). Additionally, the emphasis on vertical networking and horizontal integration underscores the necessity for collaboration and adaptability to navigate disruptions, reflecting key themes of Industrie 4.0 and digital transformation (Basu S, 2024). The confluence of AI and ML technologies within ERP systems not only promises to streamline operations but also fosters strategic innovations, fundamentally reshaping the supply chain management landscape.

5.1. Advancements in Machine Learning Algorithms

Recent years have witnessed transformative advancements in machine learning algorithms, significantly influencing various sectors, including Enterprise Resource Planning (ERP) systems and supply chain management. Innovations in deep learning and machine learning frameworks have enabled organizations to better analyze large datasets, leading to enhanced decision-making and operational efficiencies. In particular, the implementation of AI-enabled CRM systems has emerged as a pivotal factor for competitive advantage, as identified in the study highlighting the critical characteristics of AI-CRM (Yoo JW, 2024). Furthermore, the surge in the generation of time-series data within smart manufacturing contexts necessitates robust classification techniques, revealing that algorithms like ResNet and DrCIF consistently outperform traditional methods in accuracy across diverse manufacturing tasks (Mojtaba A Farahani, 2024). These advancements not only facilitate improved predictive analytics but also redefine how organizations leverage data, thereby transforming their operational strategies and reinforcing their competitive positioning in the marketplace.

5.2. The Role of IoT in Supply Chain Integration

The integration of the Internet of Things (IoT) into supply chain management has transformed traditional logistics by facilitating real-time data exchange and enhancing operational efficiency. IoT devices, such as sensors and RFID tags, enable continuous monitoring of inventory levels, shipment status, and environmental conditions, leading to improved decision-

making and reduced delays. Moreover, the ability to create Digital Twins (DTs) of supply chains allows organizations to simulate scenarios and predict disruptions, ultimately enhancing resilience and responsiveness. As noted in a recent systematic review, the development of digital technologies, including IoT and cloud computing, has increased knowledge regarding the creation of supply chain DTs, underscoring the importance of data-driven modeling with real-time synchronization (Zaidi SAH, 2024). Furthermore, as the deployment of companion chatbots becomes more prevalent, ensuring compliance with data protection regulations, such as GDPR, is essential, particularly as these digital tools process personal data continuously within supply chains (Dewitte P, 2024).The integration of the Internet of Things (IoT) into supply chain management has revolutionized traditional logistics by facilitating real-time data exchange and boosting operational efficiency. IoT devices, including sensors and RFID tags, provide continuous monitoring of inventory levels, shipment statuses, and environmental conditions, which enhances decision-making and minimizes delays. This technology has also enabled the creation of Digital Twins (DTs) of supply chains, allowing organizations to simulate various scenarios and predict potential disruptions, thereby improving resilience and responsiveness. According to a recent systematic review, the advancement of digital technologies such as IoT and cloud computing has significantly enhanced the development of supply chain DTs, emphasizing the critical role of real-time data synchronization in data-driven modeling (Zaidi SAH, 2024). Additionally, the rise of companion chatbots necessitates strict adherence to data protection regulations, like GDPR, as these tools continuously handle personal data within supply chains, highlighting the need for robust data security measures (Dewitte P, 2024).

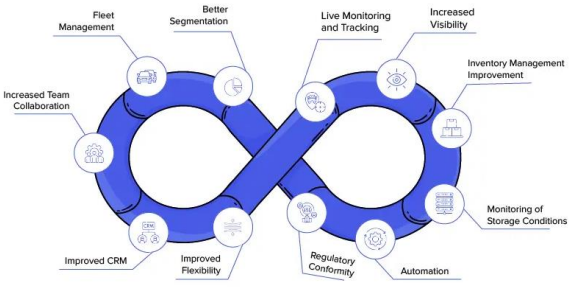

Fig 6 : Supply Chain Integration

6. Conclusion

In conclusion, the integration of Artificial Intelligence (AI) and Machine Learning (ML) within Enterprise Resource Planning (ERP) systems and supply chain management is not merely an enhancement but a transformative shift that drives operational efficiency and resilience. The convergence of AI-driven supply chain optimization with ERP systems facilitates real-time data management and predictive analytics, allowing for improved decision-making and greater agility in response to market fluctuations ((Adenekan OA et al., 2024)). Furthermore, as evidenced by the comparative analysis of global industrial manufacturing, the adoption of these technologies yields significant benefits in cost reduction,

efficiency enhancement, and regulatory compliance adherence ((Islam MK et al., 2024)). This underscores the necessity for manufacturers to prioritize the strategic implementation of AI and ML, ensuring they remain competitive in an increasingly digital landscape. The future of supply chain management thus hinges on the successful integration of these advanced technologies to foster innovation and adaptability.

6.1. Summary of Key Findings

In examining the transformative effects of artificial intelligence (AI) and machine learning (ML) on Enterprise Resource Planning (ERP) systems and supply chain management, several critical findings emerge. The integration of AI-driven data analytics within ERP frameworks significantly enhances decision-making processes, enabling organizations to not only streamline operations but also forecast demand with greater accuracy. Moreover, the adaptability of AI algorithms allows for real-time adjustments in supply chain logistics, addressing potential disruptions proactively. By automating routine tasks, firms can allocate human resources to higher-value activities, ultimately fostering innovation and competitiveness. In particular, the development of AI-enabled CRM systems demonstrates the importance of personalized customer interactions, which can lead to improved customer satisfaction and retention (Yoo JW, 2024). Additionally, the insights gleaned from microbial analysis showcase the potential for AI to refine complex datasets into actionable strategies, presenting a promising avenue for optimizing supply chain efficiencies (Patil A, 2024).

6.2. Recommendations for Future Research

While significant advancements have been made in the integration of AI and machine learning (ML) within Enterprise Resource Planning (ERP) systems and supply chain management, future research should delve deeper into the specific features that enhance organizational performance and competitive advantage. As highlighted in recent studies, understanding the critical characteristics of AI-enabled systems, such as those identified in AI-CRM, could provide substantial insights into what drives effective implementation in supply chains. Specifically, research could benefit from exploring the distinct impacts of AI-CRM features, such as marketing and sales capabilities, on ERP efficiency, particularly in real-world contexts where firms are experiencing varied outcomes ((Yoo JW, 2024)). Additionally, given the ethical considerations surrounding AI, future studies must address the societal implications of increased AI integration within ERP systems, as suggested by the evolving landscape described in (Rashid AB, 2024). This multidimensional approach will not only inform better practices but also help shape ethical guidelines for the sustainable use of AI in supply chains.

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Optimizing Production Efficiency in Manufacturing using Big Data and AI/ML

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Abstract

Manufacturers need to ensure that their facilities are in optimal working condition to achieve maximum output. The ideal scenario is to have no wasted time, no mistakes, and a consistently perfect product. Yet, we know that inefficiencies may occur that can put a stop to production, lower profits, and result in substandard outputs. Market trends and dynamics can easily drive the relevant factors that allow for a product's production efficiency to change. What if new regulations impact material purity and lead to significantly more downtime for cleaning? How will the production volume respond? What drives the number of tool changes? Should we be installing additional machines, or can we change production to mitigate the aforementioned regulation? All of these are questions that can easily be analyzed by using historical data. However, traditional analysis methods can take days or even weeks just to create a production data report before further analysis can take place, so such analysis is often avoided or not as thorough as it could be.

Keywords: Production Efficiency, Manufacturing Optimization, Big Data, AI/ML (Artificial Intelligence/Machine Learning), Operational Downtime, Regulatory Impact, Tool Changes, Historical Data Analysis, Production Volume, Data-Driven Insights.

1. Introduction

Traditionally, production landlords in the manufacturing industry have been highly experienced engineers who have spent years on the shop floor keeping plant processes running optimally during unscheduled downtime. They relied on the help of slightly less experienced engineers who spent a lot of time manually collecting process data and analyzing it. Both sets of engineers built up considerable experiential knowledge on what was likely to go wrong in, say, a rolling mill, forging process, or heat treatment of steel, and took corrective steps as necessary. What was needed was a way to capture all this experiential knowledge and integrate it with live process data in one place so that necessary action could be taken quickly and efficiently. For many years, this was not possible. Over the past 10 to 20 years, we have started to first automate the capturing of process data and now integrate process data with engineering rules and experiential knowledge to come up with intelligent decision-making systems. Today, these systems are based on data analysis tools and advanced computer science. This paper demonstrates why such support is so urgently required.

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The usual problems discussed in an advanced industry describe issues associated with the design or anticipated performance of user-defined plants or machinery. However, in a mineral processing or manufacturing environment, the machinery or equipment is highly customized, and the quality of the product is heavily influenced by feed quality, weather conditions, and machine health. It is virtually impossible to control the quality of these variable parameters and very difficult to predict how these quality parameters will affect the maintenance and response to challenges of the final product. Every good-quality IO pellet plant has to prevent a massive losing streak due to using feed ore, which causes breakage of pellets during their handling. Once a massive losing streak has happened and breakage becomes the key issue, it is already good enough to achieve significant amounts of pellets into road sweepings, etc. This paper argues for the use of offline and online data analysis tools for knowledge capture, as well as the application of advanced computer science tools for capturing experiential knowledge as an intelligent dynamic decision support system in the iron ore pellet manufacturing unit. We consider the benefits of the inclusion and expression of expert knowledge in the form of linguistic rules and decision trees in a data analysis tool to be the speed and expression as if an experienced knowledge principal discussed with his or her process trainee calmly and analytically, and the clarity of the answer to "how would you make the treatment of data more advanced?" optional application to non-synchronization, out-of-pattern detection, quality implication, system health, and applicability under conditions of uncertainty. Data analysis tools may also require an audit where probability counts the take of the input by end-user questions and the relation of the input to the output of the system. In the next section, we discuss big data analysis, advanced computer science tools, and previous work in our area of interest. In section 3, we discuss the case study that we have done. In section 4, we consider experimental results. Finally, we draw our conclusions and list points for future work.

1.1 Background and Rationale

In the world of manufacturing, terms like Industry 4.0, automated and smart factories, industrial data analytics, and data-driven approaches have acquired high popularity and have emerged as key focus areas for business leaders. A fire-and-forget approach to manufacturing to meet market demands is the fundamental force acting in this direction, driven by dynamic customer tastes. On a production floor, whenever a machine or equipment goes down due to some fault in one of its components, it has a significant impact on production efficiency, which is measured as the ratio of quantities produced to the time available. The puzzling questions that commonly occur to the managerial team are: 'How can AI/ML and big data help?' and 'Are our systems in place enough to handle manufacturing fault occurrences?' These questions can be addressed to a considerable extent with a combination of different machine learning models and methodologies like predictive maintenance. There is a need for preparing maintenance data, creating models to predict which component is likely to fail, connecting the models to equipment for decision-making, and taking preventive action to ensure that production is not halted. After identifying important parameters and generating data, data-driven modeling can be applied effectively to identify patterns of stress on particular components of equipment to find trends, clusters, and deviations from regular conditions. Benefits of building manufacturing resilience through AI and ML is shown in figure 1.

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Figure 1. Benefits of Building Manufacturing Resilience Through AI and ML

1.2 Research Aim and Objectives

A data-driven operational model was developed early on, which, when looked at retrospectively, comprises the basics of data collection, feature induction, devising an operational model with mixed AI/ML and heuristic components, model testing, deployment, and solution proposal, followed by feedback-based continuous improvement. This research aims to build upon this pre-existing model and validate the established knowledge with the benefit of newly emerged possibilities. As it applies to a specific case of cost optimization, it becomes the objective of this paper. This paper presents novel practices, namely asset utilization and maintenance gap cost, as well as asset utilization-maintenance gap cost, to close the most important gaps in traditional OEE calculations. The asset utilization-maintenance gap costs suggest that a company's production system would see upstream benefits when considering asset utilization and maintenance costs more holistically relative to OEEs.

1.3 Scope and Significance

An exhaustive study posited that "big data is the next frontier for innovation, competition, and productivity." The predecessors had estimated nine impactful strategies for large-scale recession management during the late 1990s and early 2000s, which led to explicit and worthwhile analytical activities using advances in information and digital technology. As consumers, humans produce a substantial amount of data daily. The new data production activities require no more than beings constantly being born who automatically exhibit typical features of standard data-producing information capture devices. Population growth, affluence, and the growth of AI/ML abet this enormous data creation, accumulation, processing, and analysis.

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Not only is big data efficient in describing socio-economic activities and priority project characteristics, but for most developing countries, it presents a cost-efficient way for compiling population censuses and monitoring projects, as these exercises consume substantial financial and manpower resources. In today's 'datapolis', largely financial, procurement, and construction companies already employ one AI/ML analyst per company. Because of ongoing increased data proliferation, they institute new data governance rules, seek possibilities of reclaiming personal land ownership rights of AI/ML created communities in data cloud estates, redefine organizations' big data focus, and reskill the workforce to benefit from AI/ML functionalities which, somehow, currently still do not provide a broad functional capability in terms of emulating the human thought process. These companies are exploring big data as the very cornerstone in understanding the intrinsic features of populations as agents of change behaviors in their society. The rise of big data represents a transformative opportunity for innovation and productivity, particularly in developing countries where traditional methods of data collection, like population censuses, can be prohibitively expensive and resource-intensive. As individuals generate vast amounts of data daily, driven by factors such as population growth, increased affluence, and advancements in AI and machine learning, organizations are strategically leveraging this data to gain insights into socio-economic dynamics and project characteristics. In sectors like finance, procurement, and construction, the integration of AI/ML analysts has become commonplace, prompting companies to establish robust data governance frameworks and explore new avenues for land ownership rights in digital contexts. Furthermore, as these organizations redefine their big data strategies, they are reskilling their workforces to harness the potential of AI/ML, striving to understand populations not just as data points but as active agents of change within their communities. Despite the challenges in fully replicating human cognitive processes, the ongoing exploration of big data remains pivotal in shaping informed decision-making and fostering societal advancements.

Equation 1-3 shows the Struggling with Control Chart Limits.

Upper Control Limit (UCL):

$$UCL = \bar{p} + \sqrt[3]{\frac{\bar{p}(1-\bar{p})}{n_i}} \quad (1)$$

Center Line (CL):

$$CL = \bar{p} = \frac{\sum p_i}{\sum n_i} \quad (2)$$

Lower Control Limit (LCL):

$$LCL = \bar{p} - \sqrt[3]{\frac{\bar{p}(1-\bar{p})}{n_i}} \quad (3)$$

Where:

- $\bar{p}$ is the average proportion of defects.
- p_i is the proportion of defects in each sample.
- $n_i$is the sample size for each subgroup.
- UCL and LCL are the upper and lower control limits, respectively, for the p-chart.

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2. Literature Review

The research on optimization of production efficiency starts with understanding the data stream in production for drawing inferences from them for risk and asset management. The physics overlaid on data analytics is a co-discipline. Kaizen encompasses defective patterns and can play a role in the design of big data systems. Competitive factors in production and the role of finance in CAPA are generic. R&D, supply chain, manufacturing, and service functions of any organization influence each other. Big data can be harnessed to simulate various relationships to find alignments. Production risk due to Pareto output and constraints on capacity, spending, and time interactions can limit production. Machine faults, downtime, productivity losses, maintenance, spares, methods, and equipment design are interdependent. Data needs to be available for analysis of these linkages. Preventive maintenance and optimization of equipment reliability by strengthening weak areas will lead to higher production efficiency. Tools are needed to differentiate early signs of an imminent equipment failure. They flag a downtime event coupled with high urgency. The high urgency downtimes are especially troubling from the perspective of lost production, whereas the actual machine failures, while able to produce high urgency downtimes, don't always have time to worsen sufficiently, thus producing a machine failure.

2.1 Big Data in Manufacturing

There are several examples showing how big data helps in manufacturing processes. Even if each case is unique, both horizontal and manufacturing analytics cases exist, such as reducing machine downtime, reducing product defects, predicting equipment failures, reducing energy usage, improving quality, and analyzing semiconductors and sensors to improve quality and increase yield performance. CAM site integrations in a single enterprise data warehouse increase the analysis of form factor measurement, enhance equipment efficiency in the foundry, and enable more complex analytics in the 3D NAND production process. Analytics for performing cloud-platform deployment and daily monitoring, as well as alarms for the strategic sulfur room of smart manufacturing operations, are also important. Building smart test solutions, temperature stabilization inside specific tools used in microelectronics, batch processing analysis, integrated fleet management execution, and production performance reporting are key components.

Among the identified opportunities, there was a need to have easy-to-read and critical parameters faster, such as site performance, FDC parameters, and integrated builds. Extensive use of data output reports, quality sampling reports, and reports on incoming products, as well as additional reports that map product generation and utilization, are essential. Complex interaction analytics are implemented in new products and provide product support. Product scheduling reflects the latest capacity data and commercial data to improve business analytics, including inventory with a live information base and logistics between factories and supply chains. A very interesting case is the "work from home" initiative that enables engineers to continue participating in real-time engineering meetings with data accuracy. The results of the use cases are of great value as they demonstrate the successful use of big data in the semiconductor and electronics context. Additionally, deploying and integrating big data analytics into manufacturing, maintaining regular interactions between our company staff and selected suppliers, along with a common program assessment, require a big data architecture strategy to partner on main aspects for deployment and develop a cost-effective solution with a short time to market.Big data is revolutionizing manufacturing processes, particularly in the

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semiconductor and electronics sectors, by enabling enhanced analytics and operational efficiencies. Key applications include minimizing machine downtime, predicting equipment failures, and optimizing energy consumption, all of which contribute to improved product quality and yield. Integrating data across manufacturing sites into a centralized enterprise data warehouse facilitates complex analytics, such as monitoring form factor measurements and equipment efficiency in foundries. Additionally, smart manufacturing operations benefit from real-time monitoring and alarm systems, particularly in critical areas like sulfur management. The implementation of user-friendly dashboards for key performance indicators, alongside detailed reporting on product quality and logistics, empowers decision-makers with actionable insights. Notably, the "work from home" initiative illustrates the adaptability of engineering teams to collaborate effectively, leveraging accurate data for real-time decision-making. Ultimately, a robust big data architecture strategy is essential for maintaining strong supplier relationships, optimizing production scheduling, and ensuring a swift and cost-effective deployment of analytics solutions across the manufacturing landscape. Figure 2 depicts the Big Data in Manufacturing.

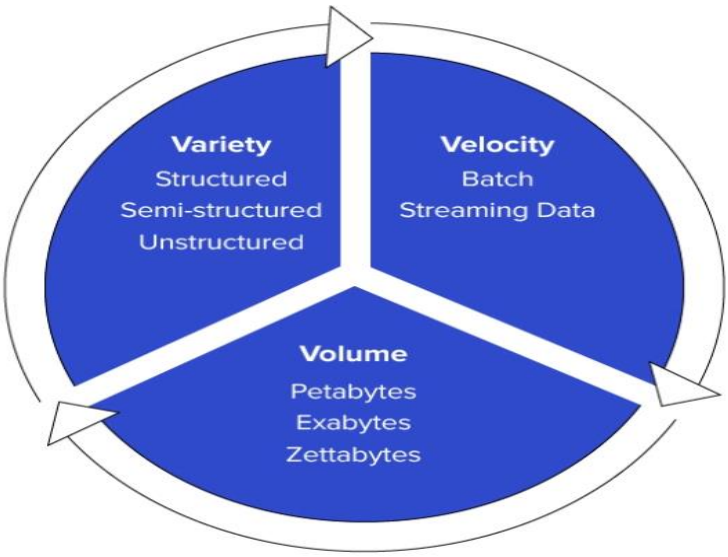

Figure 2. Big Data in Manufacturing

2.2 AI/ML Applications in Production Optimization

Artificial intelligence techniques based on either expert systems, or reinforcement learning alone, or a combination of expert systems and reinforcement learning can be applied in production optimization problems in the manufacturing sector. Here are some examples of these applications: integrating an intelligent decision support system into the production planning process. The purpose of this study is to show how an intelligent system based on an expert system and a reinforcement learning agent can be used to integrate production planning activities. When there are enough computational resources available, multi-agent systems can perform more complex intelligent operations. This can lead to the development of systems for real-time support for online adaptive decision-making that uses intelligent software.

Managing complex robotic manufacturing systems. The implementation of AI technology is performed from the automatic code for generating dispatch rules, as well as the reinforcement learning approach aimed at setting the service conditions for cyclic production and executing

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production capacity allocations based on the material flow. Automatic generation of the acceptance and dispatch rules of these tasks, with further consideration of reinforcement learning, is performed to optimize the quality and the time of the robotic assembly. Overall, the presented methods of AI integration are highly demanded in industrial sectors such as robotics, where process automation is both necessary and essential for effective performance. The benefits of the intelligent system enhancement include an increase in the quality of the work performed and a decrease in the time of robotic assembling. The structure of the intelligent system planned is designed to be applied to production planning for small batch processes in the field of the mobile industry. It is also capable of renewing production task schedules each time changes in orders and resource allocations occur.

2.3 Integration of Big Data and AI/ML in Manufacturing

In the new era of industry and production, it is common for big data and problems to exceed human expectations and traditional computing modes. People are starting to realize that technology will completely change data acquisition, model establishment, optimization theory, methods, and the mode of interaction; i.e., AI is about the evolution of the four interaction modes among people, the environment, the process, and data. It is necessary to deepen the understanding and applications of production lifecycle data at various levels, with AI being applied in the production management process, and the realization of semantic perceptions of production is expected. It is urgent to speed up the construction of production AI factories. In summary, the application of AI/ML technology in manufacturing promotes horizontal integration rather than solely manufacturers' internal improvement, which significantly reduces conventional time and budget costs associated with process optimization and new product generation. In the future, with the development of the theory and method, optimization efforts will gradually be extended to the lower levels of the manufacturing process. While optimized production will maximize the output of modern manufacturing, its specific goals will evolve from simply ensuring the quantity of product production to ensuring product quality and characteristics. These goals reflect the intelligent and customer-oriented nature of future manufacturing. Additionally, AI technology will help partially ease the mounting pressure on emerging disciplines, such as robotics and blockchain. As AI becomes the leading discipline in computer science, its steps in the field of manufacturing will also become one of the pillars of the Industry 4.0 era.

Equation 4-7 shows the inventory models for certain demand: economic order quantity.

Given values:
H = 12 (holding cost per unit), S = 150 (ordering cost), D = 250,000 (annual demand)

Economic Order Quantity (EOQ):

$$EOQ = Q^* = \sqrt{\frac{2DS}{H}} = \sqrt{\frac{2\times250{,}000\times150}{12}} = 2500 \quad (4)$$

Total Cost (TC) at EOQ:

$$TC(Q^*) = S \times \frac{D}{Q^*} + H \times \frac{Q^*}{2} = 150 \times \frac{250{,}000}{2500} + 12 \times \frac{2500}{2} = 15000 + 15000 = 30{,}000 \quad (5)$$

Optimal Number of Orders per Year:

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$$\text{Optimal number of orders per year} = \frac{D}{Q^*} = \frac{250{,}000}{2500} = 100 \quad (6)$$

Length of Order Cycle Time:

$$\text{Length of order cycle time} = 250 \text{ days in a year}/100 \text{ orders} = 2.5 \text{ days} \quad (7)$$

3. Methodology

Our methodology involves the identification of characteristic profiles that can help in carrying out condition-based maintenance after the production of any single item or batch item on the production line, namely infeed centerless grinding, automated production line for tool and die making, prismatic machining center, and wire electrical discharge machine that is developed in the center. More specifically, we use the data from the development of the hard turning center in the prism lab, a new development in the prismatic machining center for the industry, centerless grinder, abandoned development of the infeed centerless grinding machine for industrial purposes, CNC turn-mill center, the dedication of the CNC lathe tending center for TAL, design, and development of a 10-station turret with milling functionality, design and development of fork and drum processing on a horizontal machining center, and anomaly detection algorithm for the spindle of the turret indexing system for a CNC lathe tending center.

All the mentioned studies had data related to noise and vibration sensor data, characterization times, lag times, tool wear estimation through acoustic emission signals, spindle speed signals, setup times for feature extraction modules, and mean detection delay for the analysis, feature extraction module for roughness, tool wear, feature extraction through sub-band envelope analysis, cyclostationary signal analysis, fast Fourier transform, discrete wavelet transform-correlation function, pulse-coupled neural network, Karl Pearson's correlation coefficient, skewness, and wavelet-based feature extraction module. The studies also comprised laptop parameter tool wear sign prediction model development for in-line condition-based preventive maintenance for the spindle of the CNC lathe tending center, bearing parameter tool wear sign prediction model development for in-line condition-based preventive maintenance for the spindle of the turret indexing system for a CNC lathe tending center, training of neural networks, numerical validation of the results, developed setups, tool wear monitoring and forecasting models design, and results.

3.1 Data Collection and Preprocessing

Data collection in manufacturing refers to the extraction and gathering of data from numerous sources. Data is collected from a variety of sources such as equipment sensors and outputs, human inputs or outputs, operational data, and the factory network. It is important to collect clear data to extract patterns and knowledge. Thus, sensor installation in an enterprise, as well as process parameter signaling, is critical. Problems can arise from numerous sensors sharing the same parameter signal of a manufacturing process and a supervisor not having visibility into obscured production quality.

The data for the training of machine learning algorithms comes from various sensors located on the machines as shown in figure 3. All components of a sensor must be maintained at certain intervals to ensure clear data results used by RF and ML models. Thus, it is a concerning task. The datasets used in a machine learning model, as well as business rules, must be found extensively. The data collected emerges in different formats, different qualities, and different

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time frequencies. It is important to have a well-formatted dataset for the optimized model. In conclusion, a rule-based structure is required in manufacturing to start the collaboration of AI/ML applications.

Figure 3. Data Preprocessing

3.2 Machine Learning Model Selection

In the next step, it is necessary to pick the machine learning model or the big data analytics algorithm that best suits the needs and requirements of the manufacturing process at hand. It is important that the selected algorithm can solve the specific problem of decision support. It is possible to use machine learning for the classification of different machine tool behaviors within manufacturing, such as different tool-wear states and various data-based feature extraction and selection criteria. When comparing decision trees, ensemble methods, and sequential learning for machine-learning-based energy prediction through sensor monitoring during machining, different behaviors of these algorithms for different types of data are expected. When machine learning is used for industrial anomaly detection, various machine learning techniques can be applied.

Big data analytics, independent of industry type, could be tested when applied for root cause analysis with dynamic data. Using the advantages of deep learning, results with attractiveness for regular and continuous quality testing, process optimization, and process control are proven. This proposes a method to detect anomalies automatically online in regular and continuous time-series manufacturing systems. Machine learning methods like clustering, regression analysis, neural networks, decision trees, and random forests, along with a methodology designed for the selection of the best features in such systems, are applied to find the relations between the input and output signals. They were further used to forecast productivity and operations in the continuously running system of woven fabrics. Supervised and unsupervised learning methodologies were applied. In supervised methods, regression analysis, decision trees, random forests, and neural networks were used to predict the future status of the system. The findings show that neural networks outperform all other methods.

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3.3 Implementation and Testing

Implementation of morphology detection is a complex process but can be achieved with a small number of steps and data only from SEM and SAED. First, the data are collected and used to train the best architecture that can detect the optimal morphologies. By capturing more shapes and using an up-to-date list, a model that detects a dozen morphologies of desired holes was built successfully. The trained model had been validated and tested to check the stability and, in terms of input data, five different grids were used, data volume had changed, and the number of morphologies had changed. The study successfully detected target shapes across wide ranges of acquisition settings, acquisition time, and data size. Providing a very simple configuration, it is important to note that the detected shape database is the layer's quality driver, practically representing the scanner's automatic daily setup.

4. Case Studies and Applications

Title: 4.1 Steel Captive Power Plants Optimization Case Summary: 46 Steel Captive Power Plant (CPP) plants ranging from 4 MW to 400 MW were used as the case for energy efficiency and operation optimization. The data comes from 46 power plants with a combined capacity of 5 GW, 200,000 production data points, plus 1 billion operational logs. Tools of the Energy Management Data Platform using big data analytics and artificial intelligence technologies were developed and applied to achieve a high standard of sustainable energy use, efficient production, and reliable power supply. Value Proposition: The solution in service by a company achieved more than 10% energy efficiency improvement in the CPP operations, increased availability, and reduced maintenance costs. It can also offer demand-side management and predictive maintenance advisory services to utility-scale power plants in the province, autonomous territory, or self-generating industrial parks. The current deliverable service annual benefit is about 6.9 million, including increased capacity and operating power benefits. Title: 4.2 Challenges for Optimizing Wafer Manufacturing Operations Case Summary: Wafer manufacturing has a special challenge in technology due to its operational complexity and variety. This case study is concentrated on managing tens of thousands of production tools and large warehouses daily to satisfy the schedule and cycle time requirements. To fulfill the target within the acceptable operational cost, the solution has to be achieved through the application of AI/ML on process tools OEE, an AI knowledge-based warehouse system, multi-criteria scheduling, and a robust production execution system.

4.1 Real-world Examples of Production Efficiency Optimization

Solution 1: One large automotive components manufacturer provided access to the data of its MES system as well as the SCADA system. Among many possible use cases, we selected those connected with: - Identifying root causes of production losses: predictive analytics and data interpretation for analysis of production loss due to machine downtime. - Improving throughput: predictive analytics and expert rules for optimization of adjusting time. - Diagnosing problems with specific items. During the adaptation process, we found that for some equipment types, data was not reliable: e.g., a high correlation between the number of parts produced and the number of errors was found - too many errors were reported even for the records where the number of produced parts equaled zero. The delusion rate was as high as 30%. It was decided to detach this data from the data history due to the high risk of misinterpretation. The data history was quite long – about 5 years for some of the elements. The executed mission was reliable data that makes later asset measurements more informative

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and reliable and reduces diagnostic time. Customer benefits: The manufacturer had previously been occupied with the manual interpretation of the production losses reasons. The customer recognized that the monthly Loss Analysis reports are being delivered to the HQ. Each report was published to all involved parties in less than 2 working days after the end of the month. The response activity in production and maintenance was deployed, and the impact was visible in financials. The throughput of specific machines was also visually improved. Only 4 expert rules were provided to affect the output of the adjustments' optimizer. Solution 2: Another example related to the metal and mining industry. The plant utilized a maintenance management system, connected with condition monitoring data of the equipment. We selected the following use case: - Maintenance schedule optimization: AI/ML techniques for verification of scheduled breaks before they are done. Customer benefits: The customer requested the service as a claim reduction of high downtime losses. Only 5 basic expert rules could help to predict 2/3 of the breaks that did not require changing. The shared data model and subsequent communication with maintenance engineers made the trust in the output much stronger. Finally, the maintainers could estimate, after the first visible checks, that the system is reliable, and this directed significant input from the interest toward the Equipment Health Index. They could also request such a model for similar technically connected equipment. Several other cases for the same plant are under discussion, developing an automatic anomaly detector for the number of gears damaged in the upkeep process; and predictive modeling for kiln weight to replace real TR control with an AI/ML-based one. Improving the production efficiency based on algorithmizing of the planning process is shown in figure 4.

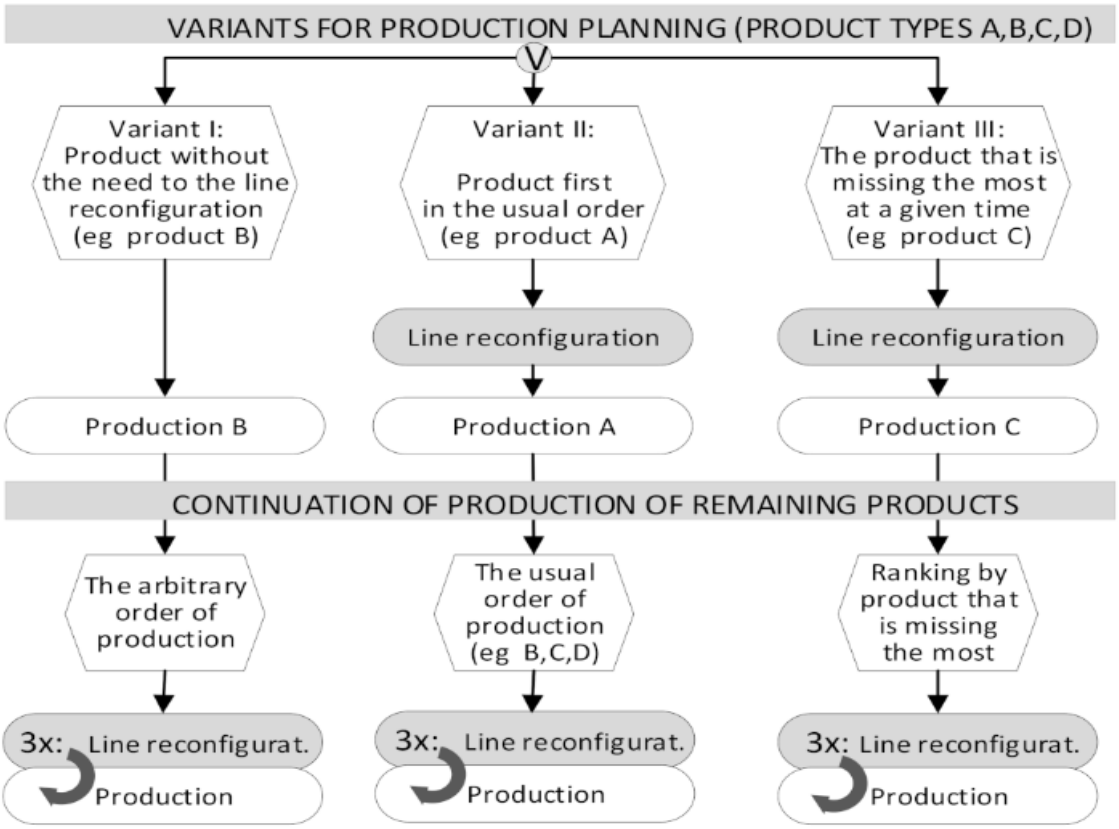

Figure 4. Improving the Production Efficiency Based on Algorithmizing of the Planning Process

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4.2 Impact of Big Data and AI/ML on Key Performance Indicators

The impact of big data in combination with AI/ML on relevant KPIs will vary according to the particular sector of manufacturing. Depending on the sector, for example, the value-add of main drug product characteristics, end-product quality attributes, and related supply chain tools can be applied to achieve better production and quality performance and substantial reductions of product lead time and production cost, as are currently being experienced in semiconductor manufacturing. On the other hand, consumer manufacturing, such as food and drink, FMCG, and textiles, both bring their complex production challenges and may be handled simultaneously at multiple sites. Within the consumer goods sector of manufacturing, largely driven by retailer price pressures, the main driver of KPIs – cost, lead time, and product quality – is the factory's manufacturing performance. Optimizing production efficiency by using machine learning models can be achieved through the continuous throughput yield of high-end APCs, first-time-right of quality requirements, reduced changeover times of the production systems, enhanced use of standards and templates, and simple product shapes, colors, and recipes, without forgetting the financial constraints of typical family-owned operations. In the associated food and drink manufacturing sector, production and quality performance concerns name but a few factors important to continuous efficient operation. A common requirement is the need for acquiring data transparency from the field to the fork, requiring a combination of digital and mobile network technologies. Furthermore, to guarantee the long shelf life demanded by many products, both product and packaging integrity analyses are required to inform seal and decoration defects, thereby ensuring customer satisfaction, reducing waste, and offering brand protection.

5. Challenges and Future Directions

The last several years have seen a substantial increase in the amount and type of digital data used in manufacturing. The growth of industrial IoT in industrial settings has been accelerated by multiple technological trends and tools, including advancements in sensor technology, edge computing, ubiquitous interconnectivity, and cybersecurity. Each of these advancements is contributing to a shift within the manufacturing domain that is enabling increasingly detailed data describing manufacturing processes. While IoT and smart manufacturing are addressing issues with data accessibility for given data types, data growth has been more limited for additional contextual data types, such as factory events, work orders, production schedules, and quality and loss information. As these data streams converge in the smart manufacturing ecosystem, the breadth of the digital data may be the tipping point, redefining the manufacturing knowledge canon.

Over the last several years, the machine learning and artificial intelligence communities have invested significant effort in building models to better predict and improve different manufacturing specializations. While these models represent a significant step forward over previous approaches, there are several impediments, or "costs of predictions," preventing the realization of scalable predictions across the domain. Using big data methodologies, the manufacturing domain can be fully characterized, and high-quality feature vectors can begin to be inferred, thereby learning directly from the high-quality expert labels spanning the domain. The coupling of these communities can provide immense value across the manufacturing landscape. However, to fulfill the potential of AI/ML, particularly in a world of limited domain and engineering knowledge, manufacturing faces a new set of challenges.

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5.1 Overcoming Implementation Challenges

Manufacturers should rely on a few proven strategies as they undertake their Industry 4.0 journey to accelerate manufacturing production efficiency improvements. To streamline the transformation, companies can start by narrowing the focus. Data is like water; too much can be a problem. Factories that spend years collecting every conceivable data point usually get mired in the complexity of integrating so much information. To succeed, manufacturers need a clear vision of the problems they are trying to solve and the tools they will need. Input from experienced partners can be invaluable in getting all the critical pieces aligned. Factory owners should not just rely on internal expertise or capabilities when deciding what to do with the data they can collect from previously unconnected or too-slow systems.

By homing in on the scenarios that have a clear return on investment, big data analytics can provide solutions in short order. Start small, measure results, and extend. The Industry 4.0 trend offers big potential, but not every road to automation involves a significant technological overhaul. It is better to look at it as a journey and to take a stepwise approach. The most powerful insights will often be the simplest ones. Interest in Industry 4.0 is growing, and in some cases, organizations are developing complex big data management strategies in anticipation of more powerful big data solutions. Rather than waiting for an ideal solution to be developed, however, organizations should catch the low-hanging fruit and begin benefiting from some returns as soon as possible. Since the time until payback and costs are low, it makes sense to reward the small off-the-shelf steps and execution phase work. As manufacturers embark on their Industry 4.0 journey, adopting a focused and strategic approach is crucial for accelerating production efficiency improvements. Companies should avoid the trap of collecting excessive data, which can lead to overwhelming complexity and integration challenges. Instead, they need a clear vision of the specific problems they aim to address and the tools required for solutions. Collaborating with experienced partners can help align critical elements and leverage external expertise. By targeting scenarios with a clear return on investment, manufacturers can implement big data analytics effectively, starting with small-scale initiatives that deliver measurable results. Viewing the transition as a journey allows organizations to take incremental steps rather than committing to extensive technological overhauls. The most impactful insights often stem from straightforward applications, so companies should prioritize quick wins and low-cost solutions, capitalizing on immediate benefits while laying the groundwork for more advanced big data strategies in the future.

Equation 8-12 shows the resource allocation.

Objective function is given by

Maximize:

$$a^*(n), p(n) \tag{8}$$

$$\sum_{i=1}^{N}(\lambda_i(n) w_i g_{ii}(n) p_i(n) - \lambda_h h * (n))$$
(8)

where

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$\sum_{j=1,j\ =1}^{N} g_{ij}(n)p_j(n) + \eta$ (9)

Subject to constraints

1. Power constraint for each i:
   $0 \leq p_i(n) \leq p_{i,max}$ (10)
2. Interference and signal quality constraint:
   $R_{i,min}(n) \leq \frac{w_i g_{ii}(n)p_i(n)}{\sum_{j=1,j\ =1}^{N} g_{ij}(n)p_j(n)+\eta} \leq R_{i,max}$ (11)

3. Maximum constraint on h*(n):
   $h^*(n) \leq h_{max}$ (12)

Where

- N represents the number of entities (e.g., users, devices).
- $\lambda_i(n), w_i, g_{ii}(n), p_i(n), \lambda_h, h^*(n), p_{i,max}, R_{i,min}(n), R_{i,max}\ and\ h_{max}$ are parameters and variables within the optimization, with specific meanings depending on the application (e.g., power control in wireless networks, interference constraints, etc.).
- η could represent a noise term or interference margin.

5.2 Potential Advances in Technology

Potential advances in technologies include:

Machine learning pioneers in manufacturing are laying the foundation for modern solutions that look for root causes of production issues and propose systematic, scalable, and user-friendly software. Current technologies include correlation-based discovery, supervised learning, and neural network-based variable importance.

In the era of Industry 4.0, the smart data paradigm in manufacturing views data analytics as a chisel and production facilities as mosaics, both indispensable for shaping and perfecting the whole. Insights from genetic data analyses underscore a simple yet indefensible fact: data analytics, especially big data analytics, disproportionately pay off in discrete data settings because they significantly reduce the probabilities of type two prediction errors and false negatives. Manufacturers are motivated by the shared belief that business-critical problems need personal attention, but data analytics will do most of the personalization. In the context of Industry 4.0, advances in machine learning are transforming manufacturing by enabling a deeper understanding of production challenges through innovative data analytics solutions. Pioneers in this field are developing systematic, scalable software that addresses root causes of issues, utilizing techniques such as correlation-based discovery, supervised learning, and neural networks to assess variable importance. The smart data paradigm positions data analytics as a vital tool, akin to a chisel in sculpting a mosaic, highlighting the significance of big data analytics in reducing type two prediction errors and minimizing false negatives, particularly in discrete data environments. Manufacturers are increasingly recognizing the value of tailored solutions for critical business problems, with data analytics taking the lead in delivering personalized insights that drive operational efficiency and informed decision-making. Artificial intelligence in manufacturing market, by region is shown in figure 5.

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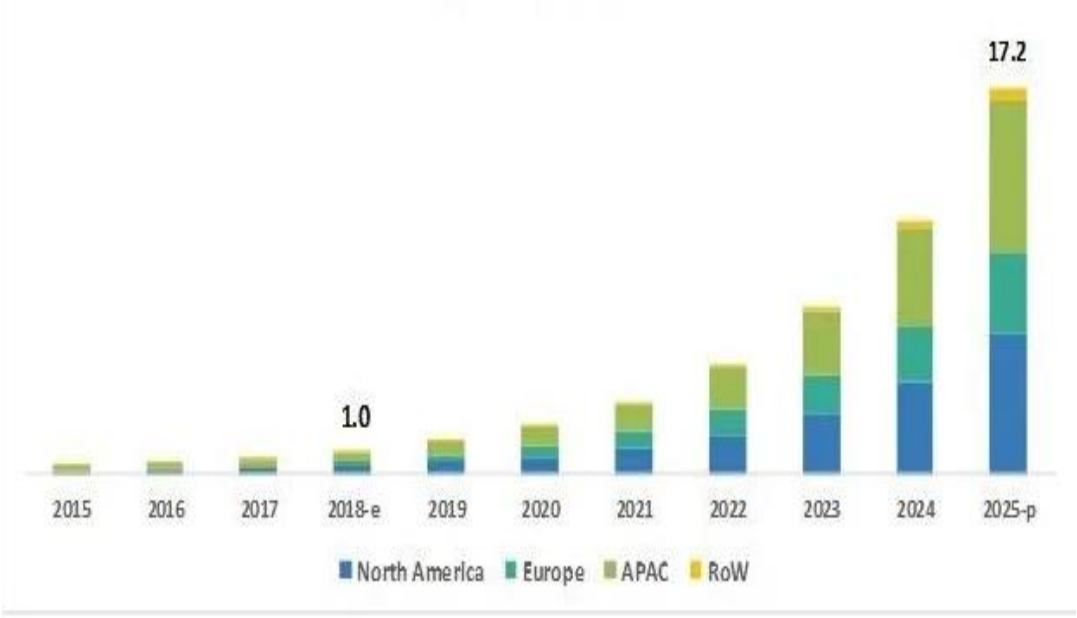

Figure 5. Artificial Intelligence in Manufacturing Market, by Region (USD billion)

6. Conclusion

The predictive and proactive value of Big Data and AI driven by sophisticated algorithms has the potential to address a multitude of issues facing computer-integrated manufacturing and the transformation to the goals of Industry 4.0. Aside from the descriptive and diagnostic applications for Big Data, it also can anticipate problems and prescribe solutions. While every manufacturing situation is unique and there are several potential complexities when embarking on the transformation to Industry 4.0, cost can be a major concern. Solutions can be crafted that work within and manage these costs, using an appropriate mix of Big Data, AI, and Machine Learning. Companies actively involved in the transformation to Industry 4.0 do indeed see a great deal of potential in the use of Big Data to handle production-related challenges. The responsive and proactive value of Big Data carried out by sophisticated algorithms has the potential to contribute to solving a very large number of challenges with which manufacturers struggle and to help users realize the real benefits of Industry 4.0. Companies are adapting their infrastructure and data methodologies to capitalize on the potential of Big Data using increasingly sophisticated software solutions that provide in-depth processing in a reasonable amount of time and at a manageable cost.

6.1 Future Trends

In a recent survey of manufacturing executives, the focus shifted to trying to capture and exploit the big data being generated on shop floors by equipment and the vast amounts of data from processes that had been received. The study also reports that predictive maintenance systems using IoT sensor data have emerged as the top use case for companies that have already implemented these types of big data services. Finding improvement opportunities faster and making those benefits more visible is compelling. Companies that are leaders in reducing downtime or improving efficiency do so through optimizations that enable them to work smarter to produce more. They often face similar trade-offs and have to consider similar constraints. They have complex configurations of equipment and are equally challenged by

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process models that cannot capture everything about their equipment configurations and still be quickly and accurately solved. They require similarly ingenious ways of approximating an optimal solution in a reasonable amount of time.

This study provides a framework for observation and measurement that increases confidence in a predictive algorithm's inherent knowledge representation and capability as needed in various stages of optimization. Though the example used is that of a specific type of data-producing equipment, the executives interviewed pointed out that the need for increased visibility and accuracy is also pertinent for other equipment and processes on the shop floor and supply chain partners. A similar approach could be taken to other manufacturing use cases that are important and have value before new equipment upgrades. Hopefully, a framework for seeding future development will be provided to practitioners who wish to leverage big data IoT and big data AI/ML tools to help them accelerate progress toward digital transformation ambitions – in days rather than years.

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Optimizing Cloud Computing Performance With Advanced DBMS Techniques: A Comparative Study

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Abstract

In the era of digital transformation, optimizing cloud computing performance has become a critical focus for organizations striving to leverage the full potential of cloud infrastructures. This study presents a comparative analysis of advanced database management system (DBMS) techniques aimed at enhancing cloud computing performance. By examining a range of strategies, including indexing optimizations, query performance tuning, data partitioning, and caching mechanisms, the research identifies key methodologies that can significantly impact efficiency and scalability in cloud environments. Through a series of tests and performance metrics, this study evaluates the effectiveness of these techniques across various cloud platforms and workloads. The findings provide valuable insights into which DBMS approaches offer the greatest benefits in terms of speed, resource utilization, and overall system performance. This comparative study not only highlights the strengths and weaknesses of different techniques but also offers practical recommendations for organizations seeking to optimize their cloud computing infrastructure.

Keywords: Cloud Computing Performance,Advanced DBMS Techniques,Database Management Systems,Performance Optimization,Cloud Database Optimization,Comparative Study,DBMS Performance Tuning,Cloud Resource Management,Scalability in Cloud Computing,Distributed Databases,Query Optimization,Data Storage Solutions,Cloud Infrastructure,Database Scalability,Data Access Efficiency,Cloud Performance Metrics,Advanced Database Techniques,Load Balancing in Cloud,Database Query Processing,Cloud-Based Database Management,Data Management Strategies,Performance Benchmarking,Cloud Application Performance,DBMS Efficiency,Cloud Storage Optimization.

1. Introduction

The primary goal of this study is to empirically ascertain whether cloud computing performance can be improved through practical methods in the database management system (DBMS) that employ basic and classic indexing techniques. Experimentation on complex real-world queries is performed during the project in order to validate these techniques. DBMS are cloud-unaware, resulting in inefficient query optimization. In this atmosphere, the surrogate-based technique performs effectively, but substantial knowledge of the data is necessary. Basic translation and indexing methods, on the other hand, do not necessitate substantial knowledge of the saved data. Even with large amounts of data, advanced techniques provide results similar to basic embedding and indexing techniques.

In modern times, monetization and digitalization have emerged as new trends, emphasizing the fundamental importance of data in this context. According to statistics, the volume of data generated each day in the world is equivalent to 2.5 quintillion bytes, and 90% of the global data to date has been generated within the last two years.

As a result, these trends have shifted much of the computing load to the cloud. Because cloud computing is a multi-tenant environment with non-shareable computing resources, database management system (DBMS) throughput and response times are important performance indicators. Despite making progress over the past several years, DBMS still faces a number of challenges when run in cloud resources.

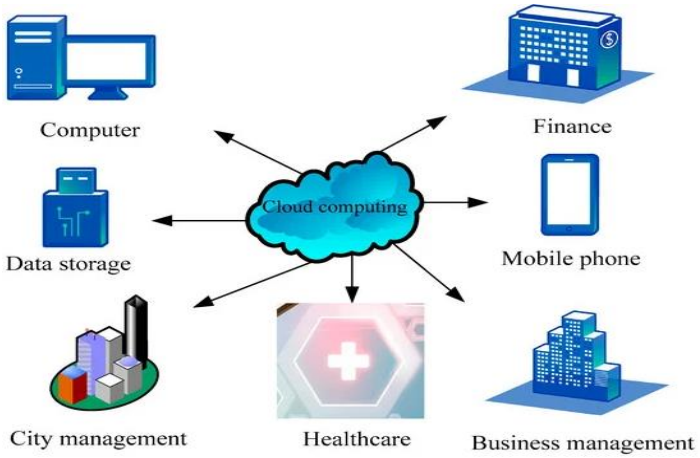

Fig 1 : Cloud Computing and Big Data

1.1. Background and Rationale

The cloud computing paradigm promises to provide a flexible IT infrastructure like hardware, software, and other resources but governed by strict Service Level Agreements (SLAs). However, the performance of cloud applications can be highly affected by the performance of the underlying Database Management Systems (DBMS). Improving the DBMS performance will lead to a subsequent increase in the cloud application performance. The authors tried to improve the performance by increasing the number of research nodes and storing the frequently accessed data locally, in order to decrease the remote read operations. Other researchers have studied and analyzed the performance of data placement strategies in the cloud. Other studies have been devoted to modeling and predicting the end-to-end performance of cloud/DBMS applications based on cluster resources such as CPU, I/O, and so forth.An important research direction that has not been completely investigated in the literature is how the architecture of the underlying DBMS, such as main memory, backup storage, indices, indexing structure, and recovery technique, can affect cloud computing performance. Such DBMS features and all the architectural decisions can have a significant impact on the amount of appropriate main memory assigned for processing the transactions as well as serving the ad-hoc queries. Since the DBMS should recover all the data accessed/used by the end user, backup storage architecture decisions are also important. In this paper, our target is to study and compare different indexing and backup/recovery techniques considering their impact on the overall system performance.

Equ 1: Multi-objective fitness function (J→(·))

Input : Search agent, ϵ_i
Output: Criterion function, $\vec{J}(\mathcal{X}_i) = \{J_1(\mathcal{X}_i) \quad J_2(\mathcal{X}_i)\}$

Assign i^{th} solution to null vector, *i.e.*, $\mathcal{X}_i \leftarrow \vartheta$ and $\xi_i \leftarrow 0$
*/ Decode parent
for $m = 1$ *to* n **do**
  if $\epsilon_{i,m} = 1$ **then**
    Computed fitness function using Eq. 3.
    $\mathcal{X}_i \leftarrow \{\mathcal{X}_i \cup x_m\}$
    $\xi_i \leftarrow \xi_i + 1$
  end
end
Compute coefficients (Θ), corresponding to $\mathcal{X}_i$
*/ Evaluate the criterion function
Determine the dynamic prediction error ($\mathcal{E}_i$)
Determine the penalty assignment ($\mathcal{P}$)
$J_1(\mathcal{X}_i) \leftarrow \xi_i + \mathcal{P}, \quad J_2(\mathcal{X}_i) \leftarrow \mathcal{E}_i + \mathcal{P}$

2. Cloud Computing and DBMS: An Overview

In the modern world, several businesses are rapidly shifting toward cloud computing to reduce costs, increase operative dexterity, and distribute office efficiency. Cloud computing possesses several eye-catching advantages: flexibility,

security, cost, consistency, and tons of others. There are several contrasts between on-site and cloud imperatives. In the underlined part, one of the requisite contrasts oversees apparent on-cloud imperatives. Cloud is an environment with so many stakeholders providing a wide variety of applications. The client/customer connects to the application that he/she is interested in by means of a cloud account. One of the most common applications of cloud computing is databases which are managed as a service for the client and the operations are executed for them in the cloud environment. Hence, with the increasing number of users, databases are becoming more and more important. The advancement of cloud computing combines a database management system (DBMS) into a pay-as-you-go idea in which the DBMS consumers can elude the burden of purchasing hardware and software. DBMS bequest has an appositive effect on cloud computing domains. Database as a service (DBaaS) is one of the pre-eminent, high-intensity stuff of cloud computing. The lucrative sides of DBaaS are the replacement of capital charges with operating charges, better-quality output, separate overhead, and the power to deploy arduous operations at a faster tempo.

Operating conventional DBMS in cloud nodes purely does not insinuate optimal conduct due to several doings and connections in the cloud globe. This encyclopedia paper submits an educational road to optimizing DB performance in cloud facilities (IaaS). The method helps a decision maker (DBA) to choose a cloud DBMS using the optimal DB selection method. The publications used in this paper were found using the systematic research method. The paper is organized as follows. Section 2 briefly depicts cloud computing and SaaS as well as their significance, allegiance to solving IT inelegance, and breeze DBSaaS models. Allocating regulations from an economic-geographic view between stakeholders and the suspected order delayed cloudy environments and adventitious pressures of global justice issues on multifold tiers. Privacy policies, the aptness of legislation to challenge jurisdictional conflicts, international law, multicultural, multilingual, complex delegation, technology threats, intentional disorientation, and other issues make cloud computing laws multifaceted. Since the cloud operating paradigms' long-existing and multifaceted regulations are non-stop from the legal surveillance and fruitful network cloud locus.In the contemporary business landscape, cloud computing has become a pivotal force driving efficiency and cost-effectiveness. By leveraging the cloud, companies can enjoy a range of benefits, including flexibility, enhanced security, and consistent performance. One prominent application within this realm is Database as a Service (DBaaS), which allows organizations to utilize database management systems (DBMS) on a pay-as-you-go basis, alleviating the need for upfront hardware and software investments. This shift from capital expenditures to operating expenses, coupled with the ability to scale operations rapidly, positions DBaaS as a significant advantage in cloud computing. However, operating traditional DBMS in cloud environments presents challenges due to the complexities of cloud infrastructure. To address these issues, an educational approach to optimizing DB performance in Infrastructure as a Service (IaaS) environments is crucial. This approach aids decision-makers in selecting the most suitable cloud DBMS by leveraging systematic research methods. The discussion extends to the broader implications of cloud computing laws, which encompass privacy policies, jurisdictional conflicts, and international regulations, reflecting the intricate nature of legal compliance in a globalized cloud landscape.

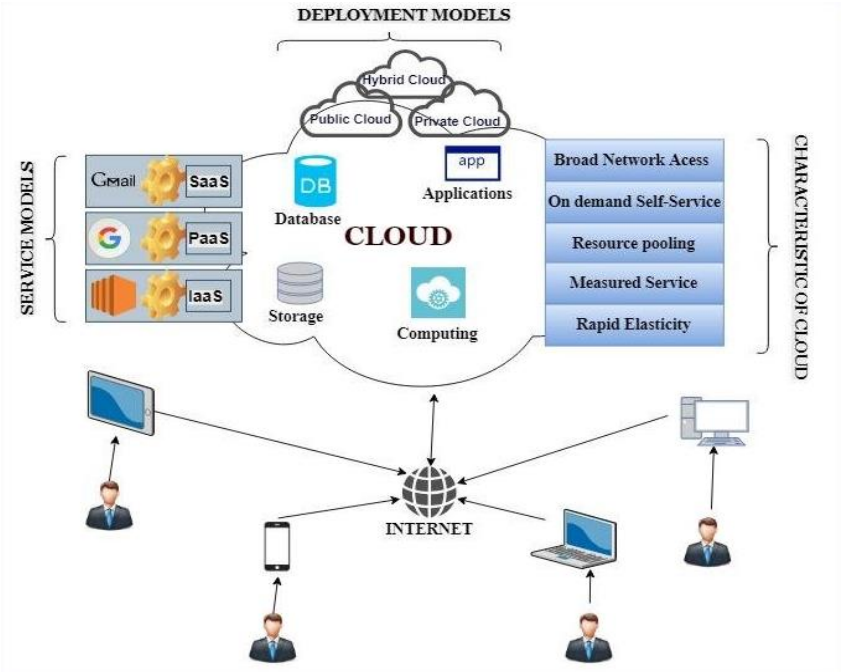

Fig 2 : Overview of Cloud Computing

2.1. Key Concepts

Cloud computing delivers storage, network, and impactful computation services over the internet. It brings substantial benefits such as high fault tolerance and resources as services. Services can be recovered if a cloud provider at any time takes back resources. In contrast, the database management system (DBMS) can be defined as a database person's copilot. At the primary level, it is a software application. At the secondary level, it talks to user applications and the database. However, the DBMS efforts to provide performance security are defined as the concept of ensuring that all important factors of database systems work to equip the database system with consistent reliability, including serving large numbers of users. An upgrading system can be nonetheless good. There are many other concepts associated with the DBMS, but authentication is critical. Efficiency and inefficiency are utilized best for strategically designing the database shape and keeping the database pieces that are posterior.

Cloud computing provides storage, networking, and computing services; a cost-efficient, consumer-centric, pay-as-you-go, on-demand, web-based utility model is on the internet. Resources: SaaS, PaaS, and IaaS provide three categories (security, privacy, legal, and reliability) of cloud applications. The data uses other different service applications. The provision of cloud database services has become increasingly popular at present. Cloud databases are offered as services that need little or no hardware or software — the application rather than the cloud database operates.The database management system (DBMS) is a very large problem for use in hardware and operating systems. Database for the physical and logical data is to securely store and retrieve effectively. The latest server-based and scale-out databases cloud workloads that developed architectures have allowed storage to add cost-effectively and ensure public/hybrid and multi-cloud data management and portability. Repositories, data warehouses, and data marts are used in conjunction with a wide industry running a larger cloud database. Baseline manufacturers, until a decade ago, primitive data by conventional file systems, mix-and-match, or are widely used in a single computational cloud is a standard database. The cloud computing climate characteristics and common DBMS technologies and other use cases would include resilience, suboptimal performance, and failure to adapt to storage tuning practices. To handle more cloud workloads, their algorithms running the GPU have been updated.

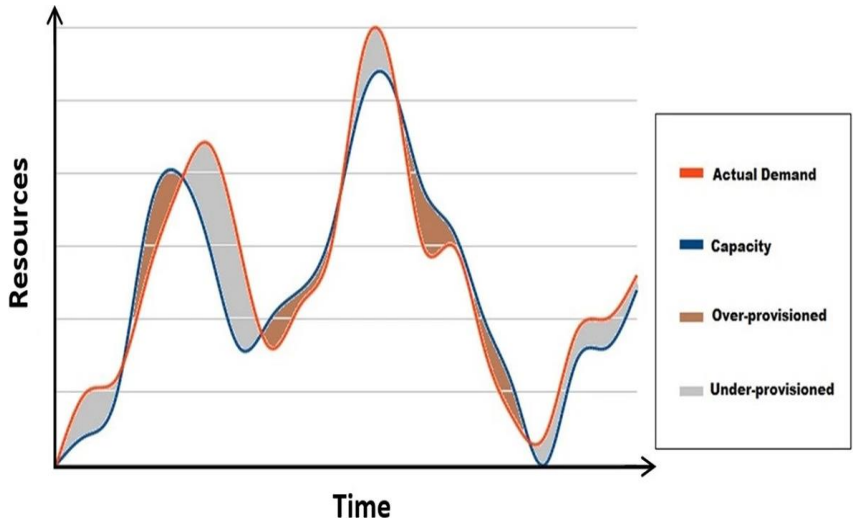

Fig : Key concepts for measuring elasticity

3. Performance Optimization in Cloud Computing

One of the primary advantages offered by cloud computing includes virtually limitless resources, be they computational, data storage, or even software and applications. In the contemporary IT landscape, cloud computing is a technological reality, and big data analytics is its killer application. However, the presence of a plethora of services exponentially deteriorates the scope of security and reduces the performance through resource contention, which is a serious issue in IaaS and PaaS models. Performance optimization in the cloud environment is arduous due to the plethora of potential combinations of candidates involving virtual machines and data management systems, e.g., database management systems (DBMS) among others. The two natural paradigms of enhancing cloud performance encompass the optimization of data management systems (DMS) and the efficient management of resources.Efficient management of database management systems (DBMSs) is a precursor of reducing the query processing overhead and correlates as a non-negligible aspect of enhancing cloud performance. In view of this, researchers and industry professionals have obtained a paradigm shift from conventional database management system features such as concurrency control, recoverability, and error-free processing of workloads in the presence of abilities, e.g., white-box and black-box optimizers among others, that pave the way for

developing an optimized query plan with the least processing latency. Therefore, by mitigating such overhead, the final objective of reducing the processing time of the workloads may be achieved in a meaningful manner. The DBMS internal enhancements involve indexing, materialized views, caching, query optimization, etc. However, resource brokers or managers heavily rely on the optimal assignment of virtual machines, which results in less resource contention and precludes resource monopolization.

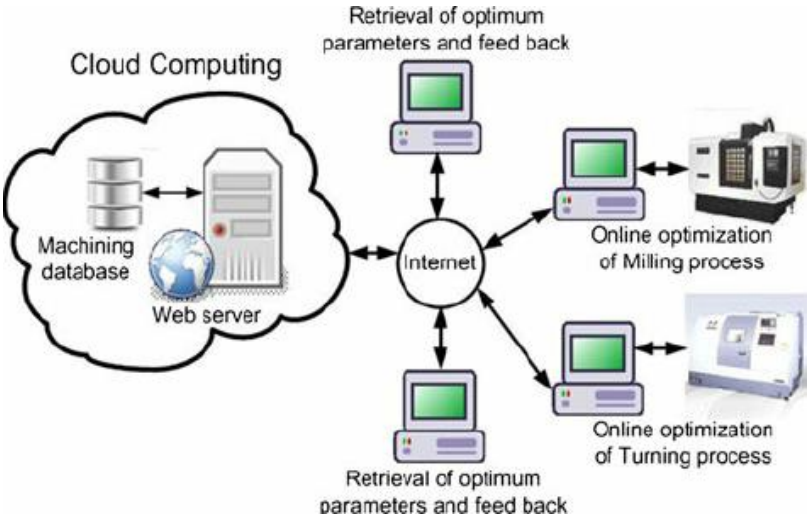

Fig 3 :Cloud computing-based optimization

3.1. Challenges and Solutions

There are many challenges to optimizing the performance of cloud computing. For example, traditional database management systems are not designed to be utilized in cloud computing environments, and challenges arise when the processing load is shared across multiple distributed and commodity hardware systems. Performance bottlenecks and interdependencies between database and application workloads make monitoring and tuning complex.In addition, with the increasing number of server nodes in cloud environments, a time loop is needed to schedule the physical resources required for processing database execution tasks and delivering the result considering multiple logical channels via the network hardware.Two ways to eliminate or mitigate these challenges. First, solutions break down the performance tuning overhead into multiple time-distributed feedback controls, each with a specific performance optimization scope. The timing control hierarchy concurrently tracks the performance of the workload and relational database management system (DBMS) at the service instance, virtual machine, and host system levels. Centralized data collection provides the diagnostic feedback variables. The outputs of the feedback controllers are control signals that direct multiple control subprocessors, each of which applies the performance optimization techniques described in this paper, thereby providing dynamic adaptability to the changing performance demands placed on the cloud resources. Control loop cross-coupling information is used to modify the adaptive algorithms so that each independent feedback control response will impact the future performance subsystem response in a manner that collaboratively serves the multi-tier e-commerce system performance as a whole to leverage the increasing number of server mules.

Equ 2: Cost-Benefit Analysis Formula

Cost Benefit Analysis Formula

$$\text{Net Present Value (NPV)} = \sum \text{Present Value of Future Benefits} - \sum \text{Present Value of Future Costs}$$

$$\text{Benefit Cost Ratio} = \frac{\sum \text{Present Value of Future Benefits}}{\sum \text{Present Value of Future Costs}}$$

4. Advanced DBMS Techniques

The sheer growth of data in digitized environments has ushered the database management system industry to enter into cutting-edge areas. This necessitated various advanced techniques for the creation and management of databases, with a focus on the need for agility and high performance. Furthermore, the availability of advanced hardware and network

technologies facilitated the deployment of databases on a large scale. Cloud computing technologies have also gained widespread popularity because of their low costs and scalability, leading to the sharpening of the focus on DBMS techniques relative to cloud computing environments to reduce response time. Some of the characteristics of database systems such as ACID properties, response time, etc., are seriously affected when transaction requests are very large or are mingled with analytic workloads.The advancement in disk drives, but fewer improvements in data access time, initiated the quest for in-memory databases as a potential solution. Another development in database management systems came as a result of the growth activities in terms of IoT and Big Data. It appears that it is important to analyze large datasets before making a decision. As a result, research communities have been working on new designs for cloud computing databases. It seems that relational databases do not suit the concept fully in this case, leading to the commencement of the analysis of analytic databases. The aforementioned databases are specifically designed based on specific hardware settings and are crucial for extracting information. There is a strong need to conduct a comparative study to see the effects of these databases from a cloud perspective. This study analyzes two types of databases, one of which is an in-memory database with traditional row-level storage techniques, and the other is an analytic database, which is columnar-based.

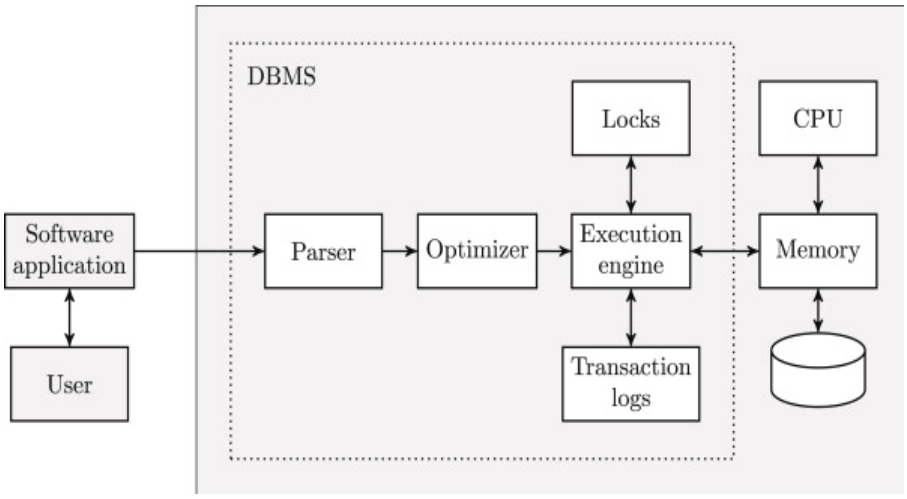

Fig 4 : Database management system performance comparisons

4.1. In-Memory Databases

One of the main techniques used for improving database performance is utilizing main memory for data storage and retrieval, which is common in in-memory databases. The concept of in-memory databases is not new, but in the recent past, due to advancements in both hardware and software, in-memory databases have been attracting both the research community and the commercial database vendors. Because cloud computing has become an attractive computing model for both industry and academia, researchers have started looking at using in-memory databases to bring massive benefits to large analytics workloads.However, as of now, there is very little information on how in-memory databases perform and scale in the cloud environment, among the big three cloud providers, i.e., Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP). To make things worse, in-memory engines are different, with no clear guidelines on which to use or when to use them. Hence, there is a clear need to understand how in-memory databases perform at scale in the cloud environment for large analytics workloads using multi-database transactional benchmarks. Given these challenges in a managed cloud environment, the need for in-depth evaluation of in-memory databases in the cloud to assess their potential has attracted widespread attention. With the potential, our goal is to compare different in-memory databases from AWS, Azure, and GCP using TPC benchmarks.

4.2. Columnar Databases

Traditional DBMS storage is organized by rows. This paper primarily investigates a new concept focused on columnar databases, which have been defined as a recent column-oriented storage technique in which column families are stored vertically and consecutively, such that all values of column 1 are stored together, all values of column 2 are stored together and so on. Moving from row-wise storage to columnar-wise storage is proposed to bring improvements in the scan time from seconds to milliseconds, leading to the performance gained in cloud computing. Increasing the performance of such queries is expected to improve the overall performance of a range of applications.In cloud computing, cloud-based data management combines two emerging technologies: cluster computing architectures, typically available in a cost-competitive on-the-fly manner, and complex data management systems. The process of storing, grooming, visualizing, and enabling the HIPO concert analysis by employing column-based processing techniques on massively-scale histograms

will potentially produce an order of magnitude savings in time and data transfer costs. This setup is especially useful for the case where analysis happens in cloud storage, and therefore minimizing memory/input/output requirements becomes critical. The inefficient use of databases can bottleneck the I/O cycle. The typical strategy of reclaiming space in database management systems (DBMS) is to replicate the table, perform transformations on the copy, and replace the original tables once permanently entangled and consistent with the query update propagation.

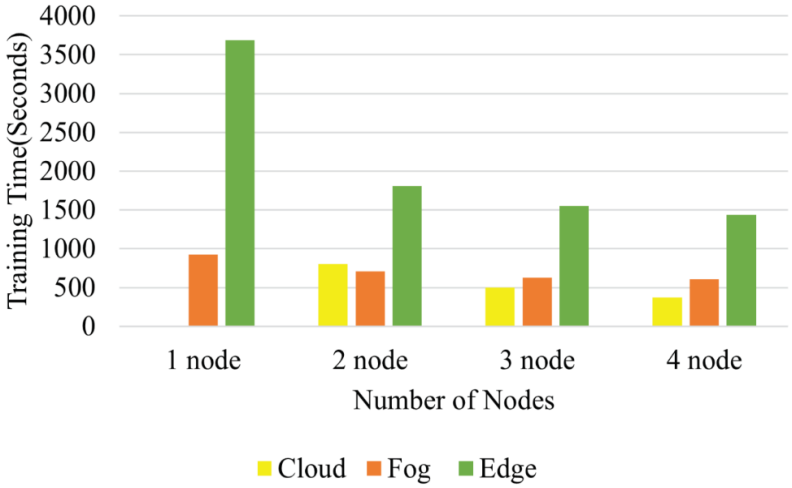

Fig : Impact of the number of nodes on performance

5. Methodology

In this section, we present the research design and approach of the paper. The overall research methodology proposed in this paper aims to empirically prove the research hypothesis introduced earlier. Concretely, research in this paper is conducted through an experimental approach by conducting an in-depth performance evaluation of IBM DashDB (Giants) as the technology representative of the advanced DBMS in comparison with the traditional DBMS. There are several methodologies used in this study to perform the performance comparison of massively parallel DBMS in a cloud computing environment. First, a cost model aggregation of the three following factors was computed. The service cost computation was done at the true-up usage period. Second, the performance comparison was performed in an on-demand situation by concurrently running complex SQL workloads to assess the performance in terms of response time. Thirdly, to verify the accuracy of performance comparison results, the complexity of various parts of the advanced DBMS and traditional DBMS will be compared.The response time performance comparison of the two different technologies of DBMS is to be performed using three phases. The first experiment is the experimental database schema design, where we will consider in which areas the DB technologies differ from one another. The second experiment will focus on validation. It is about checking which parts of the advanced DBMS are faster than others, so it will not be affected by all DB microservices. Moreover, another aspect that can be tested is the concurrency. For example, in the testing situation for the throughput, it is possible to configure one service to use one faster DB functionality module. The last performance comparing the experiment will be based on the experimental methodology in the cloud. The service-made cost represents the metrics of the DBMS workload intensity and duration. Therefore, we consider both factors in the performance testing. DBMSs also introduced the concept of "elastic service", where the extent of one or several computing resources is limited by using less and less of the rest of them.The research design of this paper is structured to empirically validate the hypothesis regarding the performance capabilities of advanced DBMS, specifically IBM DashDB (Giants), in contrast to traditional DBMS within a cloud computing framework. This study employs an experimental methodology encompassing a comprehensive performance evaluation across several dimensions. Initially, a cost model aggregation is established, considering service costs during the true-up usage period. The performance assessment is conducted in real-time, utilizing complex SQL workloads to gauge response times under concurrent execution. To ensure the robustness of the findings, the study meticulously examines the intricacies of both advanced and traditional DBMS, focusing on specific components to identify performance differentials. The experiments unfold in three phases: first, through the design of an experimental database schema to delineate the distinctions between the DB technologies; second, by validating the performance of various advanced DBMS components in isolation to mitigate microservice interference; and finally, by evaluating performance within a cloud environment, taking into account the metrics of workload intensity and duration. This multifaceted approach underscores the innovative concept of "elastic service" introduced by modern DBMS, emphasizing efficient resource utilization while maintaining performance integrity.

Equ 3: Optimal load balancing and assessment of existing load balancing criteria

```
Input: numIter: the number of iterations to compute, priorityQueue: a
       priority queue
foundLb[i] = 0∀i = 1..K;
// root node
cNode = Node(iter=0, LB=true, cost=0.0, appState, lbState, prev=∅);
while cNode.iter < numIter do
    if cNode.LB then
        foundLB[cNode.iter] = true;
    end
    dontLBNode, doLBNode = cNode.getChildren();
    if not foundLB[doLBNode.iter] then
        // Measurement of cost (i.e., time) with a
           theoretical model or a real application
        doLBNode.computeCost();
        replaceOrInsertNode(priorityQueue, doLBNode);
    end
    dontLBNode.computeCost();
    insert(priorityQueue, dontLBNode);
    cNode = priorityQueue.pop();
end
```

5.1. Research Design and Approach

Our comparative study is guided by the need to ensure an optimal configuration of the DBMS for the purpose of reducing the execution time required to process the expected workloads. Within this context, we perform the correction of a proposed DBMS configuration and assess the implications in terms of performance. The study is based on an experimental assessment using the cloud-specific DBMS engine, Amazon Aurora. Table 5.2 highlights the research design and approach containing data collection, data analysis, and comparison procedures.

- Data collection - in this phase, the experimental environment and the setup from prior similar works were used in the data collection. Given that cloud-based technologies were used in our study, we selected five TPC-C workloads, which are considered suitable for cloud deployment purposes. The data will be collected from the implemented workload performances with different available resources and different numbers of VCPUs. - Data analysis - for data analysis, a number of 50 transaction performance results were published (in milliseconds) from different workloads and then the results were compared by assessing the 95% confidence intervals of the means for 95% confidence in normal distribution. The outcome of the research, as a result of assessing the 95% confidence interval, shows that the performance difference between two means will be considered statistically significantly different if there are no overlapping confidence intervals. - Step 4 - Data comparison: The statistical experiment versus the TPC-C performance results is conducted to compare the proposed advanced techniques. These techniques were the impact of using the third normal form against column-based technology. In addition, an advanced database system feature was exploited for the purpose of enhancing faster SQL execution, which is querying the column store indexes (via In-Memory OLTP) in parallel.

6. Conclusion

This paper conducts a comparative study to evaluate the performance of the two widely used advanced DBMS techniques. To this end, we use block nested loop join using symmetric key operations in SQL Server and Intel SGX supported in the SQL Server database engine. Extensive experimental results provide several findings. We observe that SQL Server takes less time when the sizes of data selection are 1% and 10%. Intel SGX takes less time when the size of data selection is 100%. In the presence of range query, SQL Server takes less time when the product of the sizes of data selections of related tables is greater than or equal to 1% and the size of the smaller table is small. The data sizes are assumed equivalent and performance differences are always on the order of a few seconds. More interesting findings include the fact that Intel SGX encrypted U-SQL queries perform better relative to T-SQL than unencrypted U-SQL.In this study, we use the block nested loop join algorithm and propose that all block nested loop join techniques in the real system use symmetric key operation and Intel SGX technology. To the best of our knowledge, there is no existing study that has this focus. We conduct a comparative study of the DBMS taking into account the conditional range queries and employing the SQL Server 2019. Extensive experimental results from the Azure cloud environment provide several empirical findings that can be useful for cloud developers and practitioners in the optimization of cloud computing performance using current technologies. While SQL Server is the commonly utilized DBMS, we believe that modern DBMS have comparable performance. It is always possible to compare more DBMS and new trends in DBMS. We also propose profitable future trends based on the current energy efficiency for future work.

6.1. Future Trends

The domain of query processing in the upcoming clouds will continue to grow, and they will be more sophisticated and complex. There will be a greater necessity for spatial support due to the advent of mobile devices. RDBMS firms are continuously modifying and improving their techniques in an attempt to boost their position in this largely niche sector, concentrating on performance optimization, scalability, and flexibility. Besides this roadmap presented, this paper could hopefully persuade RDBMS vendors to rethink their strategy and concept concerning the introduction of new methods in order to advance RDBMS performance. Today's optimization systems are not practical when it comes to such a huge number of candidates.In addition to several application areas, cloud computing is evolving into a full-fledged infrastructure that is anticipated to provide everything as a service, from basic processing and storage to high-level services like databases. Several cloud database systems and management services have been developed. Despite ongoing research in database management systems, many areas need further exploration. One of the new emerging issues in the field of cloud computing is exploring new techniques to optimize cloud computing performance. Database management systems (DBMS) were set to continue the development and exploration of innovative methods to enhance them. In addition, future architecture enhancements will be required to allow the incorporation of new methods and concepts.

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USING AI AND MACHINE LEARNING TO SECURE CLOUD NETWORKS: A MODERN APPROACH TO CYBERSECURITY

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ABSTRACT

The need to ensure the safety of network resources has grown in tandem with the lightning-fast advancement of computing power and the exponential growth of network sizes. The design and optimisation of the method for detecting network security events to adapt to the characteristics of a cloud environment is the basis for the effectiveness of OpenFlow and is a key issue in the cloud architecture approach to detecting network security events. This paper's goal is to examine the cloud architecture method for network security detection. The purpose of this research is to examine how well four different classification models—DT, SVM, and CNN-LSTM—protect cloud networks against cyberattacks. We test the models' detection and prevention capabilities on the 374,661-sample, 19-characteristic WSN-DS dataset. The CNN-LSTM model stands out with the highest accuracy of 94.4%, complemented by precision and recall values of 95.9%, demonstrating its robust classification capabilities. Our findings reveal critical insights into the effectiveness of AI and ML techniques in securing cloud environments. This research contributes to the ongoing efforts to improve cloud security through advanced analytical methods and highlights the superiority of the CNN-LSTM model for practical applications in threat detection.

KEYWORDS: Cloud Security, Data Privacy, Cybersecurity, Artificial Intelligence, WSN-DS data, Machine Learning

1. INTRODUCTION

Robust cybersecurity is now a must for organisations globally in this digital age when cyber threats and data breaches are ever-present. The rapid advancement of technologies, particularly artificial intelligence (AI) and cloud engineering, has opened new horizons in cybersecurity, offering unprecedented opportunities to bolster defences against cyber-attacks[1][2]. Nevertheless, there are significant legal and ethical questions that arise when AI and ML are integrated into cybersecurity. To make sure these technologies are used responsibly, we need to examine issues like data privacy, algorithmic bias, and the consequences of automated decision-making thoroughly[3][4]. Cloud computing must be protected for user data in order for services to be dependable. The usual suspects in cloud computing security include data misuse, hostile insiders, unsecured interfaces and access points, common technical issues, data loss, and hijacking. Thus, installing cloud computing successfully necessitates a precise comprehension of cloud security [5][6].

The deployment of potential solutions required by consumers is hindered by various sorts of attacks, which affect cloud providers and administrators [7]. The reason for this is that various attack types provide different risks, and the relative importance of these threats varies based on other cloud service customers' security needs[8][9]. To

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fulfil critical security needs as service providers, security administrators will assess threats and put safeguards in place. It is almost impossible to design a system that is totally secure[10], yet security may be enhanced [11][12]. As a result, identifying security risks and the corresponding remedies, such as accountability, authentication, and privacy protection, are essential [13][14]. However, in addition to other common services like computing, storage, and networking, cloud providers have recently started to provide a variety of AI tools and frameworks to make it simple to create and utilise new ML models[15]. The ability of Cloud Boost to make resources and knowledge about AI available and thus accessible to everyone is one of the advantages of Cloud Boost[16].

Artificial Intelligence (AI) has fundamentally transformed the landscape of cybersecurity, offering advanced capabilities that significantly enhance threat detection and response. By leveraging machine learning and predictive analytics, AI systems can analyse vast amounts of data to identify patterns and anomalies indicative of potential cyber threats. This capability is crucial for managing the complexity and volume of modern cyber threats, providing organisations with a powerful tool to detect and mitigate risks more effectively. Machine learning algorithms, a subset of AI, are particularly valuable in cybersecurity. These algorithms are designed to learn from historical data and identify patterns that may signal malicious activit

Cybersecurity has been revolutionised by Artificial Intelligence (AI) which delivers superior elements that have increased the capabilities of threat identification and mitigation[17]v. AI systems integrate ML and big data analytics to search through the large volumes of data for symptoms of cyber threats[18]. It becomes necessary in the age of high complexity and quantity of threats to provide organisations the powerful instruments to observe and respond to risks. Machine learning as a type of AI is most useful in cybersecurity. These programs may study past data in order to spot trends that might indicate harmful behaviour[19].

2. MOTIVATION AND CONTRIBUTION OF STUDY

The study's impetus stems from the growing complexity and frequency of cyberattacks that target cloud networks, which are difficult for conventional security techniques to manage. As cloud environments host more sensitive data, there is a critical need for advanced, automated solutions. This study seeks to leverage AI and machine learning to enhance the detection and prevention of cyberattacks, ensuring more robust security in cloud-based infrastructures. The area of cloud network security has benefited greatly from this study's several important contributions.

- Employ the ML models with the help of the WSN-DS dataset.
- Implements advanced data preprocessing, including SMOTE for balancing, Min-Max scaling, and Chi-Square feature selection, to optimise model performance.
- Demonstrates the effectiveness of ML models (CNN-LSTM, DT, and SVM) for detecting various types of cloud-based cyberattacks.
- Comprehensive evaluation of model performance using accuracy, precision, and recall metrics, offering insights into each model's strengths.

3. STRUCTURE OF PAPER

The following is a synopsis of the remaining paper. In Section II, we provide a literature review of cloud security based on AI and ML. While Section IV delves into the analysis and discussion of the outcomes, Section III lays out the methodology and strategy. The study's conclusions and suggestions for further research are detailed in Section V.

4. LITERATURE REVIEW

This section provides some previous work on cloud security networks for cybersecurity based on machine learning.

In this paper, Fang, Zhang and Huang, (2021) was presented CyberEyes, a model for cybersecurity entity recognition that makes use of graph CNNs to extract non-local relationships. Our model outperformed the typical CNN-BiLSTM-CRF mode, which achieved an F1 score of 86.49% on the cybersecurity corpus, in the assessment trials, reaching a score of 90.28% under the gold standard for NER[20].

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This research used, Umamaheshwari, Kumar and Sasikala, (2021) by use of a DTC. Feature selection utilising the MRMR algorithm, the Relief algorithm, the Kruskal-Wallis (KW) test for statistical analysis, and the Fisher score were all tested in an effort to shorten the time it takes to identify attacks. Relevant performance indicators are used to assess the suggested feature selection approaches. The following metrics were measured using MRMR feature selection: accuracy (98.58%), sensitivity (92.81%), specificity (93.86%), and training time (15.12 seconds), in that order [21].

This research, Krishnan and Singh, (2021) developed a classifier using cost-sensitive ML and trained it on the WSN-DS dataset, which includes examples of flooding, TDMA/scheduling, black-hole, and grey-hole attacks. A Cost-Sensitive Bootstrapped Weighted Random Forest (CSBW-Random Forest) was suggested in light of this, and it outperformed previous efforts. The accuracy, precision, recall, and F1-score of our approach are all 0.997, and the per-class performance scores fall between 0.95 and 0.99, which is a considerable improvement over previous research [22].

In this paper, Yasarathna and Munasinghe, (2020) primary emphasis was on employing one-class classification algorithms, namely Autoencoder and OCSVM, to analyse data from cloud networks in order to spot abnormalities. Our results show that Autoencoder is 96.02% accurate while OCSVM is 79.05% accurate when it comes to identifying outliers. Furthermore, they delve further into the efficacy of a one-class classification system by using an additional benchmarked data set, UNSW-NB15. A 99.10% accuracy rate for Autoencoder and a 60.89% accuracy rate for OCSVM were achieved there[23].

This research, Hachimi et al., (2020) emphasises the implementation of a multi-stage ML-IDS in 5G C-RAN capable of detecting and categorising four distinct jamming assault types: reactive, continuous, random, and deceptive. Simplifying C-RAN structures and reducing false negatives is how this deployment improves security. Experimental testing of the proposed method is carried out using WSN-DS, a wireless dataset developed for intrusion detection purposes. A FNR of 7.84% contributes to the final assault classification accuracy of 94.51%[24]

Table I includes detailed insights, including dataset limitations and possible future research directions, for each study on cloud security network enhancements using machine learning.

Table i. Summary of previous work on cloud security networks for cybersecurity using machine learning

Authors	Data	Methods	Findings	Limitations	Future Work
Fang, Zhang, and Huang (2021)	Cybersecurity corpus	CyberEyes model with Graph Convolutional Neural Networks (GCN) for NER using non-local dependencies	Achieved an F1 score of 90.28%, outperforming the CNN-BiLSTM-CRF model (F1 score of 86.49%) in NER tasks	Limited to NER tasks in cybersecurity, requires labelled data for gold-standard evaluation.	Potential integration with other NER tasks and domains, enhancing graph-based dependency extraction capabilities
Umamahesh wari, Kumar, and Sasikala (2021)	WSN-DS dataset	Feature selection using Correlation Score, Fisher Score, Kruskal-Wallis test, MRMR, and Relief; Decision Tree classifier.	Using MRMR, achieved 98.58% accuracy, 92.81% sensitivity, 98.46% specificity, and 93.86% precision, with 15.12 sec training time.	Limited to attack detection in WSNs; computation time may still be a concern in some resource-constrained scenarios	Further optimise feature selection to reduce training time improve adaptability for other attack scenarios.
Krishnan and Singh (2021)	WSN-DS dataset	Cost-sensitive bootstrapped Weighted Random Forest (CSBW-RF) for handling class imbalance.	Achieved 0.997 accuracy; per-class precision, recall, and F1 scores between 0.95 and 0.99, demonstrating improved performance over existing methods	Focused on WSN-specific attacks, potential limitation in broader applications, like other network types	Extending the CSBW-RF to diverse datasets and integrating with multi-class and unsupervised learning techniques
Hachimi et al. (2020)	WSN-DS	Multi-stage ML-based IDS	Achieved 94.51% accuracy with a 7.84% false negative rate in detecting jamming attacks.	Relatively high false negative rate for critical attack types.	Enhance false negative mitigation; explore adaptability for non-5G network environments.
Yasarathna and Munasinghe (2020)	YAHOO Synthetic, UNSW-NB15	OCSVM, Autoencoder	Achieved 96.02% accuracy on YAHOO data and 99.10% on UNSW-NB15 with Autoencoder.	Kernel-based OCSVM had lower accuracy, especially on UNSW-NB15.	Further, refine neural networks for cloud data anomalies and test on real-world cloud datasets.

5. METHODOLOGY

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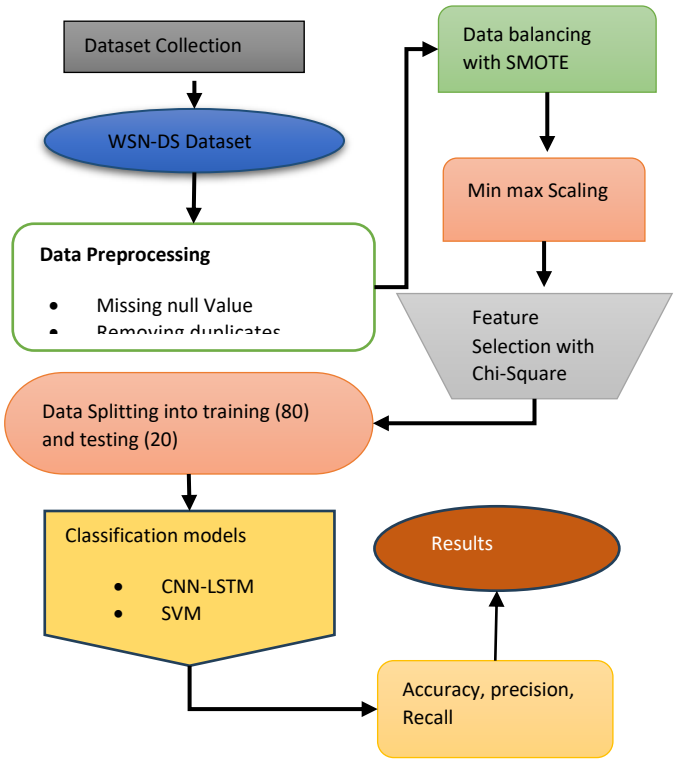
The general workflow for securing cloud networks using AI and machine learning begins with data collection, where the WSN-DS dataset, comprising 19 features and 374,661 samples, is used. In the pre-processing stage, missing values (if any) are handled, and duplicates are removed to ensure data integrity. The dataset is balanced using SMOTE, which generates synthetic samples for minority classes to alleviate class imbalance and ensure that all attack types are represented equally. After that, scaling is done using Min-Max scaling, which normalises the features by transforming them to a range between 0 and 1. Afterwards, the Chi-Square approach is used for feature selection in order to reduce irrelevant variables and discover the most important characteristics for the classification task. The models used for this task include DT, SVM, and CNN-LSTM, all trained on the preprocessed and balanced data. Lastly, the performance metrics—accuracy, precision, and recall—are evaluated to measure the models' effectiveness in securing cloud networks, with values closer to 1 indicating better performance. The following workflow of research design is shown in Figure 1.



Flowchart for cloud security network

Each step and phase of Figure 1 Flowchart for cloud security network are listed below:

Data Collection

The dataset utilised in the experiment was created by Almomani and is a simulation of a WSN-DS. The target variable (Attack Type) is one of nineteen attributes. There were no missing or null characteristic values among the 3,74,661 data samples. The analysis of the dataset is such that insights into data are visible in the following Figures 2,3 and 4.

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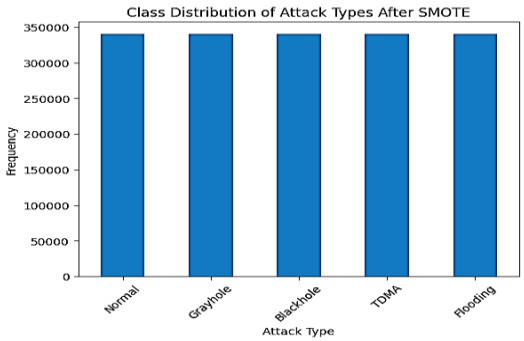
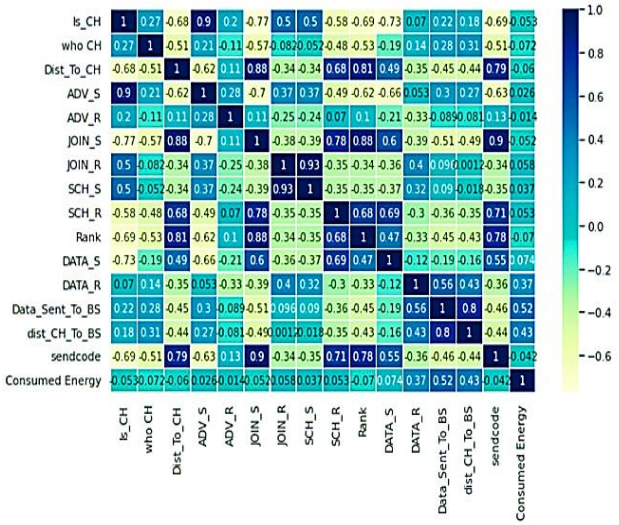


Class distribution of attack

Figure 2 shows the Class Distribution of Attack Types After SMOTE illustrates the balanced frequency of various attack types shows in x-axis. The y-axis shows the frequency 0 to 350000. Each category has a nearly identical representation, showing that SMOTE successfully addressed the class imbalance in the dataset.



Correlation matrix for features

Figure 3 shows a heatmap of a correlation matrix with a colour gradient that runs from dark blue to dark red, indicating values ranging from -1.0 to 1.0. The rows and columns are labelled with numerous acronyms, like "is_CH," "Dist_to_CH," "ADV_S," "JOIN_R," and more. Each cell in the grid displays a numerical value that correlates to the colour scale, showing the magnitude and direction of the correlation between the variables. The bottom row and the far-right column are labelled “Consumed Energy,” with appropriate values and colours, indicating their interaction with other variables in the matrix.

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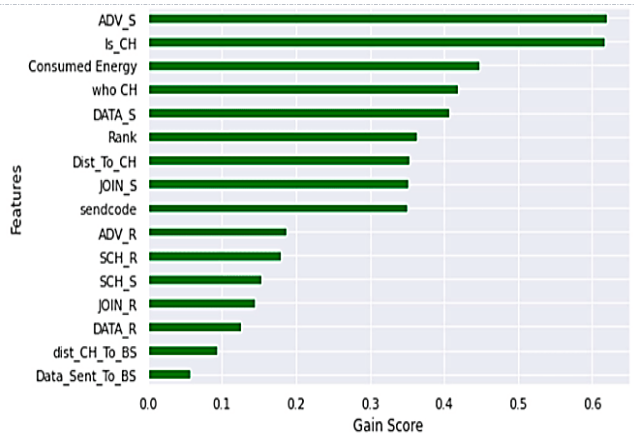

Bar graph for feature score

Figure 4 is a horizontal bar graph with several characteristics plotted against a 'Gain Score' on an x-axis that runs between 0 and 0.6. A y-axis displays characteristics such as 'ADV_S,' 'whois_CH,' 'Consumed Energy,' 'Rank,' 'DATA_S,' 'Dist_To_CH,' 'JOIN_S,' and others, with certain bars approaching 0.6 indicating a greater gain score for those qualities. This graph is employed in data analysis or machine learning to determine important characteristics in a model.

Dataset Preprocessing

Data preparation is a continuous process that tries to transform the raw data into more usable and comprehensible form. Where specific data points are absent in a dataset that were referred to as missing values, it can be expressed by blank cells or null values and sometimes by special characters such as “NA” or “unknown”. Lack of these data hampers the analysis of data and also introduces the biassing or wrong conclusion. In order to ensure that the data is correct and trustworthy for further analysis or modelling, removing duplicates is a crucial step in data cleaning and preprocessing.

Balancing with SMOTE

A small dataset is ideal for SMOTE's performance. To make matters worse, SMOTE's efficiency plummets as the dataset size increases since it takes a long time to generate false data points. In addition, SMOTE has a significant probability of overlapping data points for the minority class while making fictional data points[25]. A following Eq. (1) of smote is:

$$x_{new,\ attr} = x_{i,attr} + rand(0,1)x\ (x_{ij,attr} - x_{i,attr} \qquad (1)$$

Min-Max Scaling

Equation 2 shows how the Min-max Scaler changes an attribute's scale by dragging its values down the X-axis until the new attribute fits in the range of [0, 1].

$$x_1' = \frac{x_1 - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

This approach uses the range of a feature as a scaling factor and the lowest value of the characteristic as a translational term.

Feature Selection with Chi-Square

To decrease a number of irrelevant variables, feature selection approaches in WSN data pre-processing aim to filter the input variables down to those most likely to be related with the intrusion assault. For this reason, choose Chi-squar feature selection methods. The independence of characteristics with regard to the class is measured by chi-squared. A score is not computed until the feature and class are believed to be independent [26]. A highly reliant connection is indicated by a high score. The following Eq. (3)

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$$x^2 = \frac{(observed\ frequency - expected\ frequency)^2}{expected\ frequency} \quad (3)$$

Where:

Observed frequency = An amount of class observations.

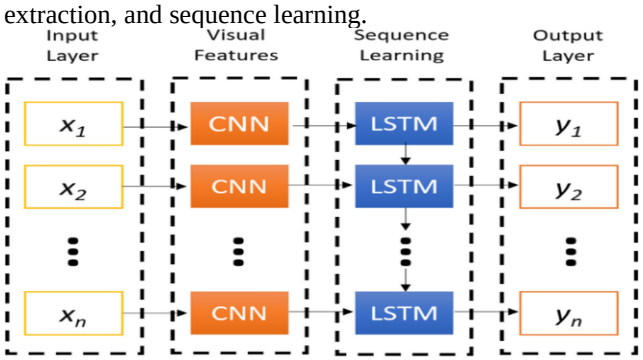
Expected frequency = The predicted number of class observations in the absence of a link among the feature and the target attribute.

Data Splitting

The dataset was divided into two parts: a testing set that is totally concealed by the training process and a training set utilised to train the detection algorithm. The 80:20 techniques are used by the two subgroups. The test set uses 20% of the whole dataset, whereas the training and validation sets utilise 80%.

Classification with CNN-LSTM model

CNN-LSTM blends the ability of CNNs to retrieve features with the ability of LSTM layers to guess sequences. The CNN-LSTM is often used for image and video tagging and activity recognition. The two work together to solve problems with visual time series forecasting and text annotation creation from image sequences. The CNN-LSTM network's layers are shown in Figure 5 in the following order: input, output, visual feature extraction, and sequence learning.



Architecture of the CNN-LSTM Network

To differentiate between malicious and benign users, a CNN-LSTM model is recommended. This may be a great way for many companies to keep hackers out of their systems. The attack label is unnecessary for testing the proposed model[27][28]. The model takes features as input so that it may correctly associate labels with input properties. The CNN-LSTM model is highly recommended because of its extensive range of features.

This ensemble model used CNN layers to extract features and LSTM layers to handle the sequential nature of the input. For multi-class classification, the model then uses a fully connected layer with sigmoid activation, producing five different output classes. We will next use the "Adam" optimiser and a learning rate of 0.001 to construct our model.

Performance Metrics

Four criteria are used to assess the findings of this study: recall (RE), accuracy (ACC), precision (PR), and precision (PR). Each of these standards has a numeric value between zero and one. Performance improves as it gets closer to 1, and it drops as it gets closer to 0. The formula for calculating these performance assessment measures is:

Accuracy: Accuracy (Acc), a frequently used indicator for classification performance, is expressed as the proportion of correctly classified samples to all samples, as shown in Equation (4).

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (4)$$

Where:

- **True Positives (TP):** TP stands for positive classes that were accurately forecasted.
- **False Positives (FP):** A positive class that was incorrectly forecasted is FP.
- **True Negatives (TN):** A negative class that was accurately forecasted in TN.
- **False Negatives (FN):** FN denotes the negative classes that were incorrectly anticipated.

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Precision: The capacity of a model to recognise only relevant things is known as precision. It represents the percentage of predictions that come true. The precision is calculated as (5):

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Recall: It is calculated by dividing the total number of relevant samples by the number of accurate positive outcomes. Here is the mathematical representation (6):

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

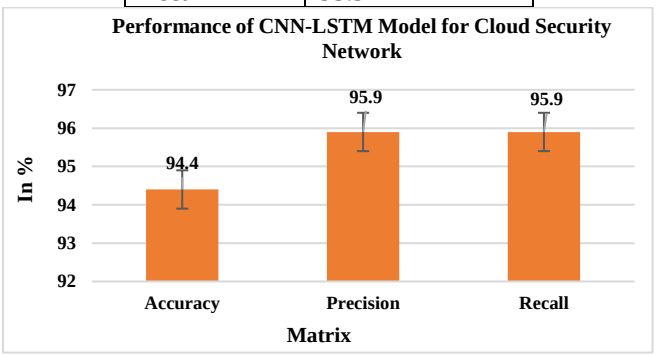
The following matrix is useful for generalising the model performance for cancer prediction.

6. RESULTS & DISCUSSION

The section evaluates the model's effectiveness. Every single trial ran on a Windows 11 PC with a 3.80 GHz Intel Core i7 CPU, 16 GB of RAM, and all the necessary hardware components. This section discusses the simulated outcomes of cloud security using ML approaches. The following models, like DT[29], SVM[30], and CNN-LSTM, are implemented on the WSN-DS dataset across performance matrices like accuracy, precision, and recall.

CNN-LSTM MODEL PERFORMANCE ON WSN-DS DATASET

Metric	CNN-LSTM
Accuracy	94.4
Precision	95.9
Recall	95.9



Bar Graph for CNN-LSTM model Performance

The results of running the CNN-LSTM model on the provided data are shown in Figure 6 and Table II. Employing a CNN-LSTM model, an accuracy level was calculated to be 94.4%; therefore, it duly classified 94.4% of occurrences of the dataset. It also obtained a precision of 95.9%, meaning that 95.9% of the predicted positives were actual positives. Also, the specificity of the model was 98%, which means the model labelled 98% of correctly identified negative instances as negative. The above metrics point that the efficiency of the CNN-LSTM model in terms of distinguishing between true positive and false positive rates is quite high and hence the proposed technique is adequate enough for the classification of the given task.

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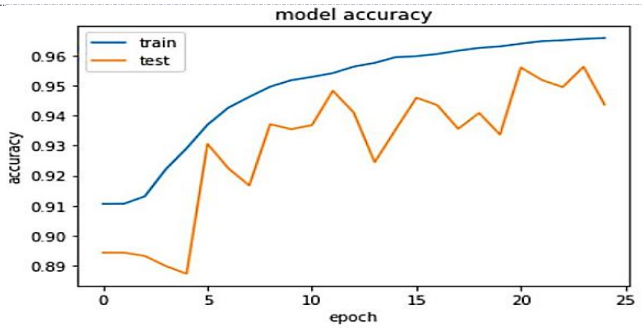
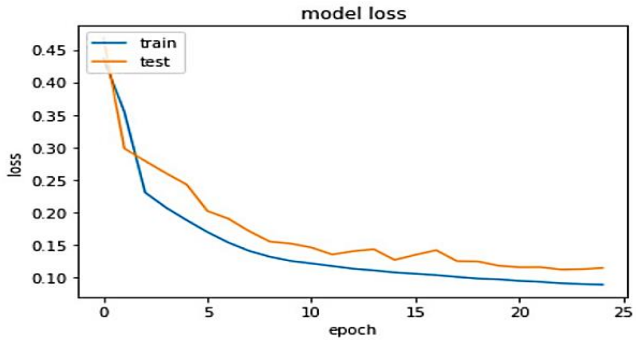


CNN-LSTM Model Training and Validation Accuracy with 25 Epochs

A line graph representing model accuracy throughout 25 epochs of training and testing is shown in Figure 7. On the horizontal axis, it is possible to discover epochs from 0 to 25, on the vertical axis, there are results regarding accuracy from 0.89 to 0.97. The plot has 2 curves: blue colour for training data accuracy, which increases from 0.90 to around 0.97, and orange colour for testing data accuracy, which fluctuates, yet it increases from 0.89 to approximately 0.93 in the 25th epoch. This graph helps to make out how the performance of the model grows with time.



CNN-LSTM Model Training Loss with 25 Epochs.

Figure 8 shows a line graph for CNN-LSTM model loss, which depicts the loss value across 25 epochs for both the training and testing datasets. An x-axis indicates epochs (0–25), whereas the y-axis represents loss (0–0.45). The blue line for training loss indicates a dramatic dip at first, then gradually levels out, demonstrating that loss decreases as training continues. The orange line for testing loss lowers as well, but with more oscillations, indicating model performance variability on unknown data. Throughout the testing and training phases, the loss of the model changes with time, as seen in this graph.

COMPARATIVE ANALYSIS OF CLOUD SECURITY NETWORK ON WSN-DS DATASET

Models	Accuracy	Precision	Recall
DT	84.3523	82.1	98.0
SVM	89	88	92
CNN-LSTM	94.4	95.9	95.9

Table III above displays the outcomes of comparing a model's performance. An CNN-LSTM model shines out when compared to others, demonstrating its better performance in classification tests with an accuracy of 94.4% and great precision and recall values of 95.9% each. In contrast, the DT model has the lowest accuracy at 84.35%, although it achieves a high recall of 98.0%, which means it is better at identifying actual positives but less precise at 82.1%. The SVM accuracy score of 89%, with SVM slightly outperforming. The CNN-LSTM model is a most efficient for a task at hand since it offers the greatest overall balance between accuracy, precision, and recall.

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7. CONCLUSION & FUTURE WORK

The current trend in Internet growth, towards cloud computing, has caused a great deal of anxiety among internet users. Research on the best practices for constructing a safe cloud computing environment is now at the forefront of the computer science community. This research illustrates the significant potential of leveraging AI and ML techniques for securing cloud networks against cyber threats. The comparative performance analysis of various classification models, including DT, SVM, and CNN-LSTM, underscores a superior efficacy of the CNN-LSTM model, which achieved an accuracy of 94.4% along with high precision of 95.9 and recall of 95.9 metrics. The study does admit to certain caveats, however, such as the fact that it only used one dataset—which could not be representative of the variety of cyber threats that exist in the actual world. Another consideration is that models with high computational complexity, like CNN-LSTM, could be difficult to implement in settings with limited resources. Future work should focus on exploring more diverse datasets to validate the model's effectiveness across different contexts, as well as investigating the integration of ensemble learning techniques to enhance classification performance further.

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Research Article

Biometric Authentication In Digital Payments: Utilizing AI And Big Data For Real-Time Security And Efficiency

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ABSTRACT

Biometrics is the technical term for body measurements and calculations. It refers to metrics related to human characteristics. Biometric authentication (or realistic authentication) is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance. The basic premise of biometric authentication is that everyone is unique and an individual can be identified by his or her intrinsic physical or behavioral traits. It allows us to capture biometrics or personal information and make digital payments fast. For the sake of digital banking, biometrics pointed the way to reinvest the identity verification process automatically into a system. As a result, financiers no longer have to substantially subdivide themselves from their customers, especially when ascertaining identity. A procedure that used to take weeks or months has now been reduced to a matter of minutes if not seconds. As an efficiency bid, it is orders of magnitude more efficient than any human could ever be to preserve the verification process by using existing biometric data. Biometric identifications are discrete physiological or behavioral characteristics that can be measured to identify a person. Digital payment alternatives are gradually replacing the traditional ways of transactions. Biometric authentication is based on inheritance and specific characteristics and is considered to be more secure compared to traditional PIN methods. Fingerprint recognition is the most common biometric identification available in various smartphones. Replacing traditional signatures with more secure and efficient fingerprint verification leads to the automation of the KYC process in the banking system. In this paper, readers will understand the working and potentiality of biometric authentication with the help of Artificial Intelligence (AI) and Big Data for correctness purposes. This paper will help non-technical readers understand the concepts and power of intelligent AI used in banks for KYC purposes.

Keywords: Biometric Authentication,Digital Payments Security,AI in Payment Systems,Big Data Analytics,Real-Time Fraud Detection,Secure Payment Solutions,Machine Learning for Security,Real-Time Authentication,Payment Fraud Prevention,Biometric Data Privacy,AI-Driven Security,Big Data in Financial Transactions,Advanced Payment Technologies,Fraud Prevention Algorithms,Biometric Verification,Real-Time Risk Assessment,AI Security Algorithms,Biometric Payment Systems,Digital Identity Verification,Data-Driven Security Solutions,Secure Payment Authentication,Adaptive Fraud Detection,Biometric and AI Integration,Financial Data Protection,Smart Payment Security.

1. Introduction

The use of biometric authentication systems has permeated into almost every aspect and culture of life. Biometric systems have been used across many industries for both commercial and legal purposes like identity,

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seeding such biometric modalities like fingerprint technology for old or elderly people. This technology focuses on what makes users for old people stand out, their faces, eyes, and voice. All these can be put together in a payment system solution hence making it easier and efficient for users to conduct a lot of transactions within a very short time as compared to what it used to be. These solutions are expected to perform specific characteristics and requirements like speed, robustness, universality, permanence, no capability of performance replication, resistance, and so on even in a variety of transaction settings. One major component of each successful transaction is the biometric component which offers real satisfaction as stated by relevant agencies. Some of these factors will be taken into consideration in this project. Moreover, there are major differences between biometric technology/solutions and other forms like cards, digital methods, etc., in terms of human behavior since biometrics has a direct relationship with the human body. Hence the biometric authentication system in the digital payments sector is considered as a very strong system that provides an appropriate level of customer satisfaction. The biometric is the measurement of physical or behavioral patterns which can be transferred into machine-readable codes or data. Biometric firms are offering a variety of hardware and software and many others are currently offering biometric bank cards. These biometric vendors intend to improve digital transactions among old people. An example is the first biometrics bank card created in the UK, launching Barclays to address the growing threat of fraud and enhance clients' everyday payments. The advent of digital technologies and the internet, as well as the increase in the number of smartphones, has laid the groundwork for digital payments. Customers can scan a QR code to make a payment, pay digitally at the POS using NFC or QR codes, send requests for money to friends, pay merchants through an unstructured fee request, and execute many other tasks. Hence, digital transactions have grown to form an alternative that is faster and more useful for customers compared to physical methods of transacting. However, one of the key challenges that digital transactions face is security. Therefore, a payment system that uses biometrics on an unsecured channel while making payment will make it impossible for anyone masquerading as you to carry out a transaction. As such, the government and appropriate authorities around the world are working to use a biometric-based authentication system.

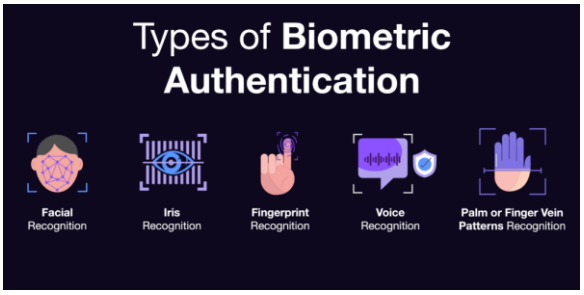

Fig 1 :Biometric Authentications

1.1. Background and Significance of Biometric Authentication in Digital Payments

Biometric authentication has been widely scrutinized in the last few decades, and substantial research and development of biometric authentication systems have been conducted. Facial, fingerprint, iris, hand geometry, and behavioral biometrics are some of the most important biometrics that have proven to be useful in practice. Biometric security systems, which have evolved considerably in the era of artificial intelligence (AI) and big data analytics, can achieve higher accuracy, identification speed, and convenience with lower operational costs. In addition, a low-cost device can be employed to capture a biometric, since we can access the internet on almost all devices. For this reason, biometric technologies for security and authentication in digital payments are extremely significant. Therefore, the corresponding research and review article demonstrates this fascinating field and its technological processes, such as its advances, significance, and features.In terms of security, biometrics is a cutting-edge technology often applied for authentication due to its accuracy and uniqueness. This paper will specifically concentrate on the application of biometric technology in digital payments. Digital payment methods have already made access to formal finance easier and more manageable, and with this trend of cashless transactions, instances of fraudulence in digital payments are also surging. In many existing digital payment systems, including credit cards, online banking, and mobile payment systems, one of the main security measures implemented is password-based authentication. Nevertheless, people are typically imprudent and use weak passwords. Thus, password theft, also referred to as account takeover fraud, is a rampant problem all over the world. As users do not have to recall passwords, employing biometric authentication ensures that only verified, proper credential holders access secure areas.

2. Biometric Technologies in Digital Payments

There are various biometric technologies of biometric recognition modalities that are available for digital payment users. A summary of some recognized and commonly used biometric technologies is discussed in this paragraph. These technologies include fingerprint recognition, facial recognition, iris recognition, and voice recognition. Customers in authenticated digital payments typically require one of these modalities. Highly

secure devices that have proper security measurements properly implemented can support multimodal biometric technologies. A multimodal biometric technology can provide any form of security when both or more biometrics are checked. A system such as an ATM can use two biometric technologies to enroll or verify a customer when he or she acquires an ATM card and opts to operate the ATM using fingerprint and iris technologies. The fingerprint enrollment is managed to verify the customer, and if the iris is checked, the enriched digit of the customer is available on the credential card for security verification.
In mobile and web payments, biometrics technology for user authentication serves as an extra protective layer and replaces tokens and cards with a biometric profile. Touching the home buttons of smartphones, users can confirm their identity through fingerprint authentication. Various digital payment services also use face recognition for user verification. In addition, iris recognition is mainly used in Android mobile devices, including mobile payment banking apps, passport apps, and others. Voice is another modality used in digital payments. Apple Siri, Microsoft Cortana, Google Now, and others have voice authentication systems to interact with mobile phones to execute some processes such as depositing or paying with a voice command like "Siri, pay with Zelle." This section is intended to enrich our readers with a full list of biometric technologies in digital payments. The following parts of this section are dedicated to the in-depth description and application examples of fingerprint recognition, facial recognition, iris recognition, and voice recognition in the domain of digital payments.

2.1. Fingerprint Recognition

Fingerprint recognition, with efficiency and accuracy, represents an alternative means for digital transaction security. Although the verification of a fingerprint cannot guarantee the authenticity of any transaction, it ensures the identity of the one who conducts the transaction. Biometric recognition is something that is neither forgotten nor stolen;
Therefore, fingerprint recognition provides a quite secure
and efficient method for payment authentication and trust. Consequently, AI-based fingerprint recognition is to transform a pattern of thin dark lines into a small amount of biometric data for recognition. Fingerprint recognition has to be accurate to ensure the true identity of customers. In addition to enhancing security, the elimination of POS-based digital payment paperwork and digitized wallet passcodes allows faster and easier digital payment, especially in a retail environment like Walmart.
Fingerprint recognition is a widely recognized biometric technology that compares a captured image of a fingerprint to the user's known fingerprints stored in the system. Features such as ridge endings, bifurcations, and ridge shape form minutiae to be extracted from fingerprints. Minutiae are recognized for their specific pattern and used for authentication. Depending on the type of data digitally stored in the fingerprint scanner machine, fingerprint recognition techniques could be categorized into two types, namely, the optic fingerprint machine and the semiconductor fingerprint machine. The optic fingerprint machine stores the digitized image of the fingerprint as well as performs the fingerprint matching task on the image, while the semiconductor fingerprint machine uses the model of the fingerprint as pre-processed data and not a model of the digitized image, and hence there would be no need to perform an intensity transformation which leads to space saving and a fast transaction due to employing a smaller digital model for the construction of the fingerprint images.

Fig 2 : Biometric technology

2.2. Facial Recognition

Facial recognition has one primary application for payment actors, and that application is to speed up payment authentication. It has to be noted that the primary alternative to facial recognition payment authentication is either to pay by cash/raise a credit/debit card or use a password-based digital payment solution to finish the transaction. Unlike fingerprints again, facial recognition simply doesn't fit in a smooth customer payment flow. Accepting such payments cannot be frictionless. It might take a few seconds to capture, analyze, verify, and confirm the person's facial biometric. This sub-second verification or payment validation can happen only when the customer voluntarily looks at the camera, to begin with, and such consent to capture the image from the camera is included in the mobile application end-user license agreement. Thus, it can be said that biometric recognition has its unique features and applications, enhancing the security and efficacy of digital transactions.

Biometric technology has permeated into almost every major industry on the global landscape, and digital payments are no exception to this. Facial recognition has emerged as a prominent biometric technology in digital payments, with Alibaba's Ant Financial having rolled out a "Smile to Pay" service in March 2017 at various KFC outlets in Hangzhou, China, where a smile at a search helped unlock a self-service process to avoid scams. In a similar context, Alipay also began an offline facial recognition payments system with KFC in China in September 2019. Essentially, facial recognition captures, analyses, and compares a person's unique facial characteristics, typically in value-driven services like border control, security access, and payment.

2.3. Iris Recognition

Iris recognition provides the best verification and time-dependent results using the Hamming distance, inclusive of both wearable and handheld verifiers, optimizing the highest volume of iris vectors per second, resulting in a match score. Thus, in a payment transaction, biometrics acts as a decisive approach over classical physical evidence that allows issuers to make a real-time identity decision resulting in card authorization. In a real-time entity, the system's speed shows the trade-off between the data capacity, the template size, and the quality of the biometric data. Biometric systems require a significant amount of data for the template because additional details are needed to improve accuracy, but they also need to minimize the size of the template to reduce the time required to calculate the matching result. In real-time matching, a micro-engine executes minutia or feature template comparisons with the pre-registered biometric data. Thus, in a digital payment system, using real-time entities makes systems more efficient by operating a wearable or handheld device closer to the eye instead of a separate server utility for backend synchronous matching. Each of the systems has fixed a threshold score, and the matching score is compared with it for verification. The digital payment system uses a single biometric matching system, which gives a matching indicator, and if the two indicators match the transaction, then it turns to authorize the payment. The score is above an acceptance threshold. Consequently, iris technology gives a real-time scoring performance for both payment transactions.

Iris recognition as a biometric trait has recently gained attention from the industry due to its almost invariant nature, extremely low False Rejection Rate (FRR), and very low False Acceptance Rate (FAR). During the process of iris recognition, the near-infrared light falls on the pupil and the cornea, which are present in the front of the eye. The working of the iris recognition system is based on the following steps: The light reflected from the iris's texture is captured by the high-resolution camera. The captured image is further processed to segment the circular iris region from the rest of the eye. The pupil is also detected and normalization is performed to compensate for variations in iris size. After normalization, the iris is split up into several layers. The segmentation of the iris is based on the bright circular pupil spot derived from the specular reflection of a light source. The extracted iris is further processed to generate feature vectors. In essence, the feature sets are abstracts obtained as the result of a trained filter acting on the image contents. This results in a set of values that reflect the combination of the factors analyzed by the trained model. It is further used in searching a gallery of the feature vectors extracted from the previous transactions and also in the current search. The final step involves verification and ultimately the decision based on the number of feature points that match; if there is a match in previously enrolled data, the transaction is granted, otherwise it is rejected. The availability of the real-time matching system, running in a standalone or connected mode to the central system during the transaction process, significantly speeds up the overall verification process.

2.4. Voice Recognition

Voice recognition is receiving worldwide attention from renowned research institutions as an effective way to secure financial digital transactions and customer personal privacy. Research scholars are making strides in the development of voice recognition technology by adding big data and artificial intelligence (AI) characteristics to the existing voice recognition technology. Big data is used to train the voice and facial recognition algorithms to realize reasonable and integrated image understanding and dynamic face and voice matching. The true positive and false positive rates of voice recognition have been improved by utilizing the rich data supplied by the function of big data. This new voice recognition method has successfully increased the hit rate while limiting the non-hit rate, effectively enhancing the system's safety and efficiency for detecting payments.

Another up-and-coming sector in the field of biometric technologies is voice recognition. A lot of complex processes involved in the collection of voice samples, such as user registration, speech extraction, feature extraction and commitment, and recognition pose challenges that are difficult to surmount. These process efficiencies and complexities are applied to a range of their corresponding applications. Most importantly, voice is also one of the biometric technologies in digital payments. The majority of digital assistants in payment applications are digitized for ease of use by their users, and their primary applications are biometric systems and digital transaction security.

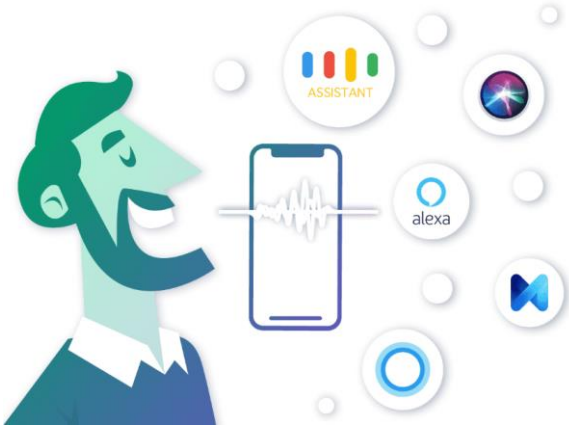

Fig 3: Voice Authentication

3. Integration of AI and Big Data in Biometric Authentication

Machine learning algorithms are used to design and develop the biometric template generation and verification unit since, daily, the related data become enormous in volume, variety, and velocity. A big data storage device, a NoSQL server, is set up on different computer systems to store this data. Furthermore, various transactions occur in the payment system. Each transaction forms a data set of multiple attributes known as the template. Then the machine learning algorithm is executed to construct the relevant problem field in the field of the training data. At the final layer, all the work is integrated into an AI model system to execute the entire work process, generating the output according to the required model. Furthermore, the AI biometric authentication collects the representative data in association with user accounts and, using templates, matches the testing features data with the registered template. Moreover, the similarity measure method is applied to compare the testing features, and utilizing the similarity threshold verifies as zero or one.

In the digital world, identity verification has become an important issue, and biometric technologies such as fingerprint, face recognition, and eyeball scans are receiving increasing attention as a method of identity verification in financial digital services. These biometric technologies have several weaknesses such as being easy to modify and replicate by malicious users. To improve the security of biometric verification, research into biometrics using ECG (Electrocardiogram), which is difficult to forge, has been conducted. In a digital financial market using the ECG biometric method, enormous workings, and real-time processes should be executed since interruptions in the sector lead to unfair losses to users. To provide the fast and efficient biometric authentication system required by a payment-processing financial firm, AI (Artificial Intelligence) is employed, and, in terms of the large amount of data in these processes, big data is also being used.

Technology, AI, and big data play a crucial role in the development of the field of biometric authentication. How are these technologies introduced in the realm of biometric authentication and utilized in this section?

Fig 4 : Artificial Intelligence (AI) Is Used In Biometrics

3.1. Machine Learning Algorithms for Biometric Data Analysis

Another group of machine learning algorithms can be termed self-learning, as they can automatically build their models from raw data. Although the majority of machine learning frameworks are conceptually similar, each is governed by a distinctive algorithm. Some of the most common methods for both supervised and unsupervised learning include Artificial Neural Networks, as seen in deep learning systems. Initially, the inputs are calculated using initial weights. These inputs are then modified iteratively until the outputs closely resemble the specification. The advances made in this area have been phenomenal thanks to the convergence of big data-driven analytics, deep learning, and other machine learning techniques. To utilize biometric data for authentication, the concept for training such algorithms is based broadly on the distance computed between

analyzed data and the gallery. The gallery serves as the authentic or genuine database meant for comparison. Moreover, many of these algorithms can be continuously trained by updating them in real-time.
Artificial intelligence plays a significant role in the authentication process with biometric data. Machine learning algorithms process millions of input parameters to recognize a certain image or sound. These parameters or attributes are automatically created by the same algorithms based on the input data. Proper algorithm construction and parameter determination ensure that the output produced by the machine learning model suits our requirements. By altering parameter values or developing new models, many machine learning algorithms are continually recalibrated. This endows them with a high degree of flexibility and adaptability to various subjective or objective demands.

3.2. Big Data Processing and Storage for Biometric Authentication

When a digital payment transaction is requested, the user's credentials are sent to the data-processing unit where the transaction is hashed. Then, that hash is utilized to generate exchangeable biometric vectors. These vectors enable the completion of biometric-based payments with efficiency, taking very little time when reading biometric vectors. Finally, integrating big data technologies has significantly impacted security and efficiency through improved verification and authentication, processing, and storage in real-time. This makes authentication robust and effective against risks including hacking, denial of service, malware, etc., thus resulting in the reduced cost associated with biometric alteration, commitment of financial crimes, and chargeback of the transactions caused by unauthorized card issuance. Hence, it has allowed biometric authentication to be an undeniably seamless real-time efficacious payment method that can be analyzed and continuously improved.
Big data analytics refers to the examination of huge volumes of data gathered from multiple sources, especially to analyze these data in real-time. Big data analytic technology has made it easier to predict and detect fraud in the payment industry when combined with credit card transactions or other personal data and records. In addition to this, AI can be integrated with blockchain technology, thus eliminating single points of failure and providing maximum security due to decentralization.
Biometric authentication technologies based on markers are being widely explored in the digital payments domain. Biometric data involves the use of physical or behavioral characteristics such as the fingerprint, finger geometry, hand vein and eye retina images, face, DNA, handwriting, and the mouse carrying style during signature, etc., for authenticating humans. Big data processing technologies include Apache Hadoop, and big data storage technologies consist of file systems like Hadoop distributed file systems (HDFS), MapReduce, and HBase. These technologies play a significant role in storing and processing structured and unstructured biometric data efficiently.

4. Benefits and Challenges of Biometric Authentication in Digital Payments

A growing body of evidence has identified that biometric information can also be used to create or strengthen a new digital payment ecosystem as it offers several advantages to users. First, using an individual's physiological or behavioral characteristics as a form of payment makes identity theft and access to personal information more difficult. Face, blood vessel, finger geometry, fingerprint, palm print, iris, retinal, signature, gait, keystroke patterns, and voice patterns are all unique and do not frequently change over time. Thus, the use of biometric authentication can protect customers from fraud. Second, payment performance has improved. Indeed, the process is faster and less complicated since cards or identification of the buyer is not necessary. Buyers simply need their unique biometric characteristics to authenticate a transaction (e.g. fingerprint, face, etc., or combination). However, there is also a potential downside as its implementation may pose privacy concerns: the unauthorized use of biometrics can have more serious concerns because an individual is forced to cancel or replace what they have. Not all individuals will be able to give permission so readily. Ethical issues must be taken into consideration when deciding how to use biometric data. Biometrics do not — and should not be able to be — changed if it is compromised or used without the individual's knowledge. That is why its use in identity verification and to secure identity requires careful consideration.
The digital payment landscape is, in many ways, an open book. Every action taken, transaction made, account used, and receipt stored can be digitally tracked. This makes electronic payment an essentially transparent payment method - one that utilizes various technologies to limit the risk of loss, theft, or fraud. Biometric authentication offers two key benefits for the use of electronic payments: 1. It increases the security of the electronic payment process by requiring legitimate users to access this payment process using their unique physical or behavioral characteristics. Hardly or infrequently do two people display the same biometric features, which makes it unique. 2. It provides greater certainty and convenience for customers, who no longer need to remember passwords to execute a transaction. This is because biometric authentication provides access through direct personal identification based on physical traits.

Fig 5 : Benefits of Biometric Authentication

4.1. Enhanced Security

In summary, biometric tools exploit unique elements of the human body to verify and/or establish and confirm identity. When used to facilitate a payment, the credit/debit/identity card is reassigned to its true owner. The amount of personalization necessary before a biometric mechanism can be successful reinforces the match efficiency of the method. Any biometric mode provides exceptional security because it relies on data and properties the user explicitly or implicitly recognizes. Therefore, only the rightful user will have access to the biometric sign necessary for its proficient validation. In this way, the usage of biometrics in payments prevents fraudulent activities and provides both credit card and individuality authentication with a robust shield.

Biometric authentication enhances digital payment security using multiple built-in security layers as they have several unique characteristics and are immutably linked to the individual. This adds security against unauthorized access to the customer's data. Through the provision of an additional validation of identity and ensuring not only does the cardholder hold the physical card or mobile device but also is present physically. This can reduce the consequence of fraud by increasing the level of complexity and confidence in the customer's identity, preventing unauthorized financial transactions, and limiting cases of identity theft. Because biometric authentication systems are unique to each customer, this will mitigate unauthorized access to the customer's financial account. The use of impervious biometrics and AI adds an increased level of security and certainty in facilitating real-time transactions globally, ensuring access only to authorized personnel and customers, thereby protecting their privacy.

4.2. Convenience and User Experience

It was also found that the reason new technologies were appealing to potential users, apart from the easy and quick login process inherent in biometrics, was that "51%...believe that biometric authentication is going to be better than physically having to pay with cards or cash in stores." Biometrics are also preferred for government services. Given the corroboration of these instances, it can be speculated that the drivers of biometric usability will also be conducive to the customer experience. Based on the findings on the efficiencies of biometrics earlier in this paper, it is suggested that biometric authentication might be an adequately comfortable, convenient, and quick feature for customer transactions. Thus, 8% believed that "it is going to be very convenient if I can confirm my transaction with my fingerprint each time I am making a transaction on my mobile." This speculation is corroborated by other studies, including research on smart cities and healthcare management, that concurred and opined that the main advantages of biometric use in the context of their studies included improved access control, client satisfaction, and smoother transactions.

Biometric authentication is a convenient security measure, helping to offer a user-friendly experience and increasing safety. With millions of transactions occurring daily, across various digital platforms and supported by different applications, payment security and customer satisfaction are of vital importance. Financial institutions, when conducting Internet and mobile banking, have their clients undergo a secure login process. When these clients wish to perform a transaction of any kind, they must go through this login process even if the biometric login feature is installed. With responses ranging from 3 to 5, with 5 indicating the strongest level of agreement, many individuals view the password entry process as "time-consuming" (49.5%), "over-complicated" (21.7%), and "inconvenient" (21.2%). Furthermore, a large percentage of the respondents (60.8%) strongly agreed that they "hate remembering passwords".

4.3. Privacy Concerns and Ethical Considerations

Moreover, there is criticism in practice where only one staged policy, driven by technical installation and concerns that lack actual evidence in value, is being made. There are other supplementary ethical issues but will focus in detail on these key areas. In all of the areas discussed, there are complex issues but when viewed in light of Mañero's framework. Furthermore, looking at these many specifically, concern is also concerning our capacity as a world society including 'global citizens' but also global corporations and states to overlook some key ethical considerations in pursuit of technology development and to do so for their vested interests. Given the complexity of these issues, there are not just technical or ethical challenges but societal ones too. What is needed is a societal paradigm around the morality, social grace, and character surrounding society-wide information technology.

The perceived ethical implications of employing biometrics in digital payments could be further classified into a variety of areas including justice, censorship, freedom, autonomy, and consent. Specifically, from a moral or

ethical viewpoint, concerns are related to developing highly effective, human-mimicking, data-dependent systems on whom defense is based. However, with knowledge of numerous technical inadequacies, detection performance, and various other ways, these systems can be circumvented. Users do not see a proper acknowledgment of these intrinsic detriments. Also, people's unique digital embodied characteristics, owned by their bodies alone, are physically attainable. Among these are biometric data including fingerprints, iris images, DNA maps, and dynamics patterns. All of these could be utilized for person verification. It highlights the response time needed in the usage and provision of such digital representations and thinks widening the variety of equipment and ongoing, even compulsive, authentication is a tool of liberation. Lastly, the challenge in maintaining user, citizen, consumer, etc. participation in deployment decisions is related to identity management systems and security mechanisms, including biometrics.
Innovations in technology have sometimes provoked unintended consequences in terms of its usage, unveiling privacy concerns, such as those linked to tapping into voice data and ethical considerations. A pertinent privacy concern is the possibility of accidental accumulation of data regarding the user's biometrics and other sensitive information. As shared databases pose a high potential for misuse, some have indicated privacy concerns about the creation of centralized biometric identity databases – a case in point being the Aadhar program in India. Another approach is a decentralized way to keep biometric information isolated on the user's device.

5. Case Studies and Real-world Applications

Case Study 2 (WeChat Pay): WeChat in China not only supports standard payment methods but also a QR code-based system known as WeChat Pay along with its counterpart (Alipay from Alibaba's popular Taobao e-marketplace). WeChat Pay went live in 2013 and in 2014, it introduced a new feature that enabled users to recharge their mobile phone accounts with a monetary value stored in their QQ Wallet through the recording and meaningful interpretation of the user's voice. This voiceprint recognition system now allows users to verbally manage a large part of their payment workflows and provides the secondary benefit of ease related to user behavior shift.
Case Study 1 (Apple Pay): Apple began its takeover of NFC-enabled payments in retail by leveraging its position in the market as a product innovation leader to quickly integrate state-of-the-art biometric security as a trust enabler for financial transactions. With the introduction of the iPhone 5S, Apple standardized and popularized the use of fingerprint (Touch ID) for unlocking the device and authenticating on-platform purchases, via Apple Pay. With the move to an all-edge-to-edge display and the removal of the home button for the iPhone X, Apple shifted device-specific authentication to a custom implementation of facial recognition called Face ID and once again used this biometric to digitally sign and bind payment transactions on the new XR, XS, and XS MAX models. Today, Apple has roughly 60 million active Apple Pay users worldwide through more than 30,000 participating banks.In this section, we describe some real-world applications of biometric authentication in digital payment systems, especially in mobile platforms, with notable examples of Apple Pay and WeChat Pay.Biometric authentication has become a cornerstone of digital payment security, significantly enhanced by the integration of AI and big data technologies. By leveraging real-time data analysis and advanced machine learning algorithms, biometric systems can now provide robust, adaptive security measures tailored to individual user profiles. For instance, facial recognition and fingerprint scanning technologies, supported by AI, can swiftly verify identities and detect fraudulent activities with remarkable accuracy. Real-world applications include seamless mobile payment solutions where users authenticate transactions through a quick fingerprint scan or facial recognition, reducing friction and enhancing user experience. Additionally, big data analytics plays a crucial role in monitoring and analyzing vast amounts of biometric data to identify patterns and anomalies, enabling proactive security measures and real-time fraud prevention. This synergy of biometric authentication, AI, and big data not only fortifies digital payment systems against threats but also streamlines the payment process, offering both heightened security and unparalleled convenience for users.

Fig 6 : Biometrics (facts, use cases, biometric security)

5.1.Apple Pay and Face ID

calls attention to biometric multi-factor authentication functions on mobile devices with fewer traffic channel options by using the Apple scenario as an example. Not only used in bio-authentication to access Apple Pay, but Face ID facial identification also recognizes depth perception as an additional feature to open, sign, and authenticate transactions in-app and online. This restriction to a proprietary ecosystem permits secure user device interaction through which verified users can quickly transact with added detail like thumb reader

biometrics, distinct identification markers, or hard-to-relay personal identification numbers (PINs) until a differing service channel is selected. While there are privacy and ethical concerns that arise with the utilization of Face ID and payment histories by Apple and its user data retention extension as a means of supporting the product, it has shown the practical implementation, impact, and preferences of companies to adopt FRS. Moreover, Apple has stronger spending patterns as a result of Apple customers being more loyal and wealthier. Apple Pay, Apple's proprietary digital wallet and mobile payment service, does not store personal information on the device, nor does the service share it when you make a transaction. Furthermore, Apple Pay replaced the base layer of passcodes for biometric authentication methods in 2017. This is demonstrative of the rapid and widespread adoption of biometric authentication for many digital convenience tools. Case in point, over half of all U.K. smartphone users have made a payment through a mobile device in 2021, according to Statista Digital Market Outlook. Integrating these convenient tools usually does not require much more than registering a personal fingerprint or type of FRS, such as Apple's Face ID. For iPhone X and later models that omit biometric scan data from device backups in the first place, user logins also convert immediate biometrics for access to Apple Pay at payment. This equips Apple Pay with biometric authentication via Face ID, which turns encountering face data into biometric verification both in-store, in-app, and online.

5.2. WeChat Pay and Voice Recognition

WeChat is a Chinese multi-purpose messaging, social media, and mobile payment app developed by Tencent. Voiceprint, voice-controlled passwords, and face recognition are available for users who have already opened WeChat Pay wallets. The question arises: can the prospective WeChat user trust such a new, or even unknown, technology on an unknown and unproven platform with unseen users? Indeed, the mitigating controls might not be used to verify digital identity in this case, being hated for causing service disruptions, hence the adequacy of the identification technology employed might be considered—the identification principle called "the handshake problem". From a security management perspective, the use of biometrics subsumes both technological and organizational issues because the use of sensitive personal data, collected mainly in sensitive transactions (e.g., financial), involves legal issues, data privacy, and ethical concerns. However, contrary to the speech recognition interface employed on the Taiwan High-Speed Rail, which we have introduced in the subsection above, this interface is used for automated voice commands for paying via a mobile wallet for groceries, as done by the lead researcher from the Pinduoduo Research Institute in 2012 when she lives in China. This suggests that the speech recognition interface is branding the idea using existing services. Thus, the more biometric identification becomes a criterion for service, the more biometric and digital transaction surveillance will be integrated.

6. Conclusion

Innovations in payment solutions have made e-commerce recognized today. Significant improvements are in progress to offer the most viable options for business or point-of-sale credit card processing. Biometric authentication can be broken down into three distinct categories: something you are, something you have, and something you know. The best example of digital payments makes use of three secure elements together to prevent default fraud. A payment card is something that is in the owner's possession. The owner possesses a secret PIN (Personal Identification Number) so that out-of-pocket usage can be insured. The last is something the owner is, and the owner will provide a facial scan, fingerprint, or voice command. Biometric scanning guarantees that facial scanning of the registered cardholder is distinctive and establishes an online payment.
Facial recognition had been a popular biometric in the past before leading players like Apple and Facebook disabled the technology due to racial bias. With increased computing power and algorithms, this technology will likely make a comeback as the required simplicity and technology development will be hard to ignore. There is also a trend in other fields to begin using it for a variety of potential applications beyond an access control system or security system. While these are the biggest trends, there is still much more room to grow in the biometric space as new possibilities are created. In addition to the Big 4, biometrics could advance through other identification measures such as DNA testing or iris scans. Dental biometrics come with an innovative method of identification in which an individual's bite is recorded for future purposes. As the technology continues to develop, these alternatives will become increasingly realistic for everyday use in security and payment applications.

6.1. Future Trends

In the coming years, innovative AI will be able to process biometric data with big data for real-time computing algorithms to understand the normal behavior of the user. Moreover, the AI will be incorporating incremental biometric learning to increase the repositories of payment service users with biometrics to provide different levels of digital payment transactions. Optimal utilization of the algorithms will provide real-time biometric authentication. The more information it has, the better will be the accuracy in the fast pace. Our devices will also be using multimodal biometrics for mobile payment systems. AI decision-makers in a distributed fashion, which controls the security at different endpoints in the CNP payment system. This includes the inclusion of multimodal sensors for better security. In the coming years, biometric capabilities of wearables and implantables can translate to receive and send payments and can be utilized for mF2F and mCP payments. The

real-time computing algorithms will be securing more IoT digital payment devices for a new era of biometric security.

1) Faster algorithms: The AI algorithms that are utilized for processing the biometric signals in deciding the authentication will become faster in terms of processing time required, in the range of milliseconds. Faster processing will lead to faster authentication of the transaction with less computational power required, which will decrease the power consumption of the IoT devices.

2) Utilization of Big Data: The AI and IoT devices will be incorporating big data to have a real-time understanding of what is normal/customer behavior, to detect abnormal behaviors, to update the models/patterns in real-time, and to detect frauds at the same time. Moreover, for fraud detection and response, big data, AI, and IoT devices can be utilized to have a full in-depth view of the fraud at hand and implement the best practices and procedures automatically.

3) Utilization of contextual information: The AI will be utilizing Contextual Biometric Artificial Intelligence (CBioAI) to process the biometric data signals along with the context information to have a tiered security approach to increase the security and provide different security measures for varying levels of transactions on the CNP payment systems.

4) Incremental learning algorithm: Artificial intelligence will be using incremental learning algorithms to enrich the biometric repositories of the payment service user. The more information is available for an AI, the better it can be at deciding on authentication for digital transactions.

5) Multimodal Biometric Devices: The upcoming devices will have multiple biometric capabilities to provide multimodal authentication for users. Moreover, these will be implemented with radar, camera, fingerprint scanner, and heart rate/pulse detection in a single practical smartphone.

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Review Article

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An Evaluation of Medical Image Analysis Using Image Segmentation and Deep Learning Techniques

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ABSTRACT

These days, the identification of brain tumours has become a standard medical cause. A braintumour is defined as an abnormal mass of tissue in which the cells develop uncontrollably and suddenly; in other words, there is no control over the rate of cell division. To isolate the aberrant tumour location inside the brain, image segmentation is used. The division of brain tissue is a crucial step in the MRI process for determining if outlines of a brain tumour are present. This research used an object segmentation algorithm to separate items in MRI data. In segmenting objects related to brain tumours in MRI images, a linked component labelling approach is used. Analyzing many deep learning pre-trained models for brain tumor detection to be used in various real-world scenarios is the focus of this paper. A goal of this research is to assess the performance of DL in diagnosing brain tumours. The goal of this study is to assess and compare the three advanced DL models: ResNet-18, AlexNet, and VGG-19. This work operate on the Brain Tumor Classification (MRI) dataset which has several tumour classes for classification. The process of automating the detection of brain tumors also goes through several phases characterized as data pre-processing, image standardization, segmentation and extraction of characteristics features. The experimental investigation assessed the models according to accuracy, sensitivity, as well as specificity. It shows that a ResNet-18 model has a higher accuracy of 93. 80% than other models, seconded by VGG-19, which has an accuracy of 91. 27%, and AlexNet with an accuracy of 87. 93%. These results demonstrate that the suggested ResNet-18 model may aid in the enhancement of medical image analysis and performs better in image classification for brain tumour detection.

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Introduction

The health sector is under increasing pressure to use cutting-edge technological solutions to address the growing number of diseases in this age of unparalleled change. Among these diseases, the most deadly one that humanity has encountered so far is the brain tumour. It is quite unlikely that a treatment will be found in time to save a patient's life, even if an illness is diagnosed in its early stages. The tumours may be categorised as either benign ormalignant. On the other hand, malignant tumours include cancerous cells that might possibly be fatal to the patient, but benign tumours do not represent any harm to medical safety. Everyone knows that a brain is a important component of a human body; whatever happens to it will have a direct effect on the patient's expected lifespan [1]. The famous medical tool known as MRI is used for the diagnosis and analysis of several ailments, including brain tumours, neurological disorders, epilepsy, and many more. Usually, this method may be automated to provide rapid and accurate results using a computer-based approach [2]. Concurrently, many applications in computer vision and image processing rely on image segmentation as their primary function. The hash algorithm relies on segmenting the image into subsets defined by predefined metrics in order to facilitate further processing. Commonly, medical professionals may manually use MRI imaging to detect brain disorders [3]. Fatigue and an overabundance of MRI slices are two of the many reasons why the large-scale manual inspection approach might

contribute to incorrect interpretation. Also, there is both intra- and inter-reader variability since it is not reproducible [4].

A valuable adjunct to the infamously challenging area of brain tumour surgery, AI plays a substantial role in the identification and diagnosis of brain tumours. New AI subfields, such as DL and ML, have completely altered neuropathology procedures [5]. Image segmentation approaches have been greatly enhanced by the rapid advancements in AI, especially DL. While it comes to image segmentation, the results of DL-based methods are rather higher than to do the same conventional multiple learning and computational vision methods as for speed and accuracy [6]. Specifically, the use of DL for medical image segmentation enables accurate estimation of tumour size and quantitative evaluation of treatment efficacy. These approaches are complex and involve several procedures such as feature extraction, data preprocessing methods, feature reduction, feature selection methods, and classification [7]. Apart from DL, there is the possibility of developing other segmentation techniques that are more reliable and precise than the current methodologies [8]. Image segmentation can hence be regarded as a classical methodological paradigm of the early stage of the development of the field of ML, which has only recently risen to the mainstream of the DL domain [9]. On the other hand, CNNs and other DL technologies changed the face of image segmentation process by enabling automated feature extraction and obtaining hierarchical representation [10]. CNNs that are deep learning algorithms have been proven to produce excellent results in image related tasks that include object recognition and segmentation.

Research Contribution and Objectives

This study aims to address the challenge of brain cancer classification by using DL methods on the brain tumour Classification (MRI) dataset. This research will use CNN architectures to classify MRI images into particular categories, such as glioma, meningioma, and pituitary tumours.This study aims to assess an efficacy of DL models in precisely differentiating various tumour types, as well as investigating the possible advantages and constraints of using these methods in a clinical environment. The resrach contribution of this work as:

- **Model Performance Improvement:** Demonstrated that ResNet-18 outperforms VGG-19 and AlexNet in classifying braintumors from MRI images, highlighting a benefits of advanced deep learning architectures.
- **MRI Preprocessing Techniques:** Provided a detailed preprocessing pipeline for MRI data, including greyscale conversion, resizing, and augmentation, which enhances image quality and model performance.
- **Comparative Model Analysis:** Compared ResNet-18, VGG-19, and AlexNet, offering insights into their effectiveness for brain tumor classification and setting benchmarks for future research.
- **Evaluation Metrics Framework:** Emphasized the use of accuracy, sensitivity, and specificity metrics for evaluating deep learning models, contributing to reliable medical image diagnostics.

Organization of the Paper

A following paper are organizaed as: Section I and II provide the introduction of topic with research contribution also existing literature review on this topic with comparative summry. Section III provide the methodlogy of this work with proposed flowchart and each methods. Section IV discussed a results and discussion of the DL models with comparative analysis. Section V provide the conclusion of this work with future work and limitaions.

Literature Review

Various techniques for medical image classification based on DL, such as transfer learning, CNNs, ML, and hybrid approaches, are covered in this section. Research into tumour segmentation is an active field. A recent validation study confirmed the usefulness of DL for analysing medical images.

In, use a suite of data pre-processing methods to improve the overall dataset and highlight specific features within the original data [11]. The enhanced DeepLab v3+ segmentation DCNN was another DL model that improved prediction and training performance on the thyroid nodule dataset. Dice similarity coefficient of 94.08% and accuracy of 97.91% are measured in the findings, demonstrating the advanced nature of our technology.

To, provide a deep levelset technique to enhance an accuracy of object segmentation and increase object boundary details [12]. We use enriched previous information into CNN's inputs to provide a level set evolution result with a more precise shape. We assess the suggested approach using two sets of medical imaging data: retinal fundus pictures and prostate magnetic resonance images. The experimental findings provide advance performance from a proposed method.

In, offers a neural network architecture that may be used to segment medical imaging data. Our selection is to conduct experiments and use different CNNs [13]. We decided to use this study on the segmentation of cerebral images that include brain tumours. Selecting the optimal architecture and parameterisation to be applied to an MRI brain tumour job while managing a small database is the primary goal. Our customised CNN architecture performs well in segmentation and learning evaluation tests.

Within this framework, create two models for anatomically directed segmentation: AG-UNet and AG-FCN [14]. Anatomically gated U-Net and fully convolutional network are the acronyms for their respective names. Results in ROI segmentation of brain MR images using the proposed AG-FCN and AG-UNet algorithms outperform other state-of-the-art methods when evaluated on the ADNI and LONI-LPBA40 datasets.

In, A DL model is used to categorise the three most prevalent forms of brain tumours: pituitary, glioma, and meningioma. With a time-efficient categorisation approach, this research aims to reduce the workload for clinicians. Ninety percent accuracy is possible using the developed method [15].

In, created a cutting-edge deep-learning segmentation model called MultiResUnet [16]. This model has 2 section: an encoder for capturing features and a decoder for accurate localisation. According to experiments conducted using LOOCV and ground-truth image comparisons employing Tanimoto similarity, MultiResUnet achieves an average accuracy of 91.47%, which is almost 2% better than the autoencoder. An improvement over our earlier model, MultiResUnet provides a method for segmenting breast IR images.

In, For the automatic identification of tumours in brain scans, a CNN-based technique is suggested [17]. The approach is evaluated using MR brain images provided from the Harvard Medical School database. The study makes use of three pre-trained models: Inception, ResNet, and VGG16. It is possible to reach 100% accuracy on the tested database.

Inspired by the recent achievements in using DL techniques for medical image processing, first provide an algorithmic architecture for cross-modality fusion in supervised multimodal image analysis at a classifier, feature learning, and decision-making stages [18]. When contrasted with networkstrained on single-modal images, a multimodal network performs far better. Rather of fusing pictures at the network output (i.e., voting), it is usually preferable to fuse images inside a network (i.e., at convolutional or fully connected layers) while doing tumour segmentation. In order to help with the development and implementation of multimodal image analysis, this study presents empirical recommendations.
Table 1 shows the performance results of the related works.

Table 1: Summary of Related Work on Image Segemntion and Classification on Medical Image Analysis

Ref	Methodology	Performance	Limitations	Future Work
[11]	DeepLab v3+ segmentation DCNN for thyroid nodule dataset	Dice similarity coefficient: 94.08%, Accuracy: 97.91%	Limited to thyroid nodules; may not generalize to other tumors	Explore generalization to other types of medical images
[12]	Deep level set method with CNN for prostate and retinal images	State-of-the-art performance	Limited to prostate and retinal images	Apply method to a broader range of medical images
[13]	CNN architecture for brain tumor segmentation from MRI images	Good performance on small database	Performance on small database may not be generalized	Test on larger datasets and other types of brain tumors
[14]	Anatomical gated FCN and U-Net for ROI segmentation of brain MR images	Superior performance compared to advance methods	May require significant computational resources	Improve computational efficiency and test on more datasets
[16]	MultiResUnet for breast IR image segmentation	Average accuracy: 91.47%	Limited to breast IR images	Apply model to other medical imaging modalities
[5]	Deep learning models for classification of Glioma, Meningioma, and Pituitary tumors	Accuracy up to 90%	Focused on common tumor types only	Explore classification for a wider range of tumor types
[17]	CNN-based tumor detection using ImageNet pre-trained models (VGG16, ResNet, Inception).	Accuracy: 100% on Harvard MRI dataset.	Overfitting on a small dataset; limited generalization to larger datasets.	Test on larger, more diverse datasets; enhance real-time implementation.
[18]	Multimodal image analysis with cross-modality fusion at feature, classifier, and decision-making levels	Superior performance with multimodal images	Complexity of multimodal fusion	Refine multimodal fusion methods and test on diverse datasets

Methodology

The process for classifying brain tumour pictures starts by gathering the Brain Tumour Classification (MRI) dataset, including 3,264 images representing four different kinds of tumours. In the data preprocessing phase, all photos undergo greyscale conversion and are then enlarged to dimensions of 224x224 pixels. Greyscale photographs, consisting only of various shades of grey, depict the light intensity shown at each individual pixel. An use of filtering techniques serves to enhance the quality of images, including sharpening filters to amplify fuzzy features and smoothing filters to diminish noise. Edging is a process used to identify sharpness in captured photographs. Following that, image augmentation is used to improve a predictive capacity of a model. Following a preprocessing stage, the braintumour areas are divided into segments, and contrast modifications are used to enhance the segmentation. Extraction of features is performed to obtain significant characteristics from the photographs. Training and testing runs are divided using an 80:20 ratio of the dataset. The employment of three DL models—ResNet-18, VGG-19, and AlexNet—led to the calculation of performance indicators like accuracy, sensitivity, specificity, and precision. By evaluating and contrasting the models using these measures, the top performing model was ultimately identified. A potential approach for categorising brain tumours is shown in the flowchart in Figure 1.

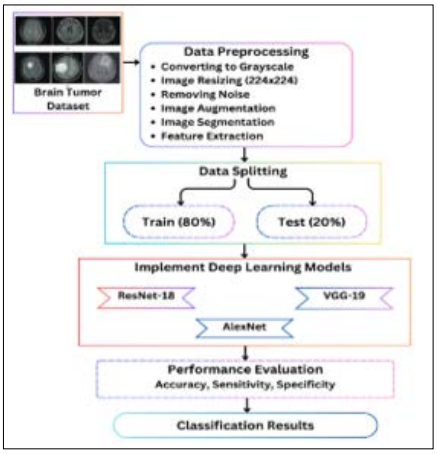

Figure 1: Proposed System Flowchart for Brain Tumor Identification

Dataset Description

An extensive open-source collection developed to aid in the interpretation of medical images—more especially, in the classification of brain tumors—the "Brain Tumour Classification (MRI)" dataset is available on Kaggle. With a total of 3,264 T1-weighted, contrast-enhanced MRI images, the collection is

organised into two main files: one with 28,70 images for training and another with 394 images for testing. The photos depict four well-defined categories: pituitary gland tumor (901images), glioma 826 images), meningioma (937images), and healthy brain (500images). Every picture in the collection is specifically labelled to indicate its category, making the dataset appropriate for the training of DL models in a classification of braintumors. Due to the fact that using machine learning methods it is possible to obtain a development of diagnostic systems capable of accurately diagnosing brain abnormalities, this resource is useful. It also has the utility of enabling medical research as well as improving the effectiveness of algorithm approaches in medicine. Sample images from a dataset to classify brain tumour are presented in Figure 2 below.

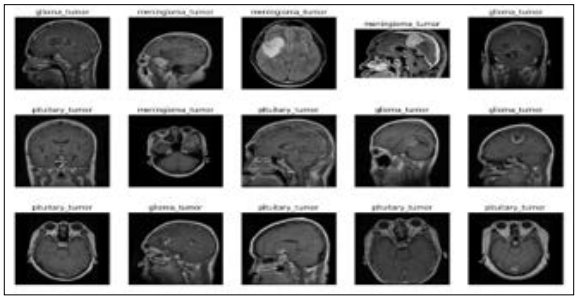

Figure 2: Sample Images of Brain Tumor Classification (MRI) Dataset

Data Pre-Processing

Data preparation remains the vital steps in each and every machine learning procedure. During this data preprocessing phase of this work all MRI pictures are first converted to greyscale. In this format, each pixel is representing the intensity of the light making easier the analysis of an images. After maintain consistency and compatibility with deep learning models, all these photos are then resized to 224 x 224 photos. There are numerous filtering procedures that are utilized to improve a quality of image and sharpening filters that are used on a fuzzy features of images, whereas, the usage of smoothing filters reduces the noise. Shading is also done in order to define the sharpness and boundaries in the photographs. To expand the dataset and enhance the model's prediction capabilities, it also employs image augmentation methods including flipping, rotating, and zooming. After preprocessing, the tumour fields are partitioned into segments and contrast adjustments for the enhancement of picture are applied.

Image Segmentation

During the data preprocessing phase, segmentation is critical to identifying brain tumors in MRI scans with high levels of accuracy. This process involves segmentation of images whereby the tumor areas are separated from the normal tissues by partitioning, thresholding, region growing and edge detection. Subsequently, enhancements are made upon the contrast in order to give more prominence to the tumor regions. These segmentation steps guarantee that the DL models' analysis concentrates on the tumor features in question, enhancing the classification algorithms' reliability.

Visualisations Results after Preprocessing

Maximizing the use of the given dataset and finding the hidden pattern in the data is crucial. The present work applied tools of data visualization that allowed to represent hidden patterns or trends in the data properly.

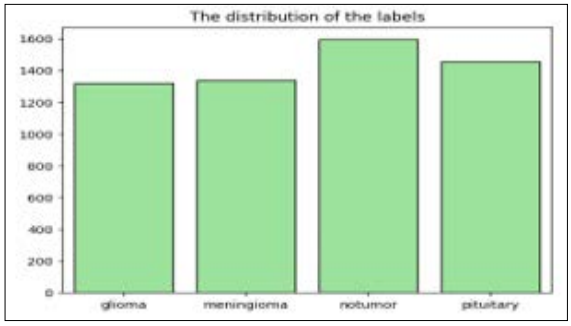

Figure 3: Count Plot for Distribution of Labels

Using count plot, the proportions of the labels in the brain tumor classification dataset are depicted in figure 3. The x-axis of plot signifies tumor classes such as glioma, meningioma, no tumor, and pituitary The y-axis in plot represents count of every tumor class starting from 0 up to 1600. The spi of the bar graph that shows information regarding the count of glioma tumor class is noted to be approximately 1250 and that of the meningioma tumor class is approximately 1300 while that of no tumor class and the pituitary tumor is noted to be approximately 1600.

Deep Learning-Based Classification Models

This section offers a complete analysis of three DL models in order to better understand their potential for identifying brain tumours.

VGG-19

Figure 4 displays the architecture of a CNN called VGG19, which consists of 19 layers. Developed by a separate group at Oxford University called the Visual Geometry Group, VGG builds upon and improves upon the concepts of its forerunners. It improves accuracy by building on previous systems' concepts and principles and by adding deep convolutional neural layers [19].

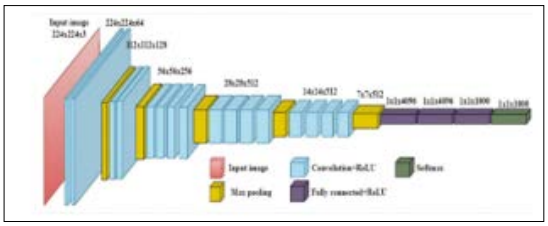

Figure 4: General Architeture of VGG-19 Model

Images may be recognised using VGG, an advanced CNN. The network's usage of an RGB image with a fixed size of 224 × 224 as input indicates that the matrix was constructed, and the characteristics of the data set were (224,224,3). To begin with, no preprocessing was carried out beyond averaging the RGB values of all the pixels in the training set. The entire image might be covered by their 3 × 3 pixel kernels with a stride size of 1 pixel. In order to maintain the spatial resolution of the image, spatial padding was used. While previous models made use of tanh or sigmoid functions, this one employed max pooling 2 x 2 pixel windows with Stride 2. ReLu

AlexNet

AlexNet is a large-scale network structure with 650,000 neurones and 60 million parameters. It far outperformed conventional techniques, highlighted the possibilities of DL, and set the stage for the later creation of DCNNs. An important advancement in image classification tasks was made by AlexNet [20]. The network's design was an eight-layer DCNN. There are three

Fully Connected (FC) layers and five convolutional layers in the eight layers. To guarantee neurone activity, the softmax layer's function is to regulate an output in a range of (0,1). A softmax layer's normalisation procedure was represented in Eq. 1.

$$softmax(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} \dots\dots\dots (1)$$

where *n* is a dimension of the input tensor and *xxii* is also its ii^{th} predicted value. ReLU were one of AlexNet's ground-breaking inventions; by employing ReLU as activation functions, training convergence was significantly accelerated. Additionally, AlexNet made good use of dropout and data augmentation methods to assist avoid overfitting. In addition to having a significant impact on many later designs and cutting-edge CNN research, AlexNet was also a major component of earlier CNN generations.

ResNet-18

Figure 5 displays a squeeze-and-excitation Basic Block (SEBB) module, which is a foundation of a DL-based ResNet model. There are a total of twenty-two layers in this design, including a fully connectedlayer, a global average poolinglayer, CV1, SEBB, CV2_x, CV3_x, CV4_x, and CV5_x. The CV1 is made up of the following layers: Convolution, Batch Normalisation, ReLU activation function, and Maximum Pooling [19]. The following parameters are currently used by the Convolution layer: stride-2, Padding-3, and a 7x7 kernel. Following this, stride-2, padding1, and a 3x3 kernel size are all part of a maximum poolinglayer's configuration. Use of a maximum poolinglayer results in a drastic reduction in both dimensions and parameters. This approach must conserve substantial feature information while simultaneously increasing the receptive fields. ResNet-18, which includes both a SE module and a residual basic block, is linked to the SEBB module. The last is the rest of the ResNet-18 network, which includes two Convolution layers, named Convolution layers 3 and 4. The basic building block of a SEBB module is a combination of the SE module and the residual block. As stated earlier, the stride-1 and 3x3 kernels represent two of the Convolution layers within the SEBB module.

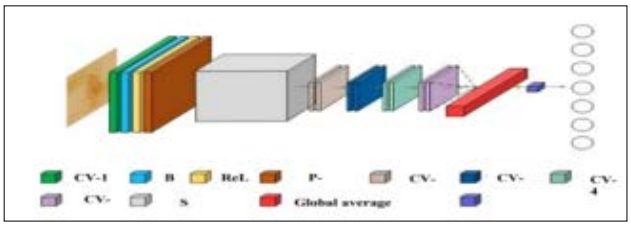

Figure 5: Architecture of ResnNet-18 Model

The model architecture comprises of two convolutional layers, namely CV-1 and CV-2, which are followed by ReLU activation and Batch Normalisation. The squeezing and the excitation procedures are part of the SE module. Here, a global average pooling layer is to convert the feature map to vector. The activation process consists of two Fully Connected layers which include ReLU and another process of Sigmoid. Fully Connected layers are defined by their 1x1xC inputs and 1x1xCx1/r outputs. The purpose of the scaling parameter r is to reduce the amount of channels used for reduction calculation to a minimum. If you take this following Fully Connected layer, its input is 1x1xC and its output is 1/r. This approach scales the 1x1xC vector and then initialises the feature map after acquiring the 1x1xC vector. When the SE module's channel output weights are multiplied by a 2D matrix, the resulting actual feature map size is WxHxC. The relevant feature map of the channel is executed using this approach to get a final solution. There is a global average pooling layer that connects CV-3 to CV-6. This layer fits an output into a 1x1 kernel size and is also called the Adaptive AvgPool function. Finally, the ResNet classification result is 7. This is provided by the fully connected layer. It is also possible to learn and classify the related data using other sorts of datasets.

The ResNet-18 model, incorporating a Squeeze-and-Excitation Basic Block (SEBB), is trained with hyperparameter tuning to optimize its performance. The Adam optimiser is a powerful tool for efficiently reaching the best solution because of its adjustable learning rate capabilities. To find out how well the model's predictions for class probabilities match up with the actual labels, we use the cross-entropy loss function as our classification accuracy metric. In terms of memory efficiency and speed of model convergence, to perform the training procedure it is using the batch size equals to 64. To ensure that the model gets adequate learning without over fitting it is trained for 10 epochs.

Model Evaluation

It is necessary to employ loss and accuracy metrics to assess how well the DL models performed with the test/validation and train/test sets. A training loss represent the ability of elements of a training dataset to fit a model. The validation set is very essential in the process of dataset division where most of the data is used for training purposes while a small portion is set aside particularly for the validation of the model. There are many metrics, but one of them must do with measurement of the DL model's validation loss. The folloqing performance model evaluation measures are discussed below:

Confusion Matrix: The most suitable way to decide on the categorisation system may involve an employ of a confusion matrix. In a confusion matrix, several model parameters are defined which includes accuracy, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). A following performance measures as:

Accuracy: Accuracy therefore measures a proportion of TP predictions to a total probability prediction. It may be accomplished with equation (2).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots\dots (2)$$

Sensitivity: Equation (3) is utilized to define a sensitivity and TP fraction when the system correctly identifies a tumour as a tumour.

$$Sensitivity = \frac{TP}{(TP + FN)} \times 100 \dots\dots\dots (3)$$

Specificity: Specificity refers to the degree to which the system accurately identifies non-tumor as non-tumour, and the real negative rate is determined by using equation (4).

$$Specificity = \frac{TN}{(TN + FP)} \times 100 \dots\dots\dots (4)$$

Where,
Tumour instances appropriately detected and labelled by the model are represented by TP, whereas non-tumor cases that were mistakenly classified as tumours are represented by FP. Unrecognised tumours (FN) are ones that the diagnostic procedure overlooked. True negatives (TN) are those that were precisely as predicted.

Result Analysis And Discussion

Using a confusion matrix and a loss/accuracy plot, this section analyses the ResNet-18 model's performance in classifying photos of brain tumours. Study examines VGG-19, AlexNet, and ResNet-18 models' specificity, sensitivity, and accuracy scores to evaluate their effectiveness in a realm of deep learning.

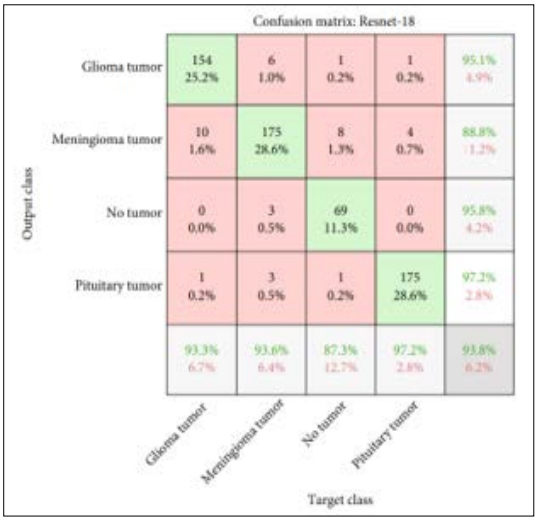

Figure 6: Confusion Matrix of ResNet-18 for Brain Tumor Detection

The effectiveness of the classifier in classifying brain tumour images is shown by a confusion matrix of a ResNet-18 model, which was evaluated employing a testing data, as shown in Figure 6. The confusion matrix's x-axis displays a target class, and a y-axis predicts an output class. According to the presented data in the confusion matrix, the ResNet-18 model accurately predicts 154 or 22.2% images of glioma tumor, 175 or 28.6% images of meningioma tumor, 69 or 11.3% images of no tumor and 175 or 28.6% images of pituitary tumor.

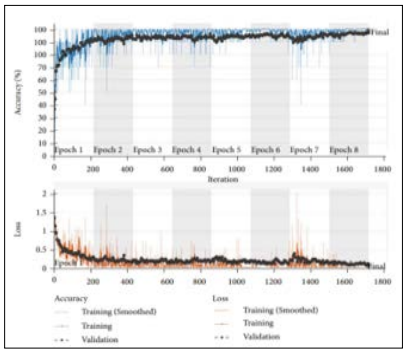

Figure 7: Training and Validation Accuracy and Loss Graph for ResNet-18 Model

Figure 7 illustrates the ResNet-18 model's accuracy and loss graphs during training and validation, which have been performed using a brain tumour classification dataset to illustrate the model's predictive capabilities for brain tumours. The graph's x-axis represents an epochs ranging from 1-8, while a y-axis represents an accuracy and loss for every epoch. In the figure, the training accuracy is increasing slowly, approaching 100%, with minor fluctuations in validation accuracy, as shown in the top (accuracy) graph. On the other hand, the loss curves for both training and validation are lowering steadily, as displayed in a bottom (loss) graph.

Table 2: Comparison Analysis of different DL models for Brain Tumor Identification Using Classification Metrics [21,22].

Models	Accuracy	Sensitivity	Specificity
VGG-19	91.27	91.92	95.98
AlexNet	87.93	84.38	92.31
ResNet-18	93.80	93.75	97.50

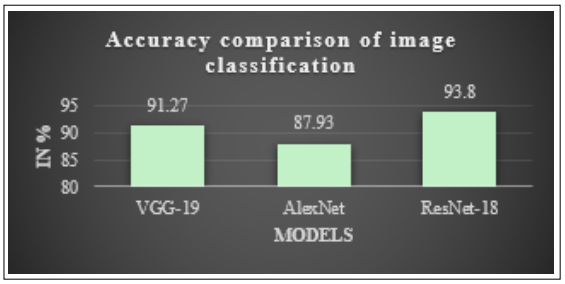

Figure 8: Comparison of Accuracy Measures for Different DL Models for Brain Tumor Detection

The above-mentioned Figure 8 and Table II provide a comparison of accuracy measures for different models to determine an optimal model for brain tumour image classification. The graph's x-axis indicates deep learning models namely VGG-19, AlexNet, and ResNet-18, while the y-axis indicates the accuracy scores of each model as a percentage. The graph clearly depicts that the ResNet-18 classifier has the highest accuracy of 93.8, VGG-19 has an accuracy of 91.27%, and the AlexNet has an accuracy of 87.93% in the testing phase. Overall, the comparison demonstrates that the ResNet-18 model outperforms others in classifying brain tumor.

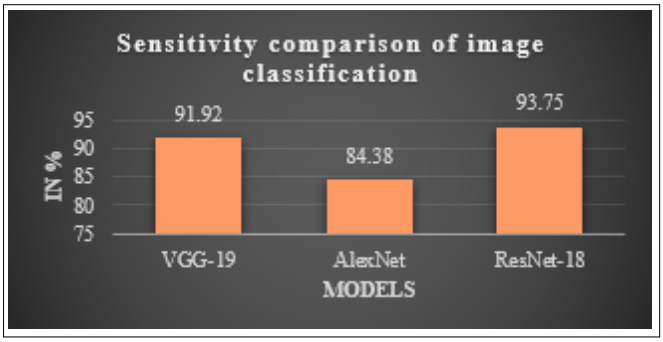

Figure 9: Comparison of Sensitivity Measures for Different DL Models for Brain Tumor Detection

Figure 9 and Table 2 provide a comparison of sensitivity measures for many models with the goal of determining which model is best suited for categorising images of brain tumours. The x-axis of the graph signifies deep learning models, namely VGG-19, AlexNet, and ResNet-18, while a y-axis shows a sensitivity scores of each model expressed as a percentage. The data graphic clearly illustrates that the ResNet-18 classifier achieves the maximum

sensitivity of 93.75%, followed by VGG-19 with a sensitivity of 91.92%, and AlexNet with a sensitivity of 84.38% throughout the testing phase. When compared to other models, the ResNet-18 model routinely outperforms them when it comes to brain tumour classification.

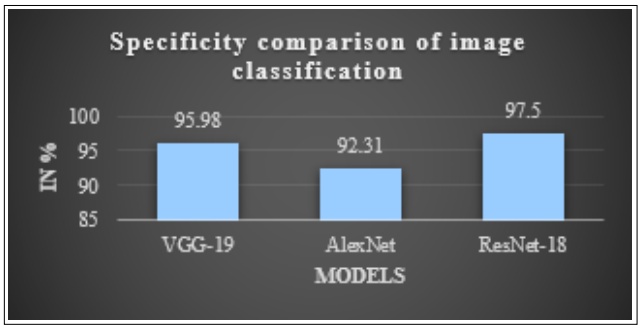

Figure 10: Comparison of Specificity Measures for Different DL Models for Brain Tumor Detection

An optimal model for brain tumour image classification may be found by comparing the specificity metrics of many models, as shown in Figure 10 and Table II. VGG-19, AlexNet, and ResNet-18 are the DL models represented on the x-axis of the graph. The specificity scores of each model are represented as a percentage on the y-axis. The graph plainly illustrates that the ResNet-18 classifier has the highest specificity of 97.5%, followed by VGG-19 with 95.98% and AlexNet with 92.31% in the testing phase. The ResNet-18 model is often shown to be superior to other models when it comes to classifying brain tumours, according to the study.

Conclusion and Future Scope

This research aims to identify how DL models with MRI can be employed to detect brain tumours at their early stage. Comparisons were made between DL models used in a classification of brain tumours and demonstrated the efficiency of intricate architecture in the medical image analysis. Therefore, three of these DL models: Alexnet, Resnet-18 and VGG-19 were trained and tested on their ability to detect brain tumour by MR images. Thus, among all of them, ResNet-18 provides the highest percentage of accuracy which is equal to 93. 80%. The next best performer was VGG-19 at 91. 27% closely followed by AlexNet at 87. 93% on the same metric. From the obtained results, it could be deduced that ResNet-18 still performs well in the classification of brain tumours no matter the complexities such as varied kinds of tumour or image quality. The general advantage of an automated technique is that it cuts down the dependence on human interpretation and increases diagnostic efficiency by a very wide margin. Apparently, the improvement of structural designs like Transformer-based models or the utilization of multimodal data to enhance the classifying precision might be the concern of the following study. Integrating the model with real cases of clinical data and applying the dataset to comprise other types of tumors may potentially enhance its applicability and adaptability. New possibilities for developing diagnostic tools that can quickly and effectively diagnose tumours in clinical practice can be the subject of future research. Developments on these aspects and employing deeper architectures to enhance the performance of the segmentation output will be the aspect of further studies.

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AI-Driven Phishing Email Detection: Leveraging Big Data Analytics for Enhanced Cybersecurity

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ABSTRACT

Big data analytics and AI are emerging technologies that can help businesses improve their email security. There is a wide range of research that implements big data analytics for email security, and phishing email detection is one dimension of email security. Therefore, the essay emphasizes the use of big data analytics and AI for developing real-time phishing email recognition. Our research demonstrates that a phishing email detection technique utilizing big-data technologies can be used to create a large-scale phishing email dataset, detect phishing emails, visualize additional features, and recognize phishing emails as soon as possible. Chapter 2 outlines present changes in the cybercrime landscape and the current situation of time and defense mechanisms for email security. Then, the concept of harnessing big data analytics and technologies to improve cybersecurity is discussed. In the third segment, an attempt is made to offer a comprehensive list of studies that have been conducted applying big-data analytics to email security and scrutinizing phishing email tactics or technologies for this type of cybercrime. In the final chapter, the implementation of a big-data-based technology utilizing Enron email traffic is highlighted.The essay discusses the application of big data analytics to designing a phishing email detection system in real time. Relevant studies are included in the content as well. Email security has become a chief concern for individuals and organizations. A cybercriminal can victimize anyone after proliferating a phishing email, and millions of phishing emails are distributed to millions of email traffic. With the continual and widespread proliferation of time, cybercriminals are using more sophisticated methods of attacking and have the capability to create more feature-rich phishing emails. This situation necessitates the use of technology to protect us from these methods. The precise recognition of phishing emails reduces their utilization, leading to decreased cybercrimes.

Keywords: AI-driven,Phishing email detection,Big data analytics,Cybersecurity,Machine learning,Email security,Threat detection,Advanced analytics,Cyber threat intelligence,Fraud prevention,Anomaly detection,Data-driven insights,Email filtering,Predictive analytics,Automated response,Neural networks,Behavioral analysis,Data mining,Risk assessment,Security protocols,Malware detection,Natural language processing,Deep learning,Cyber defense strategies,Security analytics.

1. Introduction

This paper aims to highlight the similarities between phishing email detection using machine learning and big data analytics. Thanks to machine learning big-data analytics solutions, a new research avenue is opened to improve cybersecurity based on the latest threats associated with criminal opportunities, terrorist activities, political or personal issues, illicit drugs, actors, or different transactions. The remainder of the paper is organized as follows: Section 2 presents the literature survey. Section 3 provides the early detection of phishing emails using data mining-based machine learning. The big data analytics used in cybersecurity are provided in Section 4. The similarity between the research of big data analytics and the current AI-based phishing email detection process is illustrated in Section 5. Finally, Section 6 concludes the paper.

Detecting and mitigating big data-driven phishing attacks, the first step in implementing a data-driven approach, has been at the forefront of data-driven security research in recent years. This is given that 88% of the phishing emails analyzed in 2019 were equipped with big data processing engines, amounting to 133 billion business and consumer emails per day. Using AI models to prioritize feature selection has been widely hailed as a promising trend in phishing email detection, largely due to researchers' dissatisfaction with the performance of malware detection using engineered features culled solely from a CSV of static file characteristics. Subjective and entirely based on a human's or tool's opinion, these features provide an inaccurate insight into the file's true intentions. The development of increasingly anti-forensic malware has rendered these features critical and impractical in malware detection.For quite some time, the effectiveness of traditional threat mitigation techniques has diminished in contrast to their increasing volume and sophistication, rendering organizations and enterprises equally vulnerable to cyber fraud and thefts. Leveraging big data analytics to detect and mitigate security breaches can contribute to improved cybersecurity. With cybersecurity professionals working around the clock to design techniques for rapidly detecting, classifying, and predicting unseen threats previously believed to be improbable or undiscovered, the field of "data and cybersecurity" has grown broad and promising.Phishing email detection has evolved significantly with the integration of machine learning and big data analytics, marking a pivotal advancement in cybersecurity. As phishing attacks have become more sophisticated and pervasive, analyzing vast amounts of data has become essential for effective threat detection. In 2019, a staggering 88% of phishing emails were processed through big data engines, underscoring the magnitude of the challenge faced. Traditional methods of malware detection, reliant on static features and human-curated data, have proven inadequate against the evolving landscape of cyber threats. The rise of anti-forensic malware has further exposed the limitations of these traditional approaches, emphasizing the need for dynamic and data-driven solutions. Leveraging AI models for feature selection within big data frameworks offers a promising alternative, enabling more accurate and timely identification of phishing attempts. As cybersecurity experts continue to develop innovative techniques to counteract emerging threats, the synergy between machine learning, big data analytics, and cybersecurity is paving the way for more robust defenses against an increasingly complex array of cyber risks.Phishing email detection has undergone significant advancements through the integration of machine learning and big data analytics, crucial for enhancing cybersecurity in an era of increasingly sophisticated cyber threats. In 2019, an alarming 88% of phishing emails were processed using big data engines, highlighting the scale of this challenge. Traditional malware detection methods, which rely on static features and human-curated data, have proven inadequate against evolving tactics, particularly with the rise of anti-forensic malware that circumvents these traditional approaches. In response, leveraging AI models for feature selection within big data frameworks has emerged as a promising strategy, enabling more accurate and timely identification of phishing attempts. This dynamic, data-driven approach empowers cybersecurity professionals to rapidly detect, classify, and predict previously unimagined threats, marking a pivotal shift in the fight against cyber fraud and theft. The synergy between machine learning, big data analytics, and cybersecurity is thus reshaping defenses against a complex and ever-evolving landscape of cyber risks.Phishing email detection has significantly evolved through the integration of machine learning and big data analytics, becoming essential in the fight against increasingly sophisticated cyber threats. By 2019, a striking 88% of phishing emails were processed through big data engines, underscoring the scale of the challenge organizations face. Traditional malware detection methods, which often depend on static features and manually curated datasets, have struggled to keep pace, especially with the emergence of anti-forensic malware that cleverly bypasses these approaches. In this context, employing AI models for feature selection within big data frameworks has proven to be a promising solution, facilitating more accurate and timely detection of phishing attempts. This proactive, data-driven methodology enables cybersecurity professionals to swiftly identify, classify, and predict threats that were once deemed improbable, marking a transformative shift in combating cyber fraud. Ultimately, the collaboration between machine learning, big data analytics, and cybersecurity is redefining how defenses are structured against a constantly evolving array of cyber risks.

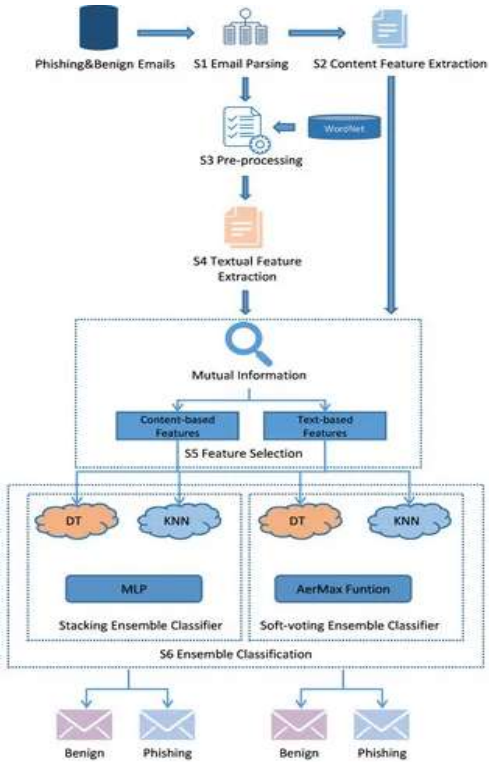

Fig 1 : Enhancing Phishing Email Detection through Ensemble Learning

1.1. Background and Significance

This implantation route motivated us to put forth research to examine and leverage the power of enormous data to provide dual-stage AI-based phishing email detection in the cloud. By building awareness, attitudes, and trust in a new cadre of business practitioners, we aim to provide a secure IAM-friendly, hand-off, SaaS-based proxy. AI-driven, with few false negatives, this solution minimizes response time, dismisses security threats, and resurrects quickly with the most recent intelligence. Phishing refers to a multi-vector attack on enticement to deceive and exploit computer users. Evaluating two main components, wherein the average clicking percentage for phishing attacks was 24.8%, with 18.2% clicking time for the normal campaign. Phishing is the number 1 cyberattack vector leading to cyber exploitation. A comprehensive solution is the need of the hour, not only to mitigate its spread but also to uncover its depths and groves. That is the growth conceptualized here.

Phishing entered the world of computing as early as the 1970s. In 1972, the first worm known as "Creeper Worm" showcased several concepts of subsequent phishing attacks. Since 2018, phishing attacks alone have compromised 70% of smartphone users in the UK, targeting net banking with malware. According to Symantec's Internet Security Threat Report (ISTR) 2021, there was a 67% increase in phishing activity in 2020 compared to 2019. In the first five months of 2021, there were about 1.6 million phishing cases making use of wildcard representations of trusted domains to evade detection. This figure is expected to grow every coming year. Using domain names that refer to a trusted brand, attackers can deceive the victim into giving up their credentials or infecting their devices with malware via email. The catastrophes were caused by simply clicking on a malicious link or attachment or responding to emails. Only about 3% of consumers can distinguish typical scam emails from genuine emails, according to a test involving 2024 consumers.

1.2. Research Objective

Research, therefore, aims to develop a machine learning model that uses big data analytics to assess the overall behavior of the system and demonstrate the proposed approach to using deep learning for AI-driven phishing email detection. A discussion of the existing literature for email phishing detection would further strengthen the rationale for developing our machine learning models. As such, the outcomes of research should include well-documented inferences to a wide range of knowledge users, especially those who are the main stakeholders in developing a cybersecurity system.The objective of this essay is to first evaluate the present state of phishing detection systems and to propose that the integration of big data in deep learning neural networks can improve the performance of an AI model. Specifically, the research identifies this opportunity in the detection of phishing emails to advance towards a better cybersecurity environment. The proposed model will not rely on a human-crafted dataset: it will learn directly from a large amount of raw input data and make decisions to detect suspicious

and malicious content in the emails. While both deep learning techniques and big data methods have previously achieved widespread success across various fields, the aim is to test the effectiveness of combining such techniques for application in cybersecurity. The research objectives have been described below.

Equ 1: Feature Extraction and Representation

1. Feature Extraction

Phishing detection typically starts with extracting features from emails, which may include text content, metadata, and behavioral patterns. Common features include:

- **Textual Features:** Frequency of certain keywords, email structure, etc.
- **Metadata:** Email sender, domain, headers, etc.
- **Behavioral Patterns:** Click-through rates, response patterns, etc.

2. Phishing Attacks and Email Security

Email has increasingly become the primary communication channel at work, but it is plagued by numerous security issues. Email security has become a major concern that is linked to cybercrime in small and medium enterprises, as email is identified as a key threat vector. The email security threat can eventually compromise the network as a result of phishing attacks. Technologies have been developed to avoid human-related problems, but these mitigations can never completely eliminate harmful messages. Furthermore, sending an email with proper attachments and with a document for the users to click on is not treated as a bad practice in an enterprise organization where developers carry out software updates via emails for users. Cybersecurity incidents are evolving and they are more sophisticated. The more the aspect of deception is built into these attacks, the more the email filtering technologies will fail, making it easier for an adversary to achieve their goal. The challenge of unwanted emails has been a long-standing problem for the security community because unwanted emails that disseminate quickly are an efficient way to carry out spam attacks.Several cyber-attacks on individuals and organizations begin with a phishing email. Phishing involves tricking people into revealing sensitive information such as credentials, personal information, and company information. As the target of a phishing attack, you might not realize you were attacked at all. This type of cybercrime often involves collecting the personal information of targets hoping to perform a highly targeted attack. These attacks, known as spear phishing attacks, are sent only to specific individuals who have valuable information that the attacker wants. Spear phishing has multiple subtypes such as whaling, vishing, and quid pro quo. There is no clear definition for any of these subtypes, but they are similar to standard spear phishing except that they use a different form of communication for the social engineering stage. Researchers have also noted differences in intent: while spear phishing targets individuals, whaling goes after giant institutions.

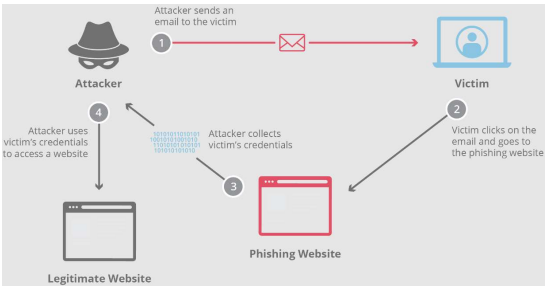

Fig 2 : Phishing attack

2.1. Definition and Types of Phishing Attacks

Phishing is a social engineering attack in which a cybercriminal poses as a trustworthy entity or leverages impersonation tools to deliver fraudulent communications (typically emails) in an attempt to trick individuals into providing sensitive information such as credit card details, bank account numbers, social security numbers, login credentials, and the like. The primary objective of a phishing attack is for the attacker to unrightfully gain access to restricted digital assets that can be monetized in various ways or used to launch more sinister attacks like ransomware or business email compromise. Historically, a phishing email informed the recipient that they had won a lottery and needed to claim their reward, hence prompting the user to share their personal details like postal address, date of birth, or to pay a fee. However, with the evolution of technology and the improvement in cyber threat-awareness training, phishing strategies have become more sophisticated and evolved. Current phishing strategies take advantage of social engineering tactics to impersonate companies and services that the recipient of the email is likely to be familiar with and open communications from. Some examples of phishing tactics and

types are detailed in the literature.In its standalone state, pure phishing is an email attack in which cybercriminals leverage psychological manipulation to trick email recipients into sharing sensitive information. However, the following is a list of major phishing tactics that cybercriminals typically execute:
- Pharming attacks: Redirect users to fake sites by corrupting the DNS servers of popular websites or default DNS servers that redirect requests to hostbypositive.com. - Spear Phishing: A more targeted and specific phishing attack in which an email recipient is selected and convinced that they are receiving information from a trusted source. Green Card offers, often purporting to be from the United States Citizenship and Immigration Services (USCIS). Links to such emails often redirect users to malicious sites from where spyware, trojans, rootkits, and other kinds of malware can be downloaded onto their systems. The goal of spear phishing emails is to induce victims to click on a link, open an attachment, or share sensitive data.

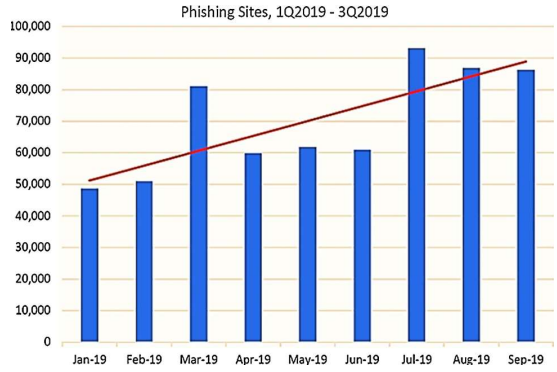

Fig : A comprehensive survey of AI-enabled phishing attacks detection techniques

2.2. Challenges in Email Security

Although some phishing emails exhibit anomalies in their text such as spelling mistakes, visual discrepancies, mismatched URLs, or use of salient brand names, it is becoming increasingly difficult to rely on text-based systems to detect phishing since attackers are finding more subtle methods by which to trigger these systems.
While the new technological advancements and current sophisticated systems have greatly impacted the automation of the cyber threats detection process, there are still many challenges in classifying phishing from legitimate email. Along with the increasingly sophisticated systems, there are email threats from phishing, spoofing, and spear phishing. Computers are slightly better than Chance at distinguishing threatening social-engineering email text between real and synthetic.To effectively classify phishing attacks, both natural language processing and domain-specific features should be employed while designing the system. Phishing by email is ages old, but it still works in the current internet and corporate environments. Phishing can either be used to exfiltrate sensitive data, spread malware, or cause denial of service by abusing server access. Hundreds of millions of user accounts are compromised per year due to phishing, causing billions of dollars in financial damage.
Blockchain offers a new possible approach to phishing email detection. Whereas the previously mentioned research focuses on the actual content of the email, blockchain email signatures take into account the source and domain of the sender by validating that these originate within the correct chain that is distributed and not fraudulent. This anti-phishing method is particularly powerful in regard to email.

3. AI in Cybersecurity

Artificial intelligence (AI) promises to aid a variety of industries, and one of the most notable areas for AI implementation in security systems is cybersecurity. Machine learning and other AI-based tools are critical in both identifying potential threats and preventing future security breaches. AI algorithms are fine-tuned to leverage a multitude of historical (structured and unstructured) data to develop patterns and understandings of how intruders and spammers/phishers function across a wide-ranging number of attack types and contexts.
These capabilities offer businesses a way to uniquely root out security threats. Additionally, machine learning tools are applicable in creating more advanced understandings of language, and how to successfully identify various types of attacks. Natural language processing tools that humanize the data can aid in improving cybersecurity and catching multiple threats from a linguistic perspective. From authenticating user identity to preventing potential fraud, AI/ML offers a multitude of dynamic cyber protection mechanisms that give corporations flexibility and intelligence when it comes to cybersecurity, stirring up a lot of demand for jobs in robotics, cybersecurity, and associated sectors.Training an AI engine to spot known phishing emails is crucial. These AI models need to encapsulate the subtle linguistic differences in order to establish the difference between junk emails and phishing attempts. The further sophistication of AI models helps strengthen the defenses of

corporations against a myriad of network attacks.Artificial intelligence (AI) is revolutionizing cybersecurity by offering advanced tools and methodologies to identify and mitigate potential threats. Leveraging machine learning algorithms, AI systems analyze vast amounts of historical data—both structured and unstructured—to recognize patterns associated with various types of cyberattacks, including phishing, spamming, and intrusions. These algorithms are fine-tuned to detect subtle linguistic nuances in phishing emails, distinguishing them from legitimate communications and enhancing the accuracy of threat detection. Furthermore, natural language processing (NLP) tools contribute to this effort by humanizing and contextualizing data, which improves the identification of threats from a linguistic perspective. As AI continues to evolve, its applications in authenticating user identities and preventing fraud are becoming increasingly sophisticated, making it a critical component in modern cybersecurity strategies. This technological advancement is driving significant demand for expertise in robotics, cybersecurity, and related fields, highlighting the growing importance of AI in safeguarding digital environments.

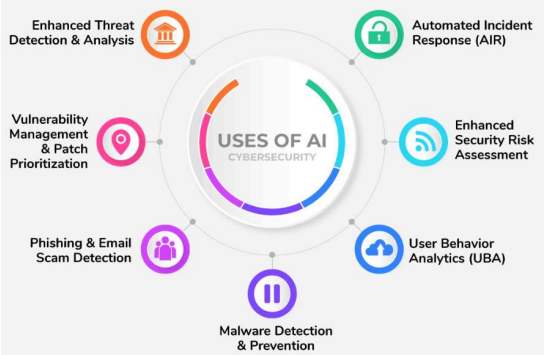

Fig 3 : AI in Cybersecurity

3.1. Applications of AI in Cybersecurity

AI is released in the various dimensions of the information technology sector that positively affect society by introducing basic methods, enhancing and adjusting suitable methods in response to interference or disruption resulting from unavoidable security breaches. Five such ways, to begin with, are raising the degree of biodiversity in the system, introducing diversity and redundancy, data sharing, data integrity, and encouraging encrypted communications. However, two common security breaches that severely affect the QoE in cyber-physical systems are largely eradicated using artificial intelligence (AI) deployed on the substantial volume of big data that bombards and deluges the system networks. To begin with, a substantial increase in risks attached to phishing emails necessitates the use of AI to enhance and decipher sophisticated email files and databases in order to increase overall security.

The bulk of online assaults, security breaches, and hacking have become increasingly direct, focused, and concentrated on individuals and businesses in recent years. A sizable collection of incidents on a limited budget, few personnel, and sponsored university students in the dark web have been capable of creating ransomware. Cybersecurity uses a big set of digital conditions and policies to safeguard data and systems from dynamic cyber threats, consisting of three perspectives such as confidentiality, the integrity of the data, and the availability of it. To begin with, having access to key resources (for example, networks and websites) and forums after they have been compromised. UserRepository of usernames and passwords is the public directive of judgment and permission management in cybersecurity.

Equ 2: Machine Learning Models

2. **Machine Learning Models**

a. **Logistic Regression**

Logistic regression is used to classify emails as phishing or non-phishing based on features.

- Logistic Function:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}}$$

where $P(Y=1|X)$ is the probability of an email being phishing given features X, and β are the model parameters.

b. **Naive Bayes**

Naive Bayes classifiers use Bayes' theorem with an assumption of feature independence:

- Bayes' Theorem:

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)}$$

where C represents the class (phishing or non-phishing), X represents the feature vector, and $P(X|C)$ is typically computed using a multinomial distribution.

c. **Support Vector Machines (SVM)**

SVM finds the optimal hyperplane to separate classes in high-dimensional space.

- Decision Function:

$$f(x) = \text{sign}(w^T x + b)$$

where w is the weight vector, x is the feature vector, and b is the bias term.

4. Big Data Analytics in Cybersecurity

Big data analytics customarily used different tools to manage a massive collection of data as per Gartner's agenda publication. These tools are popular for data storage of security operations. The adoption of Hadoop, NoSQL, and MapReduce by private and government organizations is due to the characteristics of varieties, veracity, and volume with ample velocity adaptation of structured or unstructured data. The paper consists of important pioneer use cases of big data analytics in cybersecurity, for instance: monitoring the network, risk management, fraud detection, and development of vulnerability that can be detected by public security operations (SOCs). A combination of one or more detection methods can be used to improve the accuracy of the detection process, there is no use of a single method. The work focuses on several types of active defense cyber-threats, including using dynamic malware analysis, Internet blacklisting and whitelisting, phishing websites detection, APT detection (short report), and malware-c2 traffic detection. Big data and AI-based frameworks are used to tackle the upcoming challenges.Cybersecurity is the guarantor of privacy and confidentiality of the data from unauthorized access, fast attacks, and intelligence congregate disparate sources, like massive IoT devices, social platforms, cloud databases, and end-to-end networks. Big data analytics is a vital cog in cybersecurity, which addresses the challenges of handling massive volumes peculiarly due to the characteristic of phishing emails to elude traditional methods of detection. ML with its self-sufficient AI—machine learning behavior requires the invention of a new mode of phishing email detection. Big Data analytics enables cybersecurity to handle the daunting challenge of detecting and protecting garbled data. These data are either structured or unstructured and encompass computer network visual information (packet payloads), social media networks, and external threats.Big data analytics plays a crucial role in cybersecurity by leveraging tools like Hadoop, NoSQL, and MapReduce to manage and analyze vast amounts of data generated from various sources such as IoT devices, social platforms, and cloud databases. As organizations face challenges related to the variety, veracity, volume, and velocity of data, these tools are essential for addressing complex security issues. Key use cases include monitoring network activity, risk management, fraud detection, and vulnerability assessment. By combining multiple detection methods—such as dynamic malware analysis, Internet blacklisting and whitelisting, phishing website detection, APT detection, and malware-command and control traffic analysis—organizations can enhance the accuracy of threat detection. The integration of big data and AI frameworks is pivotal in tackling emerging threats, particularly in the realm of phishing emails that evade traditional detection methods. Machine learning, with its advanced AI capabilities, is continually evolving to create new techniques for identifying and mitigating phishing attempts, thereby bolstering the protection of both structured and unstructured data against unauthorized access and sophisticated attacks.

Fig 4 : Data Analytics in Combating Cybercrime

4.1. Role of Big Data Analytics in Cybersecurity

Derived from the domains of big data and information technology, cybersecurity is a major field of knowledge and application that represents the practice of protecting information, networks, systems, and data from security breaches, data loss, and other potential forms of theft that can be used to damage an institution or a country. Big data analytics in the current era offers the most efficient performance for structuring, handling, and mining big data, which are considered object-oriented data generated and compiled on a large scale. Big data analytics can predict, sense, and respond to the huge amount of network and security data, identify potential threats to the company, and help make risk decisions.The incorporation of big data in cybersecurity has made it possible to identify anomalies, such as missing data, sluggish reporting, timely statistics, new data utilized statically, and ad-hoc data interpreted which further enhances the detection and prevention process built on viruses and spyware. The acquisition of big data in cybersecurity resolves issues concerning detection, redundancy in response, verification, and sharing of threats. The adoption maximizes the value of data, applies new security solutions in order to quickly detect sophisticated threats, and secures context-aware defense strategies that can logically sense the setting of a threat. Big data analytics assists organizations and businesses to depend on the combination of sophisticated tools, technologies, and human technological competence to sustain their security posture and reduce threats. Current trends of big data analytics on cybersecurity and conducting existing surveys, software tools, methods, and algorithms are discussed.Cybersecurity has evolved significantly with the integration of big data analytics, revolutionizing how organizations protect their information, networks, and systems. data to identify potential threats and vulnerabilities. This integration enables the detection of anomalies such as Big data analytics helps in resolving issues related to threat detection, redundancy in responses, and verification, by providing a more comprehensive view of security incidents. It facilitates context-aware defense strategies and the rapid identification of threats through advanced tools and algorithms. As a result, organizations can enhance their security posture, make informed risk decisions, and apply innovative solutions to stay ahead of emerging threats, making big data analytics a crucial component in modern cybersecurity strategies.

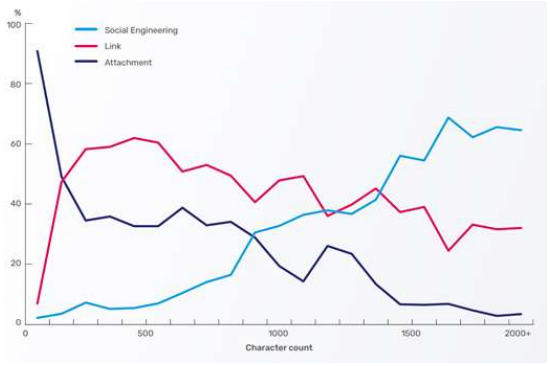

Fig : AI-Generated Phishing Emails Almost Impossible to Detect, Report Finds

5. Integration of AI and Big Data Analytics for Phishing Email Detection

The integration of AI and big data analytics can lead to a dramatic increase in detection performance, thereby saving the organization from various attacks and loss of revenue. The extraction and integration of multiple types and structuring of data then feeding them to the AI system may change the dimension of threat identification and mitigation. For instance, AI systems can work with data from different sources, such as firewall logs, IP addresses, features derived from captured traffic, action logs, etc., to identify any abnormal behavior taking place by the inside or outside threat agents.This results in more effective and accurate threat detection. For email attacks, more

credible and legitimate email-based attacks from crowd-based junk are possible and can be mitigated. To that extent, utilizing AI in conjunction with big data for phishing email detection could be a step in the right direction that has not been given attention. There have been separate studies looking at the use of AI in phishing email detection. However, the study that combines AI with big data for phishing email detection is very limited. Thus, in line with the research gap and background given, this paper introduces the investigation of the landscape of phishing email detection. It aims to show that integrating big data analytics with AI stands to have a significant impact on the identification and mitigation of phishing emails.The integration of AI and big data analytics holds the potential to significantly enhance threat detection and response, safeguarding organizations from various forms of cyberattacks and preventing financial losses. By extracting and integrating diverse types of data—such as firewall logs, IP addresses, traffic features, and action logs—AI systems can more effectively identify abnormal behaviors and potential threats from both internal and external sources. This approach not only improves the accuracy of threat detection but also addresses challenges such as distinguishing between legitimate email-based attacks and spam. Despite existing research on AI's role in phishing email detection, there is a notable lack of studies combining AI with big data analytics for this purpose. This paper seeks to bridge this gap by exploring how integrating these technologies can enhance the identification and mitigation of phishing emails, demonstrating that such an approach could significantly improve cybersecurity measures and protect against sophisticated email threats.Integrating AI with big data analytics presents a transformative opportunity for enhancing cybersecurity, particularly in the realm of phishing email detection. By harnessing diverse data sources—such as firewall logs, IP addresses, captured traffic features, and action logs—AI systems can achieve a more nuanced and accurate detection of abnormal behaviors indicative of phishing attempts. This integration allows for a more sophisticated analysis, distinguishing between genuine threats and benign activities with greater precision. Although AI's effectiveness in phishing detection has been studied, the combination of AI with big data analytics remains underexplored. This paper aims to address this gap by examining how the synergy of these technologies can improve the identification and mitigation of phishing emails, ultimately bolstering an organization's defenses against increasingly sophisticated cyber threats and preventing potential financial losses.

Equ 3: Natural Language Processing (NLP)

a. **Term Frequency-Inverse Document Frequency (TF-IDF)**

TF-IDF is used to evaluate the importance of words in an email.

- TF-IDF Calculation:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \text{IDF}(t)$$

where:

- Term Frequency (TF):

$$\text{TF}(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

- Inverse Document Frequency (IDF):

$$\text{IDF}(t) = \log\left(\frac{N}{\text{Number of documents containing term } t}\right)$$

where N is the total number of documents.

b. **Word Embeddings**

Word embeddings (e.g., Word2Vec, GloVe) convert words into dense vectors:

- Word2Vec Embedding:

$$\mathbf{v}_w = \mathbf{W}_w \mathbf{h}$$

where $\mathbf{v}_w$ is the word vector, $\mathbf{W}_w$ is the weight matrix for the word, and $\mathbf{h}$ is the hidden layer representation.

5.1. Techniques and Algorithms

The algorithms introduced are artificial intelligence (AI) and data analytics-based platform algorithms capable of integrating multiple and heterogeneous algorithms. This section includes three main algorithms along with the solution approaches and a description of each technique. Firstly, the two-step artificial intelligence (AI)-based technique for online phishing email optics (OPE) called "ABC-PEM-HPSO-RFO algorithm" with the help of high-performance parallel swarm operators (HPSO) including ridge filter operator (RFO) as well as tracking of human phishing susceptibility score and cerebral biometric mechanisms such as mismatch response and neural response, to identify and filter out the highest priority OPE in the received email box (i.e. of email box participating in email exchange protocols) for automatic and proactive phishing attack prevention. In the second algorithmic

layer, detection of the remainder OPE (RMOOP) for incidents of UPA in emails are either executed by exact and fuzzy searching for exploiting the s-Symbols, i-Symbols, and comparison Symbols (i.e. Phrase-Symbols) of potty taxonomies.Phishing email is one of the persistent attacks on the IT infrastructures of different domains. Attackers persistently lure users by employing various kinds of social engineering concepts such as urgency, curiosity, intimidation, and fear to persuade the user to open the mail and click on the embedded malicious URL. Phishing emails are usually designed using obfuscated embedded links in emails, embedded links in fake documents, and criminals using instant messaging apps. The anatomical piece of phishing emails can be the embedded link, which can be used for launching further coordinated security attacks.

With two-step AI-based detection and prevention algorithms, we have developed an AI- and big data-based architecture for detecting and preventing ubiquitous phishing email abnormalities (UPA). Techniques and algorithms utilized and integrated to develop the proposed AI-driven big data architecture include techniques for anomaly detection, k-means clustering, string matching (exact and fuzzy), big velocity, big volume, big variety, online and offline learning, and automated attack feedback as adaptive machine learning features.

Equation 4: Anomaly Detection

Anomaly detection methods identify unusual patterns that may indicate phishing.

a. **Z-Score**

The Z-score measures the number of standard deviations a data point is from the mean.

- Z-Score Calculation:

$$Z = \frac{X - \mu}{\sigma}$$

where X is the feature value, μ is the mean of the feature, and σ is the standard deviation.

b. **Isolation Forest**

Isolation Forest isolates observations by randomly selecting features and splitting values:

- Anomaly Score:

$$\text{Score}(x) = 2^{-\frac{E(x)}{c(n)}}$$

where $E(x)$ is the average path length for point x, and $c(n)$ is a constant based on the number of observations.

5.2. Benefits and Limitations

Despite the summarized challenges, there are also a number of significant advantages to integrating AI and big data analytics in the context of phishing email detection. First of all, the very limited amount of humans required in conjunction with AI for a quick and effective response to phishing email campaigns makes this approach an optimal one in case of increasingly growing numbers of new detection-worthy email instances. Furthermore, if big data becomes available in the form required, the combination of AI and big data analytics can lead to higher detection rates compared to a system using only AI, as experiments in this work show in the example of hyperparameter optimized XGBoost.Using AI cannot be taken as a panacea, however. In many cases, it is unfortunately all too easy to overcome the majority of trained systems. One example here is adversarial attacks where the attacker crafts targeted changes to inputs that are still similar to human observers, but previously trained classifiers produce completely different output. Additionally, the question of which and how much data is big data needs to be addressed as well. Furthermore, accessing raw large volumes of mail server contagions and talking to clients of companies is neither accessible nor ethically unproblematic in many cases. Moreover, building on that, the creation of a large trustworthy labeled dataset and ensuring data quality is expensive, time-consuming, and may prove challenging in some companies. Therefore, not all mentioned benefits might be realistically achievable.Integrating AI and big data analytics into phishing email detection offers notable advantages, including the reduction in human intervention required for swift and effective responses, especially given the increasing volume of phishing attempts. This integration can enhance detection rates, as evidenced by experiments using hyperparameter optimized XGBoost, which demonstrate improved performance over systems relying solely on AI. However, AI alone is not a cure-all; challenges such as adversarial attacks, where attackers subtly manipulate inputs to deceive classifiers, highlight the limitations of current AI models. Additionally, defining and accessing 'big data' presents its own set of problems, including ethical concerns, the difficulty of obtaining and managing large volumes of raw email data, and the substantial resources required to create and maintain a high-quality

labeled dataset. These factors underscore that while the integration of AI and big data has the potential to significantly advance phishing email detection, realizing these benefits in practice may be constrained by technical, ethical, and logistical challenges.

Fig 5 : Benefits of AI in Cybersecurity

6. Conclusion

AI-driven phishing email detection is only logical, given the security challenges that the playback and reproduce approach to testing legacy systems cannot accommodate. It is indicative of a new wave of cyber hacks that require countermeasures that are equally as sophisticated. It ensures that the threat surface is contained, ensuring that the weakest links in an organization are safer by identifying suspicious emails before they are deleted or tagged as spam. With steadily advancing AI, it stands to reason that using big data AI could be one of several new solutions. Going further, designers could feasibly integrate more than just email datasets, cross-referencing networks and network latency with big data could be a means to find compromised and controlled devices far sooner as well as generate more intelligence on how they operate and spread.
In parallel, future work suggests a robust data and pattern-checking approach that leverages hashtags to pass verb+noun strings back and forth; if there's anything other than a VPN, it would detect a potential phish, for example. By leveraging shared concerns on cybersecurity via projects like CIDER, the storage of big data of email and email meta-tagging is likely to make it more useful than ever. Indeed, projects such as these are seeing a resurgence in funding and participation, in part due to their timely remit and focus on cybersecurity concerns. Given that well-behaved institutions enable convergence, it is not unreasonable to assume that they are able to attract attention. A future volume in this series, covering highlights from the CIDER 2016 workshop, is currently being prepared.

6.1. Future Trend AI-driven phishing detection is very promising; however, numerous obstacles need to be conquered to make it successful. In the future, attention should be focused on the development of a robust and effective AI-based phishing email detection system that is optimized for massive-scale security operations centers (SOCs). The application of big data analytics for cybersecurity lends itself to exponential improvements in the strength of AI tools, with the potential to harness much larger datasets. As a result of this development, this enhancement also stands to improve the accuracy and strength of AI-driven phishing detection systems.Analysts were prompted to transfer from rule-based systems to machine-learning classification systems as the quantity of phishing spam continuously increased. Over the past four years, the emphasis has progressively evolved to distinguish AI and non-AI. To attain maximum detection rate and precision, deep learning (DL), frequently linked through word and character embeddings, is the most recent tendency of non-AI approaches. Despite its remarkable achievements in a range of machine learning (ML) domains, state-of-the-art (SOTA) "out of the box" deep learning (DL) methods for the classification of temperate-sequence information have historically been outperformed by feature-engineered systems. However, the ACER-NSIT-BMIL and ACER-NSIT-IBM labels are merged by the deep learning model (created by combining word and character embeddings) as ACER-BMIL, but they cannot be separated appropriately and indicate a potential concern. The utilization of few-shot learning, which facilitates the transfer of knowledge from one area to another, holds notable possibilities for the improvement of AI-driven phishing email detection. With advances in deep learning solutions for few-shot learning, research becomes restricted to the expansion of dataset size and variety.

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PREDICTING DISEASE OUTBREAKS USING AI AND BIG DATA: A NEW FRONTIER IN HEALTHCARE ANALYTICS

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Abstract

Disease forecasts how many people can be infected and die if no medicines and vaccines have been issued and offered to the population free of charge; if less than 70% of the population takes them, many will die in a short time in an outbreak. Many times, a few pockets of unvaccinated individuals will remain, thus necessitating 100% global vaccination. The risk can then lead to the development of appropriate overall clinical care and critical care for the first wave of people caught up in the outbreaks. The global distribution of resources, including such basic goods, is not in question in this short essay. A forecast for more than 300 diseases is possible using human biology, dry laboratory work, and artificial intelligence. However, this predictive health care with precise timing for the start of the disease is still experimental, due to the lack of financial support for such research. The "frontiers of science and medicine" are often overlooked by university and government agencies when they do not have financial means or thought leaders to enforce their use.This essay addresses the use of AI and Big Data in predicting disease outbreaks in a given area of a country or globally. This is a relatively new area for healthcare analytics, an expansion of what is today an extremely important component of the field. The predictive advantage of such a tool is that it will enable the world's governments to pre-order vast quantities of vaccines and antivirals once a forecast is made, thereby protecting the planet from the new contagious disease. Currently, a major disease outbreak and local epidemics can be contained if full doses of these products are delivered to 70% of the world's population within 20 to 30 days of the earliest clinical symptoms of infection. These pre-ordered vaccines and drugs can be kept in a chest somewhere in each country and region, with a "best before" date of three to four years. Thus, this is a project to protect the lives of all people in the world.

Keywords: Disease outbreak prediction, AI in healthcare, Big data analytics, Healthcare analytics, Epidemic forecasting, Predictive modeling, Machine learning in epidemiology, Data-driven disease prediction, AI-driven healthcare solutions, Health informatics, Pandemic prediction, Data science in public health, Risk assessment algorithms, Real-time outbreak monitoring, Healthcare data integration, Predictive analytics in medicine, Epidemiological data analysis, Big data in disease control, Artificial intelligence healthcare applications, Outbreak simulation models.

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1. Introduction

Epidemics and natural catastrophes occur frequently, with the more significant losses being attributed to neglected populations that are primarily situated in flood plains and fault lines. Till now, the healthcare sector lacked tools to anticipate when and where epidemics will erupt. Similarly, the power businesses do not possess the respective attribute to anticipate when and where the next sprawl of upsurge in healthcare spending will materialize. With the advancements in sensing, AI, machine learning, and data analysis, these health industry laggers are developing new big data platforms to catch up with the spree of technology spearheads in the banking and other consumer-facing verticals. How these technologies are being used to better understand and forecast disease outbreaks in these systems is what this essay will explore.In the early 2000s, SARS was among the first diseases to pioneer the then-dubious advancements of artificial intelligence (AI) and big data. With the COVID-19 pandemic, the progression and acceptance of these technologies picked up speed. Yet, while these subjects are currently center stage at gatherings from Silicon Valley to Davos, only a few discussions are devoted to a space where the use of analytics has had significant effects. In thematic sectors such as disease outbreak and preparedness, AI, big data, and predictive analytics are beginning to define a distinct set of vertices.

Epidemics and natural disasters disproportionately impact neglected populations situated in vulnerable areas, such as flood plains and fault lines, yet the healthcare sector has historically lacked the tools to predict when and where these crises will arise. Similarly, power companies struggle to anticipate surges in healthcare spending, highlighting a significant gap in predictive capabilities. However, recent advancements in sensing technologies, artificial intelligence (AI), machine learning, and data analytics are enabling the health industry to catch up with technology leaders in banking and consumer services. This essay delves into how these innovations are transforming the understanding and forecasting of disease outbreaks. The early 2000s saw SARS as a catalyst for the integration of AI and big data in health, but it was the COVID-19 pandemic that truly accelerated the adoption of these technologies. Despite their increasing prominence in discussions from Silicon Valley to Davos, the substantial impacts of analytics in sectors like disease outbreak and preparedness remain underexplored. As AI and predictive analytics carve out new pathways, they are beginning to redefine how we approach public health challenges and resource allocation in times of crisis.

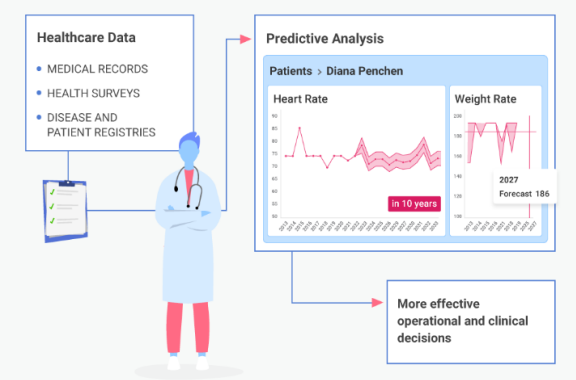

Fig 1 : Predictive Analytics In Healthcare

1.1. Background and Rationale

While standard approaches to diagnose infectious illnesses and predict their outbreaks exist, they have limitations. Moreover, non-infectious illnesses such as hypertension, obesity, coronary diseases, type 2 diabetes mellitus, and others have become a major addition to the disease bouquet and are also included in the factors contributing to high disease mortality. With the growing prevalence of significant diseases even in the richer and educated general community, one approach to decrease their condition prevalence in a country and decrease cure and therapy cost may be to try to anticipate them and begin management on a preventive path, if suitable in various ways. Public health surveillance systems may be required for infectious disease monitoring, intervention, and mitigation.Thanks to breakthroughs in modern data analytics techniques, the precision of predictive analytics, such as forecasting epidemics and other health occurrences, especially in informal data-rich conditions, has surpassed the potential of early warning devices for forecasting epidemics and other health occurrences. With the growing availability and prevalence of both big data and data analytics instruments and tactics in both academia and industry, the quality gap between the three study sites should be diminished to guarantee

the generalizability of the outcomes. In order to identify the constraints of our study, an examination of the relative evidence published in the scope of informatics in the health sector and public health surveillance is necessary.In public health, non-infectious diseases are increasingly contributing to the general disease burden, which has resulted in numerous fatalities and an overwhelming demand for treatments. In order to assist public health authorities in rapidly detecting and controlling an outbreak, advanced techniques such as AI and Big Data must be used to forecast future disease outbreak trends. Public health officers aim to anticipate and control a future outbreak of any disease before it can cause any harm to citizens. The various possibilities that AI and Data Science bring to the table can be discussed in this article.

Equ 1: Basic Reproduction Number

$$\frac{\partial E_S}{\partial t} = \underbrace{\Gamma}_{\text{influx of fresh environments}} - \underbrace{\lambda E_S H_I}_{\substack{\text{environment}\\ \text{infection}}} - \underbrace{\delta E_S}_{\substack{\text{environment}\\ \text{decay}}} \quad [\text{I}] \qquad \frac{\partial E_S}{\partial t} = \underbrace{\Gamma}_{\text{influx of fresh environments}} - \underbrace{\lambda E_S H_I}_{\substack{\text{environment}\\ \text{infection}}} - \underbrace{\delta E_S}_{\substack{\text{environment}\\ \text{decay}}} \quad [\text{I}]$$

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$$\frac{\partial H_S}{\partial t} = \underbrace{g(H_I + H_S)\left(1 - \frac{H_I + H_S}{K}\right)}_{\text{logistic growth of the host population}} - \underbrace{\omega H_S E_I}_{\substack{\text{host}\\ \text{infection}}} - \underbrace{mH_S}_{\substack{\text{host}\\ \text{death}}} \quad [\text{III}] \qquad \frac{\partial H_S}{\partial t} = \underbrace{g(H_I + H_S)\left(1 - \frac{H_I + H_S}{K}\right)}_{\text{logistic growth of the host population}} - \underbrace{\omega H_S E_I}_{\substack{\text{host}\\ \text{infection}}} - \underbrace{mH_S}_{\substack{\text{host}\\ \text{death}}} \quad [\text{III}]$$

$$\frac{\partial H_I}{\partial t} = \underbrace{\omega H_S E_I}_{\substack{\text{host}\\ \text{infection}}} - \underbrace{mH_I}_{\substack{\text{host}\\ \text{death}}} \quad [\text{IV}] \qquad \frac{\partial H_I}{\partial t} = \underbrace{\omega H_S E_I}_{\substack{\text{host}\\ \text{infection}}} - \underbrace{mH_I}_{\substack{\text{host}\\ \text{death}}} \quad [\text{IV}]$$

1.2. Research Aim and Objectives

Prior studies have presented a diverse value of dengue hazards, contemporary and past hums of value to look at. There is only one study with a retrospective and present value forecasting model of dengue in the study of Ng et al. aimed for 4-6 weeks of dengue outbreak predictions with the use of AI and big data techniques. The prediction values set in the study are roughly about 70-80%, with low MASE value, and higher scores from sensitivity, precision, specificity, and accuracy. Additionally, this study validates a new dataset of variables of dengue outbreak prediction which have normal BMI, malnourished, and obese dataset values to precede study efficiency. This is the first evidence-based documentation for the outflow of dengue outbreak forecast using alternative variants of models.

The world measures the quality of research by the aims and objectives the researcher set in the beginning. The research aimed at proposing a conceptual framework for the early prediction of the chance outbreaks of dengue by examining the demographics of a specific area for low resource configuration. The proposed framework included the details of the data pre-processing, the data sampling, and the algorithm of haze detection used in the forecasting module. Section 1 raised the intuition of the study. Objective 1 indicated that the research aimed to propose an initial framework for early prediction of dengue outbreaks using big data analytics methods for low-resource areas. Given the current state of research studies, it also proposed some initial hypotheses that may be tested in future studies. Therefore, the proposed study aimed to fill this gap and to answer the following research questions.Prior research on dengue outbreak forecasting has explored a range of methodologies, with a notable study by Ng et al. utilizing AI and big data techniques to predict dengue outbreaks 4-6 weeks in advance. This study achieved prediction accuracy between 70-80% and demonstrated low MASE values alongside high scores in sensitivity, precision, specificity, and overall accuracy. It also introduced a novel dataset incorporating variables like BMI categories—normal, malnourished, and obese—to enhance prediction efficiency, marking a significant advancement in dengue forecasting. The research aimed to establish a conceptual framework for early dengue outbreak prediction, especially tailored for low-resource settings. This framework detailed data pre-processing, sampling, and haze detection algorithms employed in the forecasting model. Section 1 of the study articulated the foundational intuition and objectives, focusing on leveraging big data analytics for early dengue prediction and proposing hypotheses for future validation. By addressing this research gap, the study sought to offer a comprehensive approach to predicting dengue outbreaks, potentially guiding future investigations and interventions.The study by Ng et al. represents a significant advancement in dengue outbreak forecasting by leveraging AI and big data techniques to predict outbreaks 4-6 weeks in advance with notable accuracy between 70-80%. This research achieved low MASE values and high sensitivity, precision, specificity, and overall

accuracy, highlighting its robustness. A key contribution of the study is its novel dataset that incorporates variables such as BMI categories—normal, malnourished, and obese—thus refining prediction efficiency. The research aimed to establish a conceptual framework for early dengue prediction, particularly for low-resource settings, detailing the processes of data pre-processing, sampling, and haze detection algorithms. By addressing a critical research gap, the study not only proposes a new predictive framework but also sets the stage for future hypotheses and investigations, enhancing the ability to anticipate and mitigate dengue outbreaks effectively.

2. The Role of AI and Big Data in Healthcare Analytics

AI and big data have disrupted various industries with their potential to understand detailed real-time data and derive useful insights from them. They are found to be very useful in the field of healthcare analytics, especially in predicting the next public health emergency. Today's machine learning techniques can analyze vast amounts of structured and unstructured data to predict how diseases evolve and spread, understand their ramifications, and customize treatments for patients. This results in an estimated economic impact of AI ranging from $7,740 billion to $15,770 billion in 2030.So, how have AI and big data proven to be so beneficial in the field of healthcare analytics, and what are the best examples of these technologies predicting impending health crises or being especially helpful in battling them? The many functions of AI and big data in healthcare analytics have made the field ripe for extraordinary growth. These technologies hold a lot of potential in predicting outbreaks, analyzing genomes and diseases, and managing medical records, among other things. AI and big data are used to make policy decisions, prioritize emergency funds, and minimize loss to economies from disruptions like travel restrictions, business closures, or supply chain breakdowns.

Apart from real-time monitoring and disease modeling, AI is also used in patient monitoring at the Mayo Clinic to monitor patients hospitalized with COVID-19. This method is safe and doesn't necessarily put more strain on other healthcare professionals. It's a process that can't be very easily automated, but it's certainly not without the help of AI and healthcare analytics. Data from CT scans or X-rays are analyzed to see who is more prone to the severity of the disease. It can, to an extent, help frontline healthcare professionals know who to prioritize, especially if healthcare resources are particularly strained.AI and big data have revolutionized healthcare analytics by enhancing predictive capabilities and optimizing patient care. These technologies excel in analyzing vast amounts of structured and unstructured data, offering invaluable insights into disease progression and outbreak forecasting. For instance, AI algorithms can sift through diverse datasets, including real-time health records, genomic data, and social media trends, to predict potential public health emergencies with remarkable accuracy. A notable example is the use of AI at the Mayo Clinic, where it assists in monitoring COVID-19 patients by analyzing CT scans and X-rays to predict disease severity. This approach helps prioritize patient care, especially in overwhelmed healthcare settings, by identifying individuals at higher risk and enabling more efficient resource allocation. The economic impact of AI in healthcare, projected to reach between $7,740 billion and $15,770 billion by 2030, underscores its potential to transform the field by improving decision-making, managing resources, and mitigating the economic consequences of health crises.AI and big data have profoundly transformed healthcare analytics by enhancing predictive capabilities and optimizing patient care. These technologies excel in processing vast amounts of both structured and unstructured data to provide deep insights into disease dynamics and outbreak forecasting. For example, AI algorithms can analyze diverse data sources, including real-time health records, genomic information, and social media trends, to predict potential public health emergencies with impressive accuracy. A prominent case is the Mayo Clinic's use of AI to monitor COVID-19 patients; the technology analyzes CT scans and X-rays to assess disease severity, enabling healthcare professionals to prioritize care and allocate resources more effectively in strained settings. This innovative approach not only improves patient outcomes but also highlights the transformative economic potential of AI in healthcare, with estimates suggesting an impact ranging from $7,740 billion to $15,770 billion by 2030.

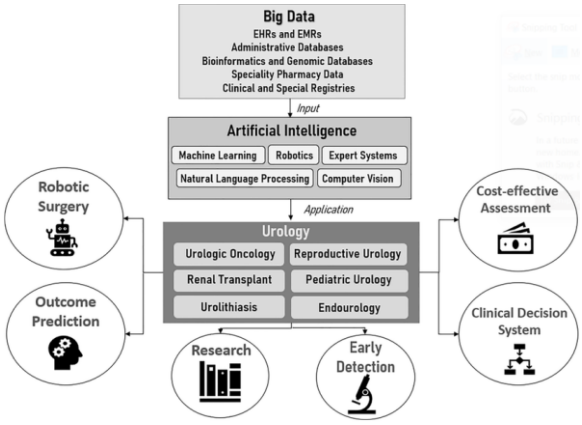

Fig 2: Role of AI and Big Data in Healthcare

2.1. Overview of AI and Big Data Technologies

Technically, AI seeks to create systems that can learn and adapt, making decisions based on data, while typically having very complex relationships and features. One of the most powerful tools of AI is deep learning, which identifies and consumes vast amounts of structured and unstructured data and makes informed predictions. It is mostly used to recognize objects in images, the semantic meaning of text (natural language processing), and the sound of spoken words (speech recognition). Machine learning, the study, and construction of algorithms that can learn from and make predictions on data, is central to predicting outbreaks. This type of AI is often used – and recommended by global health experts – for this kind of study on data from previous outbreaks to distinguish between different patterns and disease dynamics. Big data analysis is premised on a systematic approach to collecting, processing, and interpreting structured and unstructured data affordably and efficiently. In healthcare, the application of big data extends beyond analyzing data from individual sources to data mining to uncover hidden patterns, while re-contextualizing data to provide tools for recognizing symptoms and finding solutions to improve healthcare services. It is clear that AI and big data offer a new perspective on dealing with large amounts of data and identifying hidden patterns that the healthcare industry has not previously encountered. This includes tailoring diagnoses, treatments, and care programs to suit each individual, based on data.AI and big data offer exciting new opportunities for providing better healthcare to people all over the world. AI applications in healthcare are wide-ranging and include robot-assisted surgery, virtual nursing assistants, clinical trials, drug research and development, aided by AI agents, electronic health records, monitoring systems, hospital management systems, drug interaction, and precision medicine. A key driver for these applications is big data, that is, the enormous amount of healthcare data generated and recorded every day.

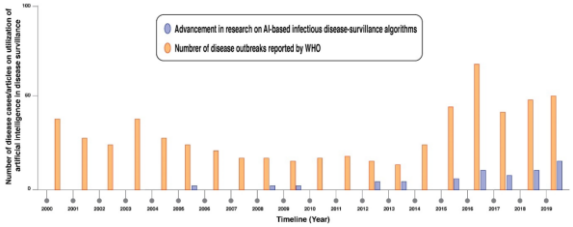

Fig: Advancement of AI-based infectious disease-surveillance algorithms

2.2. Applications in Disease Surveillance and Outbreak Prediction

In the healthcare and public health sector, the number of use cases that leverage AI (artificial intelligence) and big data has been growing rapidly, including practice at the point of care (e.g., personalized medicine and genomics studies), health-related research (e.g., precision public health), and public health programs (e.g., disease surveillance and event detection). Research shows there is a growing need for global surveillance systems to share information across national, regional, and global boundaries to detect outbreaks before they become global pandemics and to develop appropriate countermeasures against the pathogens that cause them. A number of projects have demonstrated the possibility of integrating, analyzing, and utilizing this diverse set of data to yield early detection of historic infectious disease outbreaks. Would this data combination work in detecting novel threats to the U.S.? What are the biological, social, and communications

chokepoints that could be targeted for distribution in a bioterrorism event?

Applications in disease surveillance and outbreak prediction. Early detection is critically important to curtail economic and human losses due to disease outbreaks. Currently, the healthcare industry has begun a data-inspired change where vast amounts of data regarding disease and outbreak events are being accumulated by researchers, epidemiologists, and healthcare professionals across the globe. However, the sheer magnitude of widespread global data collection poses a unique and complex problem characterized not only by data abundance but also by data heterogeneity, time lags, biases, and other sources of noise and misinformation. With the additional challenge of emerging and reemerging diseases in animals and wildlife, controlling and preventing an outbreak continues to require methods that can integrate diverse sources and multiple streams in real-time for accurate event detection. Many existing surveillance and public health tools have been based on the growing abundance of data from electronic health records (EHRs), telecommunication data, internet search queries, and social media posts, as well as informal communication or communication in petit networks where confidentiality is an issue.

3. Challenges and Limitations

Much current research has not only concentrated on health monitoring systems that employ AI and massive data of human blood and different measures but has also highlighted the processing methods and evidence utilized to understand and forecast risks or opportunities within populations. In conclusion, experts' apparent discovery of efficient AI and big data processing capabilities for forecasting illness outbreaks depends on the systematic processing of available population data. However, there are many challenges to effective implementation. An ethics barrier is first and foremost. Given the perilous political circumstances, leaders and civil society are universally aggravated. Finally, the feasibility of the data is essential for the AI advancement project. The effort of preparing the data requires time and cost for implementation, execution, and explanation, given that a lot of measures need to be transferred to generate the outcomes, thereby extending the control loop of illness prevention. Disasters are unpredictable events that transcend random occurrences. As the world continues to face a wider range of tragedies owing to the COVID-19 epidemic and other emergent diseases, an increasing number of studies have relied on modern advances in artificial intelligence (AI) and large data sets to forecast and alert the population to disorder outbreaks. However, global AI development is still in its early stages, and it is not yet uniformly common. This raises issues about moral risks and the accuracy of such improvements. Even if AI and Big Data can be used to anticipate illness outbreaks, there is still an ethical barrier to identifying possible danger areas due to privacy. Current research has increasingly focused on health monitoring systems that leverage AI and large datasets derived from human blood measures and other health indicators to understand and predict risks within populations. While experts have made significant strides in utilizing AI and big data for forecasting disease outbreaks, the success of these initiatives hinges on the systematic processing of available population data. However, several challenges hinder effective implementation, with ethical concerns at the forefront. The precarious political climate often exacerbates tensions between leaders and civil society, complicating data usage. Additionally, the feasibility of data for AI projects poses significant hurdles; the time and costs associated with preparing and processing this data can be substantial, often extending the timeline for effective disease prevention. As the world grapples with an increasing frequency of disasters, spurred by the COVID-19 pandemic and emerging diseases, reliance on AI and big data for early warning systems has grown. Yet, the uneven development of AI capabilities raises critical questions about moral implications and the accuracy of predictive models, particularly concerning privacy issues when identifying at-risk areas. Thus, while these technologies hold great promise, ethical barriers must be addressed to ensure responsible and effective utilization.

Fig 3 : Challenges

3.1. Ethical and Privacy Concerns

Although the positive effects of utilizing AI and big data to predict highly contagious outbreaks significantly limit the risks and improve the effectiveness of outbreak management, it is critical to take many ethical considerations into account before deploying these systems. Moreover, forecasting broad trends about possible outbreak locations and timelines may lead to greater social benefits by allowing early, state-to-state warning and coordination. As such, the tradeoff between potential benefits and risks must be carefully considered and enable flexible, adjustable systems. Consideration should be given to providing feedback loops that allow false alarms to be resolved and for information about true alarms to be provided in a rapid and fair manner. Further, warnings should be matched with resources and realistic plans to manage the information provided and illness reports sure to follow a large-scale warning; disasters are not a joke. Decision makers, the public, and human subjects should be provided with enough information to understand the natural capabilities and limitations of any warning system to make an informed decision about the risks and benefits of participation.

Risk assessments should seriously consider and address direct and indirect concerns about the potential impact of the warning system on the local and global economy, individual search behavioral modification (e.g., increased healthcare-seeking), and public behavioral modification (e.g., fear and avoidance of reported locations, firms, products, and/or markets).Opportunities must also be taken to offer authentic informed consent for participation in any big data outbreak surveillance or warning research across all forms of data when these data have been previously collected and stored; when they start to be collected and stored for use in warning; and particularly when they are collected specifically for warning system development on human subjects who might be noted to be in-vivo during the R&D phase. Mistakes and regulations governing privacy practices must be guided by solid ethical considerations that are up to the times in our fast-forward world. Technology limits and robust plug-in—always knowing laws (and showing them in privacy impact assessments) must underscore and make possible applications suggested by rapid methodological advancements in topic prediction, classification, and warning systems. Social assessment impacts associated with building effective big data forecasts and AI-based warning systems for disease transmission ahead of time must be studied and made publicly available. Given the potential inaccuracies of current high-speed long-distance bio-surveillance using AI technologies, ethical considerations about the use of big data, e.g., from international file-sharing of individual travel records, phone records, or commerce transactions, need to be made. When reported illness cases are used to forecast geographic spread, timing, and relative intensity of emerging infectious diseases prior to the availability of evidence, warning timing and level must be based on the best available judgment from surveillance data at the time combined with evidence from warning errors previously documented and real-time analytical judgment. For these reasons, big data and AI health surveillance researchers should provide advanced, in-depth ethical reasoning when seeking approval from institutional review boards or equivalents for any project domain in vivo. While the application of AI and big data in predicting contagious outbreaks offers substantial benefits for managing and mitigating risks, it is essential to address a range of ethical considerations before deployment. The potential for AI-driven forecasts to significantly improve outbreak management and coordination between states must be balanced against the risks of false alarms and the subsequent social and economic impacts. It is crucial to implement feedback mechanisms to resolve false positives and provide timely, accurate information for true alarms, ensuring that warnings are matched with appropriate resources and realistic response plans. Furthermore, transparency about the capabilities and limitations of warning systems is vital for

informed decision-making by the public and stakeholders. Risk assessments should address both direct and indirect impacts, such as changes in healthcare-seeking behavior and public reactions to warnings, which could affect local economies and individual behaviors. Authentic informed consent must be obtained for the use of data in surveillance and warning systems, with adherence to current privacy regulations and ethical standards. Social impact assessments should accompany the development of AI-based forecasting tools, and any use of international data must be carefully regulated. Given the potential inaccuracies of current technologies, the best available judgment and evidence should guide warning decisions, with robust ethical considerations incorporated into the approval process for research projects.

Equ 2: An adaptive social distancing SIR model

Input: $N,\ \beta,\ \gamma,\ \sigma,\ p,\ \tau,\ n$
Output: $S,\ I,\ R,\ D$
$S(0) \leftarrow N-1,\ I(0) \leftarrow 1,\ R(0) \leftarrow 0,\ D(0) \leftarrow 0;$
$tol \leftarrow 10^{-6};$
for $k \leftarrow 0$ ***to*** $n-1$ **do**
  Calculate $\Theta 0 \leftarrow \frac{N}{S(k)}\mathcal{L}\big(k, \frac{S(k)}{N}\big);$
  $Err \leftarrow 1;$
  while $\big(Err < tol\big)$ **do**
    $z_1 \leftarrow \tau(\gamma+\sigma)+1-\tau\frac{\beta}{N}(S(k)+I(k))\Theta_0;$
    $z_2 \leftarrow \tau\frac{\beta}{N}(\tau(\gamma+\sigma)+1)\Theta_0;$
    $I(k+1) \leftarrow \frac{\sqrt{z_1^2+4\,z_2\,I(k)}-z_1}{2z_1};$
    $S(k+1) \leftarrow \frac{S(k)}{1+\tau\frac{\beta}{N}\Theta I(k+1)};$
    $R(k+1) \leftarrow R(k)+\tau\gamma I(k+1);$
    $D(k+1) = N-S(k+1)-I(k+1)-R(k+1)$
    $\Theta \leftarrow \frac{N}{S(k+1)}\mathcal{L}\big(k+1, \frac{S(k+1)}{N}\big);$
    $Err \leftarrow abs(\Theta 0-\Theta);$
    $\Theta 0 \leftarrow \Theta;$
  end
end

3.2. Data Quality and Accessibility

Real-time access to credible information can bridge the gap created by misinformation and fake news during a time of emergency; for example, the COVID-19 crisis elevated the importance and widespread recognition of reliable information in service of its distribution to the public. Both of these factors are fundamental in creating transparency for the data owner, who can leverage this knowledge to help build a new suite of data sharing with partners. In a disaster like Ebola, governments were known to ritualistically degrade and withhold relevant information for years (BBC 2014). Besides the advent of suitable AI approaches, the global dissemination of trustworthy, accessible data is essential for epidemic responses. The danger of AI models that use location data is that they will flag separate geographic areas either as hotspots or cold alerts, stating risk in imperial reds and safe zones colored locked green. For them, it is harder to distinguish social distance because a crowded room will harbor both the hunter and the victim. The model should work in real-time in any situation that includes spatial density, for if not instructed to assess an outbreak, it will naturally sense the ambiance and assess the true risk in that area.

While the pervasiveness of big data is now a moot point, it's the data quality that is considered a cause of concern. For any disease forecasting model designed to predict outbreaks and patterns, the data used for the model training has to be precise, reliable, and follow ethical and privacy standards. The World Health Organization (WHO 2020) defines data quality as data that are fit for purpose. It therefore becomes essential that data are collected consistent with appropriate standards. This is because the insights obtained from a model can vary greatly depending on the uncertainty and noise levels within the data. Furthermore, models trained on imperfect or unreliable data can result in major errors in forecasting, and therefore should be carefully labeled by trusted sources that hold accountable the authenticity of the records. Furthermore, the data provided by government bodies, and medical institutions in low-middle-income (LMI) countries is scarce and can be biased toward urban living and males, while largely leaving minority and rural female patients unacknowledged. To ensure the quality of the predictions, the magnitudes and the variances

associated with bias, noise, and outlying values in the data must be considered during the model-building process. In times of crisis, such as the COVID-19 pandemic, real-time access to credible information has proven essential for combating misinformation and ensuring transparency. Effective data sharing and reliable communication can significantly enhance epidemic responses and public trust. For instance, during the Ebola outbreak, delayed and restricted information from governments hindered effective responses, underscoring the need for immediate and accurate data dissemination. AI models, while powerful, must be designed to account for spatial density and social interactions, as simplistic location-based risk assessments may overlook critical nuances. The quality of data used to train these models is crucial; it must be accurate, reliable, and adhere to ethical standards. According to the World Health Organization, data quality is defined as being fit for its intended purpose, which highlights the importance of precise and consistent data collection. Inaccurate or biased data can lead to flawed predictions and misinformed responses, particularly in low-to-middle-income countries where data availability may be limited and skewed. Addressing biases and ensuring comprehensive, representative data is essential for building effective forecasting models and making informed decisions during health crises.

4. Case Studies and Success Stories

Several platforms designed for infectious disease surveillance development have been examples of international frameworks. This type of system aims to provide the 'big picture' of infectious disease trends to complement other internet-based disease surveillance systems, widely known as syndromic surveillance systems. The increasing amount of interest in this type of internet-based data is underlined by the article of Olson et al., who presented an overview of automated disease surveillance and identified 762 systems in operation around the world as of June 2016. They classified 156 systems as event-based and 606 as indicator-based. Of these, 244 were used every week for public health tracking or to inform actual event monitoring (35 event-based and 209 indicator-based) in areas such as weekly influenza-like illness, animal health, emergency room visits, lab-based reporting of infectious diseases, open-source media, outpatient visits, participatory systems detecting symptoms or animal die-offs, disease diagnoses by autopsy, fiscal data, and mental health. Before 2009, there were only 14 systems. In this survey, we have looked at a few case studies that outline how the tools and technologies that are available today can be leveraged to effectively predict and manage disease outbreaks. This section briefly reports these case studies and success stories. In summary, the methodological choices made by these platforms can be introduced effectively in technology-scarce and human resource-scarce environments. The choice of technology should ideally follow the pressures of data access and availability, as well as human expertise and the setup and long-term strategic approach of the organization for which it is developed and deployed.

Fig 4: AI in Healthcare: Real-World Success Stories and Case Studies

4.1. Examples of Disease Outbreak Prediction Systems

1. Argus. The Argus project, developed with funding from the European 7th Framework Program, aimed to develop an early warning system for the detection, monitoring, or forecasting of health risks derived from novel pathogens or environmental changes that affect communicable diseases.

Argus "was built on the reasoning that the current requirements on new functions of modern epidemiology in the Global Health domain cannot be managed relying solely on traditional, descriptive methods. New approaches to Health Surveillance, dealing with the dynamics, complexity, and high rate of changing conditions of modern societies, often enforced by globalization, and enabling the proactive prediction and detection of events that can endanger human health, need to

be developed". This project explored a number of different types of data, including notices, reports, trained on disease outbreak data from 12 countries in order to predict future outbreak signals for 49 infectious diseases. The system's architecture used Big Data tools (e.g. ETL, Hadoop), deriving Big Data storage and data processing.

2. HealthMap. This is one of the earliest AI-based initiatives used for the early detection of outbreaks, beginning in 2006. HealthMap was designed to address the "problem of sifting through a daily deluge of health information to identify and respond to events of significance". The aim of HealthMap is to help in the early detection of a disease outbreak, as well as provide insight into where and why the outbreak occurred. It searches, aggregates, filters, and visualizes various data and alerts, to build statistical and machine-learning models

sources in multiple languages, and has been used to identify outbreaks such as H1N1 and H5N1. More than 65,000 users access HealthMap each month. The health information comes from a range of resources such as lay-public and news sources, as well as more official sources such as discussion forums, mailing lists, and other content from the group of Promed partners, which includes ministries of health around the world. HealthMap uses various NLP tools for filtering information and discovering anomalies. geospatial referencing, from which data mining of search query patterns helps to identify hot spots in real-time as a possible outbreak.

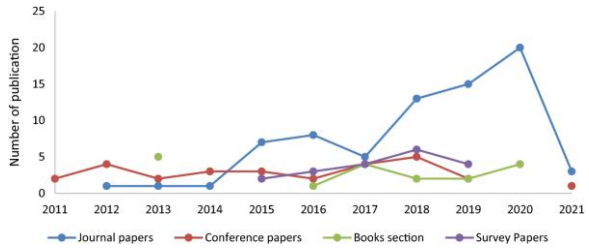

Fig : Evolution of final database by type of article and year

5. Future Directions and Implications

It is crucial to combine two or more variables for algorithms to learn because it adds predictive power to learn about the variables and outcomes. Disease prediction models will improve, with a growing trend to collect data to deal with disease maintenance, through these combinations and leverage an experience portfolio that may otherwise go unnoticed and may consequently affect the accuracy of predictions. The growing interest in healthcare analytics is that organizations are now moving from not only understanding what happened in the past, to using descriptive and diagnostic (what and why anything happened in the past) and predictive (to predict what will happen in the future) analytic tools into the realm of prescribing behaviors that will lead to certain outcomes. The use of predictive analytic tools is highly appropriate for the exploration of future events, based on historical data that inform certain outcomes. The future directions in this study include the need to start predicting various other diseases, which is crucial in implementing proactive public health interventions and policies. This may involve learning automated ways to detect and predict various aspects of communicable and noncommunicable diseases nationwide. The increasing use of AI for predicting the uptake of preventive measures will strongly reflect the growing interest of people in adopting these preventive strategies in time to prevent themselves from being infected. However, it becomes important for us to predict the impact of AI in causing panic in the healthcare system if the AI algorithm predicts a high healthcare consulting rate to avoid overstraining the system. The future implications of predicting disease outbreaks include different features that are associated with advanced public health initiatives and healthcare analytics. The first is the use of AI for disease maintenance and outbreaks. The integration of multiple variables in disease prediction models is crucial for enhancing their predictive power and accuracy, as it allows for a more comprehensive understanding of the complex relationships between variables and health outcomes. With the increasing emphasis on healthcare analytics, organizations are shifting from merely analyzing past events to employing descriptive, diagnostic, and predictive tools to forecast future occurrences and prescribe preventive measures. This advancement facilitates proactive public health interventions by enabling the prediction of various diseases and automating the detection of both communicable and noncommunicable diseases on a national scale. The growing utilization of AI in this context underscores its potential to influence preventive health behaviors and inform strategic

responses. However, it is essential to balance these advancements with the potential risks, such as the possibility of AI-induced panic within the healthcare system due to predictions of high consultation rates, which could strain resources. Future research should focus on refining AI applications for disease management and ensuring that predictive models support effective and sustainable public health strategies.

Equ 3: Recurrent Neural Networks (RNNs)

$$\nabla_{\boldsymbol{c}} L = \sum_t \left(\frac{\partial \boldsymbol{o}^{(t)}}{\partial \boldsymbol{c}}\right)^\top \nabla_{\boldsymbol{o}^{(t)}} L = \sum_t \nabla_{\boldsymbol{o}^{(t)}} L$$

$$\nabla_{\boldsymbol{b}} L = \sum_t \left(\frac{\partial \boldsymbol{h}^{(t)}}{\partial \boldsymbol{b}^{(t)}}\right)^\top \nabla_{\boldsymbol{h}^{(t)}} L = \sum_t \operatorname{diag}\left(1 - \left(\boldsymbol{h}^{(t)}\right)^2\right) \nabla_{\boldsymbol{h}^{(t)}} L$$

$$\nabla_{\boldsymbol{V}} L = \sum_t \sum_i \left(\frac{\partial L}{\partial o_i^{(t)}}\right) \nabla_{\boldsymbol{V}^{(t)}} o_i^{(t)} = \sum_t \left(\nabla_{\boldsymbol{o}^{(t)}} L\right) \boldsymbol{h}^{(t)\top}$$

$$\nabla_{\boldsymbol{W}} L = \sum_t \sum_i \left(\frac{\partial L}{\partial h_i^{(t)}}\right) \nabla_{\boldsymbol{W}^{(t)}} h_i^{(t)} = \sum_t \operatorname{diag}\left(1 - \left(\boldsymbol{h}^{(t)}\right)^2\right) \left(\nabla_{\boldsymbol{h}^{(t)}} L\right) \boldsymbol{h}^{(t-1)\top}$$

$$\nabla_{\boldsymbol{U}} L = \sum_t \sum_i \left(\frac{\partial L}{\partial h_i^{(t)}}\right) \nabla_{\boldsymbol{U}^{(t)}} h_i^{(t)} = \sum_t \operatorname{diag}\left(1 - \left(\boldsymbol{h}^{(t)}\right)^2\right) \left(\nabla_{\boldsymbol{h}^{(t)}} L\right) \boldsymbol{x}^{(t)\top}$$

5.1. Potential Impact on Public Health Policies and Interventions

One realm with many transformative applications of AI and big data is in public health emergency response in areas that could include notifiable diseases in humans, animals, or crops as well as natural and man-made disasters. In areas with low coverage given the public expenditure involved, the most compelling cases are where AI could provide a lead of at least a month over current early warning systems linked to big data available in governments and global sources about how an acute or subacute event is progressing or its likely peak such that a timely and appropriate quality and scale of response will save more lives and prevent more harm. Beyond these areas, more features and analyses may be required, for example, aspects of One Health linking possible animal reservoirs with humans, modeling of the damage that a known disease is already causing to human health or animal health and production, or the possibility of collateral or knock-on effects. The use of machine learning and big data in predicting early disease outbreaks is perceived to impact public health policies and interventions. The application of AI and big data in public health, more fundamentally, is a set of tools that could foster a new paradigm in evidence-based public health practice, which healthcare professionals have been struggling to introduce. Given the multiplicity of changes that public health would have to introduce to address the challenges of AI and big data, this form of information should also facilitate the re-engineering of public health systems and organizations to cope with new decision-making regimes and resource allocations that follow. The most compelling case is one in which precise geospatial data linked to an infectious disease can be used to guide policy actions.AI and big data have the potential to revolutionize public health emergency response by offering advanced predictive capabilities for notifiable diseases and disaster events. In regions with limited public health infrastructure and funding, AI could provide critical early warnings—up to a month in advance—by analyzing vast datasets from governmental and global sources. This lead time allows for timely and scaled responses, potentially saving lives and mitigating harm. Beyond immediate disease detection, AI can integrate complex factors such as One Health considerations, linking animal reservoirs to human outbreaks, and modeling the broader impacts on health and production systems. The integration of AI and big data into public health could usher in a new era of evidence-based practice, offering tools to improve policy and intervention strategies. This shift demands significant changes in public health systems, including the re-engineering of decision-making processes and resource allocation to adapt to these advanced technologies. The use of precise geospatial data in conjunction with AI can particularly enhance policy actions, providing a more nuanced and proactive approach to managing infectious disease threats.

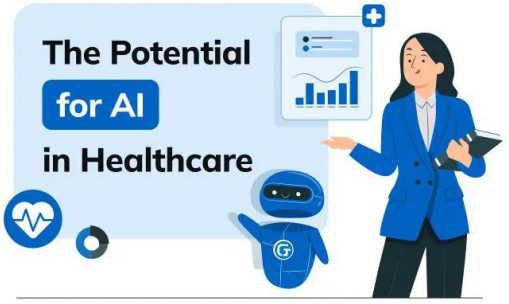

Fig 5: The Potential for AI in Healthcare

6. Conclusion

The challenges and opportunities in predicting disease outbreaks mostly revolve around two interconnected technologies: AI and big data. Nevertheless, disease outbreaks are only predicted based on historical and contemporary data within these frameworks, while all the evidence of historical and contemporary data is conjointly referred to as big data. Machine learning models begin to function when big data is provided and go through multi-staged and multi-method procedures to reply to the questions needed. Other studies indicate the prediction of unknown diseases by the functioning of a computational model that incorporates AI into predictive systems. The use of AI in big data-based computational models enhances the reliability and, to some extent, the timeliness of a prediction model to manage the impact of an outbreak situation, such as the discovery of a new pathogen. The increasing incidence of unusual and local diseases raises new issues for medical informatics, including the handling of imminent pandemic threats, the prediction of unknown local outbreaks, and the geographical spread of emerging diseases. The increasing incidence of unusual outbreaks has attracted global attention to the development of systems and frameworks that can predict the start of epidemics more accurately and in a shorter period of time. In this regard, it appears that big data and artificial intelligence have the potential to bring healthcare analytics to a new level by introducing innovative prediction methods and algorithms. Although more research would be needed to thoroughly understand the subtleties of introducing AI-generated predictions driven by big data into hospitals and clinics, early evidence suggests that such a frontier in AI and health informatics brings an era that is rich in possibilities. The use of AI-driven predictions could offer a new direction to epidemic management in order to enhance healthy lifestyles and improve individual and herd immunity. Big data can provide the necessary information for AI, as long as considerations and privacy issues are addressed.

6.1. Future Trends

By combining key terms with major topics, I have been able to carry out a systematic search of the three major databases to identify emerging issues, research gaps, and other indicators of future trends. There are four emerging issues that have attracted the attention of researchers in the domain of big data and AI. We expect that the more predictive analytics expands to this area, the more types of data sources will be used. Future researchers are encouraged to investigate text-based search engines for predicting disease outbreaks. AI can refine the identification and discovery of an epidemic or outbreak of either known or an emerging disease considering the gauge of burden, for instance, cases, deaths, and sicknesses. Enhanced sensitivity in picking up outbreaks will be applicable to different maladies characterized by AI prospects such as digital health and big data in healthcare.

As far as healthcare analytics are concerned, there is a growing interest from healthcare companies to shift away from standard descriptive analytics to predictive and prescriptive analytics due to the capabilities that AI possesses. In the future, AI and big data have great potential to change how disease outbreaks are predicted in terms of reducing falling ill and dying from diseases globally. As far as AI is concerned, it has the ability to detect and identify zoonosis events early across the globe by searching for patterns that detect diseases and healthcare changes through requested searches and digital information. As big data has been combined with healthcare big data and digitized data, it can help predict disease outbreaks in the future in the healthcare sector.

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Predictive Analytics for Project Risk Management Using Machine Learning

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Abstract

Risk management is relevant for every project that which seeks to avoid and suppress unanticipated costs, basically calling for pre-emptive action. The current work proposes a new approach for handling risks based on predictive analytics and machine learning (ML) that can work in real-time to help avoid risks and increase project adaptability. The main research aim of the study is to ascertain risk presence in projects by using historical data from previous projects, focusing on important aspects such as time, task time, resources and project results. t-SNE technique applies feature engineering in the reduction of the dimensionality while preserving important structural properties. This process is analysed using measures including recall, F1-score, accuracy and precision measurements. The results demonstrate that the Gradient Boosting Machine (GBM) achieves an impressive 85% accuracy, 82% precision, 85% recall, and 80% F1-score, surpassing previous models. Additionally, predictive analytics achieves a resource utilisation efficiency of 85%, compared to 70% for traditional allocation methods, and a project cost reduction of 10%, double the 5% achieved by traditional approaches. Furthermore, the study indicates that while GBM excels in overall accuracy, Logistic Regression (LR) offers more favourable precision-recall trade-offs, highlighting the importance of model selection in project risk management.

Keywords

Predictive Analytics, Project Risk Management, Decision-Making, Data-Driven Strategies, Risk Prediction, Machine Learning, Historical Data

1. Introduction

The current state of IT projects demonstrates that, even with the latest in technology, innovative procedures, and sophisticated systems, the success rate of IT development remains below expectations. Nevertheless, projects that fail cost billions of dollars. The success of IT projects has stagnated in 2013 [1]. Even if the success rate began to rise that year, IT initiatives are still necessary to raise the success rate. IT initiatives are risky by nature, with high stakes involved throughout the whole process. IT initiatives are fraught with a wide range of hazards, most of which have a likelihood and effect that fall between low and high [2].

The two most important things in every IT project are risk identification and management. Collaboration between predictive analytics and knowledge management would be very beneficial. Understanding the requirements, software design, human resources, technical, module integration, feasibility, and any other step in the process is fraught with potential dangers [3] [4]. The risk changes and must be closely monitored due to the fact that every project is distinct and unique. According to one source, "If senior managers fail to detect such risks, such projects may collapse completely" [5].

Numerous data points from the IT project must be analysed in order to apply IT project risk management. The report examines the project's potential outcomes [6] [7], including the causes and impacts of those outcomes, the likelihood of those outcomes occurring, and the project's influence on the business [8]. There are a lot of unknowns with the IT project, therefore, it's important to keep certain data organised and easy to find. Potential risk management tools include big data predictive analytics [9].

Several theories and methods have helped the use of predictive analytics in risk assessment; data mining extracts significant inferences from vast amounts of information. The use of data mining means analysing big data to identify patterns that help ML algorithms make future predictions [10]. The research problem addresses the persistent challenge of high failure rates in projects despite advancements in technology and management practices. Traditional risk management approaches often fall short in predicting and mitigating risks effectively. This study seeks to explore how predictive analytics and machine learning can enhance the identification and management of risks in projects by analysing historical project data, thus providing a more proactive and data-driven approach to improving project outcomes and reducing failures.

1.1. Motivation and Novelty of Study

The motivation behind this research stems from the increasing complexity of project management in modern industries, where traditional risk assessment methods struggle to handle the dynamic nature of projects and the vast amount of data generated. With increasing complexity, effective progress and timely risk responses are said to be real-time risk identification and management. This research seeks to fill these gaps by applying machine learning (ML) methods that can

predict risks from past project data in order to inform decision-making. The proposed feature engineering method uses t-SNE to reduce dimensionality successfully in a pre-processing step, and a more advanced model selection besides being based on GBM, differentiating this research from previous studies which used either static or less complex models.

1.2. Contribution of Study

This research makes a great contribution to the existing body of knowledge regarding project risk management by creating an approach based on the machine learning algorithm to drive the risk prediction model in real-time mode. The key contributions are as follows:

- Data-Driven Risk Identification: Introduces a novel ML technique of risk assessment as the client's historical data about the projects are being analysed; It brings a positive change to risk management approaches and makes decisions more accurate.
- Feature Engineering through t-SNE: Illustrates an application of t-SNE (t-distributed Stochastic Neighbor Embedding) to reduce dimensionality, combat the problem of having big data, while still keeping important defining factors for the prediction model and keeping the model efficient.
- Model Selection and Performance: Focuses on the ability to predict project risk by utilising the Gradient Boosting Machine, which is more adequate than Logistic Regression and extends the body of knowledge regarding risk modelling.
- Evaluation Metrics: Sets up a general assessment model, which includes using the F1-score, precision, recall, and accuracy while evaluating the performance of risk prediction models to avoid misunderstandings in future studies.

1.3. Justification

The approach used in this work is justified by the unpredictability of interactions in projects, which could not be captured using linear techniques like PCA or LDA; Instead, t-SNE was used for feature engineering due to its ability to maintain the local architecture of the data. The detailed pre-processing of the data, such as dealing with missing values, removing outliers and scaling down the features, provides the Gradient Boosting Machine (GBM) model with clear and high-quality input. The selected performance metrics (accuracy, precision, recall, and F1-score) provide a comprehensive evaluation of the model's effectiveness in predicting project risks, directly contributing to practical project outcomes like improved risk identification, resource optimisation, and cost reduction. This integrated approach ensures the model is both robust and impactful for managing project risks in real-world applications.

1.4. Structure of Paper

The paper consists of five main parts. Section II provides the literature review on this topic. Methodology of this paper is discussed in Section III, Section IV

provide the experimental results of ML models with comparative analysis, last Section V provide the conclusion of this work with future work.

2. Literature Review

A thorough literature review on risk management using various methodologies and strategies is presented in this section. Also, **Table 1** provide the summary of the related work with key area focused.

In this study, Roy (2023), a risk matrix is used to analyse a risk assessment that is based on recognised hazards. The study's findings address the difficulties and possible gains from using ML in the building sector. The research highlights the need for expertise in order to comprehend datasets that are special to a certain project. Examining issues with data consistency that impact data dependability, the research mainly focuses on unstructured text and image data. Despite the study's acknowledgement of ML's ability to digitalise and simplify construction procedures, it highlights obstacles, including data security [11].

This paper (2022) places an emphasis on predicting software project failure early on as a means of risk assessment. Various methods of ML will be used. Machine learning is used in the development of the model. LR, NB, SVM, DT neural networks, and adaptive neuro-fuzzy inference systems were chosen as six methods to diversify the model. This work advances the area of software system development by creating models for software project risk assessment that are broadly applicable to any software project at any stage of the software development lifecycle [12].

This study Elokby *et al.*, (2021) enforced project risk management procedures and made the IT project successful in Egypt's telecom and IT industries. There were four metrics used to evaluate the success of the IT projects: Project scope, project quality, project cost, and project time (schedule). Identification of risks, preparation for managing those risks, evaluation of those risks (both qualitative and quantitative), preparation for responding to those risks, actual execution of those responses, and monitoring of those results are all parts of risk management. In order to fulfil the goals of this study, a questionnaire was created as the primary means of gathering primary data [13].

This study Owolabi *et al.*, (2020) suggests a method for predicting completion risk using Big Data Analytics predictive modelling. There are linear regression, regression tree, RF, SVM, and DNNs were built and validated for a completion risk predictive model using the dataset of 4294 PPP project samples delivered across Europe between 1992 and 2015. The conclusion and result of the study prove that, with a less average test prediction error compared to other traditional regression tools, random forest could be a valuable tool in predicting delays in PPP projects. Other aspects included in this study are the questions related to the choice of model, its training and validation [14].

This paper Mahdi *et al.*, (2020) offers a review of current literature regarding the establishment of methodological innovations in the area of ML for software

risk analysis. The analysis of this review has also highlighted some patterns in the methodologies of ML, size measures, and the findings that have shaped and advanced progress of ML in project management. Besides, this study provides a better understanding and a profound foundation for more research about software project risk assessment work. Additionally, it offers an additional method to minimise the likelihood of failure and improve the software development performance ratio, and it increases the likelihood that a software project will be anticipated and prepared to handle [15].

The article Burkov *et al.*, (2020) takes into account the responsibility of overseeing projects' and programs' hazards. Qualitative risk assessments are often used in practice to determine the degree of effect and the likelihood of harm. A three-point risk scale (low, medium, and high) is the most often used. The approach to managing risks in projects and programs, which relies on qualitative

Table 1. Summary of previous study on project risk management using machine learning.

Authors	Focus	Methodologies	Key Findings	Limitations	Future Work
Roy [11]	Risk assessment in construction.	Risk matrix, analysis of unstructured text and image data.	Highlights ML's role in digitalising construction, emphasises need for expertise, data security issues.	Limited generalizability due to project-specific datasets.	Explore other area for broader insights.
Unnamed Authors [12]	Predicting software project failure.	Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Decision Trees (DT), Neural Networks, Adaptive Neuro-Fuzzy Inference Systems.	Develops a reliable risk assessment model applicable to any software project at any lifecycle stage.	Models may not account for all project variables and complexities.	Test models on diverse projects to enhance robustness and adaptability.
Elokby *et al.* [13]	IT project success in telecom and IT industries.	Risk management procedures, qualitative and quantitative evaluations.	Successful project metrics identified; emphasizes comprehensive risk management practices.	Limited to the telecom and IT sectors; results may not be generalised.	Expand the study to include other industries and sectors.
Owolabi *et al.* [14]	Predicting completion risk using Big Data.	Linear Regression, Regression Tree, Random Forest (RF), SVM, Deep Neural Networks (DNNs).	Random Forest found effective in predicting delays in PPP projects with lower average prediction error.	Dependence on historical data may not capture future project dynamics.	Incorporate real-time data and feedback loops for adaptive modelling.
Mahdi *et al.* [15]	Literature review on ML in software risk analysis.	Methodological innovations in ML, literature analysis.	Identifies patterns in ML methodologies; provides foundation for future research in software project risk assessment.	The review scope may overlook recent developments in ML techniques.	Update the review periodically to include emerging methodologies.
Burkov *et al.* [16]	Qualitative risk assessment in projects.	Qualitative risk assessments, three-point risk scale.	Critiques reliance on qualitative evaluations suggest the need for improved risk management strategies.	The subjective nature of qualitative assessments may lead to bias.	Develop quantitative framework to complement assessments.

evaluations and employs methods to avoid or reduce risks, have not evolved enough, in our opinion. This article provides an overview of risk aversion and risk reduction, several ways to accomplish these objectives, and a method for determining the qualitative features of potential dangers [16].

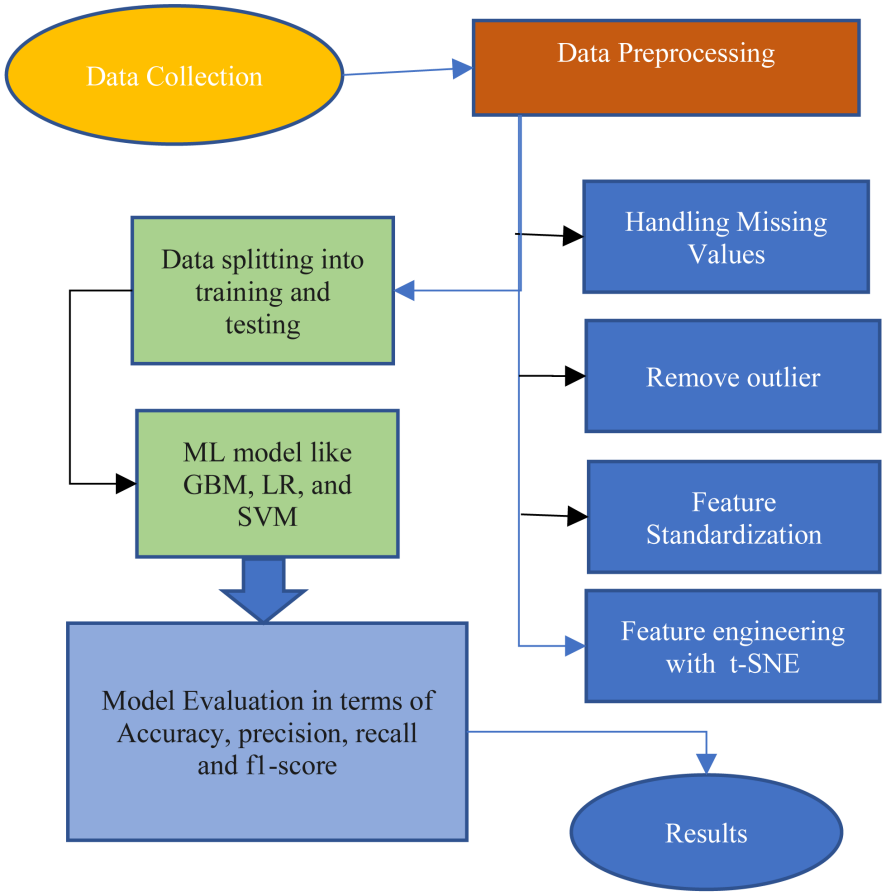

Figure 1. Flowchart for project Risk management.

As shown in **Figure 1**, there are different phases of the project risk management and all the stages are clearly explained below.

3. Methods and Materials

The methodology for Predictive Analytics for Project Risk Management Using ML begins with collecting historical project data, including timelines, task durations, resource allocations, and project outcomes, to capture key factors influencing project success. Following this, data preprocessing is conducted to handle missing values, remove outliers, and standardise features, ensuring data quality and consistency for modelling. Feature engineering is performed using t-SNE to reduce dimensionality while preserving data structure. Consequently, the data is partitioned into a training section (70%) and a test section (30%) for evaluation purposes. Gradient Boosting Machine or GBM is used as the primary classification algorithm to predict project risks based on the least loss function by iteratively

boosting the selected model. Algorithms including accuracy, precision, recall, and F1-score are used to assess the forecasts' accuracy and how best to use them to guide risk management decision-making.

3.1. Data Collection

A process starts with a large-scale data gathering campaign, with data on as broad a set of project history as possible. The collected data extends but is not limited to the following, project schedules, separate task schedules, and resources assigned to each task and project, and the results of these projects. This kind of collection of data is important since most of the aspects of project management are complex and may involve different factors that might affect a success of a project.

3.2. Data Preprocessing

Data preprocessing meaning pertains to the processes that are taken through to clean data and make them fit for other uses. However, before using it in machine learning algorithms, a set of operations has to be performed in order to enhance its quality. Data normalisation, consistency checking, and managing missing values are essential parts of data preparation. Here are the main pre-processing techniques:

- **Handling Missing Values:** The ways to deal with measurements with missing values include methods where missing values will be filled in based on median or mode of the data.
- **Remove Outliers:** The identification and other portions are ideal while conducting data preprocessing in machine learning to avoid biases. For the data efficiency, the next step is to delete the outlier from the dataset.

3.3. Feature Standardization

In cases where numerical inputs are used in feeding data, a feature standardisation process is conducted so that all inputs are normalised. This means that elements with large relative sizes cannot dominate the learning process which is very important for models that depend on the scale of the characteristics. To standardize a numerical attribute aj Compute the standardized value a_{ij}^{*} as follows (1):

$$a_{ij}^{*} = \frac{a_{ij} - \mu_{aj}}{\sigma_{aj}} \tag{1}$$

where μ_{aj} is a mean and σ_{aj} is a standard deviation of attribute aj across all projects.

3.4. Feature Engineering with t-SNE

The use of feature engineering with t-Distributed Stochastic Neighbour Embedding (t-SNE) was utilised to decrease a data dimentionality in order to retain its essential structure. This made it easy to determine features that are important to projects and whose absence would greatly affect project results, helping build

better predictive models.

t-Distributed Stochastic Neighbor Embedding (t-SNE) was chosen over alternatives like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for its ability to handle non-linear relationships between features while preserving the local structure of the data. This is crucial in project management data where task dependencies, resource allocation, and project outcomes often follow non-linear patterns.

3.5. Data Portioning

As part of the experimental setting, the dataset was divided into two parts: The training set, which included 70% of the data used to train the models, and the testing set, which had 30% of the data.

3.6. Classification with Gradient Boosting Machine (GBM)

Belonging to the family of ensemble learning methods, the GBC is an effective ML approach. By integrating boosting and gradient descent, it generates a trustworthy prediction model. One common approach to iterative optimisation is to use DT to create a set of fundamental forecasting models, which are then fed into GBC [17]. It is possible to modify the learner models and the loss function simultaneously. In order to minimize the loss function, gradient boosting is applied to certain data samples. This method uses gradient descent to reduce the loss to a minimum. Equation (2) shows that the technique minimise the loss function.

$$\hat{F}\left(x_i\right) - \min_{f\left(x_i\right)} \sum_{i=1}^{n} \mathcal{L}\left(y_i, F\left(x_i\right)\right) \tag{2}$$

The observed value is denoted as y_i, and the model formed by merging the weak learners is denoted as $\hat{F}\left(x_i\right)$ [18].

3.7. Performance Measures

A performance matrix comparing real observations with model predictions was used to assess an effectiveness of a chosen models. Some of the criteria included in the performance matrix were Recall, F1-score, precision, and accuracy. A following metrics were computed for various classes: A higher number of True Positives (TPs) indicates that positive cases were properly identified, while a lower number indicates that True Negatives (TNs) were correctly classified negative occurrences. those that are mistakenly classified as positive are known as False Positives (FPs), while those that are improperly classified as negative are known as False Negatives (FNs). The chosen performance metrics—accuracy, precision, recall, and F1-score—are all directly related to practical outcomes in project risk management.

The following formulae may be used to represent the assessment metrics:

Accuracy: An 85% accuracy indicates that the model correctly identifies project risks in the majority of cases, which provides project managers with reliable information on potential risks. It enhances decision-making and reduces the

chances of having to address emerging issues temporally. The formula (3):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Precision: Precision of 82% suggests that when the model predicts a project risk, it is mostly correct. The following formula of precision (4):

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

Recall: Recall of 85% shows the model's ability to identify actual project risks among all risks. In combination, they fine-tune the accurate identification of potential risks with low numbers of false positive findings. The formulation of recall is (5):

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

F1-score: Thus, it shows the balance between the risk identification and avoiding false positive/negative values of 80% by the F1-score, which is the harmonic mean of precision and recall. This balance is crucial for project managers as they need accurate predictions that lead to effective intervention without overburdening resources. The F1-score formula is (6):

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

As a means of aiding decision-making and providing an objective measure of the models' performance, this study used these four measures to assess the ML models.

4. Result Analysis and Discussion

The experimental study was designed to validate the effectiveness of integrating predictive analytics into project management processes, focusing on outcome prediction and resource optimization. By leveraging a dataset comprising historical project data, the study aimed to demonstrate how predictive analytics could enhance project managers' ability to forecast project outcomes accurately and allocate resources more efficiently. The following Table 2 provides the performance of GBM model across performance matrix.

Table 2. Historical project data based GBM model performance.

Measures	Gradient boosting machine
Accuracy	85
Precision	82
Recall	85
F1-Score	80

An impressive 85% accuracy, 82% precision, and 85% recall were attained by the GBM model, as shown in Table 2 and Figure 2, indicating outstanding

classification performance. Precision and recall are both well-balanced with an F1-Score of 80%.

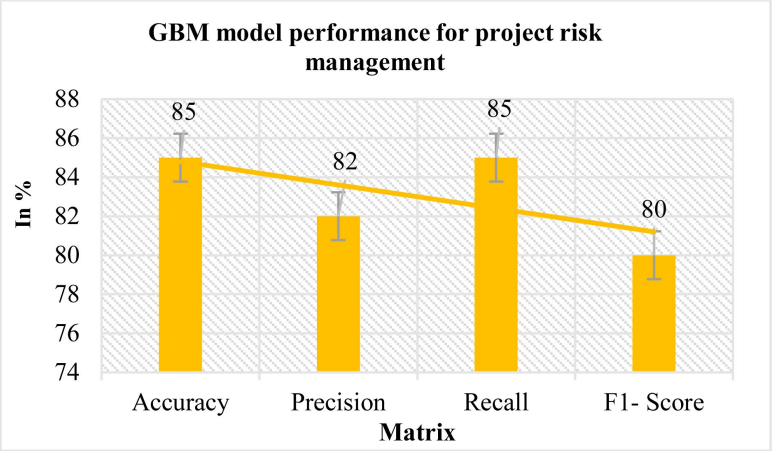

Figure 2. GBM model performance.

Figure 3. Line graph for model performance over iterations.

A line graph as shown in Figure 3 illustrates the improvement in model accuracy over different iterations of hyperparameter tuning. An x-axis displayed a total number of iterations, while a y-axis displays a percentage of correctness. A graph displays a clear upward trend, indicating that model performance improves as the tuning process progresses. This indicates that the model is capable of refining its predictions and adjusting to different types of projects.

The bar graph Resource Optimisation Efficiency and Project Cost Reduction in Figure 4 illustrates that Predictive Analytics significantly outperforms Traditional Allocation in both metrics. Predictive Analytics achieves 85% in Resource Utilization Efficiency compared to 70% for Traditional Allocation, and 10% in Project Cost Reduction, double the 5% achieved by Traditional Allocation. This demonstrates the superior effectiveness of Predictive Analytics in optimizing resources

and reducing project costs. Resource management improves concurrently with the outcome of projects since efficiency in the usage of available resources enhances the completion of projects promptly and cost-effectively.

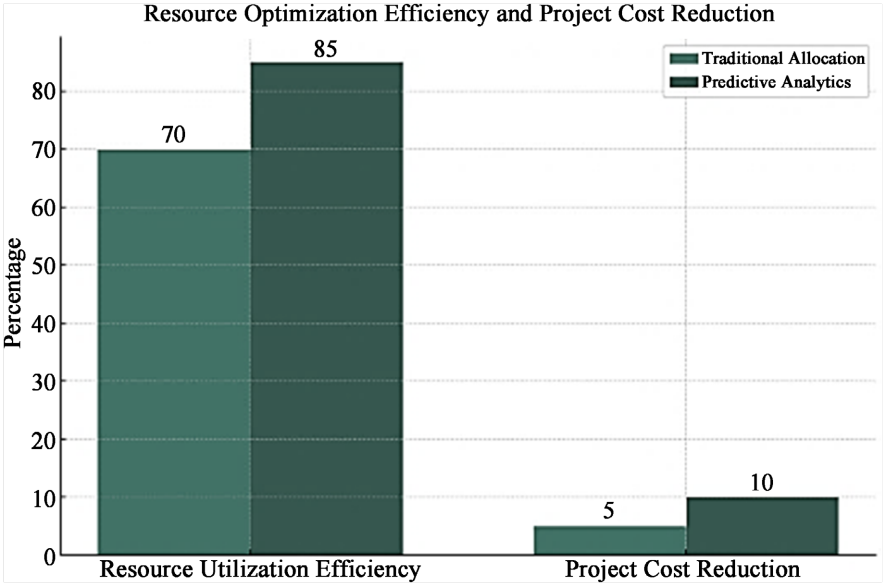

Figure 4. Resource optimization efficiency.

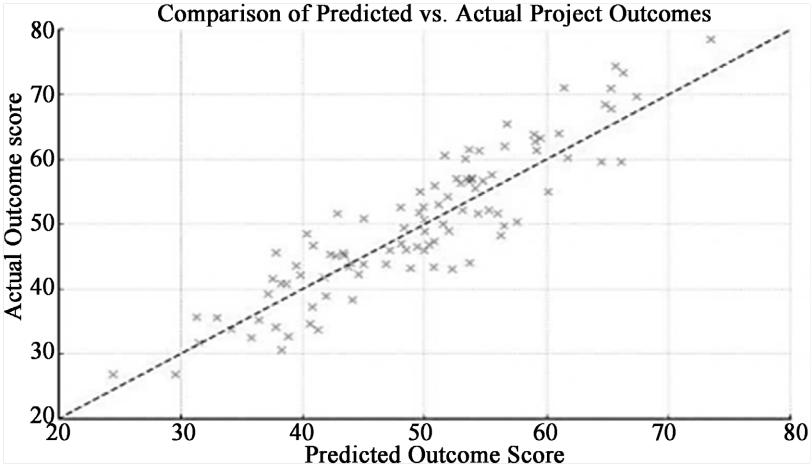

Figure 5. Comparison of predicted vs. actual project outcomes.

Figure 5, which compares projected and actual project outcomes, displays a scatter plot that demonstrates that, for most projects, the predictions and actual results are in agreement. Each green "x" represents a data point comparing a predicted score to an actual score. The red dashes on the figure line depict the state of precise predictive accuracy when the forecasted score is the same as the actual score. This supports the notion that the model can effectively predict risks and returns within projects in order to assist project managers. The proximity of the predicted values to the actual observation further corroborates the validity of applying ML in risk assessment of projects.

4.1. Discussion

The experimental findings reveal the great benefits of adopting the use of predictive analytics in project management. A significantly higher level of classification accuracy is shown by the Gradient Boosting Machine (GBM) model, with the accuracy estimated at 85%, precision at 82%, and recall at 85%, which proves the high efficiency of this model for further accurate prediction of project outcomes. The gradual increase in value of model accuracy as displayed above shows that the model can be tweaked in future hyperparameter tuning iterations with resultant better performance metrics. Additionally, predictive analytics achieves a resource utilisation efficiency of 85%, compared to 70% for traditional allocation methods, and a project cost reduction of 10%, double the 5% achieved by traditional approaches. The real-world data presenting the outcomes of the projects as plotted in the scatter plot of the predicted against actual results has shown a lot of congruity of the results of the predictive model. Overall, these findings are closely associated with the notion of how big data can change the nature of concurrent decision-making and improve the existing approaches to project management.

4.2. Comparative Study

This section provides a comparative analysis between ML models for project risk management. The ML models are GBM, LR [12], and SVM [12] that compare across performance parameters.

Figure 6 shows a comparison of model performance. The GBM achieved

Table 3. ML model comparison on historical dataset.

Model	Accuracy	Precision	Recall	F1-Score
GBM	85	82	85	80
LR	71	83	77	87
SVM	83	84	77	83

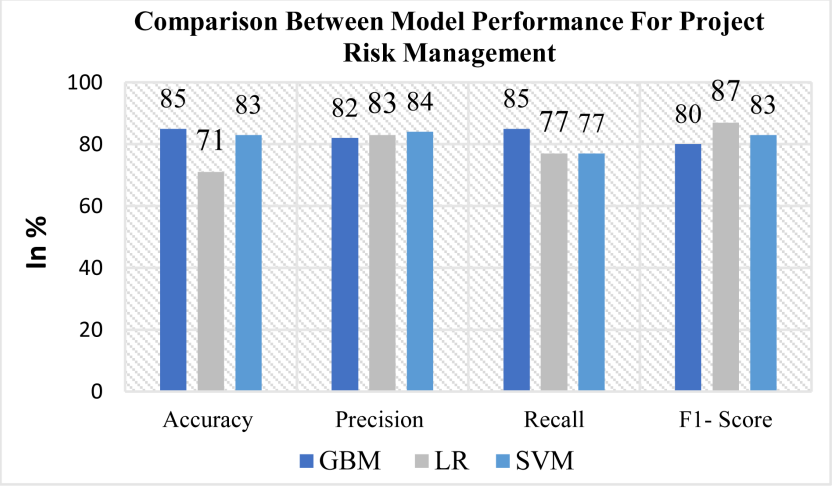

Figure 6. Comparison between model performance.

the highest accuracy at 85%, with a precision82%, a recall 85%, and an F1-score 80%. On the other hand, the LR model reported fewer accuracy at 71%, but it had the best precision at 83% and F1-score at 87% to guarantee the method's FP and FN. The SVM, provided a good performance with an accuracy 83%, precision84%, recall 77% and an F1 measure 83%. These findings imply that even though GBM is most accurate, LR provides better trade-off among precision and recall and is, therefore, more suitable in conditions where true positives are significant.

5. Conclusion and Future Scope

Risk assessment is an important part of every management process, especially for large and long-life projects and projects that exist in a state of constant change. Conventional risk management tools are mostly inadequate for such environments, perhaps explaining why a more reliable means of risk assessment is required. This study suggests the use of an (LR) and a (GBM) as ML tools to improve the risk prediction model. The characteristics, scale, cost, amount of effort and duration of project, etc., which are identified to influence the likelihood and prevalence of risks, indicated that the proposed models have a strong potential to act as risk predictors. These findings stated that GBM was more responsive with an accuracy of 85%, precision of 82%, recall of 85%, and F1-score of 80%, and thus, it can be considered a very effective tool in project risk management. Still, precision-recall trade-off was more favorable for LR, whereas this could be preferable in tasks, where both are essential.

However, the study has limitations, though the obtained results demonstrate optimism. The sources of data used in this research may not contain all the aspects of project risk because most of them revolved around time, task length, resources and results. Future studies should envisage considering more risk-related variables and the assessment of different ML methods' effectiveness. Also, the further investigation of more elaborate feature selection approaches may be beneficial for enhancing the results of a project risk-related analysis by providing for more subtle characteristics captured in the data. More data and better model calibration could enable more dependable and universally applicable findings for improving on predictive analysis for risk in projects.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Research Article

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A Comparative Analysis of Network Intrusion Detection Using Different Machine Learning Techniques

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Abstract

The security of modern communication networks cannot be adequately assured without intrusion detection systems (IDS). Pattern recognition, signature analysis, and rule violation detection were the primary goals of these systems. Recent advances in ML and DL approaches have shown promise as prospective replacements in a field of NID. Typical and anomalous patterns may be distinguished using these techniques. This paper uses the NSL-KDD benchmark data set to assess NIDS using many ML algorithms, like SVM, DT, LR, and RF classification. We evaluate the precision, recall, accuracy, and FPR of several ML techniques, such as SVM accuracy is 98.97%, Random Forests, and Decision Trees. The results demonstrate that, in comparison to conventional techniques, machine learning approaches greatly increase detection rates while reducing false alarms. And in this, a RF achieve a high accuracy which is 99.83%. The results of this investigation demonstrate that not only is it feasible to obtain a high detection rate of assaults, but also accurate prediction. It is clear from these findings that ML has great promise for developing highly efficient NIDS systems.

Keywords: *Network Intrusion Detection (NID), Machine Learning, NSL-KDD, Support Vector Machines, Random Forests, and Decision Trees.*

Introduction

In recent years, networks have become more important to the contemporary way of living. As a result, cybersecurity has emerged as a lucrative field of study that has inspired fresh ideas in data innovation [1][2]. Protecting private information passing via networks is increasingly essential to contemporary society, since networks, and security in particular, are among the most critical concerns in the area of information security. Software such as firewalls, IDS, and antivirus programs are the core components of cybersecurity techniques. Computer engineers still face several difficulties, however, since hackers and other hackers may successfully try to breach computer systems or networks. Consequently, there is a growing demand in this industry to develop more potent IDS [3].

The development of the internet in this age has positively affected several endeavours. Emerging massive data and information sets are likewise affected by this enhancement [4]. As the internet evolves, several challenges must be addressed to make it a more reliable, stable, and secure system. Firewalls, certain dynamic processes, software, etc., are only a few of the many options available for making systems more secure. IDS are among the most effective dynamic mechanisms for identifying and stopping certain types of network intrusions [4]. The primary function of an IDS is to keep an eye on network processes and analyse them for any signs of unusual activity or divergence from the norm [5][6]. Programs are made to scan network data for indications of harmful activity or infringements of policies. NIDS, HIDS, PIDS, APIDS, and HIDS consist of five distinct types of IDS. The two primary detection approaches are signature-based detection and anomaly detection, which is also called misuse detection [7][8].

IDS are classified into five types: APIDS, NIDS, PIDS, HIDS, and HIDS. Misuse detection is otherwise called signature-based detection where machine learning Strengthen the architectures of these systems and enables two pivotal detections Figure 1. Misuse detection employs machine learning techniques to match the present traffic with previously learned attack patterns, while anomaly detection applies machine learning to discover new traffic normality or the lack of it [9][10]. Through integration of the ML models, IDS will be able to analyse new threats in order to enhance the detection rate while also enhancing the response time of the system against known and unknown threats [11].

The focus of this study is to identify and analyse multiple approaches to the detection of network intrusions and improve, in general, the security of network systems in relation to the constantly emerging and more complex cyber threats. The study aims to contribute to the following goals by analysing distinct

techniques like DT, SVM, and NN, while attempting to discover the best approach to recognise known and unknown intrusions. Furthermore, this study also seeks to evaluate the effectiveness of these techniques when implemented on benchmark datasets including, but not limited to NSL-KDD, taking into account factors like accuracy and time complexity of the process with an eventual view of deploying it in real life. More effective IDSs for safeguarding network infrastructure are the ultimate goal of this project. The primary findings of the study are as follows:

- A research that compares several ML approaches, including RF and SVM, for NID.
- Utilization of the NSL-KDD dataset to address previous dataset limitations and enhance testing robustness.
- Demonstration that Random Forest significantly outperforms other models in F1-score, recall, accuracy, and precision.
- Effective use of SMOTE to address class imbalance and enhance model performance.
- Provides insights and recommendations for advancing machine learning approaches in network security.

A. Structure of Paper

This study is organised as follows: In Section II, the prior research is summarised. The study methodology is detailed in Section III, which also includes the classification models utilised for analysis. The experimental data are detailed and analysed in Section IV, with an emphasis on the performance indicators for each model. Findings and recommendations for further study are presented in Section V.

Literature Review

This section examines a range of literature centred on network intrusion detection, emphasising significant studies that investigate various methodologies for NIDS. The most relevant research publications on this topic are summarised in Table 1.

In this paper, Abraham and Bindu (2021) this research aim to investigate various DL and ML approaches to intrusion detection by analysing existing research and providing context on these algorithms as they pertain to IDS. A performance comparison of several ML classification techniques using the DARPA dataset is also included in the paper. An IDS's performance is based on how accurate it is. Raising detection rates while decreasing false alarms requires improved intrusion detection accuracy [12].

In this paper, Disha and Waheed, (2021) make employ of ML methods to construct IDS, since ML models effectively provide improved accuracy in detecting anomalies. However, in order to test the ML models that relied on binary classification, they employed the UNSW-NB 15 dataset, which is available offline. The DT, RF, GBT, and MLP were trained and tested in order to undertake performance analysis. They eliminated the characteristics that were unrelated to response employing a Chi-Square test. A result showed that DT was a most accurate classifier, with the lowest FPR. Feature deletion increased the overall performance of all models except RF. Our suggested strategy outperformed other current ML algorithms in terms of accuracy, according to experimental study [13].

In this paper, Halimaa and Sundarakantham (2019) different kinds of IDS have been developed to safeguard networks using a variety of ML and statistical methodologies. This issue is addressed in the suggested method. ML methods like SVM and NB are used. Using the NSL-KDD knowledge discovery dataset, an IDS may be evaluated [14].

In this paper, Chabathula, Jaidhar and Ajay Kumara, (2015) PCA is used to convert datasets with greater dimensions into datasets with fewer dimensions. SVM, KNN, J48 Tree algorithm, RF classification algorithm, Adaboost algorithm, Nearest Neighbours generalised Exemplars algorithm, NB probabilistic classifier, and Voting Features Interval classification algorithm are test methods used for the reduced dimension dataset. KDD 99 is the data set used throughout the whole experimen t[15].

In this paper, Aljohani and Bushnag, (2021) The KDD99 dataset is used to test the suggested method. When it comes to anomaly-based detection, the KDD99 is the gold standard. This method effectively and quickly detects assaults. When compared to all of the SVM kernel models, Neural Network demonstrated superior classification accuracy. Prevention of LAN security threats is the goal of the proposed approach, which employs SVM and NN intrusion detection models [16].

Table 1: Presents comparative table on network Intrusion detection using machine learning.

References	Methodology	Dataset	Performance	Limitations & Future Work
[12]	In-depth review of DL and ML methods for intrusion detection; comparison of ML classification methods	DARPA dataset	Comparison of various ML classification methods; performance based on accuracy	Need to improve intrusion detection accuracy to decrease false alarms and increase detection rates
[13]	Machine learning techniques (DT, RF, GBT, MLP); feature elimination with Chi-Square test	UNSW-NB 15 dataset	DT showed maximum accuracy and lowest FPR; overall performance improved feature elimination.	Limitations in other models like RF; Future work should explore other feature selection techniques and advanced ML models
[14]	Machine learning techniques (SVM, Naïve Bayes) for classification problems	NSL-KDD dataset	SVM and Naïve Bayes were applied, with emphasis on accuracy	Future work may involve exploring other datasets and advanced classification methods to further enhance detection accuracy
[15]	Principal Component Analysis (PCA) for dimensionality reduction; various classification	KDD99 dataset	TREE classification algorithms showed superior detection	Future work could include testing other datasets and improving system resource utilisation.

	algorithms (SVM, KNN, J48, RF, Adaboost, etc.)		accuracy, computational efficiency, and low false alarms	
[16]	Comparison of SVM and Neural Network models for anomaly-based detection	KDD99 dataset	Neural Networks outperformed SVM models, especially in classification accuracy.	Future work may involve optimising Neural Network models and exploring hybrid models for better efficiency.

B. Research gaps

Despite significant progress, several research gaps remain in the area of IDS that might benefit from DL and ML techniques. One notable issue is that most research focuses on particular datasets, like KDD99, NSL-KDD, or UNSW-NB 15, which cannot adequately depict a diversity of contemporary network traffic. As a result, models' generalizability across multiple datasets is limited. Furthermore, even with the great accuracy achieved by many techniques, false-positive rates remain a difficulty, resulting in unreliable detection in practical circumstances. Additionally, despite the promising findings of neural networks and other advanced models, their implementation in resource-constrained contexts is limited due to their processing cost. Lastly, research into creating scalable, effective, and reliable IDS solutions is still needed, as the integration of hybrid models and real-time adaptive mechanisms to dynamically increase detection performance is still in its early stages.

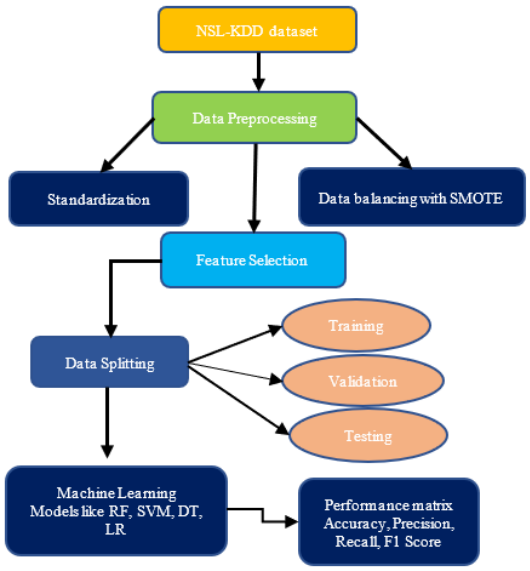

Figure 1: Data Flow Diagram of methodology for network intrusion detection system.

Methods and Materials

This study aims to find the best ML methods for network intrusion detection by comparing and contrasting several methods. The end objective is to find the best method for improving network system security by differentiating between safe and dangerous actions most rapidly and correctly. This research study involves several key steps, beginning with data collection using the NSL-KDD dataset, which addresses issues from the KDD 99 benchmark and contains 41 features. Data preprocessing is performed, which includes standardisation to normalise feature values and ensure consistent scaling, followed by feature selection using correlation analysis to eliminate redundant features. The SMOTE is used to generate synthetic data points after rectifying an issue of class imbalance. To prevent overfitting, the dataset is distributed as follows: training, validation, and testing sets, with a ratio of 70:15:15. There are a number of ML algorithms used for training models, such as RF, SVM, DT, and LR. Multiple decision trees are built using randomised data sets in the RF model; SVM is used for fast classification in DT; entropy is used to define classification rules in RF; and the likelihood of binary outcomes is modelled using LR. Each model's performance is evaluated employing metrics like as Recall, F1-score, precision, and accuracy. Figure 1 is a flow diagram depicting the network intrusion detection approach.

The steps in the data flow diagram are outlined below, providing a detailed explanation of each stage involved in the system's data processing.

A. Data Collection

The NSL-KDD dataset, which overcomes problems with the KDD 99 benchmark, was used for data collection for this work. The dataset consists of connection records with 41 features, including 34 numeric and 7 symbolic or discrete features. The NSL-KDD training set has 22 different attack kinds, whereas the testing set contains an additional 17 attack types that were not included in the training set.

B. Data Preprocessing

Data preparation for analysis or modelling is called preprocessing. Data preparation is a process of improving the quality and analytical applicability of data by cleaning, converting, and organising it. Common tasks include filling in missing values, eliminating duplicates, standardising data, and encoding categorical variables. The goal is to make data analysis and ML models more accurate and efficient.

C. Standardization:

A crucial approach to feature scaling is standardisation, which is often called z-score normalisation. The process entails dividing the value of each characteristic by its standard deviation after removing the mean. In cases when the input data has a wide range of feature values, this method shines [17]. After being standardised, all features are on the same scale, with a mean (μ) of 0 and a standard deviation (σ) of 1.

$$x_{new} = \frac{x - \mu}{\sigma} \quad (1)$$

The accuracy of our prediction models is much improved by this procedure. Normalisation of the Z-score mathematically represented in Equation (1).

D. Feature Selection

Feature selection is a method for improving and streamlining subgroups by removing irrelevant or superfluous properties and focussing on the most important ones [18]. Correlation is a well-liked and effective method for finding the most related features in any dataset; it establishes the degree of association between features on the premise that they are conditionally independent with respect to the class. Characteristics that are highly predictive of the class and not predictive of each other make up a strong feature subset.

E. Data balancing with SMOTE

Class imbalance in datasets may be addressed using the SMOTE approach, which creates synthetic samples for the minority class. It creates new instances by interpolating between existing samples, helping improve model performance in classification tasks where imbalanced data could lead to biased results[19].

F. Data splitting

In data division, data splitting is a crucial step. The dataset used in this study has been separated into three sub-sections: 70% served for training, 15% had been used for validation, and 15% was used for testing. This approach guarantees that the model will learn from one subset and be evaluated on another, hence reducing overfitting.

G. Classification Models

This section outlines the ML models employed for classification using a NSL-KDD dataset and evaluates their performance to determine their effectiveness.

1) Random forest (RF)

The RF algorithm uses the ensemble learning approach for classification and regression. This method is designed for supervised learning. It uses a combination of n regression trees to provide more accurate predictions than a single tree could on its own. When training, RF constructs a forest of decision trees, which it then uses to make a final prediction by combining their predictions. Data scientists may use RF to lower the variance of algorithms, especially DT, that have a large variation by using random sampling with replacement, or bagging in ML terminology[20]. Bagging takes a training set of features X and outputs Y, then iteratively fits the trees to random samples from a training set β times (b=1, 2,….,β).

A replacement set of cases is obtained for each tree by randomly sampling them from a training set. Every set of occurrences represents a unique tree via a random vector ∅k. The decision trees built from these sequences will also vary significantly as they will not be identical. It is proposed that Equation (2) may be used to describe a K-th tree's forecast for an input X:

$$h_k(\mathrm{X}) = \mathrm{h}(\mathrm{X}, \emptyset_k),), \forall k \in \{1,2,\ldots,K\} \qquad (2)$$

where K is a total number of trees. During a tree's branching process, every node picks characteristics at random to minimise feature correlations.

2) *Support vector machine (SVM)*

A popular ML technique for regression and classification problems is the SVM. SVM was used in cheminformatics and bioinformatics, among other fields. Using training data, the SVM classifier creates a model for the classification. The categorisation of an unidentified sample is a subsequent step [21]. The core principle of SVMs is the use of hyperplanes to establish hierarchies. When the data can be divided linearly, SVM has shown impressive accuracy. Non-linear separation of separable data is not possible using SVM output.

3) *Decision tree (DT)*

The DT algorithm is a well-recognised technique for classification. A decision tree graph resembles a tree. Based on the criteria that are implemented from the tree's root to its leaf, it classifies objects. The test nodes are located within the network, the branches represent the test results, and the leaf nodes determine the categorisation. A data set is selected based on its purity level. The quantification of this impurity is done using entropy. A high entropy level indicates a high level of impurities [22].

4) Logistic Regression (LR)

LR is a classification approach that assumes that the result is influenced by several independent factors. To determine the likelihood of an event occurring, LR applies a probability function; it is a kind of binary classification [23]. It computes the probability using the formula below. Among the benefits are its quick classification speed and ease of extension to multi-class problems. The primary drawback is that LR cannot be used to handle nonlinear problems[24].

A. Performance matrix

A number of measures were used to evaluate the model's performance, including recall, accuracy, precision, F1-score, and ROC curve. These measurements make it possible to assess every class separately. Below are the formulae needed to calculate these performance metrics.

1) Accuracy:

The percentage of all forecasts that were accurate is known as the accuracy (AC). It may be found in Equation (3):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

2) Precision:

The ratio of real positives to the total of both real and false positives is one way to describe the precision. Equation (4) provides the following:

$$Precision = \frac{TP}{TP+FP} \qquad (4)$$

3) Recall:

The word "recall" describes the proportion of correctly classified positive cases as a fraction of all positive examples. Equation (5) provides the mathematical expression for it:

$$Recall = \frac{TP}{TP+FN} \qquad (5)$$

4) F1-score:

A harmonic mean of recall and precision in a classification task is measured by the F1-score. This is given by Equation (6):

$$\text{F1- Score} = 2.\frac{(Precision\ .\ Recall)}{Precision\ + Recall)} \qquad (6)$$

Each of the four cells that comprise the output matrix represents a different outcome: TP, TN, FP, or FN. A positive relationship between the actual and projected values is shown by TP; TN occurs when the model predicts negative values while the data shows positive ones; FP indicates that the model predicts positive values whereas in fact the results are negative; and finally, a negative value for both the anticipated and actual values is denoted by FN.

5) ROC-AUC

The most crucial metric for evaluating the model is an area under a ROC curve, which is often abbreviated as AUC. Each time, a TPR and FPR were computed as the horizontal and vertical axes, respectively, based on the sorted prediction results of the model, which indicated that the samples were forecasted as positive instances in a certain sequence.

Result Analysis and Discussion

Results from testing ML models on the NSL-KDD dataset for detecting network intrusions are shown here. In addition, compare and contrast the different NIDS ML models using f1-score, recall, precision, and accuracy metrics.

Table 2: Results of Random Forest model for NIDS.

Performance Measures	Random Forest
Accuracy	99.83
Precision	99.93
Recall	99.71
F1-Score	99.82

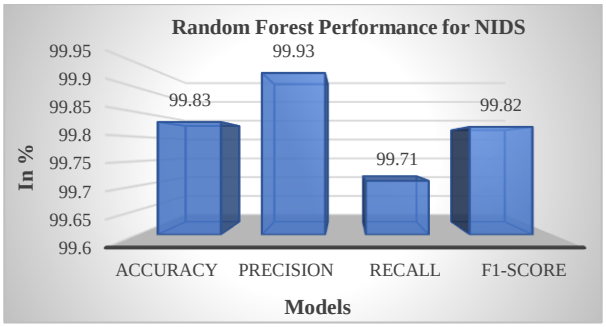

Figure 2: Results of Random Forest for NIDS.

Figure 2 illustrates a performance of the RF model, which achieved a highest result across all classification metrics. The graph displays key metrics like Recall, accuracy, precision, and F1-score. On the x-axis, a various performance metrics are presented, while a y-axis shows a corresponding metric values. The model demonstrated strong performance with an accuracy 99.83, precision 99.93, recall 99.71 and F1-score 99.82. Overall, a Random Forest model excelled in all evaluation metrics, highlighting its effectiveness in accurately classifying the data.

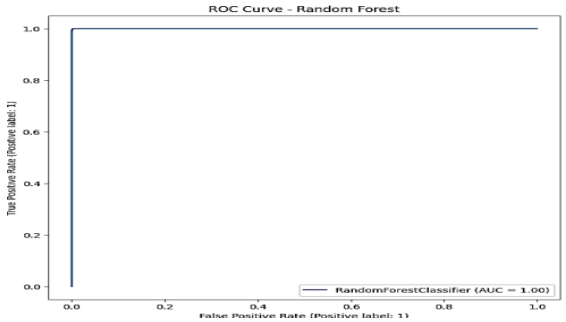

Figure 3: ROC curve of random forest model.

Figure 3 represents a ROC curve for an RF model. Plotting the TPR versus the FPR is what the curve does. The model performs quite well in differentiating among positive and negative classes, as evidenced by its AUC of 1.00, respectively.

A. Comparative Analysis

This Table displays the results of several ML algorithms that were run on the NSL-KDD dataset in order to analyse NID. The following is an examination and explanation of several ML models' performance metrics, including Accuracy, Precision, Recall, and F1-score:

Table 3: Comparison between various machine learning models for the analysis of network intrusion detection.

Model	Accuracy	Precision	Recall	F1-Score
SVM[25]	98.97	99.9	99.2	99.2
LR[26]	81.51	0.851	0.815	0.832
DT[27]	0.82	0.82	0.82	0.80
RF	99.83	99.83	99.83	99.83

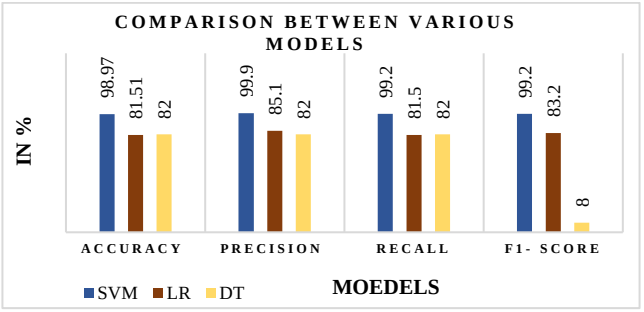

Figure 4: Comparison between various models.

Table 3 and Figure 4 also contains the outcomes of the comparison of a comparative models for the analysis of NID classification models. A present study focuses on a comparison of a machine learning models, SVM, LR, DT, RF, and identifies that the RF model is effective for intrusion detection with high precision, recall, accuracy, an F1-score of 99.83%. Next is Support Vector Machine which performs comparably to k-NN with overall accuracy of 98.97%, and precision of 99.9% which shows good classification capacity. As can be seen, the performance of the LR and DT models is much lower – LR has the accuracy of 81.51 %, while DT has the lowest result of 82%. Here LR shows only moderate levels of accuracy and recall compared to other methods such as SVM or RF. Nevertheless, the assessment of all of the metrics taken into consideration proves that the RF model is the most efficient and reliable one among all the other types of the model and, consequently, followed by the SVM model.

Conclusion and Future Scope

Security is seen as a primary problem of the network due to the increasing use of network services. Numerous networked computers are vital to the operation of businesses and other applications that rely on the network to provide services. As a result, this study evaluated the usefulness of the relevant framework algorithms when applied to the NSL-KDD dataset and suggested a NIDS based on the use of ML techniques. It is evident from the comparative study that only highly skilled IDS are capable of preserving the network's integrity. The study also reveals that the suggested method minimised false positive rates and obtained excellent detection accuracy, with DT, RF, and SVM models performing the best overall with an accuracy of 98.97%. An overview of future works is presented in the report where more detailed analysis of these algorithms has to be produced in the case of the multiclass classification and real-time applications.

Further research should be directed towards the studies of mixed and combined methods, the feature selection techniques, and solutions regarding the large-scale problem to combat contemporary network threats. Besides, the use of IDS with higher efficiency as well as ability to develop concrete actions against new types of threats will imply the integration of deep learning approaches and their application in various datasets. In conclusion, this study reveals that there is a continuous demand for new ideas into intrusion detection, which lays the foundation to future developments in Network Security.

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