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The methodology for this research paper involves conducting a comprehensive literature review encompassing two main areas: big data and deep learning. Firstly, an exploration of the big data literature will be undertaken to define the concept, outline its characteristics, identify challenges, and elucidate real-world applications. Subsequently, an extensive review of deep learning literature will delve into its historical development, architectural intricacies, training methodologies, and key models, such as neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). The research will then intersect these two domains by examining how deep learning techniques address the unique challenges posed by big data, particularly in the realms of feature learning, unsupervised learning, supervised learning, and generative modeling. This intersection will be illustrated through case studies spanning diverse industries. Furthermore, the study will highlight both the potential and limitations of applying deep learning to big data scenarios and discuss avenues for future research.

# **Introduction (***Heading 1*)

The practice of big data analytics involves examining vast datasets to uncover concealed patterns, correlations, and valuable insights. Modern technology enables the swift analysis of data, yielding immediate answers. Big Data Analytics serves as a means to enhance organizational understanding. Employing big data analytics empowers individuals to make well-informed decisions, eliminating the need for uninformed guesswork. In essence, Big Data Analysis primarily focuses on extracting valuable insights from data, benefiting not only top-level executives but also enhancing customer services

(Lodha, 2019,). Lately, the fields of Deep Learning and Big Data Analytics have been exceptionally dynamic in the realms of science and engineering. Big data encompasses digital data that poses challenges in terms of management and analysis using conventional software tools and technologies. The analysis of data, leading to the extraction of valuable insights, holds significant importance in facilitating informed decisions within organizations, catalyzing scientific discoveries, bolstering national security, and enhancing healthcare practices. The burgeoning demand for real-time data analysis has spurred the development of Big Data Analytics, a process aimed at distilling valuable information from massive datasets to facilitate optimal decision-making. Over the past decade, data volumes have witnessed a substantial increase, driven by the emergence of social networks, the Internet of Things, cloud computing, and other technological advancements. While this surge in data size offers potential opportunities across various sectors, it also presents challenges in data mining and information processing. Deep Learning, a compelling focus within Artificial Intelligence (AI), addresses these challenges, particularly its proficiency in handling both labeled and unlabeled data commonly found in Big Data environments. Deep Learning encompasses machine learning techniques, including supervised and unsupervised methods, designed to automatically derive hierarchical representations within intricate architectures. It has achieved remarkable success in essential fields such as computer vision, speech and audio processing, and natural language processing. Deep Learning's capability to extract intricate, high-level abstractions and data representations from vast datasets, especially in unsupervised scenarios, renders it invaluable as a tool for Big Data Analytics. In particular, Deep Learning can enhance various aspects of Big Data Analytics, including semantic indexing, data tagging, rapid information retrieval, and discriminative modeling. Moreover, the application of Deep Learning methods is vital in addressing the myriad challenges encountered in Big Data Analytics, including the analysis of swiftly moving streaming data, managing highly distributed input sources, handling noisy and low-quality data, dealing with high dimensionality, scalability of algorithms, processing unsupervised and uncategorized data, coping with limited supervised or labeled data, and managing the format variations of raw data (Makrufa Hajirahimova, 2020).

In this paper, we aim to provide an overview of crucial aspects related to learning from extensive datasets within the context of deep learning. While we do not intend to offer a survey of all deep learning research, our focus is on discussing significant issues, current research endeavors, and the challenges posed by big data. Specifically, we delve into the potential of unsupervised Deep Learning in handling large datasets and outline future trends. The paper's structure is as follows: Section 1 offers a concise review of big data, encompassing its types, tools for management, and challenges. Section 2 delves into deep learning, covering various architectures, applications, and associated challenges. Section 3 is dedicated to the exploration of Deep Learning in the context of big data, including its applications and challenges. Finally, in Section 4, we deliberate on the challenges and prospects associated with unsupervised deep learning for Big Data.

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# **Big data**

Big data is considered the oil of this century for its valuable contribution on many fields by providing new knowledge for better understanding to issues under study leading to innovation in many theories and technologies (Ling Tang, 2022,). Datasets contain huge volumes and complex amount of information to the extent that make it impossible to process with the traditional tools can be named as Big Data (Ishwarappa, 2015). It comes as structured, unstructured or semi structured with several different types and sources.

For this reason, big data has five characteristics: large volumes, increasing speed at which data is generated and moves around i.e. Velocity, variety of structured and unstructured data. The three V’s makes the data dirty i.e. Veracity and the last characteristic is the value of the data. To be able to implement the data, it has to be turned into value first. Therefore, value is the most important aspect of big data (Ishwarappa, 2015). After the boom in the internet Big Data can be collected from many sources on the web, Media or could (Anon., n.d.). Data formats vary from text to audio and video. The tremendous advantages of utilizing BD in decision making to increase productivity, efficient marketing, better profit in investment and forecasting research and many more remained untapped until meaningful insights are extracted from the data. The first two main processes in insight extraction are: data management to prepare the data for the analysis and data analytics to acquire knowledge form BD (Amir Gandomi, 2015). The framework of the tow processes in detail shown in **figure.1**.

The following section will discuss big data analysis and different data types and data analytical techniques for each data type.

## **Big Data Analysis**

There are five phases for data analysis to obtain information, correlations and patterns form the data together with the proper tool to make informed decisions and conclusions. The phases are sequential firstly, defining the requirement gathering, to decide what and why you are doing the analysis. Then, based on the requirements you collect the data and it is either streamed or static. Third phase is the data cleaning. The fourth phase is the data analysis during which we can use data analysis tools to understand and interpret the data. The last phase is data visualization which appear in the form of charts and graph because it is easier to comprehend (Lodha, 2019,).

The next section, we review big data analytical techniques for different formats and types of data.

-**Text mining**

Text analytics, or text mining, extracts valuable information from textual data like social media posts, emails, and more. It employs statistical analysis, computation linguistics, and machine learning. Text analytics methods include information Extraction (IE) includes Entity Recognition (ER) and Relation Extraction (RE) to categorize names and identity connections between entities for informed decision-making, such as predicting.

stock market trends form financial news (Amir Gandomi, 2015). Further, includes text summarization for creating

concise document summaries, question answering in natural language, and sentiment analysis for evaluation (Feldman, 2013,) opinions toward entities. These techniques range form extractive to abstractive approaches, using advanced Natural Language Processing (NLP) methods and can be applied across various domains.

-**Speech analytics**

Audio analytics analyzes unstructured audio data primarily in customer call centers and healthcare. In call centers, it enhances customer experiences, agent performance evaluation, sales turnover, and policy compliance monitoring. Healthcare applications include diagnosing conditions affecting communication patterns and analyzing infant cries. Two common technological approaches in speech analytics are transcript-based (LVCSR) and phonetic-based systems, both involving indexing and searching phases for extracting information form audio data. LVCSR transcribes speech content into words, while phonetic-based systems work with phonemes to distinguish words by sound (Amir Gandomi, 2015).

-**Video analytics**

Also known as video content analysis (VCA), is a field that monitors, analyzes, and extract meaningful information form video streams (Amir Gandomi, 2015). It’s increasingly important due to the proliferation of CCTV cameras and video-sharing websites. Big data technologies are being used to handle the vast amount of video data, making automatic analysis possible. The primary application is in automated security and surveillance, where it efficiently detects breaches, identifies objects, and more (Hasan, 2011,). In retail, it provides business intelligence by gathering customer demographic data and monitoring store activity. Video analytics also plays a role in indexing and retrieving multimedia content, with tow system architectures: server-based edge-based, each with its advantages and drawbacks (Hu, 2011,).

As discussed above a variety of big data has been involved across various fields and predictive analytics using historical and current data to forecast future outcomes. Techniques can be divided into groups: those extrapolating historical patterns (e.g., moving averages) and those capturing interdependencies between variables (e.g., linear regression), categorized into regression and machine learning methods (Amir Gandomi, 2015) (Ling Tang, 2022,).

Handling big data efficiently involves various technologies and techniques for managing and processing. The following section will discuss the tools to storage and process big data.

**Tools to handle big data:**

Depending on the specific interests, research questions and goals the suitable tool to be employed to attack a big data is determined. There are many techniques and technologies fast growing to attempt extract insights and patterns. Discussing all of them in detail is beyond the scope of one paper, therefore, a brief listing to the fundamental and famous technology will be provided with the relevant research papers of further reading.

**First, the Hadoop framework**:

The Hadoop framework is an open-source, distributed computing platform designed for processing and storing large volumes of data across clusters of commodity hardware. It was developed to handle big data analytics and processing tasks. Hadoop provides a scalable, fault-tolerant, and cost-effective solution for managing and analyzing massive datasets (hadoop.apache.org/, n.d.) (White, 2015).

Key components of the Hadoop framework include:

Hadoop Distributed File System HDFS is a fundamental component of the Hadoop ecosystem, designed for storing and managing large volumes of data across distributed clusters. It employs a master-slave architecture with a single NameNode for metadata management and multiple DataNodes for data storage. HDFS is optimized for data reliability, fault tolerance, and scalability, making it a core technology for big data processing in Hadoop environments (Shvachko, 2010,). Furthermore, it provides a comprehensive ecosystem of tools and libraries for various data processing tasks, including real-time stream processing (with tools like Apache Kafka and Apache Flink), data warehousing (with tools like Apache Hive), and machine learning (with tools like Apache Mahout and Apache Spark ).

**Second, MapReduce** is a programming model and data processing framework introduced by Jeffrey Dean and Sanjay Ghemawat at Google. It simplifies large-scale data processing by breaking tasks into two main phases: the Map phase, where data is divided into key-value pairs and processed in parallel, and the Reduce phase, where results are aggregated. MapReduce is designed for fault tolerance and scalability, enabling efficient processing of vast datasets across distributed clusters. This approach has become a cornerstone of big data analytics and processing, with implementations like Apache Hadoop widely adopted in various industries for data-intensive tasks (Dean, 2008).

Third, YARN (Yet Another Resource Negotiator): YARN is the resource management and job scheduling component in Hadoop. It enables multi-tenancy and supports various data processing frameworks beyond MapReduce, making Hadoop more versatile for different workloads. (hadoop-yarn-site, n.d.).

Forth, Hadoop Common: This component provides libraries and utilities used by other Hadoop modules. It includes the Hadoop Distributed File System (HDFS) client, MapReduce libraries, and various other common utilities.

Fifth,Hadoop Ecosystem: Hadoop has a rich ecosystem of related projects and tools that extend its capabilities for various data processing needs. Examples include Apache Hive for data warehousing, Apache Pig for data scripting, Apache HBase for NoSQL data storage, Apache Spark for in-memory data processing, and Apache Kafka for real-time data streaming (hadoop.apache.org/, n.d.).

Hadoop is widely adopted in industries such as finance, healthcare, retail, and more for tasks like data warehousing, log processing, machine learning, and predictive analytics.

The current tools and techniques, like Hadoop, have faced several challenges when dealing with Big Data, primarily due to the evolving nature and increasing scale of data. The next section will address some of these challenges.

**Challenges**

Common challenges in Big Data analysis are crucial to address in order to effectively harness the potential of largescale data processing. These challenges include:

**Heterogeneity** and Incompleteness in Big Data refer to the presence of diverse and incomplete data types. This complexity requires careful handling of variations in data structure and representation during analysis. Effective data analysis must also address issues related to incomplete or erroneous data to ensure accurate results (Agrawal, 2011). **The scale** of Big Data poses significant challenges due to its rapid growth, surpassing available compute resources. This challenge is exacerbated by the shift towards multi-core processors and cloud computing, introducing new complexities in data management and processing efficiency. Scalability issues are particularly pronounced as traditional tools like Hadoop may struggle to effectively analyze data at petabyte or exabyte scales, highlighting the need for more scalable solutions in the Big Data landscape (Fay Chang, 2006) (Agrawal, 2011).

**Timeliness**: Analyzing large datasets in a timely manner is essential. Real-time or near-real-time analysis is required for applications like fraud detection. Creating efficient index structures and handling data acquisition rates are crucial aspects of timeliness (Agrawal, 2011).

**Real-time Processing**: Many applications require real-time or near-real-time data processing and analysis. Hadoop's batch processing model is not well-suited for these use cases (Devin, n.d.).

**Data privacy**: the escalating collection and linkage of personal data from diverse sources have intensified concerns regarding data privacy. Safeguarding sensitive data while conforming to privacy regulations such as GDPR presents substantial challenges. This issue is thoroughly addressed in the paper "A Survey of Big Data Architecture and Machine Learning Algorithms in Healthcare" by Qiao et al. (2016), reflecting the growing complexity of handling and analyzing data in a privacy-compliant manner within the evolving landscape of Big Data (Agrawal, 2011).

Complex Data Types: Modern data sources often include diverse and complex data types, such as multimedia and unstructured data. Traditional tools designed for structured data may struggle to handle this variety effectively.

Tool Complexity: Big Data tools like Hadoop can be complex to set up and manage. This complexity can pose challenges for organizations with limited expertise. (White, 2015)

Data Quality: Ensuring data quality and consistency is crucial for accurate analysis. Dirty or inconsistent data can lead to unreliable results.

Resource Management: Efficiently managing computing and storage resources in a distributed environment is essential for cost-effective Big Data processing.

Cost Management: Storing and processing large volumes of data can be expensive. Cost-effective strategies for data storage and processing are essential. Cost management challenges are discussed in the paper (Garofalakis, 2016)

Evolving Ecosystem: The Big Data ecosystem is rapidly evolving with new tools and technologies. Keeping up with these changes and integrating them into existing workflows can be challenging.

Security: Protecting data from security threats and ensuring data integrity are significant concerns in Big Data environments. Security challenges are discussed in the paper (José Luis Fernández-Alemán, 2013).

Big data requires new statistical approaches due to massive sample sizes, computational efficiency, and unique characteristics like heterogeneity, noise accumulation, spurious correlations, and incidental endogeneity. These challenges demand advanced statistical techniques to model and analyze big data effectively (Jianqing Fan, 2014).

Organizations employ various strategies and technologies to address Big Data challenges effectively. These include leveraging distributed computing frameworks like Hadoop and Apache Spark for workload distribution and enhanced scalability, utilizing data warehousing solutions such as Amazon Redshift and Google BigQuery for structured data storage, and implementing NoSQL databases like MongoDB and Cassandra for flexibility in handling unstructured data. In-memory processing technologies like Apache Ignite and SAP HANA store data in RAM, improving data retrieval and processing, especially for real-time analytics. Techniques like data compression and storage optimization reduce storage requirements, while advanced analytics and machine learning uncover insights. Robust data governance, streamlining data ingestion, scalable cloud infrastructure, data quality processes, security measures, collaboration tools, continuous monitoring, and hybrid architectures contribute to efficient Big Data handling, analysis, and decision-making.

In addition, Deep learning, a subset of machine learning, offers significant contributions to addressing Big Data challenges. It excels in automated feature extraction, eliminating the need for labor-intensive manual feature engineering. Deep learning frameworks, scalable and parallelizable, efficiently process vast datasets. These models accommodate diverse data types, including text, images, and time series, making them ideal for comprehensive analysis. For decision-making and optimization tasks, deep reinforcement learning is applicable, while real-time processing capabilities are crucial for applications like fraud detection. Deep learning also excels in anomaly detection, natural language processing, transfer learning for domain adaptation, and data privacy through techniques like federated learning. Its ability to adapt to changing data distributions suits dynamic Big Data environments effectively.

In the following sections, we will delve deeply into the topic of deep learning.

**Deep learning:**

Machine-learning technology, especially deep learning, is powering various aspects of modern society, from web searches to image and speech recognition. Deep learning automates the discovery of representations required for detection or classification from raw data. Its key advantage is the automatic learning of multiple levels of representation, enabling complex function learning. Deep learning has made significant advances in image and speech recognition, particle physics, brain circuit reconstruction, and natural language understanding. Its success is expected to continue due to minimal hand engineering, scalability with increased computation and data, and ongoing advancements in algorithms and architectures (LeCun, 2015).

Deep learning employs multilayer architectures composed of simple modules, most of which are trainable and compute non-linear input-output mappings. These modules progressively enhance the representation's selectivity and invariance through multiple non-linear layers. Backpropagation, introduced in the mid-1980s, is the key to training these architectures efficiently. It uses the chain rule to compute gradients by working backward from module output to input, allowing gradients to propagate through all layers. Feedforward neural network structures are common in deep learning, using non-linear functions like ReLU for fast learning. Initially overlooked, deep learning's capabilities to learn complex, multistage feature extractors with little prior knowledge. Specifically, there was a prevailing belief that basic gradient descent would become stuck in unfavorable local minima, which are weight configurations where making small adjustments would not decrease the average error (LeCun, 2015). The gradient-based learning technique is discussed thoroughly in this paper (Lecun, 1998). There are several other deep learning architectures. Deep learning is a broad field with various neural network architectures designed for specific tasks and data types. Here are some notable deep learning architectures:

**Specifically Restricted Boltzmann Machines (RBMs**) have historical importance and are relatively simple compared to other deep learning models. RBMs consist of a variant of Boltzmann machines (BMs) with stochastic visible and hidden units. They simplify the topology of the network and enhance modeling efficiency. Training RBMs typically involves the Gibbs sampler, which generates data from the RBM, and maximizing the likelihood of the RBM by adjusting weights. Gradient-based contrastive divergence (CD) algorithms are commonly used for efficient RBM training (Weibo Liu, 2017,).

**Deep Belief Networks (DBNs**) were introduced by Geoffrey Hinton in 2006 to explore dependencies between hidden and visible variables, particularly in problems with unlabeled data. DBNs consist of multiple layers of stochastic and latent variables and are used for feature learning.

The structure of a DBN involves stacking Restricted Boltzmann Machines (RBMs) together. Each RBM connects the visible layer of the previous RBM to its hidden layer. Training a DBN involves two stages: pre-training and fine-tuning. Pre-training is an unsupervised layer-by-layer process that initializes the network's weights based on input data structure. Fine-tuning combines supervised and unsupervised learning to adjust network parameters further.

Variations of DBNs include top-level models, third-order Boltzmann machines, and covariance kernels for Gaussian processes. Researchers have used DBNs successfully in various applications, including speech recognition and image classification, taking advantage of their feature learning capabilities. Additionally, Convolutional Deep Belief Networks (CDBNs) have been introduced to handle high-dimensional image data effectively (Weibo Liu, 2017,).

Discussion

DBNs are a powerful tool for feature learning and have found applications in speech recognition, image classification, and other domains, contributing to improved performance and scalability.

**Autoencoders (AEs)** are a type of artificial neural network (ANN) used for unsupervised learning, primarily for dimensionality reduction and feature learning. AEs have been extensively researched over the past few decades, with various applications in data compression and generative modeling. They are designed to efficiently code datasets by transforming them into abstract representations and then reconstructing the original data from these representations, approximating the identity function to filter out irrelevant information and extract useful features. AEs have a one-hidden-layer feed-forward neural network structure, distinct from multilayer perceptrons (MLPs), focusing on input data reconstruction. Training involves minimizing the average reconstruction error between input and reconstructed data, with two stages: unsupervised learning for feature learning and supervised fine-tuning (Weibo Liu, 2017,).

**A standard neural network** **(NN)** comprises numerous interconnected processing units known as neurons. These neurons generate a series of real-valued activations. Input neurons become active through sensors that perceive the surrounding environment, while other neurons activate based on weighted connections from previously active neurons. Some neurons have the potential to influence the environment by initiating actions. The essence of learning or credit assignment lies in determining the appropriate weights that enable the NN to demonstrate the desired behavior, such as driving a car. Achieving this objective often involves establishing extended causal chains of computational stages, where each stage transforms the overall activation of the network, frequently in a nonlinear fashion. Deep Learning is fundamentally concerned with accurately attributing credit across numerous such stages

(Schmidhuber, 2015).

**The Convolutional Neural Network (CNN)** architecture consists of various components, including convolution layers, pooling layers, and fully connected layers. Typically, a CNN comprises a sequence of convolution layers followed by a pooling layer, and it may end with one or more fully connected layers. This transformation from input data to output through these layers is known as forward propagation. While the description here focuses on 2D-CNNs, similar operations can be adapted for three-dimensional (3D) CNNs. The convolution layer plays a central role in CNNs as it performs feature extraction through a combination of linear and nonlinear operations. This includes the convolution operation and an activation function. The convolution operation involves sliding a kernel over the input data to create a feature map. This process can be repeated with multiple kernels, generating different feature maps that represent various characteristics of the input data. These kernels effectively act as feature extractors. Key hyperparameters for the convolution operation are the kernel size and the number of kernels, which determines the depth of the output feature maps. One key feature of convolution operations is weight sharing, where kernels are shared across all image positions. This leads to several benefits, including the ability to detect local feature patterns invariant to translation, learning spatial hierarchies through down sampling and pooling, and increased model efficiency by reducing the number of parameters compared to fully connected neural networks (Yamashita, 2018) (Alzubaidi, 2021).

**Recurrent Neural Networks (RNNs**) are designed for sequential data, including time series analysis. The key concept behind RNNs is their ability to not only consider the current input but also incorporate information from previous time steps when making predictions. This approach allows RNNs to model sequences effectively, making them suitable for time series data. However, simple RNNs have limitations, such as difficulty in training and a tendency to forget important information. To address these issues, more sophisticated RNN models have been developed, with two notable ones being Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). LSTM and GRU are two popular RNN variants, each offering advantages in different scenarios. These models enable neural networks to capture and utilize long-term dependencies, which are essential for tasks involving sequential data. (Petneházi, 2019,)

. In this section will focus on the various subfields and concepts that deep learning focuses on such as:

**Deep Learning (DL) techniques** can be categorized into four main approaches: supervised learning, semi-supervised learning, unsupervised learning, and deep reinforcement learning (DRL).

**Deep Supervised Learning**: This approach deals with labeled data, where the environment has inputs and corresponding outputs. The goal is to train a model to make predictions based on input data. Common techniques in deep supervised learning include Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Deep Neural Networks (DNNs). This approach is suitable when you have labeled data, but it may struggle if the training set lacks samples for certain classes (Alzubaidi، 2021).

**Deep Semi-Supervised Learning**: In this technique, learning occurs using partially labeled datasets. Generative Adversarial Networks (GANs) and DRL are sometimes employed in this category. RNNs with architectures like Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) are also used for semi-supervised learning. The advantage is that it reduces the need for labeled data, but it may lead to incorrect decisions if irrelevant input features are present (Alzubaidi، 2021).

**Deep Unsupervised Learning**: Unsupervised learning doesn't require labeled data. Instead, the agent learns significant features or internal representations from unlabeled data to discover hidden structures or relationships. Techniques include generative networks, dimensionality reduction, and clustering. Examples of models used here are Restricted Boltzmann Machines, autoencoders, and Generative Adversarial Networks (GANs). Unsupervised learning is computationally complex and may not provide precise data sorting (Alzubaidi، 2021).

**Deep Reinforcement Learning (DRL)**: DRL is a distinct approach where an agent interacts with an environment and learns from these interactions. It's different from supervised learning, which relies on provided sample data. DRL poses challenges because there is no straightforward loss function, and the agent must learn through interaction with the environment. DRL is suitable for problems with many parameters to optimize, and it is used in applications like business strategy planning and industrial robotics automation. However, DRL can be computationally intensive and sensitive to parameter choices (Alzubaidi، 2021).

In summary, these DL approaches cater to different scenarios based on the availability of labeled data, the need for human interaction, and the complexity of the problem. Supervised learning works with labeled data, semi-supervised learning handles partially labeled data, unsupervised learning doesn't require labels, and reinforcement learning focuses on interaction with the environment. The choice of approach depends on the specific problem and its requirements.

The following section is about the practical applications of Deep Learning architectures.

**Applications:**

Deep learning architectures have found numerous practical applications due to their ability to handle vast amounts of unlabeled data, making them valuable tools for big data analysis in fields like cyber security, medical informatics, and social media. High-tech companies like Google, Facebook, and Microsoft have shown keen interest in deep learning. Several applications will be reviewed such as:

**Speech Recognition**: over the past few decades, machine learning algorithms, particularly in the context of automatic speech recognition (ASR) and acoustic modeling, have played a significant role. ASR essentially involves classifying word sequences from feature sequences or speech waveforms, and it faces challenges like noisy environments, multi-modal recognition, and multilingualism. Noise removal techniques, such as spectral subtraction and Wiener filtering, are often applied to pre-process speech data. Traditional machine learning methods like Support Vector Machines (SVMs), Neural Networks (NNs), and Gaussian Mixture Models (GMMs) have been used effectively in speech recognition, especially for acoustic modeling.

The combination of DBNs and HMMs led to the development of the DBN-HMM method, which incorporated Conditional Random Fields (CRFs) to model sequential information, resulting in higher accuracy. In recent years, deep learning has seen advancements in various ASR aspects, including distant talking situations, audio-visual speech recognition (AVSR), data augmentation, RBMs for enhanced sound wave representation, dialog state tracking, cross-language knowledge transfer, filter bank learning, automatic feature extraction, and speaker adaptive training**.**

In LVCSR, the context-dependent DBN-HMM approach superseded context-independent models, showing enhanced performance. Convolutional Neural Networks (CNNs) also gained attention for speech recognition, especially for modeling local correlations in speech spectral representations. Additionally, DNNs and multi-task learning (MTL) methods improved LVCSR, while CNNs proved beneficial in handling translational variance (Weibo Liu, 2017,).

**Computer vision** focuses on enabling computers to comprehend and process visual data, striving to replicate human perceptual capabilities, encompassing areas like object recognition and scene reconstruction. **Pattern recognition** aims to identify patterns in input data, incorporating sub-domains like classification and sequence labeling. Deep learning, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), has brought remarkable progress to these fields, automating feature selection and enhancing classification performance. It has excelled in tasks such as object recognition, mesh understanding, and detection, with applications spanning medical image analysis, remote sensing, and change detection, showing promise in large-scale datasets like ImageNet and offering solutions for complex problems in various domains (Weibo Liu, 2017,).

Furthermore, Deep learning is a potent technology that enables robots to learn and make informed decisions, with applications ranging from image recognition to healthcare and cybersecurity. It has significantly advanced AI capabilities, leading to innovation across various domains. Accenture utilizes deep learning to enhance data analytics, customer experiences, and operational efficiency. Enthusiasts can access valuable deep learning resources on Analytics Vidhya, offering insights, algorithms, and applications through articles, courses, and blog posts, including specialized training like the Blackbelt program. The platform fosters a vibrant community, facilitating networking, knowledge sharing, and expert advice, making it an ideal resource for those eager to expand their deep learning expertise (avcontentteam, 2023).

In summary, machine learning, particularly deep learning, has significantly impacted automatic speech recognition and acoustic modeling, advancing the field's capabilities and performance across various applications and challenges.

The next section will address the limitations and challenges arises while employing deep learning.

**Challenges:**

The first challenge is Deep learning (DL) relies heavily on extensive data, and while sufficient data is often available, shortages can pose challenges. Three methods are suggested to address this issue. Firstly, transfer learning involves leveraging knowledge from similar tasks to enhance model performance by improving the original data representation and mapping function. Secondly, data augmentation, particularly useful for image data, involves methods like translation, mirroring, and rotation to enrich the dataset without altering labels, though care is needed for certain data types like bioinformatics. Thirdly, simulated data can be generated based on a well-understood physical process, effectively increasing the training dataset. These strategies help overcome data scarcity in DL applications (Alzubaidi, 2021).

The second challenge is imbalanced data. Biological data often suffer from class imbalance, where negative samples significantly outnumber positive ones. It's important to recognize that training a DL model with imbalanced data can lead to unfavorable outcomes. To address this issue in training deep learning models, several techniques can be applied. First, appropriate criteria for loss evaluation and prediction results should be used, considering the imbalanced data, and area under curve (AUC) can be employed as the loss and evaluation criterion. Second, the weighted cross-entropy loss can be utilized to ensure the model performs well with small classes. Additionally, during training, either downsampling large classes or upsampling small classes is an option. Finally, for hierarchical label spaces, constructing models for each level can help balance the data. However, these techniques are not limited to biological problems and have been widely explored to mitigate the challenges posed by imbalanced data (Alzubaidi, 2021).

overfitting in deep learning is a common concern due to the large number of parameters involved, which can lead to reduced performance on test data. This problem is not limited to a specific field and needs careful consideration when developing DL techniques. Several approaches address overfitting in DL algorithms. The first class involves modifying both model architecture and parameters, including techniques like weight decay, batch normalization, and dropout. The second class focuses on model inputs, employing data corruption and data augmentation to mitigate overfitting caused by limited training data. The third class targets the model's output and introduces techniques like penalizing over-confident outputs to regularize the model. These approaches aim to improve DL model generalization and reduce overfitting problem (Alzubaidi, 2021).

The vanishing gradient problem is a common issue when training artificial neural networks (ANNs) using backpropagation and gradient-based learning techniques. It occurs when the gradients of the error function become vanishingly small during training, preventing weight updates and potentially causing the network to stop learning. This issue is particularly problematic when using activation functions like the sigmoid function, which compresses large input spaces into tiny ones, leading to small gradients. As a result, the early layers of the network cannot be efficiently updated, reducing overall network accuracy. Solutions to this problem include using activation functions like ReLU and employing batch normalization to normalize inputs. Additionally, faster hardware, such as GPUs, can mitigate this problem by allowing standard backpropagation for deeper network layers.

Conversely, the exploding gradient problem is the opposite issue, where large error gradientsaccumulate during backpropagation, leading to unstable weight updates and ineffective learning. This problem can be addressed byusing weight regularization techniques and redesigning the network architecture (Alzubaidi, 2021)**.**

In the preceding sections, we separately reviewed big data and deep learning. Now, the remainder of the paper will focus on reviewing the challenges and applications of deep learning in the context of big data.

**Deep learning on Big data**

Challenges facing big data analysis mentioned in big data section highlight the complexity and significance of effectively harnessing Big Data for insights and decision-making.

that deep learning can address several challenges associated with big data analytics, for instance, in dealing with complex data representation deep learning is suitable for integrating heterogeneous data, and various multi-modal deep learning models have been proposed to handle diverse data sources effectively. Another challenge is High dimensionality, Deep learning models like Convolutional Neural Networks (CNNs) and marginalized stacked denoising autoencoders (mSDAs) have shown effectiveness in handling high-dimensional data. computation scalability, streaming data, and data quality issues. Various deep learning models and techniques have been proposed to improve the analysis of large and diverse datasets. (Makrufa Hajirahimova, 2020).

**Application of deep learning in big data analytics are:**

Deep Learning for Abstract Representations: Deep Learning algorithms excel at extracting abstract representations of data through a hierarchical, multi-level learning approach. This makes them particularly attractive for working with large amounts of unlabeled or unsupervised data, such as that found in big data.

Combining Unsupervised Learning with Supervised Learning: Once abstract data abstractions are learned from unsupervised data using Deep Learning, more conventional discriminative models can be trained with fewer labeled data points. Deep Learning is effective at capturing non-local and global relationships in data compared to shallow learning architectures.

Useful Characteristics of Deep Learning Representations: Deep Learning representations have several useful characteristics, including their compatibility with relatively simple linear models, automation of data representation extraction, and the ability to extract relational and semantic knowledge from raw data. These characteristics are particularly valuable for big data analytics.

Addressing Big Data Characteristics: Deep Learning is well-suited to handle two of the four Vs of big data: Volume and Variety. It can effectively process massive amounts of data (Volume) and work with data in various formats and from different sources (Variety), reducing the need for human expert input.

Opportunities in Big Data Analytics: Big Data Analytics presents an opportunity to develop novel algorithms and models to address specific big data challenges. Deep Learning offers a solution for data analytics experts and practitioners, as the extracted representations can be used for decision-making, semantic indexing, information retrieval, and more in the context of big data (Najafabadi, 2015).

**Semantic indexing**, which organizes data more efficiently, is essential for enabling knowledge discovery and facilitating faster and more effective search engine operations. Rather than using raw data for indexing, Deep Learning offers a solution by generating high-level abstract data representations. These representations unveil intricate relationships and factors, particularly within the context of Big Data, fostering semantic understanding. Meaningful and semantically associated abstract data representations are crucial for effective semantic indexing and comprehension. Deep Learning, with its capacity to provide a semantic and relational understanding of data, can enhance information retrieval by introducing vector representations of data instances. These vector representations, derived from complex data abstractions, contain semantic and relational information, allowing for efficient semantic indexing. By presenting each data point as a vector representation, comparisons become more efficient compared to direct raw data comparisons, as similar vector representations correspond to similar semantic meanings. This approach is particularly beneficial for document indexing, where traditional methods rely on word counts. Deep Learning can extract meaningful data representations, yielding semantic features from high-dimensional textual data and reducing the dimensionality of document data representations (Najafabadi, 2015). (Hinton G, 2011 Jan) describe a Deep Learning model for learning binary codes for documents, enabling more accurate and faster document retrieval. Binary codes, representing document semantics, require less storage space and facilitate quick searches through techniques like fast-bit counting, outperforming semantic-based analysis.

**Discriminative tasks and semantic tagging**, deep learning algorithms are valuable in performing discriminative tasks in Big Data Analytics by extracting complex nonlinear features from raw data, which are then used as input for simpler linear models. This approach offers two advantages: it introduces nonlinearity into data analysis, closely associating discriminative tasks with Artificial Intelligence, and it enhances computational efficiency, a crucial factor in Big Data Analytics. Extracting nonlinear features from extensive input data allows analysts to leverage the knowledge contained in the data for further analysis using straightforward linear models. This is a significant advantage of Deep Learning in Big Data Analytics, simplifying complex tasks related to Artificial Intelligence like image comprehension and objectrecognition by employing simpler models. Thus, Deep Learning streamlines discriminative tasks in Big Data Analytics.

In Big Data Analytics, discriminative analysis can serve as the primary objective of data analysis or be utilized for tagging purposes, such as semantic tagging, to enhance search capabilities. In the Microsoft Research Audio Video Indexing System (MAVIS) for speech recognition technology. MAVIS automatically generates closed captions and keywords from digital audio and video signals, facilitating the search and accessibility of audio and video files containing speech content. With the internet's expansion and the surge in online users, digital image collections have grown rapidly in size in recent years.

Semantic tagging, a part of data indexing and retrieval, leverages Deep Learning abstract representations as features for discriminative tasks. This approach enables the tagging of extensive datasets using straightforward linear modeling on complex features generated by Deep Learning algorithms. This section primarily focuses on the outcomes of employing Deep Learning for discriminative tasks, particularly data tagging.

In the ImageNet Computer Vision Competition, Deep Learning, specifically Convolutional Neural Networks (CNNs), demonstrated remarkable capabilities for image object recognition. This approach outperformed other methods, emphasizing the significance of Deep Learning in enhancing image search. Google and Stanford also achieved success on ImageNet by utilizing a similar Deep Learning modeling approach and substantial computational resources.

While various techniques have been explored to extract features from unlabeled image data, such as RBMs, autoencoders, and sparse coding, Deep Learning stands out for constructing high-level features. Google's experiment exemplified this by training a deep neural network on a massive dataset of unlabeled images, showcasing its ability to learn high-level features like face and cat detection. This underscores the potential of Deep Learning's abstract representations for performing discriminative tasks on diverse datasets. (Najafabadi, 2015)

Discussion

Deep Learning can also be applied to various types of data to derive semantic representations, enabling semantic indexing. However, given the relatively recent emergence of Deep Learning, further research is required to fully utilize its hierarchical learning approach for semantic indexing in Big Data. An outstanding question is how to define "similarity" when extracting data representations for indexing, as semantically similar data points will exhibit analogous representations in a specific distance space.

**Challenges of applying deep leaning on big data:**

While recent deep learning frameworks can handle large datasets and parameters, scaling significantly beyond the current framework remains uncertain. Continued growth in computing power is expected, but research is needed to address computation and communication management issues for scaling up to very large datasets. To build scalable deep learning systems for Big Data, high-performance computing infrastructure-based systems and theoretically sound parallel learning algorithms or novel architectures must be developed**.** Deep learning algorithms have a unique ability to utilize unlabeled data during training, learning the data distribution without relying on label information. Therefore, the availability of large amounts of unlabeled data presents opportunities for deep learning methods. In dealing with the challenges of data incompleteness and noisy labels in Big Data, it is preferable to use vastly more data, even if it is noisy, rather than relying on a smaller number of precisely curated data.

To address the issues of noisy data and tolerate some level of messiness, advanced deep learning methods are needed. This might involve developing more efficient cost functions and novel training strategies to mitigate the impact of noisy labels. Strategies commonly used in semi-supervised learning can also be employed to alleviate problems associated with noisy labels (Chen, 2014,).

Another way to deal with the challenges deep learning facing in big data is to introduce large scale models. Large-scale deep learning models are well-suited to handle massive volumes of data.

There are two key approaches for scaling deep learning: the first is DistBelief Framework: (Dean, 2012) developed the DistBelief framework, which allows for training deep learning neural networks with billions of parameters using thousands of CPU cores. This framework supports model parallelism (both within and across machines), as well as data parallelism. It employs asynchronous stochastic gradient descent (SGD) and distributed batch optimization techniques. The primary idea is to train multiple versions of the model in parallel, each on a different node, analyzing different data subsets. This approach accelerates the training process and enables the training of larger models. (Najafabadi, 2015).

Commodity Off-The-Shelf High Performance Computing (COTS HPC): (Coates, 2013,) leverage relatively inexpensive GPU servers to develop their own system based on COTS HPC technology. They introduce a high-speed communication infrastructure to coordinate distributed computations. This system can train billion-parameter networks on just three machines and can scale to networks with over 11 billion parameters using only 16 machines, comparable to DistBelief's scalability. It is more widely accessible to researchers, making it a reasonable alternative for exploring large-scale models (Najafabadi, 2015).

**Deep Unsupervised learning in big data**

Deep Learning is highly applicable to unsupervised learning tasks, demonstrating substantial success in various applications. Unsupervised learning, which involves learning data patterns without labeled examples, benefits from Deep Learning in several ways. Deep neural networks (DNNs) excel at feature learning, automatically uncovering hierarchical data representations. Autoencoders, a neural network variant, facilitate dimensionality reduction by capturing essential features in high-dimensional data. Deep Learning is also valuable for clustering, with models like autoencoders and deep belief networks (DBNs) being used for unsupervised clustering tasks. Additionally, Deep Learning encompasses generative models such as Variational Autoencoders (VAEs) (Mirowski, 2014)and Generative Adversarial Networks (GANs) (Soumith Chanitala, 2016), which generate data resembling training data. This is useful for tasks like image generation and anomaly detection. Deep Learning can estimate data distribution densities, assist in data preprocessing, and is applied in Natural Language Processing (NLP) for distributed word representations. Moreover, it contributes to recommendation systems by uncovering userbehavior patterns and preferences, enhancing various unsupervised learning applications ({Dike, 2018).

According to (Schmidhuber, 2015) DBNs achieved notable results, such as a 1.2% error rate on the MNIST handwritten digits dataset when fine-tuned by BP. They also performed well on phoneme recognition tasks. Semantic Hashing, a technique based on DBNs, improved document similarity search. Autoencoder (AE) stacks became popular for pretraining deep FNNs before fine-tuning them with BP. Sparse coding was developed as a combination of convex optimization problems.

While DBNs and AE stacks are conceptually similar to unsupervised RNN stack-based History Compressor, the latter can process entire pattern sequences, making it more versatile. These developments have significantly contributed to the evolution of deep learning in recent years.

Unsupervised Learning using Artificial Neural Networks (ANNs) has been instrumental in the development of deep learning, which involves ANNs with multiple hidden layers. This approach has greatly contributed to the rapid progress in the Machine Learning industry. ANNs have taken inspiration from the way the human body's neurons interact, marking an initial step towards Artificial Intelligence.

Benefits of Unsupervised Learning with ANNs include the ability to approximate any function, making them suitable for complex and abstract problems. The learning process can advance hierarchically, starting from observations and progressing to more abstract representations, with each additional hierarchy learning only one step. Unsupervised Learning excels at discovering hidden patterns and grouping similar input vectors. Additionally, it can perform tasks without supervision, making it suitable for hierarchical clustering and bridging the gap between input and output observations. However, there are **challenges** associated with Unsupervised Learning using ANNs. Because each hierarchy learns only one step at a time, the learning time increases linearly with the number of levels in the model hierarchy. Predicting the number of clusters (K-value) can be challenging. The direction of the data can influence the final results, and Unsupervised Learning is sensitive to outliers ({Dike, 2018).

This article (Culurciello, 2017)provides an overview of the advantages and disadvantages of various techniques, including Autoencoders, Sparse Coding, and Stacked Autoencoders, as well as Generative Adversarial Models (GANs):

Autoencoders offer a straightforward method for input reconstruction, support layer stacking, and draw inspiration from neuroscience research. Sparse Coding excels at learning sparse representations and extracting meaningful features from data. Stacked Autoencoders enable hierarchical feature learning and are suitable for deep architectures. However, Autoencoders suffer from greedy layer training, lack global optimization, and may not achieve supervised learning performance, while Sparse Coding can be computationally demanding and presents challenges in interpretability. Stacked Autoencoders have complex training processes, potential conversion issues, and variable performance compared to supervised learning. GANs, on the other hand, facilitate global network training and are relatively easy to implement, but they can be challenging to train, may or may not match supervised learning performance, and require demonstration of the usability and quality of generated representations, a common issue in unsupervised algorithms.

**Discussion**

emphasizes that large-scale deep learning models are well-suited to handle massive volumes of data, making them valuable for big data analytics. However, determining the optimal number of model parameters and improving their computational efficiency remain challenges. Additionally, large-scale deep learning models must address other big data issues, such as domain adaptation and streaming data, leading to a need for further innovations in algorithms and architectures in this field.

**Case Study:**

**Unsupervised Deep Learning on MNIST data**

By utilizing deep learning to tackle unsupervised learning challenges, we will put our expertise into practice by addressing a real-world issue. In this context, we will illustrate this concept with the MNIST dataset, a widely recognized benchmark in the realm of deep learning endeavors. The initial task involves recognizing specific digits within an image, with accompanying labels indicating the digit in each image. However, in our case study, our objective is to identify images that share similarities and group them accordingly. As a substitute measure, we will assess the cohesion of these groups by examining the consistency of their labels. We will employ three Unsupervised Learning techniques to evaluate their performance, specifically:

1-Directly applying KMeans to the images.

2-Combining KMeans with an Autoencoder, which is a straightforward deep learning architecture (Shaikh, 2021).

We will employ the Normalized Mutual Information (NMI) score to assess the performance of our model. Mutual information is a bidirectional measure that quantifies the level of correlation between the clustering and manual classification. It relies on cluster purity (denoted as pi), which assesses the quality of an individual cluster Ci by measuring how many objects within Ci coincide with a manual class Mj, considering Ci in comparison to all manual classes within M. The normalization of NMI allows us to use it for comparing clusterings with varying cluster counts (Shaikh, 2021). KMeans model performed 81% accuracy, while, Combining KMeans with an Autoencoder performed 93% accuracy. For further details see Jupyter notebook.

**Conclusion**

Addressing the challenges in Big Data analysis necessitates innovative approaches and advanced technologies to enhance data processing efficiency, timeliness, and privacy while accommodating human collaboration and evolving data sources. These challenges highlight the imperative for ongoing innovation within the field of Big Data, driving the creation of new tools and techniques capable of effectively tackling the intricacies of contemporary data processing.

While deep learning offers many advantages for handling Big Data challenges, it also comes with its own set of complexities, including the need for substantial computational resources, large labeled datasets for supervised learning, and potential model interpretability issues. Therefore, choosing the right deep learning approach and architecture depends on the specific Big Data problem at hand

Unsupervised Deep Learning is indeed very beneficial when dealing with big data, especially considering the formidable challenges posed by large volumes, high dimensionality, and various complexities inherent to such datasets. Big data preprocessing, in particular, is one of the most time-consuming and effort-demanding aspects of data analysis. Unsupervised deep learning techniques play a crucial role in addressing these challenges by automating and enhancing the preprocessing phase. They can efficiently extract meaningful insights, reduce data dimensionality, identify hidden patterns, and aid in data cleaning and transformation. By significantly streamlining the data preprocessing pipeline, unsupervised deep learning contributes to making big data analysis more manageable and insightful, ultimately saving valuable time and resources in the process.

However, it's important to note that while Deep Learning can be highly effective for unsupervised learning, it often requires a large amount of data and computational resources. Additionally, selecting the appropriate architecture, hyperparameters, and evaluation metrics for unsupervised tasks can be challenging, and it may involve experimentation to achieve the desired results.

Further, applying unsupervised learning to big data presents challenges. First, interpretability can be an issue as models often produce complex, hard-to-interpret results, hindering actionable insights. Second, the computational complexity is a concern, with deep unsupervised models demanding significant time and computational resources. Lastly, ensuring that patterns learned from big data generalize effectively to new, unseen data remains a critical challenge. Addressing these challenges often requires a combination of algorithmic innovations, computational resources, and domain-specific expertise.

Deep unsupervised learning for handling big data is an evolving field with growing academic research, though it may not be as mature as some other areas within deep learning and big data analysis. Researchers are actively working to develop effective techniques and overcome associated challenges.

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*a**b* 

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An excellent style manual for science writers is [7].

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# References

(Ishwarappa, 2015)