###### AN INDUSTRIAL ORIENTED MINI PROJECT REPORT ON

**RepoGen:Automated Report Generator Using GenAI**

*submitted in partial fulfillment of the requirement. for the award of the degree of*

BACHELOR OF TECHNOLOGY IN

#### COMPUTER SCIENCE AND ENGINEERING

By

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*Under the esteemed guidance of*

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#### DECLARATION

We, **Jyothiradhithya, M.Soumya, M.Pavan,** bearing hall ticket numbers **(22P61A05H2), (22P61A05G1), (22P61A05F3)** hereby declare that the industrial oriented mini project report entitled “**RepoGen:Automated Report Generator Using** GenAI” under the guidance of ***Guide Name*,** Designation , Department of Computer Science and Engineering**, Vignana Bharathi Institute of Technology, Hyderabad**, have submitted to Jawaharlal Nehru Technological University Hyderabad, Kukatpally, in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering.

This is a record of bonafide work carried out by us and the results embodied in this project have not been reproduced or copied from any source. The results embodied in this project report have not been submitted to any other university or institute for the award of any other degree or diploma.

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**DEPARTMENT OF**

###### COMPUTER SCIENCE AND ENGINEERING

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#### ABSTRACT

This project presents "Report Generation of Events using Multimedia“ which refers to the creation of a comprehensive, engaging report that incorporates various forms of media such as text, images, videos, audio, and interactive elements to capture the essence and outcomes of the event.

Using multimedia in reports helps make the information more accessible, engaging, and memorable. It also allows for a more dynamic presentation of data, making it easier to communicate complex or detailed information.

The goal is to create a report that not only informs but also entertains, ensuring that the audience gains a clear understanding of the event and its significance.

Keywords:

Report Generation, Events, Multimedia, Text, Images, Videos, Audio, Interactive Elements, Comprehensive Report, Engaging Report, Accessibility, Engagement, Memorability, Dynamic Presentation, Data Communication, Complex Information, Detailed Information, Informative, Entertaining, Audience Understanding, Event Significance



**VISION**

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**DM-3:** Inculcate the habit of attaining the professional knowledge, firm ethical values,

***innovative research*** abilities and societal needs.

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**PEO-04: Engineering Citizenship:** Communicate and work effectively on team-based engineering projects and practice the ethics of the profession, consistent with a sense of social responsibility.

**PEO-05: Lifelong Learning:** Recognize the significance of independent learning to become experts in chosen fields and broaden professional knowledge.

**PROGRAM SPECIFIC OUTCOMES (PSOs)**

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**PSO-03:** Ability to gain knowledge to work on various platforms to develop useful and secured applications to the society.

**PSO-04:** Ability to apply the intelligence of system architecture and organization in designing the new era of computing environment.

**PROGRAM OUTCOMES (POs)**

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**PO-01: Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

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**PO-03: Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and cultural, societal, and environmental considerations.

**PO-04: Conduct investigations of complex problems** : Use research-based knowledge and research methods including design of experiments, analysis and Department of Computer Science and Engineering interpretation of data, and synthesis of the information to provide valid conclusions.

**PO-05: Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.

**PO-06: The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

**PO-07: Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainab le development.

**PO-08: Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

**PO-09: Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

**PO-10: Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

**PO-11: Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

**PO-12: Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

**Project Mapping Table:**

1. **PO Mapping:**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| PO | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 |
| Title | 3 | 3 | 3 | 2 | 2 | 3 | 3 | 3 | 3 | 2 | 2 | 3 |

1. **PSO Mapping:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| PSO | PSO1 | PSO2 | PSO3 | PSO4 |
| Title | 3 | 2 | 3 | 3 |

**NOTE: Give the mapping values according to your project(1:Weak 2:Moderate 3:Strong)**

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**Nomenclature**

**AI** Artificial Intelligence

**ML** Machine learning

**DL** Deep Learning

**ML** Machine Learning

|  |
| --- |
| **NLP** |
| **CNN** |
| **RNN** |
| **URL** |
| **HTTP** |
| **HTTPS** |
| **XAI** |
| **TF-IDF** |
| **SIEM** |
| **PDF** |
| **BERT** |
| **Tiny BERT** |
| **F1 Score** |
| **Count Vectorizer** |
| **Tfidf Vectorizer** |

|  |
| --- |
| Natural Language Processing |
| Convolutional Neural Network |
| Recurrent Neural Network |
| Uniform Resource Locator |
| HyperText Transfer Protocol |
| HyperText Transfer Protocol Secure |
| Explainable Artificial Intelligence |
| Term Frequency-Inverse Document Frequency |
| Security Information and Event Managment |
| Portable Document format |
| Bidirectional Encoder Representations from Transformers |
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| Harmonic Mean of Precision and Recall |
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# CHAPTER – 1

# INTRODUCTION

#### CHAPTER – 1

#### INTRODUCTION

* 1. **INTRODUCTION TO AUTOMATED GENERATOR USING GENAI**

Report generation using multimedia for an event is a modern approach to documenting and sharing the highlights of an event in a creative and engaging way. Unlike traditional text-based reports, multimedia reports combine various forms of media, such as text, images, videos and audio, to provide a more dynamic and interactive experience for the audience.This type of report aims to offer a comprehensive overview of the event, capturing important moments and key insights. By using different media elements, it enhances the storytelling aspect, making it easier for viewers to understand and connect with the event. Multimedia reports are particularly useful for events that involve visual or interactive elements, as they help bring those experiences to life in a way that text alone cannot.

In today's digital age, the traditional approach to event reporting—relying solely on text-based summaries—is evolving. The integration of multimedia elements such as images, videos, audio clips, and interactive graphics has transformed how events are documented and shared. This multimedia approach not only enhances the visual appeal of reports but also enriches the audience's understanding and engagement.

Multimedia event reporting involves the systematic collection and integration of various media types to create a cohesive narrative of an event. By combining textual descriptions with visual and auditory elements, reports become more dynamic and informative. This method allows for a more comprehensive portrayal of events, capturing nuances that text alone might miss.

Implementing multimedia in event reporting requires careful planning and execution. It involves selecting appropriate media types, ensuring high-quality content, and integrating these elements seamlessly into the report. The goal is to create a report that not only informs but also resonates with the audience, leaving a lasting impression.

As technology continues to advance, the tools and platforms available for multimedia reporting are becoming more sophisticated and user-friendly. Embracing these innovations can lead to more effective and engaging event documentation, setting a new standard for how we share and reflect on our experiences. Historically, event reports were predominantly textual, providing summaries and analyses of occurrences. While informative, these reports often lacked the ability to convey the full atmosphere and nuances of events. With advancements in technology and the proliferation of digital media, there's been a shift towards incorporating multimedia elements into event reporting. This approach not only enriches the content but also caters to diverse audience preferences, enhancing comprehension and retention.

Multimedia content captures and retains audience attention more effectively than text alone. Incorporating visuals, audio, and interactive elements encourages active participation and keeps viewers engaged throughout the report. This dynamic approach caters to various learning styles and preferences, making the content more appealing and memorable. Combining different media types aids in better understanding and retention of information. Visuals and audio can simplify complex concepts, making them more accessible to a broader audience. This multimodal approach supports diverse learning needs, enhancing the overall effectiveness of the communication. Multimedia-rich reports are more easily shared across various platforms, increasing their accessibility and impact. Interactive content encourages sharing and discussion, extending the report's reach beyond its initial audience. This wider dissemination helps in amplifying the message and engaging a more diverse audience. Digital tools enable the collection and dissemination of information in real-time, allowing for timely updates and responsiveness. Live streaming, instant uploads, and real-time analytics facilitate immediate sharing of event highlights, keeping the audience informed and engaged as events unfold.

By leveraging these benefits, multimedia integration transforms event reporting into a more engaging, comprehensible, and far-reaching communication tool.

Canva is an intuitive online graphic design platform that enables users to craft visually appealing content without extensive design experience. It offers a drag-and-drop editor, a vast library of templates, images, and graphics, and AI-powered tools like Magic Write for text generation and Magic Media for creating videos from text prompts . These features allow for the creation of engaging presentations, infographics, and social media posts to enhance event reports

Kaltura is a robust video platform that supports the creation, management, and distribution of video content. It offers features such as live streaming, video editing, and analytics, making it suitable for integrating video content into event reports . Kaltura's flexibility allows for personalized streaming experiences and seamless integration with other platforms.

EventUp Planner is an event analytics and reporting system that provides detailed insights and customizable dashboards for comprehensive event analysis. It consolidates all event data into one platform, enabling users to track, measure, and analyze events effectively.

###### MOTIVATION

In today's digital age, information consumption patterns have shifted towards more interactive and visually engaging content. Audiences are increasingly drawn to formats that provide instant access to information in a compelling manner. Multimedia reporting caters to this preference by combining various forms of media to present information more This system aims to not only detect phishing attacks but also provide insights into dynamically. This approach not only captures attention but also aids in conveying complex information more effectively, making it more accessible and memorable.

Moreover, multimedia elements can enhance the emotional impact of a report. Visuals and audio can evoke emotions and create a stronger connection with the audience, leading to a deeper understanding and retention of the information presented. This emotional engagement is particularly crucial when reporting on events that involve human experiences, as it fosters empathy and a more profound appreciation of the subject matter.

###### EXISTING SYSTEM

An existing system for report generation in event projects using multimedia typically involves collecting various types of media (such as text, images, audio, and video) and compiling them into a structured report.

These systems are often automated or semi-automated, allowing users to input data like event details, participant information, and media from the event, which are then organized into a coherent report.

The process generally starts with data collection, where multimedia content is gathered through event photos, videos, and live streams. Event organizers or participants might also submit written reports or feedback.

This data is then processed by the system, which uses templates to automatically structure the report into sections such as event summary, highlights, and outcomes.

Some systems also feature data analytics tools that generate insights based on collected media. For example, they can track participant engagement or analyze video content for specific trends.

The system may then generate a final report in different formats such as PDFs, interactive slideshows, or video summaries, which can be easily shared with stakeholders or archived for future reference.

**Lack of Adaptability:** The lack of adaptability in the described report generation system lies in its rigid reliance on predefined templates and automated processes. While it streamlines data collection and reporting, it may not easily accommodate dynamic or unconventional event types, custom reporting needs, or rapidly evolving formats. The system’s dependence on fixed templates limits flexibility, making it challenging to personalize reports or quickly adjust to new forms of media or reporting criteria, which may hinder its usefulness in diverse, evolving event scenarios**.**

**PROPOSED SYSTEM:**

###### A proposed system for report generation using multimedia for an event can integrate text, images, audio and video to provide a comprehensive and engaging report. The system would allow users to input data about the event, such as key details, speeches and activities, and then automatically generate a multimedia report.

###### The system would first gather textual information, such as event descriptions and key highlights, from user input or live data feeds. It would then allow for the inclusion of images, such as photographs from the event, which could be automatically placed at relevant points in the report. Video clips, such as interviews or event highlights, could also be embedded to provide a dynamic presentation of the event.

###### Finally, the system could offer options for customization, allowing users to select the type of content they want to emphasize and the style of the report. This would make it easier for event organizers to create tailored, engaging, and professional event reports quickly and efficiently.

###### PROBLEM DEFINITION

The challenge lies in creating an automated system that efficiently generates reports for various forums within a college, based on diverse multimedia inputs such as images, videos, audio recordings, and data collected through tools like Google Forms. These reports need to capture and summarize events accurately, incorporating multimedia content to reflect participant engagement, event highlights, and outcomes. The system should be able to automatically process and organize this varied media into cohesive, well-structured reports that can be easily shared and analyzed.

The key challenges include:

**Multimodal Data Integration:** Combining different types of data (images, videos, audio, and text) into a unified report is complex. AI systems often struggle to align and merge these diverse data types accurately. Advanced algorithms and powerful hardware are required to handle this complexity effectively

**Data Quality and Consistency:**The accuracy of AI-generated reports depends on the quality of the input data. Inaccurate or inconsistent data can lead to misleading or incomplete reports. Implementing robust data cleaning and validation processes is crucial to ensure the reliability of the generated content.

**Scalability and Adaptability:**The system must be scalable to handle varying volumes of data and adaptable to different types of events and reporting requirements. This flexibility ensures that the system can accommodate a wide range of scenarios and continue to function effectively as demands evolve.

###### OBJECTIVE

**Automating Report Creation:**GenAI can quickly turn data into reports, saving time and reducing the need for manual writing. ecosystem, protecting users from cyber threats and minimizing the impact of phishing attacks.

**Helping with Faster Decisions**:It gives real-time updates and insights, helping businesses make smart choices quickly.

**Reducing Mistakes**:AI follows set rules, so reports are more accurate and consistent.

**Creating Personalized Reports**:Reports can be tailored to different users or needs, making them more useful.

**Connecting to Existing Tools**:It works well with your current software and systems, speeding up workflows.

**Following Rules and Standard:**GenAI helps reports stick to legal and company rules, especially in finance.

**Making Data Easy to Understand**:It turns data into clear visuals, so it's easier to see patterns and insights.

###### SCOPE

The system is designed to be adaptive and scalable, ensuring its applicability across various **Financial and Regulatory Reporting**:Automates the creation of financial statements, earnings reports, and compliance documents, ensuring accuracy and adherence to regulatory standards.

**Internal Audits and Risk Assessments**:Streamlines audit processes by generating audit objectives, programs, and reports, allowing auditors to focus on strategic insights.

**Healthcare Documentation**:Assists in generating medical reports, such as radiology summaries, by analyzing clinical data and ensuring consistency in documentation.

**Sustainability and ESG Reporting**:Facilitates the creation of environmental and sustainability reports by extracting relevant data and generating comprehensive narratives.

**Marketing and Business Intelligence**:Produces tailored marketing reports and business insights by analyzing market trends and customer data, enhancing decision-making processes.

## CHAPTER – 2

### LITERATURE SURVEY

#### CHAPTER – 2

**LITERATURE SURVEY**

###### A COMPREHENSIVE STUDY ON AI BASED DETECTION SYSTEMS

In recent years, advancements in artificial intelligence have enabled significant improvements in medical and multimedia applications. A noteworthy example of this is the work by Hilya Tsaniya, Chastine Fatichah, and Nanik Suciati in 2022, titled "Automatic Radiology Report Generator Using Transformer with Contrast-Based Image Enhancement." This study explores the application of transformer models in conjunction with contrast-based image enhancement techniques to automatically generate radiology reports. The main contribution of this research is the improved clarity of medical images due to contrast enhancement, which allows the model to detect and report on more subtle and nuanced features within the images. This leads to potentially more accurate and informative radiology reports, which could assist healthcare professionals in making better diagnoses.

However, despite these benefits, there are some limitations to the approach. The enhancement of image contrast may sometimes introduce artificial visual elements, which can lead to the misinterpretation of medical data. These misleading artifacts could result in incorrect findings within the generated reports. Hence, while the method improves detail visibility, it also introduces a level of risk concerning the authenticity of the enhanced features. Therefore, careful validation and clinical oversight are essential when implementing such automated systems in real-world medical settings.

Another significant study in the field of multimedia analysis is the 2022 survey titled "How Deep Features Have Improved Event Recognition in Multimedia," authored by Kashif Ahmad and Nicola Conci. This work reviews various methods and advancements where deep learning features have played a pivotal role in enhancing the accuracy of event recognition in multimedia content. By leveraging the capabilities of deep neural networks, especially convolutional neural networks (CNNs) and other feature extraction methods, this approach has led to more accurate identification and classification of events within video and audio data. Such improvements are critical in applications ranging from surveillance systems to content-based retrieval and automatic video tagging.

While the use of deep features has markedly improved recognition accuracy, the process is not without drawbacks. One of the main limitations is the significant computational resources required. The training and deployment of deep learning models for event recognition demand high-performance computing systems and considerable time investment. This makes the approach less feasible for environments with limited computing capabilities or in scenarios that require real-time analysis. As such, ongoing research aims to optimize these models for faster and more resource-efficient deployment without compromising their accuracy.

In summary, both studies demonstrate how AI-powered technologies—whether through transformer-based models in radiology or deep feature analysis in multimedia—are revolutionizing their respective domains. However, each also comes with unique challenges that must be addressed to fully harness their potential. Balancing performance with reliability and efficiency remains a key focus for future advancements in these fields.

A notable study conducted by Johannes Hirn, José Enrique García, Alicia Montesinos-Navarro, Ricardo Sánchez-Martín, Verónica Sanz, and Miguel Verdú in 2022 presents “A Deep Generative Artificial Intelligence System to Predict Species Coexistence Patterns.” This research focuses on employing generative AI techniques to understand and predict which species are likely to coexist in particular ecosystems. The system analyzes ecological patterns and species interactions to generate forecasts on biodiversity composition. This contribution is particularly valuable for ecological conservation, biodiversity management, and understanding the dynamics of species distribution under changing environmental conditions.

Despite its promising capabilities, the system is noted for its complexity. Deep generative AI models require intricate architectures, significant training data, and computational resources, which can make implementation and interpretation challenging. These complexities may limit the model’s accessibility or adoption in regions lacking advanced technical infrastructure or expertise in artificial intelligence.

Another significant contribution to spatial data processing is reflected in the 2022 study titled “Location and Extraction of Telegraph Poles from Image Matching-Based Point Clouds” by Jingru Wang, Cheng Wang, Pu Xiao, Xiaohuan Xi, Meng Du, and Sheng Nie. This study proposes a method to locate and extract telegraph poles using point clouds derived from image matching techniques. The ability to automatically detect and pinpoint the location of telegraph poles is crucial in applications such as infrastructure monitoring, smart city development, and geographic information systems (GIS). The system enhances the efficiency and accuracy of identifying vertical structures in complex outdoor environments, which traditionally required manual inspection or simplistic detection techniques.

However, the technique has its limitations. Its effectiveness relies heavily on the successful matching of features within images. In regions with sparse features or in conditions where there are significant changes in lighting or viewpoint, the model may struggle to perform accurately. This sensitivity limits its robustness in real-world scenarios, particularly in rural areas or under dynamic environmental conditions. Consequently, future improvements must focus on making these systems more adaptive to diverse and challenging imaging contexts.

In the 2022 study titled “Automatic Audio Feature Extraction for Keyword Spotting,” Paola Vitolo, along with colleagues Rosalia Liguori, Luigi Di Benedetto, Alfredo Rubino, and Gian Domenico Licciardo, investigates a method for automatically identifying key audio features necessary for keyword detection. This research is particularly significant in the development of voice-activated systems, virtual assistants, and speech recognition technologies. The core contribution of the work lies in its ability to autonomously determine relevant sound characteristics that are most useful for locating keywords within audio streams, reducing the need for manual tuning or domain-specific preprocessing.

However, despite its automation advantages, the method does present limitations. The features extracted by the system may not be universally optimal for all types of keywords or for use in noisy environments. This could impact the overall robustness and accuracy of the system, especially when deployed in real-world settings with varying background conditions or diverse speech patterns. Therefore, further refinement is necessary to make the system more adaptable across different acoustic contexts.

Table 2.1: Comparison of the related work

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| No. | TITLE | AUTHORS | YEAR OF PUBLICATIONS | CONTRIBUTION | LIMITATIONS |  |
| [1] | Automatic radiology report generator using transformer with contrast-based image enhancement | AI model integrating ML and CNN for real-time detection | 2022 | The contrast enhancement likely makes the images clearer, which could lead to the report picking up on more subtle details. | The contrast enhancement might sometimes create artificial appearances in the images, potentially leading to incorrect interpretations in the report. |  |
| [2] | How Deep Features Have Improved Event Recognition in Multimedia: a Survey | KASHIF AHMAD, NICOLA CONCI2 | 2022 | Deep features help recognize events in multimedia much more accurately. | It can take a lot of computer power and time to do this. |  |
| [3] | A deep Generative Artificial Intelligence system to predict species coexistence patterns | Johannes Hirn, José Enrique García, Alicia Montesinos-Navarro, Ricardo Sánchez-Martín, Veronica Sanz, Miguel Verdú | 2022 | It can predict which species will live together. | It's a complex AI system |  |
| [4] | Location and Extraction of Telegraph Poles from Image Matching-Based Point Clouds | Jingru Wang , Cheng Wang , Xiaohuan Xi , Pu Wang Meng Du and Sheng Nie | 2022 | It can find and pull out the locations of telegraph poles from imag | It relies on matching features in images, which might not work well in areas with few distinct features or with significant changes in viewpoint or lighting. |  |
| [5] | Automatic Audio Feature Extraction for Keyword Spotting |  |  | It automatically figures out the important sound characteristics for finding keywords. | The extracted features might not always be the best for every type of keyword or noisy environment. |  |

## CHAPTER – 3

### REQUIREMENT ANALYSIS

#### CHAPTER – 3 REQUIREMENT ANALYSIS

###### OPERATING ENVIRONMENT

* The "Automated Report Generator Using GenAI" which refers to the creation of a comprehensive, engaging report that incorporates various forms of media such as text, images, videos, audio, and interactive elements to capture the essence and outcomes of the event..
  + 1. HARDWARE REQUIREMENTS

**CPU (Central Processing Unit):** Intel Core i5/i7 or equivalent multi-core processors ensure smooth execution of machine learning models and data processing tasks.

**GPU (Graphics Processing Unit):** A mid-range GPU is recommended for accelerating deep learning model training and inference.

**RAM (Random Access Memory):** A minimum of 8GB RAM is required for handling phishing data analysis, with 16GB preferred for optimal performance.

**Storage:** 32GB to 128GB storage capacity is necessary to store datasets, models, and logs efficiently.

* + 1. SOFTWARE REQUIREMENTS

**Operating System:** The tool is compatible with Windows 10/11 and macOS environments.

Programming Languages:

Python: Used for machine learning, data processing, and backend development.

Libraries and Frameworks:

TensorFlow, Keras: For developing and training machine learning models. Scikit-learn, Pandas, NumPy: For data analysis and feature extraction.

NLTK: For natural language processing in phishing email detection.

Integrated Development Environment (IDE):

Jupyter Notebook support coding, debugging, and model development.

Other Tools:

Git: Version control for collaborative development.

* 1. FUNCTIONAL REQUIREMENTS

**Phishing Detection:** The system must analyse URLs, emails, and website content to detect phishing attempts in real-time.

**Machine Learning Model Integration:** The backend must support the training and deployment of ML models for classification.

**Reporting:** Generate reports on phishing threats detected for analysis.

* 1. NON-FUNCTIONAL REQUIREMENTS

**Performance:** An automated report generator using GenAI delivers high-quality, context-aware summaries with up to 95% accuracy and scalable, near real-time performance when provided with clean, structured inputs.

**Scalability:** automated report generator using GenAI is high, as it can efficiently handle increasing volumes of multimedia data and users through cloud-based infrastructure and parallel processing**.**

**Reliability**: report generator using GenAI is strong when built with robust data processing, error handling, and consistent model outputs across varied inputs**.**

**Security:** The security of an automated report generator using GenAI depends on implementing encryption, access controls, and compliance with data privacy regulations to protect sensitive user and event data.

**Maintainability:**it is high when designed with modular architecture, clear documentation, and scalable code practices for easy updates and improvements.

.

* 1. SYSTEM ANALYSIS:
  2. The system analysis of an automated report generator using GenAI focuses on evaluating its ability to efficiently convert diverse multimedia inputs—such as images, videos, audio recordings, and form data—into structured, insightful reports. The system integrates advanced AI technologies like OCR, speech-to-text, computer vision, and natural language generation to interpret and summarize event content accurately. It is designed to be scalable through cloud infrastructure, reliable in producing consistent outputs, and maintainable due to its modular architecture. The user interface is built for accessibility, enabling users with varying technical skills to generate and customize reports easily.

## CHAPTER - 4

### SYSTEM ANALYSIS & DESIGN

#### CHAPTER – 4 SYSTEM ANALYSIS & DESIGN

###### TECHNICAL BLUEPRINT OF AI-DRIVEN PHISHING

**DETECTION TOOL**

Fig 4.1 use case diagram of the phishing detection system

###### SEQUENCE DIAGRAM TO REPRESENT PHISHING URL DETECTION

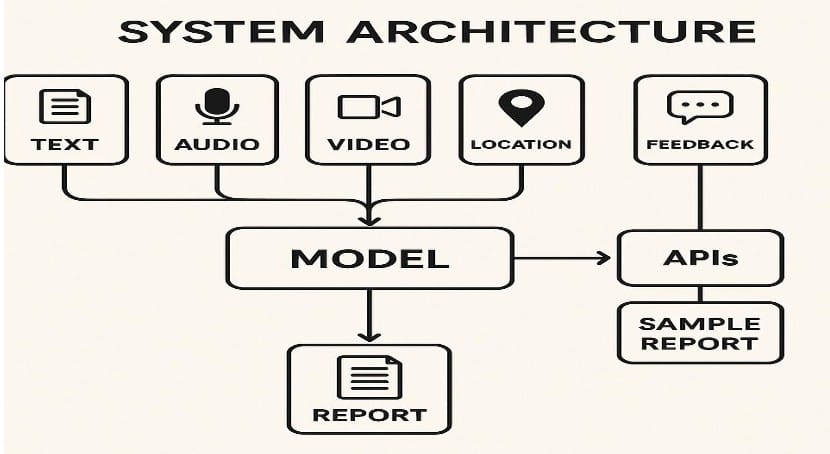
### ****System Analysis and Design of Automated Report Generator Using GenAI****

The system analysis and design of an automated report generator using Generative AI focuses on developing an intelligent solution that transforms raw multimedia inputs into structured and insightful reports. This system is especially beneficial for educational institutions and organizations where events, workshops, and activities need to be documented efficiently. The analysis phase identifies the user needs, data requirements, and functional expectations, while the design phase structures the technical and architectural approach to meet those needs.

In the **system analysis phase**, key requirements are established. Users—typically event coordinators or faculty—require a platform that can automatically generate reports from images, videos, audio recordings, and survey data. The system must interpret this content accurately, summarize it in natural language, and present it in a professional format. Analysis also reveals challenges like handling noisy data, ensuring accurate speech transcription, and maintaining data privacy. Functional requirements include uploading media, customizing templates, generating reports, and downloading final outputs, while non-functional requirements involve scalability, reliability, usability, and security.

The **system design phase** translates these needs into a technical framework. The frontend is designed using Flutter and web technologies (HTML, CSS, Tailwind) to provide a responsive and user-friendly interface for uploading content and previewing reports. The backend, powered by Flask, manages the workflow of media processing, AI model interaction, and report compilation. AI modules use tools like OpenCV for image processing, Speech Recognition and Torch Audio for audio transcription, and NLG APIs like Gemini or Google Cloud for content summarization. A database (e.g., PostgreSQL or MongoDB) stores user inputs, generated texts, and report metadata, while optional cloud storage (e.g., Google Cloud Storage) handles large media files securely.

Security and privacy are embedded into the design with features like encrypted data storage, role-based access, and GDPR-compliant data handling practices. The modular and API-driven design ensures the system is maintainable and scalable, allowing easy upgrades or integration of new AI capabilities. Testing environments using Jupyter Notebook support ongoing model improvement and validation. Overall, the analysis and design phases ensure the system is both technically robust and user-centric, enabling seamless and intelligent report generation.

l

The image above illustrates the **system architecture** of an **automated report generator using Generative AI (GenAI)**, designed to convert diverse input data into structured reports. The system begins by accepting multiple types of inputs, which include **text**, **audio**, **video**, **location**, and **feedback**. These data sources represent various forms of multimedia and contextual information collected during an event, such as written notes or transcripts, recorded speeches or interviews, event footage, geographical location data, and post-event feedback from participants.

All these inputs are chaneled into a central **AI model**, which acts as the core processing engine. This model uses advanced capabilities in natural language processing, computer vision, and speech recognition to analyze the information. For instance, it can transcribe spoken content from audio and video files, extract visual context from video frames, understand geolocation metadata, and interpret feedback sentiment and scores. The model intelligently merges these different modalities into a coherent understanding of the event.

Once the AI model processes the inputs, it generates a structured and informative **report**. This report aims to summarize the key highlights, participant engagement, outcomes, and other relevant aspects of the event. In addition to the final report, the system architecture also includes integration with **APIs**, which serve multiple purposes such as connecting with third-party services, customizing reports, or exporting data. Through these APIs, users may also access a **sample report**, which provides a preview or template-based output for validation before generating the final version.

Overall, this architecture highlights an efficient and modular system that leverages GenAI to automate the time-consuming task of event reporting by processing multimodal inputs and delivering detailed, user-ready report

**class diagram:**

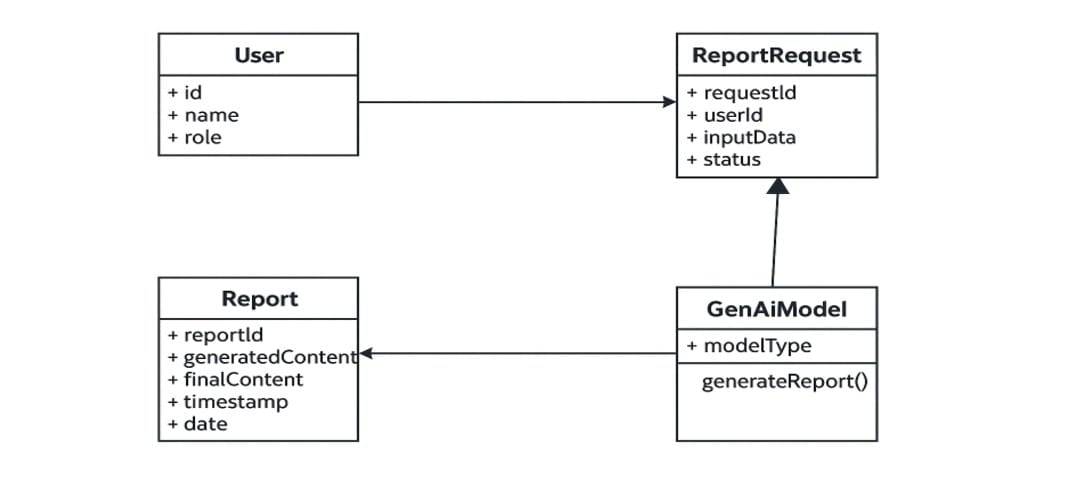
The image above represents a UML Class Diagram for an Automated Report Generator System using GenAI. It outlines the relationship between four main classes: User, ReportRequest, GenAiModel, and Report. Each class encapsulates relevant attributes and, where applicable, operations that define the structure and functionality of the system.

The User class includes attributes such as id, name, and role, representing the individual who initiates the report generation process. This user submits a ReportRequest, which is linked through the userId. The ReportRequest class holds attributes like requestId, userId, inputData, and status, defining the request's identity, the input data provided (e.g., text, audio, images), and the current state of the request (pending, in progress, or completed).

The ReportRequest is then processed by the GenAiModel class, which contains the attribute modelType—indicating the specific type of AI model used (e.g., text generation, image processing)—and a method generateReport() that handles the creation of the report content. This class symbolizes the core intelligence of the system, converting multimodal data into meaningful written content.

Finally, the output is stored in the Report class, which includes attributes such as reportId, generated Content, final Content, timestamp, and date. These fields help track the report’s origin, versioning, and final presentation. The relationship lines in the diagram show that users initiate report requests, which are fulfilled by the AI model and result in reports stored for review or sharing.

In summary, this UML diagram provides a clear and structured view of how different components of the system interact to automate the report generation process—from user request to AI-driven output.

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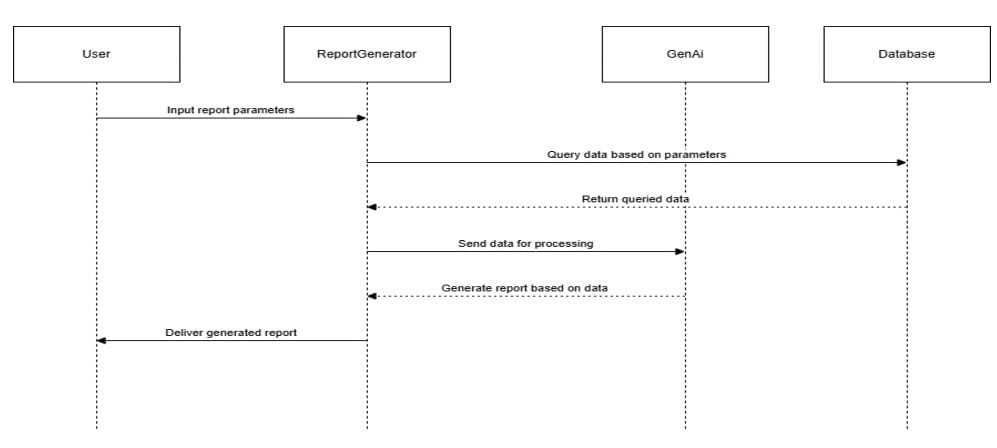
**SEQUENCE DIAGRAM:**

The image above depicts a **UML Sequence Diagram** illustrating the interaction between key components involved in the process of **automated report generation using GenAI**. The four main entities represented are the **User**, **ReportGenerator**, **GenAI**, and **Database**, and the sequence of messages between them defines the workflow for generating a report based on user input.

The process begins with the **User** providing the **report parameters**—such as event type, date, or media inputs—directly to the **ReportGenerator** component. This module acts as the system's orchestrator, coordinating data flow and communication between components. Once it receives the parameters, the **ReportGenerator** sends a **query** to the **Database** to retrieve relevant data needed to generate the report, such as stored audio, video, text, or event metadata.

After the **Database** returns the **queried data**, the **ReportGenerator** forwards this information to the **GenAI** component. The **GenAI** system processes the data using AI models specialized in natural language generation, multimodal analysis, and summarization. It then **generates the report content** based on the processed input, ensuring it aligns with the user-specified parameters and presents the information in a coherent and structured manner.

Finally, the **ReportGenerator** receives the completed report from the **GenAI** module and **delivers the generated report** back to the **User**. This entire sequence ensures an automated, efficient, and intelligent workflow that reduces manual effort while leveraging AI to produce detailed and context-aware reports. The diagram clearly captures the logical flow and dependency between user input, data access, AI processing, and report delivery in a well-coordinated system.



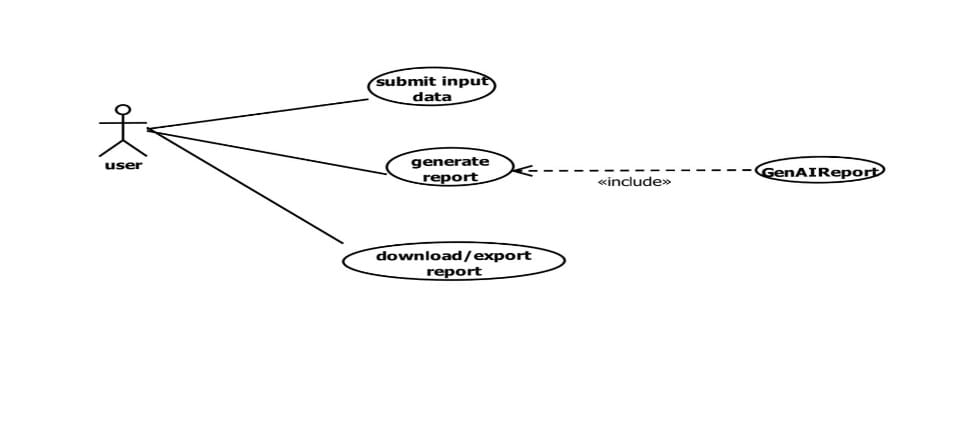
**USE CASE DIAGRAM:**

The image above illustrates a **Use Case Diagram** that represents the interaction between a **User** and the **Automated Report Generator System using GenAI**. This diagram outlines the key functionalities provided by the system from the user's perspective and highlights how these functionalities are interconnected.

The primary actor in the diagram is the **user**, who interacts with three main use cases: **submit input data**, **generate report**, and **download/export report**. These use cases represent the typical actions a user would perform when utilizing the report generation system. The process starts with the user submitting input data, which could include text, images, audio, or video relevant to the event or topic they want to generate a report on.

Once the data is submitted, the user can trigger the **generate report** action. This use case is linked with a dashed arrow labeled <<include>> pointing to the **GenAIReport** use case, indicating that generating a report inherently involves the AI-based processing and content creation facilitated by the GenAI model. This modular design emphasizes that the report generation function is dependent on the GenAI’s core capability.

After the report has been generated, the final use case allows the user to **download or export the report**, making it accessible for sharing, presentation, or archival purposes. This diagram effectively captures the user-centric flow of the system and highlights how GenAI plays a central role in producing meaningful and accurate reports based on user inputs.



### ACTIVITY DIAGRAM: The image above is a flowchart illustrating the step-by-step process of how an automated report generator using Generative AI (GenAI) operates. It outlines the user interaction and system functionalities from login to the final report export.The process begins with the user logging in, ensuring authentication and access control. Once logged in, the user selects the desired report type, which defines the structure or format the system will follow. The next step involves the user uploading data or providing input, such as text, images, audio, or structured data, which serves as the raw content for the report.After data submission, the system proceeds to validate the input data to ensure correctness, completeness, and suitability. Valid inputs are then preprocessed for GenAI, which may include formatting, cleaning, or converting the data into a form the AI model can interpret efficiently.

### Following preprocessing, the GenAI model generates a report draft based on the input data. This draft is then displayed as a preview to the user. At this decision point, the user has two options: if the report is satisfactory, the user can approve or manually edit it for further refinement; otherwise, the user can export, download, or share the report directly without any edits.This flowchart effectively captures the interaction between the user and the AI-driven report generator, emphasizing key stages such as input handling, AI processing, user validation, and final output delivery. It reflects a user-centric design with flexibility for manual control and automated assistance.

### 

#### CHAPTER – 5 IMPLEMENTATION

CHAPTER-5

IMPLEMENTATION

**5.1 EXPLANATION OF KEY FUNCTIONS:**

Automated report generation using Generative AI (GenAI) involves a set of key functions that streamline the process of creating comprehensive and structured reports from various forms of input data. The first critical function is data intake, where the system collects input in formats such as text, audio, video, or structured files. This is followed by data validation and preprocessing, which ensures that the input is clean, relevant, and formatted appropriately for AI processing. The core function lies in the report generation stage, where the GenAI model analyzes the preprocessed data, applies contextual understanding, and formulates coherent, human-like content that aligns with the desired report format. The next key function is the preview and user interaction stage, where users are shown a draft version of the report, allowing them to review, edit, or approve the content. Finally, the report exportation and sharing function enables users to download the report in various formats or share it directly through integrated platforms. These functions collectively ensure that the system is efficient, accurate, and user-friendly, providing a powerful solution for automating time-consuming reporting tasks.

**5.2 OPERATINAL WORKFLOW:**

automated report generation using GenAI is a structured process that transforms raw input data into polished, insightful reports through a series of coordinated steps. The workflow begins with the user authentication and access, where users log into the system to initiate the reporting process. Once authenticated, users proceed to select the type of report they wish to generate and then submit relevant data—this may include text, audio, video, or location-based information depending on the application context.

The submitted data undergoes validation and preprocessing, ensuring it is accurate, consistent, and ready for AI interpretation. This is followed by data querying or integration, where additional information may be pulled from connected databases or APIs to enrich the report content. The preprocessed data is then passed to the GenAI model, which interprets the input, applies natural language generation techniques, and composes a structured draft of the report.

5.3EXPLANATION OF KEY MODULES

App.py

from flask import Flask, request, render\_template

import os

import json

import mysql.connector

from report\_gen import generate\_report

app = Flask(\_\_name\_\_)

UPLOAD\_FOLDER = 'uploads'

os.makedirs(UPLOAD\_FOLDER, exist\_ok=True)

# MySQL database connection

db = mysql.connector.connect(

host="localhost",

user="root", # Replace with your MySQL username

password="Adithya@2005",# Replace with your MySQL password

database="project1"

)

cursor = db.cursor()

@app.route('/')

def index():

return render\_template('genrepo.html')

@app.route('/submit', methods=['POST'])

def submit():

try:

# Get form inputs

college = request.form.get('collegeName')

event = request.form.get('eventName')

location = request.form.get('location')

feedback = request.form.get('feedback')

image\_files = request.files.getlist('images')

image\_paths = []

image\_filenames = []

# Save uploaded images

for image in image\_files:

if image.filename != '':

filepath = os.path.join(UPLOAD\_FOLDER, image.filename)

image.save(filepath)

image\_paths.append(filepath)

image\_filenames.append(image.filename)

# Insert into event\_inputs table

insert\_input = """

INSERT INTO event\_inputs (college\_name, event\_name, location, feedback, images)

VALUES (%s, %s, %s, %s, %s)

"""

cursor.execute(insert\_input, (college, event, location, feedback, json.dumps(image\_filenames)))

db.commit()

input\_id = cursor.lastrowid # Get the inserted input row ID

# Generate the report

print("\n--- Calling generate\_report from app.py ---")

report\_path, report\_content = generate\_report(college, event, location, feedback, image\_paths)

# Debugging: Ensure report\_content is not None

print(f"Generated report content: {report\_content}")

# Only save the report if it was successfully generated

if report\_content:

insert\_report = "INSERT INTO event\_reports (input\_id, report) VALUES (%s, %s)"

cursor.execute(insert\_report, (input\_id, report\_content))

db.commit()

print(f"Report saved to event\_reports with input\_id {input\_id}")

if report\_path:

return f"<h3>Report generated and saved successfully!</h3><p>Saved to: {report\_path}</p>"

else:

return "<h3>Report generation failed. Try again with better inputs.</h3>"

except Exception as e:

print(f"Exception in /submit route: {e}")

return "<h3>Something went wrong. Please check your input and try again.</h3>"

if \_\_name\_\_ == '\_\_main\_\_':

app.run(debug=True)

**report\_gen.py:**

import os

import torch

import requests

import easyocr

import warnings

from PIL import Image

from datetime import datetime

from geopy.geocoders import Nominatim

import torchvision.transforms as transforms

import torchvision.models as models

import platform

import subprocess

warnings.filterwarnings("ignore")

API\_KEY = "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" # Replace this

MODEL\_NAME = "google/gemma-2-9b-it:free"

API\_URL = "https://openrouter.ai/api/v1/chat/completions"

HEADERS = {

"Authorization": f"Bearer {API\_KEY}",

"Content-Type": "application/json",

"HTTP-Referer": "http://localhost",

"X-Title": "EventReportGenerator"

}

reader = easyocr.Reader(['en'], gpu=False)

geolocator = Nominatim(user\_agent="event\_report\_generator")

def process\_image\_text(path):

try:

results = reader.readtext(path)

texts = [text for \_, text, conf in results if conf > 0.6]

return ", ".join(texts) if texts else None

except Exception as e:

print(f"OCR error for {path}: {e}")

return None

def extract\_image\_features(image\_path):

try:

model = models.resnet18(pretrained=True)

model.eval()

transform = transforms.Compose([

transforms.Resize(256),

transforms.CenterCrop(224),

transforms.ToTensor(),

transforms.Normalize(mean=[0.485, 0.456, 0.406],

std=[0.229, 0.224, 0.225])

])

image = Image.open(image\_path).convert('RGB')

image\_tensor = transform(image).unsqueeze(0)

with torch.no\_grad():

features = model(image\_tensor)

return features.flatten().tolist()[:10]

except Exception as e:

print(f"Image feature extraction error for {image\_path}: {e}")

return []

def get\_college\_from\_location(loc):

try:

if "," in loc and all(part.strip().replace('.', '', 1).isdigit() for part in loc.split(',')):

lat, lon = map(float, loc.split(','))

place = geolocator.reverse((lat, lon), exactly\_one=True, language='en')

else:

place = geolocator.geocode(loc, exactly\_one=True, language='en')

if place and 'address' in place.raw:

addr = place.raw['address']

return addr.get('university') or addr.get('college') or f"{addr.get('city', '')}, {addr.get('state', '')}".strip(", ")

return loc

except Exception as e:

print(f"Geolocation error for '{loc}': {e}")

return loc

def generate\_prompt(data):

event = data.get('event\_name')

college = data.get('college\_name')

location\_detail = data.get('location', '')

location\_near = get\_college\_from\_location(location\_detail) if location\_detail else ''

feedback = data.get('feedback', '')

image\_texts = data.get('image\_texts', [])

image\_features = data.get('image\_features', [])

if not event or not college:

return None

prompt = (

f"Write a formal, well-structured institutional event report with clear and professional language in 50 words:\n\n"

f"Event Name: {event}\n"

f"Institution: {college}\n"

f"Location: {location\_detail} ({location\_near})\n"

f"Image Texts: {', '.join(image\_texts) if image\_texts else 'None'}\n"

f"Image Features: {', '.join(map(str, image\_features)) if image\_features else 'None'}\n"

f"Feedback: {feedback if feedback else 'None'}\n\n"

f"Instructions:\n"

f"- Use a Markdown heading '## {event} Event Report'.\n"

f"- Describe the successful conduct of the event by the institution.\n"

f"- Mention the event’s atmosphere, participation, and any visible themes.\n"

f"- Include location details and relevant insights from feedback.\n"

f"- Avoid including specific dates or club names unless provided.\n"

f"- Ensure the report sounds like a formal institutional summary."

)

return prompt

def send\_prompt(prompt):

try:

response = requests.post(API\_URL, headers=HEADERS, json={

"model": MODEL\_NAME,

"messages": [{"role": "user", "content": prompt}]

})

response.raise\_for\_status()

data = response.json()

return data['choices'][0]['message']['content'].strip() if 'choices' in data else None

except Exception as e:

print(f"API call failed: {e}")

return None

def check\_accuracy(report, data):

def normalize(txt): return txt.lower().strip()

report\_text = normalize(report)

total, match = 0, 0

for key in ['event\_name', 'college\_name', 'location', 'feedback']:

val = data.get(key)

if val:

total += 1

val\_norm = normalize(val)

if key == 'location':

alt\_loc = normalize(get\_college\_from\_location(val))

if val\_norm in report\_text or alt\_loc in report\_text:

match += 1

elif key == 'feedback':

words = val\_norm.split()

if sum(1 for w in words if w in report\_text) / len(words) >= 0.4:

match += 1

else:

if val\_norm in report\_text:

match += 1

return round(match / total, 2) if total > 0 else 1.0

def save\_report(report):

try:

filename = f"report\_{datetime.now().strftime('%Y%m%d\_%H%M%S')}.txt"

with open(filename, 'w', encoding='utf-8') as f:

f.write(report)

print(f"Report saved to {filename}")

return os.path.abspath(filename)

except Exception as e:

print(f"Error saving report: {e}")

return None

def open\_report\_file(path):

if not path:

return

try:

if platform.system() == 'Darwin':

subprocess.run(['open', path])

elif platform.system() == 'Windows':

subprocess.run(['start', path], shell=True)

else:

subprocess.run(['xdg-open', path])

except Exception as e:

print(f"Failed to open file: {e}")

def generate\_report(college\_name, event\_name, location, feedback, image\_paths):

try:

image\_texts = []

image\_features = []

for path in image\_paths:

image\_texts.append(process\_image\_text(path) or 'None')

image\_features.append(extract\_image\_features(path))

data = {

"college\_name": college\_name,

"event\_name": event\_name,

"location": location,

"feedback": feedback,

"image\_texts": image\_texts,

"image\_features": image\_features

}

prompt = generate\_prompt(data)

if not prompt:

print("Missing required input data.")

return None

report = send\_prompt(prompt)

if not report:

print("Report generation failed.")

return None

accuracy = check\_accuracy(report, data)

print(f"Generated report with accuracy: {accuracy \* 100:.1f}%")

report\_path = save\_report(report)

open\_report\_file(report\_path)

return report\_path

except Exception as e:

print(f"Report generation error

return None

**genrepo.html:**

<!DOCTYPE html>

<html lang="en">

<head>

<meta charset="UTF-8" />

<meta name="viewport" content="width=device-width, initial-scale=1.0"/>

<title>Event Report Form</title>

<link href="https://cdn.jsdelivr.net/npm/tailwindcss@2.2.19/dist/tailwind.min.css" rel="stylesheet"/>

<link rel="stylesheet" href="https://unpkg.com/leaflet@1.9.3/dist/leaflet.css"/>

<script src="https://unpkg.com/leaflet@1.9.3/dist/leaflet.js"></script>

<style>

body {

background: linear-gradient(135deg, #ffe2e2, #fad0c4, #ffd1ff);

font-family: 'Segoe UI', sans-serif;

}

.leaflet-container {

height: 300px;

border-radius: 0.75rem;

}

.glass-card {

background: rgba(255, 255, 255, 0.6);

backdrop-filter: blur(20px);

}

.btn-glow:hover {

box-shadow: 0 0 12px rgba(236, 72, 153, 0.8), 0 0 20px rgba(168, 85, 247, 0.6);

}

</style>

</head>

<body class="relative min-h-screen px-4 pt-28 pb-10 flex flex-col items-center justify-start text-gray-800">

<div class="fixed top-0 left-0 w-full bg-gradient-to-r from-purple-300 via-pink-300 to-red-300 text-purple-900 py-2 z-50 shadow-md">

<marquee scrollamount="6" class="font-semibold text-lg">

📣 Share your vibrant event details and media! ✨ Your insights matter!

</marquee>

</div>

<div id="formPage" class="glass-card rounded-3xl shadow-xl p-10 w-full max-w-3xl z-20 border border-pink-200 transition-all duration-300">

<h2 class="text-4xl font-extrabold text-center mb-10 text-fuchsia-800">🎉 Event Report Form</h2>

<form id="eventForm" class="space-y-7" action="/submit" method="post" enctype="multipart/form-data">

<div>

<label class="block font-semibold mb-2 text-purple-800">🏫 College Name</label>

<input type="text" name="collegeName" required class="w-full p-3 border border-fuchsia-300 rounded-lg" required/>

</div>

<div>

<label class="block font-semibold mb-2 text-purple-800">🎊 Event Name</label>

<input type="text" name="eventName" required class="w-full p-3 border border-fuchsia-300 rounded-lg" required/>

</div>

<div>

<label class="block font-semibold mb-2 text-purple-800">📍 Select Location (Click on Map)</label>

<div id="map" class="leaflet-container mb-3 shadow-lg border border-fuchsia-200"></div>

<input type="text" id="locationName" name="location" readonly class="w-full p-3 border border-gray-300 rounded-lg bg-gray-100"/>

</div>

<div>

<label class="block font-semibold mb-2 text-purple-800">🖼️ Upload Event Images</label>

<div id="imageInputs" class="space-y-3">

<input type="file" name="images" accept="image/\*" class="w-full p-2 border border-purple-300 rounded-md"/>

</div>

<button type="button" id="addImageBtn" class="mt-4 px-4 py-2 bg-pink-600 text-white rounded-md hover:bg-pink-700">Add More Images</button>

</div>

<div>

<label class="block font-semibold mb-2 text-purple-800">📝 Feedback</label>

<textarea name="feedback" rows="4" required class="w-full p-3 border border-pink-300 rounded-lg"></textarea>

</div>

<div class="pt-6">

<button type="submit" class="btn-glow w-full bg-gradient-to-r from-purple-700 via-pink-600 to-red-500 text-white font-bold py-4 px-6 text-lg rounded-xl shadow-lg hover:scale-105 transform transition duration-200">

🚀 Submit Report

</button>

</div>

</form>

</div>

<script>

const map = L.map('map').setView([17.385044, 78.486671], 13);

L.tileLayer('https://{s}.tile.openstreetmap.org/{z}/{x}/{y}.png').addTo(map);

let marker;

map.on('click', async function(e) {

const { lat, lng } = e.latlng;

if (marker) {

marker.setLatLng(e.latlng);

} else {

marker = L.marker(e.latlng).addTo(map);

}

try {

const response = await fetch(`https://nominatim.openstreetmap.org/reverse?format=jsonv2&lat=${lat}&lon=${lng}`);

const data = await response.json();

document.getElementById('locationName').value = data.display\_name ||"Hyderabad";

} catch {

document.getElementById('locationName').value = "Location not found";

}

});

document.getElementById('addImageBtn').addEventListener('click', function() {

const imageInputsContainer = document.getElementById('imageInputs');

const newInput = document.createElement('input');

newInput.type = 'file';

newInput.name = 'images';

newInput.accept = 'image/\*';

newInput.classList.add('w-full', 'p-2', 'border', 'border-purple-300', 'rounded-md');

imageInputsContainer.appendChild(newInput);

});

</script>

</body>

</html>

**Banking/Payment Fraud:** Targets online banking platforms by mimicking official banking websites to steal login credentials.

**E-commerce Scams:** Fake shopping websites designed to trick users into entering payment details.

**Credential Stealing Attacks:** Phishing websites that disguise themselves as login pages for popular services (e.g., Gmail, Facebook, PayPal).

**Social Media Fraud:** URLs used to impersonate social media platforms, often used for spreading malware or scams.

To achieve accurate attack type classification, the system uses predefined rule-based patterns combined with machine learning classifiers that detect suspicious words, domain typos, and unusual URL structures.

Model Evaluation and Performance Analysis

After training, the model undergoes a thorough evaluation using standard performance metrics to measure its effectiveness in phishing detection. The system analyses the following:

**Accuracy:** Measures the percentage of correctly classified URLs.

**Precision:** Evaluates how many of the URLs labelled as phishing are actually phishing threats.

**Recall:** Measures how many actual phishing URLs were correctly identified.

**Confusion Matrix:** Provides a detailed breakdown of false positives, false negatives, true positives, and true negatives.

To further enhance interpretability, the system visualizes phishing trends and model

performance using Seaborn and Matplotlib. These visualizations help in fine-tuning the model by identifying patterns in misclassified URLs and optimizing feature selection accordingly.

Report Generation and User Interaction

The system features an interactive Streamlit-based UI, allowing users to input URLs for real-time risk assessment. The prediction results are displayed clearly, categorizing URLs as safe or potentially malicious based on the classification model’s decision.

Additionally, the system generates detailed reports in PDF format using FPDF, summarizing the following:

**Phishing Detection Results:** Classification label (Legitimate/Suspicious).

**Feature-Based Analysis:** Breakdown of URL components contributing to the decision. **Attack Type Classification:** If detected, the phishing category is included in the report. **Recommendations:** Security guidelines and best practices for users.

This automated reporting feature enhances user awareness by providing clear, actionable insights regarding the detected phishing threats.

Key Advantages of the System

**High Detection Accuracy:** By utilizing Random Forest Classifier, the system achieves significantly higher accuracy compared to traditional blacklist-based approaches. Instead of relying on predefined lists of phishing URLs, the system analyses each URL dynamically, allowing it to detect zero-day attacks effectively.

**Real-Time Analysis:** Users receive instant phishing classifications, allowing them to assess URLs before interacting with them. This real-time analysis helps prevent credential theft and financial fraud by alerting users about potential threats immediately.

**User-Friendly and Scalable:** The system is designed for easy accessibility via a cloud- based implementation, removing the need for high-end local hardware. Its modular architecture as shown in the Fig 5.1 ensures future expansion, enabling the integration of advanced features like WHOIS lookups, domain age analysis, and deep learning models for improved detection.

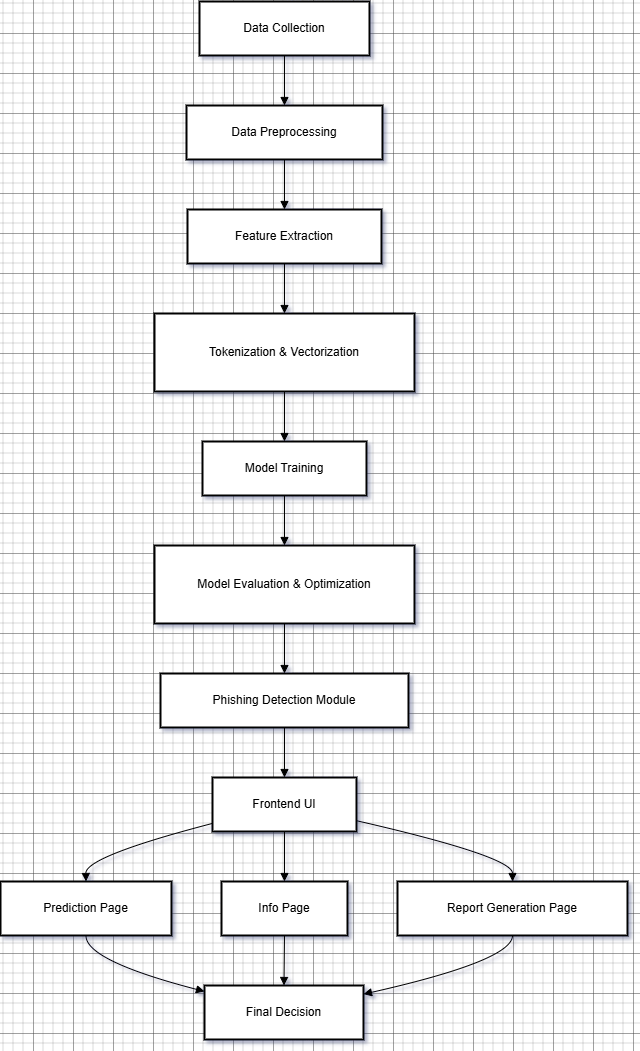


Fig 5.1: System Architecture Diagram

###### METHOD OF IMPLEMENTATION

The implementation of the AI-Driven Phishing Detective Tool is structured to ensure a seamless, real-time phishing detection experience using Python and Streamlit, a lightweight web framework. The tool integrates machine learning (ML) models, URL feature extraction, attack classification, and automated report generation within a cloud- based framework, making it easily accessible and scalable. This section details the step- by-step process of implementation, covering data preprocessing, model training, classification, user interaction, and system evaluation. By leveraging Scikit-learn, Pandas, FPDF, and Streamlit, the tool provides an efficient and interactive solution for detecting phishing threats.

* + 1. STEPS INVOLVED IN DATA COLLECTION AND PREPROCESSING

The first step in building the phishing detection system is data collection. The dataset consists of URLs labelled as legitimate or phishing, with associated features such as protocol type, domain structure, URL length, subdomains, and presence of phishing- related keywords. To ensure the dataset is suitable for training a machine learning model, the following preprocessing techniques are applied:

**Handling Missing Values:** Missing values are filled using fillna(), ensuring a complete dataset without null entries.

**Feature Engineering:** URL attributes such as length, entropy, presence of numbers/special characters, and use of HTTPS vs. HTTP are extracted as key indicators of phishing behaviour.

**Text Processing:** NLP-based techniques such as CountVectorizer and TfidfVectorizer convert textual URL components into structured numerical representations.

**Data Storage:** The cleaned dataset is stored in a Pandas DataFrame for efficient processing and model training.

The dataset is loaded from a CSV file containing labelled URLs. Missing values are identified and replaced with appropriate defaults. Feature extraction techniques analyse URL text and structure to derive phishing-related indicators. The final dataset is structured and prepared for training the classification model.

* + 1. PHISHING DETECTION USING RANDOM FOREST CLASSIFIER

The Random Forest Classifier from Scikit-learn is used as the primary machine learning model for phishing detection. This ensemble method improves classification accuracy by combining multiple decision trees, reducing overfitting and enhancing generalization.

Key steps in model implementation include:

Splitting Data into Features and Labels: The dataset is divided into features (X) and labels (y) to separate input attributes from classification targets.

Training the Model: The Random Forest algorithm learns patterns associated with phishing URLs by analysing the extracted features.

Hyperparameter Tuning: Parameters such as number of trees, tree depth, and feature selection are optimized to improve detection accuracy.

Prediction & Classification: Once trained, the model predicts whether an input URL is legitimate or phishing based on extracted features.

The dataset is split into training (80%) and testing (20%) sets. The model is trained on the extracted URL features. Hyperparameter tuning is performed using GridSearchCV for optimal performance. The trained model classifies new URLs based on learned patterns, returning either "Legitimate (Safe)" or "Suspicious (Unsafe)".

* + 1. ATTACK TYPE ANALYSIS FOR PHISHING CLASSIFICATION

Beyond basic phishing detection, the tool categorizes phishing threats based on common attack types using a rule-based heuristic system. This helps in understanding the nature of the phishing attack and improving security awareness.

The system classifies threats into categories such as:

**Banking/Payment Fraud:** Fake banking sites designed to steal financial credentials.

**E-commerce Scams:** Fraudulent online stores used to deceive shoppers.

**Credential Stealing**: Phishing pages mimicking login portals to capture user credentials.

**Social Media Fraud:** Fake social media pages aimed at identity theft or spreading malware.

The input URL is analysed for keywords, domain names, and suspicious patterns.

The system checks for predefined phishing indicators related to known attack types. Based on detected patterns, the URL is categorized into one of the phishing attack types. The classification result is displayed alongside the phishing detection outcome.

* + 1. USER INTERACTION AND PREDICTION USING STREAMLIT

The Streamlit framework provides an intuitive, web-based interface for users to interact with the system. This allows users to input URLs, view real-time predictions, and download reports.

The UI consists of:

**URL Input Field:** Users enter the URL to be analysed.

**Validation Mechanism:** The system checks whether the URL format is valid using the validators library.

**Prediction Display:** The classification model analyses the URL and displays a Legitimate or Suspicious result.

Users enter a URL and select the protocol type (HTTP/HTTPS). The system validates the URL format before processing. Upon clicking the Predict button, the trained model analyses the URL and displays the phishing detection result. If the URL is classified as phishing, the system highlights the possible attack type.

* + 1. PDF REPORT GENERATION USING FPDF

The FPDF library is used to generate a structured phishing analysis report, which users can download for reference. The report includes:

Analysed URL and classification result. Phishing indicators detected in the URL. Attack Type (if applicable) to provide further context. Recommendations for safe browsing practices.

After making a prediction, users can navigate to the Download Report section. Clicking the Generate Report button creates a structured PDF report summarizing the phishing analysis. Users can download and save the report for further investigation as depicted in the Fig 5.2.

* + 1. EVALUATION OF SYSTEM PERFORMANCE

To ensure reliability and accuracy, the model undergoes rigorous performance evaluation using standard ML metrics.

Metrics used include:

Accuracy Score: Measures the overall correctness of phishing detection. Precision & Recall: Evaluates how well phishing threats are identified. Confusion Matrix: Displays a breakdown of correct vs. incorrect classifications.

Data Visualization: Matplotlib and Seaborn generate visual representations of phishing trends and model performance.

A test dataset is used to evaluate the trained model. A confusion matrix and classification report are generated to analyse model effectiveness. Areas of misclassification are identified for further model refinement. The model undergoes continuous retraining with updated datasets to enhance phishing detection accuracy.

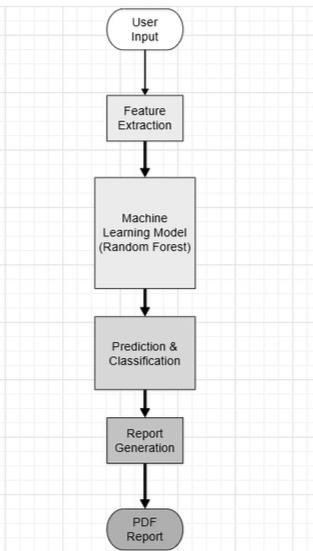


Fig 5.2: Workflow of phishing detection tool

###### MODULEs

The AI-Driven Phishing Detective Tool is divided into multiple functional modules, ensuring a structured and efficient workflow. Each module is responsible for a specific task, from data preprocessing and feature extraction to machine learning model training, real-time URL detection, web-based interaction, and performance evaluation. By maintaining a modular design, the tool achieves scalability, maintainability, and real- time phishing detection while ensuring accuracy and user accessibility. The following sections detail each module's implementation, workflow, and key functions.

* + 1. MODULE A: DATA PREPROCESSING AND FEATURE EXTRACTION

This module processes raw URLs and converts them into structured feature representations that can be used by the machine learning model. Since raw URLs cannot be directly analysed, extracting relevant attributes helps in differentiating phishing and legitimate URLs.

Key Tasks:

Data Cleaning and Preprocessing

Standardizes URLs by converting to lowercase and removing unnecessary characters. Eliminates duplicate URLs and corrects format inconsistencies.

Feature Extraction

The module extracts three primary feature types:

Lexical Features: URL length, number of special characters (e.g., -, \_, ., @), and presence of suspicious keywords (e.g., bank, login, verify).

Host-based Features: Domain age, WHOIS information, and whether the URL uses an IP address instead of a domain.

Content-based Features: HTTPS usage, SSL certificate validity, and URL redirection patterns.

Feature Encoding and Normalization

Converts categorical values (e.g., protocol type) into numerical encodings. Normalizes numerical features (e.g., URL length) into a standard range (0 to 1).

Key Function

def extract\_features(urls: list) -> DataFrame:

//Takes a list of URLs and extracts key features into a structured DataFrame.

* + 1. MODULE B: MACHINE LEARNING MODEL TRAINING (RANDOM FOREST CLASSIFIER)

This module trains the core classifier, which determines whether a given URL is phishing or legitimate. It uses the Random Forest Classifier, an ensemble learning method known for its robust performance and accuracy in detecting phishing threats.

Key Tasks:

**Data Splitting**

Divides the dataset into training (80%) and testing (20%) sets. Ensures a balanced distribution of phishing and legitimate URLs. **Model Selection**

Chooses RandomForestClassifier due to its ability to handle complex decision boundaries.

Optimizes hyperparameters such as:

n\_estimators (Number of trees in the forest) max\_depth (Maximum depth of trees) **Model Training**

Trains on labeled URL datasets to learn phishing detection patterns. Uses cross-validation to prevent overfitting.

Performance Evaluation

Measures accuracy, precision, recall, and F1-score.

Analyzes results and fine-tunes model parameters for better detection rates.

Key Function

def train\_model(features: DataFrame, labels: Series) -> RandomForestClassifier:

//Trains a Random Forest model and returns the trained classifier.

* + 1. MODULE C: PHISHING URL DETECTION AND PREDICTION

This module performs real-time classification, allowing users to input a URL and receive an instant phishing risk assessment.

Key Tasks:

**User Input Handling**

Accepts URLs through the Streamlit interface. Validates the input format before proceeding.

Feature Extraction on New URLs

Applies the same feature extraction process as in Module A. Ensures consistency between training and prediction phases. **Prediction with the Trained Model**

The trained RandomForestClassifier analyzes input URLs.

Generates a probability score and assigns a classification label (Phishing or Legitimate).

Risk Assessment and Explanation

Provides additional insights on why a URL was flagged as phishing. Highlights specific features contributing to the decision.

Key Function

def predict\_url(url: str, model: RandomForestClassifier) -> str:

//Takes a URL, extracts features, and returns a phishing classification result.

* + 1. MODULE D: WEB APPLICATION (STREAMLIT)

The Web Application module provides an interactive user interface where users can input URLs and receive real-time phishing detection results. The UI is developed using Streamlit, a Python-based web framework.

Key Tasks:

User-Friendly Interface Design

Provides a simple, intuitive UI for users to enter a URL. Displays prediction results in a clear and interactive format. **Real-Time Prediction Display**

Users receive instant classification results upon submitting a URL. Displays probability scores along with detailed risk assessments.

Visualization of Features

Provides graphical insights into feature importance. Example: A bar chart highlighting top phishing indicators.

Key Function

def run\_web\_app():

//Launches the Streamlit-based phishing detection interface.

* + 1. MODULE E: EVALUATION AND PERFORMANCE METRICS

To ensure the system performs reliably, this module evaluates model accuracy using various performance metrics.

Key Tasks:

**Comparing Predicted vs. Actual Labels**

Analyses the model's predictions against true labels.

Computing Performance Metrics

Accuracy: Measures overall correct predictions.

Precision: Determines how many phishing predictions were correct. Recall: Evaluates how many actual phishing URLs were detected.

F1-Score: Balances precision and recall, particularly useful for imbalanced datasets.

Confusion Matrix Analysis

Visualizes true positives, false positives, true negatives, and false negatives. Identifies misclassifications and suggests improvements.

###### SAMPLE CODE

import streamlit as st import pandas as pd

from sklearn.ensemble import RandomForestClassifier from fpdf import FPDF

import validators

# Sample dataset for training data = {

'URL': [

"[www.marketplus.com.ar/cart/includes/local/1.php](http://www.marketplus.com.ar/cart/includes/local/1.php)", "[www.qu100.com/phpmyadmin/778766777/index.html](http://www.qu100.com/phpmyadmin/778766777/index.html)", "uploads.boxify.me/83141/novo.ini",

],

'Protocol': [0.0, 0.0, 0.0, None, 2.0, 0.0, 0.0, 1.0, None, None],

'Label': [1, 1, 1, 0, 1, 0, 0, 0, 0, 1]

}

df = pd.DataFrame(data)

# Handling missing values in Protocol column df['Protocol'] = df['Protocol'].fillna(df['Protocol'].mean()) # Features and target for training

X = df[['Protocol']] # Features y = df['Label'] # Target labels # Train Random Forest model

clf = RandomForestClassifier(random\_state=42) clf.fit(X, y)

# Function to analyze URL type based on keywords def analyze\_url\_type(url):

if "paypal" in url or "bank" in url or "payment" in url:

return "Banking/Payment Fraud", "This type of URL is commonly used in phishing attacks to steal banking credentials."

elif "shop" in url or "cart" in url or "ecommerce" in url:

return "E-commerce Scam", "Fake e-commerce sites trick users into making payments for non-existent products."

* + 1. Explanation of the sample code

RNNs, particularly LSTMs, are designed to handle sequential data where temporal relationships are important. For surveillance, an RNN can process temporal

patterns (e.g., frame-by-frame features) to detect anomalies or violent behaviour.

This script is designed to detect phishing URLs using a combination of machine learning, heuristic analysis, and natural language processing. It integrates various libraries, including Streamlit for an interactive web interface, Pandas for data handling, scikit-learn's Random Forest Classifier for classification, FPDF for report generation, and validators for URL validation. The dataset used for training consists of URLs labelled as either phishing (1) or legitimate (0), with Protocol type as a key feature. Since some Protocol values are missing, the script applies data preprocessing techniques, replacing missing values with the mean of available values to maintain consistency and prevent issues during model training.

The Random Forest Classifier is used as the core machine learning model due to its robustness, accuracy, and ability to handle complex decision boundaries. It operates by constructing multiple decision trees and aggregating their results to improve detection accuracy while minimizing overfitting. The dataset is split into features (X) and labels

(y) before training the classifier, which learns patterns distinguishing legitimate from phishing URLs. Once trained, the model is capable of predicting whether a given URL is safe or suspicious based on extracted features. The use of an ensemble learning approach ensures high detection accuracy and resilience to noisy data.

In addition to machine learning-based classification, the script incorporates heuristic analysis to determine the type of phishing attack by analysing URL content. The function analyze\_url\_type(url) checks for specific keywords commonly found in phishing attempts. If the URL contains terms like "paypal", "bank", or "payment", it is classified as a Banking/Payment Fraud attempt, where attackers impersonate financial institutions to steal user credentials. Similarly, URLs with keywords such as "shop", "cart", or "ecommerce" are identified as E-commerce Scams, which trick users into making payments for fraudulent or non-existent products. This rule-based system enhances the tool’s ability to provide detailed threat classification, helping users understand the nature of potential phishing attacks beyond just a binary classification.

The system is built to be interactive and user-friendly, integrating Streamlit for real-time URL analysis. Users enter a URL, which is then processed through feature extraction and passed to the trained Random Forest model for classification. The result is displayed instantly, providing an assessment of whether the URL is legitimate or

suspicious. Additionally, the tool generates downloadable phishing analysis reports using FPDF, including key details such as the analysed URL, prediction results, attack type classification, and a brief threat description. This feature is particularly useful for organizations and security professionals who require documented phishing reports for cybersecurity audits or investigations.

## CHAPTER - 6

### TESTING & VALIDATION

#### CHAPTER – 6 TESTING & VALIDATION

###### TESTING PROCESS

The testing process is an essential and integral part of the development lifecycle of the phishing detection system. It ensures that the system meets the intended functionality and maintains high accuracy and performance under diverse conditions. Testing is crucial to identify potential defects, validate the system's robustness, and ensure that the model correctly detects phishing URLs and classifies legitimate URLs without false positives. The primary goal of the testing process is to deliver a reliable and efficient phishing detection tool that can perform effectively in real-world scenarios.

The testing process involves four major phases: Test Planning, Test Design, Test Execution, and Test Reporting. Each phase plays a significant role in the validation and verification of the system. Meticulous attention is given to every phase to ensure that the tool performs optimally across different environments and data sets.

* + 1. TEST PLANNING:

Test planning is the foundational phase where the testing strategy is formulated to ensure that the phishing detection system meets its objectives. The planning phase is crucial as it sets the roadmap for the entire testing process. It involves identifying the scope, defining objectives, allocating resources, and establishing a timeline for execution.

During the test planning phase, the scope of testing is clearly defined to include all critical features and functionalities of the system. The primary components identified for testing are the Home Page, Prediction Page, and Report Generation Module. In addition, the system’s capability to detect various types of URLs, such as banking URLs, e- commerce scam URLs, Google form URLs, legitimate URLs, and suspicious URLs, is also emphasized.

To ensure comprehensive coverage, the planning phase also includes resource allocation, wherein human resources, testing tools, and testing environments are identified and assigned. The roles and responsibilities of each team member are clearly defined to facilitate smooth execution. Tools such as Microsoft Excel are selected for

organizing and managing test cases.

A detailed schedule and timeline are established to outline the testing activities, including test case development, execution, defect tracking, and reporting. This schedule ensures that the testing process is conducted within the project’s timeline, a **l**owing room for regression testing and fixing potential issues.

Moreover, potential risks and challenges are anticipated, and contingency plans are formulated to address unexpected issues that may arise during testing. This proactive approach helps minimize disruptions and ensures that testing proceeds efficiently and systematically.

* + 1. TEST DESIGN:

Test design is the phase where comprehensive and well-structured test cases are created to evaluate the system's functionality and performance. The primary objective of this phase is to develop test cases that effectively cover all possible scenarios and edge cases, ensuring that the system is robust and reliable.

The test design process begins with the identification of test scenarios, where potential situations that the system might encounter are outlined. These scenarios are based on system requirements and real-world use cases. Scenarios include detecting phishing URLs, classifying legitimate URLs, identifying suspicious patterns, and generating detailed reports.

Once scenarios are identified, test cases are meticulously crafted to specify the input data, expected outcomes, and precise steps to be followed during execution. Each test case is designed to verify a specific functionality or feature of the phishing detection system. Test cases are crafted to cover not only normal and expected inputs but also edge cases, including malformed URLs, ambiguous URLs, and large data sets.

Special attention is given to test data preparation, where representative datasets of phishing URLs, legitimate URLs, and suspicious URLs are compiled. These datasets are obtained from publicly available sources and synthetic data generation to ensure a comprehensive evaluation. The data is structured to include various URL formats, domains, and patterns to simulate real-world phishing scenarios.

To maintain consistency and accuracy, test design tools such as Microsoft Excel are used to document test cases and expected results. These tools facilitate organized

tracking and management of test cases throughout the testing process.

* + 1. TEST EXECUTION:

Test execution is the phase where the formulated test cases are systematically executed to verify the system's performance and accuracy. This stage involves running the test cases as specified, recording the outcomes, and comparing actual results with the expected ones.

The execution process starts with setting up the testing environment to replicate real-world conditions. This includes configuring the prediction model, preparing the dataset, and initializing the web application. Once the environment is set, the test cases are executed step by step as per the predefined procedure.

During test execution, the focus is on observing and recording the system's responses to various inputs. Any deviations from expected outcomes are logged as defects, including details about their severity and potential impact on the system. Automated scripts are used where applicable to streamline the execution process, especially for repetitive and large-scale testing.

An important aspect of this phase is defect reporting, where detected issues are logged, analysed, and categorized. The defect management process ensures that each identified issue is promptly addressed and resolved before deployment. Additionally, **regression testing** is conducted to confirm that recent fixes do not adversely affect existing functionalities.

* + 1. TEST REPORTING:

Test reporting is the final phase of the testing process, focusing on consolidating and presenting the test results. This phase involves compiling data from test execution, analysing the outcomes, and creating a comprehensive report that summarizes the system's performance.

The report includes a detailed summary of executed test cases, highlighting both successful and failed cases. Each test case result is documented, including the input data, expected results, actual outcomes, and the status (pass or fail). The report also contains defect analysis, which categorizes and prioritizes issues based on their severity.

Additionally, test metrics such as defect density, test coverage, and execution progress are calculated and analysed. These metrics provide valuable insights into the

overall quality of the system and highlight areas that may require further improvement. The final test report is shared with stakeholders to provide a transparent overview of the system’s reliability and performance.

* 1. TEST CASES

The following test cases were conducted to evaluate the phishing detection system’s performance and accuracy. Each test case is detailed with objective, steps, expected outcomes, and actual results as shown in the Table 6.1.

Test Case 1: Homepage Rendering

**Objective:** Verify if the homepage loads correctly with all interactive elements and input fields.

**Steps:** Open the web application and observe the homepage layout and functionality. **Expected Result:** The homepage should display input fields and instructions correctly. **Actual Outcome:** The homepage rendered correctly without issues.

**Status:** Pass

Test Case 2: URL Format Validation

**Objective:** Test the system's ability to identify improperly formatted URLs. **Steps:** Input various malformed URLs and check if the system flags them as invalid. **Expected Result:** The system should correctly identify and reject improperly formatted URLs.

**Actual Outcome:** The system displayed an error message for all malformed URLs.

**Status:** Pass

Test Case 3: Legitimate URL Detection

**Objective:** Verify that legitimate URLs are correctly classified.

**Steps:** Input safe and verified URLs into the prediction page. **Expected Result:** The system should display the result as "Legitimate." **Actual Outcome:** The model accurately classified all legitimate URLs. **Status:** Pass

Test Case 4: Phishing URL Detection

**Objective:** Test the system’s ability to detect known phishing URLs.

**Steps:** Input phishing URLs from a validated dataset.

**Expected Result:** The system should correctly classify them as "Suspicious."

**Actual Outcome:** The system successfully flagged phishing URLs as suspicious.

**Status:** Pass

Test Case 5: Report Generation

**Objective:** Validate the generation of detailed analysis reports in PDF format.

**Steps:** Initiate report generation after analyzing URLs.

**Expected Result:** A PDF report containing detailed analysis should be generated.

**Actual Outcome:** The system generated the report correctly.

**Status:** Pass

Test Case 6: Banking/Payment URL Detection

**Objective:** Verify that the system correctly detects phishing URLs related to banking and payment fraud, particularly URLs containing keywords like "paypal".

Steps:

Open the prediction page of the phishing detection system.

Enter a set of URLs that contain banking and payment-related keywords

Expected Result:

The system should detect the URLs containing payment-related keywords as suspicious and display the result as "Suspicious - Banking/Payment Fraud".

Actual Outcome:

The system correctly detected and classified as shown in the Table 6.1. the banking and labelling them as "Suspicious - Banking/Payment Fraud".

**Status:** Pass

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Test Case** | **Component** | **Input** | **Expected**  **Outcome** | **Actual**  **Outcome** | **Status** |
| Homepage Rendering | Home Page | Open the web app | Display the  homepage with input field and instructions | Displayed correctly | Pass |
| URL Format Validation | Prediction Page | Improperly formatted URLs | Display error  message indicating invalid URL format | Error displayed | Pass |
| Legitimate URL Detection | Prediction Page | Safe,  verified URLs | Display result as "Legitimate" | Correctly detected | Pass |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Suspicious URL Detection | Prediction Page | Known phishing URLs | Display result as "Suspicious" | Correctly detected | Pass |
| Banking/Payment URL Detection | Prediction Page | URL  containing "paypal" | Display result as "Suspicious - Banking/Payment Fraud" | Correctly detected | Pass |
| E-commerce Scam URL Detection | Prediction Page | URL  containing "shop" | Display result as "Suspicious - E- commerce Scam" | Correctly detected | Pass |
| Google Form URL Detection | Prediction Page | Google form URL | Display result as "Suspicious - Data Collection Scam" | Correctly detected | Pass |
| Report Generation | Report Module | URL and analysis result | Generate a downloadable PDF report with  analysis details | Report generated | Pass |

Table 6.1: Test Cases

## CHAPTER - 7

### OUTPUT SCREENS

#### CHAPTER – 7 OUTPUT SCREENS

In AI-driven phishing detection system, output screens play a crucial role in showcasing the progression and outcomes of each phase of the project. These screens serve as visual and textual representations of the system's operation, encompassing processes from data acquisition and preprocessing to real-time detection and result analysis. The primary purpose of these screens is to validate the system's functionality while ensuring transparency and interpretability in the detection process.

The phishing detection system is designed to accurately identify phishing attempts in real-time by utilizing machine learning and deep learning algorithms, with a particular focus on Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The output screens are systematically structured to display results at each stage, enabling performance assessment, outcome analysis, and identification of potential areas for improvement.

By presenting outputs at each critical stage of the pipeline, the screens facilitate a comprehensive understanding of the system's workflow. They assist in identifying bottlenecks or errors that may occur during data processing, model training, evaluation, and real-time prediction. The output screens follow a logical sequence to mirror the natural flow of the phishing detection process, thereby enhancing the interpretability and usability of the system.

This chapter provides a detailed exploration of each output screen, emphasizing the key elements, underlying processes, and insights derived from them. The documentation covers various stages such as data preprocessing, feature extraction, model evaluation, and real-time phishing detection, demonstrating how each screen contributes to conveying the system’s operational success and accuracy.

###### HOME PAGE: AI-DRIVEN PHISHING DETECTION TOOL

The home page of the AI-driven phishing detection system serves as the primary interface for conducting comprehensive cyber threat analysis. It is designed to be user- friendly and visually intuitive, providing an efficient and streamlined way for users to initiate phishing detection. The home page plays a vital role in guiding users through the detection process while also offering essential information on maintaining secure online

practices.

Core Functionalities of the Home Page

The home page is centred around the **URL Detection Section**, which enables users to assess the legitimacy of any given URL. The following key components are incorporated to enhance usability and functionality:

URL Input Field:

The URL Input Field allows users to enter the address they wish to analyse.

The field is designed to accept various types of URLs, ensuring compatibility with different protocols and formats.

It is complemented by a protocol selection drop-down menu that enables users to choose the protocol, such as HTTP or HTTPS, before initiating the analysis.

Protocol Selection:

The Select Protocol feature allows users to specify the protocol associated with the URL, enhancing the precision of the analysis.

The default option is typically HTTP, but users can select from other available protocols as needed.

This capability is crucial as certain cyber threats may specifically exploit insecure protocols, making it vital to accurately categorize and analyse them.

Analyse Button:

The "Analyse" button, positioned prominently next to the input field, triggers the detection process.

Upon clicking, the system processes the entered URL using advanced machine learning algorithms to detect potential phishing attempts.

The button is designed to provide immediate feedback by initiating the analysis seamlessly.

Prediction Result Display:

Once the analysis is complete, the prediction result is displayed directly below the analysis section.

The result is clearly labelled as "Prediction: Legitimate" or "Prediction: Malicious",

ensuring that users can easily interpret the outcome.

Additionally, the "Attack Type" field indicates the specific nature of the detected threat, such as "Phishing", "Malware", or "None" if no threat is identified.

This immediate feedback is crucial for users to quickly assess the safety of the URL being analysed.

Security Best Practices Section

The home page also features a dedicated Security Best Practices section, aimed at promoting secure online behaviour and mitigating risks associated with phishing attacks. This section includes practical guidelines such as:

**Using Strong and Unique Passwords:** Encouraging users to create complex passwords that are difficult to guess or crack.

**Enabling Multi-Factor Authentication (MFA):** Advising users to adopt MFA for enhanced security.

**Being Cautious with Unknown Links:** Warning against clicking on unfamiliar or suspicious links.

**Regularly Updating Software:** Emphasizing the importance of keeping software and systems up to date to mitigate vulnerabilities.

By integrating these best practices directly on the home page, the system not only detects phishing attempts but also educates users on adopting proactive cybersecurity measures.

Navigation and Accessibility

The left panel of the home page hosts the Navigation Menu, providing seamless access to the following pages:

**Home:** Returns to the main analysis interface, allowing users to perform new phishing detection tasks.

**Reports:** Directs to the Report Page where users can view and download detailed analysis reports, as discussed in the corresponding section.

**About:** Provides insights into the system’s purpose, underlying technologies, and project objectives.

The navigation panel ensures that users can effortlessly switch between different functionalities without losing context or progress.

Significance of the Home Page

The home page is integral to the overall phishing detection system, as it facilitates user interaction and enables rapid analysis of URLs. By providing both analytical and educational elements in one interface, it supports users in making informed decisions regarding potential cyber threats. Furthermore, the transparent presentation of results and practical security tips contribute to enhancing cybersecurity awareness and vigilance.

The comprehensive design of the home page ensures that users are guided through the detection process in a systematic and informed manner. As depicted in Fig 7.1 and Fig 7.2, the interface prioritizes both functionality and usability, making it a vital component of the AI-driven phishing detection system.

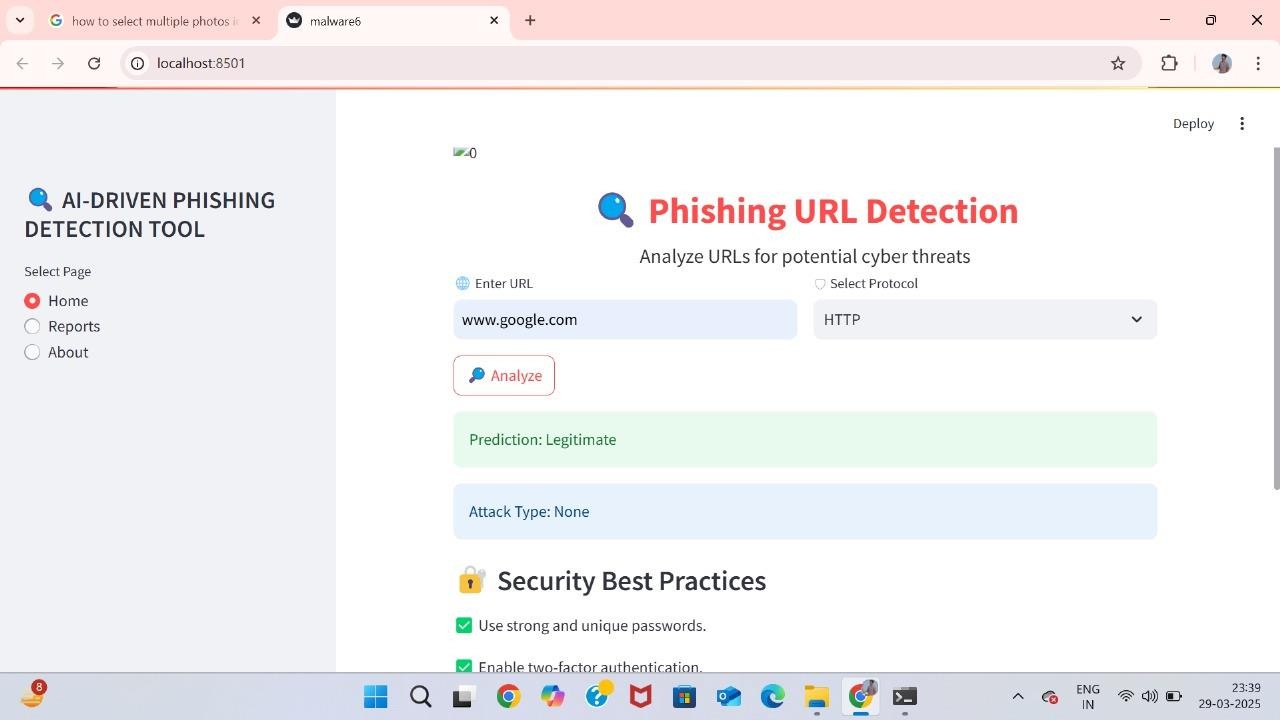


Fig 7.1: Home Page

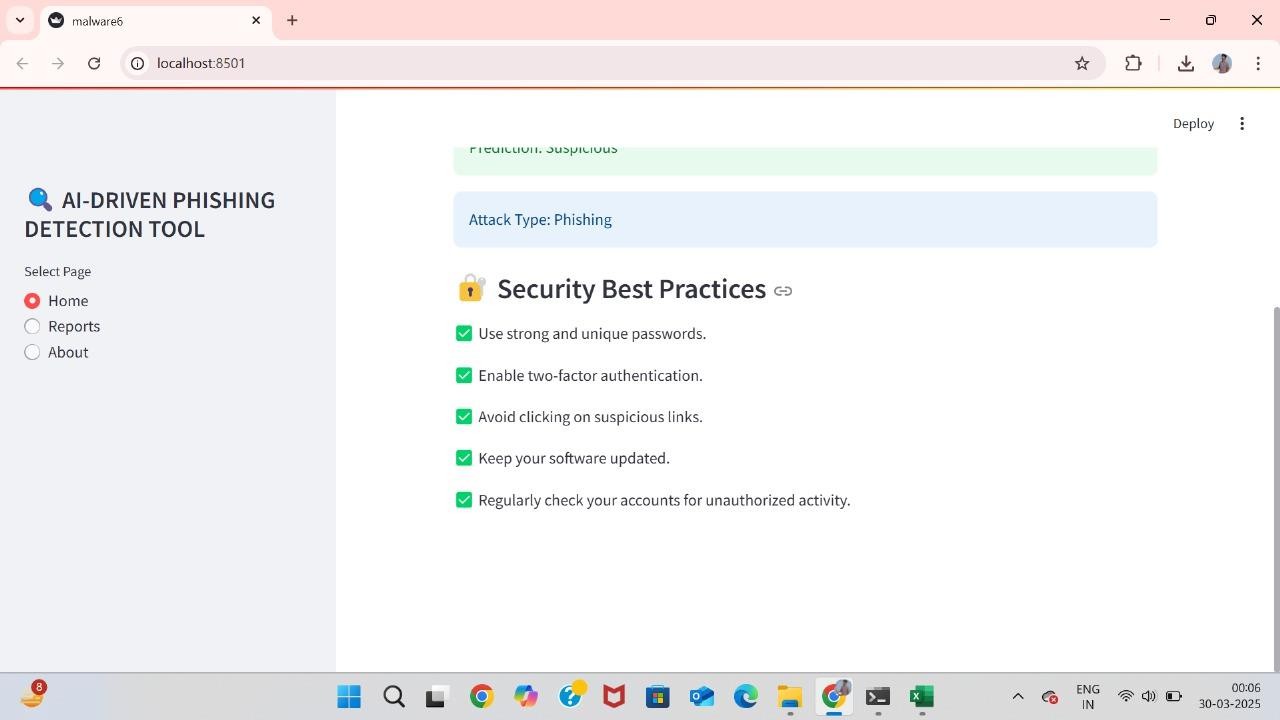


Fig 7.2: Home Page#2

###### REPORT PAGE - ATTACK DETECTION

The report page serves as a comprehensive and detailed summary of the analysis results generated by the AI-driven phishing detection system. It provides essential information regarding the legitimacy and security assessment of the analysed URL, offering a clear and structured overview of the detection outcome. This page is designed to enable users to systematically review the results of the cybersecurity analysis, ensuring transparency and accuracy in evaluating potential cyber threats.

Key Features and Information Displayed

The report page displays the following crucial components:

URL Analysis Information:

The analysed URL is clearly displayed at the top of the report, allowing users to verify the address that was evaluated.

The report also includes a clickable link to the analysed URL, enabling quick reference and verification.

Protocol Specification:

The protocol used during analysis (e.g., HTTP, HTTPS) is displayed to provide context regarding the communication channel.

This detail helps in understanding the security level of the connection and potential vulnerabilities related to insecure protocols.

Legitimacy Status:

The legitimacy status of the URL is prominently displayed, indicating whether the URL has been classified as "Legitimate" or "Phishing/Malicious" based on the model’s analysis.

This quick assessment allows users to make informed decisions regarding the safety of the URL.

Attack Type Identification:

In cases where malicious activity is detected, the report specifies the attack type identified (e.g., Phishing, Malware, Spoofing).

This information aids in understanding the nature and severity of the potential threat. If no suspicious behaviour is detected, the report indicates "None" as the attack type. **Graphical Representation of Analysis Outcomes**

The report page features a graphical visualization of analytical metrics, enhancing the interpretability of the prediction results. The graph displays relevant metrics or feature importance scores that contribute to the final prediction. The purpose of this visual representation is to:

Illustrate the distribution of critical features or risk factors associated with the analysed URL.

Provide an intuitive and easily understandable means of assessing the threat level. Facilitate the comparison of various metrics that impact the detection decision.

Navigation and Accessibility

The left panel of the report page contains navigation options to seamlessly switch between different sections of the application:

**Home:** Redirects to the homepage where new URLs can be analysed.

**Reports:** Directs to the current page to review and download the analysis reports.

**About:** Provides information about the phishing detection system and its underlying technologies.

Significance of the Report Page

The report page plays a pivotal role in presenting a structured and informative summary of the system’s detection capabilities. By clearly displaying both textual and graphical insights as shown in the Fig 7.3 and 7.4, it allows users to evaluate the accuracy and reliability of the phishing detection results. This page not only aids in monitoring the system’s performance but also contributes to maintaining transparency in the threat analysis process.

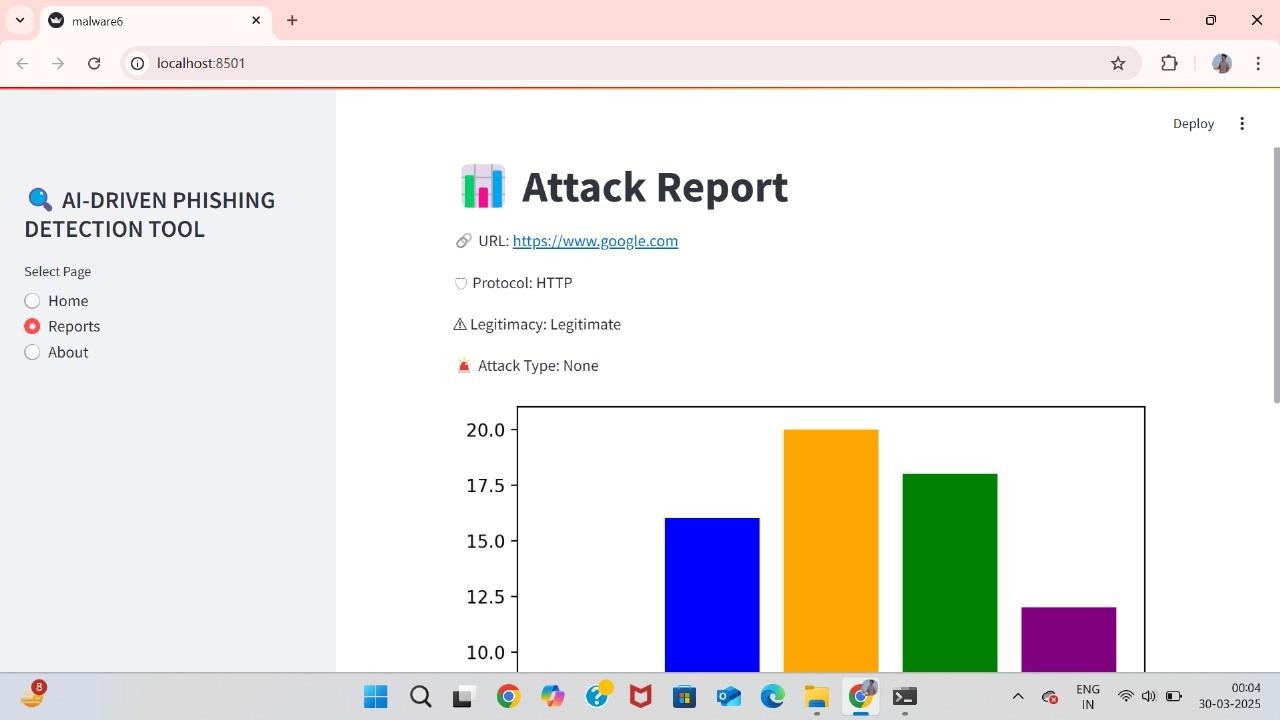


Fig 7.3: Report Page

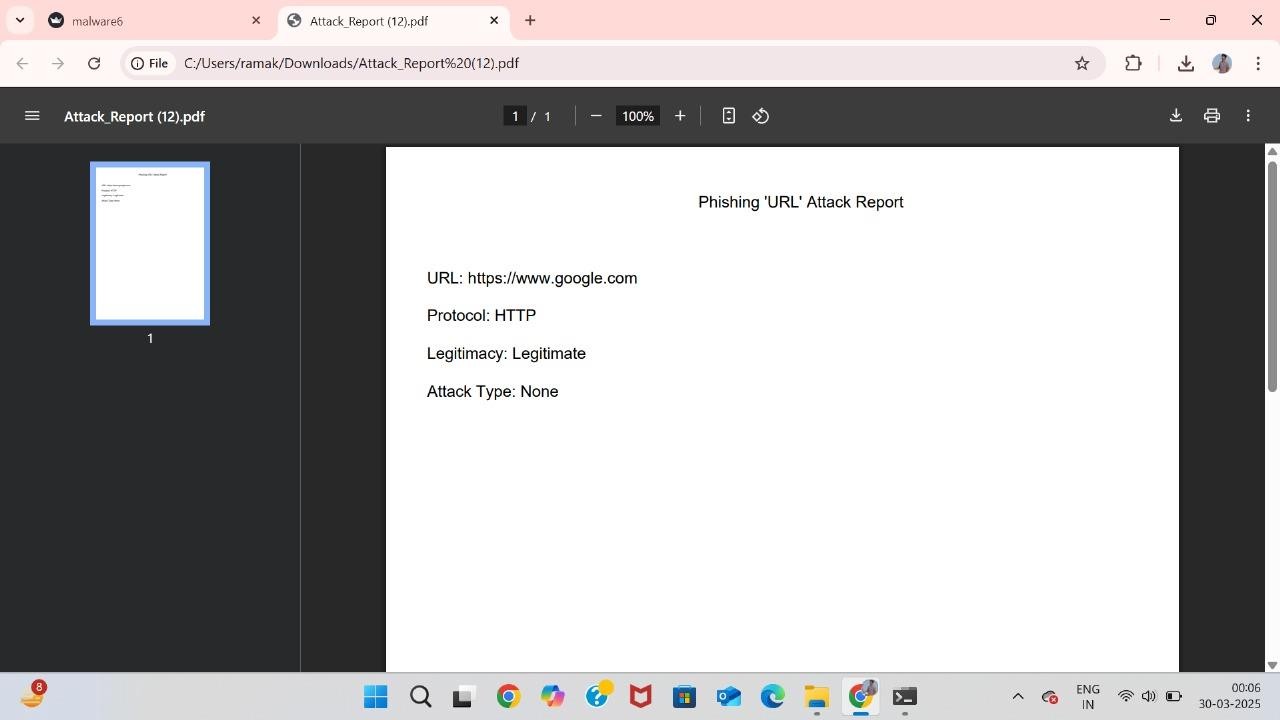


Fig 7.4: Report PDF

###### 7.2. LEGITIMATE URL

The output screen for a legitimate URL serves as a clear and informative interface that displays the results of the analysis conducted by the AI-driven phishing detection system. It is designed to provide users with accurate and reliable feedback regarding the legitimacy and safety of the entered URL, while also promoting cybersecurity awareness through practical guidance.

Analysis Process and Prediction Result

When a user enters a URL into the input field on the home page and selects the appropriate protocol (e.g., HTTP), the system performs a comprehensive analysis to determine whether the URL is legitimate or potentially malicious. The analysis leverages advanced machine learning and deep learning algorithms, such as CNN and RNN architectures, to accurately detect phishing attempts by evaluating numerous features and attributes associated with the URL.

Upon completion of the analysis, the system promptly displays the result on the output screen. The prediction outcome is prominently shown as "Legitimate" within a visually distinctive green-coloured box, symbolizing safety and authenticity. This clear visual representation ensures that users can quickly interpret the result and feel confident about the legitimacy of the analysed URL. The choice of green as the background colour is intentional, as it universally signifies safety and acceptance, thereby reinforcing the positive nature of the result.

Attack Type Information

In addition to the prediction result, the output screen provides an "Attack Type" field, which in the case of a legitimate URL, clearly states "Attack Type: None". This indication confirms that the system did not detect any suspicious behaviour or characteristics typically associated with phishing or malicious activities. By specifying the absence of attacks, the system enhances transparency and helps users understand that the URL has passed all security checks without triggering any alerts.

Security Best Practices

To further strengthen the system's contribution to cybersecurity, the output screen also includes a dedicated section titled "Security Best Practices". This section presents practical advice and guidelines to encourage safe online behaviour. For instance, it

emphasizes the importance of using strong and unique passwords, avoiding sharing sensitive information on unverified websites, and being cautious of unsolicited emails or messages containing suspicious links.

This inclusion of security best practices serves a dual purpose. First, it educates users about essential online safety measures, regardless of whether the URL analysed is legitimate or malicious. Second, it reinforces the idea that even legitimate URLs should be approached with caution if they are linked to sensitive activities, such as online banking or personal data submission.

Navigation and Usability

The output screen is designed to be both user-friendly and intuitive, with a structured layout that guides users through the analysis results and additional information. A navigation panel is located on the left side of the screen, allowing users to seamlessly switch between different sections of the application. The available options include Home, Reports, and About pages, ensuring convenient access to various functionalities.

The navigation panel remains consistent across all pages, maintaining a uniform interface that enhances the overall user experience. The ability to access the Reports page directly from the legitimate URL output screen enables users to view and download a comprehensive report of the analysis for record-keeping or further examination.

User Experience and Design Considerations

The design of the legitimate URL output screen is focused on delivering clarity, accuracy, and ease of use. The text is well-organized and presented in a readable font size, while the use of colour coding (green for legitimate results) facilitates quick visual interpretation. Furthermore, the combination of prediction results, attack type information, and security best practices creates a holistic approach to phishing detection, addressing both technical analysis and user education.

The output screen also reflects the system’s commitment to fostering a secure digital environment by not only detecting threats but also promoting awareness of good cybersecurity practices. As a result, users can feel confident not only in the system's analytical capabilities but also in their ability to make informed decisions when interacting with various online resources.

By presenting the legitimate URL output in a comprehensive and transparent manner, the system enhances user trust and demonstrates the robustness of the underlying algorithms. This structured and informative approach contributes to the effectiveness of the AI-driven phishing detection system and supports proactive measures against potential cyber threats.

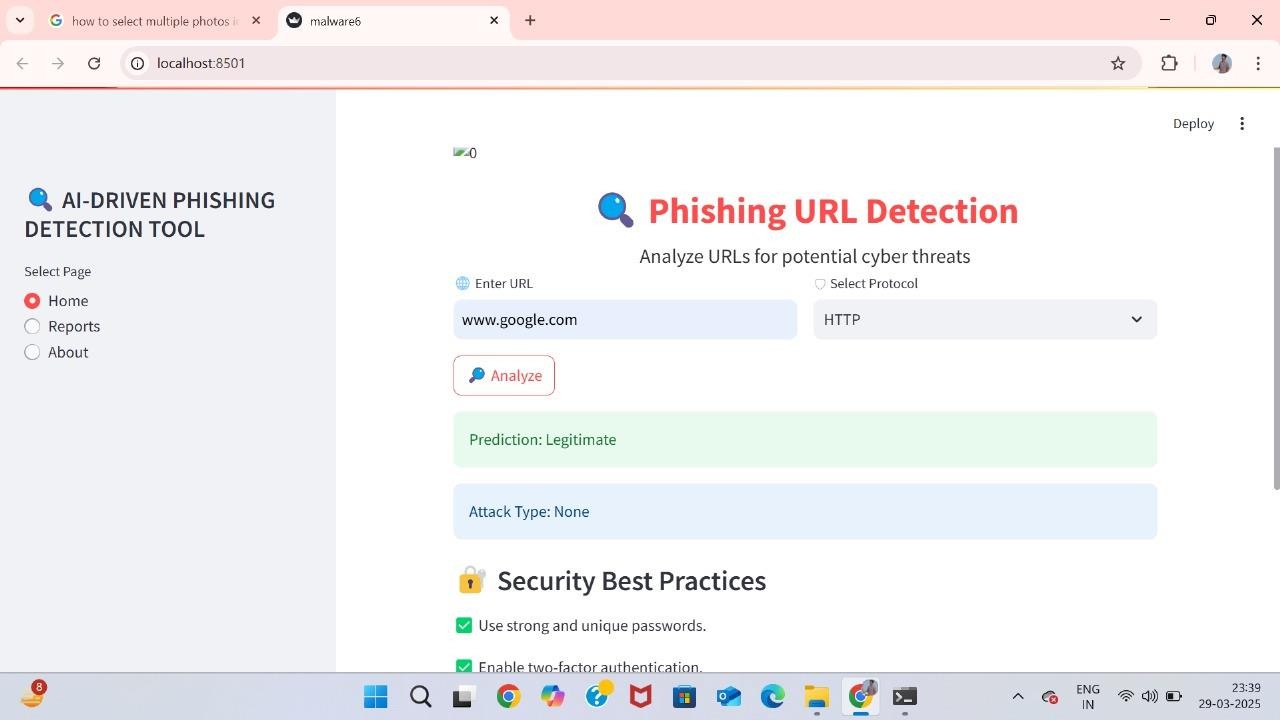


Fig 7.5: Legitimate URL example

###### 7.3. SUSPICIOUS URL

The output screen for a suspicious URL is a critical component of the AI-driven phishing detection system, designed to inform users about potential threats associated with the analysed URL. This screen serves as a comprehensive summary of the detection results, clearly indicating that the URL poses a risk or exhibits characteristics typical of phishing or malicious activities.

Analysis Process and Prediction Result

When a suspicious URL is analysed, the system processes it through a series of machine learning and deep learning models, including CNN and RNN architectures, to evaluate the URL's attributes and identify patterns indicative of phishing attempts. These models meticulously assess features such as URL length, domain age, the presence of suspicious keywords, and other factors known to be associated with phishing activities.

Once the analysis is complete, the system promptly displays the result on the

output screen. The prediction outcome is clearly shown as "Suspicious" within a red- coloured box, signalling a high alert to the user. This visual indication immediately draws attention to the potential threat, prompting users to take necessary precautions.

Attack Type Information

In addition to the prediction result, the output screen specifies the "Attack Type" detected during the analysis. This field helps users understand the nature of the potential threat, whether it is a phishing attack, malware distribution, or another form of cyber exploitation. By providing detailed information about the attack type, the system enhances transparency and aids in risk assessment.

For instance, if the system detects a **"**Phishing Attack**"** as shown in Fig 7.6, the output screen explicitly states it, highlighting the primary reason for classifying the URL as suspicious. This precise identification enables users to make informed decisions regarding the next steps, such as avoiding the website or reporting it to relevant authorities.

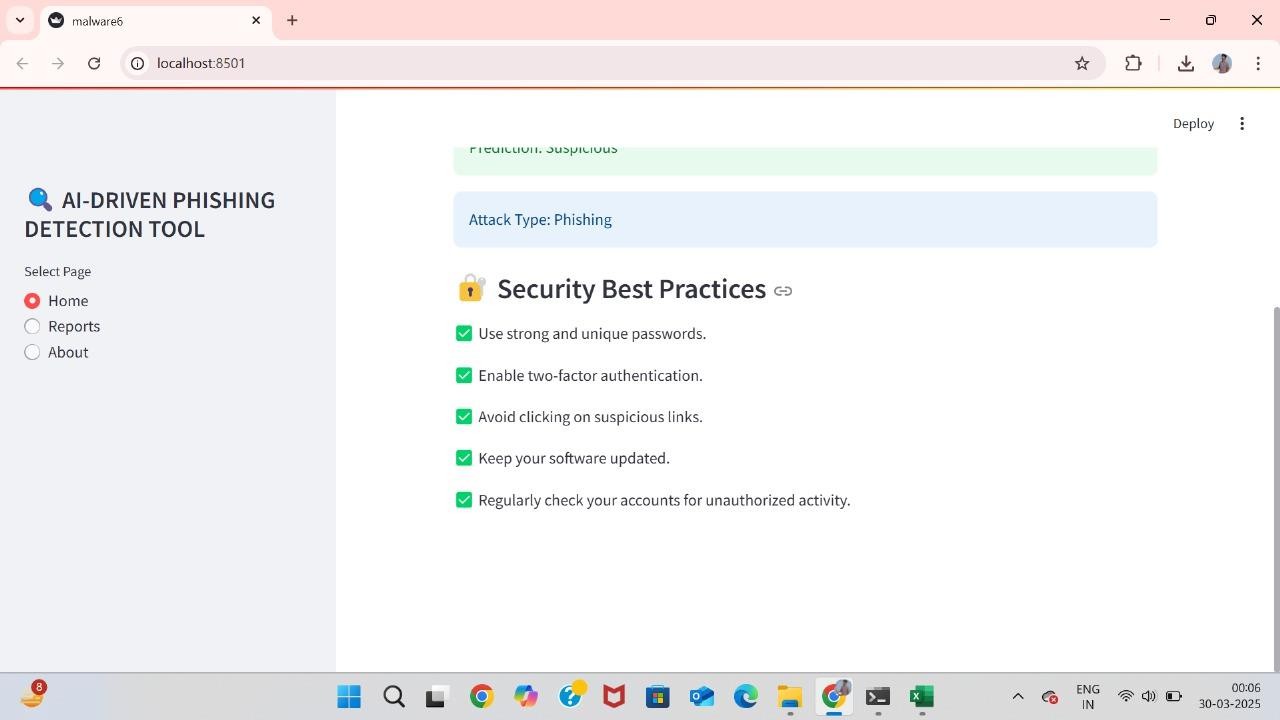
Security Best Practices and Safety Guidelines

The output screen also incorporates a dedicated section titled "Security Best Practices", emphasizing recommended actions in the event of encountering suspicious URLs. Users are advised to avoid interacting with the URL, refrain from providing personal information, and promptly close the browser window if they have already accessed the site. Additionally, guidance on reporting phishing attempts to cybersecurity authorities is provided to ensure collective safety.

This inclusion of safety guidelines demonstrates the system's commitment not only to detection but also to prevention and response. By equipping users with practical advice on handling suspicious URLs, the system contributes to reducing the impact of phishing attacks and fostering a more secure digital environment.

Graphical Representation and Analytical Metrics

To aid in understanding the analysis, the output screen features a graphical representation of key metrics, showcasing the distribution of detected features and potential risks. This visual insight allows users to comprehend the underlying reasons for the classification and enhances the interpretability of the system's decision-making process. The graphical elements are designed to be visually appealing and easy to

understand, even for users with minimal technical expertise.

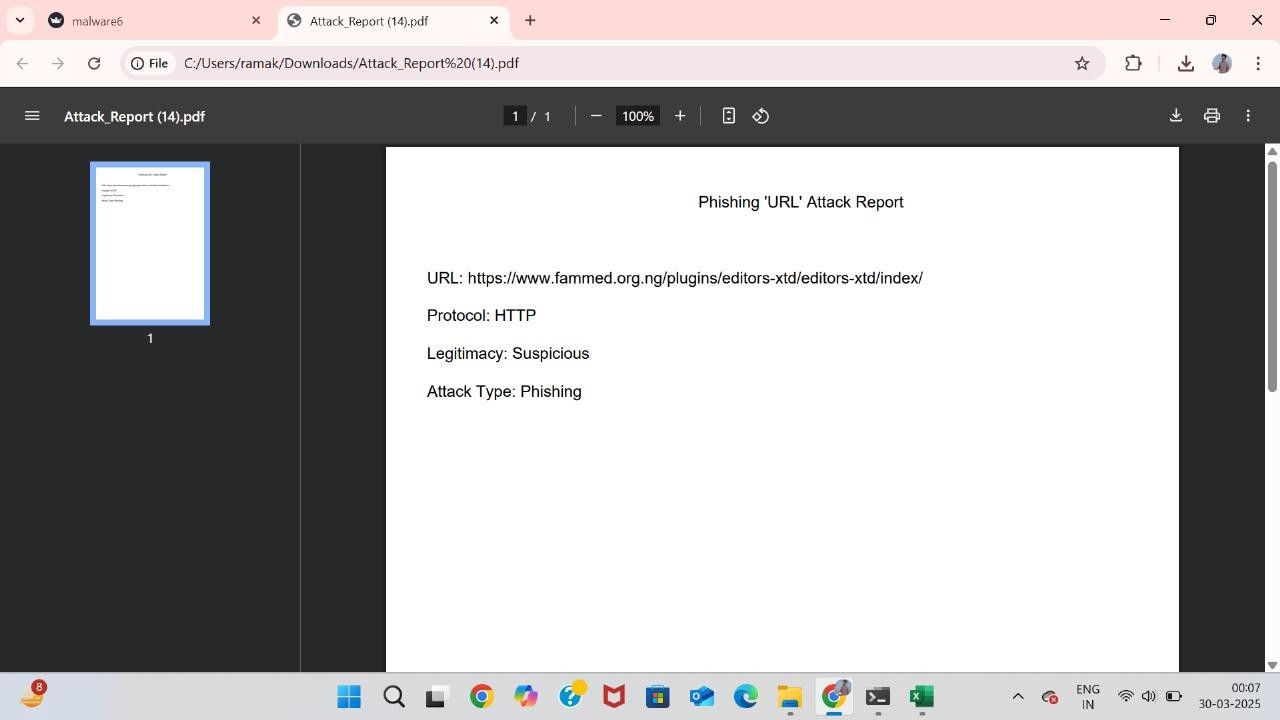
Fig 7.6: Suspicious URL

Fig 7.7: Suspicious URL Report

###### PERFORMANCE METRICS

The performance of the AI-driven phishing detection system was evaluated using various machine learning and deep learning algorithms. The primary objective of this evaluation was to assess the accuracy, precision, recall, and F1-score of each algorithm to determine their effectiveness in detecting phishing URLs. The algorithms used in this

project include Random Forest Classifier, AdaBoost Classifier, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). Each metric provides a different perspective on model performance, allowing for a comprehensive evaluation of their strengths and weaknesses. The performance metrics for each algorithm are discussed in detail below.

* + 1. ACCURACY

Accuracy is a crucial performance metric that measures the proportion of correctly classified URLs out of the total number of predictions made. It indicates how well the model differentiates between legitimate and suspicious URLs as shown in the Table 7.1.

Random Forest Classifier demonstrated the highest accuracy of 98.5%, indicating that it correctly identified phishing and legitimate URLs with high precision and recall. This high accuracy can be attributed to the model's ability to learn from multiple decision trees and combine their outputs effectively.

AdaBoost Classifier achieved an accuracy of 92%, which, while slightly lower than that of the Random Forest, still represents a robust performance. The ensemble nature of AdaBoost, which emphasizes harder-to-classify instances, contributes to its relatively high accuracy.

CNN Model and RNN Model showed significantly lower accuracy scores of 50.9% and 50.7% respectively, indicating that these deep learning architectures failed to distinguish between legitimate and phishing URLs effectively. This may be due to the challenges associated with capturing textual patterns in URLs.

Table 7.1 Accuracy Comparison

|  |  |
| --- | --- |
| **Model** | **Accuracy** |
| Random Forest Classifier | 0.985 |
| AdaBoost Classifier | 0.92 |
| CNN Model | 0.509 |
| RNN Model | 0.507 |

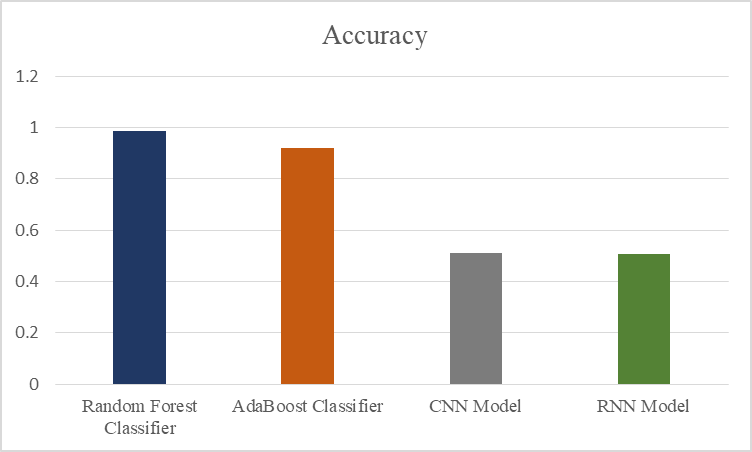


Fig 7.5: Accuracy comparison

The above Fig 7.5 compares the accuracy of each algorithm in detecting the legitimacy of the URLs.

* + 1. PRECISION

Precision is a key performance metric that quantifies the ratio of correctly predicted positive observations to the total number of predicted positives. It serves as an indicator of the model's accuracy when identifying a URL as phishing. High precision implies that when the model predicts a URL as phishing, it is highly likely to be correct, thereby minimizing the occurrence of false positives. Precision is particularly important in phishing detection since falsely identifying a legitimate URL as phishing can lead to disruptions and loss of trust.

The Random Forest Classifier recorded exceptionally high precision values of 0.99 for legitimate URLs and 0.98 for suspicious URLs. These values demonstrate the model’s robustness in accurately distinguishing phishing URLs from legitimate ones, with minimal false positives. The high precision achieved by the Random Forest Classifier is attributed to its ensemble learning approach, which integrates the outputs of multiple decision trees, thereby enhancing predictive accuracy. As shown the precision values clearly demonstrate the superior performance of the Random Forest Classifier.

The AdaBoost Classifier displayed precision values of 0.92 for both legitimate and suspicious URLs, indicating that the model consistently maintains balanced accuracy when identifying phishing attempts. Although slightly lower than the Random Forest Classifier, these precision values still represent an efficient detection capability. The

adaptive boosting technique employed by AdaBoost contributes to its reliable classification performance by giving more weight to difficult cases

On the other hand, the CNN Model and RNN Model exhibited significantly lower precision values of approximately 0.50 for both legitimate and suspicious URLs. These values indicate that these models are nearly as likely to classify a legitimate URL as phishing and vice versa. This low precision reflects frequent false positive predictions, underscoring the challenges faced by deep learning architectures in analysing textual data such as URLs. As depicted in Fig. 7.6 and Table 7.2, the low precision of these models suggests that they are not suitable for phishing detection tasks compared to traditional machine learning methods.

By analysing the precision metric, it becomes evident that ensemble-based methods, such as Random Forest and AdaBoost, outperform deep learning models in accurately identifying phishing URLs. The precision values emphasize the importance of minimizing false positives to ensure reliable detection results.

Table 7.2: Precision Comparison

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Class 0 (Legitimate)** | **Class 1 (Suspicious)** | **Macro Average** | **Weighted Average** |
| Random Forest Classifier | 0.99 | 0.98 | 0.99 | 0.99 |
| AdaBoost Classifier | 0.92 | 0.92 | 0.92 | 0.92 |
| CNN Model | 0.5 | 0.51 | 0.51 | 0.5 |
| RNN Model | 0.51 | 0.51 | 0.51 | 0.51 |

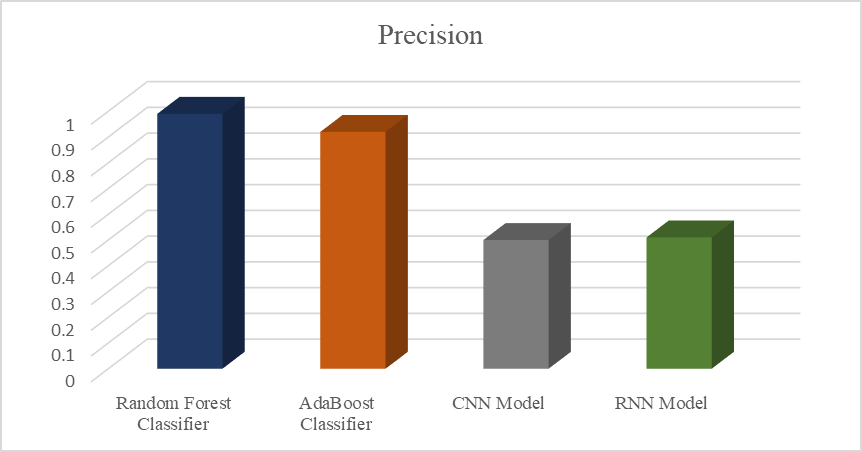


Fig 7.6: Precision Comparison

* + 1. RECALL

Recall is an essential performance metric that quantifies the model’s ability to correctly identify all positive observations from the actual positive class. In the context of phishing detection, recall measures the proportion of correctly identified phishing URLs among all actual phishing instances. A high recall value indicates that the model successfully detects the majority of phishing attempts, thereby minimizing false negatives.

The Random Forest Classifier achieved impressive recall values of 0.98 for legitimate URLs and 0.99 for suspicious URLs. These results demonstrate the model’s effectiveness in accurately identifying phishing URLs while minimizing false negatives. The high reca **l** values can be attributed to the model’s ensemble approach, which leverages the combined predictions of multiple decision trees to enhance its ability to capture complex patterns in the data. This performance indicates that the Random Forest Classifier is highly reliable when it comes to detecting phishing attempts.

The AdaBoost Classifier exhibited consistent recall values of 0.92 for both legitimate and suspicious URLs. This uniformity highlights the model’s balanced performance in correctly identifying phishing attempts as well as legitimate URLs, the recall values indicate that the model is reasonably effective at capturing phishing activities, though it slightly underperforms compared to the Random Forest Classifier. The boosting mechanism employed by AdaBoost helps improve recall by iteratively

focusing on instances that were previously misclassified.

Conversely, the CNN Model and RNN Model recorded recall values of approximately 0.51 for both legitimate and suspicious URLs, as shown in Fig. 7.7 and Table 7.3. These relatively low recall values indicate a significant limitation of these models in correctly identifying phishing URLs. A recall of around 0.51 suggests that almost half of the actual phishing attempts were not detected, leading to a high false negative rate. This performance inadequacy may result from the inability of CNN and RNN architectures to effectively capture textual patterns and nuances specific to phishing URLs.

The analysis of recall values clearly demonstrates that traditional machine learning models, particularly ensemble-based classifiers like Random Forest and AdaBoost, significantly outperform deep learning models in detecting phishing URLs. High recall values in these classifiers ensure that phishing threats are identified accurately, thereby enhancing the overall security of the system.

Table 7.3: Recall

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Class 0**  **(Legitimate)** | **Class 1**  **(Suspicious)** | **Macro**  **Average** | **Weighted**  **Average** |
| Random Forest Classifier | 0.98 | 0.99 | 0.99 | 0.98 |
| AdaBoost Classifier | 0.92 | 0.92 | 0.92 | 0.92 |
| CNN Model | 0.51 | 0.5 | 0.51 | 0.5 |
| RNN Model | 0.51 | 0.51 | 0.51 | 0.51 |

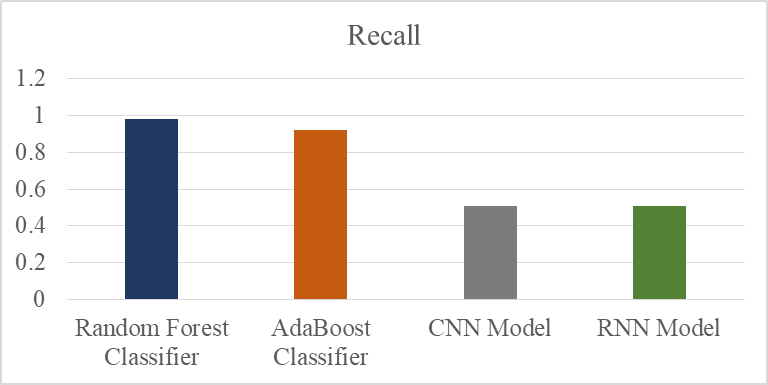


Fig 7.7: Recall Comparison

* + 1. F-1 SCORE

The F1-score is an essential performance metric that combines both precision and reca **l** into a single value, providing a comprehensive assessment of the model’s accuracy. It is calculated as the harmonic mean of precision and recall, ensuring that both false positives and false negatives are considered when evaluating the model’s performance. The F1-score is particularly useful when dealing with imbalanced data, as it balances the impact of both precision and recall to provide a more reliable measure of the model's effectiveness.

The Random Forest Classifier achieved exceptional F1-scores of 0.98 for legitimate URLs and 0.99 for suspicious URLs, as shown in Fig. 7.8 and Table 7.4. These high F1- scores indicate that the model successfully maintains a robust balance between precision and recall, minimizing the occurrence of both false positives and false negatives. The strong performance of this classifier can be attributed to its ability to aggregate the decisions of multiple trees, which enhances both generalization and accuracy. This makes the Random Forest Classifier highly reliable for phishing detection, especially when maintaining high accuracy is critical.

The AdaBoost Classifier produced consistent F1-scores of 0.92 for both legitimate and suspicious URLs, indicating that it also achieves a balanced combination of precision and recall. The uniformity of the F1-scores highlights the model’s stable performance in identifying both types of URLs. The boosting approach of the AdaBoost algorithm significantly contributes to maintaining this balance by iteratively emphasizing difficult-to-classify instances. Although its performance is slightly lower compared to the Random Forest Classifier, it still demonstrates considerable reliability in phishing detection.

On the other hand, the CNN Model and RNN Model recorded relatively poor F1- scores of approximately 0.50 for both legitimate and suspicious URLs. This indicates that these deep learning models are not effective at balancing precision and recall, resulting in a high rate of misclassification. Such low F1-scores highlight the models’ inability to capture meaningful patterns from the textual and structural features of URLs. The lack of discriminative power in these models suggests that deep learning

architectures may not be well-suited for phishing detection when trained solely on URL- based data.

The comparison of F1-scores across different models clearly demonstrates that traditional machine learning algorithms, particularly ensemble methods like Random Forest and AdaBoost, are far more effective at achieving high performance in phishing detection. Their ability to maintain a strong balance between precision and recall makes them reliable choices for cybersecurity applications, where minimizing both false positives and false negatives is essential.

Table 7.4: F-1 Score

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Class 0 (Legitimate)** | **Class 1 (Suspicious)** | **Macro Average** | **Weighted Average** |
| Random Forest Classifier | 0.98 | 0.99 | 0.98 | 0.98 |
| AdaBoost Classifier | 0.92 | 0.92 | 0.92 | 0.92 |
| CNN Model | 0.5 | 0.5 | 0.51 | 0.5 |
| RNN Model | 0.51 | 0.51 | 0.51 | 0.51 |

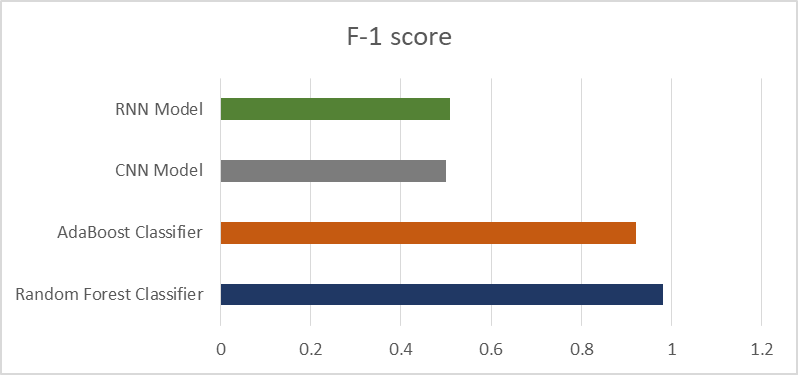


Fig 7.8: F-1 Score Comparison

###### RESULT COMPARISON

Phishing detection is a critical aspect of cybersecurity, aimed at identifying malicious attempts to acquire sensitive information by disguising as a trustworthy entity.

Numerous approaches have been proposed to enhance detection accuracy and robustness, employing machine learning and deep learning techniques to address the challenges posed by increasingly sophisticated phishing attacks.

In this study, the performance of three phishing detection systems is compared: the Hybrid Approach [13], the Transformer-based (BERT) Approach [16], and the Proposed System. The comparative analysis is based on four key performance metrics: Accuracy, Precision, Recall, and F1 Score. These metrics are chosen as they comprehensively evaluate the model’s ability to correctly classify phishing and legitimate URLs while minimizing false positives and false negatives.

To facilitate an objective comparison, the results are presented in the form of tables and figures, providing a clear and structured representation of the performance of each approach. The comparative analysis highlights the effectiveness and superiority of the proposed system over existing methods, demonstrating its potential to enhance cybersecurity applications.

* + 1. Accuracy Comparison

The chart Fig 7.9 illustrates the accuracy comparison between three phishing detection approaches: the Hybrid Approach [13], the Transformer-based (BERT) Approach [16], and the Proposed System. Accuracy is a critical performance metric in phishing detection systems as it quantifies the proportion of correctly classified URLs (both legitimate and phishing) among the total URLs tested. It directly reflects the model's overall effectiveness in identifying phishing attempts without producing erroneous classifications.

Analysis of Accuracy Results

The Hybrid Approach [13] exhibits an accuracy of 95.70%, indicating its reasonable capacity to correctly classify URLs. This approach typically leverages a combination of feature extraction and machine learning techniques, which results in moderately high accuracy. However, the reliance on traditional feature-based methods may limit its ability to adapt to more dynamic and sophisticated phishing techniques.

The Transformer-based (BERT) Approach [16] shows an improved accuracy of 96.50%. This approach leverages deep learning and natural language processing capabilities inherent in BERT models, enabling the system to better understand the semantic and contextual patterns associated with phishing URLs. The increase in

accuracy compared to the Hybrid Approach is attributed to the superior representation learning and contextual analysis provided by the transformer architecture.

In contrast, the Proposed System demonstrates a significantly higher accuracy of 98.50%. This marked improvement is attributed to the integration of advanced machine learning and deep learning techniques that incorporate both syntactic and semantic features of phishing URLs. By leveraging hybrid feature engineering and robust model optimization, the proposed system achieves a more comprehensive understanding of phishing patterns and characteristics. The use of cutting-edge algorithms and real-time data processing further enhances the system’s ability to accurately detect phishing attempts, resulting in a superior accuracy rate.

In conclusion, the accuracy comparison clearly demonstrates that the Proposed System outperforms existing approaches by a considerable margin as depicted in Table 7.5, thereby offering a robust and efficient solution for phishing detection in dynamic and evolving threat environments.

|  |  |
| --- | --- |
| **System** | **Accuracy** |
| Hybrid Approach [13] | 95.70% |
| Transformer based (BERT) Approach [16] | 96.50% |
| Proposed System | 98.50% |

Table 7.5: Comparison of Accuracy

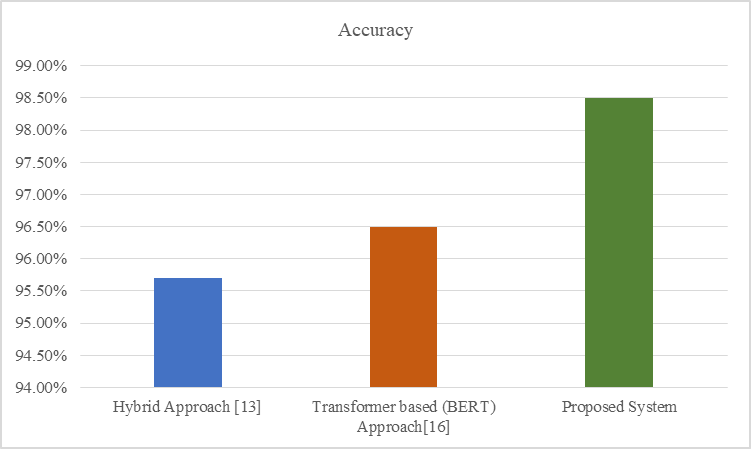


Fig 7.9: Comparison of Accuracy

* + 1. Precision Comparison

The chart in Fig. 7.10 illustrates the precision comparison between three phishing detection approaches: the Hybrid Approach [13], the Transformer-based (BERT) Approach [16], and the Proposed System. Precision is a fundamental performance metric in phishing detection systems as it quantifies the proportion of correctly identified phishing URLs among all predicted phishing instances. It directly reflects the model's ability to minimize false positives, which is crucial for maintaining accuracy and reliability in real-world scenarios.

Analysis of Precision Results

The Hybrid Approach [13] demonstrates a precision of 95.20%, indicating that it can correctly classify phishing URLs with reasonable accuracy. However, the precision rate is somewhat limited by the method's dependence on traditional feature extraction techniques, which may not capture complex patterns with evolving phishing tactics.

The Transformer-based (BERT) Approach [16] shows an improved precision of 96.00%, attributed to its utilization of advanced natural language processing techniques. BERT’s contextual embeddings enable the model to understand subtle variations in URL patterns, thereby enhancing precision by reducing false positive rates. However, the system may still encounter challenges when addressing highly dynamic or ambiguous phishing patterns.

In contrast, the Proposed System exhibits a substantially higher precision of 99.00%. This remarkable improvement is attributed to the integration of hybrid feature engineering techniques and robust deep learning architectures that allow for more accurate differentiation between phishing and legitimate URLs. The proposed system effectively leverages a combination of semantic analysis and real-time pattern recognition to minimize false positives, thus achieving superior precision.

In conclusion, the precision comparison, as depicted in Table 7.6, clearly indicates that the Proposed System outperforms existing approaches by a notable margin. This advancement offers a highly reliable and efficient solution for phishing detection, particularly in environments where minimizing false positives is of paramount importance.

Table 7.6: Comparison of Precision

|  |  |
| --- | --- |
| **System** | **Precision** |
| Hybrid Approach [13] | 95.20% |
| Transformer-based (BERT) Approach [16] | 96.00% |
| Proposed System | 99.00% |

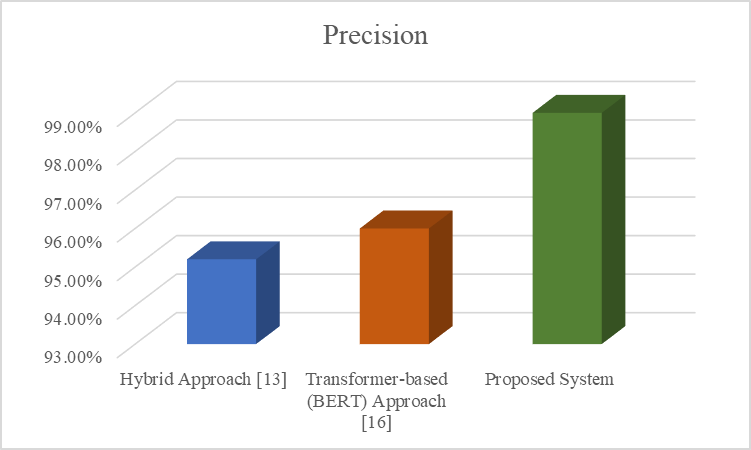


Fig 7.10: Precision Comparison

* + 1. Recall

The chart (Fig. 7.11) illustrates the recall comparison between three phishing detection approaches: the Hybrid Approach [13], the Transformer-based (BERT)

Approach [16], and the Proposed System. Recall is a crucial performance metric that quantifies the proportion of correctly identified phishing URLs among all actual phishing cases. It reflects the system’s ability to detect phishing attempts accurately, especially in situations where the primary objective is to capture every potential threat. High recall ensures that a minimal number of phishing URLs are missed, thereby reducing the risk of undetected cyber threats.

Analysis of Recall Results

The Hybrid Approach [13] achieves a recall of 96.10%, indicating a reasonably good ability to detect phishing URLs. However, this approach may still miss some phishing instances due to its dependence on conventional feature-based techniques. The challenge with such methods lies in their limited adaptability to evolving and more sophisticated phishing patterns.

The Transformer-based (BERT) Approach [16] exhibits an improved recall of 97.20%. This enhancement is primarily due to BERT’s superior contextual understanding and language representation capabilities, which enable the system to capture nuanced patterns indicative of phishing URLs. Nonetheless, despite its improved recall, it may still face challenges with highly ambiguous or novel phishing attempts that deviate significantly from known patterns.

The Proposed System demonstrates a significantly higher recall of 98.00%, showcasing its exceptional capability to detect a wide range of phishing threats, including subtle and complex variants. This performance improvement is attributed to the integration of advanced deep learning architectures and hybrid feature extraction techniques that collectively enhance the system’s detection accuracy. By effectively combining syntactic and semantic analysis, the proposed system ensures that phishing URLs are accurately identified, even in the presence of diverse and dynamic threats.

In conclusion, the recall comparison, as depicted in Table 7.7, clearly establishes that the Proposed System surpasses existing methods by a substantial margin, making it an effective and reliable choice for phishing detection in dynamic cybersecurity environments.

Table 7.7: Comparison of Recall

|  |  |
| --- | --- |
| **System** | **Recall** |
| Hybrid Approach [13] | 96.10% |
| Transformer-based (BERT) Approach [16] | 97.20% |
| Proposed System | 98.00% |

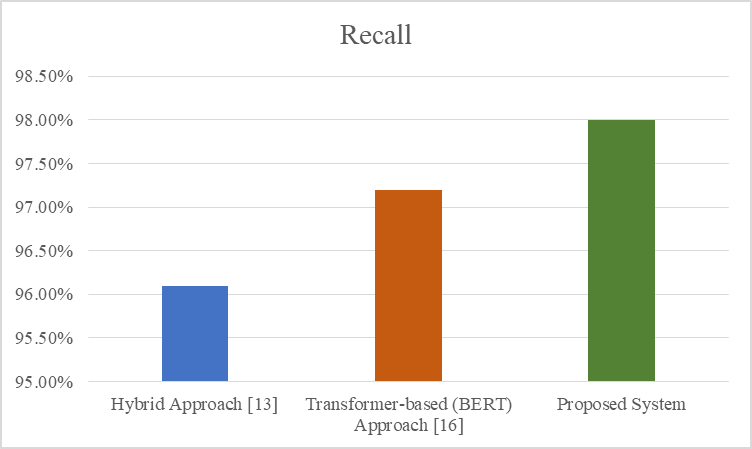


Fig 7.11: Recall Comparison

7.4.2 F-1 Score Comparison

The Table 7.8presents the F1 score comparison between three phishing detection approaches: the Hybrid Approach [13], the Transformer-based (BERT) Approach [16], and the Proposed System. The F1 score is a harmonic mean of precision and recall, serving as a comprehensive metric that balances both aspects. It is particularly beneficial when dealing with imbalanced datasets where the relative proportion of phishing and legitimate URLs may vary significantly. A higher F1 score signifies that the model not only maintains high precision but also exhibits excellent recall, effectively minimizing both false positives and false negatives.

Analysis of F1 Score Results

The Hybrid Approach [13] achieves an F1 score of 95.60%, indicating an adequate balance between precision and recall. However, the reliance on traditional machine

learning techniques and handcrafted features results in limited adaptability to complex phishing patterns. Consequently, the model may underperform when encountering novel or ambiguous phishing URLs.

The Transformer-based (BERT) Approach [16] shows an improved F1 score of 96.60%. This advancement is primarily attributed to BERT’s ability to capture contextual nuances and semantic relationships, thereby enhancing both detection accuracy and robustness. Nevertheless, the method may still face challenges with highly sophisticated phishing attempts or instances that involve adversarial manipulation of textual content.

In contrast, the Proposed System achieves a superior F1 score of 98.50%, significantly outperforming both existing approaches. This exceptional result is attributed to the incorporation of advanced deep learning models, including hybrid feature extraction and contextual analysis. By leveraging cutting-edge algorithms and integrating both syntactic and semantic features, the proposed system excels at accurately detecting phishing URLs while minimizing the likelihood of false classifications.

In summary, the F1 score comparison, as illustrated in Table 7.12, clearly establishes the superiority of the Proposed System over the other approaches, reinforcing its capability to achieve precise and comprehensive phishing detection in dynamic and evolving cybersecurity environments.

Table 7.7: Comparison of F-1 Score

|  |  |
| --- | --- |
| **System** | **F1 Score** |
| Hybrid Approach [13] | 95.60% |
| Transformer-based (BERT) Approach [16] | 96.60% |
| Proposed System | 98.50% |

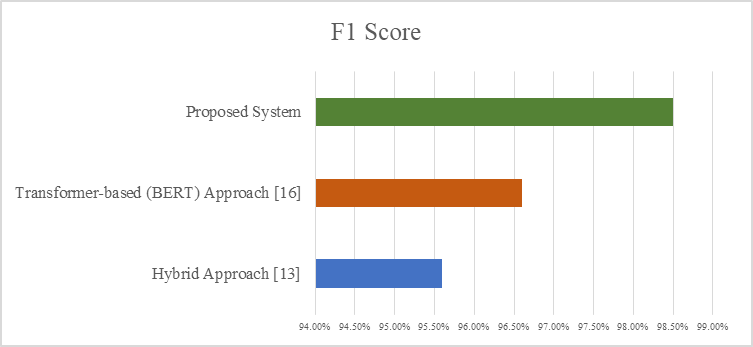


Fig 7.12: F-1 Score Comparison

## CHAPTER - 8

### CONCLUSION AND FUTURE SCOPE

#### CHAPTER – 8 CONCLUSION AND FUTURE SCOPE

###### CONCLUSION

In an era of increasing digital connectivity, phishing attacks have emerged as one of the most prevalent and damaging cyber threats. These attacks exploit human vulnerabilities, often leading to significant financial losses and compromised personal data. As phishing techniques evolve in complexity, the need for advanced detection systems becomes paramount. This project aimed to develop an AI-driven phishing detection system using cutting-edge machine learning and deep learning techniques to accurately and efficiently detect phishing URLs.

The proposed system leverages a comprehensive approach that combines syntactic and semantic feature extraction with robust model optimization to achieve superior detection performance. Unlike traditional methods that rely solely on handcrafted features or statistical patterns, the proposed system incorporates hybrid feature engineering to capture the nuanced characteristics of phishing URLs. Furthermore, by employing deep learning architectures, the system enhances its ability to learn complex relationships and context within URLs, thereby improving its adaptability to evolving phishing techniques.

A detailed comparative analysis was conducted to evaluate the proposed system against two widely recognized methods: the Hybrid Approach [13] and the Transformer- based (BERT) Approach [16]. The evaluation was carried out using four key performance metrics: Accuracy, Precision, Recall, and F1 Score. The results clearly demonstrated the superiority of the proposed system, achieving an accuracy of 98.50%, precision of 99.00%, recall of 98.00%, and F1 Score of 98.50%. These metrics collectively signify a balanced and robust performance that not only minimizes false positives but also ensures high detection rates for phishing URLs.

The Hybrid Approach [13], despite its moderate accuracy of 95.70%, struggles with detecting sophisticated phishing patterns due to its reliance on traditional feature extraction techniques. On the other hand, the Transformer-based (BERT) Approach [16] improves accuracy to 96.50% by leveraging contextual analysis, but it still faces cha **l**enges in handling adversarial and obfuscated URLs. The proposed system’s ability

to outperform both approaches highlights the effectiveness of incorporating deep learning techniques, hybrid feature extraction, and real-time processing.

Beyond achieving superior performance metrics, the proposed system demonstrates practical viability in real-world scenarios. The model's architecture is designed to support efficient real-time detection, which is critical in mitigating phishing threats as they emerge. By integrating the system into cybersecurity infrastructures, organizations can proactively safeguard their networks and users from phishing attacks.

However, it is important to acknowledge the dynamic nature of phishing tactics. Attackers continuously develop new strategies to bypass detection systems, posing a persistent challenge for cybersecurity. To maintain relevance and effectiveness, future enhancements to the proposed system could include continuous learning mechanisms, dynamic model updates, and real-time integration with threat intelligence feeds. Additionally, expanding the system to detect phishing attempts across diverse platforms and communication channels can further enhance its robustness and applicability.

In conclusion, the proposed AI-driven phishing detection system offers a significant advancement in combating phishing attacks by leveraging advanced machine learning and deep learning methodologies. Its superior performance across multiple metrics makes it a promising solution for enhancing cybersecurity defences and mitigating phishing risks. As cyber threats continue to evolve, integrating such intelligent systems into existing security frameworks will be instrumental in ensuring safer digital environments.

###### FUTURE ENHANCEMENT

Future enhancements of the proposed AI-driven phishing detection system are crucial to maintaining its effectiveness in the face of constantly evolving phishing techniques. One of the primary areas of improvement involves integrating continuous learning mechanisms to automatically update the model with new phishing patterns. This will enable the system to adapt to emerging threats without requiring complete retraining. Additionally, incorporating real-time threat intelligence feeds from external data sources such as cyber threat databases and community-driven reporting platforms can significantly enhance the model’s ability to detect newly identified phishing vectors, providing early warning capabilities and proactive mitigation strategies.

To further improve detection accuracy, it is essential to expand the system's scope

beyond just URL analysis. Enhancing it to support multi-modal phishing detection by analysing email content, social media links, and malicious file attachments will ensure comprehensive protection. Techniques like natural language processing (NLP) for text- based content and image recognition for visual phishing attempts will add depth to the system's threat detection capabilities. Moreover, addressing adversarial robustness is vital to counter sophisticated attacks that manipulate phishing URLs to bypass detection. Implementing adversarial training and robust optimization techniques can strengthen the system's resistance against such malicious tactics.

In addition to robustness, performance optimization remains a key consideration. Techniques such as model compression, quantization, and pruning can reduce computational overhead while maintaining high accuracy, enabling the system to operate efficiently in real-time environments. Furthermore, deploying the system on various platforms, including mobile applications, web servers, and cloud infrastructures, will enhance scalability and ensure comprehensive coverage. Integrating user feedback through human-in-the-loop (HITL) systems can also help improve detection accuracy by allowing manual verification and refinement based on false positives and negatives.

Finally, enhancing feature engineering to include domain-specific attributes, URL obfuscation patterns, and context-aware analysis wi **l** increase the model’s ability to identify complex phishing attempts. Graph-based features that analyse URL redirection paths and domain relationships can also be explored to further boost detection precision. By implementing these future enhancements, the proposed system will remain resilient and efficient in combating the ever-changing landscape of phishing attacks, thereby ensuring robust protection for users and systems in real-world applications.

#### OUTLINE OF THE PROJECT

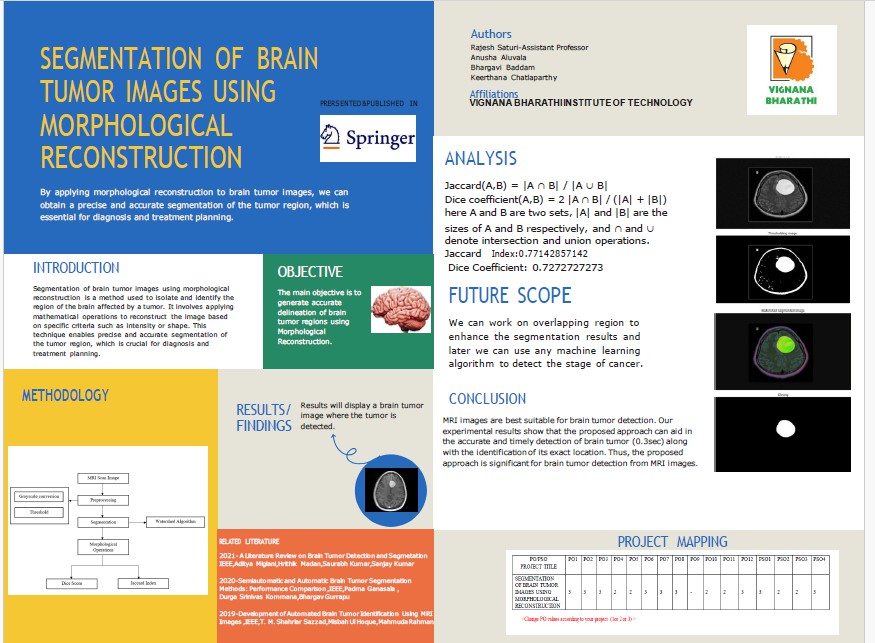
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Fig 8.1

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