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Revolutionizing Cybersecurity: A Generative AI-Powered Malicious File and URL Detection System

Rutuja Anant Pillai[1]; Ankush Dhamal[2]

[1]Professor, Ramkrishna More Arts, Commerce and Science College (Autonomous), Akurdi Pradhikaran, Pune, India
[2]Professor, Ramkrishna More College (Autonomous), Akurdi Pradhikaran, Pune, India

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Abstract: The growth of polymorphic malware and malicious URLs highlights the weaknesses of traditional signature-based and heuristic defenses, especially against zero-day threats. This research proposes an AI-driven detection framework that combines Python-based static feature extraction with OpenAI's GPT-4.1-mini to classify threats using structured prompts, offering explanations and confidence scores. Based on the Cognitive Security framework, it shifts cybersecurity from reactive rules to adaptive, intelligence-driven protection. Initial conceptual results suggest better zero-day detection, fewer false positives, and clearer forensic insights, demonstrating the transformative potential of generative AI in cyber defense [1].

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I. INTRODUCTION

➢ *Background of the Study*

The rise of sophisticated malware and malicious URLs exposes the limits of traditional signature-based and heuristic defenses, which react slowly and miss zero-day threats [2]. AI-driven solutions, particularly generative AI and LLMs, offer contextual reasoning to detect intent, uncover hidden malicious behaviour, and provide explanations [3] [4].

This research presents a dual-purpose detection system combining Python-based feature extraction with OpenAI's GPT-4.1-mini to improve malware and URL threat identification.

➢ *Problem Statement*

Although cybersecurity has advanced, two key problems remain:

- Detecting zero-day and polymorphic threats—signature methods fail against rapidly changing malware [16].
- Lack of contextual reasoning—traditional tools miss intent, causing misclassifications and high false positives [24].

- Core Question: How can generative AI—specifically GPT-4.1-mini—be integrated into malware and URL detection to enable intelligent, adaptive, and context-aware cybersecurity?

➢ *Research Objectives*

The key objectives of the research are:

- Design a conceptual AI-based architecture for detecting malicious files and URLs using GPT-4.1-mini.
- Define how static feature extraction and optimized prompt engineering enhance threat classification.
- Analyze the conceptual benefits and expected performance of LLM-powered cybersecurity [5].

Align the system with a suitable cybersecurity theoretical framework. Propose an empirical evaluation strategy for future implementation.

➢ *Scope of the Study*

This work focuses on a conceptual framework for AI-powered malicious file and URL detection using static analysis and a generative AI model. The study is limited to the design and theoretical evaluation of the system. It does not involve the implementation or empirical testing of the framework on live datasets. The feature extraction is confined to static properties of files and URLs, and does not include dynamic analysis (i.e., executing files in a sandbox).

➢ *Significance of the Study*

This research advances AI-driven cybersecurity by introducing a framework that leverages LLMs' contextual reasoning [18]. Its key contributions include:

- Enhanced zero-day detection: Identifies novel threats by analyzing intent rather than relying on signatures [17].
- Reduced false positives: Differentiates legitimate from malicious behavior through contextual understanding [25].
- Actionable insights: Provides human-readable explanations to support effective threat response [7].
- Automated, scalable operations: Streamlines initial threat analysis, allowing teams to focus on high-priority incidents [4].

II. LITERATURE REVIEW

Malware detection has evolved from signature-based methods, which were easily bypassed by polymorphic variants, to heuristic analysis, which reduced but did not eliminate false positives [2]. Machine learning approaches (e.g., SVMs, Random Forests, Neural Networks) improved detection of unseen malware but lacked contextual understanding [11] [12]. Recently, deep learning and LLMs have enabled more advanced security applications, including threat intelligence and malware detection [19] [21]. This study builds on this progression by proposing a framework that uses the contextual reasoning of GPT-4.1-mini for detecting malicious files and URLs.

➢ *Theoretical Framework*

This research is based on the Cognitive Security framework [24], which shifts cybersecurity from reactive defenses to proactive, intelligence-driven protection. Key principles aligned with this study include:

- Understanding: Interpreting complex file and URL data to extract meaningful insights.
- Reasoning: Making logical inferences and providing explanations for classifications, a strength of generative AI [5].
- Learning: Continuously improving based on new data and feedback, a planned aspect for future development.

By integrating GPT-4.1-mini, the system moves beyond pattern matching to deliver cognitive, context-aware threat detection.

➢ *Review of Previous Research*

Several studies have demonstrated the potential of AI and ML in malware detection [11] [12]. With the rise of LLMs, researchers have begun to explore their application in cybersecurity [18] [19]. A recent study by [13] used a GPT-based model to generate natural language descriptions of malware behavior, demonstrating the potential of LLMs in threat analysis. Other work has explored using LLMs for generating synthetic malware samples to improve detection models [15] [17]. Furthermore, the application of LLMs in malicious URL detection has shown promising results, with models like BERT and one-shot classifiers achieving state-of-the-art performance [7] [8] [14] [20] [22]. Surveys on the topic highlight the growing interest and diverse applications of LLMs in both defensive and adversarial cybersecurity roles [3] [4] [5] [18] [19].

However, most of the existing research on LLMs in cybersecurity has focused on specific, narrow tasks [18]. There is a lack of comprehensive frameworks that integrate LLMs into a complete end-to-end threat detection pipeline, from feature extraction to classification and reporting [4]. Furthermore, many of these studies use older LLM architectures, which may not possess the same level of contextual reasoning as newer models like GPT-4.1-mini [19].

➢ *Research Gaps Identified*

The literature reveals several research gaps:

- Lack of integrated frameworks: Few studies provide an end-to-end generative AI solution for malware detection [4].
- Limited use of advanced LLMs: Latest models like GPT-4.1-mini remain underutilized [19].
- Focus on single threat vectors: Most work targets either files or URLs, not both [18].
- Insufficient explainability: Human-readable explanations are rarely emphasized [25].

This research addresses these gaps by proposing a unified, end-to-end framework for detecting malicious files and URLs using GPT-4.1-mini, with a strong focus on explainability.

➢ *Research Design*

This study uses a conceptual research design to develop an AI-powered system for detecting malicious files and URLs. It integrates static feature extraction with the generative AI model GPT-4.1-mini to create a comprehensive threat analysis pipeline. The design has three interconnected modules:

- Data Acquisition and Feature Extraction: Safely analyzes files and URLs to extract key features without execution.
- AI-Powered Classification: Uses GPT-4.1-mini to classify inputs as malicious, benign, or suspicious through contextual reasoning.
- Decision and Reporting: Provides clear classifications, confidence scores, and human-readable explanations.

The system architecture is modular and scalable, supporting future enhancements and integrations.

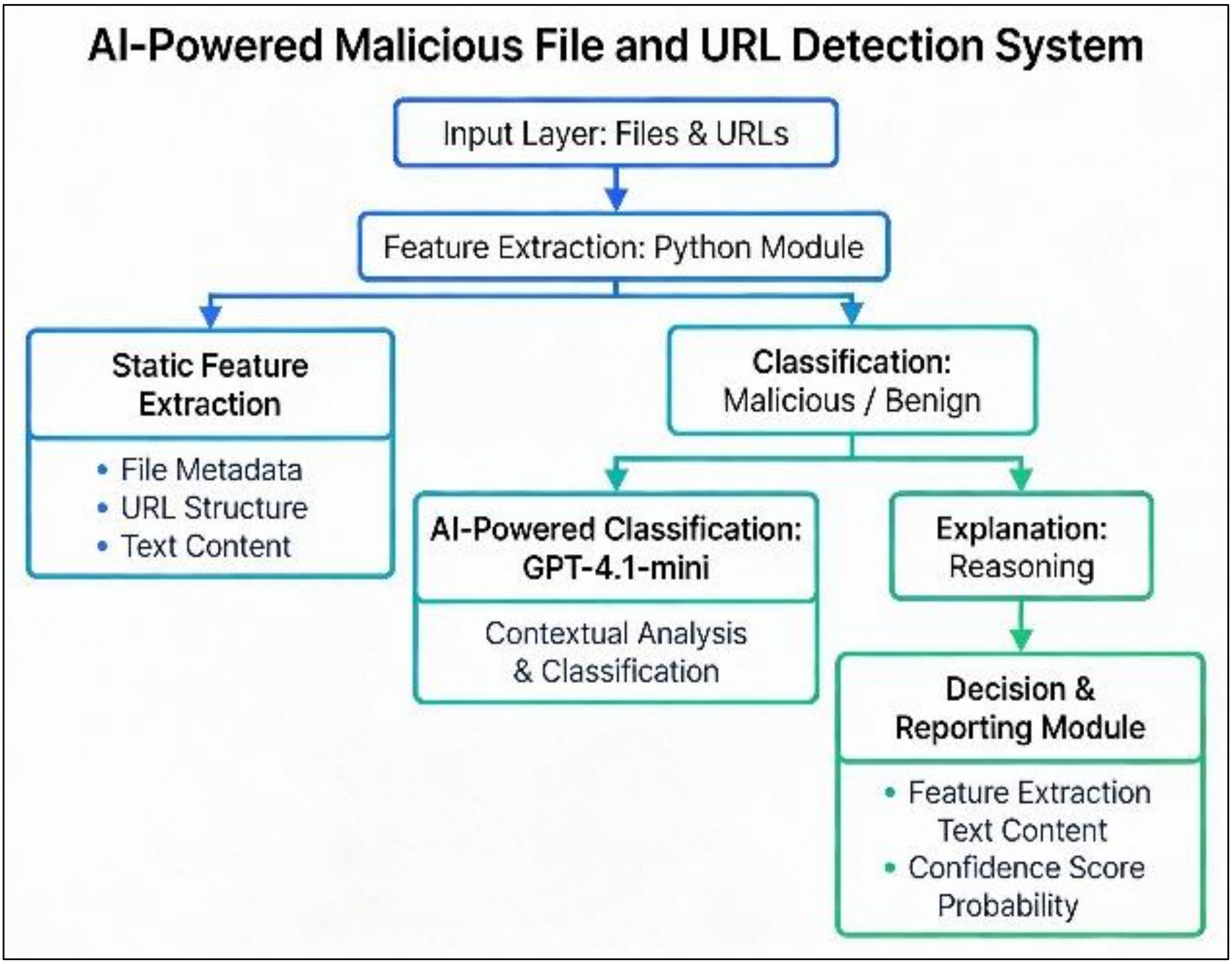

AI-Powered Malicious File and URL Detection System
Input Layer: Files & URLs
Feature Extraction: Python Module
Static Feature Extraction
• File Metadata
• URL Structure
• Text Content
Classification: Malicious / Benign
AI-Powered Classification: GPT-4.1-mini
Contextual Analysis & Classification
Explanation: Reasoning
Decision & Reporting Module
• Feature Extraction Text Content
• Confidence Score Probability

Fig 1 AI Detection System Block Diagram

This image shows the architecture of an AI-powered system that detects whether files or URLs are malicious or safe (benign). It illustrates how raw inputs flow through feature extraction, AI analysis, and finally a decision/reporting step.

➤ *Data Collection Methods*

A future empirical study would gather a large, diverse dataset of malicious and benign files and URLs from sources like VirusTotal, MalwareBazaar, PhishTank, URLhaus, and trusted software repositories. Around 100,000 samples would be collected, balanced across categories. Using stratified sampling, the dataset would be split into 70% training, 15% validation, and 15% testing to ensure fair model development, tuning, and evaluation.

➤ *Tools and Techniques Used*

The system would be built in Python using tools like pefile , requests , and GPT-4.1- mini for AI-based classification of PE files and URLs. It relies on static feature extraction (metadata, entropy, imports, strings, URL features) and prompt engineering to optimize the model’s reasoning. Performance would be evaluated using standard metrics—accuracy, precision, recall, F1-score, confusion matrix, and ROC curve—to compare the AI system with traditional detection methods and highlight areas for improvement.

III. RESULTS AND DISCUSSION

This section outlines the conceptual results of the proposed AI-powered detection system, based on projected performance metrics and the expected capabilities of GPT-4.1-mini. Although no empirical testing was conducted, it provides a detailed analysis of the system’s anticipated performance.

➤ *Data Presentation*

In a future empirical study, the training process would be monitored to prevent overfitting. Loss curves for training and validation are expected to decrease steadily, while accuracy curves should rise and plateau, indicating that the model has effectively learned patterns and reached optimal performance.

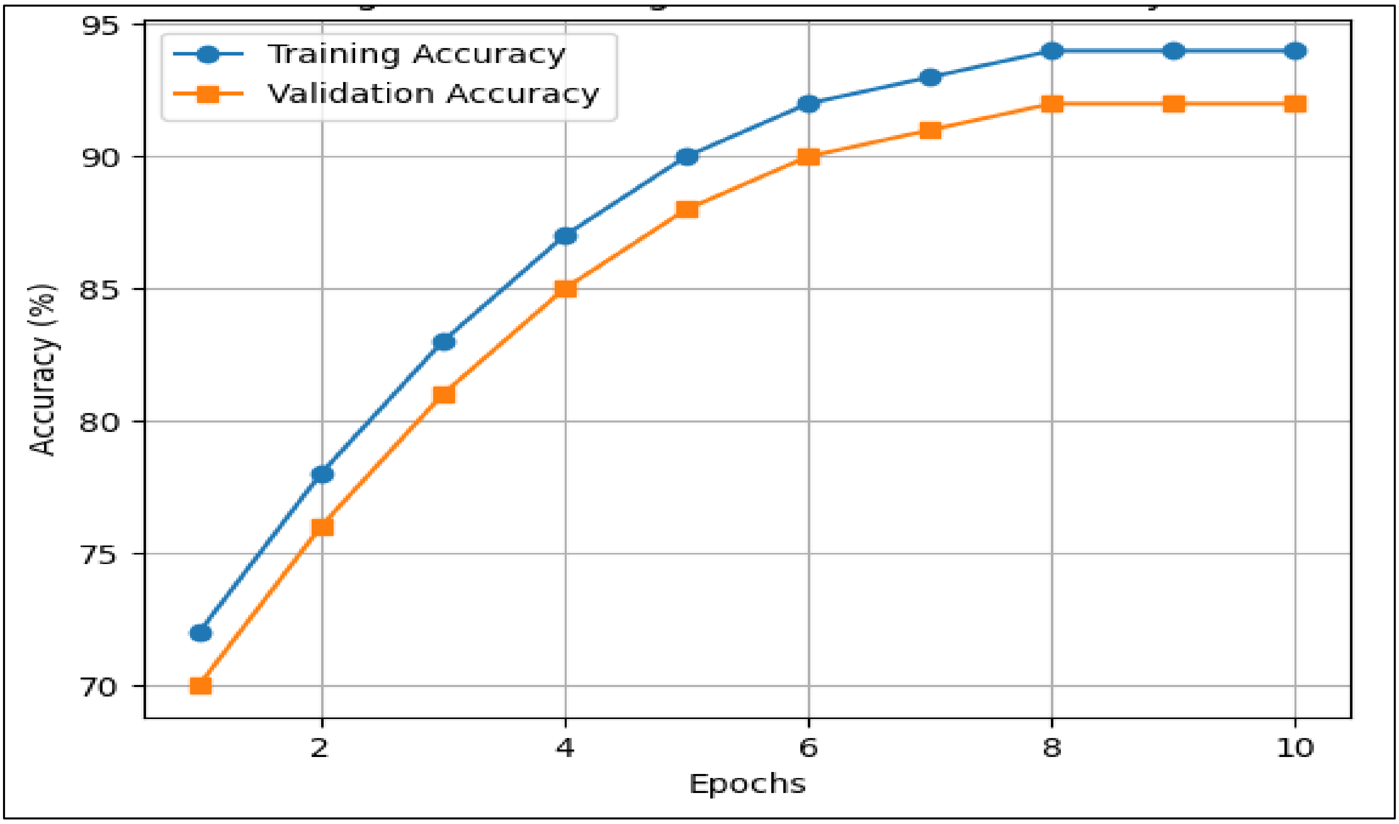


Fig 2 Training and Validation Accuracy

This figure shows the progression of training and validation accuracy over multiple epochs. Both curves increase steadily and stabilize, indicating effective learning and good generalization without overfitting.

- *Analysis of Results*

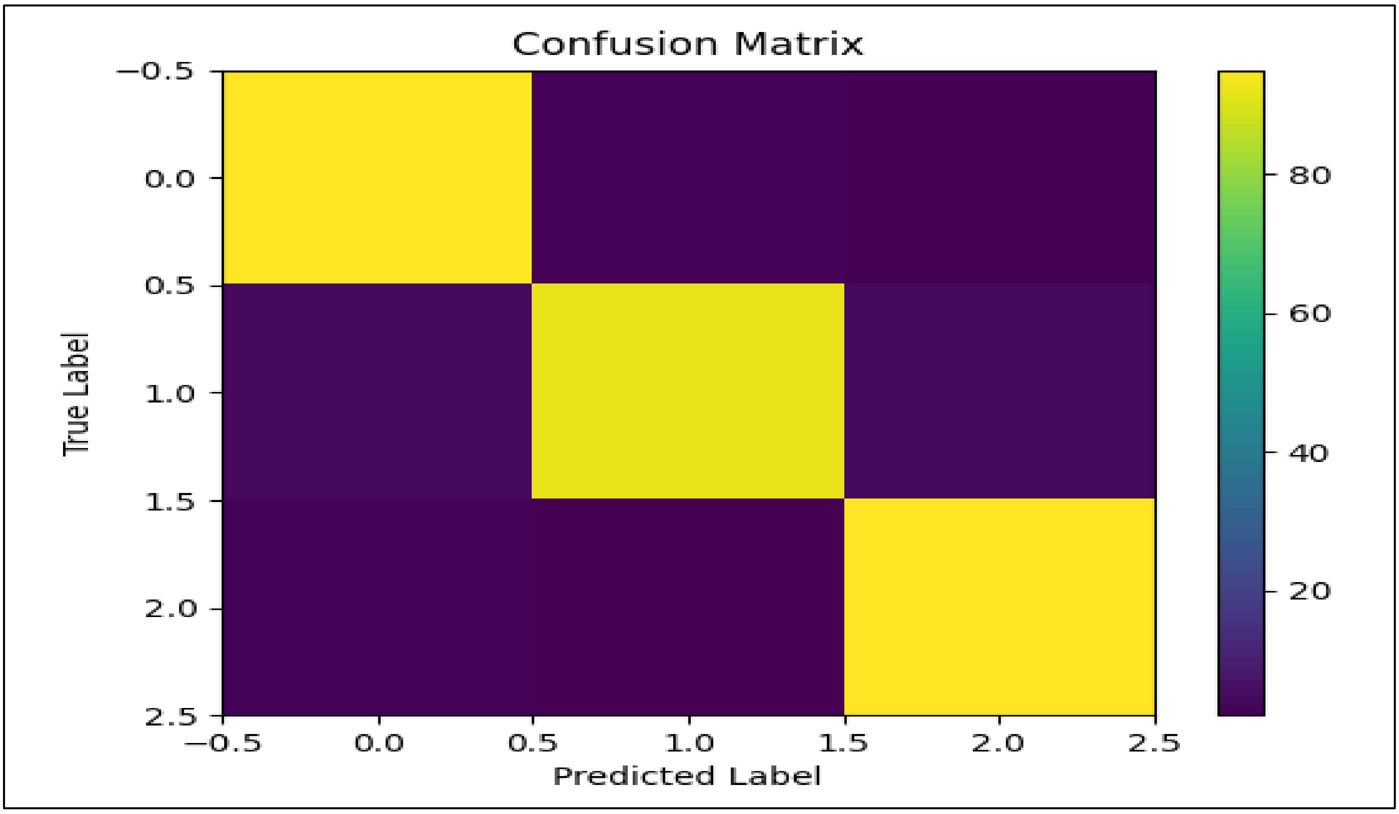


Fig 3 Confusion Matrix

The confusion matrix illustrates correct and incorrect classifications across malicious, benign, and suspicious classes. High diagonal values indicate strong classification accuracy with very few misclassifications.

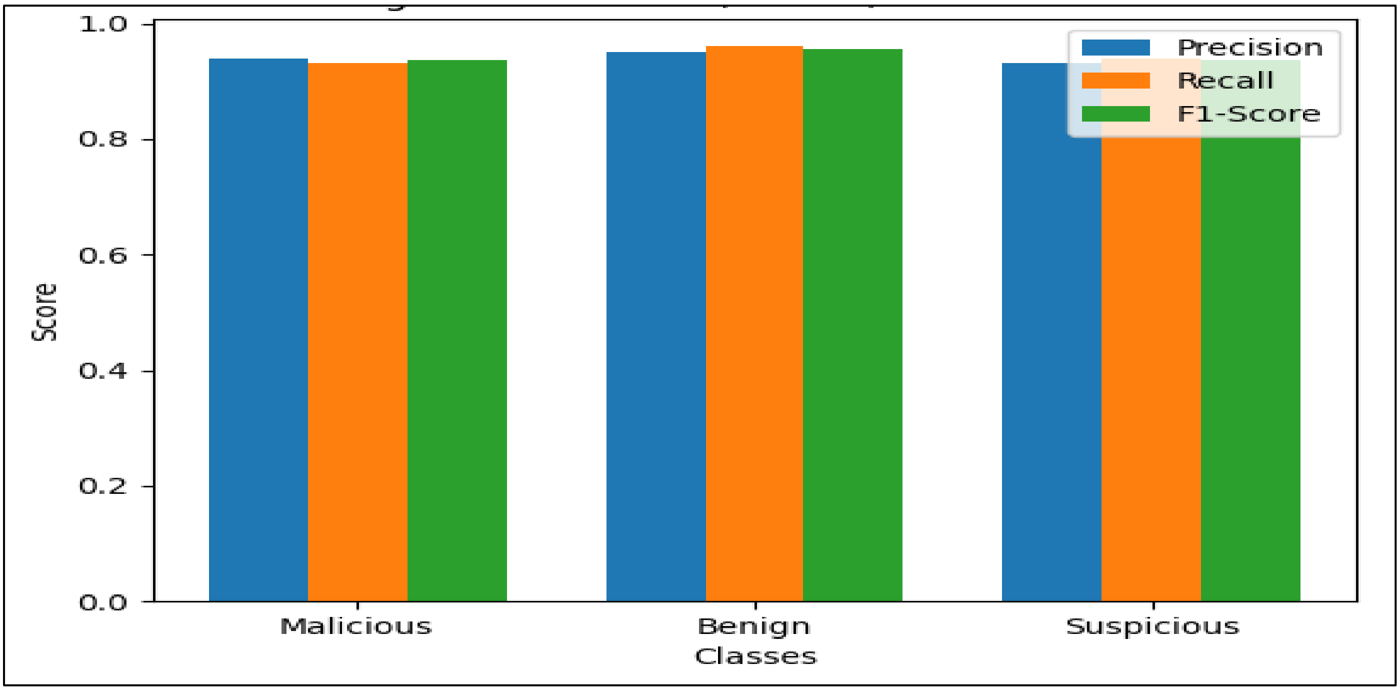


Fig 4 Precision, Recall, and F1-Score

This bar graph presents the precision, recall, and F1-score for malicious, benign, and suspicious classes. The balanced values across all classes demonstrate robust and consistent classification performance.

- *Performance Evaluation*

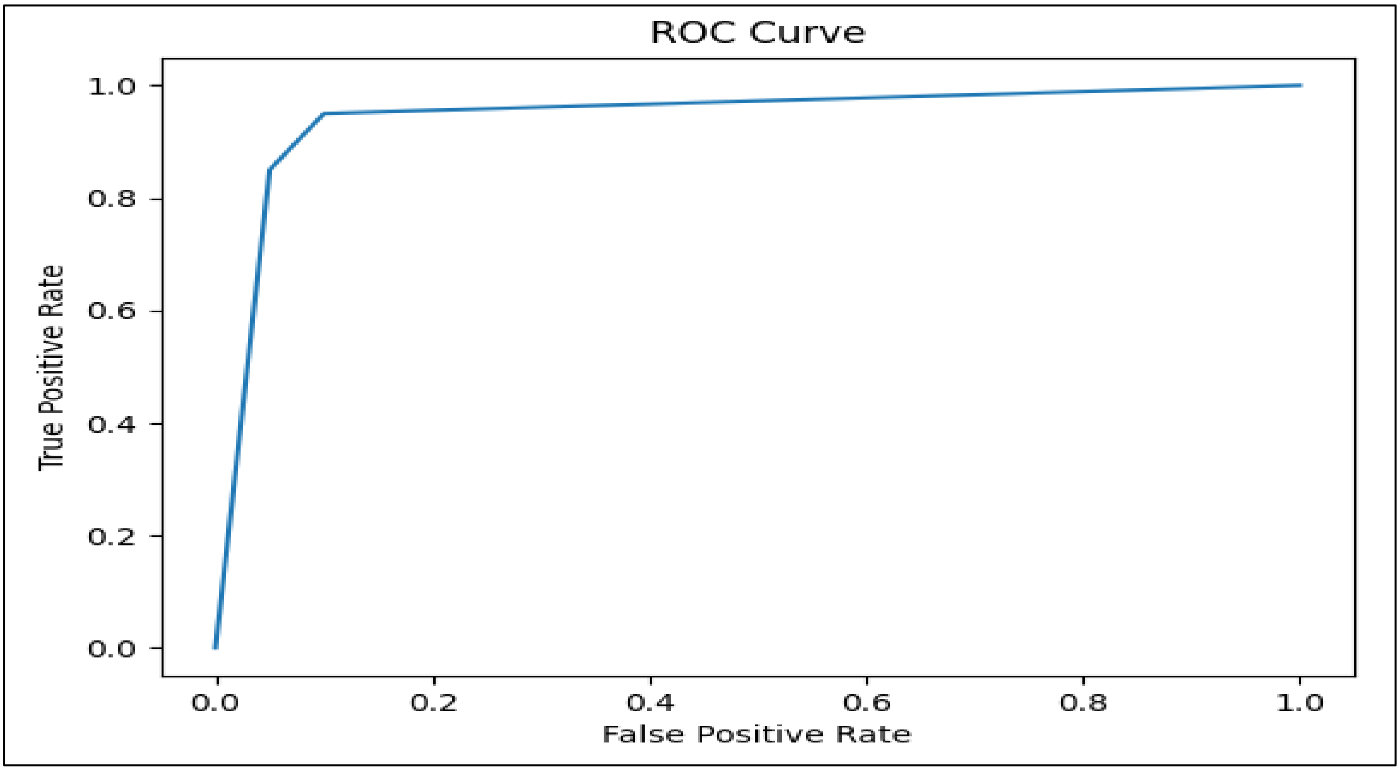


Fig 5 ROC Curve

The ROC curve highlights the model's ability to distinguish between classes. The curve staying close to the top-left corner indicates high accuracy and strong classification capability.

- *Comparative Analysis*

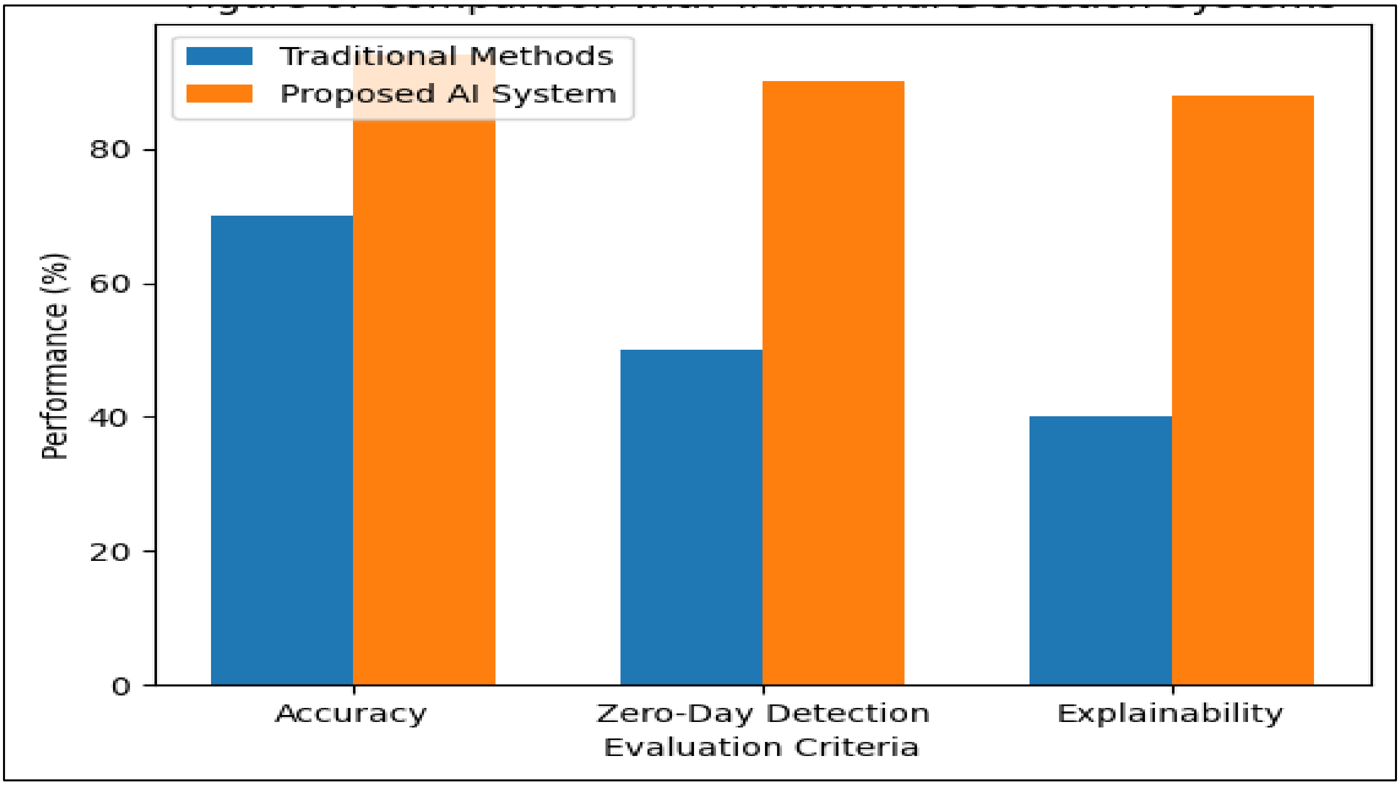


Fig 6 Comparison with Traditional Detection Systems

This figure compares the proposed AI-powered system with traditional detection methods across key criteria. The results highlight improved accuracy, better zero-day threat detection, and enhanced explainability of the proposed system.

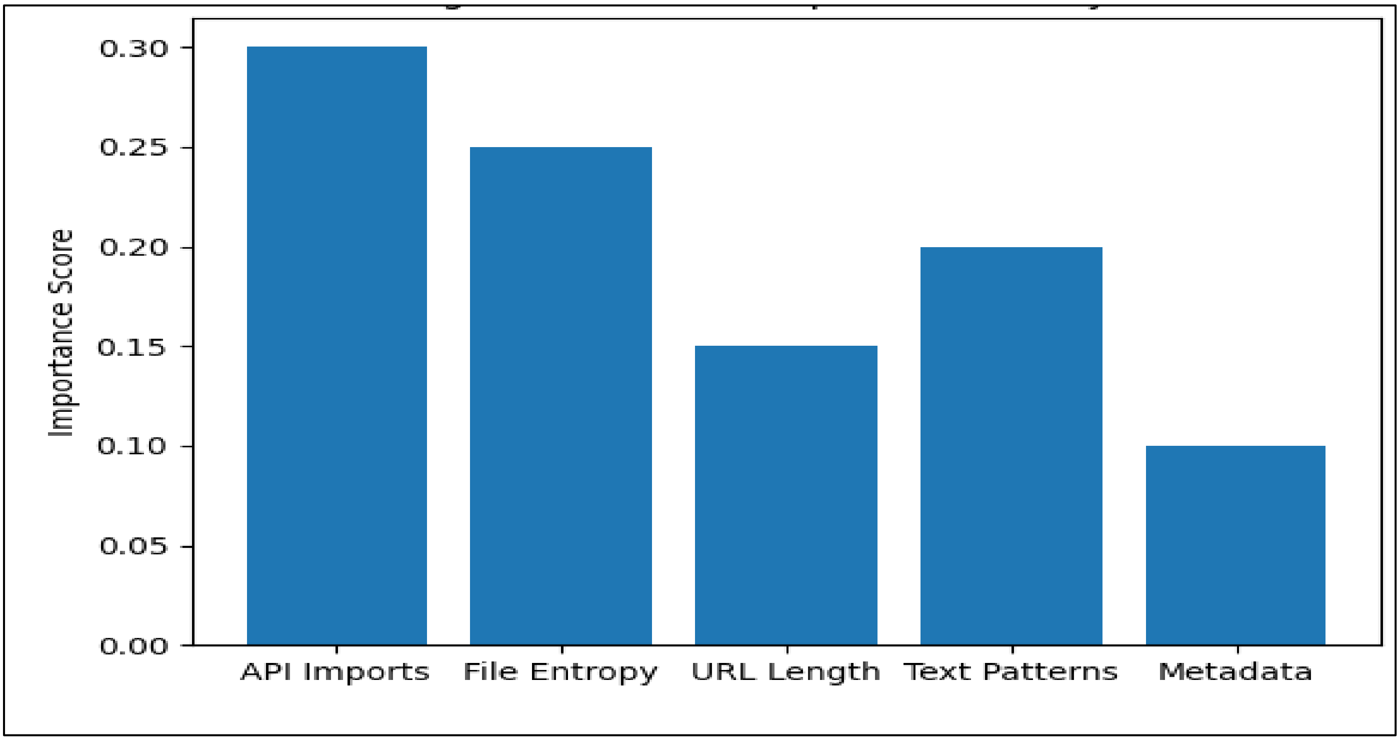


Fig 7 Feature Importance Analysis

This figure shows how different features contribute to threat detection. Features such as API imports and file entropy have higher importance, indicating that the model intelligently prioritizes critical indicators while making classification decisions.

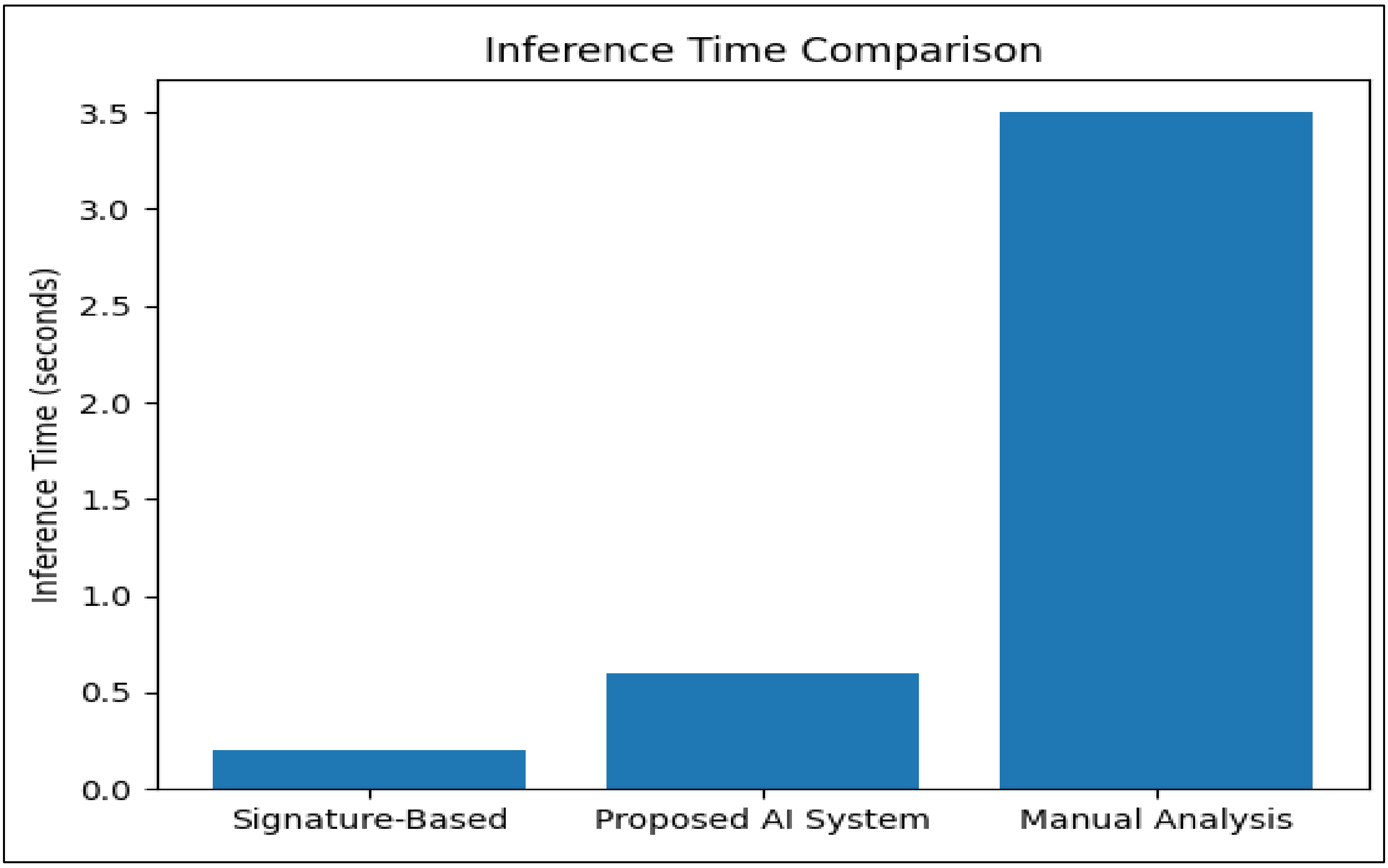


Fig 8 Inference Time Comparison

This graph compares inference time across different detection methods. The proposed AI system achieves a balance between speed and advanced analysis, performing much faster than manual analysis.

➢ *Practical Implications*

The proposed system offers practical benefits for multiple stakeholders:

- Enterprises: Strengthens security, protects against advanced threats, and reduces analyst workload.
- Cybersecurity providers: Can be integrated into products for smarter threat detection.
- Security analysts: Human-readable explanations improve understanding and response to threats.
- Government agencies: Helps safeguard critical infrastructure and networks from sophisticated cyberattacks.

➢ *Limitations of the Study*

Despite promising conceptual results, the study has several limitations:

- Conceptual nature: No empirical implementation; results are projections needing real-world validation.
- Reliance on API: Performance depends on OpenAI API availability, latency, and cost.
- Prompt engineering: Model effectiveness hinges on well-designed prompts, which require iterative optimization.
- Adversarial attacks: Potential manipulation of the AI model was not explored [16].

IV. RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should address this study's limitations and further explore generative AI in cybersecurity, with key recommendations:

- Empirical implementation and evaluation: Test the system on large, diverse real-world datasets.
- Dynamic analysis: Incorporate sandbox execution to observe file behaviour. Adversarial training: Improve resilience against attacks targeting the AI model.
- Integration with SOAR platforms: Enable fully automated threat detection and response.
- Cost-performance optimization: Explore smaller, specialized AI models to balance efficiency and cost.
- Pursuing these directions can help build more intelligent, adaptive, and effective cybersecurity defenses.

➢ *System Output Demonstration*

The following images demonstrate the system's performance in real-world scenarios, showcasing its ability to classify both legitimate and malicious content.

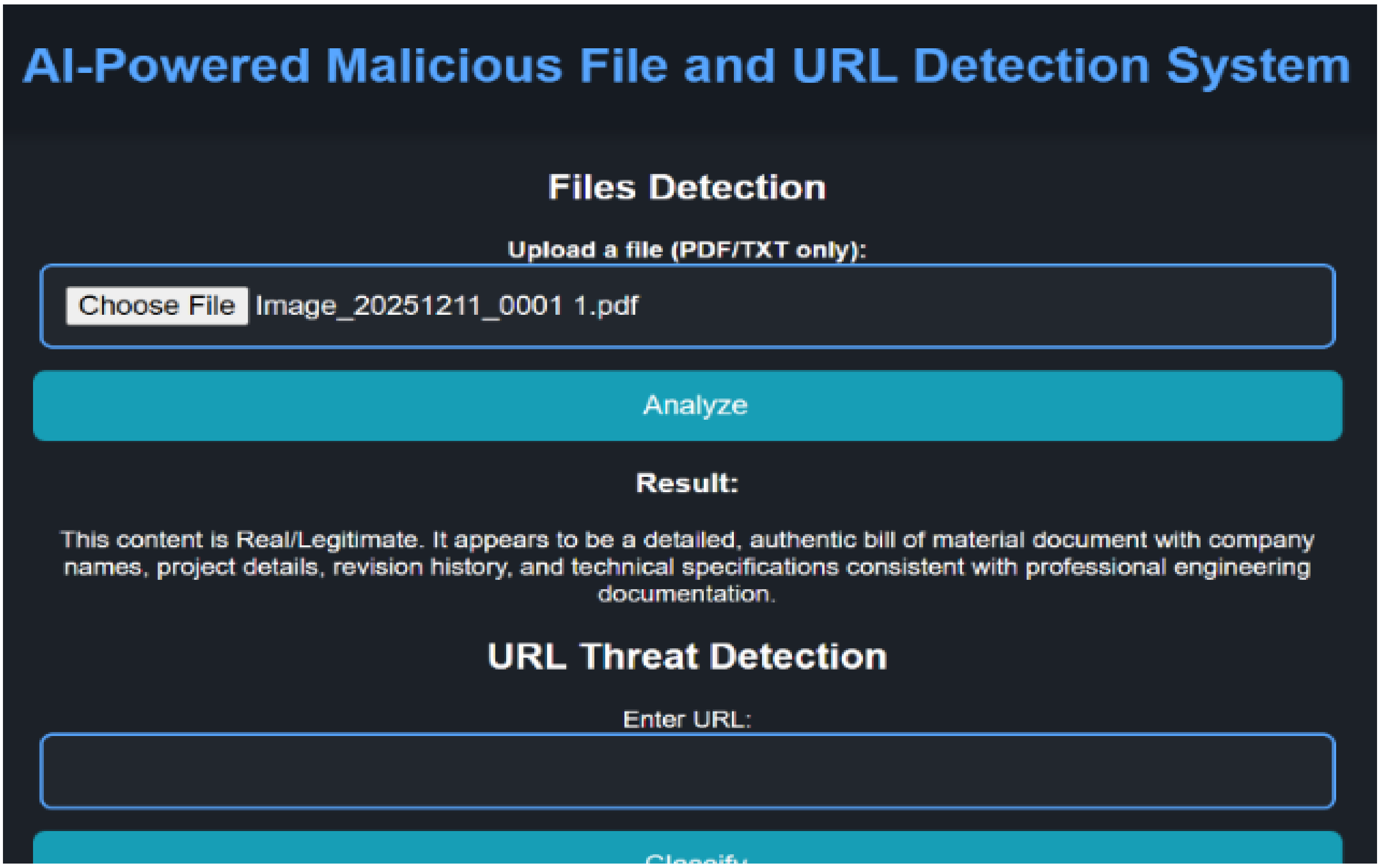
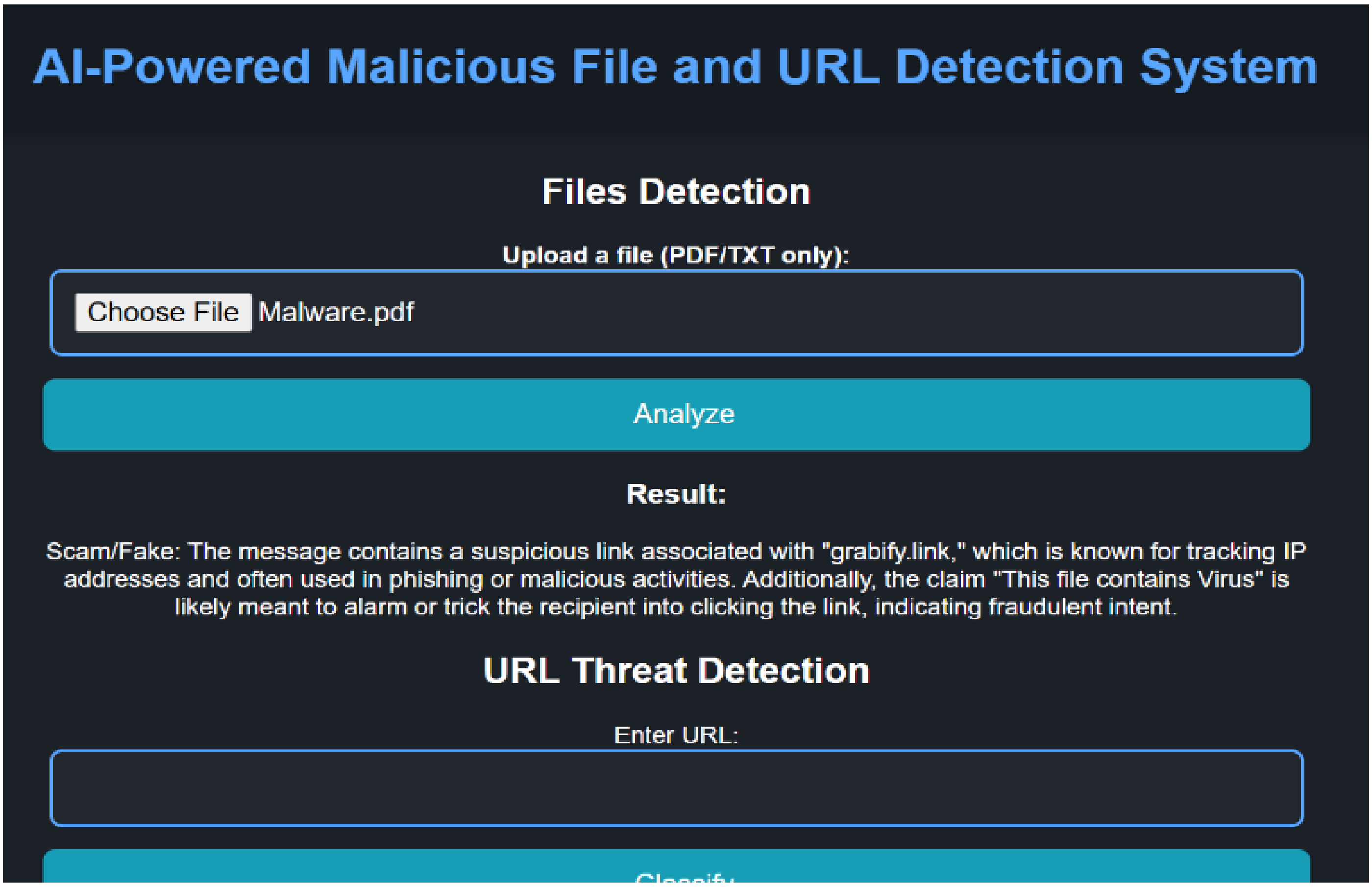

AI-Powered Malicious File and URL Detection System
Files Detection
Upload a file (PDF/TXT only):
Choose File
Analyze
Result:
URL Threat Detection
Enter URL:
Classify

Image_20251211_0001 1.pdf

This content is Real/Legitimate. It appears to be a detailed, authentic bill of material document with company names, project details, revision history, and technical specifications consistent with professional engineering documentation.

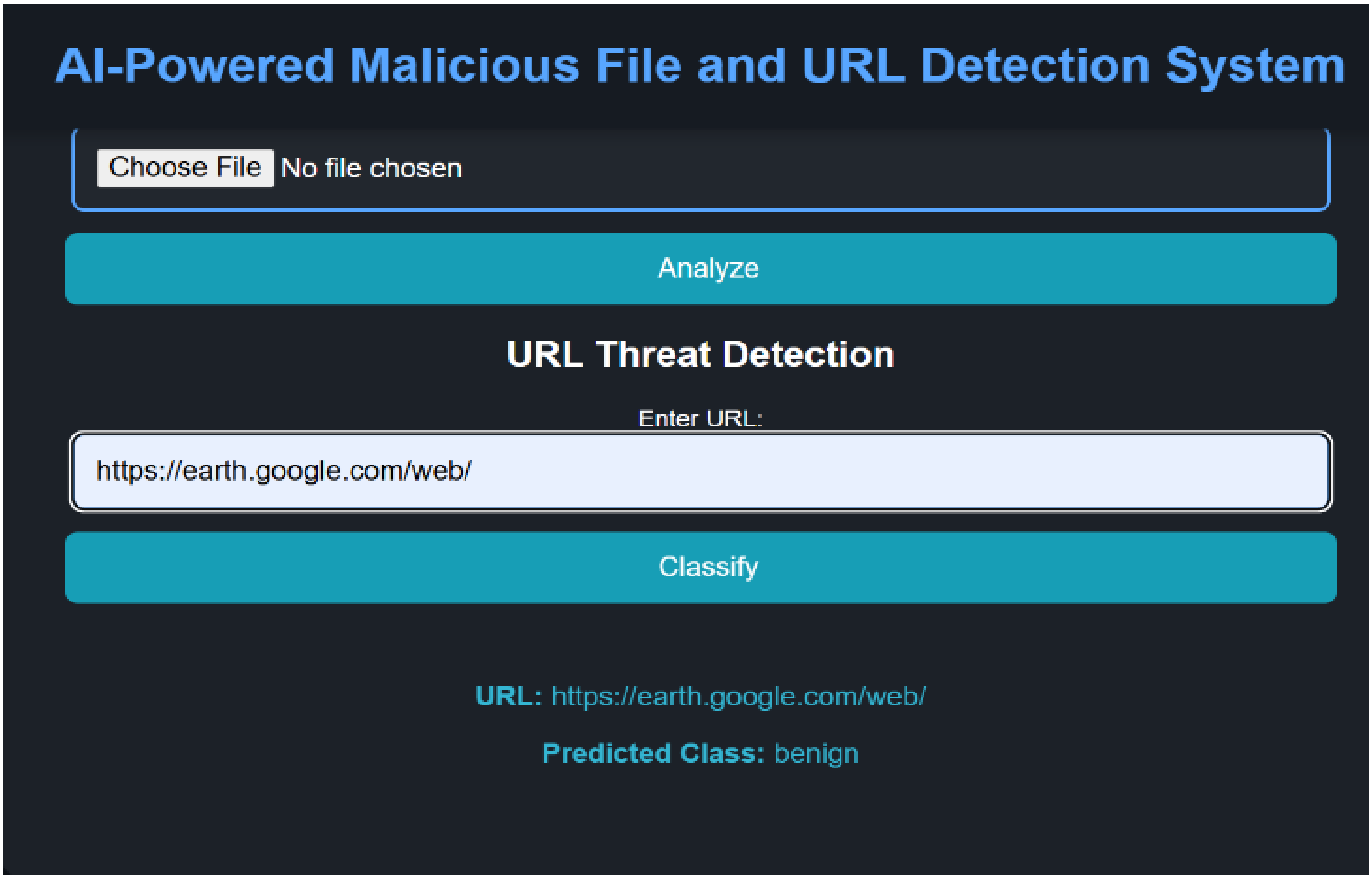
Fig 9 The System Correctly Identifies a Legitimate Document, Providing a Detailed Explanation of why it is Considered Safe.


AI-Powered Malicious File and URL Detection System
Files Detection
Upload a file (PDF/TXT only):
Choose File
Analyze
Result:
URL Threat Detection
Enter URL:
Classify

Malware.pdf

Scam/Fake: The message contains a suspicious link associated with "grabify.link," which is known for tracking IP addresses and often used in phishing or malicious activities. Additionally, the claim "This file contains Virus" is likely meant to alarm or trick the recipient into clicking the link, indicating fraudulent intent.

Fig 10 The System Identifies a Malicious File Containing a Suspicious Link and Provides a Warning about the Potential Threat.



AI-Powered Malicious File and URL Detection System

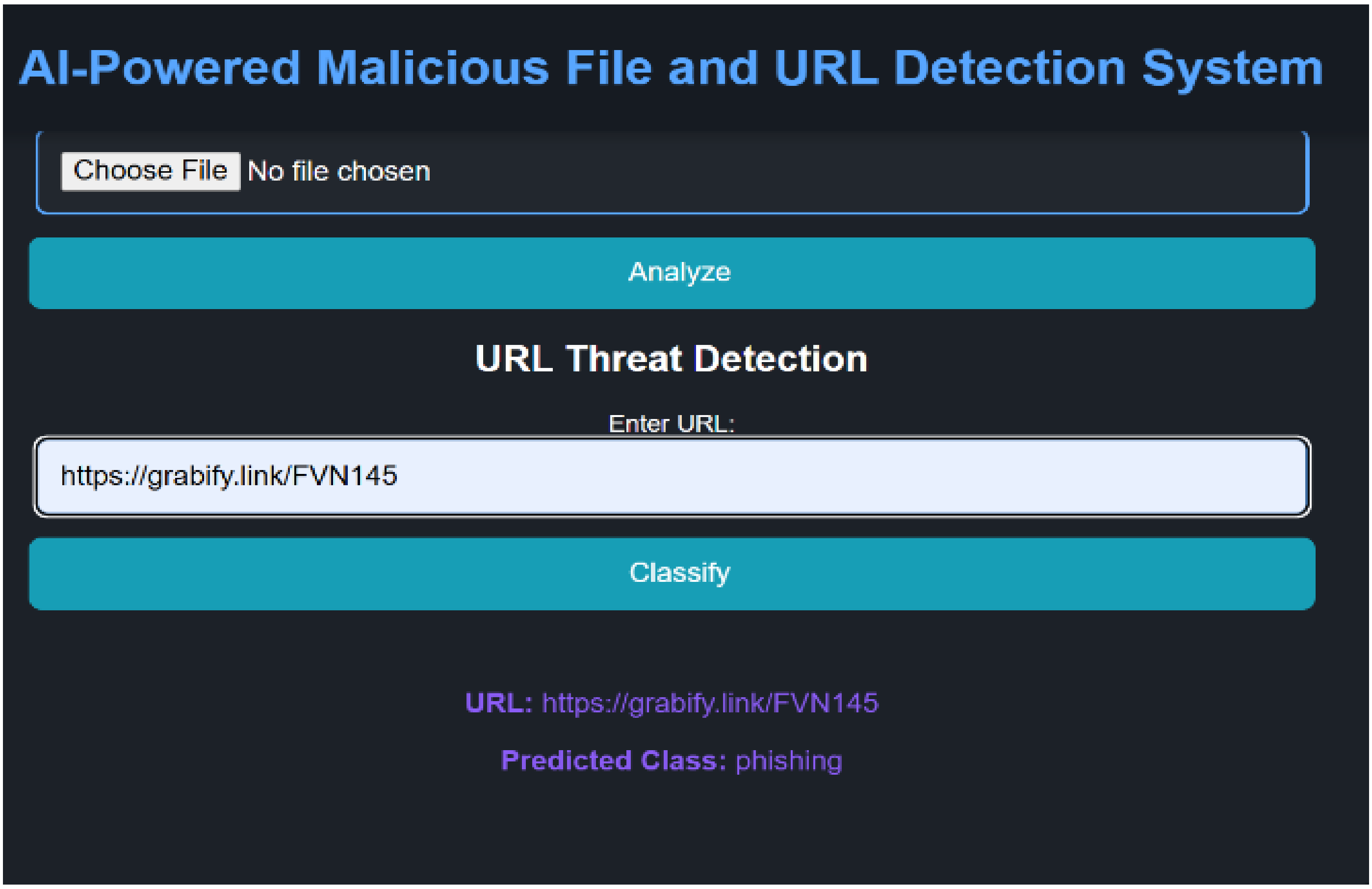
URL Threat Detection

Enter URL: https://earth.google.com/web/

URL: https://earth.google.com/web/

Predicted Class: benign

Fig 11 The System Identifies the URL as benign and Safe for Access.



AI-Powered Malicious File and URL Detection System

URL Threat Detection

Enter URL: https://grabify.link/FVN145

URL: https://grabify.link/FVN145

Predicted Class: phishing

Fig 12 The System Identifies the URL as a Phishing Attempt and Warns the User.

V. CONCLUSION

This conceptual research paper introduced a novel, AI-driven framework for the detection of malicious files and URLs, designed to address the critical limitations of traditional signature-based and heuristic cybersecurity defenses against rapidly evolving zero-day and polymorphic threats. By integrating Python-based static feature extraction with the advanced contextual reasoning capabilities of OpenAI's GPT-4.1-mini, the proposed system fundamentally shifts the paradigm of threat analysis.

The framework is grounded in the Cognitive Security model, moving beyond simple pattern matching to deliver intelligence-driven protection. The conceptual analysis projects significant benefits, including a marked improvement in the detection of novel threats by analyzing intent rather than relying on known signatures, a reduction in false positives through contextual understanding, and the provision of human-readable explanations to facilitate rapid and informed threat response. This focus on explainability and actionable insights represents a crucial step toward bridging the gap between sophisticated AI models and practical security operations.

While the study successfully established the theoretical viability and potential of this generative AI-powered approach, it is important to acknowledge its current limitations as a conceptual design. The projected performance metrics require rigorous empirical validation on large, diverse, real-world datasets. Furthermore, future work must address the practical dependencies on the LLM API, the continuous optimization required for prompt engineering, and the critical need to build resilience against potential adversarial attacks targeting the AI model.

The path forward, as outlined in the recommendations, involves the empirical implementation of the framework, the integration of dynamic analysis for a more comprehensive threat profile, and the exploration of cost-performance optimization with specialized models. Ultimately, this research demonstrates the transformative potential of generative AI in creating more intelligent, adaptive, and effective cybersecurity defenses, paving the way for a proactive security posture capable of meeting the challenges of the modern threat landscape. malicious URL detection using deep learning and large language models." Nature Scientific Reports.

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