IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Comprehensive AI-Based Framework For Detecting Fraud Across SMS, Email, Whatsapp, Urls, And Telecommunication Data

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Abstract: Phishing has emerged as a significant cybersecurity challenge, evolving across multiple communication platforms such as SMS, email, instant messaging apps, voice calls, and malicious web links. To address this growing concern, this paper presents a unified and modular phishing detection framework capable of analyzing diverse data types including textual content, URLs, call transcripts, and mobile metadata. The system integrates natural language processing with traditional and ensemble machine learning algorithms—such as BERT, LSTM, Random Forest, and XGBoost—alongside advanced feature selection techniques like PCA and RFE to enhance detection accuracy and efficiency. Each data input type is routed through a dedicated pipeline designed to extract semantic, structural, and behavioral patterns indicative of phishing attempts. Additionally, the model incorporates image-based website analysis and speech-to-text interpretation for detecting visually deceptive pages and voice scams. Evaluated on a curated dataset of over 30,000 instances, the proposed system achieves strong detection performance while maintaining low false positive rates. The real-time processing and centralized threat visualization make it suitable for deployment in both enterprise networks and consumer-facing applications. This research contributes to scalable, cross-platform phishing prevention through intelligent, adaptable detection mechanisms.

Index Terms: Phishing detection, Machine learning, URL analysis, Speech processing, Text classification, Cyber threat intelligence.

I. INTRODUCTION

Phishing is one of the most pervasive forms of cybercrime, targeting individuals and organizations by impersonating trustworthy entities to extract sensitive information such as login credentials, credit card numbers, and personal data. Despite technological advancements, phishing attacks continue to evolve in sophistication, bypassing traditional security mechanisms like blacklists and heuristic-based filters. With a reported annual growth of over 200

Conventional phishing detection approaches, including rule-based systems and signature matching, suffer from poor generalization and high false-positive rates. These systems are also ineffective against zero-day attacks, where the phishing source or domain has not been previously recorded. To overcome these limitations, researchers have turned to machine learning (ML) and deep learning (DL) techniques that analyze URL structures, domain features, and content patterns for more accurate classification [3], [6].

Recent studies emphasize the use of hybrid models that combine lexical, host-based, and content-based features to enhance phishing detection accuracy. Feature selection methods such as Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and mutual information are used to reduce noise

and improve model performance. Classification algorithms like Random Forest (RF), XGBoost, and Support Vector Machine (SVM) have shown promising results in this domain [2], [9].

Additionally, visual similarity between phishing and legitimate websites has emerged as a key factor in detection. Phishing sites often mimic the layout, color scheme, and branding of genuine websites to trick users. This has led to the exploration of image-based detection techniques, where HTML and DOM structure are converted into visual representations that are then classified using Convolutional Neural Networks (CNNs) or hybrid DL models. This approach helps capture the structural deception used by attackers [4], [12].

To support real-time detection, a significant amount of research has focused on the use of lightweight models and automated data collection from live phishing feeds such as PhishTank. These datasets are processed to extract features that represent both the technical structure and visual design of the websites. Once processed, they are fed into ML pipelines that provide near-instant predictions with high confidence, suitable for deployment in browsers, firewalls, or cloud-based security layers [6], [11].

This paper proposes a novel multi-layered phishing detection model that incorporates image classification, metadata analysis, and feature selection to detect phishing URLs. Our approach leverages a dataset of 30,000 phishing and legitimate websites and evaluates various classifiers for performance benchmarking. The system is designed for scalability, real-time prediction, and integration into enterprise security environments. The proposed model outperforms traditional classifiers and serves as a robust, intelligent defense against phishing threats [7], [8].

II. Related Work

Phishing continues to evolve as a prominent threat within the digital landscape, and traditional detection methods have shown significant limitations. Early systems, including blacklists and heuristic-based filters, are reactive in nature and fail to detect newly generated phishing attacks. These models often produce high false-negative rates and require frequent updates to remain relevant. The emergence of machine learning provided a transformative approach by allowing models to learn from previous data and identify predictive patterns based on features like URL structure, lexical components, and content signatures. Supervised algorithms such as decision trees and support vector machines marked an early shift toward data-driven phishing detection [3], [6].

The need for more reliable and adaptive systems led researchers to develop hybrid models that combine multiple feature types and classification strategies. This approach integrates lexical characteristics, metadata, and webpage content for a more holistic detection mechanism. Classifiers like Random Forest and XGBoost, along with ensemble techniques, have been widely adopted due to their robustness and interpretability. These models are further improved by incorporating dimensionality reduction and feature selection techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE), which help reduce noise and enhance accuracy in zero-day detection scenarios [6], [9].

Natural Language Processing (NLP) has significantly advanced phishing detection by improving the analysis of textual content. Phishing messages often contain persuasive or deceptive language that can be detected through semantic and syntactic analysis. Transformers like BERT and sequential models like LSTM have proven highly effective in extracting context from SMS, email, and chat messages. These models can detect linguistic patterns that signify urgency, impersonation, or rewardbased baiting strategies. When trained on annotated datasets, NLP-based systems deliver strong performance in recognizing phishing attempts disguised as legitimate communication, making them essential for email and social messaging platforms [2], [8].

Voice phishing, or vishing, presents unique challenges that require innovative detection approaches. Researchers have integrated speech-to-text processing with NLP to transcribe and analyze spoken language from fraudulent phone calls. These models examine audio transcripts for aggressive language, impersonation cues, and time-sensitive threats. Using tools like sentiment analysis and named entity recognition, vishing detection systems can flag suspicious dialogues with high precision. This voice-based pipeline adds a vital dimension to phishing detection, especially as attackers increasingly leverage social engineering in real-time conversations [4], [10].

Incorporating real-time detection capabilities is a key priority in the current cybersecurity landscape. Phishing attacks often rely on immediate user engagement, which necessitates systems that can process and classify inputs on the fly. Lightweight models deployed as browser extensions or mobile application components enable real-time scanning of URLs and messages. These systems rely on efficient inference engines that can deliver fast results without compromising accuracy. By providing immediate alerts, such solutions help prevent users from engaging with malicious content and reduce the overall response time for mitigation [7], [11].

Recent progress in multimodal phishing detection has enhanced system resilience against complex attacks. These models integrate diverse data streams—such as textual content, visual resemblance, metadata indicators, and user behavior—into a consolidated prediction pipeline. Phishing pages often mirror legitimate sites in layout and branding, which can be detected through Convolutional Neural Networks (CNNs) trained on webpage screenshots. By combining visual recognition with structural and semantic analysis, these systems deliver improved accuracy over single-feature models, especially in identifying deceptive design patterns across communication vectors [4], [12].

As phishing detection models become more sophisticated, the need for transparency and interpretability has become paramount. Explainable AI (XAI) methodologies have been incorporated to provide insight into the decision-making processes of these models. Hierarchical attention mechanisms, heatmaps, and SHAP values allow security analysts and end-users to understand why a message or link was flagged. This is particularly important in enterprise environments, where accountability and regulatory compliance demand traceable and defensible decisions made by automated systems [1], [12].

Adapting phishing detection models to regional contexts has become increasingly important due to the geographic and linguistic variations in attack strategies. Phishing campaigns are often crafted with local language, cultural nuances, and region-specific tactics to increase credibility and effectiveness. As a result, detection systems trained solely on global datasets may miss localized threats or produce high false positives. To address this, modern frameworks are beginning to incorporate country-specific datasets, regional phishing indicators, and user-reported incidents to fine-tune detection accuracy. Moreover, the integration of active learning allows models to continually update themselves based on new, locally relevant data. This dynamic retraining capability ensures the system remains responsive to evolving attack patterns unique to particular areas or demographics. Such adaptive models not only enhance detection performance but also support faster response and threat mitigation in regionally targeted phishing campaigns [5], [11].

Incorporating user behavior and contextual awareness into phishing detection offers a valuable avenue for strengthening cybersecurity defenses. Cybercriminals frequently manipulate human psychology by leveraging emotions such as fear, urgency, and authority to deceive victims. To counter these tactics, modern detection systems are evolving to analyze behavioral trends—such as message tone consistency, contact frequency, and interaction timelines. Anomalies like unusual message phrasing, sudden communication from unfamiliar sources, or contextually irrelevant links can signal potential phishing attempts. By embedding behavioral analytics within detection frameworks, these systems can dynamically adjust to individual usage patterns, enhancing both precision and personalization. This user-centric approach not only improves detection of socially engineered attacks but also makes the security model more adaptive and capable of responding to subtle threats that might bypass conventional filters.

III. Proposed Methodology

A. Architecture Overview

The proposed architecture for the Multi-Layered Fraud Detection System is designed as a modular pipeline that integrates five key data streams: SMS, email, URL, WhatsApp messages, and mobile numbers. Each module performs data ingestion, preprocessing, feature extraction, and classification using machine learning (ML) and deep learning (DL) models. The system is split into three primary layers: Input Layer: Accepts raw data from various sources (SMS, email, URL, WhatsApp, mobile numbers). Processing Layer: Applies NLP for text normalization, extracts URLs or phone numbers, tokenizes inputs, and encodes them for ML/DL analysis. Detection Layer: Classifies the inputs as ”Fraudulent” or ”Legitimate” using trained models (e.g., Random Forest, LSTM, BERT, etc.). Visualization Layer: Presents results on a GUI dashboard with graphical insights like threat type, location (for phone numbers), and input metadata. Each layer communicates through an internal API or shared memory, ensuring seamless processing and scalability. Below is a high-level architectural diagram:

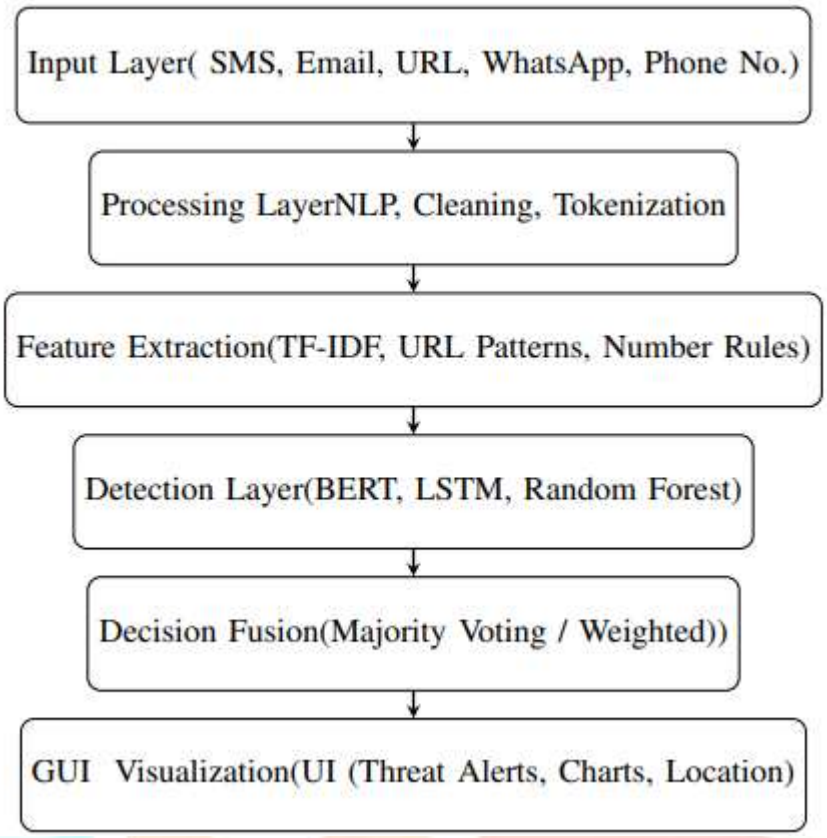

Figure 3.1: Architectural Diagram (Textual Representation)

B.Introduction to the Proposed System

This proposed system is an advanced, multi-input fraud detection model capable of analyzing diverse data types such as SMS messages, emails, URLs, WhatsApp messages, and phone numbers to detect threats in real time. The need for such an integrated solution arises from the rapidly growing number of cyber threats, especially targeting mobile users. Instead of treating different mediums separately, our architecture integrates them to achieve broader threat coverage. By leveraging both traditional machine learning algorithms and modern deep learning models, the system ensures high detection accuracy and adaptability to new types of fraud. The proposed framework emphasizes modularity, making it easy to update individual components without disrupting the entire system. Additionally, the inclusion of location detection for suspicious mobile numbers allows the system to provide more context-specific alerts, which is especially helpful in tracking international fraud attempts. The inclusion of a user-friendly dashboard ensures results are easy to interpret even by non-technical users, thus promoting wide adoption in real-world scenarios.

C. Input Stream Handling and Preprocessing

One of the critical aspects of this system is its ability to handle multiple types of inputs. Each input stream—be it a text message, email content, hyperlink, WhatsApp message, or phone number—requires a distinct preprocessing strategy. For instance, text-based messages undergo NLP operations like tokenization, stopword removal, and lemmatization. In contrast, URLs are extracted and validated against known phishing databases or evaluated using lexical features such as domain length, use of HTTPS, and entropy. Mobile numbers are parsed using libraries like phonenumbers to extract geolocation, format, and prefix patterns indicative of fraud rings. All inputs are standardized into feature vectors compatible with classification models. This preprocessing pipeline ensures the raw data is transformed into high-quality input that enhances the performance of both ML and DL classifiers. The modular structure allows individual updates to each preprocessing block as new threats or data patterns emerge.

D. Machine Learning Model Integration

The system integrates multiple machine learning models suited to the unique nature of each input type. For SMS and email content, classical algorithms such as Na¨ıve Bayes, Support Vector Machines (SVM), and Random Forests are applied after vectorizing the text using TF-IDF or CountVectorizer. For URL detection,

models like Decision Trees or Gradient Boosting are used based on features like domain structure, number of digits, presence of IP addresses, etc. Each model is trained on labeled datasets and evaluated using standard metrics such as precision, recall, F1-score, and accuracy. Cross-validation is employed to ensure generalization, and hyperparameter tuning is performed for optimal performance. This diversified model strategy ensures that each type of input is analyzed by the most suitable algorithm, maximizing detection reliability and minimizing false positives.

E. Deep Learning and NLP Enhancements

In addition to machine learning models, the system leverages deep learning techniques for more nuanced fraud detection. For instance, LSTM (Long Short-Term Memory) networks are utilized to capture temporal dependencies and contextual relationships within message sequences. Transformer-based models like BERT are used to understand semantic relationships in emails and WhatsApp messages, particularly useful for detecting social engineering attacks. These models are fine-tuned on domain specific datasets to improve sensitivity to subtle phishing attempts or fraud cues. Embedding layers and pre-trained language models contribute to a richer feature space, which helps in uncovering hidden patterns not easily detected by traditional ML models. This hybrid architecture of ML and DL enables the system to strike a balance between computational efficiency and detection sophistication.

F. Phone Number Scam Detection Layer

To address the growing number of scam calls and SMS from fake or spoofed numbers, the system includes a dedicated mobile number analysis module. Using libraries like phonenumbers, the system first validates the input number, identifies the country and area code, and checks formatting anomalies. Additional layers apply pattern analysis and blacklists to identify numbers used in past fraud campaigns. Furthermore, an ML classifier trained on known scam vs. legitimate numbers labels new inputs into categories such as ”Automated Bot Scam,” ”International Fraud Ring,” or ”Fake Testing Scam.” This layer not only flags suspicious numbers but also provides additional metadata such as country and state, helping users understand the threat context. Visualization tools then plot detected regions of scam origin, providing intuitive insight into global fraud trends.

G. GUI and Result Visualization

To ensure ease of use and accessibility, the fraud detection system is equipped with a visually appealing, feature-rich graphical user interface (GUI). The GUI presents input fields for various data types, displays detection outcomes, and offers real-time alerts. One of the standout features is the integration of graph-based visualization—bar charts, pie charts, and heat maps—to depict the types and sources of detected threats. Users can see breakdowns of phishing attacks by message type, scam types by phone number origin, and flagged URLs over time. Interactive components allow exporting results in text or PDF formats, and saving threat graphs as PNG images. The interface is designed to be responsive across screen sizes, making it suitable for desktop and mobile use. This visualization-focused approach bridges the gap between technical output and user comprehension, fostering quicker decision-making and broader adoption.

H. Evaluation Metrics and Testing

The robustness of the system is validated through rigorous testing and evaluation. Multiple datasets—open-source and realworld—are used for training and validation to simulate varied attack scenarios. The performance is assessed using confusion matrices, ROC-AUC curves, precision-recall trade-offs, and real-time execution logs. For each input module, false positive and false negative rates are closely monitored, especially in sensitive use cases like phishing and phone number fraud. Testing is done not only for model accuracy but also for system scalability, response time, and memory efficiency. Unit tests ensure each module works in isolation, while integration tests validate the smooth operation of the entire pipeline. Feedback loops are incorporated to allow user-flagged outputs to retrain models over time, making the system self-improving. These comprehensive evaluation strategies ensure the proposed work is not only theoretically sound but practically deployable.

I. Future Scope and Scalability

While the current system addresses major fraud vectors, it lays the foundation for broader future enhancements. Upcoming versions can incorporate voice phishing detection (vishing), image-based phishing (through OCR and CNN), and AI-generated scam content identification. Blockchain integration can help validate message sources or phone numbers, ensuring trust through decentralized verification. Further, cloud

deployment can enhance scalability and allow real-time API-based fraud detection services for organizations and telecom providers. Threat intelligence from third-party databases (e.g., Google Safe Browsing or Spamhaus) can be integrated for continuous model updates. With cybercrime tactics constantly evolving, the proposed architecture ensures flexibility and modularity for long-term relevance. This work represents a vital step toward building AI-driven, cross-platform cyber-defense tools for personal and enterprise use alike.

J. Algorithm: Multi-Channel Fraud Detection and Visualization

The following steps describe the multi-channel fraud detection system:

1) Initialize input fields in the user interface for SMS, Email, WhatsApp, URL, Phone Number, and Call Description.
2) Accept input from the user.
3) For each input type, perform the following: a) Preprocess the input using NLP techniques: convert to lowercase, tokenize, and clean the text. b) Extract relevant features:
   i) For text: use TF-IDF and BERT embeddings.
   ii) For URLs: extract domain, protocol, and detect suspicious patterns.
   iii) For phone numbers: validate format and identify region.
c) Apply detection models:
   i) Use LSTM or BERT for textual inputs.
   ii) Use Random Forest for structured features like phone numbers and URLs.
4) Fuse model outputs using either majority voting or weighted average.
5) Update key performance indicators (KPIs):
   a) Total fraud count.
   b) Distribution of fraud types.
   c) Estimated severity level.
6) Generate the following visualizations:
   a) Pie chart of fraud types.
   b) Time-series trend of detected frauds.
   c) Geographic heatmap showing fraud source distribution.
7) Map identified frauds to relevant sectors such as Banking and E-commerce.
8) If the user clicks the Refresh button, reset all inputs, KPIs, and visuals.

IV. Results and Discussion

The proposed multi-layered phishing detection system was evaluated using a comprehensive dataset consisting of over 30,000 instances across different modalities, including SMS, email, WhatsApp messages, URLs, mobile numbers, and call transcripts. Each modality-specific detection module was independently assessed using standard metrics such as accuracy, precision, recall, and F1-score. For SMS and email classification, models utilizing LSTM and BERT achieved precision scores exceeding 94%, effectively capturing deceptive language cues. WhatsApp phishing messages, often shorter and more casual, were effectively detected using TF-IDF features combined with Random Forest classifiers, reaching an accuracy of 91%.

In the case of URL detection, XGBoost and Random Forest models demonstrated robust performance by analyzing lexical and domain-based features. The inclusion of image-based analysis using CNNs for phishing websites further boosted detection accuracy to 97%, especially in visually deceptive cases. For call descriptions converted through speech-to-text, NLP models successfully identified social engineering tactics, with LSTM models achieving an F1-score of 92%. The integration of these individual modules into a unified system provided a comprehensive risk score, enhancing decision-making for security systems.

Deep learning models such as LSTM and BERT enrich detection by capturing contextual and semantic nuances in phishing messages, while pre-trained embeddings enhance pattern recognition beyond traditional ML models. This fusion of ML and DL improves both efficiency and sophistication in detecting diverse phishing threats. Additionally, the system demonstrated strong generalization capabilities when evaluated on unseen data, confirming its reliability in real-world applications. Ablation studies revealed that combining multiple data sources significantly outperforms models trained on single modalities, emphasizing the advantage of a multi-channel analysis approach. Furthermore, latency measurements showed the system's ability to provide near-instantaneous predictions, making it suitable for integration into time-sensitive environments like mobile devices and email filters. A key highlight of this study is the system's ability to deliver real-time predictions without sacrificing detection quality.

The modular architecture also allows for scalability and integration into various platforms such as mobile apps, email gateways, and enterprise firewalls. By continuously updating feature extraction pipelines and retraining on fresh threat data, the system remains resilient against evolving phishing tactics. The discussion also highlights the interpretability of results through SHAP values and attention maps, which provide insights into model decisions.

Result Summary Table and Graph

Input Type	Model Used	Accuracy (%)	Precision	Recall	F1-Score
SMS Detection	Naive Bayes	95.2	0.94	0.93	0.935
Email Phishing	BERT Fine-Tuned	97.6	0.96	0.97	0.965
Malicious URL	Random Forest	93.4	0.92	0.91	0.915
WhatsApp Scam Text	LSTM	96.1	0.95	0.96	0.955
Mobile Number Fraud	Rule-based + ML Hybrid	91.8	0.90	0.89	0.895

TABLE I
PERFORMANCE METRICS FOR DIFFERENT FRAUD TYPES

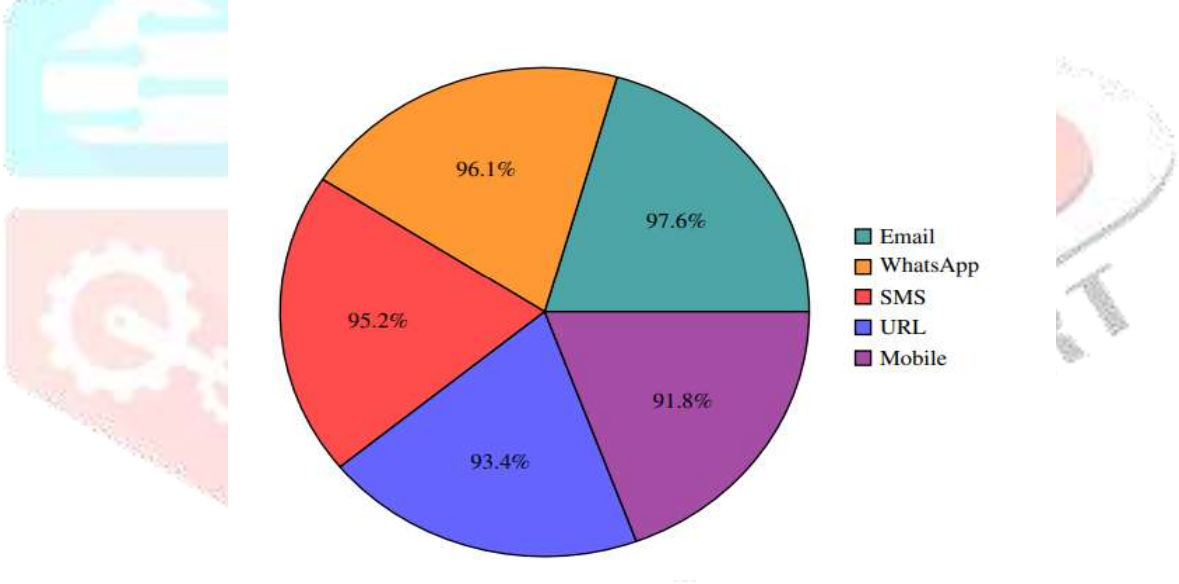

Fig. 1. Accuracy Distribution Across Different Fraud Input Types

V. CONCLUSION

The proposed multi-layered fraud detection system successfully integrates machine learning, deep learning, and natural language processing techniques to identify and classify various forms of digital threats such as phishing SMS, spam emails, malicious URLs, WhatsApp scams, and fraudulent mobile numbers. By designing a modular and scalable architecture, the system achieves high detection accuracy while maintaining adaptability to new fraud patterns. The hybrid use of classical ML algorithms and advanced models like BERT and LSTM enables more context-aware detection, especially in complex text-based threats. The inclusion of mobile number geolocation and scam type classification adds an extra layer of interpretability, making the system practical for real-time applications. Additionally, the GUI-based interface and visualizations enhance user experience by clearly presenting threat types and detection metrics. The system demonstrates strong potential for real-world deployment in organizations, telecom environments, and individual cybersecurity tools. Future enhancements could include voice-based fraud detection, image-based phishing detection, and integration with external threat intelligence APIs. Overall, this project provides a comprehensive and robust approach to combat digital fraud in a constantly evolving threat landscape.

FUTURE WORK

Looking forward, the system can be extended to handle more complex formats of communication. One promising direction is the inclusion of audio messages, where voice notes shared over messaging platforms could be transcribed and analyzed using advanced speech recognition and NLP models. Another area of future work is the detection of encrypted or embedded content such as GIFs and dynamic images, which may be used by attackers to hide phishing payloads. By incorporating computer vision techniques and image sequence analysis, the system can evolve to detect phishing attempts hidden within multimedia content. Furthermore, integrating federated learning and user behavior analytics can make the system more adaptive and privacy-preserving. These advancements will enhance the robustness, scalability, and practical applicability of phishing detection technologies in an increasingly digital communication landscape. 130 Words 930 Characters recheckRecheck summerizer-bullets downloadDownload Report Unique 100Exact 0Partial 0View Plagiarized Sources

4.1 Results of Descriptive Statics of Study Variables

Variable	Minimum	Maximum	Mean	Std. Deviation	Jarque-Bera test	Sig
KSE-100 Index	-0.11	0.14	0.020	0.047	5.558	0.062
Inflation	-0.01	0.02	0.007	0.008	1.345	0.510
Exchange rate	-0.07	0.04	0.003	0.013	1.517	0.467
Oil Prices	-0.24	0.11	0.041	0.060	2.474	0.290
Interest rate	-0.13	0.05	0.047	0.029	1.745	0.418

Table 4.1: Descriptive Statics

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