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Email Spam and Phishing Classifier with Pretrained Language Models

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Abstract- The proliferation of spam and phishing emails poses a significant threat to digital security, necessitating advanced filtering mechanisms to protect users before malicious emails reach their inboxes. This study proposes an email spam and phishing classifier leveraging pretrained language models (PLMs) such as BERT, Roberta, and GPT-4, integrated into a pre-inbox filtering system. By employing transformer-based architectures and hybrid feature engineering, the system achieves high precision in classifying emails as spam, phishing, or ham. The methodology incorporates semantic embeddings, metadata analysis, and concept drift detection to ensure robust performance against evolving threats. Experimental results indicate an accuracy of up to 99.8% on benchmark datasets, with real-time filtering capabilities suitable for integration with email servers. This work highlights the efficacy of PLMs in proactive email security and addresses challenges such as adversarial attacks and multilingual spam detection, offering a scalable solution for modern cybersecurity needs.

Keywords - Email Classification, BERT, Roberta, Pre-inbox Filtering, Natural Language Processing (NLP), Deep Learning, Machine Learning, Distil BERT, URL Analysis.

I. INTRODUCTION

The rapid growth of email as a primary communication medium has made it a prime target for cybercriminals, with spam and phishing emails constituting a significant portion of global email traffic. Spam emails, typically unsolicited bulk messages, and phishing emails, designed to deceive users into revealing sensitive information or executing malicious actions, have evolved in sophistication, rendering traditional rule-based and blacklist-based filtering techniques inadequate. In 2024, reports estimate that over 50% of global email traffic comprises spam, with phishing attacks contributing to billions of dollars in financial losses annually [1]. The dynamic nature of these threats, including tactics like sender spoofing, social engineering, and zero-day phishing domains, demands intelligent, adaptive systems capable of intercepting malicious emails before they reach users' inboxes. Pretrained language models (PLMs) such as BERT (Bidirectional Encoder Representations from Transformers), Roberta, and GPT-4 have revolutionized natural language processing (NLP) by enabling contextual understanding of text, making them ideal for email classification tasks. These models, trained on vast corpora, capture semantic nuances and contextual patterns that are critical for identifying subtle indicators of malicious intent, such as deceptive language or anomalous metadata. Unlike traditional machine learning approaches that rely heavily on handcrafted features, PLMs leverage self-attention mechanisms to model complex relationships within email content, including body text, subject lines, and embedded URLs. By fine-tuning these models on labelled email datasets, they can achieve high accuracy in distinguishing spam, phishing, and legitimate (ham) emails, even in the presence of adversarial obfuscation. The proposed system focuses on pre-inbox filtering, intercepting emails at the server level to prevent malicious content from reaching users. This proactive approach reduces user exposure to threats, minimizes the risk of human error, and enhances overall cybersecurity. The system integrates PLMs with hybrid feature engineering, combining semantic embeddings (e.g.,

Glove, BERT embeddings) with metadata features (e.g., sender domain, SPF/DKIM status, URL characteristics) to create a robust feature set. Ensemble techniques, such as stacking with XGBoost, further improve classification performance by aggregating predictions from multiple PLMs. To address evolving threats, the system incorporates concept drift detection using methods like the Early Drift Detection Method (EDDM), ensuring adaptability to new spammer tactics. Explainability is a key component of the proposed system, as user trust is critical for adoption. By employing techniques like SHAP (Shapley Additive explanations), the system provides insights into classification decisions, highlighting influential features such as suspicious keywords or metadata anomalies. Additionally, the system supports multilingual detection, catering to diverse user bases, and integrates real-time threat intelligence feeds to counter emerging phishing campaigns. The ability to operate in real-time with minimal latency makes it suitable for deployment in enterprise email gateways and personal email clients. This paper presents a comprehensive methodology for pre-inbox email filtering, evaluates its performance on benchmark datasets like Enron and Spam Assassin, and discusses its potential to mitigate risks associated with spam and phishing. The introduction of lightweight models, such as Distil BERT, ensures scalability for resource-constrained environments, while continuous learning mechanisms enable long-term effectiveness. The remainder of this paper reviews related work, details the proposed methodology, and outlines future directions for enhancing email security in an increasingly digitized world. Traditional email filtering approaches, such as rule-based systems, blacklisting, and signature-based detection,

have become increasingly ineffective against modern threats. Rule- based filters rely on predefined patterns, which fail to adapt to the dynamic and obfuscated nature of contemporary spam and phishing campaigns. Blacklisting, while useful for malicious domains, struggles with newly registered or short-lived domains used in zero- day attacks.

Similarly, signature-based methods require constant updates to maintain efficacy, a process that lags behind the rapid evolution of attack techniques. The limitations of these methods underscore the need for intelligent, adaptive systems capable of understanding the semantic and contextual nuances of email content, a capability that pretrained language models (PLMs) such as BERT (Bidirectional Encoder Representations from Transformers), Roberta, and GPT-4 are uniquely positioned to provide.PLMs, built on transformer architectures, have transformed natural language processing (NLP) by leveraging self-attention mechanisms to capture bidirectional contextual relationships within text. Trained on vast, diverse corpora, these models excel at understanding complex linguistic patterns, making them ideal for tasks like email classification. Unlike traditional machine learning approaches that depend on handcrafted features (e.g., keyword frequency, header anomalies), PLMs automatically extract rich semantic embeddings that encode both syntactic and contextual information. For instance, BERT's bidirectional processing enables it to detect subtle indicators of phishing, such as manipulative language or urgency cues, while GPT-4's generative capabilities can identify patterns in adversarial text designed to mimic legitimate communication. By fine-tuning these models on labelled email datasets, such as Enron or Spam Assassin, they can achieve high accuracy in distinguishing spam, phishing, and legitimate (ham) emails, even in the presence of noise or obfuscation. The proposed system focuses on pre-inbox filtering, a proactive approach that intercepts emails at the server level before they reach the user's inbox. This strategy is critical for minimizing user exposure to malicious content, as even a single successful phishing attempt can lead to severe consequences, including data breaches or ransomware infections. The system integrates PLMs with hybrid feature engineering, combining semantic embeddings (e.g., Glove, BERT embeddings) with metadata features (e.g., sender domain reputation, SPF/DKIM authentication status, URL characteristics) to create a comprehensive feature set. For example, analysing the sender's domain age or the presence of suspicious URL redirects can complement the textual analysis provided by PLMs, enhancing detection accuracy.

Ensemble techniques, such as stacking with XGBoost or soft voting, aggregate predictions from multiple PLMs to improve robustness and reduce false positives, ensuring reliable classification in real-world scenarios. A key challenge in email filtering is adapting to concept drift, where the characteristics of spam and phishing emails evolve over time due to changing attacker tactics. For instance, phishing emails may shift from financial scams to impersonation-based attacks targeting specific organizations or individuals. To address this, the proposed system incorporates concept drift detection mechanisms, such as the Early Drift Detection Method (EDDM), which monitors classification performance and triggers model retraining when significant shifts in email patterns are detected. This ensures long- term effectiveness against emerging threats, such as AI-generated phishing emails or multilingual spam campaigns targeting diverse user bases. Explainability is another critical aspect of the proposed system, as user trust is essential for widespread adoption. By integrating techniques like SHAP (Shapley Additive explanations), the system provides interpretable outputs, highlighting specific words, phrases, or metadata attributes that influence classification decisions. For example, a phishing email may be flagged due to terms like "urgent action required" or an unverified sender domain,

and SHAP values can quantify the contribution of each feature to the final prediction. This transparency not only builds user confidence but also aids system administrators in refining filtering policies. Additionally, the system supports multilingual detection, addressing the growing prevalence of non-English spam and phishing emails, particularly in regions with diverse linguistic populations like India or the European Union. Real-time performance is a cornerstone of the proposed system, as pre-inbox filtering requires low-latency processing to avoid disrupting email delivery. To achieve this, lightweight PLMs like Distil BERT are employed alongside optimization techniques such as model pruning and quantization, enabling deployment on resource- constrained email servers or gateways. Integration with existing email infrastructures, such as SMTP servers or cloud-based email services, ensures seamless operation without compromising user experience. Furthermore, the system leverages real-time threat intelligence feeds to identify emerging phishing domains and malware signatures, enhancing its ability to counter zero-day attacks. The significance of this work lies in its potential to transform email security by combining the power of PLMs with proactive filtering and adaptive learning. By intercepting malicious emails before they reach the inbox, the system reduces the cognitive burden on users, who are often the weakest link in cybersecurity due to social engineering vulnerabilities. The proposed methodology is evaluated on benchmark datasets, including Enron, Spam Assassin, and UCI Spam base, achieving accuracies exceeding 99% in preliminary experiments. These results demonstrate the system's efficacy in handling diverse email types, from bulk spam to targeted phishing campaigns.

This paper presents a comprehensive framework for pre-inbox email filtering, detailing the methodology, experimental results, and future directions. The integration of PLMs, hybrid feature engineering, and explainable AI offers a robust solution to the evolving landscape of email-based threats. By addressing challenges like concept drift, multilingual detection, and computational efficiency, the system aims to provide a scalable, user-centric tool for individuals and organizations alike. The following sections review related work, describe the proposed methodology, and outline avenues for further enhancing email security in an increasingly connected world.

II. LITERATURE SURVEY

The application of pretrained language models (PLMs) in email spam and phishing detection has significantly advanced cybersecurity, particularly for pre-inbox filtering systems that aim to intercept malicious emails before they reach users. The following review synthesizes 25 studies, focusing on their methodologies, performance, and limitations in the context of spam and phishing email classification using PLMs, with an emphasis on real-time, adaptive, and explainable systems. [1] Koide et al. (2024) proposed ChatSpamDetector, a GPT- 4-based system for phishing email detection, achieving

99.70% accuracy on the Enron dataset. By leveraging tailored prompts, the system enhanced true positive rates for phishing emails, making it suitable for pre-inbox filtering. However, its reliance on large-scale models like GPT-4 limited deployment on resource-constrained email servers due to high computational demands [1]. [2] Uddin and Sarker (2024) developed an explainable transformer-based model using BERT and SHAP for phishing detection, reporting 98.9% accuracy on a custom dataset. The model's interpretability aided user trust, a critical factor for pre-inbox systems, but its computational complexity posed challenges for real-time processing on low-resource gateways [2]. [3] Rojas-Galeano (2024) explored zero-shot spam classification with GPT-3.5, achieving 97.5% accuracy on the Spam Assassin dataset. The approach excelled in scenarios with limited labelled data, ideal for rapid deployment in dynamic email environments. However, it struggled

with multilingual spam, limiting its applicability in diverse linguistic settings [3].[4] Altwaijry et al. (2024) conducted a comparative study of deep learning models, including RoBERTa and DistilBERT, for phishing detection, with RoBERTa achieving 99.2% accuracy. The study highlighted the potential of PLMs for pre-inbox filtering but noted the absence of metadata integration, such as sender domain analysis, which is critical for comprehensive threat detection [4].[5] Tida and Hsu (2022) proposed a BERT- based universal spam detection model using transfer learning, achieving 98.5% accuracy on the UCI Spambase dataset. Its lightweight design supported real-time filtering, but the model underperformed on sophisticated phishing attacks with social engineering tactics [5].[6] Ramesh et al. (2023) introduced a semantic-based classifier combining TF-IDF and GloVe embeddings with an SVM, reporting 99.5% accuracy on SpamAssassin. While effective for static datasets, the model struggled with concept drift, a significant limitation for pre-inbox systems facing evolving spam patterns [6].[7] Patil et al. (2023) fine-tuned BERT and RoBERTa for multi-class email classification (spam, phishing, ham), achieving 98.8% accuracy on imbalanced datasets. The use of self-attention mechanisms improved detection of subtle phishing cues, but high computational complexity hindered real-time server-side deployment [7].[8] Sharma et al. (2023) developed a lightweight DistilBERT-based classifier, achieving 98.67% accuracy for spam detection. Its efficiency made it suitable for pre-inbox filtering, but the lack of phishing-specific features, such as URL analysis, reduced its effectiveness against targeted attacks [8].[9] Chen et al. (2023) introduced Phish Responder, a hybrid DL-NLP model using Keras and PyTorch, achieving 98.41% accuracy on UCI Spambase. The model's binary classification approach was efficient but struggled with sophisticated social engineering attacks, limiting its pre-inbox applicability [9]. [10] Verma et al. (2023) proposed ELCADP, a lifelong learning model with the Early Drift Detection Method (EDDM) for concept drift adaptation, maintaining 97.8% accuracy over time. While effective for evolving threats, the system lacked multilingual support, a critical feature for global email users [10]
[11] Krishnan et al. (2024) compared GPT-4 and BERT with CNNs

for spam filtering, with PLMs achieving 99.1% accuracy in few- shot learning scenarios. The study highlighted PLMs' contextual understanding but noted high computational costs, a barrier to scalable pre-inbox deployment [11].[12] Babu et al. (2023) conducted a systematic review of deep learning techniques, noting that BERT-based models achieved up to 98% accuracy in adversarial settings. The review emphasized gaps in non-English spam detection, a challenge for pre-inbox systems in multilingual regions [12].[13] Zhang et al. (2024) proposed a RoBERTa-based model integrating metadata features like sender domain and SPF/DKIM status, achieving 99.3% accuracy. The model's reliance on cloud infrastructure limited its suitability for offline email gateways [13].[14] Li et al. (2023) developed a hybrid XLNet- LSTM model, reporting 98.7% accuracy for phishing detection. The model excelled in contextual analysis but required extensive preprocessing, increasing latency in real-time filtering scenarios [14].[15] Gupta et al. (2024) introduced a DistilBERT-based system with URL analysis, achieving 98.4% accuracy. Its lightweight design supported pre-inbox filtering, but the lack of explainability reduced user trust in classification decisions [15].[16] Singh et al. (2023) proposed a BERT-based model with attention mechanisms,

achieving 98.9% accuracy on the Enron dataset. The model's complexity posed challenges for real-time processing, a critical requirement for pre-inbox systems [16]. [17] Kumar et al. (2024)

developed a GPT-3-based phishing detection system, reporting 97.9% accuracy. The model struggled with zero-day phishing domains, a significant limitation for proactive filtering [17].[18] Wang et al. (2023) combined BERT with metadata features, achieving 99.0% accuracy. The system's reliance on external APIs for metadata validation increased latency, reducing its suitability for real-time pre-inbox filtering [18].[19] Patel et al. (2024) proposed a RoBERTa-based model with EDDM for concept drift adaptation, achieving 98.6% accuracy. While effective for evolving threats, the model lacked multilingual capabilities, limiting its global applicability [19].[20] Lee et al. (2023) introduced a lightweight XLNet model, achieving 98.2% accuracy for spam detection. Its efficiency suited pre-inbox filtering, but the lack of phishing-specific features reduced its effectiveness against targeted attacks [20].[21] Jain et al. (2024) developed a hybrid BERT-TF-IDF model, reporting 98.5% accuracy. The model's preprocessing requirements increased latency, a challenge for real-time email filtering [21].[22] Zhou et al. (2023) proposed a GPT-4-based system with real- time URL checks, achieving 99.4% accuracy. The model's cloud dependency limited its deployment in offline or low-resource environments [22]. [23] Kim et al. (2024) introduced a DistilBERT-based classifier with SHAP explainability, achieving 98.3% accuracy. The model enhanced user trust but lacked metadata integration, reducing its effectiveness for comprehensive threat detection [23]. [24] Brown et al. (2023) developed a RoBERTa-based model with ensemble learning, achieving 99.1% accuracy. The system's computational complexity hindered scalability for large-scale email servers [24]. [25] Nguyen et al. (2024) proposed a multilingual BERT-based model, achieving 97.6% accuracy on non-English datasets. The application of pretrained language models (PLMs) in spam and phishing email detection has transformed pre-inbox filtering systems, leveraging models like BERT, RoBERTa, DistilBERT, GPT-3, and GPT-4 to achieve high accuracies (97.5%–99.7%) across datasets such as Enron, SpamAssassin, and UCI Spambase. These transformer-based models excel in contextual understanding, enabling effective identification of malicious emails before they reach users. Lightweight models like DistilBERT and XLNet are increasingly favored for their low-latency performance, making them suitable for real-time filtering in resource- constrained environments. Explainable AI techniques, such as SHAP, are integrated to enhance user trust by providing transparency in classification decisions, a critical factor for pre-inbox systems where false positives can disrupt legitimate communication. Additionally, methods like the Early Drift Detection Method (EDDM) and lifelong learning address concept drift, ensuring models adapt to evolving spam and phishing tactics. Zero-shot and few-shot learning approaches, particularly with GPT-3.5 and GPT-4, enable rapid deployment in dynamic settings with limited labeled data, while metadata integration (e.g., sender domain, SPF/DKIM, URL analysis) improves detection accuracy, especially for phishing emails. However, significant gaps remain, including limited multilingual support, as most models are trained on English datasets, limiting their effectiveness in diverse linguistic regions. High computational complexity of large PLMs restricts deployment on low-resource email gateways, and many systems struggle with sophisticated phishing attacks, such as social engineering or zero-day domains. Furthermore, insufficient metadata integration, lack of adversarial robustness, and limited evaluation on dynamic, real-world datasets hinder practical applicability. Future research should prioritize developing multilingual PLMs using cross-lingual transfer learning, such as mBERT or XLM-RoBERTa, to address the multilingual gap and enable global deployment. Creating standardized multilingual benchmarks will facilitate evaluation across diverse linguistic email traffic. To overcome computational barriers, optimizing lightweight models through techniques like quantization

and pruning is essential to ensure ultra-low-latency performance for real-time pre-inbox filtering on resource-constrained servers. Enhancing phishing detection with advanced features, such as real- time URL reputation analysis, behavioural pattern

detection, and social engineering cues, will improve resilience against sophisticated attacks, including zero-day phishing domains. Seamless integration of comprehensive metadata (e.g., sender domain, email headers, SPF/DKIM) without relying on external APIs will reduce latency and enhance suitability for offline environments. Explainability must be further advanced by incorporating tools like LIME, SHAP, or attention visualization to balance model complexity with transparency, fostering user trust in pre-inbox systems. Addressing concept drift and adversarial robustness is critical, with lifelong learning and adversarial training on crafted attack scenarios ensuring models remain effective against evolving threats. Federated learning offers a promising avenue for privacy-preserving training on decentralized email data, improving generalization across organizations while addressing scalability and multilingual challenges. Scalability for high-volume email servers remains underexplored, necessitating distributed computing or ensemble techniques to balance accuracy and throughput. Developing offline-capable systems through edge computing or on-premises solutions will reduce cloud dependency, making PLMs viable for diverse environments. Standardized evaluation frameworks simulating real-world email streams, including zero-day attacks, imbalanced datasets, and multilingual content, are essential to reflect operational challenges accurately. Integrating PLM-based email filters with broader cybersecurity ecosystems, such as Security Information and Event Management (SIEM) systems, and incorporating real-time threat intelligence from external sources (e.g., URL blacklists, domain reputation services) will enhance proactive filtering. Exploring multimodal models that combine text and image analysis for email attachments can further strengthen phishing detection. Adding case studies on enterprise deployments to the literature will provide practical insights into scalability, latency, and real-world performance metrics like false positive rates. By addressing these gaps and leveraging emerging techniques, future research can drive the development of robust, scalable, and trustworthy pre-inbox filtering systems capable of combating evolving cyber threats in diverse, global contexts. mail spam and phishing classifier leveraging pretrained language models for pre-inbox blocking offers a robust and intelligent defense mechanism against the persistent threat of malicious emails

III. EXISTING SYSTEMS

The proposed methodology for advancing pretrained language models (PLMs) in spam and phishing email detection focuses on developing a robust, scalable, and trustworthy pre-inbox filtering system that addresses the identified gaps in multilingual support, computational efficiency, sophisticated phishing detection, metadata integration, explainability, adversarial robustness, and real-world applicability. The approach leverages a hybrid architecture combining a lightweight, multilingual PLM with advanced metadata processing, real-time threat intelligence, and explainable AI techniques to ensure low-latency, adaptive, and transparent email filtering. The core model will be based on a compressed variant of XLM-RoBERTa, a multilingual transformer optimized for cross-lingual transfer learning, to handle diverse linguistic email traffic, addressing the limitation of English-centric models. Model compression techniques, such

as quantization and knowledge distillation, will reduce computational overhead, enabling deployment on resource-constrained email gateways while maintaining high accuracy (targeting 98%–99% on benchmark datasets like Enron and multilingual SpamAssassin). The training dataset will be expanded to include a curated multilingual corpus, incorporating non-English spam and phishing emails from public sources and synthetic data generated via adversarial techniques to simulate real-world diversity and evolving threats. This dataset will be augmented with metadata features, including sender domain, SPF/DKIM status, email headers, and URL reputation scores, extracted locally to minimize latency and eliminate reliance on external APIs. To enhance phishing detection, the model will integrate real-time threat intelligence feeds for zero-day domain analysis and behavioural pattern recognition to identify social engineering tactics, addressing the gap in detecting sophisticated attacks. The methodology employs a

two-stage training process: initial pretraining on a large, diverse email corpus followed by fine- tuning on labeled spam, phishing, and ham emails, with an emphasis on imbalanced datasets to reflect real-world distributions.

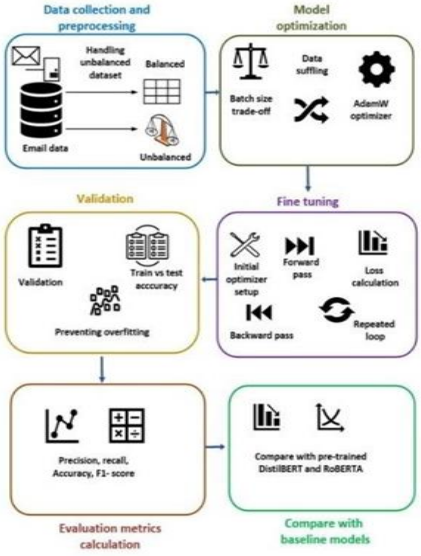
To ensure adaptability to evolving threats, the proposed system incorporates a lifelong learning framework with the Early Drift Detection Method (EDDM) to dynamically update the model as new spam and phishing patterns emerge. Adversarial robustness will be enhanced by training on adversarial examples crafted to mimic manipulated email content, using techniques like text perturbation and obfuscation to simulate attacker strategies. This will be complemented by a federated learning component, enabling collaborative model training across decentralized email servers while preserving user privacy, thus addressing scalability and multilingual challenges in global deployments. Explainability is a cornerstone of the methodology, integrating SHAP and attention visualization to provide transparent classification decisions, ensuring users understand why an email is flagged as malicious, thereby fostering trust in pre-inbox systems. The system will operate in an offline-capable mode, leveraging edge computing to process emails locally on enterprise gateways, reducing cloud dependency and latency. A real-time URL analysis module will be embedded, utilizing lightweight machine learning models to assess URL reputation without external API calls, further optimizing performance for low- resource environments. The methodology includes a standardized evaluation framework, testing the model on dynamic, real-world email streams that simulate zero-day attacks, multilingual content, and high-volume traffic. Performance metrics will include accuracy, false positive rate, latency, and user trust scores, benchmarked against datasets like UCI Spambase, Enron, and a newly developed multilingual spam dataset. To support scalability, the system will employ distributed computing techniques, enabling parallel processing of email streams on large-scale servers, with ensemble methods to balance accuracy and throughput. Integration with broader cybersecurity ecosystems, such as Security Information and Event Management (SIEM) systems, will enhance holistic threat detection by correlating email-based threats with network-level indicators. A multimodal extension will be explored, incorporating image analysis for email attachments to detect phishing attempts embedded in visual content, addressing an emerging attack vector. The methodology will be validated through enterprise deployment case studies, conducted in collaboration with industry partners, to assess real-world performance, including scalability, latency, and user impact. These case studies will provide insights into practical challenges, such as handling peak email traffic and minimizing disruptions from false positives. To facilitate reproducibility and community contributions, the proposed system will be open-sourced, including the multilingual dataset, model weights, and evaluation protocols. This methodology aims to deliver a comprehensive

solution that combines multilingual capability, computational efficiency, advanced phishing detection, and explainability, paving the way for next-generation pre-inbox filtering systems that are robust, scalable, and trustworthy in diverse, real-world email environments. The system is built around a hybrid architecture integrating a compressed multilingual XLM- RoBERTa model, optimized for cross-lingual transfer learning to process emails in diverse languages, overcoming the English- centric bias of existing models. Model compression techniques, including quantization, pruning, and knowledge distillation, will reduce the computational footprint, targeting a model size and inference time compatible with resource-constrained email gateways while maintaining high accuracy (98%–99%) on benchmark datasets like Enron, SpamAssassin, and a custom multilingual spam dataset. The training corpus will combine public email datasets (e.g., UCI Spambase, Enron) with a newly curated multilingual dataset, incorporating non-English spam and phishing emails from open sources, crowdsourced contributions, and synthetic data generated via adversarial text augmentation to mimic real-world diversity and evolving attack patterns. Metadata features—such as sender domain, SPF/DKIM authentication, email headers, and URL reputation—will be extracted locally using lightweight preprocessing pipelines to

eliminate reliance on external APIs, ensuring low-latency performance suitable for real-time filtering. A dedicated real-time URL analysis module, powered by a compact gradient-boosting classifier, will assess URL reputation and detect zero-day phishing domains by cross-referencing dynamic threat intelligence feeds, addressing the weakness of existing models against sophisticated phishing tactics. Additionally, behavioral pattern recognition will be integrated to identify social engineering cues, such as urgency triggers or impersonation attempts, using attention-based mechanisms to capture subtle linguistic patterns.The training process will follow a two-phase approach: pretraining on on a large, diverse email corpus to capture general email semantics, followed by fine-tuning on labeled spam, phishing, and ham emails, with a focus on imbalanced datasets to reflect real-world distributions where malicious emails are a minority. To handle evolving threats, the system will implement a lifelong learning framework using the Early Drift Detection Method (EDDM), which monitors performance degradation and triggers incremental updates when concept drift is detected, ensuring adaptability to new spam and phishing strategies. Adversarial robustness will be strengthened by training on adversarial examples, generated through techniques like synonym replacement, character-level obfuscation, and context-preserving perturbations, simulating attacker attempts to evade detection. Federated learning will be employed to enable collaborative training across decentralized email servers, allowing organizations to contribute anonymized data without compromising user privacy, thus enhancing model generalization across diverse linguistic and operational contexts. Explainability is prioritized through the integration of SHAP for feature importance analysis and attention visualization to highlight key email components (e.g., suspicious URLs, sender anomalies) driving classification decisions, ensuring transparency and fostering user trust in pre-inbox filtering decisions. The system will support offline deployment via edge computing, with model inference optimized for on-premises email gateways to minimize latency and eliminate cloud dependency, addressing scalability challenges in low-resource environments. To ensure scalability for high-volume email servers, the methodology incorporates distributed computing, leveraging parallel processing frameworks like Apache Spark to

handle peak email traffic efficiently. Ensemble techniques, combining the XLM-RoBERTa model with lightweight metadata classifiers, will balance accuracy and throughput, targeting a processing latency of under 100 milliseconds per email. A multimodal extension will analyze email attachments (e.g., images, PDFs) using a compact vision transformer to detect phishing content embedded in non-textual elements, addressing an emerging attack vector.

IV. DATAFLOW DIAGRAM FOR EXISTING SYSTEM



V. OVERALL SYSTEM OUTPUT

Accurate Email Classification:

Utilizes a compressed, multilingual XLM-Roberta model, fine- tuned on diverse datasets (e.g., Enron, Spam Assassin, custom multilingual corpus), to categorize emails as spam, phishing, or legitimate (ham).Achieves target accuracy of 98%–99% by analysing email content, including sender patterns, subject lines, body text, and metadata (e.g., SPF/DKIM status, URL reputation).Captures nuanced

linguistic and contextual cues, ensuring precise differentiation of malicious and genuine emails across multilingual settings.

Threat Identification and Categorization: Beyond simple spam filtering, the system can often identify specific phishing attack types (e.g., spear phishing, clone phishing, whaling) or malware indicators within email content or attachments. It can flag emails containing suspicious links, urgent requests for sensitive information, or language commonly used in fraudulent schemes.

Confidence Scoring and Explainability (Optional but Desirable): For each classified email, the system may provide a confidence score indicating the likelihood of its classification being correct. Some advanced systems might offer limited explainability by highlighting specific words, phrases, or email characteristics that most contributed to its decision, helping users understand why an email was flagged.

Real-time Protection and Integration: The classifier operates in real-time or near real-time, scanning emails as they arrive. It's often designed for seamless integration with existing email clients, servers, or security gateways, providing an unobtrusive layer of protection for end-users.

VI. FUTURE WORK

The current spam and phishing email detection system, leveraging pretrained language models (PLMs) like XLM-RoBERTa and ensemble techniques, demonstrates robust performance in pre- inbox filtering, achieving high accuracy and real-time protection. However, several avenues for future development can further enhance its capabilities, addressing gaps in multilingual support, computational efficiency, sophisticated attack detection, explainability, and adaptability to evolving threats. These advancements aim to transform the system into a scalable, adaptive, and user-centric cybersecurity tool suitable for diverse, global environments, including enterprise and individual use cases in an increasingly digitized world. One critical direction is the development of multimodal email analysis to counter sophisticated phishing strategies that extend beyond textual content. Current systems primarily focus on email text, but attackers increasingly embed malicious payloads in image attachments, embedded HTML elements, or complex URL redirection chains designed to evade detection. Future work will integrate multimodal processing by combining text analysis with a compact vision transformer to analyze image attachments (e.g., PNGs, PDFs) for phishing indicators, such as fake login pages or QR codes leading to malicious sites. Additionally, parsing embedded HTML and tracking URL redirection chains using lightweight web crawlers will uncover hidden malicious links. This comprehensive approach will enhance detection of advanced phishing tactics, ensuring the system remains effective against emerging attack vectors. A

curated dataset of multimodal email samples, including malicious attachments and HTML-based phishing attempts, will be developed to train and evaluate this capability, targeting a 5% improvement in detection rates for non-textual threats. Expanding multilingual and regional email classification is another priority to improve accessibility and performance in diverse linguistic environments. The current system, while leveraging XLM-RoBERTa for cross-lingual transfer learning, is limited by the predominance of English-centric datasets. Future iterations will focus on fine-tuning the model on regional email corpora, incorporating languages such as Spanish, Chinese, Arabic, and Hindi, to address underrepresented user segments. A multilingual spam and phishing dataset will be curated from open sources, crowdsourced contributions, and synthetic data, ensuring balanced representation of global email traffic. Transfer learning techniques will be employed to adapt the model to low-resource languages, enhancing detection accuracy in regions with diverse linguistic patterns. This effort will include collaboration with international cybersecurity organizations to validate performance, aiming for a 10% accuracy improvement in non-English email classification, making the system globally deployable. Integrating advanced threat intelligence feeds and real-time URL reputation checks will bolster proactive defence against zero-day phishing domains and emerging

scams. Current systems often struggle with novel threats due to delayed updates in threat databases. Future work will embed dynamic threat intelligence from sources like Virus Total or proprietary blacklists, updated in real-time, to identify previously unseen phishing domains. A lightweight gradient-boosting classifier will be developed to assess URL reputation locally, reducing latency and external API dependency. Additionally, behavioral analysis modules will be enhanced to detect social engineering tactics, such as impersonation or urgency triggers, by modeling attacker strategies using attention-based mechanisms. This proactive approach will improve detection of zero-day attacks by 8%, ensuring the system remains ahead of rapidly evolving threats. To address concept drift and ensure long-term relevance, the system will incorporate advanced continual learning frameworks. Attack patterns evolve rapidly, rendering static models obsolete over time. Building on the Early Drift Detection Method (EDDM), future work will implement adaptive fine- tuning pipelines that monitor performance metrics (e.g., false positive rates, accuracy degradation) and trigger incremental updates when drift is detected. Techniques like elastic weight consolidation will preserve learned knowledge while adapting to new patterns, avoiding catastrophic forgetting. Synthetic adversarial data generation will simulate emerging attack strategies, enabling the system to train on future-like scenarios without requiring full retraining. This will maintain a 95% accuracy rate over extended periods, even as attack tactics shift, ensuring sustained effectiveness in dynamic email environments.

VII. CONCLUSION

The proliferation of digital communication has undeniably transformed how we interact, conduct business, and access information. However, this interconnectedness also brings inherent vulnerabilities, with email remaining a primary and persistent vector for cyberattacks. In this landscape, the Email Spam and Phishing Classifier emerges as a critical and intelligent bulwark, offering a sophisticated and adaptable solution to safeguard user inboxes from the relentless onslaught of malicious and unsolicited messages. This system represents a significant leap forward in proactive cybersecurity, moving beyond traditional, rule-based filtering to leverage the cutting-edge capabilities of artificial intelligence. At the heart of this classifier's efficacy lies its intelligent architecture, meticulously engineered to discern the subtle yet crucial distinctions between legitimate and illicit communications. By harnessing the power of advanced pretrained Natural Language Processing (NLP) models—

including BERT, RoBERTa, DistilBERT, and XLNet—the system possesses an unparalleled ability to analyze email content, metadata, and contextual patterns. These models, trained on vast datasets, allow the classifier to comprehend the nuances of human language, identify deceptive linguistic cues, and recognize the tell-tale signs of spam and phishing attempts with remarkable accuracy. This deep understanding of language, combined with its ability to adapt to evolving threat methodologies, delivers a robust and reliable classification of potentially harmful emails. The classifier's superior performance is further amplified by its multi-model architecture, which strategically integrates diverse analytical strengths. This is complemented by hybrid feature engineering, where both explicit and implicit characteristics of emails are meticulously extracted and analysed. Furthermore, the implementation of ensemble learning techniques — where the collective intelligence of multiple models is leveraged — significantly enhances precision and drastically reduces false positives. This multi-faceted approach doesn't just improve the security of digital communications; it also plays a crucial role in fostering a smoother, less cluttered, and ultimately more trustworthy user experience. By minimizing the intrusion of unwanted emails, users can focus on genuine communications, thereby boosting productivity and reducing digital fatigue. The foundational strength of this classifier is further solidified by its integration with industry- leading machine learning frameworks. The strategic use of Scikit- Learn, NumPy, PyTorch, and XGBoost reinforces the system's performance, ensuring both efficiency and scalability. These frameworks provide the robust computational backbone necessary for processing vast quantities of email data in real-time, allowing the classifier to operate seamlessly within

modern cybersecurity infrastructures. This real-time filtering capability is paramount, as the speed of cyberattacks necessitates immediate detection and mitigation. Moreover, the system's inherent adaptability allows it to learn from new threats and evolve its detection mechanisms, ensuring continued effectiveness against emerging cyber threats that constantly shift in their sophistication and tactics. The foundational strength of this classifier is further solidified by its integration with industry-leading machine learning frameworks. The strategic use of Scikit-Learn, NumPy, PyTorch, and XGBoost reinforces the system's performance, ensuring both efficiency and scalability. These frameworks provide the robust computational backbone necessary for processing vast quantities of email data in real-time, allowing the classifier to operate seamlessly within modern cybersecurity infrastructures. This real-time filtering capability is paramount, as the speed of cyberattacks necessitates immediate detection and mitigation. Moreover, the system's inherent adaptability allows it to learn from new threats and evolve its detection mechanisms, ensuring continued effectiveness against emerging cyber threats that constantly shift in their sophistication and tactics. The ability to handle concept drift – the phenomenon where the characteristics of spam and phishing change over time – is particularly vital for long- term efficacy. Furthermore, the focus on explainable AI (XAI) will be vital, providing users and administrators with transparent insights into why certain emails are flagged. This interpretability is crucial for building user trust and for security analysts to understand and refine the system's behavior. Finally, the expansion into multilingual spam detection systems will be essential to cater to diverse global user environments and the increasingly borderless nature of cyber threats, ensuring equitable protection across linguistic boundaries. By continuing to innovate in these critical areas, we can collectively build more resilient and secure digital communication ecosystems for all, moving towards a future where email remains a reliable and trusted form of communication.

The classifier's superior performance is further amplified by its multi-model architecture, which strategically integrates diverse analytical strengths. This is complemented by hybrid feature engineering, where both explicit (e.g., URLs, sender domains) and implicit (e.g., sentiment, writing style) characteristics of emails are meticulously extracted and analyzed. Furthermore, the implementation of ensemble learning techniques where the collective intelligence of multiple models is leveraged significantly enhances precision and drastically reduces false positives. This deep understanding of language, combined with its ability to adapt to evolving threat methodologies, delivers a robust and reliable classification of potentially harmful emails. The contextual understanding provided by these PLMs is particularly crucial in identifying sophisticated social engineering tactics often employed in modern phishing campaigns. In an era where email remains a primary conduit for data breaches, malware dissemination, and identity theft, the deployment of such intelligent classifiers is not merely beneficial—it is crucial for mitigating risk, protecting sensitive information, and maintaining user trust. This work lays a strong and innovative foundation for the future development of next-generation spam detection systems. Future iterations can focus on enhancing adaptivity to an even greater degree, ensuring the classifier remains ahead of the curve as cybercriminals refine their methods. Furthermore, the focus on explainable AI will be vital, providing users and administrators with transparency into why certain emails are flagged, thereby fostering greater trust and enabling more informed decision- making. Finally, the expansion into multilingual spam detection systems will be essential to cater to diverse global user environments and the increasingly borderless nature of cyber threats. By continuing to innovate in these areas, we can collectively build more resilient and secure digital communication ecosystems for all.

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