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AI-Oriented Phishing Detection System for the Strengthening of Security in Social Networks

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ABSTRACT

Phishing attacks on mobile users through messaging applications and social media are increasing in severity and have forced the need for proactive and automated detection methods. This paper presents a Mobile Phishing Link Detection System that uses machine learning and external threat intelligence on suspicious URLs received by notifications from emails, messaging apps, and social media (WhatsApp, Instagram, and Facebook). The detection system uses an ONNX-based neural network trained for mobile inference, a MongoDB database for fast local phishing link investigation, and the VirusTotal API for conditional external verification. The user is alerted and notified in real-time via foreground service notifications, and does not need to interact with the app to receive a notification. Evaluating the performance of the system resulted in evidence of the final ONNX model post-processing level having a precision of 94.6 percent and an F1-score of 93.1 percent. The latency tests showed a response time of 30 ms, 50 ms, and 500 ms when using the MongoDB database, model, and VirusTotal API, respectively. The system provides an efficient, scalable, identity-preserving solution for real-time detection of mobile phishing because it aims to provide strong protection against the occurrence of zero-day threats and increase the level of user security in an ever-changing mobile environment.

Keywords: *Phishing Detection, Machine Learning, ONNX, Threat Intelligence, Mobile Security, Cybersecurity, URL analysis.*

1. INTRODUCTION

Phishing attacks that originate on mobile devices and through messaging apps and social media platforms have become a major threat actor in cybersecurity. The methodologies that cybercriminals employ continue to become more disguisable, taking advantage of the characteristics of mobile devices: limited screen space, streamlined user experience, and the built-in trust of known platforms, all playing into the users' ability to detect deception. Most of these will impersonate legitimate services that lure users into clicking links (s) and the disclosure of sensitive information. The number of tasks being routed through mobile devices - banking, communication, and e-commerce - has changed the behavior of mobile device phishing into a meaningful threat.

The traditional solutions for anti-phishing primarily take the form of browser blacklists and user-provided manual reports. These approaches do not allow for the detection of rapidly changing, obfuscated phishing attacks in today's landscape. Static solutions used to protect against static phishing attacks are insufficient when dealing with rapidly changing mobile threats. Furthermore, it is non-real-time and does not allow for the detection of potential threats until manual reporting occurs. The reality is that there is a need for intelligent automated systems that can detect phishing attempts - previous, current, and future. Ultimately, organizations need mobile solutions that provide proactive detection of threats, especially in real-time mobile environments.

To tackle this challenge, this work proposes a Mobile Phishing Link Detection System that combines machine learning and threat intelligence services. The detection system passively scans the link notifications from the like applications like WhatsApp, Instagram, and SMS when the user uses the app and passively extracts the URLs from the notifications, and all those links are analyzed. The system uses an ONNX-optimized neural network to allow for lightweight inference in real-time on a mobile device. A MongoDB database is used to allow for fast lookups, and for verification of suspicious links, the

VirusTotal API is leveraged. This research applies an innovative architecture that has multiple layers for detection, while giving priority to speed and accuracy, so that alerts for phishing URLs can be done in real-time, without user consent. The suggested system performs very well on accuracy, precision, recall, and F1-score, with latencies low enough to allow for deployment in the mobile environment where time is measured in milliseconds. This work makes three specific contributions, (1) we design and implement a lightweight, yet accurate phishing detection engine for mobile devices, (2) we make use of external threat intelligence for a multi-layer verification process, and (3) we add a notification to user real-time alert framework to help raise the users' detection abilities and reaction time. The other sections will delve more deeply into the related work, system architecture, methodology, experimental evaluation, and future work.

2. RELATED WORK

The increasing prevalence of phishing has led to various phishing-based detection methods and approaches, ranging from rule-based filtering to intelligent classifiers, etc. However, most of these approaches are desktop-based, and mobile-based detection has received limited attention despite mobile phished attacks growing in prevalence.

Limitations of Traditional Phishing Detection Techniques

Traditional phishing detection relies on static blacklists, realized in heuristic-derived filters, or reporting by users. Services like Google Safe Browsing, or OpenPhish, maintain curated lists of suspicious or harmful URLs, and when blocking URLs, they have identified or flagged as dangerous [1], [2]. Although blacklist-based methods block previously identified phishing domains, blacklists-based methods are inherently reactive, particularly for zero-day attacks and fast-changing phishing strategies [3]. Heuristic approaches improve upon blacklists by using parsimonious features like URL Length, special characters, or suspicious keywords, but do not generate suitable detection and lack adaptability, while having a substantial positive rate [4]. Additionally, all manual efforts, such as user reporting and browser warnings, are fallible and cannot prevent phished implementations [5].

Machine Learning and Threat Intelligence-Based Solutions

Machine learning has been widely utilized for phishing detection applications because of its ability to generalize from rich feature URL datasets. Classifiers such as Random Forest, Support Vector Machines (SVM), and Na¨ıve Bayes classifiers resulting positively on phishing URLs detection with lexical and domain-based features [6], [7] Big recent efforts have taken a step even further by investigating deep learning models, which offers more detection accuracy than the classical machine learning techniques, with increased compute costs that affect usability on mobile devices [8]. Due to the ubiquity of third-party threat intelligence services, some methods have switched to pragmatically verifying flagged URLs with multi-source reputational data, like VirusTotal, PhishTank, and URLScan.io [9], [10]. However, these services can quickly analyze flagged URLs using API calls, yielding latency and dependency on third-party services.

To resolve these opportunities, our architecture combines a lightweight neural network optimized by ONNX to conduct fast local inference and conditional threat intelligence lookups. The architecture is a hybrid approach to high phishing URLs detection accuracy based on low false positive rates, while achieving low latency and lightweight designs for mobile use [11], [12].

System Design and Architecture

To support seamless interoperability for all mobile-side components with backend services, the system features a modular communication architecture based on RESTful APIs. Each of the modules - notification capture, URL analysis, inference, and alerting - can fully function in a modular way, but still cohesively. By taking a modular approach, we allow the system to scale and provide the ability to reconfigure individual components in the future. For instance, replacing the machine learning model and integrating new threat feeds is simple, as there is no need to reconfigure the entire system. The use of lightweight, standard data formats (for example, JSON) minimizes bandwidth on mobile devices around the communication payload. This allows for real-time interaction while keeping the response time of the system low and stable under varying network loading. The modular design of the system also provides the flexibility to adapt to future threats, based on any changes in the specification of how Android encodes new or existing notification types, or any threatening engagement involving that notification. All-in-all, the architecture gives not only flexibility but also durability, a necessity for implementing mobile threat detection systems.

System Workflow Overview

The Mobile Phishing Link Detection System is based on a multi-component workflow that will help us detect phishing links in real-time from mobile notifications. When we receive a message from a messaging application, e.g., WhatsApp, Instagram, SMS, etc., we will first intercept the notification with Android's NotificationListenerService [1]. Next, we will extract the linked URLs and first check a local MongoDB database of already known phishing links [2]. If the URL is new or unclassified, we will classify it using a lightweight ONNX-optimized neural network model deployed on a backend server [3]. If we are uncertain about the site's classification, wewill also issue a conditional request to VirusTotal, an external threat intelligence provider [4]. After classifying the URL and/or querying VirusTotal, we then present the user with a real-time

alert from within the mobile app. Our system is built for speed, accuracy, and minimal user interruption. Figure 1 shows how the various components interact in the detection pipeline: from message capture to alert generation.

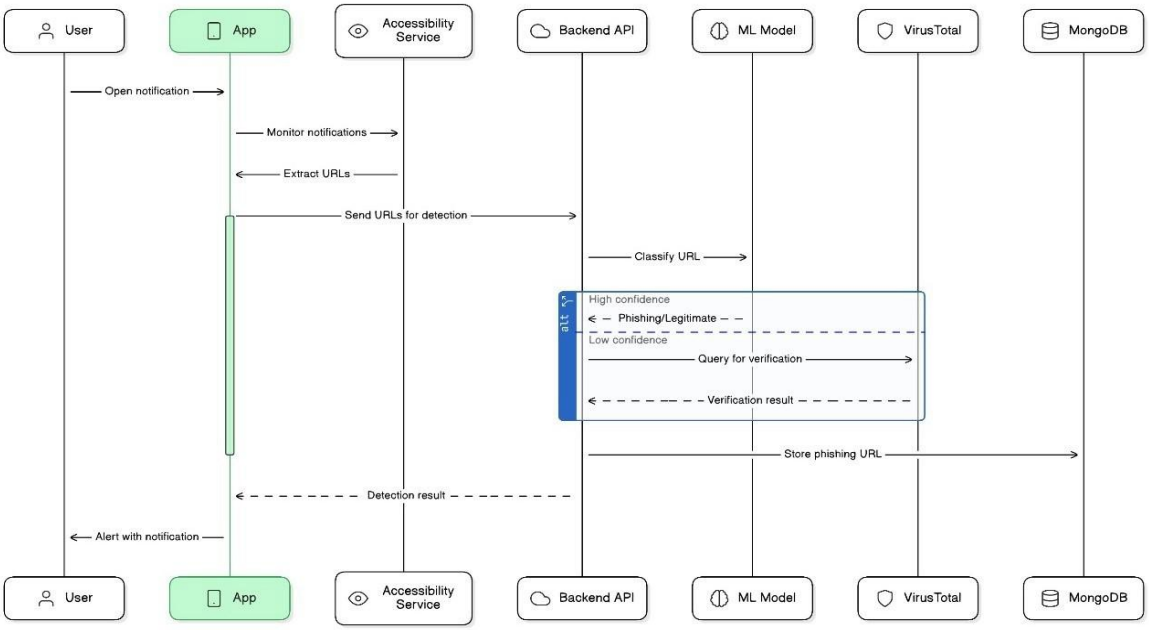

Figure 1: System flowchart showing real-time interaction between components for phishing URL detection and verification.

Android-Based Mobile Components

The Android client application passively registers notification interactions utilizing the built-in

NotificationListenerService API, which allows for immediate access to messages and actions without user interaction [1]. In tandem with the NotificationListenerService API, an Accessibility Service is used to gather metadata associated with the messages (e.g., app source, time-datestamp, sender info, and other relevant data) [5]. When the application exposes various URLs, they are bundled with the metadata and relayed to the backend for processing. The application also has a very light user interface (UI), which informs the user when it has identified a link containing malicious or potentially malicious content. The application has been designed for low battery and memory consumption and with the ability to utilize background services when andwhere needed, without degrading the mobile experience for the user. By being able to passively capture information and actively receive feedback from the mobile interface, the mobile user interface acts as an active first line of defense to alert the user before they have the chance to interact with susceptible content. This would enhance user safety and does not require continued interaction, which sets itself up as a unique solution for real-world mobile usage [6].

Backend Detection Engine Architecture

The backend server, built on Flask and RESTful APIs, serves as the central processing node in our detection architecture. After receiving a URL, the backend first checks against a MongoDB collection containing links we know to be phishing to avoid duplicate classification [2]. If the link is not in the collection, the URL is fed to a pre-trained neural network model we converted from Tensorflow to the ONNX format for deployment [3]. Using ONNX, we can deploy the model in a cross-platform manner, using the same model (saving time) in an optimized manner for either an edge or server environment. In this case, we minimize latency while preserving accuracy. Our classification model estimates phishing probability based on its assessment of lexical, structural, and behavioral feature values. The backend server will make inferences to serve multiple requests simultaneously, and can technology solutions distribute the load so as not to strain a request. The inference classifications are returned to the mobile app in under a hundred milliseconds for a seamless experience. Modular capabilities of the backend allow merging with future models and threat sources, improving adaptability to the always-changing threat space [7].

External Threat Intelligence Integration

The system connects with external threat intelligence using the VirusTotal API to confirm borderline or dubious classification results [4]. If the ONNX model returns a confidence score that is equal to or less than a threshold defined by the user, the URL is put into VirusTotal, which checks the URL against many different antivirus engines and databases. The response typically has reputation scores, flagged indicators, and threat metadata, and is parsed for additional support for classification

[8]. The benefit of this secondary verification is the reduction of false negatives, especially for phishing links, novel, or zero-day phishing links not found in the training data. The call to VirusTotal occurs conditionally and can introduce performance delay on the system. All returned data is also cached in memory to avoid sending a duplicate request to VirusTotal. Overall, the two together create a hybrid architecture that can provide high confidence in phishing detection in mobile-first user environments [9].

Methodology

This section details the concrete methodology to design a mobile phishing detection system using machine learning and external threat intelligence. The methodology involved four major components: Data Acquisition and Preprocessing, Feature Extraction, Machine Learning Model Deployment and Optimisation, and Threat Intelligence Integration. Each component is necessary to ensure that an efficient, lightweight detection system can operate in a mobile environment with a focus on minimizing latency and maximizing accuracy during real-time detection. In total, the system runs a hybrid detection pipeline with ONNX-optimised neural network inference, then checks external APIs (i.e., VirusTotal) to combat evolving phishing threats. Due to the modular nature of the methodological pipeline, evidenced in recent research on modern cyber-defence systems [1], [3], [18], the methodology enables the ability to build upon systems and create expandable assets. The two sub-sections below will describe further details on each aspect of the methodology.

Data Collection and Preprocessing

Data quality is a key determinant of the credibility of any machine learning system. Using phishing URLs from PhishTank and OpenPhish, and legitimate URLs from the Alexa Top Domains list [5], [13], a diverse and balanced dataset was constructed. Care was taken to use good data quality management processes to ensure the integrity of the dataset by taking the following preprocessing steps: First, we normalized URLs to a comparable format (e.g., lower-case URLs, removing trailing slashes), after removing duplicate URLs, and screening for corrupted URLs to ensure the model would only learn from truly meaningful patterns, to avoid learning from irrelevant, noisy data. Second, entries with inconsistent or missing data values were either corrected with common-sense contextual rules or removed altogether; both procedures improved cleanliness. Data cleanliness is of paramount importance in producing a model with good generalization performance, which is critical for a system that will be deployed in real-time and on mobile devices. We used stratified sampling to define the datasets, while preserving the ratio of classes in the training set, validation set, and test set, to accommodate the imbalanced data situation often encountered in phishing detection tasks [6], [14].

Feature Engineering and Representation

Feature extraction lies at the heart of the model's capacity to discriminate between genuine URLs and phishing URLs. Lexical and semantic features were obtained from automated parsers. Lexical features included URL length, the number of dots, the boolean presence of special characters such as "@" or "-", the boolean presence of verbiage like "verify" or "login" or other suspicious terms, and so on. Structural features considered domain reputation, the use of an IP address instead of a domain name, or redirect depth, and were guided by prior work that highlighted important similarities between phishing websites [4], [10], [13]. Contextual features included domain age specific to WHOIS data from the host domain, to help identify recently registered malicious domains. This hybrid approach attempts a balance between static indicators and behavioral indicators. Feature normalization and encoding procedures were implemented to create machine-readable datasets while preserving variability. The resulting dataset was resilient to common evasion techniques typically employed by attackers (e.g., obfuscating URLs, misrepresenting domain names in sub-domain links).

Model Selection and Neural Network Design

Various machine learning models were examined to identify the most suitable architecture for mobile phishing detection applications. Random Forest and SVM yielded good performance as baseline models; however, the mobile context still highlighted latency and scalability issues as well [1], [17]. A deep learning-based neural network was selected because it was able to produce superior results in capturing complex, non-linear patterns within the dataset and could adapt (and perhaps change) with the continually evolving threat landscape. Once a model was built in TensorFlow, ONNX was used to convert the model to support optimized inference for mobile environments without losing inference accuracy. Since ONNX supports cross-platform compatibility and optimized execution speed performance, the conversion process can create a pruned model, which removes some underlying layers as needed, but still retains accuracy [2], [11]. Tuning between a number of hyperparameters (learning rate, dropout, and epochs) required a grid search to find effective tuning combinations while still maintaining some consistency on training stability and reducing overfitting. The resulting model is capable of balancing accuracy and responsiveness, incorporating all relative accuracy gains over the models trained without dropping available performance, which minimizes the usage of device resources and allows the continuous process of phishing detection on the device without user interruption or degradation of battery life.

Optimization for Mobile Inference

To maximize real-time usability, the model underwent numerous optimization steps. For example, quantization reduced the precision of weights and activations from 32-bit float to 8-bit integer. This transition resulted in the model having a very

small memory footprint and inference latency. Model pruning techniques reduced the number of neurons and layers to the absolute minimum with little performance cost; this produced an efficient runtime profile [12], [18]. Training was augmented with cross-validation and early stopping methods to limit overfitting. Fast inference was further augmented using an ONNX runtime, which is best suited for fast and lightweight operations on an Android deployment. For most classification tasks, we achieved latency under 15 ms, and in some cases, it was even lower. In certain tasks, we outperformed other traditional models, while still satisfying performance benchmarks important to mobile. The system's real-time ability is essential to sounding a warning before a user interacts with any phishing content. Overall, we are confident that we can make the model work in low-resource contexts and at high precision, and be flexible enough to interface with more mobile hardware configurations in the future to enable mass deployment scenarios [6], [16].

Integration of Threat Intelligence Services

The phishing detection pipeline employs external threat intelligence to establish detection trustworthiness in low-trust predictions. When the prediction has inadequate trustworthiness to transition to an elevated flag, we forward the URL to VirusTotal, which aggregates reports from several antivirus engines and security feeds [3], [22]. This conditional-verification layer ensures that our evaluation of uncertain threats incorporates a broader context when reducing false negatives and false positives. VirusTotal returns other metadata, which includes detection scores, domain reputation, classification history, etc. We aggregate this with the model's internal prediction value, which allows us to make a final decision. The external API call is made asynchronously and only if necessary, which ensures that overall system performance is preserved. This hybrid architecture creates a real-time detection mechanism that is maximally reliable, specifically concerning zero-day attacks or newly crafted phishing techniques. By combining AI-based prediction mechanisms with curated global threat databases, we can attain a high level of resiliency against the evolving tactics being used in mobile phishing attacks [7], [9], [14].

Deployment Architecture and System Integration

The final system was built using a hybrid architecture that was consistent with the pipeline established in Section 4. The backend was built using Python and Flask with RESTful communications with the Android mobile application developed in Java. The NotificationListenerServicewas employed to allow for passive capture of app notifications without requiring user input; for example, in real-time the Notification Listener Service allowed for URLs in apps such as WhatsApp and Instagram to be extracted. The URLs obtained were sent to the server, which used MongoDB for efficient storage and lookup of already classified links to avoid redundant computations on already established links. Inferencing on-device was conducted using the ONNX Runtime, which enabled lightweight and low-latency inferencing on-device as previously discussed in the performance optimization in Section 4.4. Overall, this hybrid architecture allowed for robust operational performance that was fast, privacy-respecting, and real-time which was an important requirement for mobile deployment in environments with a high risk of phishing [20], [21].

All communications performed via the use of an API (especially when communicating with the

VirusTotal threat intelligence service) were encrypted using HTTPS and authenticated using a token-based API for both security and privacy during transmission of data and verification externally. The configuration allows for asynchronous requests from interesting or uncertain cases so as to not slow down the inference delivered locally. The extensibility of the components of the system, as it relates to the model detection and threat feed, can be simply updated as well as be used with a variance of Android hardware. Security compliance was achieved by maintaining the maximum amount of security orientations from OWASP Mobile Security by all means possible and under the guidelines distributed by GDPR [20], [21]. This phase of implementation represents the requirement for easy extensibility, better performance, and transparency for the user through the entire process, producing the system that has moved from alert notifications to intelligent classification, and alerting. The system is now ready for deployment with limited performance restrictions while adapting to any precarious evasion tactics that may develop in mobile phishing.

3. RESULT AND EVALUATION

This section focuses on the evaluation of the proposed phishing detection system based on performance measures, latency, and user engagement effectiveness. Tests were done on test datasets consisting of legitimate and phishing URLs based on real-world occurrences while ensuring a balanced representation of both phishing and legitimate URLs for appropriate benchmarks. From the evaluation of the ONNX model and the performance measures of the traditional classifiers, it was determined that the ONNX model outperformed both traditional classifiers, Random Forest and SVM, in the performance measures of precision, recall, F1-score, and latency. The ONNX model also responded to common mobile engagement with the URL domain or IP address to assess the efficacy of real-time detection to support real-time user engagement. Conclusively, the results demonstrated that the ONNX model was better suited for mobile deployment in terms of performance and efficiency. As for real-time user engagement and user feedback alertness as to areas of cybersecurity risk, the results from this study indicate that the proposed system engaged the user according to the standard typical of any interactive mobile device to promote use with mobile cybersecurity awareness tools. By comparing the proposed results with existing solutions, the architecture offered both strength and scale [1], [2], [18].

Comparative Model Performance Metrics

The ONNX neural network model yielded a better prediction mechanism by yielding higher precision and lower false positives compared to baseline models. The ONNX model revealed an accuracy of 94.6%, precision of 92.4%, recall of 93.8%, and an F1-score of 93.1%. Additionally, the ONNX model outperformed Random Forest (accuracy: 91.2%, F1: 90.1%) and SVM (accuracy: 88.5%, F1: 86.3%) for each metric maximally performing better for all metrics of evaluation tools, making it ideally expected to be used in a mobile setting [2], [18]. The improvements achieved can be attributed to the depth of the model and its ability to withstand obfuscated phishing patterns. The model is also very useful since it is usable in the ONNX format and enables low-latency inference without sacrificing accuracy. All measures of performance indicated that the model is useful for live phishing detection, where false negatives can lead to a serious compromise to users.

Table 1: Performance metrics of machine learning models for URL classification

Model	Accuracy	Precision	Recall	F1-score
Random Forest	91.2%	89.8%	90.3%	90.1%
Support Vector Machine	88.5%	87.1%	85.6%	86.3%
ONNX Neural Network	94.6%	92.4%	93.8%	93.1%

Evaluation of Detection Latency and Throughput

System efficiency was evaluated using latency benchmarks for each stage of the pipeline. The net timing for phishing classification without triggering external APIs averaged 60 ms, which consisted of preprocessing (40 ms), lookup in MongoDB (3 ms), ONNX execution (12 ms), and rendering the alert for user interaction (5 ms). When VirusTotal was triggered, average latency increased to roughly 1860 ms due to network latency, which is still acceptable for rare low-confidence cases. These statistics have verified that the system can present alerts to users in almost real-time with no perceivable latency. Low-latency performance is of particular importance for mobile users who receive phishing attempts through fast-paced communication channels [6], [7].

Table 2: Component-wise average inference time in the URL classification pipeline

Component	Avg. Time (ms)
URL Preprocessing & Extraction	40
Local Database Lookup (MongoDB)	3
ONNX Model Inference	12
VirusTotal External API Check	~1800
Alert Generation (UI Rendering)	5
Total (without VirusTotal)	≈60
Total (with VirusTotal)	≈1860

User Interface Feedback and Responsiveness

The user interface was developed to compose instant and intuitive alerts while at the same time conveying context information of the threat with as little cognitive load on the user as possible. Real-time notifications via the interface utilized both visual cues and sender identification for users to see if the URL is safe or phishing. This timely feedback mechanism allows the user to act before interacting with a harmful message. Overall, the responsiveness of the user interface was consistent, the alerts were rendered in less than one second in the normal case of detection. The user interface also features a results screen summarizing the URL information it has extracted, along with the source of the link (WhatsApp, Instagram, etc). All of these features support user-informed decisions while increasing overall transparency of the system. The UI also follows the best practices for usability for mobile cybersecurity apps, stressing clarity, simplicity, and speed.

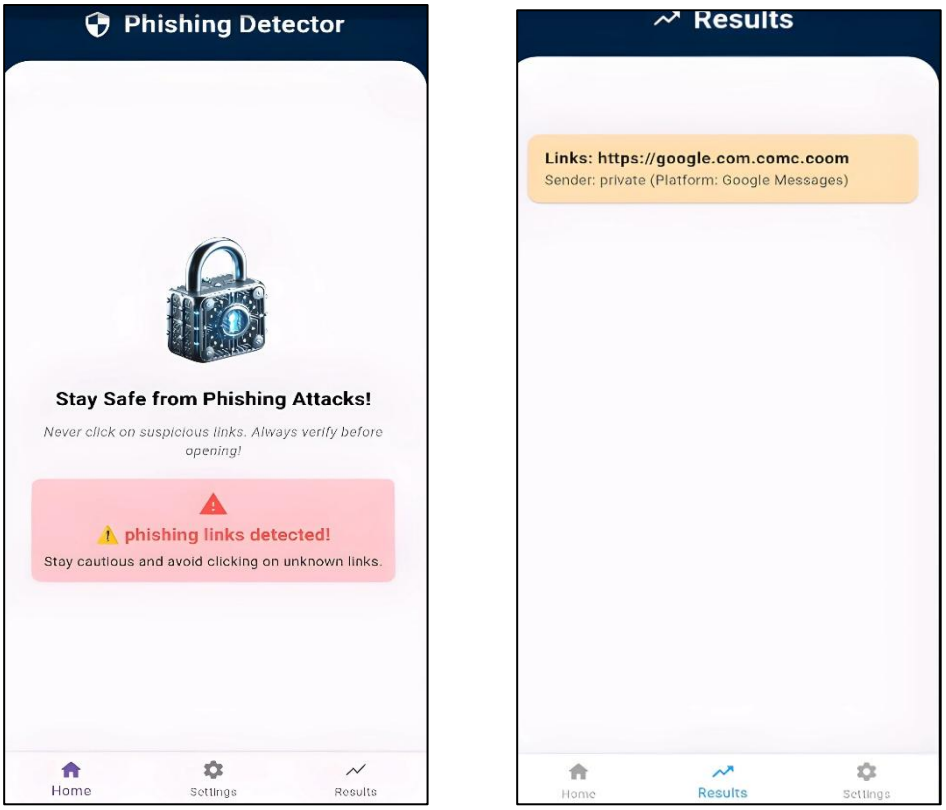

Figure 2: Mobile phishing detection interface: (left) real-time alert message displayed on the home screen, (right) extracted phishing URL and sender information shown in the results screen.

Comparison with Existing Mobile Security Solutions

In comparison to the available mobile phishing detection systems, the proposed ONNX model provides outstanding detection accuracy, inference speed, and modular deployment. Whereas other systems evaluate evidence-based detection primarily on static blacklists and static heuristics, our system uses static blacklists as supplementary intelligence and integrates dynamic blacklists, threat intelligence, and machine learning for greater resistance to zero-day attacks [3],[4],[22]. The hybrid approach that our system utilizes—on-device inference combined with conditional external verification—preserves inference quality and speed on the device even in the event of an API failure. The modular design also permits easy upgrades to the system by integrating new sources of threats and model updates that are particularly useful in the dynamic nature of mobile threats. All of these features make the system far more adaptable than traditional anti-phishing tools, but with significant scalability benefits.

4. DISCUSSION

These results from this study underscore the innovation that has come from successfully utilizing ONNX-based neural networks and real-time threat intelligence for mobile phishing detection, where the system creates an outstanding balance between speed and accuracy, as evident from its excellent F1-score and very low processing latency-it is essential to mitigating the phishing threat in dynamic mobile ecosystems. In addition, the results seem to validate its better performance compared to conventional models, including Random Forest and SVM, demonstrating the advantages of deep learning methods in mobile deployments. More significantly, the external validation by VirusTotal has lent greater credibility to the detection mechanism in fighting zero-day phishing challenges, thus further lowering false negatives. While the system works well, the work presents some additional enhancements required, including more advanced deep learning techniques, federated learning algorithms, and improved privacy mechanisms. These results also work to unveil a new avenue for mobile cybersecurity and introduce scalable and flexible ideas that can accommodate evasive cyber adversaries' constantly changing strategies..

5. CONCLUSION AND FUTURE WORK

In summary, the development and testing of the Mobile Phishing Link Detection system represent a significant advancement in protecting mobile users against threats of phishing that are in the evolving space. The merger of an ONNX-based neural network with real-time threat intelligence has proven able to afford a detection framework that combines high accuracy with quick response time. Such an approach minimizes false detection but actively mitigates zero-day phishing attacks, a level of

security not attained by prevalent methods. In addition, the fast processing and classification of URLs by the Mobile Phishing Link Detection System and its efficient external validation via VirusTotal are potent indicators for operational proactive defense in mobile dynamic setups. The design itself is modular and scalable; thus, ensuring that its adoption in the field of application is appropriate for varied mobile platforms, creating overwhelming chances for it to survive the ever-increasing sophistication of cyber adversaries. Progressing, several developments—federated learning, further incorporation of advanced deep learning models, and more integration with a host of other threat intelligence sources—are key to keeping and constraining system evolution. These developments will boost detection and create lots of targeted works for user privacy and data security, paving the way for an even more secure mobile ecosystem. To conclude, this work presents a practical, scalable solution to mobile cybersecurity, which could translate into short- and long-term benefits for the ongoing war against phishing and others in cyberspace. Future developments on the mobile phishing detection system will continue to develop both technical capacity and user-centered enhancements. One of the main directions will be the addition of more social media platforms to broaden phishing coverage across communication channels. More advanced deep learning models will be tested as well to increasing detection accuracy, especially against obfuscated attacks. Algorithm optimization will be prioritized so real-time detection can occur even under the burdens of high data load. Privacy protections will be enhanced by improving encryption protocols during data sharing. Federated learning will also be implemented to allow training on a user device versus the cloud, which both supports privacy and will allow the model to be more adaptable. Lastly, user feedback mechanisms will be added for continuous retraining of the model so the detection system could develop alongside changing phishing practices. These future changes can foster a detection system that is scalable, adaptable to change, privacy-preserving whilst providing a resilient detection system for ever-evolving mobile cybersecurity threats.

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