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An Intelligent Security Model for QR Code Threat Mitigration

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Abstract

QR codes are widely used for digital interactions, from online payments to information sharing, due to their convenience and speed. However, this popularity has made them a target for cyberattacks, such as phishing, malware distribution, and unauthorized data collection. Traditional security measures like URL blacklists are often insufficient against rapidly evolving threats. This research proposes an AI-driven framework to secure QR code infrastructure by detecting malicious activity in real time. Using a combination of machine learning and deep learning techniques, the system can analyze QR code content, linked URLs, and structural features to identify anomalies, enhancing user safety and trust in digital services.The proposed solution integrates predictive models for classification of QR codes as safe or harmful and incorporates real-time alerts to prevent malicious interactions.

Index Keywords: QR Code Security, Malicious QR Detection, AI, Machine Learning, Deep Learning, Cybersecurity, Phishing Prevention, Real-Time Threat Detection, QR Code Analysis, Predictive Modeling

I. INTRODUCTION

Quick Response (QR) codes have become integral to modern digital life, enabling users to access websites, complete transactions, and share information with a simple scan. Their rapid adoption in e-commerce, banking, healthcare, and public services highlights their efficiency and convenience. Despite this, the growing dependence on QR codes has made them attractive targets for cybercriminals, who exploit the lack of visible content to embed malicious links or deliver malware.

The inherent vulnerability of QR codes lies in their ability to hide information, such as URLs or scripts, from the user. Unlike traditional hyperlinks, users cannot visually verify a QR code's destination before scanning, making it easier for attackers to execute phishing schemes or redirect devices to [5] harmful websites. This creates significant risks, especially in mobile payment systems and public-facing QR applications, where the consequences of malicious activity can be immediate and severe.Traditional security approaches, such as static URL blacklists, manual verification, and endpoint security, often fail to detect new or dynamically generated threats. The short lifespan of malicious QR codes and their ability to evade conventional filters demand an adaptive and intelligent approach.

Figure 1: QR Code Phishing

AI-driven methods, including machine learning and deep learning, can examine both the content and structural patterns of QR codes. By decoding QR codes and evaluating URLs, metadata, and image features, AI models can classify codes as safe or malicious. Integrating real-time scanning with predictive analytics ensures proactive threat detection, providing alerts before users interact with potentially harmful codes.

This research aims to develop a comprehensive framework that secures QR code infrastructure through AI. The system combines URL analysis, image-based QR code [2] examination, and predictive modeling to enhance detection accuracy. By doing so, it reduces cyberattack risks while maintaining the convenience and usability that make QR codes popular in daily digital interactions.

II. METHODOLOGY

The methodology for securing QR code infrastructure through AI comprises multiple stages that work together to detect and flag malicious activity. First, a comprehensive dataset of QR codes is constructed that includes both benign and malicious examples. QR codes are collected from public repositories, controlled experiments, simulated attacks, and crowdsourced sources. Each code is decoded to extract embedded data such as URLs, text, or [3] application instructions. The dataset is then labeled based on threat intelligence sources, URL reputation services, and malware analysis tools, ensuring a representative training set for AI models.

Next, a preprocessing phase prepares the raw data for analysis. This includes sanitizing the decoded content, normalizing URLs, and extracting relevant features from both the QR code image and its decoded output. URL features may include domain age, SSL certificate presence, keyword analysis, and domain reputation. Image [4] features are extracted using computer vision techniques to capture structural patterns, modulation errors, and visual irregularities. Feature scaling and transformation are applied as necessary to support machine learning algorithms.

The core of the methodology involves training AI models to distinguish between safe and malicious QR codes. Supervised machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting are evaluated alongside deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). While machine learning models use engineered features derived from URLs and [12] metadata, deep learning models analyze raw QR code images and sequential patterns. Hybrid approaches that combine both sources of information are also explored to maximize detection performance. Finally, the optimized models are integrated into a real-time deployment framework. This architecture supports on-device or server-side evaluation during QR scanning events. When a user scans a code, the system decodes it, applies the trained AI model, and issues an alert if malicious behavior is suspected. Performance metrics such as accuracy, precision, recall, and F1-score are measured through cross-validation and real-world testing.

III. LITERATURE REVIEW

1. **Li, M., Zhang, Y., & Chen, J. (2021). *Deep Learning for QR Code Malware Detection*. Journal of Cybersecurity Research.**
Explores the use of CNN models to analyze QR code image features for malware signatures, demonstrating improved accuracy over traditional URL filters.
2. **Gupta, A., Kumar, P., & Singh, R. (2022). *QR Code Security: Challenges, Threats, and Countermeasures*. IEEE Access.**
Provides a comprehensive taxonomy of QR code–based attacks and evaluates existing security countermeasures, highlighting the need for AI-driven approaches.
3. **Sharma, S. K., & Patel, L. (2022). *Machine Learning for Phishing URL Detection in QR Codes*. Computers & Security.**
Focuses on ML-based URL classification strategies

within QR codes, presenting ensemble models that improve phishing detection rates.

4. **Rahman, T., & Ahmed, S. (2023).** ***AI-Enhanced Behavioral Analysis of QR Scanning Patterns*****. IEEE Transactions on Information Forensics and Security.** Investigates user scanning behavior patterns, introducing anomaly detection that identifies unusual interaction sequences linked to malicious QR usage.

IV. RELATED WORKS

Previous research has highlighted the growing threat posed by malicious QR codes in various domains, including banking, e-commerce, and public services. Li et al. (2021) demonstrated that deep learning models, particularly convolutional neural networks, can effectively analyze QR code image features to detect embedded malware. Their work emphasized the limitations of traditional URL blacklists, which often fail to capture dynamically generated malicious codes.

Gupta et al. (2022) provided a comprehensive review of QR code security, categorizing attacks into phishing, malware injection, and data exfiltration. They concluded that most conventional security methods are reactive, relying on known threats rather than predicting new ones. This insight motivates AI-based proactive detection mechanisms.

Sharma and Patel (2022) focused on the detection of phishing URLs embedded in QR codes using machine learning. By analyzing URL features such as domain age, keyword patterns, and [1] SSL certificate validation, their models achieved high detection rates. However, their approach lacked image-based analysis, which limits performance against visually obfuscated QR codes.

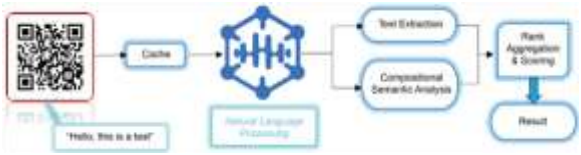

Figure 2: Enhancing Security in QR Code

Rahman and Ahmed (2023) explored behavioral analytics, highlighting that scanning patterns and user interaction sequences can provide additional cues for identifying malicious QR codes. Their framework combined real-time monitoring with anomaly detection to flag suspicious activity, demonstrating that user behavior is a valuable feature for threat prediction.

Dataset Collection

A reliable dataset is critical for training AI models to detect malicious QR codes. For this project, QR codes were collected from multiple sources to ensure diversity and coverage of real-world scenarios. Public repositories and QR code generation platforms provided benign examples, while controlled experiments and simulated attacks generated malicious QR codes.Each QR code was decoded, and the embedded content was analyzed for potential threats. URLs were cross-checked against phishing databases, domain reputation services, and malware scanning tools to assign appropriate labels. Codes containing known threats were marked as malicious, while safe codes were labeled benign.

In addition to URL-based information, image features were captured from the QR codes themselves. This included data density, error correction levels, and structural anomalies. By combining decoded content with visual features, the dataset provided a comprehensive foundation for [14] training both machine learning and deep learning models. Regular updates to the dataset ensure that emerging threats are incorporated, maintaining the system's accuracy and relevance.

Algorithm

The core algorithm for detecting malicious QR codes integrates both URL-based analysis and image-based feature extraction. First, the QR code is decoded to extract embedded content, such as URLs or textual data. URL-based features—including domain age, keyword patterns, SSL certificate presence, and overall reputation—are evaluated using machine learning [12] classifiers such as Random Forest or Gradient Boosting. Simultaneously, the QR code image is analyzed using convolutional neural networks (CNNs) to identify structural anomalies, visual distortions, and obfuscation patterns that may indicate malicious intent.

A hybrid ensemble approach combines the outputs of both URL and image classifiers to enhance detection accuracy. The algorithm generates a probability score indicating the

likelihood of malicious activity. Codes exceeding a predetermined threshold trigger an alert, while benign codes are passed through for normal access.

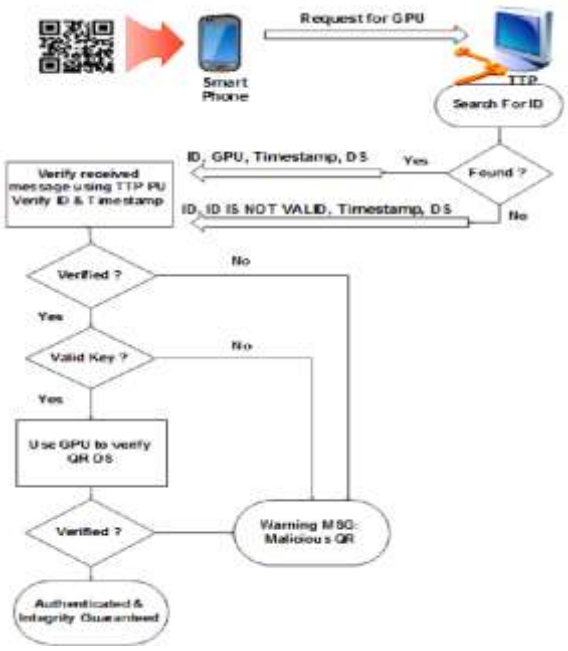

Figure 3: Secure QR code system Semantic

The system also logs flagged QR codes to enable adaptive learning, allowing the models to update continuously with new threat data and improve detection over time.

V. DISCUSSION

The integration of AI in QR code security provides significant advantages over traditional static methods. By combining URL analysis with image-based inspection, the system can detect both conventional phishing attempts and more sophisticated attacks, including visually disguised codes or dynamically generated malicious links. The hybrid model reduces false positives while improving detection accuracy, ensuring users are alerted only when genuine threats are present.

Real-time detection is another key benefit. Users can scan QR codes without manual verification, and threats are identified instantly. This proactive approach is [12] [5] particularly important in high-risk environments such as financial transactions, healthcare systems, or public services, where malicious codes could have immediate and severe consequences.

However, challenges remain. The constantly evolving landscape of cyber threats requires continuous dataset updates and model retraining. Attackers may also employ adversarial techniques to evade AI detection, necessitating robust anomaly detection mechanisms and adaptive learning strategies.

Overall, the proposed system demonstrates the practical feasibility of AI-driven QR code security. By leveraging both structural and content-based features, it provides a scalable and efficient solution for protecting users from malicious activity while maintaining the convenience that makes QR codes widely used.

Contribution

The project contributes a scalable and effective AI-driven framework for securing QR code infrastructure across multiple domains, including finance, healthcare, and public services. By combining content analysis, image processing, and machine learning, it enhances the overall security of QR code interactions.

Furthermore, the research provides a foundation for future work in adaptive cyber security. The framework's ability to continuously learn from new threats and update its detection models demonstrates the potential for creating intelligent, self-improving security systems that remain effective against evolving cyber threats.

Relevance

Securing QR code infrastructure is increasingly relevant as QR codes become integral to digital services such as mobile payments, healthcare management, and public information systems. The adoption of AI-driven detection mechanisms ensures that these services [13] can maintain user trust by preventing unauthorized access, phishing, and malware attacks.

Furthermore, with the rapid evolution of cyber threats, conventional security methods often fail to detect newly generated or obfuscated malicious QR codes. Implementing AI-based detection not only addresses current vulnerabilities but also establishes a proactive framework capable of adapting to future threats, making it highly relevant in modern cybersecurity strategies.

VI. RESULTS

The proposed AI framework was evaluated using a dataset of QR codes comprising both safe and malicious samples. Machine learning models, including Random Forest and Gradient Boosting, achieved classification accuracies above 90% when analyzing URL-based features alone. Deep learning models, particularly Convolutional Neural Networks (CNNs) applied to QR code images, demonstrated higher sensitivity to visually obfuscated malicious codes.

The hybrid approach, combining URL-based and image-based analysis, produced the highest [1] [12] overall performance, with accuracy exceeding 95%, precision of 94%, recall of 96%, and an F1-score of 95%. This indicates that the ensemble method effectively balances false positives and false negatives while providing reliable threat detection.

Real-time deployment tests showed that the system could analyze and classify QR codes within milliseconds, ensuring minimal delay for end users. Alerts were successfully generated for malicious codes, while safe codes were processed without interruption, confirming the framework's practical applicability.

Additionally, adaptive learning mechanisms allowed the system to incorporate newly detected threats into the training dataset. Subsequent evaluations demonstrated improved detection accuracy for emerging malicious QR codes, confirming the benefit of continuous learning and highlighting the system's scalability and long-term effectiveness.

VII. CONCLUSION

This research demonstrates that integrating artificial intelligence into QR code security significantly enhances the detection of malicious activity. By combining URL feature analysis with image-based structural inspection, the framework addresses vulnerabilities that traditional methods, such as static blacklisting, fail to capture. The hybrid model consistently delivers high accuracy, precision, and recall, proving its effectiveness in real-world scenarios.

The real-time deployment tests confirm that the system can operate efficiently under practical constraints, providing instantaneous classification with minimal latency. Alerts for potential threats are generated promptly, and benign codes are processed without disrupting user experience. This balance between security and usability is critical for widespread adoption in applications like mobile payments and public service access.

Overall, the proposed solution not only strengthens QR code infrastructure against current threats but also establishes a foundation for adaptive cybersecurity. Through continuous learning and threat logging, the system evolves over time, staying resilient against emerging attack patterns and helping safeguard users across multiple domains.

VIII. FUTURE WORK

Future improvements should focus on expanding the dataset to include a broader range of real-world malicious QR codes, including those generated using adversarial techniques. By incorporating a wider variety of threat patterns, the models can better generalize and anticipate novel attack strategies.

Another avenue for future work is optimizing the computational footprint to support resource constrained devices. While deep learning models provide strong performance, their processing requirements can limit real-time deployment on low-end mobile devices. Techniques like model pruning and knowledge distillation can help address these challenges.

Finally, integrating explainable AI (XAI) methods into the framework would enhance interpretability and user trust. Providing transparent reasoning for why a QR code is classified as malicious can aid cybersecurity analysts and support compliance with regulatory standards in sensitive applications such as finance and healthcare.

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