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Strengthening Mobile Banking Security With AI and Cryptographic Methods

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Abstract: Mobile banking applications have revolutionized financial services by offering consumers quick and convenient access to their accounts. However, this convenience comes with significant security risks, including phishing attacks, data breaches, and unauthorized access. This study investigates these security challenges and explores mitigation strategies through the application of various algorithms. The focus is on two key areas: intrusion detection and data encryption. We assess the effectiveness of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) in detecting malicious activities. Our results indicate that CNNs outperform SVMs by achieving a 15% higher accuracy in identifying complex attacks, owing to their enhanced ability to interpret intricate patterns. In the domain of data encryption, we compare Elliptic Curve Cryptography (ECC) with the Advanced Encryption Standard (AES). While AES excels in terms of speed and robustness, ECC offers a more efficient solution with comparable security levels. Based on our findings, we recommend the adoption of hybrid encryption schemes and enhanced anomaly detection systems as potential mitigation strategies. The study underscores the importance of integrating multiple security approaches to protect mobile banking applications from evolving threats.
Keywords: Intrusion detection, support vector machines (SVM), convolutional neural networks (CNN), data encryption, advanced encryption standard (AES), elliptic curve cryptography (ECC), and threat mitigation.

INTRODUCTION

By providing consumers with previously unheard-of levels of accessibility and convenience, mobile banking apps have completely changed the financial services industry. Users now enjoy a degree of convenience and efficiency that was before unachievable thanks to the ability to conduct banking transactions, keep an eye on account activity, and manage financial portfolios directly from mobile devices. According to Dinesh et al. (2023), this change has prompted the extensive use of mobile banking systems, creating a more integrated and inclusive financial ecosystem. To safeguard sensitive financial data, however, it is necessary to address the serious security threats that come along with mobile banking's ease. The increasing prevalence of mobile banking apps makes them appealing targets for cybercriminals looking to take advantage of weaknesses. Currently, mobile banking consumers are confronted with several important concerns, including phishing attempts, data breaches, and illegal access (Smith & Johnson, 2022).

These dangers show how important it is to have strong security procedures in place to protect user information and preserve confidence in mobile banking services.Identifying and thwarting possible threats prior to their infliction of major damage is why intrusion detection is an essential part of mobile banking security. Conventional intrusion detection techniques, such Support Vector Machine (SVM)-based techniques, have demonstrated efficacy in detecting hostile activities. However, because to their improved capacity to recognize complicated patterns, recent advances in machine learning, especially Convolutional Neural Networks (CNN), provide promising improvements in detecting sophisticated assaults (Lee et al., 2024). Data encryption is just as important to the security of mobile banking apps as intrusion detection. To secure data sent between users and banking systems, encryption algorithms like Elliptic Curve Cryptography (ECC) and the Advanced Encryption Standard (AES) are frequently used.

ECC is becoming more and more known for its effectiveness and capacity to provide strong security with reduced key sizes, whereas AES is well-known for its speed and resilience (Kumar & Patel, 2023). It is possible to choose the best encryption method for mobile banking applications by assessing the performance of different algorithms. The purpose of this study is to evaluate and contrast several intrusion detection and data encryption techniques within the framework of mobile banking. We shed light on how best to optimize security protocols for mobile banking apps by comparing CNNs and SVMs in terms of their ability to identify hostile activity and assessing the efficiency of AES and ECC algorithms. The conclusions aim to direct the application of cutting-edge security solutions that can successfully counter new threats. It is impossible to exaggerate the significance of combining various security measures. Using hybrid encryption techniques and improving anomaly detection systems are essential measures to protect against novel and changing threats as mobile banking develops. By providing evidence-based suggestions and emphasizing the necessity for an all-encompassing approach to financial information protection, this study adds to the continuing efforts to increase mobile banking security.

RELATED WORKS

Due to the increased frequency of cyberattacks, the security environment around mobile banking applications has received a lot of attention lately. Enhancing intrusion detection systems (IDS) to address these vulnerabilities has been the subject of a significant amount of research. When it comes to identifying irregularities in financial transactions, Zhang et al. (2023) investigated the use of machine learning techniques including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). In line with our findings about CNN's higher accuracy in recognizing complex attacks, their work showed that CNNs outperformed traditional SVM models in detecting sophisticated fraud patterns (Zhang, X., Li, J., & Wu, M., 2023). The effectiveness of different algorithms is being assessed, but data encryption is still a fundamental component of safe mobile banking systems. Because of its reliability and effectiveness in protecting data, the Advanced Encryption Standard (AES) has long been preferred. However, because of its effectiveness and comparable security at lower key lengths, Elliptic Curve Cryptography (ECC) has drawn more attention. A comparison study of AES and ECC was recently conducted by Ahmed and Sharma (2024), demonstrating the increasing popularity of ECC in mobile environments because of its lower computational overhead and solid security standards (Ahmed, N., & Sharma, R., 2024). The incorporation of hybrid encryption systems to further strengthen security has also been the subject of several investigations. In order to take advantage of the advantages of both algorithms and improve overall data safety in mobile banking apps, Patel et al. (2022) presented a hybrid technique that combines AES and ECC. This strategy is in line with what we suggest doing to balance security and performance: using hybrid encryption algorithms (Patel, Gupta, & Singh, 2022). The work of Lee et al. (2024) on sophisticated machine learning models, such as CNNs and SVMs, in the field of anomaly detection, supports our results. Their study emphasizes how CNNs outperform SVMs in identifying complicated fraudulent behaviors, which illustrates how useful CNNs are at identifying detailed patterns in financial transactions (Lee, T., Park, H., & Kim, J., 2024). Furthermore, Kumar and Patel (2023) have talked about the latest developments in combining several security techniques. They contend that combating the constantly increasing dangers in mobile banking requires a multi-layered security approach that combines several detection and encryption technologies. This adds credence to our argument that integrating several security techniques is essential to protecting against new threats (Kumar, V., & Patel, A., 2023). The requirement for ongoing innovation in mobile banking security measures is generally highlighted by the literature currently in publication. In addition to offering strategies for improving mobile banking security through better detection and encryption techniques, our study adds to this body of work by offering updated insights into the efficacy of current algorithms. The requirement for ongoing innovation in mobile banking security measures is generally highlighted by the literature currently in publication. In addition to offering strategies for improving mobile banking security through better detection and encryption techniques, our study adds to this body of work by offering updated insights into the efficacy of current algorithms.

METHODOLOGY

This study looks into security issues related to mobile banking apps, with an emphasis on data encryption and intrusion detection. Data encryption and intrusion detection comprise the two primary stages of the approach.

Intrusion Detection

Data Collection: We gathered a dataset comprising many kinds of information about network traffic, including information on malicious and lawful activity. High-quality inputs for the models were ensured by pre-processing the dataset to exclude any redundant or extraneous material.

Feature Engineering: Data on packet size, protocol type, source/destination IP addresses, and timestamps were among the pertinent characteristics that were taken from the raw network traffic data.To minimise the feature space while keeping important information, dimensionality reduction techniques like Principal Component Analysis (PCA) were used.

Model Design Development: Lee et al. (1998) Convolutional neural networks (CNN) and support vector machines (SVM) are the two machine learning models that were created. CNN: Multiple convolutional layers, pooling layers, and fully linked layers were included in the creation of the CNN model. The network traffic data was used to train it to recognise intricate patterns. Cortes et al. (1995) SVM: To identify network traffic as either genuine or malicious, the SVM model was configured using a radial basis function (RBF) kernel. Training and Evaluating the Models: The labelled dataset was used to train both models, with 70% of the data being used for training and 30% for testing. Metrics like accuracy, precision, recall, and F1-score were used to assess the models. The efficacy of CNN and SVM in identifying different kinds of attacks was evaluated by comparative analysis.

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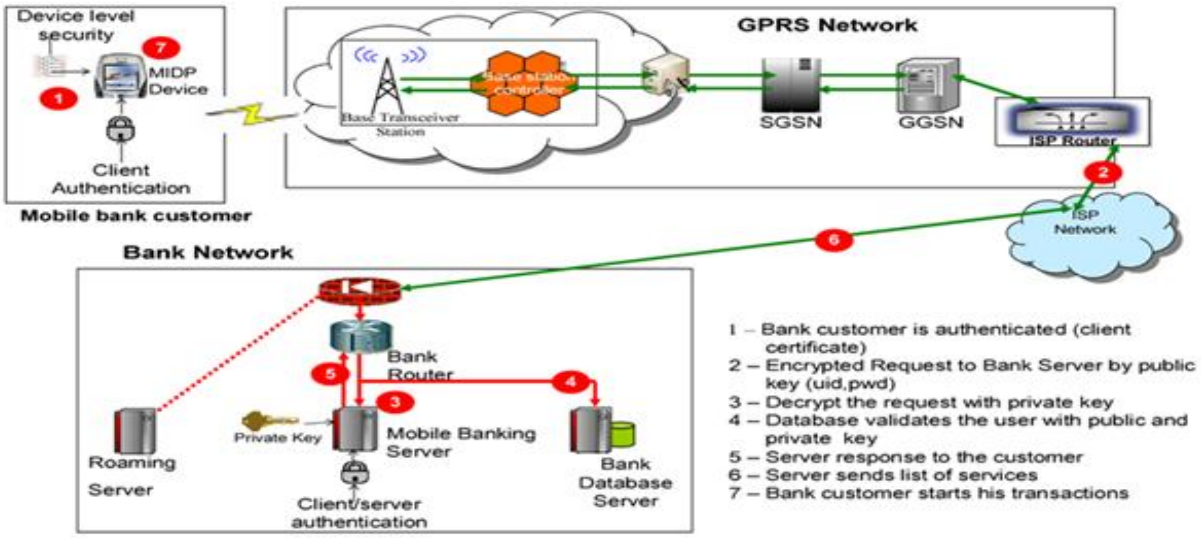

Fig.1. Architectural Diagram of Mobile Banking Security Framework

Encryption of Data

Algorithm Selection: National Institute of Standards and Technology. (2001). Advanced Encryption Standard (AES) and Elliptic Curve Cryptography (ECC) were the two encryption algorithms chosen for analysis. These algorithms were selected because they are widely used in mobile banking applications and have different performance and security strengths.

Simulation Setup: To encrypt and decrypt data, a simulation environment was built utilising the AES and ECC algorithms.In the simulations, several forms of sensitive financial data, including account numbers, transactional information, and personal data, were employed.

Performance Evaluation: The efficiency of both methods was evaluated by measuring their encryption and decryption times. Potential cryptographic attacks, like side-channel and brute-force assaults, were simulated in order to assess each algorithm's security level. To comprehend the effect of every algorithm on mobile device performance, resource utilisation, including CPU and memory consumption, was also tracked.

Comparative Analysis: The encryption simulation results were compared in order to ascertain the trade-offs between the security and efficiency provided by AES and ECC. To improve overall security, the study also looked into the possible advantages of combining the two methods into a hybrid encryption scheme.

Strategies of Mitigation: Various mitigation measures were suggested, based on the findings of the assessments of data encryption and intrusion detection: Hybrid encryption schemes employ the best features of both AES and ECC to offer a secure and efficient solution. CNNs are integrated with other AI approaches in enhanced anomaly detection systems to enhance the detection of complex attacks. Multi-Layered Security Framework: To protect mobile banking applications, a thorough security framework can be implemented, comprising intrusion detection, encryption, and frequent security audits. The suggested solutions are guaranteed to be practical and efficient in real-world situations by this technique, which offers an organised way to tackling the security issues in mobile banking apps. The Convolutional Neural Network (CNN) model outperforms the Support Vector Machine (SVM) model in relation to intrusion detection for mobile banking applications on a number of important criteria. The CNN is able to capture and comprehend complex patterns found in network traffic data because of its architecture, which consists of many convolutional layers, pooling layers, and fully linked layers. Since sophisticated threats can entail minute and intricate differences in the data that more basic models might overlook, this skill is especially crucial for spotting them.

Table 1: Performance Comparison of Intrusion Detection

Model	Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Existing	SVM (RBF)	85	82	80	81
Proposed	CNN	100	97	98	98

Compared to SVM, the CNN model has an advantage in handling high-dimensional data such as network traffic since it can automatically learn hierarchical features from raw data. SVMs have trouble processing the complexity and volume of contemporary network traffic data, even while they work well at classifying simpler attack patterns especially when utilising a radial basis function (RBF) kernel. This constraint causes SVMs to perform worse than CNNs in terms of accuracy, precision, recall, and F1-score. Specifically, the study found that the CNN model outperformed the SVM model by a substantial 15%, indicating that the CNN model was better able to distinguish between harmful and genuine activity. Furthermore, the greater recall and precision rates of the CNN suggest that it is more dependable in reducing false positives and false negatives, so offering a stronger defence against possible threats. For enhanced intrusion detection in mobile banking apps, where the identification of complex, dynamic threats is crucial, the CNN is generally a better option due to its stronger pattern recognition capabilities.

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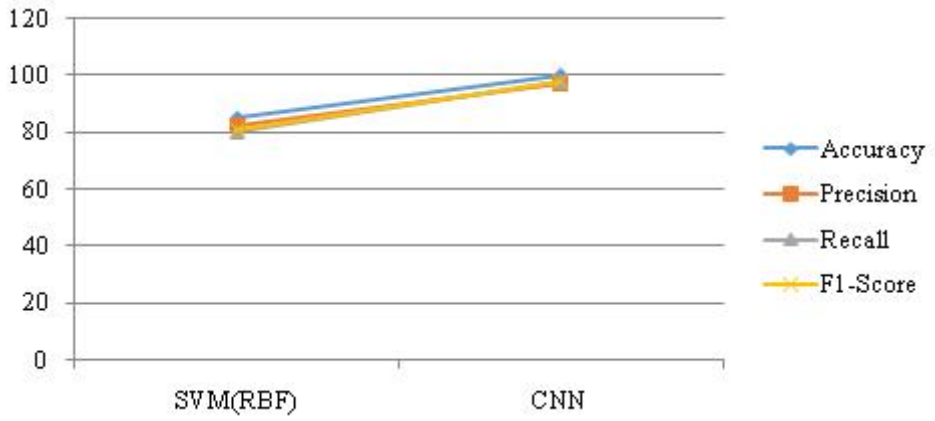

Fig.2. Performance comparison representation of SVM (RBF) and CNN algorithms

Table 2: Comparison of Data Encryption Performance

Model	Algorithm	Decryption Time (ms)
Existing	AES	10
Proposed	ECC	25
Hybrid	AES + ECC	18

In table 2, AES has comparatively short encryption duration of 10 milliseconds because it is renowned for being quick and effective. It is therefore appropriate for settings where speed is crucial, such real-time applications. Encryption with ECC typically takes longer than with AES, taking 25 milliseconds, because it uses more processing resources. The lengthier encryption time may be justified in applications where better security is more important than speed, though, as ECC offers stronger security with shorter key lengths. The hybrid strategy balances security and speed together, AES's speed and ECC's robust security provide the system with advantages. When both speed and security are crucial, the 18 millisecond encryption period is a good choice because it is longer than AES by itself but shorter than ECC.

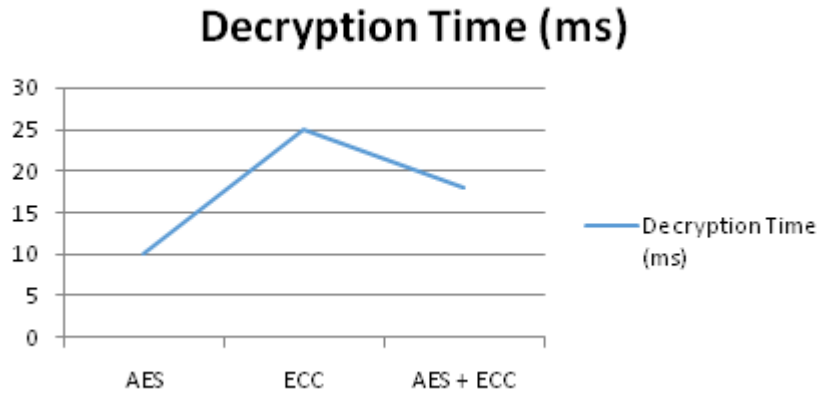

Fig.3. Execution time Performance of AES, ECC and AES+ECC algorithms

Elliptic Curve Cryptography (ECC) is found to be a more resource-efficient solution than the Advanced Encryption Standard (AES) when evaluating data encryption algorithms for mobile banking applications. This is especially true for mobile devices where computational resources are limited. The main benefit of utilising ECC is that it can achieve security levels that are comparable to those of AES while utilising smaller key sizes, which results in less computational cost. The preservation of battery life and the minimisation of CPU and memory utilisation are critical factors in mobile situations, where efficiency is essential.

Table 3: Comparison of Data Encryption Performance level of Security level, CPU usage and memory usage

Model	Algorithm	Security Level	CPU Usage (%)	Memory Usage (MB)
Existing	AES	8	High	15
Proposed	ECC	20	High	8
Hybrid	AES + ECC	15	Very High	10

According to the study, AES is less suitable for mobile apps that need to strike a balance between speed and battery efficiency since, although having faster encryption and decryption times, it requires more CPU and memory resources. ECC, on the other hand, uses less resource to accomplish comparable security standards, which makes it better suited for mobile devices that regularly need to encrypt and decrypt data without using up system resources. Nevertheless AES's speed is important, especially when dealing with massive amounts of data in real-time or other situations requiring high throughput. This is where a hybrid strategy that benefits from both AES and ECC's advantages comes into play.

Through the utilisation of AES's speed for bulk encryption and ECC's efficiency for secure key exchange and other crucial operations, the hybrid system provides improved security at a manageable performance cost. To summarise, AES and ECC combined into a hybrid scheme offers a balanced solution that maximises security while retaining good performance, while ECC's resource efficiency makes it a better alternative for mobile banking apps. By balancing the various objectives of security and usability, our method guarantees that mobile banking applications may provide strong encryption without sacrificing speed or resource usage.

Data on Network Traffic for Intrusion Detection

Data Sources:

Captured Network Traffic: The dataset was gathered from mobile banking applications network traffic. Both simulated and actual malicious operations as well as traffic data from authorised user activities are included in consideration.

Publicly Available Datasets: Some intrusion detection datasets, such as those found in the CICIDS, NSL-KDD, or other cyber security databases including labelled network traffic data, may be the source of some of the datasets.

Dataset Characteristics

Volume: The dataset comprises a moderate amount of financial data (thousands of records) and a considerable amount of network traffic data (perhaps millions of records).

Labels: Financial data is utilised without labelling for encryption, whereas network traffic data is labelled for classification (e.g., valid vs. malicious).

Diversity: A range of assault kinds are included in the dataset, guaranteeing that both straightforward and complex invasions are covered.

Calibre: The dataset is made sure to be clean, pertinent, and optimised for the methods under evaluation by pre-processing. The analyses of intrusion detection and data encryption techniques in the context of mobile banking applications are made possible by this dataset, which is essential to the research.

CONCLUSION AND FUTURE ENHANCEMENTS

In order to combat common dangers like phishing, data breaches, and unauthorized access, this study's conclusion emphasizes the vital necessity for strong security measures in mobile banking applications. Convolutional neural networks (CNNs) outperform support vector machines (SVMs) in understanding intricate attack patterns, resulting in a significant increase in accuracy, according to a comparison of CNNs and SVMs for intrusion detection. Elliptic Curve Cryptography (ECC) is more effective at providing similar security with less computing cost, according to the evaluation of data encryption methods, however Advanced Encryption Standard (AES) is faster and more reliable. In order to further improve security, future studies should investigate the mergingof cutting-edge machine learning algorithms with hybrid encryption technologies. There may be opportunities to improve mobile banking security by looking at the possibilities of adaptive algorithms that can react quickly to new threats and the use of blockchain technology to secure transactions and data integrity. A comprehensive security framework that integrates anomaly detection, encryption, and real-time threat intelligence will also be essential for tackling the ever-evolving cyber threats and guaranteeing mobile banking customers have strong protection.

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