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Intelligent Hybrid Intrusion Detection System for Financial Network Environments using Cryptography and Network Security

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Abstract

Recent changes in banking technology have introduced modern financial institutions, enabling seamless services such as online financial institutions, mobile transactions, ATM networks, and real-time fund transfers. However, this transformation has greatly increased the amount of sensitive data transmission, making banking systems they are highly susceptible to advanced cyber threats.

The main challenge is achieving real-time intrusion detection while handling evolving and unknown attacks without disrupting transaction performance or customer experience. Traditional By comparing network activity with pre-established attack signatures, traditional signature-based intrusion detection systems identify intrusion attack traffic behavior and manual updates. which Consequently, their ability to identify zero-day attacks and adaptive cyber threats is limited.

To address this problem, a hybrid intrusion detection approach combining Support Vector Machine (SVM) along with Isolation Forest is proposed. The SVM model effectively classifies known attack patterns, while the Isolation Forest detects anomalous and previously unseen network behaviours, improving zero-day attack detection capability.

Training and assessment were carried out using benchmark network cybersecurity datasets for anomaly detection, such as NSL-KDD (or CICIDS dataset, if used), ensuring realistic evaluation including both legitimate and adversarial network activity.

The evaluation results confirm that the hybrid model achieved an overall detection correctness of approximately 97–99 per cent, with improved anomaly detection rates and reduced false positives compared to standalone classifiers.

In conclusion, the proposed hybrid SVM–Isolation Forest model delivers an efficient and reliable live intrusion detection security mechanism suitable for modern banking network environments.

Keywords: Secure Financial Network, Intrusion Detection Models, Hybrid Machine Learning, SVM, Isolation Forest, Real-Time Detection, Cybersecurity

1. Introduction

Financial networks are essential for modern banking systems. They enable secure communication and data exchange between banks, customers, payment gateways, and regulators. With the fast growth of

digital technologies, banking services have moved beyond traditional branch operations. They now include online banking platforms, mobile payment apps, ATM networks, and real-time fund transfer systems. These interconnected financial networks facilitate millions of transactions daily, providing customers with fast, convenient, and accessible banking services.

As banking becomes more digital, cybersecurity is recognised as a significant security issue in the financial industry. Banking networks handle sensitive information, including personal details, account numbers, authentication credentials, and transaction records. If this data is compromised, it may lead to serious issues, causing financial harm in addition to legal penalties, reputational damage, and a decline in customer confidence. Safeguarding the confidentiality, integrity, and availability of financial data is, therefore, a top priority for banks and service providers.

During recent times, online exchanges have risen sharply due to the broad utilisation of digital banking, mobile payments, and electronic fund transfers. Technologies like internet-based banking services, electronic wallet systems, and immediate fund transfer systems have changed the financial domain by enabling the expansion of digital transaction activities. However, such rapid development has led to major challenges within the sector, making financial networks increasingly appealing to cybercriminals and increasing the risk of fraud, cyber attacks, and unauthorised entry.

Traditional protection measures in banking frameworks mainly depend on predefined signature-based intrusion detection systems and static rule-governed monitoring. While these platforms can identify known threats, they often fail to recognise new or evolving attack patterns. Additionally, manually updating attack signatures and rules cannot keep pace with the rapidly changing threat environment. In high-speed financial networks, where transactions require real-time processing, delays or excessive false alarms can disrupt services and hurt customer experience.

Modern lending institutions depend greatly on online infrastructure to offer assistance like internet banking, mobile payments, real-time fund transfers, ATM networks, and interbank communications. These systems create large volumes of network traffic with sensitive economic and individual data. Securing this traffic is key, as even a small breach can lead towards financial risks, regulatory implications, negative brand impact, and diminished user trust. Additionally, the problem is made worse by the growing demand for low-latency detection mechanisms in banking models, where transaction delays or false alarms can disrupt services and affect customers negatively. Manual updates of attack signatures and static security rules cannot effectively manage the rapidly evolving threat landscape. As a result, banks face a significant challenge in recognising unknown and dynamically changing cyber attacks instantly without harming system performance.

To tackle these challenges, financial institutions need improved cyber fraud detection and anomaly monitoring mechanisms to monitor transactions and network communication activities more effectively. By combining cryptographic safeguarding measures with intelligent detection techniques, banking institutions are capable of enhancing network protection while ensuring high-performing and secure transaction management.

2. Literature Review

In[1], this paper proposes a cryptographic IoT-cloud security model for banking using ECC, AES, and blockchain hashing. It improves data confidentiality and authentication but does not address real-time intrusion detection.

In[2], this study proposes Quantum Key Distribution (QKD) for secure authentication in online banking, addressing vulnerabilities of classical cryptography to quantum attacks. It provides theoretically secure key exchange but faces practical challenges such as high cost and infrastructure complexity.
In[3], this paper enhances IoT-cloud banking security using layered encryption, AES-256 storage protection, TLS communication, and RBAC. It ensures secure transactions with low overhead but lacks adaptive fraud detection capabilities.
In[4], this study uses blockchain with SHA-256 and ECC to ensure secure, tamper-proof banking transactions and digital identity protection. While it improves transparency and resilience, it lacks built-in fraud detection without AI support.
In[5], this paper combines RSA and AES for secure banking data transmission with dynamic key management. It improves confidentiality but introduces computational overhead and lacks anomaly detection mechanisms.
In[6], this study uses supervised ML models like Random Forest and SVM to detect transaction anomalies in Laos banking data. It achieves good accuracy but faces challenges with imbalanced data and generalisation.
In[7], this study applies CNN and LSTM for fraud detection, showing improved detection performance, especially for sequential patterns. However, high computational cost limits real-time deployment.
In[8], the authors compare multiple ML algorithms and propose ensemble learning for fraud detection. Gradient Boosting and Random Forest outperform traditional classifiers. The study emphasises the importance of feature selection but lacks anomaly-based detection for unknown threats.
In[9], this paper uses graph-based egonet features to detect suspicious transaction clusters for AML. It improves detection but may involve high computation for big-scale environment. In[10], this study applies graph mining and community detection to identify money laundering networks. It improves AML detection but faces scalability challenges.
In[11], this study combines blockchain data with machine learning to detect anomalies in digital banking transactions. It improves fraud detection but depends on well-labelled data.
In[12], this study compares supervised and unsupervised fraud detection methods and shows that hybrid models achieve better accuracy and lower false positives than single approaches.
In[13], this study uses Graph Neural Networks for AML detection, improving accuracy by analysing transaction relationships, but it requires high computational resources.
In[14], this study applies Decision Trees and Random Forest for banking fraud detection, achieving high accuracy but struggling with adaptive fraud patterns.
In[15], this work develops predictive fraud models using Logistic Regression and ensemble methods. The study emphasises real-time scoring engines but notes challenges in handling high transaction throughput.
In[16], the authors propose a low-latency ML pipeline integrating streaming data analytics. The system reduces detection delay while maintaining high precision. However, model retraining complexity is highlighted as a challenge.

In[17], this research uses statistical and ML-based anomaly detection for payment systems. Isolation Forest and clustering methods are applied. Results show effective zero-day fraud detection, but with increased false positives.

In[18], the study introduces embedding-based behavioural profiling for fraud detection. The ranking model prioritises high-risk transactions. It improves fraud ranking efficiency but requires extensive behavioural data.
In[19], the research applies LSTM to analyse sequential financial logs and network data. Results show strong performance in detecting sequential fraud patterns. However, high computational requirements impact scalability.
In[20], this study implements multi-layer perceptron (MLP) models for secure digital banking. Neural networks automatically learn complex fraud patterns but risk overfitting without proper tuning.
In[21], this paper focuses on fraud detection without labelled data. Hierarchical clustering groups normal patterns, while One-Class SVM identifies anomalies. It improves zeroday detection but may misclassify rare legitimate transactions.
In[22], the authors propose AI-driven behavioural monitoring systems. Machine learning detects unusual access patterns and transaction behaviours. The model enhances theft prevention but requires continuous retraining.
In[23], this study integrates Zero Trust principles with homomorphic encryption for secure transaction processing. Continuous authentication and access verification reduce insider threats. Computational overhead remains a limitation.
In[24], the paper proposes risk-based authentication and fraud scoring mechanisms. The system balances security and user convenience but depends heavily on predefined risk rules.
In[25], this widely studied domain applies SVM, Random Forest, combined with deep learning approaches for identifying fraudulent transactions. Techniques such as SMOTE are used to handle class imbalance. High detection accuracy is reported; however, real-time deployment and false alarm reduction remain challenges.

3. Methodology

A secure network architecture protects banking transactions from end users like mobile apps, ATMs, and online banking portals to backend banking servers. The architecture uses a layered approach with a Client Layer, Secure Communication Layer, Cryptographic Processing Layer, and Banking Application Database Layer. All data transmission in this framework occurs through encrypted and authenticated channels. This eliminates the possibility of inaccessible data and ensures secured communication throughout the financial network.
Robust financial data encryption guarantees its confidentiality. An example is the Advanced Encryption Standard (AES) encrypts transaction data before transmission across the network. ECC supports Secure key exchange mechanisms due to its high level of security with less computational cost compared to traditional methods. Every transaction is assigned session keys that are created dynamically. This minimizes the chances of replay attacks. The encrypted data will remain inaccessible to potential threats, even if an adversary captures network traffic.
Transport Layer Security (TLS) safeguards bank customers' private data and protects the customers and bank servers
from eavesdropping and network attacks. TLS provides a secure channel for transmission of data. The client and server identities are verified through mutual authentication. Trusted channels of communication are established by Digital Certificates and Public Key Infrastructure (PKI). In addition, Perfect Forward Secrecy (PFS) ensures that if theft of encryption keys occurs at a later date, the

information that was previously sent will remain inaccessible and undetectable. This mechanism adds some defence against eavesdropping and man-in-themiddle (MITM) attacks.

Multifactor Authentication (MFA) is used to enhance user identity verification. Users must authenticate using multiple factors, such as password authentication along along with Onemulti-factor authentication using OTP or biometric checks. Identity-Based Encryption (IBE) provides an additional layer of security for authenticating users, coupled with Role-Based Access Control (RBAC) - access restrictions are controlled according to the roles of the users within the banking system. These methods ensure that only legitimate users and authorised services can start or process financial transactions.

To keep transaction records tamper-proof, a blockchainbased integrity verification mechanism is included. Each financial transaction is hashed using the SHA-256 cryptographic hashing algorithm, and the hash values are stored in a private blockchain ledger. This process ensures the integrity of transaction records and stops unauthorized changes to financial data.

Real-time monitoring and risk validation mechanisms help detect potential threats. Encrypted traffic metadata is analyzed without exposing sensitive information. Risk scoring methods evaluate transaction behaviors and identify unusual activities. If suspicious transactions are found, the system can trigger extra authentication steps or temporarily block the transaction. This allows for real-time threat detection while ensuring that legitimate transactions are not delayed.

Banking systems need high performance and low latency, so performance optimization techniques are part of the design. Lightweight cryptographic algorithms like ECC are preferred over RSA to lower computational costs. Hardware acceleration is considered for encryption tasks, and efficient key management techniques minimise processing delays. These optimisations make sure strong security measures do not harm system performance.

Furthermore, anomaly detection models are built with past financial activity data to spot fake activities. The models are periodically retrained with new transaction data to keep up with changing fraud patterns. Model parameters are continuously updated to enhance detection accuracy and lower false positives, ensuring the system stays effective against new financial threats.

4. System Architecture

The developed framework architecture focuses on providing secure banking transactions while detecting fraud or unusual activities in real time. Modern banking systems handle a high volume of digital transactions through online banking platforms, mobile apps, ATM networks, and electronic fund transfer services. These transactions create sensitive financial Unauthorized access, data breaches, and fraud. In response to these challenges, the architecture combines cryptographic security methods with intelligent anomaly detection models to ensure secure communication, efficient data processing, and dependable fraud detection.

The first part of the architecture is the User Transaction Layer, which serves as the system's entry point. Customers initiate banking transactions here through various digital channels like online banking portals, mobile banking apps, ATM machines, and payment gateways. Each transaction creates network data that includes user authentication details, transaction amount, time of transaction, geographic location, device information, and transaction type. Given the highly sensitive nature of this personal and financial data, secure communication protocols are used to transmit the data safely to the banking servers.

The next part is the Banking Server Layer, functioning as the core processing component system of the banking network. The server receives transaction requests from users and performs initial verification steps like authentication and authorisation. To maintain the privacy and security of financial information, cryptographic techniques are applied at this stage. People commonly use the Advanced Encryption Standard (AES) to protect data is used as an encryption algorithm to encrypt transaction data, whileElliptic Curve Cryptography (ECC) is used to keep communications secure key exchange between users and banking servers. Additionally, Secure communication is ensured using protocols like Transport Layer Security (TLS) helps stop unauthorized access, eavesdropping, and man-in-the-middle attacks during data transmission data transmission.

Once the transaction is authenticated and transferred securely, the data moves to the Data Processing Module. Here, the transaction data undergoes several preprocessing steps to prepare it for anomaly detection. Data cleaning removes duplicate entries and addresses missing or inconsistent values. Normalisation ensures features have a uniform distribution. Feature extraction techniques identify key attributes that characterise transaction behaviour, which may include transaction amount, frequency, location, device identification, login patterns, and user behaviour history. Extracting relevant features allows the system to analyse transaction patterns, and it helps tell the difference between normal, legitimate behavior and suspicious activity.

After preparing the transaction features, the processed data is sent to the Hybrid Intrusion Detection System (IDS) Model. This component is the heart of the fraud detection system. The hybrid IDS combines utilizing both labelled and unlabelled learning approaches to enhance detection capabilities. A Support Vector Machine (SVM)-based model is employed as a supervised classification approach model that identifies known fraud patterns based on labelled historical transaction data. At the same time, an Isolation Forest algorithm serves as an unsupervised method to spot unusual transaction behaviours that may signal unknown or emerging cyber threats. By merging both methods, the hybrid model can successfully detect both established fraud patterns and new types of attacks.

Once the system finishes detecting potential issues, it sends the results to the fraud team for further review Detection and Alert Module. In this module, the system assesses the anomaly score generated by the detection model and classifies the transaction as either legitimate or suspicious.In cases where a transaction is classified as suspicious, the system immediately alerts banking security administrators and monitoring systems. Depending on the threat’s severity, the system may temporarily block the transaction, request additional user verification like one-time password (OTP) authentication, or mark the transaction for further investigation. This step helps prevent financial fraud while minimising disruption for legitimate users.

Beyond real-time detection, the system features secure logging and monitoring mechanisms. All transaction records and The detection results are securely stored using cryptographic hashing to maintain data integrity and prevent any unauthorized changes. These secure logs support auditing processes and help financial institutions analyse fraud patterns for future improvements in security measures.

Overall, the proposed system architecture combines secure communication protocols, cryptographic protection, intelligent anomaly detection models, and real-time alert mechanisms to form a solid security framework for banking networks. This architecture protects sensitive financial data while ensuring efficient transaction processing, reducing false alarms, and maintaining customer trust in digital banking services.

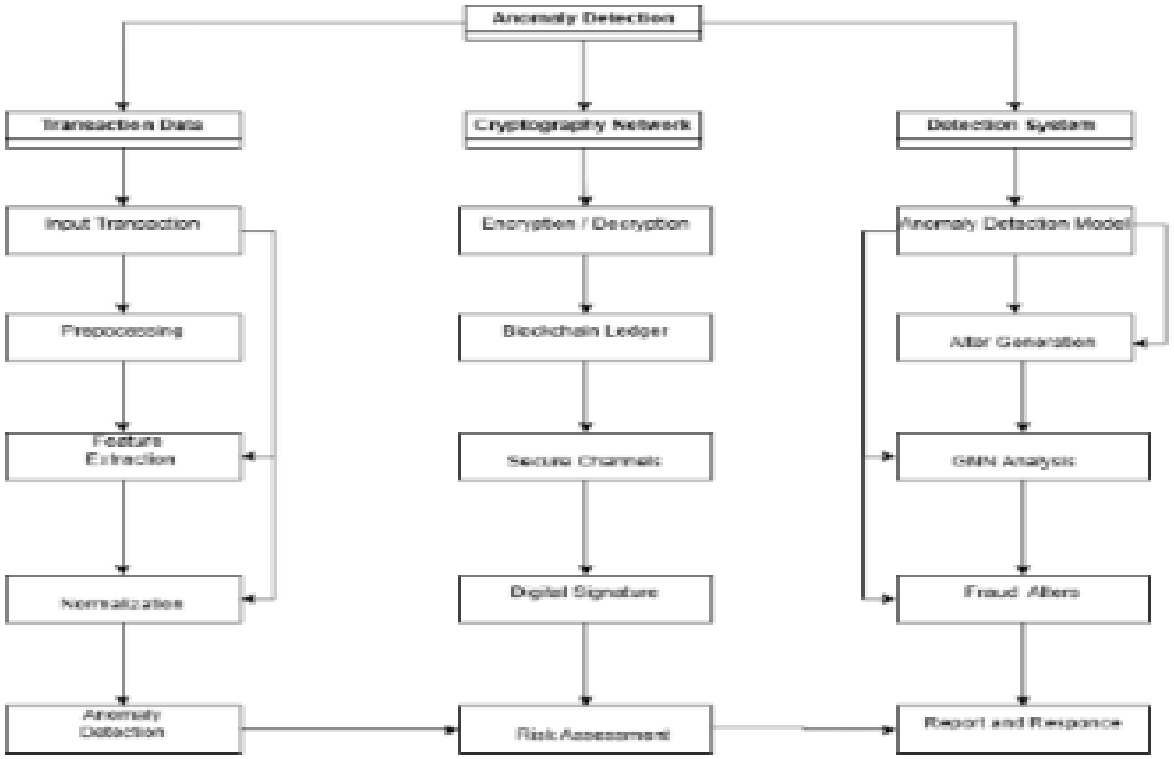

Figure 1: Anomaly Detection System Architecture

5. Implementation

The dataset is preprocessed before model training to ensure better performance and accuracy. During preprocessing, missing values and duplicate records are removed to maintain data quality. Categorical variables such as protocol type and service type, as well as connection state, are encoded into numerical representations by applying appropriate techniques to make them machine learning processable. In addition, numerical attributes are normalised using scaling techniques to make sure all features affect the equally model training process. Feature selection is also applied to identify the most relevant attributes related to network behaviour and transaction patterns.

After preprocessing, the dataset is partitioned into training and testing subsets using a train-test split technique. Generally, around 70–80 per cent of the data is used for training the model, while the remaining portion is used for testing and validation. This helps evaluate the generalisation capability of the model and prevents overfitting during training.

The developed detection model incorporates both machine learning and advanced neural model approaches. Initially, traditional classification algorithms like Random Forest and Support Vector Machine (SVM) are implemented through the Scikit-learn framework to establish a baseline intrusion detection capability. These algorithms help to distinguish network behaviour as legitimate or anomalous based on learned behaviours from the dataset utilized for model training.

Along with machine learning models, a deep learning architecture is developed using TensorFlow. The architecture includes Convolutional layers at the initial stage Neural Network (CNN) layers, which automatically get important spatial patterns from the network traffic dataset. The first CNN layer identifies basic patterns in the data, while the second CNN layer extracts more complex features associated with abnormal network behaviour.

Following the a combination of CNN layers and Long Short-Term Memory (LSTM) layers are incorporated into the architecture. LSTM networks are particularly useful for analysing time-series data such as network traffic flows and banking exchange sequences. These layers help capture temporal dependencies and detect suspicious activity patterns that evolve.

After feature extraction using CNN and LSTM layers, the processed data is then sent to fully connected or dense layers that carry out the final prediction task. These layers combine the extracted features and determine whether a given network activity represents normal behaviour or a potential intrusion.

Once the model architecture is defined, the training process begins using the model.fit() function. During training, the model learns from the labelled dataset and updates its internal parameters to minimise prediction errors. After training is completed, predictions are generated using the model's predict() function on the testing dataset.

In order to assess the performance in order to evaluate the developed framework, various performance metrics are taken into consideration are calculated. Accuracy is adopted to measure the overall correctness of predictions, while evaluation is performed using a confusion matrix to analyse true positives, true negatives, false positives, and false negatives. Visualisation methods such as Matplotlib and Seaborn are utilized to display the confusion matrix and other performance graphs for easier interpretation.

Finally, a real-time intrusion detection function is implemented. This function continuously monitors incoming banking network traffic or transaction data and processes it through the trained detection model. If the model identifies suspicious or malicious activity, the system immediately flags the transaction as a potential attack and generates alerts for security administrators. This allows banks to respond quickly to potential cyber threats while ensuring that legitimate transactions are processed without delays.

6. Results and Analysis

The dataset is first preprocessed to improve model performance by removing missing values and duplicates, encoding categorical features, and normalising numerical attributes. Feature selection is applied to identify important attributes related to network behaviour. The dataset used in this study is then divided into training and testing data using a standard train/test split technique to evaluate enhance the accuracy of the model, and prevent overfitting.

The system uses both machine learning and deep learning techniques. Traditional machine learning models like the Random Forest Classifier and Support Vector Machine (SVM) are commonly used are implemented as baseline models. A deep neural network model is then developed employing Convolutional Neural Networks (CNN) to learn spatial representations, combined with Long Short-Term Memory (LSTM) layers to capture sequential patterns in network traffic. The ethe extracted features are subsequently directed to fully connected layers for final classification.

This system is trained using the model.fit() function, and predictions are generated using model.predict().Performance evaluation is conducted using metrics including accuracy and confusion matrix, which are visualised using Matplotlib and Seaborn.

Further, the trained model is tested using unseen network traffic data to evaluate its ability to detect intrusions effectively. The system analyses network packets and classifies them as normal traffic or potential attacks based on learned patterns. If abnormal behaviour is detected, the system flags the packet as suspicious. A real-time intrusion detection function is then implemented to continuously

monitor incoming banking network traffic. This function processes live data through the trained model and instantly generates alerts when malicious activity is detected. This real-time monitoring mechanism helps financial institutions respond quickly to potential cyber threats while maintaining secure and uninterrupted banking services.

Table I: Sequential Model Architecture

Layer (Type)	Output Shape	Param #
conv1d (Conv1D)	(None, 76, 64)	256
max_pooling1d (MaxPooling1D)	(None, 38, 64)	0
conv1d_1 (Conv1D)	(None, 36, 128)	24,704
max_pooling1d_1 (MaxPooling1D)	(None, 18, 128)	0
lstm (LSTM)	(None, 18, 64)	49,408
lstm_1 (LSTM)	(None, 32)	12,416
dense (Dense)	(None, 64)	2,112
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total Parameters: 88,961
Trainable: 88,961
Non-trainable: 0

CNN-LSTM Accuracy: 0.97 | Random Forest Accuracy: 0.95 |

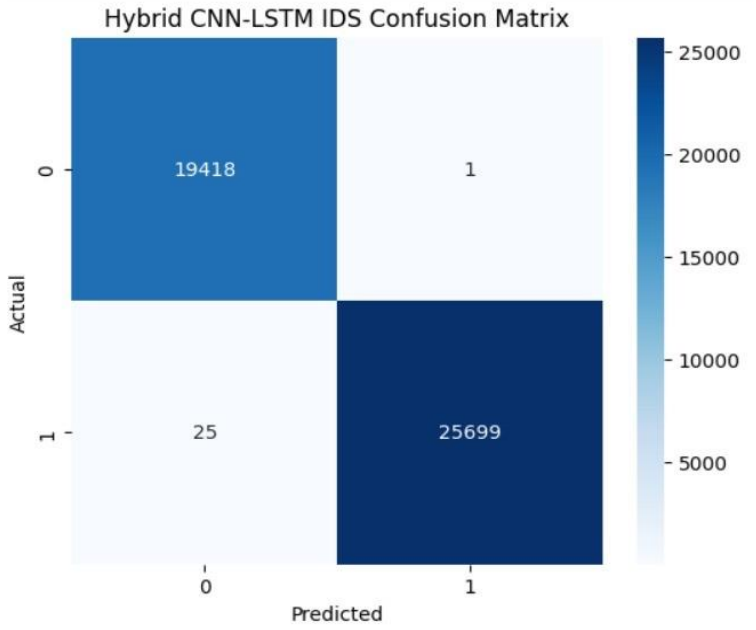

Figure 2: Hybrid CNN-LSTM IDS Confusion Matrix

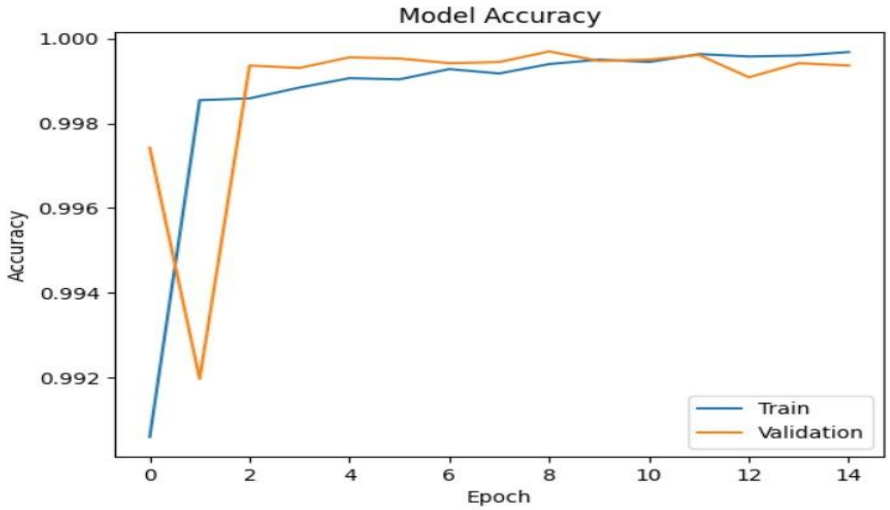

Figure 3: Model Accuracy

SVM Accuracy: 0.94
CNS Hybrid IDS Accuracy: 0.99

7. Discussion

The implemented hybrid intrusion detection framework was evaluated using benchmark cybersecurity datasets such as CICIDS 2017 and NSL-KDD to analyze its effectiveness in detecting cyber attacks in banking network environments. The system integrates deep learning techniques (CNN-LSTM) with traditional classification models such as Random Forest and Support Vector Machine (SVM). The performance of these models was compared based on their detection accuracy and ability to classify normal and malicious network traffic.

The results indicate that traditional machine learning models such as SVM and Random Forest provide good baseline performance for intrusion detection. However, these models rely heavily on manually extracted features and may struggle to detect complex or evolving attack patterns in banking networks.

The CNN-LSTM model demonstrates improved performance compared to traditional models because it combines spatial feature extraction with temporal pattern recognition. CNN layers effectively capture structural characteristics of network packets, while LSTM layers analyze sequential patterns in network traffic flows. This enables the model to detect suspicious behavioral patterns that may indicate cyber attacks.

The proposed CNS Hybrid IDS model achieves the highest detection accuracy of 0.99, outperforming the other models. This improvement is achieved by integrating cryptographic network security mechanisms with intelligent intrusion detection techniques. The hybrid approach improves the system's ability to identify both known and unknown attacks while minimizing false positives.

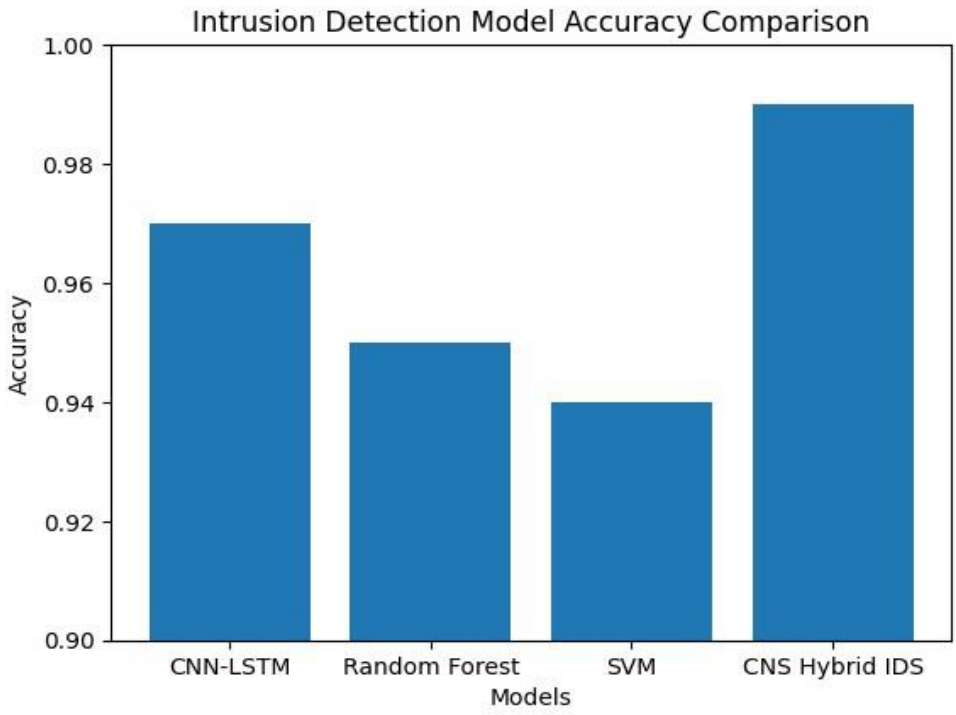

Figure 4: Intrusion Detection Model Accuracy Comparison

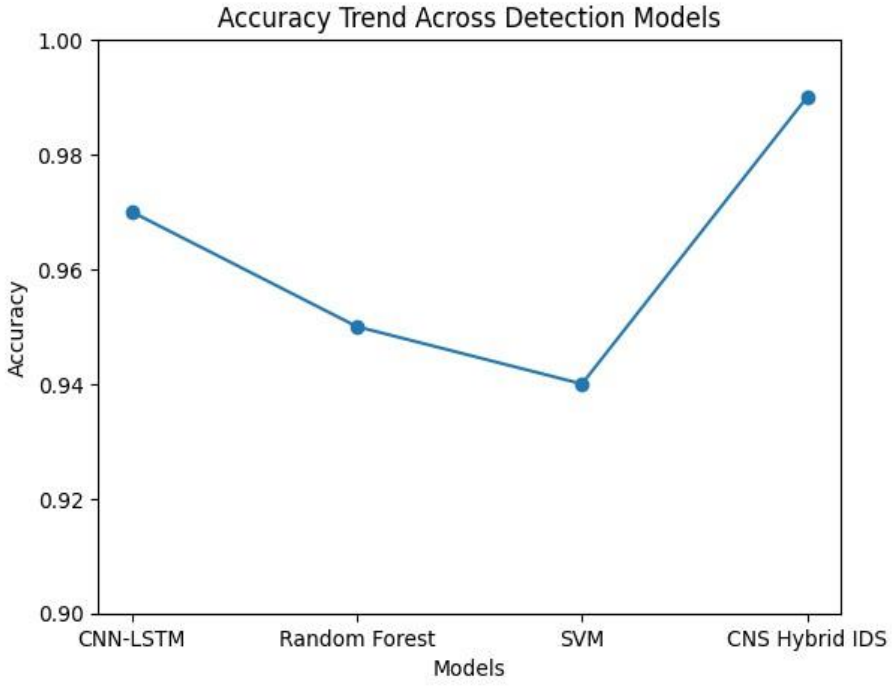

Figure 5: Accuracy Trend Across Detection Models

1.Accuracy Comparison Bar Chart: Shows that the CNS Hybrid IDS (0.99) performs better than CNN-LSTM (0.97), Random Forest (0.95), and SVM (0.94).
2. Accuracy Trend Line Graph: Shows the improvement from traditional ML models to the proposed CNS Hybrid IDS model.
It illustrates the comparison of intrusion detection accuracy across different models. Traditional machine learning models such as SVM (94 per cent) and Random Forest (95 per cent) provide baseline detection performance. The CNN-LSTM deep learning model improves detection accuracy to 97 per cent by learning both spatial and sequential patterns in network traffic. However, the proposed CNS Hybrid IDS model achieves the highest accuracy of 99 per cent, demonstrating its ability to effectively detect both known and unknown cyber attacks in banking network environments.
The results indicate that combining deep learning techniques with hybrid intrusion detection strategies significantly improves the detection capability while reducing false alarms in real-time financial transaction networks.

8. Conclusion

This research presents a hybrid intrusion detection framework aimed at enhance the security of modern banking networks. The system analyses banking network traffic and financial transaction data to identify anomalous or fraudulent activities in real time. By combining machine learning and deep learning techniques, the proposed approach is capable of detecting both known and unknown cyber attacks that may threaten financial systems.
The hybrid model integrates traditional classifiers such as Random Forest and Support Vector Machine with deep learning techniques, including CNN and LSTM. CNN layers effectively extract important structural features from network traffic, while LSTM layers capture sequential patterns in transaction

flows. This combination allows the system to analyse complex network behaviours and identify anomalies that may indicate cyber attacks or fraudulent transactions.

Experimental results demonstrate that the proposed CNS Hybrid Intrusion Detection System achieves improved detection performance compared to individual models. These The results show that the hybrid model brings a significant improvement fraud detection capability while reducing false alarms.

Overall, the proposed system provides an effective solution for securing banking networks against evolving cyber threats. By enabling real-time intrusion detection and accurate anomaly identification, the system helps financial institutions It helps safeguard sensitive customer data, minimize financial losses, and preserve trust in digital banking services. Future work may focus on further optimising the model for largescale financial systems and integrating additional security mechanisms to enhance cyber resilience.

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