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AI-DRIVEN CLOUD SECURITY FRAMEWORK FOR CYBER THREAT DETECTION AND CLASSIFICATION IN BANKING SYSTEMS

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ABSTRACT

The rapid digital transformation of banking systems has led to an increased reliance on cloud computing and AI for managing financial transactions, but it also introduces a higher risk of cyber threats, such as fraud and data breaches. Existing security solutions face challenges such as high false positive rates, scalability issues, and significant computational resource demands, which hinder their efficiency and effectiveness in threat detection. This paper presents an AI-driven cloud security framework designed to address these challenges by developing an efficient, scalable AI-driven framework that effectively detects and mitigates cyber threats. The workflow begins with collecting transaction details, user access patterns, and security logs, followed by preprocessing, which involves handling missing data and normalizing the features for consistency. Next, feature extraction is performed using Fourier Transform to identify important patterns in the data, particularly in time-series events. The extracted features are passed to the threat detection phase, where a GRU model is applied to classify and identify potential threats. Finally, the developed model is integrated into the Cloud, ensuring scalability and threat monitoring. The results demonstrate the system's high performance, with accuracy at 99.52%, precision at 99.33%, sensitivity at 99.43%, specificity at 99.27%, and an F-measure of 99.3%. Additionally, latency increases with data size, reaching 337 ms for 150 GB of data. This work gives an efficient, scalable framework that reduces false positives, processes large data volumes, and optimizes computational resources, providing a robust solution for cyber threat detection in banking systems.

Keywords: AI-driven security, cyber threat detection, banking systems, GRU model and cloud integration.

1 INTRODUCTION

The rapid adoption of cloud computing and AI technologies in the banking sector has revolutionized the way financial transactions are conducted and secured [1] [2] [3] [4]. With the increasing sophistication of cyber-attacks, it has become crucial for banking systems to implement advanced security measures that can effectively detect and mitigate threats in real-time [5] [6] [7]. As financial institutions move their operations to the cloud, they become more vulnerable to various types of cyber-attacks, such as fraud, phishing, and data breaches [8] [9] [10]. Traditional security methods are often insufficient to address the scale and complexity of modern threats, necessitating the use of AI-driven solutions that can analyze vast amounts of data in real time [11] [12] [13]. In this context, an AI-driven cloud security framework for cyber threat detection and classification is of paramount importance to safeguard sensitive financial data and ensure system integrity, reliability, and compliance with industry regulations.

Several existing methods have been proposed to enhance cyber security in banking systems, including signature-based approaches, anomaly detection systems, and machine learning models like Random Forest (RF), Support Vector Machines (SVM), and Decision Trees (DT). Signature-based systems,

while effective for known threats, often fail to detect new or evolving attack patterns [14] [15] [16]. Anomaly detection systems, such as Isolation Forest and k-Means clustering, offer improved detection of unknown threats but are prone to high false positive rates. Machine learning techniques like RF, SVM, and DT are frequently used for threat classification, but they often require extensive feature engineering and struggle to scale with large volumes of data [17] [18] [19]. Deep learning methods, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are emerging as more effective alternatives, but they often demand significant computational resources and have issues with interpretability and real-time processing in cloud environments [20] [21] [22].

The proposed framework overcomes the drawbacks of existing methods by integrating a GRU-based deep learning model with cloud computing infrastructure [23] [24] [25]. This combination enhances the framework's ability to detect and classify cyber threats more accurately and efficiently [26] [27]. Unlike traditional methods, the GRU model can process sequential data with long-term dependencies, making it well-suited for detecting complex patterns in time-series data [28] [29] [30]. Additionally, the cloud integration ensures scalability, enabling the system to handle large volumes of transactional and security data in real time. The novelty of this study lies in its ability to provide a flexible, scalable, and AI-driven solution for cyber threat detection, combining the power of deep learning with cloud-based infrastructure for seamless security management in banking systems.

The paper is organized as follows: Section 2 reviews Related Work, discussing previous methods and their limitations. Section 3 details the Methodology. Section 4 presents the Results, showcasing the performance metrics and system evaluation. Finally, Section 5 concludes the paper.

2 LITERATURE SURVEY

Several studies have explored cloud computing security challenges, particularly in the banking sector. Kodadi and Kumar (2018) proposed using Artificial Neural Networks (ANNs) with Levenberg–Marquardt based Back Propagation (LMBP) algorithms to predict cloud security performance [31]. They emphasized the importance of reducing the Mean Square Error (MSE) for model accuracy [32] [33]. Buyya, Ranjan, and Calheiros addressed the lack of mechanisms for dynamically coordinating load distribution across geographically distributed cloud data centers, advocating for an InterCloud approach to improve Quality of Service (QoS) levels [34] [35]. Alavilli and Pushpakumar (2018) focused on fault tolerance in cloud computing, proposing a modular service layer that allows users to specify their desired level of fault tolerance without knowing the technical details of the underlying techniques [36] [37] [38].

Nagarajan and Kurunthachalam (2018) proposed a privacy-preserving identity and access management system for cloud federations using blockchain technology, addressing the concerns of data leakage and misuse [39]. Chou compared cloud service models and analyzed security risks associated with cloud architectures, highlighting vulnerabilities that hackers exploit and providing countermeasures to cloud security breaches [40]. Srinivasan and Arulkumaran (2018) introduced an ontology-driven e-learning system in the cloud, which adapts to learners' behavior, integrating cloud storage to maintain data and resources [41] [42] [43]. Musam and Kumar (2018) proposed Business Intelligence as a Service (BIaaS) in the cloud for financial institutions, offering elastic computing to improve risk analysis and pricing accuracy [44] [45].

Alagarsundaram and Arulkumaran (2018) presented a fuzzy logic-based model for detecting e-banking phishing websites, emphasizing the importance of URL and domain identity in identifying phishing threats [46] [47] [48]. Mandala and Purandhar (2018) developed a fraud detection framework for online banking that combines data mining techniques to distinguish between fraudulent and genuine customer behavior, achieving higher accuracy than traditional methods [49] [50]. Kethu and Thanjaivadivel (2018) introduced the Radon-Fourier Transform (RFT) for radar target detection, showcasing its ability to improve weak target detection and radar coverage without requiring changes to radar hardware [51].

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Finally, Roengpitya and Rungcharoenkitkul applied the concept of Conditional Value-at-Risk (CoVaR) to measure systemic risk in the Thai banking sector, highlighting how larger banks contribute more to systemic risk during financial crises [52] [53].

Budda and Pushpakumar (2018) proposed an approach to secure cloud computing environments by utilizing machine learning algorithms to detect security breaches, emphasizing the need for more adaptive and efficient systems [54] [55]. Subramanyam and Mekala (2018) introduced a system for real-time monitoring and anomaly detection in cloud infrastructures, focusing on reducing false positives while maintaining high detection accuracy [56] [57]. Radhakrishnan and Mekala (2018) explored the use of hybrid models for cloud security, combining multiple machine learning techniques to improve the accuracy of threat detection and mitigate risks in dynamic cloud environments [58] [59]. Dyavani and Rathna (2018) addressed the challenges of ensuring quality of service in cloud systems, proposing a framework that dynamically allocates resources based on fluctuating demand, which aids in maintaining secure and efficient cloud operations [60] [61] [62]. These studies highlighted various approaches to cloud security, with a particular emphasis on machine learning and resource management, laying the groundwork for more efficient and scalable systems for cloud-based services.

2.1 Problem Statement

Despite significant advancements in AI-driven cyber threat detection, several critical challenges remain, such as high false positive rates, scalability issues, and substantial computational resource demands [63] [64]. Existing works have made progress, but they still struggle with the high rate of false positives, which leads to operational inefficiencies and unnecessary alarm triggers [65]. Additionally, scalability issues arise as data volumes increase, with current systems unable to handle large datasets efficiently, thus impacting their ability to detect threats [66]. Furthermore, the computational resource demands of complex deep learning models require significant infrastructure, limiting their practicality in resource-constrained environments [67]. The work is proposed to overcome these challenges by introducing a scalable, AI-driven cloud security framework that reduces false positives, handles large data volumes effectively, and optimizes resource usage, providing a more efficient and adaptive solution for banking systems.

3 METHODOLOGIES

The methodology of the proposed AI-driven cloud security framework for threat detection in banking systems begins with data collection, where transaction details, access patterns, and user behavior are gathered to build a comprehensive dataset. The collected data then undergoes data preprocessing, which involves handling missing data and normalizing the features for consistency. Next, feature extraction is performed using Fourier Transform to identify important patterns in the data, particularly in time-series events. The extracted features are passed to the threat detection phase, where a GRU model is applied to classify and identify potential threats. Finally, the developed model is integrated into the Cloud, ensuring scalability and threat monitoring. This workflow ensures efficient and accurate detection of cyber threats in banking systems. The whole framework is illustrated in Figure 1.

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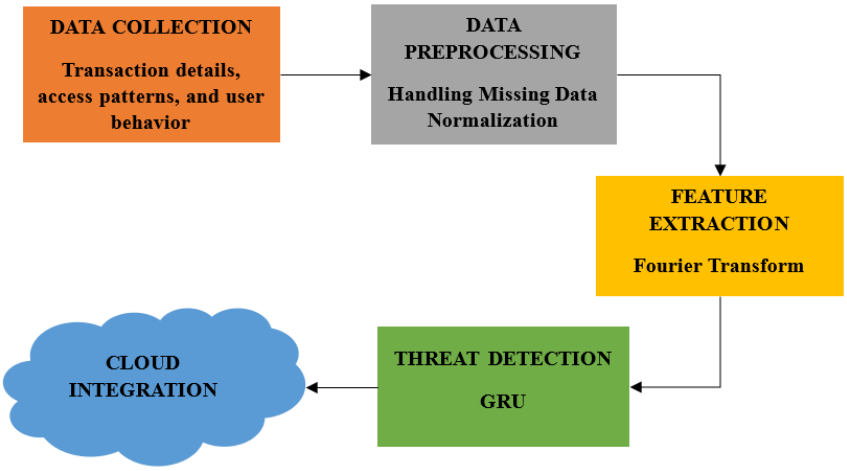

Figure 1: System Workflow for AI-Driven Cloud Framework in Banking Systems

3.1 Data Collection

Data collection for this framework involves gathering transaction logs, security logs, and customer profiles from banking systems to capture transaction details, access patterns, and user behavior. Security logs from firewalls and intrusion detection systems help identify potential breaches, while customer profiles provide insights into normal activities for accurate anomaly detection. Historical cyberattack datasets, containing labeled examples of both benign and malicious events, are used to train the AI model to recognize specific threat types. This diverse data enables the AI model to detect and respond to threats with high accuracy.

3.2 Data Preprocessing

Data preprocessing plays a critical role in preparing the collected data for effective analysis and model training.

3.2.1 Handling missing data

Data preprocessing starts with handling missing or inconsistent data, where median imputation is used to fill in missing values. This approach is more robust than mean imputation, as it avoids the distortion caused by outliers in financial data like transaction amounts. By using the median, the dataset remains realistic and retains the integrity of its distribution, which is critical for accurate threat detection.

3.2.2 Normalization

Next, Z-score normalization is applied to standardize the numerical features, ensuring that they all have a mean of 0 and a standard deviation of 1. This step is crucial because it prevents any single feature, such as transaction amount or time, from disproportionately influencing the model's learning process. With this normalization, the model can handle diverse data more effectively, improving both performance and convergence speed.

3.3 Feature Extraction

After preprocessing the data, feature extraction is performed using Fourier Transform to capture frequency-domain features from time-series data like transaction logs and security events. This method helps identify hidden periodic patterns or anomalies, such as unusual spikes in transactions or unauthorized access attempts, which may signal a cyber threat. By transforming time-domain data into frequency-domain features, it enables the model to detect subtle trends or recurring behaviors that could indicate security risks. These extracted features provide a more comprehensive view of the data, highlighting important patterns that are crucial for accurate threat detection. The Fourier Transform

helps the model focus on both the magnitude and frequency of events, enhancing its ability to spot complex cyber threats. This step significantly improves the overall effectiveness of the AI model in recognizing potential security breaches.

3.4 Threat Detection

After extracting features using Fourier Transform, threat detection is performed using a GRU (Gated Recurrent Unit) model, which is well-suited for sequential data like transaction logs and security events. The GRU model processes the extracted features, identifying patterns and anomalies in the sequence that may indicate malicious activities. By learning from historical data, the model can classify potential threats such as fraud, phishing, or unauthorized access. GRU's ability to capture long-term dependencies in time-series data allows it to recognize complex, evolving attack patterns. This enhances the system's ability to detect previously unseen threats. The result is more accurate and efficient threat classification, reducing false positives and improving overall security in banking systems.

For the GRU model used in threat detection, the key mathematical formulas involve updating the hidden states at each time step using the following equations:

Reset Gate is represented as equation (1),

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{1}$$

Where, r_t is the reset gate at time t, h_{t-1} is the previous hidden state, x_t is the input at time t, W_r is the weight matrix for the reset gate, b_r is the bias term for the reset gate, σ is the sigmoid activation function. The reset gate r_t determines how much of the previous hidden state h_{t-1} should be ignored when calculating the candidate hidden state.

Update Gate is expressed as equation (2),

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{2}$$

Where, z_t is the update gate at time t, W_z is the weight matrix for the update gate, b_z is the bias term for the update gate. The update gate z_t controls how much of the previous hidden state h_{t-1} is retained versus how much new information from the candidate hidden state $\vec{h}_t$ is incorporated.

Candidate Hidden State is expressed as equation (3),

$$\tilde{h}_t = \tanh\,(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_h) \tag{3}$$

Where, $\tilde{h}_t$ is the candidate hidden state at time t, W_h is the weight matrix for the candidate hidden state, b_h is the bias term for the candidate hidden state. The candidate hidden state $\tilde{h}_t$ is calculated using the current input x_t and the reset-modified previous hidden state, capturing new information about the sequence.

Final Hidden State is represented as equation (4),

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{4}$$

Where, h_t is the final hidden state at time t, z_t is the update gate (determining how much of the previous state is kept), $\tilde{h}_t$ is the candidate hidden state (suggested new state). The final hidden state h_t is a weighted sum of the previous hidden state and the candidate state, with the update gate z_t controlling the contribution of each. This mechanism allows the GRU model to capture important sequential dependencies in the data, making it highly effective for threat detection in time-series data, such as transaction logs and security events.

3.5 Cloud integration

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After threat detection using the GRU model, cloud integration ensures scalable and efficient deployment of the system. The detected threats are processed and classified within the cloud environment, allowing for seamless data management and analysis. Cloud computing provides the necessary infrastructure to handle large volumes of transaction and security data, enabling the system to scale dynamically with increased demand. By leveraging cloud resources, the model can be continuously updated and retrained with new data, enhancing its ability to detect emerging threats. Additionally, the cloud enables the integration of other security layers, such as firewalls and intrusion detection systems, for enhanced protection. This integration ensures that the threat detection system remains adaptable, secure, and capable of responding to evolving cyber threats in banking systems.

4 RESULTS

The results section presents the performance evaluation of the proposed AI-driven cloud security system for cyber threat detection in banking systems. The system's effectiveness is assessed using key performance metrics and its scalability with varying data sizes. The following sections provide detailed insights into the system's accuracy, latency, and overall efficiency.

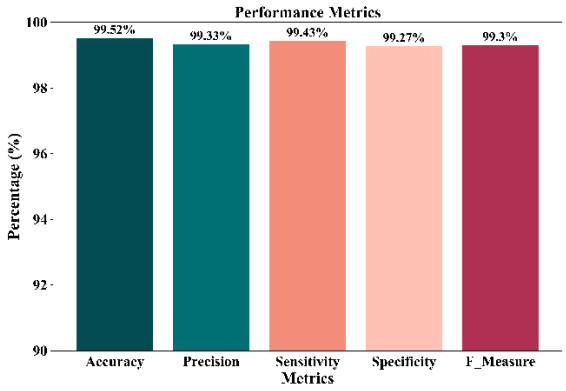

Figure 2: Performance metrics

Figure 2 illustrates the performance metrics of the AI-driven cloud security system used for cyber threat detection in banking systems. The system achieves impressive results with Accuracy at 99.52%, Precision at 99.33%, Sensitivity at 99.43%, Specificity at 99.27%, and F-Measure at 99.3%. These performance metrics demonstrate the effectiveness of the proposed system in accurately detecting and classifying cyber threats, minimizing false positives, and ensuring reliable security management. The results highlight the system's capability to maintain a high level of precision and recall, essential for safeguarding banking systems from evolving cyber threats.

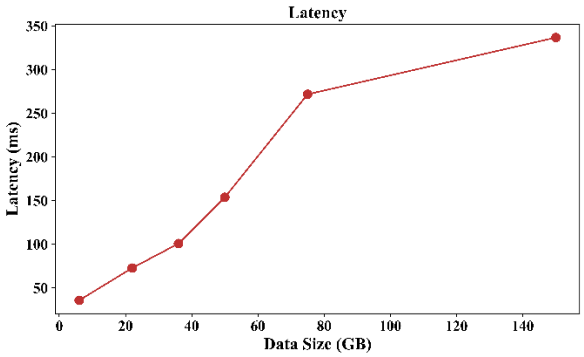

Figure 3: Latency

Figure 3 illustrates the relationship between data size and latency in the proposed cloud security system. As the data size increases from 6 GB to 150 GB, the latency also increases, with latency reaching around 337 ms for the largest data size. The rising latency with increasing data size indicates that processing larger volumes of data requires more time, which is a typical behavior in cloud-based systems. Despite the increasing latency, the system maintains efficient processing for moderate data sizes, ensuring timely threat detection. These results highlight the system's scalability and its performance trade-offs as data volumes grow.

5 CONCLUSIONS

In this work, developing a scalable, AI-driven cloud security framework for effective cyber threat detection in banking systems has been successfully achieved. The proposed framework minimizes false positives, optimizes resource usage, and efficiently processes large data volumes, ensuring threat detection. The results show high performance, with accuracy at 99.52%, precision at 99.33%, sensitivity at 99.43%, specificity at 99.27%, and an F-measure of 99.3%. Additionally, latency increases with data size, reaching 337 ms for 150 GB of data, demonstrating the system's scalability. The proposed system provides robust detection, with the ability to handle larger datasets while maintaining high accuracy and low false positives. Furthermore, the cloud integration ensures the framework can scale effectively to meet the demands of modern banking environments. Future work will focus on incorporating explainability features into the AI model to improve transparency, helping security teams understand and trust the decision-making process.

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