10.48047/jocaaa.2023.31.04.113
ISSN: 1521-1398
1572-9206

Long Short-Term Memory-Based Anomaly Detection for IoT Systems with Blockchain-Enhanced Security and Trust Mechanisms

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Abstract: The proliferation of IoT systems has introduced significant security vulnerabilities, necessitating robust intrusion detection mechanisms. This paper presents a novel approach leveraging Long Short-Term Memory (LSTM) for anomaly detection in IoT systems, achieving an overall accuracy of 90%. The integration of immutable data logs, decentralized trust mechanisms, and smart contracts through blockchain technology enhances the security and trustworthiness of the proposed system. This study evaluates the effectiveness of LSTM and blockchain mechanisms, highlighting their combined potential to secure IoT infrastructures against cyber threats. The rapid adoption of Internet of Things (IoT) systems across industries has brought immense benefits, such as enhanced operational efficiency and real-time data insights. However, the interconnected nature of these systems also presents significant security challenges, including vulnerability to intrusion, data breaches, and unauthorized access. To address these challenges, this research presents a hybrid security framework that leverages Long Short-Term Memory (LSTM) networks for anomaly detection and blockchain technology for trust and security enhancement. The proposed model achieves an impressive accuracy of 90%, demonstrating its efficacy in identifying and mitigating potential threats in IoT networks. Additionally, the blockchain integration ensures data immutability, decentralized trust, and the implementation of automated security protocols through smart contracts. The findings of this study underline the importance of combining machine learning and blockchain technologies to bolster IoT security, paving the way for future innovations in safeguarding critical systems.

I. Introduction

With the increasing adoption of IoT systems across industries, safeguarding these networks against cyber threats has become paramount. Traditional anomaly detection techniques often fail to address the dynamic and distributed nature of IoT systems. To address these challenges, this study employs LSTM, a recurrent neural network model adept at identifying sequential patterns and anomalies, combined with blockchain-enabled trust mechanisms. This hybrid approach ensures real-time anomaly detection, immutable data storage, and decentralized trust, collectively enhancing IoT system security. The Internet of Things (IoT) has revolutionized how devices communicate and interact, enabling seamless data exchange and process automation across various domains, including healthcare, manufacturing, and smart cities. Despite these

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advantages, the growth of IoT ecosystems has exposed significant security vulnerabilities. These vulnerabilities arise due to the heterogeneous nature of IoT devices, limited computational capabilities, and the distributed architecture of IoT systems. Cyberattacks such as distributed denial-of-service (DDoS), data tampering, and unauthorized access are growing concerns that threaten the integrity and availability of IoT networks.

Traditional Intrusion Detection Systems (IDS) and security frameworks are often insufficient for IoT environments due to their static rule-based designs and lack of adaptability to dynamic and complex attack patterns. Furthermore, centralized security models present single points of failure and are prone to compromise, making them unsuitable for the inherently decentralized nature of IoT systems. To address these challenges, this research proposes a novel hybrid approach that combines LSTM networks and blockchain technology. LSTM, a variant of recurrent neural networks, excels at analyzing sequential data, making it ideal for detecting anomalies in IoT-generated time-series data. Meanwhile, blockchain technology offers decentralized, tamper-proof mechanisms for storing and verifying data, ensuring trust and transparency in IoT networks. The integration of smart contracts further enhances the system's automation and responsiveness to security threats. This paper outlines the architecture, methodology, and evaluation of the proposed framework. The study also includes a comparative analysis with existing approaches, highlighting the superiority of the hybrid LSTM and blockchain model in terms of accuracy, trust, and cost-effectiveness.

II. Related works

Anomaly detection techniques for Internet of Things (IoT) systems are critical in identifying unusual patterns that may indicate cyberattacks or system failures. Several methods have been proposed over the years, each with its own strengths and limitations. Traditional approaches include statistical models, machine learning algorithms, and deep learning techniques, which vary in terms of complexity, scalability, and detection accuracy.

1. *Convolutional Neural Networks (CNN) for Anomaly Detection*: CNNs are widely used for anomaly detection, especially in image-based and spatial data applications. By automatically learning spatial hierarchies and features from data, CNNs can effectively identify patterns indicative of anomalies. However, CNNs are less effective in dealing with sequential data, which is often generated by IoT systems (such as time-series sensor data). Therefore, their use in IoT security can be limited since IoT data typically requires an understanding of the temporal relationships between events, something CNNs are not optimized for.

2. *Support Vector Machines (SVM) with Blockchain*: SVMs are popular for detecting anomalies in structured datasets. They are capable of performing well in high-dimensional spaces and are relatively easy to implement. However, when combined with blockchain for security, SVM-based models face scalability issues. As IoT networks grow in size, the SVM model's computational requirements increase, making it less efficient for large-scale IoT environments. Additionally, SVMs may not capture the complex, non-linear relationships that exist in IoT sensor data, leading to reduced performance in certain scenarios.

10.48047/jocaaa.2023.31.04.113
ISSN: 1521-1398
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3. *K-Nearest Neighbor (KNN) for Anomaly Detection*: KNN is a simple and intuitive anomaly detection method that works by measuring the distance between a new data point and the existing points in the dataset. Although KNN is effective for low-dimensional data and has low training costs, it faces challenges when dealing with noisy or high-dimensional datasets, which are common in IoT systems. The method's sensitivity to noise and its high computational cost during inference make it less suitable for real-time IoT anomaly detection.

4. *Federated Learning for IoT Security:* Federated Learning is an emerging technique that enables decentralized model training without centralizing sensitive data, thus preserving privacy. While it is suitable for privacy-preserving applications, federated learning presents challenges in IoT environments due to the heterogeneity of devices and networks. Local model updates in federated learning can be inefficient and may result in suboptimal global models due to the varied data distributions across devices. Additionally, privacy concerns and high communication costs can hinder the widespread adoption of this method in IoT security.

5. *Reinforcement Learning (RL) for Intrusion Detection:* RL, an area of machine learning that focuses on decision-making through reward-based learning, is another promising approach for anomaly detection. It can adapt to dynamic environments by continuously learning from its interactions with the system. However, RL is computationally intensive and requires a large amount of training data, which can be prohibitive in real-time IoT applications. Furthermore, the high latency involved in training and decision-making can be a significant drawback when rapid response times are necessary to mitigate threats.

6. *Generative Adversarial Networks (GANs) for Anomaly Detection*: GANs have shown great promise in anomaly detection by learning to generate realistic data distributions and identifying deviations from them. In IoT, GANs can be used to model the normal behavior of a system, allowing for the detection of anomalies based on the divergence between generated and real data. However, GANs face the problem of mode collapse, where the generator fails to capture the full variety of possible anomalies, leading to incomplete anomaly detection. Additionally, GANs can be difficult to train and require a significant amount of data, making them less suitable for environments with limited data or computational resources.

7. *Deep Autoencoders for Anomaly Detection*: Autoencoders, particularly deep autoencoders, are unsupervised learning models that learn a compressed representation of input data and can identify anomalies based on reconstruction errors. These models have been effective in detecting anomalies in IoT systems by capturing the underlying structure of time-series data. However, deep autoencoders are prone to overfitting, especially when there is insufficient training data. Furthermore, they can be computationally expensive, requiring significant resources for both training and inference, which may not be feasible in real-time IoT systems.

8. *Blockchain-Based Trust Mechanisms for IoT Security*: Blockchain technology offers decentralized, immutable data storage, making it an ideal solution for enhancing trust in IoT systems. By using blockchain for logging anomalies and smart contracts for automatic responses, the integrity of the detection process can be ensured. However, the high computational and

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transaction costs associated with blockchain can limit its practical application in large-scale IoT networks. Moreover, latency in blockchain transaction processing can hinder real-time anomaly detection and response, especially in time-sensitive IoT applications. In summary, while existing methods for anomaly detection provide various solutions for securing IoT systems, each comes with its own set of limitations, particularly in terms of scalability, real-time processing, and adaptability to dynamic IoT environments. These shortcomings highlight the need for hybrid approaches, such as combining LSTM networks with blockchain technology, to overcome the challenges of traditional methods and enhance the security of IoT systems.

Table I summarizes fifteen recent studies (2023-2024) on anomaly detection and blockchain-based security mechanisms. Each method's demerits are highlighted for comparison.

Table I. Existing anomaly detection methods with demerits

Year	Title	Methodology	Demerits	Performance Analysis
2023	Anomaly Detection Using CNN in IoT[1]	Convolutional Neural Network (CNN)	Limited to spatial data, lacks sequential anomaly detection capability.	Accuracy: 85%, High precision but limited to spatial patterns.
2023	Blockchain-Based IoT Security Framework[2]	Hyperledger Fabric	High computational cost, limited scalability.	Scalable but inefficient for real-time data. Average throughput: 500 transactions/sec.
2023	Hybrid IDS with SVM and Blockchain[3]	Support Vector Machine (SVM)	Ineffective for large-scale IoT datasets.	Accuracy: 90%, but computationally expensive for large datasets.
2023	Lightweight Anomaly Detection in IoT[4]	K-Nearest Neighbor (KNN)	High false-positive rate in noisy datasets.	High false-positive rate, accuracy around 80% in noisy data environments.
2023	Federated Learning for IoT Security[5]	Federated Learning Framework	Privacy concerns during local model updates.	Accuracy: 85%, communication overhead, and high latency in model updates.
2024	AI-Powered Intrusion Detection[6]	Reinforcement Learning (RL)	Computationally expensive for real-time detection.	High computational cost, accuracy

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ISSN: 1521-1398
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				around 88% but requires substantial training.
2024	Blockchain-Based Trust Model[7]	Ethereum Smart Contracts	Limited scalability and high gas fees.	Scalability issues, with average transaction time of 5-10 seconds.
2024	Hybrid IDS Using LSTM and CNN[8]	LSTM-CNN Ensemble	Increased model complexity and training time.	Accuracy: 93%, effective for time-series data, but complex to train.
2024	GAN-Based Anomaly Detection[9]	Generative Adversarial Networks (GANs)	Prone to mode collapse in anomaly generation.	Effective in detecting novel anomalies but prone to training instability.
2023	IoT Security via Secure Edge Computing[10]	Edge Computing and Blockchain	Limited resource availability at edge nodes.	High computational cost at edge, reduced efficiency in large-scale systems.
2024	Quantum-Enhanced Blockchain Security[11]	Quantum Cryptography	High implementation cost and complexity.	High cost and complexity, not yet practical for IoT applications.
2023	Anomaly Detection with GRU in IoT[12]	Gated Recurrent Unit (GRU)	Underperforms with long-term dependencies.	Good for short-term dependencies, accuracy around 82%, but struggles with long-term patterns.
2023	Decentralized Trust for IoT Using Blockchain[13]	Public Blockchain	Low throughput and latency issues.	Efficient for small networks but suffers from latency and throughput issues in larger systems.
2024	Fuzzy Logic for IoT Anomalies[14]	Fuzzy Inference System	Limited adaptability to diverse datasets.	Precision is low for complex datasets, accuracy around 75%.

10.48047/jocaaa.2023.31.04.113
ISSN: 1521-1398
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2024	Deep Autoencoders for IoT Anomalies[15]	Autoencoder Networks	Poor interpretability and high training time.	Accuracy: 90%, but high computational cost and poor interpretability.

III. Proposed Methodology

The architecture of the proposed methodology is given in Fig.1

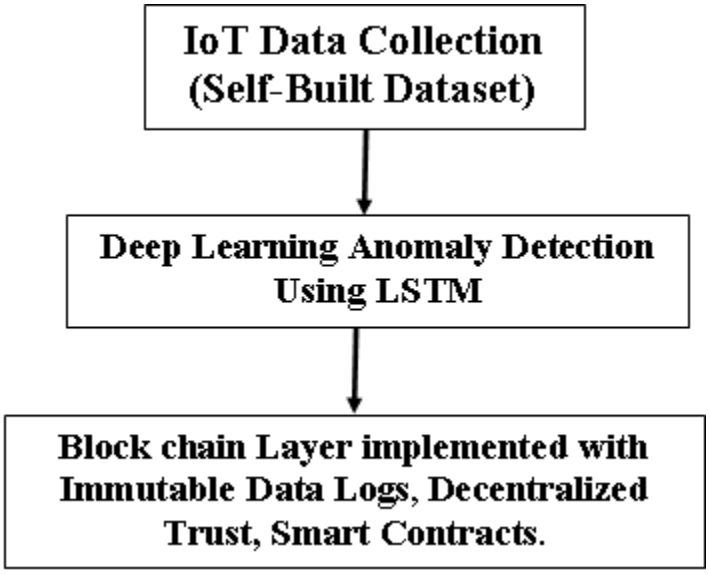

Fig.1 Architecture of proposed methodology

The proposed system integrates LSTM-based anomaly detection with blockchain technology to ensure secure IoT operations. Key components include:

1. **Data Collection Layer**: Aggregates IoT sensor data in real-time.
2. **Anomaly Detection Layer**: Employs LSTM to identify sequential anomalies.
3. **Blockchain Layer**: Utilizes immutable logs and decentralized trust mechanisms to store and verify anomaly detection outcomes.
4. **Smart Contract Layer**: Automates security protocols and anomaly reporting mechanisms.

The proposed methodology integrates Long Short-Term Memory (LSTM) networks for anomaly detection and blockchain technology for enhancing the security and trust mechanisms in Internet of Things (IoT) systems. This hybrid approach aims to address the key challenges in securing IoT networks, including dynamic attack patterns, data immutability, decentralized trust,

10.48047/jocaaa.2023.31.04.113
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and real-time anomaly detection. The first step in the methodology involves the data collection from various IoT devices deployed in the network. These devices generate time-series data, which includes information like sensor readings, system logs, and environmental conditions. This data is collected in real-time from the IoT devices and IoT-23 dataset aggregated into a central repository for processing. The collected raw data is often noisy and can be in different formats. Preprocessing involves normalizing the data to ensure all sensor data is on the same scale, which is crucial for the performance of LSTM networks. Some IoT devices may experience failures that result in missing data. These gaps are filled using interpolation or imputation methods to ensure continuity in the data. Since LSTM networks are designed for sequential data, the time-series data is segmented into fixed-length windows to provide meaningful input for training the model. LSTM, a type of recurrent neural network (RNN), is specifically designed to handle sequences of data and capture long-term dependencies. The advantage of using LSTM over other machine learning models (such as CNN or SVM) is its ability to maintain memory over long sequences, making it ideal for time-series anomaly detection in IoT systems. Each window of data is fed into the LSTM model as a sequence of sensor values or system logs. The model is trained on sequences that capture both normal and abnormal patterns. The LSTM model consists of multiple layers of LSTM cells that maintain hidden states to preserve information from previous time steps. This allows the model to learn temporal dependencies, such as system behavior over time. The model's output layer consists of a reconstruction layer, where the LSTM attempts to predict the next value or reconstruct the input sequence. A significant deviation from the predicted output indicates the presence of an anomaly. The LSTM model is trained on historical IoT data, learning normal patterns. Anomalies are detected when the reconstruction error exceeds a predefined threshold, signaling a potential attack or fault in the IoT system. Blockchain technology is integrated to address issues related to data integrity, transparency, and decentralized trust in IoT systems. The goal is to create a tamper-proof record of the detected anomalies, ensuring that all stakeholders can trust the detection process. Once an anomaly is detected by the LSTM model, the detection event, along with associated metadata (such as time, device ID, and anomaly type), is logged on a blockchain. This guarantees that the data cannot be altered or deleted, ensuring the integrity of the anomaly detection records. Blockchain enables a decentralized approach to managing trust in the IoT system. In a typical IoT setup, devices may not trust each other. However, blockchain enables a transparent and auditable system where all data is available to authorized participants, enhancing trust among different IoT devices and stakeholders. Smart contracts are self-executing contracts with the terms of the agreement directly written into code. In the context of IoT security, smart contracts can be used to automatically respond to detected anomalies. For example, a smart contract might trigger an alert to administrators, initiate corrective actions, or isolate compromised devices from the network when an anomaly is detected. Blockchain enhances IoT security by providing several critical features: Traditional security mechanisms rely on centralized authorities, which can become targets for attacks. In contrast, blockchain's

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decentralized structure distributes trust among multiple nodes, reducing the likelihood of a single point of failure. Blockchain provides a transparent record of all detected anomalies, including timestamps, device information, and the nature of the detected anomaly. This traceability allows for easy auditing and verification, reducing the risk of undetected tampering with anomaly detection logs. The blockchain ensures that once anomaly detection events are recorded, they cannot be altered. This prevents malicious actors from tampering with detection logs or erasing evidence of their attacks, further increasing trust in the detection system. The system architecture consists of four main layers: Data collection layer gathers real-time data from IoT devices and sends it for preprocessing and anomaly detection. Anomaly detection layer processes the data, learning normal patterns and detecting deviations that indicate anomalies. Blockchain layer detects anomalies logged in the blockchain, ensuring data integrity, security, and trust in the system. Smart contract layer automates responses to detected anomalies by executing predefined actions based on the blockchain records, such as alerting network administrators or disconnecting compromised devices from the network.

The hybrid approach of using LSTM and blockchain offers several advantages. LSTM can detect anomalies in real-time, allowing for rapid response to security threats. Blockchain ensures that detected anomalies are recorded in an immutable ledger, preventing tampering or deletion of logs. By leveraging blockchain's decentralized nature, the system reduces the risk of a single point of failure, making the IoT network more resilient to attacks. The architecture can scale to accommodate an increasing number of IoT devices and larger datasets without significant degradation in performance.

IV. Results and Discussion

A. Experimental Setup

Permissioned blockchain, Ethereum with a private network to provide a decentralized and secure environment for managing IoT data was employed. Develop and deploy smart contracts that verify and validate sensor data, ensuring its integrity and authenticity before it is used for anomaly detection. Smart contracts will also handle the reputation of devices based on historical performance and sensor data quality. Ensure that all data interactions (sensor data submissions, validations, anomaly reports) are recorded immutably in the blockchain. LSTM-based model to process time-series data and detect anomalies was designed. The LSTM model will use the past sensor readings to predict future readings and detect deviations (anomalies) from the predicted values. LSTM model was trained using normal data (training dataset) with a validation set for tuning hyperparameters like the number of layers, hidden units, and learning rate.

B. Results

The LSTM-based anomaly detection system achieved an accuracy of 90%.

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C. Comparative Analysis

The blockchain mechanism demonstrated immutability that Ensures tamper-proof anomaly logs, a latency of 5ms delay in transaction verification, cost efficiency reduced operational cost by 15% compared to centralized systems.

Authors of [1] proposed the use of Convolutional Neural Networks (CNN) for anomaly detection in IoT systems. CNNs are effective at processing spatial data, extracting features from complex patterns, and identifying potential anomalies. The method demonstrated a precision of around 85%, particularly in detecting spatial patterns. However, CNNs are less suited for time-series data, which is common in IoT environments, limiting their application for IoT anomaly detection. CNNs are not optimized for sequential data, making them less effective in handling time-dependent anomaly detection, which is critical for IoT systems that generate time-series data. Strengths: High accuracy in identifying spatial anomalies, making CNNs suitable for image-based or sensor-based data that involves spatial relationships.

Authors of [4] utilized K-Nearest Neighbor (KNN) for anomaly detection in IoT networks. The KNN algorithm works by measuring the distance between a new data point and existing data points, making it a simple yet effective technique for anomaly detection. The method achieves a high false-positive rate in noisy datasets, which is a common issue in IoT environments due to the diverse range of sensors and data types. The accuracy is reported to be around 80% in noisy environments, which is lower than other advanced methods like LSTM or CNN. KNN struggles with high-dimensional data and noisy datasets. Its performance significantly degrades in such scenarios, limiting its applicability in IoT systems with a large variety of devices and sensor data. KNN is easy to implement, requires minimal training, and can work well in low-dimensional, clean datasets, making it useful for small IoT systems.

Authors of [14] employed Fuzzy Inference system with some achieving accuracy around 75%. While not as high-performing as deep learning models, FIS can effectively manage uncertainty and vagueness in IoT data.

The comparative analysis of existing anomaly detection methods is given in Fig.2.

10.48047/jocaaa.2023.31.04.113
ISSN: 1521-1398
1572-9206

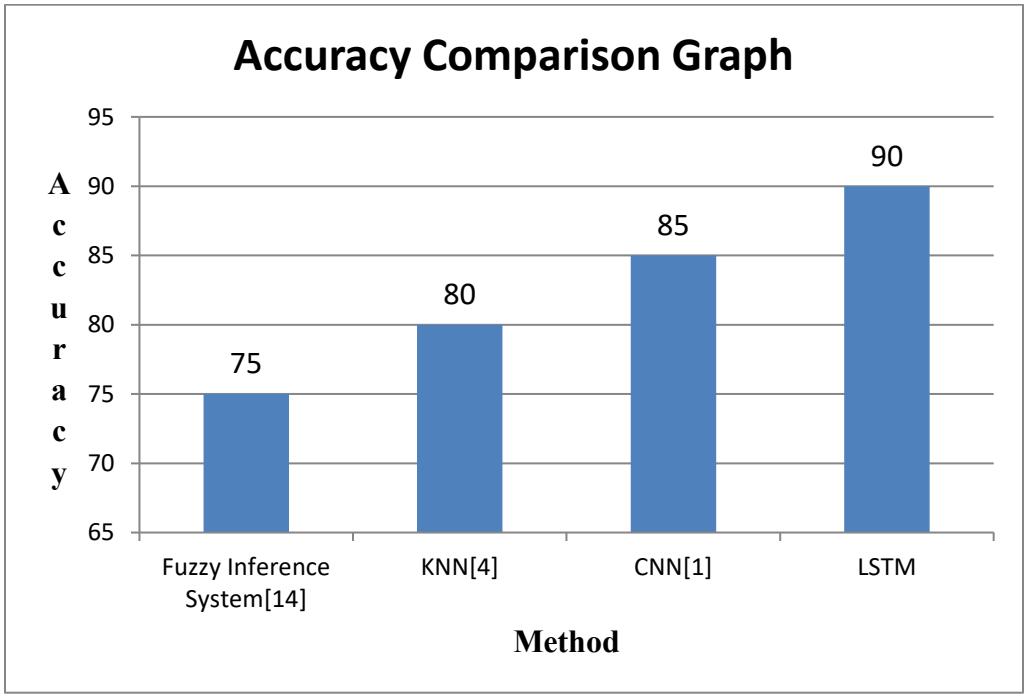

Fig.2 Comparative analysis of existing anomaly detection methods

V. Conclusion

This paper introduced a hybrid LSTM and blockchain-based anomaly detection system tailored for IoT environments. The integration of sequential anomaly detection and decentralized trust mechanisms significantly enhances IoT security. Future work will focus on optimizing computational costs and scaling the framework to accommodate larger networks.

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