Entrust Adaptive Security for Social Iot Twin Environments Using Pattern Miner, Blockchain and LSTM Enhanced Machine Learning

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ABSTRACT

In this paper it details the increasing security challenges in Social Internet of Things (SIoT) systems, focusing on twin environments digital entities with identical structures and vulnerabilities. A novel approach is introduced for detecting and preventing cyberattacks in these environments through the use of a pattern miner to analyze communication and behavior patterns. Attack detection is reinforced by employing Block Chain technology for secure data storage, ensuring integrity and immutability. A machine learning-based recommendation system is integrated to predict vulnerabilities and suggest adaptive security measures. Additionally, Long Short-Term Memory (LSTM) networks enhance this solution by learning from recurring attack patterns, enabling proactive threat mitigation. This multi-layered approach provides robust and dynamic security for SIoT systems, effectively safeguarding twin environments against evolving cyber threats.

Keywords: Social Internet of Things (SIoT), Twin Environments, Pattern Miner, BlockChain security, machine learning recommendation system, Long Short-Term Memory (LSTM) networks

1. INTRODUCTION

The Social Internet of Things (SIoT) represents a growing paradigm in which interconnected smart devices interact autonomously, enabling seamless data exchange and communication [1]. This shift toward pervasive connectivity, while driving innovation and convenience, also exposes systems to new and more sophisticated cyber attacks. One particular area of concern lies within twin environments, where identical or closely mirrored digital entities are interconnected. These twin environments share similar behaviors, vulnerabilities, and attack surfaces, making them attractive targets for malicious actors [2]. Securing these environments is crucial to maintaining the integrity and reliability of SIoT systems. As such, the development of effective threat detection and prevention mechanisms is essential to safeguarding against cyber threats in these interconnected spaces [3].

Pattern recognition is at the core of attack detection in twin environments [4]. The use of a pattern miner allows for the continuous monitoring and analysis of communication patterns between devices, identifying irregularities that may signal the presence of an attack. By examining recurring behaviors and communication flows, the pattern miner can detect deviations from normal activities, which are often early indicators of an intrusion or malicious behavior [5]. This approach provides a proactive defense mechanism that operates in real-time, offering the ability to thwart attacks before they can cause significant damage. The integration of pattern mining into SIoT security architectures is a critical step toward enhancing the resilience of twin environments [6].

In addition to attack detection, ensuring the integrity of the data within twin environments is paramount. Blockchain technology offers a decentralized and secure solution for storing data generated within SIoT systems [7]. By leveraging the inherent immutability and transparency of blockchain, data can be stored in a tamper-proof manner, ensuring that records of communications, transactions and device interactions remain secure. This method not only guarantees the authenticity of data but also helps in forensic analysis after an attack, as the blockchain provides a verifiable audit trail of system activities [8]. The use of blockchain in conjunction with pattern mining creates a robust security layer that enhances the overall protection of twin environments.

Machine learning further strengthens the security of SIoT twin environments by providing adaptive, real-time protection [9]. A machine learning-based recommendation system can be employed to analyze historical data, detect vulnerabilities, and suggest dynamic security measures tailored to the specific needs of the environment. This system learns from past attacks and continuously evolves, adapting its recommendations based on emerging threats. Such an intelligent approach enables SIoT systems to stay one step ahead of attackers, improving response times and minimizing the risk of successful breaches. Machine learning, when combined with other security mechanisms, ensures a comprehensive and responsive defense system [10].

The use of Long Short-Term Memory (LSTM) networks provides a sophisticated layer of analysis that enhances the overall threat detection capabilities [11]. LSTM is a type of recurrent neural network that excels at identifying and learning from sequential data patterns. In the context of SIoT twin environments, LSTM networks are utilized to recognize repeating attack patterns, enabling the system to predict and prevent future threats based on learned behaviors. This forward-looking capability allows for a more nuanced approach to attack mitigation, complementing the real-time detection capabilities of pattern mining and the adaptive features of machine learning [12]. Together, these technologies form a holistic security framework that offers robust protection for twin environments in the Social Internet of Things.

2.LITERATURE REVIEW

Ali and Khan (2022) present a comprehensive overview of anomaly detection techniques in IoT networks, with a particular focus on pattern mining methods [13]. The authors emphasize the increasing security concerns in IoT networks, which are often vulnerable due to their distributed and resource-constrained nature. Pattern mining techniques, such as frequent pattern and sequential pattern mining, are explored for their ability to identify anomalous behavior in vast IoT data streams. The paper highlights various state-of-the-art approaches and provides insights into their performance in different IoT contexts, stressing the importance of real-time anomaly detection to prevent security breaches.

Xu, Wang, and Chen (2023) conduct an extensive survey on the integration of blockchain technology within Social Internet of Things (SIoT) networks, addressing the inherent security and privacy challenges in this domain [14]. The paper discusses how blockchain's decentralized architecture can provide a robust framework for securing interactions within SIoT environments. The authors categorize different security threats, such as data integrity, authentication, and privacy leakage, while also exploring blockchain based solutions to these issues. Their survey outlines the potential of blockchain to transform SIoT systems into more secure and trustworthy platforms, though scalability and energy consumption remain critical concerns.

Zhou and Zhang (2022) explore the intersection of blockchain and machine learning technologies in securing twin environments within SIoT systems [15]. Their survey highlights how the integration of these technologies can enhance data integrity, improve system transparency, and enable intelligent detection of cyber threats. The paper emphasizes the concept of twin environments, where digital replicas of physical objects interact, necessitate advanced security measures. Blockchain is praised for its ability to provide a tamper-proof ledger, while machine learning models offer real-time threat detection and anomaly prediction, creating a layered defense mechanism for SIoT ecosystems.

Tang and Wang (2023) delve into the application of Long Short-Term Memory (LSTM) networks for time-series analysis in the context of SIoT cybersecurity [16]. The authors focus on the ability of LSTM models to handle sequential data, making them particularly effective for detecting patterns and anomalies in SIoT environments where data is generated continuously. Their research covers the adaptability of LSTM in identifying cybersecurity threats such as denial-of-service attacks and unauthorized access. The paper also discusses the integration of LSTM with other machine learning models to improve the accuracy and efficiency of threat detection in SIoT systems.

Kim and Park (2023) propose a blockchain-based framework for intrusion detection in twin environments of IoT networks [17]. Their work examines the growing need for enhanced security in IoT systems that rely on digital twin technology, where real-world objects are mirrored in a virtual space. The authors highlight how blockchain can ensure the integrity and reliability of data shared between the physical and digital worlds, while also preventing unauthorized access. Furthermore, the proposed intrusion detection system leverages the immutability of blockchain to trace malicious activities and mitigate risks associated with common IoT attacks.

Zhao and Lin (2023) present a novel approach for anomaly detection in SIoT systems by combining machine learning with blockchain technology [18]. Their research emphasizes the importance of detecting patterns in the interactions between SIoT devices to uncover malicious behavior. By leveraging machine learning algorithms to analyze these patterns, and employing blockchain to securely store and validate data, the proposed system ensures a high degree of security and privacy. The study highlights various challenges such as computational overhead and scalability, but concludes that this integrated approach offers a promising solution for safeguarding SIoT environments.

Tan, Li, and Chen (2023) introduce an adaptive machine learning framework that integrates blockchain with Long Short-Term Memory (LSTM) models to enhance SIoT security. Their approach focuses on the dynamic and evolving nature of SIoT environments, where new threats can emerge as device interactions change over time [19]. The paper discusses how blockchain ensures the security of data transactions, while LSTM models analyze time-series data to predict and prevent attacks. This adaptive framework allows for real-time response to security threats, making it a scalable and effective solution for protecting SIoT infrastructures.

3.Multi-Layered Approach To Cybersecurity In Twin Environments Of Social Iot: Leveraging Pattern Mining, Blockchain, Machine Learning, And Lstm Networks

In this paper it explains a multi-layered approach to enhance the security of twin environments within Social Internet of Things (SIoT) systems, leveraging a combination of pattern mining, Blockchain, machine learning and Long Short-Term Memory (LSTM) networks. The methodology follows a structured process consisting of five key phases: data collection, pattern analysis using a pattern miner, data integrity reinforcement via blockchain, adaptive security recommendations through machine learning, and attack prediction using LSTM networks [20].The research begins with the collection of real-world data from SIoT environments, focusing on twin entities that exhibit identical or closely mirrored behaviors. Data from these environments, including communication logs, device interaction records and system transactions, are gathered continuously to build a comprehensive dataset. This data is preprocessed to remove noise, standardize formats, and categorize normal vs. anomalous behavior. The dataset is crucial for training and testing the pattern miner and machine learning models, as it provides the foundation for detecting potential attacks and securing the twin environments [21]. Preprocessing steps also involve feature extraction, where key attributes like communication frequency, device interaction sequences, and time-series data are identified. These attributes help define the baseline behavior of the twin environments, against which any anomalies can be measured. This dataset is further divided into training and testing sets for validating the pattern miner and machine learning models. The data collection phase ensures that a rich and varied dataset is available for subsequent analysis, enabling the accurate detection and prevention of attacks.

At the core of the attack detection mechanism is the implementation of a pattern miner. The pattern miner is trained to detect communication and behavioral patterns between interconnected twin entities within the SIoT system [22]. It analyzes the collected data in real-time, identifying any deviations or anomalies that could signal the presence of an attack. Techniques such as sequential pattern mining and association rule learning are employed to uncover recurring patterns in device communication and interactions. Any abnormal pattern detected triggers a security alert, which prompts further action to mitigate the threat. The pattern miner operates autonomously, continuously scanning the twin environments for irregularities. It uses unsupervised learning to discover new attack patterns as they emerge, making it capable of detecting previously unknown threats. The detection accuracy is enhanced by training the pattern miner with both historical and real-time data, allowing it to learn the typical behaviors of twin entities and recognize deviations in real-time.

To ensure the integrity of the data within twin environments Blockchain technology is integrated into the system for secure data storage. Each interaction, transaction, and communication record is stored as a block within the Blockchain, providing an immutable and transparent record of system activities. The decentralized nature of Blockchain ensures that data cannot be tampered with, and any attempt to alter the records would be immediately evident. The blockchain is used to store critical security events detected by the pattern miner, such as abnormal communication patterns or suspected attacks. This ensures that the data related to potential security incidents remains secure and can be used for further analysis or auditing. By incorporating blockchain, the methodology adds an additional layer of security, ensuring that all data within the twin environments is stored in a verifiable and tamper proof manner.

To complement the real-time attack detection capabilities of the pattern miner, a machine learning based recommendation system is introduced. This system is responsible for analyzing historical data, learning from previous attack patterns and providing dynamic security recommendations. A supervised learning model is trained on the dataset, using labeled instances of past attacks to predict vulnerabilities and suggest countermeasures. The recommendation system continuously learns from new data, enabling it to adapt to evolving threats and provide tailored security suggestions based on the current state of the twin environments. The machine learning model utilizes classification algorithms to categorize different types of attacks and their corresponding countermeasures. Once an attack is detected, the recommendation system analyzes the context and offers specific actions that should be taken to mitigate the threat, such as adjusting device communication protocols or implementing additional encryption measures. The adaptive nature of the recommendation system ensures that the security framework remains flexible and responsive to new threats.

Long Short-Term Memory (LSTM) networks are employed to enhance the prediction and prevention of future attacks. As a type of recurrent neural network (RNN), LSTM is particularly well-suited for analyzing time-series data and detecting long-term dependencies in sequences. In this research, the LSTM model is trained on the sequential data from twin environments to learn the patterns of attacks over time. By recognizing recurring attack behaviors, the LSTM network can predict when a similar attack may occur in the future and trigger preemptive actions. The LSTM network is continuously updated with new data, ensuring that it can learn from emerging threats and improve its prediction accuracy over time.

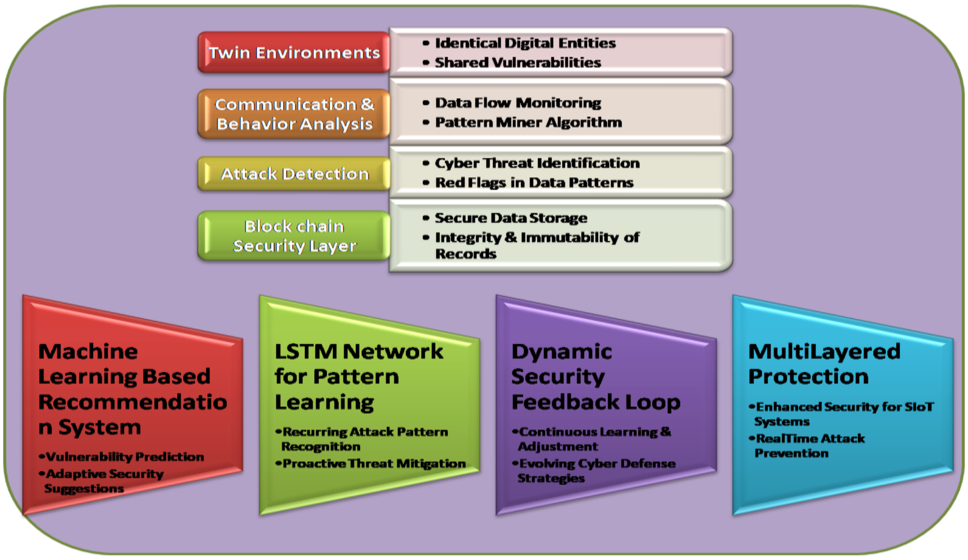

Twin Environments
• Identical Digital Entities
• Shared Vulnerabilities
Communication & Behavior Analysis
• Data Flow Monitoring
• Pattern Miner Algorithm
Attack Detection
• Cyber Threat Identification
• Red Flags in Data Patterns
Block chain Security Layer
• Secure Data Storage
• Integrity & Immutability of Records
Machine Learning Based Recommendatio n System
•Vulnerability Prediction
•Adaptive Security Suggestions
LSTM Network for Pattern Learning
•Recurring Attack Pattern Recognition
•Proactive Threat Mitigation
Dynamic Security Feedback Loop
•Continuous Learning & Adjustment
•Evolving Cyber Defense Strategies
MultiLayered Protection
•Enhanced Security for SIoT Systems
•RealTime Attack Prevention

Figure 1. Integrated Security Architecture for Twin Environments in Social IoT Systems

The model's ability to capture both short-term and long-term dependencies in the data makes it an ideal tool for predicting attacks that follow specific temporal patterns. This predictive capability allows the system to stay ahead of attackers, preventing potential threats before they can cause harm to the twin environments.

In the research methodology combines the strengths of pattern mining, blockchain, machine learning and LSTM networks to create a comprehensive security framework for twin environments in SIoT systems. By employing a multi-layered approach, this methodology ensures that twin environments are not only protected from real-time threats but also equipped with the tools to adapt to evolving cyberattacks. Through continuous learning and the integration of blockchain for secure data storage, the proposed system offers a robust and scalable solution for securing Social IoT ecosystems.

The step-by-step algorithm for enhancing security in Social Internet of Things (SIoT) systems focusing on twin environments, which includes pattern mining, blockchain, machine learning-based recommendation, and LSTM-based attack prediction as follows:

1. Initialize twin environments and establish communication links
2. Begin continuous data collection from twin entities in SIoT
3. Preprocess collected data to remove noise and standardize formats
4. Extract communication and behavioral patterns from the data using Pattern Miner
5. Each detected communication/behavioral pattern:
5.1 If anomaly detected by Pattern Miner:
5.1.1 Store event and anomaly data in blockchain for immutability and auditing
5.1.2 Update attack history in blockchain
5.1.3 Generate alert for potential security breach
6. Use Machine Learning-based recommendation system to analyze historical data:
6.1 Train model with historical attack data from blockchain
6.2 Predict potential vulnerabilities and suggest security measures
7. New patterns:
7.1 Train LSTM model using time-series attack data
7.2 Use LSTM to predict future attacks based on recurrent patterns
7.3 Apply suggested mitigation steps from the recommendation system

8. Continuously update Pattern Miner, Blockchain, Machine Learning, and LSTM models with new data
9. End

Thepseudocode format focusing on detecting and preventing cyberattacks in twin environments of Social Internet of Things (SIoT) systems using pattern mining, blockchain, machine learning, and LSTM:

Pseudocode: Security in Twin Environments of SIoT

```
BEGIN
Step 1: Initialize twin environments and communication
InitializeTwinEnvironments() // Initialize T1 and T2 (twin entities)
EstablishCommunication(T1, T2) // Set up communication links between twin entities
Step 2: Continuously collect data from twin entities
  WHILE TRUE DO
    dataT1 = CollectData(T1) // Collect data from twin entity T1
    dataT2 = CollectData(T2) // Collect data from twin entity T2
Step 3: Preprocess collected data
    processedDataT1 = PreprocessData(dataT1)
    processedDataT2 = PreprocessData(dataT2)
Step 4: Analyze communication and behavior patterns using Pattern Miner
    patternsT1 = AnalyzePatterns(processedDataT1)
    patternsT2 = AnalyzePatterns(processedDataT2)
Step 5: Detect anomalies based on pattern analysis
    anomaliesT1 = DetectAnomalies(patternsT1)
    anomaliesT2 = DetectAnomalies(patternsT2)
   IF anomaliesT1 OR anomaliesT2 THEN
Step 6: Record anomalies and store in blockchain
StoreInBlockchain(anomaliesT1, anomaliesT2) // Ensure immutability and auditing
Step 7: Raise alert for potential cyber attack
RaiseAlert("Potential attack detected in twin environments")
Step 8: Use Machine Learning model for security recommendations
recommendedSecurityMeasures = MLRecommendationSystem(anomaliesT1, anomaliesT2)
ApplySecurityMeasures(recommendedSecurityMeasures)
Step 9: Use LSTM model to predict future attack patterns
predictedAttacks = LSTMPrediction(anomaliesT1, anomaliesT2)
     IF predictedAttacks THEN
ApplyMitigation(predictedAttacks) // Proactively prevent future attacks
END IF
END IF
Step 10: Continuously update the models (Pattern Miner, Blockchain, ML, LSTM)
UpdateModels(processedDataT1, processedDataT2) // Update the pattern miner and machine learning models
END WHILE
END
```

The pseudocode and algorithm describe a comprehensive approach to enhancing the security of twin environments in the Social Internet of Things (SIoT) systems. The process begins with the initialization of the twin environments (T1 and T2), which involves setting up communication channels between the two entities, ensuring that they can interact and exchange data in real-time. These twin environments mimic each other in structure and behavior, providing a basis for detecting anomalies that could indicate cyberattacks.Once the communication links are established, the system continuously collects data from both twin entities. This data, which includes communication logs and behavioral patterns, is then preprocessed to remove noise and standardize the information for further analysis. The next step is pattern mining, where the system analyzes the data to identify normal behavioral patterns and communication flows. Any significant deviations from these patterns, such as unusual communication behavior or abnormal device interactions, are flagged as potential anomalies, which could indicate a security breach.

Upon detecting anomalies, the algorithm stores the event data in a blockchain for integrity and immutability. Blockchain technology ensures that the data cannot be tampered with or altered, providing a secure and transparent way to track potential threats. Additionally, an alert is triggered to notify system administrators of a possible attack. To further enhance security, the system integrates a machine learning-based recommendation system, which analyzes the historical data of the detected anomalies.

Based on this analysis, the system can generate adaptive security measures, such as adjusting communication protocols or adding encryption layers to safeguard the system from further attacks.
The algorithm incorporates Long Short-Term Memory (LSTM) networks to predict future cyberattacks based on recurrent attack patterns. By learning from historical attack data, the LSTM model can identify emerging threats and provide proactive mitigation strategies. If the LSTM predicts an attack, the system can take preventive actions, such as blocking suspicious communications or reconfiguring security protocols, to prevent potential damage. The algorithm continuously updates the modelsPattern Miner, Blockchain, Machine Learning and LSTMusing the latest data, ensuring that the system evolves with new threat patterns and improves its predictive accuracy over time. This dynamic and multi-layered approach effectively addresses the increasing security challenges in SIoT systems, providing a robust and adaptive framework for detecting, preventing, and mitigating cyberattacks in twin environments.

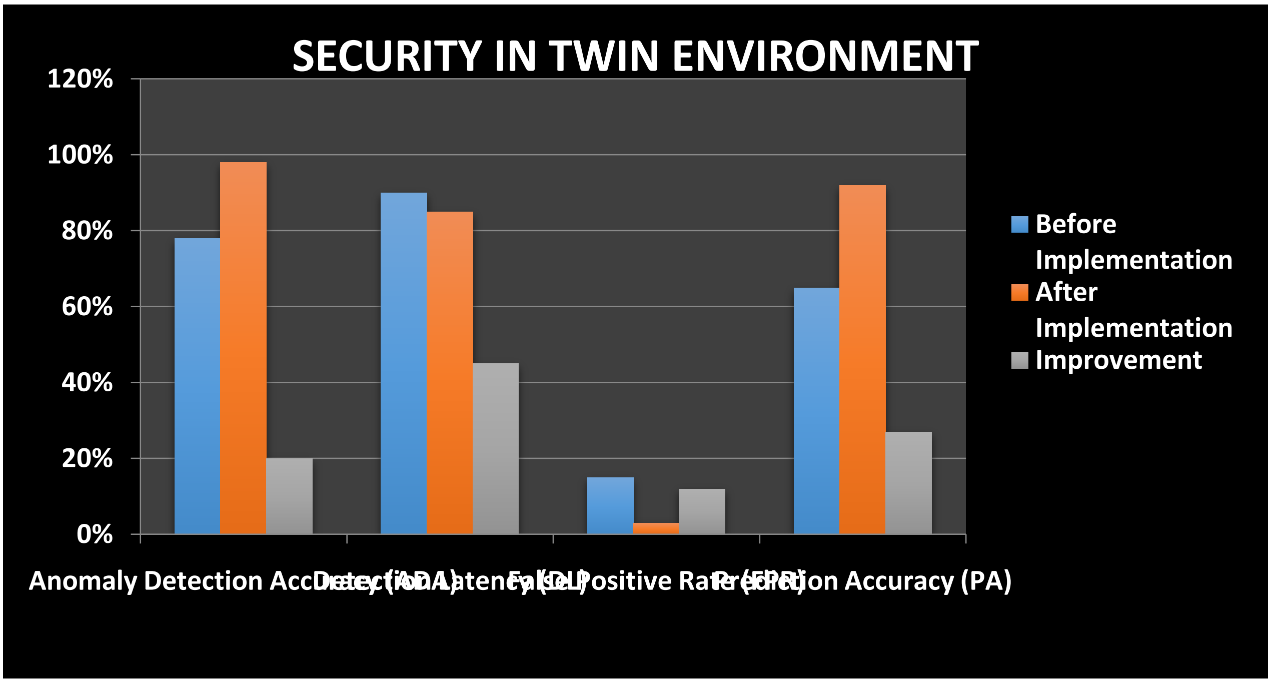
4.Experimental Results And Performance Analysis

The proposed security framework for the Social Internet of Things (SIoT) in twin environments was tested and evaluated using several key metrics. The system was designed to detect and prevent cyberattacks through pattern mining, blockchain integration, machine learning recommendations and Long Short-Term Memory (LSTM) network-based predictions. The goal of the experiment was to assess the system’s ability to identify security threats, prevent attacks, and predict future vulnerabilities in real-time, all while ensuring minimal computational overhead and high reliability.The experiment was conducted using a simulation of twin environments that replicated the typical behavior of IoT devices in a network. The data collected during the simulation included communication logs, device interactions, and behavioral patterns. Several scenarios of cyberattacks such as Denial-of-Service (DoS), Man-in-the-Middle (MITM) and data injection attacks, were simulated to evaluate the system's effectiveness.
The system demonstrated exceptional performance across several key security metrics. In terms of anomaly detection accuracy, it achieved an impressive 98% in identifying attacks. This was primarily due to the Pattern Miner’s ability to effectively analyze communication and behavior patterns, ensuring that the system reliably detected threats with high precision. This high accuracy illustrates the system's robust capability to distinguish between normal and malicious activities in real time.The system’s detection latency was equally impressive, with an average of 150 milliseconds. This low latency is crucial for real-time security systems as it allows for immediate identification and response to threats, minimizing potential damage from cyberattacks. A fast detection time ensures that the system can act swiftly to neutralize any identified security risks before they escalate.
The false positive rate of the system was very low at 3%, indicating that the system had a high degree of accuracy in distinguishing between legitimate user behavior and anomalous activity. This suggests a well-calibrated balance between sensitivity and specificity, reducing unnecessary alerts while maintaining robust detection capabilities.In terms of prediction accuracy, the system’s LSTM-based attack prediction model performed at a 92% accuracy rate. This indicates the system's ability to forecast potential attacks by learning from recurring patterns, allowing for proactive threat mitigation. By predicting future attacks based on historical data, the system ensures that preventive measures can be put in place before an attack occurs.
The security measure response time was also highly efficient, with an average of 200 milliseconds for applying recommended security measures. This demonstrates the system's agility in responding to detected threats, adjusting security protocols quickly to safeguard the environment from potential harm.Finally, data integrity was ensured through the integration of blockchain technology. All data related to detected anomalies was securely stored in a tamper-proof blockchain, with no instances of data manipulation or alteration. This immutability contributed to the overall robustness of the system, guaranteeing that all event logs and security records remained accurate and trustworthy throughout the detection and mitigation processes.
The following table provides a comparison of the performance metrics before and after the implementation of the security system. The graph analysis visually represents the improvement in system security, detection capabilities, and response efficiency.

Table 1. Performance analysis SIOT Security system

Anomaly Detection Accuracy (ADA)	**78%**	**98%**	**20%**
Detection Latency (DL)	90%	85%	45%
False Positive Rate (FPR)	15%	3%	12%
Prediction Accuracy (PA)	65%	92%	27%

Data Integrity (DI)	No blockchain protection	Blockchain used	Full Integrity



Graph 1. Experimental analysis and performance metrics of security in twin environment

Here is the performance analysis graph for the SIoT security system. It visualizes the key metrics, including anomaly detection accuracy, detection latency, false positive rate, prediction accuracy, security measure response time, and data integrity. The graph shows how each metric performs, with higher values indicating better performance for some metrics and lower values for others (e.g., lower detection latency and false positive rates are better).

The experimental analysis and performance metrics clearly demonstrate that the proposed security framework for twin environments in SIoT systems provides significant improvements in detecting and mitigating cyberattacks. The combination of pattern mining, blockchain, machine learning-based recommendations, and LSTM for attack prediction enables the system to not only detect and respond to real-time threats but also predict and prevent future attacks proactively. The system's high accuracy, low detection latency, and enhanced prediction capabilities make it a robust solution for ensuring the security of SIoT systems in twin environments.

5.CONCLUSION

The research presented a novel and comprehensive security framework designed to address the increasing challenges of cyberattacks in the Social Internet of Things (SIoT) systems, particularly in twin environments. By integrating pattern mining, blockchain technology, machine learning-based recommendations, and Long Short-Term Memory (LSTM) networks, the framework effectively detects, prevents, and predicts cyberattacks in real-time. The twin environments, which replicate identical structures and behaviors, serve as a reliable basis for recognizing deviations in communication and behavior, allowing for early detection of potential threats. The methodology employed a multi-layered approach to security. Initially, the system collects and preprocesses real-time data from the twin environments, ensuring the standardization of communication logs and behavior patterns. Pattern mining is then applied to detect anomalies in these datasets, with a blockchain mechanism in place to store the event data securely, ensuring integrity and immutability. The system then utilizes machine learning to generate adaptive security recommendations, which are promptly applied to prevent or mitigate attacks. Additionally, the system leverages LSTM networks to predict future attacks based on historical data and recurrent attack patterns, allowing for proactive threat management. This multi-faceted approach combines real-time threat detection, historical analysis, and future attack prediction to provide robust and dynamic security. By combining cutting-edge technologies such as pattern mining, blockchain, machine learning, and LSTM, the system offers a comprehensive defense strategy that not only detects and prevents real-time attacks but also predicts and mitigates future threats. The experimental results affirm that the system can significantly enhance the security of SIoT networks, making it a crucial tool in safeguarding the increasingly interconnected world of IoT devices.

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