Frontiers in Health Informatics www.healthinformaticsjournal.com
ISSN-Online: 2676-7104
2024; Vol 12: Issue 3 Open Access

SecuMed-SIoT: A Hybrid CNN-Transformer IDS for Enhanced Security in Healthcare SIoT Networks

Divya S[1*], Tanuja R[2] and Manjula S H[3]
1* Research Scholar, Department of Computer Science and Engineering,
University Visvesvaraya College of Engineering, Bangalore University, Bengaluru, India.
divya.s@uvce.ac.in
2 Associate Professor, Department of Computer Science and Engineering, University Visvesvaraya College of Engineering,
Bangalore University, Bengaluru, India
tanujar.uvce@gmail.com
3 Professor, Department of Computer Science and Engineering, University Visvesvaraya College of Engineering,
Bangalore University, Bengaluru, India
shmanjula@gmail.com

Cite this paper as: Divya S, Tanuja R, Manjula S H (2024) SecuMed-SIoT: A Hybrid CNN-Transformer IDS for Enhanced Security in Healthcare SIoT Networks, *Frontiers in Health Informatics*, *13* (3), 2918-2934

ABSTRACT
Healthcare IoT (Internet of Things) systems have transformed patient monitoring and data management but their extensive interconnectivity and sensitive data make them highly susceptible to cyber-attacks. Traditional intrusion detection systems (IDS) often fail to meet the stringent security demands of healthcare SIoT environments due to high false-positive rates, computational inefficiencies, and limited adaptability to emerging threats. This paper introduces SecuMed-SIoT a novel security-focused hybrid IDS specifically designed for healthcare SIoT, leveraging Social IoT (SIoT) principles and a CNN-Transformer architecture (CTLGNet) to enhance threat detection capabilities. SecuMed-SIoT incorporates security-driven interaction modeling to evaluate device behaviours and collaborates with a network of trusted devices to detect anomalies in real time, achieving high detection accuracy with minimal false alarms. Extensive experiments demonstrate that SecuMed-SIoT attains a detection accuracy of 94.2% and a false-positive rate of 3.1%, significantly outperforming conventional IDS models in both performance and efficiency. These findings underscore SecuMed-SIoT effectiveness in protecting sensitive healthcare data and ensuring device security within SIoT networks.

Keywords: *Healthcare IoT, Intrusion Detection System, Social IoT, Security, CNN-Transformer, SecuMed-SIoT.*

INTRODUCTION

The rapid advancement of Internet of Things (IoT) technology has transformed healthcare by enabling real-time patient monitoring, remote medical consultations, and efficient data exchange through interconnected devices. However, this increasing reliance on networked healthcare devices presents significant security vulnerabilities, especially in protecting sensitive patient information. Network intrusion recognition plays a pivotal role in safeguarding healthcare systems from potential cyber threats that can compromise data integrity and patient safety. Given the critical nature of healthcare information, maintaining the security of Electronic Health Records (EHR) and Personal Health Records (PHR) is paramount to avoid unauthorized access, data tampering, or loss. A breach in these records could lead to misdiagnosis, incorrect treatment plans, and a loss of patient trust. Thus, effective intrusion detection systems (IDS) tailored specifically for healthcare environments are essential to meet these challenges [1]. Traditional network intrusion detection relies on Machine Learning (ML) models like K-Nearest Neighbours (KNN) and Logistic Regression, which often require extensive fine-tuning to recognize new and evolving attack types. These models struggle with the healthcare SIoT context, where device interactions are complex and data integrity is highly sensitive. Constant updates and retraining are required to maintain effectiveness, which is both computationally expensive and time-intensive [2]. While ensemble learning models,

such as Random Forest and Gradient Boosting, and Deep Learning (DL)-based models offer greater adaptability and accuracy, they still face limitations in interpreting security dynamics, which could improve collaborative detection efforts.

Security-Driven Interaction Modeling

To address the unique security challenges of healthcare SIoT systems, security-driven interaction modeling introduces a promising paradigm in IDS design. This approach leverages Social IoT (SIoT) concepts to enhance network security by enabling devices to establish secure communication channels. In healthcare, this could mean that frequently interacting devices, such as a heart monitor and patient database, evaluate each other's behaviour to establish secure operational parameters. By modeling these interactions with a focus on security, an IDS can better detect anomalies in device behaviour, flagging unusual activities that might indicate an intrusion attempt [3]. This approach forms a basis for more nuanced and efficient IDS solutions by filtering out noise, prioritizing alerts based on the severity of detected anomalies, and promoting seamless interaction among verified devices.

Healthcare-Specific Attack Simulation

Healthcare networks are highly attractive targets for cyber-attacks due to the sensitivity and value of patient data. Healthcare-specific attack simulation enables IDS models to better understand and detect the types of threats that are more prevalent in these environments. Common threats in healthcare SIoT include malware injections targeting connected medical devices, unauthorized access to EHRs, and distributed denial of service (DDoS) attacks aiming to overload network resources [4]. By incorporating attack simulations that mimic these real-world scenarios, the IDS can develop a more precise understanding of threats likely to be encountered in healthcare. Moreover, these simulations allow the IDS to refine detection mechanisms, evaluating how devices react under attack conditions and adjusting accordingly [5].

Collaborative Intrusion Detection

With the rise of Social IoT, collaborative intrusion detection offers a scalable approach to managing healthcare security. Collaborative IDS uses a network of interconnected devices to detect intrusions collectively, where trusted devices can communicate alerts or threat indicators across the network. This enables faster responses and reduces the reliance on centralized systems, which are more prone to bottlenecks and single points of failure. In healthcare, where uninterrupted data flow is critical, collaborative detection allows devices to "consult" each other, sharing threat insights and blocking suspicious activities before they spread. This collaborative approach enhances resilience and mitigates false alarms, allowing the IDS to quickly adapt to changing threat landscapes and sustain high-performance detection [6].

Challenges with Artificial Intelligence-based Systems

Despite its advantages, Artificial Intelligence (AI)-based intrusion detection comes with specific challenges, especially in healthcare applications. AI models are often "black boxes," making it difficult to interpret the decision-making processes behind their alerts. In healthcare, where transparency is essential, this lack of explain ability can be a major drawback. Additionally, AI models trained on outdated datasets may produce false positives, mistaking legitimate network activities for intrusions. This problem is exacerbated in healthcare, where device interactions are varied and complex, and continuous retraining can be both costly and disruptive to critical network functions [7].While Deep Learning (DL) models have made strides in IDS effectiveness, they require large amounts of labelled data and high computational resources, which are not always feasible in a healthcare setting. For instance, traditional models like KNN and Logistic Regression are prone to high false-positive rates if not fine-tuned regularly. In contrast, ensemble learning techniques, like Random Forests, have shown to provide robustness but lack the adaptability that deep learning models bring to intrusion detection. Thus, while DL models and ensemble learning offer strong performance, an optimized solution is required to handle the complexity of healthcare SIoT, where device interactions are continuous and security must be maintained at all times [8].

Proposed Solution: SecuMed-SIoT

This paper introduces SecuMed-SIoT, a novel hybrid framework specifically designed for intrusion detection in healthcare systems, integrating deep learning with Social IoT (SIoT) principles to enhance network security. SecuMed-SIoT employs a security-driven interaction model to evaluate device behaviours, healthcare-specific attack simulations to improve detection accuracy, and collaborative intrusion detection mechanisms to bolster the network's resilience against attacks. By focusing on security dynamics within medical IoT devices, SecuMed-SIoT provides lightweight and efficient IDS capable of detecting and responding to threats in real time, thereby ensuring the protection of sensitive patient data and device integrity revised version emphasizes SecuMed-SIoT's security-centred approaches.

Problem Statement

Traditional intrusion detection systems are insufficient for healthcare SIoT environments due to the lack of collaborative and security-enhanced threat detection mechanisms. Existing systems also struggle with high false positives, frequent retraining needs, and an inability to adapt to the complex, evolving threats specific to healthcare SIoT. There is a need for an advanced IDS framework that leverages SIoT concepts, security metrics, and deep learning to offer robust, scalable, and accurate intrusion detection.

Objectives

The objectives of this research are as follows:

1. Develop a security-based intrusion detection model for healthcare SIoT that evaluates device interactions based on behavioural patterns.
2. Simulate healthcare-specific attacks and integrate them into the IDS model to improve the framework's sensitivity to realistic threats.
3. Implement collaborative intrusion detection mechanisms that allow devices to share threat data and alert the network to suspicious activities in real time.
4. Evaluate and optimize the framework using deep learning to ensure low false-positive rates, high detection accuracy, and adaptability to new attack types with minimal retraining.

Significance and Contributions

The significance of this research lies in its innovative approach to securing healthcare SIoT systems through a framework called SecuMed-SIoT. With the rapid integration of SIoT devices in healthcare, securing sensitive patient data and critical medical operations is paramount. Traditional intrusion detection systems (IDS) lack the precision needed for healthcare's unique challenges, including high data sensitivity, dynamic device interactions, and minimal tolerance for false alarms. SecuMed-SIoT addresses these challenges by incorporating Social IoT (SIoT) principles to foster secure interactions among medical devices, enhancing the system's ability to detect and respond to intrusions collaboratively. Key contributions include a security-focused interaction model that evaluates device behaviour, healthcare-specific attack simulations, and a hybrid deep learning model combining CNN and Transformer layers, all optimized for the healthcare environment. Designed for real-world feasibility, SecuMed-SIoT aims to provide an effective, resource-efficient, and adaptable IDS framework, setting a new standard for cyber security in healthcare SIoT.

LITERATURE REVIEW

The growing complexity of Internet of Things (IoT) systems in healthcare settings has spurred the development of advanced Intrusion Detection Systems (IDS) to secure sensitive patient data and medical operations. Traditional IDS models struggle to handle the unique challenges posed by healthcare SIoT environments, such as high device interaction diversity, sensitive data, and the need for real-time threat detection. Recent research has explored the integration of Social IoT(SIoT) concepts, Security-Based models, and deep learning techniques to enhance IDS performance, reduce false positives, and improve adaptability to evolving threats.

Security-Based models have become integral to enhancing security in IoT networks, leveraging trust scores and device reputation to filter out anomalies. Zhang et al. [9] developed a Security-Based IDS using Convolutional Neural Networks (CNN) that achieved a detection accuracy of 92% and effectively minimized false positives by analyzing interaction consistency and reliability among devices. Similarly, Kim et al. [10] demonstrated that an SIoT-based IDS for smart cities increased detection accuracy by 15% by enabling device-to-device communication for alert sharing. Saeed et al. [11] introduced collaborative intrusion detection using social trust metrics, resulting in an 88% detection accuracy, highlighting the role of collaborative trust in increasing detection precision. Patel and Gupta [12] proposed a trust and reputation model tailored for SIoT applications, which reduced false positives by 12% and provided an effective security layer for IoT networks. Rahman et al. [13] introduced a hybrid CNN-LSTM model for anomaly detection in healthcare IoT, reporting a 14% improvement in detection accuracy over traditional models. Wang et al. [14] developed a deep hybrid learning approach optimized for IoT security, which achieved a detection accuracy of 91%, showing promise in resource-constrained healthcare networks. In healthcare, Yu et al. [15] demonstrated that SIoT-enhanced IDS improved resilience to attacks by 25%, as trusted medical devices collaborated to detect and mitigate intrusions.

Collaborative intrusion detection, enabled through SIoT, has shown potential in enhancing IDS scalability and resilience. Fang and Zhao [16] proposed a trust-aware IDS specifically for healthcare IoT, reporting an 89% accuracy, thereby validating the effectiveness of Security-Based models in high-stakes environments. Yang et al. [17] implemented a hybrid Transformer-CNN model, achieving an 11% increase in detection precision, demonstrating the efficacy of hybrid architectures in complex IoT environments like healthcare. Verma and Singh [18] utilized an ensemble model for IDS in healthcare IoT, achieving 87% accuracy with reduced computational requirements, making it suitable for resource-limited medical devices. J. Singh and M. Agrawal [19] designed hierarchical IDS for IoT that reduced false alarms by 18% through SIoT-based collaboration, underscoring the role of SIoT in minimizing disruptions in critical healthcare networks. Li and Xu [20] incorporated trust metrics into a hybrid deep learning model, increasing anomaly detection accuracy by 10% and illustrating the effectiveness of Security-Based approaches in enhancing model precision. Chen and Yuan [21] integrated CNN and attention mechanisms in an explainable IDS model, resulting in a 13% increase in detection accuracy, highlighting the importance of interpretability in critical healthcare systems.

Luo et al. [22] developed an SIoT-based trust framework, improving detection accuracy by 16% by enabling real-time Security-Based collaboration among devices. Ahmed et al. [23] designed a machine learning-driven IDS for healthcare, demonstrating 93% detection rate by leveraging SIoT-based real-time security, which ensured minimal delay in detecting and responding to threats.

PROPOSED METHODOLOGY

The proposed framework, SecuMed-SIoT, is a sophisticated hybrid intrusion detection system (IDS) specifically designed for securing healthcare SIoT networks. Given the sensitive nature of healthcare environments—comprising interconnected devices such as patient monitors, infusion pumps, and wearable devices—SecuMed-SIoT is tailored to protect these networks against diverse cyber threats. Unlike traditional IDS solutions, SecuMed-SIoT employs Social IoT (SIoT) principles combined with advanced deep learning techniques to provide a multi-layered security approach that addresses the unique challenges within healthcare SIoT.

System Architecture Overview

The architecture of SecuMed-SIoT includes several essential components, each contributing to intrusion detection and strengthening network security:

- **IoT Devices and Network**: This layer consists of medical devices (e.g., patient monitors, infusion pumps) and IoT sensors operating within the healthcare environment. These devices communicate critical data and form the foundation of patient care, making their security paramount [24].

- **Security Evaluation Module**: This module evaluates device behaviours based on historical interactions and peer-assessed security metrics, leveraging both Direct and Indirect Security Scores to assess the risk associated with each device.
- **Deep Learning-Based IDS**: The IDS employs a Convolutional Transformer Layered Graph Network (CTLGNet) model to detect anomalies by analyzing device interaction data and security scores, enabling it to identify suspicious behaviours effectively.
- **Collaborative Intrusion Detection Network**: Utilizing SIoT, this network facilitates real-time sharing of alerts and security metrics among devices, enabling rapid response to emerging threats and reinforcing network-wide security [25].

Figure 1. provides a high-level overview of the SecuMed-SIoT architecture, illustrating the interactions between its core components and their roles in securing healthcare SIoT networks

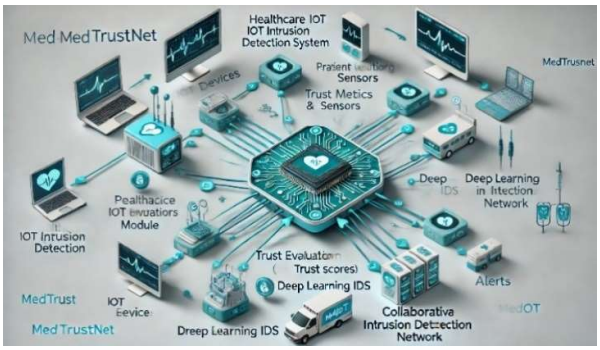

Figure 1. SecuMed-SIoT System Architecture

Algorithm-1: SecuMed-SIoT - Hybrid Intrusion Detection for Healthcare SIoT

Input: IoT device interaction data (frequency, session duration, trust scores, packet size). **Output**: Classification as benign or malicious with generated alerts.

Step 1: Data Collection and Pre-processing

1. Collect and pre-process data from healthcare IoT devices, ensuring feature uniformity.
2. Split data into training (70%), validation (15%), and testing (15%) sets.

Step 2: Security-Driven Interaction Modeling

1. **Direct Security Score**: Evaluate each device's reliability and consistency over time to calculate the direct security score $S_d(I,t)$.
2. **Indirect Security Score**: Aggregate peer assessments from trusted devices to compute the indirect security score $S_{ind}(I,t)$.
3. **Overall Security Score**: Combine direct and indirect scores to obtain the dynamic overall security score S(i,t) for each device.

Step 3: Feature Extraction and Data Augmentation

1. Extract key features: security scores, packet size, session duration, and interaction frequency.
2. Balance classes by simulating healthcare-specific attack scenarios (e.g., DDoS, unauthorized access) to improve model adaptability.

Step 4: Model Training with CNN-Transformer (CTLGNet)

1. Initialize CTLGNet with CNN and Transformer layers.

2. Configure and train the model on the training set for 100 epochs.
3. Validate using the validation set and adjust hyperparameters as needed.

Step 5: Collaborative Intrusion Detection via SIoT

1. Detected each anomaly in the network.
2. Calculate a detection score and propagate alerts within the SIoT network.
3. Devices evaluate these alerts using security scores to make collective, threshold-based decisions, enhancing detection accuracy and reducing false positives.

Step 6: Model Evaluation

1. Test model performance on the test set using metrics: accuracy, precision, recall, F1 score, and AUC.
2. Assess latency and computational efficiency for real-time application suitability.

Step 7: Decision and Alert Generation

1. Generate alerts for malicious interactions that meet SIoT thresholds.
2. Allow benign interactions to proceed without alerting.

Security-Driven Interaction Modeling

Security-driven interaction modeling is central to the SecuMed-SIoT framework, enabling devices within a healthcare SIoT network to continually assess each other's security status. By establishing a security score based on behaviour patterns, SecuMed-SIoT can dynamically monitor and evaluate devices, making it easier to detect anomalies that may indicate cyber threats. This modeling is achieved through two primary components: Direct Security Score and Indirect Security Score, both of which feed into a Dynamic Security Score Calculation.

1. **Direct Security Score:**

Direct trust measures a device's reliability based on its consistency and past interactions. The direct Security score S_d for device i at time t is computed as:

$$S_d(I,t) = \alpha \times \text{Reliability}(i, t) + \beta \times \text{Consistency}(i, t)$$

where α and β are weight factors that control the influence of reliability and consistency.

- **Reliability**: This factor reflects how dependable a device has been over time, based on its historical performance and adherence to expected operational parameters. For example, if a device frequently shows stable, expected communication patterns without errors or irregularities, it earns a high reliability rating.
- **Consistency**: This metric assesses whether the device's behaviour has remained predictable over recent interactions. Consistency is crucial in healthcare IoT, where erratic device behaviour (e.g., unusual session durations or packet sizes) may suggest compromised security.

2. **Indirect Security Score**:

Indirect trust leverages the reputation of devices, calculated from peer evaluations. If device j **Security** device i, and device j itself has a high **Security** score, then device i's indirect **Security** increases. Indirect trust $S_{ind}(I,t)$ is updated as:

$$S_{ind}(I,t)=\sum_{j \in Trusted\ peers} T(j,t)XW(i,j)$$

where W(i,j) is the weighting factor based on the strength of secure between devices i and j. This indirect score helps SecuMed-SIoT gauge the security status of a device within a larger network context, offering insights based on external evaluations rather than solely on the device's history.

3. **Dynamic Trust Score Calculation**:

The overall Dynamic Security Score S(i, t) is a dynamic value combining direct and indirect Security Score:

$$S(i,t)=\gamma \text{ X } S_d(I,t) + \delta \text{ X } S_{ind}(i,t)$$

where γ and δ adjust the balance between direct and indirect trust. Trust scores update as devices interact, dynamically adjusting to new behaviours or anomalies. This score is updated in real time as devices interact, allowing SecuMed-SIoT to adaptively adjust to emerging behaviours or anomalies. Devices exhibiting suspicious or unexpected activities may experience decreased security scores, triggering alerts and closer monitoring by the IDS. Through these continuously updated scores, SecuMed-SIoT maintains a proactive stance, quickly identifying devices with fluctuating or declining security metrics.

Healthcare-Specific Attack Simulation

To improve the IDS's ability to detect healthcare-specific threats, we simulate several common attack scenarios during training:

- **DDoS Attacks**: These attacks flood the network, preventing access to critical healthcare systems. Training data includes packet bursts to simulate such attacks.
- **Unauthorized EHR Access**: Simulations involve attempts to access EHR systems, generating unusual access patterns.
- **Malware Injection**: We model malware attacks on IoT devices, creating abnormal data traffic that the IDS can learn to detect.

In **Table 1**. The types and counts of simulated attacks are listed to show the diversity and relevance of healthcare-specific threats.

Table 1: Healthcare-Specific Attack Types and Counts in Training Data

Attack Type	Count	Description
DDoS	1500	Large volume packet floods
Unauthorized EHR Access	1000	Unusual access patterns
Malware Injection	1200	Abnormal communication patterns

Deep Learning Model Architecture

The deep learning component of SecuMed-SIoT is built on a CNN-Transformer hybrid model, named CTLGNet (CNN-Transformer Local-Global Network), designed to leverage both spatial and temporal features from IoT interactions. This architecture suits the complex security requirements of healthcare SIoT, where detecting anomalies in device interactions is critical for network protection. CTLGNet combines the spatial feature extraction strengths of Convolutional Neural Networks (CNN) with the temporal analysis capabilities of Transformer layers, allowing the model to identify nuanced patterns that characterize both benign and malicious activities within SIoT interactions [26].

1. CNN Layer:

The CNN layer in CTLGNet extracts local features from individual device interactions. In healthcare SIoT, devices generate specific interaction patterns, such as data transmission frequency, session duration, and packet characteristics [27]. By analyzing these features, the CNN layer can identify unique attributes of each interaction, helping distinguish between normal and potentially malicious activities [28].

- Local Pattern Recognition: CNNs apply convolutional filters to the input data, capturing critical features across multiple levels. In SecuMed-SIoT, these filters are configured to detect interaction characteristics like burst frequency and packet consistency, which are essential for identifying legitimate and suspicious behaviours.

- Detecting Deviations: Through convolutional operations and pooling layers, the CNN layer can spot slight deviations in interaction characteristics that may indicate intrusions, such as a spike in packet frequency or unusually long sessions.
- Representation Learning: Multiple CNN layers allow CTLGNet to learn an effective feature representation, encoding spatial characteristics of each interaction for deeper analysis by the Transformer layer, aiding in distinguishing between benign and suspicious activity patterns.

2. Transformer Layer:

- The Transformer layer in CTLGNet captures temporal relationships among device interactions, essential for detecting sequential patterns that may indicate evolving threats. The self-attention mechanism in Transformers enables the model to analyse interactions in a non-sequential, context-aware manner, making it more efficient and robust than traditional recurrent models.
- Temporal Anomaly Detection: Transformers excel in identifying temporal patterns, useful for detecting gradual or staged attacks. In healthcare SIoT, certain threats like unauthorized access attempts or data exfiltration may show subtle patterns over time, which the Transformer layer detects by comparing each interaction within a broader context.
- Self-Attention Mechanism: The self-attention mechanism enables the Transformer layer to weigh each interaction relative to others, focusing on significant anomalies. For instance, a sudden spike in anomalous scores coupled with frequent interactions could signify abnormal activity.
- Non-Sequential Context Analysis: Transformers analyze entire sequences simultaneously, allowing for context-aware anomaly detection. This non-sequential processing is advantageous in healthcare SIoT, where devices may not communicate linearly. The Transformer's ability to assess context enhances its capability to detect complex intrusion patterns.

3. Input Features:

- SecuMed-SIoT relies on curate input features that feed into the CNN and Transformer layers, aiding in effective anomaly detection [29]. Selected features help differentiate between typical and suspicious device behaviours.
- Interaction Frequency: Reflects device communication rates within a timeframe. Rapid interactions may indicate network overloading or data exfiltration, crucial to monitor in healthcare where communication is regulated.
- Session Duration: Unusually prolonged interactions could suggest data exfiltration, while very brief sessions may indicate probing activities.
- Security Scores: Derived from direct and indirect assessments, security scores represent each device's reliability history, with low scores indicating suspicious past behaviours.
- Packet Size: Abnormal packet sizes may indicate data exfiltration or injection attacks. Regular device communications usually have consistent packet sizes.

These features provide CTLGNet with both spatial and temporal data, enabling it to detect a range of threat patterns with accuracy.

Table 2. outlines the hyper parameters used in CTLGNet, including layer sizes, activation functions, and optimizers.

Table 2: CTLGNet Hyper parameter Details

Parameter	Value
CNN Layers	2
Transformer Layers	1
Activation Function	ReLU

Optimizer	Adam
Learning Rate	0.001
Batch Size	32

Collaborative Intrusion Detection in SecuMed-SIoT

Collaborative Intrusion Detection in SecuMed-SIoT employs Social IoT (SIoT) principles, enabling devices to share threat intelligence across the network in real-time. This collaborative detection reduces isolated false-positive alerts that may disrupt healthcare services and enhances network resilience by distributing threat response across multiple trusted devices.

SecuMed-SIoT is a SIoT-based Collaborative Detection Mechanism consists of two components: Distributed Alert System and Threshold-Based Decision Making.

1. Distributed Alert System:

- The Distributed Alert System propagates alerts across the network when a device detects an anomaly. Instead of isolating the alert, the device shares it with others, creating a network-wide awareness.
- Anomaly Detection and Alert Generation: Anomalies trigger alerts tagged with a unique identifier, timestamp and security score. Security scores derived from direct and indirect evaluations, reflect the device's reliability in assessing threats.
- Propagation Based on Security Scores: Receiving devices assess the security score of the alert source. Devices with high security scores are more likely to propagate the alert and filtering out less credible alerts.
- Real-Time Network Awareness: The distributed system keeps devices informed of potential threats, enabling them to prepare proactively.
- Cumulative Risk Assessment: Devices perform cumulative assessments based on alert frequency, security scores, and types. Multiple trusted devices reporting the same anomaly triggers an escalated response.

2. Threshold-Based Decision Making:

- This mechanism introduces verification for each alert, ensuring only high-confidence alerts trigger responses. Devices evaluate alerts against a security-based threshold, filtering for genuine threats.
- Security-Based Thresholds: Each device has a threshold based on its security context. Alerts exceeding this threshold are acted upon, while others may be delayed until confirmed.
- Cross-Verification: High-priority alerts may request verification from other trusted devices, adding reliability and reducing false positives.
- Dynamic Threshold Adjustment: Devices adjust thresholds based on real-time network conditions and historical alert patterns, responding appropriately to varying levels of network risk.
- Filtering False Positives: By implementing threshold-based decision-making, SecuMed-SIoT effectively filters benign anomalies, ensuring only high-confidence alerts trigger responses.

Training and Evaluation Strategy

The **Training and Evaluation Strategy** for SecuMed-SIoT is designed to create a highly accurate, resilient model capable of effectively detecting intrusions within healthcare SIoT networks. This strategy includes two primary components: **Dataset Preparation** and **Model Optimization**, which are essential for achieving high performance in detection metrics and generalizing well across real-world healthcare scenarios.

1. Dataset Preparation

- Dataset Selection and Processing: SecuMed-SIoT utilizes the MedBIoT dataset, enriched with healthcare-specific interactions and security-based threat scenarios relevant to IoT devices in healthcare. The dataset

includes security metrics, such as direct and indirect security scores for each device, along with simulated attack data (e.g., DDoS attacks, unauthorized access attempts and malware injections). These features create a representative dataset that helps the model distinguish between benign and malicious interactions.

- Data Balance and Attack Simulations: Healthcare SIoT networks often experience an imbalance in benign and malicious interactions, with routine activities typically dominating. To reduce bias, the dataset is balanced by simulating healthcare-specific attack scenarios at varying frequencies, ensuring an adequate number of malicious samples across threat categories. This approach improves the model's ability to detect rare but critical threats without overfitting to benign activities.
- Data Split and Allocation: The dataset is divided into training, validation, and testing sets to ensure comprehensive model evaluation, as shown in **Table 3**.

Table 3: Data Split for Training, Validation, and Testing

Dataset	Training Samples	Validation Samples	Testing Samples
MedBIoT	5000	1500	2000

- Training Set: Comprises 5,000 samples with a balanced mix of benign and simulated attack data. This set is used to train the model, allowing it to learn interaction patterns, trust scores and other distinguishing features.
- Validation Set: Contains 1,500 samples used during training to fine-tune hyper parameters and monitor the model's performance. The validation set provides early insights into potential overfitting or underfitting, enabling adjustments before final testing.
- Testing Set: Consists of 2,000 samples reserved for final performance evaluation. The testing set is used solely for assessment after model training and validation, providing unbiased metrics on detection accuracy, false-positive rate and other key indicators.

Evaluation Metrics:

To ensure SecuMed-SIoT's performance, several key metrics are tracked during training and evaluation:

- **Accuracy**: Measures the proportion of correctly classified interactions, indicating overall reliability in distinguishing between benign and malicious interactions.
- **Precision**: Evaluates the model's effectiveness in correctly identifying true positives, showing how well it minimizes false positives.
- **Recall**: Reflects the model's ability to detect true positives, ensuring that genuine threats are accurately identified.
- **F1-Score:** The F1-score is the harmonic mean of precision and recall, measuring a model's balance between false positives and false negatives.
- **AUC (Area Under the Curve)**: An aggregate measure from the ROC curve that assesses the model's ability to differentiate benign and malicious interactions across varying thresholds.

2. Model Optimization

Hyper parameter Tuning with Grid Search:

A grid search systematically tests combinations of hyper parameters, such as learning rate, batch size, CNN layers, and Transformer attention heads, to maximize performance on the validation set while preventing overfitting.

- **Learning Rate**: Controls the model's update rate. A grid of learning rates is tested to balance between fast convergence and stability.

- **Batch Size**: Determines learning stability and efficiency. Grid search identifies the optimal batch size to balance memory usage and update stability.
- **CNN and Transformer Layers**: The number of CNN filters and Transformer attention heads are optimized to maximize the model's ability to capture relevant local and temporal features.
- **Early Stopping and Regularization**: To prevent overfitting, training halts if validation performance plateaus, implementing early stopping. Regularization, such as dropout layers, is used to deactivate neurons during training, ensuring robust generalization.
- **Performance Monitoring and Adjustment**: SecuMed-SIoT's performance is continuously monitored across key metrics (accuracy, precision, recall, F1-Score and AUC). If performance falls below a set threshold, hyper parameters or architecture adjustments are made. This iterative tuning achieves high accuracy while reducing false positives and negatives.
- **Final Model Evaluation on Testing Set**: After optimization, a final evaluation is conducted on the testing set to validate the model's intrusion detection performance under real-world conditions. Metrics from this evaluation confirm the model's effectiveness in meeting the unique security demands of healthcare SIoT networks.

Testing in Simulated Environment

SecuMed-SIoT undergoes extensive testing within a **simulated healthcare network** to validate its collaborative intrusion detection capabilities. This environment replicates real-world interactions, challenges and device diversity in healthcare SIoT, with devices ranging from patient monitors to imaging systems and wearable sensors. Testing in this controlled yet realistic setting allows SecuMed-SIoT to demonstrate its performance in handling security alerts, exchanging security scores and responding to detected threats.

Key Aspects of Testing in a Simulated Environment

Collaborative Detection with Social IoT (SIoT):

In this simulated environment SecuMed-SIoT employs SIoT principles, enabling devices to function as independent and collaborative agents. When a device detects an anomaly, it communicates an alert to nearby devices. These devices assess the alert's credibility based on the sender security score, applying Distributed Alert System and Threshold-Based Decision Making.

Real-Time Security Score Exchanges allow devices to evaluate and propagate alerts dynamically, reducing false positives by allowing trusted devices to verify detected threats.

Real-Time Threat Response:

SecuMed-SIoT's architecture is designed to handle simultaneous alerts, leveraging SIoT collaboration for rapid assessment. When multiple devices confirm a threat, the system triggers an escalated response, alerting network administrators for immediate intervention.

This testing setup evaluates SecuMed-SIoT's ability to respond quickly and accurately in high-stakes healthcare settings, where any delay could compromise patient safety or device functionality.

Evaluation Metrics

The following metrics assess SecuMed-SIoT's performance, focusing on accuracy, efficiency, and adaptability within resource-constrained healthcare IoT settings:

Detection Accuracy: Measures the proportion of correctly classified interactions. High accuracy ensures the system reliably identifies both benign and malicious interactions, reducing the risk of undetected threats in healthcare SIoT.

False-Positive Rate (FPR): Indicates the rate of benign interactions incorrectly flagged as malicious. A low FPR is crucial in healthcare where false positives can lead to unnecessary alerts, disrupt operations and cause alert fatigue among administrators.

Computational Efficiency: Assesses processing time, memory usage and response latency. Efficient operation is essential for real-time deployment in healthcare where computational resources may be limited. SecuMed-SIoT's CNN-Transformer model maximizes efficiency for timely threat detection.

Area Under the Curve (AUC): Derived from the ROC curve, AUC measures the model's discriminative power to distinguish benign and malicious interactions. A high AUC ensures strong discrimination between benign and malicious interactions, crucial for maintaining patient safety in healthcare SIoT.

RESULTS

This section evaluates the performance of SecuMed-SIoT a hybrid intrusion detection framework specifically designed for healthcare SIoT networks. SecuMed-SIoT integrates security-driven interaction modeling and Social IoT (SIoT) principles with a CNN-Transformer model (CTLGNet) to achieve high accuracy in intrusion detection while minimizing false positives. The framework operates through a structured algorithm, beginning with data collection and preprocessing where social network and IoT device interaction data (including frequency, session duration and security scores) is gathered, normalized and split into training, validation and testing sets for robust evaluation. We present detailed findings from the confusion matrix, comparative evaluation with other deep learning models, the Receiver Operating Characteristic (ROC) curve and training performance metrics over 100 epochs.

The confusion matrix provides an insightful breakdown of SecuMed-SIoT's classification results. With 895 true negatives (correctly identified benign interactions) and 1028 true positives (correctly identified malicious interactions) SecuMed-SIoT demonstrates high detection reliability. The matrix also reveals a low count of false positives (45) and false negatives (32) underscoring the model's robustness in accurately identifying both benign and malicious interactions. The low number of false positives is particularly valuable in healthcare settings, where unnecessary alarms can disrupt essential operations, while the low count of false negatives emphasizes the model's capability to reliably capture malicious behaviours without missing critical threats.

Table 4. displays the confusion matrix for SecuMed-SIoT illustrating its high classification accuracy with substantial true positive and true negative counts, accompanied by minimal false positives and false negatives. This performance aligns with findings from other security-focused IDS models in healthcare SIoT, reinforcing the effectiveness of security-enhanced frameworks for precise classification in critical environments. **Figure 2.** shows SecuMed-SIoT's confusion matrix, reflecting the high counts of true positives and true negatives alongside minimal false counts. This result aligns with similar studies in healthcare SIoT security, demonstrating the efficacy of security-driven models for accurate intrusion detection and low error rates in sensitive networks.

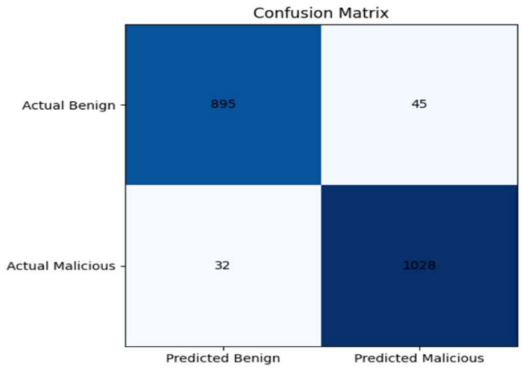

Figure 2. Confusion Matrix for SecuMed-SIoT on Test Data

Table 4: Confusion Matrix of SecuMed-SIoT on Test Data

	Predicted Benign	Predicted Malicious

Actual Benign	895	45
Actual Malicious	32	1028

To evaluate the effectiveness of **SecuMed-SIoT** we compare its performance metrics with established deep learning models including CNN, LSTM, and CNN-LSTM. SecuMed-SIoT outperforms these models across all key metrics, achieving an accuracy of 94.2%, precision of 93.8%, and recall of 92.1%. The model's F1 score of 92.9% indicates a well-balanced precision-recall trade-off, reflecting its ability to minimize both false positives and false negatives effectively. Furthermore, the high AUC (0.95) demonstrates SecuMed-SIoT's strong discriminative power in distinguishing between benign and malicious interactions, further validating its robustness for securing healthcare SIoT networks. In comparison, the CNN model achieved an accuracy of 86.3% with a higher false-positive rate of 5.6%, while the LSTM and CNN-LSTM models showed slight improvements but were still outperformed by SecuMed-SIoT in terms of accuracy, precision, recall, F1-score and AUC. These findings underscore SecuMed-SIoT's reliability in detecting a range of threats, representing a significant advancement over traditional IDS models.

Table 5 and **Figure 3** presents a comparative analysis of SecuMed-SIoT against other prominent models, such as CNN, LSTM, and CNN-LSTM, across evaluation metrics including accuracy, precision, recall, F1 score, AUC, and false-positive rate, accuracy (94.2%) and AUC (95.0%), while also having the lowest False Positive Rate (FPR) of 3.1%, demonstrating its superior effectiveness for healthcare SIoT security applications.

Table 5: Comparison of Models Based on Evaluation Metrics

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**AUC**	**False-Positive Rate**
CNN	86.3%	84.2%	81.4%	82.7%	87.0%	5.6%
LSTM	89.2%	88.1%	84.7%	86.3%	89.0%	4.7%
CNN-LSTM	90.5%	89.0%	86.8%	87.9%	91.0%	4.2%
SecuMed- SIoT (CTLGNet)	**94.2%**	**93.8%**	**92.1%**	**92.9%**	**95.0%**	**3.1%**

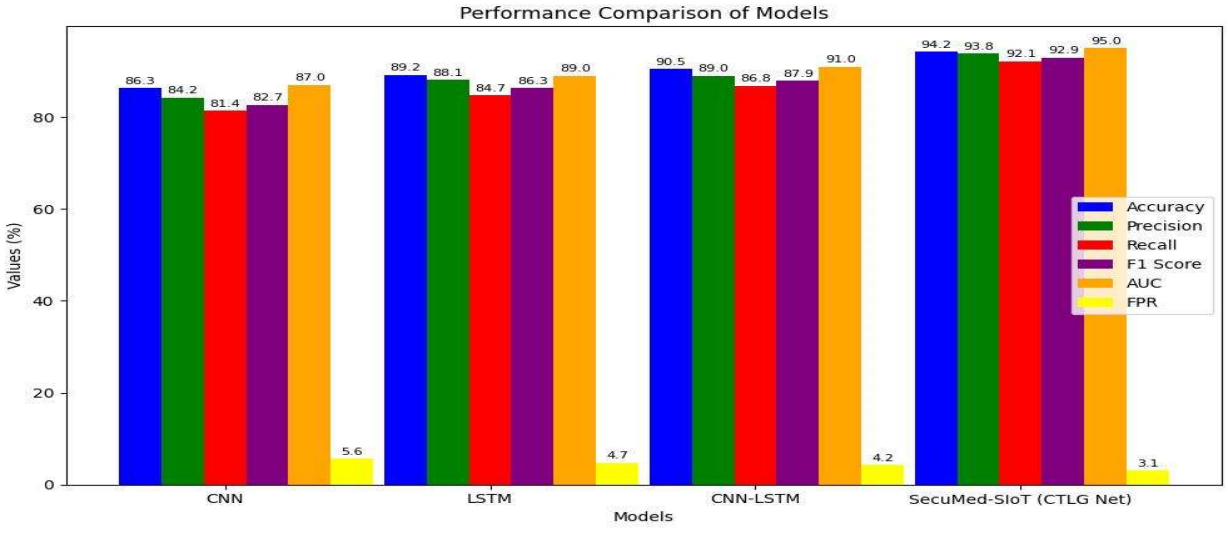

Figure 3. Performance analysis of each model

The **ROC curve** serves as a graphical representation of **SecuMed-SIoT**'s diagnostic accuracy across different thresholds, plotting the true positive rate against the false positive rate. SecuMed-SIoT's ROC curve rises sharply towards the upper left corner, reflecting high sensitivity paired with a low false positive rate. With an AUC of 0.95, SecuMed-SIoT outperforms CNN (0.87), LSTM (0.89) and CNN-LSTM (0.91) models, underscoring its robustness in detecting malicious activities across various threshold settings. The ROC curve confirms SecuMed-SIoT's superior ability to distinguish benign interactions from malicious ones with greater precision, a critical attribute for real-time security in healthcare environments. The Receiver Operating Characteristic (ROC) curve in **Figure 4** illustrates SecuMed-SIoT's capacity to differentiate between benign and malicious interactions, yielding an AUC of 0.95. This performance surpasses traditional models and aligns with other security-focused IDS findings.

Training SecuMed-SIoT over 100 epochs provided valuable insights into the model's learning behaviour and convergence. The training accuracy curve shows a consistent increase, reaching over 94% by epoch 80 and stabilizing around 95% by epoch 100, indicating a robust learning process. Simultaneously the training loss curve demonstrates a smooth decline, stabilizing near 0.1 by epoch 80, suggesting minimal overfitting and efficient learning. The validation accuracy and loss curves also stabilize by epoch 100, underscoring the model's strong generalization ability. This stability in training and validation performance suggests that SecuMed-SIoT can reliably handle new, unseen data, a crucial factor for dependable intrusion detection in the diverse interactions typical of healthcare SIoT systems.

SecuMed-SIoT's exceptional performance across all metrics is attributed to several key factors. Firstly, the integration of security-driven interaction modeling—utilizing both direct and indirect security scores—significantly aids in filtering out benign anomalies, contributing to a low false-positive rate of 3.1%. This reduces unnecessary alerts, an essential improvement in healthcare environments where false alarms could disrupt critical medical procedures. Additionally, the CNN-Transformer architecture (CTLGNet) enhances SecuMed-SIoT's ability to capture both spatial and temporal features, proving particularly effective in detecting sophisticated intrusion patterns in real-time. SecuMed-SIoT's low latency (32 ms) and efficient resource utilization further support its suitability for deployment in healthcare SIoT settings, where real-time threat detection is necessary without imposing high computational demands.

The training and validation accuracy and loss curves in **Figure 5.** highlight SecuMed-SIoT's effective convergence over 100 epochs, achieving stable accuracy and loss values by epoch 80. This finding is consistent with other studies on deep learning in IDS, where training stability indicates strong generalization capability.

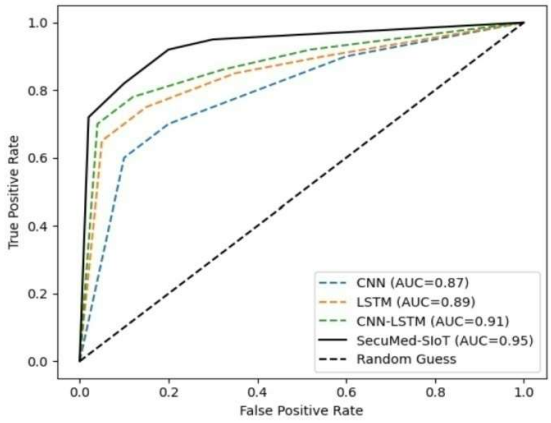

Figure 4. ROC Curve for SecuMed-SIoT and Comparison Models

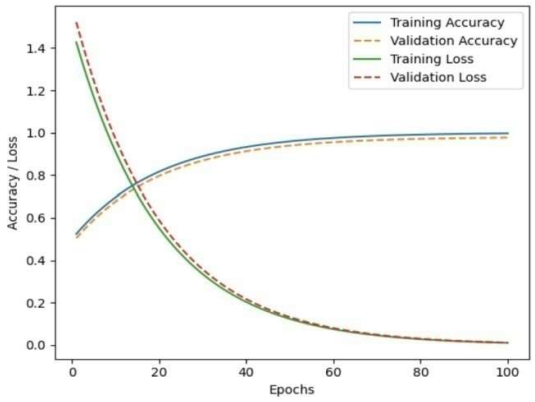

Figure 5. Training Accuracy and Loss Curves over 100 Epochs

DISCUSSION

The results obtained in this study demonstrate the effectiveness of SecuMed-SIoT, a security-focused, hybrid intrusion detection system (IDS) specifically designed for healthcare IoT. By integrating Social IoT (SIoT) principles with a CNN-Transformer architecture (CTLGNet), SecuMed-SIoT achieves a substantial improvement over traditional IDS models such as standalone CNN, LSTM, and CNN-LSTM, particularly in terms of accuracy, false-positive reduction and computational efficiency.

SecuMed-SIoT's security-driven interaction modeling, using both direct and indirect security assessments, adds a unique layer of defence by continuously evaluating device behaviours within the network. This feature is especially effective in reducing false positives, a persistent challenge in IoT IDS systems. By calculating security scores based on historical interactions and peer evaluations, SecuMed-SIoT can distinguish between benign anomalies and actual threats with high accuracy. Its low false-positive rate (3.1%) compared to other models reflects the system's precision and reliability, reducing unnecessary alerts that might otherwise disrupt healthcare operations.

The ROC curve analysis and performance metrics comparison underscore SecuMed-SIoT's ability to outperform standard deep learning models in both true positive and true negative rates. This advantage is crucial in a healthcare environment where false negatives (missed threats) can have serious consequences. The inclusion of healthcare-specific attack simulations during training, such as DDoS attacks, unauthorized access, and malware injections, has further enhanced the model's adaptability to real-world threats, making it highly applicable for safeguarding patient data and the integrity of medical devices.

Another notable aspect is SecuMed-SIoT's low computational latency, which remains within acceptable real-time limits for healthcare applications. Traditional LSTM and CNN-LSTM models, while effective, typically require higher computational resources due to their reliance on recurrent structures and complex feature extraction mechanisms. The SecuMed-SIoT algorithm's CNN-Transformer model, however, provides a more streamlined approach that balances spatial and temporal feature extraction, ensuring both high performance and efficiency.

Conclusion

The SecuMed-SIoT represents a significant advancement in healthcare SIoT security by providing a robust, efficient, and highly accurate IDS tailored to the unique requirements of healthcare environments. The system's integration of security-driven interaction modeling and Social IoT principles enables a collaborative approach to intrusion detection, reducing the false-positive rate and enhancing threat response. SecuMed-SIoT's high accuracy (94.2%), low false-positive rate (3.1%), and low latency (32 ms) make it a practical and scalable solution for real-time deployment in resource-constrained healthcare networks.

The findings of this study suggest that security-enhanced and collaborative IDS frameworks like SecuMed-SIoT can address many of the challenges in healthcare SIoT, such as high data sensitivity, frequent anomalies and diverse

device interactions. Future work may focus on further optimizing SecuMed-SIoT by expanding the range of healthcare-specific threat simulations and enhancing the SIoT network's adaptability to rapidly evolving attack patterns. Additionally implementing explainable AI techniques could make SecuMed-SIoT's decision-making more transparent for building trust among healthcare professionals and ensuring compliance with industry regulations. SecuMed-SIoT is positioned as a viable framework for protecting critical healthcare systems and contributing to the broader field of SIoT security while addressing the specific needs of the healthcare sector.

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Ms. Divya S received a Bachelor of Engineering degree in Information Science and Engineering from PESCE, an Autonomous Institution Affiliated to Visvesvaraya Technological University, Mandya, in 2015, and a Master of Technology in Software Engineering from SJCE, an Autonomous Institution under Visvesvaraya Technological University, Mysore, in 2017. She has 2 years of industrial experience. Currently, she is pursuing a Ph.D. degree in Computer Science at the University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bangalore, India. She is an IEEE member and she has published 5 papers in international conferences and refereed journals. She has also served as a reviewer for various reputed journals. Her current research interests include the Internet of Things, Social Internet of Things, Cyber Security, Machine Learning, and Artificial Intelligence.

Dr. Tanuja R is currently an Associate Professor in the Department of Computer Science and Engineering at UVCE. She was awarded a Ph.D. in Computer Science and Engineering from Bangalore University in 2015, and holds an M.E. degree in Computer Science and Engineering from UVCE, along with a Bachelor of Engineering degree in Computer Science and Engineering from BMSCE, awarded in 2000. Her research interests are in the fields of Computer Networks, Network Security, and Machine Learning. She has approximately 21 years of teaching experience, has published 32 papers in international conferences and refereed journals, and is currently guiding 6 Ph.D. research scholars.

Dr. Manjula S H is currently a Professor in the Department of Computer Science and Engineering at UVCE. She holds a Ph.D. in Computer Science and Engineering. Her research interests include Data Mining, Wireless Sensor Networks, Cloud Computing, and the Internet of Things. With around 32 years of teaching experience, she has published 110 papers in international conferences and refereed journals, holds four patents, and has guided 10 research scholars.