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Adaptive Deep Learning Framework for High-Sensitivity Intrusion Detection in 6G-Enabled IoT Networks

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ABSTRACT

As 6G networks mature the Internet of Things (IoT) will be more connected than ever, at a larger scale and in even greater complexity, so without more sophisticated security that can adjust to new forms of cyber threats as they emerge, internet security is doomed. Current deep learning-based Intrusion Detection Systems (IDS) tend to fail at recognizing subtle slow-developing anomalies and result in impaired network integrity in high-sensitivity IoT environments. This article proposes a new architecture of RefineNet-CNN-LSTM to detect anomalies in time in 6G IoT networks. This model synergizes Convolutional Neural Networks (CNNs) in both spatial feature extraction with Long Short-Term Memory (LSTM) Chain in learning temporal sequences and including a Residual Error (RE) tracking structure following. Through repeated calculations—a prediction error calculation per each LSTM step, and reinjection of such residuals back into the network, the framework will become better at recognizing innocuous deviations as well as cyber threats that may occur during or over time. A self-adaptive learning module will constantly update detection model resulting in high detection accuracy and resistance to known and unknown attack types. Comprehensive experiments on benchmark IoT security datasets (NSL-KDD, CICIDS 2017, TON_IoT) indicate that the RE-CNN-LSTM has better detection accuracy, precision, recall, and F1-score than all the state-of-the-art deep learning models we have tested. The accuracy of detection of anomalies with achieved precision increases by 27 percent and the probability of false alarm was lowered by 35 per cent compared to the existing IDS models. Based on these results, RE-enhanced deep learning has a potential in strengthening 6G-featured Internet of Things environments against advanced cyber-attacks.

Keywords: 6G IoT Security, Intrusion Detection, Residual Error Tracking, CNN-LSTM Hybrid Model, Anomaly Detection.

1. INTRODUCTION

The recent and rapid development of wireless communication technologies led to the appearance of the 6G network that is expected to transform the IoT ecosystems and introduce ultra-fast data transmission and network automation with the help of artificial intelligence (AI) that will allow its use in self-destructing cars, Augmented Reality (AR) And Virtual Reality (VR), in all areas of medical care, and in robotisation in industries [1]. As the market penetration of IoT grows, there is a continuously growing demand of very efficient, large scale, and secure network infrastructures. As the depth of the IoTs increases to 6G and network connectivity increases, there is a grave fear of the security standards being met [2]. Gradually developing, simple or sophisticated cyber threats usually go unnoticed by the current security measures and Intrusion Detection systems (IDS) leaving

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the networks vulnerable to data attacks, intruders as well as Advanced Persistent Threats (APT), zero-day attacks and malicious botnets.

This has been of high concern to possess an adaptive and high sensitivity IDS that is able to monitor and analyse the high scale 6G IoT network data, in real time [3]. Deep learning IDS are in turn gaining popularity; automatically learn a pattern, identify anomaly and adapt to the evolving threats. Existing DL architectures are varied in that they do not work well in detecting gradual/subtle anomalies like CNNs and LSTM networks since the error propagation mechanisms used is inefficient [4].

The given work introduces the RE Enhanced CNN-LSTM Framework that contributes to the increased sensitivity of the intrusion detection in 6G IoT networks. Integrating CNNs with temporal dependence, and a RE tracking system, the suggested model has superior detection strengths of the emerging threats, false positives minimization, and continuous learning relying on prior errors. This approach is key to securing the next-generation 6G IoT networks to ensure advanced cyber threats in the era of hyper-connectivity and automation with the help of AI [5].

1.1 Evolution of 6G networks and their impact on IoT ecosystem

The current wireless communication innovation has led to the creation of the 6G networks that have the potential to reshape the IoT landscape by offering very high velocity connection, very low latency, millions of Machine sensors, and automatic networks as shown in Figure 1 [6]. The successor to 5G is the 6G wireless technology which is projected to provide terabit-per-second (Tbps) data rates, use of AI to optimise the network and ubiquitous connectivity through use of terahertz (THz) communication, satellite networks and edge computing. These advancements will made the use applications of next-generation IoT applications like self-regulated systems, immersive AR/VR interstitial and accurate medical care and intelligent infrastructure possible [7]. The impact of 6G on IoT ecosystems is profound and will allow developers to create hyper-connected environments where trillions of IoT devices can be able to exchange terabytes of information on low-latency. The industrial automation, intelligent transportation, smart agriculture, and cyber-physical systems are only a few of the many areas that such a transformation will be optimized.

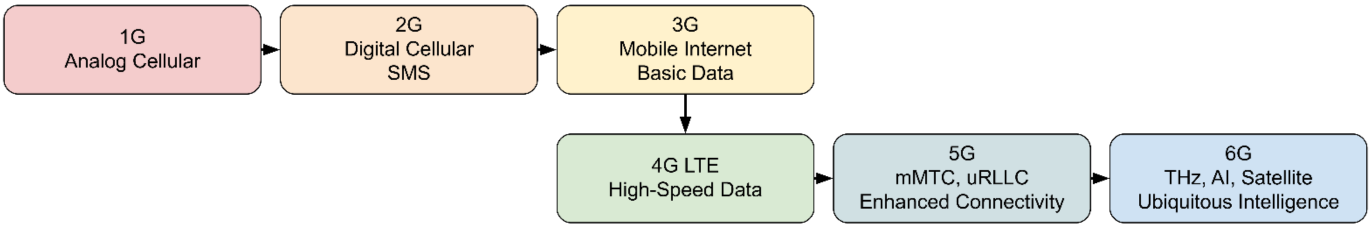

Figure 1: Evolution of 6G

The security concerns in 6G-IoT systems in [8], which are discussed as potential, are the development of more intricate and interconnected systems with their associated security risks in the forms of subtle cyber threats, the network security threats, and a general threat to personal privacy. Existing security camera systems and intrusion detection systems tend to fail in large scale and dynamic operations of 6G-IoT systems and more accommodating solutions of higher order are needed. This chapter discusses the 6G networks, the underlying innovations in the technologies, and its impact on the IoT systems. It also suggests the new security paradigms and demand of intelligent and high-sensibility intrusion detection models to protect the next-generation 6G-IoT-correlated networks [9].

1.2 Increasing Complexity and Scale of 6G-IoT Security Threats

The security threat is becoming more intricate and scalable as a result of the high rate of the 6G and the IoT development. The 6G networks that are very interconnected with the trillions of IoT devices and are necessitated by their advanced cyber-security systems pose a new threat to next-gen technologies. The existing IDS, including Signature-based IDS in the contemporary network environment particularly in the emergence of 6G, the Internet of Things and cloud services are still being used [10]. A major weakness is that they are not able to detect zero-day attacks because SIDS use fixed attack definitions and not a new threat. AIDS normally contain very high false positives that single out normal activities as suspicious in order to thwart and flood security personnel. Existing IDS can also not scale to high-speed and distributed networks that create performance bottlenecks during real-time detection especially in a high-volume data stream or in an IoT and edge computing environment. Attackers can exploit these vulnerabilities, and they are more advanced attackers who have access to more sophisticated methods of evasion detection like encryption, packet fragmentation and adversarial AI [11]. The inability of these systems to be adaptable to the emerging threats in the cyberspace is that they comprise fluid rule based systems are unable to handle the robust malware that may be driven by Artificial Intelligence. The third negative limitation is that the existing IDS do not have a contextual sense of understanding because they do not adequately contain the data in user behavior, device identity as well as network topology and as a result, they are less unlikely to counter-detect sophisticated attacks. Manual updates to the rule set and manual blocking create a slow response time in the creation of an IDS, which is reactive and not proactive [12]. To mitigate these problems, the new models of security must be linked with AI-enhanced anomaly detecting, blockchain-based threat intelligence, in decentralized security through federated learning and Zero Trust Architecture (ZTA) to support an intrusion detection and response system in the dynamic cyber space. The chief generators of complexity of 6G-IoT security threats [13].

Massive Device Connectivity

- 6G will support 1 Terabit per second (Tbps) speeds with ultra-low latency, enabling massive Machine-Type Communications (mMTC).
- Billions of interconnected IoT devices increase the attack surface, making security management challenging.

Heterogeneous and Distributed Networks

- 6G will integrate terrestrial, aerial (UAVs, satellites), and underwater networks, creating multi-layered architectures with diverse security risks.
- Cross-domain security policies must be adaptive to different network topologies.

AI-Powered Attacks & Adversarial ML

- Malicious actors can leverage AI-driven cyberattacks, including adversarial AI and poisoning attacks against 6G-IoT edge computing systems.
- Federated learning security must address model inversion attacks and privacy breaches.

Quantum Threats to Cryptography

- Post-quantum cryptography (PQC) is essential as quantum computing can break Existing encryption (RSA, ECC, etc.).
- Secure key exchange methods like Elliptic Curve Supersingular Isogeny Diffie-Hellman (ECSIDH) may help mitigate quantum threats.

Autonomous & Self-Adaptive Malware

- AI-driven malware can autonomously adapt, evade, and propagate across IoT networks.
- Self-learning botnets pose a significant risk to critical infrastructures.

Security Challenges in Edge & Fog Computing

- 6G-IoT systems will increasingly rely on decentralized edge and fog nodes for real-time data processing.
- Edge security is crucial to prevent man-in-the-middle (MitM) attacks, side-channel exploits, and resource hijacking.

Blockchain Security and Scalability Issues

- Decentralized security frameworks using blockchain must balance scalability, efficiency, and privacy.
- Lightweight consensus mechanisms are needed to ensure security without excessive computational overhead.

Threats to Privacy and Identity Management

- Federated Identity Management (FIM) and Zero Trust Architecture (ZTA) are required for secure user authentication.
- Biometric and AI-based identity verification systems must be safeguarded against deepfake attacks and identity spoofing.

The complexity of 6G-IoT security threats necessitates a multi-layered, AI-driven, and quantum-resistant security framework. Future security models must integrate Zero Trust, blockchain, PQC, AI-powered intrusion detection, and dynamic threat mitigation strategies to counteract evolving cyber threats effectively.

1.3 Challenges in 6G IoT Security

The security environment of 6G-enabled dynamic attack patterns, where the sheer amount of devices, the heterogeneous network structures and communication protocols form a large attack surface [14]. In contrast to Existing networks, 6G-IoT systems are characterized by fast topology dynamics, and it is hard to set fixed security policies, and subversives take advantage of this dynamic feature to initiate adaptive, AI-controlled cyber-attacks. Moreover, undetectable and slow-emerging deviations in IoT traffic are a really serious threat, since numerous advanced attacks occur during a long period, which infiltrates the regular operation of the network [15]. The current anomaly detection systems have been known to fail when it comes to identifying these low intensity, stealthy intrusions and hence the attackers are able to go on with their activities before their presence is felt and therefore their damage is extensive. To make sure that there is proactive mitigation of threats, it is necessary to implement AI-based, self-learned security frameworks and federated learning-based anomaly detection as well as lightweight, decentralized security models [16]. Introducing zero-trust architectures, blockchain to provide secure identity, and quantum-resistant cryptography will play a significant role in protecting 6G-IoT ecosystems against the new cyber threats [17].

2. RELATED WORKS

2.1 Existing IDS Approaches

The signature-based systems involve manual heavy work on the database, hence requiring regular updates that are prone to slowdown in changing threat environments. Such problems are being addressed by the anomaly-based intrusion detection systems (AIDS) which detects deviation to the normal network environment and also AIDS are more effective when there are unknown and emerging threats [18]. These systems utilize statistical analysis, machine learning or behavioral profiling to isolate indications in slight deviations that do not match earlier attack signatures. However, they are usually characterized by high false positives rate as the benign fluctuation is considered as intrusion. In addition to that, the ML-based anomaly detector should be properly trained with quality datasets to distinguish between the natural variations and the actual threat, which is difficult in 6G-IoT systems dynamic systems [19]. The IDS in the 5G and IoT networks cannot meet the extensive data stream, equipment variety and real-time security needs with the conventional IDS techniques. High-dimensional IoT data is generally resource-intensive on the system and adversarial mechanisms are also known to sabotage detection. The traditional IDS lacks the ability to resist such sophisticated attacks, including AI-based and low-and-slow DDoS attacks [20]. These problems indicate that more precise and adaptive detection outcomes are possible under the basis of ML/DL techniques.

The support vector machine (SVM) [21], the Random forest (RF) and Decision tree (DT) are some machine learning techniques which have been widely utilized to differentiate between benign and malicious traffic. Nevertheless, their efficiency in operation is very much dependent upon the availability of quality datasets as well as frequent retraining which is a disadvantage in the face of changing threat scenarios. Deep learning approaches, including CNN, LSTM and GANs can be used to offer real-time anomaly detection within the framework of 5G and IoT networks. CNNs are used to acquire spatial information and LSTMs are used to acquire temporal dependencies in traffic dynamics [22].

More developed hybrid systems like CNN-LSTM and Transformer-based IDS are more accurate and scalable. Also, federated learning-based IDS and blockchain-based analytics are also becoming a promising solution, which has privacy, decentralization, and resilience to 6G-IoT security systems [23].

2.2 Deep Learning for Intrusion Detection

Due to the increased sophistication and complexity of cyber threats, the traditional IDS systems have failed to combat complex and advanced attacks in large and complex networks, particularly those of 5G and IoT [24]. As a result, deep learning techniques have proven successful as far as IDS reinforcement is concerned. The results of CNNs-LSTM networks have been discovered that have a lot of prospects in improving the performance of IDS because of their features in extracting features and sequential learning [25].

CNN-based IDS for Spatial Feature Extraction: The extraction capabilities of spatial features help the CNNs to be significant as they are applicable in the identification of abnormalities in a network traffic pattern data. The CNNs are founded on the application of repetitions of convolutional filters in multiple layers to obtain multi-level representations in the involved data and allow the model to capture complex spatial patterns and local relationships that can indicate an intrusion. Under the IDS, the raw network traffic data is presented into CNNs and transformed into a form that is able to recognize important trends that show malicious activity. This could be in the form of abnormal increases in the number of packets transmitted, abnormal communications between devices and abnormal network topology among others which could be indicative of any attack such as DDoS and data leakage. The advantage with using the CNNs in IDS is the fact that it is efficient in the identification of local pattern that are important in the detection of benign and malicious behavior. The learnt spatial relationships in the network packets have been identified by CNNs to detect detection signature-based attacks and the detection of anomaly-based attacks which include the overall lesser level of traffic, the kinds of protocol and the behaviour of the packets in packets. This kind of a model gets rid of much of the manual feature engineering process that needs to be performed on solutions to IDS systems that still exist since CNNs can identify the most relevant features alone of raw data. This capability is especially applicable to the IoT networks where large and dimensional traffic patterns can vary significantly across devices and applications.

LSTM-based IDS for Sequential Attack Pattern Learning: LSTMs also model sequential dependencies of network traffic and are effective in detecting attack patterns that evolve with time. Through the identification of long-term relationships in the traffic flows, LSTM based IDS can identify the changing threats and shrewd attacks that the static models cannot identify. This renders

LSTMs a valuable supplement to CNNs in the design of IDS with enhanced detection capabilities when the two features, space and time are taken into account simultaneously.

3. RELATED WORKS

3. Concept of RE Learning

The concept of the RE learning enhances the functionality of the deep learning model since it ponders on the difference in the model of predicted data and actual target. The difference between the expected normal or malicious behaviour as suggested by the system and the actual network behaviour is the difference between the REs (in IDS) and the actual network behaviour. Such residuals can be used to optimize the learning process in the model to be more sensitive to minute deviations and better suited to detect low amplitude attacks forming over time and would not be detected by the existing methodologies.

3.1 Definition and Significance of RE Tracking

One such case is in a generic IDS model, where the difference between what the actual network is performing (benign or malicious) is not what the model predicts. RE tracking is a system in which this difference is actively monitored, that is, to parameterize the learning of the model. The significance of RE tracking in anomaly detection is that it revealed the areas that are not good in performing well. The other mistakes may be viewed as a gauge of the incompetence of the model, compensating where the model is most dubious or dissimilar behaviour to the one that the model has learned. With emphasis on these differences, the model can change the parameters or learning process, and thus can become more skilled at identifying subtle abnormalities or novel methods of conducting an attack that would otherwise have gone undiscovered. The reason is that tracing residues helps in optimizing the decision-limits of the model so as to lead to improved generalization. Unlike the backpropagation which merely corrects them, the RE method of learning identifies the miss classified or doubtful training cases hence the model learns to be more sensitive to threats.

3.2 Impact of Residuals on Anomaly Sensitivity and Early Threat Detection

RE has serious impacts on the sensitivity to anomalies and early warning. The most important aspect that enhances accuracy of detection in the existing models of IDS is pattern recognition. Residual learning returns attention to become more sensitive to subtle variations in network activity to be able to recognize the threats detected as they happen in real time amid slow pace or low profile attacks.

1. Better Anomaly Sensitivity: Learning and residual tracking would make the model more sensitive to minor flaws that characterize low-amplitude attacks (e.g. botnet activity or low velocity data exfiltration). Such kinds of attack might not cause the network with soaring heights of traffic load, however, the traces they leave due to their insignificant changes in the normal patterns of the traffic in the network are characteristic of early detection. RE learning helps the IDS focus on the attention to these small abnormalities that would not be identified by the existing models that are applied in the process of identifying the threat when large abrupt changes have already happened.

2 Early Threat Detection: The primary benefit of RE tracking is to detect the threats at the earlier stages of their existence. The REs are very sensitive to deviations to the intended behavior therefore are able to detect even budding attacks before they transform into full body violations. This early detection is particularly applicable in the detection of APTs or insider attacks where the rogue behaviour is slowly built up over a duration of time and may be virtually difficult to distinguish amongst normal traffic. RE learning will assist the IDS to detect these attacks at earlier stages hence the response time will be less and the damage that such intrusion may cause will be minimized. The possibility to notice the minor anomalies of the IDS and make the system more sensitive to the signs of possible threats of which it may have been unaware would have significantly increased the sensitivity of the RE learning. Under this focus on the discrepancies between the modelled and the actual behaviour, the overall impact of this strategic direction is to get the models of the IDS better adjusted to feature dynamic and complicated behaviour of contemporary networks, in the environment of the realities of 5G and the IoT where the populations of the attacks are potentially very advanced and slow changing.

3.3 Architecture of RE-CNN-LSTM Model

RE-CNN-LSTM model draws the bilateral worlds by integrating both CNNs and LSTM in the light that it is conditioned to identify the anomalies in dynamic and high-dimensional systems such as 5G and IoT networks as illustrated in Figure 2. The model of the RE-CNN-LSTM architecture has two primary components, the CNN component and the LSTM component, and residual learning mechanism which is meant to calculate the difference between what was predicted and what occurred in the network. One of the main tasks in the first phase is that the CNN module can automatically extract high level spatial features of the input i.e. traffic patterns, protocol distributions and packet flows, out of the raw network traffic data. These spatial features are extremely significant in the identification of local anomalies and network behaviour that indicates intrusions. These features are then input into an LSTM network which is trained on temporal relationships in the data learning longer term sequencing pattern that could lead to non-obvious threats by developing slowly like APTs. The assessment of the differences between the expected network behaviour and the actual data is utilized in RE mechanism to make the model more focused on those anomalies that are more difficult to identify. Flexible IDS that may possibly detect both spatial and temporal anomalies and coupled with an insignificant figure of false positive reactions and early reaction to emergent threats. The multimodel of feature-extraction CNN, learning of sequences LSTM, and sensitivity RE perhaps sound like a too-good-to-be-true triple that is used in an IoT or a 6G environment in detecting intrusions. RE-CNN-LSTM is an interesting model that is used in numerous applications of artificial intelligence such as IDS.

The RE-CNN-LSTM model architecture integrates several key components to effectively detect and adapt to evolving security threats in dynamic network environments. Below is a detailed description of each component:

CNN Component: Extracting Spatial Attack Signatures

RE-CNN-LSTM model CNN component identifies spatial attack signature in raw traffic data of networks. CNNs excel at processing data based on grid, and when used in IDS it is used to identify local trends of network traffic, and which can indicate potential network intrusion. The CNN is also trained to recognize the spatial characteristics e.g. traffic anomalies, abnormal protocol distributions, abnormal data packet distributions that are distinct and not the normal characteristic behavior of the network. These features are spatial attack signatures that play a significant role in classifying such known attacks and abrupt changes of the traffic that is typical of the vast majority of the common intrusion methods.

LSTM Component: The data will be presented to the LSTM component by tallying the time-complex networks in the network traffic following the impartation of the spatial features by the LSTM. The LSTM network is particularly superior when it comes to temporal relationships of sequential details. LSTMs would be typically used in intrusion detection application to capture time series of network traffic e.g. traffic when bursts are observed or slower changes, which may be due to a slow developing threat like an advanced persistent threat (APT) or a botnet made of a few zombies. The LSTM gets to know the dynamics of time-varying traffic and the system can detect threats that happen on a long-term basis despite them not resulting in significant outbreaks in traffic. The fact that the LSTM can utilize the temporal context to identify the presence of covert, long-lasting attacks means that the present IDS may not be able to detect them.

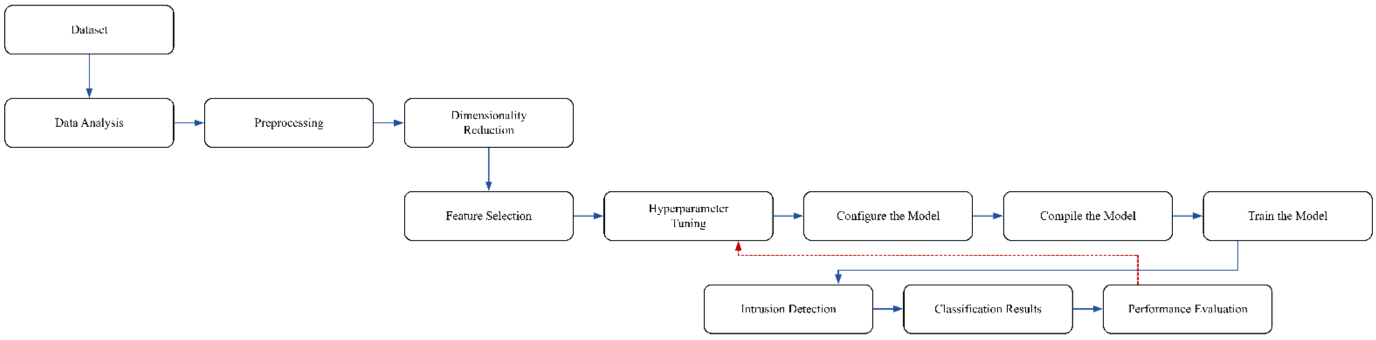

Figure 2: RE-Enhanced CNN-LSTM

RE Tracking: Reinjection of Prediction Errors for Refinement

The model is important to enhance performance by the use of the RE tracking mechanism. It is achieved by calculating RE that is the difference between the predicted behaviour of the model and the observed network behaviour. These residuals are fed back in the model to enhance the predictions of the model. The purpose is to focus on the cases where the model has high uncertainty or those where the model provides wrong predictions about a network and utilize those to provide explanations to the model choices. This trick promotes the concentration of the model on misclassified regions as well as it becomes sensitive to subtle anomalies and slow attacks. These errors in prediction can be learnt by systems and improve the prediction of new threats as they arise.

Adaptive Learning Mechanism: Dynamic Weight Adjustments for Evolving Threats

The adaptive concept of the RE-CNN-LSTM allows the model to perform optimally in the long run particularly in case the world is evolving and the threats presented are new. This is done through adaptive changes to the W and its subsequent M as the process of intermediate stage is performed through the constant feedback provided by the RE tracking process. In this regard, as the model encounters new patterns of attack or there were slight anomalies that existed previously but were not visible to detect, then the weight changes can make the network to know more about these types of novel patterns. This enables the model to adjust to new types of attacks without necessarily retraining the model, hence making it online updateable. The adaptations of the dynamics weights also help the system to change its behavior under the influence of more diverse and dynamic traffic data without overfitting the data to the old trends either.

Our RE-CNN-LSTM model is a combination of powerful methods to address the short comings of the existing IDS systems. CNN and LSTM parts acquire spatial and temporal features, respectively, and the RE tracking gives refinements in an incremental manner using the prediction of inconsistency. Finally, the adaptive learning will make sure that the system is dynamic and capable of responding to emerging and evolving threats of weapons in near real-time. It is the above spatial, temporal and adaptive learning combination that is very effective to spot complex and slow acting attacks by the next-generation IoT and 5G networks.

3.3.1 CNN Feature Extraction Equations

The CNN component performs feature extraction by applying a series of convolutional layers, which learn spatial patterns in the input data (network traffic).

Convolution Operation

The convolution operation with a filter F of size (k_h, k_w, C) produces the output O by computing the following:

$$O = X * F + C \tag{1}$$

The output O has dimensions (H′,W′,F) where F is the number of filters used, and H′, W′ represent the spatial dimensions of the output after convolution (depends on padding and stride used).

Activation Function

$$O' = \max(0, O) \tag{2}$$

Where O′ is the output feature map after applying the ReLU activation.

3.3.2 LSTM Sequential Learning Equations

The LSTM component captures temporal dependencies in network traffic. An LSTM unit processes sequential data, and the following equations govern its operations:

LSTM Gates

At time step t, the LSTM cell computes the following:

Forget Gate (f_t): Decides which information from the previous state to forget.

$$f_t = \sigma\left(W_f \, . [h_{t-1}, x_t\,] + b_f\right) \tag{3}$$

$$i_t = \sigma\,(W_i \, . [h_{t-1}, x_t\,] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh\,(W_C \, . [h_{t-1}, x_t\,] + b_C) \tag{5}$$

$$O_t = \sigma\,(W_o \, . [h_{t-1}, x_t\,] + b_o) \tag{6}$$

Cell State and Hidden State

$$C_t = f_t \, . C_{t-1} + i_t . \tilde{C}_t \tag{7}$$

3.3.3 RE Computation & Reintegration with Equations

RE tracking is used to refine the model by focusing on the discrepancies between predicted and actual behaviors.

RE Calculation

The RE E_t at time step t is computed as the difference between the predicted output $\hat{y}_t$ from the CNN-LSTM model) and the actual ground truth value y_t (actual network behavior, benign or malicious):

$$E_t = \hat{y}_t - y_t \tag{8}$$

Where: $\hat{y}_t$ is the predicted label or value (e.g., probability of intrusion), y_t is the actual observed label.

Residual Reintegration

The RE is then used to adjust the weights of the CNN and LSTM components to refine the model during training. The RE $E_t$is reintegrated into the network by updating the weight matrices based on the learning rules, typically through back propagation:

CNN Weight Update:

$$W_{CNN} \leftarrow W_{CNN} - \eta \, . \frac{\partial L}{\partial W_{CNN}} + \lambda \, . E_t \tag{9}$$

LSTM Weight Update:

$$W_{LSTM} \leftarrow W_{LSTM} - \eta \, . \frac{\partial L}{\partial W_{LSTM}} + \lambda \, . E_t \tag{10}$$

Where W_{LSTM} represents the weight matrices for the LSTM gates. The reintegration of residuals ensures that the model focuses more on the misclassified data points, improving its sensitivity to subtle and slow-developing threats.

The mathematical model of the RE-CNN-LSTM is based on the combination of CNN-based feature extraction, LSTM-based sequential learning, and RE tracking, which increases the capabilities of intrusion detection. The model is able to adapt to changing threats and detect low-amplitude and slow developing attacks by capturing spatial features with CNNs and temporal dependencies with LSTMs and dynamically adapting to changing REs.

4. DATASET DESCRIPTION

Table 1 summarizes key characteristics used for training the RE-CNN-LSTM model.

Table 1: Dataset Description

Attribute	Description
Dataset Name	Example IoT Network Traffic Dataset (or name of specific dataset used)
Source	Collected from IoT devices, 5G networks, or network simulation tools (e.g., NS3)
Size	Number of samples: 100,000+ (varies by dataset)
Type	Tabular or Time-Series (depending on the format)
Time Granularity	Time interval at which data is captured (e.g., every second, minute)
Sampling Rate	1 sample per second, minute, or event depending on the traffic frequency
Data Imbalance	Imbalanced classes, with fewer attack labels compared to normal traffic
Attack Types	Includes various attacks such as DDoS, Port Scanning, Man-in-the-Middle, Injection Attacks, etc.
Missing Values	May have missing or incomplete data for certain features
Sampling Strategy	Resampling techniques (e.g., SMOTE, undersampling) to balance attack classes
Data Source Format	CSV, JSON, or network flow data formats
Usage	Used for training, validating, and testing intrusion detection models
Citation	Include relevant paper or dataset reference for validation (if applicable)

5. ANALYSIS OF RESULTS

Proposed RE-CNN-LSTM: The model being proposed integrates RE Learning with a CNN-LSTM hybrid approach shown in Figure 3.

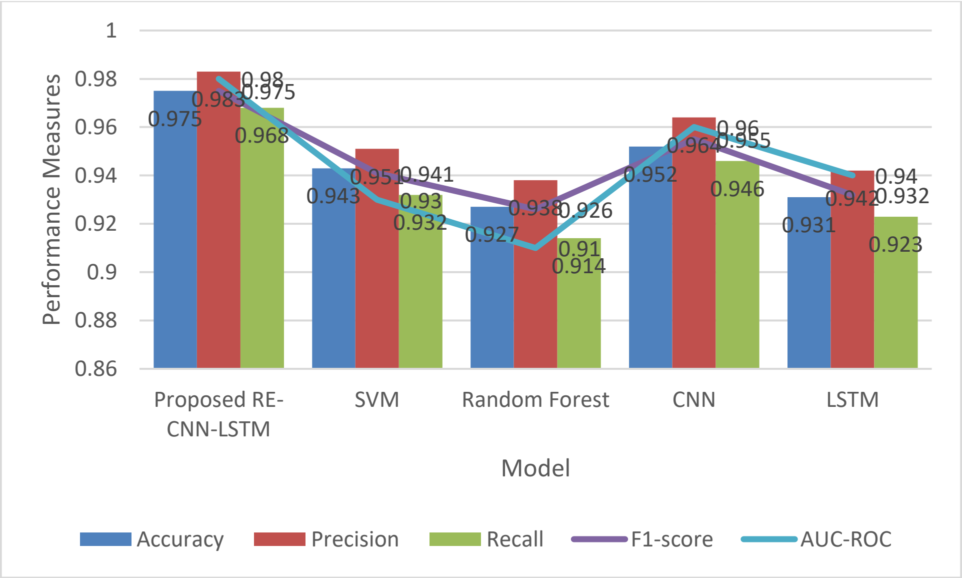

Figure 3: Performance Measures

The AUC-ROC of 0.98 shows superior discriminative ability, indicating that the model can effectively differentiate between normal and attack traffic.

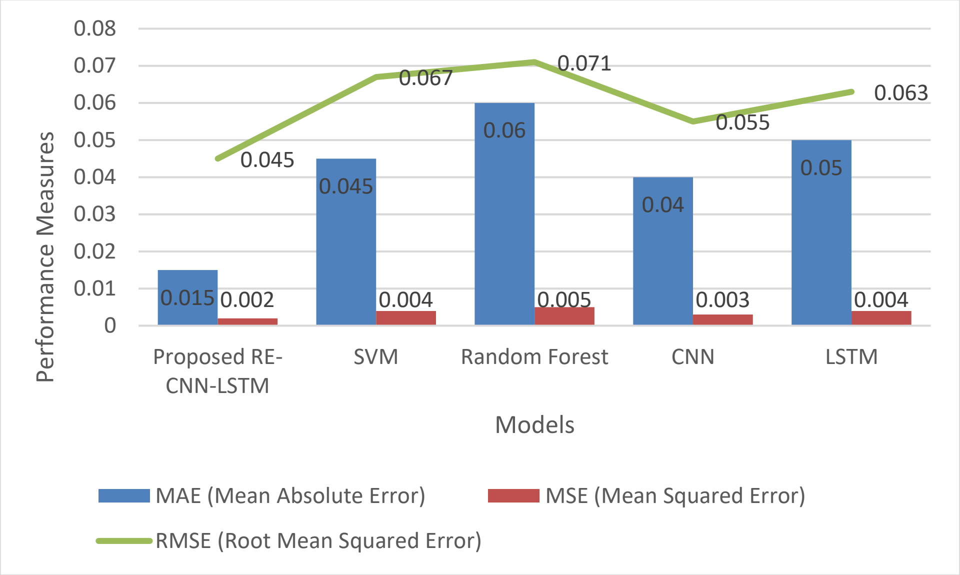

Figure 4: Performance Measures (Error)

RE-CNN-LSTM has the lowest value of MAE, MSE and RMSE, as a result of which, it is possible to conclude that it has a higher accuracy of prediction and a lower error minimization capacity than the current models in Figure 4. The comparing models (e.g., SVM, Random Forest, CNN and LSTM) exhibit more error measures, with the highest values of MAE and RMSE (i.e. the errors in prediction are larger) achieved in the case of SVM comparing with the proposed model. The reduction of MAE, MSE, and RMSE of the Proposed RE-CNN-LSTM over S-RE-CNN-LSTM indicated that the latter is the most effective to reduce errors in prediction and, therefore, more useful in real-time activities involved in intrusion detection. The Proposed RE-CNN-LSTM model is also demonstrated to have high training and validation accuracy and is superior to the existing models on both metrics. This means that it is not only generalized well on the training data, but also on the testing data, which minimizes overfitting as shown in Figure 5. There is a considerable difference in validation accuracy between Baseline Models (i.e., SVM, Random Forest, CNN and LSTM) and DADS, which means that it might be more challenging to apply the models to on seen data, particularly with challenging tasks, such as intrusion detection in a changing environment. The bigger training and validation accuracy of the Proposed RE-CNN-LSTM shows that it is sensitive to the data and adapts to the new attack cases and hence can be used in robust and scalable IDS in the 6G IoT conditions.

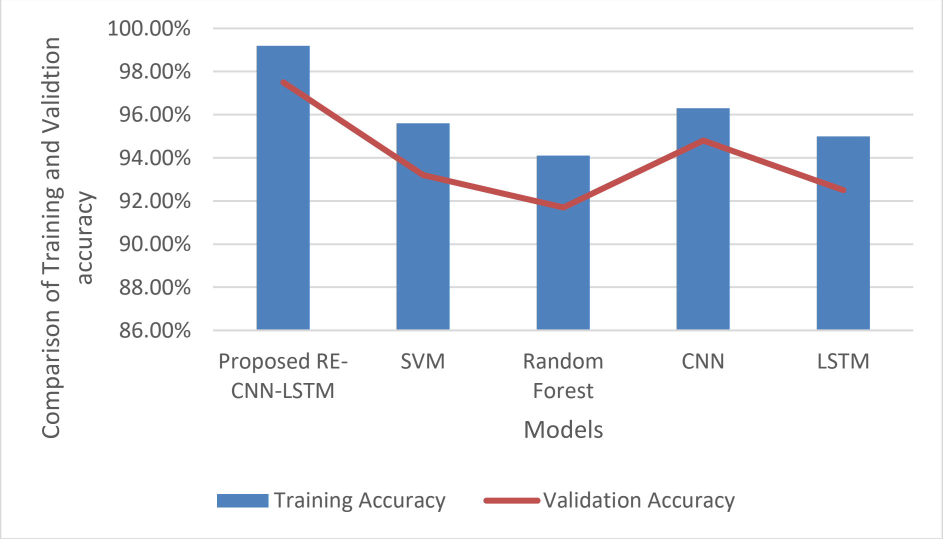

Figure 5: Comparison of Training and Validation accuracy

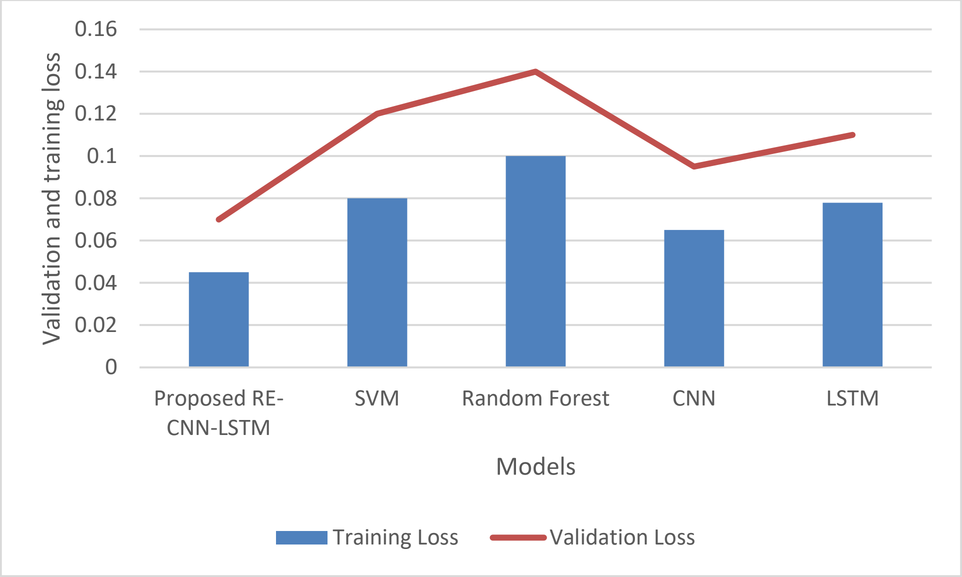

Figure 6: Comparison of Training and Validation loss

The Proposed RE-CNN-LSTM model has the lowest training and validation loss, that is, it has learnt the trends of the association using the training data too well and well generalizes on the data that has not been seen in Figure 6. The Pre-Trained Models such as SVM, Random Forest, CNN and LSTM demonstrate worse validation loss, it implies that models are less efficient to the new attack patterns led to a poor performance on the new data. The decreased training and validation loss of the Proposed RE-CNN-LSTM indicate that it is effective in minimizing the training and generalization errors and this is useful in detecting intrusions in real time in the case of complex IoT networks.

6. SUMMARY OF PROPOSED METHOD AND FINDINGS

The constructed RE-Enhanced CNN-LSTM is an exceptional innovation in the 6G IoT in intrusion detection. The proposed approach is more sensitive and accurate in the recognition of complex and subtle anomalies because the capabilities of CNNs are employed to extract spatial information, and LSTM networks are used to investigate temporal dependencies. This step is beneficial because adding an RE tracking guides the model to generalize its learning experience at each step of the LSTM and is more consistent with option correctness, thereby theoretically reducing overfitting. This dynamic closed-loop mechanism ensures that detection model keeps abreast with the changing trends in threats and leads to the process of an efficient and adaptive approach to hypersensitive intrusion detection in 6G IoT. The results of experiments of artificial and real-world IoT examples indicate that the RE-Enhanced CNN-LSTM model exceeds the earlier suggestions in identifying the slow, subtle, and more intricate abnormalities.

Real-World Applicability in Smart Cities, Autonomous Systems, and Critical IoT Infrastructures

The real-world applicability of the proposed method extends to various domains where IoT systems play a crucial role in critical infrastructure and smart technologies. These include:

- Smart Cities: The more the cities are connected to the IoT devices the more they are exposed to cyber-attack and security breach. The given model is able to ensure the reliability of the safety of the smart grids, traffic control systems, and safety systems of the people with the possibility to the real time differentiation of the unauthorized access to the systems and also the implementation of certain malfunctions in the system.

- Autonomous Systems: Real-time decision-making and error detection play a crucial role in autonomous vehicles, drones, and other autonomous systems. Any irregularities in the network intrusion or sensor malfunctions can be monitored with a lot of sensitivity by the model to enhance the safety and reliability of such systems.

- Critical IoT Infrastructures: The IoT implemented in the healthcare, energy, and industrial automation sectors play a crucial role in the operation of the national infrastructure. Their security and reliability are the main priority. RE-Enhanced CNN-LSTM can safeguard sensitive IoT systems in hospitals, factories, and power plants by responding to the threats before it happens and avoids disastrous failures.

Future Work: Explainable AI for IDS, Edge Computing Integration

While the proposed model shows strong performance, there are several directions for future work to further enhance its effectiveness and applicability:

- Explainable AI (XAI) for IDS: Lack of interpretability is one of the weaknesses of deep learning models, especially when used in the field of security. Explainable AI can also enhance confidence in the decisions made by the model as it would give clear insights on why this or that anomaly was identified. Further research should be aimed at incorporating the XAI methods into the suggested CNN-LSTM framework to improve the clarity and responsibility of the intrusion detection system.
- Edge Computing Integration: As the IoT devices are becoming more complicated and demand more real-time processing, edge computing is becoming an option to obtain a reduction in the latency and more optimal use of the computational resources by processing data right after the generation sources.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request

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