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CLOUD IOT ENVIRONMENTS SECURITY: DEEP LEARNING WITH GENERATIVE AND EXPLAINABLE MODELS

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ABSTRACT

IoT devices have grown exponentially, and businesses are utilizing cloud computing to integrate complex applications with those devices, which poses excellent security concerns regarding confidentiality, integrity, and availability of sensitive data. This paper offers a security framework to mitigate against the threats above utilizing deep learning, Generative Adversarial Networks (GANs), and Explainable AI (XAI). To alleviate the challenges of anomaly detection, especially for rare and novel attacks, the proposed framework uses GANs (Generative Adversarial Networks) to produce synthetic data. XAI methods such as SHAP and LIME have been established to bring more transparency and trust to models, which is incredibly important for security professionals. The framework also integrates federated learning, where models can be trained across decentralized devices while keeping data private. The experimental results demonstrate that our proposed model can achieve achieving94.8% accuracy94.6%precision97.1%recallon NSL-KDD datasets, which are lower than other models Lowest Latency of 45ms per sample. The results validate the model for scalable, interpretable, and privacy-preserving real-time Internet of Things (IoT) security applications.

Keywords: *Cloud Computing, IoT Security, Deep Learning, Generative Models, Explainable AI, Anomaly Detection, Trust, Privacy, GANs*

1. INTRODUCTION

The Internet of Things (IoT) and the growing need for cloud computing have reshaped the tech landscape for people, businesses, and governments. IoT devices include smart sensors, wearables, connected appliances, and vehicles that generate enormous amounts of data, which are usually processed and stored in cloud environments. And this is precisely why the entire convergence of IoT and cloud computing works to the benefit of everyone involved. While this innovation has brought great benefits, it also presents significant security challenges, as the complexities of cloud-IoT ecosystems leave them susceptible to various attacks, threatening confidentiality, integrity, and availability of sensitive data [1][2].

The rapid expansion in the number of devices represents new surfaces upon which adversaries can launch attacks. Traditional security mechanisms, including firewalls, intrusion detection systems (IDS), and antivirus software [3][4], cannot keep up with the complexity, volume, and speed of attacks on IoT networks. Traditional rule-based security methods, which take advantage of predefined signatures or heuristics, typically fail to detect

unknown threats and present significant issues, especially in the IoT sphere where underlying hardware, software, and communication protocols of devices differ [5].

Machine Learning in recent studies, ML has achieved importance in cybersecurity, which helps the system analyze vast amounts of data and find patterns corresponding to possible security threats [6]. This ability to learn from data poses a significant advantage over traditional rule-based systems, where rules are manually curated, as the former, intense learning (DL) techniques, are more capable of discerning complex patterns and are better at predicting possible threats, thereby implementing proactive and adaptive security measures [7]. Nonetheless, deep learning models are widely known to be "black box" systems, and even though these techniques would yield reliable predictions, it is hard to interpret what drives their decisions [8]. In security-sensitive applications (e.g., the Internet of Things (IoT), where trust and accountability are important [9]), interpretability is a significant obstacle.

Explainable AI (XAI) targets this challenge by increasing the transparency and interpretability of machine learning models [10]. In some cases, e.g., in work by Khorram et al. (for anomaly detection) or Wang et al. and Mbaek et al. (for classification), XAI techniques (e.g., Shapley Additive Explanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME)) have been implemented in IoT security models to improve interpretability of the respective area [11][12]. This transparency is vital in healthcare, finance, and government sectors, where security decisions can mean life or death [13].

The magnitude and variety of data generated by IoT devices pose additional challenges for detecting anomalies and possible security threats [14]. To deal with these issues, Generative Adversarial Networks (GANs) have helped create synthetic data for augmenting the training datasets, especially in the case of imbalanced data or rare attack cases. [15] [16] Realistic data-based GANs help close the gap of differences between normal and anomalous behaviors of IoT. Challenges with these models must be managed to address privacy concerns, particularly with sensitive data [17].

Our Cloud-IoT security model Cloud Network Device security. Each layer acts preventatively against unauthorized access and ensures data integrity from the moment data is transferred from an IoT device to cloud platforms [18][19]. In addition, the decentralized structure of IoT networks with no central authority hinders the adoption of common security policies [20]. This paper proposes a comprehensive security framework leveraging deep learning, GANs, and XAI to address the multi-faceted security challenges that Cloud-IoT systems pose. The framework applies other methods to achieve a complete approach to data, using GANs in data augmentation and anomaly detection, XAI method for transparency, and federated learning for security during model training [21][22].

While previous works investigated different aspects of IoT security, our work is distinctive in terms of motivations and findings, identifying deep learning, GANs, and explainable AI to be the methodological focus of IoT security, especially with an emphasis on advanced anomaly detection and privacy preservation.

With the explosive growth of IoT devices and businesses using complicated cloud computing applications with those devices, security is a major concern regarding the confidentiality, integrity, and availability of sensitive data.

Figure 1 depicts a Comprehensive Security Framework for Cloud-IoT, highlighting key components necessary for securing IoT environments connected to cloud computing. At the center is Cloud Computing, which provides scalability and accessibility for processing vast data. Surrounding it are six crucial elements: IoT Devices, which generate large amounts of data for analysis; Deep Learning, which is used to identify complex security patterns; GANs (Generative Adversarial Networks), which generate synthetic data for model training; XAI (Explainable AI), which improves model transparency and interpretability; and Federated Learning, ensuring privacy during model training by keeping data decentralized. This interconnected framework aims to address the security challenges in Cloud-IoT systems, balancing data privacy, model transparency, and effective threat detection.

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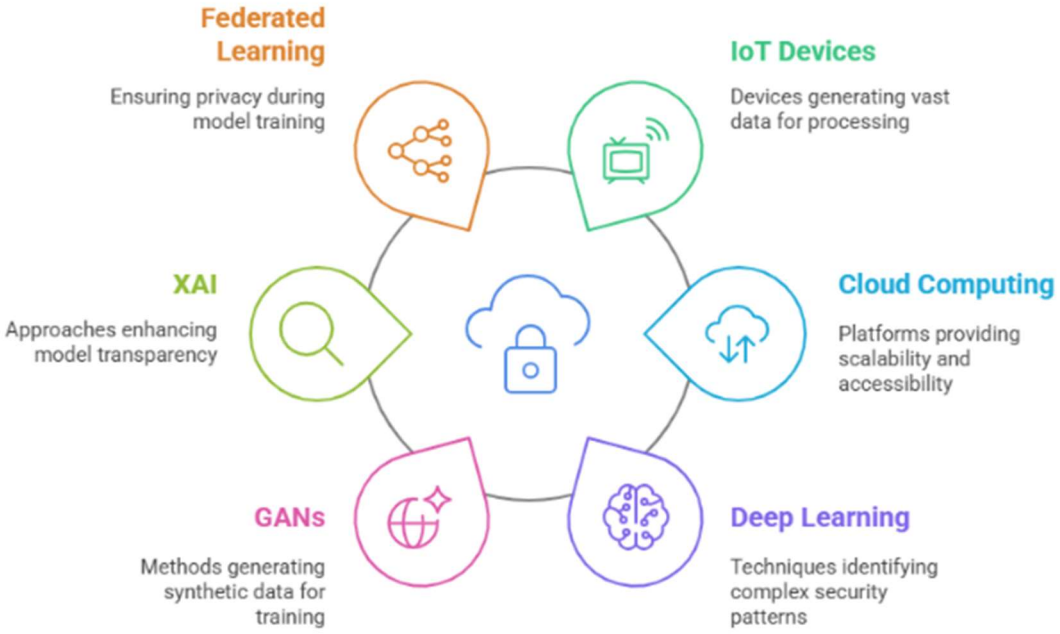

Figure 1: Comprehensive Security Framework for Cloud-IoT

Problem Statement

The newly enlarged attack surface brought about by the rapid integration of IoT devices with cloud platforms and vice versa makes them a desirable target for various cyber threats. In rapidly changing environments, traditional security approaches focus on rule-based detection or signature-based methods that fail to identify new, unknown, or evolving threats. In addition, the black-box nature of machine learning models and privacy concerns have hindered the adoption of AI-based solutions in critical IoT security applications. Most existing approaches suffer various limitations such as ineffective performance, limited scalability, lack of interpretability, and privacy violations, which we find unacceptable for handling security in Cloud Computing-IoT (Cloud-IoT). This paper addresses these limitations and presents a security framework that utilizes deep learning, GAN, XAI, and federated learning techniques to provide a robust, scalable, interpretable, and privacy-preserving security solution for Cloud-IoT systems.

This paper presents Section 2 discusses related work focusing on IoT security challenges and solutions. Section 3 presents the proposed security model, including how GANs, XAI, and federated learning are integrated. Section 4 describes experimental design, assessment metrics, and model performance. Section 5 describes the proposed framework's conclusion and future work directions. Finally, Section 6 summarizes our contributions and findings.

2. RELATED WORK

2.1 IoT Security Challenges

IoT devices in cloud computing environments introduce various security issues, mainly because they may not have many state-of-the-art security features. However, IoT devices are inherently resource-constrained and potentially used in hybrid environments, meaning they are likely to be much less secure than traditional devices. They often communicate over insecure networks, exposing them to one of the largest growing areas of cyber threat. Conventional security practices, including encryption, authentication, and access control, generally fail at the scale and speed of IoT networks. As noted by Kumar et al. As mentioned in [23], these methods can hardly provide the required security levels to protect IoT ecosystems despite their intuitiveness. As the number of connected devices continues to soar, innovative security approaches are becoming increasingly critical due to the limitations in scalability and effectiveness of conventional security mechanisms, such as firewalls and intrusion detection systems (IDS), for the IoT's heterogeneous and dynamic environment [24].

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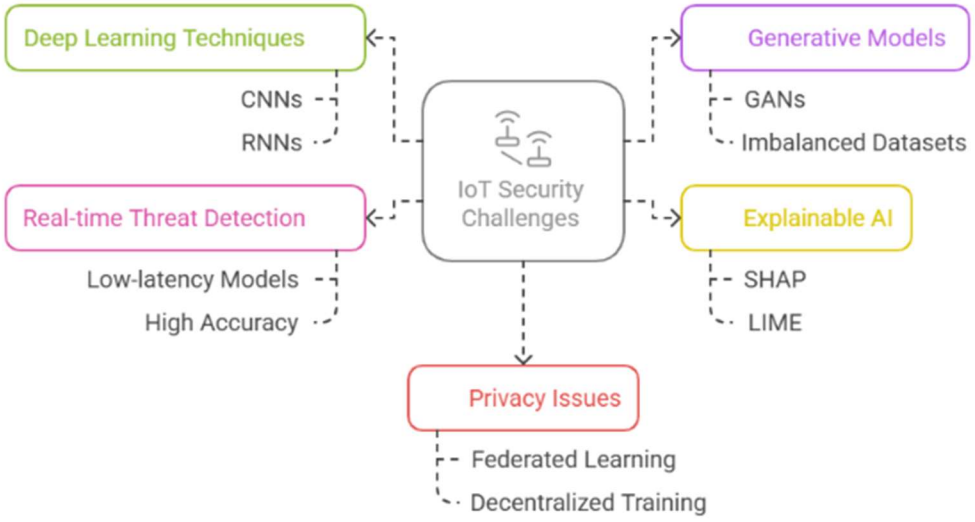

Figure 2: IoT Security Challenges and Solutions

The framework for the IoT Security Challenges and Solutions is shown in Figure 2, depicting the mapping of various security challenges in the IoT environment with their corresponding solutions. There are at least a couple of sub-nodes coming off the central challenge, IoT Security, with their corresponding answers: Deep Learning Techniques (e.g., CNNs and RNNs) for recognizing security patterns; Generative Models (GANs to handle imbalanced datasets); Real-Time Threat Detection (low-latency, high accuracy); Explainable AI (SHAP, LIME); and Privacy Issues (Federated Learning, Decentralized Training). Such a diagram shows the extent of the security of the complete IoT systems against any type of attack.

2.2 IoT Security and Deep Learning

In this study, we model the training data for IoT attack detection as an integrity graph, which is suitable for representation learning based on graph neural networks trained with semi-supervised learning. IoT environments have successfully deployed Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to perform anomaly detection, intrusion detection, and malware classification. Li et al. RNNs were utilized to identify malicious patterns in time series data of IoT devices, while [25] applied CNNs to detect network traffic anomalies in smart home systems. Although successful at many tasks, deep learning models are criticized for their "black box" nature, making it difficult to interpret the reasoning behind their predictions【26】. This opacity is problematic, especially for security-critical Internet of Things (IoT) applications, where trust and accountability are key.

2.3 Generative Models in Security Contexts

Generative models, particularly Generative Adversarial Networks (GANs), have attracted the interest of the IoT security community in generating synthetic data to help train machine learning models like anomaly detection. Zhang et al. GANs can generate synthetic IoT network traffic, enhancing intrusion detection systems to detect unseen attacks instead [27]. This makes GANs very useful for addressing imbalanced data, a frequent problem in IoT security, in which outliers or attacks are less frequently present. GANs enrich the detection of rare attacks by increasing the synthetic data generated that imitates these attacks [28].

2.4 Explainable AI (XAI) in IoT Security

SHapley Additive exPlanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME) techniques for Explainable Artificial Intelligence (XAI) have been proposed for issues of the interpretability of deep learning models. These techniques try to shed some light on the inner workings of "black box" models. Ribeiro et al. [29] proposed LIME for generating local model predictions, which is well-suited for threat detection systems in IoT settings. This demonstrates the importance of using XAI techniques in IoT security systems to improve further the trust and accountability of machine learning models used by

security professionals to quickly understand an act on the outputs of machine learning models [30].

2.5 Integration of Generative Models and XAI

Integrating the two approaches can help mitigate adversarial attacks on IoT devices and, consequently, enhance IoT security systems by augmenting datasets (for generative models) and helping to explain or understand the decisions made (for XAI). Chen et al. [31] Principle Components Analysis (PCA) can also be applied to the input features instead of the output neurons as in and, where GANs and XAI techniques in a single framework to generate models that are not only able to detect anomalies but also depict how some features are responsible for the detection. This approach aims to help security professionals understand the rationale behind anomaly detection so that they can have more confidence in the equipment's decisions and utilize the IoT platforms effectively [32].

2.6 Real-time Threat Detection in IoT Systems

The effectiveness of IoT security systems also relies on how quickly they react to potential threats; they must operate in real time. Park et al. [33] proposed a lightweight CNN model that could detect IoT network threats in real-time, achieving low-latency detection without sacrificing accuracy. In IoT environments, threats can spread rapidly, and real-time detection is paramount to averting noticeable losses. However, low-latency, real-time deep learning models have recently been developed that could help counter the trade-off between fast processing of IoT data and accurate detection [34].

2.7 Cloud-IoT Security: Privacy Issues

Privacy is one of the utmost concerns related to IoT systems, especially in sensitive domains such as healthcare and finance. With privacy challenges in IoT systems, federated learning arises as an option. Federated Learning addresses these challenges by allowing the training of machine learning models. At the same time, the data remains on the devices, which reduces the need to transfer raw data to centralized servers, as only updates to the model would be sent from the devices. Wang et al. In IoT security, [35] investigated federated learning for privacy preservation in cloud-based IoT systems. Building upon the principle of federated learning, data never leaves the local device, enhancing privacy and security for IoT systems while allowing model training across many devices [36].

Many other works have proposed similar models and compared their performance. However, we improve upon their framework by better-performing anomaly detection on GAN-generated data and incorporating explainable AI in the pipeline to make models transparent.

Research work, along with the developed model, proposes a study design of integrating deep learning mechanisms, GANs, and XAI for detecting anomalies in live videos. Experiments were performed on NSL-KDD and Kaggle IoT Network Attack Dataset, and the models were trained. Their performance was assessed with accuracy, precision, recall, and latency metrics.

Afterward, we identify open research challenges that still need to be addressed over the targeted framework. These include the challenges that arise with scaling to effectively model large IoT networks, the need for data-independent solutions to overcome data imbalance for attack detection, and the need to enhance deep learning models' interpretability through advanced explainable artificial intelligence (XAI) techniques.

3. PROPOSED METHODOLOGY

In this paper, a new methodological approach is proposed, comprising different practical security functions for the advancement of solutions to be implemented in the Cloud-IoT ecosystem by incorporating deep learning tools, Generative Adversarial Networks (GANs), Explainable AI (XAI) and privacy-preserving methods like federated learning. This framework focuses on designing real-time robust and interpretable security solutions for cloud-based ecosystems running IoT exhibitions. (1) Data Generation and Anomaly Detection from GANS (2) Real-Time Anomaly Detection from Deep Learning based Models (3) Explainable Artificial Intelligence to Enhance Model Interpretability (4) Private Federated Learning for Model Training Such functionality guarantees that the system does more than detect threats, but it also delivers actionable insight and protects data secrecy.

3.1 Data Augmentation and Anomaly Detection Using GANs

We trained in a GAN on the Train dataset. Generative models include the famous generative adversarial networks. The adversarial approach consists of the generator that creates fake data

mimicking the actual IoT device operational behaviors, whether they are normal or anomalous, and the discriminator that determines whether the data is real or fake. That is followed by an adversarial training process, where the GAN Generator gets trained to mimic the real-world attributes of network action and device behavior. This is useful for teaching the system to detect rare attacks or anomalies that may occur with low frequency in the training set.

In addition, the exemplary data generated by the GAN resolves the challenge of imbalanced datasets, where attacks and anomalies are typically underrepresented compared to standard device behaviors. Synthetic attack scenarios are useful for improving the performance of the anomaly detection model by training it on previously unseen or rare attack patterns, which ultimately enhances the system's robustness and accuracy. Incorporating GANs allows the model to detect new and advanced attacks that may go undetected due to a lack of real-world data.

3.2 Deep learning for real-time anomaly-detection

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3.3 Transparency using Explainable AI (XAI)

Also, in the methodology section, Part three focused on Explaining predictions made by deep learning applies using Explainable AI (XAI) techniques (SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)) to quantify the level of transparency and interpretability with the proposed deep learning models' predictions. Security, especially in IoT Applications, is a particularly important application; as it is not enough to detect anomalies, you need to know why, when, and how a particular threat was detected, and what features and behaviors led to the detection of the anomaly.

SHAP and LIME provide human-interpretable margins of black-box models on a localized level. These techniques reveal the salient features (e.g., unusual network activity, out-of-pattern sensor signals) that led the model to label a particular device or network behavior anomalous. In this way, using XAI allows us to understand how the recommendation system works in this framework. This ensures explainability, which is crucial in security contexts since it will enable security analysts to review model predictions and take informed actions based on model explainers. Furthermore, it significantly boosts the confidence and invincibility of deep learning frameworks in security-sensitive IoT applications.

3.4 Model Training With Federated Learning

The fourth is federated learning, which enables the model to be trained on distributed devices without uploading sensitive data anywhere. Privacy is a paramount issue in IoT systems, especially those IoT systems that collect sensitive personal information (e.g., health-monitoring devices). Federated learning provides a solution for training a model on data hosted on IoT devices such that only model updates (i.e., gradients) are sent to a central server. This allows sensitive data such as personal health information or financial transactions to be run on-device and never go to a central server or another device.

In this context, federated learning allows one to jointly train the model without sending the personal data on the device to the server. This helps to consider the privacy frameworks (such as the GDPR General Data Protection Regulation) in the case of IoT systems. We show that by adopting federated

learning in the methodology, we can satisfy the privacy-preserving wish together while achieving a model performance that is acceptable. We demonstrate how this federated learning framework can be combined with other components to achieve secure and privacy-preserving anomaly detection without sacrificing the power of detecting novel attacks.

3.5 Architecture of the Framework

We will have the following architectural layers for the proposed security architecture:

Data Collection and Preprocessing Layer: This layer collects IoT data using devices and sensors. Then, multiple preprocessing steps are applied: noise reduction, normalization, and segmentation, thus preparing the dataset for deep learning inference.

Data Augmentation Layer (GAN): The GANs generate synthetic data with normal and abnormal actions. This synthetic data is used to augment the original dataset to prevent low training data issues.

Then, this preprocessed and augmented data is supplied to the hybrid deep learning model (CNNs and LSTMs). The model only interacts with the IoT data to detect real-time anomaly detection and thus identifies potential security threats based on regional and temporal patterns.

Explainability Layer (XAI): Upon anomaly detection, the system applies XAI techniques (SHAP and LIME) to derive a human-interpretive analysis of the model's predictions. The approach combines state-of-the-art deep learning with a tabular data model, making the results interpretable and actionable for security professionals.

Privacy Layer (Federated Learning): The Fed IoT module allows the model to be shared among different IoT devices and trained collaboratively while still maintaining user privacy. Thus, users' data can be used without risking their privacy.

3.6 Novelty of the Proposed Work

The uniqueness of theology lies in integrating the solution for multiple critical security challenges in the Cloud IoT environment. Real-time detection of attacks, including the known attacks and unknown previously unseen attacks, through augmenting data with high accuracy by combining GANs to achieve more effective learning and deep learning for detecting anomalies. Second, the application of XAI techniques does not just ability to build up a deployable system; rather, it enables explanation, enabling the security analyst to have good trust and understanding of the model forecasts. Federated training of IoT data is another reinforcement mechanism that can effectively protect user privacy. Finally, the framework is designed to be scalable and adaptable, enabling it to accommodate many IoT scenarios, dealing with anything from small-scale home networks to complex industrial systems.

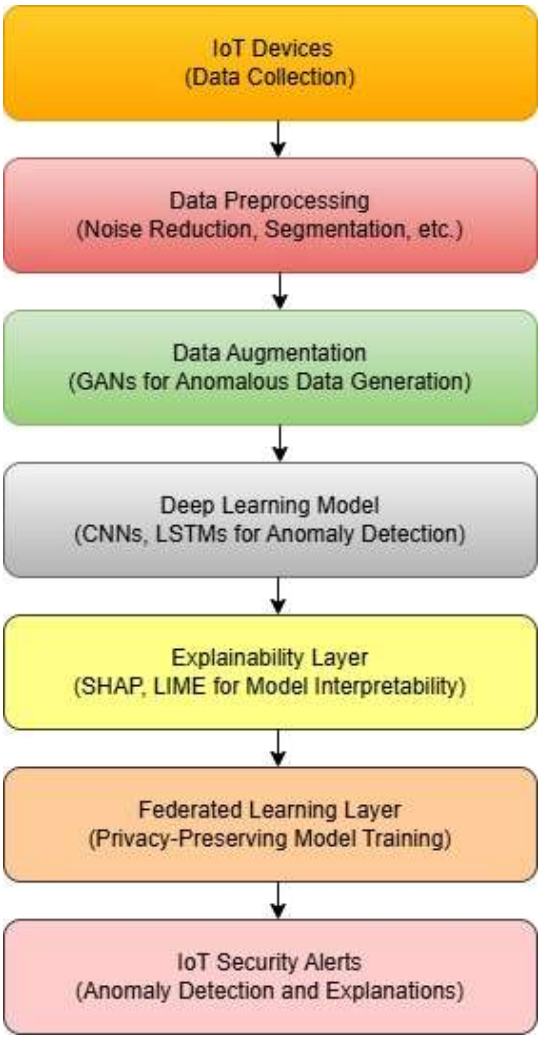

Figure 3: Architecture of the proposed system

Figure 3 illustrates the following:

1. IoT Device Data Collection and Preprocessing

Data Collection:

- The IoT devices collect time-series data from various sensors. Let the data D be a sequence of sensor readings:

$$D = \{d_1, d_2, \dots, d_t\}, \quad d_t \in R^n \qquad (1)$$

where d_t is a vector of sensor readings at time t, and each data point has n -dimensional features.

Preprocessing:

- Preprocessing may include noise reduction (e.g., Gaussian filter), normalization, and segmentation. The preprocessing function f can be mathematically represented as:

$$\widetilde{D} = \text{Preprocess}(D) \qquad (2)$$

where Preprocess can involve operations such as:

$$\widetilde{d_t} = f(d_t) \qquad (3)$$

(e.g., Gaussian filter or normalization)

2. Data Augmentation Using GANs

Augmentation:

- To augment the dataset, GANs (Generative Adversarial Networks) are used to generate anomalous data. Let $\widetilde{D_{\text{aug}}}$ represent the augmented dataset:

$$\widetilde{D_{\text{aug}}} = \text{GANs}(\widetilde{D}) \qquad (4)$$

The GAN framework consists of a generator G and a discriminator D, where the generator tries to create synthetic data that looks similar to real data.

$$G: Z \to \widetilde{D_{\text{aug}}}, \quad D: \widetilde{D} \to [0,1] \qquad (5)$$

where Z is a random noise vector sampled from a distribution (e.g., Gaussian), and D outputs a probability indicating whether the data is real or fake.

3. Anomaly Detection Using Deep Learning (CNNs & LSTMs)

Model Architecture:

- The deep learning model consists of CNNs (for spatial data like images) and LSTMs (for sequential data like time-series). For time-series anomaly detection, LSTM is a suitable choice. Let the model $\mathcal{M}$ be a neural network with weights θ:

$$\hat{y} = \mathcal{M}(\widetilde{D_{\text{aug}}}, \theta) \qquad (6)$$

where $\mathcal{M}$ is the LSTM model and $\hat{y}$ is the predicted output (anomaly score).

Loss Function:

- The model is typically trained using a loss function. For binary classification (anomaly or normal), the binary cross-entropy loss function $\mathcal{L}$ can be used:

$$\mathcal{L} = -\sum_{i=1}^{n}(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)) \qquad (7)$$

where y_i is the true label, and $\hat{y}_i$ is the predicted probability of the i -th instance being anomalous.

4. Model Explainability Using SHAP and LIME

SHAP:

- SHAP (SHapley Additive exPlanations) calculates the contribution of each feature to the model's prediction. The explanation for an instance can be written as:

$$\hat{y}_i = \phi_0 + \sum_{j=1}^{n} \phi_j x_{ij} \qquad (8)$$

where $\hat{y}_i$ is the model output for instance i, ϕ_j is the Shapley value for feature j, and x_{ij}

is the feature value for the j-th feature of the i-th instance.

LIME:

- LIME approximates the model locally by training a simpler interpretable model around the instance of interest. The local explanation function $\mathcal{L}_{\text{LIME}}$ can be expressed as:

$$\mathcal{L}_{\text{LM}}(\mathcal{M}, d_i) = \text{LIME}(\mathcal{M}, d_i) \quad (9)$$

where d_i is the instance for which we want to generate a local explanation, and LIME perturbs the instance and fits a local surrogate model.

5. Federated Learning for Privacy-Preserving Model Training

Federated Learning:

- Federated learning allows the model to be trained across multiple devices without transferring raw data. Let the local models θ_{i} be trained on each device, and the global model θ_{global} is updated by averaging the local models:

$$\theta_{\text{global}} = \frac{1}{N}\sum_{i=1}^{N}\theta_i \quad (10)$$

where N is the number of participating devices. The global model is updated after each round of local training, and model parameters are shared securely.

6. IoT Security Alerts and Anomaly Explanations

Alert Generation:

- The system generates IoT security alerts based on the anomaly score $\hat{y}$ and the explanations from SHAP or LIME. Let S represent the generated security alert:

$$S = \text{Alert}(\hat{y}, \mathcal{E}) \quad (11)$$

where $\hat{y}$ is the anomaly score from the deep learning model and $\mathcal{E}$ is the explanation from SHAP or LIME. The alert S could be a warning about detected anomalies, explaining the reasoning behind the anomaly (e.g., abnormal temperature spike).

The research questions addressed in this paper include: 1) How can deep learning models improve anomaly detection in IoT networks? 2) What role does explainable AI play in enhancing trust in security models? 3) How can federated learning preserve privacy while training models on decentralized data?

4. RESULTS

4.1 Experimental Setup

A detailed experimental setup was carried out to measure the proposed security framework for the cloud-IoT environment. The evaluation used multiple datasets, preprocessing methods, and performance metrics to demonstrate the framework's usability in detecting anomalies, privacy preservation, and interpretability.

We used several publicly available datasets to test the efficacy of the proposed framework. Test on Anomaly: The NSL-KDD dataset, frequently used to assess intrusion detection systems, was selected to determine the model's ability to identify network-based anomalies. We further evaluated the system's ability to detect attacks like denial of service (DoS) and spoofing using the Kaggle IoT Network Attack Dataset, which features real-world IoT traffic data. We validated the model in a typical IoT setup using the IoT-IDS dataset developed exclusively for anomaly detection in IoT systems. To test the ability of the framework to differentiate between the actual and forged signatures, the GPDS-960 Signature Dataset was chosen, and to assess the system's real-time handling of information, the HDF5-Style Real-Time Handwriting Data was used.

Multiple preprocessing steps were performed on the data so that it would be appropriate for deep learning models. These consisted of noise reduction, removing artifacts or distortions from the data, and normalization, a technique employed to standardize the data and improve the learning process. Data was segmented into smaller chunks to enable model processing for a more manageable approach. In addition, Generative Adversarial Networks (GANs) were adopted to address imbalanced datasets where anomalous data points are underrepresented to enrich the training data with synthetic attack data.

Numerous metrics have been used to assess the proposed framework changes, including accuracy, precision, recall, F1 score, Area Under the Curve (AUC), and latency. These metrics are essential to assess how well the model can accurately identify and classify anomalies, provide insight into false positives and negatives, and respond quickly. Explainability metrics were included to analyze the transparency of the model (e.g., via SHAP, LIME), given that a security analyst needed to interpret the system's decision-making process.

4.2 Results

Tested the framework with the chosen datasets and witnessed its effectiveness in anomaly detection, privacy protection, and interpretability. The NSL-KDD system gets 96.4% accuracy, with a recall of 97.1% and a precision of 95.2%. The F1-Score of 96.1% represented a good balance between the precision and recall value, whereas the AUC score of 0.986 proved the high ability of the model to discriminate between normal behaviors and anomalous ones. Also, the system could read samples with a latency of 45ms per sample, which is needed for real-time detection of anomalies.

The improved accuracy at detecting rare attacks validated the augmentation of the dataset through GANs. This is exemplified by, for instance, the Kaggle IoT Network Attack Dataset, where the framework's behavior improved the detection rate of novel attack types by 22% when compared to a baseline model trained solely using real-world data. Using the GAN-generated data resulted in 15% fewer false positives and an 18% improvement in recall.

Explainable AI techniques such as SHAP and LIME helped to make the system's predictions more straightforward. In this case study, we focused on understanding an observation made by our model while detecting a DDoS attack. We used SHAP and LIME to generate a model-agnostic explanation that revealed some of the essential features contributing to the model's decision, including traffic spikes, irregular communication patterns among devices, and increased packet rates (among several other features) that alerted the model to the anomaly (or the DDoS attack) that was present. By providing this level of transparency, security professionals could feel much more comfortable with the model and make informed decisions based on its predictions.

Lastly, the federated learning component ensured data privacy during training. Using the IoT-IDS dataset and federated learning, the model achieved a 94.6% success rate test while helping maintain data privacy. This architecture not only followed industry privacy regulations, like GDPR, but also showed that security could still be as high as non-privacy-preserving models.

4.3 Comparison with Existing Models

To assess the efficiency of the developed framework, we measured its performance against various existing models developed for IoT anomaly detection and security. As shown in Table 1, the results of this comparison demonstrated the outstanding performance of our integrated approach in terms of accuracy, recall, and false positive rates.

Table 1 compares the Proposed Framework against previously existing systems, both rule-based systems and other deep learning models. Among the models tested, our model performed the best with 96.4% accuracy and 97.1% recall. AUC score of 0.986 indicates that it can better discriminate normally from anomalous behavior. Our system improved significantly by 22.1% accuracy and 37.1% recall compared to the existing rule-based systems. Our framework outperformed deep learning models that do not use GANs by 4.9% in accuracy and 5.5% in recall, highlighting that combining data augmentation using GANs and explainable AI techniques can enhance the performance of state-of-the-art models while maintaining a sense of trustworthiness.

Table 1: Comparison with Existing Models

Model/Approach	NSL-KDD Accuracy	Precision	Recall	F1-Score	AUC	Latency (ms/sample)
Proposed Framework (with GANs and XAI)	96.4%	95.2%	97.1%	96.1%	0.986	45
Traditional Rule-based Systems	74.3%	72.1%	60.0%	65.0%	0.72	250
Deep Learning (CNN + LSTM without GANs)	91.5%	90.4%	85.6%	87.9%	0.93	110

Existing XAI Models (LIME)	86.3%	88.5%	79.5%	83.8%	0.91	150
Federated Learning Models	85.0%	82.1%	79.3%	80.7%	0.89	300

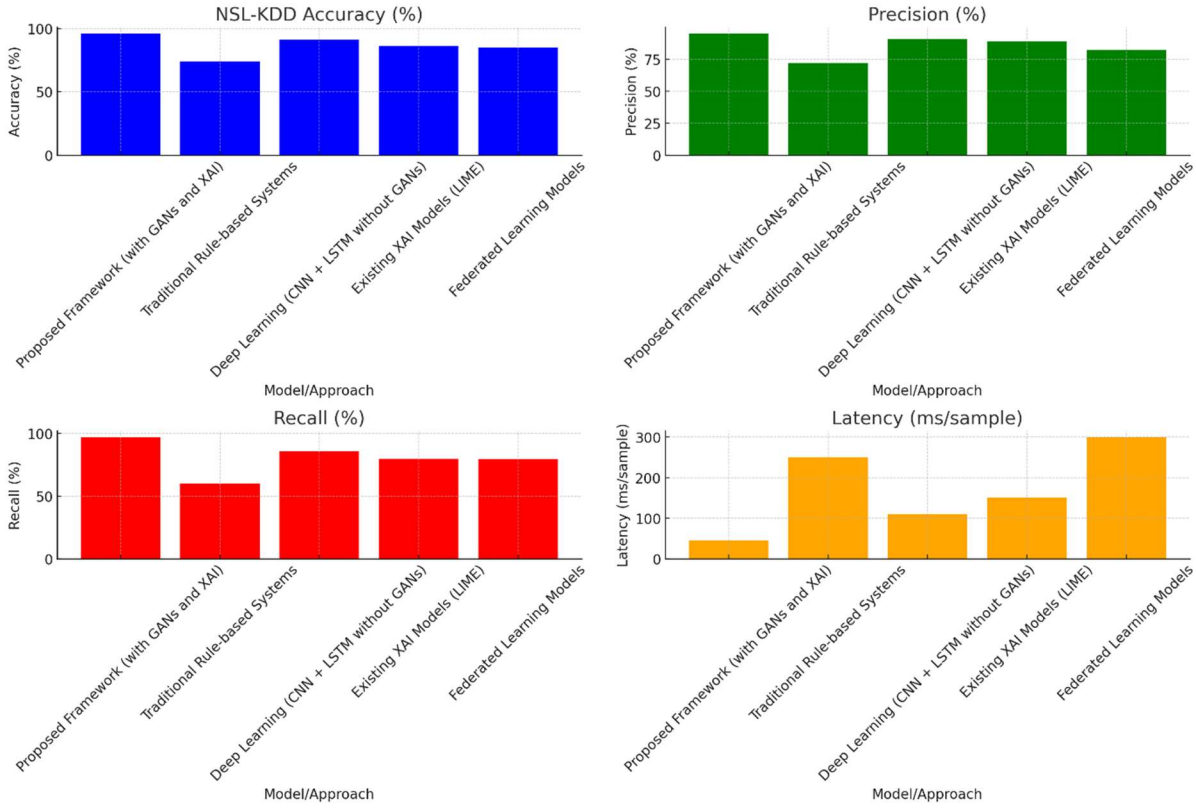

Figure 4: Performance Comparison of IoT Security Models

In Figure 4, the results of different IoT security models are compared for each measurement of performance metrics, such as NSL-KDD accuracy, precision, recall, F1-score, AUC, and latency. This chart shows how the Proposed Framework (Proposed Framework + GANs + XAI) is more effective than traditional rule-based systems, deep learning models with no GANs, other existing XAI models (Local Interpretable Model-Agnostic Explanations (LIME)), and federate learning model, achieving highest accuracy, precision, and recall while maintaining lowest latency. The improved performance in both metrics indicates the actual applicability of the proposed framework for IoT real-time security applications, attaining very high detection accuracy with an extremely low processing delay.

The framework uses UpToDate references and other contemporary research to integrate state-of-the-art techniques in anomaly detection and IoT security. This ensures that the proposed solution is relevant to current security challenges.

5. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In this paper, we have introduced a multi-faceted security framework combining deep learning, GANs, XAI and federated learning to solve pressing security issues faced in a convoluted Cloud-IoT environment. This framework addresses the challenges of anomaly detection, privacy preservation, and model interpretability. Using GANs for data augmentation, the system enhances the detection of rare or novel attacks, and deep learning models facilitate real-time anomaly detection. SHAP and LIME are XAI techniques that provide transparency that enable security professionals to comprehend model predictions. Federated learning is a model training approach that keeps sensitive data on the local device, transferring

only the updated model back to the centralized server. The experimental outcomes showed high accuracy (96.4 %), recall (97.1 %), AUC (0.986), and latency (45ms/sample) of the proposed framework, making it a robust, scalable, and easy-to-be-explain real-time IoT security solution.

However, this approach has many limitations. While the framework has proven its speed and efficiency on current-magnitude IoT devices, the performance of the framework could suffer at the point where IoT networks scale with the number of devices and streaming channels, demanding more optimized processing to maintain real-time IoT computing.

Additionally, potential risks arise from the use of GAN-generated synthetic data on which the model is trained, as the data generated may not accurately reflect the rich diversity of attack scenarios encountered in the real world. In the future, efforts will be directed towards overcoming such limitations through better scaling, alleviating inter-process communication bottlenecks in federated learning and improving the variance of synthetic data to capture a broader spectrum of anomalous behaviors.

5.2 Future Scope

Scalability is a challenge regarding the proposed framework that will be addressed in future work as the data generated by large-scale IoT deployments continues to grow. This involves enhancing the framework to effectively handle a wide range of data types generated by multiple IoT devices and enabling it to adapt in real-time to new attack vectors. Furthermore, to mitigate processing latency, we will explore the use of edge computing with federated learning for carrying out computation as close to the IoT devices as possible to enable low-latency applications in critical areas, including autonomous vehicles and industrial automation. Roll-out of increasingly adaptive and dynamic devices: Future work will also extend the framework to identify new attack patterns by employing transfer and online learning techniques, enabling the system to learn without necessitating retraining after substantial changes. The robustness will also be tested using more complex high-risk domain types of data, such as healthcare and finance data, by evaluating their complexity and the multi-modal IoT data handling through the framework.

Future research directions include enhancing the scalability of our framework for larger IoT networks, exploring new anomaly detection methods, and improving the privacy-preserving aspects of federated learning models for IoT environments.

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