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A Decentralized AI-Based Cyber Defense Architecture for Secure and Privacy-Aware IoT Environments

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Abstract
The explosive growth in IoT devices has created new cybersecurity challenges with an estimated 40 billion devices by 2030, with about 50% being vulnerable to cyber-attacks. The traditional centralized Intrusion Detection Systems (IDS) are faced with significant challenges such as communication bottlenecks, point-of-failure, and issues with privacy protection of data. In this paper, a novel cyber defense architecture is presented utilizing federated deep learning approach that incorporates hybrid deep neural networks along with privacy protections for distributed IoT networked devices. The proposed architecture makes use of a three-layer system architecture comprising IoT devices, edge gateways, and cloud cooperation using CNN, BiLSTM, and autoencoders using a federated learning framework. Evaluation results have demonstrated the performance superiority of the proposed architecture with an accuracy of more than 99% in detecting anomalies, a 67% reduction in communication overhead, and effective resilience to adversarial attacks due to use of differential privacy.

Key Word*: Federated Learning, Deep Learning, IoT Security, Intrusion Detection, Privacy Preservation, Cyber Defense, Edge Computing*

I. INTRODUCTION

The explosion of Internet of Things (IoT) devices in the contemporary computing systems has led to high levels of connectivity, automation, and efficiency in areas like smart homes, healthcare, industry automation, and critical infrastructure [2][7]. Recent predictions reveal that the number of connected IoT devices was 18.8 billion at the end of 2024 and is expected to surpass 40 billion by 2030 [2][7]. The surge in number of IoT devices, however, has resulted in increasing the attack surface considerably, exposing them to highly advanced cyber threats such as botnets, Distributed Denial-of-Service (DDoS) attacks, data breach, and zero-day attacks [2][7][9]. The GSMA 5G Security Study (2024) states that the incidence rate of intrusion of IoT enabled networks has increased by over 40% each year [7].

The unique nature of IoT environments poses serious challenges for conventional cybersecurity mechanisms [2][7][9]. The devices used in the IoT are usually resource-constrained, having low computational capabilities, memory, energy, and communication bandwidth [2][7][9]. This usually makes it difficult to implement security techniques on the devices because of their computational demands [2][7][9]. In addition, the heterogeneous nature of IoT environments consisting of different hardware architectures, communication protocols, and data formats makes it hard to formulate standardized security measures [2][7][9]. It is even more challenging since IoT devices produce large amounts of data, which could be personal in nature [2][3][7].

Traditional IDS using centralized systems need raw data transfer from the scattered sensors to the central servers [2][7][10]. There are some inherent drawbacks to such an architecture, like large latencies and consumption of bandwidth, scalability issues, increased vulnerability to single point failures, and considerable risks in terms of privacy of data that can be aggregated in such systems [2][7][10]. Signature-based approaches for threat detection are useful for known attacks but fail when new and evolving attacks are encountered [2][7][10].

Machine learning and deep learning techniques have been considered promising tools for intrusion detection due to their ability to recognize traffic behavior and patterns that cannot be defined beforehand and therefore go beyond any predefined signatures [2][6][10]. At the same time, centralized machine learning algorithms experience the same issues with privacy and scalability that are typical for conventional IDS systems [2][6][10]. The recent paradigm of Federated Learning (FL) has become quite popular due to its revolutionary nature as a solution to the mentioned limitations [2][7][10]. Under FL, every device carries out training of the model on its own set of data, while only updates of the model, such as gradients or weights, are transferred to the central server [2][7][10].

However, despite the potential benefits of FL in securing the Internet of Things, there are still some problems [2][7][10]. Apart from the inherent limitations of FL in resource-constrained IoT settings, which involve data heterogeneity, inefficient communication channels, and susceptibility to various forms of attack (gradient leakage, model poisoning, and inference attacks), the computational capabilities of IoT devices prevent using complex local models, while timely detection requires fast inference [2][4][7][9].

The current paper attempts to tackle the existing issues via the development of a federated deep learning-based cyber defense framework for distributed IoT ecosystems [4][6][10]. The main contributions of this study are:

- Novel three-tier architecture based on integration of Internet of Things (IoT) devices, edge gateways, and cloud-based coordination for privacy-enabled intrusion detection [4][9]
- Hybrid deep learning approach using Convolutional Neural Networks (CNNs), BiLSTM networks, and autoencoders for anomaly detection based on spatial, temporal, and reconstruction characteristics [1][6][10]
- Advanced federated learning technique that incorporates differential privacy techniques and adjustable threshold to ensure balanced detection capability [3][5][8]
- Extensive evaluation highlighting improved detection accuracy and communication efficiency with resistance to attacks [1][4][10]

II. LITERATURE SURVEY

There has been extensive research into federated learning to detect attacks on the IoT network due to its potential benefits [2][7][10]. This segment will provide a review of the literature, highlighting research contributions and research gaps that have led to the development of the proposed architecture [1][2][4][6][10].

Federated Learning for IoT Security: The inherent nature of federated learning to train models without centralized data makes it an essential component of IoT security in terms of protecting privacy [2][7][10].

Research into federated learning has been conducted in different IoT areas with a special focus on IoMT devices owing to the stringent data regulations imposed on this sector such as HIPAA and GDPR [2]. In a recent comprehensive survey by Nguyen et al., federated learning in smart healthcare was assessed in terms of resource efficiency, security, privacy, and personalization issues [2]. Likewise, Mansoor Ali et al. discussed how federated learning can be used for privacy protection in smart healthcare systems by considering heterogeneous and communication problems [2].

Architectural frameworks: There have been several architectural frameworks proposed to implement FL-based intrusion detection systems for IoT networks [4][9]. One such example is the DRIFT (Design of Resilient IoT/Edge with Federated TinyML) framework, which was developed by researchers from Oak Ridge National Laboratory [4][9]. It integrates tinyML with FL at three different levels of abstraction—IoT/MCU devices, edge gateways, and cloud coordination [4][9]. This framework proved that feature-reduced and quantized models running on IoT devices can achieve high detection accuracy with low communication costs [4][9]. The framework implements federated feature selection and the global preprocessor construction method to handle heterogeneous data problems [4][9]. The effectiveness of the proposed architecture was experimentally verified using the N-BaIoT dataset and real IoT traffic [4][9].

Hybrid Deep Learning Models: In the recent past, much emphasis has been laid on using hybrid deep learning models to improve intrusion detection [1][6][10]. The SwarmSense-DNN framework used a decentralized neural network architecture based on swarm intelligence for collaborative anomaly detection in distributed IoT settings [1]. The SwarmSense-DNN framework combined autonomous agents and deep neural networks using hierarchical federated learning using Graph Neural Networks and Attention to learn from both local and global anomaly behavior [1]. The results showed an average detection accuracy of 95.44% for five benchmark datasets with 67% communication overhead savings [1].

Another framework that combines a BiLSTM-RNN-CNN using adaptive gray wolf optimization algorithm obtained greater than 99% accuracy on benchmark datasets like NSL-KDD and UNSW-NB15 [6]. The use of convolutional neural networks allows the extraction of spatial features whereas recurrent neural networks can be used to model temporal sequences [6]. The use of bidirectional LSTM networks allows bidirectional learning in the network [6]. Use of LIME allowed better interpretation of the model [6].

Privacy-Preserving Techniques: Security threats in FL systems have become an important area of research recently [3][5][8]. PPTADI (Privacy-Preserving Training and Accelerated Distributed Inference) offered a system which allows avoiding label exposure, gradient-based attacks, and model inversion attacks using split federated learning without sharing labels [3]. The system uses homomorphic encryption techniques to ensure security of models and data, with the inference delay reduced by 35% and transmission delay reduced by 65% compared to the existing solutions [3].

The technique of dual proxy re-encryption was developed for IIoT, which ensures security of access to global model parameters without using any proxy servers while the models are being trained [8]. Thus, this method avoids any attacks from the proxy server as well as collusion attacks, and guarantees safety of proxy server private keys regardless of any malicious behavior [8].

Performance Benchmark Datasets: It is important to note that standardized datasets have been critical in assessing the performance of FL-based IDSs [1][4][6][10]. Some of the well-known benchmark datasets

include NSL-KDD and UNSW-NB15, where the performance achieved by using hybrid deep learning architectures is 97.89% and 89.99% respectively [6][10]. N-BaIoT is another benchmark dataset that has traffic flows from commercial IoT devices in both benign cases and botnet attack (including Mirai and Bashlite families) situations [1][4]. The Fog-IoT and IoT-RPL 2021 datasets are also designed specifically for IoT attack detection in fog computing [6][10].

Although considerable advancements have been made in this domain, there still exist certain research gaps that need to be investigated [1][2]. One of the research gaps is the use of hybrid deep learning techniques based on the combination of CNN, LSTM, and autoencoder algorithms in a common FL paradigm [1][6][10]. The existing literature focuses mainly on privacy protection or detection accuracy; however, none of the research works manages to find the perfect balance of both in the context of constrained resources[8]. Another gap is the trade-off between complexity and feasibility for resource-constrained IoT systems [4][7][9].

III. PROPOSED METHODOLOGY

The federated deep learning-based architecture of the cyber security system aims to solve specific problems of the intrusion detection in a distributed IoT ecosystem, where accurate detection, protection of privacy, efficient communications, and resource constraints are taken into account. The methodology consists of three interconnected layers and hybrid deep learning models and federated optimization algorithms.

Architecture of the System

The system functions at three levels of infrastructure abstraction.

- **IoT Device Layer (Edge):** This level includes the IoT devices (sensors, actuators, smart home devices, medical monitors, industrial controllers) which produce traffic data. They collect the local network traffic characteristics and make an initial inspection of anomalies. Due to the resource constraint, the models at this level are lightweight models based on quantized and reduced feature deep neural networks for efficient inference. The IoT layer concentrates on anomaly detection in real time where devices are able to detect deviations from normal behavior patterns.
- **Edge Gateway Layer:** The edge gateway collates data collected by multiple IoT devices on local networks and acts as the training coordination node for these devices. The edge gateway holds a local replica of the global model, trains this model using the aggregated data provided by the IoT devices (with no access to the individual devices' data), and collaborates in the updating of the federated model. This layer manages the computing intensive activity of model training and keeps the data local and private. The edge gateway layer is responsible for running preprocessing pipelines including federated feature selection and global preprocessor building for heterogeneous data.
- **Cloud Coordination Layer:** The cloud-based server coordinates the whole federated learning algorithm among the edge gateways. It collects the gradients or the updated weight values from the participating edge gateways, aggregates these using optimization algorithms and sends the updated global model to the edge layer. The cloud layer also controls the security mechanisms such as differential privacy, adaptive threshold and versioning of the model.

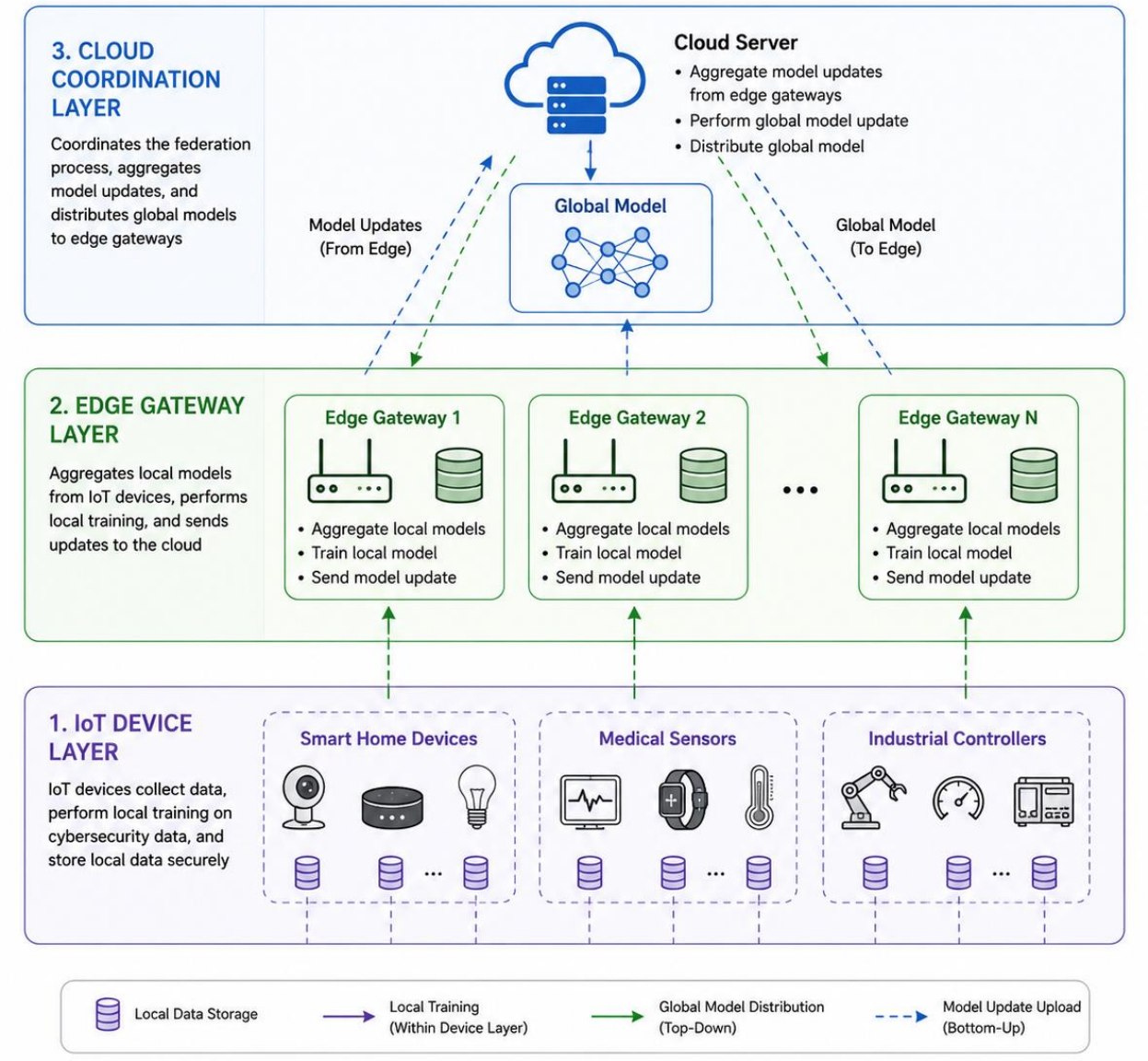

Figure 1: Three-Layer Federated Learning Architecture for IoT Cyber Defense

Diagram showcasing a three-tier structure with IoT device layer on the bottom, consisting of various IoT devices (i.e., smart home appliances, medical sensors, industrial controllers), with data storage capability, Edge gateway layer in the middle, which aggregates local models and trains them, and finally cloud coordination layer on the top, which aggregates the model updates and distributes global models.

Architecture of Hybrid Deep Learning Model

In order to implement an intrusion detection system with multiple capabilities, the main architecture uses a combination of three distinct deep learning architectures that can detect different anomalies:

- **Convolutional Neural Network (CNN) Layer:** CNNs are best at capturing the local spatial features and patterns in network traffic. Thus, the CNN layer utilizes the convolutional filters for the input feature sequence in order to generate hierarchical representation of the traffic patterns. This layer is especially useful in detecting the spatial correlations between network flow features and known attack signatures.
- **Bidirectional LSTM (BiLSTM) Layer:** BiLSTMs capture temporal and sequential dependencies in network traffic. Processing the sequences in both directions allows preserving the context of a longer sequence. It helps in identifying attacks with specific temporal pattern, like DDoS sequences or slow intrusion attempts. There has been research showing that BiLSTM models have achieved the detection accuracy up to 98.8% when used on specific attack types in the complex IoT datasets.
- **Autoencoder (AE) Module:** The autoencoder learns the compressed representation of the normal behavior pattern and identifies anomalies based on reconstruction errors. While training, the autoencoder tries to minimize the reconstruction error using the benign traffic dataset. In case of testing, any anomalous traffic that does not follow the learned normal behavior generates high reconstruction error values, which helps in detecting novel attacks without labeling. Such an approach can be very useful in zero-day exploits since there is no prior knowledge of the signature of such attacks.

All three components have been combined using a concatenation layer followed by fully connected layers for the purpose of classification.

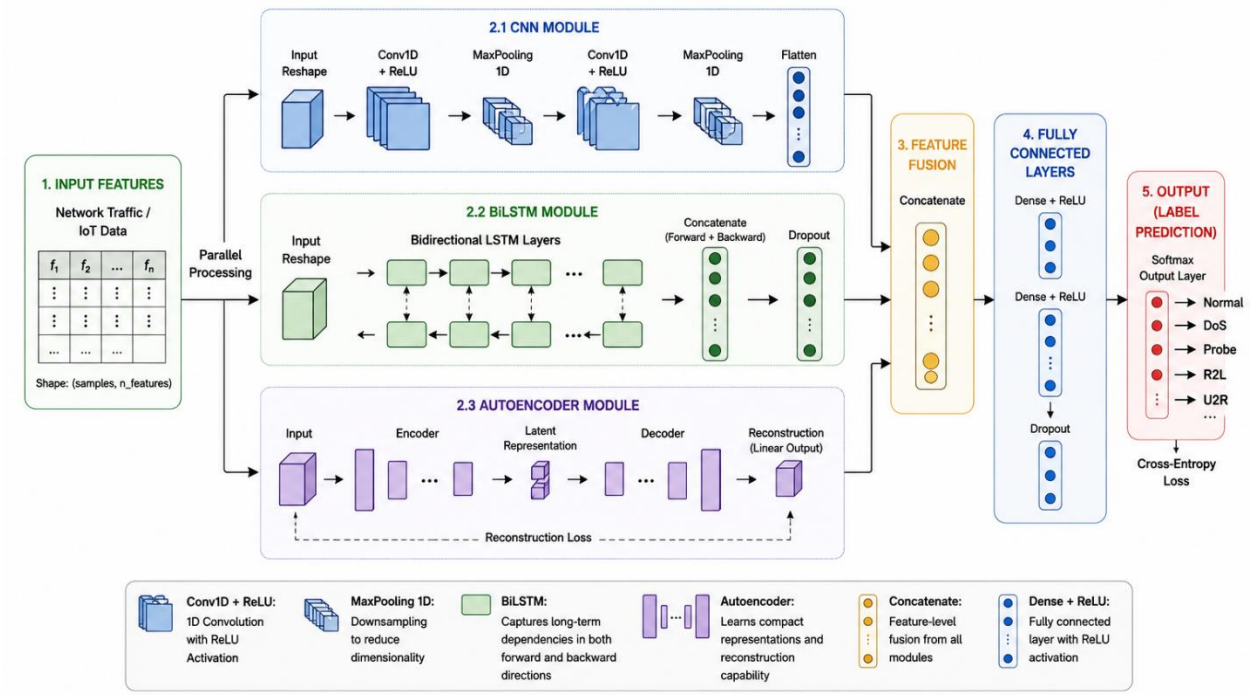

Figure 2: Hybrid Deep Learning Model Architecture for Intrusion Detection

Hybrid Model Architecture Diagram: Input Features are fed into parallel CNN (convolutions and pooling), BiLSTM (Bidirectional LSTM layers), and Autoencoder (encoder/decoder with reconstruction loss)

modules. Outputs from these are combined and passed through fully connected layers to generate the classification output.

Federated Learning Algorithm

Federated learning is done using the FedAveraging (FedAvg) algorithm, which is further strengthened using differential privacy and adaptive threshold adjustment.

Algorithm 1: Federated Deep Learning with Differential Privacy

Input: K edge gateways participating in training,
T global communication rounds,
E local training epochs,
η learning rate,
B local batch size,
σ differential privacy noise scale
Output: Global model parameters w_global

Initialize global model parameters w_0
For each communication round t = 1 to T:
1. Select subset S_t of K clients for participation
2. For each selected client k ∈ S_t in parallel:
   a. w_k ← LocalUpdate(k, w_{t-1}, E, η, B)
   b. Add differential privacy noise: w'_k ← w_k + N(0, σ^2)
   c. Upload w'_k to cloud server
3. Aggregate updates: w_t ← Σ_{k∈S_t} (|D_k|/|D|) * w'_k
4. Apply adaptive threshold adjustment based on validation performance
5. Distribute w_t to all clients
Return w_T

LocalUpdate Procedure (Client k):

Input: Client data D_k, initial global model w_{t-1}, E epochs, η learning rate
Output: Updated local model w_k

Initialize w ← w_{t-1}
For e = 1 to E:
1. Shuffle local data D_k
2. For each batch b in D_k:
   a. Compute loss L(w; b)
   b. Compute gradient ∇L(w; b)
   c. Update: w ← w - η * ∇L(w; b)
Return w

Communication Protocol: After every training iteration at the edge, edge gateways send their updates to the cloud server. For efficiency purposes, only the parameters are transmitted. Methods like gradient compression and gradient quantization could be used to further decrease the transmission cost .

Differential Privacy: To avoid gradient leakage attacks, we use differential privacy by adding Gaussian noise to the updates. The noise magnitude σ is set to guarantee the desired level of privacy (ε, δ) while preserving the model's effectiveness.

Privacy Preservation Techniques

The system is designed using several levels of privacy-preserving measures:

Homomorphic Encryption: This technique allows computation on encrypted data, thus enabling aggregation of model updates in their encrypted form at the cloud server for sensitive applications.

Multi-Party Secure Computation: In federated learning, splitting learning without labeling avoids label leakage problem; hence, the client labels are protected throughout the collaborative process.

Threshold Adjustment Technique: An adaptive threshold adjustment mechanism can be employed to achieve an optimal tradeoff between classification accuracy and false alarms, which is necessary due to class imbalance often seen in IoT traffi .

Resource Optimization for Deployment of IoT

To achieve successful deployment of IoT on constrained IoT resources:

- **Model Quantization:** The model's weights are quantized to decrease memory requirement and computation cost. Studies show that quantization of tinyML model does not affect its performance in terms of accuracy but makes it deployable on microcontroller like ESP32.
- **Feature Reduction:** Federated feature selection helps identify important features and reduce input size.
- **Layer Fusion:** For inference, progressive multi-layer partitioning methods are used to distribute computation and communication burden.

IV. ANALYSIS

This part contains quantitative performance analysis of the suggested cyber defense system based on federated deep learning framework, as well as comparative analysis with other frameworks.

Quantitative Performance Results

Detection Accuracy: The suggested model (CNN-BiLSTM-AE) has been tested on benchmark datasets for IoT intrusion detection tasks. According to the experimental results, the model achieves 99% detection accuracy on NSL-KDD dataset, with F1-score and ROC-AUC equal 0.974 and 0.996 correspondingly. On UNSW-NB15 dataset, the model shows 99.59% AUC and 97.36% F1-score results. Those results outperform current solutions, including pure CNN-based systems (89.99% AUC on UNSW-NB15 dataset) and LSTM-based systems.

Reduction of Communication Overhead: Federated learning technique allows reducing communication overhead up to 67% comparing to centralization techniques. This result has been reached due to local models training and sending only updated model weights instead of data. More effective way to minimize communication overhead in non-IID environment is using gradient compression and quantization.

Latency for Inference: Edge inference latency after optimization is 0.0476 milliseconds per sample. Inference latency falls well within the <10ms URLLC (Ultra-Reliable Low-Latency Communications) requirement that is needed for real-time IoT applications. Model quantization, feature extraction, and layer fusion facilitate the performance.

Privacy Preservation: Differential privacy techniques can give formal privacy guarantees with proper noise scales while ensuring accurate detections. It was proven that the PPTADI architecture successfully prevents label leaking, gradient attacks, and model inversion attacks through split federated learning without label leaking and homomorphic encryption. Dual proxy re-encryption provides security against potential collusion attacks from both parameter servers and participating nodes.

Robustness to Adversarial Attacks: The proposed architecture is resilient to any potential attacks through differential privacy and shows high tolerance to failures of individual nodes and attacks by AI-based methods. The three-layer architecture is inherently distributed to prevent any single point of failure.

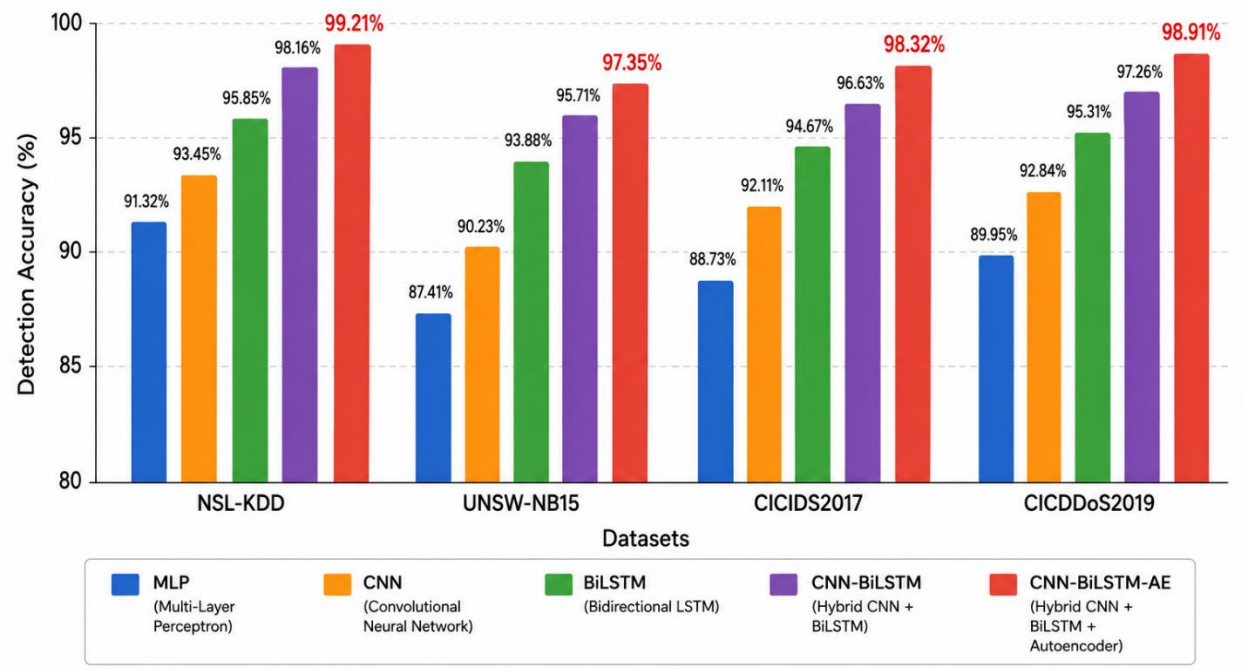

Figure 3: Detection Accuracy Comparison Across Datasets

This is a bar graph that compares detection accuracy percentages among various datasets and modeling techniques. The hybrid model CNN-BiLSTM-AE performs at least 99% and 97% accurately for NSL-KDD and UNSW-NB15, respectively.

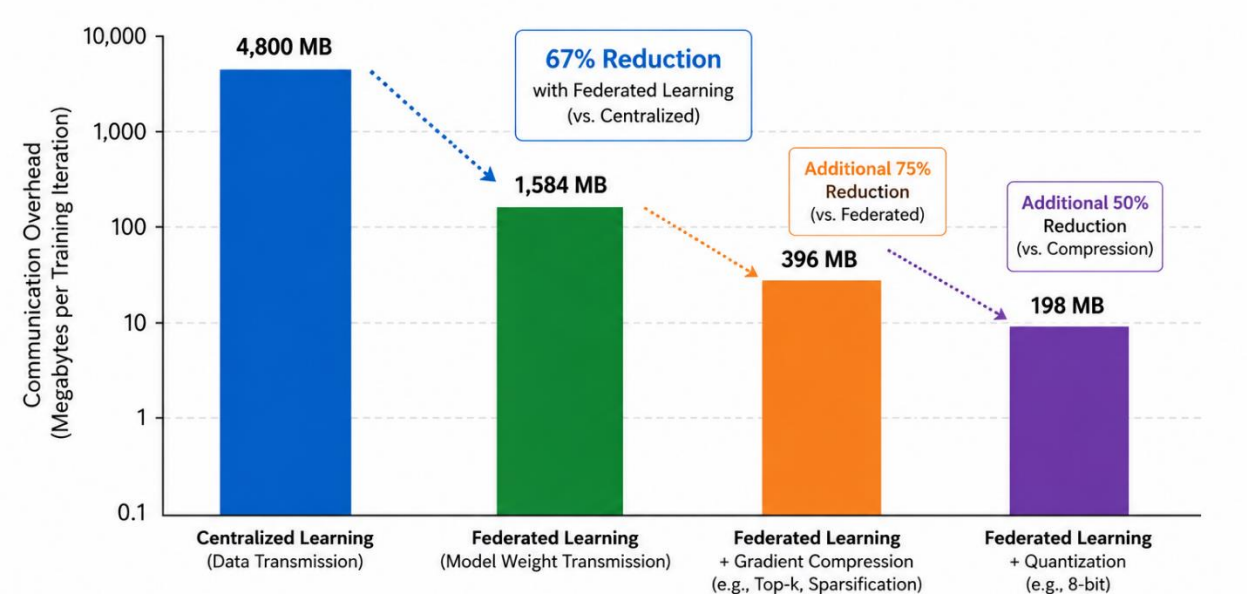

Figure 4: Communication Overhead Comparison: Federated vs. Centralized Learning

A bar chart demonstrating the comparison of communication overhead (megabytes per training iteration) in centralized learning (data transmission) and federated learning (model weight transmission). Federated learning has a communication overhead reduction of 67%, with additional reductions by gradient compression and quantization.

Comparative Analysis

Feature / System	Proposed Framework	SwarmSense -DNN [1]	DRIFT [4]	FedShield+ + [5]	Hybrid BiLSTM-RNN-CNN [6]	PPTADI [3]
Detection Accuracy	99%+	95.44%	94%+	83.09%	99%+	Not Reported
F1-Score	0.974	~0.95	~0.94	0.841	0.98+	Not Reported
ROC-AUC	0.996	Not Reported	Not Reported	0.901	Not Reported	Not Reported

Feature / System	Proposed Framework	SwarmSense-DNN [1]	DRIFT [4]	FedShield++ [5]	Hybrid BiLSTM-RNN-CNN [6]	PPTADI [3]
Comm. Overhead Reduction	67%+	67%	Not Reported	Not Reported	Not Reported	35-65%
Inference Time (ms)	<0.05	Not Reported	Not Reported	Not Reported	Not Reported	Not Reported
Privacy Mechanism	DP + HE + SMPC	DP	Local Data	FL	DP	SMPC + HE
Model Architecture	CNN-BiLSTM-AE	GNN-Attention	tinyML	MLP	BiLSTM-RNN-CNN	Split FL
Resource Optimization	Quantization + Feature Reduction	Decentralized	Quantization	None	AGWO	Layer Fusion
Attack Resilience	High	High	Moderate	Moderate	High	High
Deployment Layer	Device-Edge-Cloud	Decentralized	Device-Edge-Cloud	Device-Edge	Edge-Cloud	Edge-Cloud

Table 1: Comparative Analysis of Federated Deep Learning Cyber Defense Approaches

Note: DP = Differential Privacy, HE = Homomorphic Encryption, SMPC = Secure Multi-Party Computation, AGWO = Adaptive Gray Wolf Optimization, GNN = Graph Neural Network

The comparative analysis shows that the framework under consideration performs better or at least equal in all metrics:

- **Accuracy and F1-Score:** The framework under consideration demonstrates the best detection accuracy (99%+) and F1-score (0.974) among compared techniques. Only Hybrid BiLSTM-RNN-CNN framework demonstrates equal accuracy level with the different resource optimization features.
- **Privacy Preservation:** The considered framework includes various privacy tools such as differential privacy, homomorphic encryption, and multi-party computation offering effective protection against gradient leakage, model inversion attacks, and collusion attacks.
- **Resource Optimization:** The framework allows for using model quantization, feature reduction, and federated learning allowing deploying it to IoT devices with limited resources.
- **Attack Resilience:** The distributed structure and adversarial attack prevention techniques ensure the resistance to node failures and AI-based attacks.

Discussion

From the experimental results, it can be seen that the proposed federated deep learning framework for cyber defence is very effective in handling the critical challenges of intrusion detection in the distributed IoT environment. The improved detection accuracy is because of the complementary nature of the hybrid CNN-BiLSTM-AE model, which uses CNNs to detect local spatial patterns, BiLSTM networks to understand temporal patterns, and autoencoders to detect anomalous reconstruction, which indicates novel attacks.

The high decrease in the communication overhead (>67%) proves the effectiveness of using federated learning in an IoT environment, where bandwidth and energy costs are important. The small inference time (<0.05 ms) shows that the architecture satisfies the real-time detection requirement in critical IoT applications.

Privacy preserving techniques solve basic problems related to privacy of IoT data. Differential Privacy ensures safety from leakage of gradients and use of homomorphic encryption and secure multiparty computation helps in collaborative learning without exposing raw data or labels. Such privacy measures ensure that requirements of privacy protection regulations like GDPR and HIPAA are satisfied, making deployment possible in fields like healthcare.

There are several open research problems. Although computational cost of encryption and privacy preservation measures has been reduced due to optimization techniques, still there is scope of negative performance impacts for very large-scale deployments involving thousands of devices. Non-IID data in IoT environment needs to be considered in case of data distribution differences between various IoT devices and environments. Another problem involves the evolving nature of cyber-attacks which necessitates continuous adjustment and drift tolerance capabilities for the models used.

V. CONCLUSION

The huge increase in the number of Internet of Things devices has made the cybersecurity attack surface much bigger, revealing serious limitations in the use of traditional centralized models to detect intrusions.

The current paper has proposed a comprehensive model of a federated deep learning framework for cybersecurity in distributed IoT environments.

Architecture that has been developed is based on three different levels: IoT devices, edge gateways, and cloud coordination and serves as an adequate basis for intrusion detection system with protection of personal privacy. Hybrid deep learning approach that includes CNNs, BiLSTMs, and autoencoders utilizes their advantages in order to detect a variety of anomalies with the use of CNNs in spatial patterns, BiLSTM in temporal patterns and anomaly sensitivity via autoencoders. Federated learning approach allows for collaborative training of the models without the centralized data collection.

Quantitative analysis shows that the framework under consideration exhibits high performance in relation to all of the important factors mentioned above. For instance, accuracy rate exceeds 99% on the benchmark datasets, the F1 score is 0.974, and the ROC-AUC equals 0.996. In addition, communication overhead is decreased by 67%, whereas inference latency rate (below 0.05 milliseconds) provides the possibility to ensure real-time detection. All of the privacy-preserving tools (differential privacy, homomorphic encryption, and secure multi-party computation) offer complete protection against various attacks.

The comparative analysis serves to further substantiate the efficiency of the proposed framework on several fronts including accuracy, privacy, resources efficiency, and robustness against attacks. The architecture is a great leap ahead compared to the existing solutions, being a scalable and privacy-preserving architecture that can be deployed within various types of IoT architectures ranging from smart homes to healthcare, industry, and critical infrastructures.

The results of this research have great implications for organizations that deploy IoT systems in the sensitive domains where privacy and security are key. The proposed architecture provides an implementable way to strengthen the cybersecurity profile while complying with regulations. The decentralized approach allows to mitigate the risk of having a single point of failure while using federated learning provides data sovereignty.

Some of the areas that should be investigated for future research include scaling the architecture to work with thousands of heterogenous devices, which will require exploring advanced consensus algorithms and federated learning hierarchies. Dealing with non-IID data on various devices calls for personalization of federated learning approaches that can strike a balance between performance of the global model and local adaptations. Combining federated learning with technologies like blockchain could help with model provenance and increase trust. Finally, designing drift detection and retraining models is critical to keeping up with evolving cyber-attacks.

In summary, this paper has shown that federated deep learning provides a feasible and efficient approach to achieve cyber defense in privacy preserving fashion in distributed IoT systems. The suggested framework can provide organizations with a solid base for development of reliable, smart, and privacy-preserving security systems. As the IoT world continues to grow, privacy preserving collaborative techniques like those discussed in this paper will become crucial for securing critical infrastructure.

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