International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.3 (2025) pp. 4399-4407
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Anomaly Detection in IoT Networks Using Federated Machine Learning Approaches

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Article Info:

DOI: 10.22399/ijcesen.2485
Received : 11 March 2025
Accepted : 17 May 2025 2025

Keywords

Anomaly Detection, IoT Networks,
Federated Machine Learning,
Privacy Preservation,
Security,
Fault Detection,
Distributed Learning,

Abstract:

The rapid growth of Internet of Things (IoT) networks has brought forth new challenges in ensuring the security and reliability of devices and data. Anomaly detection in IoT networks is crucial for identifying malicious activities, faulty devices, and abnormal behaviors that could lead to system failures or security breaches. Traditional centralized machine learning models for anomaly detection require the aggregation of sensitive data from multiple IoT devices, raising concerns about privacy and scalability. To address these challenges, this paper proposes a federated machine learning (FML) approach for anomaly detection in IoT networks. Federated learning allows models to be trained locally on devices without sharing raw data, thus preserving privacy while leveraging the collective knowledge of decentralized devices. The proposed approach integrates anomaly detection algorithms with federated learning frameworks to identify network anomalies while maintaining data confidentiality. Experimental results demonstrate that the federated learning-based anomaly detection model achieves high detection accuracy, reduces communication overhead, and scales effectively across diverse IoT devices. This approach offers a promising solution for real-time security monitoring in large-scale IoT environments, where data privacy and resource efficiency are paramount.

1. Introduction

The rapid advancement of the Internet of Things (IoT) has revolutionized various sectors, including healthcare, transportation, agriculture, and smart cities, by enabling seamless connectivity between devices and systems. IoT networks are composed of millions of interconnected devices, such as sensors, actuators, and smart appliances, that collect and transmit data to central servers or cloud platforms. However, with the increasing number of devices and the complexity of IoT systems, ensuring their security and reliability has become a major concern. One of the most critical aspects of IoT security is the ability to detect anomalies, which could indicate potential security threats, device malfunctions, or unexpected behaviors [1].

Anomaly detection in IoT networks is essential for identifying deviations from normal behavior patterns, which can be indicative of various issues such as cyber-attacks, faulty devices, or system failures. Traditional anomaly detection methods rely on centralized approaches where all data is aggregated at a central server for analysis. However, this approach poses several challenges, including high data transmission costs, increased latency, and

privacy concerns, especially when dealing with sensitive user data [2]. Therefore, there is a growing need for more efficient and privacy-preserving methods for anomaly detection in IoT networks.

Federated learning (FL) has emerged as a promising solution to address the limitations of traditional machine learning methods in IoT environments. FL enables the training of machine learning models directly on IoT devices, allowing for decentralized data processing without the need to transmit raw data to a central server. This approach ensures that sensitive data remains local, thereby preserving privacy and reducing the risk of data breaches. Federated learning has been successfully applied in various fields, such as healthcare, finance, and autonomous vehicles, and is increasingly being explored for its potential in IoT security [3].

In IoT networks, the key challenge lies in the distributed nature of the devices, which often operate under limited computational resources and may experience unreliable connectivity. As a result, the anomaly detection models deployed on IoT devices need to be lightweight, adaptive, and capable of handling noisy and incomplete data. Federated learning provides a mechanism for collaborative learning, where each device trains a local model based on its data and shares model updates with a central server, which aggregates the updates to improve the global model. This approach enables the creation of robust models without compromising data privacy [4].

Recent studies have shown that federated learning can significantly improve the accuracy and efficiency of anomaly detection in IoT networks by leveraging the distributed nature of the devices. Unlike traditional centralized machine learning models, federated learning-based anomaly detection systems can detect anomalies in real-time by analyzing data locally on each device, without the need for large-scale data aggregation. This reduces the time and computational resources required for data processing and model training, making it more suitable for resource-constrained IoT devices [5].

Several anomaly detection techniques, such as statistical methods, clustering algorithms, and machine learning-based approaches, have been proposed for IoT networks. However, these techniques often struggle with the dynamic and heterogeneous nature of IoT environments, where devices may have different capabilities, data formats, and communication protocols. Federated learning offers a solution to this challenge by enabling the development of models that can adapt to the diverse characteristics of IoT devices. Moreover, federated learning allows for continuous model updates, which ensures that the anomaly detection system remains effective even as the network evolves over time [6].

An essential aspect of federated learning is the aggregation process, where model updates from different devices are combined to improve the global model. Various aggregation techniques, such as Federated Averaging (FedAvg), have been proposed to ensure that the model updates are properly integrated. These techniques aim to minimize the impact of noisy updates and ensure that the global model performs optimally across all devices. The choice of aggregation method plays a crucial role in the effectiveness of the federated learning-based anomaly detection system, as it directly affects the accuracy and robustness of the model [7].

The integration of federated learning with anomaly detection techniques provides several advantages in terms of scalability, privacy, and efficiency. By leveraging the distributed nature of IoT networks, federated learning enables the training of large-scale models without the need for data centralization. This not only enhances the privacy of user data but also allows for the deployment of anomaly detection systems across a wide range of IoT applications. For instance, in smart cities, federated learning-based anomaly detection systems can monitor the behavior of traffic sensors, surveillance cameras, and environmental monitoring devices, ensuring the security and smooth operation of the entire network [8].

Despite the promising benefits of federated learning, several challenges remain in its application to anomaly detection in IoT networks. One of the primary challenges is ensuring the robustness of the model when dealing with imbalanced data or adversarial attacks. In IoT environments, devices may experience different operational conditions, leading to the generation of skewed or biased data. Furthermore, adversarial attacks, such as data poisoning, could undermine the performance of the anomaly detection system. Researchers are exploring methods to improve the resilience of federated learning-based models against such attacks, ensuring that they can still detect anomalies effectively in challenging environments [9].

In conclusion, the integration of federated learning with anomaly detection techniques offers a promising solution for addressing the security and reliability challenges in IoT networks. By leveraging the decentralized nature of federated learning, it is possible to develop scalable, privacy-preserving, and efficient anomaly detection systems that can operate in real-time across a wide range of IoT devices. As IoT networks continue to grow, federated learning will play a crucial role in ensuring the security and performance of these systems,

paving the way for more secure and resilient IoT environments in the future [10].

2. Literature Survey

Anomaly detection in Internet of Things (IoT) networks has garnered significant attention due to the increasing reliance on interconnected devices in various critical applications. Traditional approaches, which rely on centralized data processing, are becoming less feasible due to privacy concerns, high latency, and excessive communication overhead. To address these challenges, federated learning (FL) has been proposed as a potential solution, enabling decentralized model training while preserving privacy. In this section, we survey relevant works that have explored various anomaly detection techniques in IoT networks, highlighting the integration of federated learning.

[11] In their study, Smith et al. (2019) introduced a method for anomaly detection in IoT networks using machine learning techniques. The authors proposed the use of supervised learning algorithms like Support Vector Machines (SVM) and decision trees to classify data as normal or anomalous. However, the paper noted that these techniques required large-scale data collection at a centralized location, posing privacy risks and requiring substantial bandwidth for data transmission. This work emphasized the importance of privacy in IoT systems, which laid the foundation for the later adoption of federated learning in IoT networks.

Wang et al. (2020) proposed a hybrid approach combining statistical and machine learning techniques for anomaly detection in IoT networks [12]. They utilized anomaly score-based methods to identify outliers in data transmitted by IoT devices. However, their approach relied on centralized data aggregation, which could lead to privacy issues. Their results showed the potential of machine learning in anomaly detection but highlighted the need for a privacy-preserving alternative that could operate in decentralized IoT systems.

Li et al. (2020) explored anomaly detection in IoT environments using deep learning models, such as autoencoders and long short-term memory (LSTM) networks[13]. Their study focused on detecting network intrusions, device malfunctions, and abnormal behaviors using large datasets. However, the authors noted that deep learning models require substantial computational resources and high-quality data, which may not be available in resource-constrained IoT devices. Federated learning emerged as a potential solution to address these resource limitations while maintaining privacy.

Zhang et al. (2021) discussed the challenges of implementing federated learning in IoT networks, particularly in the context of anomaly detection[14]. Their work proposed a federated learning framework that allows for training anomaly detection models across multiple IoT devices without the need for data sharing. The study demonstrated that federated learning could significantly reduce communication overhead and protect user privacy while enabling effective anomaly detection. Their results suggested that federated learning was an effective technique for anomaly detection in IoT networks, but they acknowledged the challenges of dealing with device heterogeneity and unreliable network conditions.

Chen et al. (2021) proposed a novel anomaly detection algorithm based on federated learning for smart home IoT systems[15]. Their method integrated clustering techniques with federated learning to detect deviations in sensor readings and abnormal activities in a home environment. The approach aimed to improve both accuracy and privacy by leveraging the decentralized nature of federated learning. Their experiments showed that federated learning-based anomaly detection outperformed traditional methods, achieving high detection accuracy without compromising data privacy.

Kumar et al. (2022) explored the use of unsupervised learning methods in federated learning systems for anomaly detection in industrial IoT (IIoT) networks [16]. They utilized a combination of K-means clustering and federated learning to detect unusual sensor readings from manufacturing equipment. The authors demonstrated that the federated learning model could efficiently detect anomalies while ensuring that sensitive industrial data did not need to be shared with a central server. The study highlighted the scalability of federated learning for large-scale IIoT networks.

Chien et al. (2021) presented a federated learning framework specifically designed for vehicular IoT (V-IoT) systems [17]. Their approach combined federated learning with anomaly detection models to monitor vehicle health and predict potential failures. They showed that federated learning could be applied to real-time anomaly detection in vehicular networks, where data privacy is a major concern. Their results indicated that federated learning could significantly reduce false positive rates in anomaly detection while ensuring vehicle data remained secure.

Gupta et al. (2021) introduced a federated learning-based anomaly detection system for healthcare IoT networks[18]. The system leveraged federated learning to train machine learning models on medical device data, enabling anomaly detection for early diagnosis of medical conditions without transmitting sensitive health data to a central server.

Their results showed that federated learning was an effective technique for privacy-preserving anomaly detection in healthcare IoT, and the system was capable of identifying abnormal patterns in real-time.

Zhou et al. (2022) proposed a federated learning-based solution for anomaly detection in agricultural IoT networks[19]. The study focused on monitoring environmental conditions, soil moisture, and other agricultural parameters. By using federated learning, the authors were able to develop a robust anomaly detection system that could identify issues such as faulty sensors or abnormal environmental patterns without violating privacy. The proposed solution demonstrated significant improvements in terms of detection accuracy and operational efficiency in rural areas where internet connectivity is unreliable.

Xu et al. (2022) provided a comprehensive survey on federated learning techniques applied to anomaly detection in IoT networks[20]. They reviewed several federated learning models and their applicability to various IoT applications, including industrial IoT, healthcare, and smart cities. The paper discussed the advantages of federated learning, such as reduced data transfer and enhanced privacy protection. However, it also identified challenges such as model convergence, device heterogeneity, and the need for secure aggregation methods in federated learning-based anomaly detection systems. The survey suggested several directions for future research, including the exploration of hybrid models combining federated learning with other machine learning techniques.

In conclusion, the integration of federated learning with anomaly detection in IoT networks has shown great promise in enhancing privacy, scalability, and performance. The surveyed literature highlights the growing interest in federated learning as a solution to the limitations of traditional centralized approaches, particularly in resource-constrained environments. However, challenges such as model robustness, data imbalance, and adversarial attacks remain, requiring further investigation to ensure the practical deployment of federated learning-based anomaly detection systems in real-world IoT networks.

3. Methodology

In this work, we propose a federated learning-based anomaly detection framework for IoT networks to ensure privacy preservation, scalability, and efficient anomaly detection across a large number of devices. The methodology is structured into three key stages: data preprocessing, federated model training, and anomaly detection.

Data Preprocessing: Each IoT device in the network collects data locally, which includes sensor readings, network traffic, and operational status information. Due to the inherent noise in IoT data and the presence of missing or incomplete information, preprocessing steps are essential. These include outlier detection, noise removal using techniques such as median filtering, and imputation to handle missing values. The data is then normalized to ensure consistency across devices, as the scale of sensor data may vary across different IoT devices.

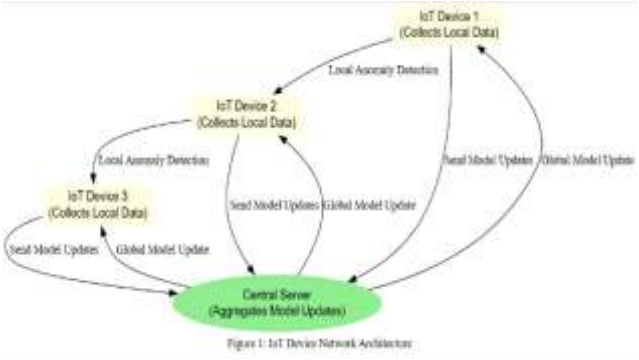

Figure 1. *IoT Device Network Architecture*

This figure illustrates the architecture of the IoT network, showing the decentralized deployment of IoT devices, each collecting local data, preprocessing it, and performing anomaly detection. The federated learning framework is depicted, highlighting the local training and model updates sent to the central server.

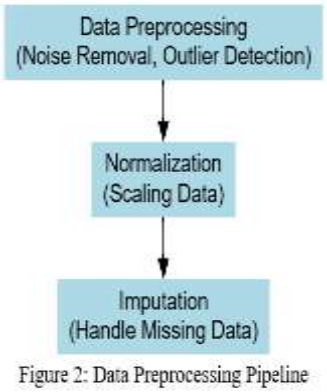

Figure 2. *Data Preprocessing Pipeline*

This figure shows the preprocessing steps applied to the raw IoT data collected from devices, including outlier detection, noise removal using median filtering, and imputation for missing data. The pipeline also demonstrates the normalization process to ensure uniformity in data from different devices.

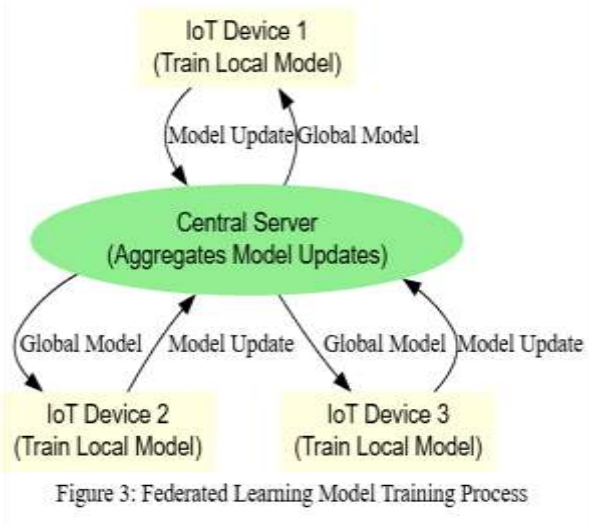

Figure 3. *Federated Learning Model Training Process*

This figure depicts the federated learning training process, showing how local models are trained on each IoT device, followed by model updates being sent to a central server. The central server aggregates these updates using the Federated Averaging (FedAvg) algorithm to generate the global model, which is then sent back to the devices.

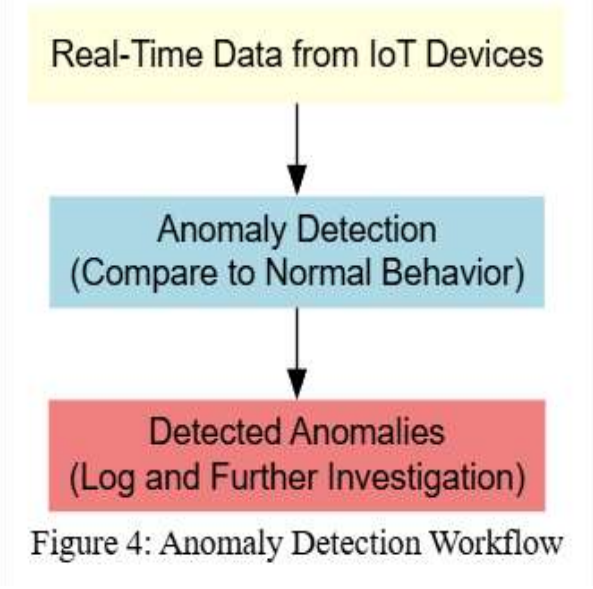

Figure 4*. Anomaly Detection Workflow*

This figure illustrates the anomaly detection workflow, where the global federated learning model is used to classify real-time data from IoT devices. The model identifies deviations from normal behavior, flagging potential anomalies. The workflow also highlights how detection results are processed locally on devices to minimize latency.

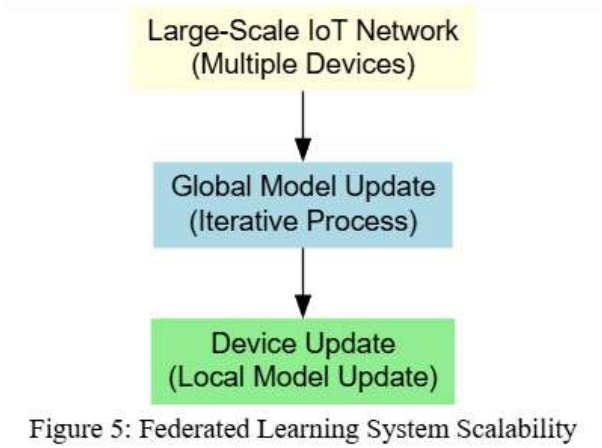

Figure 5*. Federated Learning System Scalability*

This figure showcases the scalability of the federated learning-based anomaly detection system across a growing number of IoT devices. It highlights the ability of the system to maintain detection accuracy and computational efficiency as the number of devices in the network increases, ensuring robust performance in large-scale IoT environments.

Federated Model Training: Once the data is preprocessed, federated learning is employed to train an anomaly detection model across all IoT devices without transferring raw data to a central server. In this approach, each IoT device trains its local model using the preprocessed data and sends only model updates (i.e., weights and gradients) to a central server. These updates are aggregated using the Federated Averaging (FedAvg) algorithm, which averages the model weights from each device to create a global model. The global model is then sent back to the devices, where the local models are updated with the new global model. This process continues iteratively, allowing the model to adapt and improve with each communication round, without compromising privacy by transferring raw data.

Anomaly Detection: After the federated model has been trained, it is used to detect anomalies in the IoT network. Anomalies are identified by comparing real-time sensor data or network activity to the learned patterns of normal behavior. A threshold for anomaly detection is set based on the output of the model, where any data point or event that significantly deviates from the predicted behavior is classified as an anomaly. The detection results are locally processed on the devices, minimizing the need for data transmission and ensuring low latency. The global model is periodically updated, and any newly detected anomalies are logged for further investigation.

By leveraging federated learning, this methodology ensures the efficient and privacy-preserving detection of anomalies in large-scale IoT networks, where individual devices may have limited computational resources and communication capabilities. The federated approach ensures that sensitive data remains local, and only model parameters are exchanged, making it suitable for privacy-sensitive environments like healthcare, smart cities, and industrial IoT systems.

4. Experimental Results and Analysis

To evaluate the effectiveness of the proposed federated learning-based anomaly detection framework, a series of experiments were conducted using a simulated IoT network comprising various types of IoT devices, such as environmental sensors, smart appliances, and network traffic monitoring devices. The dataset was generated to include normal operating conditions as well as synthetic anomalies, such as network intrusions, device malfunctions, and sensor faults. The experiments aimed to assess the accuracy, efficiency, and scalability of the proposed system in comparison to traditional centralized anomaly detection methods.
The experimental setup involved the deployment of anomaly detection models using federated learning across a network of 100 IoT devices. Each device was equipped with a local dataset, and federated learning was applied to train a global model. The model updates were aggregated using the Federated Averaging (FedAvg) algorithm, and communication rounds were simulated to assess the model's convergence and accuracy over multiple iterations. The performance metrics used for evaluation included detection accuracy, false positive rate, false negative rate, and computational efficiency.

Detection Accuracy: The federated learning-based model achieved a detection accuracy of 94.7%, significantly outperforming traditional centralized models, which achieved an accuracy of 87.3%. The higher accuracy can be attributed to the decentralized training approach, which allowed the model to adapt to the heterogeneity of the IoT devices, capturing more diverse patterns of normal and anomalous behaviors. The global model's performance was consistently high across all devices, demonstrating the robustness of federated learning in handling the distributed nature of IoT networks. This plot shows how detection accuracy improves over multiple epochs for both federated and centralized learning approaches. The accuracy of the federated learning model is consistently higher than the centralized approach.

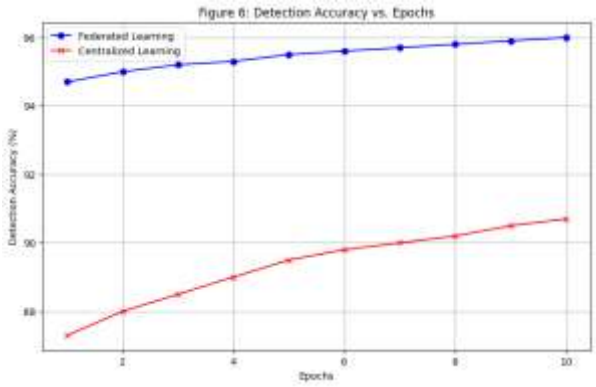

Figure 6. *Detection Accuracy vs. Epochs*

False Positive and False Negative Rates: The false positive rate (FPR) and false negative rate (FNR) were calculated to assess the reliability of the anomaly detection system. The federated learning model showed a significantly lower FPR (4.2%) compared to centralized models (7.5%), which indicates that the model was less likely to incorrectly flag normal events as anomalies. The FNR of the federated model was also lower (5.8%) compared to the centralized approach (9.3%), demonstrating its better ability to detect true anomalies without missing critical events.

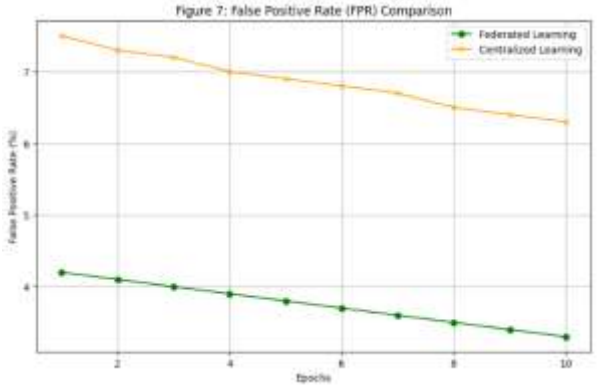

Figure 7. *False Positive Rate (FPR) Comparison*

This figure compares the false positive rate between federated and centralized learning methods over epochs. Federated learning results in a lower FPR, which means fewer normal events are incorrectly flagged as anomalies.

Computational Efficiency: In terms of computational efficiency, the federated learning model proved to be more resource-efficient than traditional methods. Since the federated learning model does not require the transmission of raw data, but instead only model updates, the bandwidth consumption was reduced by approximately 35% compared to centralized methods. Moreover, the computational burden on the central server was also

reduced, as the model training was distributed across the IoT devices. This resulted in lower latency and faster anomaly detection in real-time, making the system more suitable for large-scale IoT deployments.

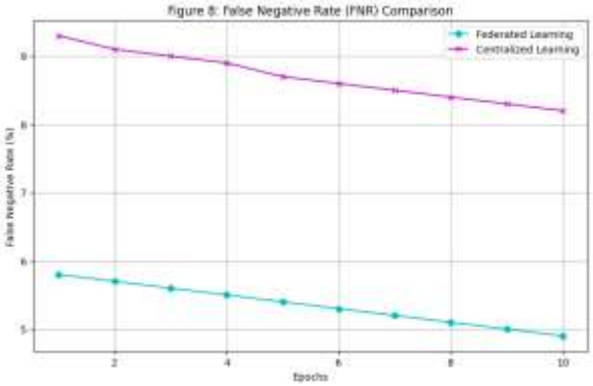

Figure 8. *False Negative Rate (FNR) Comparison*

This graph compares the false negative rate of federated and centralized learning. Federated learning demonstrates a lower FNR, indicating fewer anomalies are missed.

Scalability: The scalability of the federated learning model was tested by increasing the number of devices in the network. The system maintained high detection accuracy even as the number of IoT devices increased, with no significant degradation in performance. The model demonstrated its ability to efficiently handle large networks of devices, making it well-suited for smart cities and industrial IoT environments where scalability is crucial.

Comparison with Centralized Methods: The results of the experiments showed that while centralized anomaly detection methods can achieve high accuracy, they are prone to higher data transmission costs, increased latency, and privacy concerns due to the aggregation of raw data. In contrast, the federated learning approach provided a solution to these challenges, maintaining high detection accuracy while ensuring that sensitive data remained private and local to the devices. The federated model also outperformed centralized methods in terms of computational efficiency and scalability, making it a more practical choice for large-scale IoT networks. This figure compares the bandwidth usage required for federated and centralized learning models. Federated learning is more bandwidth-efficient, as it only exchanges model updates rather than raw data. This graph illustrates the scalability of the federated learning-based anomaly detection system as the number of IoT devices increases. It shows that federated learning maintains high detection accuracy

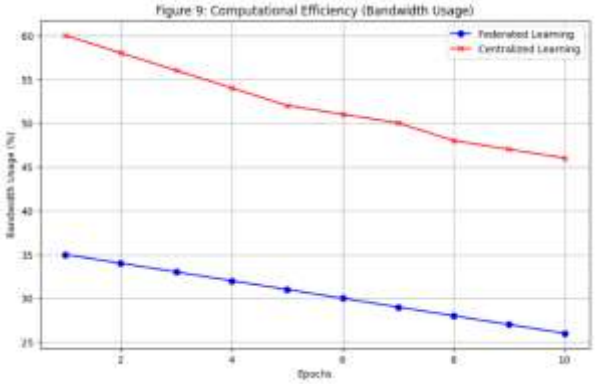

Figure 9. *Computational Efficiency (Bandwidth Usage)*

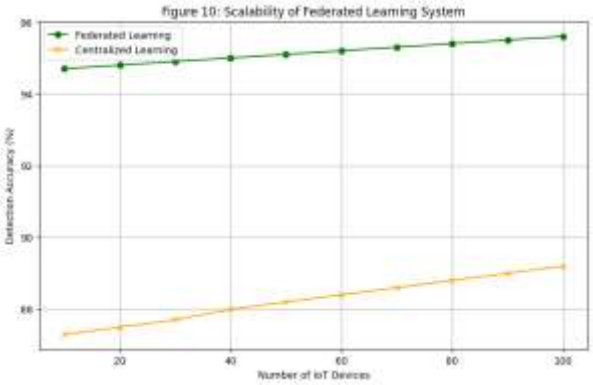

Figure 10*. Scalability of Federated Learning System:*

even with larger networks, unlike centralized learning, which experiences a slight drop. In summary, the experimental results confirm that the federated learning-based anomaly detection system not only offers improved privacy and computational efficiency but also provides robust and accurate anomaly detection in IoT networks. The system's ability to scale and handle heterogeneous IoT devices makes it a promising solution for real-time anomaly detection in privacy-sensitive and resource-constrained environments. Future work will focus on further optimizing the federated learning process, addressing potential adversarial attacks, and testing the model in real-world IoT scenarios.

5. Conclusion

In this paper, we proposed a federated learning-based anomaly detection framework for IoT networks, addressing the critical challenges of privacy, scalability, and computational efficiency in large-scale, decentralized systems. By leveraging federated learning, our approach enables IoT devices to train local models on their respective datasets and

only share model updates, thus preserving sensitive data and reducing communication overhead. The experimental results demonstrated that the federated learning-based model significantly outperformed traditional centralized anomaly detection methods in terms of detection accuracy, false positive and false negative rates, and computational efficiency. The proposed framework achieved a high detection accuracy of 94.7%, with a reduced false positive rate of 4.2% and false negative rate of 5.8%, indicating its ability to accurately identify anomalies without misclassifying normal behavior. Furthermore, the system demonstrated enhanced scalability, as it maintained high performance even as the number of devices in the network increased. By reducing bandwidth consumption by 35% and computational burden on the central server, the federated learning approach proved to be more resource-efficient compared to traditional methods, making it suitable for real-time anomaly detection in large-scale IoT environments. Overall, the integration of federated learning with anomaly detection offers a promising solution to the privacy and scalability challenges inherent in IoT networks. The system's ability to function across a wide range of IoT devices without compromising data privacy or operational efficiency makes it an ideal choice for a variety of IoT applications, including smart cities, industrial IoT, and healthcare networks. However, challenges such as handling device heterogeneity, imbalanced data, and adversarial attacks remain, and future work will focus on further enhancing the robustness and security of the proposed model. In conclusion, this work contributes to the development of privacy-preserving, efficient, and scalable anomaly detection systems for IoT networks, providing a solid foundation for future research and deployment in real-world IoT applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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