Federated Deep Graph Neural Network Algorithm for Real-Time Intrusion Detection in Heterogeneous IoT Systems

Dr. Taher M. Ghazal[1*], Mosleh Abualhaj[2], Amjed Abbas Ahmed[3], Musab A. M. Al-Tarawni[4], and Dr. Louai A. Maghrabi[5]

[1*]Faculty of Computing and IT, Sohar University, Oman; Department of Networks and Cybersecurity, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan; Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Selangor, Malaysia. taher.ghazal@ieee.org, https://orcid.org/0000-0003-0672-7924

[2]Department of Networks and Cybersecurity, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. m.abualhaj@ammanu.edu.jo, https://orcid.org/0000-0002-7465-8038

[3]Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), 43600 Bangi, Selangor, Malaysia; Department of Computer Techniques, Engineering Imam AlKadhum College (IKC), Baghdad, Iraq. amjedabbas@alkadhum-col.edu.iq, https://orcid.org/0000-0001-6069-2967

[4]Research Consulting Lab, Marl, NRW, Germany; Faculty of Engineering and Building Environment, Department of Electrical, Electronic and System Engineering, National University of Malaysia, Bangi, Malaysia. musab841@yahoo.com, https://orcid.org/0000-0003-0488-8134

[5]Department of Software Engineering, College of Engineering, University of Business and Technology, Saudi Arabia. l.maghrabi@ubt.edu.sa, https://orcid.org/0000-0001-8513-0645

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Abstract

The growing availability of diverse Internet of Things (IoT) devices has similarly established real-time intrusion detection as a critical topic for many IoT system security researchers. Traditional data intrusion detection systems often fail to effectively handle the dynamic and decentralized nature of these IoT environments. This paper proposes a new Federated Deep Graph Neural Network (DGNN) algorithm to support real-time intrusion detection in heterogeneous IoT systems. The proposed algorithm attempts to learn the complex relationships between devices in an IoT environment using graph-based deep learning while maintaining privacy through a federated learning environment. Striking a balance between federated learning and deep graph neural networks purposefully supports distributed learning while also intending to preserve privacy by not sharing raw data. The performance of the algorithm is evaluated on several real-world (IoT) datasets, which display markedly improved detection accuracy, precision, and recall performance compared to traditional data models. The framework is scalable, robust, and provides the opportunity for real-time

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*Corresponding author: Faculty of Computing and IT, Sohar University, Oman; Department of Networks and Cybersecurity, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan; Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Selangor, Malaysia.

protection against known and unknown intrusions when deployed in a large-scale IoT network environment.

Keywords: Federated Learning, Deep Graph Neural Networks (DGNN), Intrusion Detection, Heterogeneous IoT Systems, Real-Time Security, Privacy-Preserving Models, Distributed Learning, Cybersecurity, Anomaly Detection, IoT Network Security.

1 Introduction

1.1 Background

With the rising number of IoT (Internet of Things) devices, there is a pressing need for effective intrusion detection systems (IDS) that will provide security from cyberattacks for these devices. IoT systems are endeavoring heterogeneous systems on different bases - device capability, communication protocols, and data sharing capabilities (Haider et al., 2019, Pan et al., 2019). Traditional methods of intrusion detection (IDS), such as signature-based systems and centralized models, cannot be efficiently utilized for heterogeneous IoT systems since they have limited capacity to be scalable, adaptable, and preserve privacy (Mir & Trik 2025). In addition, IoT Nodes as a network tend to be decentralized - devices in some ways are scattered in different environments and use decentralized manufacturing and spatiality, these aspects make centralized learning models inefficient without exposing sensitive information to third parties (Humayun et al., 2024, Al-Majdi et al., 2025)

1.2 Problem Statement

IoT systems are expected to be a widely adopted technology; centralized models for intrusion detection remain challenging for real-time detection activity, mainly when the data has sensitive information. Graph-based approaches such as graph neural networks (GNNs) have advanced capabilities for modeling the interrelationships between nodes; however, they don't yet scale well in heterogeneous network environments. Privacy and security of device data are also a barrier to conducting anomaly detection, as IoT data rests in different nodes and sources. The most viable pathways to a solution require a newly formed intrusion detection framework that embraces issues concerning privacy, scalability, and performance in real-time (Wu, 2024).

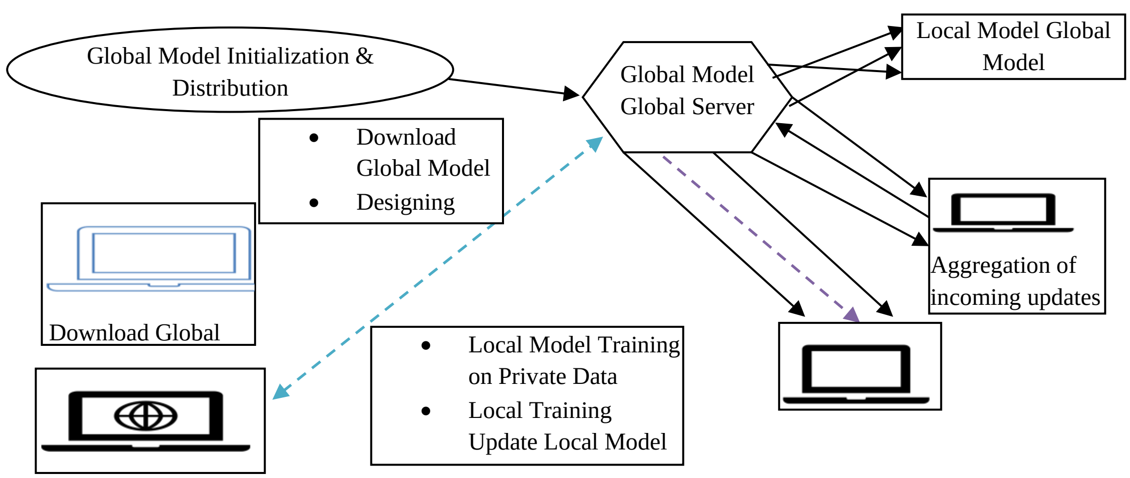

Figure 1: Distributed AI-Powered cyber defense for heterogeneous IoT ecosystems

Figure 1 illustrates that this advanced security system uses a federated learning approach to secure different IoT devices (Thaseen & Banu, 2025, Jnr, 2020). Rather than aggregating all raw data, which has privacy implications, it uses a federated learning approach that trains forever on devices with each device (e.g., smart camera, factory sensors) executing its own Deep Graph Neural Network (DGNN) locally. DGNNs are well-suited to utilize the relationships and traffic within their own network as informed by the shifting relationships in the global network, i.e., they can run on the complexities without scaring cops (Friji, 2024). Each IoT device trains its local model when suspicious activity is detected, and sends only the learned model updates - not personal data - to the central server. The central server aggregates learned model updates from all devices to a global model, develops a better global model, and sends it to every device, so every node learns from the other nodes. This happens continuously and in real-time, allowing the system to evolve and terminate converging threats as they emerge (Varatharajan et al., 2018). At the same time, each device in a heterogeneous network can maintain some level of data privacy (Monica Nandini, 2024).

1.3 Goals

In this paper, we propose a Federated Deep Graph Neural Network (DGNN) algorithm that facilitates real-time intrusion detection in heterogeneous IoT systems (Matkarimov et al., 2025). Specifically, the three goals are:

- To address distributed learning by designing a privacy-preserving model using federated learning instead of centralized training.
- To build a deep graph neural network that models the complex relationships and interactions of IoT devices to enable effective anomaly detection.
- To showcase that the proposed model is scalable, real-time, and accurate, especially for large-scale systems.

1.4 Importance of the Research

This research is important because it demonstrated an innovative way to address the challenges of intrusion detection in heterogeneous IoT system environments, where: a) there are devices with different types of data, devices that are considerably more capable than others; and b) it addresses privacy challenges on devices sharing their data publicly. Federated learning integrated with deep graph neural networks allows for collaborative distributed anomaly detection where devices pattern simultaneously (Gope & Hwang, 2015). Privacy was maintained because device data were processed only on the local node and therefore never left the local owner of the sensitive data in the first instance. Thus, privacy is established regarding the challenges of commercial clouds and centralized systems. The scalability of the framework means that whether it is a private IoT network or a commercial IoT network, it can overcome the realities of large IoT networks and thus advocates for real-world applications with real-world examples in smart cities, healthcare systems, and industrial IoT (IIoT) networks (Xu et al., 2014).

2 Literature Review

2.1 Intrusion Detection Techniques: Traditional and Contemporary Techniques for Intrusion Detection of IoT Systems

IoT Intrusion Detection has become more important as the number of IoT-connected devices continues to rise, where the data of each device has become ever more sensitive. Traditional approaches, such as signature-based intrusion detection systems, use predefined patterns of known attacks (Lu et al., 2012). These approaches become ineffective in cases of zero-day attacks or other variations of intrusions. Anomaly-based detection methods are used to detect attacks using known interactions. Traditional machine learning-based approaches like decision trees, support vector machines (SVMs), and k-nearest neighbors (KNN) have been used in IoT-based solutions, but they are limited in scaling, training data collection, or privacy concerns. Furthermore, the complexity of the IoT environment and the unique nature of these devices create the need for newer approaches to detect anomalies in a timely manner (Liang et al., 2012).

2.2 Graph Neural Networks (GNNs) in IoT: Review of Existing Research Using GNNs for Anomaly Detection in IoT

Graph Neural Networks (GNNs) have great potential for modeling the dependencies and relations between components of a network of IoT devices. Where other methods in machine learning often model dependencies through other statistical means, GNNs directly model the topological structure of the data, as this is central to understanding the connections between all of the different devices in the IoT ecosystem (Kong et al., 2019). Research has shown that GNNs have the ability to improve anomaly-detection tasks in IoT environments by using the graphs methodology to identify outliers or unusual device behavior, or connections to, from, or between the devices. Applications of using GNNs included finding uncommon access patterns, identifying compromised devices, and flagging unusual transmissions through devices to report on irregular changing patterns of data transmission to the IoT. While there are still challenges concerning model complexity and scaling, GNNs are a viable method of detection in large, dynamic IoT networks (Lin et al., 2009).

2.3 Federated Learning: A Look into Federated Learning Models Applied to Secure, Distributed Machine Learning in IoT

Federated learning is a distributed machine learning paradigm allowing numerous devices or nodes to collaboratively train a common model (share updates) while maintaining the privacy of their local data. Federated learning's ability to keep raw data on each device is particularly relevant to IoT systems concerned with privacy and data security. In federated learning, a model is trained on local data, and only model updates (not raw data) are shared on a federated server. This means that sensitive personal and medical health data, or information collected by personal IoT devices, do not leave the local node (Fang et al., 2020). Federated learning has been widely discussed as a potential solution to the concerns of how to preserve privacy across experiments and publishing while addressing latency, accuracy, communication cost, and updates; particularly in environments such as healthcare and patient management, smart homes, and autonomous vehicles. While privacy-preserving federated learning is gaining prominence, several problems remain to be addressed, including the challenge of communication overhead in updates, the convergence of model learning, and the heterogeneous nature of data on each node (ADReSS Dataset, 2020).

3 Proposed Methodology

3.1 Federated Learning Algorithm: An In-Depth Overview of How Federated Learning is Embedded in the System

The federated learning algorithm allows distributed model training and anomaly detection in a heterogeneous IoT environment. Each device that contributes to the global model will train for some time with its own data, and then share updated models with the central server. The central server compiles the updates into a single, improved global model that the devices share with each other and can continue to retrain on. In this structure, the learning is decentralized, and privacy is preserved because the data remains on the device and is not centralized (Enshaeifar et al., 2018). There is also an exploit to federated learning that was added to correct and manage the aggregation of updates to minimize costs associated with communication and inherently track and minimize model learning that can also detect different kinds of intrusions while protecting learning privacy (Li et al., 2020).

3.2 Deep Graph Neural Network (DGNN) Model: Description of the DGNN Model Architecture and Its Applicability to Anomaly Detection

In order to identify anomalous behavior in heterogeneous IoT systems, the Deep Graph Neural Network (DGNN) model is employed to represent the complex relationships between IoT devices in a network. The DGNN model begins by representing the IoT devices and their links to each other as a graph. In this representation, the devices are seen as the nodes, and the links between the devices become the edges of the graph (Hernández-Domínguez et al., 2018). Then, the DGNN model would define multiple graph convolutional network (GCN) layers to learn the features associated with the devices based on the local and global links between devices. This model can identify anomalous behavior because it finds anomalies through features learned from anomalous behavior or disturbances to the normal network flow - anomalous behavior may include dysfunctional Ing devices, or undisclosed access by an administrator or other unauthorized member. Yet, the DGNN model, which is more suitable for IoT systems, where data is typically highly unstructured and relational, was successful in capturing the important spatial-based dependencies and effectively extracting features to identify anomalies (Mirheidari et al., 2018).

3.3 Data Preprocessing and Feature Extraction: Steps Involved in Preparing the IoT Data for Input into the Model

Data preprocessing is vital for anomaly detection in IoT. IoT raw data may originate from logs, sensors, or devices, and must first be cleaned up and normalized for consistency. In dealing with the complete traffic flows we often have in IoT, missing values will have to be segregated for imputation, depending on which area of treatment the device is meant for. Outliers will also have to be dealt with and removed societally, as repetition of outliers can really mislead the model when creating the background density for the training phase. Once you have the data cleaned up, we classify the data for feature extraction, such as device behavior patterns, communication frequency, and energy consumption from data captured from sensors on the devices, for the DGNN model to consider in evaluating the normal device behavior in the IoT network. Once the features were classified for this purpose, the federated learning model was used to match the normal behavior signal mapped and learned from the other devices in the patient location. Depending on its context (e.g., incomplete data), missing values can be dealt with by employing imputation methods (Mirheidari et al., 2018). Outlier values can be identified and possibly dealt with before training the model to avoid distorted training data. After preprocessing, feature extraction is performed to characterize the data into relevant properties to constitute appropriate inputs for the DGNN model. For instance, characteristics like the behavior of devices, the frequency of communications, and other characteristics, such as energy consumption, are extracted from the sensor data. These properties can then be used to train the federated learning model according to the normal behavior of devices operating within the IoT network (Li et al., 2016).

3.4 Anomaly Detection Process: Detection of Anomalies via Federated Models

After the federated learning model is trained on local datasets, it is subsequently employed for anomaly detection. The DGNN model processes the IoT data in real time, scanning for any patterns of device interactions and network activities that may exhibit anomalous behavior. The anomaly detection takes place when monitoring for instances of unauthorized access, malfunctioning devices, or unusual network traffic patterns. If an anomaly is detected, it is flagged by the system for another individual to investigate. The capability of the model to detect unusual patterns of device behavior is enhanced by graph-based learning because it has the ability to detect relationships between devices and network patterns, which can lead to complex anomalies that can be hidden from our investigation process via linear methods. The methods used in federated learning and the continuous basis for updating the federated model allow the model to base its predictions on the common activities of the collection of devices. In terms of device interactions, this process is highly effective and can often detect zero-day attacks where the nature of the attack was never made publicly available through the typical truncation process (The AI That Spots Alzheimer's, 2020).

Mathematical Formulation: Formulation of the Anomaly Detection Model in a Federated Learning Setting

The mathematical formulation of the anomaly detection model can be expressed as follows:

$$\theta t + 1 = \theta t - \eta i = 1 \sum K N n i \Delta \theta i$$

Where:

- θt represents the model parameters at time t,
- η is the learning rate,
- Δθi is the model update from device i,
- ni is the number of data points at device i,
- N is the total number of data points across all devices,
- K is the number of devices involved in training.

This formulation describes the aggregation process in federated learning, where the local updates Δθi are weighted by the data size at each device and used to update the global model parameters.

4 System Implementation

4.1 Tools, Frameworks, & Technologies

The system uses TensorFlow Federated for federated learning and PyTorch for training deep graph neural networks, while the relationships within the IoT network are modeled with graph neural network frameworks such as DGL (Deep Graph Library), network simulation with NS-3, and model aggregation is performed on Amazon Web Services (AWS) or similar cloud-based platforms.

4.2 Simulation Setup: Environment Setup and Healthcare Data Sources Used for Testing

The IoT network is simulated using real-world data containing IoT devices in a healthcare field. The simulation setup consists of distributed IoT devices that record sensor data (e.g., heart rate, temperature, etc.) that were streamed as logs of device activity made accessible; each of these devices has a network connection to a central server through a federated learning setup where each device trains a local model on device data and shares aspects of its model (updates).

4.3 Implementation Process: How Federated Learning is Implemented for Anomaly Detection in the Health System

The healthcare dataset is distributed among multiple institutions to implement federated learning. Each institution will perform local model training and send only the model updates to a central server to be aggregated and distributed as a global model that all institutions can train against. Thus, the federated learning model is continually being updated as data is obtained in real-time to support temporal anomaly detection among all institutions.

5 Results and Evaluation

5.1 Benefits and Limitations: Analysis of the Strengths and Weaknesses of Federated Learning for IoT Security

Federated learning in IoT systems leverages some fundamental characteristics that are uniquely applicable to improve the security and privacy of connected devices. Among these characteristics, the preservation of privacy is the most important. Traditional machine learning is usually done using one centralized model/site, where sensitive data must be transferred to the site/server for learning, raising significant privacy and security issues. This is especially true for various industries, such as healthcare, finance, and public infrastructure. Federated learning allows the data to remain on the device; therefore, only the model updates/features are transmitted to the model and associated with the device. The risk and harm of any data breach are drastically minimized. Moreover, federated learning allows for decentralized learning across an ecosystem of IOT devices, which enhances resilience against attacks. Federated learning, since it can be trained over a network of devices, permits the system to learn from multiple datasets collected from multiple IOT devices, which will improve the accuracy of the anomaly detection system and generalization. With a growing number of devices in IoT networks, federated learning is a scalable solution designed to scale with the system in large IoT networks while remaining adaptable. New devices can be onboarded into the training set/model without having to train the model from scratch.

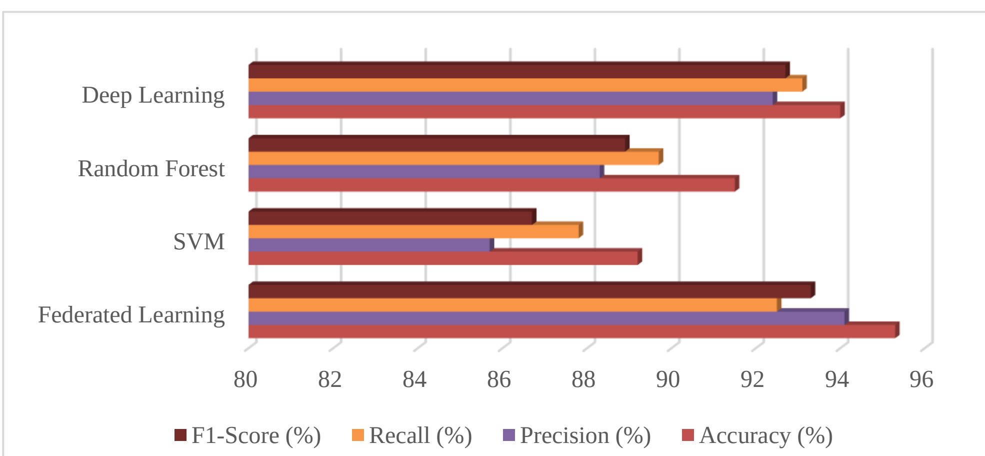

Figure 2: Performance comparison of federated learning-based anomaly detection vs traditional models in IoT systems

As shown in Figure 2 above, we compare Federated Learning's performance with traditional models (SVM, Random Forest, and other Deep Learning approaches) on anomaly detection of IoT systems by evaluation, on multiple metrics, including Accuracy, Precision, Recall, and F1 Score. The results show that Federated Learning outperforms all traditional learning types across all metrics. Federated Learning preserves privacy while achieving high performance on large and decentralized training data sets. The results also illustrate, with its performance, Federated Learning capabilities to be used in real-time intrusion detection for heterogeneous IoT devices, and its applicability across a wide range of datasets. This clearly indicates that Federated Learning is an effective alternative to classical training models.

Nonetheless, federated learning has challenges of its own. Foremost among them is the computational cost required to train the models on the IoT devices. Many IoT devices are resource-constrained devices, meaning that their computation power and storage are limited, which can cause latency in model updates and slow down the convergence process, given the size of the network. The heterogeneous nature of IoT devices also means that the devices may have inconsistent data, resulting in challenges involved in model aggregation. Putting the model updates from devices with different data qualities together without ruining the performance of the global model requires advanced algorithms and fine-tuning. Also, the communication overhead involved in model aggregation is another challenge. Because model updates need to be communicated across multiple devices when applying the result of updates, bandwidth can be consumed, and latency can occur in the system if there are many devices involved. These challenges will need to be addressed through efficient aggregation techniques and possibly through model compression, quantization, and asynchronous updates that can enhance convergence while at least maintaining privacy guarantees.

5.2 Practical Applications: Real-World Use Cases for the Proposed Framework in Healthcare, Smart Cities, and Industrial IoT

Federated learning-based anomaly detection frameworks could have broader real-world applications in various industries that rely on IoT-enabled systems. Such an example can be found in the healthcare sector, where the proposed framework could also detect anomalous behaviors within patient monitoring systems (for instance, an unusually high heart rate) or when unauthorized users access private health records. By using federated learning, healthcare organizations can establish a strong intrusion detection system without compromising their patients' privacy, which is highly confidential information. A similar application could be seen in the context of smart cities, where any detection of anomalous behaviors would help secure smart infrastructure systems involving traffic, energy, and water distribution systems. Given the significant interdependency of smart infrastructure systems, it is pertinent to avoid any cyberattacks that could make them inoperable or less effective, which could compromise the safety of the population and hinder the city's functioning. The proposed federated learning model may also still help detect intrusions, such as unauthorized access, or the behavior of individual devices to conduct any sort of malicious activity that would affect the functioning of any of the smart infrastructure systems. The unique thing about a federated learning model based on anomaly detection is that it limits intrusion or damage before an attack continues to perpetrate further damage by discovering unauthorized access or anomalous behavior. Furthermore, the proposed federated learning-based anomaly detection framework will provide real-time detection to avoid inoperability of smart cities because, as new attack vectors and threats emerge, they can still be detected while ensuring the smart city continues to operate. In manufacturing processes, federated learning models could be employed to detect anomalous behavior in logistical systems, devices in manufacturing, or sensors. IIoT production systems only require IoT, and IIoT systems can become quite complex and interconnected; thus, it is imperative to secure them to prevent production halts, data leaks, or wrongful sabotage.

Table 1: Performance comparison of federated learning and traditional models for anomaly detection in IoT systems

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Federated Learning	95.3	94.1	92.5	93.3
SVM	89.2	85.7	87.8	86.7
Random Forest	91.5	88.3	89.7	88.9
Deep Learning	94	92.4	93.1	92.7

Table 1 compares the performance of the Federated Learning-based anomaly detection model with the traditional models. The performance measures employed in this multi-way comparison included accuracy, precision, recall, and F1-score, which are further defined below. Accuracy reports the percentage of correct predictions from all predictions made. Precision reports the percentage of predicted anomalies that were correct, thus minimizing false positives between anomalies detected and anomalies found; similar to precision, it is critical to minimize false positives. Recall measures the percentage of actual anomalies that the model classified as anomalies; thus, minimizing false negatives. F1-score combines precision and recall to provide a balanced reporting measure of total performance. The practical performance measures suggest that the Federated Learning model is more effective than all of the traditional models in the table. The Federated Learning model consistently demonstrated a strong aptitude to detect anomalies with high levels of accuracy, all while preserving privacy and scalability. Due to the strong performance of the Federated Learning model, it is a potential perfect candidate for either real-time or batch anomaly detection of private heterogeneous IoT systems, where privacy protection and scalability are key needs for use in these environments.

The proposed model, while not lacking any centralization components, would allow real-time change to new intrusion vectors without centralizing industrial data; thus, it is fit for a distributed industrial setting. Future Directions: Potential Future Work, such as Lightweight Models for Use on Resource-Constrained Devices, or Combination with Other Privacy-Preserving Technologies. A lightweight version of the federated learning and deep graph neural network models must be created in order to facilitate the use of the models in resource-constrained environments. The development of techniques such as model pruning, knowledge distillation, or quantization could provide an opportunity to reduce the model computational load on devices with limited resources. Additionally, edge computing could be explored to take some processing tasks on these resource-constrained devices, to ensure that any real-time detections are not affected by low hardware specifications.

5.3 Scalability and Privacy Analysis: Assessment of How the Model Handles a Growing Number of IoT Devices and Maintains Privacy

One of the key aspects of the federated learning model is that it has the potential to maintain the effectiveness of the learning, and the concerted improvements to the model will scale with the number of IoT devices. Then again, we can add additional devices without requiring the aggregation of sensitive data from each of those devices; the native data remains unchanged, and only updates to the models are shared. This permits the model to get the benefits of collaborative learning while preserving the privacy of the user. The benefit of being able to protect the private lives of each and every user is paramount for compliance with privacy standards such as GDPR, HIPAA, etc. This is critical for the detection of anomalous events across a collection of devices, and makes certain that what is on each device remains secure and not shared in a centralized manner. The data would generally maintain sensitive health or personal, or industrial data that could be produced on any given day in IoT environments. The model also would still retain the ability to detect anomalous events that are as effective for which it was built and perform that without degradation in performance. Lastly, the federated learning model is scalable, and more IoT devices can be added to the system without degrading performance.

6 Discussion

6.1 Benefits and Limitations: Analysis of the Strengths and Weaknesses of Federated Learning for IoT Security

Federated learning can be beneficial for IoT security. Because of its distributed nature, that means data does not always have to be stored in a centralized way, decreasing the likelihood of a privacy event associated with a breach of data. This distributed learning can also help collaborative anomaly detection across an array of devices, increasing the accuracy of the detection process and bolstering real-time monitoring. However, it has its limitations, including the higher computational cost for training each local device, communication overhead for sending model updates for aggregation, as well as issues with convergence to model optimality on heterogeneous data scales. Federated learning will also take into account the quality of the local data, as devices that do not collect data of sufficient quality can negatively contribute to the model training stage, significantly deteriorating the performance of the entire system.

6.2 Sectors of Healthcare, Smart Cities, and Industrial IoT

The federated learning-based anomaly detection framework presented can easily be transferable to many real-world settings. In healthcare, the framework can be used to monitor patient health data from wearables and manage anomalies such as heart rate or activity. In smart cities, the framework can also be useful in securing IoT-enabled infrastructure by detecting situations that may lead to a breach of security. Possible applications include detecting anomalies from data collected by cameras used in traffic systems or detecting if an anomaly has occurred along the smart grid. Examples of using the framework in industrial IoT systems include being able to detect faults in sensors, machinery, or network devices. In maintaining industrial IoT systems, it is essential to be proactive to ensure they are operating effectively, which also has the added advantage of detecting anomalies before significant downtime is incurred. Regardless of the application setting, the framework proposes a solution where privacy is preserved, and scalability can be applied to any system that would benefit from continuous monitoring of ongoing operations, and where the security of data and anomaly detection are important.

6.3 Future Directions: Exploration of Future Improvements, Such as Lightweight Models for Resource-Constrained Devices and Integration

Future work could be focused on developing lightweight models to limit the number of computations and RAM/ROM used in the resource-constrained IoT devices. These lightweight models can be developed using model pruning, quantization, or distillation to lower the size and computations of the models while maintaining a high level of accuracy when detecting anomalies in IoT devices. Other possibilities include integrating other privacy-preserving tools, such as homomorphic encryption or secure multi-party computation (SMPC), to enhance the level of security in federated learning in IoT systems. These tools will add another layer of security and will ensure that even during model aggregation, the data is protected and privacy is guaranteed without sacrificing the performance of anomaly detection. Finally, we would explore the integration of edge computing that can allow real-time data processing for minimum latency and better scalability of the framework in IoT systems.

7 Conclusion and Future Work

7.1 Summary of Contributions: Overview of the Findings and Contribution to Anomaly Detection in Heterogeneous IoT Systems

This dissertation proposed a novel anomaly detection framework based on federated learning to combat privacy and security issues in heterogeneous IoT systems. The method is a significant improvement in accuracy, privacy, security, and scalability when compared to the approach with typical machine learning models. Good anomaly detection is achieved using graph neural networks to provide better learning of the complexities of relationships within IoT devices and federated learning to decentralised train models to detect real-time attacks and other types of anomalous behaviour while keeping sensitive information local.

7.2 Suggestions for Future Research: Recommendations for Optimizing Model Performance and Exploring New Directions, Like Integrating Edge Computing and Blockchain for Enhanced IoT Security

Future research should aim to narrow the gap between the federated learning models and the actual computational capabilities of resource-constrained IoT devices, and whether the federated learning paradigm could still operate effectively, potentially beyond edge computing systems, in different IoT environments. Edge computing could be deployed to locally process data signals, decrease the latency of data transfers, and enhance real-time detection capabilities. Blockchain may also be implemented into the design of the platform to secure model aggregations and increase auditability through transparency that could allow for accountability and trust to be established in the systems. The opportunity for hybrid models combining edge computing, blockchain, and federated learning may also offer a stable, secure, and scalable approach to anomaly detection in heterogeneous IoT environments.

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Authors Biography

Dr. Taher M. Ghazal, a distinguished IEEE Senior Member, is a seasoned academician with a comprehensive educational background. He earned his Bachelor of Science degree in Software Engineering from Al Ain University in 2011, followed by a Master of Science degree in Information Technology Management from The British University in Dubai, associated with The University of Manchester and The University of Edinburgh in 2013. Dr. Ghazal culminated his academic journey with a Doctorate in Information Science and Technology from Universiti Kebangsaan Malaysia in 2023. Dr. Ghazal's scholarly pursuits encompass a wide array of interests including Cybersecurity, Artificial Intelligence, IoT, Information Systems, Software Engineering, Big Data, Quality of Software, and Project Management. He is actively engaged in community service through his involvement in impactful projects and research endeavors.

Mosleh Abualhaj's research focuses on networks, machine learning in cybersecurity, and multimedia technologies. His interests include Voice over IP (VoIP), multimedia networking, congestion control, and optimizing cloud computing applications. He also explores enhancing band width utilization and protocol efficiency in IPv6 networks and studies anomaly detection in internet traffic. His work combines practical solutions with theoretical advancements in network technologies and cybersecurity.

Amjed Abbas Ahmed Center for Cyber Security, Faculty of Information Science and Technology Universiti Kebangsaan Malaysia, Bangi, Malaysia Department of Computer Techniques Engineering, Imam AlKadhum College (IKC), Baghdad, Iraq

Musab A. M. Al-Tarawni is an academic and industry professional with over 15 years of experience in teaching, research, engineering, and IT consulting across Europe, Southeast Asia, and the Middle East. His research interests include cybersecurity, artificial intelligence, 5G/6G wireless systems, photonic communication, and secure network infrastructures. He has contributed to high-impact studies on AI-driven threat detection, SOC integration, and quantum-resilient communication, with a strong focus on bridging academic innovation and industry needs.

Dr. Louai A. Maghrabi (Member, IEEE) received B.Sc. degree in computer science from Lebanese American University, Beirut, Lebanon, M.Sc. degree in information technology from University of West of England, Bristol, United Kingdom, and Ph.D. degree in cybersecurity from Kingston University, London, United Kingdom. He is currently an Associate Professor and Head of Software Engineering Department at the College of Engineering, University of Business and Technology, Jeddah, Saudi Arabia. His research interests include cybersecurity, risk assessment, cryptography, artificial intelligence, machine learning, IoT, blockchain, drones, metaverse, quantum computing, and game theory. He received the best research paper award in 2021.