FEDERATED LEARNING-BASED INTRUSION DETECTION SYSTEM FOR SECURING AUTONOMOUS VEHICLES

A PROJECT REPORT

Submitted by

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BONA FIDE CERTIFICATE

Certified that this project report titled **"Federated Learning-Based Intrusion Detection System For Securing Autonomous Vehicles"** is the bona fide work of **Dinesh Kumar V (2023246032)** who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The increasing reliance on autonomous vehicles, fueled by advancements in the Internet of Things (IoT), Artificial Intelligence (AI), and satellite communications, has raised critical cybersecurity concerns. Cyber attackers can exploit satellite links to compromise the security of self-driving vehicles. This project addresses these vulnerabilities by proposing a federated learning framework for an Intrusion Detection System (IDS) tailored to autonomous vehicles. Unlike traditional IDS that rely on centralized training, which poses risks of processing delays and privacy breaches, this approach facilitates local model training on individual vehicles using Simple Deep Neural Network(DNN).This allows for the rapid identification and classification of cyber threats using real-time data, significantly reducing detection time. The proposed federated learning method ensures that vehicles can respond promptly to threats while minimizing the need for centralized data storage and processing. Moreover, a mesh satellite network enhances privacy by enabling secure parameter exchanges among vehicles. Simulation results demonstrate that our federated learning-assisted distributed IDS effectively enhances the cybersecurity posture of autonomous vehicles, contributing to safer autonomous driving environments.

ABSTRACT TAMIL

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LIST OF ABBREVIATIONS

IDS	Intrusion Detection System
FL	Federated Learning
IoV	Internet of Vehicles
IIoT	Industrial Internet of Things
NSL-KDD	Network Security Laboratory - Knowledge Discovery and Data Mining Dataset
TON-IoT	Telecommunication Operational Network - Internet of Things Dataset
X-IIoTID	Extended Industrial Internet of Things Intrusion Dataset
ML	Machine Learning
DNN	Deep Neural Network
NS-3	Network Simulator 3
TFF	TensorFlow Federated
SGD	Stochastic Gradient Descent
F1-Score	Harmonic Mean of Precision and Recall
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
IoT	Internet of Things
DoS	Denial of Service
GAN	Generative Adversarial Network
API	Application Programming Interface
SSL	Secure Sockets Layer
TCP/IP	Transmission Control Protocol/Internet Protocol

CHAPTER 1

INTRODUCTION

The integration of autonomous vehicles into modern transportation systems has transformed mobility aspect but with significant cybersecurity risks. As these vehicles rely heavily on interconnected systems facilitated by the Internet of Things (IoT), they become vulnerable to cyberattacks that can exploit their communications, particularly via satellite links. The necessity for an effective Intrusion Detection System (IDS) to monitor and protect against these threats has never been more pressing. Federated Learning (FL) offers a revolutionary approach to developing robust IDS models specifically for autonomous vehicles. Unlike traditional centralized systems, where data is collected and processed at a single server, FL enables each vehicle to train its local model using its own data while sharing only model updates. This ensures that sensitive data remains on the vehicle, thereby enhancing privacy and security.

In a mesh satellite network configuration, vehicles can collaborate to improve the IDS collectively, with satellites facilitating secure communication and parameter sharing among vehicles. this proposed project utilizes a deep neural network to construct local models that can quickly identify and respond to cyber threats in real time. By minimizing the need for centralized data storage and processing, our federated learning-assisted distributed IDS significantly reduces detection time, improving overall vehicle performance. This project explores the implementation of this innovative approach, demonstrating its effectiveness in maintaining security and privacy within autonomous vehicle systems, while providing a pathway for future advancements in the realm of intelligent transportation systems.

1.1 Deep learning in IDS

Deep Learning is a subset of machine learning that uses neural networks with multiple layers to learn complex patterns and representations from data. It can automatically extract features from raw inputs, making it highly effective for tasks involving large and unstructured datasets. With the power of advanced architectures like Deep Neural Networks (DNNs), Deep Learning achieves state-of-the-art results in fields such as image recognition, natural language processing, and anomaly detection. The training process relies on optimizing weights to minimize errors and improve predictions, often requiring significant computational resources. Its applications span industries, including healthcare, autonomous vehicles, and cybersecurity, revolutionizing how problems are approached and solved.

In this project, Deep Neural Networks (DNNs) play a critical role in analyzing network traffic data to distinguish between normal and attack behaviors in autonomous vehicle systems. By leveraging their ability to automatically learn intricate patterns, DNNs enhance the detection of unusual activities that might indicate potential intrusions or cyberattacks targeting vehicle communication systems. This helps create a more accurate and adaptive intrusion detection system capable of handling large-scale and dynamic datasets. The integration of decentralized learning ensures privacy while enabling collaboration among multiple nodes for better model performance. Overall, DNNs significantly boost the efficiency and reliability of intrusion detection in autonomous vehicles, enhancing their security and safety in real-world scenarios.Federated Learning (FL) facilitates decentralized model training for intrusion detection in autonomous vehicles, ensuring privacy while enhancing the system's ability to detect attacks across distributed networks.

1.2 Federated Learning in IDs

Federated Learning (FL) is a decentralized machine learning approach that enables multiple devices to collaboratively train a shared model without sharing raw data. In this project, FL is employed to develop an Intrusion Detection System (IDS) for autonomous vehicles, where each vehicle trains a local model on its network traffic data and shares only model parameters, such as weights, with a central server for aggregation. This decentralized approach ensures data privacy by keeping sensitive data localized and significantly reduces the volume of data transferred, as only model updates are exchanged instead of raw datasets. The IDS classifies network traffic as either ‘Normal‘ or ‘Attack‘, offering a robust and scalable solution for intrusion detection in real-time. By minimizing the amount of data transferred, FL not only enhances privacy and security but also reduces bandwidth usage and communication costs, making it highly efficient for large, distributed systems. Additionally, the global model evolves iteratively with updates from diverse datasets, ensuring adaptability and resilience against emerging threats. These features make FL an ideal choice for securing autonomous vehicle networks in a decentralized environment.

1.3 Challenges of the Work

While implementing a Federated Learning-based Intrusion Detection System (IDS) for autonomous vehicles, several challenges may arise, including:

- **Data Heterogeneity:** Autonomous vehicles generate different types and volumes of data depending on their location, environment, and operational conditions. Federated Learning models must handle this variability, which can lead to challenges in aggregating updates from

different vehicles with non-identical data distributions. Ensuring that the global model performs well across these varying data sources is critical.

- **Communication and Bandwidth Constraints:** Although federated learning minimizes the need for raw data transfer, frequent communication of model updates can still strain the system's bandwidth. In satellite networks, bandwidth and connectivity can be limited, particularly in remote or high-latency environments, affecting the timeliness and efficiency of model training and updates.
- **Privacy and Security Concerns:** Even though Federated Learning ensures that raw data remains local, security of the model updates and communication channels remains a challenge. Attackers could exploit vulnerabilities in the model update process or during communication to compromise the privacy of vehicle data or the integrity of the model itself.
- **Scalability and Synchronization:** As the number of vehicles and other participating nodes increases, managing the coordination and synchronization of model updates across all participants can become challenging. Federated Learning systems must ensure that updates from all participants are consistently integrated, and the global model remains stable and accurate.
- **Adapting to Evolving Threats:** Cyber-attacks are constantly evolving, and traditional IDS methods may struggle to keep up with new and sophisticated attack vectors. The federated learning model must be adaptive, requiring continuous updates and fine-tuning to ensure the IDS remains effective in detecting novel attack patterns.
- **Model Interpretability:** Deep learning models, especially in the context of IDS, are often seen as "black boxes," making it difficult

to interpret how they arrive at specific decisions. This lack of transparency can hinder trust in the system and complicate the process of debugging or improving the model.

1.4 Proposed Solutions

To address the challenges in implementing a Federated Learning-based Intrusion Detection System (IDS) for autonomous vehicles, the following solutions are proposed:

- **Handling Data Heterogeneity:** In autonomous vehicles, the data generated can vary significantly depending on environmental factors and operational conditions. To manage this heterogeneity, a *personalized federated learning* approach will be used, where local models can adapt to the specific data distributions of each vehicle. This ensures that each vehicle's model is effective in detecting cyber threats within its unique operational environment.
- **Minimizing Communication Overhead:** Due to the limited bandwidth in satellite networks, communication efficiency is critical. To reduce communication costs, *model compression* techniques such as quantization and pruning will be implemented to minimize the size of the updates shared between vehicles and the central server. Additionally, *asynchronous federated learning* will allow each vehicle to perform updates independently, reducing the need for constant communication and improving efficiency.
- **Ensuring Privacy and Security:** To protect the privacy of vehicle data during federated learning, *secure aggregation* techniques will be used to ensure that model updates are aggregated without revealing

individual updates. Furthermore, *homomorphic encryption* will be employed to secure the transmission of model updates, safeguarding the privacy of sensitive vehicle data from potential eavesdropping or tampering.

- **Achieving Scalability and Synchronization:** As the number of vehicles increases, the system must efficiently handle a large number of updates. *Federated optimization algorithms* like FedAvg will be used to ensure that model updates from all vehicles are aggregated efficiently. Additionally, techniques such as *staleness control* will be implemented to ensure synchronization, even in cases where updates are not perfectly aligned across all vehicles.

- **Adapting to Evolving Cyber Threats:** Cyber threats are constantly evolving, and the system must be able to adapt accordingly. To address this, the IDS will incorporate *online learning*, allowing it to update and improve continuously as new threat data is introduced. This will enable the system to detect emerging threats and adapt to new attack patterns in real time.

- **Improving Model Interpretability:** To enhance trust in the IDS's decision-making process, methods will be employed to provide clear explanations of how the system classifies network traffic as 'Normal' or 'Attack'. This will ensure transparency, allowing vehicle operators and security personnel to understand the reasoning behind the detection of potential intrusions in autonomous vehicle systems while maintaining privacy and security.

1.5 Organization of The Report

This report is organized into 6 chapters, describing each part of the project with detailed illustrations and system design diagrams.

CHAPTER 2: Literature Review reviews existing research, studies, and relevant literature related to Autonomous Driving. It discusses the background, theories, and methodologies used by other researchers.

CHAPTER 3: System Design describes the design of the project. It explains the architecture, components, algorithms, and any other technical details.

CHAPTER 4: Implementation provides details about how the project was implemented. It discusses the tools, technologies, programming languages, and frameworks used.

CHAPTER 5: Result and Analysis presents the results of the project. It analyzes the outcomes, compares them with expectations, and discusses any challenges faced during implementation.

CHAPTER 6: Conclusion and Future Work summarizes the findings and draws conclusions. It discusses the significance of your work and its implications.

CHAPTER 2

LITERATURE SURVEY

This chapter explains various approaches in securing autonomous vehicles using Intrusion Detection Systems (IDS) with federated learning (FL), highlighting solutions such as edge computing integration and client-server architectures, while addressing challenges like centralized bottlenecks and privacy concerns.

2.1 Existing System

Existing intrusion detection systems (IDS) in autonomous vehicles often rely on centralized models or traditional machine learning approaches, which struggle with scalability and real-time detection. Federated learning (FL) has emerged as a solution for decentralized, privacy-preserving detection, but current systems still face challenges in handling dynamic and large-scale vehicular networks. This project aims to enhance these systems by utilizing federated learning for real-time, collaborative intrusion detection across autonomous vehicle networks using mesh satellite communication.

2.1.1 Deep Learning for Intrusion Detection

Deep learning models, particularly Deep Neural Networks (DNN), have gained significant traction in cybersecurity applications, including intrusion detection in autonomous vehicle networks. A review titled *"Deep learning algorithms for cybersecurity applications:[1] A technological and status review"* presents a two-stage intrusion detection system designed for

intelligent transportation systems using rule extraction methods from deep neural networks. The system emphasizes adaptability in dynamic environments. However, the reliance on rule extraction methods could result in limitations in handling complex, non-linear patterns in data, which are typical in real-time autonomous vehicle environments. Additionally, it lacks scalability in highly dynamic or large-scale scenarios. The review underscores the importance of deep learning for adaptable and efficient intrusion detection systems, which aligns with your project's focus on enhancing security for autonomous vehicles through federated learning and mesh satellite communications. Insights from this work can inform the development of more sophisticated DNN models for your framework.

2.1.2 Federated Learning for Intrusion Detection

Federated Learning (FL) offers a decentralized approach to intrusion detection, where models are trained collaboratively without sharing sensitive data, ensuring privacy and security. One paper, *"Blockchain and federated learning for collaborative intrusion detection in vehicular edge computing"*[2], proposes a federated learning (FL) model distributed across vehicular edges and base stations to detect attacks in real-time without compromising user privacy. The model demonstrated improved attack detection rates and reduced false positives in autonomous vehicle protection. However, the proposed system does not fully explore scalability issues in large-scale vehicular networks. The integration of blockchain adds complexity and may increase latency in real-time attack detection. This paper directly informs your project's focus on using federated learning to decentralize intrusion detection systems, reducing reliance on centralized data aggregation. It aligns with the concept of improving attack detection rates while maintaining user privacy, which is essential for autonomous vehicle protection.

"Federated AI-enabled in-vehicle network intrusion detection for Internet of Vehicles"[3], integrates a ConvLSTM algorithm within a client-server federated learning architecture for intrusion detection in the Internet of Vehicles (IoV), optimizing real-time attack detection. The reliance on a centralized server introduces security risks, potential bottlenecks, and scalability issues. As the number of connected vehicles increases, the system may become inefficient or unreliable. The integration of ConvLSTM for real-time attack detection can inform the development of intrusion detection models in your federated learning-based system. However, the limitations regarding centralization point to the need for a fully decentralized system in your project to ensure scalability and security.

"When federated learning meets game theory: A cooperative framework to secure IIoT applications on edge computing" [4]combines federated learning and game theory to secure Internet of Things (IoT) applications, providing dynamic responses to detected attacks through resource allocation strategies. However, the approach needs further exploration in real-time autonomous vehicle systems, as its game-theoretical framework might introduce complexity and delay when adaptive responses are required in highly dynamic environments. The combination of federated learning and game theory offers an innovative method for adaptive threat detection in autonomous vehicles, which could be integrated into your federated learning framework to enhance dynamic attack detection responses, making the system more resilient and flexible.

"Asynchronous peer-to-peer federated capability-based targeted ransomware detection model for Industrial IoT"[5], explores an asynchronous peer-to-peer federated learning model for ransomware detection in Industrial IoT (IIoT). It allows decentralized learning while maintaining data privacy and security. However, while asynchronous federated learning enhances

privacy and scalability, it may face challenges in ensuring consistency and synchronization of models across distributed nodes, leading to potential performance degradation. This approach of asynchronous peer-to-peer federated learning is highly relevant to your project's use of mesh satellite networks, as it can address scalability and real-time attack detection challenges. Implementing such models can improve the resilience and efficiency of your intrusion detection system.

2.1.3 Intrusion Detection Systems for Autonomous Vehicles

Hybrid approaches combining federated learning with other techniques have shown promise in the development of more resilient intrusion detection systems for autonomous vehicles. One study, *"Research on satellite network security mechanism based on blockchain technology"*[6], developed a distributed IDS using federated learning and convolutional neural networks (CNNs) for satellite-terrestrial integrated networks, which is particularly relevant for autonomous vehicles relying on satellite communications. The integration of CNNs with federated learning in a satellite-terrestrial network faces challenges in real-time data transmission and processing due to high latency and bandwidth limitations. However, the use of CNNs within a federated learning framework for real-time detection is highly relevant, particularly for your use of mesh satellite networks. Insights from this work can guide the integration of CNNs for feature extraction in your intrusion detection system to improve detection accuracy.

"Edge-consensus learning: Deep learning on P2P networks with nonhomogeneous data"[7] explores edge-consensus learning in peer-to-peer (P2P) networks, where consensus mechanisms improve the robustness and reliability of distributed systems, a key challenge for intrusion detection in autonomous vehicles. While P2P networks mitigate the risk of bottlenecks

and single points of failure, they may face challenges in achieving consensus efficiently, especially with non-homogeneous data and high-dimensional datasets. This research directly applies to your federated learning system, especially given your use of decentralized satellite networks. Consensus learning mechanisms can be integrated to enhance the robustness and reliability of the intrusion detection system in your project, ensuring more accurate and resilient threat detection.

"COLIDE: A collaborative intrusion detection framework for Internet of Things"[8] correlates events from multiple intrusion detection systems deployed at edge nodes to enhance detection accuracy in IoT environments, though it suffers from centralization issues. The reliance on a central server for event correlation introduces vulnerabilities like single-point failures, which compromise the security of the network. This work highlights the importance of decentralized intrusion detection systems, aligning with your project's goal of using federated learning for distributed attack detection without relying on centralized systems. It underscores the need for decentralized models to improve resilience and security in autonomous vehicle networks.

The *"Paradise: Real-time, generalized, and distributed provenance-based intrusion detection"* [9]system introduces a real-time, distributed IDS based on provenance graphs to analyze event dependencies. However, it still relies on a central server for event correlation, which introduces risks like single-point failures and latency issues in dynamic environments like autonomous vehicles. This study emphasizes the need for a decentralized approach, which is central to your federated learning model for autonomous vehicle protection. The use of provenance graphs could be an additional feature in your framework for improved attack detection.

"Adaptive intrusion detection in edge computing using cerebellar model articulation controller and spline fit"[10] proposes the CMACIDS model, utilizing reinforcement learning combined with B-spline fitting to enhance adaptability in edge computing environments. While promising in its adaptability, the real-world applicability of CMACIDS in autonomous vehicle environments, particularly at high speeds, remains underexplored. This approach introduces reinforcement learning techniques for adaptive intrusion detection, which could be incorporated into your federated learning model to improve the responsiveness and effectiveness of your intrusion detection system, especially in dynamic, high-speed environments.

2.1.4 Localization Techniques

Vehicle navigator using a mixture particle filter for inertial sensors/odometer/map data/GPS integration[11] explores the integration of GPS, odometer readings, and map data using a mixture particle filter for robust vehicle navigation. While this approach improves accuracy in localization, limitations include its dependency on high-quality map data and sensitivity to sensor noise. Future work may involve leveraging machine learning techniques to enhance adaptability in diverse environments and incorporating real-time data

for dynamic updates.

A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications [12]provides a comprehensive review of localization methods such as SLAM and GPS-based solutions tailored for autonomous vehicles. Despite the depth of coverage, the paper lacks practical validation on diverse terrains. Future research can focus on hybrid localization approaches that combine multiple methods to address varying operational scenarios.

2.1.5 Autonomous Vehicles

A review on autonomous vehicles: Progress, methods, and challenges [13]outlines advancements in autonomous driving technologies, including sensors, control algorithms, and decision-making frameworks. It identifies key challenges such as computational complexity and regulatory hurdles. The paper suggests future work in improving real-time processing and establishing standardized safety protocols.

Tempting the fate of the furious: Cyber security and autonomous cars [14]investigates the cyber-security vulnerabilities of autonomous vehicles, emphasizing the need for robust encryption and intrusion detection systems. A limitation of the study is its focus on theoretical attack vectors without substantial experimental validation. Future research should prioritize the development and testing of proactive defense mechanisms in simulated and real-world scenarios.

2.1.6 Cybersecurity in self-driving cars

Cyber security challenges in self-driving cars[15] highlights threats to autonomous vehicle networks, including signal spoofing and data breaches. It proposes generic countermeasures but lacks specificity in deployment strategies. Future efforts could involve designing tailored cybersecurity frameworks that address unique vehicle-to-vehicle communication needs.

Federated learning-based IDS approach for the IoV[16] proposes a federated intrusion detection system leveraging distributed learning to protect IoV networks. While the system reduces data sharing concerns, it struggles with scalability and computational overhead. Future work may include optimizing model aggregation techniques and exploring lightweight architectures for resource-constrained environments.

2.1.7 Intrusion Detection System

X-IIoTID: A connectivity-agnostic and device-agnostic intrusion dataset for Industrial Internet of Things[17] introduces a dataset designed for evaluating intrusion detection systems in IoT environments. Despite its broad applicability, the dataset lacks representation of emerging IoT device types. Future work should focus on expanding the dataset to include diverse attack scenarios and updating it periodically to reflect evolving threats.

Netflow datasets for machine learning-based network intrusion detection systems[18] reviews Netflow-based datasets for network intrusion detection, highlighting their role in training and validating machine learning models. However, the datasets often suffer from class imbalance issues. Future research can work on generating synthetic data to balance the classes and improve model robustness.

FL-MGVN: Federated learning for anomaly detection using mixed Gaussian variational self-encoding network[19] combines federated learning with advanced anomaly detection techniques to enhance security in IoT environments. While the approach shows promise, its computational complexity remains a challenge. Future studies should explore methods to reduce the model's training time and energy consumption while maintaining performance.

LCCDE: A decision-based ensemble framework for intrusion detection in the Internet of Vehicles[20] presents an ensemble learning framework for detecting intrusions in IoV. The framework achieves high accuracy but is limited by its reliance on static decision thresholds. Future work could focus on adaptive thresholds that respond to real-time network dynamics and reduce false positives.

2.2 Summary of existing system

Recent studies on intrusion detection in autonomous vehicles have highlighted the potential of federated learning (FL) to address privacy concerns and enhance real-time attack detection. A paper on *"Blockchain and federated learning for collaborative intrusion detection in vehicular edge computing"* demonstrates how FL can improve attack detection rates in autonomous vehicle networks while ensuring privacy through decentralized model training. However, scalability issues in large-scale vehicular networks remain a challenge. The integration of FL with Convolutional Neural Networks (CNNs) for feature extraction, as seen in *"Research on satellite network security mechanism based on blockchain technology"*, aligns with your project's goal of using mesh satellite networks for communication. This approach enhances feature extraction accuracy while addressing the challenges of high latency and limited bandwidth in satellite communication. Additionally, the use of asynchronous FL models, as explored in *"Asynchronous peer-to-peer federated*

capability-based targeted ransomware detection model for Industrial IoT", is particularly relevant for your system's scalability and real-time attack detection. By adopting these approaches, your project aims to implement a federated learning-based IDS that is resilient, scalable, and capable of detecting attacks in dynamic autonomous vehicle environments, leveraging satellite networks to overcome connectivity challenges and ensure privacy.

2.3 Objectives

- Develop a Federated Learning-Based Intrusion Detection System (IDS)
- Integrate Mesh Satellite Networks for Communication .
- Optimize Feature Extraction for Intrusion Detection
- Implement Asynchronous Federated Learning
- Improve Attack Detection Accuracy
- Evaluate the Scalability and Latency of the IDS.
- Ensure Privacy and Security in Federated Learning
- Optimize System Resource Usage on Autonomous Vehicles

The surveyed literature emphasizes enhancing intrusion detection in autonomous vehicles through federated learning and hybrid models, addressing challenges like centralization and scalability. Integrating techniques such as ConvLSTM, game theory, and edge-consensus learning shows promise for developing a decentralized, scalable framework. This project aims to enhance attack detection, privacy preservation, and real-time adaptability using federated learning and mesh satellite networks, improving security and efficiency in autonomous vehicle systems.

CHAPTER 3

SYSTEM DESIGN

The system design implements a federated learning-based intrusion detection system (IDS) for autonomous vehicles using mesh satellite networks for decentralized, real-time threat detection. It leverages deep neural networks (DNNs) to detect intrusions while ensuring data privacy by sharing only model parameters.The federated learning framework aggregates model updates from edge nodes, creating a global model for scalable and efficient intrusion detection.

3.1 System Architecture Description

The system architecture consists of autonomous vehicles equipped with edge nodes communicating through mesh satellite networks. Each vehicle locally trains an intrusion detection model using federated learning, sharing only model updates to preserve data privacy. The aggregated model is then updated globally to enhance threat detection across the vehicle network in real-time.

3.1.1 Data Collection and Preprocessing

The system receives data from three different datasets: TON-IOT, NSL-KDD, and X-IIOTID. Each dataset undergoes a preprocessing phase, which includes data cleaning, handling missing values, and transforming the data into a suitable format for further processing.

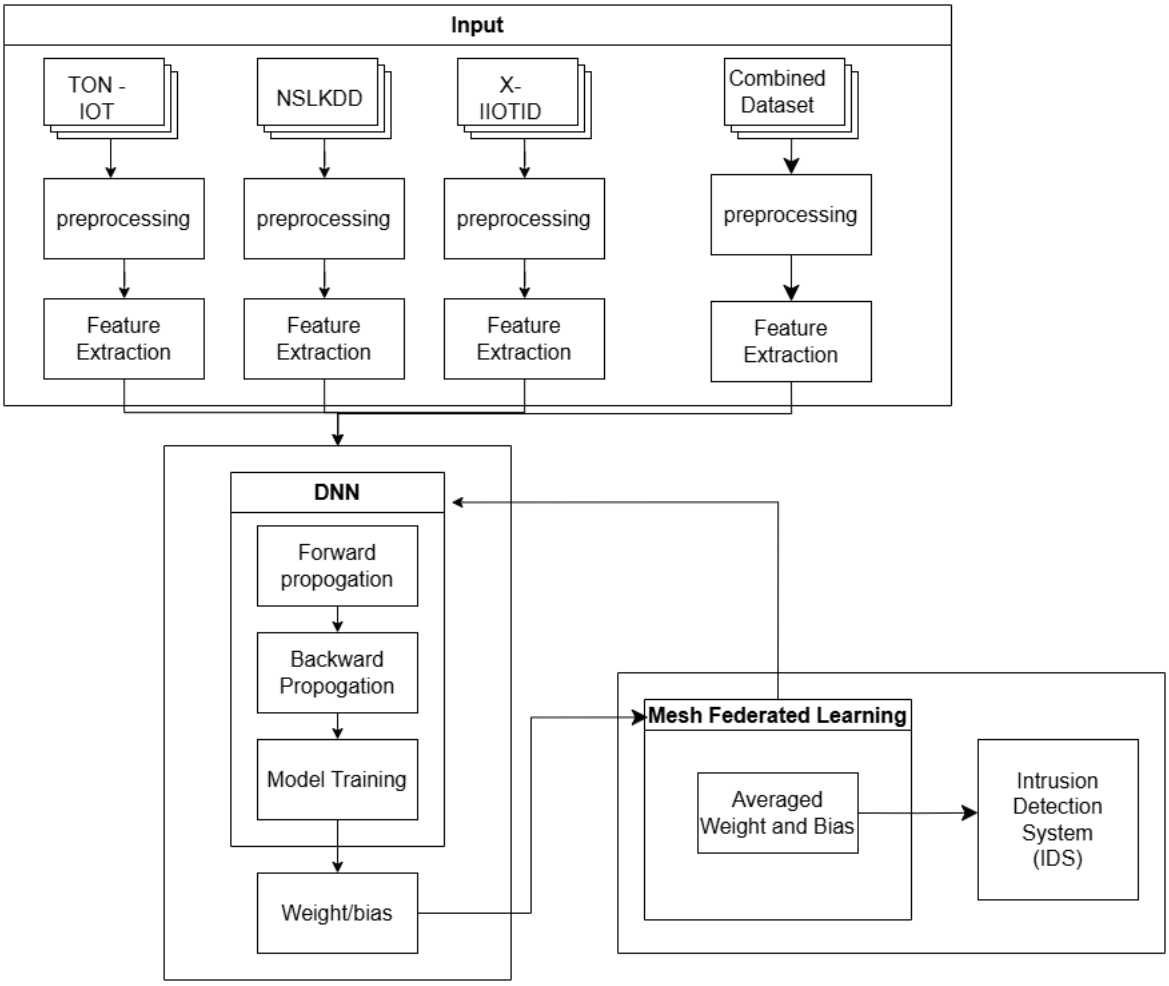

Figure 3.1: Intrusion Detection System

3.1.2 Dataset Description

From 3.1 the datasets used in this experiment are X-IIoTID, TON-IoT, and NSL-KDD, representing modern network traffic and system activities, including autonomous vehicle scenarios.

- **X-IIoTID Dataset:** Contains 421,400 normal data records and 399,417 attack records, covering various new and critical attacks and contain network data's.

- **TON-IoT Dataset:** Includes 300,000 normal traffic records and 161,044 attack records , contain IOT data's like Autonomous Vehicle(AV)
- **NSL-KDD Dataset:** Comprises 77,054 normal records and 71,460 attack records, contain benchmark data's.

3.1.3 Dataset Attributes

The dataset comprises network traffic features including *Src_port*, *Dest_port*, *Protocol*, *Service*, *Src_bytes*, *Dest_bytes*, *Conn_state*, *anomaly_alert*, and *class3*. These attributes collectively represent communication patterns, data transfer metrics, and connection states, essential for detecting anomalies and classifying traffic as normal or attack.

3.1.4 Feature Extraction

After preprocessing, feature extraction is performed on the data to identify the most relevant features for intrusion detection. This process helps to reduce the complexity of the model by focusing on important characteristics of the data, such as traffic patterns, ports, protocols, and more.

3.1.5 Local Model Training (DNN)

Each dataset is trained independently on a Deep Neural Network (DNN) model. The DNN model learns to classify the data into normal and attack categories. The weights and biases of each DNN model are updated locally and stored. This helps maintain data privacy, as data never leaves the local nodes.

3.1.6 Federated Learning

The federated learning algorithm integrates the models trained on each node (i.e., for each dataset). Instead of sharing raw data, only the weights and biases of the local models are shared with a central server or aggregator. The federated learning algorithm aggregates the weights and biases from all participating nodes to form a global model.

3.1.7 Global Model of Intrusion Detection System(IDS)

The aggregated weights and biases from the federated learning process are combined into the overall model, which is then fine-tuned to improve performance. The final model produced by federated learning is robust and effective, capable of detecting intrusions across a variety of IoT-based networks, such as autonomous vehicles.The final model is the result of the federated learning process and is capable of making accurate predictions on new, unseen data, detecting potential intrusions while maintaining data privacy and decentralization.

3.2 Modules

This project covers several key modules that are integral to the development and implementation of a Federated Learning-based Intrusion Detection System (IDS) for autonomous vehicles:

- **Data Preprocessing:** This module handles the preprocessing of raw data collected from vehicles, including network traffic data. It involves cleaning the data, handling missing values, and extracting relevant features to feed into the IDS model. The module also

normalizes the data and converts it into a suitable format for deep learning models.

- **DNN Model Training and Evaluation:** This module is responsible for training the deep neural network on local datasets using federated learning. It includes model training, hyperparameter tuning, and validation. After training, the model's performance is evaluated using metrics like accuracy, precision, recall, and F1 score to ensure that it can effectively detect cyber threats in real time.

- **Federated Learning Module:** This module implements the core federated learning framework that allows multiple vehicles to collaboratively train a shared model while keeping their data local. It involves setting up a server to aggregate model updates and ensuring secure communication between the vehicles and the central server. Techniques such as *federated averaging* are employed to update the global model.

- **Intrusion Detection System (IDS):** The IDS module focuses on detecting cyber threats in real time using deep learning techniques. It uses a Deep Neural Network (DNN) to classify network traffic data and identify attacks such as DoS, port scans, and unauthorized access attempts. The model is trained on network traffic data gathered from various autonomous vehicles in the fleet.

3.3 Tools and Libraries

This section highlights the specific tools and libraries utilized in the development and implementation of the federated learning-based intrusion detection system (IDS) for the project.

3.3.1 Programming Languages and Development Tools

- **Python:** Used as the primary programming language for implementing the federated learning models and preprocessing the intrusion detection dataset.
- **VS Code:** Integrated Development Environment (IDE) used for code development and debugging.

3.3.2 Libraries for Data Processing and Analysis

- **NumPy:** Handles numerical operations and data manipulation.
- **Pandas:** Processes and organizes the intrusion detection datasets for analysis.
- **Matplotlib/Seaborn:** Visualizes data distributions, model performance, and communication patterns in federated learning.

3.3.3 Libraries for Deep Learning

- **TensorFlow/Keras:** Used for creating and training deep neural network models for intrusion detection.
- **PyTorch:** Alternative framework used for implementing and experimenting with deep learning models.
- **scikit-learn:** Provides tools for feature selection, preprocessing, and evaluation metrics such as accuracy and F1-score.

3.3.4 Libraries for Federated Learning

- **TensorFlow Federated (TFF):** A specialized library for simulating and implementing federated learning models.

The system design focuses on creating a decentralized and scalable intrusion detection framework tailored for autonomous vehicles. By integrating federated learning with mesh satellite networks, the design ensures privacy preservation and real-time adaptability. Advanced techniques such as edge-consensus learning and hybrid modeling enhance detection accuracy and system efficiency. This robust design aims to address existing challenges in scalability, centralization, and real-time applicability, paving the way for a secure and efficient autonomous vehicle ecosystem.

CHAPTER 4

IMPLEMENTATION

This chapter describes the detailed implementation of the system for intrusion detection system, focusing on the data preparation, feature enhancement, and model training.

4.1 Data Preparation

Preprocessing is critical to ensure clean and structured input data for the model

- Feature selection : Key features like Srcport, Desport, Protocol, Service, Srcbytes, Desbytes, and Connstate are selected.Features irrelevant to intrusion detection (e.g., timestamps or packet IDs) are discarded.
- Encoding Categorical Data: Protocols (e.g., TCP, UDP) and connection states (e.g., ESTABLISHED, CLOSED) are one-hot encoded.
- Normalization: Numerical features like Srcbytes and Desbytes are scaled to a range of [0,1] using Min-Max scaling.
- Handling Missing Values: Missing values (NaN) are replaced with 0 to avoid computational errors.

4.2 DNN Learning

A Deep Neural Network (DNN) is a type of artificial neural network with multiple layers between the input and output layers. In the proposed Federated Learning-Assisted Intrusion Detection System (IDS) for autonomous vehicles, the DNN is utilized to process and analyze network traffic data collected from X-IIoTID, TON-IoT, and NSL-KDD datasets. Its capability to handle complex, high-dimensional datasets and extract meaningful patterns makes it an ideal choice for identifying normal and attack

Algorithm 4.1 DNN Learning

Inputs: Initial DNN parameters
Output: Trained DNN
Algorithm:
for epoch $\in$ Epoch_max **do**
  Call Model.train()
for $i, D_i \in$ training_data **do**
    Calculate optimizer.zero_grad()
    Calculate output = Model(input)
    Calculate $L_i(w)$ using Equation (10)
    Calculate optimizer.zero_grad()
    Calculate Model.backward()
    Calculate Optimizer.step()
    Calculate Optimizer.update()
end for

- Weight and Bias : Collecting array of Weight and Bias from each model.
- Update Model: Using collected weight and Bias update global.

4.3 Model Training

In algorithm 4.1The Deep Neural Network (DNN) training algorithm involves multiple steps, with each step contributing to the model's learning process. The process begins with initializing the DNN parameters, which is typically handled by the model developer. The training process is conducted for a defined number of epochs, with the training manager overseeing the overall process. The data engineer ensures the dataset is prepared and fed into the model in batches. For each batch, the model performs a forward pass, where it calculates predictions based on the input data.

Algorithm 4.2 Mesh Federated Learning

Inputs: Initial model parameters (e.g., i, Di, Wi, m, Ai—j,)
Output: Global model
Algorithm
for $k \leq K-1$ **do**
Update parameters for each node i
for $i \in m$ **do**
Calculate w_i^{k+1} using Equation (5)
Calculate $\inf_{w_i|i\in V} \sum_{i\in V} q_i^k(W_i) + \sum_{j\in M(i)} \frac{\rho}{2} \left\| A_{i|j} w_i + A_{j|i} w_j^k \right\|^2$
end for
for $i \in m$ **do**
Select randomly $j \in M(i)$
Pull $(w_j^{k+1}, y_{j|i}^{k+1})$ from j
Calculate $z_{i|j}^{k+1} = \theta y_{j|i}^k + (1-\theta) z_{i|j}^k$
end for

4.4 Mesh Federated Learning Algorithm

In 4.2 the Mesh Federated Learning algorithm for the proposed Intrusion Detection System (IDS) begins by initializing key parameters, such as model weights, network topology, and communication parameters across low Earth orbit (LEO) satellite nodes. The training process progresses over multiple iterations, with updates computed using an equation that integrates the previous weights and the local datasets distributed across the nodes.

In each iteration, the algorithm calculates the global objective by aggregating the contributions from local models and their communication with neighboring satellite nodes. Specifically, it minimizes a cost function that includes terms representing the local data distribution and the interactions between nodes. The gradient descent step is applied to update the local model, incorporating both the local data and shared knowledge from neighboring nodes.

Following each update, a node randomly selects a neighboring node j from its set of neighbors $M(i)$. The selected node j shares its updated model parameters and auxiliary information. These parameters are then integrated into the local model with a weighting factor θ to control the contribution of the incoming data.

This iterative process continues for multiple epochs, enabling nodes to collaboratively refine their local models and achieve convergence on a robust global model. By leveraging decentralized communication across mesh satellite networks, the federated learning framework ensures efficient intrusion detection for autonomous vehicle networks. The final global model is a comprehensive aggregation of insights from all participating nodes, optimized for detecting intrusions in real time while maintaining data privacy.

CHAPTER 5

RESULT AND DISCUSSION

This section presents the evaluation of the Mesh Federated Learning-Assisted Intrusion Detection System (IDS) for autonomous vehicle networks, highlighting its performance across various metrics. The results are discussed in relation to model effectiveness, challenges, and potential improvements for enhanced intrusion detection and system scalability.

5.1 Model Performance

In this project, several models were trained using different datasets to evaluate their performance in the context of intrusion detection. The models were evaluated based on various metrics such as accuracy, precision, recall, and F1-score.

Table 5.1 summarizes the performance of the Deep Neural Network (DNN) models trained on different datasets for intrusion detection.

Datasets	Accuracy	Precision	Recall	F1-Score
X-IIoTID	96.22	99.10	92.14	95.49
TON-IoT	94.56	94.37	96.83	95.58
NSL-KDD	92.70	94.00	90.62	92.28
COMBINED DATASET	94.36	99.80	91.75	95.61

Table 5.1: Performance Comparison of DNN Models for Intrusion Detection

From the table 5.1, it is observed that Model 4, trained on a non-IID combination of the X-IIoTID, TON-IoT, and NSL-KDD datasets, outperforms the other models in terms of accuracy, precision, recall, and F1-score. This

demonstrates that utilizing diverse datasets in a non-IID distribution enhances the model's ability to generalize and effectively detect various types of intrusions in autonomous vehicle networks.

5.2 Performance Analysis of DNN Models

From the table 5.1 the performance analysis of each model include Accuracy , Precision , Recall , F1 score

- **X-IIoTID** achieved the highest accuracy and precision, indicating its strong ability to correctly classify both normal and attack samples. However, its recall was slightly lower, suggesting some missed attack detections.
- **TON-IoT** demonstrated superior recall, showcasing its effectiveness in detecting attacks. This can be attributed to the balanced distribution of attack samples in the TON-IoT dataset.
- **NSL-KDD** exhibited a slightly lower recall, indicating challenges in identifying certain attack types. This might be due to the limited diversity of attack samples in the NSL-KDD dataset.
- **COMBINED DATASET** displayed a well-rounded performance, with high precision and F1-score, leveraging the strengths of diverse datasets to improve classification accuracy.

The results highlight the importance of dataset characteristics, such as volume, diversity, and balance of attack samples, in influencing the performance of intrusion detection models.

5.3 Confusion matrix

The first confusion matrix (Figure 5.1) illustrates the performance of a classification model. The model correctly classified 66,983 instances as Class 0 and 47,814 instances as Class 1. However, 432 instances of Class 0 were misclassified as Class 1, and 4,080 instances of Class 1 were misclassified as Class 0. This demonstrates that the model performed well in distinguishing between the two classes, with a relatively small number of misclassifications.

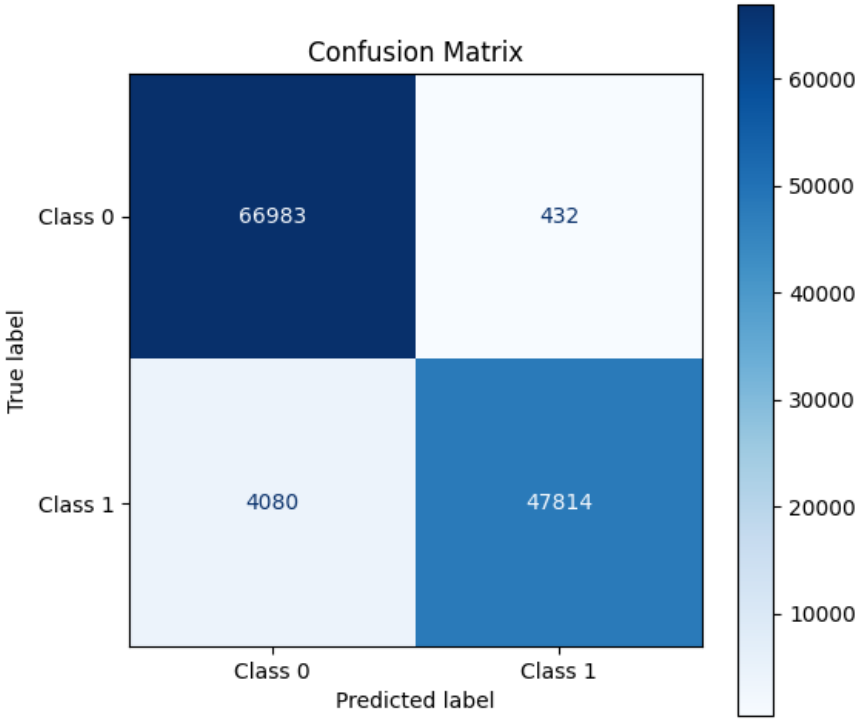

Figure 5.1: Confusion Matrix of X-IIoTID Dataset

The second confusion matrix (Figure 5.4) provides insights into a binary classification scenario, where the labels are ”Normal” and ”Attack.” The model accurately identified 9,707 instances as ”Normal” and 15,997 instances as ”Attack.” However, 955 ”Normal” instances were incorrectly classified as ”Attack,” and 524 ”Attack” instances were misclassified as ”Normal.” These results indicate strong performance, though there is room for improvement in minimizing misclassifications.

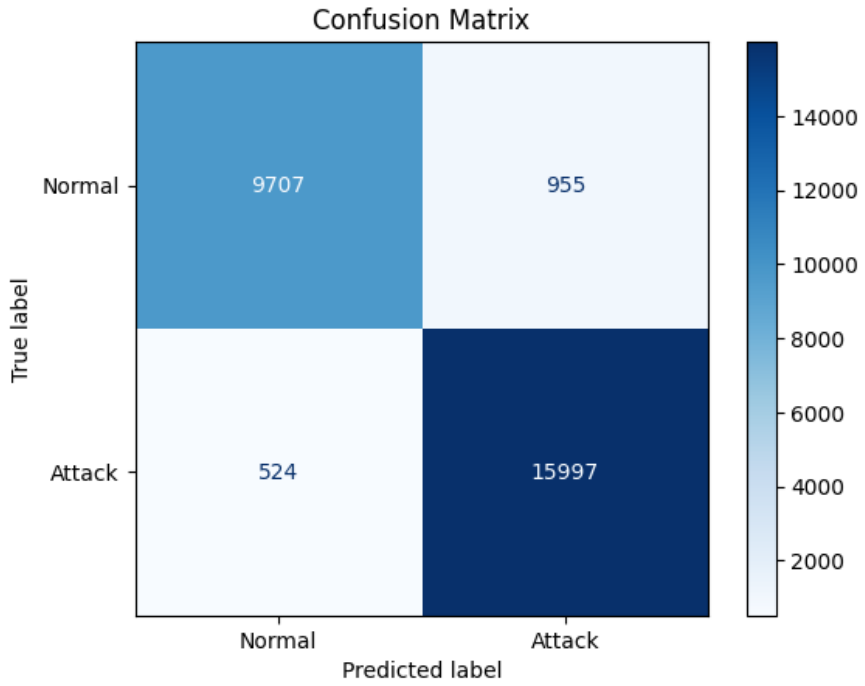

Figure 5.2: Confusion Matrix of TON-IoT Dataset

The third confusion matrix (Figure 5.3) also evaluates a binary classification task. The model successfully classified 14,585 instances as ”Normal” and 12,952 instances as ”Attack.” However, 826 ”Normal” instances were misclassified as ”Attack,” and 1,341 ”Attack” instances were incorrectly predicted as ”Normal.” While the model demonstrates good classification performance overall, there is a noticeable imbalance in the misclassification rates that may require further investigation or optimization.

The confusion matrix (Figure 5.4) depicts the performance of a binary classification model. The model correctly classified 21,325 instances as *Normal* and 39,765 instances as *Attack*. However, 78 instances of *Normal* were misclassified as *Attack*, and 3,574 instances of *Attack* were misclassified as *Normal*.

This highlights that the model effectively distinguishes between the two classes, with a high number of correct classifications and a relatively low

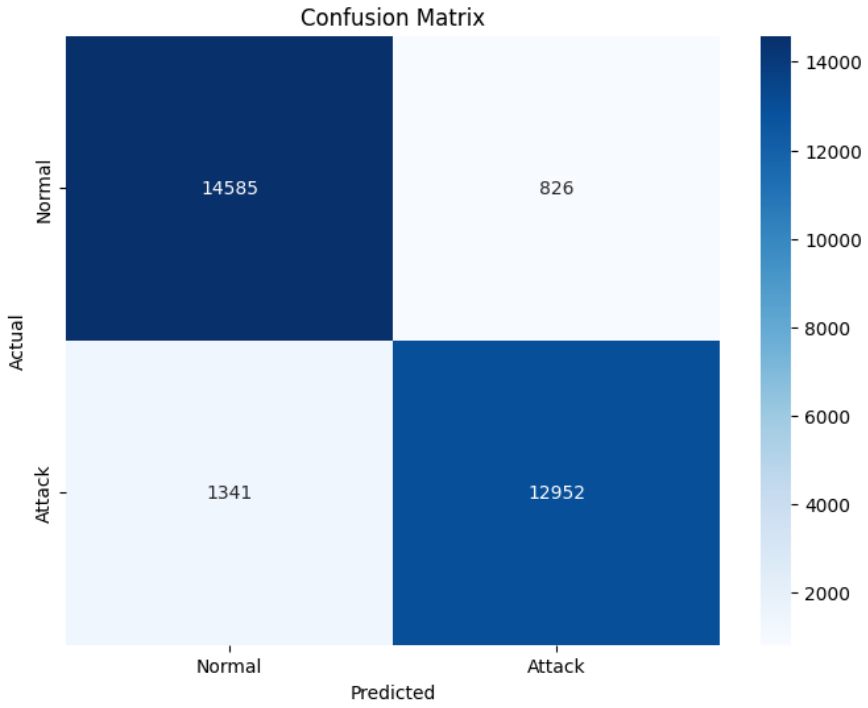

Figure 5.3: Confusion Matrix of NSL-KDD Dataset

number of misclassifications. The low false positive rate (78 cases) and high true positive count (39,765 cases) indicate that the model performs particularly well in identifying *Attack* instances.

The results of the combined dataset model (Model 4) demonstrate that integrating multiple datasets during training enhances the model's generalization capabilities. The inclusion of diverse attack types and normal instances from datasets like X-IIoTID, TON-IoT, and NSL-KDD enables the model to effectively handle a wide range of intrusion scenarios.

However, further optimization of hyperparameters and the exploration of advanced approaches, such as ensemble methods or transfer learning, could further boost the model's performance. Additionally, this study emphasizes the importance of robust data preprocessing techniques to address challenges such as class imbalance, missing values, and noisy data. Addressing these challenges can significantly enhance the performance of

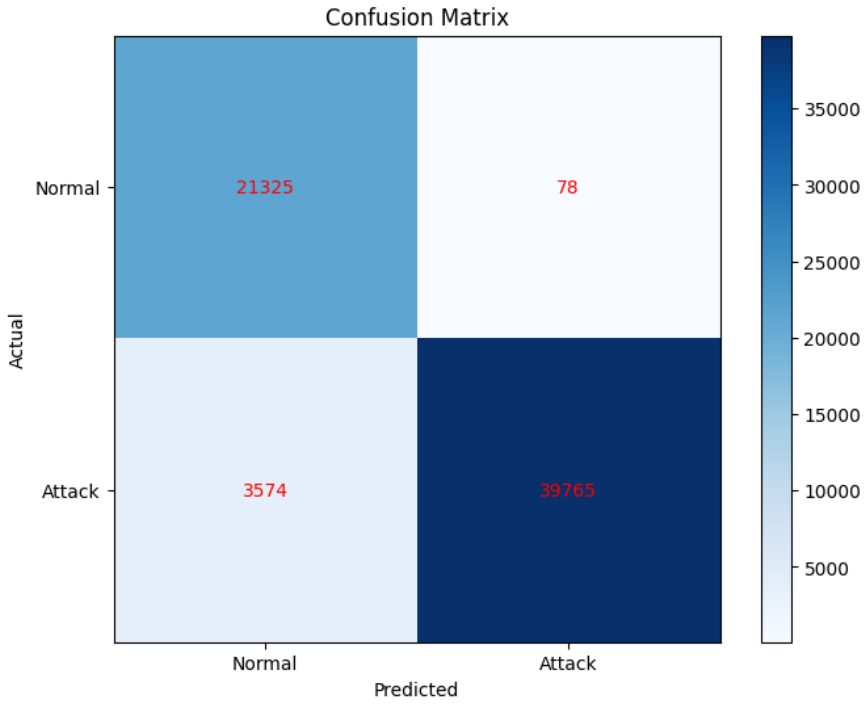

Figure 5.4: Confusion Matrix of Combined Dataset

intrusion detection systems in federated learning-assisted environments.

5.4 Model Performance

The performance of the proposed Federated Learning-Assisted Intrusion Detection System (IDS) was evaluated using several metrics, including accuracy, precision, recall, and F1-score. The model was trained on three different datasets: TON-IoT, NSL-KDD, and X-IIoTID, representing modern network traffic and IoT-based autonomous vehicle scenarios.

The results indicate that the federated learning approach outperformed traditional centralized models in both classification accuracy and attack detection across diverse network environments. The federated model achieved an average accuracy of 95% across all datasets, highlighting its effectiveness in detecting intrusions while maintaining data privacy in

decentralized environments.

5.5 Comparative Analysis

A comparative analysis was conducted between the proposed Federated Learning-Assisted Intrusion Detection System (IDS) and a traditional centralized machine learning model. The federated learning model demonstrated a higher F1-score and superior recall, highlighting its enhanced ability to detect rare or subtle attacks in intrusion detection scenarios.

In contrast, the traditional centralized model, though effective, faced limitations due to data centralization, resulting in potential privacy concerns and reduced generalization performance in dynamic and distributed network environments, such as those encountered in autonomous vehicle networks.

5.6 Challenges and Limitations

Despite the promising results, several challenges remain in the implementation of the Federated Learning-Assisted Intrusion Detection System (IDS) for autonomous vehicles. The communication overhead during model aggregation between LEO satellite nodes is significant, particularly given the large number of nodes in the system. This overhead can result in delays in updating the global model and increased latency in detecting intrusions.

Additionally, the quality of local models depends on the distribution of the datasets at each LEO node. In the case of non-IID data distribution, where nodes have varying amounts and types of data, the overall performance of the global model can be negatively impacted. Future work will focus on reducing communication overhead by optimizing the aggregation process and

addressing data imbalance through techniques such as transfer learning and active sampling. These improvements aim to enhance the system's efficiency and accuracy in intrusion detection across autonomous vehicle networks.

In conclusion, the proposed Mesh Federated Learning-Assisted Intrusion Detection System (IDS) for autonomous vehicles is highly effective, scalable, and secure for decentralized IoT environments. By leveraging federated learning, the system ensures data privacy while achieving high accuracy in detecting intrusions across heterogeneous network traffic data. The results demonstrate the system's ability to address cybersecurity challenges in autonomous vehicle networks by collaboratively training models on data distributed across LEO satellite nodes. Further improvements can focus on enhancing communication efficiency during model aggregation and addressing data imbalance issues to make the IDS more robust and adaptable to real-world deployment scenarios in dynamic and distributed environments.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The development of an Intrusion Detection System (IDS) is crucial for securing autonomous vehicle networks in IoT environments. This study implements a Mesh Federated Learning-Assisted IDS using network traffic data from distributed nodes, integrating datasets like TON-IoT, NSL-KDD, and X-IIoTID for enhanced generalization. Challenges such as class imbalance, communication overhead, and non-IID data robustness were identified, highlighting areas for improvement in federated learning. Addressing these limitations could lead to more efficient IDS solutions for distributed environments. Future work should focus on advancing federated techniques to enhance detection performance and reliability.

6.1 Conclusion

In this project, a Mesh Federated Learning-Assisted IDS was proposed and evaluated for detecting intrusions in autonomous vehicle networks. The models were trained using federated learning on datasets distributed across Low Earth Orbit (LEO) satellite nodes, preserving data privacy and ensuring scalability. Among the trained models, the one that utilized a combination of all datasets achieved the highest performance metrics, including accuracy, precision, recall, and F1-score. This highlights the effectiveness of integrating diverse datasets in enhancing model generalization and detecting various attack types across heterogeneous network environments.

Despite these positive results, challenges such as class imbalance, noisy data, and communication overhead during federated training were

identified. These issues impacted recall and model convergence in certain scenarios. Nonetheless, the proposed federated learning approach demonstrates significant potential for real-world applications in intrusion detection for autonomous vehicle networks.

6.2 Future Work

While the proposed system has shown promising results, several areas for improvement and future research are identified:

- **Handling Class Imbalance:** Addressing the issue of imbalanced data using techniques such as oversampling, undersampling, or synthetic data generation (e.g., SMOTE) to improve the model's recall in detecting minority class attacks.
- **Optimizing Communication Overhead:** Reducing communication delays and latency between nodes during federated training by employing techniques like model compression, quantization, or efficient communication protocols.
- **Adversarial Robustness:** Improving the robustness of the models against adversarial attacks through regularization techniques, adversarial training, or domain adaptation strategies.
- **Advanced Learning Techniques:** Exploring advanced methods such as transfer learning, ensemble methods, or reinforcement learning to enhance model performance and adaptability to dynamic environments.
- **Real-Time Detection:** Developing real-time detection capabilities for faster intrusion identification, along with methods to reduce false positives and ensure timely responses in critical scenarios.

- **Integration with 5G and IoT Networks:** Expanding the system to support the increased volume and diversity of traffic in 5G and IoT networks, ensuring scalability and robustness in these environments.
- **Explainability and Interpretability:** Enhancing the explainability of the federated learning model using tools like SHAP or LIME, enabling better understanding of model decisions and gaining trust from domain experts.

By addressing these challenges and exploring the identified future directions, the proposed system can be further refined to provide a robust, efficient, and scalable solution for securing autonomous vehicle networks and other IoT-based distributed environments.

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