BLOCKCHAIN-ENABLED FEDERATED LEARNING FOR INTRUSION DETECTION IN VEHICULAR EDGE COMPUTING

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled **BLOCKCHAIN-ENABLED FEDERATED LEARNING FOR INTRUSION DETECTION IN VEHICULAR EDGE COMPUTING** is the bonafide work of **ARSHIYA KHIASUDEEN (2021115017), SHREE RAIVATH (2021115103), SHREYA ELIZABETH FRANKLIN (2021115104), JOBSON CHARLES (2021115303)** who carried out project work under my supervision. Certified further that to the best of our 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

Intrusion detection in vehicular edge computing is important to protect networks from cyberattacks that can impact safety and performance. Traditional centralized methods face issues such as data privacy, slow processing, and scalability. In addition, malicious updates within these systems can weaken security.

The main focus of the project is on building a blockchain-enabled federated learning system for intrusion detection. Federated learning (FL) is used to train models across edge nodes without sharing raw data, ensuring privacy. Blockchain securely stores and combines model updates, making the process transparent and immutable. The system uses the UNSW-NB15 dataset for two tasks, detecting attacks through binary classification and identifying specific attack types using multiclass classification. It applies ensemble learning techniques, combining XGBoost, LightGBM, and CatBoost classifiers to improve accuracy. Models are trained locally at edge nodes, and updates are securely aggregated using blockchain.

In Phase 1, the focus is on training models locally, classifying attacks, and securely aggregating results using blockchain. In Phase 2, improvements will address blockchain weaknesses like Sybil attacks and optimize system performance for larger vehicular networks. This project provides a secure, efficient and privacy-preserving solution for intrusion detection in vehicular edge computing.

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LIST OF ABBREVIATIONS

BC	BlockChain
CatBoost	Categorical Boosting
DoS	Denial of Service
FL	Federated Learning
IoV	Internet of Vehicles
IDS	Intrusion Detection System
LGBM	Light Gradient Boosting Machine
ROC AUC	Receiver Operating Characteristic - Area Under Curve
SGD	Stochastic Gradient Descent
UNSW	University of New South Wales
VANET	Vehicular Ad Hoc Network
XGBoost	Extreme Gradient Boosting

CHAPTER 1

INTRODUCTION

1.1 NEED FOR INTRUSION DETECTION IN VEHICULAR NETWORKS

The increasing use of vehicular networks, including Vehicular Ad Hoc Networks (VANET) and the Internet of Vehicles (IoV), has greatly improved road safety, traffic management, and user experiences. Nonetheless, these networks are extremely dynamic, with vehicles constantly communicating and sharing sensitive information such as their location, speed, and control signals. This real-time data exchange makes the network vulnerable to cyber threats. Successful attacks can jeopardize vehicle safety, disrupt traffic, and even threaten human life.

Due to the critical importance of vehicular systems, conventional intrusion detection methods are inadequate for managing the real-time, decentralized, and limited-resource nature of vehicular edge networks. Thus, there is a significant demand for intelligent, scalable, and privacy-focused intrusion detection systems to secure communications and build trust among vehicles.

1.2 FEDERATED LEARNING FOR INTRUSION DETECTION

In vehicular networks, where vehicles constantly produce large amounts of data, federated learning facilitates the development of intrusion detection systems without revealing raw data. This method is especially crucial since vehicles frequently gather personal and location-based information,

which, if leaked, could result in serious privacy violations. By enabling the aggregation of model updates from various distributed nodes, federated learning promotes collaborative intelligence while keeping the data locally at each node.

1.3 BLOCKCHAIN FOR SECURE MODEL AGGREGATION

To enhance the security and reliability of the federated learning process, blockchain technology is integrated into the system. Blockchain provides a decentralized and immutable ledger to securely store model updates sent by the participating edge nodes. This ensures transparency, prevents malicious tampering of model parameters, and mitigates attacks such as model poisoning, which are common in federated systems.

1.4 MODELS USED FOR CLASSIFICATION

1.4.1 XGBoost (Extreme Gradient Boosting)

XGBoost is a highly efficient implementation of gradient boosting algorithms designed for speed and performance. It builds an ensemble of decision trees in a sequential manner, optimizing a differentiable loss function. XGBoost employs advanced features like regularization, sparsity awareness, and parallel processing, making it one of the most popular algorithms for structured data tasks.

Strengths: XGBoost excels in handling large datasets with high-dimensional features. It is robust against overfitting due to built-in

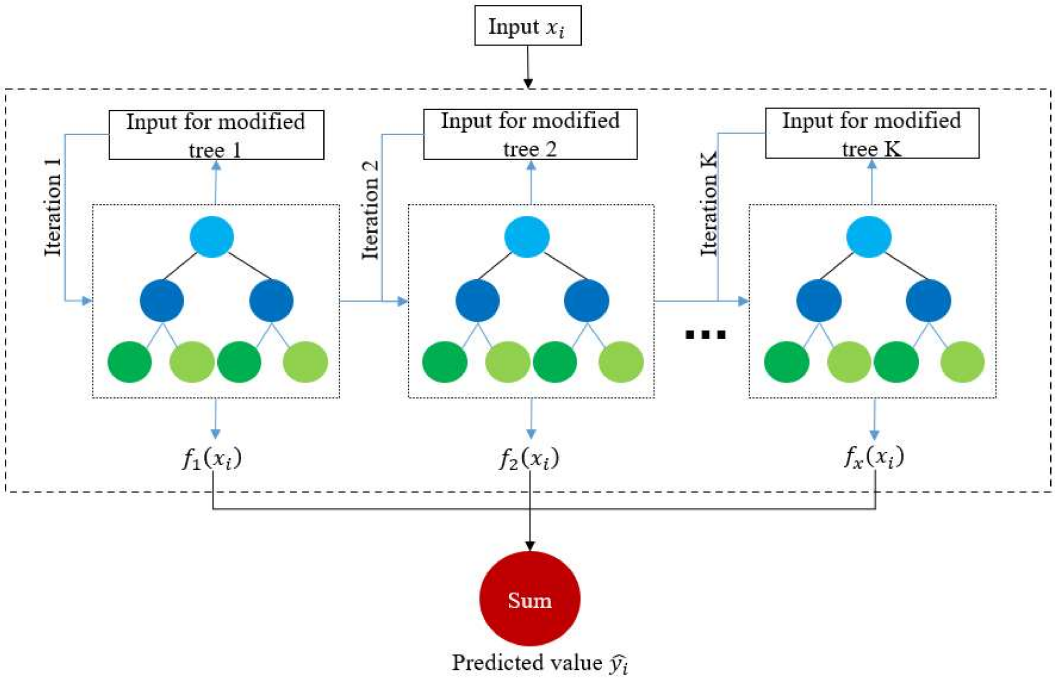

Figure 1.1: XGBOOST ARCHITECTURE

regularization (L1 and L2), and its distributed computing support enables efficient scalability.

1.4.2 LGBM Classifier (Light Gradient Boosting Machine)

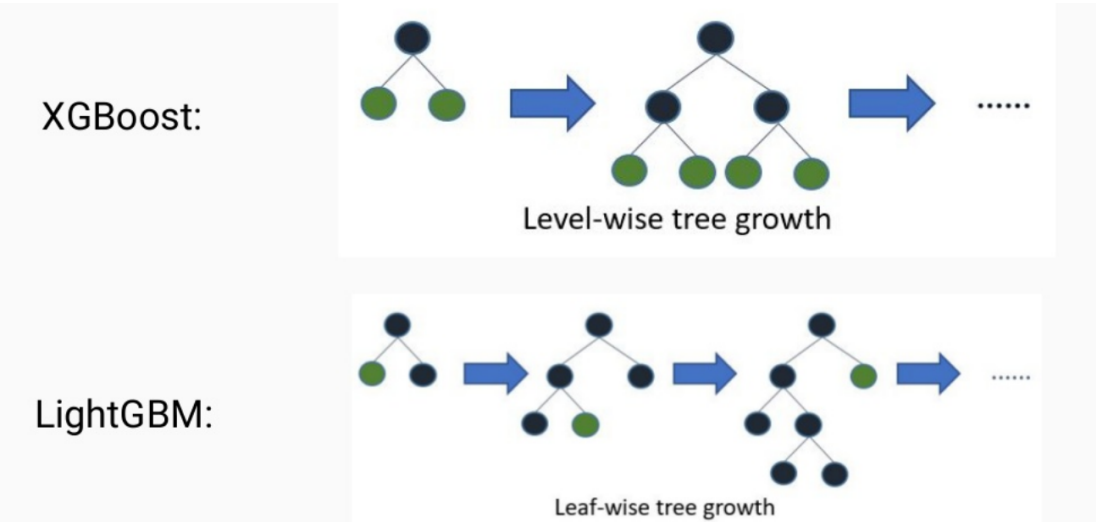

Figure 1.2: COMPARISON OF TREE GROWTH METHODS: XGBOOST VS LIGHTGBM

LightGBM is a fast, distributed, and efficient gradient-boosting framework that uses decision tree algorithms. It focuses on leaf-wise tree growth instead of level-wise growth, making it highly efficient for large datasets.

Strengths: LGBM is well-suited for large-scale datasets and excels in handling categorical features. It is faster and more memory-efficient compared to traditional gradient boosting methods.

1.4.3 CatBoost (Categorical Boosting)

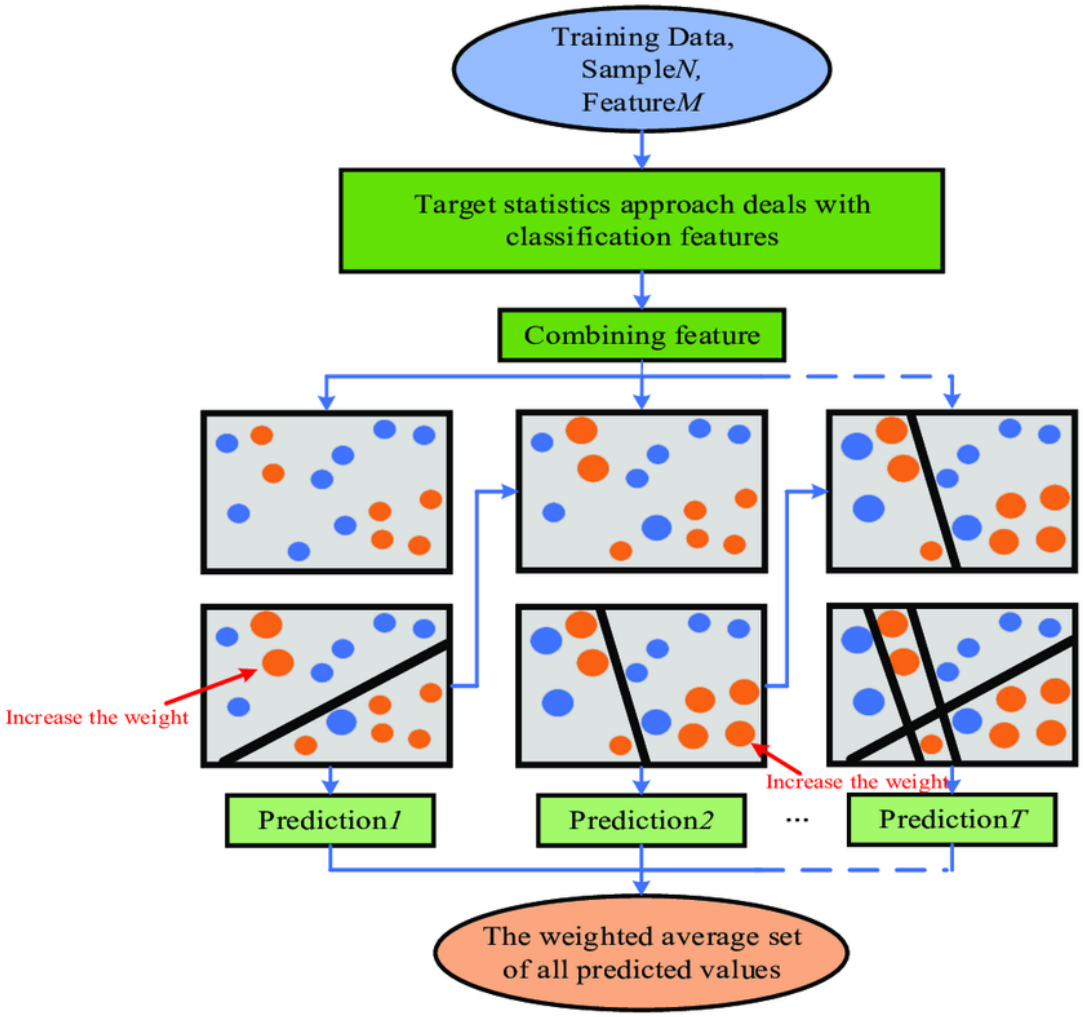

Figure 1.3: CATBOOST ARCHITECTURE

CatBoost is another gradient boosting method that handles

categorical features natively.It performs categorical feature encoding in a way that preserves relationships, ensuring better model performance, particularly in datasets with significant categorical data.

Strengths: CatBoost provides high performance with less hyperparameter tuning. It is fast, accurate, and particularly efficient in handling categorical data without requiring extensive preprocessing.

1.4.4 VotingClassifier (Ensemble Learning Method)

The VotingClassifier is an ensemble method that combines predictions from multiple models, such as XGBoost, LGBM, and CatBoost, by voting on the final prediction. This improves model robustness and generalization performance.

Strengths: It combines the strengths of different classifiers, improving prediction accuracy and reducing the likelihood of overfitting. It works well when individual models have complementary strengths.

1.4.5 Federated Learning with Blockchain Integration

In this project, federated learning is employed to train models in a decentralized manner, ensuring data privacy by keeping the data on local devices. The model updates are securely stored and aggregated via a blockchain network, providing transparency and robustness against malicious activities.

Strengths: Federated learning offers privacy-preserving benefits, while blockchain integration ensures secure and verifiable model updates. This method is particularly effective in distributed environments like vehicular edge computing.

1.5 ATTACK CLASSIFICATION

The classification of attacks is carried out by the system using federated learning and ensemble models. The system aims to detect and classify various cyberattacks while ensuring the privacy of sensitive data. By utilizing the UNSW-NB15 dataset, which includes nine types of attacks such as Denial of Service (DoS), Backdoors, and Shellcode, the data is preprocessed and essential features are extracted for effective model training. Through federated learning, the model updates from the edge nodes are aggregated without sharing raw data, preserving user privacy. The classification process includes both binary classification (distinguishing between normal and attack traffic) and multi-class classification (identifying specific attack types). Ensemble models such as XGBoost, LightGBM, and CatBoost are applied to improve accuracy and robustness. This methodology enables the system to detect attacks efficiently in real-time, enhancing the security of vehicular networks.

1.6 PROBLEM STATEMENT

The primary challenge is the increasing risk of security threats in vehicular networks, where large volumes of sensitive data are generated and transmitted between vehicles. These networks are vulnerable to attacks that can compromise the privacy and safety of users. This highlights the need for developing a system that enables secure and collaborative threat detection across multiple vehicles, while ensuring that sensitive data is kept private and not exposed during the process.

1.7 PROPOSED SOLUTION

This project aims to improve security in vehicular networks by

detecting potential attacks while ensuring the privacy of vehicle data. It uses a combination of federated learning and blockchain technology. In this approach, vehicles collaborate to identify threats without sharing their sensitive information. Federated learning enables the system to update the intrusion detection model based on local data, while blockchain ensures that model updates are securely shared and aggregated. An ensemble model of XGBoost, LightGBM and CatBoost is used to analyze vehicle data and detect attacks. In the next phase, real-time network data will be utilized, and additional measures will be implemented to prevent attacks from unauthorized clients, further enhancing the security of the network.

1.8 ORGANIZATION OF REPORT

- **Chapter 1:** Introduces the project background, outlines the problem statement, defines objectives, and specifies the scope.
- **Chapter 2:** Provides a review of related literature, focusing on feature extraction,model implementation,data collection.
- **Chapter 3:** Discusses the system architecture and the modules implemented, tools and methods used in the project.
- **Chapter 4:** Describes the system design of the intrusion detection system including the analysis.
- **Chapter 5:** Presents the results of the project, including an analysis of the system's performance using metrics such as ROC-AUC curve, Confusion matrix , Accuracy etc
- **Chapter 6:** Summarizes the conclusions drawn from the project.
- **References:** Lists all sources cited in the report.

CHAPTER 2

LITERATURE SURVEY

2.1 BLOCKCHAIN-ENABLED FEDERATED LEARNING

Zhou et al. [3] proposes a federated learning model that incorporates differential privacy to safeguard against poisoning attacks in edge computing environments. This study uses a weight-based anomaly detection mechanism to identify and filter out malicious updates from participating nodes. This study ensures that differential privacy protects sensitive data during local model updates, minimizing the risk of leakage. This study strikes a balance between maintaining data privacy and ensuring the accuracy of the global model. This study demonstrates resilience against adversarial threats while preserving performance through extensive testing.

Toyoda et al. (2020). [8] has proposed to integrate blockchain with federated learning using mechanism design to incentivize honest contributions from participating nodes. This study introduces a reward-based system to prevent free-riding behavior, ensuring that each node contributes fairly to the global model. This study uses blockchain as a transparent ledger for securely recording and validating contributions, preventing malicious manipulation. This study optimizes the distribution of efforts among the nodes, enhancing collaboration. This study validates the effectiveness of the proposed approach in ensuring both fairness and security in federated learning environments.

Jiang et al. (2023). [14] has proposed to combine differential privacy and adaptive compression to secure federated learning in industrial edge computing environments. This study ensures that differential privacy maintains

local data privacy while compressing model updates reduces communication overhead. This study employs adaptive compression, selectively determining which model parameters to send, optimizing the trade-off between accuracy and efficiency. This study addresses concerns about inference attacks that could compromise model integrity in edge environments. This study's evaluations confirm that the model enhances privacy while improving efficiency in industrial IoT settings.

Muneeb et al. [15] proposed to introduce SmartCon, a dual blockchain framework designed for managing smart contracts and transactions, supporting Decentralized Autonomous Organizations (DAO) and organizational processes. This study separates the transaction layer from the contract execution layer, enhancing security and scalability in blockchain systems. This study leverages blockchain's immutability and transparency to ensure that smart contracts are executed fairly and efficiently, reducing the risk of disputes. This study includes tools for monitoring and auditing transactions, promoting trust among participants. This study's test scenarios demonstrate the scalability and security of the system in decentralized applications.

Abdel-Basset et al. [1] had proposed to integrate blockchain with federated learning to improve collaborative intrusion detection in vehicular edge computing networks. This study uses a reputation-based mechanism to ensure that only trustworthy edge nodes contribute to the model, reducing the risk of malicious updates. This study employs blockchain to guarantee the integrity of model updates, enhancing security and preventing tampering. This study tests the system on public intrusion detection datasets, achieving over 99 percent accuracy in detecting cyberattacks. This study effectively combines federated learning and blockchain to ensure high security and reliability in vehicular networks.

Li et al. [17] proposes to introduce a blockchain-based decentralized trust aggregation model to ensure secure cyber-attack classification in SDN-enabled maritime transportation systems. This study utilizes blockchain's transparency and immutability to ensure the trustworthiness of cyber-attack classification updates from multiple nodes. This study uses a lightweight CNN-based model for efficient attack classification, improving detection accuracy without compromising system performance. This study's decentralized blockchain framework allows for trust aggregation across a network of edge nodes, improving system resilience. This study demonstrates that the system effectively detects attacks while maintaining security and scalability in maritime environments.

2.2 FEDERATED LEARNING FOR INTRUSION DETECTION

Abdel-Basset et al. [30] proposes FED-IDS, a federated deep learning framework designed for detecting cyberattacks in smart transportation systems. This study uses blockchain technology to ensure secure model updates, ensuring data integrity and trustworthiness in the distributed environment. This study leverages federated learning to allow decentralized training without exposing sensitive data from individual vehicles. The model is evaluated on real-world transportation datasets, demonstrating its effectiveness in detecting a wide range of cyber threats. This study highlights the potential of combining federated learning and blockchain to enhance security in smart transportation networks.

Moustafa et al. [18] had proposed to introduce a federated learning model that adapts to real-time cyber threats by leveraging context-aware deep learning techniques. This study uses a decentralized update mechanism, allowing edge devices to independently update models based on local data, reducing communication overhead. This study's model is capable of detecting

emerging threats quickly by continuously learning from new data without centralizing sensitive information. The approach ensures privacy preservation and enhances threat detection capabilities across diverse environments. This study's results show that federated learning can improve response times and accuracy in dynamic cybersecurity scenarios.

Gyawali et al. [19] proposed to combine machine learning with reputation-based systems to detect misbehavior in vehicular communication networks. This study addresses the issue of false alerts and position falsification attacks, which can mislead the network and degrade its performance. The reputation system helps identify unreliable nodes by evaluating their past behavior and contributions to the network. This study also implements a machine learning model that classifies the behavior of vehicles, improving the accuracy of misbehavior detection. Through simulations, this study demonstrates the effectiveness of the combined approach in improving security and trust in vehicular networks.

Abdel-Basset et al. [20] had proposed to integrate blockchain technology with federated learning to enhance intrusion detection in IoT networks, ensuring secure and reliable model updates. This study addresses challenges related to malicious updates and privacy concerns by utilizing blockchain's transparency and immutability features. Federated learning enables the model to train on decentralized data, protecting user privacy while still benefiting from collective learning. The system is tested in IoT environments, demonstrating its ability to detect a variety of intrusion attempts effectively. This study emphasizes the potential of blockchain-enabled federated learning for securing IoT systems against cyberattacks.

2.3 POISONING ATTACKS AND THREAT MITIGATION

Zhou et al. [21] proposes a study that comprehensively explores poisoning attacks in federated learning (FL), identifying various methods that adversaries use to manipulate the model. This study categorizes defenses into three primary approaches: model analysis, robust aggregation techniques, and verification-based methods. It provides an in-depth analysis of how these defenses can be applied to detect and mitigate poisoning attempts in decentralized learning environments. The survey also discusses the trade-offs between security and model accuracy, particularly in resource-constrained edge computing environments. This study is valuable for researchers working on enhancing the resilience of FL systems against malicious attacks.

Jiale Zhang et al. [22] had proposed PoisonGAN, a generative adversarial network (GAN) designed to simulate poisoning attacks that degrade the performance of federated learning models. This study demonstrates how PoisonGAN generates malicious model updates that can mislead the global model aggregation process, undermining the accuracy of the global model. The authors focus on edge computing systems, where federated learning is increasingly used, to highlight the risks of poisoning attacks in these environments. Through extensive experiments, this paper shows the effectiveness of PoisonGAN in crafting subtle yet impactful poisoning attacks. The study also proposes potential countermeasures to address this emerging threat in federated learning systems.

Cui et al. [23] had proposed to employ differential privacy as a defense mechanism to mitigate the impact of poisoning attacks in federated learning by adding noise to local gradients. This study demonstrates how introducing controlled noise at each update step protects individual model updates from adversarial manipulation. The approach ensures that even if a node attempts to inject poisoned data, the noise makes it difficult to significantly alter the global model. The effectiveness of this method is evaluated in

various FL environments, showing that it can maintain both privacy and model performance. This study contributes to securing federated learning models against malicious attacks while preserving data privacy.

2.4 VEHICULAR EDGE AND SMART TRANSPORTATION SYSTEMS

Abdel-Basset et al. [30] had proposed a context-aware transformer network for analyzing vehicular data in smart transportation systems. By utilizing spatial-temporal analysis, the network improves the detection of complex patterns and anomalies in traffic data. Blockchain technology is integrated to ensure secure and reliable federated learning (FL) updates, preserving the integrity of the collaborative model. The system enhances the accuracy of intrusion detection by allowing decentralized nodes to learn from local data without compromising privacy. This study demonstrates the system's effectiveness in real-world smart transportation datasets, achieving high detection rates for cyberattacks.

Gyawali et al. [19] proposes machine learning techniques with reputation systems to detect misbehavior in vehicular communication networks. Reputation scores are used to evaluate the trustworthiness of nodes in the network, helping to identify and mitigate false alerts and position falsification attacks. The machine learning model classifies vehicle behavior, improving the detection of abnormal activities. This study also addresses the challenges posed by dynamic environments, where vehicle behavior can rapidly change, requiring continuous monitoring. Simulation results show that this hybrid approach significantly improves accuracy and reliability in detecting misbehaving vehicles.

Ranwa Al Mallah et al. [24] proposes an asynchronous federated learning (FL) framework designed for distributed Internet of Things (IoT)

systems, with a focus on enhancing privacy and security. The framework utilizes Byzantine fault tolerance to safeguard the system against faulty or malicious nodes, ensuring robust model updates. Asynchronous FL enables devices to participate in model training independently, reducing synchronization delays and improving system efficiency. Differential privacy techniques are incorporated to further protect sensitive data during the learning process. The study demonstrates that this approach improves both privacy and model performance in distributed IoT environments, particularly in vehicular systems.

2.5 SMART CONTRACTS AND BLOCKCHAIN-BASED SYSTEMS

Muneeb et al. [15] proposes SmartCon, a dual blockchain framework designed to manage smart contracts and transactions securely. The framework leverages two blockchains, one for handling smart contract logic and the other for transaction validation, ensuring efficiency and separation of concerns. It aims to address scalability and security challenges in decentralized applications (DApps) by using a hybrid approach. SmartCon also integrates a consensus mechanism to validate transactions, ensuring that all interactions are transparent and tamper-proof. The study demonstrates the framework's applicability in decentralized autonomous organizations (DAOs), where secure and efficient contract execution is critical for system functionality.

Zainudin et al. [25] proposes blockchain and reputation systems to address misbehavior detection in edge computing environments. By using blockchain's immutable ledger, the framework records and verifies the reputation of devices in decentralized edge networks. The reputation system evaluates nodes based on their past behavior, helping identify unreliable or malicious devices that could compromise the network. This work introduces a decentralized approach to reputation management, reducing the reliance on

central authorities while ensuring data integrity and trustworthiness. The system's effectiveness is evaluated in various edge computing scenarios, showing enhanced security and reliability in detecting and preventing misbehaving nodes.

2.6 BLOCKCHAIN FOR SECURE EDGE COMPUTING

Toyoda et al. [8] proposes incentivized federated learning (FL) by integrating blockchain technology to ensure secure model training and fair contribution evaluation. The proposed mechanism uses a blockchain-based reward system to incentivize honest participation and prevent free-riding among nodes. It ensures that nodes contribute effectively to the model while maintaining data privacy and security. By leveraging blockchain's decentralized nature, the model allows for transparent tracking of contributions and rewards. The study demonstrates how this approach enhances the fairness and security of FL in distributed environments such as edge computing.

Yan et al. [26] proposes trust-based approaches for enhancing federated learning (FL) security using blockchain technology for model validation and reputation management. The paper explores how decentralized trust models can prevent malicious activities by evaluating the reputation of nodes based on their past behavior and contributions. By integrating blockchain, the study ensures that all trust-related data is immutable and transparent, fostering a reliable environment for collaborative model training. Trust validation mechanisms help detect adversarial participants who may attempt to sabotage the learning process. The study shows that these trust models enhance the overall robustness and security of FL in distributed systems.

Moustafa et al. [27] proposes the integration of blockchain with federated learning (FL) to enhance the security of edge computing in

cyber-physical systems. The model aims to secure the communication and computation layers by using blockchain to validate and secure model updates from distributed devices. By combining the transparency and immutability of blockchain with the collaborative nature of FL, this approach prevents unauthorized data manipulation and ensures trust among participating nodes. The system protects against common threats in cyber-physical environments, including data breaches and model poisoning attacks. The effectiveness of this framework is demonstrated through case studies in industrial applications, showcasing its potential to safeguard edge systems.

Wang et al. [28] proposes a hybrid consensus mechanism to ensure both security and performance in blockchain-enabled edge networks. The hybrid approach combines the strengths of traditional consensus algorithms, such as Proof of Work (PoW), with more energy-efficient mechanisms, such as Proof of Stake (PoS), to provide a balance between security and scalability. The mechanism is designed to address the unique challenges faced by edge systems, where computational resources are limited, and real-time processing is critical. The study demonstrates how this hybrid consensus algorithm improves the efficiency and reliability of blockchain operations in decentralized edge computing environments. Through simulations, the paper proves that the hybrid mechanism significantly enhances the network's performance while maintaining strong security.

Cui et al. [29] proposes a framework that integrates blockchain and federated learning (FL) to improve the efficiency and scalability of decentralized edge computing systems. The framework leverages blockchain's decentralized features to facilitate secure and transparent model training, while FL allows for collaborative learning across multiple edge nodes without sharing sensitive data. By utilizing blockchain for model update verification and aggregation, the system prevents tampering and ensures the integrity of the model. The study

highlights how this approach can be applied in smart cities and industrial IoT environments, where decentralized data processing is essential. Experimental results show that the integration of blockchain and FL can significantly enhance the overall performance and security of edge systems.

2.7 ENSEMBLE LEARNING FOR INTRUSION DETECTION

Arreche et al. [31] proposes a two-level ensemble learning framework to improve network intrusion detection systems (IDS). The framework incorporates feature selection at both levels, with XAI-based feature selection in the first level and Information Gain-based selection in the second. The framework is evaluated on three datasets: RoEduNet-SIMARGL2021, NSL-KDD, and CICIDS-2017, showing improvements in metrics such as accuracy and false positive rates, particularly with ensemble methods like boosting, stacking, and bagging.

Das et al. [32] proposed a machine learning-based IDS that combines multiple classifiers through an ensemble approach and integrates ensemble feature selection methods. The model is tested on three datasets (NSL-KDD, UNSW-NB15, CICIDS2017) and achieves a 99.3 percent intrusion detection rate with minimal false alarms. The authors emphasize the importance of feature selection in improving accuracy and reducing false positives.

Lucas et al. proposed a Comprehensive Survey on Ensemble Learning-Based Intrusion Detection Approaches in Computer Networks. This survey [33] comprehensively reviews the use of ensemble learning techniques in intrusion detection systems (IDS). It analyzes a wide range of works from 2015 to 2022, covering classifiers, datasets, and algorithms used in ensemble learning for IDS. The survey highlights trends, challenges, and the evolution of the field, providing valuable insights into emerging methods and future directions for

improving intrusion detection with ensemble techniques.

2.8 LITERATURE SUMMARY

The literature survey explores the integration of federated learning (FL) and blockchain technology to enhance security and privacy in edge computing systems, particularly for intrusion detection. Several studies focus on leveraging blockchain for secure model updates and preventing tampering, such as in vehicular edge computing and smart transportation systems. The use of differential privacy and reputation-based mechanisms has been proposed to protect against malicious updates and poisoning attacks. Moreover, blockchain's transparency and immutability play key roles in ensuring the integrity of contributions in decentralized environments. Privacy-preserving techniques, such as differential privacy, are also emphasized to safeguard sensitive data during the learning process. Ensemble learning methods have been found to improve intrusion detection systems' accuracy, reducing false positives while enhancing detection rates. Overall, it is observed that the combination of federated learning, blockchain, and ensemble techniques provides a robust framework for improving cybersecurity, efficiency, and fairness in distributed systems.

CHAPTER 3

SYSTEM ARCHITECTURE

The Blockchain-Enabled Federated Learning system is a framework that integrates federated learning and blockchain technology for intrusion detection in vehicular edge computing. It includes modules for binary and multi-class classification using ensemble models, federated learning at edge nodes, and blockchain-based model aggregation. The system preprocesses the UNSW-NB15 dataset, trains the local model at two simulated edge nodes, and detects and predicts the type of attack in the global model, as shown in Figure 3.1.

3.1 DATA PREPROCESSING

• **Purpose:** Transforms raw data into a clean, structured format to prepare it for machine learning models.

• **Input:** UNSW-NB15 dataset containing various features for network intrusion detection.

• **Process:** The preprocessing phase includes handling missing values to ensure completeness, applying normalization techniques to scale features for compatibility with machine learning models, shuffling the data to introduce randomness and prevent overfitting, and splitting the dataset into training and testing sets for effective evaluation and validation.

• **Output:** Cleaned, normalized, and structured dataset ready for training and testing machine learning models.

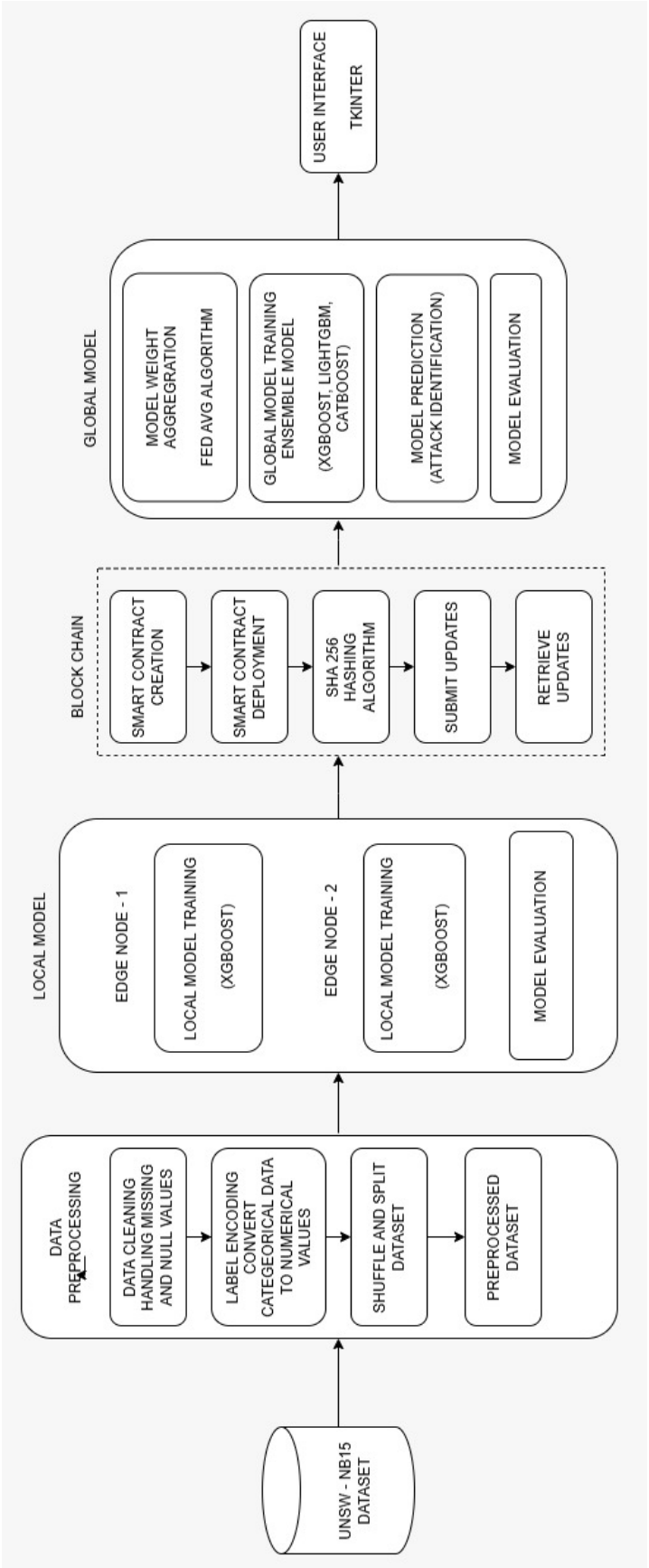

Figure 3.1: SYSTEM ARCHITECTURE OF INTRUSION DETECTION FRAMEWORK

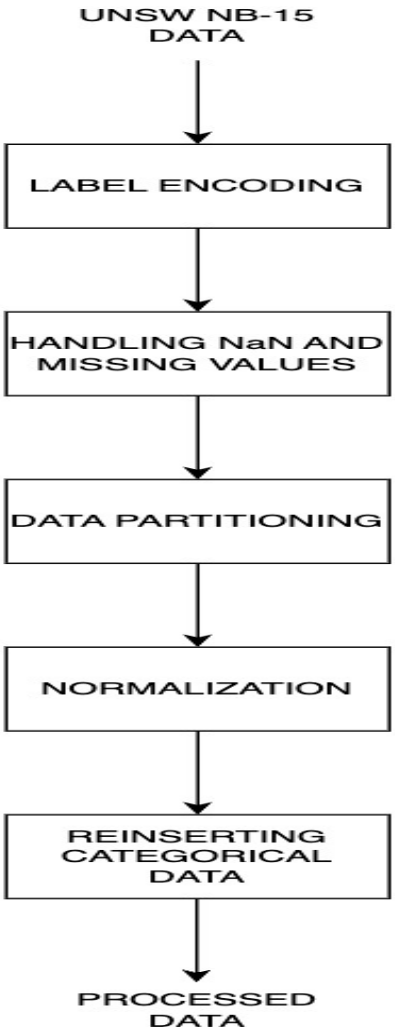

Figure 3.2: FLOW DIAGRAM OF DATA PREPROCESSING MODULE

The preprocessing module is crucial for preparing data to train federated learning models effectively. In this project, the UNSW-NB15 dataset, with various features for intrusion detection, was carefully processed. This included handling missing values, normalizing the data, and shuffling it to ensure fairness and randomness during training.

The processed data was then split into training and testing sets, providing a strong base for the machine learning models. By cleaning and organizing the data, preprocessing greatly improves the model's accuracy,

reliability, and performance.

3.2 LOCAL MODEL TRAINING

Purpose: Enables edge nodes to perform local model training using an ensemble of XGBoost, CatBoost, and LightGBM for intrusion detection.

Input: Preprocessed data specific to each edge node.

Process:
- Each edge node (e.g., Edge Node 1 and Edge Node 2) trains an ensemble model combining XGBoost, CatBoost, and LightGBM.
- The ensemble model uses a voting mechanism for binary or multi-class classification.
- Local models are evaluated to measure their individual performance on the preprocessed dataset.

Output: Trained local ensemble models with performance metrics for evaluation.

The Local Training Model module is integral to the federated learning system, as it allows edge nodes to independently train models using localized data. At each edge node, an ensemble approach is implemented by combining the strengths of XGBoost, CatBoost, and LightGBM, leveraging their complementary features for robust classification. The ensemble model utilizes a voting mechanism to provide final predictions. Once trained, the models are evaluated locally to assess accuracy, precision, recall, and F1-score. These trained ensemble models form the basis for aggregating a global model in the federated learning setup, ensuring high performance and data privacy.

3.3 BLOCKCHAIN INTEGRATION

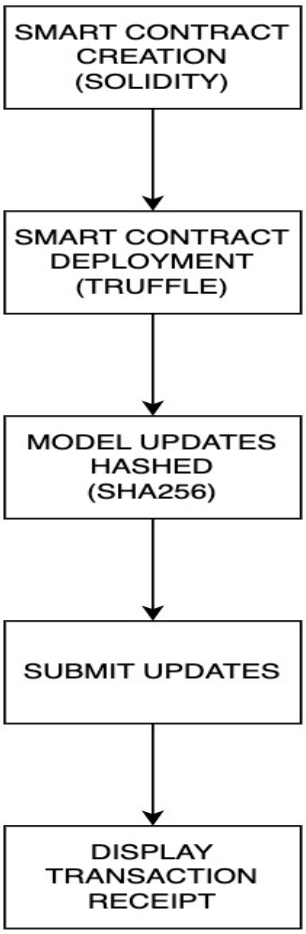

Figure 3.3: FLOW DIAGRAM OF LOCAL MODEL TRAINING MODULE

Purpose: Enables edge nodes to perform local model training using an ensemble of XGBoost, CatBoost, and LightGBM for intrusion detection.

Input: Preprocessed data specific to each edge node.

Process:
- Each edge node (e.g., Edge Node 1 and Edge Node 2) trains an ensemble model combining XGBoost, CatBoost, and

LightGBM.

- The ensemble model uses a voting mechanism for binary or multi-class classification.
- Local models are evaluated to measure their individual performance on the preprocessed dataset.

Output: Trained local ensemble models with performance metrics for evaluation.

The Blockchain Integration module is responsible for securing and validating updates from the local models in the federated learning setup. Each local model, after training on its respective dataset, hashes its updates using the SHA-256 algorithm to ensure that the updates are tamper-proof and secure. These hashed updates are then submitted to the blockchain, where smart contracts play a crucial role in managing the data submission and retrieval process. The blockchain ensures that the updates are securely stored and can be retrieved with integrity during the model aggregation phase. The output of this module is the set of updates stored in the blockchain, ready for aggregation and inclusion in the global model.

3.4 GLOBAL MODEL TRAINING

Purpose: Aggregates updates from local models and trains the global model using an ensemble of machine learning algorithms.

Input: Updates from local models (binary and multi-class).

Process: Federated averaging (FedAvg) to aggregate updates, followed by training with XGBoost, LightGBM, and CatBoost algorithms.

Output: Global model ready for attack identification predictions.

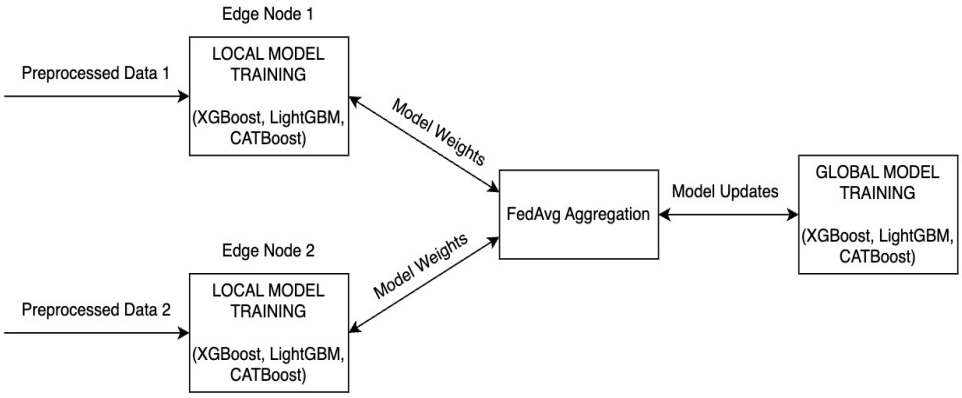

Figure 3.4: FLOW DIAGRAM OF GLOBAL MODEL TRAINING MODULE

The Global Model Training module is responsible for aggregating updates received from the local models in the federated learning setup. The updates are aggregated using the Federated Averaging (FedAvg) algorithm, which ensures that the contributions from each local model are combined effectively. After aggregation, the global model is trained using an ensemble of machine learning algorithms, including XGBoost, LightGBM, and CatBoost. These algorithms work together in an ensemble to improve the accuracy and robustness of the global model. The trained global model is then evaluated to assess its performance in predicting potential attacks. This module ensures that the global model is optimized and ready for deployment in the intrusion detection system.

3.5 USER INTERFACE

Purpose: Provides an interactive interface for users to view attack identification results from the global model's predictions.

Input: Final predictions from the global model (attack identification results).

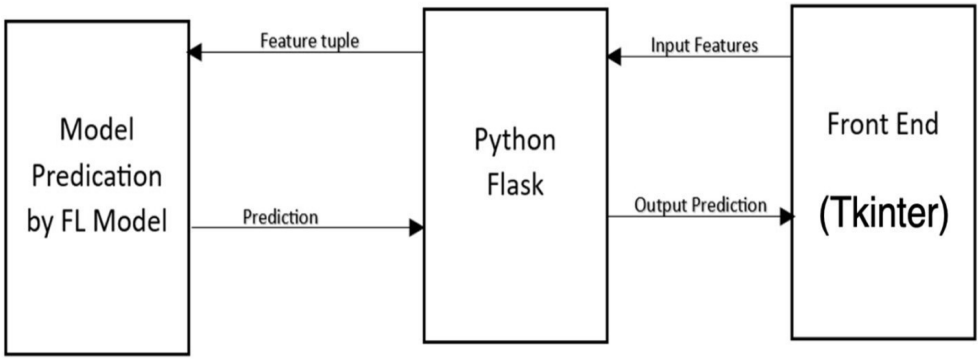

Figure 3.5: FLOW DIAGRAM OF USER INTERFACE MODULE

Process: Displaying results through a Tkinter-based graphical user interface (GUI).

Output: Attack identification results shown to the user in a readable format.

The User Interface module is designed to provide a seamless experience for users to interact with the system and view the attack identification results. After the final global model's predictions are made, the results are made accessible through a Tkinter-based GUI. This interface allows users to input data and view the model's attack identification results in real-time. It ensures that users can easily interact with the system to understand the performance and predictions of the model. The GUI also supports visualizations and displays necessary performance metrics to help users evaluate the system's effectiveness.

3.6 TOOLS AND TECHNOLOGIES USED

3.6.1 Programming Language

Python is the primary programming language for the project. It offers a wide range of libraries and frameworks for data processing, machine learning, and blockchain interaction, making it ideal for this task. Solidity is the programming language used to write smart contracts deployed on the Ethereum blockchain. It is used to create contracts that manage the blockchain-based aggregation of model updates in federated learning.

3.6.2 Required Libraries

Web3.py: Web3.py is a Python library that facilitates interaction with the Ethereum blockchain. It is used for smart contract deployment and transaction management, enabling the integration of blockchain into the federated learning model.

Tkinter: Tkinter is the Python library used to build the graphical user interface (GUI) for the application. It enables users to interact with the blockchain-enabled federated learning system, upload datasets, view results, and visualize model predictions.

NumPy: NumPy is utilized for numerical operations like matrix manipulation, crucial for preprocessing the datasets or managing the embeddings generated for model training.

XGBoost: XGBoost is a high-performance gradient boosting library used to build classification models for binary and multi-class classification tasks in the project. It is used to train models on the preprocessed data and make predictions.

LightGBM: LightGBM is another gradient boosting framework used in the project for building efficient and scalable classification models. It supports

faster training and can handle large datasets well.

CatBoost: CatBoost is a gradient boosting algorithm that handles categorical features natively, making it suitable for models that deal with datasets containing categorical variables.

scikit-learn: scikit-learn is a versatile library for machine learning that is used for various tasks, including model training, evaluation, and preprocessing of data in the project.

Matplotlib: Matplotlib is used for data visualization, allowing the creation of plots, charts, and graphs to visualize the performance of models, results of federated learning, and blockchain interactions.

Seaborn: Seaborn is built on top of Matplotlib and provides additional functionality for creating attractive and informative statistical graphics, helping in data analysis and model evaluation.

3.6.3 Development Tools

VS Code: A lightweight, powerful IDE used for writing and debugging Python code and smart contracts.

Truffle Suite: Provides an integrated environment for writing, testing, and deploying smart contracts on the Ethereum blockchain.

Ganache: A personal Ethereum blockchain used to deploy contracts, develop, and test the blockchain interactions locally during development.

Node.js: Node.js is used for running the backend server and handling

blockchain interactions through Web3.js, which enables communication with the Ethereum blockchain from the application.

Ethereum: Ethereum is the blockchain platform used to store and manage federated learning model updates. It ensures decentralized and secure aggregation of models across edge nodes.

CHAPTER 4

SYSTEM DESIGN

In this chapter, we will discuss the system design for the Intrusion Detection project along with the algorithms implemented in each of the modules.

4.1 DATA DESCRIPTION

Datasets	Number of Samples	Number of Features	Number of Attack Categories
UNSW-NB15	2,540,000	49	9

Table 4.1: DATASET DETAILS FOR INTRUSION DETECTION

The input for this module consists of the UNSW-NB15 dataset, which is widely used in intrusion detection system (IDS) research. This dataset contains network traffic data featuring both continuous and categorical attributes, representing various aspects of network connections. The continuous features include byte counts, packet counts, flow duration, and other characteristics that describe the traffic patterns of network connections. The categorical features include connection types (e.g., TCP, UDP), protocol types (e.g., HTTP, FTP), and attack categories (e.g., fuzzers, DoS, normal). Additionally, the dataset is labeled for both binary classification tasks, where traffic is classified as either normal or anomalous, and multi-class classification tasks, where traffic is categorized into specific attack types such as DoS (Denial of Service), Probe, and others. This combination of continuous, categorical, and labeled data forms the basis for training and evaluating machine learning models in the intrusion detection system.

4.2 ALGORITHMS

This section presents the algorithms used for data preprocessing, local model training, blockchain submission of model weights, and global model aggregation in the federated learning system integrated with blockchain.

4.2.1 Data Preprocessing

Data preprocessing is the first step before training any machine learning model. It ensures that the dataset is clean, formatted correctly, and ready for analysis. The dataset may contain missing values, categorical features, or inconsistent data, all of which need to be handled before feeding the data into the model. Preprocessing also involves normalization and splitting the data into training and testing sets.Below is the algorithm for the data preprocessing process:

Algorithm 4.1 Data Preprocessing

Input: Raw Dataset (`dataset`)
Output: Processed Dataset
Step 1: Load Dataset
Load the dataset from a file source into the `dataset`.
Step 2: Handle Missing Values
For each column with missing values in the dataset:
    Impute with mean or drop rows/columns as needed.
Step 3: Encode Categorical Features
Apply one-hot encoding or label encoding to categorical columns.
Step 4: Drop Target Columns
Drop target (label) columns for training data, if necessary.
Step 5: Normalize the Dataset
Apply feature scaling (e.g., MinMaxScaler or StandardScaler).
Step 6: Shuffle the Dataset
Shuffle the data to avoid bias.
Step 7: Train-Test Split
Split the dataset into training and test sets (e.g., 80-20 split).
Output: Return the processed dataset ready for model training.

Time Complexity: $O(n)$

Where: n is the number of samples in the dataset, and the time complexity is linear with respect to the dataset size due to preprocessing tasks such as handling missing values, encoding, normalization, and data splitting.

Space Complexity: $O(n \cdot d)$

Where: n is the number of samples, and d is the number of features in the dataset. The space complexity is determined by the amount of space required to store the dataset, including feature values for each sample.

4.2.2 Local Model Training (Edge Node)

Local model training occurs on each edge node, where the model is trained using local data. The edge node performs training using ensemble methods for binary classification and XGBoost for multi-class classification. This step also includes saving feature importances and submitting the model weights to the blockchain for aggregation.Below is the algorithm for local model training:

Time Complexity: $O(T \cdot n \cdot d)$

- T is the number of trees in the ensemble model (for binary classification).
- n is the number of training samples.
- d is the number of features (or dimensions) in the dataset.

Algorithm 4.2 Local Model Training (Edge Node)

Input: Preprocessed Dataset (`train_data`), Client-ID (`client_id`)
Output: Model Weights and Evaluation Metrics
Step 1: Split Data
Split the dataset into binary and multi-class training and test sets.
Step 2: Train Ensemble Model on Local Data (Binary Classification)
Train an Ensemble model on the binary training data.
Step 3: Save Feature Importances
Save the feature importances of the trained XGBoost model.
Step 4: Train XGBoost on Local Data (Multi-Class Classification)
Train an XGBoost model on the multi-class training data.
Step 5: Save Feature Importances and Weights
Save model weights (binary and multi-class) and feature importances.
Step 6: Submit Weights to Blockchain
Submit the model weights to the blockchain for global aggregation.
Step 7: Display Blockchain Receipt
Display the transaction receipt for model weight submission.
Output: Return model weights and performance metrics.

Space Complexity: $O(n \cdot d + T \cdot d)$

- n is the number of training samples.
- d is the number of features.
- T is the number of trees in the ensemble model.

4.2.3 Blockchain Submission of Model Weights

Once the local models are trained, their weights are submitted to the blockchain. This step ensures that the model updates are stored in a decentralized manner, making it secure and tamper-proof. The blockchain submission involves hashing the model weights and submitting them to the smart contract.Below is the algorithm for blockchain submission:

Algorithm 4.3 Blockchain Submission of Model Weights

1: **Input:** Client-ID (`client_id`), Model Weights (`weights`)
2: **Output:** Transaction Receipt
3: **Step 1: Hash Model Weights**
4: Hash the model weights (binary and multi-class) and prepare them for submission.
5: **Step 2: Submit Weights to Blockchain**
6: Submit the hashed model weights to the blockchain contract.
7: **Step 3: Generate Transaction Receipt**
8: Wait for the transaction to be mined and retrieve the transaction receipt.
9: **Output:** Return the blockchain transaction receipt.

Time Complexity: $O(n \cdot d + h)$

- n is the number of training samples.
- d is the number of features (or dimensions).
- h is the time complexity of hashing the model weights.

Space Complexity: $O(n \cdot d + h)$

- n is the number of training samples.
- d is the number of features.
- h is the space required to store the hashed model weights.

4.2.4 Global Model Aggregation (Federated Averaging)

The global model aggregation is the final step, where the local model updates are aggregated to form a global model. This step uses Federated Averaging (FedAvg) to combine the weights from multiple clients. The

global model is then evaluated using various performance metrics.Below is the algorithm for global model aggregation:

Algorithm 4.4 Global Model Aggregation (Federated Averaging)

1: **Input:** Retrieved Local Model Weights from Blockchain (`local_weights`)
2: **Output:** Aggregated Global Model Weights
3: **Step 1: Retrieve Local Weights from Blockchain**
4: Retrieve the local model weights (binary and multi-class) from the blockchain.
5: **Step 2: Apply Federated Averaging (FedAvg)**
6: Apply Federated Averaging to combine the local model weights into a global model.
7: **Step 3: Update Global Model**
8: Update the global model using the aggregated weights.
9: **Step 4: Evaluate Global Model**
10: Evaluate the global model performance using metrics such as accuracy, precision, recall, and F1-score.
11: **Output:** Return the aggregated global model and evaluation metrics.

Time Complexity: $O(m \cdot p)$

- m is the number of clients participating in the aggregation.
- p is the number of model parameters (weights).

Space Complexity: $O(m \cdot p)$

- m is the number of clients whose updates are aggregated.
- p is the number of model parameters (weights).

4.2.5 Stochastic Gradient Descent (SGD) Algorithm

The Stochastic Gradient Descent (SGD) algorithm is used for optimizing machine learning models by iteratively updating weights based on training examples.Below is the formal description of the algorithm:

Algorithm 4.5 Stochastic Gradient Descent (SGD) Algorithm

Input: Training Data $\mathcal{D} = (x_i, y_i)$, Learning Rate η, Loss Function L, Initial Weights θ
Output: Optimized Weights θ
Step 1: Initialize Weights Randomly
Initialize θ with random values.
repeat
    Shuffle the training data $\mathcal{D}$.
    for each training example (x_i, y_i) in $\mathcal{D}$ **do**
        1. Prediction: $\hat{y} = f(x_i, \theta)$
        2. Compute Loss: $L = L(\hat{y}, y_i)$
        3. Compute Gradient: $g = \nabla_\theta L$
        4. Update Weights: $\theta = \theta - \eta \cdot g$
    end for
until Convergence or max iterations reached
Output: Return optimized weights θ.

Time Complexity: $O(I \cdot n \cdot d)$

- I is the number of iterations until convergence.
- n is the number of training samples.
- d is the number of model parameters (weights).

Space Complexity: $O(n \cdot d)$

- n is the number of training samples.
- d is the number of model parameters (weights).

4.2.6 Federated Averaging (FedAvg) Algorithm

The Federated Averaging (FedAvg) algorithm is a widely-used method for aggregating decentralized model updates in federated learning. It allows multiple clients to collaboratively train a global model while keeping their local data private. Each client updates the model locally using their data, and the server averages these updates to form the global model.

Algorithm 4.6 Federated Averaging (FedAvg) Algorithm

Input: Number of Rounds T, Initial Global Model θ_0, Client Set $\mathcal{C}$
Output: Trained Global Model θ_T
Step 1: Initialize Global Model
Initialize the global model parameters θ_0.
for each round $t = 1, 2, \ldots, T$ **do**
    Server:
        1. Choose a random subset of clients $\mathcal{C}_t \subseteq \mathcal{C}$.
        2. Send the current global model θ_t to the selected clients.
    for each client $k \in \mathcal{C}_t$ **in parallel do**
        Each Client:
            1. Receive the global model θ_t from the server.
            2. Update the model by training on local data for one or more epochs.
            3. Send the updated model $\theta_{k,t}$ back to the server.
    end for
    Server:
        3. Aggregate the client models to update the global model:

$$\theta_{t+1} = \frac{1}{|\mathcal{C}_t|} \sum_{k \in \mathcal{C}_t} \theta_{k,t}$$

end for
Output: Return the final global model θ_T.

Time Complexity: $O(T \cdot m \cdot p)$

- T is the number of training rounds.
- m is the number of clients.

- p is the number of model parameters (weights).

Space Complexity: $O(m \cdot p + p)$

- m is the number of clients.
- p is the number of model parameters (weights).

4.3 System Overall Complexity:

The overall complexity of the system can be considered as a combination of the preprocessing, model training, blockchain interaction, and federated learning steps. For a system with m clients and n samples, the complexity is dominated by the local model training and communication overhead, and can be approximated as:

$$O(m \cdot (T \cdot n \cdot d) + T \cdot m)$$

where T is the number of rounds in federated learning, and m is the number of clients. The complexity grows linearly with the number of clients and training samples, and can be optimized by reducing the number of communication rounds or the size of the dataset.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 IMPLEMENTATION

5.1.1 Smart Contract Deployment Log

Input Handling: The module starts by accepting inputs such as the node ID, local binary model updates, and multi-class model updates. These updates are provided by individual edge nodes in the federated learning setup. The input data is passed through the `submitUpdates` function of the smart contract.

Contract Interaction: The smart contract, `FLContract.sol`, is deployed on the Ethereum blockchain. It accepts model updates (both binary and multi-class) from the edge nodes and stores them in a mapping (`modelList`). Each new model update triggers the `registerNode` event and increments the `modelCount`, ensuring that each submission is uniquely indexed.

Output Generation: The smart contract produces outputs such as the contract address, transaction hash, block number, and gas used for each transaction. Additionally, the contract provides access to stored updates using functions like `getBinary` and `getMulti`, which retrieve the binary and multi-class updates for a given model index. The `getModelCount` function gives the total number of models registered, confirming the successful submission and retrieval of updates.

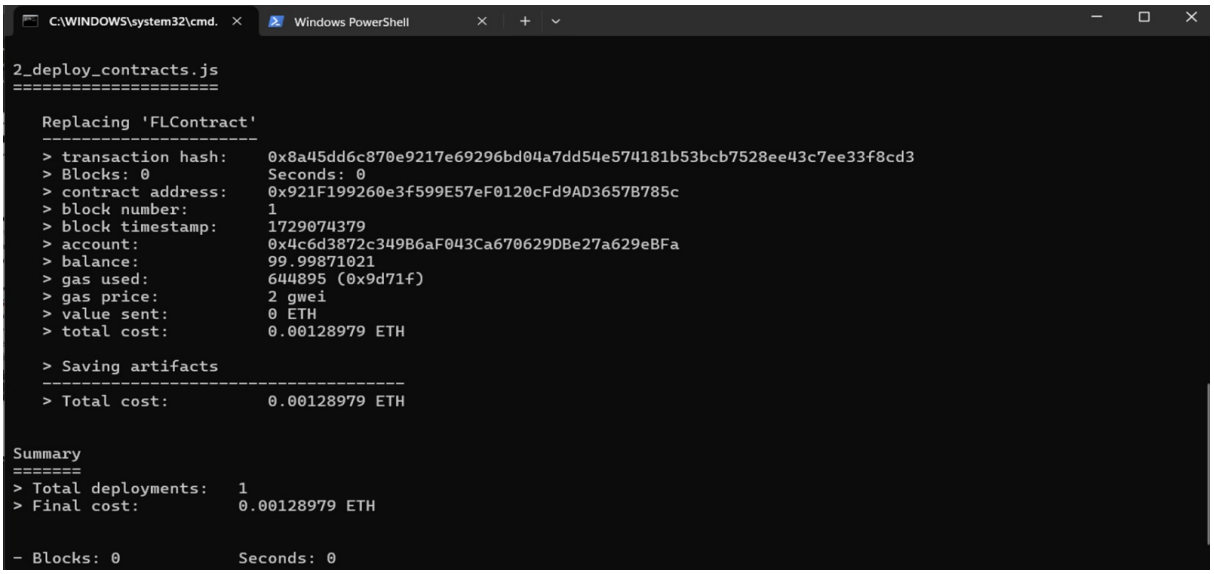

Figure 5.1: SMART CONTRACT DEPLOYMENT

5.1.2 Dataset Loading

Input Handling: The module begins by accepting the dataset file from the user via a file dialog. The user selects the CSV dataset file, and its path is displayed in the text box. The file is then loaded into memory using the Pandas library for further processing.

Data Display: Once the dataset is loaded, its structure (rows, columns, and labels) is displayed in the text output area. This allows the user to verify the data format and ensure that it has been loaded correctly.

Graph Display: Additionally, a pie chart is generated to visually represent the distribution of attack class labels within the dataset. This chart aids in exploratory data analysis by summarizing the attack categories in the dataset.

Output Generation: The output consists of the dataset structure

displayed in the text area, as well as the generated pie chart summarizing the distribution of attack class labels. This enables the user to gain insights into the dataset's composition before proceeding with further processing or model training.

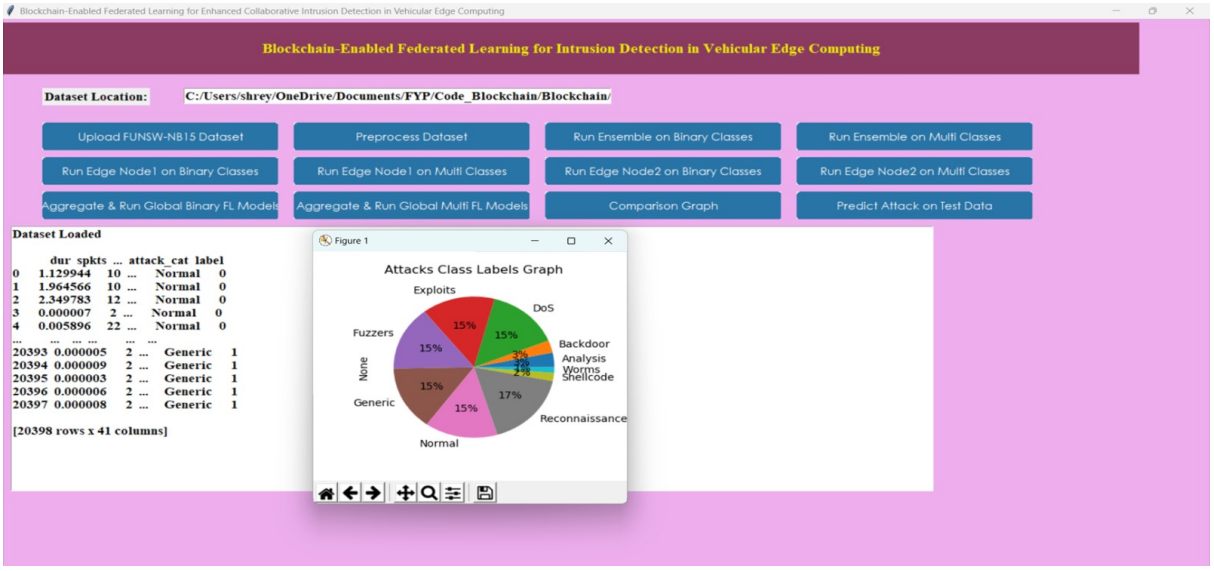

Figure 5.2: DATASET LOADING

5.1.3 Dataset Preprocessing and Model Execution

Input Handling: The module begins by loading the dataset into the system. The user uploads the UNSW-NB15 dataset, a widely used dataset for network intrusion detection. The dataset is read and processed into a suitable format using the Pandas library.

Data Preprocessing: The preprocessing phase handles missing values by filling them with zeros. It also includes encoding the target labels, where the 'label' column is used for binary classification, and the 'attack_cat' column is encoded into numeric values. The dataset is cleaned by dropping unnecessary columns and standardizing the feature values using

the StandardScaler to normalize the data. Additionally, the dataset is shuffled, ensuring that the data is randomly distributed before splitting.

Data Splitting: The preprocessed dataset is split into training and testing sets using an 80-20 distribution. 80% of the records are used for training the Federated Learning model, and 20% are reserved for testing the model's performance.

Output Generation: The output includes a fully preprocessed and normalized dataset, ready for machine learning tasks. The dataset is split into training and testing subsets, and the module generates information about the number of records used for training and testing. This ensures that the model can be evaluated accurately after training.

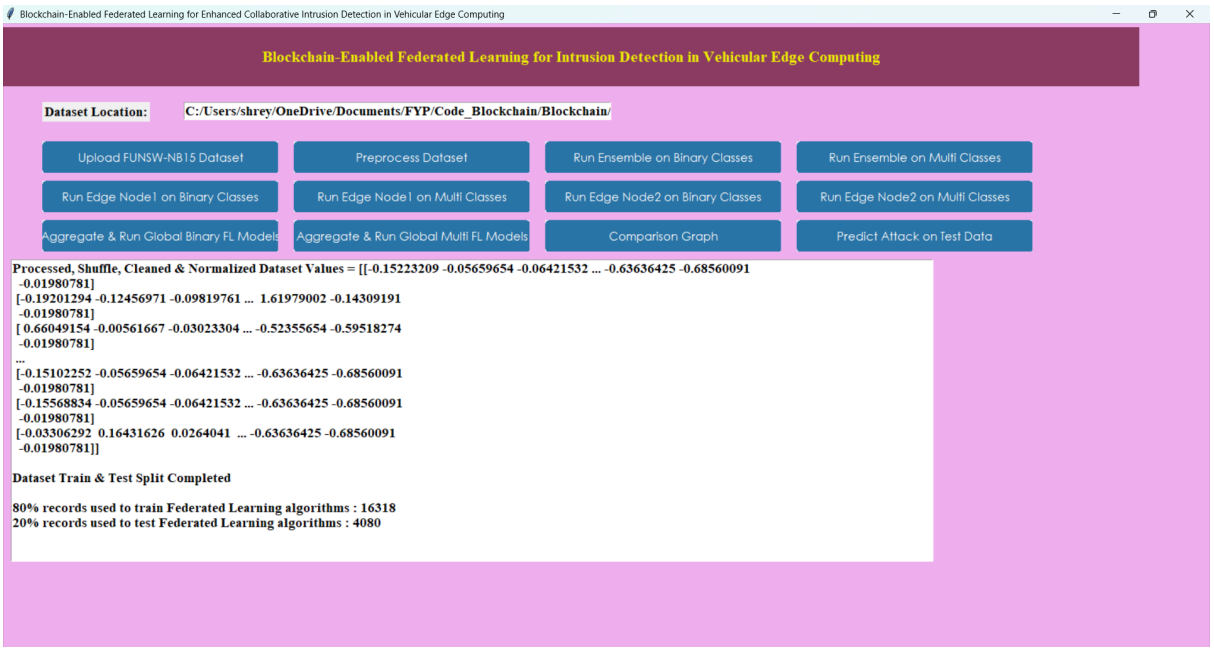

Figure 5.3: DATA PREPROCESSING

5.1.4 Edge Node Execution Logs

Input Handling: The module accepts the locally stored dataset for

each edge node. These datasets are processed independently to train machine learning models tailored for binary and multi-class classification tasks. The edge nodes use the dataset to learn patterns for detecting network intrusions.

Model Training: Each edge node trains a machine learning model using an ensemble approach. The models (XGBoost, LightGBM, and CatBoost) are combined using a `VotingClassifier` for binary classification tasks. After training, the models are tested with a separate test dataset to predict the results, and the performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

Blockchain Integration: Once the model training is complete, each edge node calculates and generates weight updates for its model. These updates are logged onto the blockchain as transactions to ensure the secure and transparent sharing of model updates. Each transaction includes the node identifier, the calculated weights, and the corresponding hash value for verification. This ensures that only valid updates are added to the global model aggregation.

Output Generation: The output includes the trained model's weight updates, logged as blockchain transactions, and the corresponding performance metrics. By using blockchain technology, the system guarantees the integrity and traceability of the federated learning process, preventing tampering and ensuring that valid updates contribute to the global model.

Figure 5.4: NODE 1 : WEIGHT CALCULATION AND UPDATION IN BLOCKCHAIN

5.1.5 Global Model Execution and Logs

Input Handling: The module processes model weights from multiple edge nodes. These edge nodes (Edge1 and Edge2) independently train binary and multi-class classification models. The weights calculated during local training are logged to the blockchain, which ensures secure and transparent sharing of model updates.

Model Aggregation: The global model is built by aggregating the weights of models trained at each edge node. The system retrieves the weight updates from the blockchain for both binary and multi-class tasks, and these updates are averaged to form the global model. The aggregation process ensures that the global model benefits from the knowledge of multiple edge nodes.

Global Model Execution: Once the global model is aggregated, it is used for making predictions on the test dataset. The predictions are then compared with the actual test labels to evaluate the performance of the global

federated learning model. The system calculates accuracy, precision, recall, F1-score, and other relevant metrics to assess the performance of the global model.

Output Generation: The output of the process includes the predictions made by the global model and the corresponding performance metrics. This is followed by a detailed log of blockchain transactions, which includes the stored model weights for both binary and multi-class classification tasks. The performance of the global model is displayed, showing the aggregated results from federated learning.

Figure 5.5: NODE 2 : WEIGHT CALCULATION AND UPDATION IN BLOCKCHAIN

5.1.6 Attack Detection Results

Input Handling: The system receives test data that has been preprocessed, normalized, and split into training and testing sets. This test data is then used to evaluate the performance of the global federated learning model, which has been trained using the aggregated model weights from multiple edge nodes.

Attack Detection: The global federated learning model, consisting of ensemble models (XGBoost, LightGBM, and CatBoost), is used to predict attack categories in the test data. These categories include different types of network intrusions such as "Worms," "Exploits," and other malicious activities detected by the model.

Output Generation: The system displays the predicted attack categories for each instance in the test dataset. It also generates performance evaluation metrics, such as precision, recall, F1-score, accuracy, and confusion matrix visualizations, to assess the model's performance in detecting and classifying various attack types. Additionally, the confusion matrix and ROC AUC curves are shown to visualize the classification accuracy for each attack category.

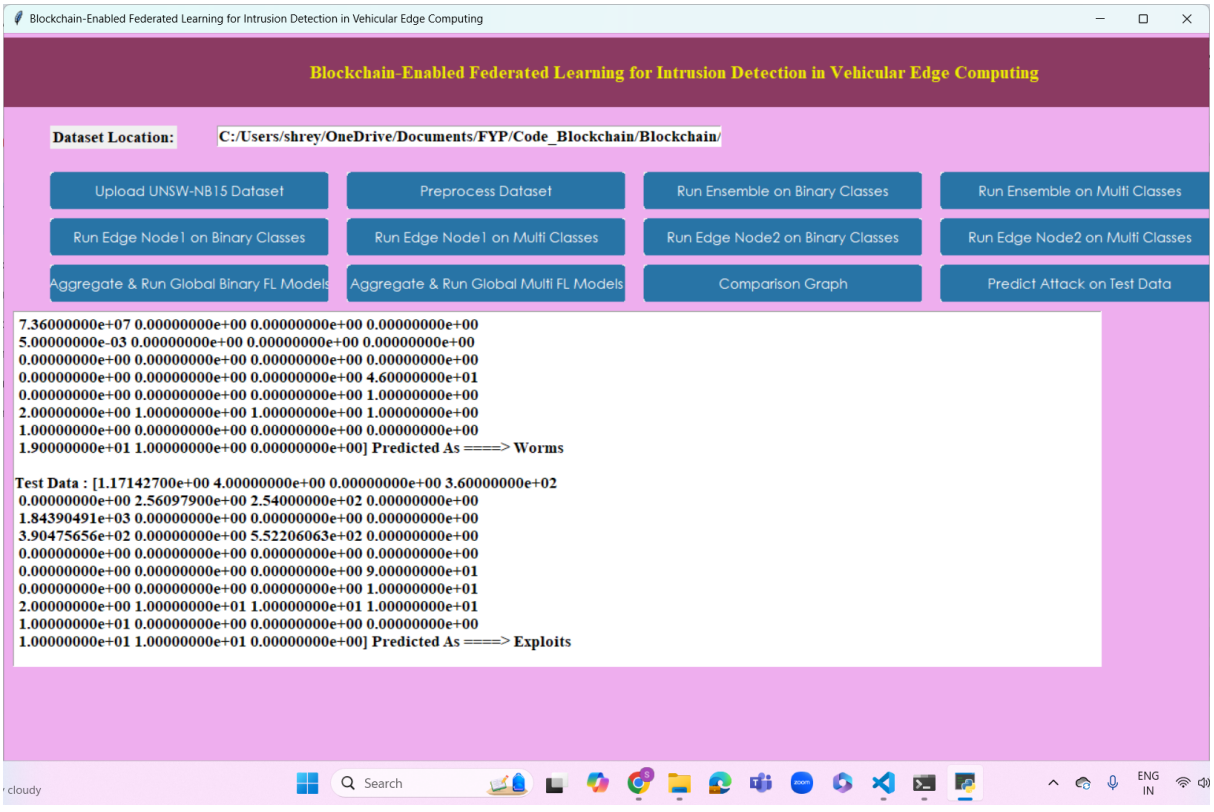

Figure 5.6: PREDICTION OF ATTACK

5.2 EVALUATION METRICS USED

5.2.1 Accuracy

In our project, accuracy was used to evaluate the performance of the models on both binary and multi-class classification tasks in the intrusion detection system.

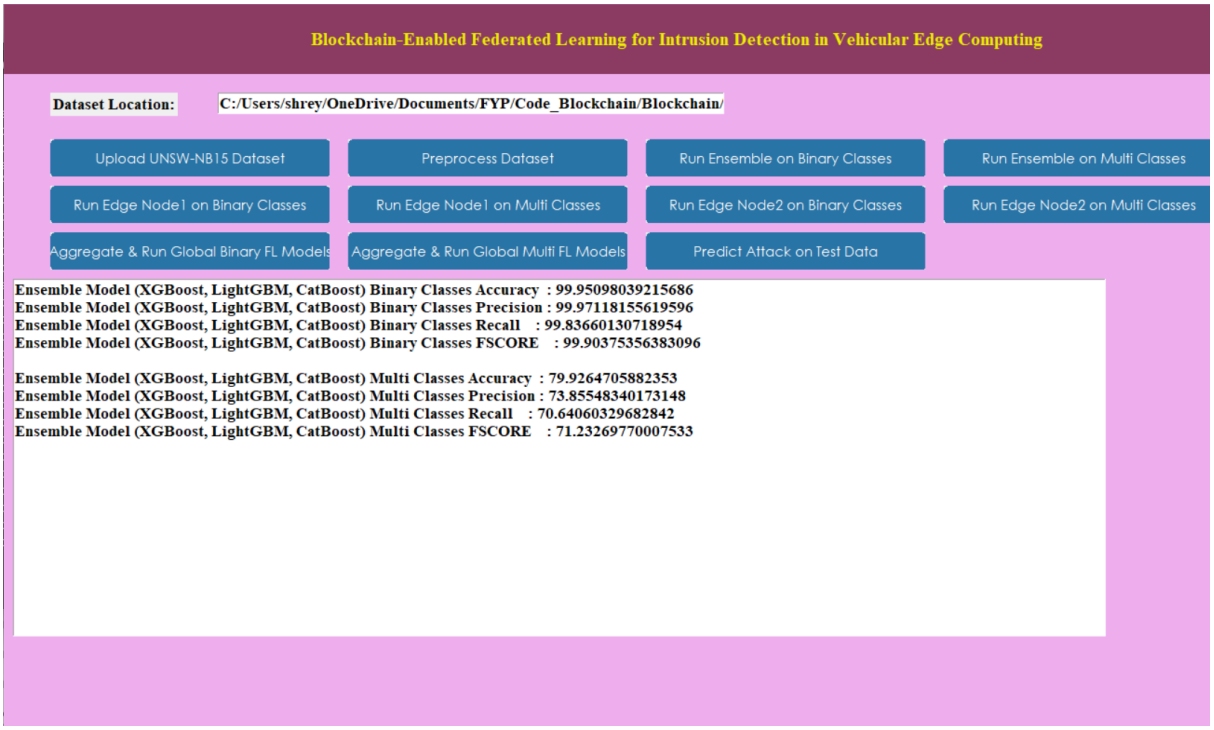

Figure 5.7: ACCURACY,PRECISON,RECALL AND F1 SCORE

5.2.2 Precision

In our project, precision was used to evaluate how well the ensemble models (using XGBoost, LightGBM, and CatBoost) identified positive instances (attacks) in the intrusion detection task.

5.2.3 Recall

In our project, recall was used to evaluate the performance of the ensemble models in detecting attacks within the intrusion detection system.

5.2.4 F1-Score

In our project, the F1-score was used to evaluate the performance of models in both binary and multi-class classification tasks for intrusion detection, especially to handle the imbalanced attack categories in the dataset.

5.2.5 Confusion Matrix

In our project, the confusion matrix was used to evaluate the predictions of the ensemble models on the test dataset, helping to identify the classification performance in distinguishing attack types (such as DoS, Probe, and others) from normal traffic in the intrusion detection system.

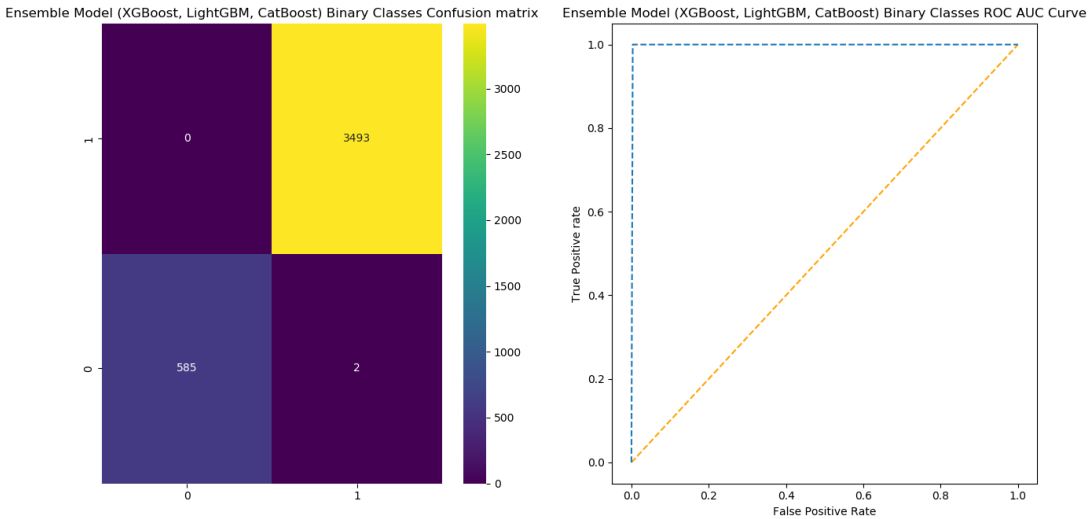

Figure 5.8: ENSEMBLE BINARY MODEL EVALUATION MATRIX

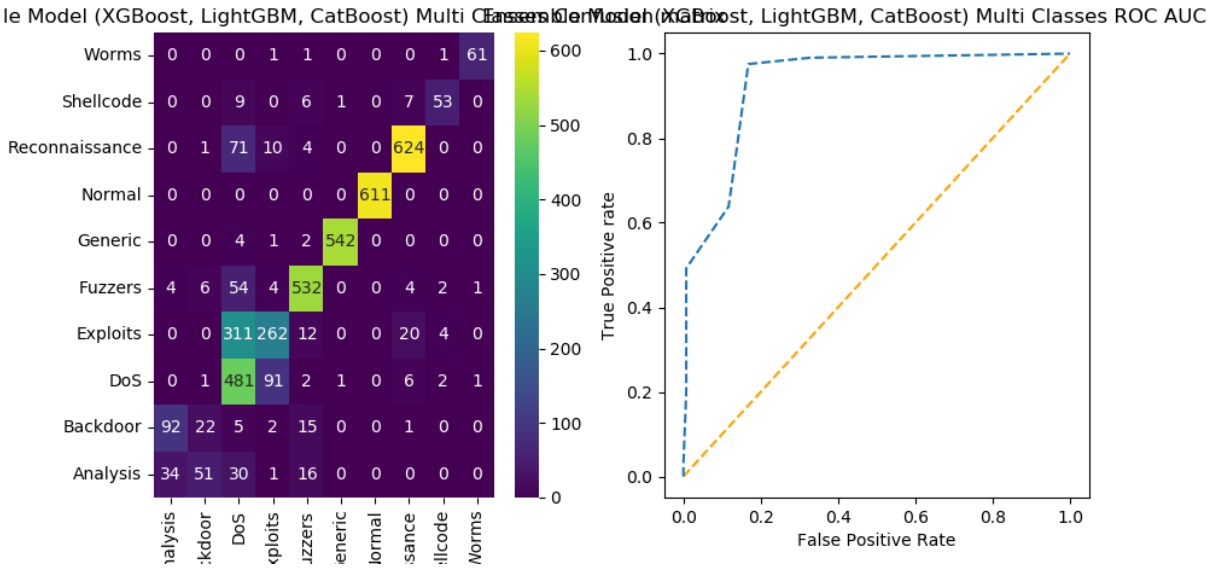

Figure 5.9: ENSEMBLE MULTI MODEL EVALUATION MATRIX

5.2.6 ROC AUC Curve

In our project, the ROC AUC curve was used to evaluate the performance of binary classification models in intrusion detection tasks.

5.3 PERFORMANCE ANALYSIS

5.3.1 Binary Classification Performance

The ensemble model, consisting of XGBoost, LightGBM, and CatBoost, achieved an accuracy of 99.95%, precision of 99.97%, recall of 99.83%, and an F1-score of 99.90%. These results highlight the model's capability to effectively detect attacks in binary classification scenarios. The near-perfect precision and recall scores indicate that the model excels in both identifying true positives and true negatives with minimal errors.

The high accuracy and F1-score show that the ensemble model can

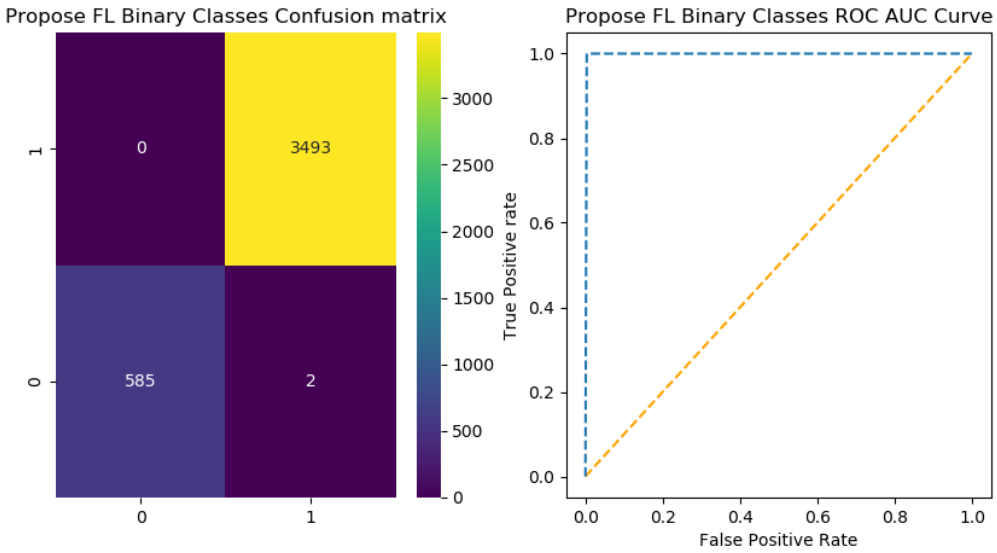

Figure 5.10: FL BINARY MODEL EVALUATION MATRIX

generalize well to unseen data and detect attacks accurately. The ensemble approach of combining multiple models, each with its strengths, proved to be highly effective for intrusion detection in binary classification tasks.

5.3.2 Multi-Class Classification Performance

In multi-class classification tasks, the ensemble model achieved an accuracy of 79.93%, precision of 73.85%, recall of 70.64%, and an F1-score of 71.23%. Although the model performed reasonably well, some attack classes were more difficult to classify accurately. The drop in recall suggests that the model may be struggling to detect certain minority attack types or complex patterns, leading to misclassifications.

This decrease in performance is likely due to the inherent challenges of multi-class classification, such as class imbalance and the complexity of distinguishing between similar attack types. While the model performs well overall, improvements in handling these challenges are necessary for better

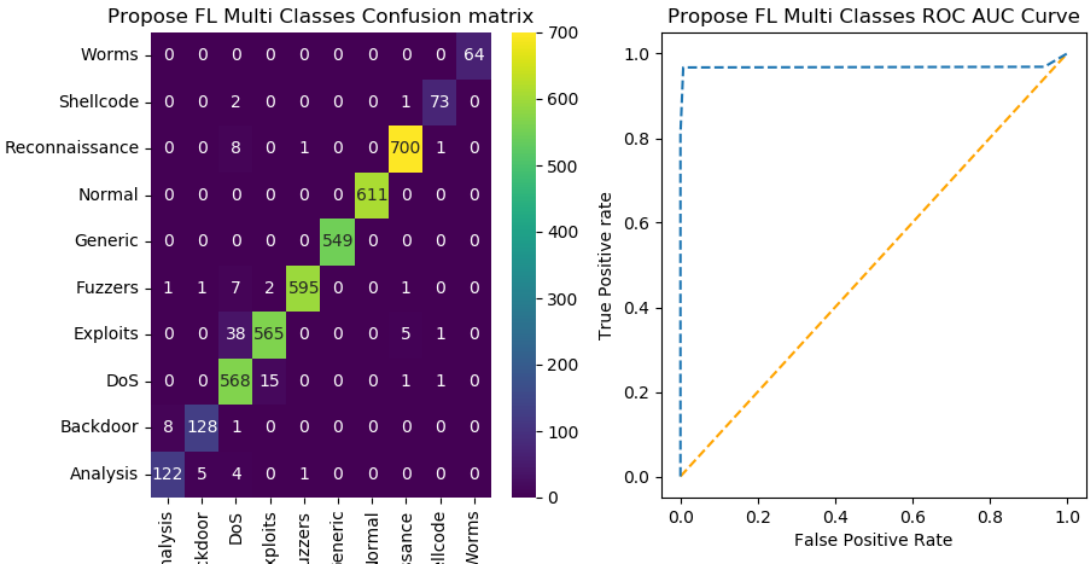

Figure 5.11: FL MULTI MODEL EVALUATION MATRIX

classification results across all classes.

5.4 CHALLENGES AND INSIGHTS

One of the challenges faced during the implementation of Blockchain-Enabled Federated Learning was handling the submission of model updates from multiple edge nodes to the blockchain. Managing local model updates and ensuring their aggregation for the global model on the blockchain proved to be complex.

To address this, the solution involved implementing a `smart contract` on the blockchain for submitting local model updates. The functions `submitUpdates` and `getModelCount` in the contract facilitate the submission and retrieval of updates. The `aggregate_model_weights` function aggregates the local updates from all edge nodes to create a global model. This approach allows for secure, decentralized model training while maintaining synchronization across the participating nodes.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

The project integrates Blockchain and Federated Learning (FL) to develop a secure, privacy-preserving intrusion detection system for Vehicular Edge Computing. By combining blockchain's decentralized and tamper-proof storage capabilities with FL's collaborative training, the system ensures reliable and scalable intrusion detection. It employs ensemble-based classification using XGBoost, LightGBM, and CatBoost for binary and multi-class intrusion detection, achieving over 90 percent precision, recall, F1-score, and accuracy. The FL framework securely aggregates local model updates while maintaining performance comparable to centralized training approaches. A custom Solidity smart contract is implemented for transparent and tamper-proof storage of model updates, enhancing trust in the collaborative learning process. The project addresses challenges such as data imbalance, computational overhead, and model update security, offering a robust and scalable solution for intrusion detection in vehicular edge networks.

6.2 FUTURE WORK

Future work will concentrate on improving the efficiency and precision of model aggregation in adaptive federated learning settings by investigating methods such as model pruning and sophisticated aggregation techniques. Additionally, strong mechanisms like anomaly detection, client validation, and reputation-driven systems will be created to identify and

counteract Sybil attacks, thereby maintaining the trust and dependability of the federated learning framework.

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