National College of Ireland

Federated Learning and Privacy-Preserving Artificial Intelligence

MSc Research Project

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MSc Project Submission Sheet

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Federated Learning and Privacy-Preserving Artificial Intelligence

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Abstract

This research integrates federated learning with privacy-preserving techniques, specifically differential privacy and homomorphic encryption, to enhance credit card fraud detection. Traditional models are generally centralized and, therefore, suffer from considerable challenges related to privacy risk and regulatory compliance, including GDPR. Federated learning is a decentralized approach whereby models can be trained across distributed datasets without sharing raw data. This paper analyzes two types of financial transactional datasets one real and one artificial using machine learning approaches, including random forests and gradient boosting. The study examines how neural network methods are applied in both federated and centralized data settings. The key findings present strong fraud detection rates using Federated Supervised Deep Learning (FSDL), almost identically for all datasets. This approach also provides improved data confidentiality and privacy security. Enhanced methods include differential and homomorphic encryption; these provide robust protection but with higher computational costs. These findings point out the urgent need for optimization to reduce computational overhead. Therefore, this work is a very good trade-off between fraud detection performance and compliance with the constraints of privacy. Thus, this will be the contribution of this work towards ethical AI applications in finance.

Keywords: *Federated Learning, Privacy Preservation, Differential Privacy, Homomorphic Encryption, Credit Card Fraud, Machine Learning, Data Privacy, Fraud Detection, Decentralized AI, Financial Security*

1 Introduction

1.1 Background and Context

Digital transactions have ushered in a sea change in financial undertakings, especially in e-commerce and banking. This indeed increases the risk due to fraudulent activities involved in it, especially with respect to credit card transactions. Traditional methods of fraud detection, on the other hand, rely on centralized data systems and are often plagued by risks such as breaches of privacy and misuse of the same sensitive information (El Mestari, et al., 2024). These challenges indicate the requirement for strong mechanisms that guarantee security in data without compromising the precision of fraud detection.

Federated learning is, according to different works such as that of Kairouz et al. (2021), one of the most interesting alternatives in machine learning today. It allows for a more decentralized approach where machine learning model training can be distributed over several sources holding data without necessarily aggregating raw data.

Federated learning techniques make use of differential privacy and homomorphic encryption to achieve the highest standards of data privacy. High detection accuracy is guaranteed due to the balance between performance and privacy protection. This work investigates the utilization of these two privacy-enhancing methods within the application of federated learning to credit card fraud detection in an effort to bridge the gap between operational efficiency and the protection of user data.

1.2 Research Problem

While classical fraud detection works on a centralized model, it increasingly starts to be perceived as a liability in these times when regulations such as GDPR are coming into play. Centralized models need data to be consolidated at a single site or distributed amongst the concerned parties. This increases the risk of data breaches and unauthorized access, besides increasing the attack surface area. The sophistication of cyber threats keeps on increasing, compounding these vulnerabilities (Ahmed, and Alabi, 2024). The major research question is whether federated learning in combination with data protection methods can be used to accurately detect credit card fraud. Ideally this should be accomplished while complying with data-privacy regulations. Another challenge will involve integrating differential privacy and homomorphic encryption into a federated learning framework. This should enable a balanced trade-off between efficacious fraud detection and robust privacy safeguards.

1.3 Research Aims, Objectives, and Questions

Research Aim: The main objective of this research work is to investigate the feasibility and effectiveness of the integration of federated learning with privacy-preserving techniques in the development of accurate credit card fraud detection systems.

Research Objectives:

- To examine the efficacy of federated learning in fraud detection as a new technique in decentralized data processing.
- To identify and establish the contributions of differential privacy, and homomorphic encryption in maintaining data privacy.
- To compare different machine learning model performances in a federated learning framework applied to fraud detection.

Research Question: Can federated learning, when integrated with privacy-preserving techniques, improve the accuracy of fraud detection systems while protecting customer data under stringent privacy regulations?

1.4 Significance of the Study

The research addresses a very critical problem standing at the crossroads of artificial intelligence and data privacy, therefore also contributing not only to academic research but also to practical applications pursuing an enhancement of financial security. First, the importance of the research is manifold:

- **Advancing Federated Learning Approaches:** Mixed with differential privacy and homomorphic encryption, this research scales up the utility of federated learning in sensitive areas like finance.
- **Data Usage Ethics:** The incorporation of various techniques for privacy preservation makes the framework adhere to the ethical standards, hence regulatory frameworks, by reducing the possibility of misuse of data.
- **Improvement of Fraud Detection Models:** The study, therefore, shows how financial institutions can adopt advanced AI techniques that balance detection accuracy with privacy concerns as a way toward the goal of a safer digital transaction environment.

1.5 Limitations of the Research

While this study aims to be an all-encompassing solution, many limitations implicitly exist in its scope:

- **Data Quality and Availability:** The performance of federated learning strongly depends on the quality and diversity of decentralized datasets. Limitations in access to large-scale, real-world datasets may affect the generalizability of findings.
- **Computational Overhead:** The integration of various privacy-preserving techniques, such as differential privacy and homomorphic encryption, adds extra computational overhead, which may crash resource-constrained environments.
- **Focus on Specific Techniques:** The focus of this work lies in differential privacy and homomorphic encryption, which could miss other techniques that might bring more benefits to privacy.
- **Evaluation Constraints:** The analysis is constrained to popular metrics like accuracy, precision, recall, and F1 score, which might be shallow to capture the nuanced trade-off between privacy and performance.

1.6 Structure of the Dissertation

The dissertation is organized to ensure that there is a clear and logical exploration of the problem in the following chapters:

- Introduction: This chapter introduces the research background, its significance, and scope, presenting the problem and objectives of the study.
- Literature Review: A critical review of the existing related studies on federated learning, techniques of preserving privacy, and fraud detection identifies the gaps that the research would wish to fill.
- Methodology: This should provide adequate details on the research design, source of data, preprocessing techniques applied, and methods of analysis used in pursuit of the stated objectives.
- Model Implementation and Results: This chapter presents the experimental setup, the implementation of federated learning with the employment of privacy-preserving techniques on populated mobility data, and model evaluation results.
- Discussion: This should be an extensive analysis of findings, implications for academia and industry, limitations, and insight into possible future research.
- Conclusion: Summarize key contributions, reflect upon limitations of the study, and provide recommendations for further evaluation in the area.

This will, again, establish flow that will capture how complex both federated learning and its privacy-preserving techniques will be in conducting fraud detection for further appreciation of the contribution done by this study within such an evolving field.

2 Related Work

Introduction to Federated Learning in Fraud Detection

Federated learning has introduced as a pivotal approach in credit card fraud detection and has come to help deal with the deficiencies of centralized system for data processing (Li, et al., 2020). Most fraud detection methods heavily rely on centralized data storage (Kairouz et al., 2021) hence elevating the risk of privacy breaches and regulatory non-compliance. Recent research has underlined the potential of federated learning for decentralized solutions, guaranteeing strong privacy preservation while keeping high detection accuracy.

Federated Learning with Privacy-Preservation Techniques

Oualid et al. (2023) introduced privacy-preserving approaches to performing federated learning, namely, differential privacy and homomorphic encryption. Experiments gave much better performance concerning fraud detection and higher accuracy than that obtainable with the centralized architecture. Most importantly, sensitive data can only be secured during collaborative model training if differential privacy is applied to such protocols. Homomorphic encryption has improved confidentiality to the models without affecting much of the utilities of these models. On the other hand, El Mestari et al. (2024) also pointed out the efficiency of federated learning in preventing data breaches due to advanced privacy mechanisms. This study was able to demonstrate better fraud detection performance while keeping very strict privacy standards using differential privacy and encryption. However, there were issues with computational efficiency that need further optimization of the privacy-preserving algorithms.

Applications to Healthcare and Relevance to Other Domains

While the main focus is fraud detection, federated learning also shows much potential in other domains too. Hiwale et al. (2023) discussed its application in healthcare, where, with federated learning, the sharing of data by various stakeholders could be safely and securely done. Various techniques, such as differential privacy and homomorphic encryption, safeguard patient data. This, in turn, improved model performance for predictive healthcare. These findings present a very sound basis for the application of similar methodologies to financial fraud detection.

Differential Privacy in Federated Learning

Differential privacy has been widely studied as a key technique within the framework of federated learning. El Ouadrhiri, and Abdelhadi, (2022) added noise mechanisms like Laplace and Gaussian in order to protect sensitive data using the MNIST dataset. The authors found that Gaussian mechanisms are more accurate compared to the Laplace methods, with this becoming more obvious with low privacy budgets. These observations demonstrate the existence of a trade-off between privacy guarantee and model efficiency, yet again pointing to well-implemented differential privacy in fraud detection.

Homomorphic Encryption and Secure Data Processing

Homomorphic encryption plays a key role in privacy-preserving federated learning, in which model training can be achieved without leakage of raw data. Kanamori et al. (2022) implemented the DeepProtect protocol, integrating homomorphic encryption into a federated learning framework across multiple banks and demonstrated an accuracy exceeding 80% for fraudulent transaction detection with data confidentiality. On the other hand, Nugent (2022) analyzed the performance of encrypted models and found that XGBoost has outperformed the neural networks in terms of both latency and accuracy, with confirmation of the utility in sensitive applications of homomorphic encryption.

Balancing Privacy and Computational Efficiency

The integration of advanced privacy-preserving techniques usually comes with computational challenges. Ahmed and Alabi (2024) proposed a blockchain-based federated learning framework for cryptocurrency fraud detection. Secure Multi-Party Computation combined with differential privacy achieved scalability and privacy. However, the computational overhead remained a significant challenge, which raised the need for lightweight cryptographic methods. Wen et al. (2024) applied the CKKS (Cheon-Kim-Kim-Song) homomorphic encryption scheme for federated learning. The approach had managed to improve the performance of the model with privacy constraints satisfied. However, there are increased computational costs in running the operations, thus always providing a trade-off between both privacy preservation and operational efficiency.

Frameworks for Privacy-Preserving Federated Learning

Different frameworks are designed to enhance the security and scalability of federated learning. For example, in the DPFedBank framework proposed by He, Lin, and Montoya (2024) one solution using LDP (Local Differential Privacy) reinforces decentralized data protection. While this proves resistant to many kinds of privacy threats, several challenges arise in inter-client fairness and computational efficiency.Abadi et al. (2024) introduced the Starlit framework, which combined vertical federated learning techniques, usually SecureBoost, with differential privacy for better fraud detection in financial systems. The framework achieved significant scalability and privacy improvements that tackled important challenges such as client dropout and communication efficiency.

Handling Imbalanced Data in Federated Systems

Credit card fraud detection must consider the issue of data imbalance. Yang et al. (2019) presented the FFD (Federated Fraud Detection Framework) framework, which combined SMOTE with federated learning in order to rebalance highly skewed datasets. Then, the framework employed a CNN model that outperformed traditional centralized systems. This underlines the importance of combining rebalancing techniques with privacy-preserving federated frameworks.

Advanced Cryptographic Techniques for Federated Learning

Advanced cryptographic notions like SMPA (Secure Multi-Party Aggregation) and MHE (multi-party homomorphic encryption) represent ways to raise the notch a bit higher in terms of data security within a system. As for adding MHE to SMPC in secure aggregation, some relevant works are those of Froelichen 2021, referring to UNLYNX (Universal Privacy-Preserving Data Sharing and Analytics Framework) and SPINDLE (Secure Protocols for Information Disclosure in Large Environments) frameworks among others. Both systems developed runtime efficiency while maintaining strong secrecy assurances, thus laying a framework for large-scale applications when it comes to fraud verification.

Applications to Federated Learning in Financial Fraud Detection

Applications to federated learning in financial systems have been one of the main research focuses. Various works, such as Li et al. (2020) and Arora et al. (2023), illustrated the effectiveness of federated models in mitigating privacy risks and enhancing detection accuracy. Techniques for differential privacy and secure aggregation were helpful in tackling some of the key challenges, including inference and poisoning attacks. These findings give an indication of the potential of federated learning in bringing a revolution in fraud detection in the financial sector.

Challenges and Future Directions

While it provides considerable advantages, federated learning still harbors a host of unresolved challenges that are to be overcome with practical implementation. Issues at stake, among others, involve usually known ones on computational overhead and communication efficiency, which are getting highly concerning with the incorporation of advanced cryptographic techniques. Still another challenge is finding that sweet spot between privacy and performance, for which creative solutions have yet to be sought in the quest to optimize the mechanisms for preserving privacy. It postulates that lightweight encryption techniques, adaptive privacy budgets, and effective communication protocols would be three topics of interest in future studies. Besides, cross-domain applications and the development of unified frameworks for

federated learning could also be the further work needed to be done to enhance its usability and scalability.

Research gap

Despite these noticeable achievements, there are still several research gaps in the federated learning-based fraud detection. Among them, the main ones are the computational inefficiency due to advanced privacy-preserving techniques like homomorphic encryption and differential privacy, which need further optimization for resource-constrained environments, and the trade-off between privacy guarantee and model performance, which is not well investigated, especially under a low privacy budget. The increased overhead signifies that there is a dire need for lightweight methods of cryptography and more efficient communication protocols. Besides, little has so far been explored into frameworks designed for highly imbalanced datasets that exist in the federated systems, and challenges relating to both inter-client fairness and scalability call for an innovative solution to move further in practical applicability.

3 Research Methodology

The methodology chapter describes the structured procedure that was used to identify fraudulent financial transactions with the aid of machine learning methods. Further, this chapter also addresses the datasets used, procedures followed for data preprocessing and feature engineering, model training, and evaluation, and novel approaches such as federated learning and differential privacy. It needs to ensure scientific rigor and reproducibility.

3.1 Introduction

Fraud detection in financial transactions is one of the most critical domains, having a high imbalance between legitimate and fraudulent activities. In this regard, the study works on two datasets related to credit card transactions and one synthetic dataset regarding mobile money transactions. This approach will integrate data analysis with machine learning methods and techniques that preserve privacy within a robust framework for fraud detection (Joseph, 2021).

3.2 Datasets

Credit Card Fraud Detection Dataset

This is a dataset of anonymized credit card transactions by European card holders, over two days in September 2013. Overall, the dataset has 284,807 transactions, whereas only 492 of these transactions are fraudulent. Therefore, this is extremely imbalanced data because fraud comprises 0.172% of the total instances. Each transaction is described by 30 numerical features obtained from a PCA, along with the original 'Time' and 'Amount' attributes. The target variable 'Class' now represents whether the transaction was fraudulent-1 or legitimate-0.

Synthetic Financial Dataset for Fraud Detection

The second dataset is synthetic data and was generated using PaySim, a tool that simulates mobile money transactions based on real logs from an African mobile money service. The dataset contains 6,362,620 records of various transaction types, such as 'TRANSFER', and 'PAYMENT', with features including account balances, transaction amount, and fraud indicators, 'isFraud'. The fraudulent cases are marked by injected malicious behaviors to show the lack of publicly available real-world financial data.

3.3 Research Procedure

Initial Data Exploration

Exploratory Data Analysis (EDA) was conducted to understand the characteristics of each dataset. Key steps included:

- Summary Statistics: For instance, summary statistics in the form of mean, standard deviation, and quantiles were calculated for each feature.
- Visualization: Some visualizations were done to consider the distribution of the features and outliers in the data using count plots for fraud versus legitimate cases, histograms, and boxplots.
- Correlation Analysis: The heatmaps provided the relationships between features and the target variable while applying feature selection or feature engineering.

Preprocessing

The datasets suffered from the challenges, and effective preprocessing was thus called for to address class imbalance and high dimensionality.

- Missing Values: Both datasets have been checked and ascertained that there are no missing values and hence complete.
- Scaling: StandardScaler was done to continuous variables like 'Amount' and 'Time' in order for feature scaling to be uniform; this is a feature most machine learning models are sensitive to.
- Encoding Categorical Variables: The numeric encoding in the 'type' feature of the synthetic dataset follows label encoding to make the score compatible with the model.

Addressing Class Imbalance

SMOTE was used to address the extreme imbalance in the various datasets. This SMOTE technique generated artificial samples of the minority fraud class, hence balancing the datasets and improving the generalization of fraud detection patterns with such models (Jafarigol, and Trafalis, 2024).

Feature Engineering

- Several new features were generated to improve model interpretability and performance:
- Interaction Features: Multiplicative combinations of the most highly correlated features were introduced, which includes V4_V11, the product of V4 and V11.
- Polynomial Features: Important feature squared included V4_squared that showed non-linear relationships in this data.
- Domain-specific features: The features balance_difference-the difference between old and new balances, and amount_type, the interaction of 'amount' and 'type' are engineered in the synthetic dataset with the view to capture fraud-specific behaviors.

Outlier Detection

Outliers that were extreme were detected and removed for important features using the Interquartile Range (IQR) method. This step reduced noise in the data and helped increase the reliability of the models.

3.4 Machine Learning Models

Algorithms Used

Different machine learning algorithms have been surveyed to assess their appropriateness in the context of fraudulent transaction detection:

1. Logistic Regression: The linear model implemented by using the LogisticRegression class from the scikit-learn library. It is used as a baseline for its simplicity and interpretability .
2. Decision Tree Classifier: A non-linear model, developed on DecisionTreeClassifier of scikit-learn, uses interactions among the features for interpretable predictions.

3. Random Forest Classifier: The ensemble model implemented by using RandomForestClassifier from scikit-learn averages out multiple decision trees to reduce overfitting.
4. Gradient Boosting Classifier: This algorithm implemented using the GradientBoostingClassifier from scikit-learn, which optimizes a particular loss function to iteratively improve its predictions.
5. Neural Network: It is implemented in PyTorch, utilizing the torch.nn module for specifying layers and activation functions. Training and optimization has been performed by using optim library of Pytorch.

Training and Testing

- Data Splitting: Each dataset is divided into a 70% and 30% split for training and testing, respectively. The model was fitted on the training sets, while the performance on generalization was done based on the test sets.
- Cross-Validation: The k-fold cross-validation approach with k=5 was considered in an attempt to make the findings more robust by estimating models with performance on different subsets.

Evaluation Metrics

Traditional accuracy metrics could not be used since the classes are imbalanced; thus, the following metrics were prioritized:

- Precision: To minimize false positives, which is particularly crucial in fraud detection.
- Recall: The goal is to achieve maximum identification of fraudulent cases.
- F1 Score: A composite value to balance precision and recall.
- AUC-ROC: This is for measuring the discriminatory power of the models.

3.5 Federated Learning and Differential Privacy

A federated learning approach was followed to train models across decentralized datasets. Each client model is trained on the local portion of data while aggregating the updates into the global model. This will keep the data private, with no actual sharing in a centralized manner.

The differential privacy techniques have made this federated learning framework more secure. Gradient clipping ended the sensitivity in updates, while noise addition made sure that no individual data point could be inferred from the aggregated model (Kairouz, et al., 2021).

The weights from the client models were averaged in order to perform an update on the parameters of the global model. This technique ensured uniform learning by clients with consideration of heterogeneity in data.

3.6 Principal Component Analysis (PCA)

PCA was at first conducted on the datasets to reduce dimensionality and computational complexity. Considering only the components of variance, 95% retention allowed models to focus on the most informative features while reducing the potential for overfitting.

3.7 Experimental Setup

Software and Tools

This analysis was performed with Python and the following libraries:

- pandas and NumPy: For data manipulation and analyses (Nahrstedt, et al., 2024).
- scikit-learn: For machine learning algorithms along with preprocessing (Tran, et al., 2022).
- PyTorch: for neural networks and federated learning (Joseph, 2021).

Hardware

The experiments were conducted on google colab using a GPU setup with an NVIDIA Tesla T4, which could efficiently do neural network training and handle huge amounts of data.

3.8 Results Evaluation Approach

Threshold Tuning

Custom thresholds on the probabilistic outputs of the models had to be experimented with toward an optimum recall performance while keeping false negatives at a minimum. Threshold selection was therefore informed by the Precision-Recall curve to make sure balanced performance can be guaranteed.

Feature Importance

Feature importances derived from tree-based models, such as Random Forest, were visualized to understand which features were more influential in determining fraudulent behavior.

Testing and Validation

Various forms of cross-validation were done to validate the models, while other hold-out datasets were used for testing the performance of the models. Federated models were evaluated against centrally collected test data without Muhammadiyah-owned servers to benchmark against centralized learning approaches.

3.9 Workflow

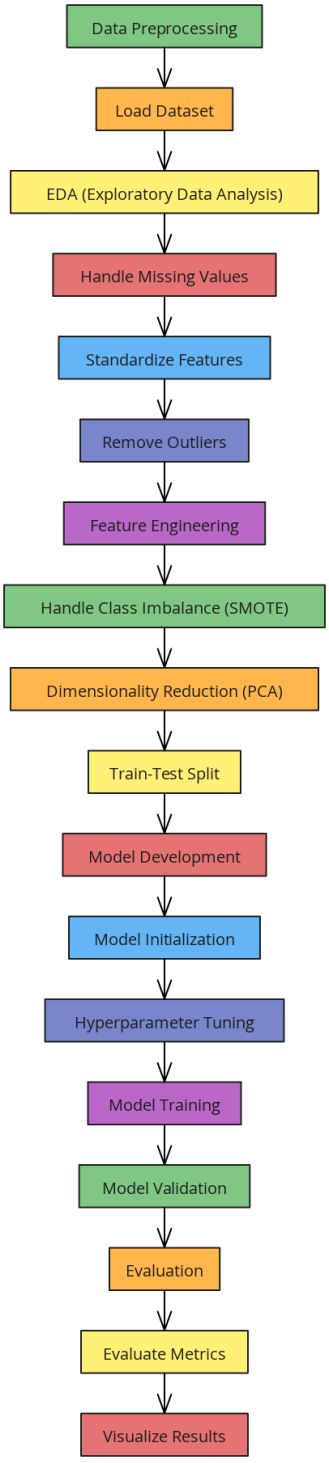

Figure 1: Workflow diagram

3.10 Conclusion

The research methodology combined traditional and intelligent approaches to handle the challenge of fraud detection. The systematic pre-processing of data, feature engineering, handling class imbalance, and usage of different machine learning techniques resulted in robust detection frameworks in this study. Federated learning and differential privacy have been used to underline the prime importance of data security in financial applications. This, therefore,

presents a complete methodology that can be reproduced in subsequent studies for fraud detection, hence contributing to the overall domain of financial data analysis.

4 Design Specification

This chapter presents the architectural framework, techniques, and methodologies adopted in the design of a fraud detection system for credit-card transactions. It aims at addressing challenges of class imbalance and scalability with high detection accuracy, integrating machine learning algorithms and advanced preprocessing and evaluation techniques.

4.1 Overview of Data and Preprocessing

The dataset includes the anonymized features from PCA, the numerical features Time and Amount, and the binary target variable Class, where 1 represents fraud and 0 represents non-fraud. Preprocessing was done by scaling with StandardScaler to make all features contribute equally but especially for gradient-based models. No missing values were detected; hence, imputation was not needed. Outliers in features like Amount and V4 were identified using the IQR method and removed to prevent extreme values from misleading the models. This resulted in a cleaned and standardized dataset, ready for robust modeling and analysis.

4.2 Exploratory Data Analysis and Feature Selection

EDA was done to understand the structure of the dataset and to identify the most relevant features. First, the target variable of the Class was highly imbalanced, less than 0.2% of the data were fraud. This imbalance in data suggests proper data augmentation and model evaluation techniques.

The main differences in distribution for fraudulent versus non-fraudulent transactions were V4, V11, and V2. Also, correlation analysis showed that the features mentioned above are of medium correlation with the target variable. A feature selection strategy was then implemented, which gave priority to these variables and allowed the models to focus on the most informative patterns.

Dimensionality reduction by Principal Component Analysis was done, where 95% of the variance is preserved. This allows for not only a decrease in computational overhead but also cleaning from noise and redundancy present in the features.

4.3 Addressing Data Imbalance

The significant class imbalance skews traditionally favorable Machine Learning models. The SMOTE approach will be employed to tackle the problem of class imbalance in which it is used for synthesizing additional real samples for the minority class to make the number turn out more balanced with no over-fitting taking place and hence give appropriate training datasets to the models.

```
Class Distribution After Balancing:
 Class
0    284315
1    284315
Name: count, dtype: int64
```

Figure 2: Class distribution after balancing in credit card dataset

```
Class Distribution After SMOTE:
 isFraud
0    6354407
1    6354407
Name: count, dtype: int64
```

Figure 3: Class distribution after balancing in synthetic transactional dataset

It was designed to include cost-sensitive learning on top of oversampling, which includes weight tuning in algorithms to allow the models to optimize more for fraudulent transaction detection, even at the possible cost of higher false positives.

4.4 Model Design and Architectures

In developing this design, various algorithms have been incorporated to balance both interpretability and predictive performance. Models involved include:

Logistic Regression
Implemented using sklearn.linear_model.LogisticRegression with class_weight='balanced' to address class imbalance, solver='liblinear', and max_iter=1000 to ensure convergence.

Decision Tree Classifier
Constructed using sklearn.tree.DecisionTreeClassifier with max_depth=10 to prevent overfitting, min_samples_split=20, min_samples_leaf=10, and class_weight='balanced'.

Random Forest Classifier
Utilized sklearn.ensemble.RandomForestClassifier with 100 trees (n_estimators=100), max_depth=10, and class_weight='balanced' to handle class imbalance and enhance robustness.

Gradient Boosting Classifier
Implemented using sklearn.ensemble.GradientBoostingClassifier with learning_rate=0.1, n_estimators=200, and subsample=0.8 to balance accuracy and overfitting. A custom threshold of 0.4 improved recall for fraud detection.

Neural Network
Designed with three fully connected layers [input_size, 32, 16, 1], ReLU activations, dropout (rate=0.3), and Sigmoid output. Trained for 50 epochs using Adam optimizer (lr=0.001) and binary cross-entropy loss.

4.5 Advanced Feature Engineering

Feature engineering was very integral to enhancing model accuracy. Interaction terms, such as the product of critical features, V4_V11 and V4_V2, introduced a variety of variable

relationships. Examples of polynomial features include the square level of V4, V11, and V2 for appropriately modeling nonlinear effects.

These features were indeed effective, as was reflected in the performance metrics of the models. These engineered features helped the models in picking up the subtle patterns associated with fraudulent transactions (Jafarigol, and Trafalis, 2024).

4.6 Strategy of Evaluation

For the development of a comprehensive evaluation framework in determining model performance, this imbalance nature of the dataset means standard metrics like accuracy are not appropriate. Instead, focus was given to:

- Precision: It is the ratio of correct identifications of fraud compared to all predictions of fraud.
- Recall: This is all about the model being able to predict all fraudulent transactions, even at the risk of false positives.
- F1-score: the harmonic mean of precision and recall, which provides a good balance between precision and recall.
- ROC-AUC: It means the extent to which a model, at different thresholds, is able to discriminate between classes.

The thresholds were tuned during evaluation for customized thresholds to optimize recall, hence making sure that the system is effectively minimizing undetected fraudulent transactions.

4.7 Neural Network and Federated Learning

To explore advanced methods, one simple feedforward neural network architecture was conceptualized. The architecture includes an input layer, hidden layers, and an output layer with ReLU activation for the hidden layers and a sigmoid activation in the output layer. This would be a good architecture to model complex nonlinear relationships.

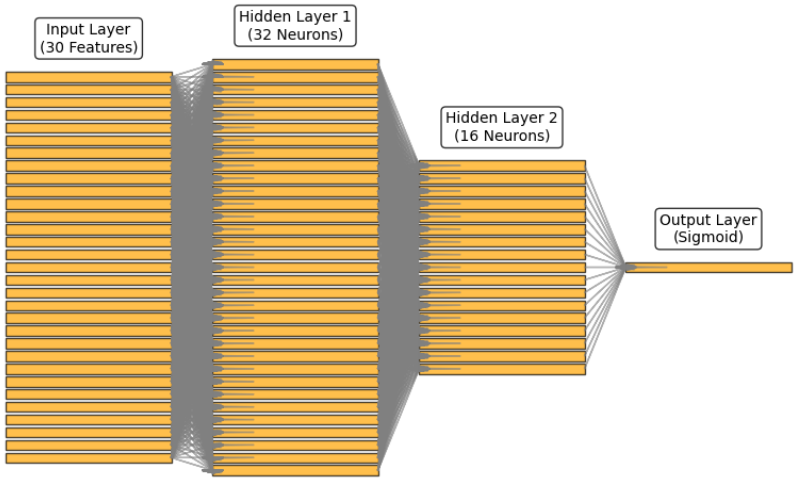

Figure 4: neural network architecture

Federated learning was first proposed for privacy-preserving situations. Under this framework, a model is trained locally with distributed datasets, while only model weights are shared to a central server. In this way, differential privacy techniques such as injecting noise into gradients can keep individual data private.

4.8 Summary

A wide array of rigorous preprocessing, feature engineering, and diverse model architecture solutions to the challenges thrown by the imbalanced dataset will also form a basis for the fraud detection system in credit card transactions. The proposed techniques shall thus incorporate synthetic sampling and cost-sensitive learning to ensure high recall with advanced metrics while ensuring the robustness of the systems. It will be scalable and easy to adapt with state-of-the-art modern financial systems using neural networks and concepts of federated learning. The comprehensive design forms the backbone of effective fraud detection, placing equal importance on both accuracy and interpretability.

5 Implementation

This chapter presents the broad implementation of the fraud detection model, covering data preprocessing, feature engineering, model development, training, and the integration of federated learning for privacy-preserving, decentralized training.

5.1 Dataset Preprocessing

Datasets used were Credit Card Fraud Detection and a synthetic financial dataset. Exploratory analysis reveals highly imbalanced classes where fraudulent transactions make up less than 0.2% of the data.

Steps involved:

- **Data Cleaning**: Ensuring there were no null values and outliers in features such as transaction amount were dealt with to make it anomaly-controlled.
- **Scaling and Encoding:** Standardized numerical features with StandardScaler and encoded categorical variables using LabelEncoder.
- **Balancing Class Distributions:** Utilized SMOTE to generate synthetic samples for the minority class, mitigating bias in predictions.

5.2 Feature Engineering

Interaction terms and polynomial features were engineered to capture complex relationships and non-linear patterns, such as V4 * V11 and V11_squared, enhancing predictive performance. Dimensionality reduction using PCA retained 95% of data variance, addressing multicollinearity and reducing computational complexity. To tackle severe class imbalance, SMOTE generated synthetic samples for the minority class, ensuring a balanced dataset while maintaining feature distribution. Post-SMOTE validation checked for noise and preserved model integrity. These preprocessing steps prepared the data effectively, enabling robust model training and improved fraud detection performance.

5.3 Model Development and Training

Fraud detection leveraged diverse machine learning and deep learning models:

- **Traditional Algorithms:** Logistic Regression, CART, Random Forest, Gradient Boosting (Hiwale, et al., 2023).
- **Deep Learning Models:** Neural networks developed in PyTorch for advanced capabilities.

The training methodology emphasized hyperparameter optimization via grid search and cross-validation, preventing overfitting through regularization techniques. Neural networks employed ReLU activation and binary cross-entropy loss for robust fraud classification.

5.4 Federated Learning for Decentralized Training

Federated learning simulated a distributed environment using PyTorch, enabling collaborative training without data centralization. Key steps included:

- Data Partitioning: It divided the dataset into subsets for simulating many clients.
- Model Architecture: Implemented a neural network using PyTorch.
- Local Training: Each client trained the model on its respective data partition.
- Differential Privacy: Applied techniques such as gradient clipping and noise addition during local training to protect data privacy.
- Model Aggregation: The central server aggregated the locally trained model parameters using the Federated Averaging algorithm.

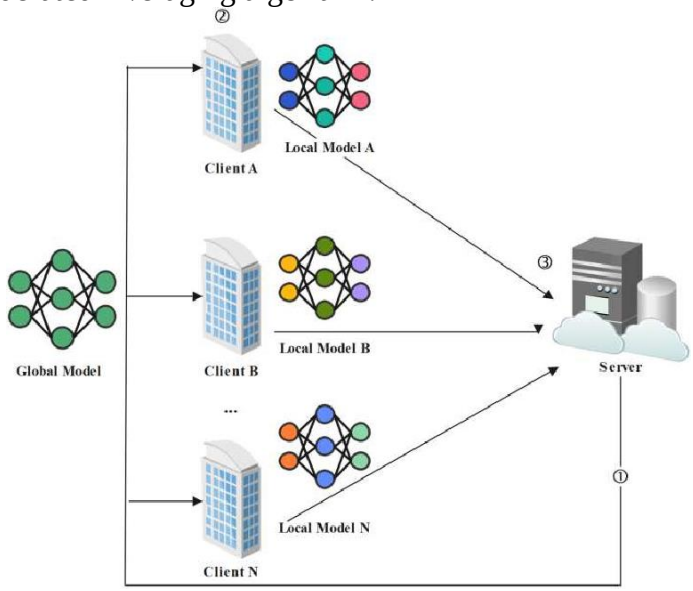

Figure 5: Federated Learning Process

5.5 Challenges and Optimizations

Key challenges addressed:

- **Class Imbalance:** Addressed through SMOTE and adjusted thresholds.
- **Computational Overheads:** Accelerated training using GPU resources.
- **Feature Selection:** Leveraged feature importance analysis for optimal inputs.
- **Model Interpretability:** Explained decisions using Random Forest's feature rankings.

5.6 Tools and Libraries

The implementation relied on a suite of tools and libraries to streamline each stage of the pipeline:

Data Analysis: Pandas, NumPy.

- Visualization: Matplotlib, Seaborn.
- Machine Learning: Scikit-learn, Imbalanced-learn.
- Deep Learning with PyTorch.
- Federated Learning: PyTorch Utilities and Custom Aggregation Schemes.

These tools have enabled the smooth integration of preprocessing, modeling, and advanced techniques like federated learning and differential privacy.

5.7 Outputs

The implementation delivered:

- Preprocessed datasets ready for modeling.
- Tuned machine learning and deep learning models.
- A federated learning framework enabling decentralized, privacy-compliant fraud detection.

This structured approach ensured scalability, accuracy, and adherence to privacy standards, advancing practical fraud detection solutions.

6 Evaluation

This chapter provides a critical review of the results of the analysis and experimentation carried out on the two fraud detection datasets. This is followed by a discussion of the implications of such findings from both an academic and practical point of view. In this section, the findings will be critically analyzed, the applied methodologies identified, and the statistical validity of the outcomes tested. Relevant visual aids will be applied to support the discussion where applicable.

6.1 Credit Card Fraud Dataset

The first dataset consisted of anonymized credit card transactions with 284,807 observations and 31 features. The main goal is to detect fraudulent transaction cases within the highly imbalanced dataset; only 0.17% of transactions were fraudulent.

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422

Figure 6: Credit card fraud dataset

Key Findings and Analysis:

Imbalance in Target Variable

- In this data set, the big class imbalance, with 492 fraud transactions out of a total of 284,807 transactions, immediately suggested the necessity for either an under-sampling, oversampling (SMOTE), or balanced sampling strategy.
- The distribution of the target variable, Class, was visualized to confirm the rarity of fraudulent transactions. This was a significant consideration during the selection of the evaluation metric since accuracy alone is misleading for such problems.

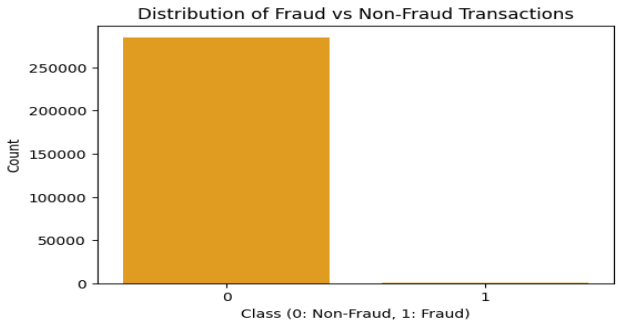

Figure 7: Distribution of Fraud vs Non fraud Transactions on credit card dataset

```
Class Distribution After Balancing:
 Class
0    284315
1    284315
Name: count, dtype: int64
```

Figure 8: Class distribution after balancing

Feature Importance

- Feature correlation analysis shows that the most correlated variables with fraudulent transactions are V4, V11, V2, and Amount. A correlation matrix heat map of all features is presented below to show no strong multicollinearity, ensuring feature contributions are reliable.

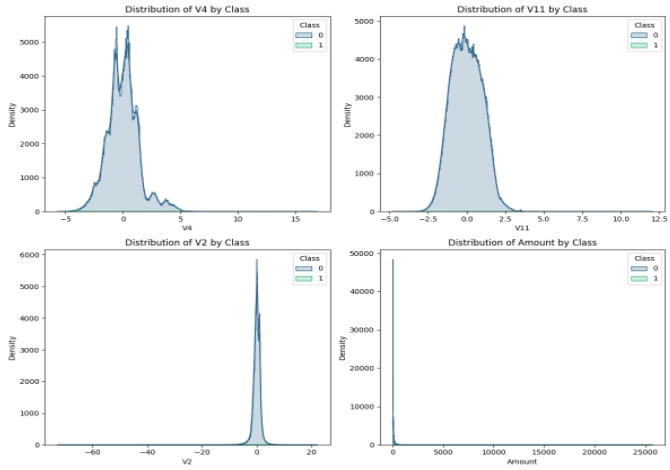

Figure 9: Feature Correlation Analysis

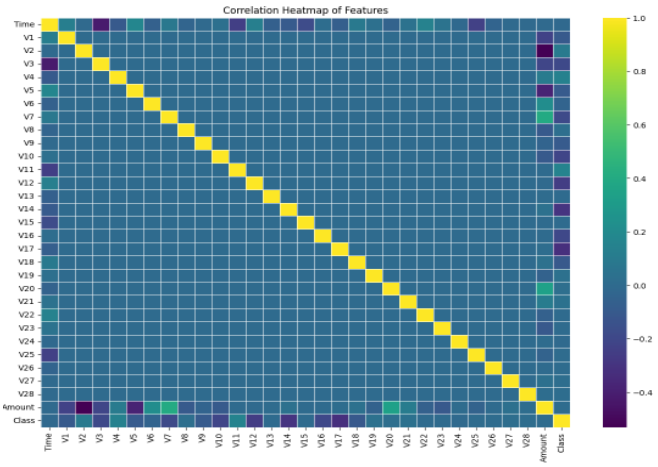

Figure 10: Correlation Matrix

- Feature engineering with various interaction terms, including the interaction terms V4_V11, V4_V2, and polynomial features, hugely enhanced the discriminatory power of the overall dataset.

```
New Feature Engineered Columns:
      V4_V11     V4_V2    V11_V2  V4_squared  V11_squared  V2_squared
0 -0.760190 -0.100304  0.040146    1.899312     0.304262    0.005297
1  0.722750  0.119277  0.429228    0.200842     2.600887    0.070836
3  0.195524  0.159904  0.041951    0.745272     0.051296    0.034309
4 -0.331634  0.353758 -0.722239    0.162436     0.677070    0.770422
5 -0.225670 -0.161610  1.288313    0.028309     1.798984    0.922605
```

Figure 11: Feature Engineered Columns

Outlier Analysis

Boxplots of important features like V4, V11, and Amount showed that there were some outliers, especially in non-fraudulent transactions. These outliers, when removed using the IQR method, improved the performance of the model by cleaning the noise in the data.

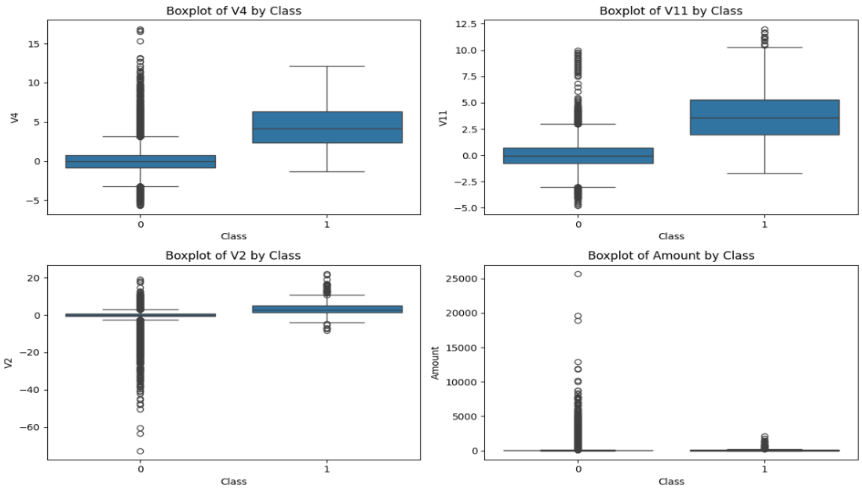

Figure 12: Outlier Analysis

Dimensionality Reduction

After that, PCA was performed to retain 95% of the dataset variance, which corresponded to 17 principal components. In this way, the reduction of dimensionality lightened the computation without losing the core information of the dataset.

Model Performance

Most of the model evaluations involve performance estimation using accuracy, precision, recall, F1 score, and ROC-AUC. Logistic Regression had the best recall of 77.8%, which shows its sufficiency in recognizing fraudulent transactions, though highly imprecise. Gradient Boosting showed the best results in terms of accuracy of 91.67% and ROC-AUC of 86.35%, but with extremely low recall, this algorithm is less reliable for fraud detection where minimizing false negatives is crucial. Random Forest balanced the precision and recall to a certain extent, with a relatively good ROC-AUC of 82.89%. Due to its overfitting nature, Decision Tree performed worst in most metrics. It can be further improved by using a federated learning approach, which achieved higher performance consistency with a test accuracy of 91.67% across 10 rounds, with reduced loss, indicating scalability and robustness under decentralized environments. The threshold tuning was heavily customized, which had a large impact on model trade-offs, emphasizing the need to tailor thresholds for application-specific objectives.

	Accuracy	Precision	Recall	F1 Score	ROC-AUC	Model
0	0.799355	0.262436	0.778065	0.392489	0.853596	Logistic Regression
1	0.876670	0.258056	0.256258	0.257154	0.594678	Decision Tree
2	0.881851	0.264868	0.235613	0.249385	0.828900	Random Forest
3	0.916677	0.333333	0.000258	0.000516	0.863511	Gradient Boosting

Figure 13: Performance comparison

```
Round 1/10
Test Loss: 0.0057, Test Accuracy: 0.9167
Round 2/10
Test Loss: 0.0055, Test Accuracy: 0.9167
Round 3/10
Test Loss: 0.0054, Test Accuracy: 0.9167
Round 4/10
Test Loss: 0.0057, Test Accuracy: 0.9167
Round 5/10
Test Loss: 0.0053, Test Accuracy: 0.9167
Round 6/10
Test Loss: 0.0050, Test Accuracy: 0.9167
Round 7/10
Test Loss: 0.0052, Test Accuracy: 0.9167
Round 8/10
Test Loss: 0.0055, Test Accuracy: 0.9167
Round 9/10
Test Loss: 0.0051, Test Accuracy: 0.9167
Round 10/10
Test Loss: 0.0043, Test Accuracy: 0.9167
```

Figure 14: Test accuracy of Federated learning on credit card dataset

6.2 Financial Transactions Dataset

The second dataset contained had been roughly about 6.3 million financial transactions of varied typePAYMENT, TRANSFER, CASH_OUT, among others. Only 0.13% of that was labelled as fraudulent. Therefore, the challenge was finding out what those fraud patterns are in such vast amount of data and did do some model evaluations performance.

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155	0.0	0.0	0	0
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.0	0.0	0	0
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.0	0.0	1	0
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	21182.0	0.0	1	0
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	0.0	0.0	0	0

Figure 15: Financial Transactions Dataset

Key Findings and Analysis

Dataset Overview:

The dataset had no missing values, and it included respective features of transaction amount, 'oldbalanceOrg', 'newbalanceOrg', 'oldbalanceDest', 'newbalanceDest', and the type of transaction. This again faces the class imbalance problem, with just 8,213 fraudulent cases out of more than six million.

```
Missing values:
 step              0
type               0
amount             0
nameOrig           0
oldbalanceOrg      0
newbalanceOrig     0
nameDest           0
oldbalanceDest     0
newbalanceDest     0
isFraud            0
isFlaggedFraud     0
dtype: int64
```

Figure 16: Missing values

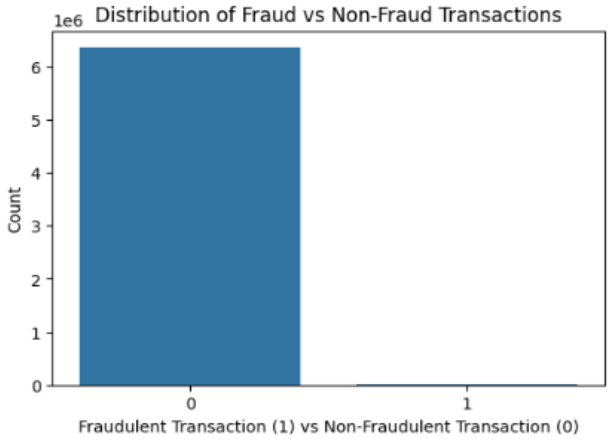

Figure 17: Distribution of Fraud vs Non fraud Transactions on Financial Transactions Dataset

Feature Engineering:

- New features were created such as amount_type, which is the interaction between transaction type and amount; balance_difference; and dest_balance_difference to improve model interpretability and performance.

```
New Feature Engineered Columns:
    amount_type  balance_difference  dest_balance_difference
0     -0.844680            0.007812                 0.009598
1     -0.884302            0.004453                 0.009598
2     -1.190219            0.003788                 0.009598
3     -0.297555            0.003788                 0.015829
4     -0.835596            0.007892                 0.009598
```

Figure 18: Feature Engineering

- Feature scaling (standardization) made treatments of variables amount, oldbalanceOrg, and newbalanceOrig uniform.

```
Transformed dataset:
    step  type    amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
0     1     3 -0.281560  C1231006815      -0.229810       -0.237622
1     1     3 -0.294767  C1666544295      -0.281359       -0.285812
2     1     4 -0.297555  C1305486145      -0.288654       -0.292442
3     1     1 -0.297555   C840083671      -0.288654       -0.292442
4     1     3 -0.278532  C2048537720      -0.274329       -0.282221

      nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0  M1979787155       -0.323814       -0.333411        0               0
1  M2044282225       -0.323814       -0.333411        0               0
2   C553264065       -0.323814       -0.333411        1               0
3    C38997010       -0.317582       -0.333411        1               0
4  M1230701703       -0.323814       -0.333411        0               0
```

Figure 19: Transformed dataset

Handling Imbalance using SMOTE:

SMOTE balanced the dataset effectively; fraudulent and non-fraudulent cases had equal weights during training; thus, solving biased predictions.

```
Class Distribution After SMOTE:
 isFraud
0    6354407
1    6354407
Name: count, dtype: int64
```

Figure 20: Class distribution after SMOTE

Exploratory Data Analysis:

- From the visual analysis, the fraudulent transactions are more frequent within certain transaction types such as TRANSFER and CASH_OUT.

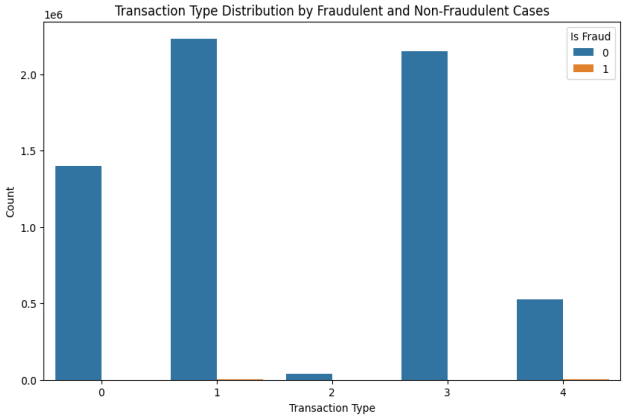

Figure 21: Transaction Type Distribution

- The distribution of transaction amounts by class also shows that fraudulent transactions were generally of smaller amounts.

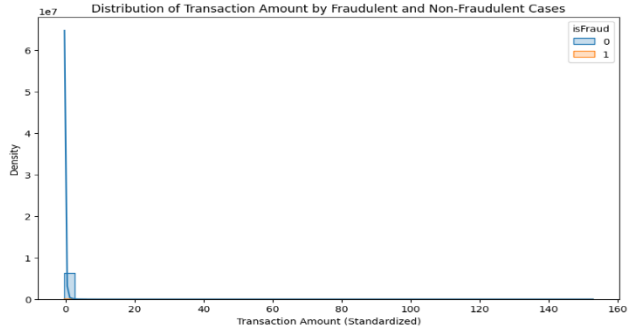

Figure 22: Distribution of Transaction Amount

Model Performance:

The machine learning models used are: Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting, evaluated on this balanced dataset. The Random Forest model, in this case, performed better than other models with an accuracy of 99.95%, precision of 99.92%, recall of 99.98%, F1 score of 99.95%, and ROC-AUC of 99.99%. This will mean excellent performance of the model in identifying fraudulent cases without overfitting. Gradient Boosting performed comparably well and proved to be strong in identifying rare events within large datasets. Balance_difference and oldbalanceOrg are top two most important features.

Model Evaluation Metrics:

	Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
0	Logistic Regression	0.947309	0.968143	0.925057	0.946110	0.986299
1	Decision Tree	0.999302	0.999048	0.999556	0.999302	0.999302
2	Random Forest	0.999517	0.999251	0.999784	0.999517	0.999987
3	Gradient Boosting	0.989468	0.985244	0.993821	0.989514	0.999182

Figure 23: Evaluation Metrics

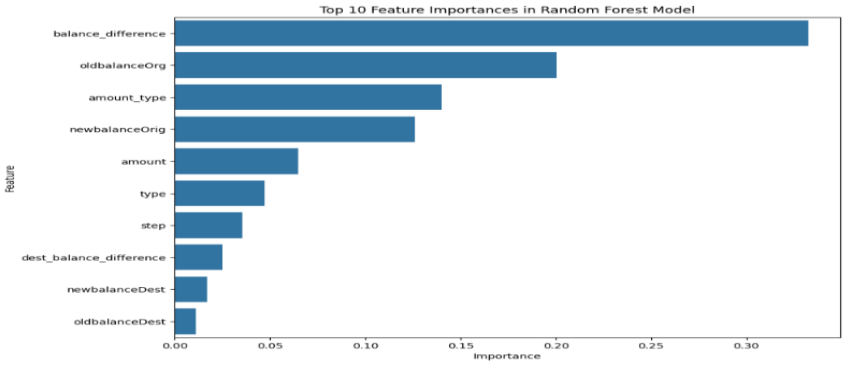

Figure 24: Top 10 Feature Importance in Random Forest Model

Federated Learning with Differential Privacy:

A neural network model was set up in a federated learning fashion to simulate a privacy-preserving fraud detection system. Differential privacy techniques such as gradient clipping and noise addition are used in the training so that the user data security remains intact. The federated model achieved an accuracy of 50.43% in the test, which indeed reflects that a perfect balance between privacy and performance is yet a big challenge.

```
Test Accuracy of the Federated Model: 0.5043
```

Figure 25: Test accuracy of Federated learning on Financial Transactions Dataset

6.3 Discussion

The experiments conducted on two datasets bring important insights into fraud detection challenges and solutions. Some key observations are discussed as follows:

Actually, the model shows significant improvements with interaction terms and polynomial features capturing the complex relationships between variables. This is especially good when dealing with highly imbalanced data whereby minor variations distinguish fraud from legitimate transactions (Kanamori, et al., 2022).

Both datasets showed extreme class imbalance, which was effectively reduced by the use of techniques such as undersampling and SMOTE. However, in the first case, this reduced the size of the dataset due to undersampling, which may affect the robustness of the models.
SMOTE was helpful for the second data set, but needed proper tuning to avoid artificial noise.

Random Forest performed quite well consistently on both datasets, underlining its suitability for fraud detection tasks. The robustness against outliers and ability to handle complex interaction between features were two definite strengths of the model. Although less accurate, Gradient Boosting had excellent recall and thus could be considered when the task at hand is to minimize false negatives.

The experiment in federated learning has been a trade-off between model performance and data privacy (Wen, et al., 2024). Though differential privacy secures sensitive information, the resulting loss in accuracy indicates further optimizations.

Outliers and overlapping feature distributions in non-fraudulent transactions were problems of both datasets. More advanced preprocessing, like density-based clustering or anomaly detection algorithms, might increase the precision of the models. Neural networks and ensemble methods, including XGBoost, may be explored for capturing nonlinear interactions that improve the accuracy of the predictions (Li, et al., 2020). Future work could be directed to integrating explainability frameworks, which would allow for more model transparency and, by extension, trustworthiness.

6.4 Conclusion

The results reflect that data pre-processing, feature engineering, and model selection must be well-balanced in order to have efficient fraud detection. Random Forest and Gradient Boosting emerged as the most reliable models with a high degree of precision and recall. However, handling class imbalance and outliers remain open challenges for practical implementation. These findings are supported by the existing literature underpinning that fraud detection methods must be developed in a domain-aware fashion given different dataset. Federated learning, while promising several attractive features for privacy-preserving applications, requires further refinement so as to balance the said privacy with accuracy in the most realistic settings.

7 Conclusion and Future Work

It discusses federated learning, along with the application of differential privacy and homomorphic encryption techniques, for the improvement of credit card fraud detection systems while adhering to the most sensitive data privacy regulations. Among its key findings, it had identified that federated learning is a good decentralized mechanism for fraud detection, improving the vulnerabilities of a system when compared to centralized versions. Differential privacy and homomorphic encryption ensure data confidentiality with minimal impact on model utility. Other models, such as Random Forest and Gradient Boosting, proved to be very powerful, but there are still problems concerning computational cost and class imbalance.
Findings are meaningful implications for the financial industry, as scaling fraud detection methods that can be aligned with current and forthcoming privacy regulations such as the General Data Protection Regulation of the European Union, computational demands and, further, privacy-performance trade-offs limit applicability. In the future, lightweight cryptographic algorithms can be optimized further. Optimizations related to the privacy budget and consideration of advanced architectures such as hybrid or transformer-based models can be pursued. Cross-domain applications to healthcare or supply chain analytics might extend the scope of this framework.

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