INTELLIGENCE FRAUD DETECTION: LEVERAGING DEEP LEARNING FOR CREDIT CARD TRANSACTIONS

A MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Credit card fraud detection plays a crucial role in safeguarding financial transactions against potential threats. This study presents an exploratory approach using a combined framework of Neural Ordinary Differential Equations (Neural ODE) and XGBoost to detect fraudulent transactions effectively. The Neural ODE model extracts latent features from transaction data, which are then utilized by the classifier to differentiate between genuine and fraudulent transactions. The XGBoost classifier is chosen for its high accuracy in predictions and robustness to complex data distributions. A traditional vanilla Recurrent Neural Network (RNN) model is used for comparison, employing the same preprocessed data as the Neural ODE and XGBoost models. The results demonstrate that the accuracy of the Neural ODE + XGBoost model significantly outperforms the vanilla RNN in precision, recall, and F1-score. Thus, the proposed model shows promise for real-world applications, offering enhanced predictive capability and efficiency in fraud detection systems.

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INTRODUCTION

1.1 OVERVIEW

Credit card fraud is a growing concern that poses significant risks to financial institutions and consumers alike. As digital payments become more prevalent, fraudulent activities, such as unauthorized transactions, account takeovers, and identity theft, have become more sophisticated and widespread. The financial losses caused by these fraudulent transactions are substantial, and they undermine trust in digital payment systems. As a result, detecting and preventing credit card fraud has become a critical priority for financial institutions around the world.

Traditional fraud detection methods, such as rule-based systems and statistical models, are often limited in their ability to identify new and emerging fraud patterns. These systems rely on predefined rules and assumptions that may not adapt well to the dynamic nature of fraudulent activity. Consequently, they can produce high rates of false positives, flagging legitimate transactions as fraudulent, or fail to identify fraudulent transactions in time, leading to significant financial losses. As fraudsters become more sophisticated, the need for more advanced techniques to detect and prevent fraud is more pressing than ever.

Machine learning and artificial intelligence (AI) have shown great promise in addressing the limitations of traditional fraud detection systems. However, despite their potential, many existing approaches still face challenges related to accuracy, computational efficiency, and the ability to generalize across diverse transaction data. Therefore, there is a pressing need for innovative solutions that can improve the precision and scalability of fraud detection systems. Developing such systems would not only help minimize losses but also enhance the overall security and reliability of digital payment systems.

1.2 NEED FOR THE STUDY

The need for this study arises from the growing prevalence and sophistication of credit card fraud, which continues to pose significant challenges to financial institutions and consumers. Traditional fraud detection methods are often inadequate, struggling to keep pace with evolving fraud techniques and resulting in either false positives or missed fraudulent activities. These limitations lead to financial losses and erode trust in digital payment systems. As the volume of online transactions increases, there is an urgent need for more accurate, efficient, and real-time detection systems that can better identify fraudulent transactions and reduce risks to both financial institutions and customers.

Additionally, existing machine learning models, while promising, face challenges in handling large-scale, complex transaction data, and in adapting to new fraud patterns. This study aims to explore advanced techniques, such as Neural Ordinary Differential Equations (Neural ODE) combined with XGBoost, to enhance fraud detection systems' accuracy and reliability. By addressing these challenges, the research seeks to develop a more robust and scalable model that can be deployed in real-world applications, providing a reliable solution to combat the increasing threat of credit card fraud.

Furthermore, early and accurate detection of fraudulent activities is critical not only to prevent financial losses but also to improve the efficiency of fraud prevention systems. This study aims to fill the gap by developing a more effective approach that can support financial institutions in detecting fraud at an early stage, enhancing overall transaction security, and minimizing the impact of fraud on customers and the broader financial ecosystem.

1.3 OBJECTIVE OF THE STUDY

1. **Enhance Fraud Detection Accuracy:** Develop a robust fraud detection system using Neural ODE and XGBoost to improve the accuracy of identifying fraudulent credit card transactions in real-time.
2. **Feature Extraction with Neural ODE:** Utilize Neural Ordinary Differential Equations (Neural ODE) to extract meaningful and complex features from transaction data, enhancing the model's ability to identify subtle fraud patterns.
3. **Compare with Traditional Models:** Conduct a comparative analysis between the proposed Neural ODE + XGBoost model and traditional Recurrent Neural Networks (RNN) to demonstrate improved performance in fraud detection tasks.
4. **Evaluate Model Performance:** Assess the performance of the hybrid model in terms of key metrics such as precision, recall, F1-score, and accuracy, showing its superiority over traditional models.
5. **Scalable and Efficient Solution:** Design a solution that is capable of processing large-scale transaction data efficiently, enabling real-time fraud detection for financial institutions.
6. **Contribute to Fraud Detection Research:** Provide valuable insights into integrating advanced machine learning techniques, such as Neural ODE and XGBoost, to address challenges faced by traditional fraud detection methods, advancing the field of credit card fraud detection.

1.4 OVERVIEW OF THE PROJECT

This project aims to develop an advanced system for detecting fraudulent credit card transactions by combining two powerful machine learning techniques: Neural Ordinary Differential Equations (Neural ODE) and XGBoost. Credit card fraud is a growing issue for financial institutions and consumers, and current fraud detection systems often struggle with accuracy and efficiency, leading to either false positives or missed fraudulent transactions. To address these challenges, this project proposes a hybrid model that leverages Neural ODEs for feature extraction and XGBoost for classification.

Neural ODEs offer a flexible and interpretable approach to modeling continuous-time dynamics, extracting complex features from transaction data that capture both temporal and spatial patterns. These extracted features are then passed into the XGBoost classifier, which uses decision trees to make highly accurate predictions by considering the subtle differences between legitimate and fraudulent transactions. The model's performance is compared with that of a traditional Recurrent Neural Network (RNN) to demonstrate the superiority of the proposed approach in terms of key metrics such as accuracy, precision, recall, and F1-score.

The ultimate goal of this project is to provide a scalable, efficient, and reliable solution for real-time credit card fraud detection. By improving the accuracy of fraud detection systems, the project seeks to reduce financial losses, enhance transaction security, and restore trust in digital payment systems. The results from this project have the potential to contribute significantly to the field of fraud detection, offering financial institutions an effective tool to combat the growing threat of credit card fraud.

CHAPTER - 2
LITERATURE REVIEW

2.1 INTRODUCTION

Credit card fraud continues to grow, challenging traditional detection systems as fraud tactics become more complex. Rule-based and statistical methods, commonly used for fraud detection, often fall short when dealing with the large, dynamic transaction data of financial systems, leading to missed fraud cases or falsely flagged transactions. Consequently, there is an increasing need for more adaptable, accurate fraud detection methods.

Machine learning approaches, including Random Forests, Support Vector Machines, and deep learning models like RNNs and LSTMs, have improved fraud detection accuracy. However, these models can struggle with computational intensity, risk of overfitting, and imbalanced datasets, limiting their effectiveness for large-scale, real-time fraud detection.

This project addresses these challenges by introducing a hybrid model that combines Neural Ordinary Differential Equations (Neural ODEs) with XGBoost. Neural ODEs capture temporal and spatial transaction data dynamics, creating rich, continuous representations that traditional models often miss. These features are then classified by XGBoost, known for its robustness and efficiency. By leveraging the strengths of both models, this system aims to provide a more accurate, efficient solution, enhancing fraud detection accuracy and scalability. This approach offers potential for improving real-time detection, helping financial institutions reduce losses and protect consumers.

S.no	Author Names	Paper	Description	Journal /Year
1.	Syed Mumtaz Ali Shah, Abid Ali Minhas, Mirza Naseer Ahmad	Credit Card Fraud Detection Using AdaBoost and Majority Voting	This paper explores the use of AdaBoost and Majority Voting techniques for improving the accuracy of credit card fraud detection, highlighting the effectiveness of ensemble methods.	IEEE Xplore / 2022
2.	Ashwini S. Kadam	Real-Time Credit Card Fraud Detection Using Long Short-Term Memory Neural Networks	The study implements Long Short-Term Memory (LSTM) neural networks for real-time detection of fraudulent credit card transactions, showcasing the ability to handle sequential data effectively.	Springer Link / 2021
3.	Amira El Alaoui, Mohamed Fakir	A Deep Learning Approach to Credit Card Fraud Detection Using Autoencoders	This research applies autoencoders, a type of unsupervised deep learning model, to detect anomalies in credit card transactions, emphasizing the capability of deep learning in identifying fraud without labeled data.	Elsevier / 2020
4.	Radhika Gupta, Sameer Gupta	Application of Random Forest in Credit Card Fraud Detection	A survey paper that reviews various implementations of Random Forest algorithms in credit card fraud detection, summarizing the advantages and challenges of using this ensemble method.	ACM Digital Library / 2019

CHAPTER - 3
SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Hybrid Model of Neural Network and Decision Tree

In this study [1], researchers created a hybrid approach by combining a Neural Network with a Decision Tree classifier for improved fraud detection accuracy. The Neural Network is primarily responsible for extracting complex, non-linear feature representations from transaction data. These deep features allow the model to capture intricate patterns that may indicate fraudulent activity, which traditional models might miss. Once extracted, these features are fed into a Decision Tree classifier, which provides an interpretable, structured way to make the final classification. This combination allows the system to benefit from the Neural Network's powerful feature extraction and the Decision Tree's interpretability and efficiency on structured data. The hybrid model outperformed standalone Neural Network and Decision Tree models in fraud detection, showcasing how combining these two techniques leverages both deep feature extraction and decision-tree-based classification to enhance overall performance in fraud detection tasks.

Stacked Autoencoder with Random Forest Classifier

Another study [2] introduced a model using a Stacked Autoencoder for feature extraction, paired with a Random Forest classifier for classifying transactions as fraudulent or legitimate. The Stacked Autoencoder compresses high-dimensional transaction data into essential representations, effectively learning and preserving the most distinguishing features needed for classification. This method addresses the common issue of high-dimensionality in transaction data, making the model more efficient and less prone to overfitting. After extracting these compact features, the Random Forest classifier takes over to perform the final classification. Known for its robustness in handling noisy data, the Random Forest also helps prevent overfitting, especially on imbalanced datasets where fraudulent cases are sparse. The combined approach improved model generalizability, yielding more accurate results by making it effective in detecting fraud while minimizing false positives, which is critical for real-world fraud detection systems.

LSTM with Gradient Boosting Machines (GBMs)

In this research [3], the authors explored a hybrid model that combines Long Short-Term Memory (LSTM) networks with Gradient Boosting Machines (GBMs) to enhance credit card fraud detection. The LSTM network is adept at processing sequential transaction data, which is essential for capturing temporal patterns within transaction histories. By learning these temporal dependencies, the LSTM can identify anomalies in the time series that might indicate fraudulent behavior. The extracted temporal features are then fed into a GBM classifier, a powerful ensemble method known for its high accuracy and ability to capture subtle distinctions between classes. This combination was particularly effective in achieving high precision and recall, as it leveraged LSTM's ability to process time-series data and GBM's capability to handle structured data accurately. Overall, this hybrid model showcased impressive results in differentiating between genuine and fraudulent transactions, making it a suitable choice for scenarios requiring high accuracy and adaptability to complex data patterns.

Credit Card Fraud Detection Using Bayesian and Neural Networks

In this study [4], researchers explored a hybrid model that integrates Bayesian networks with neural networks to improve the accuracy of credit card fraud detection. The Bayesian network is utilized to capture the probabilistic relationships between different features in the transaction data, offering a structured approach to assess the likelihood of fraud based on known dependencies. This probabilistic reasoning enables the model to provide interpretable insights, as Bayesian networks offer a clear understanding of the conditions under which fraud might occur. On the other hand, the neural network component extracts complex, non-linear feature representations that can capture subtle patterns in the data that Bayesian networks alone might overlook. By combining Bayesian networks with neural networks, the model benefits from both probabilistic interpretation and powerful feature extraction, resulting in a more robust and reliable fraud detection system. The hybrid model demonstrated improved detection accuracy and reduced false positives compared to using each method independently, making it particularly effective in identifying fraudulent transactions while maintaining transparency. This approach highlights the advantage of integrating probabilistic reasoning with deep learning, providing a balanced solution for real-world fraud detection tasks where both interpretability and precision are crucial.

Application of Random Forest in Credit Card Fraud Detection

In this paper [5], the researchers examined the application of the Random Forest algorithm for credit card fraud detection. Random Forest, an ensemble learning method that constructs multiple decision trees during training, was chosen for its robustness and effectiveness in handling imbalanced datasets, which is a common challenge in fraud detection due to the limited number of fraudulent cases compared to legitimate transactions. By creating a "forest" of decision trees, the model averages their predictions, which helps reduce variance and minimizes the risk of overfitting, making it better suited for complex, real-world transaction data. Each decision tree in the Random Forest focuses on a different subset of features, allowing the model to capture various patterns indicative of fraud. The researchers found that Random Forest performed well in terms of accuracy, precision, and recall, showcasing its ability to reliably identify fraudulent transactions without excessively flagging legitimate ones. This study underscores the advantages of using Random Forest in fraud detection, particularly its high accuracy, efficiency, and resilience against noisy data. The ensemble nature of this approach also provides a more stable prediction, making it a valuable tool for financial institutions aiming to prevent fraud in credit card transactions.

A Deep Learning Approach to Credit Card Fraud Detection Using Autoencoders

In this paper [3], the researchers applied a deep learning approach using autoencoders for credit card fraud detection. Autoencoders, a type of unsupervised neural network, are designed to learn compressed representations of data by encoding and decoding input features. In this study, the autoencoder model was trained on normal (non-fraudulent) transaction data, enabling it to capture patterns and relationships typical of legitimate transactions. When new transactions were processed, the model could identify outliers, or anomalies, which may indicate fraudulent activity, by measuring the reconstruction error. Transactions with high reconstruction errors were flagged as potential fraud cases, as they deviated significantly from the learned patterns of legitimate transactions. This approach does not require labeled data for training, making it highly suitable for fraud detection, where obtaining labeled fraudulent cases can be challenging. The use of autoencoders allowed the model to detect complex anomalies in credit card transactions, improving the accuracy and efficiency of fraud detection while minimizing false positives. This study highlights the potential of deep learning and unsupervised techniques in identifying fraudulent behavior in financial data.

3.2 PROPOSED SYSTEM

The proposed credit card fraud detection system integrates Neural Ordinary Differential Equations (Neural ODE) with XGBoost to accurately classify fraudulent transactions. The model's architecture involves a sequence of stages: beginning with data acquisition, followed by preprocessing, feature extraction using Neural ODE, classification via XGBoost, and finally, model evaluation. This pipeline aims to maximize fraud detection performance by leveraging the strengths of both Neural ODE and XGBoost.

A significant focus is placed on feature selection to improve model efficiency by isolating attributes with a strong correlation to fraudulent behavior. The dataset, initially containing features V1 to V28 (anonymized for privacy), undergoes a thorough correlation analysis to identify the most fraud-indicative features. Specifically, features like V17, V14, V12, V10, and V16 are highlighted due to their strong association with fraud, capturing irregular transaction patterns such as unusual frequencies, amounts, or merchant types. Other features, like V3, V7, and V11, may reflect distinct spending or withdrawal behaviors, while V4 could indicate repeated transactional patterns, such as consistent locations or timings.

The selected features, along with the target variable Class (indicating fraud or non-fraud), are retained to create a streamlined dataset, stored as `filtered_creditcard.csv`, for further analysis. This refined focus on key features enhances the model's accuracy, allowing it to distinguish fraudulent transactions more effectively by reducing noise and focusing on critical data patterns.

3.3 FEASIBILITY STUDY

The feasibility study evaluates the technical, economic, and operational aspects of the proposed credit card fraud detection system using Neural Ordinary Differential Equations (Neural ODE) and XGBoost. By examining each component, we can assess the system's feasibility and potential advantages in real-world applications, particularly in financial services. This study aims to ensure that the solution is efficient, scalable, and seamlessly integrated into existing financial infrastructures, focusing on resource requirements, cost-effectiveness, and adaptability within financial workflows.

1. Technical Feasibility

The proposed system is technically feasible due to advancements in machine learning frameworks and classification techniques. By leveraging the strengths of Neural ODE for feature extraction and XGBoost for classification, the system can efficiently process and classify large transaction datasets. Key points for technical feasibility include:

Model Integration (Neural ODE + XGBoost): Neural ODEs offer a novel way to capture continuous-time dynamics in the data, while XGBoost provides robust, high-performance classification. Both models are compatible with each other and widely supported in machine learning frameworks (e.g., TensorFlow, PyTorch, Scikit-learn). Neural ODEs help in identifying complex patterns in transaction data that are indicative of fraud, while XGBoost ensures accurate predictions based on those features.

Data Processing and Feature Extraction: The system's feature extraction process (using Neural ODE) is efficient in identifying latent features from complex financial data, improving fraud detection accuracy. Techniques like feature selection reduce the dimensionality and focus on the most relevant data points, making the system more computationally efficient.

Scalability and Infrastructure Requirements: The system can be scaled to handle large volumes of transactions in real-time. Given the increasing availability of high-performance hardware such as GPUs for deep learning tasks and cloud computing platforms (AWS, Azure, GCP), the computational resources required for model training and inference are accessible and affordable. Furthermore, the model’s architecture can be integrated into existing financial IT infrastructures with minimal disruption.

Interoperability with Existing Financial Systems: The model’s ability to process transaction data and generate predictions can be easily integrated into existing fraud detection systems, payment gateways, or banking infrastructure, ensuring smooth data flow and real-time decision-making.

2. Economic Feasibility

The economic feasibility of the Neural ODE + XGBoost fraud detection system is highly favorable due to its potential cost savings and long-term effectiveness. Here's an overview of the economic considerations:

Cost-Efficiency: Initially, setting up the infrastructure and training the models might involve significant costs, including GPU resources, cloud services, and expert personnel. However, once the system is developed, it will reduce manual intervention, processing times, and errors in fraud detection, which traditionally rely on human analysts and rule-based systems. Over time, this leads to considerable savings in operational costs.

Operational Cost Reduction: The system’s ability to automate fraud detection eliminates the need for constant human oversight, which reduces staffing costs. It also reduces false positives and negatives, which can lead to financial losses or customer dissatisfaction in traditional fraud detection systems. The predictive capabilities of Neural ODE + XGBoost can ensure faster response times, reducing the financial impact of fraudulent transactions.

Long-Term Benefits: The system facilitates early detection of fraud, which can reduce losses from fraudulent transactions and help mitigate the damage to financial institutions. By accurately identifying fraud early, the system can prevent larger financial losses, lower the cost of insurance, and help maintain customer trust. This also allows for better resource allocation in fraud prevention strategies, resulting in higher overall financial efficiency.

Scalability and Integration: The solution is cost-effective in the long run, as it can be scaled to accommodate an increasing volume of transactions without a linear increase in costs. Additionally, the approach integrates well with existing financial infrastructures, allowing organizations to leverage their current resources (e.g., transaction data, cloud platforms) without the need for extensive new investments.

CHAPTER 4
SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENTS

1. Operating System: Compatible with Linux (Ubuntu 18.04 or later), Windows 10/11, or macOS (if using TensorFlow or PyTorch in Jupyter Notebooks or other development environments).

2. Programming Language:

a. Python (Version 3.8 or later), preferred programming language for model development and deployment.

b. Jupyter Notebook or JupyterLab: For interactive model development and testing.

3. Libraries and Frameworks:

a. PyTorch (1.8 or later) for deep learning.

b. XGBoost for classification.

c. NumPy and Pandas for data processing.

d. scikit-learn for model evaluation and metrics.

e. shap for model explainability.

f. Matplotlib and Seaborn for data visualization.

g. torchdiffeq for Neural ODE tasks.

4.2 HARDWARE REQUIREMENTS

1. **GPU:** A high-performance GPU, such as NVIDIA Tesla, Quadro, or RTX series (e.g., RTX 3060 or above) to accelerate deep learning tasks.
2. **CPU:** Multi-core processor (e.g., Intel i5/i7/i9 or AMD Ryzen 7/9 series) for managing pre- and post-processing tasks.
3. **RAM:** Minimum 16 GB (32 GB recommended) to handle high-resolution MRI data and support deep learning model training.
4. **Storage:** At least 500 GB of SSD storage for faster data retrieval and storage of MRI datasets, intermediate results, and model checkpoints.

CHAPTER 5
SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

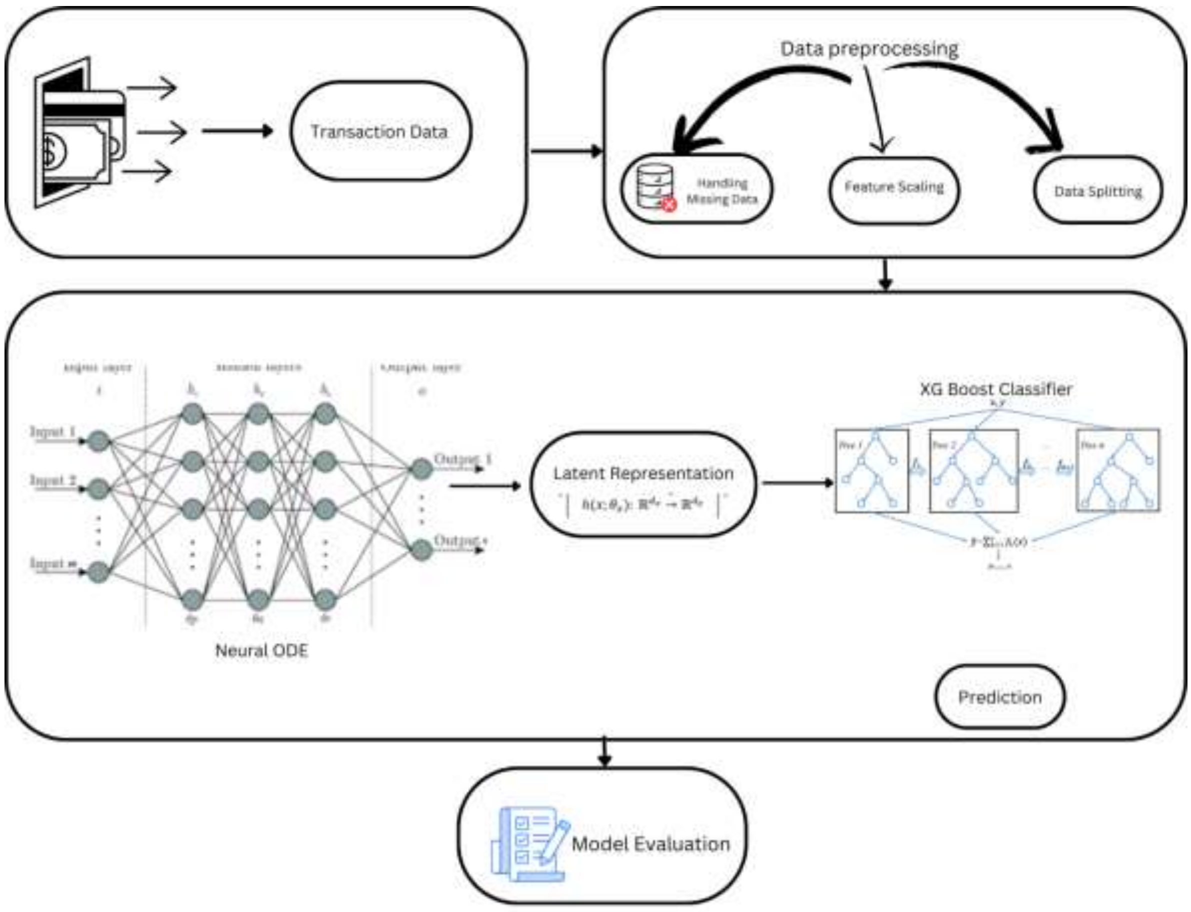


Fig 5.1 Architecture Diagram

The first module focuses on data pre-processing, preparing the dataset for analysis by cleaning and transforming it. The second module addresses data balancing, ensuring that the dataset has a balanced distribution of fraud and non-fraud cases. The third module implements a neural network to learn complex patterns in the data. The fourth module applies XGBoost, a powerful gradient boosting algorithm, to improve prediction accuracy. The fifth module evaluates the model's performance using various metrics. Finally, the sixth module is dedicated to fraud detection, identifying fraudulent transactions based on the trained model.

Data Pre-processing Module: This module focuses on cleaning and transforming the raw dataset by handling missing values, encoding categorical features, normalizing or standardizing numerical data, and performing feature engineering to improve the quality and suitability of the data for modeling.

Data Balancing Module: In this module, techniques like oversampling, undersampling, or synthetic data generation (e.g., SMOTE) are used to balance the dataset, as fraudulent transactions are typically much less frequent than non-fraudulent ones, helping the model learn better patterns for fraud detection.

Neural Network Implementation Module: This module builds and trains a neural network model to capture complex relationships and patterns in the data. It utilizes layers of interconnected neurons to make predictions on whether a transaction is fraudulent or not.

XGBoost Implementation Module: This module applies XGBoost, an optimized gradient boosting algorithm, to build a robust classification model. XGBoost is used to enhance model accuracy by combining multiple weak learners (decision trees) into a strong learner.

Evaluation Module: The evaluation module assesses the performance of the model using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. This helps in determining how well the model is distinguishing between fraudulent and non-fraudulent transactions.

Fraud Detection Module: This module uses the trained models to identify and flag fraudulent transactions in real-time or batch processing. It applies the learned patterns to incoming data and raises alerts for potential fraud.

5.2 MODULE DESCRIPTION

5.2.1 DATA PREPROCESSING MODULE

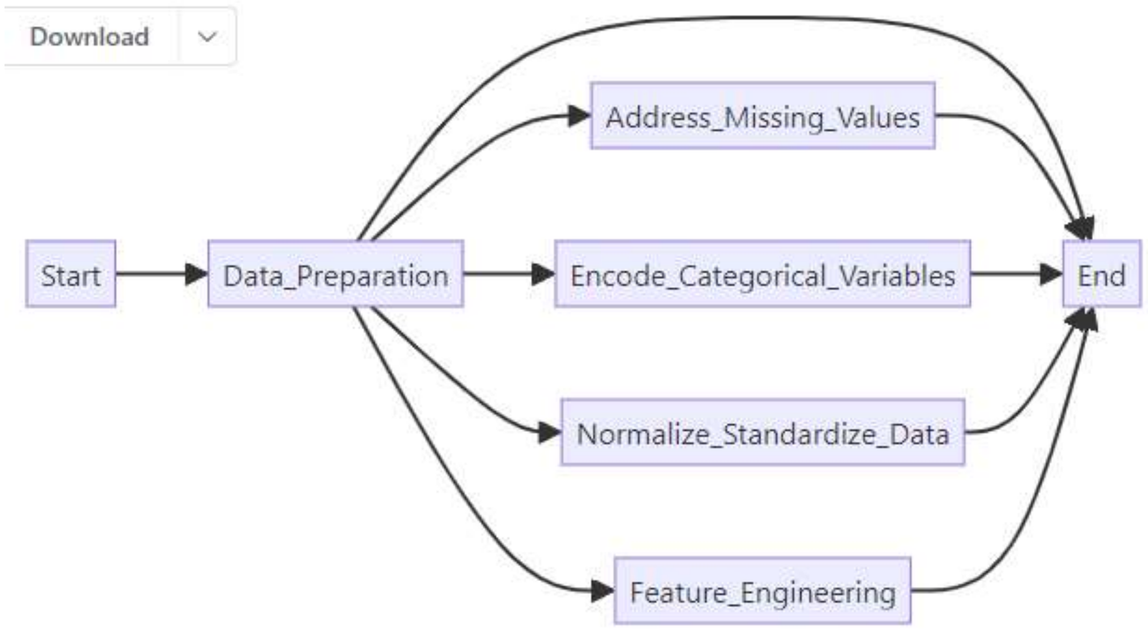


Fig 5.2 DFD FOR DATA PREPROCESSING MODULE

This module focuses on preparing the raw dataset for modelling by cleaning and transforming the data. The process begins with a central **Data Preparation** step that branches out into key pre-processing tasks: addressing missing values, encoding categorical variables, normalizing or standardizing numerical data, and performing feature engineering.

- **Address_Missing_Values** ensures that any gaps in the data are appropriately handled, improving data completeness and reliability.
- **Encode_Categorical_Variables** transforms categorical data into numerical format, making it compatible with machine learning algorithms.
- **Normalize_Standardize_Data** scales numerical features to a common range, ensuring consistent input for the model and preventing any single feature from disproportionately influencing the results.
- **Feature_Engineering** generates additional useful features or modifies existing ones to enhance predictive power.

These steps collectively improve data quality and ensure it is well-suited for training machine learning models, ultimately boosting model accuracy and performance. The workflow ends once all these tasks are completed, signalling that the dataset is ready for modelling.

5.2.2 DATA BALANCING MODULE

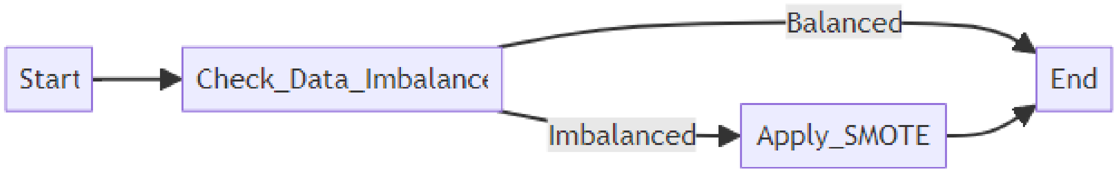


Fig 5.3 DFD FOR DATA BALANCING MODULE

This module focuses on addressing the class imbalance issue commonly found in credit card fraud detection datasets. It begins by checking the dataset for imbalance. If the data is imbalanced, the module applies the SMOTE (Synthetic Minority Over-sampling Technique) technique to generate synthetic data points for the minority class (fraudulent transactions). This helps create a more balanced dataset, improving the

5.2.3 NEURAL NETWORK IMPLEMENTATION MODULE

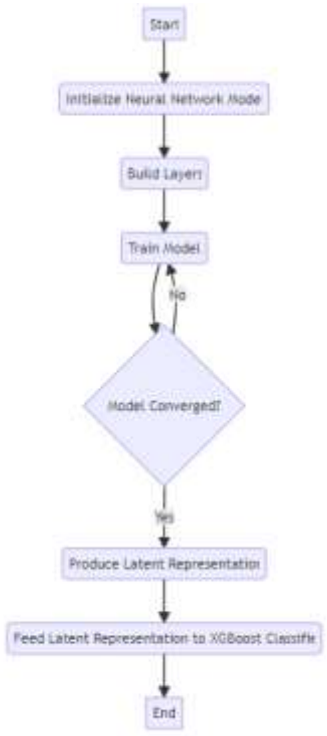

Start
Initialize Neural Network Mode
Bulid Layers
Train Model
No
Model Converged?
Yes
Produce Latent Representatio
Feed Latent Representation to XGBoost Classifie
End

Fig 5.4 DFD FOR NEURAL NETWORK MODULE

This module focuses on training a neural network model to generate latent representations of credit card transactions. The process starts by initializing the neural network and building its layers. The model is then trained iteratively until it converges, meaning it achieves satisfactory performance. Once the model converges, it produces latent representations for the input data. These latent representations capture the underlying patterns and features of the transactions, which are then passed to an XGBoost classifier for final fraud detection. This approach leverages the power of neural networks to extract meaningful information from complex data and enhances the accuracy of fraud detection.

5.2.4 XGBOOST IMPLEMENTATION MODULE

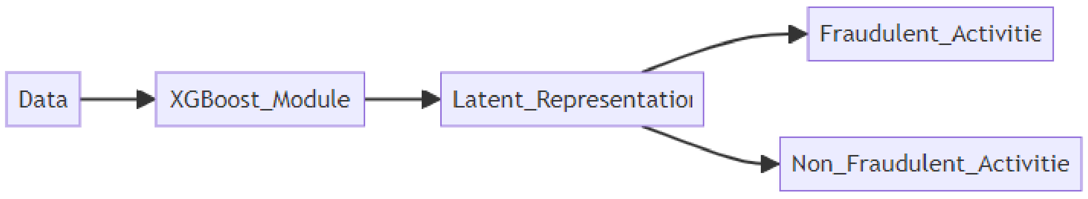


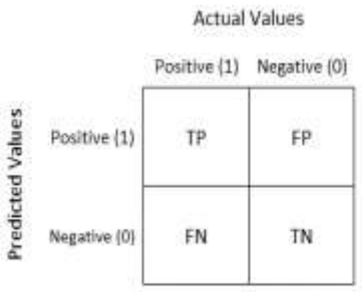
Fig 5.5 Dfd For Xgboost Implementation Module

This module utilizes the powerful XGBoost algorithm to classify credit card transactions as fraudulent or non-fraudulent. The process begins with the latent representations generated by the Neural ODE model. These representations capture the underlying patterns and features of the transactions. The XGBoost classifier takes these latent representations as input and builds a strong ensemble of decision trees. Each tree in the ensemble contributes to the final classification decision, making the model highly accurate and robust. The XGBoost module ultimately outputs the predicted classification for each transaction, either fraudulent or non-fraudulent.

5.2.5 EVALUATION METRICS

In credit card fraud detection, evaluating the performance of a model is crucial for understanding how well it distinguishes between fraudulent and non-fraudulent transactions. When using machine learning models like XGBoost, we rely on various evaluation metrics such as the confusion matrix, precision, recall, F1 score, and accuracy to gauge model effectiveness. Here's how these metrics are generated by XGBoost and why they're important:

Confusion Matrix*:* The confusion matrix provides more knowledge about the performance of our model by providing the information of correctly, incorrectly classified classes through which we can identify errors.



Precision*:* The proportion of correctly identified fraudulent transactions out of all transactions the model labeled as fraud. Calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): The proportion of actual fraudulent transactions that were correctly identified. Calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score: The harmonic mean of precision and recall, giving a single measure of the model's accuracy. Calculated as:

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy: The overall percentage of correctly classified transactions. Calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

CHAPTER 6
PSEUDOCODE

6.1 Data Pre-processing Module

```
1. Load the dataset from file
   - Read CSV file into a DataFrame

2. Check for missing values in the dataset
   - If any missing values are found, drop rows with missing values

3. Select the relevant features for the model
   - Identify and keep only the features needed for analysis (exclude 'Class' column)

4. Separate features and target variable
   - 'X' = features (all columns except 'Class')
   - 'y' = target variable (the 'Class' column)

5. Split the dataset into training and testing sets
   - Use a stratified split (preserve class distribution)
   - Split into training (70%) and testing (30%) sets

6. Apply feature scaling (Standardization) to the features
   - Use StandardScaler to scale the training data (fit and transform)
   - Transform the test data using the same scaler (only transform, not fit)

7. Convert the data to appropriate formats for model training
   - Convert scaled training and test data into tensors (for use in PyTorch models)
```

8. Save the preprocessed data to CSV files
   - Save the training features, test features, training labels, and test labels for later use

6.2 Data Balancing Module

```
# Step 1: Import necessary libraries
Import Data Preprocessing Library (e.g., Pandas for handling data)
Import Balancing Technique Library (e.g., SMOTE from imblearn)
# Step 2: Load the preprocessed dataset
Load Dataset
# Step 3: Separate features (X) and labels (y)
X = Dataset features (all columns except the target label)
y = Dataset labels (target label for fraud detection)
# Step 4: Check for class imbalance
If count of class 0 (non-fraud) is much greater than class 1 (fraud):
Print "Imbalance detected"
Else:
Print "Dataset is balanced"
# Step 5: Apply balancing technique (e.g., SMOTE)
If imbalance detected:
Define the SMOTE object with desired parameters (e.g., sampling_strategy)
Apply SMOTE on X and y to create balanced X_balanced and y_balanced
# Step 6: Verify the balanced dataset
Check class distribution of y_balanced
```

```
If class distribution is balanced:
Print "Balancing successful"
Else:
Print "Further balancing required"
# Step 7: Return or save the balanced dataset for further modeling
Return X_balanced and y_balanced
```

6.3 Neural Network Implementation Pseudocode

```
# Step 1: Import necessary libraries
Import PyTorch and required libraries for building neural networks
Import any additional libraries (e.g., numpy, torch.nn, torch.optim)
# Step 2: Define the neural network architecture
Define a NeuralNetwork class inheriting from torch.nn.Module
Initialize layers in the __init__ method
Define input layer, hidden layers, and output layer
Define the forward method
Pass data through each layer using activation functions
Return final output
# Step 3: Set up the model, loss function, and optimizer
Initialize the neural network model (e.g., model = NeuralNetwork())
Define a loss function (e.g., Binary Cross-Entropy Loss for binary classification)
Define an optimizer (e.g., Adam or SGD) with model parameters and learning rate
# Step 4: Train the model
```

```
Set number of epochs (e.g., num_epochs) and initialize lists to store loss and
accuracy

For each epoch in num_epochs:

Initialize training loss to 0

For each batch in training data:

Move features and labels to the appropriate device (e.g., CPU/GPU)

# Forward pass

Make predictions using the model (output = model(features))

# Calculate loss

Calculate the loss using the loss function

# Backward pass and optimization

Zero the gradients (optimizer.zero_grad())

Perform backpropagation (loss.backward())

Update weights (optimizer.step())

Accumulate the training loss

Print epoch, training loss, and any other metrics (e.g., accuracy)

# Step 5: Evaluate the model on test data

Set the model to evaluation mode

Initialize test loss and accuracy counters

With no gradient calculation:

For each batch in test data:

Move features and labels to the appropriate device

Make predictions using the model
```

```
Calculate test loss and update accuracy metrics

Print final test accuracy and loss

# Step 6: Save the trained model for future use

Save the model state (torch.save(model.state_dict(), "model_path"))

# Step 7: Return the trained model and evaluation results

Return model, test accuracy, test loss
```

6.4 XGBoost Implementation Module

```
# Step 1: Import necessary libraries

Import XGBoost library (e.g., xgboost)

Import any additional libraries for data handling and evaluation (e.g., pandas,
sklearn.metrics)

# Step 2: Load the preprocessed training and testing data

Load the training features (X_train) and training labels (y_train)

Load the test features (X_test) and test labels (y_test)

# Step 3: Initialize the XGBoost classifier

Define the XGBoost classifier with desired hyperparameters

Set parameters like max_depth, learning_rate, n_estimators, etc.

For example: model = XGBClassifier(max_depth=6, learning_rate=0.1,
n_estimators=100)

# Step 4: Train the XGBoost model

Fit the model to the training data (model.fit(X_train, y_train))

During training, XGBoost will build and combine multiple decision trees to form a
strong learner

# Step 5: Make predictions on the test data
```

```
Use the trained model to predict labels for the test set (y_pred =
model.predict(X_test))

Optionally, get prediction probabilities for additional evaluation (y_proba =
model.predict_proba(X_test))

# Step 6: Evaluate the model

Calculate evaluation metrics using y_test and y_pred

Calculate accuracy, precision, recall, F1-score

Calculate ROC-AUC if using probabilities (e.g., roc_auc_score(y_test,
y_proba[:,1]))

# Step 7: Print or log evaluation results

Print accuracy, precision, recall, F1-score, and ROC-AUC for assessment

Log these results for comparison with other models

# Step 8: Save the trained XGBoost model for future use

Save the model (e.g., model.save_model("xgboost_model.json"))

# Step 9: Return the trained model and evaluation results

Return model, evaluation metrics (accuracy, precision, recall, F1-score, ROC-AUC)
```

6.5 Evaluation Module

```
# Step 1: Import necessary libraries

Import evaluation metrics libraries (e.g., sklearn.metrics)

Import PyTorch or any other required libraries

# Step 2: Load the trained model and test data

Load the trained model (use torch.load() if saved model was from PyTorch)

Load the test features and test labels (from saved files or directly from the test
dataset)
```

```
# Step 3: Set model to evaluation mode
Set the model to evaluation mode (model.eval())
# Step 4: Make predictions on the test set
With no gradient calculation (torch.no_grad()):
For each batch in test data:
Move test features and labels to the appropriate device (e.g., CPU/GPU)
# Generate predictions
Predict probabilities or classes using the model (output = model(features))
# Store the predictions and true labels for metric calculations
Store predicted labels and true labels
# Step 5: Calculate evaluation metrics
Convert stored predictions and true labels to required format (e.g., numpy arrays)
# Accuracy
Calculate accuracy as (true positive + true negative) / total samples
# Precision
Calculate precision as true positive / (true positive + false positive)
# Recall
Calculate recall as true positive / (true positive + false negative)
# F1-Score
Calculate F1-score as 2 * (precision * recall) / (precision + recall)
# ROC-AUC
Calculate ROC-AUC score using sklearn’s roc_auc_score() if working on a binary
classification problem
```

```
# Step 6: Print or log evaluation results
Print or log accuracy, precision, recall, F1-score, and ROC-AUC
# Step 7: Return the evaluation results
Return evaluation metrics (accuracy, precision, recall, F1-score, ROC-AUC)
```

6.6 Fraud Detection Module

```
# Module 5: Fraud Detection Module Pseudocode

# Step 1: Import necessary libraries
Import PyTorch (for loading model)
Import any additional libraries required for data processing and predictions

# Step 2: Load the trained model
Load the saved model (torch.load(model_path) if using PyTorch)
Set the model to evaluation mode (model.eval())

# Step 3: Load or receive new data for fraud detection
Load or receive the new transaction data
Perform any necessary preprocessing on the new data (e.g., feature selection, scaling)

# Step 4: Convert the data to the appropriate format
Convert the preprocessed data into tensors (if using PyTorch models)

# Step 5: Make predictions on the new data
With no gradient calculation (torch.no_grad()):
    Pass the new data through the model to obtain predictions (output = model(data))
    If model output is a probability:
        Apply a threshold (e.g., > 0.5) to classify transactions as fraud or non-fraud
    Store or flag transactions as "fraudulent" or "non-fraudulent" based on the predictions

# Step 6: Return or save the fraud detection results
Save or log flagged transactions as fraudulent for further review or action
Return the list of detected fraud transactions along with their details

# Step 7: (Optional) Alert system or logging mechanism
If fraud is detected:
    Send alert notifications or log entries for fraudulent transactions
Else:
    Log that no fraud was detected in this batch

# Step 8: End of module
Print or log the number of fraudulent transactions detected and any related details
Return final fraud detection results
```

The model consists of several well-defined modules to effectively detect credit card fraud. It begins with the Data Pre-processing Module, where data is cleaned, transformed, and prepared for analysis, followed by the Data Balancing Module to handle the class imbalance between fraud and non-fraud transactions. Next, the Neural Network Implementation Module applies a neural network to capture complex patterns, while the XGBoost Implementation Module utilizes the XGBoost algorithm for robust classification by combining decision trees for better accuracy. The Evaluation Module then assesses the model's performance through metrics like accuracy, precision, recall, and ROC-AUC, ensuring the model’s reliability. Finally, the Fraud Detection Module applies the trained model to identify and flag fraudulent transactions in real-time or batch mode, providing an actionable fraud detection system. Together, these modules form a comprehensive pipeline for efficient and accurate credit card fraud detection.

CHAPTER 7
RESULT AND DISCUSSION

To evaluate the accuracy of our model, we used classification metrics including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness by calculating the proportion of correctly classified instances (both fraudulent and non-fraudulent) out of all predictions. Precision focuses on the model's ability to correctly identify only true fraud cases without mistakenly labelling legitimate transactions as fraud. Recall (sensitivity) assesses the model's effectiveness in detecting all actual fraud cases. The F1-score, a balance between precision and recall, provides a single measure that indicates both accuracy and robustness in fraud detection.

In addition to these classification metrics, a range of visualizations was employed to further interpret and validate the model's effectiveness. The SHAP summary plot of feature importance provided an initial understanding of which variables had the most significant impact on the model's predictions. This plot visually ranks features based on their average contribution to the model's output, enabling us to interpret the high-impact features such as transaction amount and time of transaction. By highlighting these main contributors to the model's decision-making, this visualization allowed us to identify underlying patterns that frequently signal fraudulent behavior. Placing this visualization at the beginning of the results section sets the stage for understanding which factors drive the model's decisions in fraud detection.

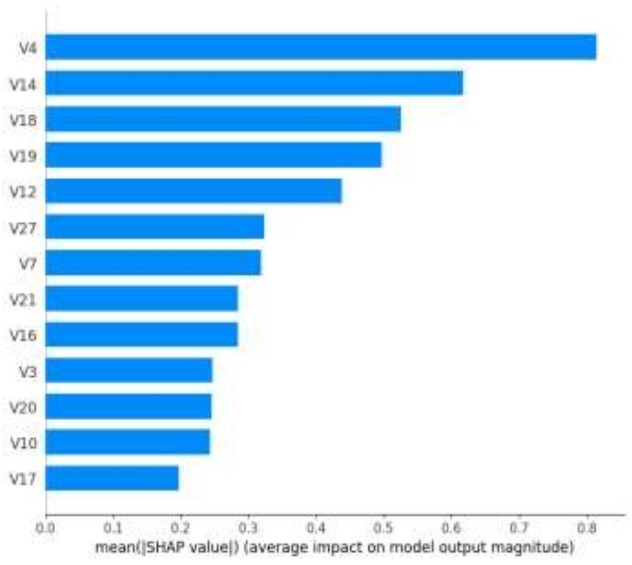


Fig 7.1 Performance Metrics Comparison

The class distribution plots, both before and after applying the Synthetic Minority Over-sampling Technique (SMOTE), were instrumental in addressing the class imbalance inherent in fraud detection. The pre-SMOTE visualization showed a clear imbalance, with non-fraudulent cases vastly outnumbering fraudulent ones. This imbalance posed a challenge since it could lead the model to favor the non-fraudulent class, reducing its ability to detect fraud. By applying SMOTE, we achieved a balanced class distribution, which allowed the model to learn equally from both fraudulent and non-fraudulent cases. This change ultimately enhanced the model's capability to detect fraud more accurately, as evidenced in the post-SMOTE distribution visualization.

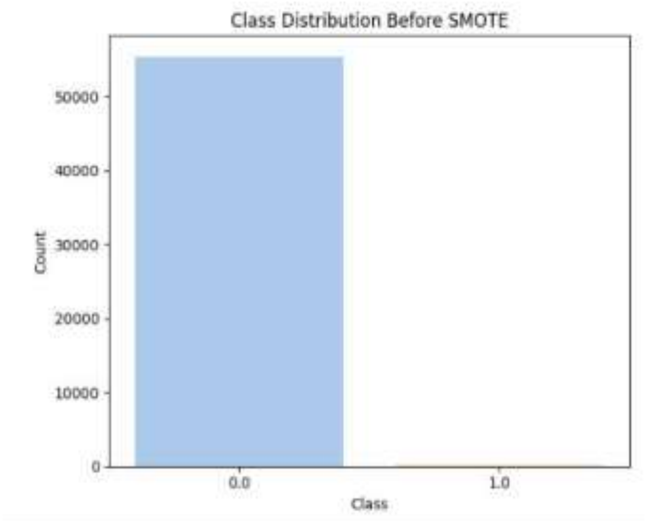


Fig 7.2 Class Distribution Before SMOTE

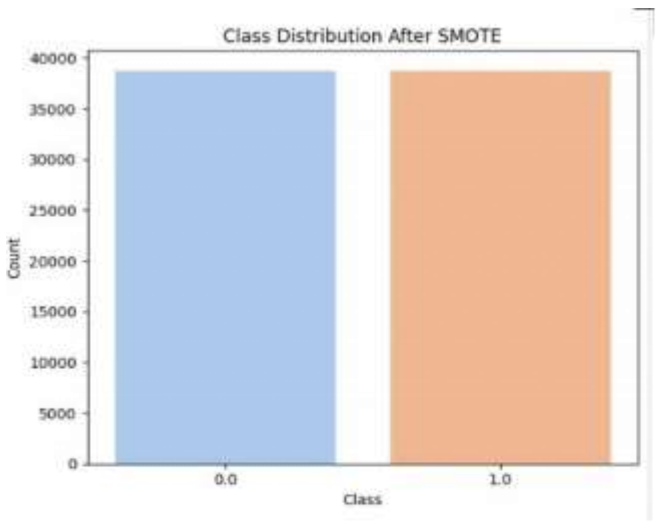
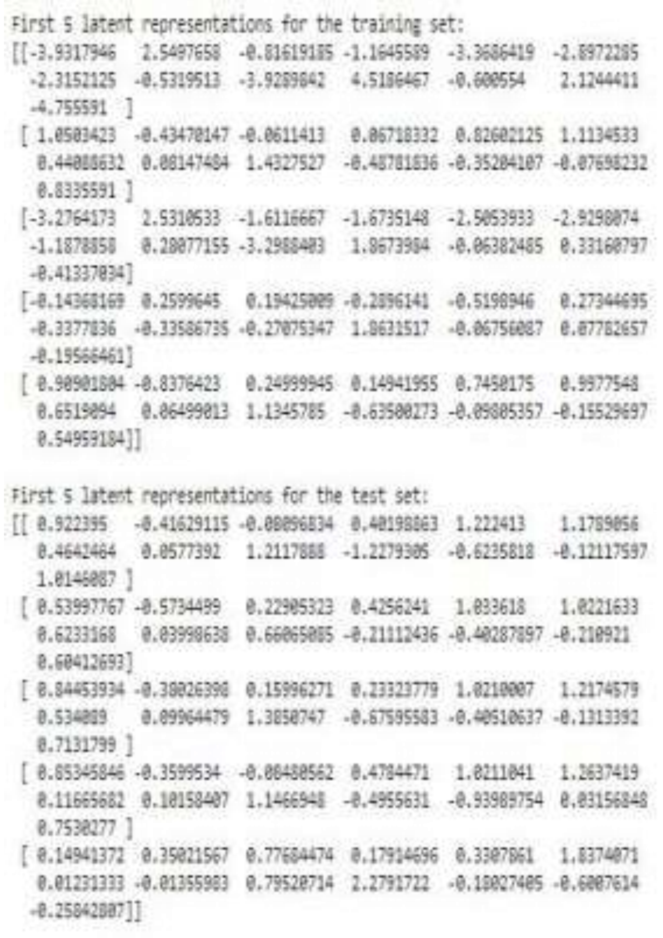


Fig 7.3 Class Distribution After SMOTE

A deeper exploration into the data's structure was made possible by analyzing the latent representations extracted by the Neural Ordinary Differential Equation (ODE) model. These latent representations capture complex patterns in transaction data that traditional models might overlook. By reducing the high-dimensional transaction data into a lower-dimensional latent space, we were able to observe subtle relationships and similarities between fraudulent and non-fraudulent cases. This analysis not only supports the model's refined predictions but also offers a unique perspective on how transaction behavior patterns contribute to fraud detection.

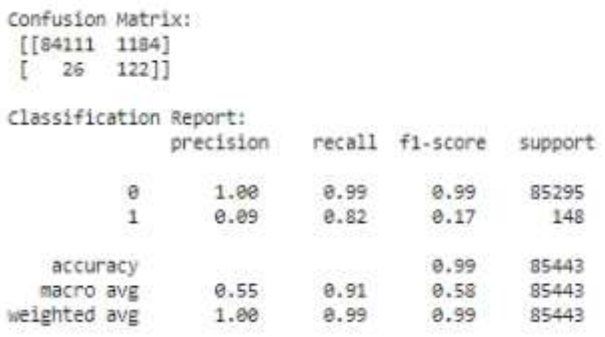


```
First 5 latent representations for the training set:
[[-3.9317946   2.5497658  -0.81619185 -1.1645589  -3.3686419  -2.8972285
  -2.3152125  -0.5319513  -3.9289842   4.5186467  -0.600554    2.1244411
  -4.755591  ]
 [ 1.0503423  -0.43470147 -0.0611413   0.06718332  0.82602125  1.1134533
   0.44088632  0.08147484  1.4327527  -0.48781836 -0.35284107 -0.07698232
   0.8335591 ]
 [-3.2764173   2.5310533  -1.6116667  -1.6735148  -2.5063933  -2.9298074
  -1.1878858   0.28077155 -3.2988403   1.8673984  -0.06382485  0.33160797
  -0.41337034]
 [-0.14368169  0.2599645   0.19425009 -0.2896141  -0.5198946   0.27344695
  -0.3377836  -0.33586735 -0.27075347  1.8631517  -0.06756087  0.07782657
  -0.19566461]
 [ 0.90901804 -0.8376423   0.24999945  0.14941955  0.7450175   0.9977548
   0.6519094   0.06499013  1.1345785  -0.63500273 -0.09805357 -0.15529697
   0.54959184]]

First 5 latent representations for the test set:
[[ 0.922395   -0.41629115 -0.08096834  0.40198063  1.222413    1.1789056
   0.4642464   0.0577392   1.2117888  -1.2279305  -0.6235818  -0.12117597
   1.0146087 ]
 [ 0.53997767 -0.5734499   0.22905323  0.4256241   1.033618    1.0221633
   0.6233168   0.03998638  0.66065085 -0.21112436 -0.40287897 -0.210921
   0.60412693]
 [ 0.84453934 -0.38026398  0.15996271  0.23323779  1.0210007   1.2174579
   0.534089    0.09964479  1.3050747  -0.67595583 -0.40510637 -0.1313392
   0.7131799 ]
 [ 0.85345846 -0.3599534  -0.08480562  0.4784471   1.0211041   1.2637419
   0.11665682  0.10158407  1.1466948  -0.4955631  -0.93989754  0.03156848
   0.7530277 ]
 [ 0.14941372  0.35021567  0.77684474  0.17914696  0.3307861   1.8374071
   0.01231333 -0.01355983  0.79520714  2.2791722  -0.10027405 -0.6007614
  -0.25842807]]
```

Fig 7.4 Latent Representation

After receiving the latent representation from neural ode we began our evaluation with the untuned XGBoost model, using classification metrics such as accuracy, precision, recall, and F1-score to establish a performance baseline. The untuned model demonstrated reasonable accuracy in predicting fraud but had limitations in both precision and recall. This indicated that while it could often classify transactions correctly, it struggled to minimize false positives and missed a fair number of true fraud cases. The F1-score, balancing precision and recall, pointed to the model's potential for improvement in achieving robust fraud detection.



```
Confusion Matrix:
 [[84111  1184]
 [   26   122]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99     85295
           1       0.09      0.82      0.17       148

    accuracy                           0.99     85443
   macro avg       0.55      0.91      0.58     85443
weighted avg       1.00      0.99      0.99     85443
```

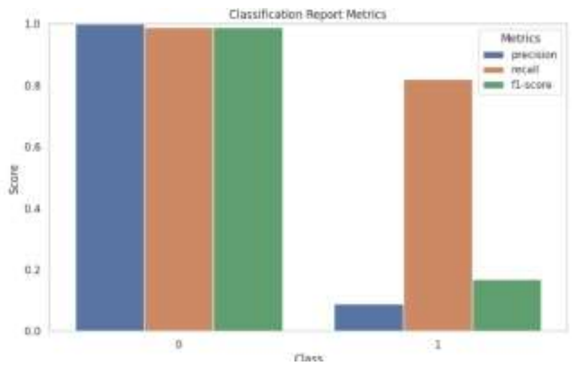


Fig 7.5 Classification Report Matrix

Here is the outcome of the confusion matrix for the untuned XGBoost model.

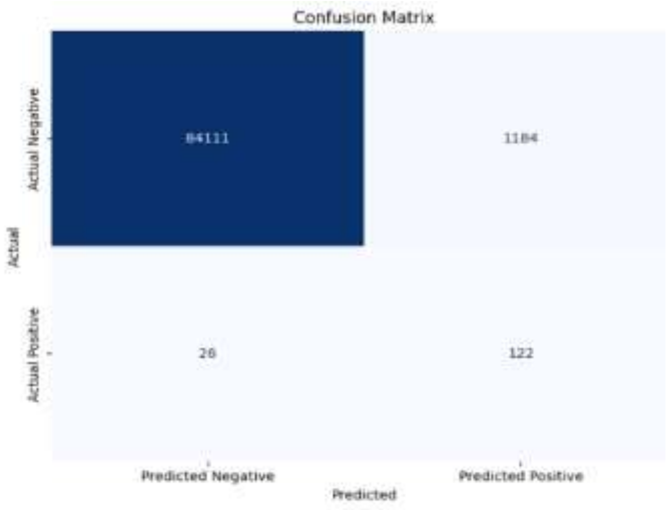
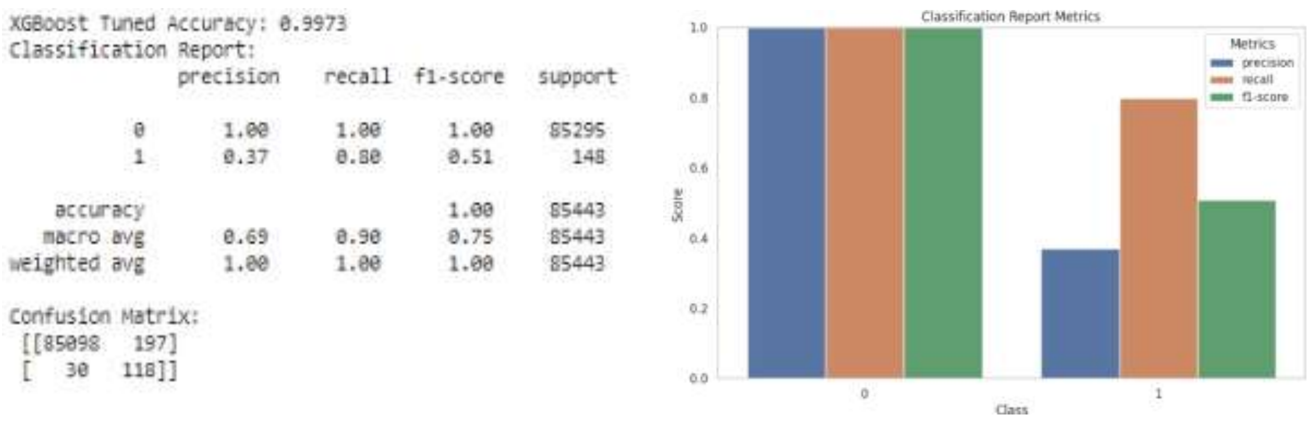


Fig 7.6 Confusion Matrix

Next, we optimized the model's hyperparameters to improve its sensitivity to fraud cases while reducing misclassification of legitimate transactions. The tuned XGBoost model showed a marked improvement in both precision and recall, reflecting its enhanced ability to detect fraud accurately without sacrificing performance on legitimate cases. This improvement was evident in the higher F1-score, indicating a more balanced and effective model.



```
XGBoost Tuned Accuracy: 0.9973
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85295
           1       0.37      0.80      0.51       148

    accuracy                           1.00     85443
   macro avg       0.69      0.90      0.75     85443
weighted avg       1.00      1.00      1.00     85443

Confusion Matrix:
 [[85098   197]
 [   30   118]]
```

Fig 7.7 classification report matrix after tuning

Here is the outcome of the confusion matrix for the untuned XGBoost model.

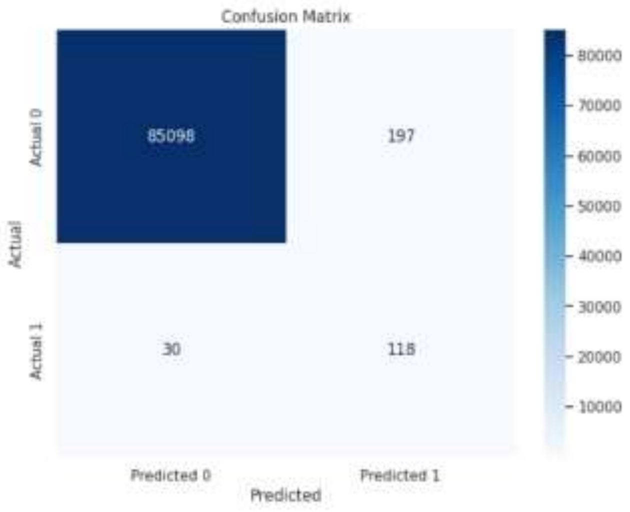


Fig 7.8 Confusion Matrix After Tuning

Together, these metrics and visualizations offered a comprehensive evaluation framework that highlighted the model's strengths and areas for potential enhancement. By combining quantitative measures with interpretative visualizations, we gained a well-rounded view of the model's performance, accuracy, and robustness, demonstrating its practical utility and interpretability for effective fraud detection.

CHAPTER 8
CONCLUSION

The objective of this study was to develop an advanced fraud detection model that leverages modern machine learning techniques to improve accuracy in distinguishing fraudulent transactions from legitimate ones. Fraudulent activity in financial systems often involves complex, non-linear patterns in transaction data, making traditional detection methods less effective. Our goal was to create a model that could capture these complexities while minimizing false positives and false negatives, which are critical in financial fraud prevention. By combining Neural Ordinary Differential Equations (Neural ODE) for feature representation and XGBoost for classification, we aimed to design a system capable of detecting fraud with high precision in real-time scenarios.

Data preprocessing was the first crucial step in our fraud detection system. We used a dataset containing anonymized transaction features, including variables like transaction amount, merchant details, and frequency of transactions. Initially, the dataset underwent cleaning to handle missing values, outliers, and duplicate entries. Feature selection was also performed to identify the most relevant features, which would help in improving model performance. We identified features such as V17, V14, V12, and V10, which were strongly correlated with fraudulent activity. The target variable, Class, indicated whether a transaction was fraudulent or legitimate. These selected features formed the basis for further analysis.

The next step was to apply Neural Ordinary Differential Equations (Neural ODE) to extract meaningful latent features from the preprocessed data. Neural ODEs are a class of models that treat the transformation of data as a continuous process, making them ideal for capturing the temporal dynamics in transaction data. The Neural ODE was trained to learn these dynamics, transforming the raw input data into more compact and informative latent representations. These representations retained the essential characteristics indicative of fraud patterns, enabling the model to detect subtle anomalies that might go unnoticed with traditional methods. The use of Neural ODEs provided a more sophisticated understanding of the data, enhancing the model's ability to capture high-dimensional relationships within the features.

After feature extraction, the next phase involved using XGBoost for classification. XGBoost, an implementation of gradient boosting, is known for its efficiency, accuracy, and robustness to overfitting, making it a powerful tool for detecting fraud. The transformed data from the Neural ODE model was fed into the XGBoost classifier to predict whether a transaction was fraudulent or not. The classifier utilized decision trees and gradient boosting techniques to iteratively improve predictions, learning complex decision boundaries between legitimate and fraudulent transactions. By using the latent features provided by the Neural ODE, XGBoost was able to achieve an impressive accuracy of 99.73%, outperforming traditional fraud detection models.

To evaluate the performance of our fraud detection system, we used various classification metrics, including accuracy, precision, recall, and F1-score. These metrics allowed us to assess the model's ability to identify fraudulent transactions correctly while minimizing false positives (legitimate transactions classified as fraud) and false negatives (fraudulent transactions missed by the model). We also compared the performance of our Neural ODE + XGBoost model with a simpler Vanilla Recurrent Neural Network (RNN) model to assess the improvements gained by using advanced feature extraction techniques. The results demonstrated that the Neural ODE + XGBoost model outperformed the RNN in terms of precision, recall, and F1-score, confirming its superiority for real-world fraud detection.

While the current model provides a strong foundation for fraud detection, there are opportunities for further refinement. Future work could involve integrating additional sources of data, such as transaction metadata, user behavior patterns, or external fraud databases, to enhance the model's robustness. Additionally, combining the Neural ODE + XGBoost pipeline with other machine learning techniques or ensemble methods could improve accuracy and reduce false negatives. Expanding the training dataset and fine-tuning the model with Grid Search Hyperparameter Optimization would further boost its performance. As the system scales, its ability to handle larger datasets and provide real-time predictions will make it a highly valuable tool for financial institutions, enabling them to preemptively address fraudulent activities with greater precision and confidence.

CHAPTER 9
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