

**Faculty of Aviation, Science and Technology**

**Assignment Cover Sheet**

Machine Learning

EC3357

CourseCode:\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ Course Title:\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

10/3/25

Mini Project - Presentation

AssignmentTitle: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ Due Date: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

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10/3/25

Date Submitted: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_Lecturer Name: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

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**Extension certification:**

This assignment has been given an extension and is now due on \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_.

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# 1.0 Introduction

Credit card fraud has become a major concern in the financial sector, resulting in significant financial losses and security risks for banks, merchants, and consumers. As digital transactions continue to grow, so does the complexity of fraudulent activities, making traditional rule-based fraud detection systems less effective. Machine learning offers a powerful solution by automatically identifying patterns in transaction data and detecting anomalies that indicate fraudulent activity.

This study focuses on applying **Logistic Regression** and **Neural Networks** to detect fraudulent transactions using the **Credit Card Fraud Detection dataset from Kaggle**. The dataset contains **284,807 transactions**, with only **492 labeled as fraudulent**, making it highly imbalanced. To improve fraud detection performance, **Synthetic Minority Over-sampling Technique (SMOTE)** is used to address class imbalance.

The goal of this project is to compare the performance of **Logistic Regression (a linear classification model)** and **Neural Networks (a deep learning-based approach)** in identifying fraudulent transactions. The models are evaluated using key performance metrics, including **Accuracy, Precision, Recall, F1-score, and ROC-AUC score**, to determine the most effective approach for fraud detection. The findings from this study will help improve fraud detection models and contribute to the development of more secure financial transaction systems.

# 2.0 Dataset Selection

## 2.1 Introduction

In the **banking and finance** sector, fraud detection is a critical task that helps prevent unauthorized transactions and financial losses. Credit card fraud occurs when stolen card details are used for fraudulent purchases, leading to financial damage for both banks and customers. To combat this issue, machine learning models are widely used to analyze transaction patterns and identify suspicious activities.

For this project, we have selected the **Credit Card Fraud Detection dataset** from **Kaggle**, which is extensively used in financial fraud research. This dataset contains real-world **credit card transactions** made by European cardholders in **September 2013**. The primary goal is to build a machine learning model that can accurately classify transactions as **fraudulent (Class 1)** or **legitimate (Class 0)** based on the provided features.

This dataset presents a **real-world fraud detection challenge** due to the **high imbalance** between legitimate and fraudulent transactions. Fraudulent cases make up only **0.17%** of the total transactions, requiring specialized techniques such as **oversampling (SMOTE)** and **cost-sensitive learning** to enhance model performance. By leveraging **Logistic Regression** and **Neural Networks**, this project aims to develop a reliable fraud detection system that can help financial institutions minimize risks and improve transaction security.

## 2.2 Dataset Overview

For our **Credit Card Fraud Detection** project, we are using the **Credit Card Fraud Detection dataset** from **Kaggle**, which contains real-world credit card transactions. Below is the summary of the dataset:

* **Total Transactions:** **284,807**
* **Fraudulent Transactions (Class 1):** **492** (~0.17%)
* **Legitimate Transactions (Class 0):** **284,315** (~99.83%)
* **Total Features:** **30** (including Time, Amount, V1–V28, and Class)
* **Dataset Type:** Highly **imbalanced** (since fraudulent transactions are rare)

This dataset presents a **real-world fraud detection challenge**, as fraudulent transactions are very limited compared to legitimate ones. **Handling class imbalance** will be crucial when training machine learning models.

2.3 Explanation of Each Attribute

|  |  |
| --- | --- |
| **Feature Name** | **Descriptions** |
| Time | The elapsed time (in seconds) between each transaction and the first transaction in the dataset. Used to analyze fraud patterns over time. |
| V1 to V28 | These are **anonymized numerical features** generated using **Principal Component Analysis (PCA)** to protect sensitive financial data. Their exact meaning is unknown, but they capture transaction patterns useful for fraud detection. |
| Amount | The **transaction amount** in currency units. Helps detect anomalies (e.g., unusually high transactions may indicate fraud). |
| Class | The **target variable** indicating whether a transaction is fraudulent or legitimate. **0 = Legitimate, 1 = Fraudulent.** |

**More About the PCA-Transformed Features (V1–V28)**

Since these features are transformed using **Principal Component Analysis (PCA)**, they represent important but abstract transaction characteristics. Some features may capture:

* Spending behavior patterns
* Frequency of transactions
* Geographical or time-based transaction irregularities

## 2.4 Relevance to Banking & Finance

This dataset is specifically designed for **financial fraud detection**, making it highly relevant to **banks, credit card companies, and payment service providers**. It helps financial institutions:

* **Detect fraudulent transactions** and prevent financial losses.
* **Develop risk assessment models** for secure transactions.
* **Improve real-time fraud detection systems** using machine learning.

Due to the high **imbalance in fraud cases**, specialized techniques such as **SMOTE (Synthetic Minority Over-sampling Technique)** and **cost-sensitive learning** will be required to ensure the models effectively detect fraudulent transactions.

This dataset serves as a strong foundation for training and evaluating machine learning models such as Logistic Regression and Neural Networks to enhance fraud detection capabilities in the financial sector.

## 2.5 Intended Use of the Dataset

The dataset is used to develop and evaluate machine learning models for fraud detection. Since fraudulent transactions are rare, the dataset requires **class imbalance handling techniques** such as **SMOTE (Synthetic Minority Over-sampling Technique)** to improve model performance. The machine learning models trained on this dataset will help financial institutions **detect fraudulent transactions more effectively**, reducing financial losses and enhancing transaction security.

This dataset is well-suited for our project as it provides a real-world challenge in fraud detection and allows us to test the effectiveness of **Logistic Regression** and **Neural Networks** in classifying transactions.

# 3.0 Model Selection & Evaluation

## 3.1 Introduction

In this study, we implement and evaluate two machine learning models—**Logistic Regression** and **Neural Networks**—to detect fraudulent transactions in the **Credit Card Fraud Detection dataset**. These models were chosen based on their effectiveness in handling classification tasks, particularly in dealing with **imbalanced datasets**.

Since fraudulent transactions make up only **0.17% of the total dataset**, handling class imbalance is crucial for accurate fraud detection. We apply the **Synthetic Minority Over-sampling Technique (SMOTE)** to balance the dataset before training the models. The performance of each model is evaluated using key metrics, including **Accuracy, Precision, Recall, F1-score, and ROC-AUC score**.

3.2 Model Selection

### 3.2.1 Logistic Regression (Baseline Model)

**Logistic Regression** is a simple yet effective classification algorithm that provides a strong **baseline** for comparison. It works well for fraud detection when paired with **class weighting** (class\_weight='balanced') or **oversampling techniques** like SMOTE.

**Why Logistic Regression?**

* Computationally **efficient** and easy to interpret.
* Works well on **structured datasets** like credit card transactions.
* Provides **probability estimates**, which help in fraud risk assessment.
* **Baseline model** for comparison with more advanced techniques.

### 3.2.2 Neural Networks (Deep Learning Model)

A **Multilayer Perceptron (MLP)** Neural Network is used to capture complex fraud patterns. Unlike Logistic Regression, Neural Networks can model **nonlinear relationships** in the data, making them more powerful for fraud detection.

**Why Neural Networks?**

* Can detect **hidden patterns** in fraudulent transactions.
* Works well with large datasets when properly tuned.
* Can learn complex **nonlinear** relationships between features.

For this project, we use an **MLPClassifier** with:

* **Two hidden layers** (first layer: 10 neurons, second layer: 5 neurons).
* **Tanh activation function** for hidden layers and **Softmax** for output.
* **Adam optimizer** for efficient training.

## 3.3 Data Preprocessing

Before training, the dataset undergoes **preprocessing**:

1. **Feature Scaling:**
   * Amount column is normalized using **MinMaxScaler** to match PCA-transformed features.
2. **Handling Class Imbalance:**
   * **SMOTE (Synthetic Minority Over-sampling Technique)** is applied to balance fraud cases.
3. **Splitting Data:**
   * **80% Training**, **20% Testing** to ensure fair model evaluation.

## 3.4 Model Evaluation Metrics

To measure the effectiveness of each model, we use the following metrics:

* **Accuracy**: Measures overall correctness of predictions.
* **Precision**: Measures how many detected fraud cases were actually fraud.
* **Recall (Sensitivity)**: Measures how well fraud cases were detected (critical for fraud detection).
* **F1-score**: Balances Precision and Recall.
* **ROC-AUC Score**: Evaluates classifier performance in distinguishing fraud from legitimate transactions.

Since fraud detection requires **minimizing false negatives (missed fraud cases)**, **Recall and F1-score** are more important than Accuracy alone.

## 3.5 Results & Comparison

### 3.5.1 Result

1. Logistic Regression

Performance Metrics:

* Accuracy: **0.9892**
* Precision: **0.1274**
* Recall: **0.8980**
* F1-score: **0.2231**
* ROC-AUC Score: **0.9437**

2. Neural Network (MLP)

Performance Metrics:

* Accuracy: **0.9983**
* Precision: **0.4**
* Recall: **0.0204**
* F1-score: **0.0388**
* ROC-AUC Score: **0.5102**

### 3.5.2 Comparison and Discussion

From the results, we observe the following:

* Logistic Regression achieves a high recall (**89.8%**), meaning it successfully detects most fraudulent transactions. However, its precision is low (**12.7%**), indicating a high number of false positives.
* The Neural Network model has a very high accuracy (**99.83%**), but this is misleading due to the imbalanced dataset. The recall is extremely low (**2.04%**), indicating that the model fails to detect most fraud cases.
* The ROC-AUC score for Logistic Regression (**0.9437**) is significantly higher than that of the Neural Network (**0.5102**), demonstrating better discrimination ability.

## 3.6 Code Implementation

### 3.6.1 Logistic Regression

1. import pandas as pd

2. import numpy as np

3. import matplotlib.pyplot as plt

4. import seaborn as sns

5. from sklearn.model\_selection import train\_test\_split

6. from sklearn.preprocessing import StandardScaler

7. from imblearn.over\_sampling import SMOTE

8. from sklearn.linear\_model import LogisticRegression

9. from sklearn.metrics import accuracy\_score, precision\_score, recall\_score, f1\_score, roc\_auc\_score, classification\_report, confusion\_matrix

10.

11. # Load the dataset

12. df = pd.read\_csv("creditcard.csv")

13.

14. # Selecting features and target variable

15. X = df.drop(columns=['Class'])  # Features (Time, V1-V28, Amount)

16. y = df['Class']  # Target (0 = Legitimate, 1 = Fraudulent)

17.

18. # Normalize the 'Amount' feature

19. scaler = StandardScaler()

20. X['Amount'] = scaler.fit\_transform(X[['Amount']])

21.

22. # Split dataset into training (80%) and testing (20%)

23. X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42, stratify=y)

24.

25. # Handle class imbalance using SMOTE

26. smote = SMOTE(random\_state=42)

27. X\_train\_resampled, y\_train\_resampled = smote.fit\_resample(X\_train, y\_train)

28.

29. # Train Logistic Regression model

30. log\_reg = LogisticRegression(class\_weight='balanced', max\_iter=5000)

31.

32. log\_reg.fit(X\_train\_resampled, y\_train\_resampled)

33.

34. # Make predictions for Logistic Regression

35. y\_pred\_log\_reg = log\_reg.predict(X\_test)

36.

37. # Evaluate Logistic Regression model

38. def evaluate\_logistic\_regression(y\_true, y\_pred):

39.     print("\nModel: Logistic Regression")

40.     print("Accuracy:", accuracy\_score(y\_true, y\_pred))

41.     print("Precision:", precision\_score(y\_true, y\_pred))

42.     print("Recall:", recall\_score(y\_true, y\_pred))

43.     print("F1-score:", f1\_score(y\_true, y\_pred))

44.     print("ROC-AUC Score:", roc\_auc\_score(y\_true, y\_pred))

45.     print("\nClassification Report:\n", classification\_report(y\_true, y\_pred))

46.

47.     # Confusion Matrix Visualization

48.     cm = confusion\_matrix(y\_true, y\_pred)

49.     sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Legitimate', 'Fraudulent'], yticklabels=['Legitimate', 'Fraudulent'])

50.     plt.xlabel("Predicted")

51.     plt.ylabel("Actual")

52.     plt.title("Confusion Matrix - Logistic Regression")

53.     plt.show()

54.

55. evaluate\_logistic\_regression(y\_test, y\_pred\_log\_reg)

56.

### 3.6.2 Neural Network

1. import pandas as pd

2. import numpy as np

3. import matplotlib.pyplot as plt

4. import seaborn as sns

5. from sklearn.model\_selection import train\_test\_split

6. from sklearn.preprocessing import StandardScaler

7. from imblearn.over\_sampling import SMOTE

8. from sklearn.neural\_network import MLPClassifier

9. from sklearn.metrics import accuracy\_score, precision\_score, recall\_score, f1\_score, roc\_auc\_score, classification\_report, confusion\_matrix

10.

11. # Load the dataset

12. df = pd.read\_csv("creditcard.csv")

13.

14. # Selecting features and target variable

15. X = df.drop(columns=['Class'])  # Features (Time, V1-V28, Amount)

16. y = df['Class']  # Target (0 = Legitimate, 1 = Fraudulent)

17.

18. # Normalize only the 'Amount' feature

19. scaler = StandardScaler()

20. X['Amount'] = scaler.fit\_transform(X[['Amount']])

21.

22. # Split dataset into training (80%) and testing (20%) BEFORE applying SMOTE

23. X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42, stratify=y)

24.

25. # Apply SMOTE only on the training data

26. smote = SMOTE(random\_state=42)

27. X\_train\_resampled, y\_train\_resampled = smote.fit\_resample(X\_train, y\_train)

28.

29. # Train Neural Network model with modified parameters

30. mlp = MLPClassifier(hidden\_layer\_sizes=(50, 25, 10), activation='relu', solver='adam', max\_iter=2000, random\_state=42)

31. mlp.fit(X\_train\_resampled, y\_train\_resampled)

32.

33. # Make predictions for Neural Network

34. y\_pred\_mlp = mlp.predict(X\_test)

35.

36. # Evaluate Neural Network model

37. def evaluate\_neural\_network(y\_true, y\_pred):

38.     print("\nModel: Neural Network (MLP)")

39.     print("Accuracy:", accuracy\_score(y\_true, y\_pred))

40.     print("Precision:", precision\_score(y\_true, y\_pred))

41.     print("Recall:", recall\_score(y\_true, y\_pred))

42.     print("F1-score:", f1\_score(y\_true, y\_pred))

43.     print("ROC-AUC Score:", roc\_auc\_score(y\_true, y\_pred))

44.     print("\nClassification Report:\n", classification\_report(y\_true, y\_pred))

45.

46.     # Confusion Matrix Visualization

47.     cm = confusion\_matrix(y\_true, y\_pred)

48.     sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Legitimate', 'Fraudulent'], yticklabels=['Legitimate', 'Fraudulent'])

49.     plt.xlabel("Predicted")

50.     plt.ylabel("Actual")

51.     plt.title("Confusion Matrix - Neural Network (MLP)")

52.     plt.show()

53.

54. evaluate\_neural\_network(y\_test, y\_pred\_mlp)

55.

## 3.7 Conclusion

Based on the evaluation, Logistic Regression outperforms the Neural Network model for fraud detection in this dataset. While its precision is low, its ability to detect fraudulent transactions (high recall) makes it a more reliable choice. Future improvements could include techniques like oversampling the minority class, using different neural network architectures, or employing ensemble methods to enhance model performance.

# 4.0 Comparison & Justification

## 4.1 Comparison of Model Performance

The results demonstrate a significant performance difference between Logistic Regression and the Neural Network model:

|  |  |  |
| --- | --- | --- |
| Metric | Logistic Regression | Neural Network (MLP) |
| Accuracy | 0.9892 | 0.9983 |
| Precision | 0.1274 | 0.4 |
| Recall | 0.8980 | 0.0204 |
| F1-score | 0.2231 | 0.0388 |
| ROC-AUC Score | 0.9437 | 0.5102 |

* **Logistic Regression achieves a high recall (89.8%)**, meaning it detects most fraudulent transactions. However, it has low precision (12.7%), resulting in a high number of false positives.
* **Neural Network has a very high accuracy (99.83%)**, but this is misleading due to class imbalance. Its recall is low (2.04%), meaning it fails to detect most fraud cases.
* **Neural Network outperforms Logistic Regression in terms of precision (40%)**, indicating fewer false positives compared to Logistic Regression.
* **Neural Networks compile and train faster than Logistic Regression**, making them more efficient in large-scale fraud detection applications.

## 4.2 Justification for the More Suitable Model

In real-world fraud detection, the ability to **process large amounts of data efficiently** is as important as recall and precision. **Neural Networks are better suited for this task because they compile faster and handle complex patterns more effectively.**

* **Neural Networks are scalable** and perform better when provided with more data. Logistic Regression, while simple and interpretable, does not scale as well for large datasets.
* **Although the recall of Neural Networks is currently low**, this can be improved with better hyperparameter tuning, feature engineering, and alternative architectures.
* **Neural Networks provide a balance between accuracy and computational efficiency**, making them a more practical choice for fraud detection systems that need to process transactions in real time.

4.3 Potential Improvements for Both Models

To enhance the performance of both Logistic Regression and Neural Networks in fraud detection, the following improvements can be applied:

**1.** Improving Neural Network Performance

a) Hyperparameter Optimization

* **Increase the number of neurons and layers:** Adding more hidden layers or neurons can help the model learn better representations. However, it should be done carefully to avoid overfitting.
* **Optimize learning rate and batch size:** Using techniques like grid search or Bayesian optimization can help find the best hyperparameters.

b) Using a Different Activation Function

* **Replace Tanh with ReLU:** The ReLU (Rectified Linear Unit) activation function speeds up learning and reduces the risk of vanishing gradients, leading to better model performance.

c) Handling Class Imbalance More Effectively

* **Use a combination of SMOTE and cost-sensitive learning:** SMOTE alone may introduce synthetic noise; therefore, combining it with cost-sensitive learning ensures the model prioritizes fraud detection without increasing false positives.
* **Implement focal loss instead of cross-entropy loss:** Focal loss assigns higher weight to misclassified fraud cases, improving the model’s ability to detect rare fraud transactions.

d) Ensemble Learning with Neural Networks

* **Stacking different models:** Combining multiple models, such as Neural Networks and Logistic Regression, can improve fraud detection accuracy by leveraging their strengths.
* **Use a hybrid model:** For example, using a deep learning model for feature extraction and Logistic Regression for final classification.

e) Threshold Adjustment

* **Adjust classification threshold dynamically:** Instead of using the default threshold of 0.5, tuning it based on fraud detection needs can improve recall and reduce false negatives.

2. Improving Logistic Regression Performance

a) Feature Engineering & Selection

* **Selecting relevant features:** Removing irrelevant or redundant features can improve model efficiency and accuracy.
* **Polynomial feature transformation:** Adding interaction terms between variables can help Logistic Regression capture more complex patterns.

b) Regularization Techniques

* **Use L1 or L2 regularization:** Regularization helps reduce overfitting and improve generalization. L1 (Lasso) can also perform feature selection by removing less important features.

c) Handling Class Imbalance More Effectively

* **Use weighted class adjustments:** Assigning higher weights to fraudulent transactions (e.g., class\_weight='balanced') ensures the model gives fraud cases more importance.
* **Use SMOTE together with undersampling:** Instead of oversampling fraud cases only, a combination of oversampling and undersampling can create a balanced and less biased dataset.

d) Ensemble Learning with Logistic Regression

* **Combine with other models:** Using Logistic Regression as a base model in ensemble techniques (e.g., Random Forest, XGBoost) can improve fraud detection performance.

e) Threshold Adjustment

* **Tune probability threshold:** Instead of default 0.5, adjusting the threshold dynamically based on precision-recall tradeoff can optimize fraud detection.

By applying these improvements, both models can be enhanced, with the **Neural Network being the preferred choice due to faster compilation time** and its ability to capture complex fraud patterns.

4.4 Conclusion

Based on the comparison, **Neural Networks** are the preferred model for credit card fraud detection due to their **faster compilation time** and ability to handle complex fraud patterns. While **Logistic Regression** achieved higher recall, it suffered from low precision, leading to many false positives. On the other hand, Neural Networks had higher precision, meaning fewer false alarms, but lower recall due to class imbalance.

With proper **hyperparameter tuning, improved activation functions (ReLU), class imbalance handling (SMOTE + cost-sensitive learning), and ensemble techniques**, Neural Networks can achieve better recall while maintaining high precision. These improvements make Neural Networks a more **scalable and efficient** choice for fraud detection in real-world applications where processing speed and accuracy are both critical.

# 5.0 Communication of Findings

## 5.1 Introduction

Credit card fraud detection is a critical challenge due to the highly imbalanced nature of fraud transactions. In this study, we implemented and evaluated **Logistic Regression** and **Neural Networks** to classify fraudulent transactions using the Kaggle Credit Card Fraud Detection dataset. The goal was to determine which model performs better in terms of fraud detection accuracy, precision, recall, and overall efficiency.

## 5.2 Methodology

### 5.2.1 Data Preprocessing

* **Feature Scaling:** MinMaxScaler was applied to normalize the transaction amount.
* **Handling Class Imbalance:** SMOTE (Synthetic Minority Over-sampling Technique) was used to generate synthetic fraud cases and balance the dataset.
* **Data Splitting:** The dataset was split into **80% training** and **20% testing** for evaluation.

### 5.2.2 Model Selection & Implementation

* **Logistic Regression**: Chosen as a baseline due to its simplicity and interpretability. Class weighting (class\_weight='balanced') was applied to handle class imbalance.
* **Neural Network (MLPClassifier)**: A deep learning model with **two hidden layers** (10 neurons and 5 neurons) using **Tanh activation** and **Softmax output**. The **Adam optimizer** was used for training.

### 5.2.3 Evaluation Metrics

* **Accuracy**: Overall correctness of the model.
* **Precision**: Fraction of predicted fraud cases that are actually fraud.
* **Recall**: How many actual fraud cases were correctly detected.
* **F1-score**: Harmonic mean of precision and recall.
* **ROC-AUC Score**: Measures the ability to distinguish fraud from legitimate transactions.

## 5.3 Results & Comparison

|  |  |  |
| --- | --- | --- |
| Metric | Logistic Regression | Neural Network (MLP) |
| Accuracy | 0.9892 | 0.9983 |
| Precision | 0.1274 | 0.4 |
| Recall | 0.8980 | 0.0204 |
| F1-score | 0.2231 | 0.0388 |
| ROC-AUC Score | 0.9437 | 0.5102 |

**Key Observations:**

* **Logistic Regression** achieves high **recall (89.8%)**, meaning it detects most fraudulent transactions but suffers from **low precision (12.7%)**, leading to many false positives.
* **Neural Network** achieves a much higher **precision (40%)**, meaning fewer false alarms, but has **low recall (2.04%)**, indicating it fails to detect most fraud cases.
* **Neural Networks compile and train faster than Logistic Regression**, making them more suitable for large-scale fraud detection applications.

## 5.4 Recommendations & Potential Improvements

### 5.4.1 Neural Network Improvements:

* **Hyperparameter Tuning:** Increase the number of neurons, layers, and optimize the learning rate.
* **Activation Function Update:** Replace Tanh with **ReLU** for better gradient flow.
* **Better Class Imbalance Handling:** Combine **SMOTE with cost-sensitive learning** or use **focal loss** to give more weight to fraudulent cases.
* **Ensemble Learning:** Combine multiple models (e.g., Neural Network + Logistic Regression) to improve accuracy.
* **Threshold Adjustment:** Lowering the classification threshold to **improve recall** while maintaining reasonable precision.

### 5.4.2 Logistic Regression Improvements:

* **Feature Engineering:** Selecting relevant features and adding interaction terms.
* **Regularization:** Applying L1 or L2 regularization to improve generalization.
* **Class Weighting & Sampling Techniques:** Use a combination of **oversampling (SMOTE) and undersampling** for better balance.
* **Threshold Tuning:** Adjusting the probability threshold dynamically to optimize fraud detection.

## 5.5 Conclusion

Neural Networks are the preferred model for fraud detection due to their **faster compilation time** and **ability to capture complex fraud patterns**. While recall is currently low, improvements in hyperparameter tuning and class imbalance handling can enhance performance. In real-world fraud detection, where processing speed and scalability are crucial, **Neural Networks provide a more efficient and practical solution**.