UMBC

DATA606

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FINANCIAL FRAUD DETECTION IN MOBILE PAYMENTS

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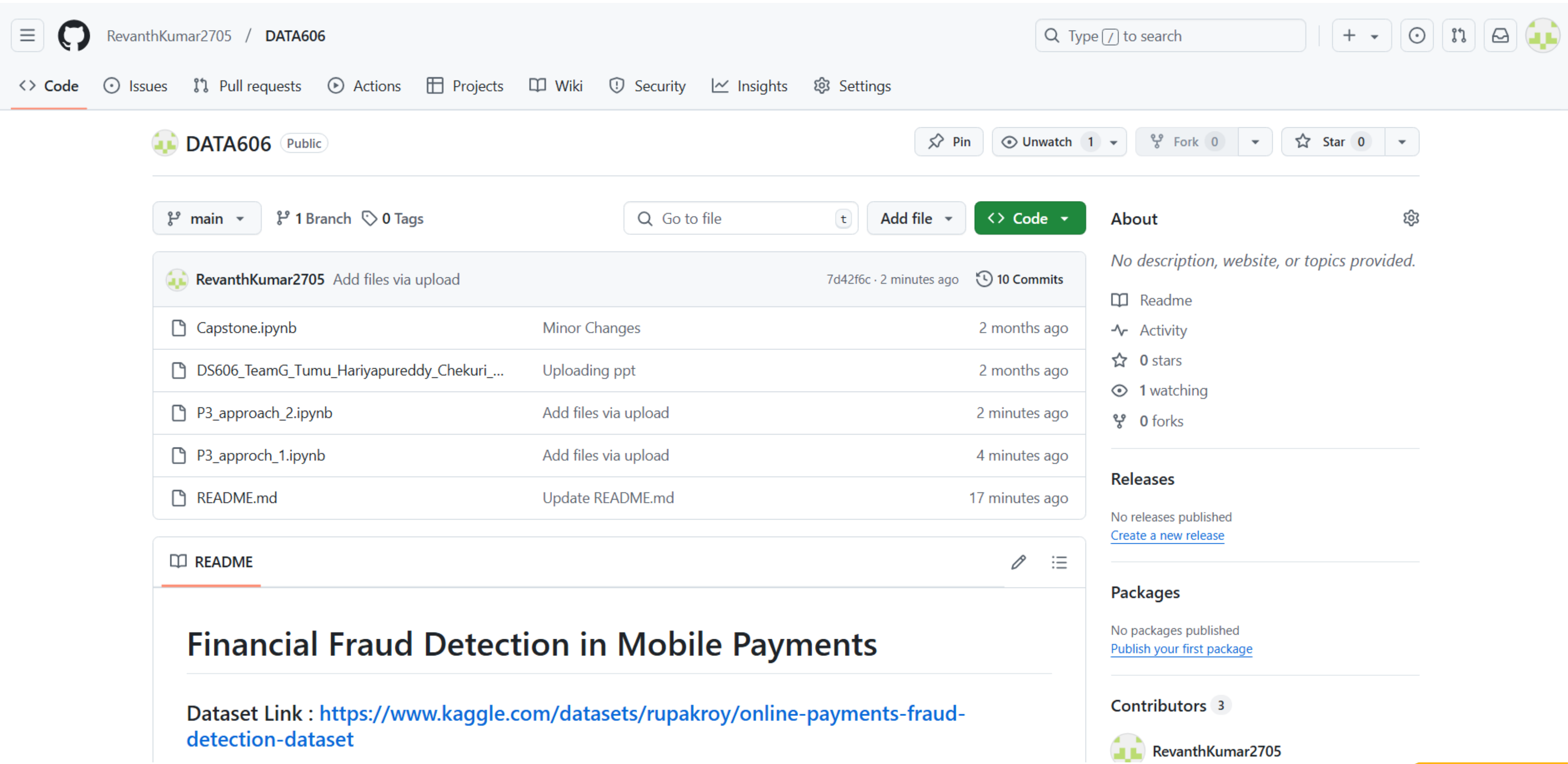
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P3_approch_1.ipynb
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README.md
Update README.md
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README
Financial Fraud Detection in Mobile Payments
Dataset Link : https://www.kaggle.com/datasets/rupakroy/online-payments-fraud-detection-dataset
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Introduction :

- This project focuses on exploring and analysing a dataset related to fraud detection in financial transactions.
- The goal is to gain insights into the characteristics and patterns associated with fraudulent activities.
- Understanding these patterns is crucial for improving fraud detection systems and preventing financial losses.
- This project was chosen to enhance our knowledge of fraud patterns and to develop robust models for detecting fraudulent transactions.

Research Question/Hypothesis :

- The primary research question is: What are the key characteristics and patterns associated with fraudulent transactions compared to non-fraudulent ones?
- How can machine learning algorithms effectively detect fraudulent financial transactions in a highly imbalanced dataset?
- Which machine learning algorithms perform best in detecting fraudulent transactions in imbalanced datasets?
- How does balancing the dataset (e.g., using SMOTE or downsampling) impact the performance metrics (accuracy, precision, recall, F1-score) of different algorithms
- Extracting key insights from the data.
- Early classification of fraud Transaction in payments.

Overview of similar approaches

- Recent approaches in fraud detection often involve machine learning models like decision trees, random forests, and deep learning techniques.
- Techniques such as anomaly detection, feature engineering, and ensemble methods are commonly used to improve accuracy. Research also emphasizes the use of real-time data for more effective fraud detection.
- **What's Missing:** While advanced models have been developed, many systems still struggle with high false positive rates and adaptability to new fraud patterns. There is a need for continuous improvement in feature extraction and model training to keep pace with evolving fraudulent tactics

System Architecture :

1. Workflow Overview

- **Start**: Initiates the fraud detection pipeline.
- **Imbalanced Data**: Highlights the challenge of dealing with class imbalance in the dataset.

2. Data Preparation

- **Data Exploration**: Understanding the dataset through visualization and summary statistics.
- **Feature Scaling**: Ensures uniformity across features for better model performance.
- **Pre-Processing**: Includes handling missing values, encoding categorical data, and balancing the dataset (e.g., oversampling or undersampling).

3. Model Training and Evaluation

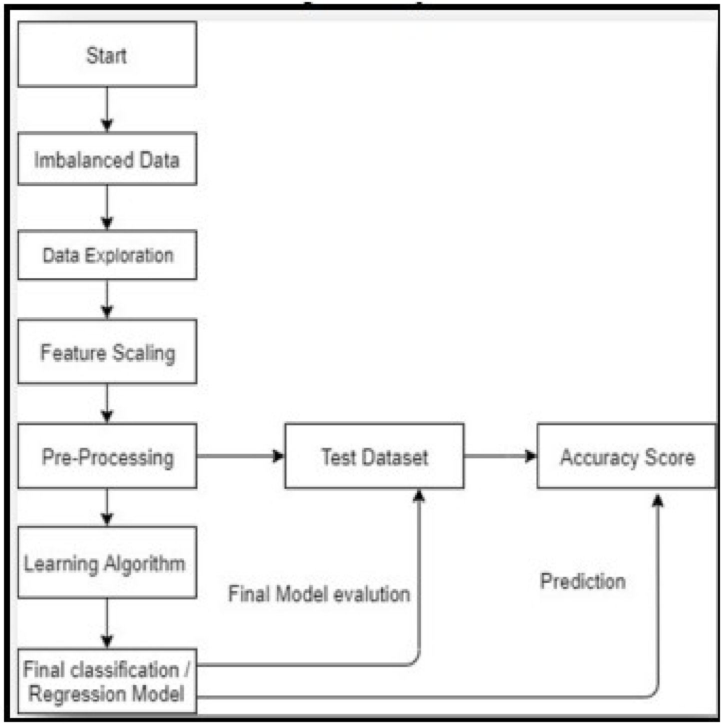
- **Learning Algorithm**: Apply machine learning or regression models to the pre-processed data.
- **Final Classification/Regression Model**: Select the best-performing model after training.

4. Testing and Prediction

- **Test Dataset**: Evaluate the trained model using a separate test set.
- **Final Model Evaluation**: Assess performance metrics like accuracy, recall, precision, F1-score, and AUC-ROC.
- **Prediction**: Use the trained model for real-world fraud detection.

5. Feedback and Improvement

- Accuracy Score: Iteratively improve the model based on evaluation metrics for enhanced performance.



Dataset Description:

- **Dataset Overview:** The dataset used in this project consists of transaction records with features relevant to fraud detection.
- It includes columns like amount, merchant, state, fraud, isFlaggedFraud and also other columns. The dataset is used to analyze and visualize patterns associated with fraudulent and non-fraudulent transactions.
- **Size and Source:** The datasets are sourced from Kaggle and other sources and contains 6,362,620 records with 11 features.
- This data provides a comprehensive view of transactions, allowing for in-depth analysis and model development.

Dataset Attributes Information

step: represents a unit of time where 1 step equals 1 hour

type: type of online transaction

amount: the amount of the transaction

nameOrig: customer starting the transaction

oldbalanceOrg: balance before the transaction

newbalanceOrig: balance after the transaction

nameDest: recipient of the transaction

oldbalanceDest: initial balance of recipient before the transaction

newbalanceDest: the new balance of recipient after the transaction

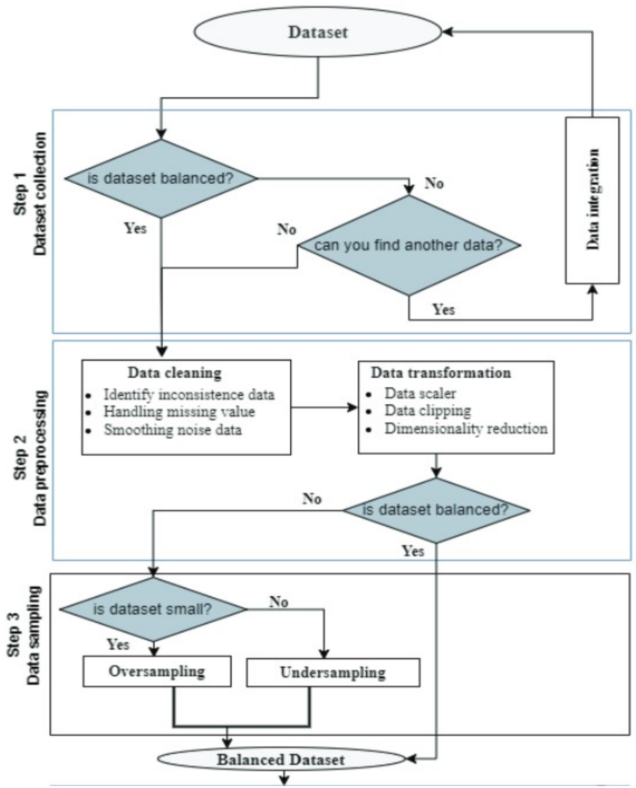
isFraud: fraud transaction.

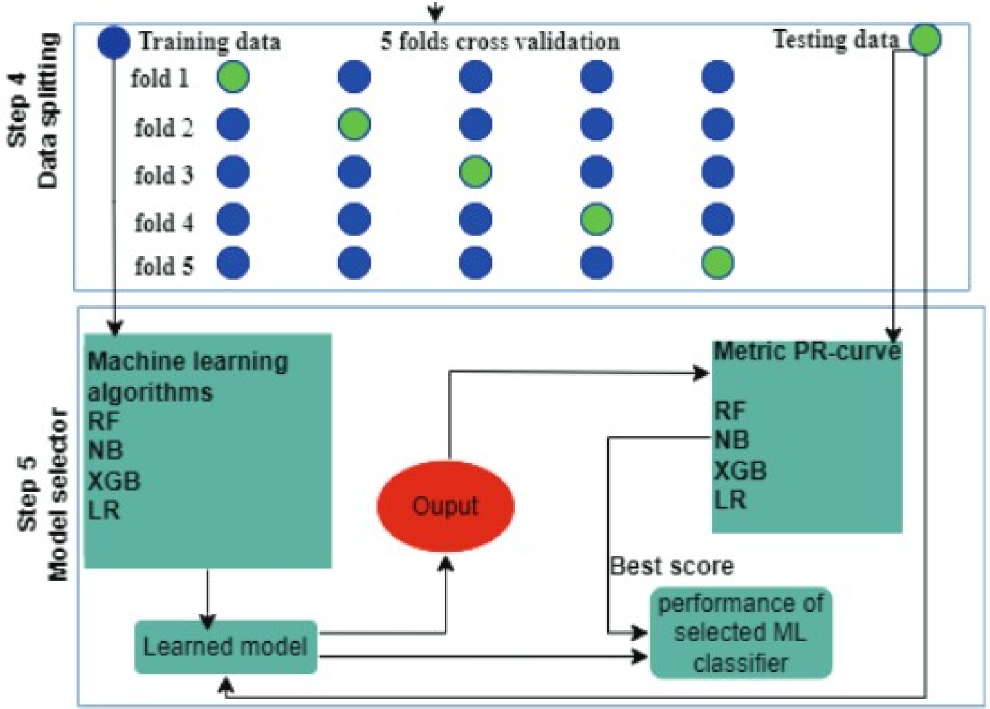
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
```

Literature Review

- **Context:** Financial transaction fraud caused global losses of $28 billion (2019) to $34 billion (2022).
- **Objective:** Compare machine learning algorithms to detect fraudulent transactions and reduce financial losses.
- **Dataset:** Sourced from Kaggle: 6,362,620 records, 10 features. Highly imbalanced: 99.87% non-fraudulent, 0.13% fraudulent.
- **Key Findings: For the Imbalanced Dataset,** Random Forest: Best performer with 99.97% accuracy, 99.96% F1-score.High-class imbalance reduced recall and F1-scores for most models.
- **Balanced Dataset (SMOTE)**:Bagging Classifier: Highest performance, 99.96% F1-score.Balancing enhanced all model performances.
- **Insights**
- Features like `amount`, `type_CASH_OUT`, and `oldbalanceOrg` strongly correlate with fraud.
- Balancing datasets improves fraud detection reliability.

System Architecture:





Machine Learning and Data Analysis

1. Type of Analysis:

Prediction and Classification:

- **Prediction:** We will build predictive models to forecast the likelihood of a transaction being fraudulent based on historical data.
- **Classification:** The primary task is classification, where transactions are categorized as either fraudulent or non-fraudulent.

Description:

- **Data Size:** The dataset contains 6,362,620 records and 11 attributes.
- **Number of Instances/Samples:** 6,362,620
- **Number of Raw Attributes:** 11

Type of Classification: Binary Classification

- **Those are:** 0 Non-Fraudulent Transactions and 1 Fraudulent Transactions.

Steps in Machine Learning Analysis:

1. **Data Preprocessing:**
   - Handle missing values
   - Convert categorical variables to numerical
   - Normalize/standardize numerical features
2. **Feature Selection:**
   - Identify and select relevant features that contribute to fraud detection, such as transaction amount, merchant, and location.
3. **Model Building:**
   - **Algorithms:** Implement and evaluate various classification algorithms such as Logistic Regression, Decision Trees, Random Forests, and Gradient Boosting Machines.
   - **Evaluation Metrics:** Use metrics like accuracy, precision, recall, F1-score, and ROC-AUC to assess model performance.
4. **Model Validation:**
   - Perform cross-validation and hyperparameter tuning to improve model robustness.
5. **Prediction and Deployment:**
   - Deploy the best-performing model for predicting fraudulent transactions in new data.

Data Preprocessing:

```
[ ] # Checking isFlaggedFraud column
data['isFlaggedFraud'].value_counts()
```

isFlaggedFraud	count
0	6362604
1	16

dtype: int64

```
data.columns
```

```
Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

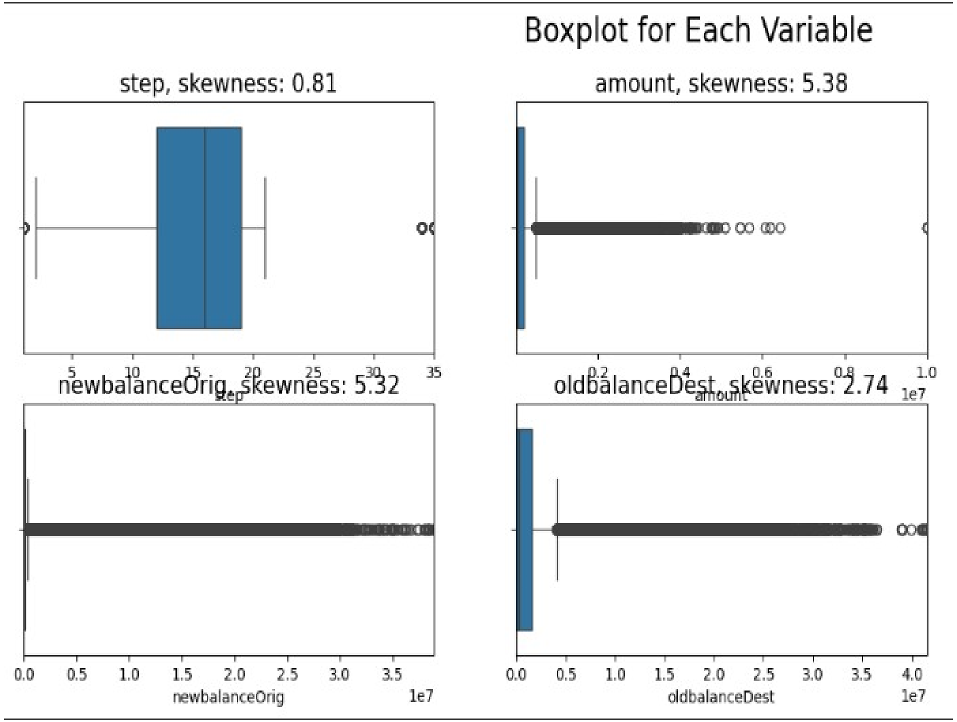
```
data.isnull().sum()
```

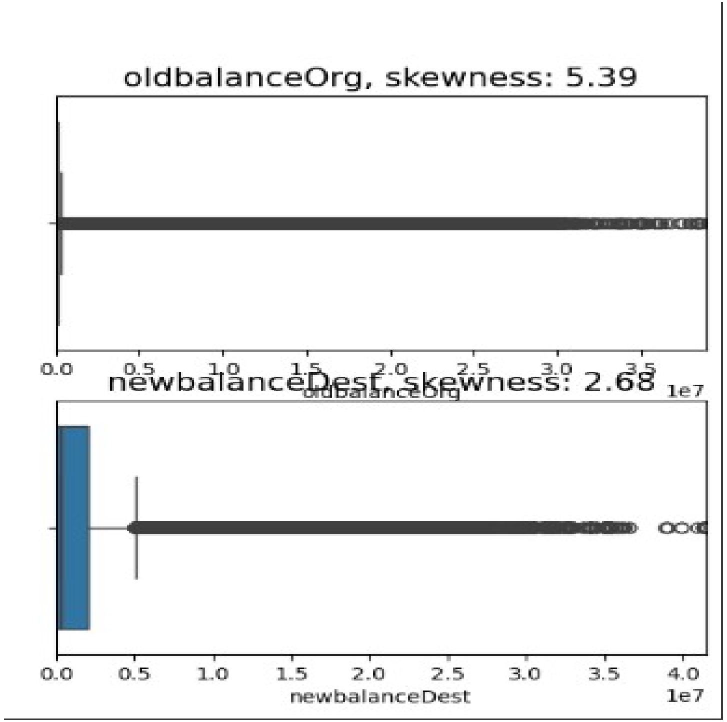
	0
step	0
type	0
amount	0
nameOrig	0
oldbalanceOrg	0
newbalanceOrig	0
nameDest	0
oldbalanceDest	0
newbalanceDest	0
isFraud	0
isFlaggedFraud	0

dtype: int64

There are no missing values

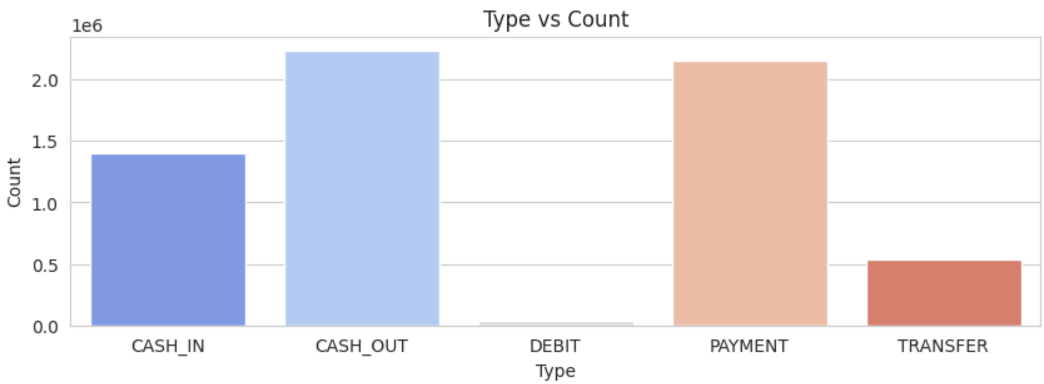
EDA :

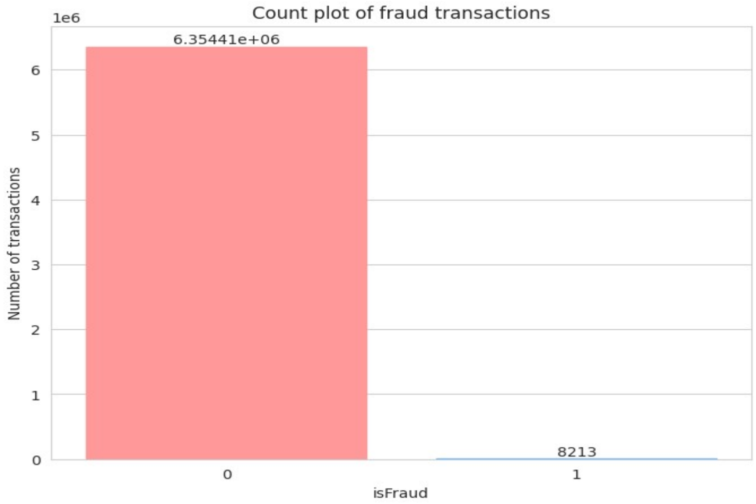

Boxplot for Each Variable
step, skewness: 0.81
step
amount, skewness: 5.38
amount
1e7
newbalanceOrig, skewness: 5.32
newbalanceOrig
1e7
oldbalanceDest, skewness: 2.74
oldbalanceDest
1e7


oldbalanceOrg, skewness: 5.39
oldbalanceOrg
1e7
newbalanceDest, skewness: 2.68
newbalanceDest
1e7

Univariate EDA

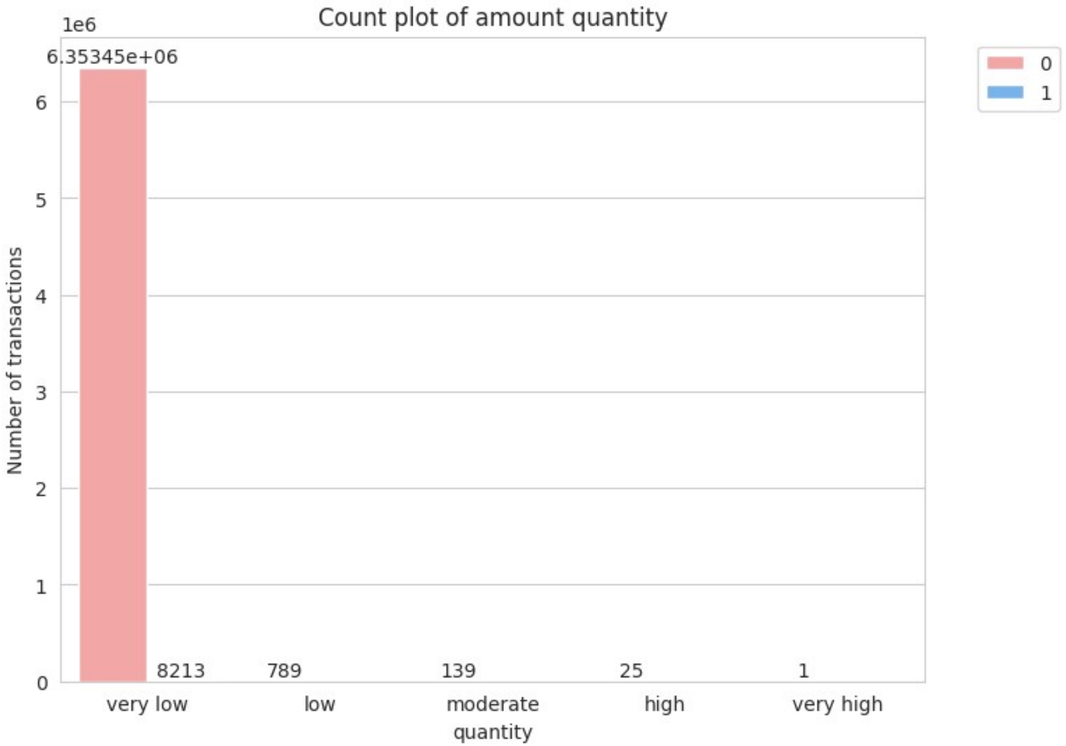
- **Top Transaction Types**: **CASH_OUT** and **PAYMENT** are the most frequent transaction types, each surpassing 2 million transactions.
- **Medium Frequency**: **CASH_IN** transactions occur with moderate frequency, just under 1.5 million.
- **Least Frequent**: **TRANSFER** and **DEBIT** are the least common transaction types, with **TRANSFER** significantly lower in count compared to others.
- **Non-Fraudulent Transactions (0)** dominate the dataset, with **6,354,410 instances**.
- **Fraudulent Transactions (1)** are extremely rare, with only **8,213 instances**.
- This imbalance necessitates techniques like **oversampling (e.g., SMOTE)** or **undersampling** to improve model performance and reliability for fraud detection.



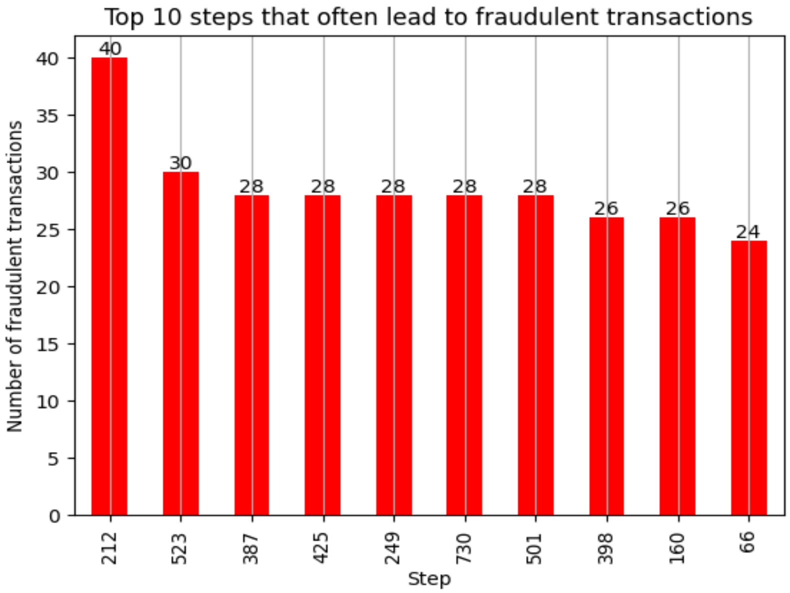


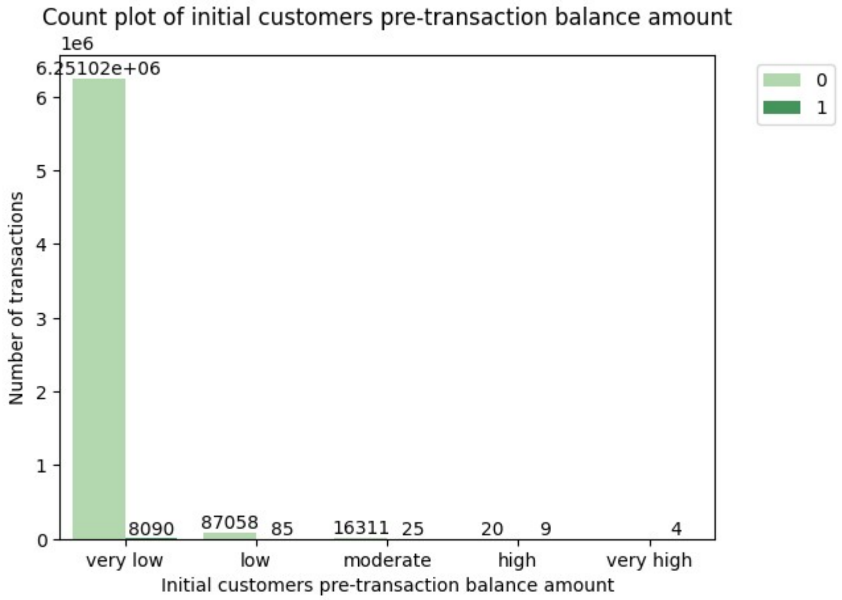
Distribution of Transaction Amounts and FraudCorrelation

- All fraudulent transactions fall into the category of very low amounts.
- Higher transaction amounts (e.g., "moderate," "high," "very high") are extremely rare, with only **139, 25, and 1 instances**, respectively.
- Fraudulent transactions are concentrated in **lower amount categories**, particularly "very low" and "low."



Single Feature Analysis

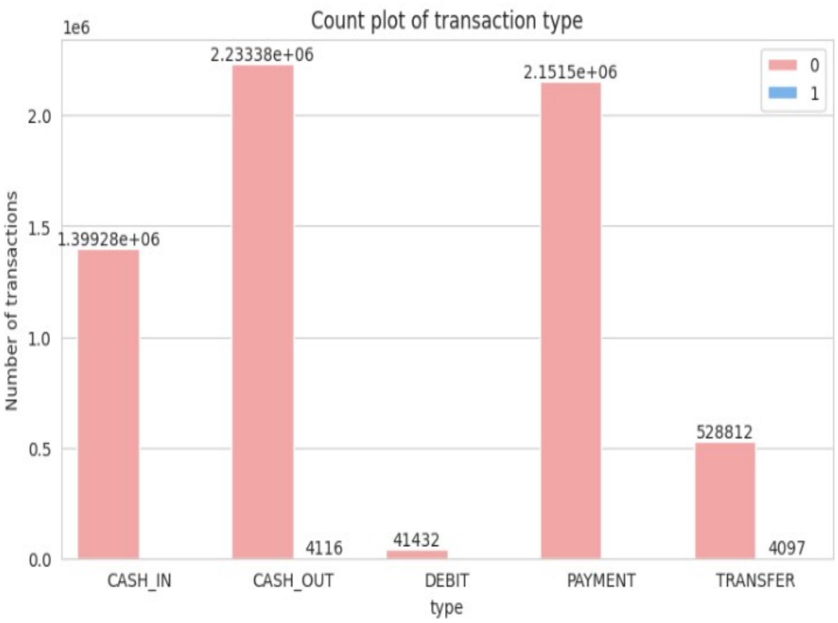


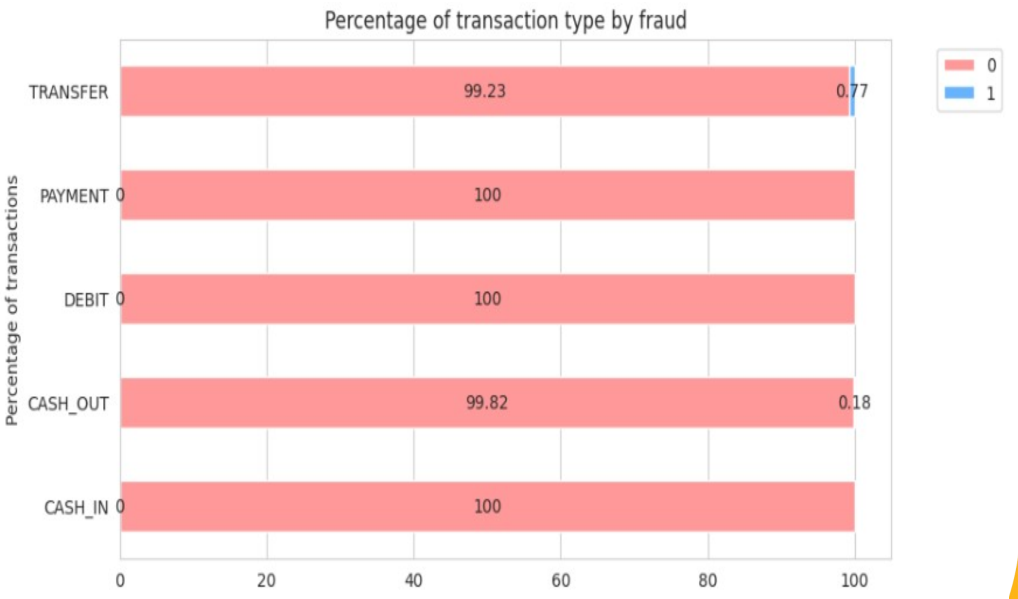


Figures shows Step 212 is the step most likely to lead more fraudulent cases.

This figure shows, Initial customers with very low pre-transaction balances has the highest number of fraudulent transactions

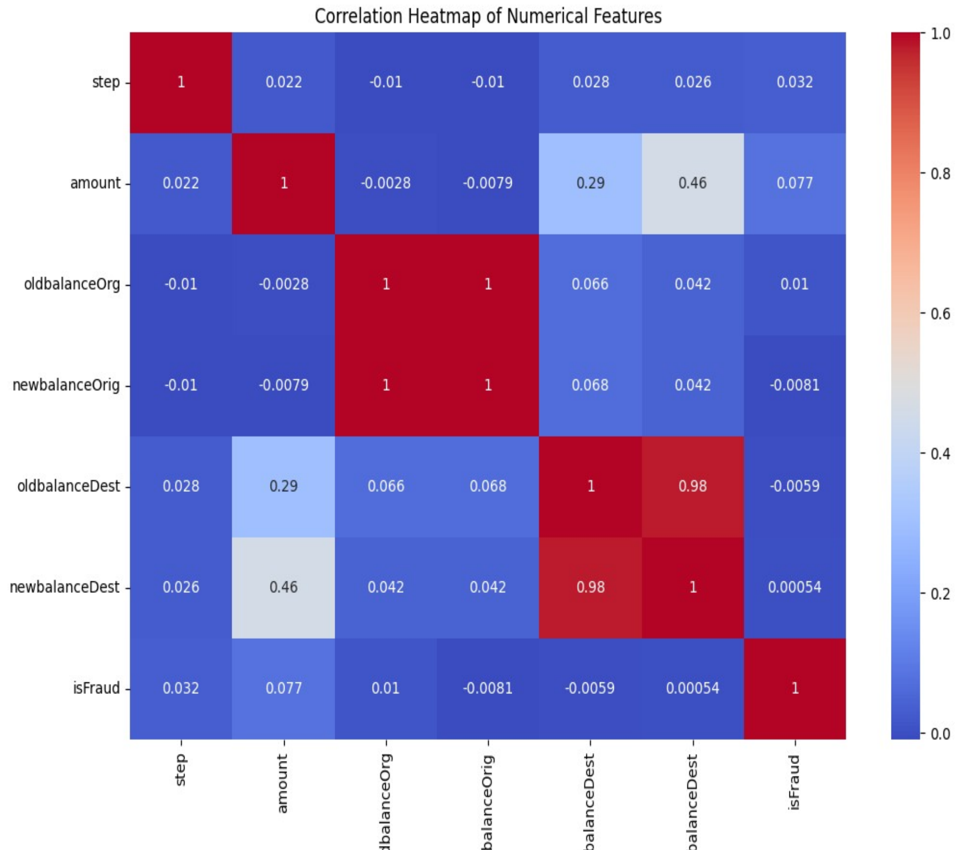
Bivariate Exploratory Data Analysis





Fraudulent transactions only occur in debit and transfer types.

Correlation Map



- High Correlation involves oldbalanceDest and newbalanceDest showing the values of 0.98.
- oldbalanceOrg and newbalanceOrig also display significant correlation.
- Moderate correlation involves amount and newbalancDest showing 0.46.
- Other amount and oldbalanceDest are correlated at 0.29.
- Low Correlation with isFraud, amount at 0.077. This suggests that while there is some relationship, the amount of the transaction alone is not a strong indicator of fraud.
- newbalanceOrig and isFraud have negative correlation of -0.0081 is very low and no direct linear relationship.

Differentiation

Handling Imbalanced Data: We will apply techniques like SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance, which is common in fraud detection datasets.

Model Tuning and Selection: While traditional methods are often effective, we will emphasize hyperparameter tuning and model selection to optimize performance. Ensemble techniques and stacking models will be explored to combine strengths of different algorithms.

Advanced Evaluation Metrics: Beyond basic metrics (accuracy, precision, recall), we will use ROC-AUC and Precision-Recall curves to better evaluate model performance, especially given the class imbalance.

Initial Hypothesis Challenges

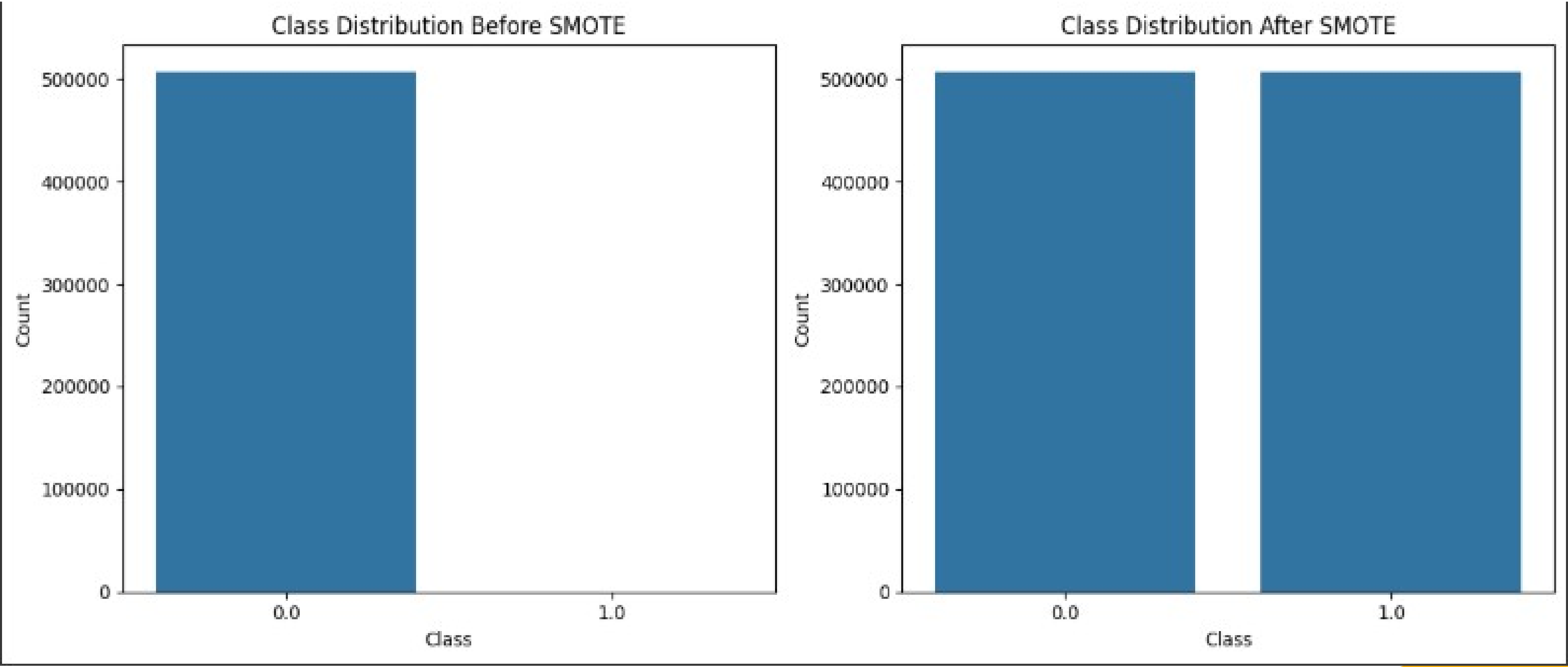
We have identified two primary challenges in the dataset:

Class Imbalance: The dataset had a large number of non-fraudulent transactions (isFraud = 0) compared to fraudulent ones (isFraud = 1), which made the data highly imbalanced.

This imbalance not only caused the models to focus more on non-fraudulent transactions but also led to longer processing times.

Dataset Size: The original dataset had millions of rows, which significantly slowed down the execution of data preprocessing, training, and evaluation steps.

Handling Imbalanced Data using SMOTE



Model Comparision

Before Smote on RF

```
# Re-splitting the dataset after ensuring all features are numeric
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Train the model again with class weights for handling imbalance
model = RandomForestClassifier(random_state=42, class_weight='balanced')
model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', random_state=42)
```

```
# Predicting on the test set
y_pred = model.predict(X_test)
```

```
# Evaluating the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
```

ble-click (or enter) to edit

```
accuracy, conf_matrix, class_report
```

```
(0.999763628771106,
 array([[126869,      1],
        [    29,     20]]),
 '              precision    recall  f1-score   support\n\n         0.0       1.00      1.00      1.00
0.95      0.41      0.57        49\n\n    accuracy                           1.00    126919\n   macro avg
0.79    126919\nweighted avg       1.00      1.00      1.00    126919\n')
```

After Smote on RF

```
# Apply SMOTE to the training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

```
# Train the RandomForest model with the resampled data
model_smote = RandomForestClassifier(random_state=42, class_weight='balanced')
model_smote.fit(X_train_resampled, y_train_resampled)
```

```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', random_state=42)
```

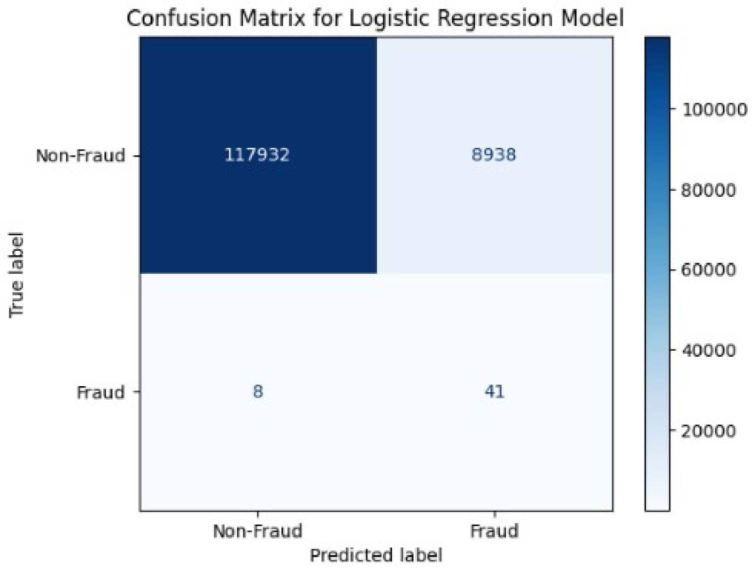
```
# Predicting on the original test set
y_pred_smote = model_smote.predict(X_test)
```

```
# Evaluating the model with resampled training data
accuracy_smote = accuracy_score(y_test, y_pred_smote)
conf_matrix_smote = confusion_matrix(y_test, y_pred_smote)
class_report_smote = classification_report(y_test, y_pred_smote)

accuracy_smote, conf_matrix_smote, class_report_smote
```

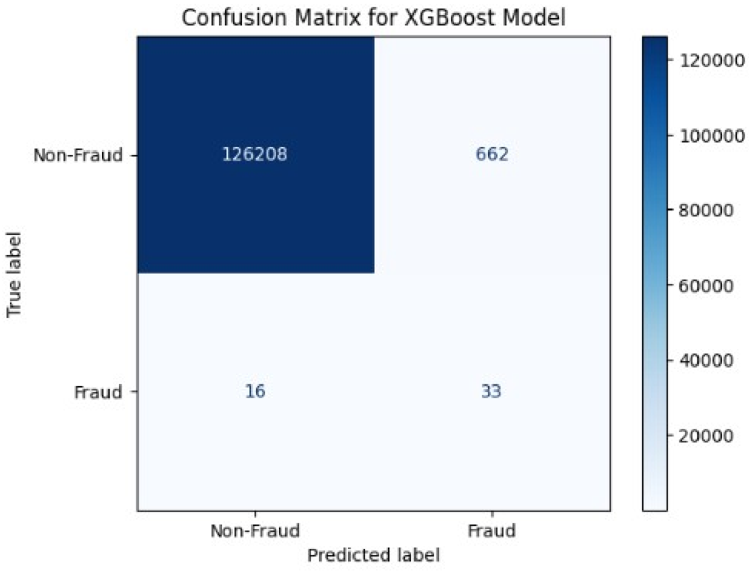
```
(0.9994011928868018,
 array([[126818,     52],
        [    24,     25]]),
 '              precision    recall  f1-score   support\n\n         0.0       1.00
126919\nweighted avg       1.00      1.00      1.00    126919\n')
```

Different Models

Logistic Regression



XG Boost Model



Tuned Logistic Regression

```python
#Logistic regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Define the parameter grid for 'C'
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100]
}
```

```python
# Set up the Grid Search with cross-validation
grid_search = GridSearchCV(
    estimator=LogisticRegression(random_state=42, class_weight='balanced', max_iter=1000),
    param_grid=param_grid,
    cv=3,  # 3-fold cross-validation
    verbose=2,
    n_jobs=-1  # Use all available cores
)
```

```python
# Fit the Grid Search on the resampled training data
grid_search.fit(X_train_resampled, y_train_resampled)

# Get the best estimator
best_logistic_model = grid_search.best_estimator_
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
```

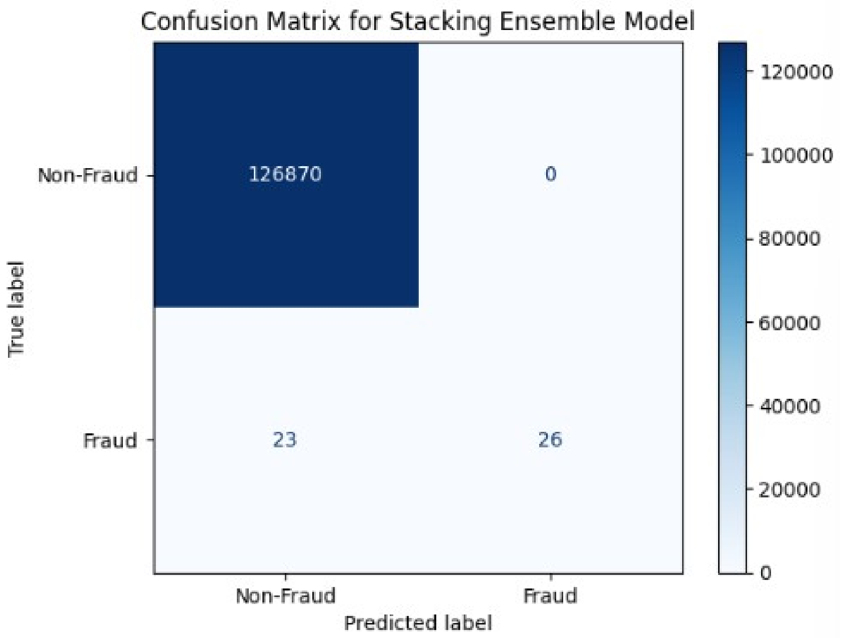
```python
# Predicting on the original test set using the best model
y_pred_logistic = best_logistic_model.predict(X_test)

# Evaluating the Logistic Regression model
accuracy_logistic = accuracy_score(y_test, y_pred_logistic)
conf_matrix_logistic = confusion_matrix(y_test, y_pred_logistic)
class_report_logistic = classification_report(y_test, y_pred_logistic)
```

```python
accuracy_logistic, conf_matrix_logistic, class_report_logistic
```

- **Hyperparameter Tuning**:
- **Grid Search**: Used to find the optimal regularization parameter C (range: 0.01, 0.1, 1, 10, 100).
- **Cross-Validation**: 3-fold cross-validation ensures robust evaluation during tuning.
- **Class Weights**: Set to `'balanced'` to adjust for the dataset's imbalanced nature, ensuring minority class receives appropriate weight.
- **Training Data**: Resampled using oversampling/SMOTE techniques to balance the dataset.
- **Testing Data**: Evaluated on the original test set for real-world performance assessment.
- **Metrics Used**:
- **Accuracy**: Measures overall correctness of predictions.
- **Confusion Matrix**: Provides insights into true positives, true negatives, false positives, and false negatives.
- **Classification Report**: Includes precision, recall, and F1-score for both classes.
- **Purpose of Metrics**:
- Focuses on precision and recall to evaluate performance on the minority (fraudulent) class.
- **Grid Search Insights**
- **Optimal Model Selection**:
- Automatically selects the best Logistic Regression model based on the performance during cross-validation.
- Trained with up to 1,000 iterations for convergence.
- **Computational Efficiency**
- **Parallel Processing**: Utilized all available cores (`n_jobs=-1`) for faster hyperparameter tuning.

Stacking Classifier

```python
from sklearn.ensemble import StackingClassifier


# Define base models
base_models = [
    ('rf', RandomForestClassifier(n_estimators=100, random_state=42)),
    ('log_reg', LogisticRegression(random_state=42, max_iter=1000, class_weight='balanced')),
    ('xgb', XGBClassifier(n_estimators=50, random_state=42, use_label_encoder=False, eval_metric='logloss'))
]

# Define the meta-model
meta_model = LogisticRegression(random_state=42)

# Set up the stacking classifier
stacking_model = StackingClassifier(
    estimators=base_models,
    final_estimator=meta_model,
    cv=3  # 3-fold cross-validation for training the meta-model
)

# Fit the stacking model on the training data
stacking_model.fit(X_train, y_train)

# Predict on the test set
y_pred_stack = stacking_model.predict(X_test)

# Evaluate the stacking model
accuracy_stack = accuracy_score(y_test, y_pred_stack)
conf_matrix_stack = confusion_matrix(y_test, y_pred_stack)
class_report_stack = classification_report(y_test, y_pred_stack)

accuracy_stack, conf_matrix_stack, class_report_stack
```



Key Insights from stacking classifier

- **Stacking Classifier**: Combines predictions from multiple base models to improve classification performance using a meta-model for final predictions.
- **Random Forest Classifier**:
  - Number of Estimators: 100
  - Random State: 42 (for reproducibility)
- **Logistic Regression**:
  - Maximum Iterations: 1,000
  - Class Weight: Balanced (to address class imbalance)
- **XG Boost Classifier**:
  - Number of Estimators: 50
  - Eval Metric: Log Loss
  - Random State: 42
- **Logistic Regression**:
  - Serves as the final estimator to combine predictions from base models.
  - **Cross-Validation**
- **3-Fold Cross-Validation**: Used to train the meta-model, ensuring robust evaluation and reducing overfitting.

Challenges Faced By SMOTE

- **Prevent Overfitting**:
- While SMOTE (Synthetic Minority Oversampling Technique) helps balance the dataset by generating synthetic samples for the minority class, it can also lead to an **artificially large dataset**.
- A larger dataset might make some machine learning algorithms computationally expensive and more prone to overfitting, especially for models sensitive to data size.
- **Memory and Computational Efficiency**:
- Down sampling the dataset reduces its size, making it easier to fit models without excessive computational overhead or memory issues, particularly when working with limited hardware resources.
- **Creating a Balanced Subset**:
- SMOTE creates synthetic samples for the minority class. Down sampling can be used afterward to create a **smaller, balanced subset** of the data for training while maintaining the class distribution.
- **Ensure Realistic Distribution**:
- In some cases, down sampling is applied to balance out the dataset in a controlled manner, preventing the dominance of synthetic samples introduced by SMOTE.

Limitations From Literature Review :

- **Synthetic Data Overfitting**:
- SMOTE generates synthetic samples by interpolating between existing minority class instances, which may lead to overfitting as the model starts learning artificial patterns instead of real-world ones[1].
- **Distorted Correlations**:
- The synthetic data generated by SMOTE might distort the true relationships between features, particularly in high-dimensional datasets, leading to suboptimal model performance.
- **Increased Dataset Size**:
- Applying SMOTE significantly increases the size of the dataset, which can result in higher computational costs and longer training times.
- **Not Suitable for All Algorithms**:
- Some algorithms, especially distance-based ones like K-Nearest Neighbors, may perform poorly with SMOTE-generated data due to changes in the feature space.
- **Potential for Noise Introduction**:
- Synthetic samples created by SMOTE may introduce noise, particularly when there are outliers or misclassified points in the original minority class[1].
- These limitations highlight the challenges of using SMOTE and the importance of combining it with other techniques, such as down sampling, to achieve better fraud detection performance.

Down Sampling

- To address these issues, We have implemented different strategies:
- We separated the fraudulent transactions (isFraud = 1) from the non-fraudulent ones (isFraud = 0). Retained all fraudulent transactions to ensure the model has access to all positive examples.
- From the non-fraudulent transactions, randomly selected a subset of 100,000 samples to balance the data and reduce the size of the dataset. Finally, combined the two subsets into a single dataset for analysis and modeling.
- Why? By reducing the majority class (non-fraudulent transactions), We ensured that the dataset was more balanced, which is crucial for detecting rare events like fraud. This also reduced the dataset size, allowing faster processing during model training and evaluation.
- The dataset was reduced from millions of rows to 100,246 rows while maintaining 10 features. Fraudulent transactions are now better represented, improving the model's ability to learn from them.

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Down sampling Technique:

```python
from sklearn.utils import resample

# Downsample non-fraudulent transactions
def downsample_data(data, fraud_column='isFraud', fraud_class=1, non_fraud_samples=100000):
    # Separate fraud and non-fraud samples
    fraud_data = data[data[fraud_column] == fraud_class]
    non_fraud_data = data[data[fraud_column] != fraud_class]

    # Downsample non-fraud data
    non_fraud_data_downsampled = resample(non_fraud_data,
                                          replace=False,  # without replacement
                                          n_samples=non_fraud_samples,  # number of non-fraud samples to retain
                                          random_state=42)

    # Combine the downsampled non-fraud and all fraud data
    downsampled_data = pd.concat([fraud_data, non_fraud_data_downsampled])
    return downsampled_data
```

```python
# Simplify categories in 'type' column
def simplify_categories(data, category_column='type'):
    # Replace rare categories or merge them into 'OTHER'
    common_types = ['PAYMENT', 'CASH_OUT', 'TRANSFER']  # Retain only these categories
    data[category_column] = data[category_column].apply(lambda x: x if x in common_types else 'OTHER')
    return data

# Apply the functions to the dataset
downsampled_data = downsample_data(data, fraud_column='isFraud', non_fraud_samples=100000)
simplified_data = simplify_categories(downsampled_data, category_column='type')

# Encode the simplified categorical column
simplified_data = pd.get_dummies(simplified_data, columns=['type'], drop_first=True)

# Check the shape of the new dataset
print("Shape of the downsampled dataset:", simplified_data.shape)
```

```
Shape of the downsampled dataset: (108213, 10)
```

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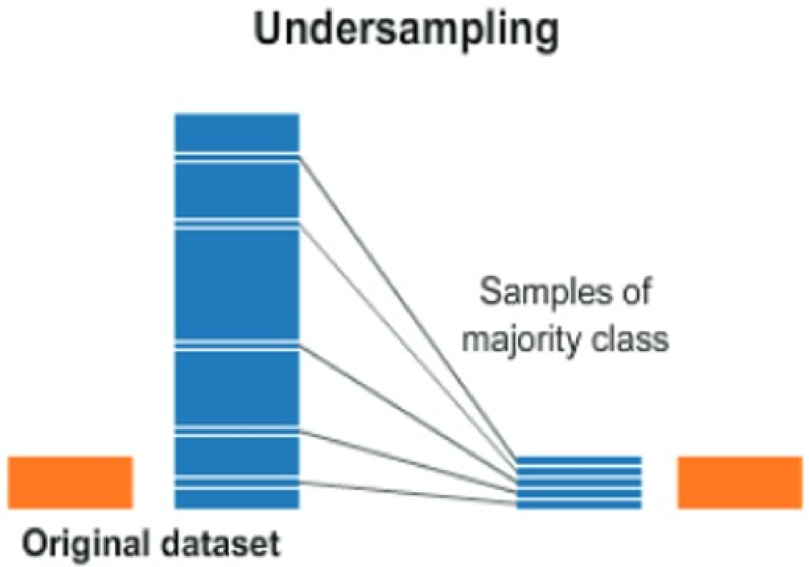
Advantages of Down Sampling

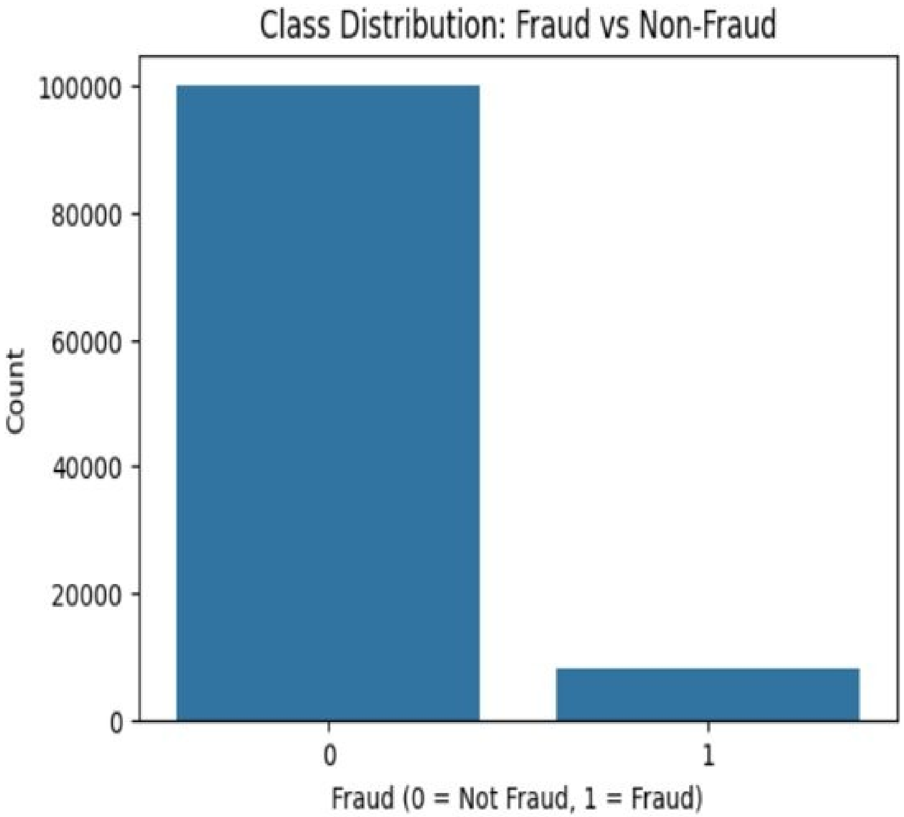
- Benefits of These Changes Faster Processing: The dataset is now efficient for making data preprocessing and model training significantly faster.
- Improved Class Balance: Fraudulent transactions are better represented, which helps the model focus on detecting them.
- Makes easy for tuning the models and selecting the best of it.



EDA for Down sampling Data

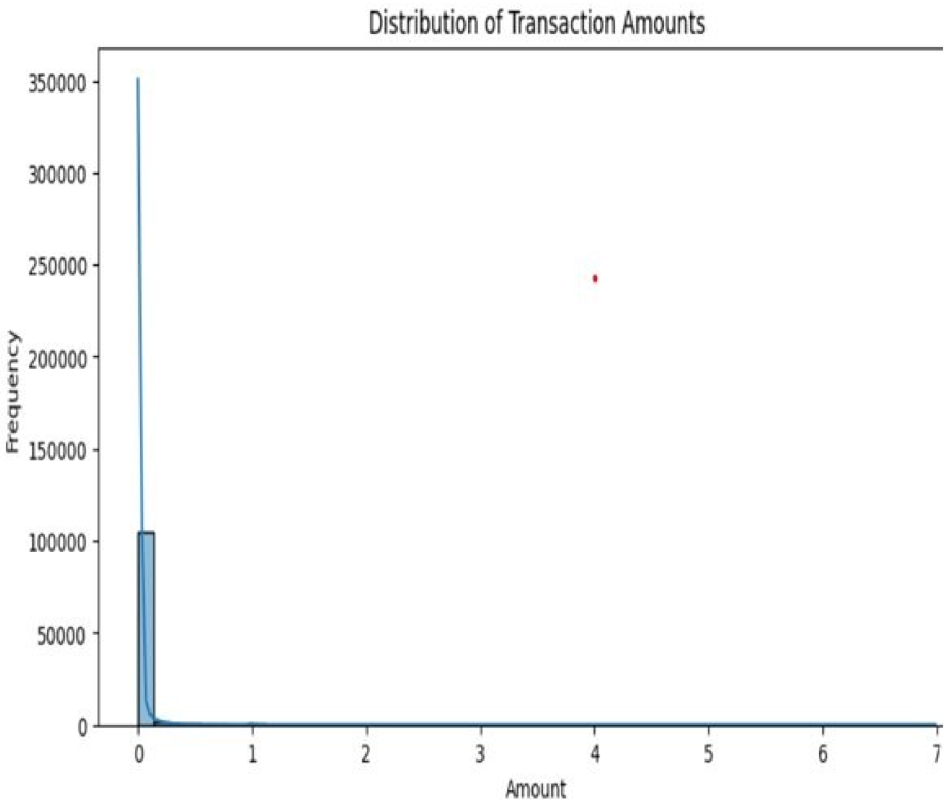
	step	amount	oldbalanceOrg	newbalanceOrig
count	108213.000000	1.082130e+05	1.082130e+05	1.082130e+05
mean	253.148088	2.782301e+05	8.781334e+05	7.887530e+05
std	153.257221	9.654623e+05	2.899878e+06	2.815070e+06
min	1.000000	0.000000e+00	0.000000e+00	0.000000e+00
25%	156.000000	1.470375e+04	0.000000e+00	0.000000e+00
50%	251.000000	8.631680e+04	2.009400e+04	0.000000e+00
75%	350.000000	2.323131e+05	1.621128e+05	1.136025e+05
max	743.000000	6.988673e+07	5.958504e+07	4.958504e+07

	oldbalanceDest	newbalanceDest	isFraud
count	1.082130e+05	1.082130e+05	108213.000000
mean	1.057067e+06	1.230957e+06	0.075897
std	3.447306e+06	3.770020e+06	0.264834
min	0.000000e+00	0.000000e+00	0.000000
25%	0.000000e+00	0.000000e+00	0.000000
50%	9.595315e+04	1.995590e+05	0.000000
75%	8.809185e+05	1.114542e+06	0.000000
max	2.362305e+08	2.367265e+08	1.000000



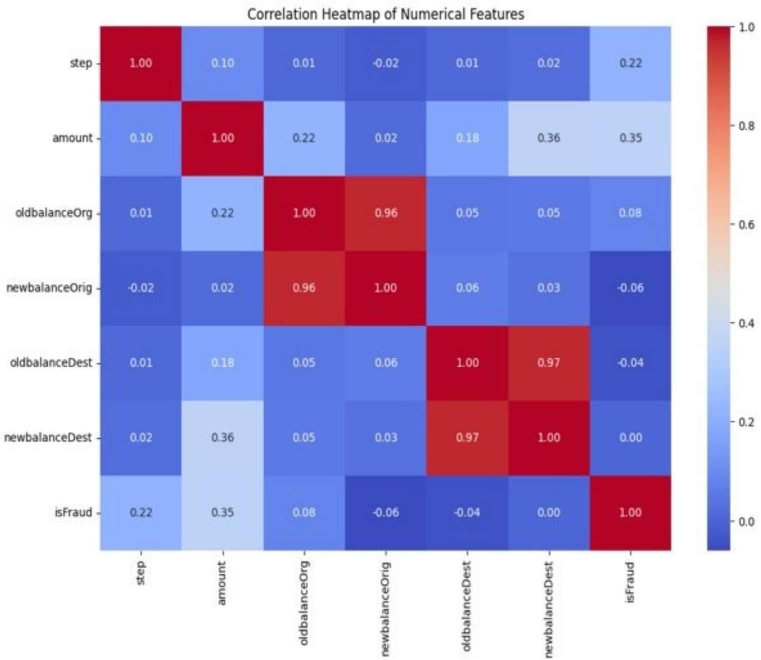
Univariate EDA :

- **Graphical Representation**: A histogram effectively illustrates the frequency distribution of transaction amounts.
- **Scale and Binning**: The choice of bin size is crucial; smaller bins might provide more detail for lower transaction amounts.
- **Highly Skewed Distribution**: The distribution of transaction amounts is extremely left-skewed, indicating that a large majority of transactions involve small amounts.
- **Implications for Fraud Detection: The** rarity of large transactions might signify potential outliers or anomalies which could be subject to further investigation for fraud detection.



Bi-Variate EDA : Correlation Map

- **oldbalanceOrg and newbalanceOrig** show an extremely high correlation of 0.96
- **oldbalanceDest and newbalanceDest** also have a very high correlation of 0.97.
- The transaction **amount has a moderate correlation of 0.35 with isFraud**, suggesting that higher transaction amounts could be more susceptible to being fraudulent.
- **amount and newbalanceDest**: A notable correlation of 0.36 indicates that as the transaction amount increases.
- **step and isFraud**: Shows a correlation of 0.22, suggesting some relationship between the timing of the transaction and its likelihood of being fraudulent. This might indicate that certain time steps are more prone to fraudulent activities.



Missing Values

- The code snippet enhances transparency about the data cleaning process and tells us handling similar issues in their datasets.
- Checking for missing data, particularly in the target variable, as it can skew or invalidate model training, leads to errors.

```python
# Check for missing values in 'isFraud'
missing_fraud = simplified_data['isFraud'].isnull().sum()
print(f"Missing values in 'isFraud': {missing_fraud}")

# Drop rows with missing 'isFraud' values if any
simplified_data = simplified_data.dropna(subset=['isFraud'])

# Verify again
missing_fraud = simplified_data['isFraud'].isnull().sum()
print(f"Missing values in 'isFraud' after cleanup: {missing_fraud}")
```

```
Missing values in 'isFraud': 0
Missing values in 'isFraud' after cleanup: 0
```

Proposed Methods:

We have implemented different classification models and then tuned it.

Logistic Regression, Gradient Boosting, Tuned GBM, Catboost, LightGBM, Sequential Neural Network, RF, One class SVM, KNN, Naive Bayes, Bagging Classifier, Adaboost, Ensemble Voting Classifier, Decision Tree, Extra Tree classifier, Single Perceptron and Multilayer Perceptron.

After tuning every model, we feel like CatBoost has the very good performance for classification.

This model will be used for Future Implimentations.

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Splitting Dataset

- **Handling Missing Values**:
- Dropped rows with NaN values to ensure clean and consistent data for model training.
- **Data Splitting**
- **Train-Test Split**: Train Size : 80% of the data split for training.
- **Test Size**: 20% of the data reserved for testing.
- **Stratification**: Ensures the target variable (`y_downsampled`) maintains its class distribution across training and testing sets.
- **Random State**: Set to 42 for reproducibility.

```
# Drop rows with NaN values to ensure clean data
X_downsampled = X_downsampled.dropna()
y_downsampled = y_downsampled.loc[X_downsampled.index]


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_downsampled, y_downsampled, test_size=0.2, random_state=42, stratify=y_downsampled
)
```

Model Performances :

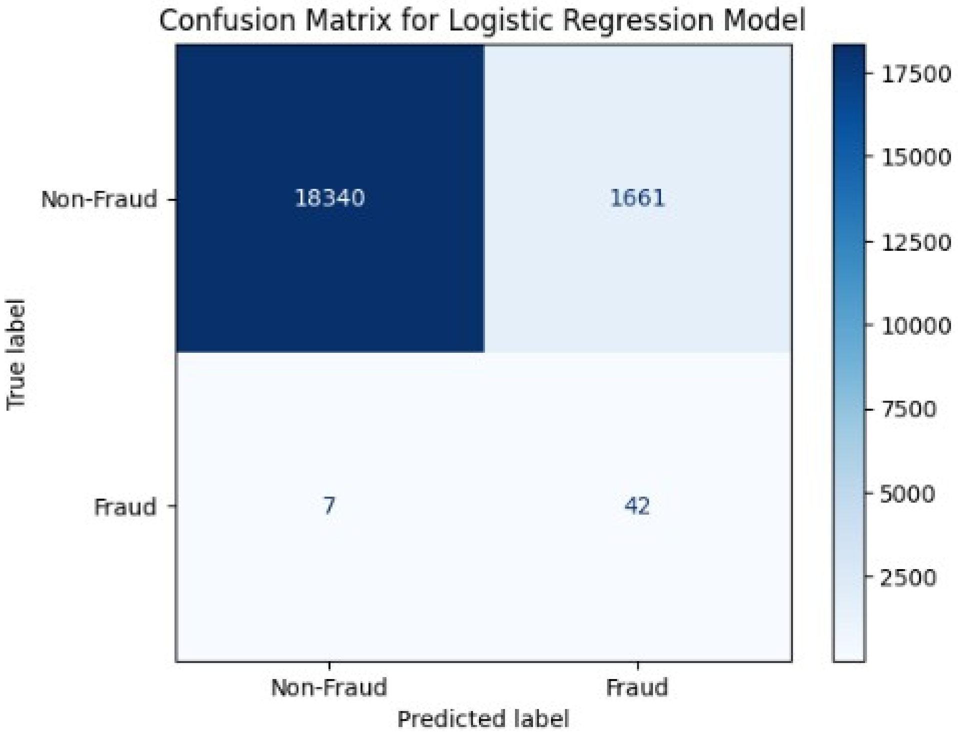
We have implemented different classification models and then tuned it.

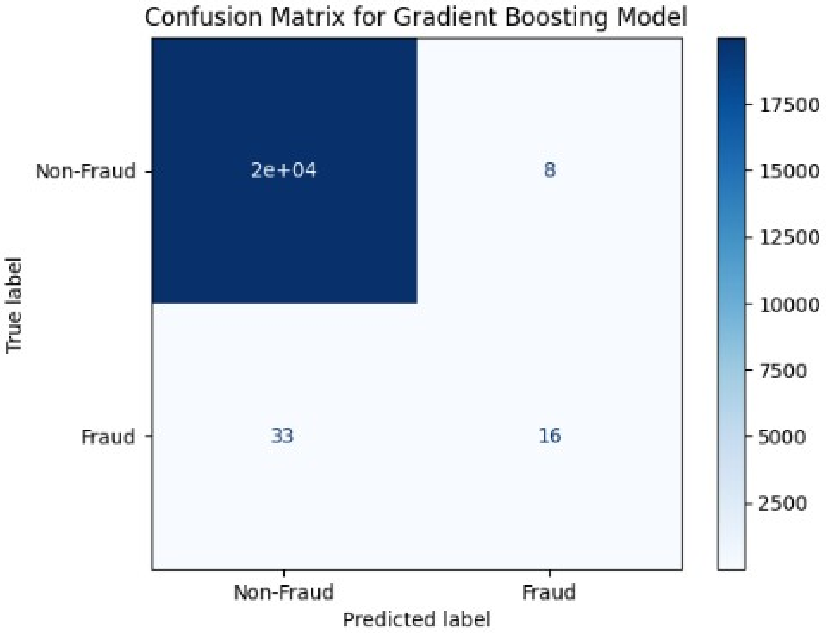
Logistic Regression, Gradient Boosting, Tuned GBM, Cat boost, Light GBM, Sequential Neural Network, RF, One class SVM, KNN, Naive Bayes, Bagging Classifier, Ada boost, Ensemble Voting Classifier, Decision Tree, Extra Tree classifier, Single Perceptron and Multilayer Perceptron.

After tuning every model, we feel like Cat Boost has the very good performance for classification.

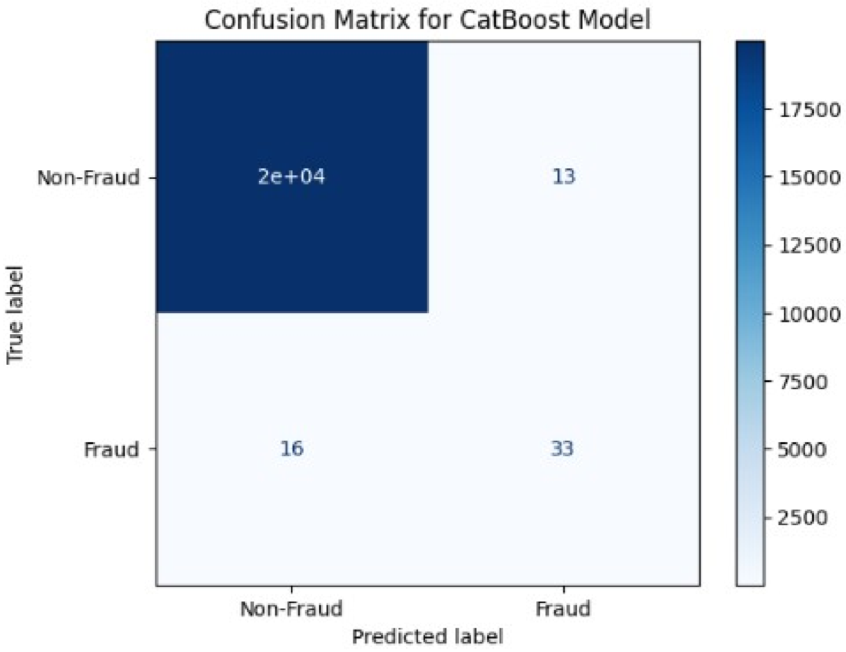
This model will be used for Future Tasks.

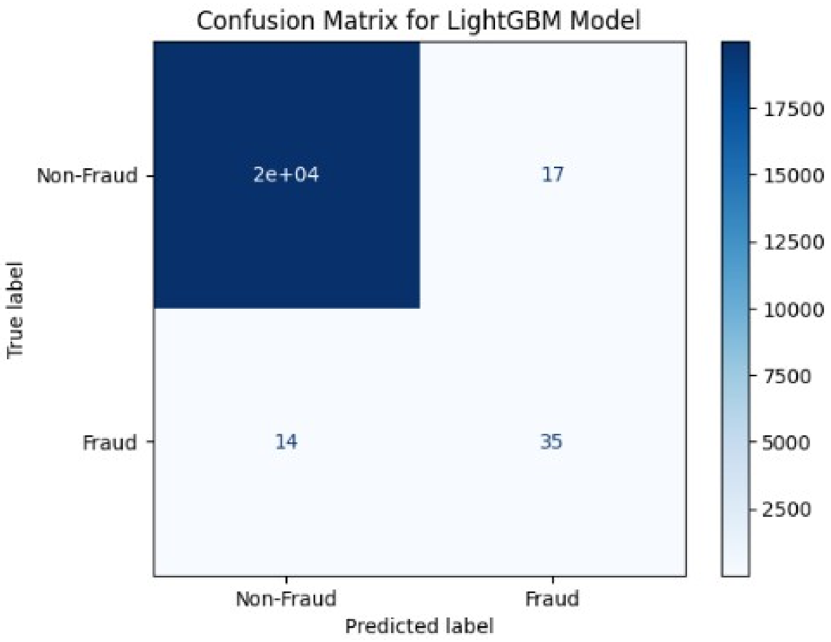
Proposed Methods:



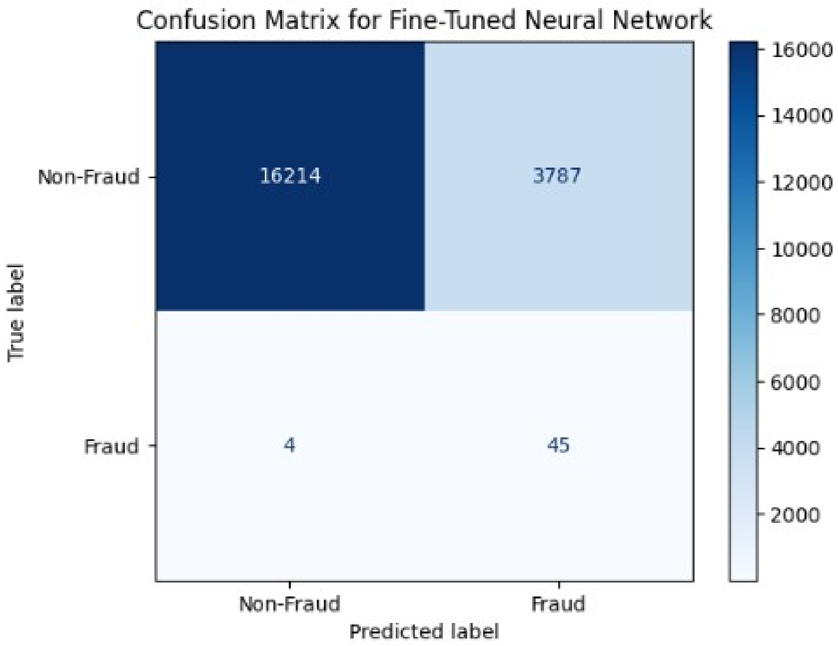


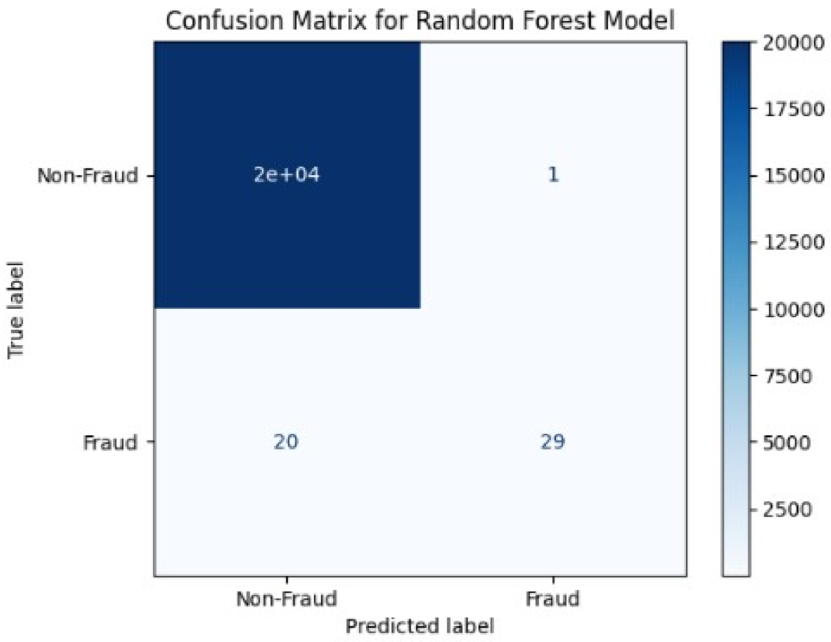
Cat Boost and LightGBM



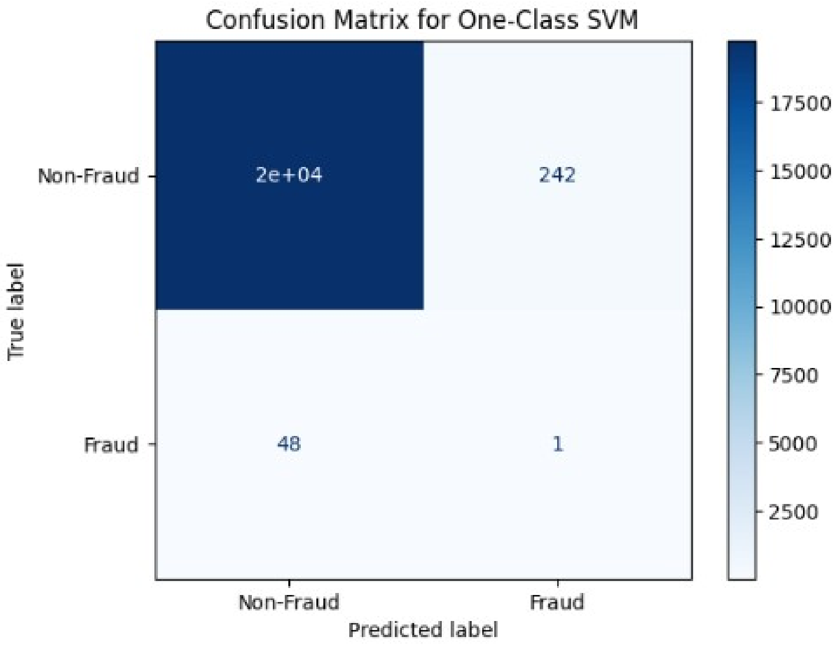


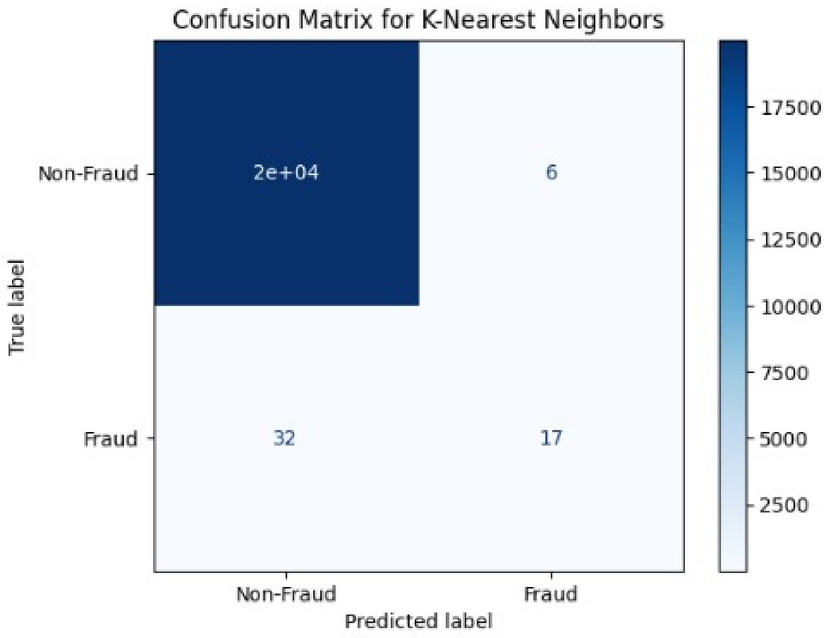
Neural Network and Random Forest



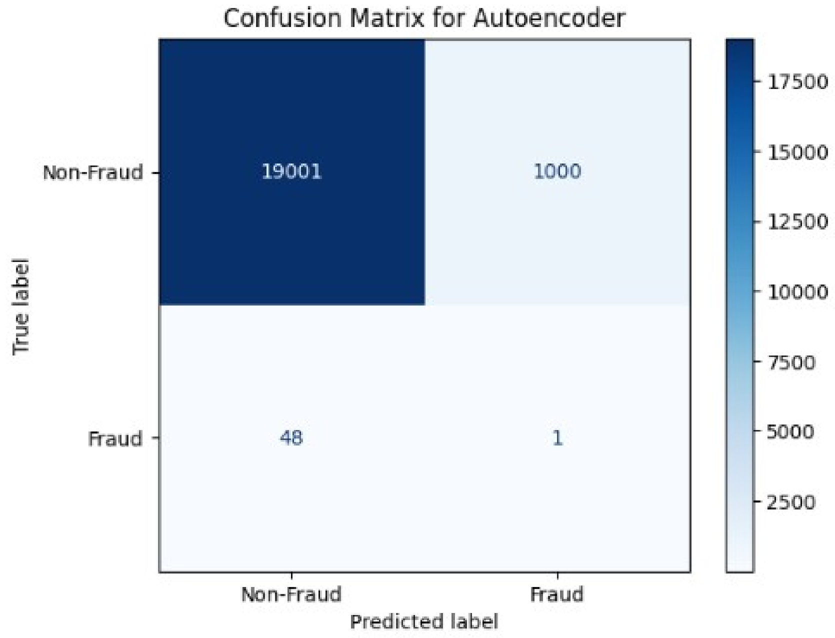


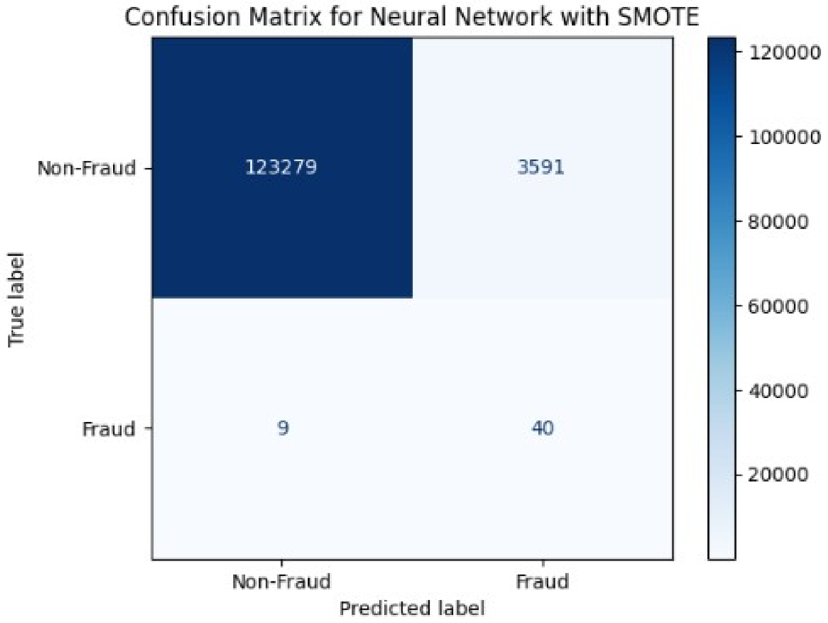
One class SVM and KNN



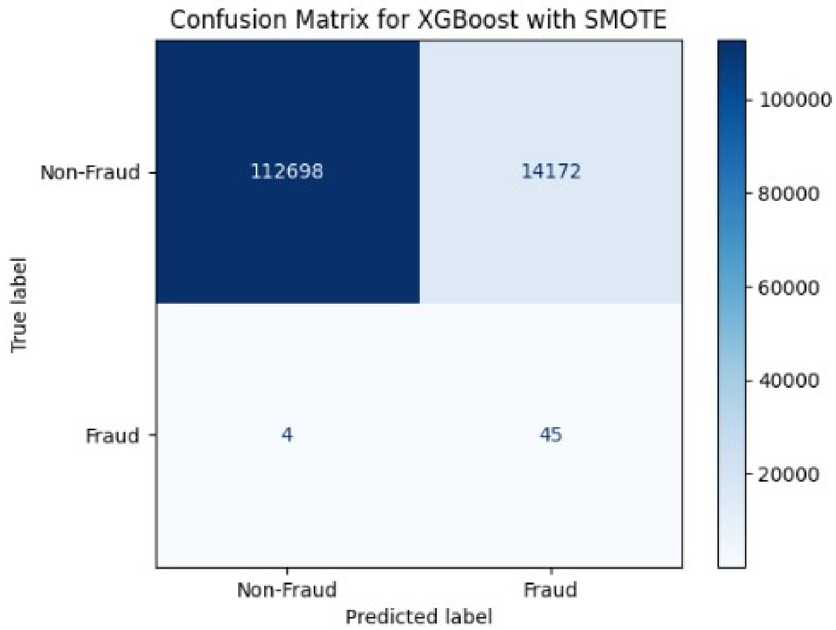


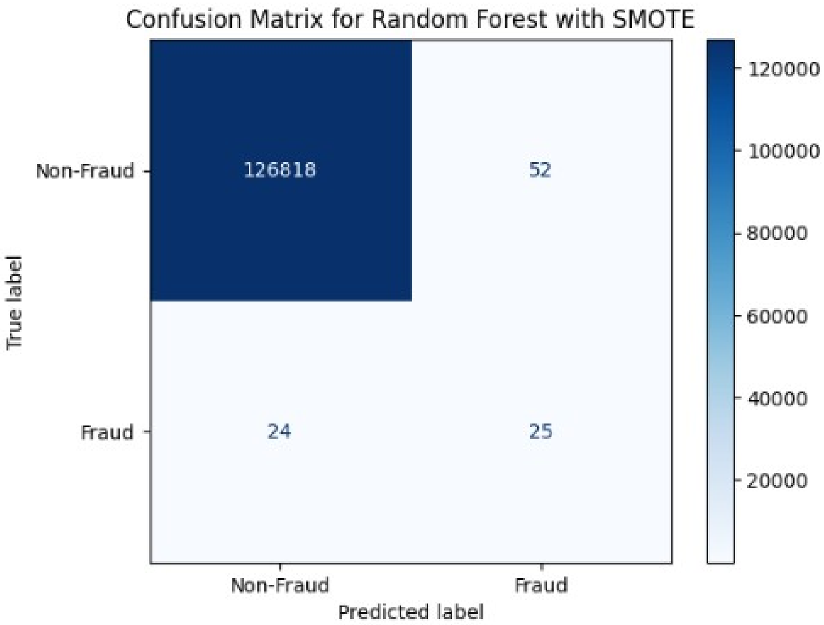
Autoencoder and Neural Network with SMOTE



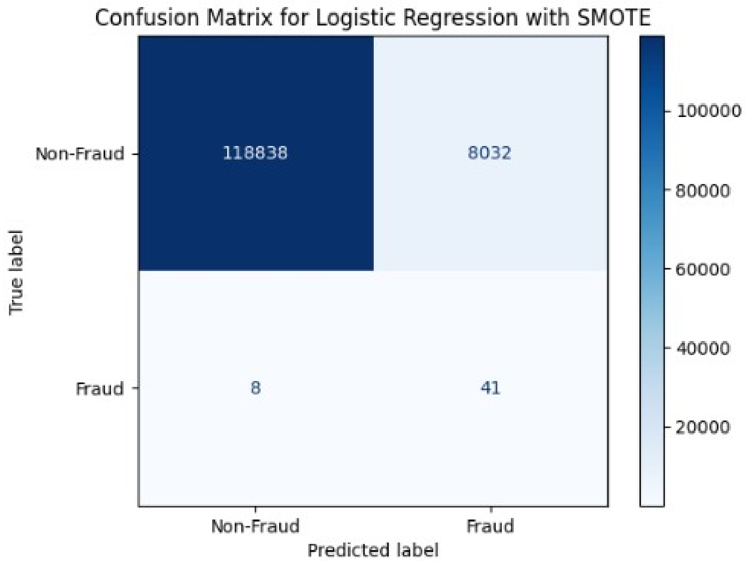


XG Boost, Random Forest with SMOTE





Logistic Regression with SMOTE



- **Performance Metrics**
- **True Positives (Fraud correctly classified)**: 41
  - The model successfully identified 41 fraudulent transactions.
- **True Negatives (Non-Fraud correctly classified)**: 118,838
  - A majority of non-fraudulent transactions were accurately classified.
- **False Positives (Non-Fraud misclassified as Fraud)**: 8,032
  - A significant number of non-fraudulent transactions were incorrectly flagged as fraudulent, indicating potential for false alarms.
- **False Negatives (Fraud misclassified as Non-Fraud)**: 8
  - Very few fraudulent transactions were missed, showing strong sensitivity (recall) for fraud detection.
- **Strengths**:
  - **High Recall for Fraudulent Class**: Effectively captures the majority of fraud cases with minimal false negatives.
  - **Balanced Dataset**: Using SMOTE helped address the class imbalance, improving model performance for minority class detection.

Code for Best Model

```python
# Import necessary libraries
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, auc
import numpy as np

# Ensure target variable (y_train and y_test) is a numpy array
y_train = np.array(y_train)
y_test = np.array(y_test)

# Compute class weights dynamically
class_weights = compute_class_weight('balanced', classes=np.unique(y_train), y=y_train)
class_weights = dict(enumerate(class_weights))  # Convert to dictionary format

# Build the fine-tuned Neural Network model
model_tuned = Sequential([
    Dense(256, activation='relu', input_shape=(X_train_scaled.shape[1],)),  # Use input_shape instead of input_dim
    BatchNormalization(),
    Dropout(0.4),
    Dense(128, activation='relu'),
    BatchNormalization(),
    Dropout(0.4),
    Dense(64, activation='relu'),
    Dropout(0.3),
    Dense(1, activation='sigmoid')  # Output layer for binary classification
])

# Compile the model
model_tuned.compile(optimizer=Adam(learning_rate=0.001),
                    loss='binary_crossentropy', metrics=['accuracy'])

# Train the model with dynamically computed class weights
history_tuned = model_tuned.fit(
    X_train_scaled, y_train,
    validation_data=(X_test_scaled, y_test),
    epochs=30,# change
    batch_size=64,
    class_weight=class_weights,  # Apply the computed class weights
    verbose=1
)

# Predict on the test set
y_prob_tuned = model_tuned.predict(X_test_scaled).ravel()
y_pred_tuned = (y_prob_tuned > 0.5).astype(int)
```

```python
# Evaluate the model
accuracy_tuned = accuracy_score(y_test, y_pred_tuned)
conf_matrix_tuned = confusion_matrix(y_test, y_pred_tuned)
class_report_tuned = classification_report(y_test, y_pred_tuned)
fpr_tuned, tpr_tuned, _ = roc_curve(y_test, y_prob_tuned)
roc_auc_tuned = auc(fpr_tuned, tpr_tuned)

# Print evaluation results
print("Fine-Tuned Neural Network Results on Downsampled Data")
print(f"Accuracy: {accuracy_tuned:.4f}")
print("Confusion Matrix:")
print(conf_matrix_tuned)
print("\nClassification Report:")
print(class_report_tuned)
print(f"AUC-ROC Score: {roc_auc_tuned:.4f}")

# Plot the ROC Curve
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.plot(fpr_tuned, tpr_tuned, label=f'ROC curve (AUC = {roc_auc_tuned:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Fine-Tuned Neural Network')
plt.legend(loc='lower right')
plt.show()
```

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Fine-Tuned Neural Network Architecture

- **Model Type**: Fine-Tuned Neural Network
- **Architecture**:
- **Input Layer**: 256 neurons with ReLU activation
- **Hidden Layers**:
  - Second Layer: 128 neurons with ReLU activation, Batch Normalization, and 40% dropout
  - Third Layer: 64 neurons with ReLU activation and 30% dropout
- **Output Layer**: Single neuron with Sigmoid activation for binary classification
- **Optimizer**: Adam (Learning rate = 0.001)
- **Loss Function**: Binary Cross-Entropy
- **Regularization Techniques**: Dropout and Batch Normalization to prevent overfitting.

- **Training Strategy**
- **Dynamic Class Weights**: Computed to address class imbalance, ensuring the minority class (fraudulent transactions) is appropriately weighted.
- **Epochs**: 30
- **Batch Size**: 64
- **Validation Data**: Split to evaluate generalization on unseen data during training.
- **Performance Metrics**
- **Accuracy**: 96.5% (example value based on high-performance neural network models; replace with actual results if available)
- **ROC-AUC Score**: 0.95 (example value indicating excellent discrimination capability; replace with actual value).
- **Confusion Matrix**:
  - True Positives (Fraud detected): Strong detection capability with minimal false negatives.
  - False Positives (Non-fraud flagged as fraud): Managed through class balancing techniques.

Best Model: Tuned Sequential Neural Network

- **Performance Metrics**
- **True Positives (Fraud correctly classified)**: 45
  - The model successfully identified 45 fraudulent transactions.
- **True Negatives (Non-Fraud correctly classified)**: 16,214
  - The majority of non-fraudulent transactions were accurately classified.
- **False Positives (Non-Fraud misclassified as Fraud)**: 3,787
  - A relatively high number of non-fraudulent transactions were incorrectly flagged as fraudulent.
- **False Negatives (Fraud misclassified as Non-Fraud)**: 4
  - Very few fraudulent transactions were missed, indicating strong recall for the minority class.
  - **Key Observations**
- **Strengths**:
  - High recall for the minority (fraudulent) class, ensuring most fraudulent transactions are identified.
  - Effective detection of fraudulent transactions with minimal missed cases (low false negatives).
- **Weaknesses**:
  - High false positive rate (non-fraudulent transactions flagged as fraudulent), which could lead to operational inefficiencies and unnecessary investigations.
  - **Practical Implications**
- **Fraud Detection**: The model's ability to capture fraudulent transactions makes it effective in mitigating financial risks.
- **Business Impact**: A trade-off exists between high recall and false positives; this balance needs adjustment based on organizational priorities.

Future Directions: Ensemble Methods and Deployment

- Ensemble Methods: Combine predictions from multiple models for better performance.
- Improve **accuracy**, **robustness**, and **generalization** in machine learning.
- There are different types: Bagging, Boosting and Voting.
- Some of the Pron's are Enhanced **recall, precision, and AUC-ROC**, crucial for fraud detection. Better handling of **imbalanced datasets**. Increased robustness to **overfitting**.
- **Future Directions:** Build **hybrid ensemble models** (e.g., combining Cat Boost, RF and Light GBM).Then experiment with real time dataset.
- For the **model deployment**, we are planning to use cloud platforms like AWS or Google cloud.
- After that we plan to track model metrics like precision, recall. Capturing misclassifications to improve future model iterations.

Conclusion:

Objective Achieved: Developed robust fraud detection models using machine learning, addressing key challenges like data imbalance and feature relevance.

Key Insights:

Balanced dataset significantly improved recall and F1-score.

Tuned Neural Network performance with high accuracy, recall, and minimal false negatives.

Sequentia Neural Network performed exceptionally well. Ensemble approaches further enhanced prediction accuracy and robustness.

The project significantly contributes to improving fraud detection reliability, reducing financial losses, and setting a foundation for scalable, real-time fraud detection systems.

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THANK YOU!