FindDefault-Credit card fraud detection

Introduction

Problem Statement:

A credit card is one of the most used financial products to make online purchases and payments. Though the Credit cards can be a convenient way to manage your finances, they can also be risky. Credit card fraud is the unauthorized use of someone else's credit card or credit card information to make purchases or withdraw cash.

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

The dataset contains transactions made by credit cards in September 2013 by European cardholders. This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

We have to build a classification model to predict whether a transaction is fraudulent or not.

Data Exploration

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V21	V22
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	...	-0.018307	0.277838
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	...	-0.225775	-0.638672
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	...	0.247998	0.771679
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	...	-0.108300	0.005274
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	...	-0.009431	0.798278
...	...	...	...	...	...	...	...	...	...	...	...	...	...
284802	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	4.356170	...	0.213454	0.111864
284803	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	-0.975926	...	0.214205	0.924384
284804	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	-0.484782	...	0.232045	0.578229
284805	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	-0.399126	...	0.265245	0.800049
284806	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	-0.915427	...	0.261057	0.643078

284807 rows × 30 columns

	V23	V24	V25	V26	V27	V28	Class	Scaled_Amount
0	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	0	0.244964
1	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	0	-0.342475
2	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	0	1.160686
3	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	0	0.140534
4	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	0	-0.073403
...	...	...	...	...	...	...	...	...
284802	1.014480	-0.509348	1.436807	0.250034	0.943651	0.823731	0	-0.350151
284803	0.012463	-1.016226	-0.606624	-0.395255	0.068472	-0.053527	0	-0.254117
284804	-0.037501	0.640134	0.265745	-0.087371	0.004455	-0.026561	0	-0.081839
284805	-0.163298	0.123205	-0.569159	0.546668	0.108821	0.104533	0	-0.313249
284806	0.376777	0.008797	-0.473649	-0.818267	-0.002415	0.013649	0	0.514355

To protect the user's identity and the security of their confidential information, the dataset provider has applied Principal Component Analysis transformation on the original numerical features and compressed it into 28 principals components.

Only two features have not been transformed i.e. 1) Time and 2) Amount

The feature class will be target column with user labels as:

0 : non-fraudulent 1 : fraudulent

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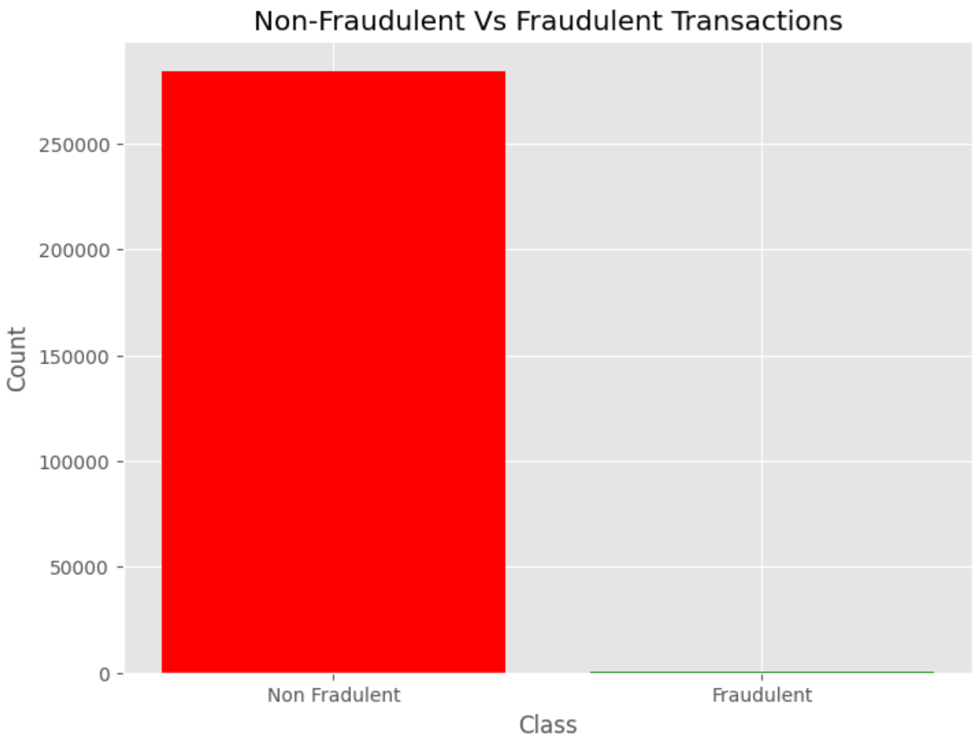
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
```

We will get the information about the columns in the DataFrame we have created as :

The dataset exclusively comprises numerical features, and notably, there are no instances of missing values. Consequently, there is no need for null-value handling in this dataset.

Exploratory Data Analysis

- For the subsequent step, we will conduct fundamental Exploratory Data Analysis (EDA) on the dataset to enhance our understanding and extract valuable insights.



- The barplot reveals a significant imbalance between classes (0-Non Fradulent) and (1-Fraudulent).

- Majority of features are in PCA form , with the exceptions being Time and Amount ,a more in-depth examination of these two features is required.

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```
df['Amount'].describe()
```

```
count    284807.000000
mean         88.349619
std         250.120109
min           0.000000
25%           5.600000
50%          22.000000
75%          77.165000
max       25691.160000
Name: Amount, dtype: float64
```

```
df['Time'].describe()
```

```
count    284807.000000
mean      94813.859575
std       47488.145955
min           0.000000
25%       54201.500000
50%       84692.000000
75%      139320.500000
max      172792.000000
Name: Time, dtype: float64
```

- We will initiate the visualization of transaction counts across hours, starting with the entire dataset. Subsequently, we will partition the dataset into fraudulent and non-fraudulent transactions to gain a more detailed perspective.

- Now we will check the number of occurrences of each class label and we will plot the information using matplotlib.

```
Number of Non-Fraudulent Transactions:  284315
Number of Fraudulent Transactions:  492
Percentage of Fraudulent Transactions:  0.17
```

- We can observe that the genuine transactions are over 99%.
- We will apply scaling techniques on the "Amount" feature to transform the range of values.
- We will drop the original "Amount" column and add a new column with the scaled values. We will also drop the "Time" columns as it is irrelevant.

- Now, we will split the credit card data with a split of 70-30 using train_test_split().
- train_test_split() function in scikit-learn is a useful utility for splitting a dataset into training and testing sets.
- Parameters
- X: Feature matrix
- Y: Target variable
- test_size: Proportion of the dataset to include in the test split. Here we have set the test_size as 0.3 means 30% of the data we take as testing data set.
- random_state: we have set the seed for random number generation, to ensure the reproducibility

```
Shape of the training dataset train_X:  (199364, 29)
Shape of the testing dataset test_X:  (85443, 29)
```

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Applying Machine Learning Algorithm to Credit Card Dataset

- We will explore various machine learning algorithms to determine the most effective model for our binary classification problem.
- The task involves predicting one of the two class labels. We plan to access the performance of different algorithms, such as Random Forest and Decision Tree identify the most suitable solution for our specific problem
- Our approach involves constructing Random Forest and Decision Tree classifiers to identify the most effective model.

Decision Tree Algorithm

The Decision Tree Algorithm is a supervised machine learning technique employed for both classification and regression tasks. Its objective is to create a training model capables of predicting the value of a target class variable.This is achieved by learning straighforward if-then-else decision rules derived from the patterns present in the training data.

Random Forest Algorithm

Random Forest is supervised Machine Learning algorithm. It creates a "forest" out of an ensemble of "decision trees", which are normally trained using the "bagging" technique. The bagging method's basic principal is that combining different learning models improved the outcome.To get a more precise and reliable forecast, random forest creates several decision trees and merges them.

```
# Decision Tree
decision_tree = DecisionTreeClassifier()

# Random Forest
random_forest = RandomForestClassifier(n_estimators=100)
```

- Here we are creating a **RandomForestClassifier** with 100trees in the forest.
- The large number of trees will generally lead to better performance, but it may also increase the training time.

Now we will check the score of the Decision Tree model

Decision Tree Score is: **99.91**807403766254

Random Forest Score is: **99.96**254813150287

```
# Printing the scores of the both classifiers
print("Decision Tree: ", round((decision_tree_score),4))
print("Random Forest: ", round((random_forest_score),4))
```

```
Decision Tree:  99.9181
Random Forest:  99.9625
```

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The Random Forest classifier has a slight edge over the Decision Tree Classifier.

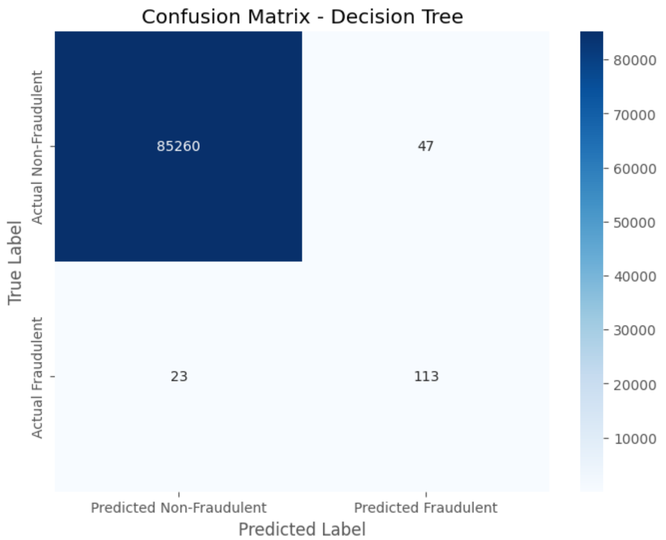
- We will create a function to print the metrics:

1. **Accuracy_score**
2. **Precision_score**
3. **Confusion_matrix**
4. **Recall_score**
5. **F-1 score**

```
Evaluation of Decision Tree Model:
Accuracy: 0.9992
Precision: 0.7062
recall_score: 0.8309
F1-Score: 0.7635
```

```
Evaluation of Random Forest Model:
Accuracy: 0.9996
Precision: 0.9561
recall_score: 0.8015
F1-Score: 0.872
```

Confusion Matrix



In-short summary:

1. The model correctly identified 107 fraudulent transactions.

2. It incorrectly identified 29 transactions as non-fraudulent.

3. It correctly identified 85265 non-fraudulent transactions.

4. It incorrectly identified 42 non-fraudulent transactions as fraudulent

We understand from the confusion matrix:

- Non-Fraudulent transactions:

1. Correctly predicted as non-fraudulent(True Negative) 85265 transactions.
2. Incorrectly predicted as fraudulent(False Positive) 42 transactions.

- Fraudulent Transactions:

1. Incorrectly predicted as non-fraudulent(False Negative) : 29 transactions
2. Correctly predicted as fraudulent(True Positive) : 107 transactions

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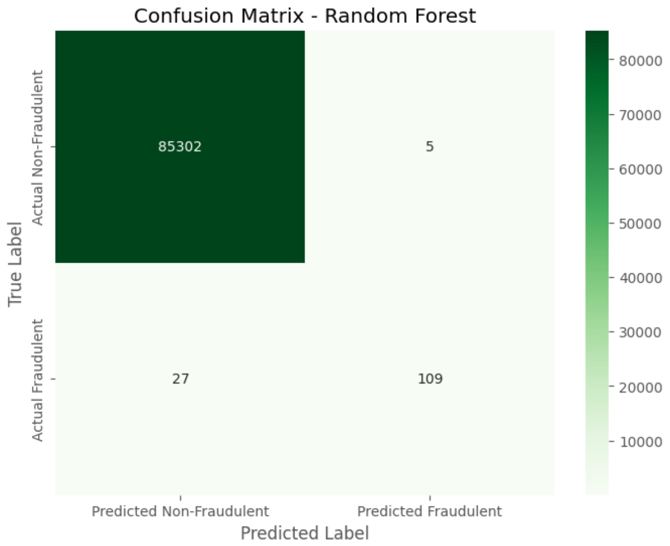

In-short summary:

1. The model correctly identified 109 fraudulent transactions.
2. It incorrectly identified 27 transactions as non-fraudulent.
3. It correctly identified 85302 non-fraudulent transactions.
4. It incorrectly identified only 5 non-fraudulent transactions as fraudulent.

We understand from the confusion matrix:

- Non-Fraudulent transactions:

1. Correctly predicted as non-fraudulent(True Negative) 85302 transactions.
2. Incorrectly predicted as fraudulent(False Positive) 5 transactions.

- Fraudulent Transactions:

1. Incorrectly predicted as non-fraudulent(False Negative) : 27 transactions
2. Correctly predicted as fraudulent(True Positive) : 109 transactions

Class-Imbalance

- The Random Forest model works better than Decision Trees. In the presenece of a class-Imbalance issue, where genuine transactions account for over 99% of the dataset and credit card fraud transactions constitute only 0.17%.

- Training the model without addressing the imbalance can lead to biased predictions.

- Despite the apparent accuracy, such a model may not effectively capture the nuances of the minority class (fraud transactions) and may not generalize well to real-world situations.

- The class imbalance problem can be solved by various techniques. Oversampling is one of them.

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We will use the SMOT (Synthetic Minority Oversampling Technique, or SMOTE).It is the method of data augmentation for the minority class.

```
from imblearn.over_sampling import SMOTE

X_resampled, Y_resampled = SMOTE().fit_resample(X,Y)

print("Resampled shape of X: ",X_resampled.shape)
print("Resampled shape of Y: ",Y_resampled.shape)
```

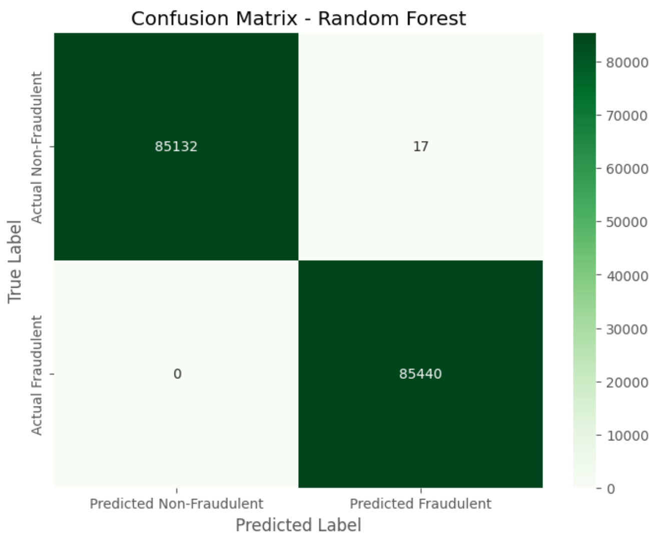
```
Resampled shape of X:  (568630, 29)
Resampled shape of Y:  (568630,)
```

```
predictions_resampled = rf_resampled.predict(test_X)
random_forest_score_resampled = rf_resampled.score(test_X, test_Y) * 100
```

```
print(random_forest_score_resampled)
```

```
99.99003452743142
```

Confusion matrix for resampled data



We understand from the confusion Matrix is:

- The model correctly identified 85440 fraudulent transactions.
- It incorrectly identified 0 transactions as non-fraudulent.
- It correctly identified 85131 non-fraudulent transactions.
- It incorrectly identified only 17 non-fraudulent transactions as fraudulent.

We understand from the confusion matrix:

- Non-Fraudulent transactions:
- Correctly predicted as non-fraudulent(True Negative) 85131 transactions.
- Incorrectly predicted as fraudulent(False Positive) 17 transactions.
- Fraudulent Transactions:
- Incorrectly predicted as non-fraudulent(False Negative) : 0 transactions
- Correctly predicted as fraudulent(True Positive) : 85440 transactions

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```
Evaluation of Resampled Random Forest Model:
Accuracy: 0.9999
Precision: 0.9998
recall_score: 1.0
F1-Score: 0.9999
```

We can see that our model performed much better than the previous Random Forest classifier without oversampling.

We have applied the techniques to address the class imbalance issues and achieved an accuracy of more than 99%.

- We will import the pickle to dump the dataframe and the model for the model deployement as the future scope.

```
] import pickle
  pickle.dump(df,open('df.pkl','wb'))
  pickle.dump(rf_resampled,open('rf_resampled.pkl','wb'))
```