Credit Card Fraud Prediction

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1. Introduction

The project aimed to predict credit card fraud using machine learning techniques. The dataset, sourced from Kaggle, consisted of credit card transactions, highly imbalanced, with 492 frauds among 284,807 transactions. The report explores feature selection, modelling using various classifiers, and evaluates model performance under different sampling techniques.

2. Data Overview

Exploratory Data Analysis (EDA)

The data set contains 284807 rows and 31 columns, and found 1081 duplicated rows, after removing all the duplicated rows found the actual data that 473 fraud transactions and 283253 normal transactions.

3. Feature Selection

Top Variables for Prediction

Explanation of the most influential variables for predicting fraud, potentially derived from correlation analysis or feature importance.

PCA Implementation

By doing correlation matrix heatmap found top features of the class and keep the high featured columns alone with Class and removed rest of the columns from the data set to proceed further modelling.

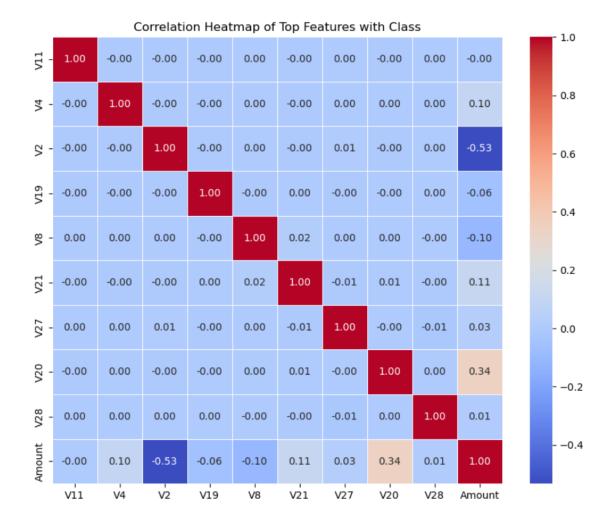


Fig:1 – Correlation heatmap of Top Features with Class

4. Modelling

Imbalanced data set is balanced by applying Under Sampling & Over Sampling method to get which of the balanced data set will give more accuracy.

Under Sampling:

| | Logistic Regression | Decision Tree | Classifier | SVM Method |
|-----------|---------------------|---------------|------------|------------|
| Accuracy | 0.915789 | | 0.878947 | 0.905263 |
| Precision | 0.941176 | | 0.867257 | 0.915094 |
| Recall | 0.905660 | | 0.924528 | 0.915094 |
| F1 Score | 0.923077 | | 0.894977 | 0.915094 |

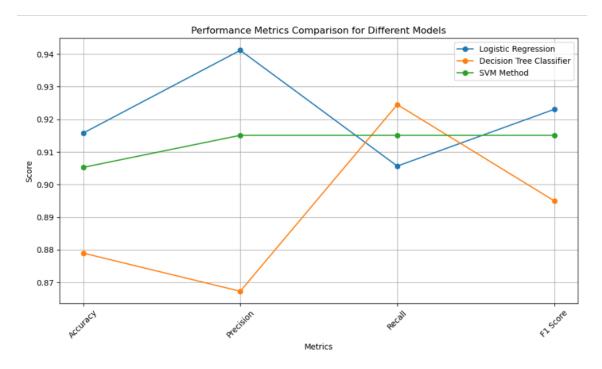


Fig:2 – Performance metrics comparison among all the models (Under Sampling)

Over Sampling:

| | Logistic Regression | Decision Tree Classifi | er SVM Method |
|-----------|---------------------|------------------------|---------------|
| Accuracy | 0.916383 | 0.9997 | 62 0.946065 |
| Precision | 0.942884 | 0.9995 | 25 0.971922 |
| Recall | 0.887043 | 1.0000 | 0.919030 |
| F1 Score | 0.914112 | 0.9997 | 63 0.944736 |

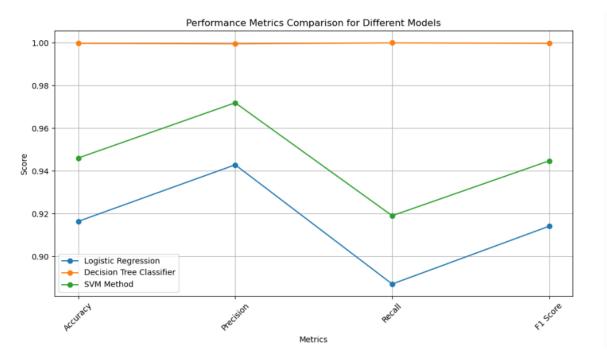


Fig:3 – Performance metrics comparison among all the models (Over Sampling)

5. Conclusion

Under Sampling

Logistic Regression: High accuracy and decent across other metrics.

Decision Tree Classifier: Good overall performance but slightly lower precision and F1 score compared to the other models.

SVM Method: High accuracy and balanced precision, recall, and F1 score.

Oversampling

Logistic Regression: Slightly improved performance across all metrics.

Decision Tree Classifier: Significant improvement in all metrics, almost perfect scores.

SVM Method: Improved accuracy and precision, slightly lower recall but an improved F1 score.

Model Selection

Based on the provided results, the oversampling method has notably improved the performance of all models. The Decision Tree Classifier exhibits impressive performance with almost perfect scores across the board in the oversampling scenario.