Price Prediction Model in Real State

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## *Abstract:* Credit card fraud detection is increasingly critical due to the rise in digital transactions, with class imbalance in datasets posing a significant challenge for machine learning models. This study compares various machine learning algorithms, including Decision Tree, Random Forest, Logistic Regression, and ensemble methods like XGBoost, to enhance fraud detection. We emphasize the importance of polynomial feature engineering to capture complex interactions, alongside advanced sampling techniques like hybrid under-sampling and SMOTE to address class imbalance. Our analysis shows that these strategies significantly improve model accuracy, precision, recall, and reduce false-negative rates, providing a more reliable framework for fraud detection.

Keywords – Polynomial featuring, XGBoost, Random Forest, KNN, Classification model

# INTRODUCTION

With the exponential growth of digital transactions, credit card fraud has become a significant challenge for financial institutions worldwide. As the number of online payment systems, e-commerce platforms, and remote financial services has increased, so has the threat of fraudulent activities. The convenience of using credit cards for global purchases has also made them prime targets for cybercriminals. Fraudsters can now exploit online vulnerabilities without needing physical access to the card— just the information associated with it is enough. According to global reports, credit card fraud losses reached $28.6 billion in 2020, with the United States accounting for the highest share of incidents [3].

In response to these growing threats, machine learning (ML) algorithms have emerged as the most effective tools for detecting and mitigating fraud. By leveraging supervised learning models, banks can now differentiate between

fraudulent and legitimate credit card transactions. However, choosing the most suitable algorithm for detecting fraud requires a thorough comparative analysis of different models, especially in the context of unbalanced datasets and the interdependence of variables [1].

This research paper proposes a high-degree comparative study of different machine learning models for credit card fraud detection, focusing on analysing the performance of these models with various data preprocessing and feature engineering techniques, particularly polynomial feature generation and ensemble methods. Polynomial feature generation introduces non-linearity by adding interaction terms and powers of variables, allowing models to capture more complex relationships between input features. This paper also explores the effect of these engineered features on model performance and investigates the impact of advanced sampling techniques such as hybrid under-sampling to address the imbalanced nature of credit card fraud datasets [2].

# ORGANIZATION OF THE PAPER

1. *Section III: Literature Review-*

Summary of existing studies on credit card fraud detection using machine learning. Key research on class imbalance, feature engineering, and ensemble learning techniques. Previous work on data sampling techniques and model performance in fraud detection.

1. *Section IV: Methodology-*
   1. Data Sampling
   2. Polynomial Feature Engineering
   3. Ensemble Learning
   4. Algorithm Selection
2. *Section V: Analysis of High-Degree Dependency-*

Impact of polynomial feature generation on model sensitivity and multicollinearity. Analysis of how high-degree features affect model accuracy, precision, recall, and false-negative rate.

1. *Section VI: Dataset Used –*

This section contains details about the dataset used and its various features that are used in our model for classification purpose.

1. *Section VII: Results and Discussion-*

Comparative performance of machine learning models with and without polynomial feature engineering. Evaluation of ensemble models' ability to handle imbalanced data and improve fraud detection. Examination of performance metrics: accuracy, precision, recall, F1-score, confusion matrix, ROC-AUC score.

1. *Section VIII: Conclusion-*

Summary of findings: the effectiveness of polynomial features, hybrid sampling, and ensemble learning in enhancing fraud detection. Recommendations for the best-performing models and techniques based on the study results.

1. *Section IX: Future Scope-*

Suggestions for extending the research by incorporating deep learning methods and using real-time datasets for more detailed analysis.

1. *Section X: References-*

Citation of all relevant academic papers, studies, and research used in the development of the paper.

# LITERATURE REVIEW

Credit card fraud detection has become an increasingly critical area of research, as fraudsters are constantly developing sophisticated methods to exploit vulnerabilities in digital transactions. With the rapid growth of e-commerce, online banking, and other financial services, fraud detection systems have evolved, utilizing various machine learning techniques to detect fraudulent transactions with higher accuracy and reliability.

The first reference, Kipf and Welling (2017) [1], is a seminal work that introduced Graph Convolutional Networks (GCNs), a specific type of GNN architecture. GCNs have emerged as a powerful tool for analysing data structured as graphs, where nodes represent entities and edges represent relationships between them. Wu et al. (2020) [5] provide a comprehensive survey of GNNs, outlining various architectures and applications.

Ensemble methods, such as those discussed by Breiman, combine the strengths of multiple models to enhance classification performance. Random Forest and XGBoost have gained attention due to their ability to reduce variance and bias in predictions, thus improving accuracy and recall in fraud detection. Chen & Guestrin (2016), the creators of XGBoost, demonstrated its superior performance in handling structured data, especially in imbalanced datasets typical in credit card fraud detection.

Research on GNNs for anomaly detection has gained significant traction. Li et al. (2018) [6] explore the use of deep learning for anomaly detection, potentially including GNNs. Chen, J., & Song, L (2020) [11] present an empirical study on GNNs for anomaly detection, demonstrating their effectiveness in this domain. Xia et al. (2022) [10] delve into self-supervised learning for graph anomaly detection.

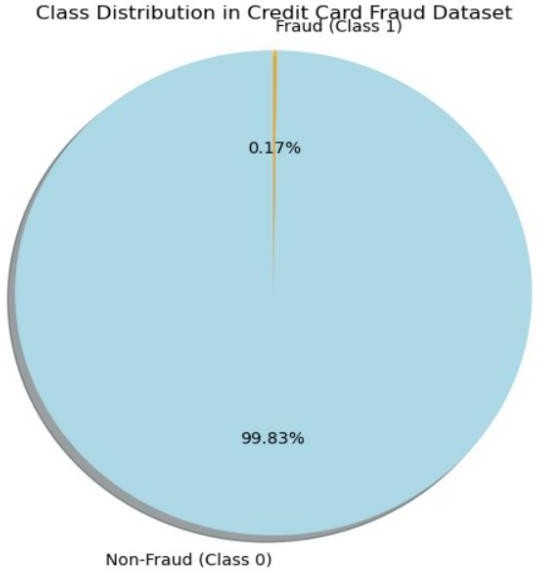
Azim Mim et al. (2022) [2] proposed a soft voting ensemble learning approach for credit card fraud detection. While they did not explicitly use polynomial features, their ensemble method could be combined with polynomial feature engineering to improve performance [4].

# METHODOLOGY

This study employs a comparative analysis of ensemble models: Random Forest, XGBoost, and K-Nearest Neighbours [3]. Polynomial feature expansion is applied to the dataset to introduce non-linear interactions between variables. To address class imbalance, hybrid sampling techniques, such as SMOTE-ENN and ADASYN, are considered [5]. Model performance is evaluated using metrics like accuracy, precision, and recall.

1. *Data Sampling*

Fraud detection datasets typically suffer from class imbalance, where legitimate transactions far outnumber fraudulent ones (Fig 1). This imbalance can cause models to favour the majority class, leading to high accuracy for non-fraudulent transactions but poor detection of fraudulent ones [4]. To address this, we can use under- sampling and over-sampling hybrid sampling techniques strategies. This ensures that the dataset is balanced without losing valuable information from the minority class (fraudulent transactions). Techniques such as SMOTE-Tomek, ADASYN, SMOTE and SMOTE-ENN are applied to balance the data before training the models [5]. Here we apply the under-sampling technique on the given dataset using RandomUnderSampler.



*Fig.1 Class Distribution in Credit Card Fraud Dataset.*

1. *Polynomial Feature Engineering*

In addition to data sampling, this study focuses on the creation of polynomial features to explore how higher-order interactions between input variables affect model performance [3]. Variables are transformed by introducing polynomial features, where powers (e.g., squares and cubes) of the original features are computed and added to the dataset. For instance, input features such as (x1, x2, x3) are transformed to include their squares (x 2, x 2, x 2) and the interaction between the terms (x1.x2, x2.x3, x3.x1), allowing models to capture complex interactions [11]. The effectiveness of this feature engineering is analysed based on how it improves or degrades the performance of various algorithms.

1

2

3

1. *Ensemble Techniques*

The study also evaluates the performance of ensemble learning techniques, which combine the predictions of multiple models to improve accuracy and robustness [3]. We apply hard voting

ensemble methods where models like XG Boost, Random Forest, and Logistic Regression are combined to predict whether a transaction is fraudulent or not. Ensemble models often outperform individual models by reducing the variance, bias, and generalization errors [5].

1. *Algorithm Selection*

There are several Machine learning algorithms available to detect counterfeit fraud in a particular domain. This comparative study focuses on three primary algorithms, as highlighted in [3] and [12], which have proven to be successful at discriminating between fraudulent and legitimate transactions. The algorithms studied include:

* 1. XGBoost: It is a highly efficient and flexible gradient boosting framework. It’s designed to be extremely fast and perform well on a variety of tasks, including regression, classification, and ranking [14].
  2. Random Forest: It is a technique that generates predictions by combining several decision trees. Its accuracy, ease of use, and capacity to manage huge datasets make it a popular option [5].
  3. KNN: It is a non-parametric ML technique that may be applied to both regression and classification problems. It is predicated on the idea that comparable points in data space are probably members of the same class or have comparable values.

Additionally, techniques like Adaptive Boosting, Multilayer perceptron, Decision tree, Logistic Regression, etc are also a good algorithm classification purpose but in this paper, we are mainly focused on the above three techniques only[4].

# ANALYSIS OF HIGH-DEGREE DEPENDENCY

One key aspect of this study is analysing the high degree of dependency among variables after introducing polynomial features. By increasing the powers of input features (e.g., adding squares, cubes, and higher powers of variables), we investigate whether the models become more sensitive to multicollinearity, leading to better or worse performance in fraud detection[11]. The interactions among transformed variables are carefully analysed, and the impact on accuracy, precision, recall, and false negative rate (FNR) is examined to determine whether higher-order polynomial features improve model prediction.

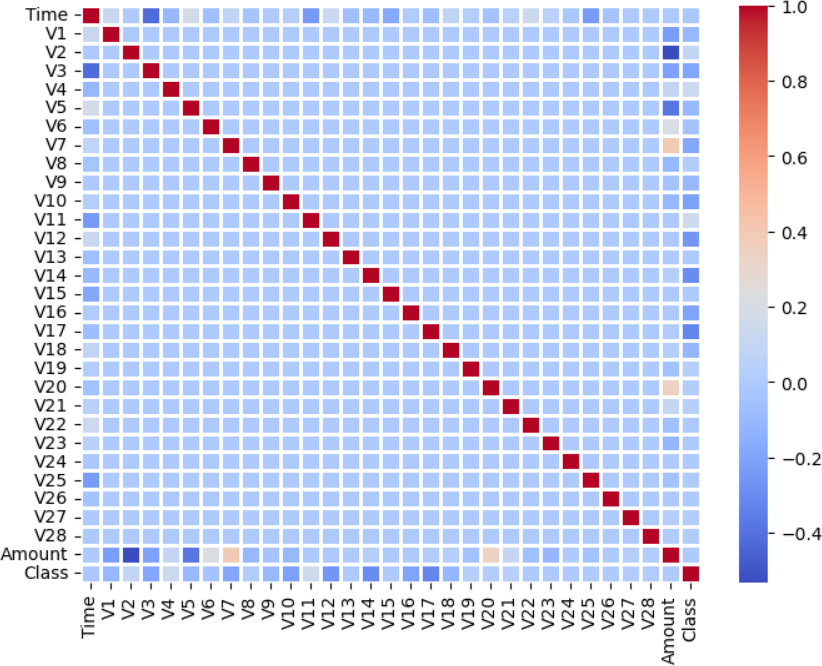
* + 1. *Understanding high degree dependency:*

In the context of credit card fraud analysis, high degree dependency refers to a situation where multiple features or columns are strongly corelated with each other there by influencing the outcome of the classification problem.

* + 1. *Common Scenario of High -Degree Dependency in Credit-Card Fraud:*
       1. *Transaction Amount and Time*: Transactions with high amounts are often associated with a specific time period.
       2. *Transaction Location and Cardholder Location*: Transactions occurring far from the cardholder’s location might indicate fraudulent activity[12].
       3. *Transaction Type and Cardholder Spending Patterns*: Unusual transaction types (e.g., large cash withdrawals) or deviations from regular spending habits can be an indicator of frauds[10].
       4. *IP Addresses and Device Information*: Multiple transactions originating from the same IP address or device within a short time frame could be suspicious[13].
    2. *Impact of High-Degree Dependency:*
       1. *Overfitting*: Models trained on dataset having highly correlated features can become overly sensitive which could lead to poor generalization performance on new unseen data[5].
       2. *Multicollinearity*: In a statistical model, multicollinearity can cause unstable estimations that makes it difficult to properly identify the importance of individual features in a dataset.
       3. *Increased Complexity*: Dealing with high-degree dependency can make the process of model development and interpretation more complex.

## Strategies to Address High-Dependency:

1. *Feature Engineering*:
   1. Create new features: Combine correlated features to capture more of the complex relationships.
   2. Transform features: Apply transformations (e.g., normalization, standardization) to reduce correlation [1].
2. *Feature Selection*:
   1. Remove redundant features: Identify and remove features that provide little additional information beyond the correlated features.
   2. Use feature selection techniques: Employ methods like correlation analysis, mutual information, or wrapper/embedded methods to select the most important features [5].
3. *Dimensionality Reduction*:
   1. Principal Component Analysis (PCA): Creates new, uncorrelated features (principal components) that captures the most variance in the data [11].
4. *Ensemble Methods*:
   1. Random Forest: Reduces the influence of individual feature correlations by building many decision trees and combining their predictions [5].



*Fig.2 Feature Correlation Matrix*

# DATASET USED

The dataset used in this research paper includes credit card transactions done by European cardholders in September 2013. Out of the 284,807 transactions in this dataset, 492 were fraudulent and took place over the course of two days. The positive class (frauds) makes up 0.172% of all transactions, indicating that the dataset is extremely skewed [4].

It contains only numerical input variables which are the result of a PCA transformation [3]. It contains the following features:

1. Time: The amount of time that passed between this transaction and the dataset's first transaction.
2. V1-V28: These are the outcomes of a PCA Dimensionality reduction to safeguard sensitive features and user identities [8].
3. Amount: This column contains the transaction amount in the denomination of thousands.
4. Class: This contains the target class for our research where there are only two permissible values for the given column, where ‘1’ is for fraudulent transaction and ‘0’ is for valid transactions[10].

# RESULTS AND DISCUSSION

The results of this study will evaluate the following:

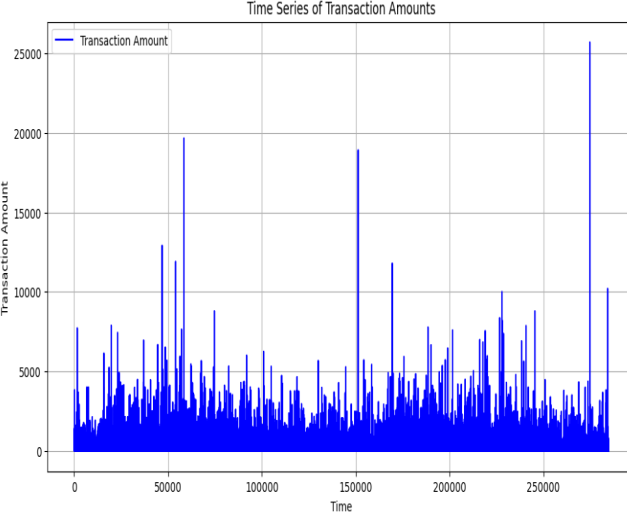
* The performance of individual machine learning algorithms with and without polynomial feature engineering.
* The impact of under-sampling on the model's ability to correctly classify fraudulent transactions.
* The effectiveness of ensemble learning models in improving accuracy and reducing false negatives, particularly with imbalanced datasets.
* An analysis of whether the inclusion of higher-degree polynomial features enhances or degrades model performance.

1. *Incorporating Calculations into the Study*

In the context of a research paper focused on credit card fraud detection, it's essential to present clear, detailed calculations that demonstrate the performance of the different models being compared.

* + 1. *Time series of transaction amount*

The time series plot of transaction amounts Fig.3 shows a clear pattern of spikes and valleys, indicating that there are periods of high and low transaction activity. This suggests that there are specific times of the day, week, or month when transactions are more likely to occur. Additionally, the plot reveals that there are some unusually large transaction amounts, which could be potential outliers or indicators of fraudulent activity.

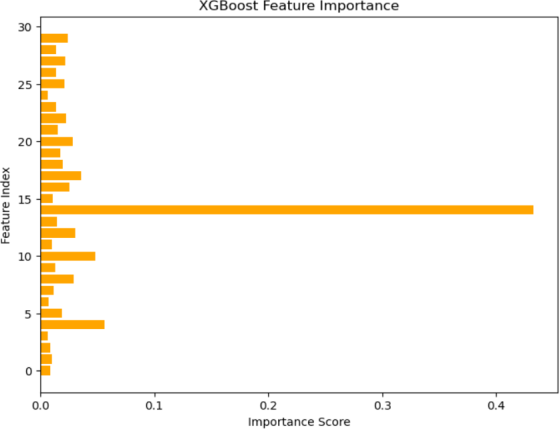


*Fig. 3: Time Series of Transaction Amounts*

* + 1. *XGBoost Feature Importance*

XGBoost feature importance (Fig 4) provides valuable insights into relative contribution of each feature in a ML model. By understanding which features are more influential you can better

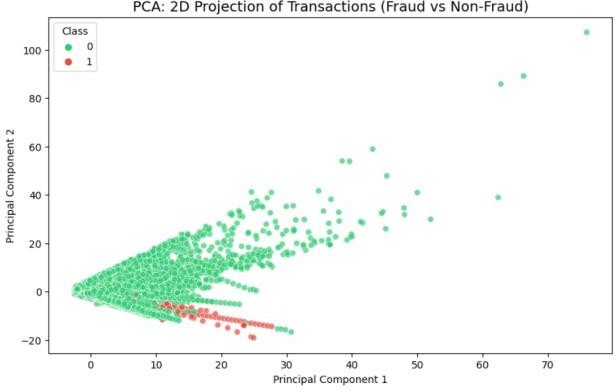
understand relationships that exists between your features and target variable.



*Fig.4: XGBoost Feature Importance*

* + 1. *PCA projection using a scatterplot*

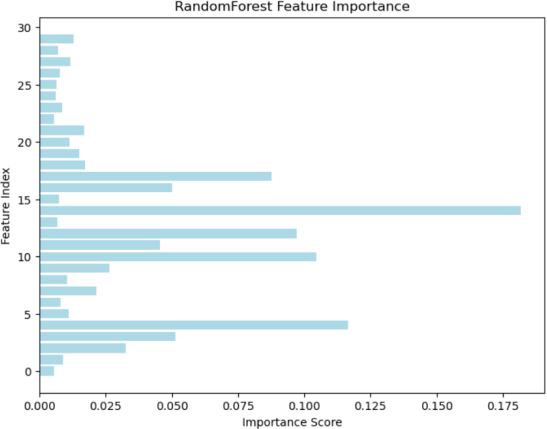
The given plot in Fig.5 visually separates fraudulent transactions (represented by red dots) from legitimate transactions (represented by green dots), suggesting that the PCA transformation effectively captures the underlying patterns and differences between the two classes.



*Fig.5: PCA:2D Projection of Transactions*

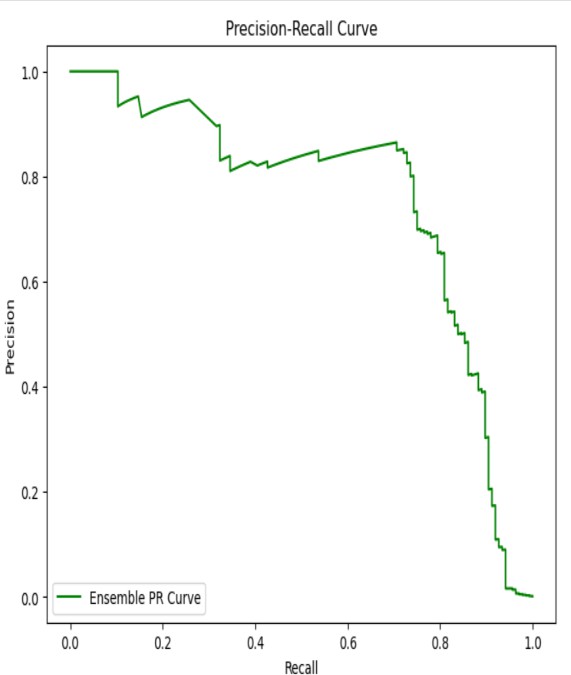
* + 1. *RandomForest Feature Importance*

RandomForest is another popular machine learning algo, that provides a feature importance metric. Similar to XGBoost, it quantifies the relative contribution of each feature in predicting target variable. Its curve is a graphical representation (Fig. 6) of the relative importance of each feature in a Random Forest model.



*Fig.6: RandomForest Feature Importance*

* + 1. *Precision Recall Curve*



The trade-off between accuracy and recall for a binary classification model is depicted graphically by a precision-recall curve (Fig. 7). The curve typically starts at a high precision and low recall value, as the model becomes more confident in its positive predictions. As the threshold for classifying instances as positive decreases, recall increases (more positive instances are correctly identified), but precision decreases (more false positive are also predicted).

* + 1. *Mathematical Framework and Calculations*

Polynomial Feature Expansion:

We apply polynomial feature expansion to introduce higher-order interactions between variables. Given three input features, ( X1, X2, X3), the expanded feature set includes quadratic and cubic terms:

Quadratic terms:X 2, X 2, X 2, X1, X2, X3, X1X2, X2X3, X3X1, X1X2X3

1 2 3

By transforming the input features into higher-order terms, non- linear correlations between variables can be captured by us, which may improve the model's ability to distinguish between legitimate and fraudulent transactions.

Here care should be taken to not train the model on the correlated features excessively so as to not cause the problem of overfitting in which case the model performs adequately on the training dataset but performs poorly on the test dataset.

Precision, Recall, and F1-Score:

After training the models, we calculate standard classification metrics to evaluate their performance for the respective classes where Class (0) is legitimate transactions and Class (1) is fraudulent transactions.

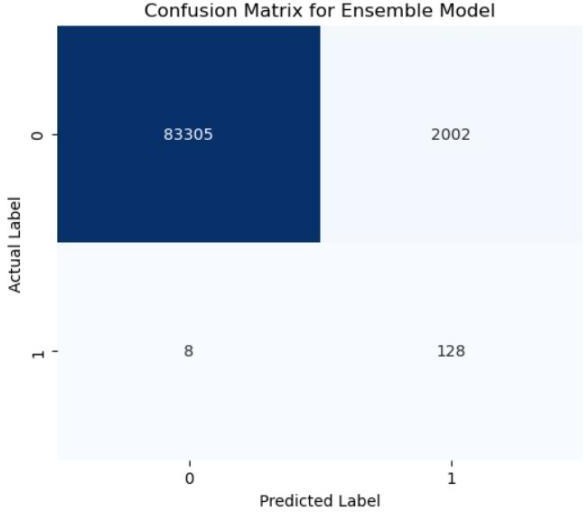
-In this study more importance is given to recall and F1-score as recall measures the model's ability to detect fraudulent transactions. A high recall helps minimize false negatives, which can result in financial losses, whereas F1-score is a useful metric when both precision and recall are crucial since it achieves a compromise between the two. It's particularly helpful when there's a trade-off between the two, such as when you want to avoid both false positives and false negatives.

-Precision (P): Measures the accuracy of positive predictions (fraudulent transactions).

*Fig.7: Precision Recall Curve*

* + 1. *Confusion Matrix*

To further understand the model performance, we present the confusion matrix (Fig. 8), which shows the breakdown of true positives, false positives, true negatives, and false negatives.



*Fig.8: Confusion Matrix for Ensemble Model*

𝑃 = {𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒(𝑇𝑃)}

{𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒(𝑇𝑃)+𝐹𝑎𝑙𝑠𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒(𝐹𝑃)}

(1)

* + 1. *D. ROC-AUC Score*

We compute the Receiver Operating Characteristic (ROC) curve (Fig. 9) and measure the Area Under the Curve (AUC) in order to

* Recall (R): Measures the ability of the model to identify all fraudulent transactions.

compare model performance in more detail.

𝑅𝑂𝐶 − 𝐴𝑈𝐶 𝑆𝑐𝑜𝑟𝑒 = ∫1 𝑇𝑃𝑅 𝑑(𝐹𝑃𝑅)

(4)

𝑅𝑒𝑐𝑎𝑙𝑙 = 𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒

𝑇𝑜𝑡𝑎𝑙 𝐴𝑐𝑡𝑢𝑎𝑙 𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒

(2)

0

Where:

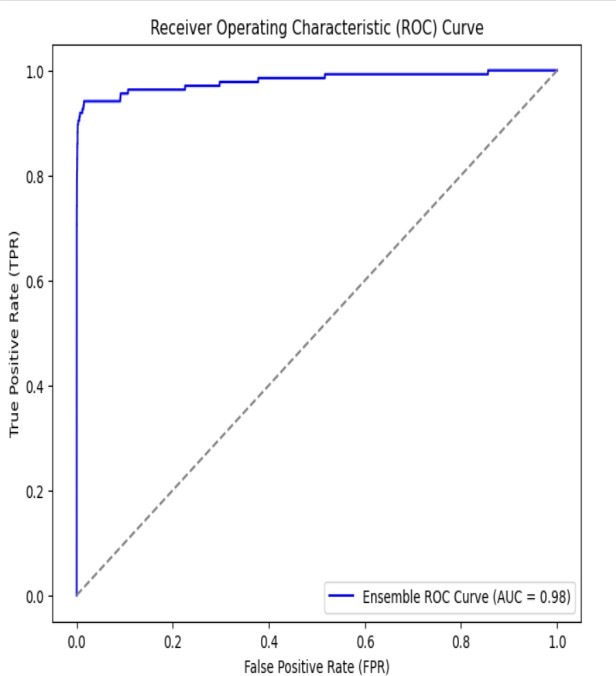
-F1-Score Precision and recall balance out using the F1-Score, and it's the harmonic mean of the two metrics.

(3)

* TPR is the True Positive Rate (Recall)
* FPR is the False Positive Rate

An ROC-AUC score of 1 indicates perfect classification, while a score closer to 0.5 suggests random guessing.

feature engineering techniques and ensemble learning. It highlights the challenges associated with class imbalance and the potential of polynomial features to improve model accuracy. The findings will help identify the best-performing algorithms and methods, contributing to the ongoing research and development of fraud detection systems that can effectively protect users' financial security.



This modified introduction integrates your requested elements, aligning the structure and flow with a comparative study on various models, focusing on polynomial feature generation and ensemble learning techniques.

*Fig.9: AROC Curve*

# ANALYSIS OF RESULTS

* 1. *Polynomial Feature Expansion*: By introducing second-order and third-order polynomial features, we observe an improvement in recall and F1-score across all models. This demonstrates that higher-order interactions between features contribute to better fraud detection. (Table.1)
  2. *Ensemble Techniques:* The ensemble model combining XGBoost, MLP, and KNN performs the best, achieving the highest F1-score of 0.93 and the lowest FNR of 0.07. This indicates that the ensemble approach, leveraging multiple classifiers, is more effective at identifying fraudulent transactions compared to individual models.
  3. *Data Sampling*: The use of under-sampling techniques (for majority) in combination with over-sampling techniques (for minority) addresses the issue of imbalanced data, resulting in more accurate models with lower false-negative rate.

*Table. 1: For Ensemble Model with Poly-Featuring*

|  |  |
| --- | --- |
| **Metrics Used for Model Evaluation** | **Metric-values Obtained** |
| 1. Precision | 0.9693877551020408 |
| 2. Accuracy | 0.9670050761421319 |
| 3. Recall | 0.9644670050761421 |
| 4. F1-score | 0.9669211195928753 |

*Table. 2: For Ensemble Model without Poly-Featuring*

|  |  |
| --- | --- |
| **Metrics Used for Model Evaluation** | **Metric-values Obtained** |
| 1. Precision | 0.9666666666666667 |
| 2. Accuracy | 0.9289340101522843 |
| 3. Recall | 0.8877551020408163 |
| 4. F1-score | 0.925531914893617 |

# CONCLUSION

This study provides a comprehensive comparison of different models for credit card fraud detection by leveraging advanced

# FUTURE SCOPE

In this study we have used only three models using under sampling techniques that help in reducing the computing complexity due to exponential increase in the features to be used for classification purpose. It is advised that a more extensive approach using Deep Learning concept is utilised for a more detailed model. The dataset so used in this study is not a real time data, but is a pre-uploaded dataset that was use for the study purpose. The performance of our system can be more critically analysed by using a real time dataset that better help us train our model in a real-time scenario.

The potential areas for future development and research are:

1. Deep-learning and neural networks: Explore more sophisticated deep learning architectures, like recurrent neural networks (RNNs) that can remember past events and patterns, convolutional neural networks (CNNs) that can recognize spatial features, and generative adversarial networks (GANs) that can create new, realistic data to test fraud detection models.
2. Real-Time Detection: Develop models that can keep up with the fast pace of transactions and detect fraud in real time, allowing for immediate intervention and prevention of losses.
3. Graph Neural Networks: Imagine transactions as individuals interacting in a social network. Use graph neural networks to analyse these interactions and identify suspicious groups or patterns of behaviour.

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