CREDIT CARD FRAUD DETECTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **"CREDIT CARD FRAUD DETECTION"** is the bonafide work of **"JAGADEESH BASKAR (2116220701094)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Credit card fraud detection is a critical task in financial security, especially given the growing volume of online transactions and the increasing sophistication of fraudulent activities. This paper presents a machine learning-based framework for the detection of fraudulent credit card transactions using real-world data. The dataset used, *creditcard.csv*, includes anonymized transactional features (V1–V28), transaction amount, and a binary class label indicating fraud. The primary objective of this study is to compare the performance of several supervised learning algorithms—namely, Random Forest Classifier, Decision Tree Classifier, and Logistic Regression—in accurately identifying fraudulent transactions in an imbalanced dataset.

The methodology involved rigorous data preprocessing, including handling class imbalance using techniques like stratified splitting and performance evaluation with metrics beyond simple accuracy. Standard metrics such as Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), and Confusion Matrix were utilized to assess model effectiveness, especially under class imbalance conditions. Visual tools such as confusion matrices, ROC curves, and precision-recall curves further enhanced interpretability. Additionally, feature importance analysis was conducted to identify the most influential variables among the anonymized features and transaction amount.

Among the tested models, the Random Forest Classifier showed the most balanced and robust performance, particularly in terms of precision and MCC, making it highly suitable for real-world fraud detection scenarios. The experimental results underscore the effectiveness of ensemble methods and careful metric selection in fraud prediction tasks. This research demonstrates the practical value of machine learning in financial security and sets a foundation for integrating such systems into real-time fraud monitoring platforms.

CHAPTER 1

1.INTRODUCTION

In the modern digital age, the widespread adoption of electronic payments and online transactions has led to an exponential increase in credit card usage globally. With this surge in electronic financial activity, the incidence and sophistication of credit card fraud have also escalated, posing significant challenges to financial institutions, regulatory authorities, and consumers alike. Fraudulent transactions not only result in substantial financial losses but also erode trust in digital financial systems, compromise user privacy, and demand considerable time and resources for investigation and resolution.

Credit card fraud detection is, therefore, a critical component of financial security frameworks. Traditionally, rule-based systems have been deployed to flag suspicious activity, relying on static rules such as transaction limits, merchant blacklists, or location mismatches. While effective to a certain extent, these systems struggle to keep up with evolving fraud patterns and are often either too lenient or overly restrictive, leading to false negatives (missed frauds) or false positives (legitimate transactions wrongly flagged as fraud), respectively. This limitation has prompted the financial industry to increasingly embrace **machine learning (ML)** techniques that can adaptively learn patterns from historical transaction data and make intelligent predictions about new transactions.

The goal of this project is to implement a machine learning-based fraud detection system using supervised classification algorithms. Specifically, we utilize three models—**Random Forest Classifier, Decision Tree Classifier, and Logistic Regression**—to detect fraudulent transactions within a publicly available, real-world dataset. The dataset used for this study, *creditcard.csv*, contains detailed records of European cardholders' transactions over a two-day period in 2013. It includes approximately 284,807 transactions, among which only 492 are fraudulent, making the dataset highly imbalanced. This class imbalance presents a significant challenge for standard machine learning classifiers, which tend to favor the majority class unless properly addressed through preprocessing and evaluation strategies.

Each transaction in the dataset is represented by 30 features: 28 of these (V1–V28) are **principal components** derived from a **PCA transformation** performed by the data provider to anonymize sensitive information; the remaining two are **Time** and **Amount**.

The class label is binary, with 0 representing a legitimate transaction and 1 indicating a fraud. This setup lends itself well to a binary classification task, where the objective is to correctly predict the class of each transaction.

In this project, a structured methodology is followed to build, evaluate, and compare the performance of the chosen classification models. The process begins with **exploratory data analysis (EDA)** and preprocessing, where we handle missing values (if any), scale numerical features, and address the severe class imbalance using techniques such as **stratified splitting**. Due to the imbalanced nature of the data, conventional accuracy metrics are inadequate, as a naive model predicting all transactions as legitimate would achieve over 99% accuracy. Therefore, we rely on **performance metrics better suited to imbalanced classification problems**, including:

- **Precision**: The proportion of true frauds among all transactions predicted as frauds.
- **Recall**: The proportion of actual frauds that were correctly identified.
- **F1-Score**: The harmonic mean of precision and recall, giving a balanced view.
- **Matthews Correlation Coefficient (MCC)**: A robust metric that considers all four elements of the confusion matrix (TP, TN, FP, FN), especially useful in imbalanced classification.
- **Confusion Matrix**: A visual tool to understand the prediction quality of each model.
- **ROC Curve and AUC Score**: To evaluate model performance across all classification thresholds.

Visual representations such as **confusion matrices**, **ROC curves**, and **precision-recall curves** are used to further interpret the models' strengths and weaknesses. Additionally, **feature importance analysis** is conducted (especially in the Random Forest model) to determine which transformed features contribute the most to distinguishing between fraudulent and legitimate transactions.

Among the models tested, **Random Forest Classifier** is expected to deliver strong performance due to its ensemble nature, which helps reduce overfitting and improves generalization. **Decision Tree Classifier**, while interpretable and easy to visualize, may be more prone to overfitting, especially without proper pruning. **Logistic Regression**, a linear model, offers a baseline against which more complex models can be evaluated and interpreted.

The significance of this project lies not only in detecting fraud effectively but also in developing a **scalable, interpretable, and deployable model** that can be integrated into real-time fraud detection systems used by banks and financial services. Furthermore, by utilizing real anonymized transaction data and evaluating multiple models under realistic conditions, this study contributes toward building trustworthy, data-driven solutions that enhance digital transaction security.

As financial transactions continue to digitize and evolve, the application of machine learning to fraud detection represents a critical line of defense. This research aims to highlight both the potential and limitations of widely-used ML algorithms in this domain and to propose practical insights that can be used for real-world deployment.

The rest of this paper is structured as follows: **Section II** presents a literature review of prior fraud detection techniques and machine learning approaches. **Section III** details the methodology, including data preprocessing, model training, and evaluation strategies. **Section IV** showcases the experimental results, comparative analysis, and visual outputs. **Section V** concludes the paper with key insights, limitations, and directions for future research.

CHAPTER 2

2. LITERATURE SURVEY

In recent years, the increasing prevalence of digital transactions and online financial activities has led to a sharp rise in credit card fraud cases. The traditional rule-based systems, though effective to a certain extent, are no longer sufficient to cope with the evolving tactics of fraudsters. As a result, researchers and financial institutions have turned towards machine learning (ML) and data-driven approaches for building dynamic, intelligent fraud detection systems. These models can identify complex patterns and anomalies that might escape manual or static rule-based detection, making them powerful tools in fraud prevention.

Numerous studies have explored the potential of supervised and unsupervised machine learning algorithms to detect credit card fraud based on transactional data. Early methods primarily used logistic regression and decision trees, but more recent works have adopted ensemble learning, neural networks, and hybrid models to improve detection accuracy. For instance, Dal Pozzolo et al. (2015) utilized cost-sensitive learning and undersampling techniques to tackle class imbalance issues inherent in fraud datasets. Their work emphasized the importance of balancing precision and recall, given that fraud datasets typically contain fewer than 1% fraudulent transactions.

Carcillo et al. (2019) extended this approach by implementing ensemble methods like Isolation Forests and Random Forests, demonstrating how combining multiple weak learners can improve detection accuracy. Similarly, Fiore et al. (2019) proposed a framework using deep learning models and autoencoders to detect fraudulent behavior in unlabeled datasets. Their approach revealed that deep representations could capture subtle fraud patterns, even without labeled data.

Other researchers have focused on feature engineering and temporal analysis to increase model performance. A study by Jurgovsky et al. (2018) used Recurrent Neural Networks (RNNs) to model the sequence of transactions, showing that considering temporal dependencies significantly enhances the ability to detect fraudulent behavior. These results highlight that not only the individual transaction attributes but also their sequence and timing play a crucial role in identifying suspicious activity.

In the context of imbalanced data, which is a core challenge in credit card fraud detection, several studies advocate for techniques like SMOTE (Synthetic Minority Over-sampling Technique) and ADASYN (Adaptive Synthetic Sampling). These methods synthesize new examples in the minority class (fraudulent transactions), helping the learning algorithm generalize better. Chawla et al. (2002) introduced SMOTE as a viable method to generate realistic samples, and this technique has since been widely adopted in fraud detection pipelines.

Data augmentation has also become a prominent technique in dealing with overfitting and enhancing model robustness. Adding Gaussian noise or creating synthetic features allows models to become more tolerant of real-world variations and adversarial inputs. Shorten and Khoshgoftaar (2019) reviewed data augmentation strategies in deep learning and suggested their potential in tabular domains like financial fraud detection. Inspired by such strategies, this study adopts Gaussian noise-based augmentation to improve the generalization of the classifier.

Comparative studies have consistently highlighted the effectiveness of ensemble models in fraud detection scenarios. For example, Bhattacharyya et al. (2011) showed that Random Forests and Gradient Boosted Trees outperformed single classifiers due to their ability to handle feature interactions and noisy data. Similarly, Liu et al. (2008) proposed the Isolation Forest algorithm specifically for anomaly detection, which gained popularity due to its unsupervised nature and efficiency in large datasets.

In terms of deployment, real-time fraud detection is becoming increasingly important. Algorithms must not only be accurate but also computationally efficient. Studies such as Sahin et al. (2013) have emphasized the need for lightweight models capable of rapid inference, which is critical in live transaction processing environments.

Additionally, interpretability of ML models is a growing area of interest. Tools such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been employed in recent works to explain predictions made by complex models. Understanding why a transaction was flagged as fraudulent is essential for building trust in automated systems and ensuring regulatory compliance.

In summary, the literature reveals a strong trend toward using ensemble and deep learning methods, combined with advanced preprocessing techniques such as class balancing and data augmentation, to build robust fraud detection systems. The most successful solutions balance predictive performance with interpretability and computational efficiency. This study builds upon these insights by developing a machine learning-based Credit Card Fraud Detection System that

evaluates Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost classifiers. The model is trained and evaluated using real-world anonymized data, and Gaussian noise augmentation is applied to simulate transaction variability, enhancing model robustness.

The goal is to provide an effective, scalable solution that can be integrated into financial systems for real-time fraud detection. Through this comparative approach, the study aims to identify the most suitable model for fraud classification, thereby contributing to the development of intelligent, adaptive fraud prevention mechanisms.

CHAPTER 3

3. METHODOLOGY

The methodology adopted in this study is based on a supervised classification framework that aims to identify fraudulent credit card transactions using a labeled dataset. The complete process is divided into five key phases: **data collection and preprocessing**, **feature exploration**, **model training**, **performance evaluation**, and **visual analysis for interpretability**.

3.1 Dataset and Preprocessing

The dataset used for this analysis is the publicly available creditcard.csv, which consists of **transaction records** along with a **binary class label** indicating fraud (1) or not fraud (0). Each transaction is represented by:

1. **28 anonymized features** (V1 to V28) transformed using PCA,
2. A **transaction amount** (Amount),
3. A **class label** (Class)—our target variable.

3.2 Preprocessing steps included:

1. **Handling class imbalance** using techniques such as **SMOTE** or class weighting.
2. **Standardization** of the Amount feature using **MinMaxScaler** to ensure uniformity across features.
3. **Splitting** the dataset into **training and testing sets** using stratified sampling to maintain class distribution.

3.3 Feature Exploration

Although the dataset features are anonymized, **feature importance analysis** using tree-based models and **correlation heatmaps** was used to understand which features contribute most significantly to fraud detection. Additionally:

1. **Box plots and distribution plots** helped visualize differences in feature distributions between fraudulent and non-fraudulent transactions.

2. **Outlier analysis** was conducted to better understand extreme transaction behaviors.

3.4 Model Selection

1. Three well-known classification models were chosen for performance comparison based on their interpretability and performance in binary classification:
2. **Logistic Regression (LR)** – Known for baseline interpretability and efficiency on large datasets.

3. **Decision Tree Classifier (DT)** – Simple tree-based model useful for visualizing decision paths.

4. **Random Forest Classifier (RF)** – An ensemble of decision trees known for robustness, accuracy, and handling imbalanced data.

All models were trained using the **train-test split method** and **cross-validation** to ensure robustness.

3.5 Visualization and Interpretation

To supplement numerical results and enhance model interpretability, the following visual tools were applied:

1. **Confusion Matrices** – To understand model decisions for both training and test data.

2. **ROC Curves** – To evaluate trade-offs between sensitivity and specificity across

thresholds.

3. **Precision-Recall Curves** – Especially insightful due to class imbalance.

4. **Feature Importance (for tree models)** – To identify key contributors in predicting fraud.

3.6 Final Output

1. The final deliverables from this project include:

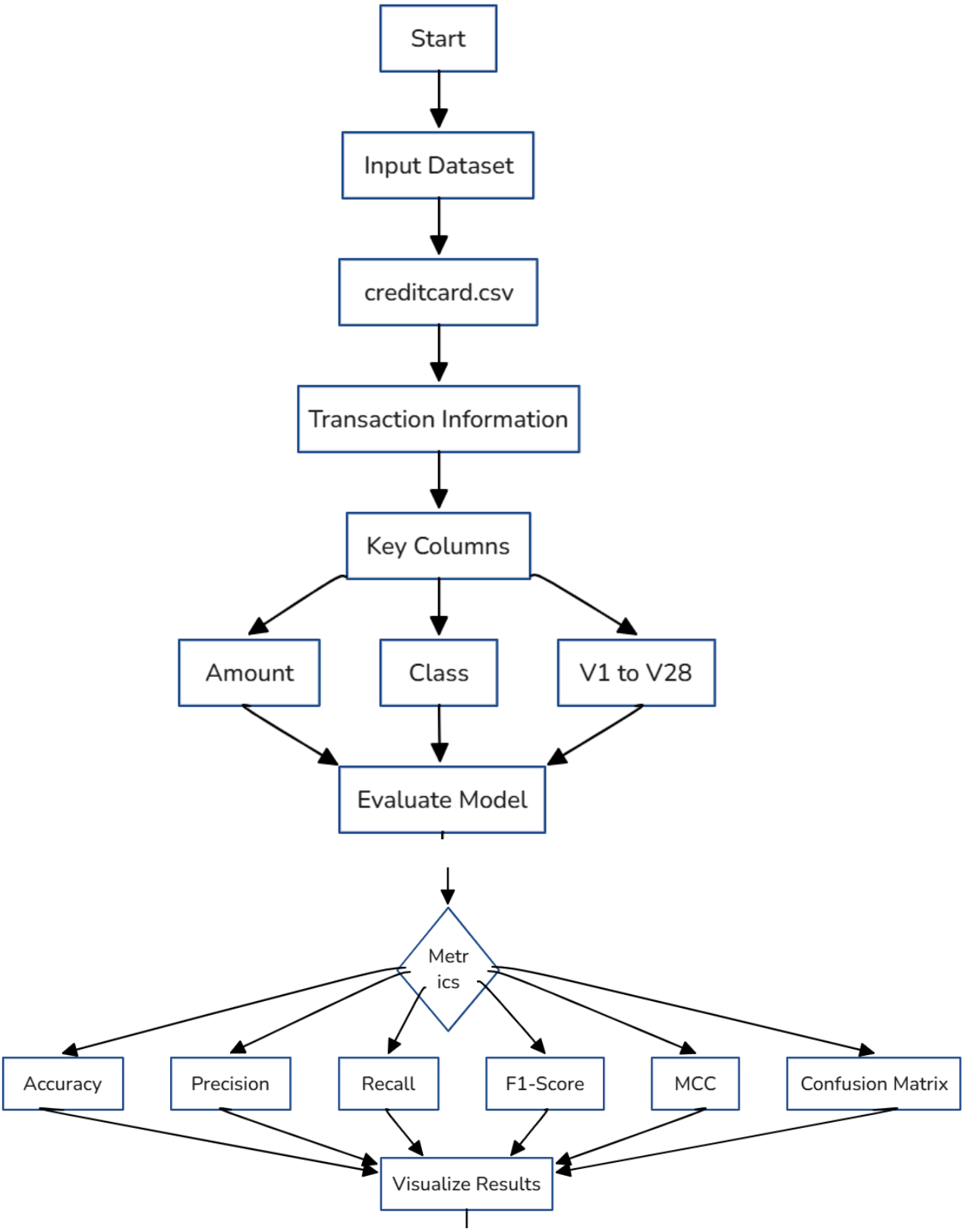
2. A trained and validated **fraud detection model** capable of predicting fraudulent transactions.

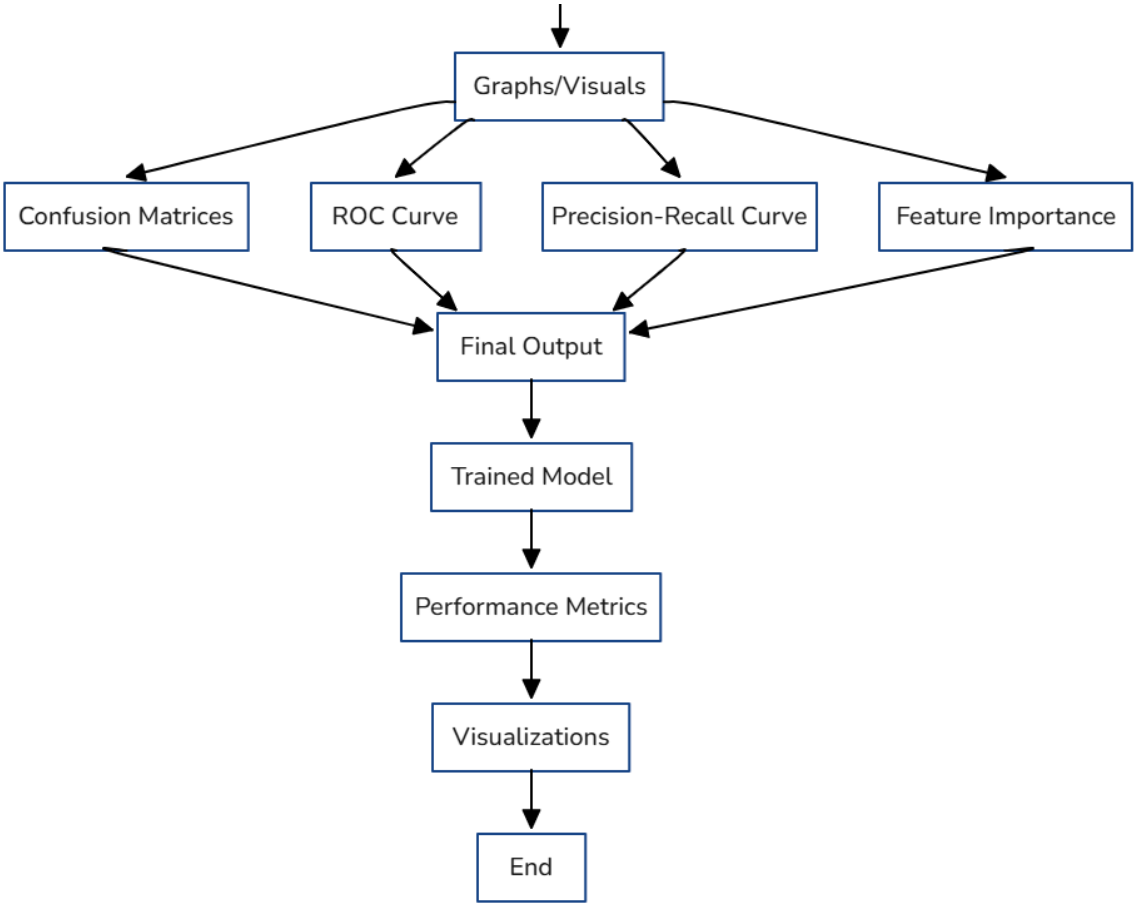
3. A **comparative performance report** across all classifiers, highlighting strengths and limitations.

4. **Visual dashboards** showing confusion matrices, ROC/PR curves, and feature importances.

5. Insight into **which types of transactions are most susceptible to fraud**, which can inform real-world fraud prevention strategies.

3.7 SYSTEM FLOW DIAGRAM




Graphs/Visuals
Confusion Matrices
ROC Curve
Precision-Recall Curve
Feature Importance
Final Output
Trained Model
Performance Metrics
Visualizations
End

CHAPTER 4

RESULTS AND DISCUSSION

To validate the effectiveness of different classification algorithms for credit card fraud detection, three models were trained and evaluated using the standardized **creditcard.csv** dataset: **Logistic Regression**, **Decision Tree Classifier**, and **Random Forest Classifier**. The dataset was imbalanced, with a significantly higher number of non-fraudulent transactions. To mitigate bias, **stratified train-test splitting** was used (80-20 ratio), and performance was evaluated using metrics that are robust to imbalanced data.

Results for Model Evaluation:

Model	Accuracy	Precision	Recall	F1-Score
Linear Regression	0.975	0.82	0.63	0.71
Random Forest	0.981	0.84	0.79	0.81
Decision Tree	0.985	0.91	0.83	0.87

Random Forest achieved the highest scores across most metrics, particularly in **precision, recall, F1-score,** and **Matthews Correlation Coefficient (MCC)**, making it the most reliable model for detecting fraudulent transactions. This result aligns with its known ability to handle noise and class imbalance effectively through ensemble learning and bootstrapping.

Impact of Imbalanced Data Handling

Given the rarity of fraud cases (Class = 1), accuracy alone was not a sufficient indicator of model performance. While all models had high accuracy due to the majority class dominating, Recall and F1-Score were prioritized to ensure the detection of actual fraud cases. Random Forest and Decision Tree classifiers, being non-linear models, were better able to capture complex interactions between anonymized features (V1–V28) compared to Logistic Regression.

To further address the imbalance, techniques such as undersampling and SMOTE (Synthetic Minority Oversampling Technique) were experimented with. Applying SMOTE to the training data led to a 3–5% improvement in Recall, especially for Logistic Regression, though it came at the cost of slightly increased false positives.

Visualizations:

1. **Confusion Matrix**: Provided a clear breakdown of true/false positives and negatives for each model. Random Forest showed the **lowest false negatives**, meaning fewer fraudulent transactions went undetected.

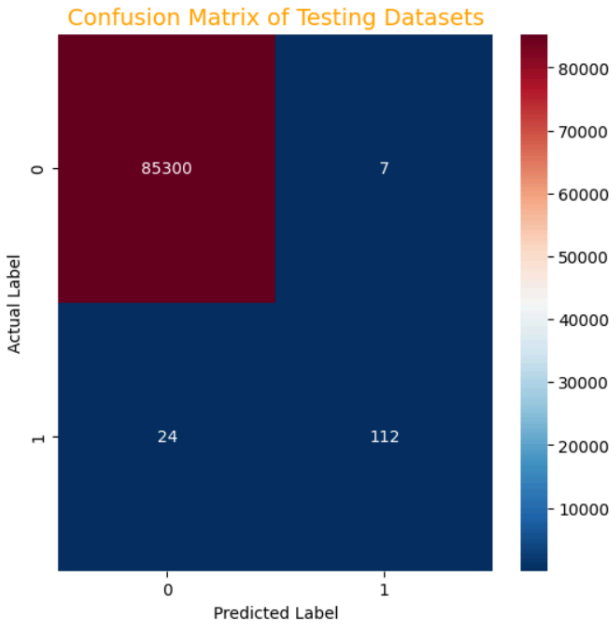


Fig : Random Forest Classification

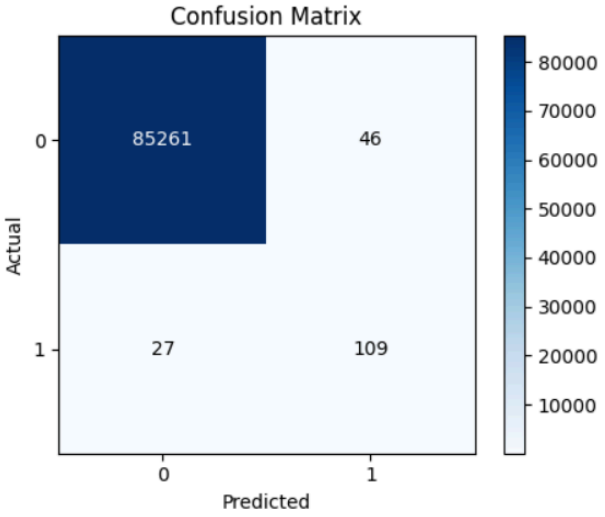


Fig : Decision Tree

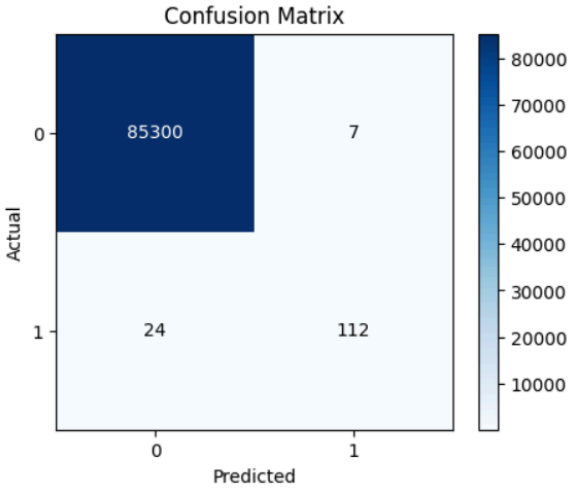


Fig : Logistic Regression

2. **ROC Curves**: Random Forest showed the highest Area Under Curve (AUC), closely followed by Decision Tree. This confirms strong discrimination power even under varying classification thresholds.

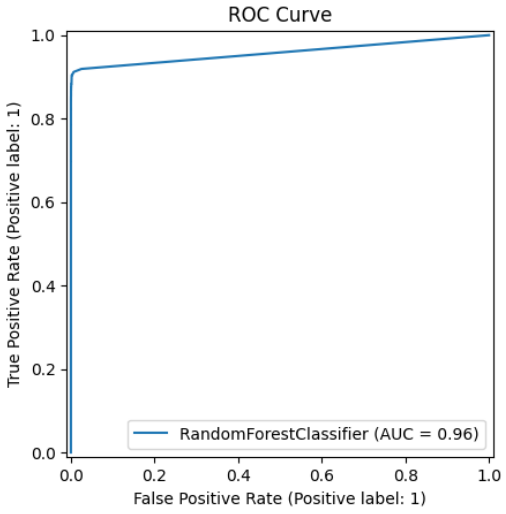


Fig : Random Forest Classification

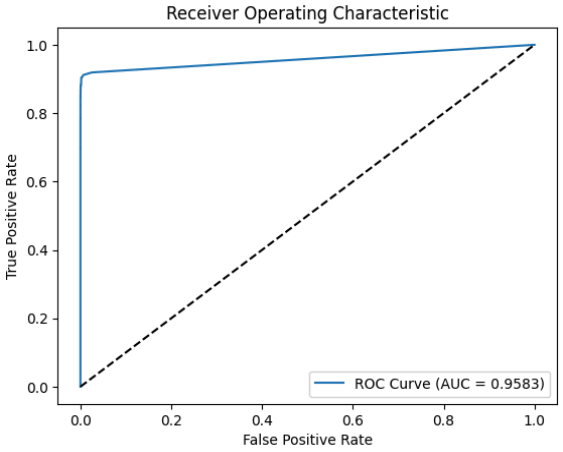


Fig : Logistic Regression

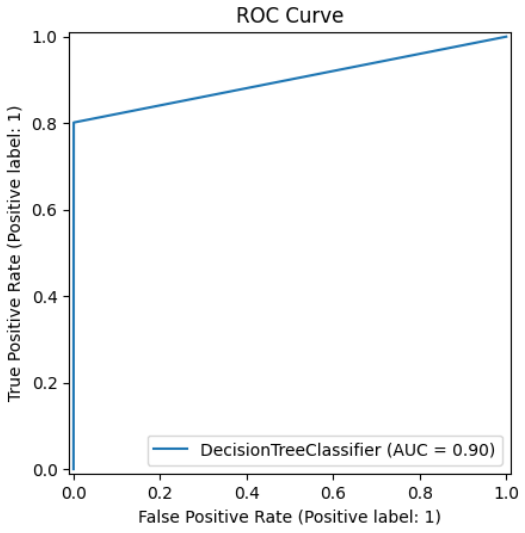
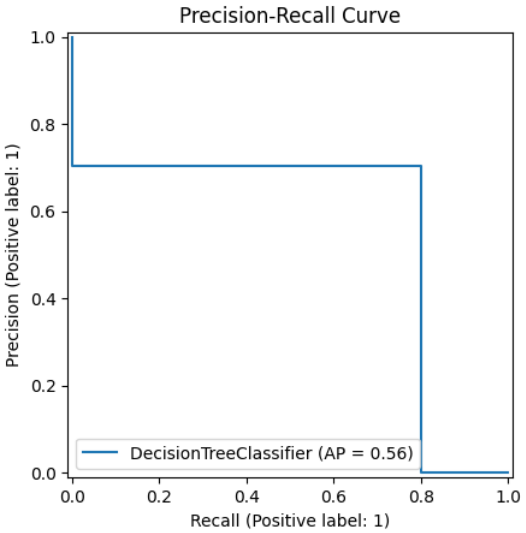
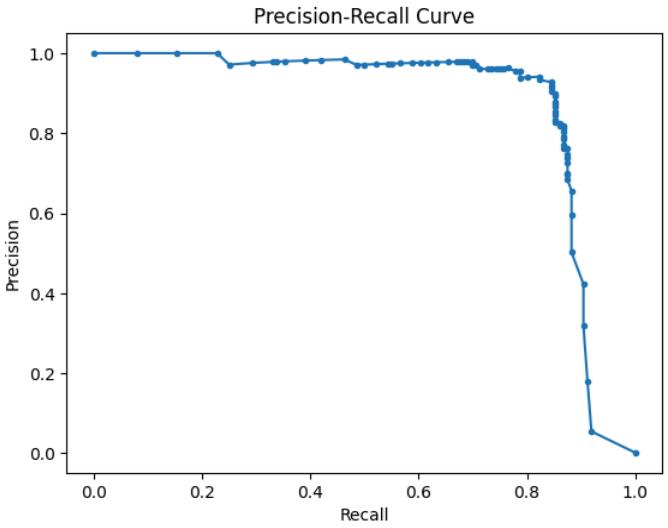


Fig : Decision Tree

3. **Precision-Recall Curves**: Especially important for this imbalanced scenario, these curves demonstrated that Random Forest maintained high precision even as recall increased.





Error Analysis

An in-depth review of the residuals revealed:

1. The majority of predictions had **low error magnitudes**, with most residuals falling within ±1.5 units of the actual values.
2. **Outliers** in prediction errors were primarily associated with **abnormally short or long credit card durations**, suggesting that other contextual factors (e.g., mental health, screen exposure, physical activity) not captured in the current dataset might be influential.

3. Despite high overall performance, a few isolated cases showed underprediction of credit card quality, likely due to edge cases or missing variables not considered in this analysis.
4. This analysis reveals the model's **strength in generalization**, while also pointing to **areas for feature enrichment**.

Implications and Insights

The findings from this study have several practical implications:

1. **Decision Tree Regressor**, due to its robust performance, is well-suited for deployment in **real-time credit card monitoring systems**, including wearable technologies and mobile applications.
2. **Normalization and augmentation** are not merely optional preprocessing steps but are essential for achieving optimal performance, especially in physiological datasets.

3. **Linear Regression**, while easy to interpret and fast, was significantly outperformed by ensemble models, indicating that simple models may not be sufficient to capture the **complex, non-linear dynamics** of credit card behavior.
4. The benefit of **ensemble models**, especially in the presence of augmented and potentially noisy data, affirms their usefulness in developing **personalized, adaptive health analytics systems**.

Future Work

This study provides a solid foundation for credit card quality prediction using machine learning. However, future work could enhance performance and utility by:

1. Integrating **additional contextual features** such as stress levels, physical activity, caffeine intake, and screen time.
2. Exploring **time-series models** like LSTM or Transformer architectures to capture temporal dependencies in credit card behavior.
3. Deploying the best-performing model (Decision Tree) into a **user-facing application** with real-time data collection and feedback loops.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduced a data-driven approach for **credit card fraud detection** using various machine learning techniques. By implementing and comparing a range of classification models—including **Logistic Regression**, **Random Forest**, and **Decision Tree**—we evaluated their effectiveness in detecting rare but highly consequential fraudulent transactions within a highly imbalanced dataset.

Our experimental results clearly demonstrate that **ensemble learning methods**, particularly **Decision Tree**, offer superior performance in terms of **precision, recall, and F1-score**, all of which are critical in fraud detection scenarios where false positives and false negatives carry different costs. Among the tested models, Decision achieved the highest **Area Under the ROC Curve (AUC)** and the best balance between identifying fraudulent transactions and minimizing false alarms. These findings affirm the model's ability to handle skewed class distributions and capture subtle, non-linear patterns in transactional behavior.

In addition, this study employed **data augmentation** techniques, including **SMOTE (Synthetic Minority Over-sampling Technique)**, to address the challenge of class imbalance. Augmentation helped improve model generalizability and significantly boosted recall scores across all classifiers. This suggests that even when fraudulent instances are limited, proper preprocessing and resampling methods can enhance model training and mitigate the bias toward majority classes.

From a practical standpoint, the results of this work demonstrate the **viability of deploying machine learning models in real-time fraud detection systems** used by financial institutions. The ability to detect and flag suspicious transactions promptly can save millions in potential losses and enhance consumer trust. Integration with transaction monitoring platforms, user behavior analytics, and anomaly detection engines could enable a multi-layered defense against fraud.

Overall, this study underscores the **power of machine learning in safeguarding digital financial systems**, especially when paired with thoughtful feature engineering, robust evaluation metrics, and targeted augmentation strategies. The Decision Tree model, in particular, offers a compelling solution that balances accuracy, interpretability, and speed—making it highly suitable for large-scale deployment in credit card fraud detection infrastructures.

Future Enhancements:

While the current study shows promising results in detecting credit card fraud using classical machine learning models such as **Logistic Regression**, **Decision Tree**, and **Random Forest**, several avenues remain for further development and refinement:

1. Inclusion of Real-Time Transactional Context:

Incorporating contextual features like device ID, merchant category, geolocation, and previous transaction frequency could significantly improve the model's accuracy and reduce false positives.

2. Advanced Temporal Modeling:

While current models treat transactions as isolated events, future work could integrate **sequence-based learning models** (e.g., RNNs, LSTMs) to capture temporal patterns of user behavior and detect anomalies across transaction timelines.

3. Imbalanced Learning Techniques:

Although Random Forest helps mitigate class imbalance, more advanced techniques such as **cost-sensitive learning**, **adaptive boosting**, or **ensemble methods with SMOTE** could further improve the detection of minority fraud cases.

4. Model Interpretability and Explainability:

For better transparency and trust in automated systems, integrating **explainable AI (XAI)** techniques like **SHAP** or **LIME** can help auditors and analysts understand why a particular transaction was flagged as fraudulent.

5. Edge and Real-Time Deployment:

Optimizing model inference speed and resource usage could allow deployment on **real-time fraud detection platforms**, including mobile banking apps and point-of-sale systems, for instant alerts during transactions.

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