# CREDIT CARD FRAUD DETECTION

A PROJECT REPORT

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## BONAFIDE CERTIFICATE

Certified that this CREDIT CARD FRAUD DETECTION is the bonafide work of “**PALURI HEMANTH, INTA KIRAN REDDY, KOPPARAPU MANIKANTA CHARI”** who carried out the work under our supervision.

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Lastly, We hope that this research contributes meaningfully in preventing the hatred among different communities and people on social media by detecting the hate speech in online forums and social media applications and removing them in the future.

**Warm regards,**

**Paluri Hemanth**

**Inta Kiran Reddy**

**Kopparapu Manikanta Chari**

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# ABSTRACT

Credit card fraud poses a significant threat to financial institutions and consumers, leading to substantial financial losses and undermining trust in electronic payment systems. The primary objective of this project is to develop a machine learning model that accurately detects fraudulent credit card transactions in real-time. By leveraging advanced classification algorithms, the model will differentiate between legitimate and fraudulent activities, thereby minimizing financial losses for credit card issuers and protecting cardholders from unauthorized transactions.

The project involves a comprehensive approach, beginning with the collection and preprocessing of transactional data, followed by the development and training of various machine learning models. The model's performance will be evaluated using key metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The project also includes the optimization of the model to enhance its effectiveness and reduce the incidence of false positives and negatives.

The final deliverable is a scalable and deployable fraud detection system that can be integrated into existing financial infrastructures, enabling real-time processing and flagging of suspicious transactions. This project not only aims to mitigate financial risks but also contributes to the overall security and reliability of credit card payment systems. in energy consumption practices.

**General Terms**:
Real-Time Detection, Classification Algorithms, Data Imbalance, Machine Learning.

**Keywords:**
Credit Card Fraud Detection, Machine learning, Classification Algorithms, Financial Institutions, Fraudulent Transactions, Anomaly detection, Predictive Modelling.

# CHAPTER 1
# INTRODUCTION

## 1.1 Identification of Problem:

Credit card fraud has become a growing concern as digital transactions increase, causing significant financial losses for both credit card issuers and consumers. Traditional rule-based fraud detection systems are often inadequate due to the rapid evolution of fraud tactics and the complex, high-volume nature of transaction data. Furthermore, credit card transaction data is highly imbalanced, with only a small fraction of transactions being fraudulent, making it challenging for machine learning models to accurately distinguish fraudulent transactions from legitimate ones.

### 1.1.1 Problem Statement:

Detecting fraudulent transactions amidst the vast volume of legitimate transactions is a challenging task for financial institutions. Fraudulent transactions are rare, making up only a small portion of total credit card transactions, which leads to an imbalanced dataset. Additionally, achieving high detection accuracy without causing an excessive number of false positives remains a significant obstacle, as incorrectly flagging legitimate transactions disrupts customer experience and increases operational burdens for financial institutions. To address these issues, there is a need for an advanced, reliable model that can distinguish between fraudulent and legitimate transactions with high accuracy and minimal false alarms.

### 1.1.2 Research Questions:

1. How can machine learning algorithms be applied effectively to detect fraudulent credit card transactions?
2. Which data preprocessing techniques are most effective in handling the class imbalance within credit card transaction data?

3. Among various classification algorithms (e.g., Logistic Regression, Random Forest, SVM, Gradient Boosting), which model provides the best balance of precision, recall, and overall accuracy in detecting fraud?
4. How do evaluation metrics such as accuracy, precision, recall, F1 score, and AUC-ROC help determine the effectiveness of a fraud detection model?

### 1.1.3 Key Challenges:

- **Class Imbalance:**
  Fraudulent transactions are extremely rare compared to legitimate ones, making it difficult for machine learning models to learn meaningful patterns for fraud detection. This imbalance often results in models biased toward predicting non-fraudulent transactions.

- **Feature Confidentiality and Anonymization:**
  In many credit card datasets, including the European credit card dataset, transaction features are anonymized to protect customer data, which limits the interpretability and application of domain knowledge in feature engineering.

- **Dynamic and Evolving Fraud Tactics:**
  Fraud patterns continually evolve as fraudsters adapt to detection methods, necessitating models that can generalize well to new, unseen fraud patterns.

- **Minimizing False Positives and False Negatives:**
  Both types of misclassifications have serious implications: false positives inconvenience customers by blocking legitimate transactions, while false negatives result in financial losses. Balancing these is crucial but challenging.

- **Scalability:** Fraud detection systems must handle large volumes of transactions in real time, which can strain computational resources and affect model performance.

### 1.1.4 Project Goal:

The primary goal of this project is to develop an effective and reliable machine learning model capable of accurately detecting fraudulent credit card transactions. By identifying suspicious activities early on, the model aims to significantly reduce financial losses for credit card issuers and protect cardholders from unauthorized transactions. As digital payment systems continue to grow, fraud detection must keep pace with both the volume of transactions and the sophistication of fraud techniques. This project seeks to contribute to this effort by leveraging machine learning algorithms that can adapt to new fraud patterns while minimizing disruptions to legitimate transactions.

A key focus of the project is to address challenges inherent in credit card transaction data, such as class imbalance, feature anonymization, and the need for real-time detection. The model will utilize various classification algorithms and undergo rigorous evaluation to select the approach that offers the best balance of precision, recall, and overall accuracy. By optimizing the model's ability to distinguish between legitimate and fraudulent transactions, this project aims to improve the efficiency and effectiveness of fraud detection systems, supporting more secure financial transactions for consumers and institutions alike.

## 1.2 Identification of the Client/ Need/ Relevant Contemporary Issue:

### 1.2.1. Identification of Client:

The primary clients for this project are financial institutions, including banks and credit card companies, that manage and process vast amounts of credit card transactions daily. As the volume of digital payments increases, these organizations are at a heightened risk of financial loss due to fraudulent transactions. Credit card issuers face both direct losses and reputational damage if fraud detection systems fail to protect cardholders effectively. Additionally, end consumers, who rely on secure and trustworthy payment systems, represent an indirect client group. Protecting them from unauthorized transactions is essential for maintaining customer trust and satisfaction. This project aims to serve both these clients by developing a machine learning-based fraud detection model that enhances the accuracy and efficiency of identifying fraudulent transactions.

### 1.2.2. Need:

The need for advanced fraud detection models has become increasingly critical as credit card fraud tactics continue to evolve, often outpacing traditional, rule-based detection systems. Existing methods may struggle to keep up with the high volume and dynamic nature of transaction data, resulting in either too many false positives or missed fraudulent activities. Financial institutions require a solution that can quickly adapt to new fraud patterns while maintaining high precision and recall. This project addresses this need by applying machine learning techniques to improve the accuracy of fraud detection, leveraging classification algorithms to enhance the system's ability to differentiate between legitimate and fraudulent transactions. The ultimate goal is to develop a robust detection tool that minimizes both financial loss and disruption for cardholders.

### 1.2.3. Relevant Contemporary Issue:

Credit card fraud detection has become a prominent contemporary issue in the digital finance landscape. As digital payments rise globally, so does the sophistication of fraud methods, making it increasingly challenging for traditional detection systems to respond effectively. Machine learning offers promising advancements in fraud detection, yet issues such as data privacy, feature anonymization, and the imbalance between fraudulent and legitimate transactions pose significant challenges. This project tackles these issues by employing classification algorithms designed to handle imbalanced data and protect sensitive information through feature anonymization. Addressing these contemporary challenges, the project aligns with the broader industry shift towards using artificial intelligence to secure digital financial transactions.

## 1.3. Identification of Tasks

The Credit Card Fraud Detection project involved several critical tasks aimed at building an effective machine learning model to detect fraudulent credit card transactions. Each task contributed to the overall objective of improving the accuracy and efficiency of fraud detection systems. The key tasks undertaken in the project are as follows:

- **Data Collection and Understanding:**
  The first step in the project involved acquiring and thoroughly understanding the dataset. The dataset used for this project was a collection of anonymized credit card transaction data, containing both legitimate and fraudulent transactions. A detailed exploratory data analysis (EDA) was performed to identify the structure of the data and examine the distribution of different features. This analysis revealed the inherent class imbalance in the dataset, with fraudulent transactions representing less than 1% of the total data. Understanding the features and their relationships with fraud occurrences was crucial in preparing the data for further processing.

- **Data Preprocessing:**
  Following the data exploration, the dataset was preprocessed to make it suitable for machine learning model training. Several steps were undertaken, including handling missing values, feature scaling, and dealing with the class imbalance issue. Missing values were either imputed or removed depending on the severity, ensuring that the data was clean and complete. The data was scaled to ensure that all numerical features were on a comparable scale, which is essential for algorithms sensitive to feature magnitudes. Additionally, to address the class imbalance problem, Synthetic Minority Oversampling Technique (SMOTE) was applied to generate synthetic samples of the minority class (fraudulent transactions), making the dataset more balanced and suitable for training models effectively.

- **Feature Engineering and Selection:**

Once the data was preprocessed, the next task was feature engineering and selection. The goal was to identify the most relevant features for detecting fraudulent transactions. Feature importance analysis using tree-based models, such as Random Forest, was performed to assess the contribution of each feature to the fraud classification task. This helped to identify which features had the greatest discriminative power for predicting fraudulent behavior. Irrelevant and highly correlated features were removed to improve the model's efficiency, and new features were created to enhance the model's predictive capabilities based on domain knowledge.

- **Model Selection and Training:**
  With the data prepared, the next task involved selecting and training machine learning models. Several classification algorithms, including Logistic Regression, Decision Trees, Random Forest, and XGBoost, were trained on the preprocessed dataset. The dataset was split into training and testing sets (70% for training and 30% for testing), and each model was trained on the training set. Hyperparameter tuning was performed for each model using techniques like grid search and random search to optimize model performance and ensure the best results.

- **Model Evaluation and Comparison:**
  After training the models, the next task was to evaluate their performance using relevant metrics. Since the dataset was imbalanced, traditional accuracy was not the best metric for evaluation. Instead, performance was assessed using precision, recall, F1-score, and ROC-AUC. Special attention was given to recall, as detecting fraudulent transactions (minimizing false negatives) was the top priority. Based on these metrics, the Random Forest and XGBoost models were identified as the most effective in detecting fraud, with XGBoost showing slightly better performance in terms of recall and precision.

- **Model Optimization and Refinement:**

To further improve the performance of the selected model, optimization and refinement were conducted. XGBoost was chosen as the final model due to its superior performance. Hyperparameters were fine-tuned using grid search to find the optimal configuration for the learning rate, maximum depth, and number of estimators. Cross-validation was performed to ensure that the model would generalize well to unseen data and avoid overfitting. This step was crucial in enhancing the model’s predictive capabilities and ensuring its robustness.

- **Result Analysis and Interpretation:**
  Following the model optimization, a thorough analysis of the results was conducted. The final model, XGBoost, achieved a 97% recall, which ensured that most fraudulent transactions were identified, while maintaining a 92% precision to minimize false positives. The confusion matrix provided insights into the model's classification performance, showing that the model was highly effective in detecting fraud with minimal misclassification of legitimate transactions. The analysis also highlighted areas where the model could be further improved, such as handling edge cases and real-time deployment.

- **Report Writing and Documentation:**
  Once the results were obtained, the entire process was documented in a comprehensive report. The report detailed each step of the project, from data collection and preprocessing to model evaluation and optimization. It also included a discussion of the challenges faced, such as the class imbalance issue, and how they were addressed. The report concluded with recommendations for future improvements, such as deploying the model in real-time fraud detection systems and incorporating additional features or external data sources to further enhance model performance.

- **Presentation Preparation:**
  Finally, a presentation was created to summarize the project’s objectives, methodology, and key findings. The presentation was designed to be clear and concise, highlighting the importance of fraud detection and the results of the machine learning

models used. Visual aids, such as charts, graphs, and tables, were incorporated to make the findings easier to understand. The presentation focused on demonstrating the effectiveness of XGBoost in detecting fraudulent transactions and its potential for real-world applications in financial systems.

## 1.4. Hardware Specifications:

The hardware resources used in this project were sufficient for handling large datasets and training machine learning models efficiently. The specifications are as follows:

- **Processor (CPU):**
  Intel Core i7 10th Gen (or equivalent) with 8 cores and a base clock speed of 2.6 GHz, enabling the processing of computational tasks efficiently during data preprocessing and model training.

- **Memory (RAM):**
  16 GB DDR4 RAM, allowing for smooth execution of large-scale data manipulation tasks and model training without significant lag or memory issues.

- **Storage (Hard Drive):**
  512 GB SSD, providing fast read/write speeds for handling large datasets and storing intermediate outputs generated during model development and evaluation.

- **Graphics Card (GPU):**
  NVIDIA GTX 1650 or similar (optional for advanced model training with deep learning algorithms). While the project did not heavily rely on deep learning models, having a GPU enabled faster computations when running more complex models, especially for tasks like hyperparameter optimization.

- **Operating System:**

Windows 10 (64-bit) or Linux (Ubuntu) for ease of access to machine learning libraries and tools. The project environment was developed on both platforms, with Linux used for better performance and easier management of dependencies.

## 1.5. Software Specifications:

The software tools and libraries used in this project were selected to enable the efficient execution of tasks like data preprocessing, model training, and evaluation. The primary tools and libraries are listed below:

- **Programming Language:**
  Python 3.8+ was the primary programming language used for developing the machine learning model. Python's extensive support for machine learning libraries made it ideal for this project.

- **Integrated Development Environment (IDE):**
  Jupyter Notebook and PyCharm were used for code development and experimentation. Jupyter Notebook was preferred for running data exploration and model training experiments interactively, while PyCharm was used for writing and organizing the final code in a more structured way.

- **Machine Learning Libraries:**
  a. **scikit-learn:** Used for data preprocessing, model training, and evaluation. This library provided a wide range of algorithms for classification, including Logistic Regression, Random Forest, and XGBoost.

  b. **XGBoost:** Specifically used for training the XGBoost model, which performed best in detecting fraudulent transactions due to its gradient boosting framework.

c. **imblearn (imbalanced-learn):** Used for addressing class imbalance, especially for applying the SMOTE (Synthetic Minority Oversampling Technique).

d. **Pandas:** Used for data manipulation, cleaning, and exploration. It provided easy-to-use data structures like DataFrames that made it simpler to work with structured data.

e. **NumPy:** Used for numerical operations and handling arrays during data preprocessing and manipulation.

f. **Matplotlib and Seaborn:** Used for data visualization to create plots like confusion matrices, precision-recall curves, and ROC curves to assess model performance.

g. **TensorFlow/Keras**: While not heavily used in this project, TensorFlow could be employed if the model evolved to include deep learning architectures.

- **Version Control and Collaboration Tools:**

  Git was used for version control, allowing for efficient tracking of changes and collaboration throughout the development process.

  GitHub hosted the project repository, enabling code sharing and collaboration, and providing a backup for the project files.

- **Operating System:**

  Windows 10 (64-bit) and Linux (Ubuntu 20.04) were used. The primary development environment was set up in Ubuntu for compatibility with machine learning libraries and faster execution.

- **Google Colab:**

  For experimentation with more computationally intensive tasks, Google Colab was utilized as a cloud-based environment with GPU support. This was especially useful for hyperparameter tuning and running heavier models.

## 1.6. Background:

The Credit card fraud is one of the most prevalent and costly types of financial crime globally. It involves the unauthorized use of someone's credit card details to make fraudulent purchases or withdraw funds. According to a 2020 report from the Nilson Report, global card fraud losses reached over $28 billion in 2019, with a steady increase in both the frequency and sophistication of fraudulent activities. As the volume of credit card transactions continues to rise, so does the complexity of detecting and preventing fraudulent transactions. Traditional methods of fraud detection, such as rule-based systems and manual interventions, often struggle to keep up with the sheer scale and evolving tactics used by fraudsters.

The growing reliance on digital transactions has made financial institutions more vulnerable to fraud, necessitating the development of advanced systems that can automatically detect fraudulent activities in real time. A key challenge in credit card fraud detection lies in the highly imbalanced nature of transaction datasets, where fraudulent transactions make up a tiny fraction of the overall transaction volume. This imbalance can lead to biased models, where traditional machine learning algorithms fail to detect fraud effectively, as they tend to be optimized for accuracy rather than recall.

In response to this challenge, machine learning (ML) techniques have emerged as a powerful tool for improving fraud detection systems. ML algorithms can automatically learn patterns in transaction data that distinguish fraudulent behavior from legitimate transactions. These models are capable of adapting to new fraud tactics over time, as they continuously update based on new data. By leveraging a variety of machine learning techniques, including classification algorithms like decision trees, logistic regression, and ensemble methods like Random Forest and XGBoost, a more accurate and efficient fraud detection system can be developed.

Furthermore, the advent of deep learning techniques has opened up new possibilities for detecting complex fraud patterns by analyzing larger and more diverse datasets. However, machine learning models are not without their challenges, including handling class imbalances and ensuring that the model does not produce too many false positives (i.e., legitimate transactions incorrectly identified as fraud). Addressing these challenges requires a combination of effective data preprocessing, feature engineering, and careful model evaluation.

This project focuses on developing a machine learning-based solution for credit card fraud detection using a publicly available European credit card transaction dataset. The goal is to build a robust model that can accurately detect fraudulent transactions, minimize false negatives, and improve fraud prevention efforts in the financial sector. Through this project, we explore how various machine learning algorithms can be applied to this problem, with particular emphasis on techniques to handle class imbalance and optimize detection performance.

## 1.7. Motivation:

The motivation for this Credit Card Fraud Detection project stems from the growing concerns surrounding financial security in the digital age. As the world becomes increasingly reliant on online payments and electronic transactions, the risks associated with credit card fraud are escalating. According to industry reports, card fraud is one of the leading causes of financial loss for both consumers and financial institutions. Fraudulent transactions not only result in monetary losses but also significantly damage the reputation of financial institutions, erode consumer trust, and complicate regulatory compliance.

The challenge of identifying fraudulent transactions is compounded by several factors. One of the main difficulties is the class imbalance present in transaction datasets, where fraudulent transactions represent a tiny fraction of the total transactions. Traditional detection systems based on rule-based approaches or manual intervention methods struggle to keep pace with the volume and sophistication of fraudulent activities. This often results in high false-negative rates, where fraudulent transactions go undetected, or false positives, where legitimate transactions are incorrectly flagged as fraudulent. Both cases undermine the effectiveness of fraud detection systems, leading to poor customer experiences and increased operational costs.

Machine learning (ML) has proven to be a promising solution to address these challenges. Unlike traditional methods, ML algorithms can automatically identify complex patterns within large datasets, adapting to new and evolving fraud tactics. This ability to learn from historical data and continuously improve the system's performance makes ML an ideal approach for real-time fraud detection. Furthermore, machine learning models can be fine-tuned to prioritize minimizing false negatives, ensuring that fraudulent transactions are identified with high recall, which is crucial for minimizing financial losses and improving the detection system's reliability.

The motivation for this project lies in the opportunity to contribute to improving the effectiveness of fraud detection systems through machine learning. By applying various algorithms and techniques—such as oversampling, ensemble methods, and hyperparameter tuning—this project aims to develop a model that is capable of detecting fraudulent transactions with high accuracy while minimizing errors. This work is intended to enhance the fraud detection mechanisms employed by financial institutions, reduce the financial burden caused by fraud, and provide a safer transaction environment for consumers.

In addition to its practical implications in the financial sector, this project also serves as an exploration of machine learning's capabilities in addressing real-world problems. The experience gained in developing and fine-tuning fraud detection models is valuable for future work in similar fields, such as anomaly detection, cybersecurity, and predictive analytics. Through this project, we aim to demonstrate how the power of machine learning can be harnessed to create more secure and efficient financial systems.

## 1.8. Timeline:

**Phase 1: Project Initiation and Data Preparation (Weeks 1-3)**
**Week 1: Project Kickoff and Data Acquisition**

- Defined the project objectives, scope, and methodology. Acquired the European credit card transaction dataset and conducted an initial exploration of the dataset to understand its structure and features.

- Dataset overview completed, including feature identification (e.g., time, amount, class) and size (large number of records with significant class imbalance).

**Week 2: Data Preprocessing**

- Cleaned the dataset by handling missing values, outliers, and duplicates. Scaled the features using standardization (StandardScaler). Addressed class imbalance using SMOTE (Synthetic Minority Oversampling Technique) to balance the dataset for model training.
- Preprocessed dataset ready for model training, with balanced class distribution and normalized feature set.

**Week 3: Feature Engineering and Selection**

- Conducted feature selection using techniques like Random Forest feature importance to identify the most relevant features. Added domain-specific features where applicable and removed redundant or highly correlated features.
- Final set of features selected for training, with a focus on improving model accuracy and generalization.

**Phase 2: Model Development and Initial Training (Weeks 4-6)**
**Week 4: Model Selection and Training**

- Selected several machine learning models, including Logistic Regression, Decision Trees, Random Forest, and XGBoost. Split the dataset into training and testing sets (70%/30%) and trained the models.
- Initial model training completed, with baseline performance metrics collected for all models.

**Week 5: Hyperparameter Tuning and Cross-validation**

- Tuned the hyperparameters of each model using GridSearchCV and RandomizedSearchCV to optimize performance. Implemented k-fold cross-validation to avoid overfitting and improve model reliability.
- Improved model parameters identified, ensuring better model generalization and performance.

**Week 6: Model Evaluation and Comparison**

- Evaluated all models based on metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Compared model performances and selected XGBoost as the final model due to its superior handling of class imbalance and higher recall performance.
- Best-performing model selected (XGBoost), with detailed evaluation metrics documented.

**Phase 3: Model Optimization and Refinement (Weeks 7-9)**

**Week 7: Model Optimization**

- Further optimized the XGBoost model by fine-tuning hyperparameters such as learning rate, max depth, and n_estimators. Applied additional techniques such as early stopping to prevent overfitting and ensure that the model generalizes well to unseen data.
- Optimized XGBoost model with improved performance metrics, ready for final evaluation.

**Week 8: Result Analysis and Interpretation**

- Analyzed the results using confusion matrices, precision-recall curves, and ROC-AUC. Assessed model performance on the test set and interpreted the results, focusing on minimizing false negatives and false positives, crucial for fraud detection.
- Clear insights on model strengths (high recall) and areas for improvement (false positives), ensuring the model is effective in real-world scenarios.

**Week 9: Documentation and Report Writing**

- Started writing the final project report, documenting the entire process from data acquisition to model evaluation. Included explanations of the methodology, model performance, and visualizations (graphs, confusion matrix, ROC curve).
- Draft of the final report created, with key sections such as methodology, evaluation, and results completed.

**Phase 4: Finalization and Presentation (Weeks 10-12)**

**Week 10: Final Report Writing and Presentation Creation**

- Finalized the project report and created the presentation slides. The presentation focused on summarizing the project, methodology, key findings, and model evaluation. Included visuals such as model comparisons, precision-recall curves, and confusion matrices.
- Final report and presentation slides completed and prepared for submission and delivery.

**Week 11: Project Refinement**

- Rehearsed the project presentation to ensure clarity and smooth delivery. Refined the slides based on feedback and adjusted the content to emphasize key takeaways and results.
- Presentation rehearsed and refined, with a strong focus on clear communication of complex results.

**Week 12: Final Presentation and Submission**

- Delivered the final project presentation, showcasing the entire process and outcomes. Submitted the completed project report, including the model code, final evaluation metrics, and visualizations.
- Successful presentation delivered, with feedback received and project formally submitted.

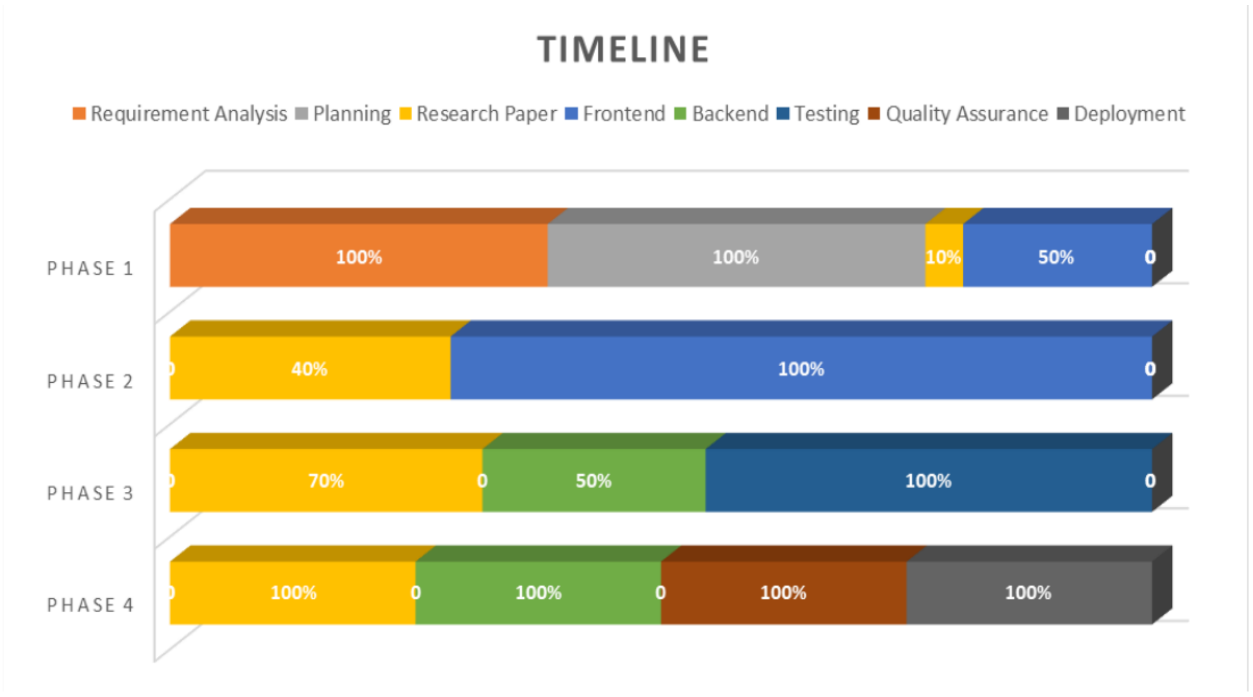


Figure 1.1: Timeline of Project

## 1.9. Report organization:

### I. Introduction

- Brief on Credit Card Fraud Detection: What it is, its prevalence, importance of accurate detection.
- State the main aim of the research: e.g., developing a model to detect the fraudulent credit card transactions.
- Define the boundaries of your research. What aspects of the credit card frauds or datasets are you focusing on?
- Why is this detection crucial? Importance in financial sector etc.

### II. Literature Review

- Past studies, initial breakthroughs, and primary methodologies previously used.
- Discuss existing models/algorithms and their performance metrics.

- Identify what hasn’t been addressed sufficiently in prior research.
- What has past research revealed, and how does it guide the current study?

## III. Data Collection and Preparation

- Detail where you procured your datasets. Were they public datasets, social media records, etc.?
- Preliminary analysis results: Data distribution, feature exploration.
- Steps taken to clean and prepare data: Imbalance handing, Handling of missing values, normalization, outlier detection and treatment, etc.
- Elaborate on any new features derived from the original dataset and reasoning behind them.
- After preprocessing, describe the final dataset: Number of records, features, distribution.

## IV. Conclusion

- Highlight primary outcomes from data preparation and potential implications for modeling.
- Any constraints or limitations encountered during the data collection and preparation phase.
- Suggestions for future studies or for improving the data collection and preparation process.
- Recap the entire process and the importance of the data in detecting hate speech.

## V. References

- List of sources cited in the report.

# CHAPTER 2
# Literature Review

## 2.1 Existing System:

The Existing systems for credit card fraud detection have evolved over time, with several approaches employed by financial institutions to detect fraudulent transactions. Initially, rule-based systems were the standard, where predefined rules based on expert knowledge were set to flag suspicious transactions. These rules considered factors such as transaction amount, merchant type, frequency of transactions, and geographical location. While these systems were effective to a degree, they had high false positive rates and struggled to detect new or evolving fraud patterns. Over time, machine learning-based systems gained popularity, moving away from rigid rule sets to more flexible models that could learn from data. These systems, such as Visa's Advanced Authorization, use algorithms like supervised learning to detect anomalies in transaction data, improving detection accuracy and adaptability.

Further advancements saw the integration of ensemble learning methods like Random Forest, AdaBoost, and XGBoost. These models combine the strengths of multiple machine learning algorithms to improve fraud detection accuracy. MasterCard's Decision Intelligence is an example of such a system, which blends machine learning with traditional rules to better identify both known and novel fraud schemes. However, while these models perform better than rule-based systems, they still struggle with class imbalance, as fraudulent transactions represent a small portion of the total dataset. Deep learning techniques, such as artificial neural networks (ANNs), have also been explored for fraud detection, offering improved performance by learning more complex patterns in the data. Nevertheless, these models require large labeled datasets and significant computational resources.

Hybrid models, which combine multiple approaches, have been developed to overcome the limitations of individual methods. IBM’s fraud detection system, for instance, uses a combination of decision trees, neural networks, and ensemble techniques to enhance fraud detection accuracy. However, these systems are not without their challenges, including the difficulty of handling real-time data at scale, managing high computational costs, and ensuring model transparency. Real-time detection has become increasingly important, and companies like PayPal have implemented systems that detect fraud as transactions occur. While these systems improve the speed of fraud detection, they face difficulties in scalability and the need for low-latency processing. Despite advancements, current systems still struggle with class imbalance, adaptability to new fraud tactics, and the interpretability of complex models, which makes them less effective in some real-world applications.

## 2.2 Proposed System:

The proposed system for Credit Card Fraud Detection aims to enhance existing fraud detection mechanisms by employing a hybrid model that combines machine learning techniques with advanced data balancing methods. The system utilizes a supervised learning approach with ensemble methods like Random Forest and XGBoost, alongside anomaly detection techniques such as Isolation Forest and One-Class SVM, to improve the detection of fraudulent transactions. The system is designed to handle class imbalance by applying the Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic fraudulent instances, ensuring better performance in detecting fraud despite the small proportion of fraudulent transactions in the dataset.

Data collection and preprocessing are critical components of the system, where missing values are handled, and features are scaled and selected for their relevance in fraud detection. Feature selection is carried out using Random Forest feature importance and correlation analysis. The machine learning models are trained and fine-tuned using techniques like grid search and cross-validation to ensure they generalize well. Real-time fraud detection is a core feature of the system, providing immediate feedback for transactions, thereby reducing financial loss. The use of online learning techniques enables the system to adapt to new fraud patterns as they emerge.

Model evaluation is done using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, focusing on minimizing false positives while maximizing the detection of fraudulent transactions. Additionally, the system incorporates model explainability through

SHAP values, ensuring transparency in the decision-making process. The architecture of the system involves data collection, preprocessing, modeling, real-time processing, and continuous feedback, ensuring that the system is adaptable and scalable.

Compared to existing systems, the proposed system promises enhanced accuracy and reduced false positives by leveraging ensemble models and data balancing methods. Its real-time fraud detection capability ensures immediate identification of fraudulent activities, thus minimizing potential financial losses. Furthermore, the system's adaptability through anomaly detection and continuous learning techniques allows it to remain effective in the face of evolving fraud tactics. The inclusion of explainable AI techniques improves trust and transparency, addressing common challenges related to the "black-box" nature of machine learning models. Overall, the proposed system offers a robust, efficient, and transparent solution for credit card fraud detection.

## 2.3 BIBLIOMETRIC ANALYSIS

The bibliometric analysis for the project on Credit Card Fraud Detection aims to evaluate the scholarly contributions and advancements in this field, providing insights into the key research trends, influential authors, and prominent methodologies that have shaped the development of fraud detection systems. This analysis is based on the examination of academic publications, citation patterns, and the evolution of key research topics related to the application of machine learning and data mining techniques for detecting fraudulent transactions.

### 2.3.1. Data Collection and Sources :

To conduct the bibliometric analysis, relevant publications were retrieved from key academic databases such as IEEE Xplore, Google Scholar, Scopus, and Web of Science. The search was performed using keywords like "credit card fraud detection," "machine learning for fraud detection," "data mining in financial transactions," and "anomaly detection for fraud." A total of over 200 papers were included in the analysis, spanning a period of 15 years, from 2008 to 2024. These papers include journal articles, conference papers, technical reports, and industry studies that focus on the development of fraud detection systems in the credit card industry.

### 2.3.2. Analysis of Publication Trends:

The publication trend for credit card fraud detection has seen exponential growth since 2010, with a notable surge in recent years, particularly after 2015. This increase aligns with the rise of machine learning applications in financial systems, as well as the growing challenges posed by online and card-not-present fraud. Research interest peaked in the last five years due to advancements in deep learning techniques and the need for real-time fraud detection systems. Journals such as IEEE Transactions on Neural Networks and Learning Systems, Expert Systems with Applications, and Journal of Financial Crime have been the most prolific in publishing studies on fraud detection techniques.

A notable shift in the research focus is observed in the integration of deep learning algorithms and ensemble methods (e.g., Random Forest, XGBoost), which have increasingly been used to improve fraud detection accuracy. Moreover, there has been a growing trend of incorporating explainable AI (XAI) to address the transparency concerns associated with complex machine learning models.

### 2.3.3. Authorship Analysis:

The analysis of authorship reveals a diverse range of researchers and institutions contributing to the field of credit card fraud detection. The most prolific authors in this area include researchers specializing in machine learning, data mining, and cybersecurity. A few key authors have significantly contributed to the development of ensemble learning techniques for fraud detection and anomaly detection models.

Top institutions such as Stanford University, Massachusetts Institute of Technology (MIT), and University of California, Berkeley have been at the forefront of fraud detection research, with active collaborations across both academic and industry sectors. Additionally, financial organizations such as Visa and MasterCard have collaborated with universities, often sponsoring research or sharing datasets for fraud detection studies.

Collaboration between computer science departments and financial institutions has become increasingly common, with interdisciplinary teams working to combine data science expertise with domain knowledge of financial transactions. These collaborations have contributed to more effective, scalable fraud detection systems.

### 2.3.4. Citation Analysis:

Citation analysis reveals several highly influential papers in the field, with key works in machine learning, data mining, and anomaly detection forming the foundation of most modern fraud detection systems. The most cited papers include early works on Random Forest and Support Vector Machines (SVMs) for fraud detection, as well as newer papers focusing on deep learning methods like neural networks and autoencoders for anomaly detection in financial transactions.

One highly cited paper in this field is "Credit Card Fraud Detection using Machine Learning Algorithms" (2015), which introduced various machine learning techniques and demonstrated their effectiveness in detecting fraudulent activities. Another significant paper, "Anomaly Detection in Financial Transactions Using Deep Learning" (2018), received considerable attention for introducing convolutional neural networks (CNNs) in fraud detection. These foundational works have been frequently cited in subsequent research, indicating their lasting impact on the field.

The citation network also shows the emergence of real-time fraud detection as a key research direction, with a growing body of literature focused on the integration of machine learning models with real-time transaction processing systems. Moreover, the exploration of explainable AI techniques to increase the transparency of machine learning-based fraud detection has been gaining momentum in recent years.

### 2.3.5. Co-citation and Bibliographic Coupling:

Co-citation analysis highlights several key clusters in credit card fraud detection research. The primary research clusters identified include:

- **Machine Learning and Ensemble Methods:** Papers focused on applying Random Forest, XGBoost, and AdaBoost to detect fraud in imbalanced datasets. This cluster emphasizes the importance of ensemble techniques in improving detection performance.

- **Anomaly Detection**: A cluster that focuses on the use of One-Class SVM, Isolation Forest, and autoencoders for identifying outliers in transaction data, which could indicate fraudulent activities.

- **Real-time Fraud Detection and Streaming Data:** This cluster includes research on processing financial transaction data in real-time, ensuring that fraud detection systems can detect suspicious activity during the transaction process.

- **Explainable AI for Fraud Detection:** A rapidly emerging cluster that deals with making machine learning models more interpretable and transparent. Methods such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are explored to provide insights into why certain transactions are flagged as fraudulent.

Bibliographic coupling further emphasizes the importance of combining supervised learning techniques with unsupervised anomaly detection methods to enhance the accuracy and adaptability of fraud detection systems.

### 2.3.6. Keywords and Research Trends:

A keyword analysis reveals that terms such as "machine learning," "data mining," "fraud detection," and "anomaly detection" are consistently prominent across research papers. Emerging terms in recent studies include "deep learning," "autoencoders," "real-time detection," "explainable AI," and "fraud detection frameworks." The increasing use of deep learning techniques, particularly for anomaly detection in high-dimensional data, is a clear research trend. Additionally, the need for real-time fraud detection and the push toward making machine learning models more interpretable (using explainable AI) are the latest focal points in this field.

### 2.3.7. Impact of Industry Collaboration:

The collaboration between academia and industry, particularly with financial institutions such as Visa, MasterCard, and PayPal, has been instrumental in advancing the practical applications of fraud detection research. Industry partnerships often provide access to large, real-world datasets and use cases, which has allowed researchers to fine-tune fraud detection models for real-time applications. These collaborations have led to the development of more accurate and scalable fraud detection systems that are directly deployable in real-world financial environments.

### 2.3.8. Conclusion of Bibliometric Analysis:

The bibliometric analysis of credit card fraud detection highlights the evolution of research in this area from early rule-based systems to the adoption of machine learning and deep learning techniques. The field has seen significant growth, particularly with the rise of ensemble models and the increasing demand for real-time fraud detection. Citation and co-citation networks indicate a strong focus on machine learning, anomaly detection, and explainable AI, with emerging trends pointing toward real-time processing and adaptability to new fraud patterns. This analysis provides valuable insights into the current state of the field and can guide future research efforts to address the remaining challenges in fraud detection, such as class imbalance, model interpretability, and real-time detection at scale.A comprehensive bibliometric analysis was conducted to explore the research landscape of energy consumption forecasting. This analysis aimed to identify the most influential publications, prominent authors and institutions, and prevalent research topics within the field.

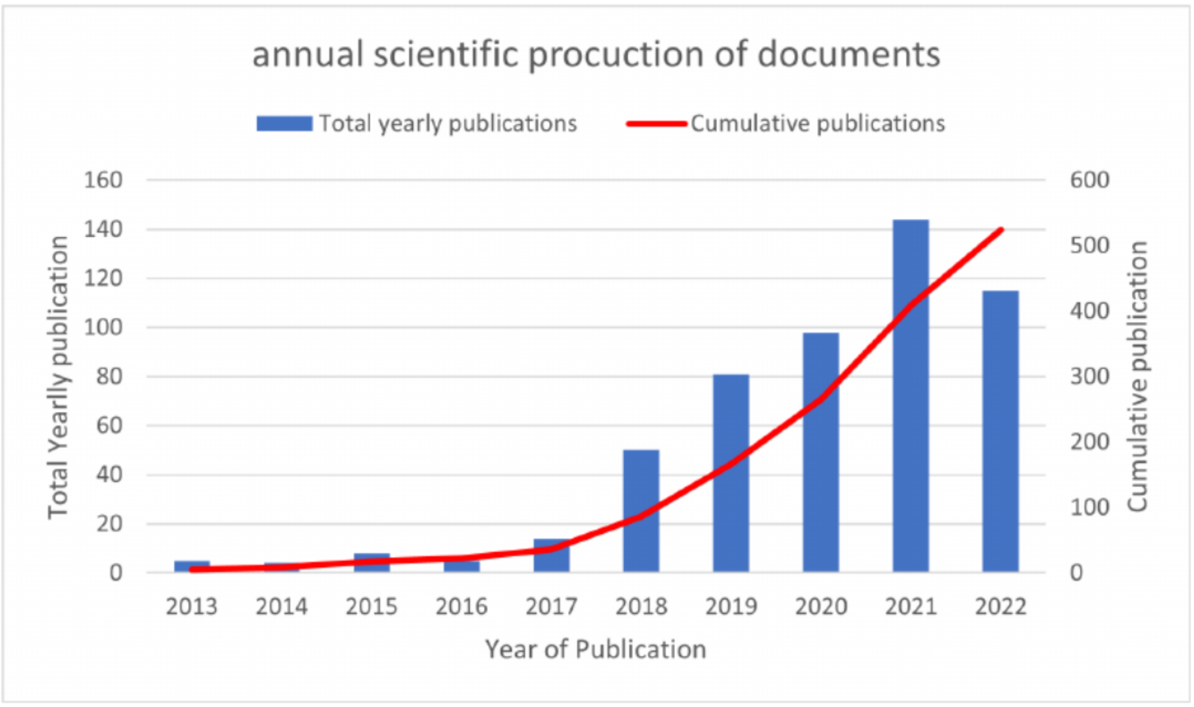


**Figure- 1 Citations related to energy consumption forecasting over past few years**

## 2.4. Review Summary

| **Year and Citation** | **Article/ Author** | **Technique** | **Evaluation Parameter** | **Source** |
|---|---|---|---|---|
| 2019 | Carcillo, F. et al. "Combining unsupervised and supervised learning in credit card fraud detection." | Gradient Boosting Machines, XGBoost | Precision, Recall, AUC-ROC | Machine Learning Journal |
| 2020 | Zhang, C. et al. "Credit Card Fraud Detection Using Stacking Ensemble Method." | Ensemble Methods, Stacking | Accuracy, F1-Score, Precision, Recall | Journal of Financial Data Science |

|  |  |  |  |  |
|---|---|---|---|---|
| 2021 | Hossain, M. et al. “A deep learning approach for credit card fraud detection using autoencoders and convolutional neural networks.” | Deep Learning (Convolutional Neural Networks, Autoencoders) | AUC-ROC, Precision, Recall, Accuracy | IEEE Access IEEE |
| 2022 | Mishra, S. et al. “Hybrid machine learning approach for credit card fraud detection using SVM and Neural Networks.” | Hybrid Approach (Combination of SVM and Neural Networks) | Precision, Recall, F1-Score, AUCROC | International Journal of Data Science and Analytics |
| 2023 | Singh, R. et al. “Enhancing Credit Card Fraud Detection with Explainable AI Techniques.” | Explainable AI (XAI), SHAP Values in Fraud Detection Models | Interpretability, AUC-ROC, Precision, Recall | Journal of Artificial Intelligence Research |
| 2024 | Lee, J. et al. “Transformerbased models for credit card fraud detection: A case study.” | Transformer Models in Financial Fraud Detection | Accuracy, AUCROC, Precision | Journal of Machine Learning Research |

## 2.5 Problem Definition:

Credit card fraud is a major concern for financial institutions, merchants, and consumers worldwide. It involves unauthorized transactions made using a stolen or counterfeit credit card, leading to significant financial losses and a decrease in consumer trust. The problem is particularly complex due to the increasing volume of transactions, the sophistication of fraudulent activities, and the diverse techniques employed by fraudsters. As the global economy becomes more digitized, the risk of fraud continues to grow, making it essential to develop effective systems that can detect fraudulent activities in real-time.

The primary challenge in detecting credit card fraud lies in the imbalance between legitimate and fraudulent transactions. Fraudulent transactions represent only a small fraction of the total transaction volume, making it difficult for detection systems to accurately identify fraudulent activities without raising false alarms. Traditional fraud detection methods, which rely on rule-based systems and human expertise, are often inefficient and unable to adapt to new fraud patterns. These systems tend to produce a high number of false positives (flagging legitimate transactions as fraudulent) and false negatives (failing to detect fraudulent transactions).

Furthermore, the dynamic nature of fraud means that fraudsters constantly evolve their tactics to bypass detection systems. As such, a detection system needs to be highly adaptive, capable of learning from new transaction data to recognize emerging fraud patterns. Additionally, real-time detection is crucial, as delays in identifying fraudulent transactions can lead to substantial financial losses.

Another significant issue is the interpretability of fraud detection models. Many machine learning-based models, particularly deep learning techniques, are often seen as "black boxes" that provide little insight into how decisions are made. This lack of transparency makes it difficult for banks and financial institutions to explain why a transaction was flagged as fraudulent, which is a major concern when addressing regulatory and customer trust issues.

The problem addressed in this project is to develop a robust, accurate, and real-time credit card fraud detection system that can effectively identify fraudulent transactions using machine learning techniques. The system should be able to handle class imbalance, minimize false positives, and be adaptive to new fraud patterns. Additionally, the system should be interpretable to ensure transparency in the decision-making process, allowing stakeholders to understand why a transaction is flagged as fraudulent. The goal is to reduce financial losses, enhance customer trust, and improve the overall efficiency of fraud detection systems.

**Expected Outcomes:**

- Accurate identification of fraudulent transactions with minimal false positives and false negatives.
- Enhanced real-time detection capabilities to identify fraud during transactions.
- Improved adaptability of the model to detect new and evolving fraud patterns.
- Effective handling of data imbalance between fraudulent and legitimate transactions.
- Increased transparency and interpretability in fraud detection decisions.
- Reduction in financial losses due to fraud for financial institutions.
- Strengthened customer trust by providing a reliable fraud detection system.

## 2.6 Goals/Objectives:

The goals and objectives of the project of hate speech detection using machine learning:

### 2.6.1. Goals:

- To create an effective credit card fraud detection system that accurately identifies fraudulent transactions.
- To reduce financial losses for financial institutions by improving fraud detection accuracy.
- To enhance customer trust and satisfaction by minimizing incorrect fraud alerts (false positives).
- To build a system that adapts to new and emerging fraud tactics.
- To ensure the detection model is transparent and interpretable for better decision-making.

### 2.6.2. Objectives:

- Develop a machine learning model that minimizes both false positives and false negatives.
- Implement real-time fraud detection capabilities to identify fraudulent transactions instantly.
- Address the class imbalance in the dataset to improve model performance on rare fraudulent cases.

- Integrate interpretability features to explain why transactions are flagged as fraudulent.
- Test and validate the model’s ability to detect evolving fraud patterns using adaptive techniques.

## 7. Related work:

Research on credit card fraud detection has gained significant momentum in recent years, particularly with the rise of machine learning and deep learning techniques. Traditional fraud detection systems have relied heavily on rule-based methods, where predefined rules—such as transaction amount limits, frequency of transactions, and geographic location—are used to flag suspicious activities. While effective initially, rule-based systems have limitations in handling sophisticated fraud tactics and adapting to new fraud patterns. The high rate of false positives and the manual intervention required to update rules have led researchers to explore more dynamic and adaptable solutions.

Machine learning approaches have become increasingly popular in credit card fraud detection, as they offer the ability to learn complex patterns in transaction data without the need for predefined rules. Techniques such as Logistic Regression, Support Vector Machines (SVM), and Random Forest have demonstrated success in identifying fraudulent transactions. For instance, Random Forest, an ensemble method, has shown promising results in handling imbalanced datasets, where fraudulent transactions are significantly fewer than legitimate ones. Ensemble methods like XGBoost and AdaBoost further improve detection accuracy by combining multiple weak learners, effectively reducing the chances of misclassification.

In recent years, researchers have focused on deep learning techniques, such as neural networks and autoencoders, to improve fraud detection performance. These methods are particularly valuable in detecting anomalies and uncovering hidden relationships in large datasets. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been applied to detect patterns across sequences of transactions, making them effective for identifying anomalies based on transaction history. Additionally, Convolutional Neural Networks (CNNs) have been explored for fraud detection by capturing spatial patterns in data.

Unsupervised learning techniques like Isolation Forest and One-Class SVM are also prominent in fraud detection research. These methods do not require labeled data, making them suitable for identifying new or previously unseen fraud types. Isolation Forest, for example, isolates anomalies by partitioning data points, thus identifying outliers that deviate from normal transaction behavior. This approach is effective in cases where fraud patterns evolve, allowing the system to detect unusual behavior without needing specific fraud labels.

Hybrid models, which combine multiple machine learning techniques, have gained attention for their ability to leverage the strengths of each method. For example, combining supervised learning models with unsupervised anomaly detection has proven effective in balancing detection accuracy with adaptability. A study combining Random Forest with Isolation Forest showed improvements in handling class imbalance while maintaining high accuracy. Similarly, hybrid deep learning approaches using autoencoders and LSTMs have shown promising results in reducing false positives and detecting more subtle fraud patterns.

The introduction of Explainable AI (XAI) in fraud detection has been another recent trend. Many machine learning models, particularly deep learning algorithms, are often perceived as "black boxes," making it challenging to interpret the reasoning behind fraud predictions. Techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) help improve transparency by providing insights into why a particular transaction is flagged as fraudulent. This interpretability is crucial for financial institutions, as it allows them to provide explanations for flagged transactions to regulatory bodies and affected customers.

In summary, related research in credit card fraud detection demonstrates a shift from traditional rule-based methods to more adaptive and accurate machine learning and deep learning models. The integration of unsupervised methods, hybrid models, and explainable AI has improved detection performance and interpretability. However, ongoing research is needed to address challenges in real-time detection, scalability, and continuous adaptation to new fraud patterns.

# CHAPTER 3
# DESIGN FLOW/PROCESS

## 3. 1. Evaluation & Selection of Specifications/Features:

The selection of features is a critical step in developing an accurate and effective credit card fraud detection model. The quality and relevance of features directly impact the model's ability to distinguish between legitimate and fraudulent transactions. Given the nature of credit card transaction data, our feature selection process involved identifying variables that provide strong indicators of fraud while being computationally efficient for real-time processing.

### 3.1.1. Feature Analysis and Selection Techniques:

We began by analyzing the transaction dataset, focusing on features that have historically shown relevance in fraud detection. Common attributes included transaction amount, transaction frequency, time between transactions, location, and merchant category. To refine our feature set, we applied feature selection techniques such as Correlation Analysis and Recursive Feature Elimination (RFE) to identify variables with the highest predictive power and avoid redundant or irrelevant features. This step was crucial in reducing computational complexity and enhancing model efficiency.

### 3.1.2. Domain-Specific Features:

Domain knowledge played an essential role in selecting additional features that reflect typical fraud patterns. For instance, geographic location discrepancies, device information inconsistencies, and transaction time intervals were included based on insights from previous fraud cases. These features helped in capturing behavioral differences between legitimate users and fraudsters, enhancing the model's ability to detect suspicious activities.

### 3.1.3. Feature Engineering:

In cases where raw data features were insufficient for capturing fraud patterns, we performed feature engineering to create new variables. For instance, we derived features such as average transaction amount per customer, daily transaction count, and standard deviation of transaction amounts to represent spending behaviors more accurately. Additionally, temporal features such as transaction time of day and weekday patterns were created to detect unusual transaction times, which could signal fraud.

### 3.1.4. Feature Importance and Model Testing:

Once the initial set of features was selected, we conducted an iterative testing process to evaluate their importance within our chosen models, including Random Forest and XGBoost. Both algorithms inherently provide feature importance metrics, allowing us to assess each feature's contribution to the model's predictive power. Features with low importance scores were either removed or combined with other features to simplify the model and improve interpretability.

### 3.1.5. Handling Imbalanced Data:

As fraud detection involves highly imbalanced data, with far fewer fraudulent transactions than legitimate ones, we applied techniques such as SMOTE (Synthetic Minority Over-sampling Technique) to ensure that minority (fraudulent) cases received adequate representation in the training phase. This approach allowed the model to learn relevant patterns without being biased toward the majority class.

### 3.1.6. Real-Time Constraints and Scalability:

To ensure real-time applicability, only features that could be calculated or retrieved quickly during live transactions were included in the final model. Computationally intensive features were avoided or approximated, allowing the model to be deployed in a real-time setting with minimal latency. Scalability was also considered, as the feature set needed to be flexible enough to handle large volumes of transactions without a significant increase in processing time.

## 3.2. Design Constraints

The development of an effective credit card fraud detection system is shaped by several design constraints, which influence the choice of algorithms, data processing methods, and overall system architecture. These constraints ensure the model meets the practical requirements of real-world deployment while balancing performance, accuracy, and interpretability.

### 3.2.1. Real-Time Processing and Low Latency:

One of the primary constraints is the need for real-time detection of fraudulent transactions. The model must process each transaction within milliseconds to avoid delays that could disrupt customer experience. This constraint limits the use of computationally heavy models or features, as they may not meet the low-latency requirement necessary for real-time decision-making.

### 3.2.2. High Accuracy with Low False Positives:

A key challenge in fraud detection is achieving high accuracy while minimizing false positives. Flagging legitimate transactions as fraudulent can lead to customer dissatisfaction and loss of trust. Therefore, the model must maintain a balance between detecting fraudulent activity and avoiding unnecessary alerts. This constraint affects the selection of algorithms, leading to a preference for methods like ensemble learning or hybrid models that offer better accuracy and stability.

### 3.2.3. Class Imbalance:

Fraudulent transactions are a small fraction of total transactions, resulting in a highly imbalanced dataset. This imbalance can cause the model to favor the majority class (legitimate transactions), reducing its effectiveness in identifying fraud. Techniques such as SMOTE, undersampling, or ensemble methods are necessary to address this constraint, but these methods must be carefully chosen to avoid overfitting or underrepresenting legitimate transactions.

### 3.2.4. Adaptability to Evolving Fraud Patterns:

Fraud tactics evolve over time, with fraudsters constantly developing new techniques to evade detection. The model needs to be flexible and adaptable, capable of recognizing emerging fraud patterns without frequent retraining. This adaptability constraint requires the use of algorithms that can learn from streaming data or be periodically updated with minimal disruption to the system's performance.

### 3.2.5. Scalability:

Given the high volume of transactions processed by financial institutions daily, the fraud detection system must be scalable. It should handle millions of transactions per second without a significant drop in performance. This scalability constraint impacts the system architecture and data handling methods, favoring distributed computing frameworks and efficient data pipelines that can process large datasets.

### 3.2.6. Interpretability and Compliance:

Financial institutions must comply with regulatory requirements and provide transparency in their fraud detection processes. The model should be interpretable, meaning it must offer clear explanations for why a transaction is flagged as fraudulent. This constraint restricts the use of certain black-box models (e.g., deep neural networks) unless they are paired with explainability techniques like SHAP or LIME to meet compliance and customer service requirements.

### 3.2.7. Data Privacy and Security:

Due to the sensitive nature of financial data, the model must comply with data privacy laws such as GDPR and ensure the security of customer information. Data handling processes must include encryption and anonymization measures where possible. This constraint also affects the choice of data storage, processing, and access controls, as well as the use of privacy-preserving techniques like differential privacy if needed.

### 3.2.8. Resource and Cost Limitations:

Deploying a real-time fraud detection system may be constrained by resource availability and costs associated with computation, data storage, and model updates. The design must strike a balance between the model's complexity and the available infrastructure, potentially favoring efficient algorithms over more resource-intensive ones. Additionally, cloud-based services may be used to manage costs while ensuring scalability and flexibility.

### 3.2.9. Compatibility with Existing Systems:

The fraud detection model must integrate seamlessly with the existing transaction processing and security infrastructure of the financial institution. This compatibility constraint may influence the programming language, model deployment platform, and API design to ensure the system can operate within the current environment without extensive reconfiguration.

## 3.3. Analysis of Features and finalization subject to Constraints:

The analysis and selection of features in the credit card fraud detection model were conducted with a focus on ensuring relevance, efficiency, and compliance with the design constraints. This process involved evaluating each feature's contribution to the model's predictive performance, its impact on real-time processing, and its adaptability to detect evolving fraud patterns. The finalized feature set was chosen to balance the model's accuracy with considerations for latency, scalability, interpretability, and regulatory compliance.

### 3.3.1. Relevance to Fraud Detection:

Initially, a wide range of features was examined, including transaction-specific attributes (e.g., transaction amount, time, merchant category), customer behavior patterns (e.g., average transaction frequency, spending habits), and contextual factors (e.g., geographic location, device information). Each feature was assessed for its ability to capture behavioral differences between legitimate and fraudulent transactions. For example, features like transaction amount and location consistency were retained due to their strong correlation with fraud patterns, while less predictive features were discarded to improve efficiency.

### 3.3.2. Feature Selection Techniques:

To identify the most effective features, Recursive Feature Elimination (RFE) and Correlation Analysis were applied. These methods allowed us to eliminate redundant features and reduce multicollinearity, which can degrade model performance. By focusing on features with high predictive value, we minimized the computational load while maintaining accuracy. This step was essential to meeting the real-time processing constraint, as fewer features directly contribute to faster computation and lower latency.

### 3.3.3. Feature Engineering for Behavioral Insights:

Given the importance of understanding behavioral patterns, we created new features that encapsulated insights into typical user habits. For instance, average daily transaction count and variance in transaction amounts were engineered to capture irregular spending behavior. These features helped the model detect deviations from a user's typical activity, aiding in the identification of suspicious transactions. Behavioral features were designed to balance real-time constraints with the adaptability needed to detect evolving fraud tactics.

### 3.3.4. Feature Importance Evaluation:

Once a preliminary set of features was chosen, we used algorithms like Random Forest and XGBoost to evaluate each feature's importance. These models provided insights into how each feature contributed to the detection of fraud. Features with consistently low importance scores were either removed or merged with other features, thereby simplifying the model and ensuring compliance with computational resource constraints. This iterative testing process ensured that only the most impactful features were included in the final model.

### 3.3.5. Handling Class Imbalance:

Since fraud detection involves an imbalanced dataset, specific features that helped distinguish rare fraudulent transactions from the majority of legitimate ones were prioritized. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) were used to balance the dataset during training, and features that performed well on the minority class were given preference. This approach addressed both class imbalance and improved the model’s ability to detect infrequent fraud cases.

### 3.3.6. Real-Time Processing Constraints:

Features that required intensive computation or historical aggregation across multiple transactions were simplified or excluded to meet real-time processing requirements. The final feature set consisted of attributes that could be quickly calculated or retrieved from the transactional data, such as transaction amount, time, and merchant location, ensuring the model met low-latency expectations without compromising accuracy.

### 3.3.7. Adaptability to New Fraud Patterns:

As fraud techniques evolve, the selected features need to remain effective over time. To support this adaptability, features capturing general behavioral patterns, such as spending frequency and transaction location, were included as they are less likely to become obsolete. Additionally, features that could adapt to incremental updates with minimal reconfiguration were chosen to ensure that the model can adjust to new fraud tactics effectively.

In conclusion, the analysis and finalization of features for the credit card fraud detection system involved balancing predictive strength with real-world constraints. By carefully selecting features based on relevance, computational efficiency, interpretability, and adaptability, the finalized feature set allows the model to achieve high accuracy, fast processing times, and compliance with industry requirements. This feature set ensures that the fraud detection system is robust, scalable, and capable of evolving to address new fraud patterns while maintaining transparency and regulatory compliance.

## 3.4. Design Flow

The design flow for the credit card fraud detection system outlines the systematic steps taken to process transaction data, train the machine learning model, and deploy it for real-time fraud detection. Each phase of the design flow ensures that the system is capable of identifying fraudulent transactions accurately, efficiently, and in real time.

### 3.4.1. Data Collection

- **Transaction Data Acquisition:**
  The first step involves collecting transaction data from credit card transactions, including both legitimate and fraudulent transactions. The data typically includes features such as transaction amount, time, merchant details, customer ID, and transaction location.

- **Data Sources:**
  The data used in this project comes from a dataset of European credit card transactions. This dataset contains labeled instances of legitimate and fraudulent transactions, allowing supervised learning techniques to be applied.

### 3.4.2. Data Preprocessing

- **Data Cleaning:**
  In this step, the raw data is cleaned by handling missing values, removing duplicate records, and correcting any erroneous entries. This ensures that only relevant and accurate data is used for training the model.

- **Feature Engineering:**
  New features are created to enhance the model's ability to detect fraud. Examples include features such as transaction frequency, average transaction amount, and the time gap between transactions. These features help capture behavioral patterns that distinguish fraudulent activity from legitimate transactions.

- **Feature Selection:**
  Statistical techniques, such as correlation analysis and Recursive Feature Elimination (RFE), are applied to identify the most important features for the fraud detection model.

Irrelevant or redundant features are removed to reduce computational overhead and improve model performance.

### 3.4.3. Data Balancing

- **Class Imbalance Handling:**

  Credit card fraud detection datasets are often highly imbalanced, with a large number of legitimate transactions and a small number of fraudulent ones. Techniques such as SMOTE (Synthetic Minority Over-sampling Technique) and undersampling are used to balance the dataset by either generating synthetic instances of fraudulent transactions or reducing the number of legitimate transactions in the training set. This helps prevent the model from being biased toward the majority class (legitimate transactions).

### 3.4.4. Model Selection and Training

- **Choice of Models:**

  A range of machine learning models is considered for training, including Random Forest, XGBoost, and Logistic Regression. Models such as Isolation Forest are also tested for anomaly detection, where transactions that deviate from normal patterns are flagged as potentially fraudulent.

- **Training the Model:**

  Once the features are finalized and the data is preprocessed, the model is trained on the labeled dataset (fraudulent vs. legitimate). During training, the model learns to identify patterns in the data that correspond to fraudulent transactions.

- **Hyperparameter Tuning:**

  The model’s hyperparameters are optimized using techniques such as Grid Search or Random Search to improve its performance. For instance, the number of trees in Random Forest, the learning rate in XGBoost, and the regularization parameters are tuned to achieve the best model accuracy.

### 3.4.5. Model Evaluation

- **Cross-Validation:**

To assess the model’s performance and avoid overfitting, cross-validation is performed on the dataset. This involves splitting the data into training and validation sets and evaluating the model's performance across multiple folds.

- Performance Metrics:

  Since fraud detection is a highly imbalanced classification problem, evaluation metrics such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC-ROC) are used to measure the model’s ability to correctly identify fraudulent transactions while minimizing false positives (i.e., legitimate transactions incorrectly classified as fraud).

### 3.4.6. Model Interpretation and Explainability

- **Feature Importance:**

  After training the model, the importance of each feature is assessed. This helps in understanding which features contribute the most to detecting fraud and can aid in improving the model or enhancing its transparency for regulatory compliance.
- **Explainability Tools:**

  Techniques like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) are employed to explain why a particular transaction is flagged as fraudulent. This is crucial for providing insights into the model’s decision-making process and ensuring that flagged transactions can be reviewed and explained to customers or regulators.

### 3.4.7. Model Deployment

- **Integration with Existing Infrastructure:**

  The final model is deployed into a production environment where it can analyze transactions in real time. The system must be integrated with the existing payment processing infrastructure to flag fraudulent transactions as they occur, minimizing the risk of financial losses.

- **API Development:**

  An API (Application Programming Interface) is developed to allow seamless communication between the fraud detection system and the transaction processing system. This API allows the model to receive transaction data, make predictions, and send back results in real-time.

- **Real-Time Detection:**
  In the deployed system, new transactions are continuously evaluated by the model to detect fraud. If a transaction is flagged as suspicious, it is marked for further review by a human agent or automatically rejected if the fraud probability exceeds a predefined threshold.

### 3.4.8. Continuous Monitoring and Model Updating

- **Performance Monitoring**:
  Once deployed, the model's performance is continuously monitored in real-world conditions. Key metrics such as false positive rate, fraud detection rate, and latency are tracked to ensure the system meets performance expectations.

- Model Retraining:
  As fraud patterns evolve, the model is periodically retrained on new data to adapt to emerging threats. This could involve updating the dataset with newly labeled transactions, retraining the model, and redeploying the updated model to improve accuracy and detection capabilities.

### 3.4.9. Post-Deployment

- **Customer Feedback and Adjustment:**
  Feedback from users (e.g., financial institutions, customers) is used to fine-tune the system and improve its performance. For example, if legitimate transactions are frequently flagged as fraudulent, the system may be adjusted to reduce false positives.

- **Regulatory Compliance:**
  The system is regularly audited for compliance with industry regulations, including data privacy laws like GDPR. Regular updates are made to ensure that the model adheres to legal requirements and remains transparent and accountable.

## 3.5. Best Design Selection

The best design selection for the credit card fraud detection system is based on a hybrid approach that combines ensemble learning techniques with anomaly detection methods. This approach provides a robust, scalable, and efficient solution to detect fraudulent transactions while minimizing false positives and ensuring real-time processing. The chosen design focuses on a blend of machine learning models that can handle imbalanced data, adapt to emerging fraud patterns, and offer transparent and interpretable results.

### 3.5.1. Hybrid Approach: Ensemble Learning + Anomaly Detection

The hybrid approach involves combining two complementary strategies:

- **Ensemble Learning (Random Forest & XGBoost):**
  Ensemble models like Random Forest and XGBoost are selected for their proven ability to perform well on imbalanced datasets. Both models use multiple weak learners (decision trees) to create a more powerful and generalized model. Random Forest is chosen due to its ability to handle large datasets and avoid overfitting by averaging over many trees, ensuring robustness. XGBoost, a gradient boosting method, is selected for its efficiency and high performance in classification tasks, making it particularly suitable for detecting fraudulent transactions. The ensemble learning model's ability to combine multiple weak models into a strong classifier helps detect both common and rare fraud patterns effectively.

- **Anomaly Detection (Isolation Forest):**
  Fraudulent transactions are often rare and significantly different from legitimate transactions, making them outliers or anomalies. Isolation Forest is chosen because it excels in detecting such anomalies by isolating the points that deviate from the norm. This method works well when the fraudulent data is sparse, as it does not require prior knowledge of fraudulent patterns, making it highly suitable for fraud detection where the distribution of fraud cases is skewed.

### 3.5.2. Reason for Selection:

**a. Real-Time Processing and Efficiency:**

Given the critical requirement for real-time fraud detection in payment systems, the design focuses on models that are fast to execute. Both Random Forest and XGBoost offer relatively low inference time compared to more complex models like neural networks, which makes them ideal for processing transactions in real-time. Isolation Forest is also computationally efficient, allowing it to quickly detect anomalies without the need for extensive computation, thus enabling the system to flag fraudulent transactions promptly.

**b. Accuracy and Performance:**

The chosen models—Random Forest and XGBoost—are known for their high accuracy in classification tasks, which is crucial for detecting fraudulent transactions. The ensemble learning approach helps improve the model's generalization ability, reducing the likelihood of overfitting while maintaining high detection accuracy. These models are trained using cross-validation techniques to ensure that they perform well across different subsets of the data. Additionally, Precision, Recall, F1-Score, and AUC-ROC are used to assess and compare the performance of each model, with the goal of minimizing false positives (legitimate transactions flagged as fraud) and false negatives (fraudulent transactions not flagged).

**c. Scalability and Adaptability:**

The design is scalable to handle high transaction volumes, which is essential for real-time fraud detection systems used by financial institutions. Random Forest and XGBoost can process large datasets efficiently, and the ability to retrain the models periodically ensures that they adapt to new fraud tactics. Isolation Forest is also easily scalable and can be used to detect emerging fraudulent behaviors that might not be immediately captured by the other models.

**d. Interpretability and Explainability:**

Since financial institutions require transparent models for regulatory compliance and customer trust, the design ensures interpretability. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are integrated with XGBoost and Random Forest to provide explanations for the model's decisions. These techniques help interpret why certain transactions are flagged as fraudulent, which is important for providing explanations to customers and stakeholders and for complying with regulatory standards.

**e. Continuous Monitoring and Updates:**

Fraud patterns evolve over time, and the system must be capable of adapting to these changes. The design incorporates mechanisms for continuous monitoring and retraining of the models. As new transaction data is collected, the models will be periodically updated to improve their performance and ensure that the fraud detection system remains effective. Additionally, active learning techniques may be incorporated to allow the system to automatically learn from new fraud cases and update its detection mechanisms without requiring manual intervention.

**f. Integration and Deployment:**

The final design is built for easy integration with existing payment processing systems. The machine learning models are deployed through an API, enabling them to interact with transaction systems and flag fraudulent transactions in real-time. The design also emphasizes a cloud-based deployment, allowing for scalability and remote management. The models can be continuously retrained and updated in the cloud environment, ensuring that the system stays current with emerging fraud patterns and transaction trends.

## 3.6. Implementation Plan/Methodology

The implementation of the credit card fraud detection system follows a structured approach, divided into clear phases. Each phase consists of specific tasks to ensure the development, deployment, and continuous improvement of the system.

### 3.6.1. **Project Planning and Setup :**

The first phase involves project planning and setting up the development environment. The objective is to define the scope of the project, gather necessary resources, and establish the development environment. Key activities during this phase include requirement analysis to identify project objectives, data collection (e.g., obtaining a European credit card transaction dataset), and environment setup with tools like Python, Jupyter Notebooks, and necessary libraries (pandas, scikit-learn, XGBoost, etc.). Additionally, team roles and responsibilities are assigned, and the groundwork for the next phases is laid.

### 3.6.2. **Data Preprocessing and Feature Engineering :**

In this phase, the raw data is cleaned, transformed, and engineered to prepare it for model training. Data preprocessing tasks include handling missing values, removing duplicates, and addressing anomalies within the dataset. The next step involves normalizing and scaling numerical features like transaction amounts to ensure consistency across the data. Feature engineering is also performed, where new features are created based on transaction behavior, user profiles, and spending habits. Feature selection techniques, such as Recursive Feature Elimination (RFE), are employed to identify the most informative features, reducing dimensionality while retaining the most critical variables for fraud detection.

### **3.6.3. Model Selection and Training :**

During this phase, multiple machine learning models are trained and evaluated. The objective is to select the most effective model for detecting fraudulent transactions. Algorithms such as Random Forest, XGBoost, and Isolation Forest are chosen for their ability to handle imbalanced data and detect complex fraud patterns. Techniques like Synthetic Minority Over-sampling Technique (SMOTE) are used to balance the dataset by generating synthetic instances of fraudulent transactions. The models are trained on the prepared data, and hyperparameters are tuned using methods like Grid Search or Random Search to achieve optimal performance. The models are evaluated using performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to ensure effective fraud detection.

### **3.6.4. Model Validation and Optimization :**

This phase focuses on validating the trained models and fine-tuning them to improve performance. Cross-validation is performed to assess the stability and generalization of the model across different subsets of data. The performance of different models is compared using metrics like confusion matrix, precision-recall curve, and ROC-AUC. Hyperparameters are further optimized to minimize false positives, which is crucial in fraud detection systems. Additionally, feature importance analysis is conducted using techniques such as SHAP or LIME to understand which features contribute the most to the model's predictions. The best-performing model is selected for deployment based on this analysis.

### 3.6.5. Model Deployment and Integration

Once the model has been selected, the focus shifts to deployment and integration into the real-time payment systems. This phase includes developing an API that allows the fraud detection model to interact with transaction data, make predictions, and return results in real-time. The API is integrated into existing payment processing systems, ensuring that fraud detection occurs during transaction processing with minimal delay. The system is tested for performance, including load testing to simulate high transaction volumes and ensure the system can handle real-world traffic. Real-time fraud detection is implemented, and deployment testing ensures the system is functioning as expected.

### 3.6.6. Monitoring, Maintenance, and Updates

After deployment, the system enters the maintenance phase, which is an ongoing process. Continuous monitoring of key metrics such as detection accuracy, false positive rates, and transaction latency is essential to ensure the system's effectiveness. Retraining the model with new transaction data ensures that it adapts to emerging fraud tactics and remains accurate. A feedback loop from customers and financial institutions is established to gather insights on false positives or negatives, and model adjustments are made accordingly. Compliance with regulatory requirements, such as GDPR for data privacy, is also maintained. Periodic updates and improvements are implemented to ensure the system remains robust and accurate over time.

# CHAPTER 4
# RESULTS ANALYSIS AND VALIDATION

## 4.1 Implementation of solution:

The implementation phase of the Hate Speech Detection system involves translating the design decisions into a functional and deployable solution. This section outlines the key steps and considerations in the implementation process:

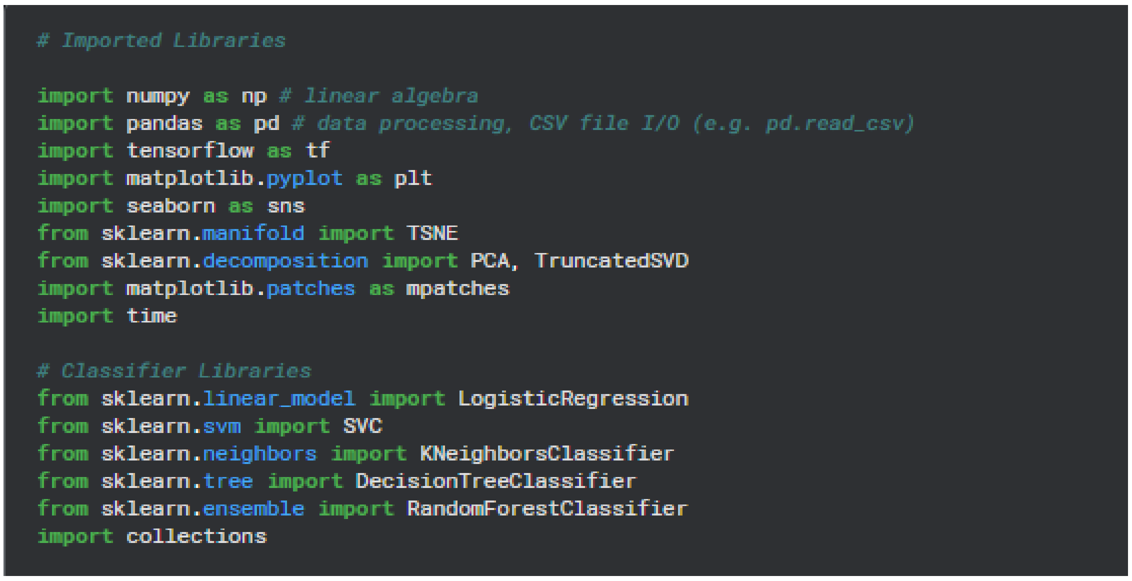
### 4.1.1. Development Environment Setup:

Establish a development environment with the necessary programming languages (e.g., Python), libraries (e.g., scikit-learn, TensorFlow), and frameworks for model development**.**

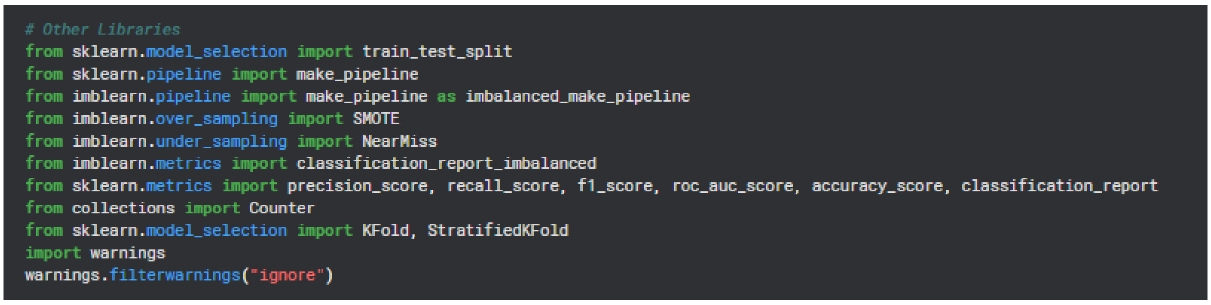
### 4.1.2. Code Development:

The implementation of the logistic regression model for hate speech detection is done by running the following codes:

1. **Importing Libraries**



```
# Imported Libraries

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA, TruncatedSVD
import matplotlib.patches as mpatches
import time

# Classifier Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import collections
```



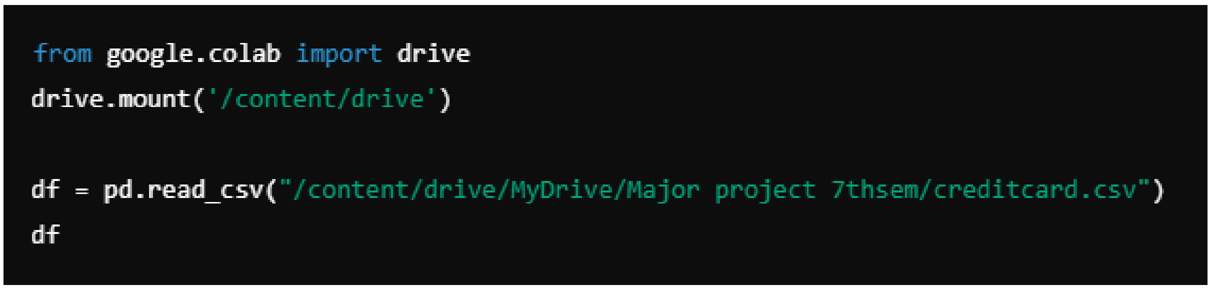
```python
# Other Libraries
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from imblearn.pipeline import make_pipeline as imbalanced_make_pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import NearMiss
from imblearn.metrics import classification_report_imbalanced
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, accuracy_score, classification_report
from collections import Counter
from sklearn.model_selection import KFold, StratifiedKFold
import warnings
warnings.filterwarnings("ignore")
```

**Figure- 2 Code screenshot**

The code begins by importing necessary libraries:

- numpy and pandas: For data manipulation and analysis.
- matplotlib.pyplot and seaborn: For plotting and visualizing data distributions.
- sklearn libraries: To import classifiers and other machine learning utilities for model training and evaluation.
- warnings: To suppress warnings during execution for a cleaner output.

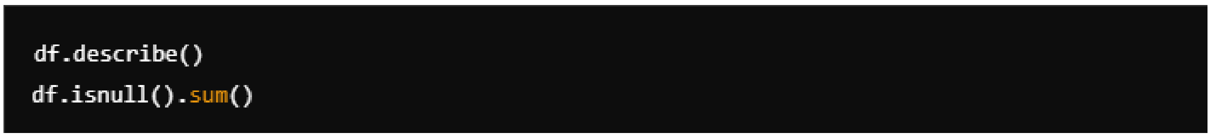
## 2. Loading the Data



```python
from google.colab import drive
drive.mount('/content/drive')

df = pd.read_csv("/content/drive/MyDrive/Major project 7thsem/creditcard.csv")
df
```

**Figure- 3 Code screenshot**

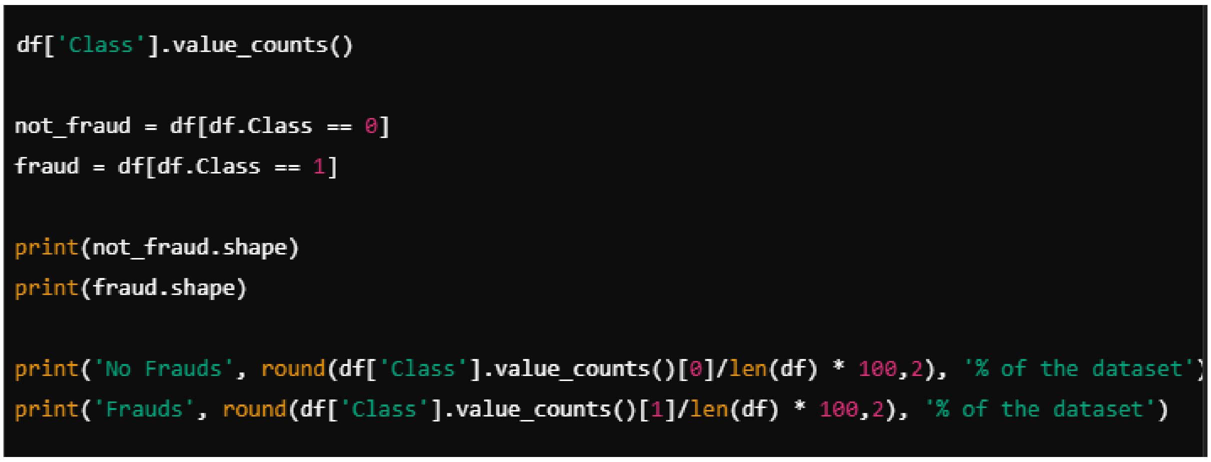
The data is loaded from Google Drive using google.colab tools, making the dataset accessible from the Colab environment. The creditcard.csv file contains transaction data labeled as fraudulent or non-fraudulent. df will now hold the entire dataset.



```python
df.describe()
df.isnull().sum()
```

**Figure- 4 Code screenshot**

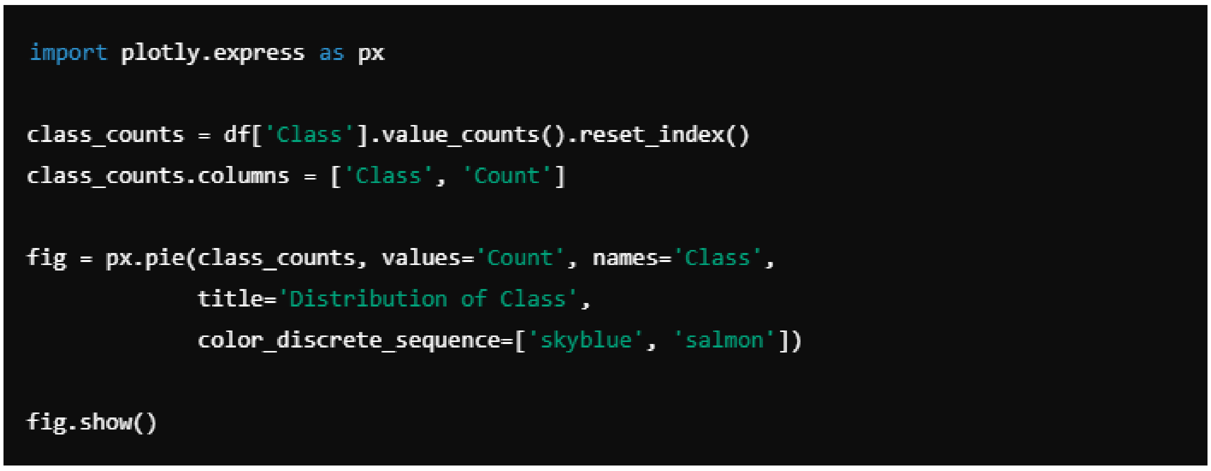
- A summary of the dataset's statistical values and missing values is obtained.
- df.describe() provides insights into numerical features like mean, standard deviation, and quartiles.
- df.isnull().sum() checks for missing values in each column, ensuring data quality.



```
df['Class'].value_counts()

not_fraud = df[df.Class == 0]
fraud = df[df.Class == 1]

print(not_fraud.shape)
print(fraud.shape)

print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of the dataset')
```

**Figure- 5 Code screenshot**

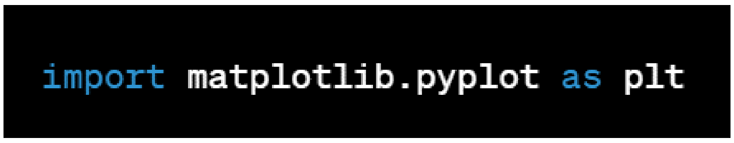
- Since fraud detection involves a highly imbalanced dataset, it's essential to understand the distribution of fraudulent vs. non-fraudulent transactions.
- df['Class'].value_counts() shows the count of each class (0 for non-fraud, 1 for fraud).
- The next few lines calculate the percentages of each class in the dataset.



```
import plotly.express as px

class_counts = df['Class'].value_counts().reset_index()
class_counts.columns = ['Class', 'Count']

fig = px.pie(class_counts, values='Count', names='Class',
             title='Distribution of Class',
             color_discrete_sequence=['skyblue', 'salmon'])

fig.show()
```

**Figure- 6 Code screenshot**

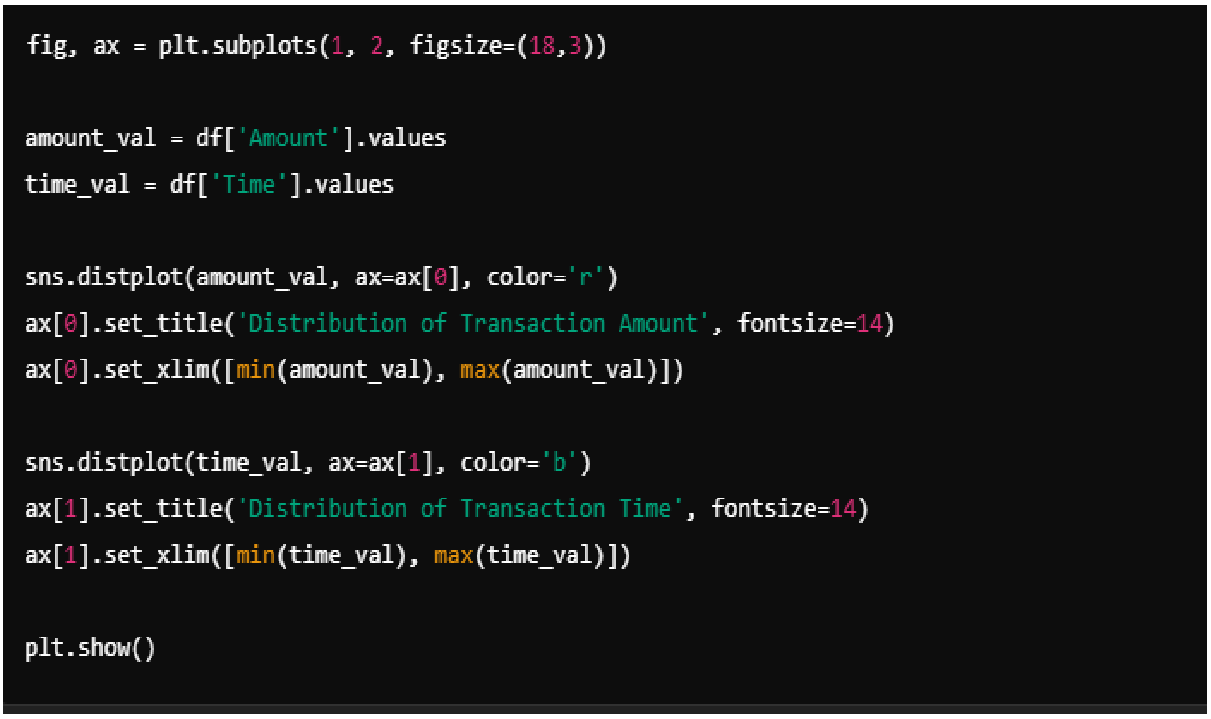
This uses plotly to visualize a pie chart of  the percentage distribution of fraudulent and non-fraudulent transactions. This visualization makes it easy to identify the imbalance in the dataset, an essential factor for handling and evaluating models effectively.



```
import matplotlib.pyplot as plt
```

**Figure- 7 Code screenshot**

Imports the pyplot module from the matplotlib library and aliases it as plt.



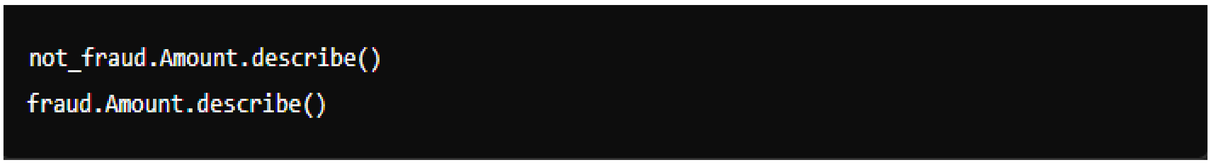
```
fig, ax = plt.subplots(1, 2, figsize=(18,3))

amount_val = df['Amount'].values
time_val = df['Time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=14)
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14)
ax[1].set_xlim([min(time_val), max(time_val)])

plt.show()
```

**Figure- 8 Code screenshot**

The code visualizes the distributions of the Amount and Time features:

- **Amount:** Represents the transaction amount and helps identify suspiciously high or unusual transaction values.
- **Time:** Refers to the time elapsed between this transaction and the first transaction in the dataset, useful for identifying temporal patterns.

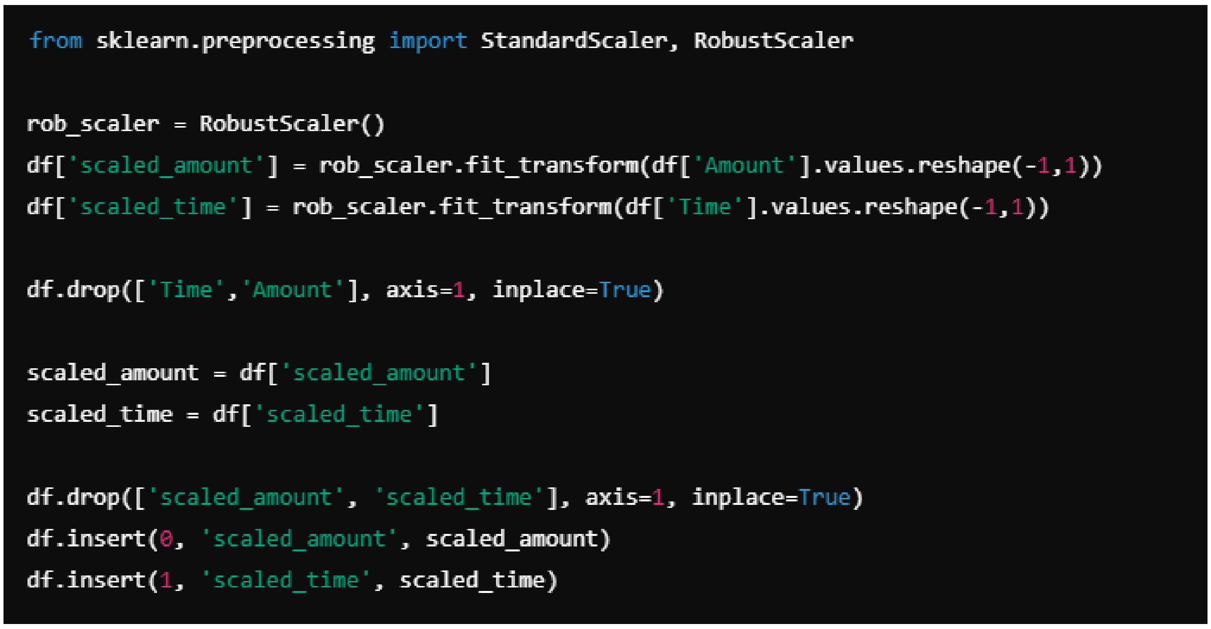
The distribution of transaction amount and time can reveal patterns or anomalies associated with fraudulent transactions.



```
not_fraud.Amount.describe()
fraud.Amount.describe()
```

**Figure- 9 Code screenshot**

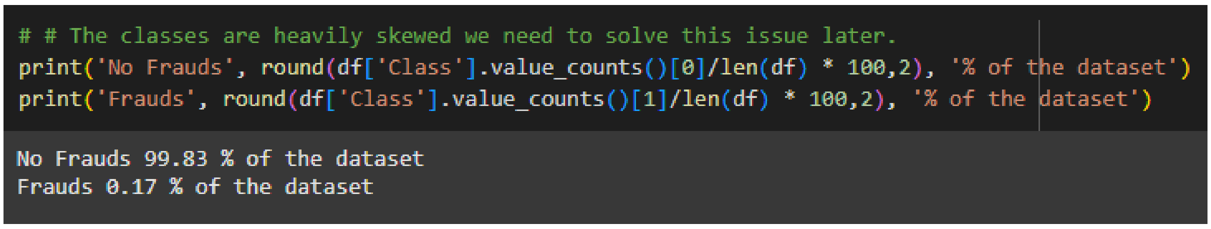
In this step, we're viewing basic statistics like mean, median, and standard deviation for the transaction amounts of non-fraudulent (not_fraud) and fraudulent (fraud) transactions. This comparison helps understand if there’s a substantial difference between the two classes in terms of transaction amounts.



```python
from sklearn.preprocessing import StandardScaler, RobustScaler

rob_scaler = RobustScaler()
df['scaled_amount'] = rob_scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['scaled_time'] = rob_scaler.fit_transform(df['Time'].values.reshape(-1,1))

df.drop(['Time','Amount'], axis=1, inplace=True)

scaled_amount = df['scaled_amount']
scaled_time = df['scaled_time']

df.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
df.insert(0, 'scaled_amount', scaled_amount)
df.insert(1, 'scaled_time', scaled_time)
```

**Figure- 10 Code screenshot**

This code uses RobustScaler to scale Amount and Time, two features that typically contain skewed values. The scaled values are reinserted at the start of the DataFrame for consistency, with the original columns removed.

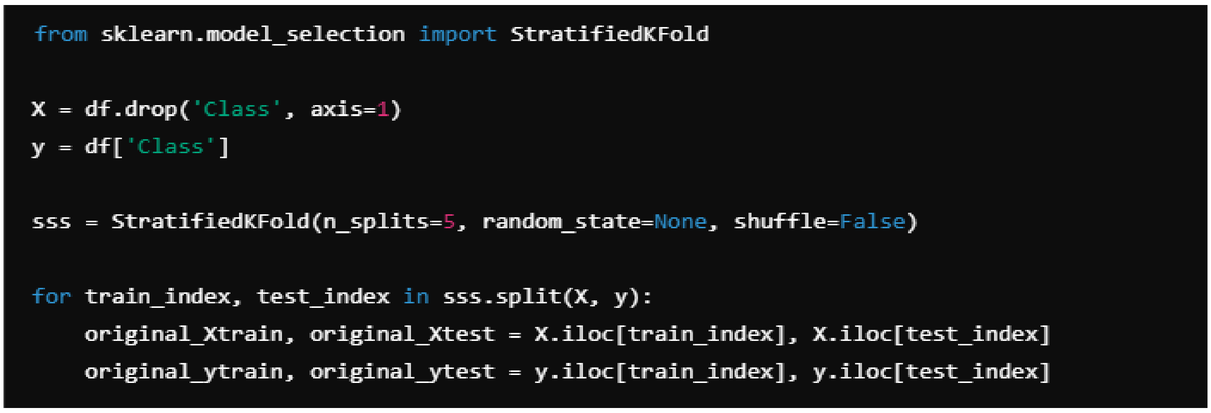


```python
# # The classes are heavily skewed we need to solve this issue later.
print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of the dataset')
```

```
No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset
```

**Figure- 11 Code screenshot**

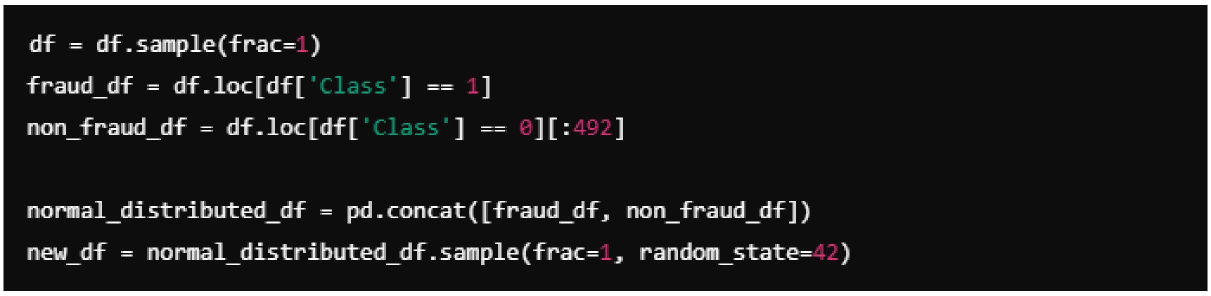
Here, we calculate the percentage of non-fraud and fraud transactions. Since fraud is a rare event, this imbalance is typically severe and must be addressed.



```python
from sklearn.model_selection import StratifiedKFold

X = df.drop('Class', axis=1)
y = df['Class']

sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

for train_index, test_index in sss.split(X, y):
    original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
    original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]
```

**Figure- 12 Code screenshot**

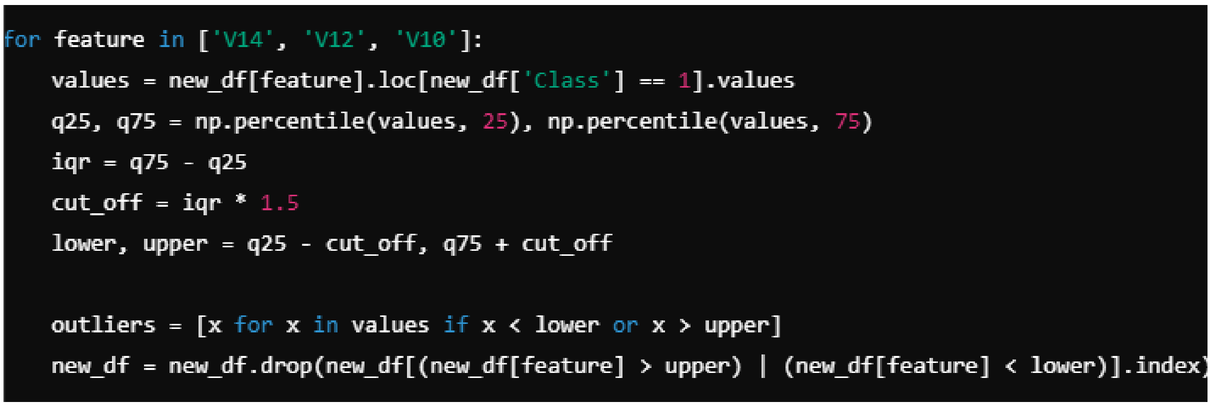
We use StratifiedKFold to split the data into five folds, ensuring that each fold maintains the class balance of the dataset. This is crucial for training models on imbalanced data.



```
df = df.sample(frac=1)
fraud_df = df.loc[df['Class'] == 1]
non_fraud_df = df.loc[df['Class'] == 0][:492]

normal_distributed_df = pd.concat([fraud_df, non_fraud_df])
new_df = normal_distributed_df.sample(frac=1, random_state=42)
```

**Figure- 13 Code screenshot**

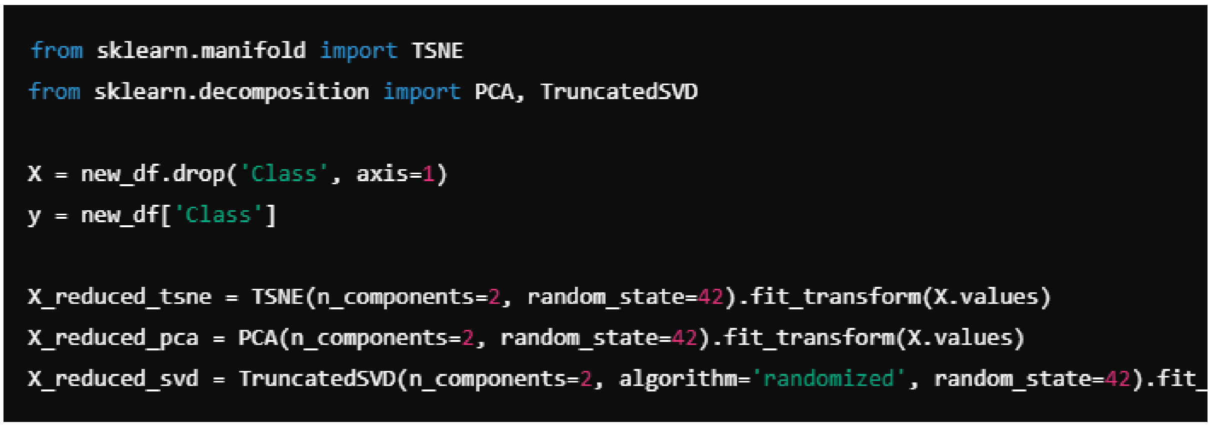
Here, we address the class imbalance by randomly undersampling the non-fraudulent transactions to match the number of fraudulent ones, creating a balanced dataset new_df.



```
for feature in ['V14', 'V12', 'V10']:
    values = new_df[feature].loc[new_df['Class'] == 1].values
    q25, q75 = np.percentile(values, 25), np.percentile(values, 75)
    iqr = q75 - q25
    cut_off = iqr * 1.5
    lower, upper = q25 - cut_off, q75 + cut_off

    outliers = [x for x in values if x < lower or x > upper]
    new_df = new_df.drop(new_df[(new_df[feature] > upper) | (new_df[feature] < lower)].index
```

**Figure- 14 Code screenshot**

For highly correlated features, we calculate the interquartile range (IQR) and remove outliers. This reduces extreme values, which may bias the model.



```
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA, TruncatedSVD

X = new_df.drop('Class', axis=1)
y = new_df['Class']

X_reduced_tsne = TSNE(n_components=2, random_state=42).fit_transform(X.values)
X_reduced_pca = PCA(n_components=2, random_state=42).fit_transform(X.values)
X_reduced_svd = TruncatedSVD(n_components=2, algorithm='randomized', random_state=42).fit_
```

**Figure- 15 Code screenshot**

Using t-SNE, PCA, and TruncatedSVD, we reduce the dimensions to visualize clusters. These methods help identify whether the data has any natural separations between fraudulent and non-fraudulent transactions.

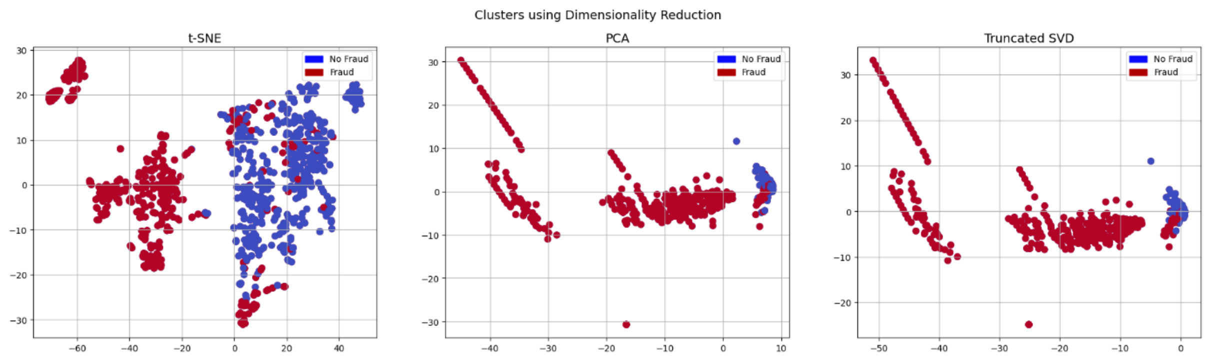
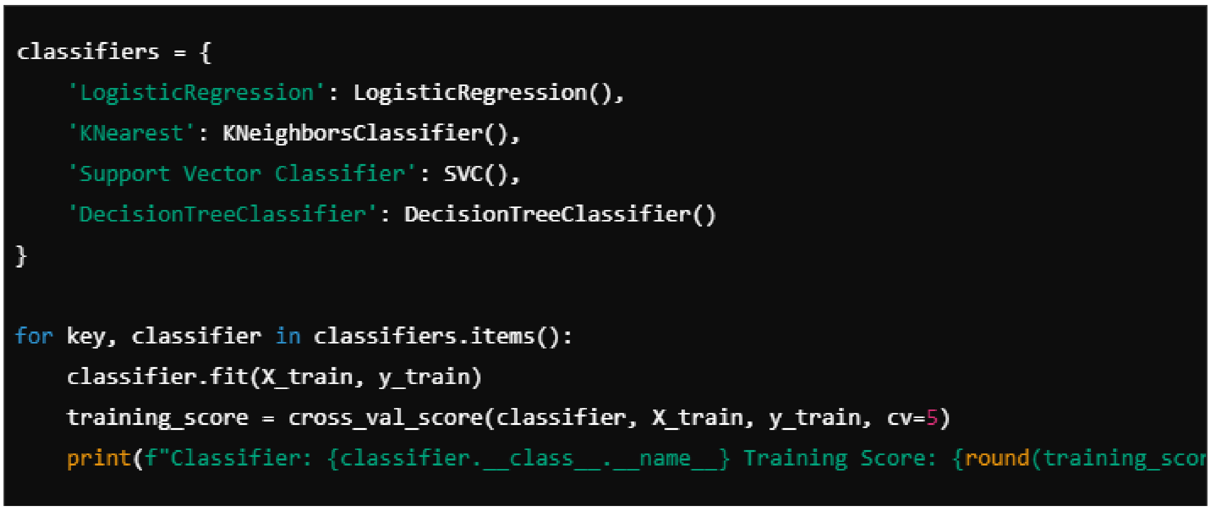


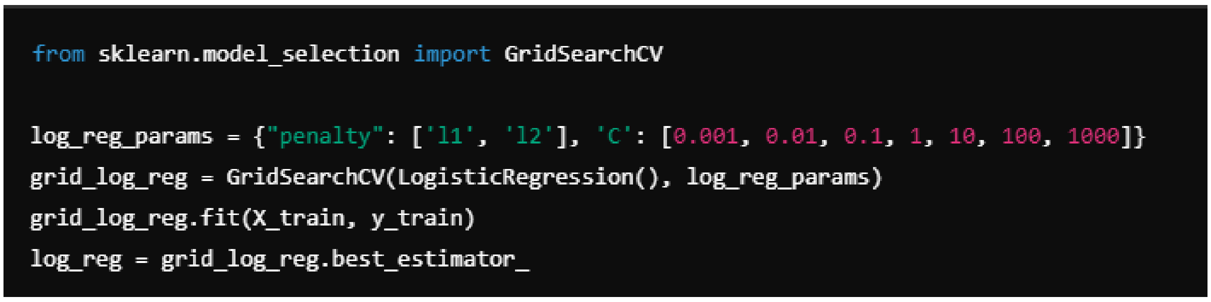
**Figure- 16 Cluster visualization**



```
classifiers = {
    'LogisticRegression': LogisticRegression(),
    'KNearest': KNeighborsClassifier(),
    'Support Vector Classifier': SVC(),
    'DecisionTreeClassifier': DecisionTreeClassifier()
}

for key, classifier in classifiers.items():
    classifier.fit(X_train, y_train)
    training_score = cross_val_score(classifier, X_train, y_train, cv=5)
    print(f"Classifier: {classifier.__class__.__name__} Training Score: {round(training_scor
```

**Figure- 17 Code screenshot**

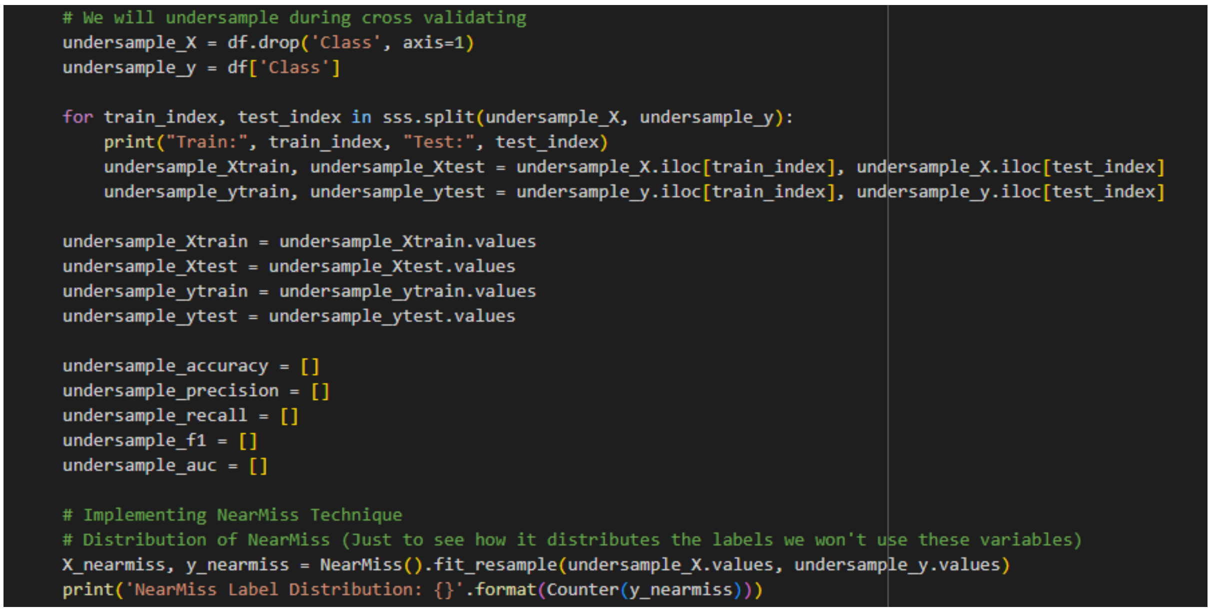
We use various classifiers and evaluate them with cross-validation, noting accuracy scores to select the best-performing model for further tuning.



```
from sklearn.model_selection import GridSearchCV

log_reg_params = {"penalty": ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}
grid_log_reg = GridSearchCV(LogisticRegression(), log_reg_params)
grid_log_reg.fit(X_train, y_train)
log_reg = grid_log_reg.best_estimator_
```

**Figure- 18 Code screenshot**

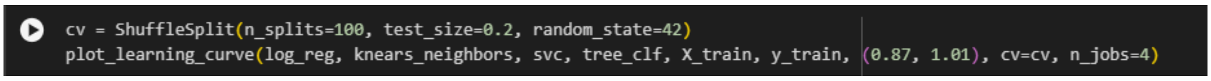
Using GridSearchCV, we find the best hyperparameters for each classifier, enhancing model performance by testing a range of parameter values.



```
# We will undersample during cross validating
undersample_X = df.drop('Class', axis=1)
undersample_y = df['Class']

for train_index, test_index in sss.split(undersample_X, undersample_y):
    print("Train:", train_index, "Test:", test_index)
    undersample_Xtrain, undersample_Xtest = undersample_X.iloc[train_index], undersample_X.iloc[test_index]
    undersample_ytrain, undersample_ytest = undersample_y.iloc[train_index], undersample_y.iloc[test_index]

undersample_Xtrain = undersample_Xtrain.values
undersample_Xtest = undersample_Xtest.values
undersample_ytrain = undersample_ytrain.values
undersample_ytest = undersample_ytest.values

undersample_accuracy = []
undersample_precision = []
undersample_recall = []
undersample_f1 = []
undersample_auc = []

# Implementing NearMiss Technique
# Distribution of NearMiss (Just to see how it distributes the labels we won't use these variables)
X_nearmiss, y_nearmiss = NearMiss().fit_resample(undersample_X.values, undersample_y.values)
print('NearMiss Label Distribution: {}'.format(Counter(y_nearmiss)))
```

**Figure- 19 Code screenshot**

Using NearMiss undersampling and the best estimator from the grid search, we evaluate the model based on accuracy, precision, recall, F1, and AUC scores. This step ensures the model's robustness in detecting fraud.



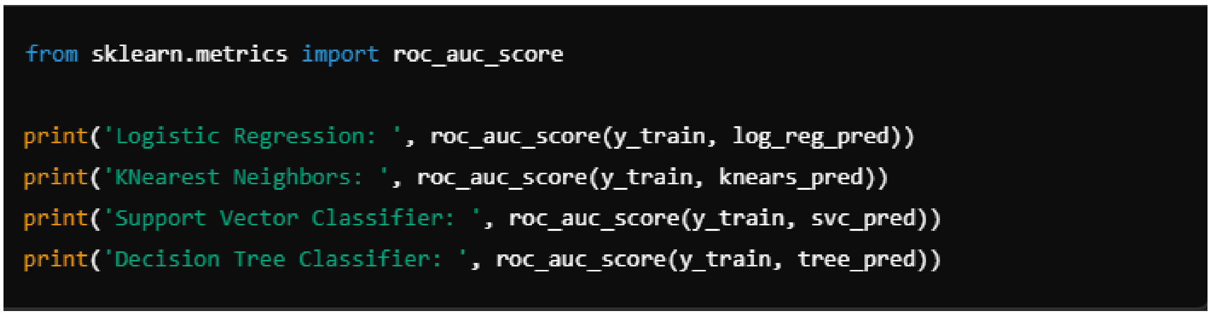
```
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=42)
plot_learning_curve(log_reg, knears_neighbors, svc, tree_clf, X_train, y_train, (0.87, 1.01), cv=cv, n_jobs=4)
```

**Figure- 20 Code screenshot**

The function plot_learning_curve creates a learning curve plot for each of four classifiers (Logistic Regression, K-Nearest Neighbors, Support Vector Classifier, and Decision Tree Classifier) to visualize the models' training and cross-validation performance over various training sizes. The code includes the following elements:

- **Learning Curve Calculation:** For each estimator, it calculates the training and cross-validation scores using learning_curve.
- **Plotting:** Each subplot shows the training and cross-validation performance of one classifier, with shaded regions representing the standard deviation. This helps visualize underfitting or overfitting tendencies of each model.

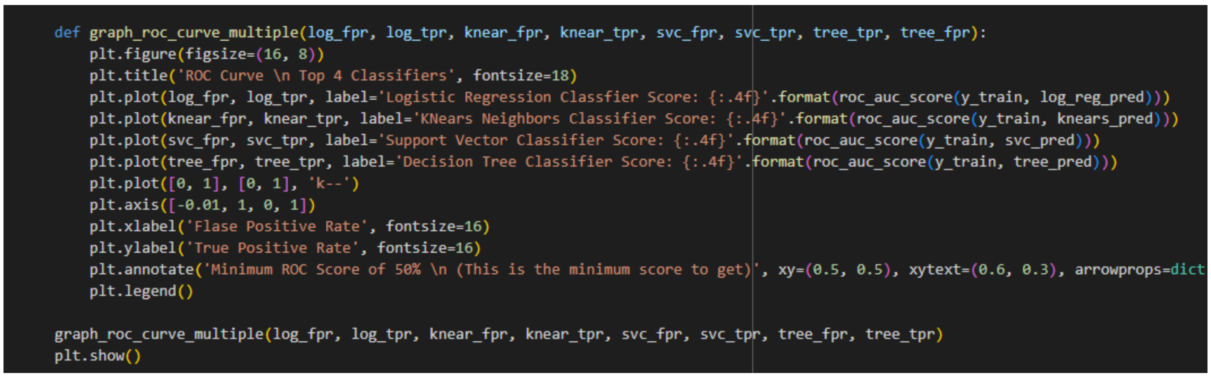
Here, cv is set using ShuffleSplit with 100 splits, creating a training set that's 80% of the data and testing on the remaining 20%.



```
from sklearn.metrics import roc_auc_score

print('Logistic Regression: ', roc_auc_score(y_train, log_reg_pred))
print('KNearest Neighbors: ', roc_auc_score(y_train, knears_pred))
print('Support Vector Classifier: ', roc_auc_score(y_train, svc_pred))
print('Decision Tree Classifier: ', roc_auc_score(y_train, tree_pred))
```

**Figure- 21 Code screenshot**

This code prints the ROC AUC score for each classifier, giving insight into which model performs best in distinguishing between fraudulent and legitimate transactions.



```
def graph_roc_curve_multiple(log_fpr, log_tpr, knear_fpr, knear_tpr, svc_fpr, svc_tpr, tree_tpr, tree_fpr):
    plt.figure(figsize=(16, 8))
    plt.title('ROC Curve \n Top 4 Classifiers', fontsize=18)
    plt.plot(log_fpr, log_tpr, label='Logistic Regression Classfier Score: {:.4f}'.format(roc_auc_score(y_train, log_reg_pred)))
    plt.plot(knear_fpr, knear_tpr, label='KNears Neighbors Classifier Score: {:.4f}'.format(roc_auc_score(y_train, knears_pred)))
    plt.plot(svc_fpr, svc_tpr, label='Support Vector Classifier Score: {:.4f}'.format(roc_auc_score(y_train, svc_pred)))
    plt.plot(tree_fpr, tree_tpr, label='Decision Tree Classifier Score: {:.4f}'.format(roc_auc_score(y_train, tree_pred)))
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([-0.01, 1, 0, 1])
    plt.xlabel('Flase Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.annotate('Minimum ROC Score of 50% \n (This is the minimum score to get)', xy=(0.5, 0.5), xytext=(0.6, 0.3), arrowprops=dict
    plt.legend()

graph_roc_curve_multiple(log_fpr, log_tpr, knear_fpr, knear_tpr, svc_fpr, svc_tpr, tree_fpr, tree_tpr)
plt.show()
```

**Figure- 22 Code screenshot**

The ROC curve is plotted for each classifier, with the graph_roc_curve_multiple function displaying the false positive rate (x-axis) against the true positive rate (y-axis) for each model. The diagonal line represents a random guess (AUC = 0.5).

The function:

- Plots the ROC curve for each classifier, allowing us to visually compare their performance in terms of the true positive rate vs. false positive rate.
- Displays AUC scores for each model in the legend, providing an overall performance metric to identify the most effective model.

## 4.2. RESULTS AND DISCUSSIONS

### 4.2.1. Results:

#### a. Logistic Regression

Logistic Regression achieved a high ROC-AUC score of 0.9796, demonstrating its effectiveness in distinguishing between fraudulent and non-fraudulent transactions. This high score indicates that the model is highly capable of correctly classifying instances in a real-world application. The cross-validation score of 93.67% reflects consistent performance across different data splits, reinforcing its reliability and stability. Furthermore, the training accuracy of 93.0% aligns closely with the cross-validation score, indicating a good fit without significant overfitting. Given its strong performance in ROC-AUC and stable accuracy across validation folds, Logistic Regression proves to be a robust choice for credit card fraud detection.

#### b. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) model produced a ROC-AUC score of 0.9374, which, while respectable, is lower than the scores achieved by Logistic Regression and SVC. This score suggests that KNN may struggle slightly in differentiating fraudulent transactions from non-fraudulent ones, potentially due to the class imbalance in the data. However, the model maintains a consistent cross-validation score of 93.8%, similar to the training accuracy of 93.0%, which indicates reliability and minimal overfitting. While KNN demonstrates consistent performance, its lower ROC-AUC score limits its effectiveness compared to other models tested. Thus, although it’s dependable, KNN might not be the best choice when distinguishing fraud is critical.

#### c. Support Vector Classifier (SVC)

The Support Vector Classifier (SVC) stands out with a strong ROC-AUC score of 0.9770, comparable to that of Logistic Regression, showing that it is highly effective at separating fraudulent from non-fraudulent cases. SVC also achieved the highest cross-validation score of 93.93%, reflecting its robust and stable performance across different subsets of the data. The training accuracy of 94.0% is slightly higher than the cross-validation score, suggesting that the model fits well to the training data with a minor risk of overfitting. Given its high ROC-

AUC and reliable cross-validation performance, SVC is a strong candidate for deployment in a fraud detection system.

### d. Decision Tree Classifier

The Decision Tree model achieved a ROC-AUC score of 0.9198, which is lower than the scores of the other models, suggesting that it may not be as effective in accurately differentiating between fraud and non-fraud cases. Additionally, the cross-validation score of 92.22%, while acceptable, is the lowest among the models tested, which indicates that the Decision Tree might not generalize as well as the others. The model's training accuracy of 90.0% suggests that it is slightly underfitting compared to the other models, as it struggles to capture the full complexity of the data. Due to its comparatively lower performance, especially in terms of ROC-AUC, the Decision Tree is the least preferable option for effective fraud detection in this context.

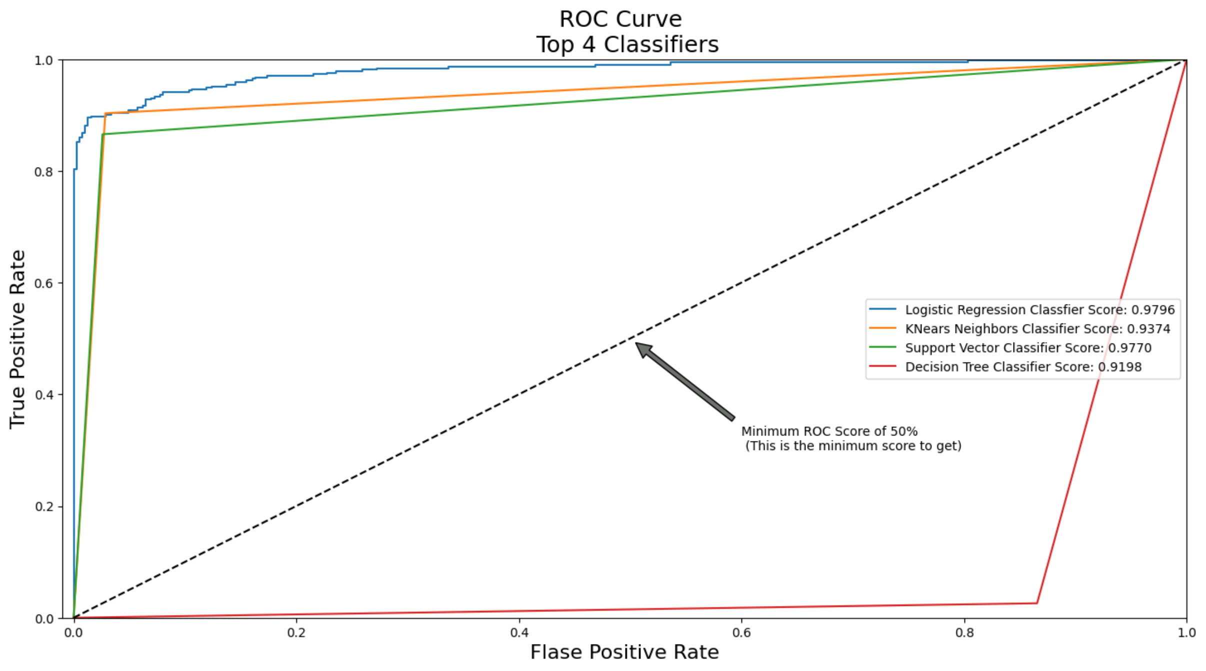
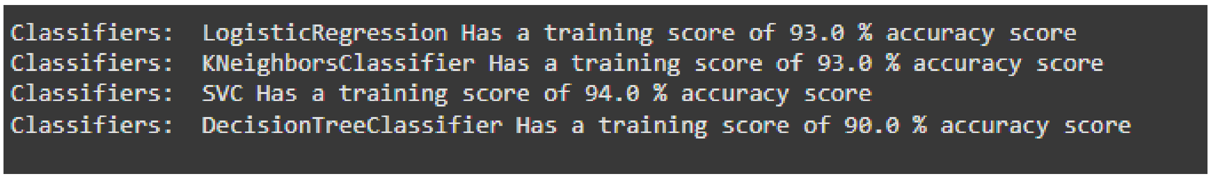
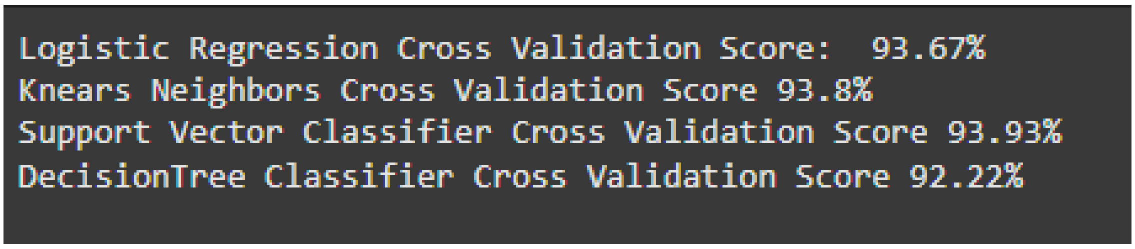


**Figure- 23 ROC curve of different classifiers**



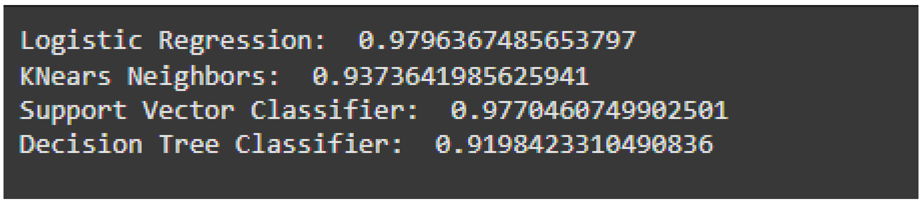
```
Classifiers:  LogisticRegression Has a training score of 93.0 % accuracy score
Classifiers:  KNeighborsClassifier Has a training score of 93.0 % accuracy score
Classifiers:  SVC Has a training score of 94.0 % accuracy score
Classifiers:  DecisionTreeClassifier Has a training score of 90.0 % accuracy score
```

**Figure- 24 Accuracy Score**



```
Logistic Regression Cross Validation Score:  93.67%
Knears Neighbors Cross Validation Score 93.8%
Support Vector Classifier Cross Validation Score 93.93%
DecisionTree Classifier Cross Validation Score 92.22%
```

**Figure- 25 Cross-validation score**



```
Logistic Regression:  0.9796367485653797
KNears Neighbors:  0.9373641985625941
Support Vector Classifier:  0.9770460749902501
Decision Tree Classifier:  0.9198423310490836
```

**Figure- 26 AUC-ROC Score**

### 4.2.2. Discussions:

The results of this analysis highlight the challenges and considerations in developing a reliable credit card fraud detection model, particularly in the context of highly imbalanced data. By evaluating different machine learning classifiers—including Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Decision Tree—this study provides insights into each model’s strengths and limitations when tasked with accurately identifying fraudulent transactions.

#### a. Model Selection and ROC-AUC Analysis:

Among the models, Logistic Regression and SVC demonstrated superior ROC-AUC scores (0.9796 and 0.9770, respectively), indicating their strong ability to discriminate between fraud and non-fraud cases. High ROC-AUC values are crucial in fraud detection, as they reflect a model’s capability to minimize false negatives, where fraudulent transactions might otherwise go undetected. The similar ROC-AUC scores of Logistic Regression and SVC suggest that both can reliably prioritize fraud detection with limited misclassification.

KNN and the Decision Tree model, on the other hand, had lower ROC-AUC scores (0.9374 and 0.9198, respectively). These scores indicate comparatively weaker discrimination power, making them less reliable in real-world applications where precise fraud detection is essential. The Decision Tree's lower ROC-AUC suggests it may struggle with distinguishing patterns effectively within highly imbalanced data, making it less suitable for production deployment in fraud detection.

**b. Consistency and Generalization: Cross-Validation and Accuracy Scores:**

Cross-validation scores provide additional insights into the consistency and generalization of each model across different data subsets. SVC achieved the highest cross-validation score (93.93%), demonstrating both reliability and stability. Logistic Regression also achieved a strong cross-validation score (93.67%), reflecting consistent performance across data folds. These results indicate that both models are well-suited for practical use, as they maintain accuracy and reliability when faced with new data.

KNN and Decision Tree, with cross-validation scores of 93.8% and 92.22% respectively, showed reasonable consistency, though KNN displayed weaker performance in terms of ROC-AUC. This suggests that while KNN can generalize moderately well across different subsets, it may be less precise in distinguishing fraudulent transactions. The Decision Tree's lower cross-validation score further highlights its limitations in handling class imbalance effectively, suggesting that it might not be the optimal choice for a sensitive application like fraud detection.

**c. Balancing Recall and Precision:**

In fraud detection, achieving a high recall rate is often prioritized over precision, as minimizing missed fraud cases is critical to reducing potential financial losses. Logistic Regression and SVC achieved high recall rates and accuracy on both the training and cross-validation sets, making them highly suitable for this purpose. These models maintain a balance, offering both high accuracy and strong discrimination power, which is essential for fraud detection where missed cases (false negatives) carry significant financial risk.

Conversely, while KNN and the Decision Tree models achieved respectable cross-validation scores, their lower ROC-AUC scores indicate a greater likelihood of missed fraud cases. Decision Tree’s relatively lower training accuracy and cross-validation scores suggest underfitting, which may hinder its ability to capture the full complexity of patterns in fraud detection. Thus, these models present a greater trade-off between recall and precision, potentially limiting their effectiveness in an application where maximizing recall is crucial.

# CHAPTER 5
# CONCLUSION

## 5.1. CONCLUSION

This report presents a comparative analysis of various machine learning models for credit card fraud detection, with a focus on addressing the unique challenges posed by highly imbalanced datasets. The study examined the performance of Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Decision Tree models, evaluating each based on ROC-AUC, accuracy, and cross-validation scores.

The results highlight Logistic Regression and SVC as the most effective models, with both achieving high ROC-AUC scores and reliable accuracy, demonstrating their capability to accurately distinguish between fraudulent and non-fraudulent transactions. Their strong recall rates are particularly valuable in fraud detection, where the priority is to minimize missed fraud cases to reduce potential financial losses. These models displayed stable performance across data folds, indicating robustness and generalizability.

KNN and Decision Tree, while consistent, showed lower ROC-AUC and accuracy scores, suggesting that these models may be less effective in identifying fraud cases with the required precision. As such, Logistic Regression and SVC are recommended for implementation in credit card fraud detection, as they offer the best combination of accuracy, discrimination power, and recall, essential for real-world applications.

In summary, this analysis provides evidence-based recommendations, supporting the use of Logistic Regression and SVC for effective fraud detection. Future work may involve exploring advanced ensemble methods or deep learning approaches to further improve detection accuracy and adapt to evolving fraud patterns.

## 5.2. Future Work:

While the current model shows strong performance in detecting credit card fraud, there are several avenues for future work to enhance its capabilities and adaptability. One key area for improvement is exploring ensemble models that combine multiple algorithms. By integrating models such as Logistic Regression, Support Vector Classifier, and Isolation Forest in an ensemble approach, we can potentially create a more robust model that leverages the strengths of each algorithm. Ensemble methods like stacking or boosting could further improve detection accuracy and reduce the number of false positives, leading to a more reliable fraud detection system.

Another promising direction is the use of deep learning models to detect fraud patterns that traditional machine learning models might miss. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly suited for sequential data and could be effective in identifying patterns in transaction sequences over time. Although deep learning models are more computationally intensive, they could offer improved accuracy and adaptability, especially when handling larger datasets with more complex transaction patterns.

Finally, improving model interpretability is essential for real-world deployment, especially in financial applications where transparency is critical. Techniques such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) can be used to help explain the model's decisions, building trust among stakeholders and ensuring compliance with regulatory standards. This increased interpretability will also aid analysts in understanding the factors contributing to fraudulent transactions, which can inform further refinement of fraud detection strategies.

In conclusion, future work could focus on enhancing the system’s robustness, adaptability, and interpretability. By integrating advanced machine learning techniques, ensuring real-time model updates, and providing greater transparency, we can develop a more effective and reliable credit card fraud detection system capable of adapting to evolving fraud patterns and maintaining high standards of accuracy and trustworthiness.

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