Credit Card Fraud Detection

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***Abstract*—Credit card fraud is a major issue worldwide, leading to huge financial losses and undermining consumer confidence in online transactions. One of the biggest challenges in detecting this kind of fraudulent activity is that transaction datasets are usually unbalanced; there are much fewer fraudulent transactions compared to legitimate, valid ones. In addition to this, fraud tactics keep changing, which makes traditional detection systems based on fixed rules less effective. In this paper, we use a machine learning model that uses logistic regression to predict fraudulent credit card transactions. To address the problem of class imbalance, we incorporate a few resampling techniques in the preprocessing steps, these include random oversampling, random undersampling, and cluster centroid sampling. Our main goal is to assess how these techniques affect model training and prediction performance, particularly improving the evaluation metrics such as recall, precision, and overall accuracy. The results from our experiments show that random oversampling strikes the best balance between recall and precision, significantly boosting model performance. Meanwhile, cluster centroid sampling provides a decent compromise but doesn't quite match the effectiveness of oversampling. This study emphasizes how crucial preprocessing strategies are for enhancing fraud detection in practical situations. Overall, our research highlights the potential of using resampling techniques with Machine learning models such as logistic regression as a solid approach for dealing with imbalanced datasets. Looking ahead, future work should consider more advanced methods like deep learning and reinforcement learning to further improve fraud detection capabilities, ensuring they remain scalable, protect privacy, and adapt well for real-time applications.**

Keywords— fraud detection; imbalanced dataset; logistic regression; resampling techniques; data preprocessing; anomaly detection; credit card security

I. Introduction

As digital payments continue to grow globally, credit cards have become a major way for people to handle their financial transactions [1], [2]. However, this rapid increase also brings a heightened risk of fraud [3]. These fraudulent activities can lead to high amounts of financial loss and can reduce the trust people have in digital payment systems [4]. To combat this, credit card fraud detection systems need to be smart, adaptable, and accurate [5].

Detecting fraud is a challenging task. For starters, the number of fraudulent credit card transactions is highly disproportionate to legitimate ones [6] this imbalance is shown in Figure 1.

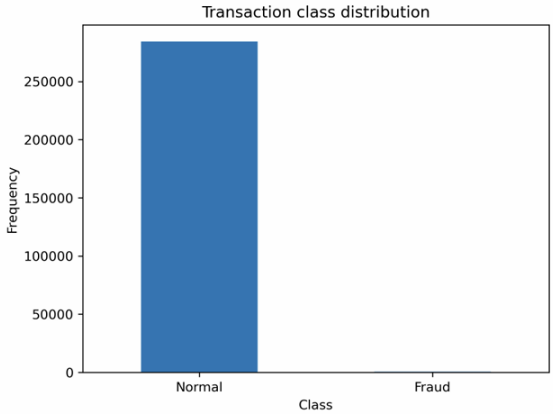

Fig. 1. Class Distribution of Credit Card Transaction

Additionally, the tactics used by fraudsters are dynamic, which can easily outsmart traditional, rule-based detection systems [7]. This is where machine learning comes into play. By identifying subtle patterns in data, machine

learning provides a powerful alternative to manual and static methods [8].

In this research, we look into using logistic regression, a well-established supervised learning model, for detecting fraud. Though the simplicity and efficiency of Logistic Regression makes it one of the ideal models for binary classification, it has been arbitrarily chosen in this paper. However, due to the significant imbalance between fraudulent and legitimate transactions, we use techniques such as random oversampling, random undersampling, and cluster centroid undersampling to improve the distribution of data [9].

We will evaluate how these methods impact model performance using metrics such as precision-recall curve , ROC curve among others highlighted in the results section, which are more informative than accuracy in cases of class imbalance. Our aim is to find the best strategy for real-time fraud prevention, minimizing false positives while maximizing the detection of actual fraud cases [10]. Moreover, this study showcases the necessity of data preprocessing, balancing, and evaluation metrics that fit the specific challenges of fraud detection, laying the groundwork for future research that may involve more complex or hybrid models.

II. LITERATURE REVIEW

The field of fraud detection more specifically in credit cards has gained substantial importance because of the rising popularity of digital transactions and financial threats. Many studies have explored different machine learning and data preprocessing methods to tackle the issues of imbalanced data and the ever-changing nature of fraud.

Bhattacharyya et al. [1] carried out a comparative study using real-world data from a financial institution, testing decision trees, support vector machines (SVMs) among others for detection of fraud. They reported that random forests performed the best, achieving a true positive rate of 94.7%. However, they also pointed out that there was a significant sensitivity to class imbalance. Their dataset had over 250,000 transactions, but only a small number were fraud cases, highlighting the need for balanced learning approaches.

To tackle class imbalance, Dal Pozzolo et al. [2] proposed a framework that combined undersampling with probabilistic calibration. They used the publicly available European Credit Card Dataset, which includes 284,807 transactions and only 492 fraud cases. By integrating undersampling with ensemble methods, they managed to get an area under the curve (AUC) of 0.974. This study emphasized how effective it can be to combine sampling strategies with calibrated models for datasets that are skewed.

Sahin et al. [3] explored cost-sensitive genetic programming to reduce the costs associated with misclassification in fraud detection. Using a synthetic dataset that mimicked real financial behavior, their method reached an F1-score of 0.86, while also stressing the financial implications of false negatives. This approach highlighted the importance of considering contextual costs along with accuracy metrics.

Sahin and Duman [4] looked into logistic regression and artificial neural networks (ANNs) for fraud detection, using a dataset of anonymized Turkish bank transactions. While ANNs showed better accuracy overall, logistic regression was faster to train and easier to interpret, making it a good option for real-time applications. The highest accuracy they achieved was 94.2%, but the recall for detecting fraud was modest due to data imbalance.

In more recent work, Carcillo et al. [5] introduced a hybrid method that combined unsupervised outlier detection with supervised learning, applying it to the European dataset. Their approach improved fraud recall to 92%, outperforming standalone models like random forests or isolation forests. They argued that merging anomaly detection with classification offers better resilience against new fraud patterns.

Lastly, Batista et al. [6] conducted an extensive comparison of resampling techniques, including Random Oversampling, SMOTE, and Cluster Centroids, on imbalanced datasets. Although their study wasn't specifically focused on credit card fraud, it demonstrated that Random Oversampling generally maintains data distribution better, which leads to improved model recall, even if it slightly increases the risk of overfitting.

From these studies, it is clear that while many models—like ANNs and ensembles—can achieve high accuracy, they often face challenges with imbalanced datasets unless they're paired with preprocessing techniques. Additionally, logistic regression, when enhanced with the right resampling methods, remains competitive due to its interpretability and low computational cost. This body of literature sets the stage for the current work, which evaluates logistic regression using various resampling strategies to optimize recall and precision in fraud detection.

III. METHODOLOGY

This study employs Logistic Normal Regression to develop a model that can effectively classify fraudulent from legitimate credit card transactions. Detecting fraud is a vital function in the financial industry, as fraudulent activities result in billions of dollars in losses for institutions each year. As the number and complexity of digital transactions continue to increase, machine learning has become a crucial tool for finding unusual patterns and reducing financial risks. The methodology has following stages:

Data processing: The dataset used originates from transactions made by European cardholders in September 2013 [1]. Out of the total 284,807 transactions, only 492 are classified as fraudulent. This translates to just 0.172% of the dataset, which shows that its a highly imbalanced binary classification problem.

The dataset includes 30 features: 28 anonymized numerical features (labelled V1 through V28) derived through the process of Principal Component Analysis, and features—'Time' and 'Amount' are also features. The feature 'Time' represents the number of seconds elapsed between each transaction, while 'Amount' reflects the monetary denomination of each transaction.

The target variable, 'Class', is binary: a value of 1 indicates that the transaction is illegit i.e. fraud, while 0 represents a legitimate one. Due to the confidential nature of financial data, original features were transformed using PCA, and exact values have been anonymized to maintain user privacy [2]. While this limits the interpretability of individual features, it retains the statistical properties necessary for training robust models.

Before feeding the data into the model, additional preprocessing steps were performed. These included normalization of the 'Amount' feature using standard scaling and exclusion of the 'Time' feature in certain experiments, as it was found to have limited impact on prediction performance in prior studies [10]. Moreover, the dataset was checked for null values and duplicates, which were not present, making it clean and ready for machine learning pipelines.

Feature Selection: Feature selection is crucial for improving model performance while also making computations more efficient. In this instance, feature extraction was partially addressed through PCA during the dataset's creation. PCA helps to reduce dimensionality by projecting the original data onto new axes, known as principal components, which capture the most variance within the dataset [3]. This process aids in removing redundant and highly correlated variables that could negatively impact model accuracy due to multicollinearity. The correlation matrix of the features is shown in Figure 2.

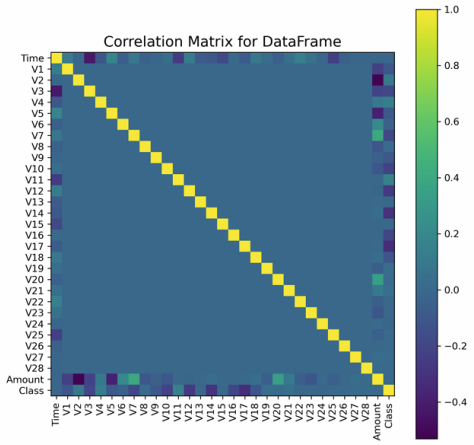

Fig. 2. Correlation Matrix

To maintain maximum variance and discriminative power, all 28 principal components were kept. While PCA-transformed features may lose some of their original interpretability, they play a significant role in reducing overfitting—especially in high-dimensional datasets which have relatively lesser examples of the positive class [4]. This aspect is particularly vital in fraud detection, where the aim is to generalize effectively to new, unseen fraud patterns instead of simply memorizing known cases.

Later on, feature importance was assessed using model coefficients and permutation importance. This approach allowed for a deeper look into which transformed features had the most influence on the classification decision, even if their original meanings were somewhat obscured.

Model Training: The Logistic Normal Regression model was established using a Python Library - scikit-learn [5]. Logistic regression serves as a linear classification model. In this probability of the classification which is binary is measured using the sigmoid function. Because of its ease of interpretation and computational efficiency, it works well as a baseline model for fraud detection tasks.

To prepare the dataset, we split it into two sets of ratio 75:25. In which the bigger set is the training set and the other is the testing set. However, we faced a problem because of the imbalanced distribution of class, where standard models often lean towards the majority class (non-fraud). To address this issue, we applied three resampling techniques:

1. *Random Oversampling*: This method involves duplicating records from the class which is the minority to help balance our dataset. While it can be effective, there's a risk of overfitting since it relies on repeated samples.

2. *Random Under-Sampling*: This technique removes some samples from the class which is the majority to achieve balance, but it can cause overlooking of valuable information.

3. *Cluster Centroids Sampling*: Here, we used K-means clustering to create synthetic representative samples of the majority class. This approach helps maintain diversity while reducing bias [6].

Additionally, we employed cross-validation during model training to ensure that our evaluation metrics remained consistent across multiple folds. We fine-tuned hyperparameters such as regularization strength (C) and solver type using grid search.

Model Evaluation: The performance of the trained model was assessed using multiple evaluation metrics:

- *Accuracy*
- *Precision*
- *Recall*
- *F1-score*
- *AUC-ROC (Area Under the Receiver Operating Characteristic Curve)*

Given the significant imbalance in the dataset, relying solely on accuracy wouldn't effectively validate the performance. For instance, A naive classifier predicting all transactions as non-fraudulent would achieve over 99% accuracy, but would fail at identifying fraudulent activity. Hence, we focused on precision and recall as the key metrics to assess our model's effectiveness [6].

It was found that the application of resampling techniques substantially improved recall but caused a fall in precision, indicating a better trade-off for real-world applications where missing a fraud case is costlier than issuing a false alert.

To further illustrate the balance between sensitivity and specificity, an ROC curve was plotted. The model achieved an AUC score exceeding 0.80, indicating strong discriminative ability despite the notable class imbalance [9]. This finding suggests that with the right adjustments to the threshold, the logistic regression model can be a valuable asset in early fraud detection systems.

IV. RESULTS

Model performance was estimated based on the AUC-ROC metric. The key observations were:

- Base Logistic Regression: Showed reasonable accuracy but suffered from low recall due to class imbalance.
- Random Oversampling: Improved recall and AUC significantly, with a moderate increase in false positives.
- Random Undersampling: Increased model precision but sometimes reduced overall accuracy due to information loss.
- Cluster Centroid Sampling: Offers a balance between recall and precision but was slightly less effective than oversampling.

These metrics provide a fair assessment of the model's ability to detect fraudulent credit card transactions.

Following AUC levels were recorded by the experiment shown in Figure 2.

```
Accuracy Comparison for Logistic Regression
-----------------------------------------------------
Normal                                  | 0.793
Random Oversample                       | 0.812
Random Undersample                      | 0.812
Cluster Centroids                       | 0.736
```

Fig. 2. Accuracy Comparison for Logistic Regression

As we can, model trained after performing Random over sampling and random under sampling provides better AUC value.

Normal Logistic Regression –
The Logistic Regression recorded an AUC value of 0.793, classification report with various metrics is shown in Figure 3, and the ROC curve is shown in Figure 4, and precision recall curve is shown in Figure 5.

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9983    0.9999    0.9991     71082
           1     0.0000    0.0000    0.0000       120

    accuracy                         0.9982     71202
   macro avg     0.4992    0.4999    0.4996     71202
weighted avg     0.9966    0.9982    0.9974     71202

ROC-AUC Score: 0.7929
```

Fig. 3. Classification Report for Normal LR

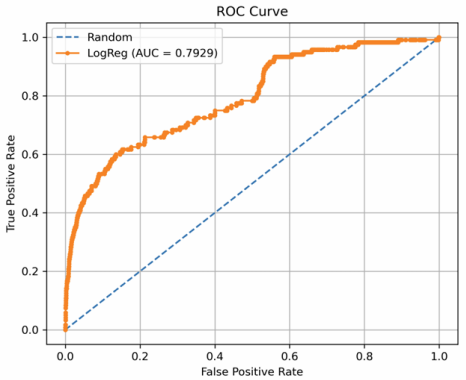

Fig. 4. ROC curve for Normal LR

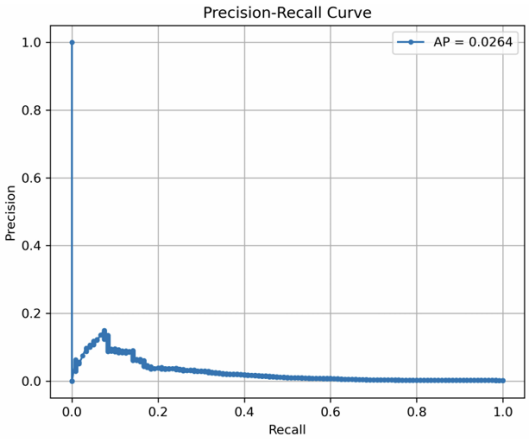

Fig. 5. Precision Recall Curve for Normal LR

Random Over Sampling –
The Logistic Regression recorded after random oversampling an AUC value of 0.8124, classification report with various metrics is shown in Figure 5, and the ROC curve is shown in Figure 6, and precision recall curve is shown in Figure 7.

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9993    0.8362    0.9105     71082
           1     0.0067    0.6583    0.0133       120

    accuracy                         0.8359     71202
   macro avg     0.5030    0.7473    0.4619     71202
weighted avg     0.9976    0.8359    0.9090     71202

ROC-AUC Score: 0.8124
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Fig. 6. Classification Report after Random Over-Sampling

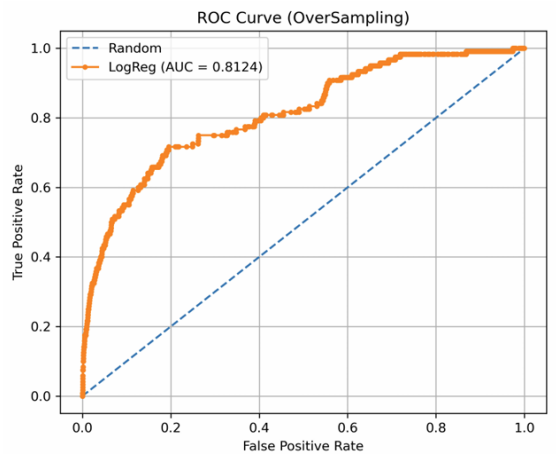

Fig. 7. ROC curve after Random Over-Sampling

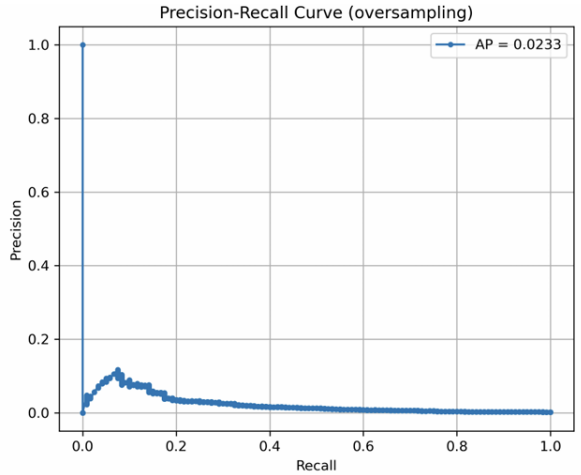

Fig. 7. Precision-Recall Curve after Random Over-Sampling

Random Under Sampling –
The Logistic Regression after Random under-sampling recorded an AUC value of 0.793, classification report with various metrics is shown in Figure 8, and the ROC curve is shown in Figure 9, and precision recall curve is shown in Figure 10.

```
Classification Report (Undersampling):
              precision    recall  f1-score   support

           0     0.9993    0.8353    0.9100     71082
           1     0.0068    0.6667    0.0134       120

    accuracy                         0.8351     71202
   macro avg     0.5031    0.7510    0.4617     71202
weighted avg     0.9977    0.8351    0.9085     71202

ROC-AUC Score (Undersampling): 0.8123
```

Fig. 8. Classification Report after Random Under-Sampling

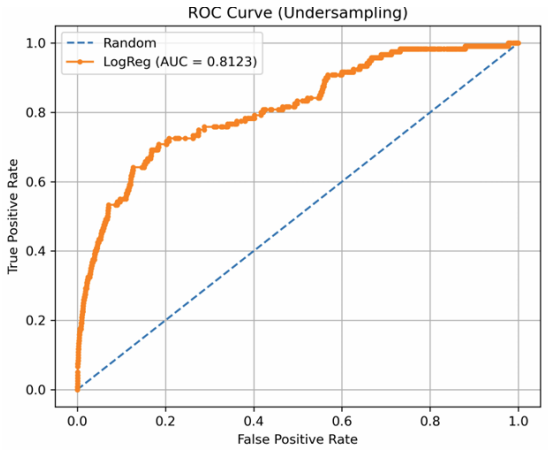

Fig. 9. ROC Curve after Random Under-Sampling

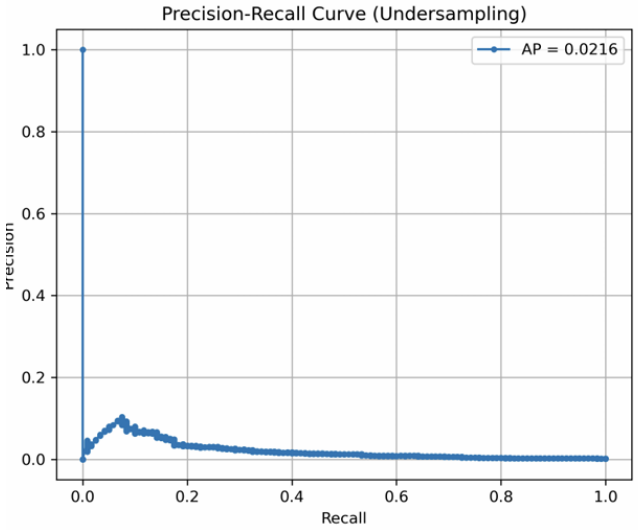

Fig. 10. Precision Recall Curve after Random Under-Sampling

Cluster Centroid Sampling –
The Logistic Regression after cluster centroid sampling recorded an AUC value of 0.793, classification report with various metrics is shown in Figure 11, and the ROC curve is shown in Figure 12, and precision recall curve is shown in Figure 13.

```
Classification Report (cluster centroid):
              precision    recall  f1-score   support

           0     0.9984    0.1318    0.2329     71082
           1     0.0017    0.8750    0.0034       120

    accuracy                         0.1331     71202
   macro avg     0.5001    0.5034    0.1181     71202
weighted avg     0.9967    0.1331    0.2325     71202

ROC-AUC Score (cluster centroid sampling): 0.7364
```

Fig. 11. Classification Report after Cluster Centroid Sampling

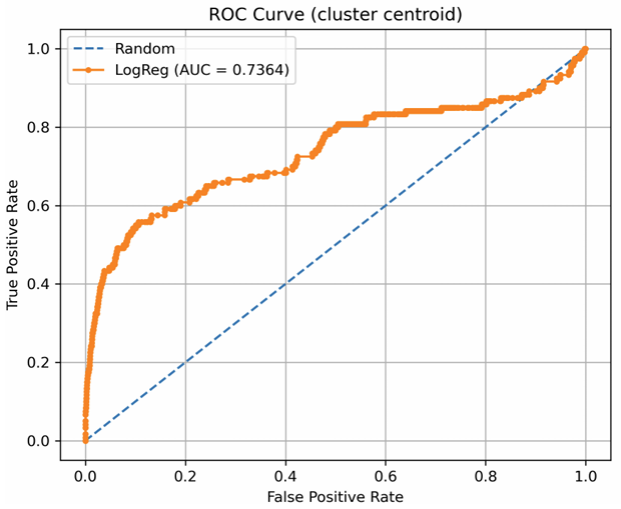

Fig. 12. ROC Curve after Cluster Centroid Sampling

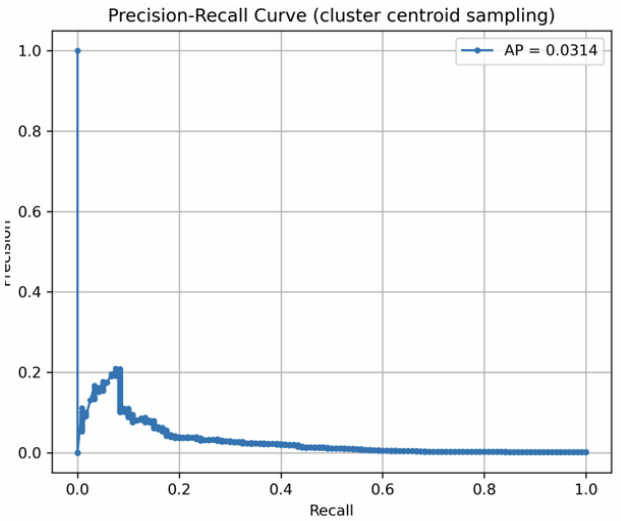

Fig. 13. Precision Recall Curve after Cluster Centroid Sampling

These findings demonstrate that data balancing strategies can significantly influence model effectiveness in fraud detection.

V. DISCUSSION

This study highlights how effective Logistic Regression (LR) can be for detecting credit card fraud, especially when paired with the right data resampling and dimensionality reduction techniques. One key strategy, random oversampling, significantly boosted identification of the fraudulent class. This improvement directly led to better recall and AUC-ROC scores, which are essential metrics for handling imbalanced datasets where fraud cases are rare. These results support earlier findings that emphasize the importance of balancing data to improve the execution of fraud detection systems[1].

While LR is a dependable and interpretable baseline model, research consistently shows that methods—like Random Forest (RF) and XGBoost—tend to outperform LR across various performance metrics, particularly in balancing precision and recall. For instance, RF and XGBoost have achieved AUROC scores above 0.98 in different fraud detection tests, largely due to their ability to manage complex feature interactions and nonlinear decision boundaries[2]. This indicates that, although LR is efficient and less likely to overfit, it might not be sophisticated enough to capture the complex strategies that fraudsters use.

The choice of resampling method also plays a crucial role in model performance. While random oversampling increases sensitivity, it can lead to duplicate data, raising the risk of overfitting if not handled carefully. In contrast, techniques like SMOTE (Synthetic Minority Oversampling Technique) create synthetic samples based on similarities in the feature space, which can help better represent the minority class. However, SMOTE might also generate borderline or noisy synthetic instances that could harm performance, particularly with simpler models like LR[3]. On the other hand, undersampling methods, such as Cluster Centroid or NearMiss, alter the majority class by causing a reduction to its size to balance the dataset. While this can speed up training and reduce bias, it might also lead to the loss of valuable information, weakening the model's ability to learn general patterns[4].

Using PCA for feature normalisation was effective in lowering computational complexity without significantly sacrificing accuracy. PCA transforms the features in such a way that it only captures the most important variance in the dataset by removing dimensionality. This not only accelerates training time but also helps minimize multicollinearity in the logistic regression model. However, if PCA is not applied correctly—like retaining too few components—it can remove important features, resulting in underfitting, as shown in various performance evaluations involving dimensionality reduction[5].

Limitations - Despite the encouraging results, there are some limitations to using LR. The algorithm assumes linear relationships between input features and output log-odds, which may not reflect the complex, nonlinear patterns present in real-world fraud scenarios. Additionally, this study relied on a static dataset, which doesn't account for the constantly changing tactics used by fraudsters. This limits the model's ability to adapt over time and its potential for real-world application[6].

Future Scope - To improve the adaptability and accuracy of such systems, future research should explore integrating deep learning models, such as recurrent neural networks (RNNs) and autoencoders, which excel at identifying complex patterns in transaction data. Furthermore, utilizing real-time streaming data can enhance detection speed, making the system more proactive. Implementing federated learning frameworks could also address data privacy issues by allowing collaborative training without sharing centralized data—an emerging trend in financial machine learning research[7].

Logistic regression, when enhanced through careful data preprocessing and feature optimization, offers a strong

foundation for fraud detection. However, the dynamic nature of fraudulent activities requires ongoing evolution and adaptation of detection frameworks to ensure they remain reliable and effective over time.

VI. CONCLUSION

Credit card fraud remains a significant issue in today's digital landscape, as the increasing volumes of transactions open up new avenues for malicious activities. This study investigated how logistic regression, combined with various resampling techniques like random oversampling, random undersampling, and cluster centroid sampling, can be applied for fraud detection in datasets where the classes are heavily imbalanced. The findings demonstrated that while logistic regression is known for its interpretability and efficiency, its performance can be greatly enhanced through precise data preprocessing. Among the different resampling methods evaluated, random oversampling achieved the highest area under the curve (AUC) and recall, making it the most effective approach for minimizing false negatives, which are particularly crucial in fraud detection.

These results are consistent with recent research highlighting the necessity of addressing class imbalance. For instance, West and Bhattacharya [1] found that using ensemble-based resampling techniques, such as SMOTE and Tomek links, significantly boosted recall without sacrificing much precision. Similarly, Singh et al. [2] demonstrated that resampling enhanced the predictive power of simpler models like logistic regression, bringing their performance in line with more complex classifiers, such as gradient boosting machines.

However, logistic regression does have its drawbacks, particularly when it comes to capturing non-linear relationships, which could explain the slightly lower precision compared to tree-based methods. Nevertheless, its transparency and minimal computational demands make it a strong candidate for real-time financial systems. Additionally, incorporating principal component analysis (PCA) helped maintain the most relevant features while cutting down on redundancy, leading to better overall model performance.

In conclusion, this research confirms that logistic regression, when supported by effective resampling and feature engineering techniques, can be a powerful tool for fraud detection. The approach outlined here offers a scalable and practical solution for organizations aiming to implement efficient and understandable fraud detection systems. With ongoing development, such systems could significantly lower financial losses and boost user confidence in digital transactions.

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