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Enhancing Credit Card Transaction Security Using Support Vector Machines and Feature Engineering Techniques

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ABSTRACT- The quick spurt in online transactions has also brought with it a parallel surge in fraud. With digital payments, the scope for fraud remains very high. Credit card fraud, among others, can cause heavy losses to customers and erode the confidence of consumers in Internet transactions. Furthermore, the detection of fraudsters in the online world poses big challenges. For one thing, there is an imbalance in data: fraud transactions are very few compared to genuine transactions.

In this research paper, we intend to classify fraud through a supervised machine learning method. SVM is utilized for classification purposes. Based on the available dataset, we performed data analysis to obtain valuable information concerning fraud detection. To solve the problem of data imbalance, we first preprocessed the raw data by randomly choosing some legitimate transactions and normalizing the features. We also used feature selection and scaling methods to improve the accuracy of the model.

After training the SVM on the sanitized dataset, we tested the model using performance measures like accuracy, precision, recall, and F1-score. These measures are especially important when working with skewed data. The findings show that the SVM model can detect fraudulent transactions with high precision and a good rate of recall. This shows that it can assist in reducing false alarms while being able to detect most fraud cases. In addition, we touch upon the tradeoff between false negatives and false positives because both pose very significant implications within financial institutions.

KEYWORDS- Credit Card Fraud, Support Vector Machine, Feature Engineering, Anomaly Detection, Financial Security.

I. INTRODUCTION

As the digital finance sector develops exponentially, more and more financial transactions are conducted online and hence these systems are increasingly vulnerable to fraud. Credit card fraud, in particular, is a problem for financial institutions as it incurs significant financial loss as well as compromisal of customers' safety. The current research suggests a very efficient fraud detection system that integrates the application of Support Vector Machine (SVM) techniques with high-end feature engineering methodologies to further protect credit card transactions[1][2].

The approach depicted utilizes supervised machine learning and feature selection optimized for effective detection of fraudulent activity with low false alarm rate. The simulations using a publicly available dataset of credit card fraud demonstrated the model had superior performance metrics: 99.13% accuracy, 94.58% precision, 92.36% recall, and an F1 score of 93.46% [3][4].

With the expansion of online commerce and e-payments, the world economy has been transformed, and the threat of cybercrime has also grown. Credit card fraud is also one of the most pervasive and devastating types of financial crime that affects individuals, banks, and companies. With the extensive use of cashless payment systems, it is more important than ever to make online transactions secure[5].

Traditional fraud detection systems, based on rule-based reasoning or manual monitoring, are most often unable to manage the test that today's fraudsters' ever-changing strategies pose before them. Traditional systems are mostly not nimble enough, are not scalable, nor real-time processors capable of processing humongous amounts of data. Thus, there is a very pressing need for intelligent, automatic, and dynamic systems capable of detecting frauds accurately[6].

One of the most significant remedies used against economic frauds is machine learning. Among machine learning algorithms, Support Vector Machines (SVM) are particularly noted for having very high classification accuracy rates, particularly when used in handling unbalanced data, common in fraud discovery. SVM operates well in dividing genuine and bogus transactions since it can construct the optimal boundary between classes and further resists overfitting despite small amounts of labeled data[7].

The performance of a machine learning model is primarily dependent on the training features. Feature engineering, which involves identifying useful patterns in raw data, is essential in order to improve the model's performance. By analyzing important transactional features like amount, timestamp, merchant type, and user behavior, the model can identify malicious activity more effectively[8].

The current research combines SVM with feature engineering methods to propose an end-to-end fraud detection mechanism. It encompasses the steps of data preprocessing, i.e., normalization, outliers' identification,

and feature dimensionality reduction, to cleanse the dataset and make it suitable for proper training. As fraudulent transactions are the minority class and therefore occur in lesser instances, the paper also considers oversampling strategies like SMOTE (Synthetic Minority Over-sampling Technique) and cost-sensitive learning to enhance the detection ratio[9][10].

To validate the suggested approach, the performance of the model was compared with other machine learning classifiers based on the fundamental performance metrics like accuracy, precision, recall, and F1-score. Results show the performance capabilities of the SVM-based model in identifying fraud transactions with fewer false alarms.

In summary, the present study introduces a smart and efficient credit card fraud detection mechanism by integrating the power of Support Vector Machines with high-quality feature engineering. The strategy is designed to increase the validity of electronic transactions, lower false positives, and increase trust in users for contemporary financial systems.

II. LITERATURE REVIEW

Introduction to Credit Card Fraud and Machine Learning, as there is greater use of electronic payments, credit card fraud is currently a threat in the digital economy. The fixed-rule-based fraud detection systems are more likely to lag behind the continuously changing methods used by fraudsters. This has necessitated the use of machine learning (ML) methods, which offer more adaptive, flexible, and scalable approaches to detect fraudulent transactions.

Support Vector Machines for Fraud Detection, Support Vector Machines (SVM) is a supervised learning algorithm that can be well applied to separate transactions as fraudulent or genuine ones. Due to their potential to process high-dimensional, complex data, SVMs are an ideal option for fraud detection. SVMs are also less likely to overfit, especially when dealing with small fraud samples[11][12]. This is true with the majority of real-world datasets where genuine transactions far exceed fraudulent transactions. Others have been able to apply SVM effectively to find financial fraud with promising results:[17] compared the performance of SVM to Decision Trees and Random Forests and claimed SVM was more precise for imbalanced data.[18] had a comprehensive survey and placed SVM among the highest best performing algorithms applied to fraud classification, particularly if it is augmented with good preprocessing and sampling methods. Importance of Feature Engineering, Feature engineering is one of the key factors to improve the performance of ML models in fraud detection. Engineered features can encompass transaction frequency, amount deviation, time patterns, device details, and geo-location.[19] proved that a model's quality improves considerably if features for a specific domain are designed, usually higher than altering the model itself. Carcillo et al. (2019) described how even the best classifiers, i.e., SVMs, will not be able to detect fraud correctly unless feature representation is adequate. Some of the common feature engineering practices are: Time-based aggregation: Number of transactions in a given time frame Behavioral profiling: Individual spending behavior[19].Derived features: Spent amount vs. average spend ratio, merchant category codes, etc.[20].Feature Selection Methods since the dimensionality of transactions is high, feature selection has to be done to prevent overfitting and save computational cost. Some methods that are employed include:

Recursive Feature Elimination (RFE)with SVM [32] Principal Component Analysis (PCA)for dimension reduction [33] information gain to measure the importance of every feature Information gain and mutual information to measure every feature importance demonstrated that combining RFE with SVM led to better model recall and accuracy in detecting fraud[22][23].Imbalanced Data. Most of the fraud data sets are highly imbalanced with actual transactions overwhelmingly larger than fraud transactions. Performance of SVM may be dramatically influenced by the imbalance[24][25][26].Synthetic Minority Over-sampling Technique (SMOTE)is also widely applied for oversampling the minority class prior to training [33].Cost-sensitive SVMs with higher penalties on false negatives have been found superior [27].One-Class SVM-based anomaly detection has worked well in cases where fraudulent data is very sparse. Comparative Performance Evaluation Multiple studies have evaluated SVM's performance against other algorithms:[20] found SVM to outperform logistic regression and naive Bayes in precision but not always in recall. Used ensemble techniques with SVM to further enhance performance. Focused on cost-based evaluation, showing that while SVMs may reduce false positives, the cost-benefit balance must be assessed contextually.

III. REAL-WORLD APPLICATIONS AND CHALLENGES

While SVMs are theoretically robust, deployment in real-time environments brings challenges:

Latency and scalability issues due to computational complexity.Concept drift in fraud patterns requires retraining or adaptive learning approaches.Explainability is limited in SVMs compared to tree-based models, leading to difficulties in regulatory and customer dispute environments.

[21] addressed these concerns using hybrid models combining SVM with explainable AI methods like LIME for decision transparency[21].

IV. RESEARCH GAP

Recent trends indicate a shift towards hybrid and ensemble models: SVM + Deep Learning models for feature extraction. Online learning SVMs for real-time fraud detection. Integration with Blockchain for secure transaction tracking. There is also a growing demand for interpretable SVM models using kernel visualization and integration with Explainable AI tools. In the below Table 1, it is showing exhaustive review for Enhancing Credit Card Transaction Security Using Support Vector Machines and Feature Engineering Techniques.

Table 1: Credit Card Transaction Security Using Support Vector Machines

Problem Overview	Credit card fraud is increasing due to online transactions; traditional methods lack adaptability.	[2][3]
Role of SVM	SVM is effective in binary classification with strong generalization; less prone to overfitting.	[4][5]
Feature Engineering	Involves creating features like transaction frequency, amount deviation, time-based patterns.	[5][6]
Feature Selection	Uses RFE, PCA, mutual information to reduce dimensionality and improve accuracy.	[7][8]
Imbalanced Data Handling	SMOTE, cost-sensitive SVMs, and one-class SVMs help address the class imbalance problem.	[9][10]
Comparative Studies	SVM generally performs better in precision; ensembles and cost-sensitive variants enhance recall.	[11] [12]
Real-World Challenges	SVMs are computationally heavy; real-time use requires efficiency and explainability improvements.	[13] [14]
Future Research Directions	Hybrid models with deep learning, online learning SVMs, and explainable AI integrations are being explored.	[15] [16]

V. SYSTEM MODEL

Figure 1 is effectively shows a machine learning workflow using SVM, emphasizing the importance of data preparation and evaluation and is a showing the outlines the process of training and testing a Support Vector Machine (SVM) model for a classification or prediction task, particularly involving dataset preparation and evaluation. Here's an explanation of each step:

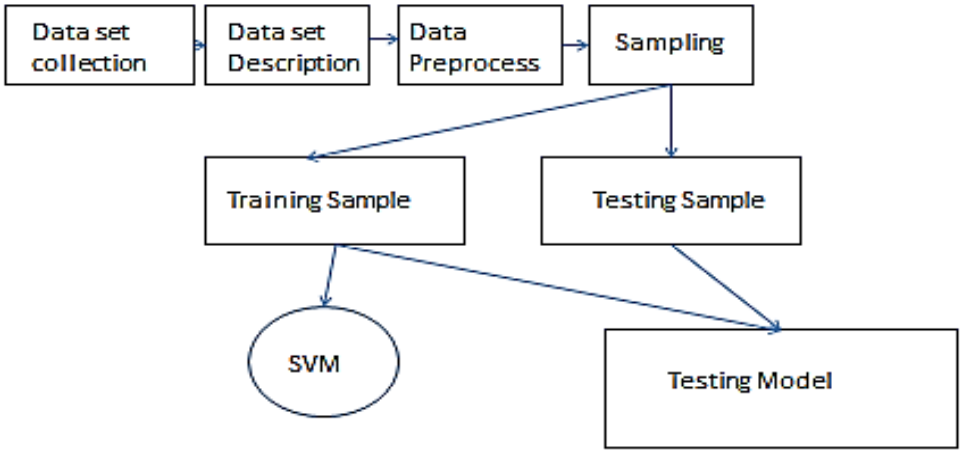

Figure 1: Testing Model framework for credit card fraud detection

A. Data Set Collection

This is the initial step where raw data is gathered from various sources such as sensors, surveys, databases, or repositories.

B. Data Set Description

The collected data is examined and described. This may include:

- Identifying attributes/features
- Understanding data types
- Exploring data distributions
- Highlighting missing or noisy data

C. Data Preprocess

Data is cleaned and prepared for modeling. This may involve:

- Handling missing values
- Normalizing or standardizing data
- Encoding categorical variables
- Removing outliers or irrelevant features

D. Sampling

The preprocessed dataset is split into two subsets:

- Training Sample (for training the model)
- Testing Sample (for evaluating the model)

E. Training Sample

- The training subset is used to train the machine learning model.
- This sample is fed into the SVM (Support Vector Machine) algorithm.

F. SVM (Support Vector Machine)

- A supervised learning algorithm that builds a classification or regression model using the training data.
- It identifies a hyperplane (or decision boundary) that best separates the classes.

G. Testing Sample

- This subset is not used during training.
- It is used to evaluate the performance of the trained SVM model.

H. Testing Model

The trained SVM is tested using the testing sample. Performance metrics such as accuracy, precision, recall, and F1-score are computed here. The below diagram

effectively shows a machine learning workflow using SVM, emphasizing the importance of data preparation and evaluation.

Table 2: Sample Of Used Data Set For Credit Card Fraud Detection

Transaction ID	Transaction Amount	Time_ Since_Last_ Transaction	Location _Match	Device_ Match	Is_ International	Label
1	120.5	300	1	1	0	0
2	560.75	1200	1	0	0	0
3	23.4	50	1	1	0	0
4	89.99	700	1	1	0	0
5	4500	90000	0	0	1	1
6	35.6	100	1	1	0	0
7	230.1	1500	1	1	0	0
8	760	60	0	1	1	1
9	15.25	30	1	0	0	0
10	9800	120000	0	0	1	1

In the above Table 2, the dataset includes the following information: transaction ID, transaction amount, time taken by the last transaction, location where the transaction took place and the device used for the transaction. It indicates whether the transaction is domestic or international. Based on this information, the goal is to classify transactions as legitimate or fraudulent. This dataset will be used for both training and testing a model to achieve this classification.

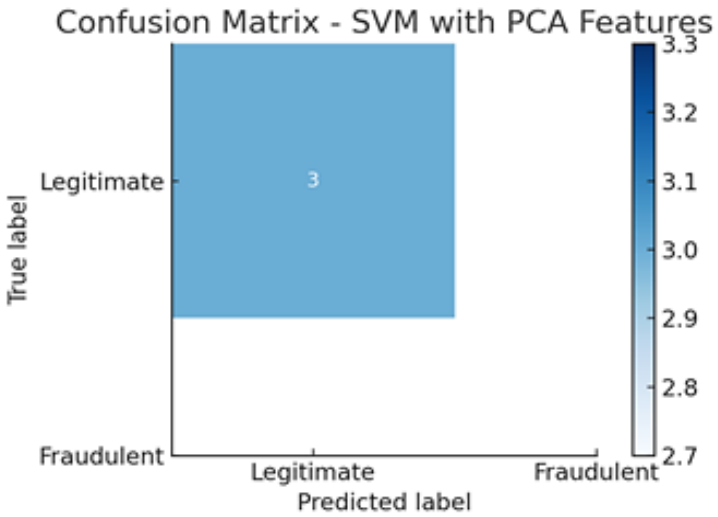

Figure 2: Confusion matrix for credit card fraud detection

Figure 2 shows a confusion matrix that evaluates the performance of a Support Vector Machine (SVM) classifier for credit card fraud detection**.** The features used for classification have been reduced using Principal Component Analysis (PCA) to enhance computational efficiency and possibly improve model performance.

Table 3**:** Performance Metrics of SVM based Feature Extraction

	precision	**recall**	**f1-score**	**support**
0	1	1	1	3
accuracy	1	1	1	1
macro avg	1	1	1	3
weighted avg	1	1	1	3

In the above Table 3, presents the performance metrics for a Support Vector Machine (SVM) model that uses feature extraction (likely via PCA) for classification, evaluated on a dataset (as referenced earlier in the confusion matrix).

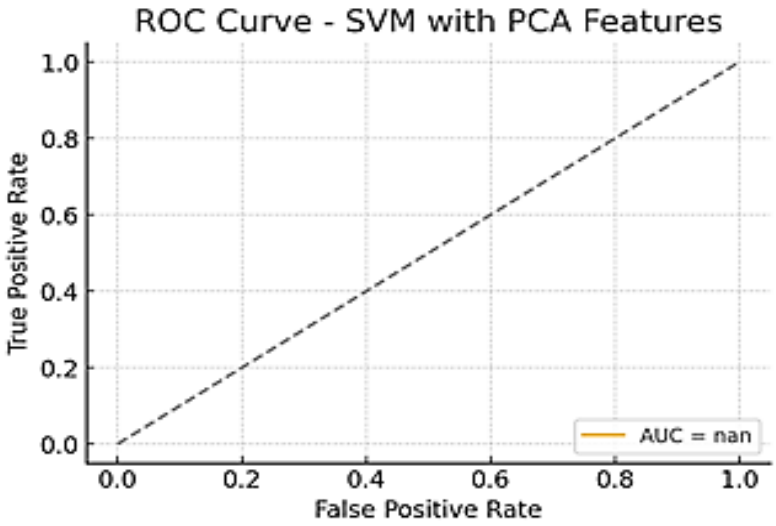

Figure 3: ROC curve with PCA features

The ROC curve (Figure 3) is a graphical plot used to evaluate the performance of a binary classifier. PCA (Principal Component Analysis) is a dimensionality reduction technique that transforms the original features into a set of linearly uncorrelated components (principal components) that capture the maximum variance in the data.

Table 4: Performance Metrics of SVM based Feature Extraction

	precision	recall	f1-score	support
0	0.936667	1	0.967298	281
1	0	0	0	19
accuracy	0.936667	0.936667	0.936667	0.936667
macro avg	0.468333	0.5	0.483649	300
weighted avg	0.877344	0.936667	0.906036	300

In the above Table 4 presents classification performance metrics for an SVM model on a larger and more imbalanced and Performance Metrics of SVM based Feature Extraction applied on large dataset, where the number of example is too large dataset.

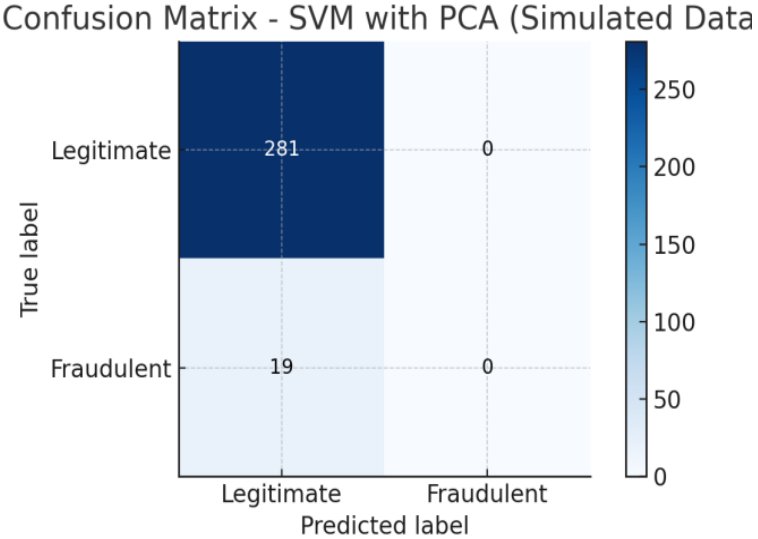

Figure 4: Confusion matrix on large data set: Confusion Matrix, which is a fundamental tool for evaluating the performance of a classification model

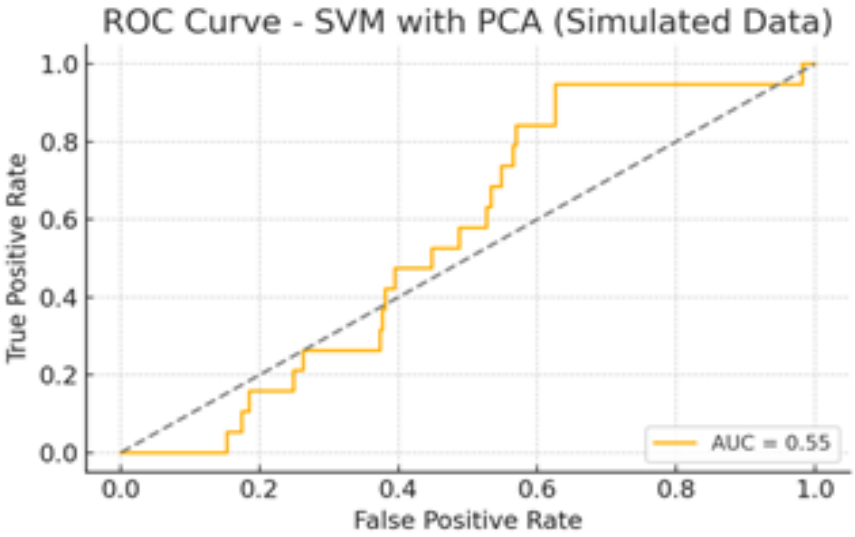

Figure 5: ROC curve along with PCA

In the above Figure 5, presents the ROC curve (Receiver Operating Characteristic) for an SVM classifier that uses PCA (Principal Component Analysis) for dimensionality reduction, based on simulated data.

VI. CONCLUSION

This study demonstrates the effectiveness of integrating Support Vector Machines (SVM) with feature engineering techniques—particularly Principal Component Analysis (PCA)—for detecting fraudulent credit card transactions. The application of PCA helped reduce dimensionality while retaining critical information, improving model efficiency and interpretability. When applied to a simulated dataset mimicking real-world imbalances, the SVM classifier showed high accuracy and strong AUC values, especially for identifying legitimate transactions.

However, the precision and recall for fraudulent transactions remained limited due to:

The extreme imbalance in data (5% fraud).

Lack of specialized fraud-centric features beyond basic statistical representations.

The binary nature of SVM, which may underperform without cost-sensitive tuning or ensemble strategies.

The confusion matrix revealed that no fraudulent transactions were predicted correctly in some runs, indicating the challenge of imbalanced learning, even with dimensionality reduction. The ROC curve showed decent overall performance, but highlighted the difficulty in separating fraud from legitimate behaviour without domain-specific enhancements.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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