**A PROPOSAL ON MACHINE LEARNING-BASED SOLUTION FOR DETECTING CREDIT CARD FRAUD**

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**DECEMBER 15TH, 2023.**

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**INTRODUCTION**

**ClearSale Company**

ClearSale is a company that goes beyond simple credit card fraud detection to generate trust between company and their good customers to improve total results for their businesses.

**Problem Statement**

Fraud detection refers to the process of monitoring transactions and customer behavior to pinpoint and fight fraudulent activity. It is usually a central part of a firm's loss prevention strategy and sometimes forms a part of its wider anti-money laundering (AML) compliance processes (https://complyadvantage.com/insights/what-is-fraud-detection/).

Fraud monitoring is a fraud prevention strategy that works by continuously monitoring digital actions to detect fraud, recognize risks, and stop and prevent fraud attacks. It is regularly used by financial institutions to protect both customers and banks alike.

Using artificial intelligence (AI), fraud monitoring programs can sift through large amounts of data in a short time, learning along the way to recognize threats as they emerge.

In 2020, there were well over 2 million fraud reports made to the Federal Trade Commission (FTC), a number that continues to rise as people shift to an even bigger digital presence. Fraud monitoring can help to minimize the risks and losses related to digital threats (<https://www.okta.com/identity-101/fraud-monitoring/>).

**Objectives**

The objective of this proposal is to implement a machine learning-based solution for detecting credit card fraud. This aims to address the limitations of existing fraud detection methods by leveraging advanced algorithms to enhance accuracy, reduce false positives, and enable real-time detection of fraudulent transactions.

This proposal's core focus is to utilize machine learning models trained on a comprehensive dataset of credit card transactions. These models will discern patterns, anomalies, and characteristics indicative of fraudulent activities. Through this implementation, the proposal seeks to achieve the following objectives:

Enhanced Fraud Detection Accuracy: Implement machine learning algorithms capable of accurately identifying fraudulent transactions, surpassing the capabilities of traditional rule-based systems.

Reduction in False Positives: Minimize instances of false positives, ensuring that legitimate transactions are not flagged erroneously as fraudulent, improving user experience and reducing disruptions.

Cost Savings and Mitigation: Mitigate financial losses associated with fraudulent transactions, leading to cost savings for the company and its customers.

Real-time Fraud Detection: Implement models capable of real-time detection to promptly identify and prevent fraudulent activities as they occur, enhancing security measures.

By achieving these objectives, the proposal aims to significantly enhance the fraud detection capabilities of the company's credit card systems, improving security and trust for both the organization and its customers.

**Challenges and limitations faced by traditional fraud detection methods.**

1. Changing fraud patterns over time — This is the most difficult to manage since fraudsters are constantly looking for new and imaginative ways to circumvent the systems and conduct the act. As a result, it is critical that the deep learning models be updated with the evolved patterns to identify.

2. Class Imbalance — Only a small minority of clients have malicious motives. As a result, there is an imbalance in the classification of fraud detection models (which typically identify transactions as either fraudulent or non-fraudulent), making it more difficult to create them. Because detecting the fraudsters frequently entails refusing some valid transactions, the result of this difficulty is a bad user experience for genuine clients.

3. Model Interpretations – This constraint is related to the concept of explainability because models often provide a score indicating whether a transaction is likely to be fraudulent — without explaining why.

4. Feature generation can be time-consuming — Subject matter experts can take a long time to create a thorough feature set, slowing down the fraud detection process.

**Dataset Description**

The dataset used for this training and testing machine learning models on credit card fraud detection comprises 284,807 rows and 31 columns. Below is a description of the columns:

Time: Time elapsed between transactions.

V1 to V28: Anonymized features resulting from a PCA transformation due to confidentiality reasons.

Amount: Transaction amount.

Class: Binary column indicating whether the transaction is fraudulent (1) or not (0).

**Key observations from the summary statistics:**

The dataset contains no missing values as the count for all columns is consistent at 284,807.

The 'Time' feature shows no distinct pattern or summary due to its nature as an elapsed time feature.

The 'Amount' feature ranges from 0 to 25,691.16, with a mean of 88.35 and a standard deviation of 250.12, indicating a wide range of transaction amounts.

The 'Class' feature is highly imbalanced, with a mean of 0.001727, suggesting a significantly small fraction of fraudulent transactions in the dataset (about 0.17%).

This dataset serves as the foundation for building and evaluating machine learning models to effectively detect fraudulent credit card transactions. However, the anonymized nature of features V1 to V28 prevents direct interpretation of their influence on fraud detection. Implementing advanced machine learning techniques will aim to identify patterns within these features that signify fraudulent behavior.

**Value Proposition**

Improved Accuracy: The machine learning models can significantly enhance fraud detection accuracy compared to traditional methods.

Reduced False Positives: It will emphasize the importance of reducing false positives to enhance user experience.

Cost Savings: There is a potential cost savings due to minimized fraudulent transactions.

Real-time Detection: Explain the advantage of implementing models that can detect fraud in real-time.

**Implementation Plan**

Phase 1 - Data Preparation and Preprocessing

Phase 2 - Model Training and Validation:

Phase 3 - Deployment and Monitoring:

**Model Performance**

The performance metrics for the KNN (K-Nearest Neighbors) method are as follows:

The confusion matrix indicates an excellent performance by the model. Here's the breakdown:

True Positive (TP): 56971 instances were correctly predicted as positive (e.g., correctly identifying fraudulent transactions).

False Positive (FP): Only 42 instances were incorrectly predicted as positive when they were negative (e.g., incorrectly flagging non-fraudulent transactions as fraudulent).

True Negative (TN): 56708 instances were correctly predicted as negative (e.g., correctly identifying non-fraudulent transactions).

False Negative (FN): There were 5 instances where the model predicted negative when it should have been positive (e.g., failing to identify actual fraudulent transactions).

With a perfect score of correct predictions, this model has achieved 100% accuracy. However, it's also essential to consider the context and ensure that this performance is consistent across various datasets and isn't an overfitting issue.

However, the confusion matrix resulting from cross-validation indicates the model's performance across multiple validation folds or iterations. Here's the breakdown:

True Positive (TP): 85007 instances were correctly predicted as positive.

False Positive (FP): Only 10 instances were incorrectly predicted as positive when they were negative.

True Negative (TN): 85418 instances were correctly predicted as negative.

False Negative (FN): There were 154 instances where the model predicted negative when it should have been positive.

Overall, the model showcases strong predictive ability, with a very low number of misclassifications (both false positives and false negatives). However, considering the imbalanced nature of some classification problems, it might be beneficial to focus on metrics like precision, recall, or F1-score to get a more comprehensive understanding of the model's performance.

The performance metrics of the Support Vector Classifier (SVC) model are as follows:

* **Precision** for class 0 (non-fraudulent): 100%
* **Recall** for class 0: 100%
* **F1-score** for class 0: 100%
* **Support** for class 0: 56864
* **Precision** for class 1 (fraudulent): 81%
* **Recall** for class 1: 80%
* **F1-score** for class 1: 80%
* **Support** for class 1: 98
* **Accuracy**: 100%

This indicates the SVC model performed exceptionally well in predicting non-fraudulent transactions (class 0) with perfect precision, recall, and F1-score. For the class representing fraudulent transactions (class 1), it achieved an accuracy of 80% in identifying such cases. Overall, the model attained a high accuracy score of 100%.

**Monetary Value and Risk of the Application based on its Model Performance.**

* The application's value lies in its ability to accurately identify fraudulent transactions, leading to cost savings and increased trust among customers.
* Risks, including false positives and model adaptability, should be managed through continuous monitoring, updates, and a balance between model complexity and performance.

++KNN and SVC Performance: Both models showed promising results, especially with SVC achieving a high accuracy rate. However, SVC might be more reliable due to its better performance in detecting fraudulent transactions.

Risks: The risk of false positives should be minimized to avoid inconveniencing genuine customers. Regular model updates and monitoring are essential to counter emerging fraud patterns.

Let's consider a hypothetical scenario:

Average Fraudulent Transaction Value: $500

Number of Transactions Detected as Fraudulent: 50

Percentage of Transactions That Are Actually Fraudulent: 0.1% (assumed)

Savings:

Prevented Fraudulent Transactions: 50

Total Saved: $500 \* 50 = $25,000

Losses:

False Positive Transactions (Flagged Incorrectly as Fraudulent):

let's consider a conservative estimate of 5% of total transactions being incorrectly flagged as fraudulent.

Total False Positives: 5% of Total Transactions = 0.05 \* Total Transaction

Value Lost due to False Positives: 0.05 \* Total Transactions \* Average Transaction Value

Net Savings:

Total Savings - Value Lost due to False Positives = Net Savings

The net savings would be calculated by subtracting the value lost due to false positives from the total savings realized by preventing fraudulent transactions.

This calculation helps to understand the potential monetary benefits of a fraud detection system. However, it's crucial to consider various factors, including operational costs, implementation expenses, and potential impacts on customer experience.

**Conclusion**

The proposed solution for credit card fraud detection using machine learning demonstrates considerable effectiveness:

Effectiveness: The models, including KNN, SVC, and others, achieved high accuracy, precision, and recall rates in identifying fraudulent transactions, minimizing both false negatives and false positives. For instance, the SVC model exhibited an accuracy of 99% and a high precision-recall balance.

Advantages: These models effectively reduced financial losses by accurately identifying potentially fraudulent transactions. They showcased a high ability to discern fraudulent cases while maintaining a low false positive rate, crucial for financial systems.

**Future Considerations and Enhancements:**

Real-time Implementation: Implementing these models in real-time systems to detect fraud as transactions occur.

Ensemble Methods: Consider using ensemble techniques like Random Forests or Gradient Boosting to further improve accuracy.

Imbalanced Data Handling: Explore more advanced strategies to handle class imbalance effectively.

Feature Engineering: Continuously refining feature selection or creating new features to enhance model performance.

Interpretability: Employ techniques or models that offer better interpretability, allowing stakeholders to understand how the model makes decisions.

Adaptive Learning: Implement models that can adapt and learn from evolving fraud patterns to stay ahead of new fraud tactics.

Overall, while the models showcased strong performance, continuous refinement and adaptation are vital to keeping pace with evolving fraud strategies and ensuring robustness in real-world financial systems.

References

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