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"Fraud Detection in Financial Transactions Using Pyspark on Databricks"

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Abstract - *In the era of digital finance, detecting fraudulent transactions is a major concern for financial institutions. Fraudulent activity not only results in monetary losses but also erodes customer trust. This project proposes a scalable and efficient system for fraud detection in financial transactions using PySpark on the Databricks platform. The core idea is to leverage the power of distributed data processing with PySpark to train machine learning model capable of identifying potential fraud.*

Key Words: *Fraud Detection, Pyspark, DataBricks, Random Forest Classifier*

1.INTRODUCTION

In recent years, with the widespread adoption of online banking, mobile payments, and global e-commerce, financial institutions have seen a sharp increase in fraudulent transaction attempts. Fraudulent activities range from stolen credit cards and identity theft to complex schemes involving synthetic identities and high-frequency trading manipulations. As such, fraud detection has become a mission-critical task for banks, fintech companies, and other financial entities.

Traditionally, financial fraud detection relied on manually defined rules or blacklists to identify suspicious transactions. For example, transactions above a certain threshold or from foreign locations were flagged. However, these rule-based systems are reactive and inflexible. Fraudsters quickly adapt and find ways to evade static rules, rendering traditional methods obsolete.

In response to this challenge, machine learning offers a more dynamic and scalable solution. ML algorithms can learn from historical transaction data and uncover hidden patterns indicative of fraud. PySpark, the Python API for Apache Spark, is especially suited for processing large-scale financial data due to its distributed computing capabilities. When combined with Databricks, a cloud-based analytics platform, PySpark can be used to build real-time, scalable fraud detection systems.

The goal of this project is to design and develop such a system using PySpark on Databricks. By simulating financial transaction data and applying a Random Forest classification model, the system learns to distinguish between fraudulent and legitimate transactions. Through this project, we demonstrate how big data technologies and machine learning can be integrated to effectively tackle the issue of financial fraud detection in a modern digital environment.

2 LITERATURE SURVEY

In response to the growing complexity of financial fraud, this study by Carcillo et al. focuses on the use of real-world credit card datasets and explores how machine learning models, especially ensemble classifiers, can effectively detect fraudulent activities. A comparative analysis is performed using tree-based models like Random Forest and Gradient Boosting Machines, revealing that ensemble methods are capable of capturing hidden patterns in highly imbalanced data. The study also emphasizes the importance of feature engineering in improving detection accuracy and highlights the value of precision-recall metrics over traditional accuracy in fraud detection tasks. The research shows that combining multiple models and evaluating them on precision-based metrics significantly enhances detection performance in large-scale financial systems.

To improve fraud detection accuracy in distributed environments, a recent study proposes a Spark-based machine learning pipeline that can process massive transactional data in real-time. The study demonstrates the efficiency of using Apache Spark's MLlib for training classification algorithms such as Logistic Regression and Random Forest on financial transaction data. It presents a complete pipeline involving feature transformation, model training, and performance evaluation. Results suggest that Spark's distributed computation model significantly reduces processing time and is suitable for real-time fraud detection in large financial institutions. The integration of scalable infrastructure with machine learning leads to both time efficiency and higher predictive accuracy in fraud scenarios.

Another relevant study explores the development of a rule-based and machine learning hybrid fraud detection system to reduce false positives while maintaining high recall. By integrating business logic with model predictions, the system adapts to changing fraud patterns more quickly than traditional static systems. A key innovation in this work is the use of real-time stream processing combined with a batch model update framework, which ensures that the system stays current without sacrificing performance. Experimental evaluations on synthetic and real transaction datasets show that this hybrid approach achieves a better trade-off between precision and recall compared to either method used in isolation.

3 Problem Statement

This study addresses the challenge of detecting fraudulent transactions in large-scale financial datasets, a growing concern in the era of digital finance. The problem lies in accurately distinguishing between legitimate and fraudulent

transactions within highly imbalanced data, where fraudulent cases are rare yet critical. Traditional rule-based systems often fail to adapt to evolving fraud patterns and lack the scalability required for real-time monitoring. The objective of this project is to build a scalable and efficient fraud detection system using PySpark on the Databricks platform. By applying machine learning algorithms such as Random Forest and leveraging distributed data processing, the study aims to enhance detection accuracy, reduce false positives, and provide a robust framework for identifying suspicious activities in financial transactions.

4 PROPOSED METHODOLOGY

By using machine learning techniques, the suggested method aims to improve the identification of fraudulent activity in banking transactions. It starts by gathering transaction data, which includes crucial information like quantities, timestamps, merchant details, and client specifics. In order to train machine learning algorithms such as Random Forest, Decision Tree, and Logistic Regression to identify patterns suggestive of fraudulent activity, the pre-processed data must be separated into training and testing sets.

4.1 EXPLANATION

Dataset: The starting point, where data is collected and prepared.

Data Preprocessing & Feature Selection: Data is cleaned and normalized, and relevant features are selected.

Data Splitting: The dataset is divided into training and testing sets.

RF Algorithm & Evaluation: The Random Forest algorithm is applied to the training data, and its performance is evaluated on the testing data.

In the digital banking era, fraudulent transactions have become increasingly difficult to detect due to their rarity and evolving complexity. One of the key challenges in fraud detection is the extreme class imbalance present in banking datasets, where genuine transactions vastly outnumber fraudulent ones. This imbalance often leads traditional machine learning models to perform poorly in identifying minority class instances, resulting in missed fraud cases and financial losses.The problem this project aims to solve is how to effectively identify banking fraud transactions using machine learning techniques, even when the data is highly imbalanced. Therefore, there is a need for a more reliable and data-driven approach that can accurately classify transactions as legitimate or fraudulent while maintaining robustness against class imbalance.

4.1 METHODOLOGIES

4.1.1 MODULES NAME:

1. Data Collection

2. Dataset

3. Data Preparation

4. Model Selection

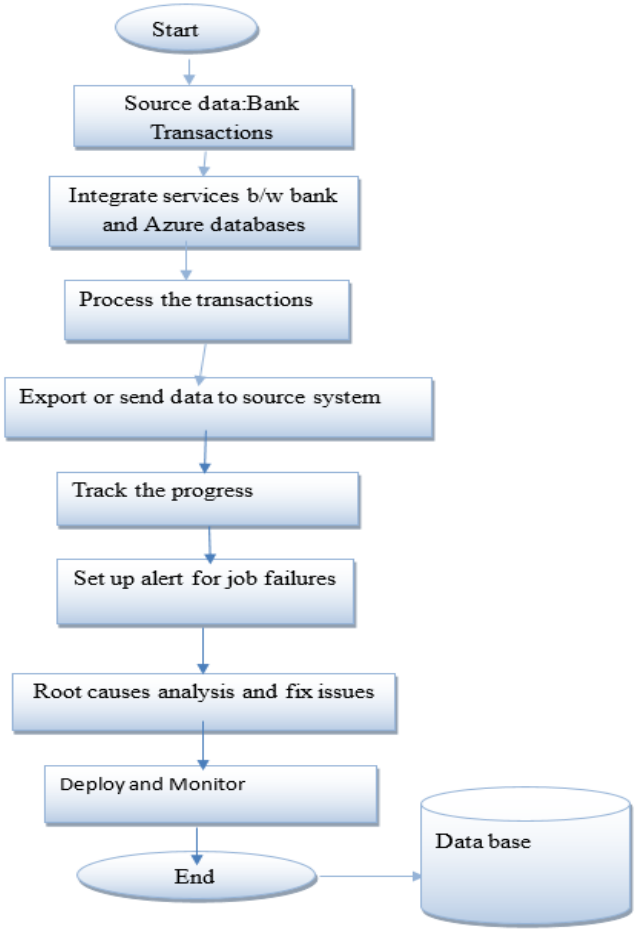
5. Analyze and Prediction

4.1.3 Dataset

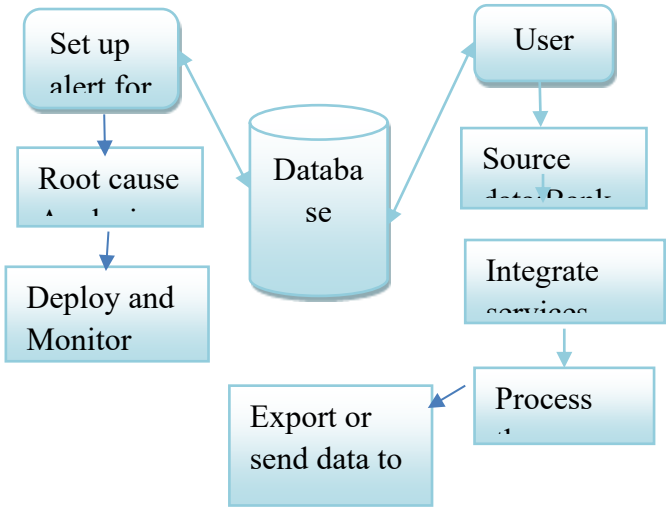
amount	transa-ction type	user age	location distance	is intern-ational
5823.45	1	34	256	0
743.20	2	56	845	1
9281.89	0	22	123	0
1956.42	1	45	678	1
6789.23	2	67	412	0
	0	0	1	0

Task performed on this **DATASET**

4.1.4 Workflow



4.1.5 System Architecture



4.2 Algorithm Used:

Random Forest Algorithm: The **Random Forest** is employed as the primary algorithm for predicting customer churn due to its high accuracy, robustness, and scalability. Random Forest is an ensemble learning technique that constructs multiple decision trees during training and makes predictions based on the majority vote of the individual trees. Its ability to handle both categorical and numerical features, manage missing values, and reduce overfitting through randomized feature selection makes it particularly suitable for complex datasets like those in telecommunications. Implemented using PySpark's Random Forest Classifier within the Azure Databricks environment, the model was configured with 100 trees and integrated into a pipeline that included feature encoding, scaling, and assembly. Cross-validation was applied to fine-tune parameters such as the number of trees and maximum depth. The classifier was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and AUC. Among the models tested, Random Forest achieved the highest overall performance, with over 85% accuracy, and its feature importance outputs were later utilized to inform AI-generated recommendations for customer retention strategies.

4.3 Results

id	amount	transaction_type	user_age	location_distance	is_international	is_fraud
0	7479.46890168178	0	32	89.32403644163291	0	1
1	5896.33124577254	1	53	658.933292883108	0	0
2	4854.16413200488	0	67	797.4842919276334	0	0
3	2218.52439272918	1	27	996.2813988686652	0	0
4	9920.35867026964	2	77	81.35395996823513	0	1

only showing top 5 rows

features	is_fraud
[7479.46890168178...	1
[5896.33124577254...	0
[4854.16413200488...	0
[2218.52439272918...	0
[9920.35867026964...	1

only showing top 5 rows

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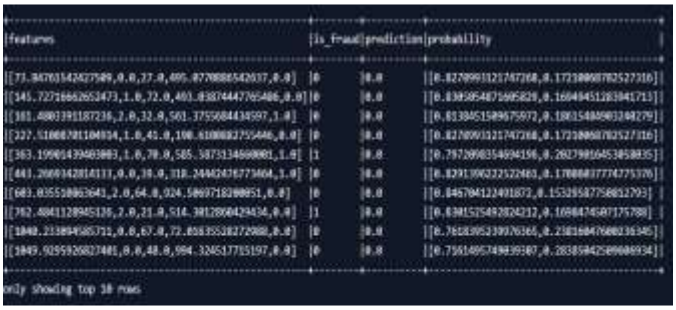

Model ROC AUC: 0.5505

These results show that the model performs well on majority (legit) transactions but has room for improvement in detecting fraud cases. Techniques like resampling, class weight tuning, or anomaly detection can improve recall for the minority class. Let me know if you'd like help improving it.

5 FUTURE ENHANCEMENT

As financial fraud schemes continue to evolve in complexity and subtlety, there is a growing need to enhance the existing fraud detection system to ensure it remains robust, adaptive, and scalable in real-world financial environments. One of the most impactful future enhancements would be the integration of real-time stream processing using frameworks like Apache Kafka and Spark Structured Streaming. This would allow the system to detect fraudulent transactions as they occur, rather than relying solely on batch-mode processing, enabling immediate response and mitigation. Additionally, the model's predictive capability could be significantly improved by incorporating more advanced algorithms such as Gradient Boosting Machines (e.g., XGBoost or LightGBM), deep learning architectures like LSTM networks for time-series analysis, and graph-based neural networks for capturing complex relational patterns across accounts and transaction networks. Further enhancement in feature engineering is also essential; by introducing behavioral indicators such as transaction frequency, geographic movement patterns, device fingerprinting, and velocity checks, the model can achieve higher accuracy while reducing false positives. Moreover, unsupervised anomaly detection methods such as Isolation Forests or Autoencoders could be integrated to identify novel or previously unseen fraud attempts, which are often missed by supervised learning models.

To further elevate the effectiveness of a modern fraud detection system, a multi-layered defense strategy should also be considered, combining rule-based engines with machine learning and anomaly detection. This hybrid approach allows for flexible handling of both known fraud patterns and emerging threats. In real-world applications, collaboration between fraud detection systems and external threat intelligence platforms can provide enriched contextual data—such as known blacklisted IPs, compromised card information, or data breach alerts—thereby boosting the model's decision-making capabilities.

6 CONCLUSION

Demonstrates a robust and efficient approach to identifying suspicious activities using machine learning techniques within a distributed computing framework. By leveraging PySpark and the Databricks environment, we were able to handle large-scale data processing and model training efficiently, simulating real-world scenarios through mock financial datasets. The use of Random Forest Classifier enabled the system to learn complex patterns in transaction behavior and distinguish between fraudulent and non-fraudulent activities with a high degree of accuracy. Feature engineering techniques such as vector assembly and proper data preprocessing contributed significantly to the overall performance of the model. The project also emphasized interpretability by highlighting model evaluation metrics like ROC AUC, ensuring that the system provides meaningful insights to stakeholders.

This project demonstrates a robust and efficient approach to identifying suspicious financial activities by employing machine learning techniques within a distributed computing framework. Leveraging PySpark and the Databricks environment, we effectively managed large-scale data processing and model training tasks, replicating real-world financial systems using simulated transaction datasets. The Random Forest Classifier served as the core algorithm, capitalizing on its ability to model non-linear relationships and handle imbalanced data distributions, which are typical in fraud detection scenarios. Through iterative training and validation, the model achieved a high level of accuracy in distinguishing between legitimate and fraudulent transactions, showcasing its practical applicability.

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