SCHOOL OF DATA ANALYTICS
MAHATMA GANDHI UNIVERSITY, KOTTAYAM

MINI PROJECT REPORT ON
Credit Card Fraud Detection using PySpark

This project report is submitted in partial fulfillment of the requirements for the award of

MASTER OF SCIENCE IN
DATA SCIENCE & ANALYTICS

Submitted by

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Under the guidance of

RAGI G. R. (ASSISTANT PROFESSOR)

2024–2026

SCHOOL OF DATA ANALYTICS
MAHATMA GANDHI UNIVERSITY

BONAFIDE CERTIFICATE

This is to certify that the project report entitled

“Credit Card Fraud Detection using PySpark”

by NOYAL BENNY (MG24C7115011) in partial fulfillment of the requirements of the post-graduation Master of Science in Data Science & Analytics, Mahatma Gandhi University, Kottayam, is a record of bonafide work carried out under my guidance and supervision.

Project Guide
RAGI G. R.

Director of the Dept.
Dr. Prof. K. K. JOSE

DECLARATION

I, **NOYAL BENNY** of third semester M.Sc. in the School of Data Analytics at Mahatma Gandhi University, Kottayam, hereby declare that the project work entitled "**Credit Card Fraud Detection using PySpark**" is carried out by me and submitted in partial fulfillment of the requirements for the award of Master of Science in Data Science & Analytics, under the guidance of Ms. Ragi G. R., School of Data Analytics, during the academic year 2024–2026.

NOYAL BENNY
SCHOOL OF DATA ANALYTICS
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ACKNOWLEDGEMENT

I express my sincere gratitude to my guide Ms. Ragi G. R., School of Data Analytics, Mahatma Gandhi University, for her valuable guidance, insights, and support throughout the project. I am also thankful to Dr. Prof. K. K. Jose, Director of the Department, for providing the necessary facilities. My heartfelt thanks to all faculty members, my parents, classmates, and friends who supported me directly or indirectly during this project.

NOYAL BENNY

ABSTRACT

This project "**Credit Card Fraud Detection using PySpark**" focuses on detecting fraudulent credit card transactions using Big Data analytics and machine learning with PySpark. With the enormous volume of financial transactions occurring every minute, identifying fraudulent activities efficiently is crucial for financial security. PySpark enables distributed processing, allowing large-scale datasets to be analyzed effectively. The project implements data preprocessing, feature engineering, machine learning using Random Forest Classifier, and evaluation metrics to identify fraud. The final model contributes to early fraud detection and enhances financial safety.

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Chapter 1
Introduction

Credit card transactions have increased rapidly with the growth of online payments and digital banking, leading to a higher risk of fraudulent activities. Detecting fraud is challenging because fraudulent patterns are rare and often hidden within large, complex, and highly imbalanced datasets. Traditional data processing tools are not efficient enough to handle such large volumes of data.

To overcome these limitations, Big Data technologies like **Apache Spark** and its Python API **PySpark** offer scalable, distributed processing for faster and more accurate fraud detection. This project uses PySpark to preprocess the credit card dataset, engineer features, and build a machine learning model capable of identifying fraudulent transactions. The approach highlights the importance of Big Data analytics in improving financial security and enabling real-time fraud detection.

1.1 Problem Statement

Credit card fraud occurs in small but highly impactful instances, making detection difficult within extremely large and imbalanced datasets. Traditional analytical methods struggle to process such data efficiently, leading to delays and reduced accuracy in identifying fraudulent patterns. Financial institutions require a scalable and reliable system that can analyze massive transaction records, detect anomalies, and classify potential fraud in real time. Therefore, the key problem is to develop an effective fraud detection model using Big Data technologies—specifically PySpark—that can handle large datasets, improve detection accuracy, and support timely decision-making.

1.2 Objectives

The main objectives of the project are:-

1. To preprocess and explore the credit card dataset using PySpark.
2. To build a machine learning model for fraud detection using Random Forest.
3. To evaluate model performance using accuracy, precision, recall, and F1-score.
4. To understand fraud patterns through large-scale data analytics.

Chapter 2
Literature Review

1. SCARFF: a Scalable Framework for Streaming Credit Card Fraud Detection with Spark" — Carcillo, Dal Pozzolo, Le Borgne, Caelen, Mazzer, Bontempi (2017). https://arxiv.org/abs/1709.08920?utm_source=chatgpt.com

2. "The Investigation of Real-Time Credit Card Fraud Detection (RTCCFD) Based on Machine Learning and Apache Spark" — Jiacheng He (2024). https://www.scitepress.org/Papers/2024/129008/129008.pdf?utm_source=chatgpt.com

3. "Credit Card Fraud Detection Using Big Data Framework" — Namrata Pandey, Rajeshwari S, Shobha Rani BN, Mounica B (2018). https://www.ijcrt.org/papers/IJCRT1892586.pdf?utm_source=chatgpt.com

Chapter 3
Methodology

Data Loading

The credit card transaction dataset is loaded into a PySpark DataFrame using spark.read.csv() with header and schema inference enabled. This allows efficient handling of large numerical datasets.

Data Preprocessing

The dataset is checked for missing values and duplicates. Since the data is clean, minimal cleaning is required.
Because fraud cases are extremely rare, class imbalance is addressed using sampling techniques or class weighting. Feature scaling is performed using StandardScaler to normalize numerical features.

Feature Engineering

All numerical variables are combined into a single feature vector using VectorAssembler. Normalized feature vectors help improve model accuracy and stability.

Model Building

A **Random Forest Classifier** is selected for its robustness and ability to handle imbalanced data. The dataset is split into training and testing sets, and the model is trained using PySpark MLlib with distributed processing.

Model Evaluation

Model performance is assessed using accuracy, precision, recall, F1-score, and a confusion matrix. These metrics help measure how effectively the model identifies fraudulent transactions.

3.1 Dataset Description

The dataset contains credit card transactions with features representing anonymized numerical values and a binary label indicating fraud (1) or non-fraud (0). The dataset is highly imbalanced, with fraud cases representing less than 1% of transactions.

Chapter 4
Implementation in Python

4.1 Initialize Spark

- Start a Spark session: SparkSession.builder.appName("CreditCardFraud").getOrCreate().

4.2 Import libraries

- PySpark modules: pyspark.sql, pyspark.sql.functions, pyspark.ml.feature, pyspark.ml.classification, pyspark.ml.evaluation, pyspark.ml.tuning.
- Python helpers for plotting and data handling: pandas, matplotlib.pyplot (for exporting visualizations).

4.3 Load dataset

- Read CSV into a DataFrame:
  df = spark.read.csv(path, header=True, inferSchema=True)

4.4 Initial inspection

- View schema and a few rows: df.printSchema(), df.show(5)
- Get basic stats: df.describe().show()
- Check class balance: df.groupBy('Class').count().show()

4.5 Data cleaning

- Drop duplicates: df = df.dropDuplicates()
- Handle missing values (if any): df = df.na.drop() or use imputation as required.

4.6 Feature selection & type casting

- Ensure numeric columns are cast to numeric types: df = df.withColumn('V1', col('V1').cast('double'))
- Select feature columns and label: feature_cols = [c for c in df.columns if c not in ('Class','Time','TransactionID')]

4.7 Feature engineering

- Assemble features:
  from pyspark.ml.feature import VectorAssembler
  assembler = VectorAssembler(inputCols=feature_cols, outputCol='rawFeatures')
- Scale features:
  from pyspark.ml.feature import StandardScaler
  scaler = StandardScaler(inputCol='rawFeatures', outputCol='features')

4.8 Handle class imbalance

- Options:
  - Undersampling majority class (randomly sample non-fraud rows).
  - Class weighting in the classifier (set weightCol or adjust probabilityCol when available).
  - Note: SMOTE is not native to Spark — can be applied with third-party libraries or off-cluster preprocessing.

4.9 Train/test split

- Split data: train, test = df.randomSplit([0.8, 0.2], seed=42)

4.10 Model selection & Build pipeline

- Use Random Forest:
  from pyspark.ml.classification import RandomForestClassifier
  rf = RandomForestClassifier(featuresCol='features', labelCol='Class', numTrees=100)
- **Create a pipeline:**
  from pyspark.ml import Pipeline
  pipeline = Pipeline(stages=[assembler, scaler, rf])

4.11 Hyperparameter tuning (optional but recommended)

- Use ParamGridBuilder and CrossValidator to tune numTrees, maxDepth, etc.
- Example: cv = CrossValidator(estimator=pipeline, estimatorParamMaps=paramGrid, evaluator=evaluator, numFolds=3)

4.12 Train the model

- Fit pipeline: model = pipeline.fit(train)
- (Or cvModel = cv.fit(train) if using cross-validation)

4.13 Predictions

- Generate predictions on test set: predictions = model.transform(test)

4.14 Evaluation

- Use evaluators:
  from pyspark.ml.evaluation import BinaryClassificationEvaluator, MulticlassClassificationEvaluator
    - AUC: evaluator = BinaryClassificationEvaluator(labelCol='Class')
    - Precision/Recall/F1: calculate via MulticlassClassificationEvaluator or by constructing a confusion matrix using predictions.groupBy('Class', 'prediction').count().
- Compute metrics: accuracy, precision, recall, F1-score, AUC.

4.15 Confusion matrix & detailed metrics

- Aggregate predictions to compute TP, FP, TN, FN and then derive precision/recall/F1.

4.16 Save model

- Persist model: model.save('/path/to/model') (or cvModel.bestModel.save(...))

4.17 Visualization & reporting

- Convert small samples to pandas for plotting:
  predictions.select('probability','Class').toPandas()
- Create plots: class distribution, ROC curve, confusion matrix heatmap — save as images and insert in the Word document.

4.18 Reproducibility notes

- Set random seeds where applicable (randomSplit, classifier seeds) and document Spark configuration (driver/executor memory, cores) used during experiments.

4.19 Cleanup

- Stop Spark session at the end: spark.stop()

Chapter 5
Analysis & Results

5.1 Class Distribution Analysis

The dataset was found to be **highly imbalanced**, with fraudulent transactions representing less than **1%** of the total records.

- Majority class (Legitimate): ~99%
- Minority class (Fraudulent): ~1%
  This imbalance justifies the need for sampling methods and robust evaluation metrics such as precision, recall, and F1-score.

5.2 Feature Scaling and Engineering Results

After combining all numerical variables using VectorAssembler, the features were standardized to ensure consistent ranges across all attributes.
Scaling improved model stability and reduced the impact of extreme values in the dataset.

5.3 Model Performance

A **Random Forest Classifier** was trained using the processed dataset. The test results showed strong performance in identifying fraudulent transactions despite the severe class imbalance.

Key evaluation metrics obtained:

- **Accuracy:** High accuracy due to dominance of legitimate transactions
- **Precision:** High precision indicates that most detected fraud cases were actually fraud
- **Recall:** The model successfully detected a good proportion of actual fraud cases
- **F1-Score:** Balanced performance between precision and recall

These metrics demonstrate that the Random Forest model is effective for fraud detection when combined with distributed processing.

5.4 Confusion Matrix Insights

The confusion matrix revealed the following:

- **True Positives (TP):** Fraud correctly identified
- **True Negatives (TN):** Legitimate transactions correctly classified
- **False Positives (FP):** Legitimate transactions incorrectly flagged as fraud
- **False Negatives (FN):** Fraudulent transactions missed by the model

The model achieved **low FP** and **reduced FN** values, indicating reliable fraud detection with minimal misclassification.

5.5 Model Interpretation

Feature importance analysis showed that certain components (e.g., PCA-transformed variables) contributed significantly to fraud detection. Random Forest provided interpretability by ranking these features, helping understand the behavior of fraudulent transactions.

5.6 Summary of Results

- PySpark enabled efficient handling of the large dataset.
- Data preprocessing and scaling improved model accuracy.
- The trained Random Forest model achieved strong precision, recall, and F1-score.
- The system successfully identified fraud patterns with minimal false detections.
- The results confirm that PySpark is a suitable framework for large-scale fraud detection tasks.

Chapter 6
Conclusion & Future Works

6.1 Conclusion

This project successfully demonstrates the use of PySpark as an efficient and scalable framework for credit card fraud detection. By leveraging distributed data processing, the system is able to handle large volumes of transaction data and perform preprocessing, feature engineering, and model training much faster than traditional single-machine methods. The Random Forest Classifier used in this study achieved strong performance in accurately identifying fraudulent transactions, even within a highly imbalanced dataset.

The results highlight the importance of combining Big Data technologies with machine learning techniques for fraud detection. The model provided meaningful insights into fraud patterns and demonstrated the potential for real-time fraud detection in modern financial systems. Overall, this work shows that PySpark is a reliable and powerful tool for large-scale fraud analytics.

6.2 Future Works

There are several ways this project can be extended to improve performance and practical applicability:

1. Real-Time Fraud Detection:
   Incorporating Spark Streaming or Kafka to detect fraudulent transactions in real time.
2. Deep Learning Models:
   Exploring advanced algorithms such as Autoencoders, LSTMs, or Graph Neural Networks for improved detection of complex fraud patterns.
3. Enhanced Sampling Techniques:
   Integrating SMOTE, ADASYN, or GAN-based synthetic data generation for better handling of class imbalance.
4. Explainability and Interpretability:
   Using SHAP or LIME to provide clear explanations for each fraud prediction, improving trust in the model.
5. Deployment as an API:
   Deploying the trained model using Flask, FastAPI, or Spark endpoints for integration into real banking systems.

6. Interactive Dashboards:
   Creating fraud monitoring dashboards using Tableau, Power BI, or Spark notebooks for better visualization and decision-making.

These enhancements can transform the current system into a fully functional fraud detection pipeline suitable for real-world financial applications.

Reference

1. Carcillo, F., Dal Pozzolo, A., Le Borgne, Y. A., Caelen, O., Mazzer, Y., & Bontempi, G. (2017). *SCARFF: A Scalable Framework for Streaming Credit Card Fraud Detection with Spark.* arXiv:1709.08920. Available at: https://arxiv.org/abs/1709.08920

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