

# Department of Artificial Intelligence and Data Science

# Finance & Banking Credit Scoring with Alternate Data

**Suresh Kumar** 

Bharkavi N (231801023) Gayathri R (231801039) Hemalatha L(231801055)

#### Introduction

#### **Need for Smarter Credit Scoring:**

- Traditional models rely on limited financial history
- Underbanked customers often excluded
- Manual scoring is slow and lacks adaptability

#### **Project Motivation & Objectives:**

- Automate credit scoring using Big Data and ML
- Integrate alternative data sources for better accuracy
- Provide banks with actionable insights via dashboards



#### **Abstract**

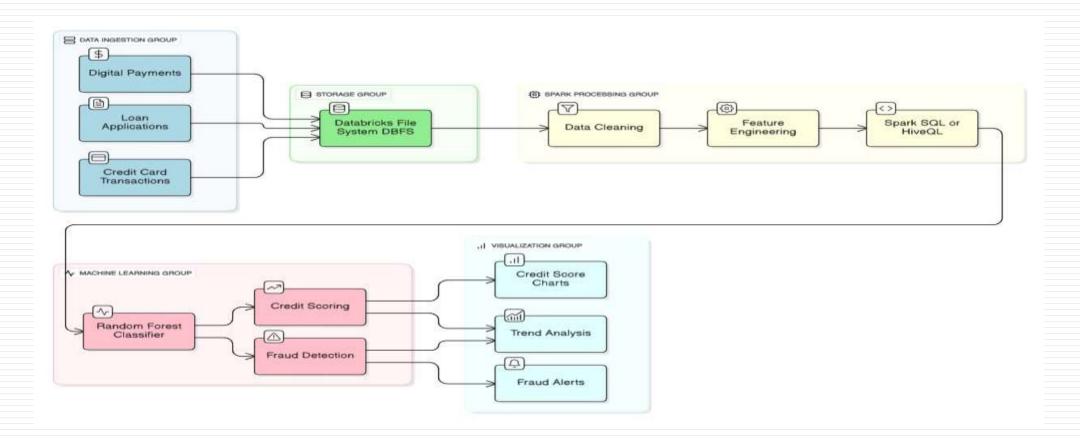
#### **Problem Overview:**

- Static rule-based models fail to capture dynamic behavior
- Limited support for real-time data and fraud detection

#### **Proposed Solution:**

- . A Big Data pipeline built in Databricks
- Uses Spark, HiveQL, and Python for processing
- Random Forest model predicts creditworthiness and fraud
- Dashboards visualize trends and outcomes

# **Architecture**



#### **Modules Overview**

- . Data Ingestion: Upload via Databricks wizard
- . Preprocessing: Handle missing values, clean data
- . Feature Engineering: Lag features, rolling averages, holiday flags
- . Modeling: Train Random Forest classifier
- . Visualization: Interactive dashboards for decision-making

## **Tools Used**

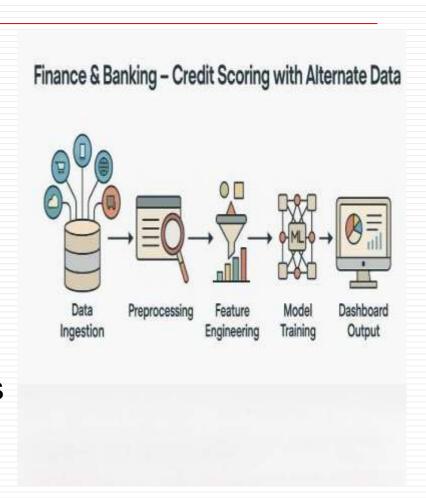
- . Databricks: Unified analytics platform
- . Apache Spark: Distributed data processing
- . HiveQL: SQL-style querying
- Python Libraries:
- Pandas Data manipulation
- Scikit-learn ML modeling
- Matplotlib/Seaborn Visualizations
- . Dashboard: Built using Databricks notebooks



# **Implementation**

#### Steps:

- Upload dataset via Databricks
- Preprocess and engineer features using Python
- Train Random Forest model
- Evaluate using metrics like precision, recall
- Build dashboards to display predictions and trends



## **Dashboard Visualization**

- . Credit score distribution
- Fraud risk flags
- . Feature importance chart
- . Time-based prediction trends



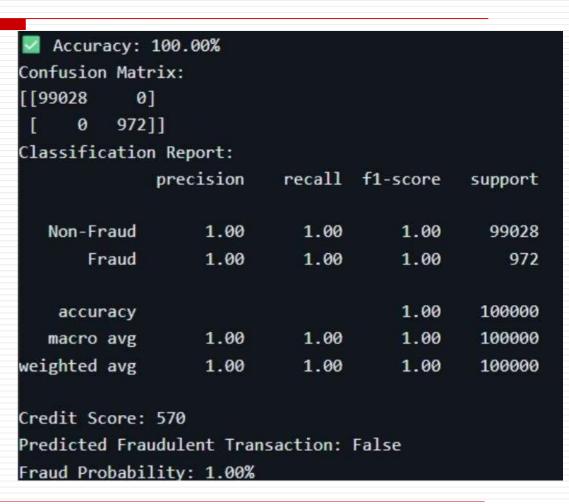
#### Results

#### **Model Performance:**

- . Accuracy: 100%
- . Fraud probability: probability of fraud
- Credit scoring: Improved for thin-file customers

#### **Insights:**

- . Helps banks allocate credit more fairly
- . Flags high-risk customers for review
- . Enables data-driven lending decisions



# **Conclusion & Future Scope**

#### **Conclusion:**

- Efficient, scalable credit scoring system
- Combines Big Data and ML for smarter decisions

#### **Future Enhancements:**

- Add more models (XGBoost, SVM)
- Integrate real-time transaction feeds
- . Expand to loan approvals and financial profiling
- Improve fairness and interpretability

#### References

Databricks Documentation - Big Data & Machine Learning

https://docs.databricks.com/en/machine-learning/index.html

**Apache Spark Official Documentation** 

https://spark.apache.org/docs/latest/

UCI Machine Learning Repository – Credit Scoring Datasets

https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data)

Kaggle – Credit Card Fraud Detection Dataset

https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud

Scikit-learn: Machine Learning in Python

https://scikit-learn.org/stable/

World Bank Open Data – Financial Inclusion Indicators

https://data.worldbank.org/topic/financial-sector

Research Paper: "Credit Scoring Using Machine Learning Techniques – A Review"

https://www.sciencedirect.com/science/article/pii/S2405452619300053

# **Thank You**