### **Project Report: Fraud Detection Using Machine Learning**

### **Objective:**

To develop machine learning models that predict fraudulent transactions from a bank transaction dataset. The goal is to classify transactions into **fraudulent** or **non-fraudulent** categories.

#### **Dataset Overview:**

• Source: Kaggle

#### Features:

- **TransactionAmount**: The amount of the transaction.
- **AccountBalance**: Account balance during the transaction.
- **TransactionHour**: The time of day the transaction occurred.
- **DaysSinceLastTransaction**: Number of days since the last transaction.
- **DeviceID**: The device used for the transaction.
- **Location**: The location of the transaction.
- **TransactionCount**: Number of transactions by the account.
- Fraudulent Flag: Whether the transaction is fraudulent (1 = fraud, 0 = non-fraud).

## **Model Development:**

### 1. Logistic Regression:

• **Accuracy**: 98.94%

• Precision (Fraud): 1.00

Recall (Fraud): 0.11

• Issues: High precision but low recall for fraud. The model misses most fraud cases.

# 2. Support Vector Classifier (SVC):

• **Accuracy**: 98.94%

• Precision (Fraud): 1.00

• **Recall** (Fraud): 0.11

• Issues: Similar performance to Logistic Regression. The model struggled with fraud detection.

#### 3. Random Forest Classifier:

• Accuracy: 99.34%

• **Precision** (Fraud): 0.70

• Recall (Fraud): 0.78

• **F1-Score** (Fraud): 0.74

• Improvements: Better recall for fraud detection, but still some false positives.

### 4. XGBoost:

• Accuracy: 99.60%

• **Precision** (Fraud): 0.75

• **Recall** (Fraud): 1.00

• **F1-Score** (Fraud): 0.86

• **Key Insight**: Perfect recall (1.00) for fraud detection, minimal false positives (3).

### **Model Performance Comparison:**

| Model                        | Accuracy | Precision<br>(Fraud) | Recall<br>(Fraud) | F1-Score<br>(Fraud) | Precision (Non-<br>Fraud) | Recall (Non-<br>Fraud) |
|------------------------------|----------|----------------------|-------------------|---------------------|---------------------------|------------------------|
| Linear Regression            | 0.02     | N/A                  | N/A               | N/A                 | N/A                       | N/A                    |
| Logistic Regression          | 98.94%   | 1.00                 | 0.11              | 0.20                | 0.99                      | 1.00                   |
| Support Vector<br>Classifier | 98.94%   | 1.00                 | 0.11              | 0.20                | 0.99                      | 1.00                   |
| Random Forest                | 99.34%   | 0.70                 | 0.78              | 0.74                | 1.00                      | 1.00                   |
| XGBoost                      | 99.60%   | 0.75                 | 1.00              | 0.86                | 1.00                      | 1.00                   |

# **Key Insights:**

- **XGBoost** is the best-performing model with **perfect recall for fraud detection (1.00)** and minimal false positives.
- Random Forest also showed strong performance, with **78% recall** for fraud detection, but more **false positives** compared to XGBoost.

- Logistic Regression and SVC performed well on non-fraud transactions but had low recall for fraud (only 11%).
- The dataset is **imbalanced**, with fraud transactions being rare, which challenges the model to detect fraud effectively.

#### **Future Work:**

- 1. **Hyperparameter Tuning**: Optimize the hyperparameters of **XGBoost** and **Random Forest** to improve performance.
- Resampling: Use techniques like SMOTE (Synthetic Minority Over-sampling
   Technique) or undersampling to balance the dataset and enhance fraud detection.
- 3. **Real-time Fraud Detection**: Implement the **XGBoost** model for real-time fraud detection in a live system.

# **Conclusion:**

- The **XGBoost** model provided **outstanding performance**, achieving **perfect recall for fraud detection**, which is crucial for fraud detection tasks.
- The project demonstrates the importance of choosing the right model for imbalanced datasets, and **XGBoost** proved to be the most suitable for this task.