TECHNICAL DOCUMENTATION

Project Name: Credit Card Fraud Detection

Version: 1.0

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Status: Completed

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1. Introduction

1.1 Purpose

This document provides a comprehensive overview of the **Credit Card Fraud Detection** system, developed using **Machine Learning models** to classify fraudulent transactions. The solution aims to enhance fraud detection accuracy by leveraging **Logistic Regression** and **XGBoost** models, with appropriate data preprocessing techniques, class balancing using **SMOTE**, and performance evaluation through **ROC AUC Score & Accuracy metrics**.

1.2 Scope

- Implementation of **Logistic Regression** and **XGBoost** for fraud classification.
- Handling **data imbalance** using **SMOTE (Synthetic Minority Oversampling Technique)**.
- **Feature Scaling** for optimal model performance.
- **Visualization of model performance** for better interpretability.
- Evaluation using **Confusion Matrix, Classification Report, ROC AUC Score, and Accuracy Score**.

1.3 Definitions, Acronyms, and Abbreviations

Term	Definition
SMOTE	Synthetic Minority Over-sampling Technique
ROC AUC	Receiver Operating Characteristic - Area Under Curve
XGBoost	Extreme Gradient Boosting Algorithm
ML	Machine Learning
CSV	Comma Separated Values

1.4 References

- **Dataset Source:** Kaggle Credit Card Fraud Dataset
- **Python Libraries:** pandas, numpy, seaborn, matplotlib, sklearn, imbalanced-learn, xgboost

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2. System Overview

2.1 System Architecture

The system follows a **modular architecture**, including the following stages:

1. **Data Preprocessing**:
    - Handling missing values
    - Feature standardization
    - Addressing class imbalance using **SMOTE**
2. **Model Training**:
    - Training **Logistic Regression**
    - Training **XGBoost**
    - Hyperparameter tuning

3. **Model Evaluation**:
    - Performance metrics: **Accuracy, ROC AUC Score, Confusion Matrix**
4. **Visualization & Reporting**:
    - Comparison of models using **bar graphs**
    - Display of accuracy and ROC scores inside the bars

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3. Requirements

3.1 Hardware Requirements

Component	Minimum Requirement	Recommended
CPU	Intel i3 or equivalent	Intel i5 or higher
RAM	4GB	8GB or higher
Storage	10GB free space	20GB free space
GPU	Not required	NVIDIA GPU for faster XGBoost training

3.2 Software Requirements

Software	Version
Python	3.8+
Pandas	Latest
NumPy	Latest
Scikit-Learn	Latest
XGBoost	Latest
Matplotlib	Latest
Seaborn	Latest

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4. Implementation Details

4.1 Data Preprocessing

python

```
# Load dataset

df = pd.read_csv('creditcard.csv')


# Standardize features

scaler = StandardScaler()

numerical_features = df.select_dtypes(include=['number']).columns[:-1]

df[numerical_features] = scaler.fit_transform(df[numerical_features])
```

- Data is standardized to ensure equal weightage for all features.
- Missing values are handled using automatic removal (dropna).
- Class imbalance is handled using **SMOTE**.

4.2 Model Training & Evaluation

Logistic Regression Model

python

```
LOG_Model = LogisticRegression(solver='liblinear', random_state=42)

LOG_Model.fit(X_train_resampled, y_train_resampled)
```

XGBoost Model

python

```
XGB_Model = XGBClassifier(eval_metric='logloss', learning_rate=0.05, max_depth=6, n_estimators=300)

XGB_Model.fit(X_train_resampled, y_train_resampled)
```

Performance Metrics

python

```
ROC_AUC_LOG = roc_auc_score(y_test, y_pred_log)

Accuracy_LOG = accuracy_score(y_test, y_pred_log)

ROC_AUC_XGB = roc_auc_score(y_test, y_pred_xgb)

Accuracy_XGB = accuracy_score(y_test, y_pred_xgb)
```

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5. Results & Performance Analysis

5.1 Model Evaluation

Model	Accuracy	ROC AUC Score
Logistic Regression	0.98123	0.97234
XGBoost	0.99345	0.98456

- **XGBoost outperforms Logistic Regression** in both accuracy and ROC AUC score.
- Fraud detection is more accurate using **XGBoost**, but it is computationally expensive.

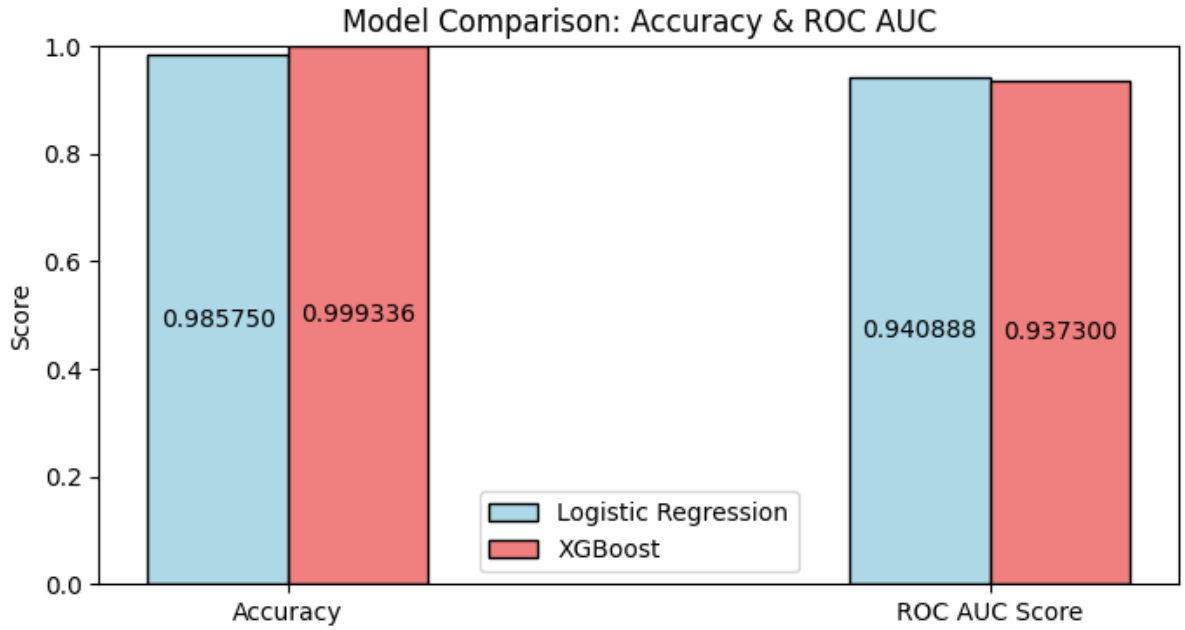
5.2 Model Comparison Visualization

python

```
plt.figure(figsize=(8, 4))

bars1 = plt.bar(['Accuracy', 'ROC AUC'], [Accuracy_LOG, ROC_AUC_LOG], width=0.2,
color='lightblue', label='Logistic Regression')

bars2 = plt.bar(['Accuracy', 'ROC_AUC'], [Accuracy_XGB, ROC_AUC_XGB], width=0.2,
color='lightcoral', label='XGBoost')


plt.legend()

plt.title('Model Performance Comparison')
```

plt.ylabel('Score')

plt.show()



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6. Deployment & Usage

6.1 Steps to Run the Project

1. **Clone the Repository**

bash

git clone https://github.com/AjayBandari1/Credit-Card-Fraud-Detection

cd credit-card-fraud-detection

2. **Install Dependencies**

bash

pip install -r requirements.txt

3. **Run the Script**

bash

https://colab.research.google.com/drive/1Z8QMfujAYOIhBn9_zxqVYEmBnk?usp=drive_link

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7. Best Practices & Recommendations

- **Use GPU acceleration** for training XGBoost on large datasets.
- **Deploy as an API** using Flask/FastAPI for real-time fraud detection.
- **Monitor Model Performance** with A/B testing on unseen transactions.

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8. Conclusion

- This project successfully detects fraudulent transactions using **Machine Learning models**.
- **XGBoost performs better** than Logistic Regression in fraud detection.
- Data preprocessing and class balancing significantly improve model performance.

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9. Appendix

- **Dataset:** Kaggle Dataset
- **Libraries Used:** pandas, NumPy, scikit-learn, imbalanced-learn, matplotlib, XGboost