SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

B. TECH CSE-AI

Subject: Advance Machine Learning

Subject Code: 23CSE514

MINI PROJECT

AI-Based Fraud Detection in credit card transactions

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1. INTRODUCTION

1.1 Background

Credit card fraud represents one of the most critical challenges in the financial sector, causing billions of dollars in losses annually. With the exponential growth of digital transactions and e-commerce, fraudulent activities have become increasingly sophisticated, necessitating advanced detection mechanisms beyond traditional rule-based systems.

1.2 Motivation

The increasing sophistication of fraudulent transactions and the massive volume of daily credit card operations make manual detection practically impossible. Machine learning offers an automated, scalable, and adaptive solution that can identify complex patterns indicative of fraud while minimizing false positives that negatively impact customer experience.

1.3 Objectives

This project aims to:

- Develop an AI-based fraud detection system using machine learning algorithms
- Handle highly imbalanced datasets (fraud cases < 1% of total transactions)
- Achieve high detection accuracy while maintaining low false positive rates
- Provide comprehensive performance metrics and visualizations
- Create a reproducible and scalable solution using Google Colab

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2. LITERATURE REVIEW (PRIOR STUDIES)

2.1 Traditional Approaches

Rule-Based Systems: Early fraud detection systems relied on predefined rules such as transaction amount thresholds, geographical anomalies, and velocity checks. While simple to implement, these systems lack adaptability and generate high false positive rates.

Statistical Methods: Techniques like logistic regression and statistical outlier detection were employed to identify unusual patterns. However, these methods struggle with high-dimensional data and complex non-linear relationships.

2.2 Machine Learning Approaches

Supervised Learning:

- Random Forests (Baranauskas et al., 2008): Ensemble methods demonstrating robustness to overfitting and ability to handle imbalanced datasets
- Support Vector Machines (SVM): Effective for high-dimensional spaces but computationally expensive for large datasets
- Neural Networks (Deep Learning): Capable of learning complex patterns but requiring substantial computational resources and training data

Key Studies:

1. Dal Pozzolo et al. (2015) - Introduced the Kaggle Credit Card Fraud dataset used in this project, employing undersampling and cost-sensitive learning
2. Bhattacharyya et al. (2011) - Demonstrated the effectiveness of Random Forests for fraud detection with feature importance analysis
3. Ngai et al. (2011) - Comprehensive survey showing machine learning outperforming statistical methods by 15-20% in detection rates

2.3 Handling Class Imbalance

Research has identified class imbalance as the primary challenge in fraud detection:

- SMOTE (Synthetic Minority Over-sampling Technique)
- Undersampling majority class
- Cost-sensitive learning - assigning higher penalties to misclassified fraud cases
- Ensemble methods combining multiple models

3. PROJECT DETAILS

3.1 Problem Statement

Objective: Build a machine learning model to accurately classify credit card transactions as fraudulent or legitimate while minimizing false positives and false negatives.

Challenges:

1. Extreme Class Imbalance: Only 0.17% of transactions are fraudulent (492 frauds in 284,807 transactions)
2. Privacy Concerns: Features are anonymized using PCA transformation
3. Real-time Requirements: Model must be fast enough for production deployment
4. Cost Considerations: False positives inconvenience customers; false negatives result in financial losses

Success Criteria:

- Accuracy > 99%
- Recall (fraud detection rate) > 80%
- Precision > 90%
- ROC-AUC > 0.95

3.2 Dataset Description

Source: Kaggle - Credit Card Fraud Detection
URL:

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

Provider: Machine Learning Group - ULB (Université Libre de Bruxelles)

Dataset Statistics:

- Total Transactions: 284,807
- Fraudulent Transactions: 492 (0.1727%)
- Legitimate Transactions: 284,315 (99.8273%)
- Features: 30 numerical features + 1 target variable
- Time Period: September 2013 (2 days of transactions)
- File Size: 150.83 MB
- Format: CSV

Feature Description:

Feature	Type	Description
Time	float	Seconds elapsed between first transaction and current transaction
V1-V28	float	Principal components obtained from PCA transformation (anonymized)
Amount	float	Transaction amount (actual monetary value)
Class	int	Target variable (0 = Normal, 1 = Fraud)

Data Characteristics:

- No Missing Values: Dataset is complete with 0 null values
- Normalized Features: V1-V28 are already scaled via PCA
- Amount Feature: Ranges from $0 to $25,691.16
- Highly Imbalanced: Fraud ratio of 1:578

3.3 Methodology

3.3.1 Workflow Pipeline

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Data Loading → Exploratory Analysis → Preprocessing →
Model Training → Evaluation → Visualization → Deployment
```

3.3.2 Exploratory Data Analysis (EDA)

Steps Performed:

1. Dataset Information: Verified data types, shape, and memory usage
2. Missing Value Check: Confirmed no missing values
3. Class Distribution Analysis: Identified severe imbalance (0.17% fraud)
4. Statistical Summary: Analyzed mean, std, min, max for all features
5. Visualization: Created count plot for class distribution

Key Findings:

- Dataset is clean with no missing or duplicate values
- Features V1-V28 have mean ≈ 0 and std ≈ 1 (normalized)
- Amount feature has high variance (mean: $88.35, std: $250.12)
- Fraud transactions show different statistical patterns than normal transactions

3.3.3 Data Preprocessing

Feature Engineering:

- Separated features (X) from target variable (y)
- Retained all 30 features for model training

Train-Test Split:

- Split Ratio: 80% training, 20% testing
- Strategy: Stratified split to maintain class distribution
- Random State: 42 (for reproducibility)
- Training Set: 227,845 transactions (394 frauds)
- Testing Set: 56,962 transactions (98 frauds)

Feature Scaling:

- Algorithm: StandardScaler from sklearn
- Applied to: Training and testing features

- Purpose: Normalize feature ranges for optimal model performance
- Formula: z = (x - μ) / σ

3.3.4 Model Selection: Random Forest Classifier

Rationale for Choosing Random Forest:

1. Handles Imbalanced Data: Naturally manages class imbalance through ensemble voting
2. Robustness: Resistant to overfitting due to averaging multiple decision trees
3. Feature Importance: Provides interpretable feature rankings
4. Non-linearity: Captures complex relationships without explicit feature engineering
5. Computational Efficiency: Parallelizable training process

Hyperparameters:

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RandomForestClassifier(
    n_estimators=100,       # Number of decision trees
    random_state=42,        # Reproducibility
    n_jobs=-1,              # Use all CPU cores
    verbose=1               # Show training progress
)
```

Training Process:

- Duration: 5.1 minutes on Google Colab (2 CPU cores)
- Backend: ThreadingBackend with parallel processing
- Trees: 100 decision trees trained independently
- Features per Split: sqrt(30) ≈ 5-6 features

3.4 Implementation Code

Complete Python Implementation:

python

```
# ============================================
# Step 1: Import Required Libraries
# ============================================
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (classification_report,
confusion_matrix,
                             roc_auc_score, roc_curve,
                             precision_score, recall_score,
                             f1_score, accuracy_score)
import warnings
warnings.filterwarnings('ignore')

print("Libraries imported successfully!")

# ============================================
# Step 2: Load Dataset
# ============================================
from google.colab import files
import io

print("Upload the creditcard.csv file from Kaggle")
uploaded = files.upload()

# Load the dataset
for filename in uploaded.keys():
    df = pd.read_csv(io.BytesIO(uploaded[filename]))
```

```
print("\nDataset loaded successfully!")
print(f"Dataset shape: {df.shape}")
print(f"\nFirst few rows:")
print(df.head())

# ============================================
# Step 3: Exploratory Data Analysis
# ============================================
print("Dataset Information:")
print(df.info())

print("\n" + "="*50)
print("Checking for missing values:")
print(df.isnull().sum())

print("\n" + "="*50)
print("Class Distribution (0=Normal, 1=Fraud):")
print(df['Class'].value_counts())

print("\n" + "="*50)
print("Statistical Summary:")
print(df.describe())

# Visualize class distribution
plt.figure(figsize=(8, 5))
sns.countplot(x='Class', data=df)
plt.title('Class Distribution (0: Normal, 1: Fraud)')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()

print(f"\nFraud percentage: {df['Class'].sum() / len(df) *
100:.4f}%")

# ============================================
# Step 4: Data Preprocessing
# ============================================
```

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# Separate features and target
X = df.drop('Class', axis=1)
y = df['Class']

print(f"Features shape: {X.shape}")
print(f"Target shape: {y.shape}")

# Train-test split (80-20)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print(f"\nTraining set size: {X_train.shape[0]}")
print(f"Testing set size: {X_test.shape[0]}")
print(f"\nTraining set fraud cases: {y_train.sum()}")
print(f"Testing set fraud cases: {y_test.sum()}")

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("\nData preprocessing completed successfully!")

# ============================================
# Step 5: Train Random Forest Model
# ============================================
print("Training Random Forest Classifier...")
rf_model = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    n_jobs=-1,
    verbose=1
)
rf_model.fit(X_train_scaled, y_train)

print("\nRandom Forest model training completed!")
print(f"Number of trees: {rf_model.n_estimators}")
```

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print(f"Number of features: {rf_model.n_features_in_}")

# ============================================
# Step 6: Model Evaluation
# ============================================
print("Making predictions on test set...")
y_pred = rf_model.predict(X_test_scaled)
y_pred_proba = rf_model.predict_proba(X_test_scaled)[:, 1]

print("\n" + "="*60)
print("RANDOM FOREST MODEL PERFORMANCE")
print("="*60)

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)

print(f"\nAccuracy:  {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall:    {recall:.4f}")
print(f"F1-Score:  {f1:.4f}")
print(f"ROC-AUC:   {roc_auc:.4f}")

print("\n" + "="*60)
print("CLASSIFICATION REPORT")
print("="*60)
print(classification_report(y_test, y_pred,
                            target_names=['Normal', 'Fraud']))

print("\n" + "="*60)
print("CONFUSION MATRIX")
print("="*60)
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
# ============================================
# Step 7: Visualizations
# ============================================
fig, axes = plt.subplots(2, 2, figsize=(15, 12))

# 1. Confusion Matrix Heatmap
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[0,
0])
axes[0, 0].set_title('Confusion Matrix')
axes[0, 0].set_ylabel('Actual')
axes[0, 0].set_xlabel('Predicted')
axes[0, 0].set_xticklabels(['Normal', 'Fraud'])
axes[0, 0].set_yticklabels(['Normal', 'Fraud'])

# 2. ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
axes[0, 1].plot(fpr, tpr, color='darkorange', lw=2,
               label=f'ROC curve (AUC = {roc_auc:.4f})')
axes[0, 1].plot([0, 1], [0, 1], color='navy', lw=2,
               linestyle='--', label='Random Classifier')
axes[0, 1].set_xlim([0.0, 1.0])
axes[0, 1].set_ylim([0.0, 1.05])
axes[0, 1].set_xlabel('False Positive Rate')
axes[0, 1].set_ylabel('True Positive Rate')
axes[0, 1].set_title('ROC Curve')
axes[0, 1].legend(loc='lower right')
axes[0, 1].grid(True, alpha=0.3)

# 3. Feature Importance (Top 15)
feature_importance = pd.DataFrame({
    'feature': X.columns,
    'importance': rf_model.feature_
```

3.5 RESULTS AND ANALYSIS

3.5.1 Model Performance Metrics

The Random Forest Classifier demonstrated exceptional performance on the test dataset:

Metric	Score	Interpretation
Accuracy	99.96%	Correctly classified 99.96% of all transactions
Precision	94.12%	Of predicted frauds, 94.12% were actual frauds
Recall	81.63%	Detected 81.63% of all actual fraud cases
F1-Score	87.43%	Balanced measure of precision and recall
ROC-AUC	96.30%	Excellent ability to distinguish fraud from normal

3.5.2 Confusion Matrix Analysis

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                Predicted
                Normal  Fraud
Actual Normal   56,859    5      (99.99% correct)
       Fraud       18    80      (81.63% detected)
```

Key Insights:

- True Negatives (56,859): Correctly identified legitimate transactions
- False Positives (5): Only 5 legitimate transactions wrongly flagged as fraud
- False Negatives (18): Missed 18 fraudulent transactions (18.37% fraud miss rate)
- True Positives (80): Successfully detected 80 out of 98 fraud cases

Business Impact:

- Customer Experience: Only 0.009% false positive rate minimizes customer inconvenience
- Financial Protection: 81.63% fraud detection saves significant losses
- Cost-Benefit: Low false positive rate reduces investigation costs

3.5.3 Classification Report

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	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	56864
Fraud	0.94	0.82	0.87	98
accuracy			1.00	56962
macro avg	0.97	0.91	0.94	56962
weighted avg	1.00	1.00	1.00	56962

3.5.4 Feature Importance Analysis

Top 15 Most Important Features:

1. V17, V14, V12, V10 (highest importance for fraud detection)
2. V16, V11, V4, V3 (medium-high importance)
3. Amount, V7, V2, V1 (moderate importance)

Insight: PCA-transformed features (V14, V17, V12) are most discriminative for fraud detection, confirming the effectiveness of the dataset's anonymization approach.

3.5.5 ROC Curve Analysis

The ROC curve shows:

- AUC = 0.9630 indicates excellent model discrimination ability
- Curve significantly above diagonal (random classifier)

- Near-optimal trade-off between True Positive Rate and False Positive Rate
- Model performs well across all classification thresholds

3.5.6 Comparison with Baseline

Approach	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Guess	50.00%	0.17%	50.00%	0.34%	50.00%
Logistic Regression	99.92%	88.24%	61.22%	72.27%	91.50%
Random Forest	99.96%	94.12%	81.63%	87.43%	96.30%

Our Model Advantages:

- 4.41% higher recall than Logistic Regression
- 5.96% better precision
- 15.16% improvement in F1-Score
- 4.8% higher ROC-AUC score

Google Colab
link:-https://colab.research.google.com/drive/1UZc9YyielhMREjcDp0EUevS_TIvgWFPe?usp=sharing

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