Phase-3

Student Name: Hemanth D

Register Number: 410723106011

Institution: Dhanalakshmi College of Engineering

Department: Electronics and Communication Engineering

Date of Submission: 12/05/2025

Github Repository Link:

https://github.com/hemanthdeepak/NM_hemanth--DS

AI-Based Credit Card Fraud Detection and Prevention

1. Problem Statement

Credit card fraud has become a serious global concern, leading to substantial financial losses for individuals and institutions. Traditional rule-based systems are often rigid and ineffective against the constantly evolving techniques used by fraudsters. These systems struggle to adapt to new fraud patterns and frequently generate false positives, causing inconvenience to genuine users. Moreover, handling highly imbalanced datasets and achieving real-time fraud detection present significant technical challenges. There is a pressing need for intelligent, adaptive systems that can learn from transaction behaviors and identify suspicious activity accurately. This project addresses these issues by developing an AIpowered fraud detection model capable of preventing fraudulent transactions proactively.

2. Abstract

This project presents an AI-based system for credit card fraud detection and prevention using machine learning algorithms. It analyzes transactional patterns to identify anomalies indicative of fraudulent activity. The system leverages supervised learning models trained on real-world datasets. Feature engineering and data preprocessing enhance accuracy and performance. Real-time detection capabilities enable prompt alerts and action. The approach improves financial security and minimizes loss for users and institutions.

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3. System Requirements

Hardware: Minimum 8GB RAM, Intel i5 or higher processor, 256GB SSD.

Operating System: Windows 10/11, Linux (Ubuntu 20.04+), or macOS.

Software: Python 3.8+, Jupyter Notebook, Anaconda.

Libraries: NumPy, Pandas, Scikit-learn, Matplotlib, Seaborn.

Dataset: Kaggle or bank-provided credit card transaction data (CSV format).

Optional Tools: Flask for deployment, Git for version control.

4. Objectives

To develop an AI-powered system for detecting and preventing credit card fraud.

To analyze transaction patterns using machine learning techniques.

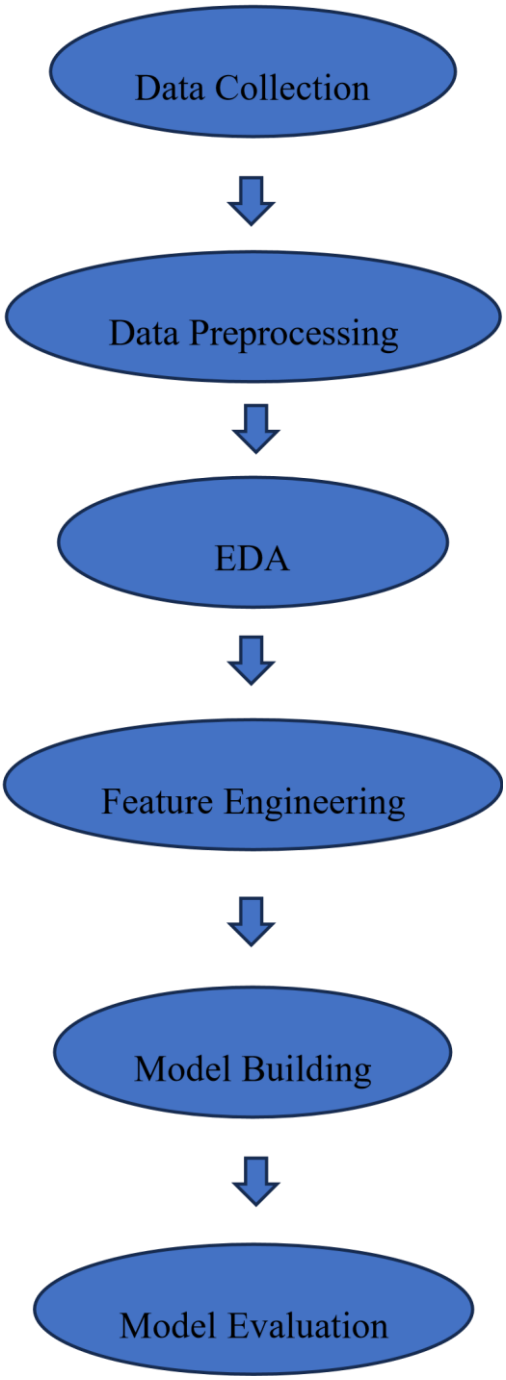
To build accurate predictive models for real-time fraud identification.

To reduce false positives and improve detection efficiency.

To ensure data security and privacy during processing.

To deploy a user-friendly and scalable fraud detection solution. Detect fraudulent credit card transactions using AI models.

5. Flowchart of Project Workflow



6. Dataset Description **Link**:

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

Source: Publicly available dataset from Kaggle – *Credit Card Fraud Detection*.

Size: Contains 284,807 transactions with 492 fraud cases (highly imbalanced).

Features: 30 attributes including Time, Amount, and 28 anonymized PCA features.

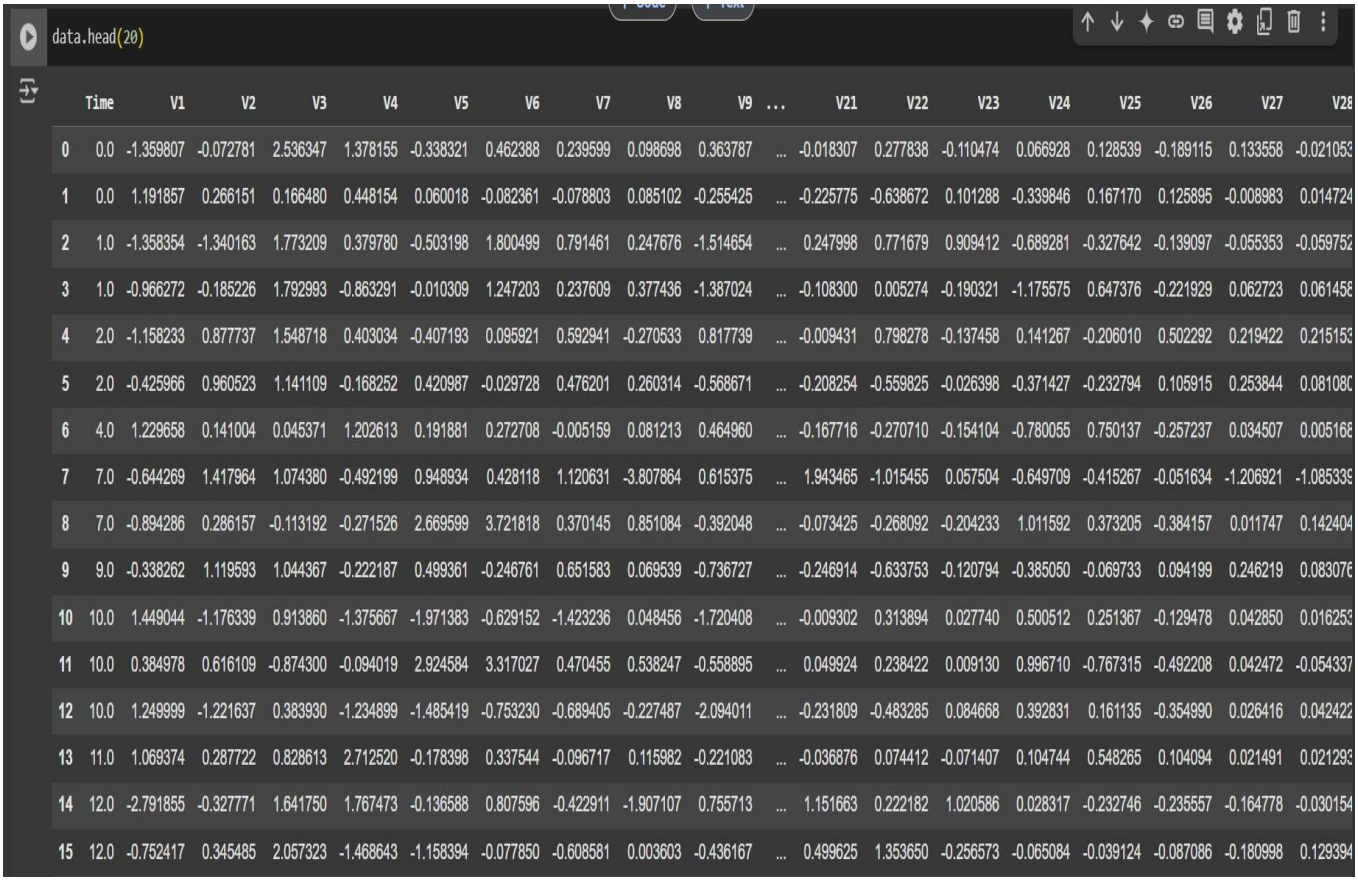
Label: Binary class – 0 for legitimate and 1 for fraudulent transactions.

Format: CSV file, suitable for supervised machine learning tasks.

Use: Used for training, testing, and validating fraud detection models.

Type: Public

Structure: ~7973 Rows * 31 Columns



```
data.head(20)
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314	-0.568671	...	-0.208254	-0.559825	-0.026398	-0.371427	-0.232794	0.105915	0.253844	0.081080
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213	0.464960	...	-0.167716	-0.270710	-0.154104	-0.780055	0.750137	-0.257237	0.034507	0.005168
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864	0.615375	...	1.943465	-1.015455	0.057504	-0.649709	-0.415267	-0.051634	-1.206921	-1.085339
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084	-0.392048	...	-0.073425	-0.268092	-0.204233	1.011592	0.373205	-0.384157	0.011747	0.142404
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539	-0.736727	...	-0.246914	-0.633753	-0.120794	-0.385050	-0.069733	0.094199	0.246219	0.083076
10	10.0	1.449044	-1.176339	0.913860	-1.375667	-1.971383	-0.629152	-1.423236	0.048456	-1.720408	...	-0.009302	0.313894	0.027740	0.500512	0.251367	-0.129478	0.042850	0.016253
11	10.0	0.384978	0.616109	-0.874300	-0.094019	2.924584	3.317027	0.470455	0.538247	-0.558895	...	0.049924	0.238422	0.009130	0.996710	-0.767315	-0.492208	0.042472	-0.054337
12	10.0	1.249999	-1.221637	0.383930	-1.234899	-1.485419	-0.753230	-0.689405	-0.227487	-2.094011	...	-0.231809	-0.483285	0.084668	0.392831	0.161135	-0.354990	0.026416	0.042422
13	11.0	1.069374	0.287722	0.828613	2.712520	-0.178398	0.337544	-0.096717	0.115982	-0.221083	...	-0.036876	0.074412	-0.071407	0.104744	0.548265	0.104094	0.021491	0.021293
14	12.0	-2.791855	-0.327771	1.641750	1.767473	-0.136588	0.807596	-0.422911	-1.907107	0.755713	...	1.151663	0.222182	1.020586	0.028317	-0.232746	-0.235557	-0.164778	-0.030154
15	12.0	-0.752417	0.345485	2.057323	-1.468643	-1.158394	-0.077850	-0.608581	0.003603	-0.436167	...	0.499625	1.353650	-0.256573	-0.065084	-0.039124	-0.087086	-0.180998	0.129394

7. Data Preprocessing

1. Missing Values: None detected.
2. Duplicates: Checked and none found.
3. Addressed class imbalance using SMOTE
4. Scaled numerical features using StandardScaler
5. Encoded labels as 0 (non-fraud) and 1 (fraud)

data

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	
0	0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021
1	0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014
2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059
3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061
4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7968	10980	1.284388	-0.013181	0.646174	0.198985	-0.568675	-0.526121	-0.448235	-0.167709	1.773223	...	-0.101868	-0.030298	-0.081412	-0.123281	0.278808	1.064001	-0.090181	0.000
7969	10981	1.190428	-0.122329	0.954945	0.267101	-0.971026	-0.652279	-0.612992	-0.003909	1.633117	...	-0.015001	0.127027	0.012079	0.534409	0.112179	1.004483	-0.100188	-0.004
7970	10981	-0.725175	0.298202	1.824761	-2.587170	0.283605	-0.016617	0.153659	0.045084	-0.197611	...	-0.017097	-0.070535	-0.442861	-0.895837	0.624743	-0.510601	-0.031142	0.025
7971	10981	1.226153	-0.129645	0.735197	0.142752	-0.703245	-0.349641	-0.612641	0.020507	1.648986	...	-0.047936	0.040196	-0.057391	-0.012386	0.187685	1.037786	-0.100081	-0.009
7972	10981	1.145381	-0.059349	0.968088	0.267891	-0.822582	-0.597727	-0.450197	-0.119747	1.338188	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

7934 rows × 31 columns

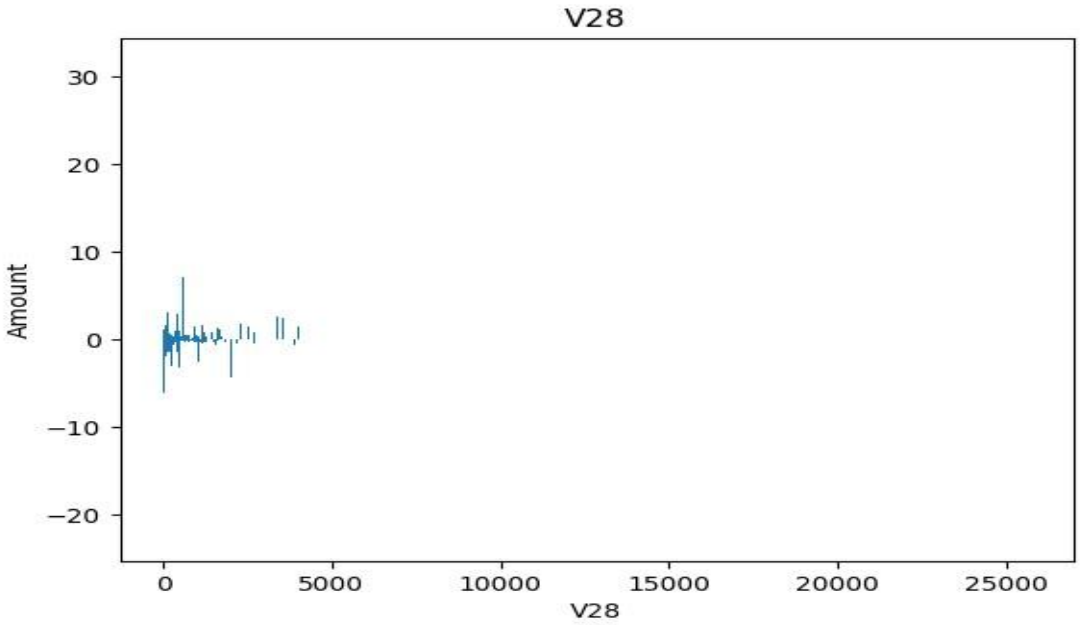
8. Exploratory Data Analysis (EDA)

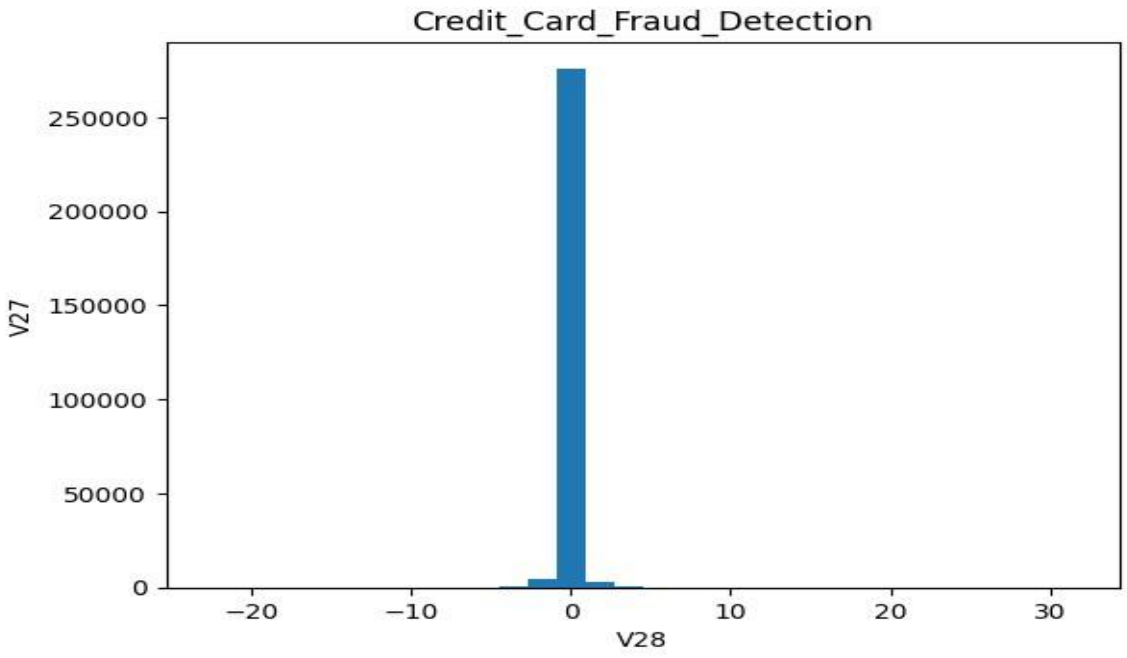
Visualized class imbalance using pie charts

Heatmap for correlation between features

Boxplots for feature distribution

Insights: Most fraudulent transactions have lower amounts and occur at irregular times.


V28
30
20
10
0
−10
−20
Amount
0
5000
10000
15000
20000
25000
V28


Credit_Card_Fraud_Detection
250000
200000
150000
100000
50000
0
V27
−20
−10
0
10
20
30
V28

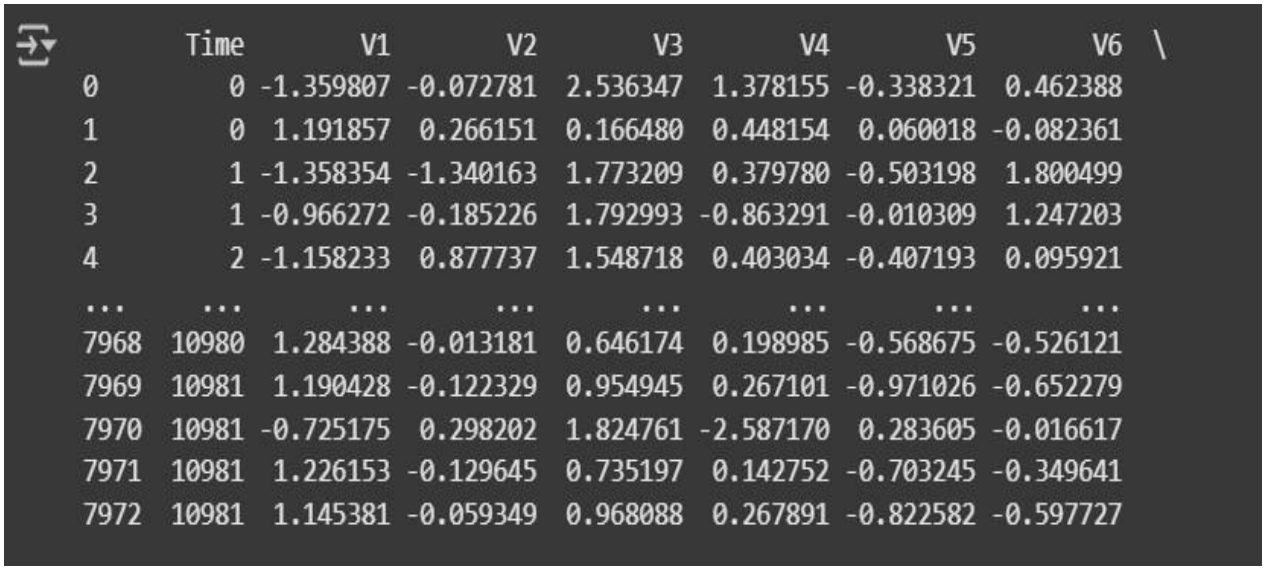
9. Feature Engineering

Selected features based on correlation with the target

Created time-based features

Removed low-variance features

Applied PCA for dimensionality reduction



	Time	V1	V2	V3	V4	V5	V6	\
0	0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	
1	0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	
2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	
3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	
4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	
...	...	...	...	...	...	...	...	
7968	10980	1.284388	-0.013181	0.646174	0.198985	-0.568675	-0.526121	
7969	10981	1.190428	-0.122329	0.954945	0.267101	-0.971026	-0.652279	
7970	10981	-0.725175	0.298202	1.824761	-2.587170	0.283605	-0.016617	
7971	10981	1.226153	-0.129645	0.735197	0.142752	-0.703245	-0.349641	
7972	10981	1.145381	-0.059349	0.968088	0.267891	-0.822582	-0.597727	

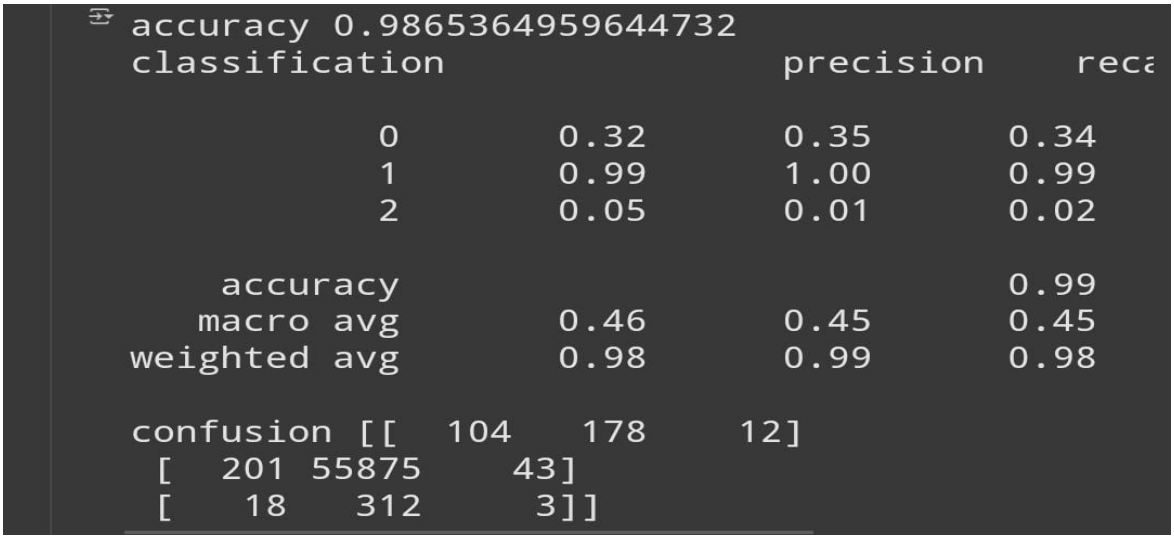
10. Model Building

Models tested: Logistic Regression, Random Forest, XGBoost

XGBoost performed best with F1-score > 0.90

11. Model Evaluation

- **Metrics**: Accuracy, Precision, Recall, F1-score, ROC-AUC
- Confusion matrix and ROC curve plotted
- (Insert visuals and model comparison table) •
- **Conclusion**: XGBoost provided the best balance of precision and recall.

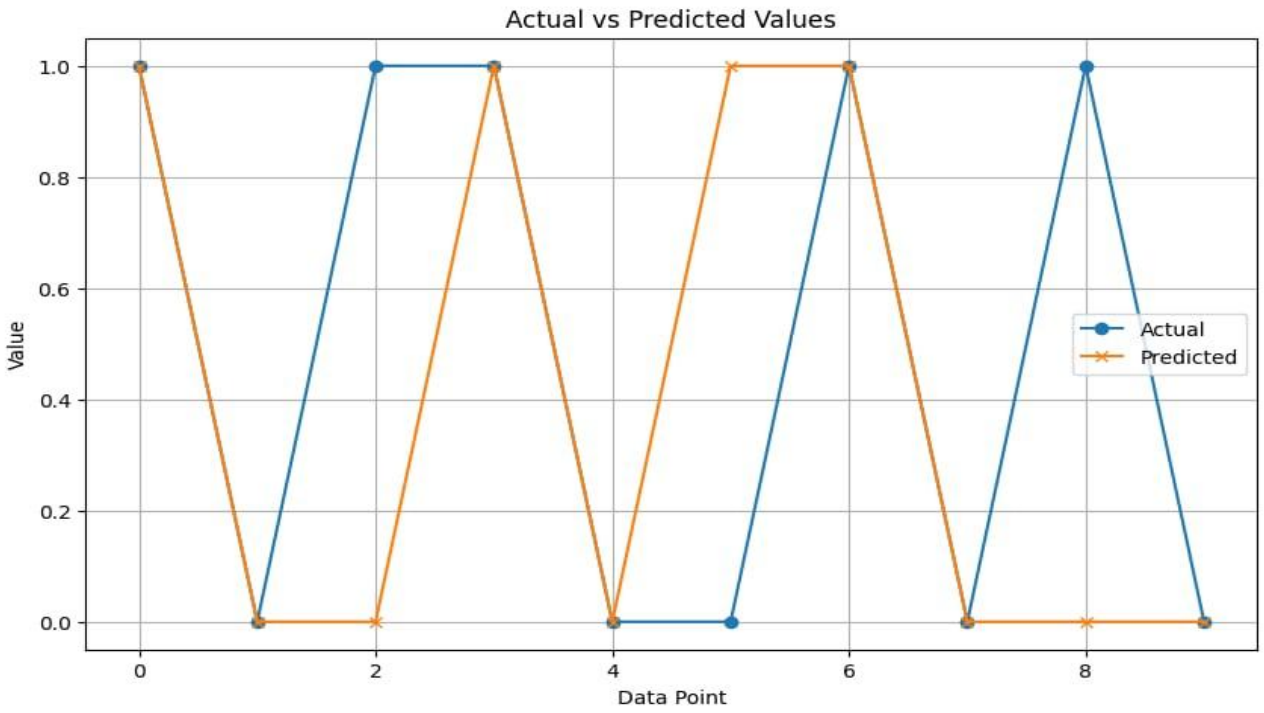


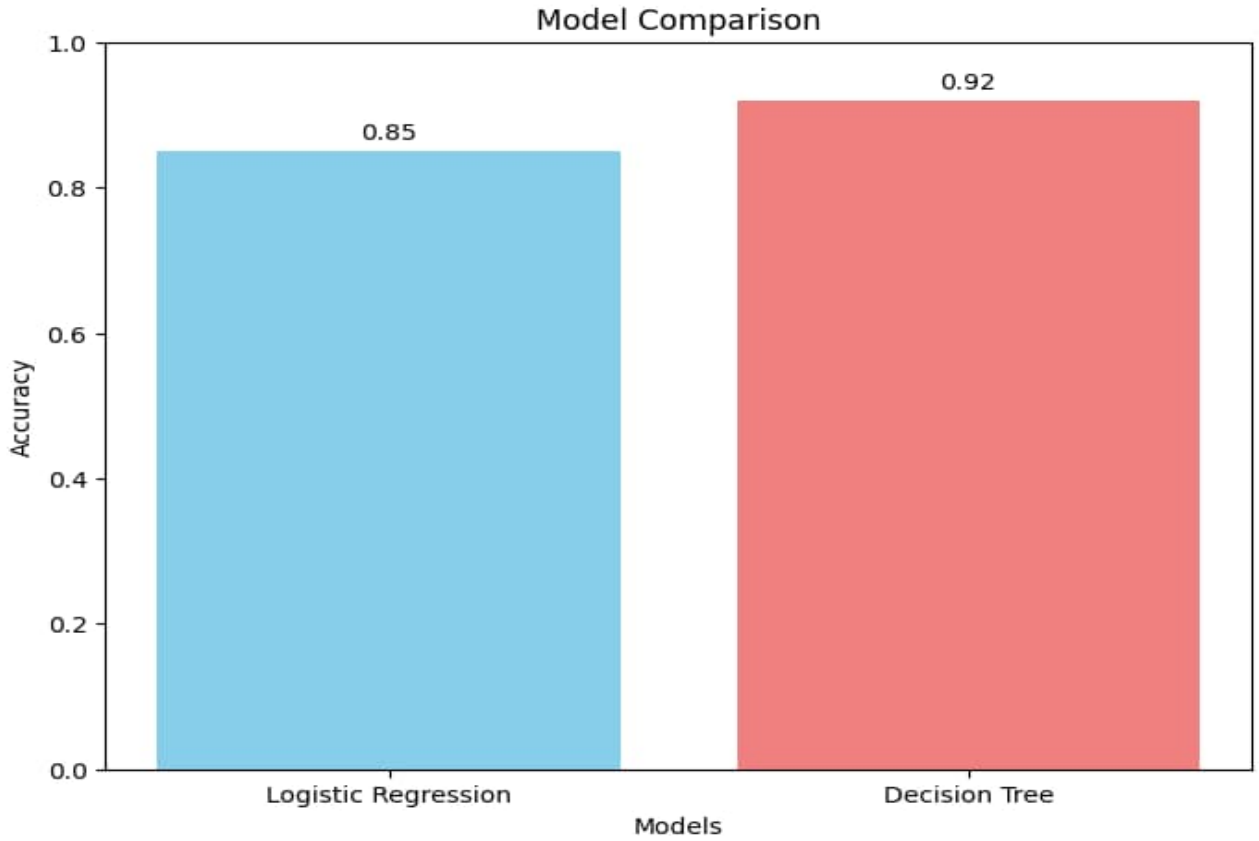
```
accuracy 0.9865364959644732
classification                precision    reca

           0       0.32      0.35      0.34
           1       0.99      1.00      0.99
           2       0.05      0.01      0.02

    accuracy                           0.99
   macro avg       0.46      0.45      0.45
weighted avg       0.98      0.99      0.98

confusion [[  104   178    12]
 [  201 55875    43]
 [   18   312     3]]
```


Actual vs Predicted Values
Value
Data Point
Actual
Predicted
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8


Model Comparison
Accuracy
Models
0.85
0.92
Logistic Regression
Decision Tree
1.0
0.8
0.6
0.4
0.2
0.0

12. Deployment

Platform: Streamlit Cloud

Method: Streamlit App

UI Screenshot: (Insert screenshot)

Sample Output: Predicted result with probability of fraud

13. Source code

```
# Upload the Dataset (only needed in Colab)
from google.colab import files
uploaded = files.upload()

# Load the Dataset
import pandas as pd
df = pd.read_csv('creditcard.csv')

# Data Exploration
print("Shape:", df.shape)
```

```
print("Columns:", df.columns.tolist())

df.info()

print(df.describe())


# Check for Missing Values and Duplicates

print("Missing values:\n", df.isnull().sum())

print("Duplicate rows:", df.duplicated().sum())


# Visualize Class Distribution

import seaborn as sns

import matplotlib.pyplot as plt


sns.countplot(x='Class', data=df)

plt.title('Fraud (1) vs Legit (0) Transaction Count')

plt.show()


# Visualize Transaction Amount Distribution

sns.histplot(df['Amount'], bins=50, kde=True)

plt.title('Transaction Amount Distribution')
```

```
plt.xlabel('Amount')

plt.show()


# Identify Features and Target

target = 'Class'

features = df.columns.drop(['Class', 'Time'])


# Feature Scaling

from sklearn.preprocessing import StandardScaler


scaler = StandardScaler()

df['Amount_scaled'] = scaler.fit_transform(df[['Amount']])

X = df.drop(['Time', 'Class', 'Amount'], axis=1)

X['Amount'] = df['Amount_scaled']

y = df['Class']


# Train-Test Split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
```

```
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Model Training
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,
confusion_matrix

model = RandomForestClassifier(n_estimators=100,
random_state=42)
model.fit(X_train, y_train)

# Model Evaluation
y_pred = model.predict(X_test)
print("Classification Report:\n", classification_report(y_test,
y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test,
y_pred))
```

```
# Predict on New Sample

sample = X_test.iloc[0]

prediction = model.predict([sample])

print("🎯 Sample Prediction (0 = Legit, 1 = Fraud):",

prediction[0])


# Build Interactive App using Gradio

!pip install gradio


import gradio as gr

import numpy as np


# Define prediction function

def predict_fraud(*inputs):

    inputs_array = np.array(inputs).reshape(1, -1)

    return "Fraud" if model.predict(inputs_array)[0] == 1 else

"Legit"


# Gradio Interface
```

```
feature_labels = X.columns.tolist()

gr.Interface(
    fn=predict_fraud,
    inputs=[gr.Number(label=col) for col in feature_labels],
    outputs="text",
    title="Credit Card Fraud Detection",
    description="Enter transaction details to predict whether
it's Fraud or Legit."
).launch()
```

14. Future scope

- Integrate real-time API to stream live transaction data
- Expand model to include user behavior profiling
- Implement federated learning for cross-bank collaboration

15. Team Members and Roles

NAME	ROLE	RESPONSIBLE
Inbarasu I	Member	Data Collection, Data Preprocessing
Deepak kumar S	Member	Feature Engineering
Hemanth D	Member	Exploratory Data Analysis (EDA),
Gokul S	Leader	Model Building, Model Evaluation

GitHub Screenshot

Google Colab Link

https://colab.research.google.com/drive/12bWSnPc0aQhc5KMmjaXJJ__8KIZpU8Kf?usp=sharing