```
from google.colab import files
Upload=files.upload()
```



```
Choose files No file chosen
```

Upload widget is only

available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving creditcard.csv to creditcard.csv

```
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.metrics import classification_report, confusion_matrix, roc_auc_score
from imblearn.over_sampling import SMOTE
# Load Dataset
df = pd.read_csv("creditcard.csv")
# Basic info
print("Dataset shape:", df.shape)
print(df['Class'].value_counts())
# Data preprocessing
X = df.drop(['Class', 'Time'], axis=1)
y = df['Class']
# Scale Amount
X['Amount'] = StandardScaler().fit_transform(X['Amount'].values.reshape(-1, 1))
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
# Handle imbalance using SMOTE
sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X_train, y_train)
print("After SMOTE:", y_res.value_counts())
# Train model
clf = RandomForestClassifier(n estimators=100, random state=42)
clf.fit(X_res, y_res)
# Predictions
y_pred = clf.predict(X_test)
y_proba = clf.predict_proba(X_test)[:, 1]
# Evaluation
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion matrix(y test, y pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_proba))
# Plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
```

plt.ylabel("Actual")
plt.show()

⇒ : shape: (284807, 31)

34315 492

:ount, dtype: int64

SMOTE: Class

)9008 )9008

:ount, dtype: int64
ication Report:

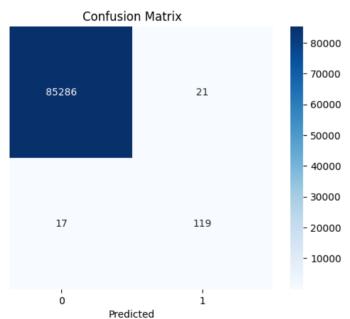
	precision	recall	f1-score	support
0	1.00	1.00	1.00	85307
1	0.85	0.88	0.86	136
:uracy			1.00	85443
o avg	0.92	0.94	0.93	85443
ed avg	1.00	1.00	1.00	85443

.on Matrix:

36 21]

' 119]]

: Score: 0.9766445188623236

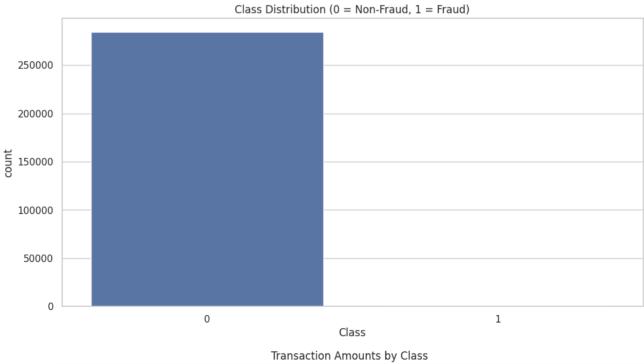


import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model\_selection import train\_test\_split

```
df = pd.read csv("creditcard.csv")
# View dataset shape and class balance
print("Dataset shape:", df.shape)
print("Class distribution:\n", df['Class'].value_counts())
# Drop 'Time' column (not useful for prediction)
df = df.drop(columns=['Time'])
# Scale the 'Amount' feature
scaler = StandardScaler()
df['Amount'] = scaler.fit_transform(df['Amount'].values.reshape(-1, 1))
# Define features and target
X = df.drop('Class', axis=1)
y = df['Class']
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.3, random_state=42, stratify=y
)
# Show results
print("Training data shape:", X_train.shape)
print("Testing data shape:", X_test.shape)
→ Dataset shape: (284807, 31)
    Class distribution:
     Class
    0
          284315
     1
             492
    Name: count, dtype: int64
    Training data shape: (199364, 29)
    Testing data shape: (85443, 29)
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
df = pd.read csv('creditcard.csv') # Update path if needed
print("Shape of data:", df.shape)
print(df.info())
print(df.describe())
print("Missing Values:\n", df.isnull().sum())
sns.countplot(x='Class', data=df)
plt.title('Class Distribution (0 = Non-Fraud, 1 = Fraud)')
plt.show()
sns.boxplot(x='Class', y='Amount', data=df)
plt.title('Transaction Amounts by Class')
```

```
plt.show()
df['Hour'] = df['Time'].apply(lambda x: np.floor(x / 3600) % 24)
sns.histplot(data=df, x='Hour', bins=24, hue='Class', multiple='stack', kde=True)
plt.title('Transaction Distribution by Hour')
plt.xlabel('Hour of the Day')
plt.show()
corr = df.corr()
sns.heatmap(corr, cmap='coolwarm', linewidths=0.5)
plt.title('Feature Correlation Matrix')
plt.show()
pca_features = df.iloc[:, 1:29]
pca_features.boxplot(rot=90)
plt.title('PCA Features Distribution')
plt.show()
fraud_count = df['Class'].value_counts()
fraud_percent = fraud_count[1] / fraud_count.sum() * 100
print(f"Fraudulent Transactions: {fraud_count[1]} ({fraud_percent:.4f}%)")
```

	-	_
<b>→</b>	Time	0
	V1	0
	V2	0
	V3	0
	V4	0
	V5	0
	V6	0
	V7	0
	V8	0
	V9	0
	V10	0
	V11	0
	V12	0
	V13	0
	V14	0
	V15	0
	V16	0
	V17	0
	V18	0
	V19	0
	V20	0
	V21	0
	V22	0
	V23	0
	V24	0
	V25	0
	V26	0
	V27	0
	V28	0
	Amount	0
	Class	0
	dtype:	int64



```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, RobustScaler
df = pd.read_csv('creditcard.csv') # Update path if needed
df.dropna(inplace=True)
df['Hour'] = np.floor(df['Time'] / 3600) % 24
df['Log_Amount'] = np.log1p(df['Amount'])
rs = RobustScaler()
df['Scaled_Amount'] = rs.fit_transform(df['Amount'].values.reshape(-1, 1))
df['Rolling_Amount_1hr'] = df.groupby('Hour')['Amount'].transform(lambda x: x.rolling(wing))
df.drop(['Time', 'Amount'], axis=1, inplace=True)
print("Transformed Dataset:\n", df.head())
print("\nFeature Columns:", df.columns.tolist())
print("Shape:", df.shape)
→ Transformed Dataset:
                         V2
                                    V3
                                              V4
                                                         V5
                                                                   V6
    0 -1.359807 -0.072781
                            2.536347
                                       1.378155 -0.338321
                                                            0.462388
                                                                       0.239599
       1.191857
                 0.266151
                            0.166480
                                       0.448154 0.060018 -0.082361 -0.078803
    2 -1.358354 -1.340163
                            1.773209
                                       0.379780 -0.503198
                                                            1.800499
                                                                       0.791461
    3 -0.966272 -0.185226
                            1.792993 -0.863291 -0.010309
                                                            1.247203
                                                                       0.237609
    4 -1.158233 0.877737
                                       0.403034 -0.407193
                            1.548718
                                                            0.095921
                                                                       0.592941
              V8
                        V9
                                  V10
                                                  V24
                                                            V25
                                                                       V26
                                                                                 V27
       0.098698
                            0.090794
                                                       0.128539 -0.189115
                  0.363787
                                            0.066928
                                                                            0.133558
                                       . . .
       0.085102 -0.255425 -0.166974
                                       ... -0.339846
                                                       0.167170
                                                                 0.125895 -0.008983
    1
    2
       0.247676 -1.514654
                            0.207643
                                       ... -0.689281 -0.327642 -0.139097 -0.055353
                                       ... -1.175575
                                                       0.647376 -0.221929
       0.377436 -1.387024 -0.054952
                                                                            0.062723
    4 -0.270533
                 0.817739 0.753074
                                            0.141267 -0.206010
                                                                 0.502292
                                                                            0.219422
             V28
                  Class
                         Hour
                                Log_Amount
                                            Scaled Amount
                                                            Rolling_Amount_1hr
    0 -0.021053
                      0
                          0.0
                                  5.014760
                                                  1.783274
                                                                     149.620000
       0.014724
                                                 -0.269825
                                                                      76.155000
                          0.0
                                  1.305626
                      0
    2 -0.059752
                                                  4.983721
                                                                     176.990000
                      0
                          0.0
                                  5.939276
       0.061458
                          0.0
                                  4.824306
                                                  1.418291
                                                                     168.283333
    3
                      0
       0.215153
                          0.0
                                  4.262539
                                                  0.670579
                                                                     190.716667
                      0
    [5 rows x 33 columns]
    Feature Columns: ['V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10']
    Shape: (284807, 33)
```

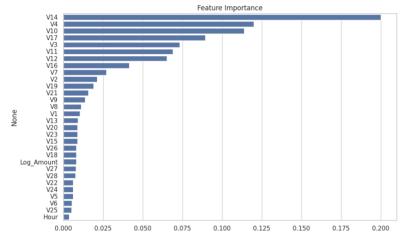
```
mport pandas as pd
mport numpy as np
rom sklearn.model_selection import train_test_split
rom sklearn.ensemble import RandomForestClassifier
rom sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, precis:
rom sklearn.utils import resample
f = pd.read_csv('creditcard.csv') # Replace with your processed data path
f['Hour'] = np.floor(df['Time'] / 3600) % 24
f['Log_Amount'] = np.log1p(df['Amount'])
f.drop(['Time', 'Amount'], axis=1, inplace=True)
raud = df[df['Class'] == 1]
on_fraud = df[df['Class'] == 0].sample(len(fraud), random_state=42)
alanced_df = pd.concat([fraud, non_fraud])
 = balanced_df.drop('Class', axis=1)
 = balanced df['Class']
_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, :
odel = RandomForestClassifier(n_estimators=100, random_state=42)
odel.fit(X_train, y_train)
_pred = model.predict(X_test)
_proba = model.predict_proba(X_test)[:, 1]
rint("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
rint("\nClassification Report:\n", classification_report(y_test, y_pred))
rint("ROC AUC Score:", roc_auc_score(y_test, y_proba))
mport matplotlib.pvplot as plt
mport seaborn as sns
mportances = model.feature_importances_
eatures = X.columns
ndices = np.argsort(importances)[::-1]
lt.figure(figsize=(10, 6))
ns.barplot(x=importances[indices], y=features[indices])
lt.title("Feature Importance")
lt.tight_layout()
lt.show()
```

## 

## Classification Report:

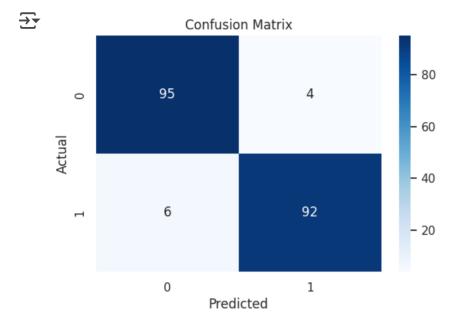
	precision	recall	f1-score
0 1	0.94 0.96	0.96 0.94	0.95 0.95
accuracy macro avg weighted avg	0.95 0.95	0.95 0.95	0.95 0.95 0.95

ROC AUC Score: 0.9888167388167388



```
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    roc_auc_score,
    roc_curve,
    precision_recall_curve,
    average_precision_score
import matplotlib.pyplot as plt
import seaborn as sns
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
print("Classification Report:\n")
print(classification_report(y_test, y_pred))
fpr, tpr, _ = roc_curve(y_test, y_proba)
```

```
roc_auc = roc_auc_score(y_test, y_proba)
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label=f"ROC Curve (AUC = {roc_auc:.2f})")
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend(loc="lower right")
plt.show()
precision, recall, _ = precision_recall_curve(y_test, y_proba)
avg_precision = average_precision_score(y_test, y_proba)
plt.figure(figsize=(6, 4))
plt.plot(recall, precision, label=f"AP = {avg_precision:.2f}")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.show()
```



Classification Report:

import joblib

joblib.dump(model, 'fraud\_model.pkl')

$\rightarrow$	['frædd <u>r</u> mddel.pl	0.95		
]	macro avg	0.95	0.95	0.95
		2 25	0 05	2 25

import gradio as gr
import pandas as pd