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In [1]: FindDefault (Prediction of Credit Card fraud)
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In [ ]: # Importing necessary 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.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve
from imblearn.over_sampling import SMOTE
```

```
In [2]: # Load the dataset
data = pd.read_csv('creditcard.csv')
```

```
In [3]: # 1. Exploratory Data Analysis (EDA)
print("Dataset Overview:")
print(data.head())
```

Dataset Overview:

	Time	V1	V2	V3	V4	V5	V6	V7	\
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	

	V8	V9	...	V21	V22	V23	V24	V25	\
0	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	
1	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	
2	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	
3	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	
4	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	

	V26	V27	V28	Amount	Class
0	-0.189115	0.133558	-0.021053	149.62	0
1	0.125895	-0.008983	0.014724	2.69	0
2	-0.139097	-0.055353	-0.059752	378.66	0
3	-0.221929	0.062723	0.061458	123.50	0
4	0.502292	0.219422	0.215153	69.99	0

[5 rows x 31 columns]

```
In [4]: print("\nDataset Info:")
print(data.info())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Time        284807 non-null  float64
1   V1          284807 non-null  float64
2   V2          284807 non-null  float64
3   V3          284807 non-null  float64
4   V4          284807 non-null  float64
5   V5          284807 non-null  float64
6   V6          284807 non-null  float64
7   V7          284807 non-null  float64
8   V8          284807 non-null  float64
9   V9          284807 non-null  float64
10  V10         284807 non-null  float64
11  V11         284807 non-null  float64
12  V12         284807 non-null  float64
13  V13         284807 non-null  float64
14  V14         284807 non-null  float64
15  V15         284807 non-null  float64
16  V16         284807 non-null  float64
17  V17         284807 non-null  float64
18  V18         284807 non-null  float64
19  V19         284807 non-null  float64
20  V20         284807 non-null  float64
21  V21         284807 non-null  float64
22  V22         284807 non-null  float64
23  V23         284807 non-null  float64
24  V24         284807 non-null  float64
25  V25         284807 non-null  float64
26  V26         284807 non-null  float64
27  V27         284807 non-null  float64
28  V28         284807 non-null  float64
29  Amount      284807 non-null  float64
30  Class       284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
None
```

```
In [5]: print("\nSummary Statistics:")
        print(data.describe())
```

Summary Statistics:

	Time	V1	V2	V3	V4 \
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01

	V5	V6	V7	V8	V9 \
count	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	9.604066e-16	1.487313e-15	-5.556467e-16	1.213481e-16	-2.406331e-15
std	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+00	1.098632e+00
min	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+01	-1.343407e+01
25%	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-01	-6.430976e-01
50%	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-02	-5.142873e-02
75%	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-01	5.971390e-01
max	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+01	1.559499e+01

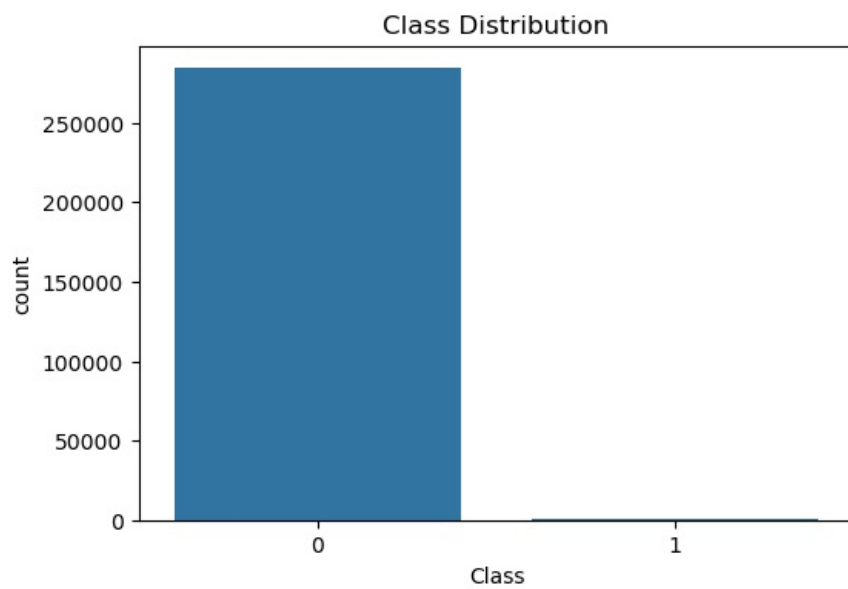
	...	V21	V22	V23	V24 \
count	...	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	...	1.654067e-16	-3.568593e-16	2.578648e-16	4.473266e-15
std	...	7.345240e-01	7.257016e-01	6.244603e-01	6.056471e-01
min	...	-3.483038e+01	-1.093314e+01	-4.480774e+01	-2.836627e+00
25%	...	-2.283949e-01	-5.423504e-01	-1.618463e-01	-3.545861e-01
50%	...	-2.945017e-02	6.781943e-03	-1.119293e-02	4.097606e-02
75%	...	1.863772e-01	5.285536e-01	1.476421e-01	4.395266e-01
max	...	2.720284e+01	1.050309e+01	2.252841e+01	4.584549e+00

	V25	V26	V27	V28	Amount \
count	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	284807.000000
mean	5.340915e-16	1.683437e-15	-3.660091e-16	-1.227390e-16	88.349619
std	5.212781e-01	4.822270e-01	4.036325e-01	3.300833e-01	250.120109
min	-1.029540e+01	-2.604551e+00	-2.256568e+01	-1.543008e+01	0.000000
25%	-3.171451e-01	-3.269839e-01	-7.083953e-02	-5.295979e-02	5.600000
50%	1.659350e-02	-5.213911e-02	1.342146e-03	1.124383e-02	22.000000
75%	3.507156e-01	2.409522e-01	9.104512e-02	7.827995e-02	77.165000
max	7.519589e+00	3.517346e+00	3.161220e+01	3.384781e+01	25691.160000

	Class
count	284807.000000
mean	0.001727
std	0.041527
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[8 rows x 31 columns]

```
In [6]: # plt.figure(figsize=(6, 4))
# sns.countplot(data['Class'])
# plt.title('Class Distribution')
# plt.show()
plt.figure(figsize=(6, 4))
sns.countplot(x='Class', data=data)
plt.title('Class Distribution')
plt.show()
```

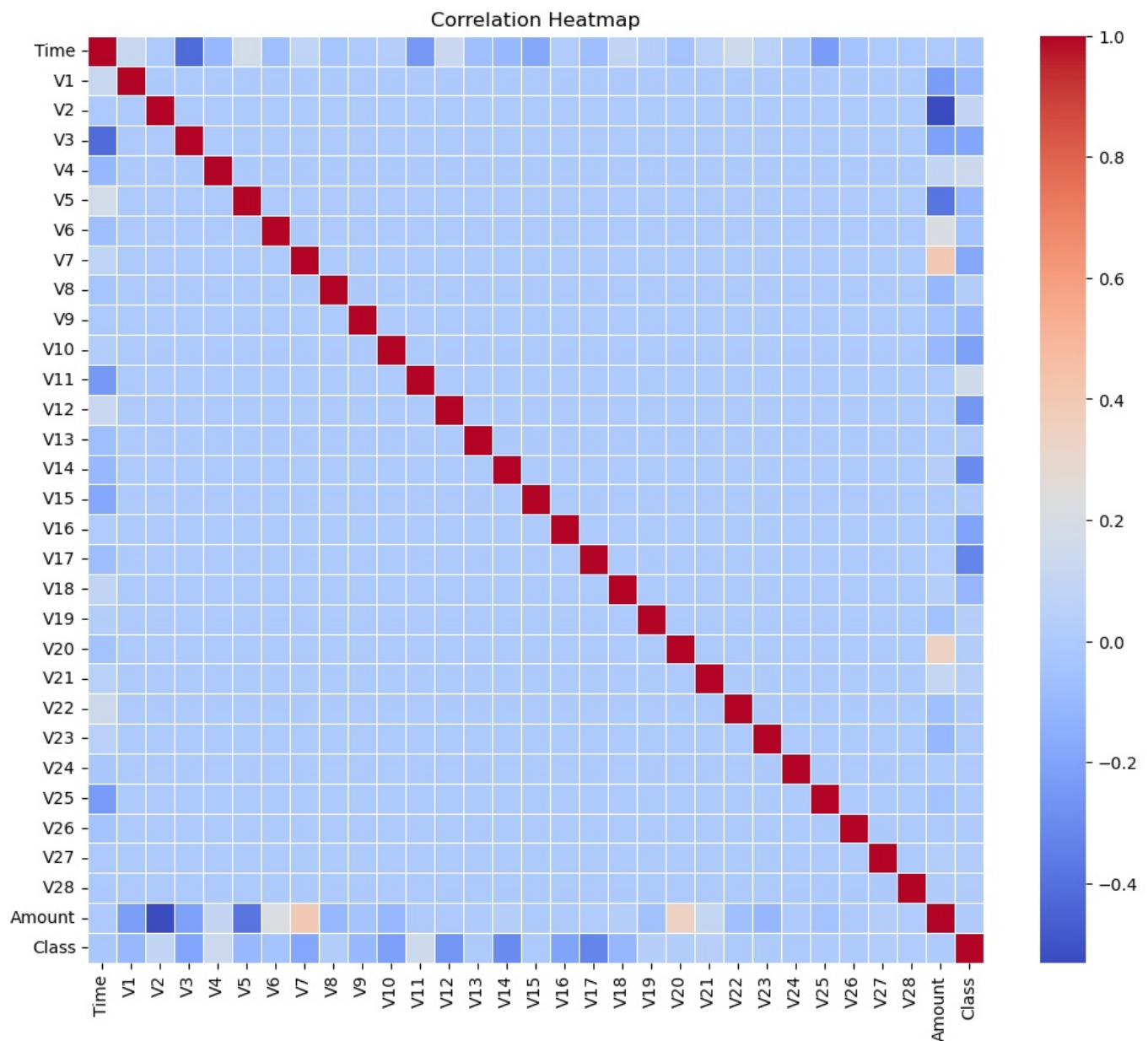


```
In [7]: # Check for missing values
print("\nMissing Values:")
print(data.isnull().sum())
```

Missing Values:

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

```
In [8]: # Correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(data.corr(), cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



```
In [9]: # 2. Data Cleaning (if needed)
# Check for outliers (optional, based on EDA)
# For simplicity, assuming no missing values or significant outliers in this example.
```

```
# 3. Dealing with Imbalanced Data
X = data.drop('Class', axis=1)
y = data['Class']
```

```
In [10]: # Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

```
In [11]: # Balancing the dataset using SMOTE
smote = SMOTE(random_state=42)

X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
print("\nClass Distribution After Resampling:")
print(y_train_resampled.value_counts())
```

```
Class Distribution After Resampling:
Class
0    227451
1    227451
Name: count, dtype: int64
```

```
In [12]: # 4. Feature Engineering
# Standardizing numerical features
scaler = StandardScaler()
X_train_resampled = scaler.fit_transform(X_train_resampled)
X_test = scaler.transform(X_test)
```

```
In [13]: # 5. Model Selection
# Using Random Forest Classifier as an example
# model = RandomForestClassifier(random_state=42)
# If You have multiple CPU use below line and comment above line
```

```
model = RandomForestClassifier(n_jobs=-1, random_state=42)
```

```
In [14]: # 6. Model Training
model.fit(X_train_resampled, y_train_resampled)
```

```
Out[14]: RandomForestClassifier
RandomForestClassifier(n_jobs=-1, random_state=42)
```

```
In [15]: # 7. Model Validation
y_pred = model.predict(X_test)
```

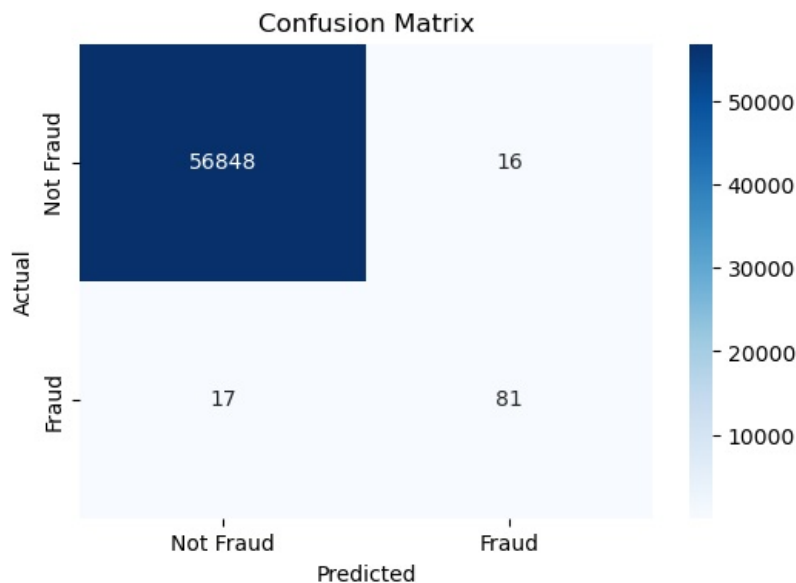
```
In [16]: # Classification Report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

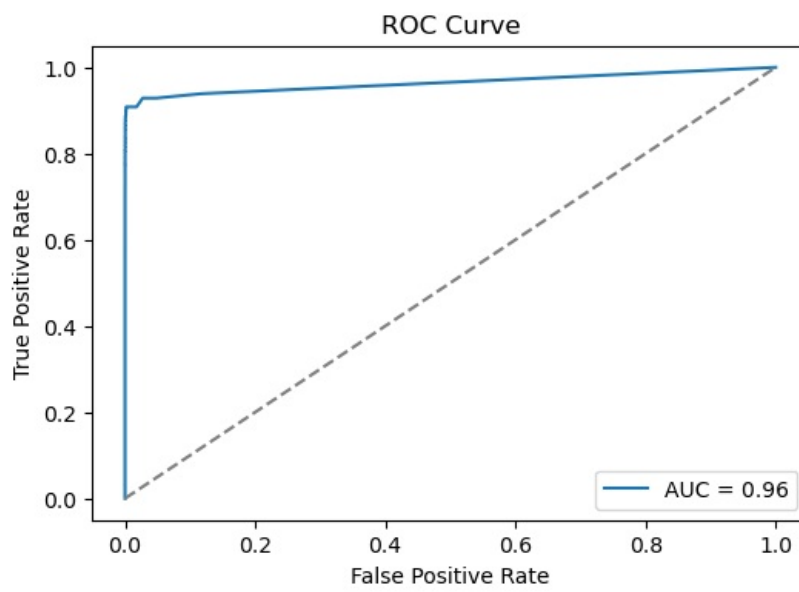
     0           1.00        1.00        1.00     56864
     1           0.84        0.83        0.83         98

 accuracy          0.92        0.91        0.92     56962
 macro avg          0.92        0.91        0.92     56962
 weighted avg          1.00        1.00        1.00     56962
```

```
In [17]: # Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Fraud', 'Fraud'], yticklabels=['Not Fraud', 'Fraud'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



```
In [18]: # ROC Curve
y_pred_prob = model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = roc_auc_score(y_test, y_pred_prob)
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



```
In [19]: # 8. Model Deployment
# Save the model using joblib (for example)
import joblib
joblib.dump(model, 'credit_card_fraud_model.pkl')
print("Model saved as 'credit_card_fraud_model.pkl'")
```

Model saved as 'credit_card_fraud_model.pkl'

In []:

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