Import Modules

```
import numpy as np
import pandas as pd
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from imblearn.over sampling import SMOTE # Assuming you have imblearn installed
from sklearn.linear model import LogisticRegression
from sklearn.metrics import classification_report, f1_score
import seaborn as sns
import matplotlib.pyplot as plt
Loading Dataset
df=pd.read csv('creditcard.csv')
df.head()
df clean = df.dropna() # Ensure no NaN values are present
X = df clean.drop(columns=['Class'])
y = df clean['Class']
df.describe()
```



	Time	V1	V2	V3	V4	V5	V6	V7	
count	284807.000000	2.848070e+05	2.8480						
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15	9.604066e-16	1.487313e-15	-5.556467e-16	1.2134
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.1943
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.3216
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.0862
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.2358
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.2734
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.00072

8 rows × 31 columns



df.info()

<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 284807 entries, 0 to 284806
 Data columns (total 31 columns):

Data	COTUIIII	(cocar	JI COIUMII	٥,٠
#	Column	Non-Nu	ll 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

Untitled1.ipynb - Colab

```
12 V12
           284807 non-null float64
           284807 non-null float64
13 V13
14 V14
           284807 non-null float64
           284807 non-null float64
15 V15
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
           284807 non-null float64
21 V21
22 V22
           284807 non-null float64
           284807 non-null float64
23 V23
24 V24
           284807 non-null float64
  V25
25
           284807 non-null float64
26 V26
           284807 non-null float64
27 V27
           284807 non-null float64
28 V28
           284807 non-null float64
   Amount 284807 non-null float64
30 Class
           284807 non-null int64
```

dtypes: float64(30), int64(1)

memory usage: 67.4 MB

Preprocessing the Data

df.isnull().sum()



Time 0

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

V22 0

V23 0

V24 0

V25 0

V26 0

V27 0

V28 0

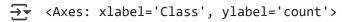
Amount 0

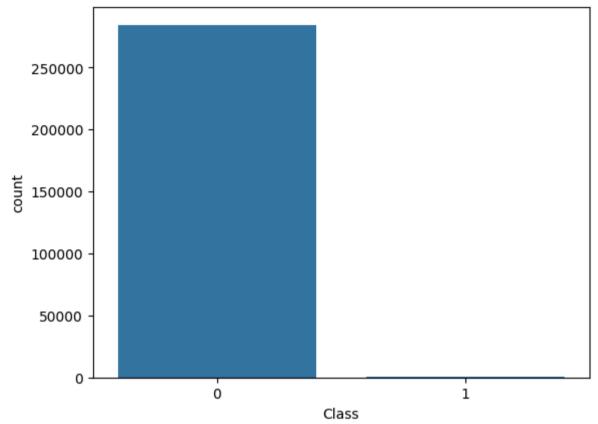
Class 0

dtype: int64

Exploratory Data Analysis

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





Input Split

Standard Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x scaler = sc.fit transform(X)
x scaler[-1]
    array([ 1.64205773, -0.27233093, -0.11489898, 0.46386564, -0.35757 ,
            -0.00908946, -0.48760183, 1.27476937, -0.3471764, 0.44253246,
           -0.84072963, -1.01934641, -0.0315383, -0.18898634, -0.08795849,
             0.04515766, -0.34535763, -0.77752147, 0.1997554, -0.31462479,
             0.49673933, 0.35541083, 0.8861488, 0.6033653, 0.01452561,
            -0.90863123, -1.69685342, -0.00598394, 0.04134999, 0.51435531])
Model Training
print("NaN Count in x scaler:", np.isnan(x scaler).sum())
print("NaN Count in y:", y.isnull().sum())
→ NaN Count in x scaler: 0
     NaN Count in v: 0
# Drop NaN values before scaling
df clean = df.dropna()
# Separate features and target only from the cleaned DataFrame
X = df clean.drop(columns=['Class'], axis=1)
y = df clean['Class']
# Perform standard scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x scaler = sc.fit transform(X)
```

x_train, x_test, y_train, y_test = train_test_split(x_scaler, y, test_size=0.25, random_state=42, stratify=y)

Split the data

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
# training
model.fit(x_train, y_train)
# testing
y_pred = model.predict(x_test)
print(classification_report(y_test, y_pred))
print("F1 Score:",f1_score(y_test, y_pred))
```

₹		precision	recall	f1-score	support
	0	1.00	1.00	1.00	71079
	1	0.84	0.62	0.71	123
	accuracy			1.00	71202
	macro avg	0.92	0.81	0.85	71202
	weighted avg	1.00	1.00	1.00	71202

F1 Score: 0.7102803738317757

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
# training
model.fit(x_train, y_train)
# testing
y_pred = model.predict(x_test)
print(classification_report(y_test, y_pred))
print("F1 Score:",f1_score(y_test, y_pred))
```

⋺	precision	recall	f1-score	support
0	1.00	1.00	1.00	71079
1	0.96	0.77	0.86	123
accuracy			1.00	71202
macro avg	0.98	0.89	0.93	71202
weighted avg	1.00	1.00	1.00	71202

F1 Score: 0.8558558558558559

```
from xgboost import XGBClassifier
model = XGBClassifier(n_jobs=-1)
# training
model.fit(x_train, y_train)
# testing
y_pred = model.predict(x_test)
print(classification_report(y_test, y_pred))
print("F1 Score:",f1_score(y_test, y_pred))
```

→		precision	recall	f1-score	support
	0	1.00	1.00	1.00	71079
	1	0.95	0.79	0.86	123
	accuracy			1.00	71202
	macro avg	0.98	0.89	0.93	71202
	weighted avg	1.00	1.00	1.00	71202

F1 Score: 0.862222222222222

Class Imbalance

```
smote = SMOTE(random_state=42)
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)

from sklearn.linear_model import LogisticRegression
log_model = LogisticRegression()
log_model.fit(x_train_smote, y_train_smote) # Training with SMOTE data
y_pred_log = log_model.predict(x_test)
print("Logistic Regression")
print(classification_report(y_test, y_pred_log))
print("F1 Score:", f1 score(y test, y pred_log))
```

→ Logistic Regression precision recall f1-score support 0 1.00 0.98 0.99 71079 1 0.06 0.89 0.11 123 71202 accuracy 0.98 macro avg 0.55 71202 0.53 0.93 weighted avg 0.98 0.99 71202 1.00

F1 Score: 0.11082867310625318

```
rf_model = RandomForestClassifier(n_jobs=-1)
rf_model.fit(x_train_smote, y_train_smote) # Training with SMOTE data
y_pred_rf = rf_model.predict(x_test)
print("Random Forest Classifier")
print(classification_report(y_test, y_pred_rf))
print("F1 Score:", f1_score(y_test, y_pred_rf))
```

Random Forest Classifier recall f1-score precision support 0 1.00 1.00 1.00 71079 1 0.88 0.80 0.84 123 71202 accuracy 1.00 macro avg 0.94 0.90 0.92 71202 weighted avg 1.00 1.00 1.00 71202

F1 Score: 0.8376068376068376