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[ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪roc_auc_score, precision_recall_curve, roc_curve
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
df=pd.read_csv('/content/creditcard.csv')
```

[ ]:
```
df
```

[ ]:
```
            Time         V1         V2        V3        V4        V5  \
0            0.0  -1.359807  -0.072781  2.536347  1.378155 -0.338321
1            0.0   1.191857   0.266151  0.166480  0.448154  0.060018
2            1.0  -1.358354  -1.340163  1.773209  0.379780 -0.503198
3            1.0  -0.966272  -0.185226  1.792993 -0.863291 -0.010309
4            2.0  -1.158233   0.877737  1.548718  0.403034 -0.407193
…             …          …          …         …         …         …
284802  172786.0 -11.881118  10.071785 -9.834783 -2.066656 -5.364473
284803  172787.0  -0.732789  -0.055080  2.035030 -0.738589  0.868229
284804  172788.0   1.919565  -0.301254 -3.249640 -0.557828  2.630515
284805  172788.0  -0.240440   0.530483  0.702510  0.689799 -0.377961
284806  172792.0  -0.533413  -0.189733  0.703337 -0.506271 -0.012546

              V6        V7        V8        V9  …       V21       V22  \
0       0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838
1      -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672
2       1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679
3       1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274
4       0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278
…            …         …         …         …  …       …         …
284802 -2.606837 -4.918215  7.305334  1.914428  …  0.213454  0.111864
```

```
284803  1.058415  0.024330  0.294869  0.584800  …  0.214205  0.924384
284804  3.031260 -0.296827  0.708417  0.432454  …  0.232045  0.578229
284805  0.623708 -0.686180  0.679145  0.392087  …  0.265245  0.800049
284806 -0.649617  1.577006 -0.414650  0.486180  …  0.261057  0.643078

             V23       V24       V25       V26       V27       V28  Amount  \
0      -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62
1       0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69
2       0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66
3      -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50
4      -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99
…            …         …         …         …         …         …       …
284802  1.014480 -0.509348  1.436807  0.250034  0.943651  0.823731    0.77
284803  0.012463 -1.016226 -0.606624 -0.395255  0.068472 -0.053527   24.79
284804 -0.037501  0.640134  0.265745 -0.087371  0.004455 -0.026561   67.88
284805 -0.163298  0.123205 -0.569159  0.546668  0.108821  0.104533   10.00
284806  0.376777  0.008797 -0.473649 -0.818267 -0.002415  0.013649  217.00

        Class
0           0
1           0
2           0
3           0
4           0
…         …
284802      0
284803      0
284804      0
284805      0
284806      0

[284807 rows x 31 columns]
```

[ ]:
```
df.describe()
```

[ ]:
```
                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]
```

[ ]:
```
df.shape
```

[ ]:
```
(284807, 31)
```

[ ]:
```
df.isnull().sum()
```

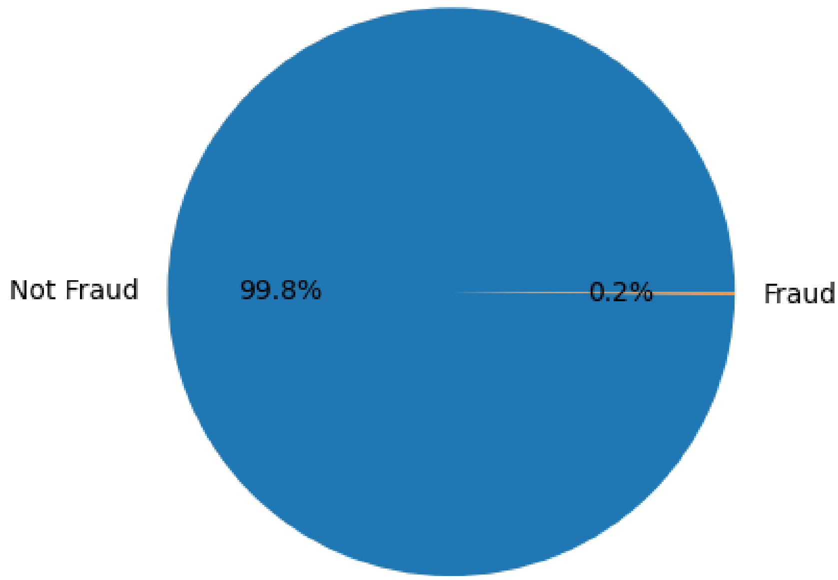
[ ]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
1081
```

[ ]:
```
df.drop_duplicates(inplace=True)
```

[ ]:
```
plt.pie(x=df['Class'].value_counts(),labels=['Not Fraud','Fraud'],autopct="%0.
 ↪1f%%")
plt.show()
```




```
[ ]: X = df.drop('Class', axis=1)
     y = df['Class']
```

```
[ ]: scaler = StandardScaler()
     X_scaled = scaler.fit_transform(X)
```

```
[ ]: smote = SMOTE(random_state=42)
     X_resampled, y_resampled = smote.fit_resample(X_scaled, y)
```

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,␣
      ↪test_size=0.2, random_state=42)
```

```
[ ]: log_model = LogisticRegression(max_iter=1000)
     log_model.fit(X_train, y_train)
     y_pred_log = log_model.predict(X_test)
```

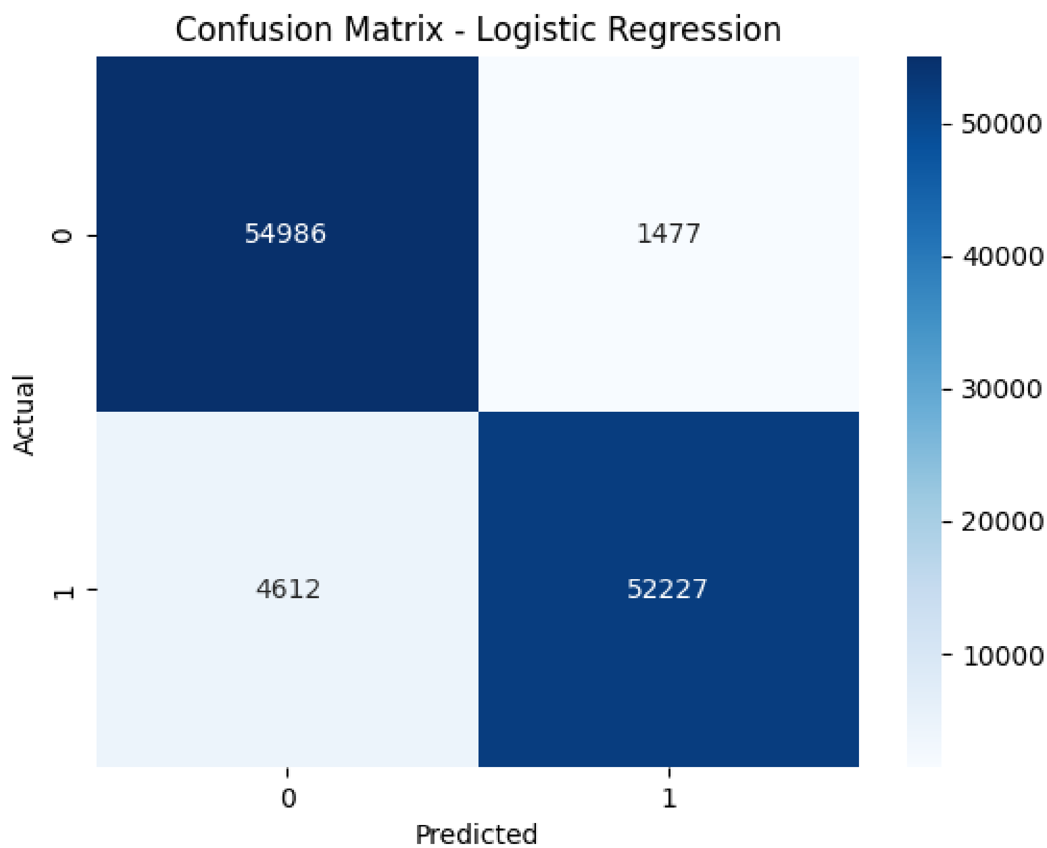
```
[ ]: rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
     rf_model.fit(X_train, y_train)
     y_pred_rf = rf_model.predict(X_test)
```

```
[ ]: def evaluate_model(y_test, y_pred, model_name):
         print(f"\nModel: {model_name}")
         print("Classification Report:")
```

```
    print(classification_report(y_test, y_pred))
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```

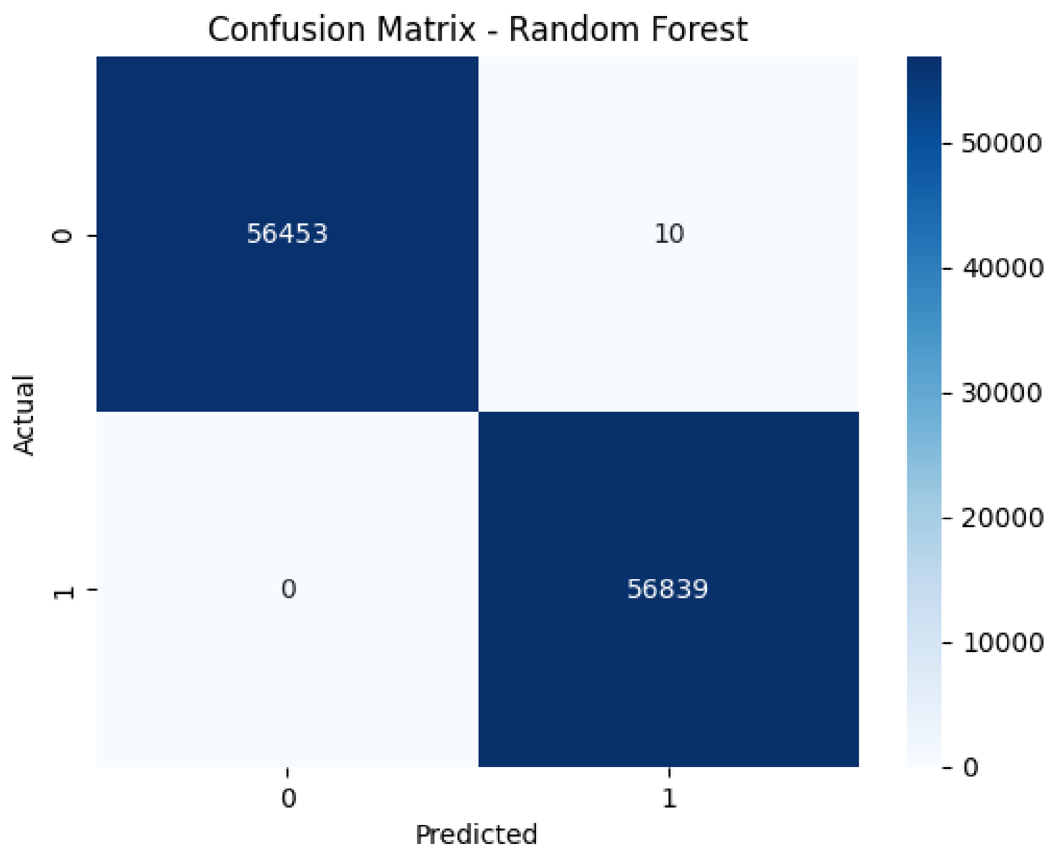
[ ]:
```
evaluate_model(y_test, y_pred_log, "Logistic Regression")
evaluate_model(y_test, y_pred_rf, "Random Forest")
```

```
Model: Logistic Regression
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.97      0.95     56463
           1       0.97      0.92      0.94     56839

    accuracy                           0.95    113302
   macro avg       0.95      0.95      0.95    113302
weighted avg       0.95      0.95      0.95    113302
```



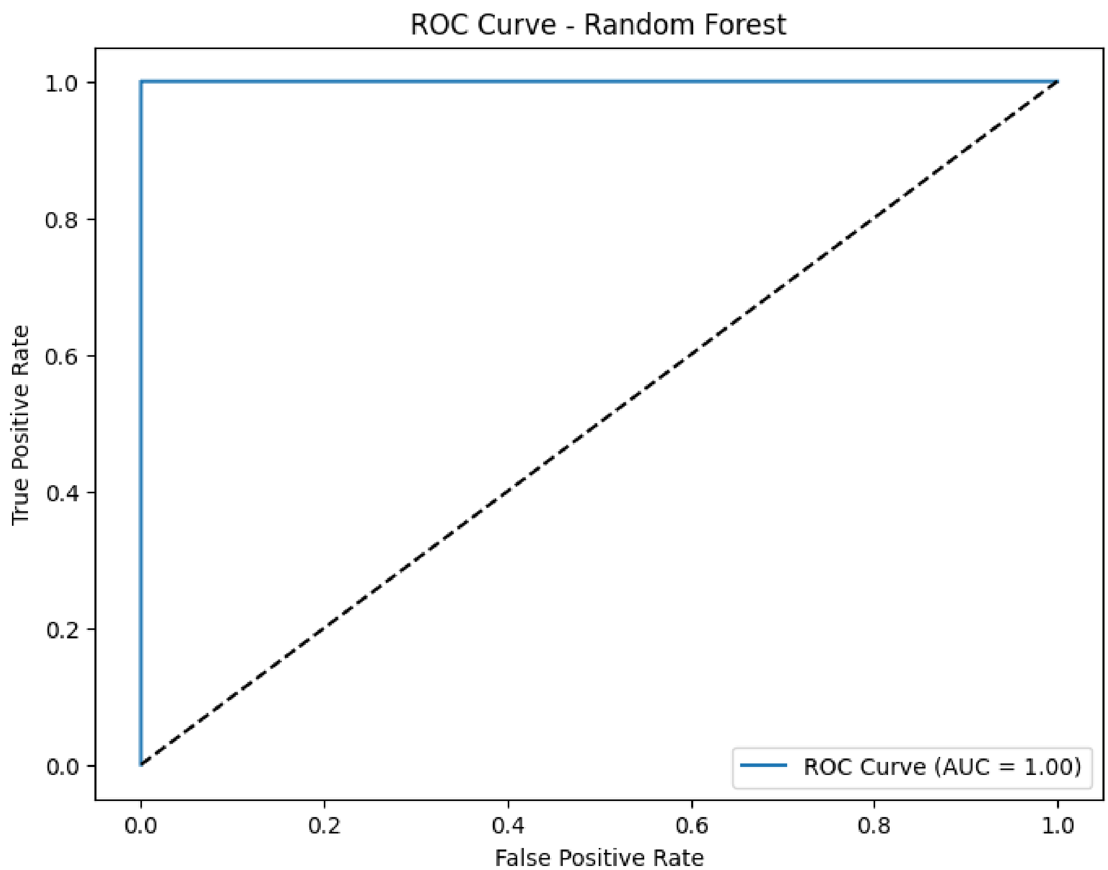
Model: Random Forest
Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56463
1	1.00	1.00	1.00	56839
accuracy			1.00	113302
macro avg	1.00	1.00	1.00	113302
weighted avg	1.00	1.00	1.00	113302



[ ]:
```
y_scores = rf_model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_scores)
roc_auc = roc_auc_score(y_test, y_scores)
```

[ ]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Random Forest')
plt.legend(loc='lower right')
plt.show()
```


ROC Curve - Random Forest
True Positive Rate
False Positive Rate
ROC Curve (AUC = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0