ml-credit-card-fraud-detection

August 6, 2025

1 Credit Card Fraud Detection - ML

The goal of this project is to develop a machine learning model that can accurately detect fraudulent credit card transactions using historical data. By analyzing transaction patterns, the model should be able to distinguish between normal and fraudulent activity, helping financial institutions flag suspicious behavior early and reduce potential risks.

Importing all the necessary Libraries

[8]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import gridspec
```

#Loading the Data

[9]:
```
data = pd.read_csv("/content/creditcard (1).csv")
data.head(5)
```

[9]:
```
   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]
```

#Understanding the Data

[10]:
```python
print(data.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]
```

#Describing the Data

#Imbalance in the data

[11]:
```
fraud = data[data['Class'] == 1]
valid = data[data['Class'] == 0]
outlierFraction = len(fraud)/float(len(valid))
print(outlierFraction)
print('Fraud Cases: {}'.format(len(data[data['Class'] == 1])))
print('Valid Transactions: {}'.format(len(data[data['Class'] == 0])))
```

```
0.0017304750013189597
Fraud Cases: 492
Valid Transactions: 284315
```

#Print the amount details for Fraudulent Transaction

[12]:
```
print("Amount details of the fraudulent transaction")
fraud.Amount.describe()
```

```
Amount details of the fraudulent transaction
```

[12]:
```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

2 Print the amount details for Normal Transaction

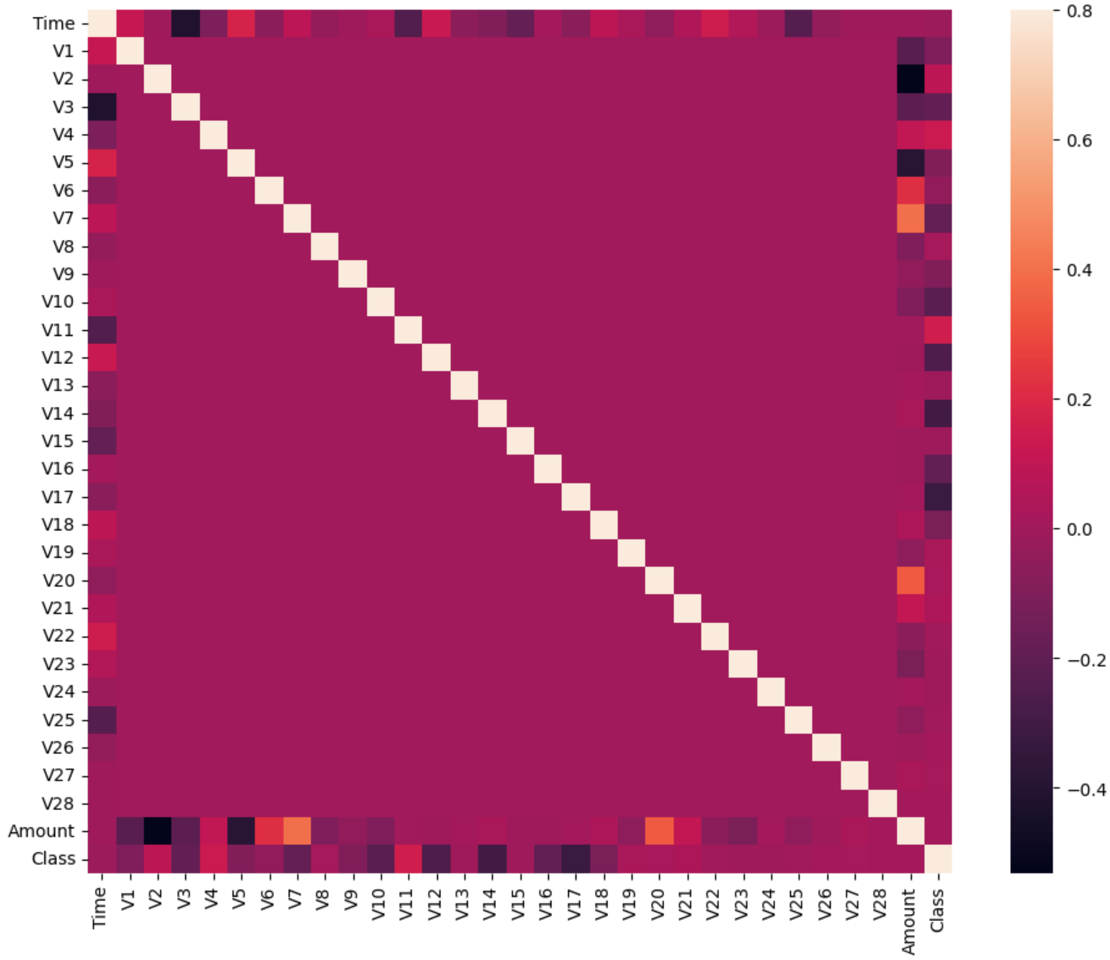
[13]:
```
print("details of valid transaction")
valid.Amount.describe()
```

```
details of valid transaction
```

[13]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

#Plotting the Correlation Matrix

[14]:
```
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



#Separating the X and the Y values

[15]:
```
# dividing the X and the Y from the dataset
X = data.drop(['Class'], axis = 1)
Y = data["Class"]
print(X.shape)
print(Y.shape)
# getting just the values for the sake of processing
# (its a numpy array with no columns)
xData = X.values
yData = Y.values
```

```
(284807, 30)
(284807,)
```

#Training and Testing Data Bifurcation

[16]:
```python
# Using Scikit-learn to split data into training and testing sets
from sklearn.model_selection import train_test_split
# Split the data into training and testing sets
xTrain, xTest, yTrain, yTest = train_test_split(
        xData, yData, test_size = 0.2, random_state = 42)
```

#Building a Random Forest Model using scikit learn

[17]:
```python
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier()
rfc.fit(xTrain, yTrain)
# predictions
yPred = rfc.predict(xTest)
```

[20]:
```python
from sklearn.impute import SimpleImputer
print("NaN values in yTest before imputation:", np.isnan(yTest).sum())

imputer = SimpleImputer(strategy='most_frequent')
yTest = imputer.fit_transform(yTest.reshape(-1, 1)).flatten()
print("NaN values in yTest after imputation:", np.isnan(yTest).sum())
```

```
NaN values in yTest before imputation: 0
NaN values in yTest after imputation: 0
```

3 Building all kinds of evaluating parameters

[21]:
```python
# Evaluating the classifier
# printing every score of the classifier
# scoring in anything
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, matthews_corrcoef
from sklearn.metrics import confusion_matrix

n_outliers = len(fraud)
n_errors = (yPred != yTest).sum()
print("The model used is Random Forest classifier")

acc = accuracy_score(yTest, yPred)
print("The accuracy is {}".format(acc))

prec = precision_score(yTest, yPred)
print("The precision is {}".format(prec))

rec = recall_score(yTest, yPred)
print("The recall is {}".format(rec))
```

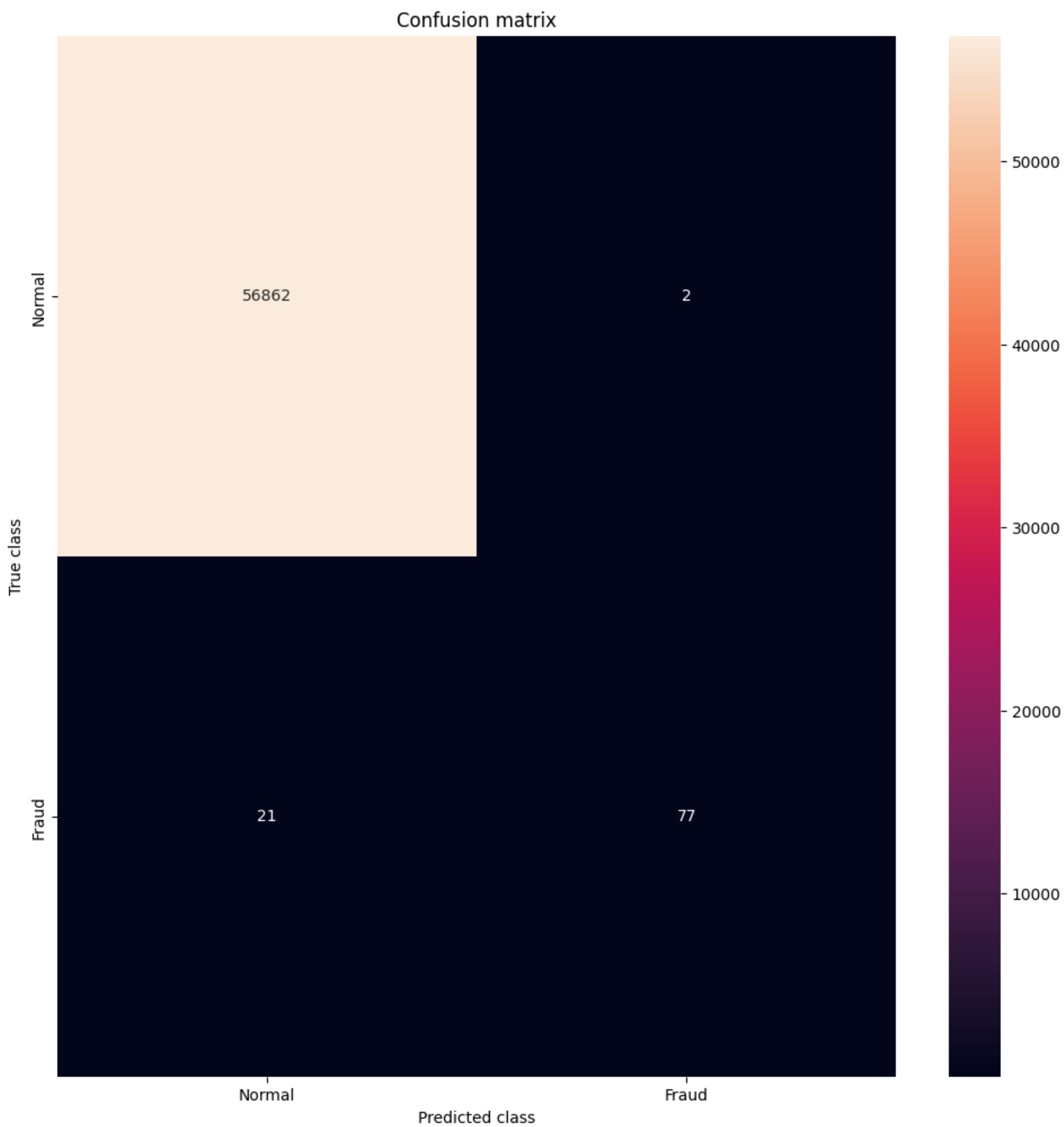
```
f1 = f1_score(yTest, yPred)
print("The F1-Score is {}".format(f1))

MCC = matthews_corrcoef(yTest, yPred)
print("The Matthews correlation coefficient is{}".format(MCC))
```

```
The model used is Random Forest classifier
The accuracy is 0.9995962220427653
The precision is 0.9746835443037974
The recall is 0.7857142857142857
The F1-Score is 0.8700564971751412
The Matthews correlation coefficient is0.8749276812909632
```

#Visualizing the Confusion Matrix

[19]:
```
# printing the confusion matrix
LABELS = ['Normal', 'Fraud']
conf_matrix = confusion_matrix(yTest, yPred)
plt.figure(figsize =(12, 12))
sns.heatmap(conf_matrix, xticklabels = LABELS,
            yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```


Confusion matrix
Normal
Fraud
True class
56862
2
21
77
Normal
Fraud
Predicted class
50000
40000
30000
20000
10000