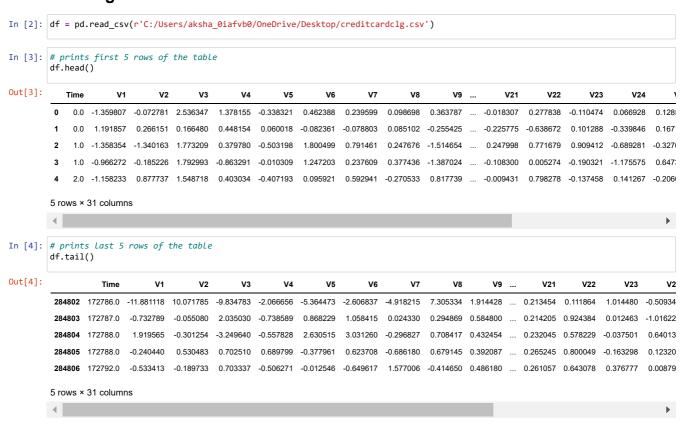
Importing packages

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB #naive bayes
from sklearn import tree #decision tree
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score # for checking gini score
import catboost
from catboost import CatBoostClassifier
```

Loading the data



Checking the shape of data

```
In [5]: df.shape
Out[5]: (284807, 31)
```

Checking for null values

```
In [6]: |df.isnull().sum()
Out[6]: Time
        ٧1
        V2
                  0
        V3
        ٧4
                  0
        ۷5
                  0
        ۷6
                  0
        ٧7
        V8
                  0
        V9
                  0
        V10
                  0
        V11
                  0
        V13
        V14
        V15
                  0
        V16
        V17
                  0
        V18
                  0
        V19
                  0
        V20
                  0
        V21
                  0
        V22
                  0
        V23
        V24
        V25
        V26
                  0
        V27
        V28
                  0
        Amount
                  0
                  0
        Class
        dtype: int64
In [7]: # print full summary
        df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 284807 entries, 0 to 284806
        Data columns (total 31 columns):
            Column Non-Null Count
         0
             Time
                     284807 non-null float64
                     284807 non-null float64
         1
             V1
         2
                     284807 non-null float64
             V2
                     284807 non-null
         3
             V3
                                     float64
                     284807 non-null
             ٧4
                                      float64
             ۷5
                     284807 non-null
                                      float64
         6
                     284807 non-null
             ۷6
                                      float64
             V7
                     284807 non-null
                                      float64
             ٧8
                     284807 non-null
         9
             ۷9
                     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
                     284807 non-null
                                      float64
         14
             V14
                     284807 non-null
                                      float64
         15
             V15
                     284807 non-null
                                      float64
         16
             V16
             V17
                     284807 non-null
                                      float64
         18
             V18
                     284807 non-null
         19
             V19
                     284807 non-null
         20
             V20
                     284807 non-null
                                      float64
         21
             V21
                     284807 non-null
                                      float64
         22
             V22
                     284807 non-null
                                      float64
                     284807 non-null
         23
             V23
                                      float64
                                      float64
         24
             V24
                     284807 non-null
                     284807 non-null
         25
             V25
                                      float64
         26
                     284807 non-null
             V26
                                      float64
                     284807 non-null
         27
             V27
                                     float64
                     284807 non-null float64
             V28
             Amount
                     284807 non-null
                                      float64
```

30 Class

dtypes: float64(30), int64(1)
memory usage: 67.4 MB

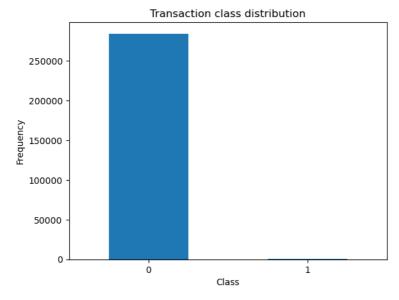
284807 non-null int64

```
In [8]: # describe the data
                             df.describe()
Out[8]:
                                                                                                2.848070e+05
                                                                                                                                                                                    2.848070e+05
                                                                                                                                                                                                                              2.848070e+05
                                                                                                                                                                                                                                                                        2.848070e+05
                                                                                                                                                                                                                                                                                                                   2.848070e+05
                                                                                                                                                                                                                                                                                                                                                                                                       2.848070e+05
                               count 284807.000000
                                                                                                                                          2.848070e+05
                                                                                                                                                                                                                                                                                                                                                             2.848070e+05
                                                                                                                                                                                                                                                                                                                                                                                                                                                 2.848070e+05
                                                      94813.859575
                                                                                                 3.918649e-15
                                                                                                                                            5.682686e-16 -8.761736e-15
                                                                                                                                                                                                                                2.811118e-15 -1.552103e-15
                                                                                                                                                                                                                                                                                                                    2.040130e-15 -1.698953e-15 -1.893285e-16
                                                                                                                                                                                                                                                                                                                                                                                                                                                -3.147640e-15
                                     std
                                                      47488.145955
                                                                                             1.958696e+00 1.651309e+00 1.516255e+00 1.415869e+00
                                                                                                                                                                                                                                                                      1.380247e+00 1.332271e+00 1.237094e+00
                                                                                                                                                                                                                                                                                                                                                                                                     1.194353e+00
                                    min
                                                                  0.000000 \quad -5.640751e + 01 \quad -7.271573e + 01 \quad -4.832559e + 01 \quad -5.683171e + 00 \quad -1.137433e + 02 \quad -2.616051e + 01 \quad -4.355724e + 01 \quad -7.321672e + 01 \quad -1.343407e + 01 \quad
                                   25%
                                                      54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01 -6.915971e-01
                                                                                                                                                                                                                                                                                                                  -7.682956e-01 -5.540759e-01 -2.086297e-01
                                                                                                                                                                                                                                                                                                                                                                                                                                                 -6.430976e-01
                                    50%
                                                      84692 000000 1 810880e-02 6 548556e-02 1 798463e-01 -1 98463e-02 -5 433583e-02 -2 741871e-01 4 010308e-02 2 235804e-02 -5 142873e-02
                                    75% 139320.500000 1.315642e+00 8.037239e-01 1.027196e+00 7.433413e-01
                                                                                                                                                                                                                                                                      6.119264e-01
                                                                                                                                                                                                                                                                                                               3.985649e-01
                                                                                                                                                                                                                                                                                                                                                              5.704361e-01
                                    max 172792.000000 2.454930e+00 2.205773e+01 9.382558e+00 1.687534e+01 3.480167e+01 7.330163e+01 1.205895e+02 2.000721e+01
                                                                                                                                                                                                                                                                                                                                                                                                                                              1.559499e+01
                             8 rows × 31 columns
```

Checking number of records of each kind of transaction class (Fraud and Non-Fraud)

```
In [9]: count_classes = pd.value_counts(df['Class'], sort = True)
    count_classes.plot(kind = 'bar', rot=0)
    plt.title("Transaction class distribution")
    plt.xticks(range(2))
    plt.xlabel("Class")
    plt.ylabel("Frequency")
```

Out[9]: Text(0, 0.5, 'Frequency')



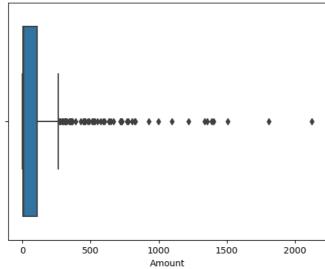
```
In [10]: df['Class'].nunique()
Out[10]: 2
In [11]: df.groupby(['Class'])['Class'].count()
Out[11]: Class
              284315
         0
         1
                 492
         Name: Class, dtype: int64
In [12]: (492/(492+284315))*100
Out[12]: 0.1727485630620034
In [13]: # The data set is highly imbalanced. Looking at each of the fraud(1) and non-fraud(0) transactions.
         frauds = df[df['Class']==1]
         normal = df[df['Class']==0]
In [14]: frauds.shape
Out[14]: (492, 31)
```

```
In [15]: normal.shape

Out[15]: (284315, 31)
```

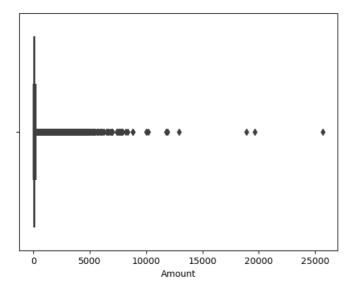
Checking the amount of money involved in each kind of transaction

```
In [16]: # Fraud transactions
         frauds.Amount.describe()
Out[16]: count
                   492.000000
                   122.211321
         mean
                   256.683288
         std
         min
                     0.000000
         25%
                     1.000000
         50%
                     9.250000
         75%
                   105.890000
                  2125.870000
         max
         Name: Amount, dtype: float64
In [17]: # Non-fraud transactions
         normal.Amount.describe()
Out[17]: count
                  284315.000000
                     88.291022
         mean
                     250.105092
         std
                       0.000000
         min
         25%
                       5.650000
                      22.000000
         75%
                      77.050000
                   25691.160000
         Name: Amount, dtype: float64
In [18]: # Box plot of frauds transactions
         sns.boxplot(x=frauds['Amount'])
Out[18]: <AxesSubplot:xlabel='Amount'>
```



```
In [19]: # box plot of normal transactions
sns.boxplot(x = normal['Amount'])
```

```
Out[19]: <AxesSubplot:xlabel='Amount'>
```



```
In [20]: # heat map of correlation between variables
#sns.heatmap(df, cmap="RdYLGn", annot=True)

correlation_matrix = df.corr()

# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=.5)
plt.title('Correlation Heatmap')
plt.show()
```

```
Correlation Heatmap
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        1.0
                                         V2 -0.000 (0) EN CONTROL CENTROL CENTR
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        0.8
                                                                    V4 -0. THE OCT. (C). As an accordance of the control of the con
                                                 V5 9, 17/000H0001 00. IDOODDEN OODDEN OODDEN
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        0.6
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                - 0.4
                                                 0.2
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        0.0
                                                      V22 9. EA OCEDIO OCEDIO CEDIO CEDIO CEDIO CONTROLO CEDIO CEDIO CEDIO CONTROLO CEDIO 
                                                      -0.2
                                                      V26-0, 440 CEN 40 OCEN 40 OCEN
```

In [22]: y

```
Out[22]:
                                            Class
                                                      0
                                                      0
                                                      n
                           284802
                           284803
                                                      0
                           284804
                           284805
                                                      0
                           284806
                         284807 rows × 1 columns
In [23]: x
Out[23]:
                                                     Time
                                                                                  V1
                                                                                                          V2
                                                                                                                                 V3
                                                                                                                                                        V4
                                                                                                                                                                               V5
                                                                                                                                                                                                      V6
                                                                                                                                                                                                                             V7
                                                                                                                                                                                                                                                     V8
                                                                                                                                                                                                                                                                            V9 ...
                                                                                                                                                                                                                                                                                                                               V21
                                                                                                                                                                                                                                                                                                                                                       V22
                                                                                                                                                                                                                                                               0.363787 ...
                                                                    -1.359807
                                                                                            -0.072781
                                                                                                                    2.536347
                                                                                                                                            1.378155 -0.338321
                                                                                                                                                                                         0.462388
                                                                                                                                                                                                                 0.239599
                                                                                                                                                                                                                                        0.098698
                                                                                                                                                                                                                                                                                              0.251412
                                                                                                                                                                                                                                                                                                                   -0.018307
                                                                      1.191857
                                                                                              0.266151
                                                                                                                     0.166480
                                                                                                                                            0.448154
                                                                                                                                                                  0.060018 -0.082361 -0.078803
                                                                                                                                                                                                                                        0.085102 -0.255425 ...
                                                                                                                                                                                                                                                                                            -0.069083 -0.225775
                                                                  -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461 0.247676 -1.514654 ... 0.524980 0.247998
                                                        1.0
                                                                                                                                                                                                                                                                                                                                            0.771679 0.909
                                                        1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203 0.237609 0.377436 -1.387024 ... -0.208038 -0.108300 0.005274 -0.190
                                                                   -1.158233
                                                                                          0.877737 \quad 1.548718 \quad 0.403034 \quad -0.407193 \quad 0.095921 \quad 0.592941 \quad -0.270533 \quad 0.817739 \quad \dots \quad 0.408542 \quad -0.009431 \quad 0.798278 \quad -0.13799279 \quad 0.009431 \quad 0.00941 \quad 0.00941 \quad 0.00941 \quad 0.
                                                        2.0
                           284802 172786.0 -11.881118 10.071785 -9.834783 -2.06656 -5.364473 -2.606837 -4.918215 7.305334 1.914428 ... 1.475829 0.213454 0.111864 1.014
                           284803 172787.0 -0.732789 -0.055080 2.035030 -0.738589 0.868229 1.058415 0.024330 0.294869 0.584800 ... 0.059616 0.214205 0.924384 0.012
                                                                  1.919565 -0.301254 -3.249640 -0.557828 2.630515 3.031260 -0.296827 0.708417
                           284805 172788.0 -0.240440 0.530483 0.702510 0.689799 -0.377961 0.623708 -0.686180 0.679145 0.392087 ... 0.127434 0.265245 0.800049 -0.1633
                           284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546 -0.649617 1.577006 -0.414650 0.486180 ... 0.382948 0.261057 0.643078 0.376
                         284807 rows × 30 columns
                         Spiting the data into 80% training and 20% testing
In [24]: # train test split
                         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=2)
In [25]: print(x_train.shape,y_train.shape,x_test.shape,y_test.shape)
                         (227845, 30) (227845, 1) (56962, 30) (56962, 1)
In [26]: # different model functions
                        y_train.groupby(['Class'])['Class'].count()
```

```
Out[26]: Class
          227437
               408
```

In [27]: y_test.groupby(['Class'])['Class'].count()

Name: Class, dtype: int64

Out[27]: Class 56878 Name: Class, dtype: int64

Training the credit card fraud detection model

1. Logistic Regression Model

```
In [28]: |model = LogisticRegression()
                     # Fit the model to the data
                     model.fit(x_train, y_train)
                     C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vector y was passe
                     d when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
                          y = column_or_1d(y, warn=True)
                     C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge
                     (status=1):
                     STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
                     Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessing.html)
                     Please also refer to the documentation for alternative solver options:
                              https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-regression (https://scikit-regression (https://scikit-re
                     ear_model.html#logistic-regression)
                          n_iter_i = _check_optimize_result(
Out[28]: LogisticRegression()
In [29]: # Make predictions
                     y_pred = model.predict(x_test)
In [30]: set(y_pred)
Out[30]: {0, 1}
In [31]: # convert array into pandas dataframe
                     d=pd.DataFrame(y_pred)
In [32]: d
Out[32]:
                               0 0
                               1 0
                               2 0
                               3 0
                               4 0
                       56957 0
                       56958 0
                       56960 0
                       56961 0
                     56962 rows × 1 columns
In [33]: |gini=2*roc_auc_score(y_test['Class'],d[0])-1 # formula to predict gini score
In [34]: gini # prints the gini score
Out[34]: 0.7492439959210944
In [35]: # checking the accuracy score predicted by the logistic regression model
                     accuracy = accuracy_score(y_test, y_pred)
                     print("Accuracy:", accuracy)
                     Accuracy: 0.9988764439450862
```

2. Random Forest

```
11/23/23, 11:06 AM
                                                                        project - Jupyter Notebook
     In [38]: # convert array into pandas dataframe
              d=pd.DataFrame(y_pred)
     In [39]: d # prints the dataframe after converting into pandas from array
     Out[39]:
                     0
                  0 0
                  1 0
                  2 0
                  3 0
                   4 0
               56957 0
               56958 0
               56959 0
               56960 0
               56961 0
              56962 rows × 1 columns
     In [40]: gini=2*roc_auc_score(y_test['Class'],d[0])-1 # formula to predict gini score
     In [41]: gini #prints the gini score
     Out[41]: 0.8213406639775358
     In [42]: # Calculate accuracy by Random Forest Classifier
              accuracy = accuracy_score(y_test, y_pred)
              print("Accuracy:", accuracy)
              Accuracy: 0.9996488887328394
              3. Support vector Machine (SVC)
     In [43]: svm_classifier = SVC()
               # Train the classifier
              svm_classifier.fit(x_train, y_train)
              C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vector y was passe
              d when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
                y = column_or_1d(y, warn=True)
```

```
Out[43]: SVC()
In [44]: # Make predictions on the test set
         y_pred = svm_classifier.predict(x_test)
In [49]: set(y_pred)
Out[49]: {0}
In [50]: # convert array into pandas dataframe
         d=pd.DataFrame(y_pred)
In [51]: d # prints the dataframe after converting into pandas from array
Out[51]:
             0 0
             1 0
             2 0
             3 0
             4 0
          56957 0
          56958 0
          56959 0
          56960 0
          56961 0
         56962 rows × 1 columns
```

```
In [52]: gini=2*roc_auc_score(y_test['Class'],d[0])-1 # formula to predict gini score
In [53]: gini #prints the gini score
Out[53]: 0.0
In [54]: # Calculate accuracy by svc model
         accuracy = accuracy_score(y_test, y_pred)
         print("Accuracy:", accuracy)
         Accuracy: 0.9985253326779256
         4. Naive's bayes
In [55]: # Build a Gaussian Classifier
         model = GaussianNB()
         # Model training
         model.fit(x_train, y_train)
         # Predict Output
         predicted = model.predict(x_test)
         C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vector y was passe
         d when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
          y = column_or_id(y, warn=True)
In [56]: # convert array into pandas dataframe
         d=pd.DataFrame(predicted)
In [57]: d # prints the dataframe after converting into pandas from array
Out[57]:
             0 0
             1 0
             2 0
             4 0
          56957 0
          56958 0
          56959 0
          56960 0
          56961 0
         56962 rows × 1 columns
In [58]: gini=2*roc_auc_score(y_test['Class'],d[0])-1 # formula to predict gini score
In [59]: gini #prints the gini score
Out[59]: 0.7073410256539059
In [60]: #checking the accuracy by naive bayes model
         accuracy1 = accuracy_score(y_test, predicted)
         print("Accuracy:", accuracy1)
         Accuracy: 0.9926442189529862
         5. Decision Tree Classifier
In [61]: # defining decision tree classifier
         model = tree.DecisionTreeClassifier(min_samples_split=10)
         # train data on new data and new target
         model=model.fit(x_train, y_train)
In [62]: prediction = model.predict(x_test) # assign removed data as input
```

```
In [64]: # convert array into pandas dataframe
         d=pd.DataFrame(prediction)
In [65]: d # prints the dataframe after converting into pandas from array
Out[65]:
                0
             0 0
             1 0
             2 0
             3 0
             4 0
          56957 0
          56958 0
          56959 0
          56961 0
         56962 rows × 1 columns
In [66]: gini=2*roc_auc_score(y_test['Class'],d[0])-1 # formula to predict gini score
In [67]: gini #prints the gini score
Out[67]: 0.7496835331762719
In [68]: #accuracy score by decision tree classifier
         accuracy1 = accuracy_score(y_test, prediction)
         print("Accuracy:", accuracy1)
         Accuracy: 0.9993153330290369
```

ploting a decision tree of the dataset

```
In [69]: tree.plot_tree(model)
Text(0.06145966709346991, 0.87037037037037037), 'X[27] <= 1.175\ngini = 0.465\nsamples = 106\nvalue = [39, 67]'),
            Text(0.040973111395646605, 0.83333333333334, 'X[14] <= -2.87\ngini = 0.284\nsamples = 76\nvalue = [13, 63]'),
            Text(0.030729833546734954, 0.7962962962962963, 'X[29] <= 1.05\ngini = 0.138\nsamples = 67\nvalue = [5, 62]'),
             \label{eq:text} \texttt{Text} (0.020486555697823303, \ 0.7592592592592592593, \ 'X[28] <= 0.165 \\ \texttt{ngini} = 0.415 \\ \texttt{nsamples} = 17 \\ \texttt{nvalue} = [5, \ 12]'), 
           Text(0.010243277848911651, 0.722222222222222, 'gini = 0.0\nsamples = 11\nvalue = [0, 11]'),
           Text(0.030729833546734954, 0.722222222222222,
                                                                'gini = 0.278\nsamples = 6\nvalue = [5, 1]'),
           Text(0.040973111395646605, 0.7592592592592593, 'gini = 0.0\nsamples = 50\nvalue = [0, 50]'),
           Text(0.05121638924455826, 0.7962962962962963, 'gini = 0.198\nsamples = 9\nvalue = [8, 1]'),
Text(0.08194622279129321, 0.833333333333334, 'X[29] <= 94.99\ngini = 0.231\nsamples = 30\nvalue = [26, 4]'),
Text(0.07170294494238157, 0.7962962962963, 'gini = 0.0\nsamples = 25\nvalue = [25, 0]'),
                                                               'gini = 0.32\nsamples = 5\nvalue = [1, 4]'),

'X[11] <= 1.135\ngini = 0.098\nsamples = 214\nvalue = [11, 203]'),
           Text(0.09218950064020487, 0.7962962962963,
            Text(0.11267605633802817, 0.8703703703703703,
            Text(0.10243277848911651, 0.83333333333333334,
                                                                gini = 0.444\nsamples = 6\nvalue = [4, 2]'),
            Text(0.12291933418693982,\ 0.83333333333333333333,\ 'X[5] <= -22.585 \\ |ngini = 0.065 \\ |ngini = 208 \\ |nvalue = [7,\ 201]'),
            Text(0.11267605633802817, 0.7962962962962963,
                                                               'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
           Text(0.13316261203585147, 0.7962962962963, 'X[4] <= -0.304\ngini = 0.047\nsamples = 206\nvalue = [5, 201]'),
```

6. Catboost Model

```
In [70]: df
Out[70]:
                                  Time
                                                     V1
                                                                     V2
                                                                                    V3
                                                                                                   V4
                                                                                                                   V5
                                                                                                                                  V6
                                                                                                                                                 V7
                                                                                                                                                                V8
                                                                                                                                                                               V9 ...
                                                                                                                                                                                                 V21
                                                                                                                                                                                                                 V22
                                                                                                                                                                                                                                V23
                                                                            2.536347
                                                                                           1.378155 -0.338321
                                                                                                                         0.462388
                                                                                                                                                       0.098698
                                                                                                                                                                       0.363787 ... -0.018307 0.277838 -0.110474
                         0
                                            -1.359807
                                                            -0.072781
                                                                                                                                        0.239599
                                                                                                                                                                                                                                        0.066
                                     0.0
                                                                            0.166480 \quad 0.448154 \quad 0.060018 \quad -0.082361 \quad -0.078803 \quad 0.085102 \quad -0.255425 \quad \dots \quad -0.225775 \quad -0.638672 \quad 0.101288 \quad -0.3398102 \quad -0.082102 \quad -0.082361 \quad -0.0
                         1
                                     0.0
                                             1.191857
                                                             0.266151
                                           -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461 0.247676 -1.514654 ... 0.247998 0.771679 0.909412 -0.689.
                         2
                                     1.0
                                     1.0
                                           3
                                     2.0
                                           -1.158233 0.877737 1.548718 0.403034 -0.407193 0.095921 0.592941 -0.270533 0.817739 ... -0.009431 0.798278 -0.137458 0.141
                  284802 172786.0 -11.881118 10.071785 -9.834783 -2.066656 -5.364473 -2.606837 -4.918215 7.305334 1.914428 ... 0.213454 0.111864 1.014480 -0.5091
                  284803 172787.0 -0.732789 -0.055080 2.035030 -0.738589 0.868229 1.058415 0.024330 0.294869 0.584800 ... 0.214205 0.924384 0.012463 -1.016
                                                          -0.301254 -3.249640 -0.557828 2.630515 3.031260 -0.296827
                                                                                                                                                        0.708417
                                                           0.530483 0.702510 0.689799 -0.377961 0.623708 -0.686180 0.679145 0.392087 ... 0.265245 0.800049 -0.163298 0.123
                  284805 172788.0 -0.240440
                  284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546 -0.649617 1.577006 -0.414650 0.486180 ... 0.261057 0.643078
                                                                                                                                                                                                                       0.376777
                284807 rows × 31 columns
'V21', ''
y=df[['Class']]
In [72]: # train test split
                x_temp, x_test, y_temp, y_test = train_test_split(x, y, test_size=0.2, random_state=2)
In [73]: # train test split
                x_train, x_val, y_train, y_val = train_test_split(x_temp, y_temp, test_size=0.25, random_state=2)
In [74]: # Create CatBoost classifier
                cat_model = CatBoostClassifier( depth=5,
                                                                        learning_rate=0.01,
                                                                        iterations=1500.
                                                                     random seed=2.
                                                                     loss function='Logloss',
                                                                     eval_metric='AUC',
                                                                     od_type='Iter',
                                                                     boosting_type='Plain',
                                                                     use_best_model=True,
                                                                     one_hot_max_size=2)
In [75]: # Train the model
                model=cat_model.fit(x_train, y_train,early_stopping_rounds=100,eval_set=(x_val,y_val))
                0:
                              test: 0.8568622 best: 0.8568622 (0)
                                                                                                     total: 231ms
                                                                                                                                 remaining: 5m 46s
                1:
                              test: 0.9022036 best: 0.9022036 (1)
                                                                                                     total: 284ms
                                                                                                                                 remaining: 3m 32s
                2:
                              test: 0.9549925 best: 0.9549925 (2)
                                                                                                     total: 334ms
                                                                                                                                 remaining: 2m 46s
                3:
                              test: 0.9639464 best: 0.9639464 (3)
                                                                                                     total: 383ms
                                                                                                                                 remaining: 2m 23s
                4:
                              test: 0.9649631 best: 0.9649631 (4)
                                                                                                     total: 438ms
                                                                                                                                 remaining: 2m 10s
                                                                                                     total: 493ms
                5.
                              test: 0.9680959 best: 0.9680959 (5)
                                                                                                                                 remaining: 2m 2s
                              test: 0.9677843 best: 0.9680959 (5)
                6:
                                                                                                     total: 546ms
                                                                                                                                 remaining: 1m 56s
                              test: 0.9709125 best: 0.9709125 (7)
                                                                                                     total: 594ms
                                                                                                                                 remaining: 1m 50s
                7:
                                                                                                                                 remaining: 1m 46s
                              test: 0.9682731 best: 0.9709125 (7)
                                                                                                     total: 644ms
                8:
                              test: 0.9662186 best: 0.9709125 (7)
                                                                                                     total: 697ms
                                                                                                                                 remaining: 1m 43s
                9:
                10:
                              test: 0.9655670 best: 0.9709125 (7)
                                                                                                     total: 746ms
                                                                                                                                 remaining: 1m 41s
                11:
                              test: 0.9660417 best: 0.9709125 (7)
                                                                                                     total: 798ms
                                                                                                                                 remaining: 1m 38s
                              test: 0.9621671 best: 0.9709125 (7)
                                                                                                     total: 862ms
                                                                                                                                 remaining: 1m 38s
                               test: 0.9620320 best: 0.9709125 (7)
                                                                                                     total: 918ms
                13:
                                                                                                                                 remaining: 1m 37s
                              test: 0.9621649 best: 0.9709125 (7)
                                                                                                     total: 978ms
                                                                                                                                 remaining: 1m 36s
                14:
                15:
                              test: 0.9605312 best: 0.9709125 (7)
                                                                                                     total: 1.04s
                                                                                                                                 remaining: 1m 36s
                16:
                              test: 0.9592117 best: 0.9709125 (7)
                                                                                                     total: 1.09s
                                                                                                                                 remaining: 1m 35s
                17:
                              test: 0.9610342 best: 0.9709125 (7)
                                                                                                     total: 1.15s
                                                                                                                                 remaining: 1m 34s
                              test: 0.9624094 best: 0.9709125 (7)
                18:
                                                                                                     total: 1.2s
                                                                                                                                 remaining: 1m 33s
In [76]: # Make predictions
                y_pred = model.predict(x_test)
In [77]: # Evaluate the model
                accuracy = accuracy_score(y_test, y_pred)
                print(f"Accuracy: {accuracy}")
                Accuracy: 0.9995611109160493
In [78]: d=pd.DataFrame(y_pred) # converting the array into pandas dataframe
```