import the libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn import svm
```

load the data

In [2]:
```
data = pd.read_csv("/home/tamanna/Downloads/creditcard.csv")
data
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.23
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.07
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.79
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.23
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.59
...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.91
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.02
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.29
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.68
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.57

284807 rows × 31 columns

data preprocessing

In [3]:
```
data.head()
```

Out[3]:

	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	0.098
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270

5 rows × 31 columns

In [4]:
```
data.tail()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577

5 rows × 31 columns

In [5]:
```
# generating descriptive statistics
data.describe()
```

Out[5]:

	Time	V1	V2	V3	V4	
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15	9.604
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480

8 rows × 31 columns

In [6]:
```
data.shape
```

Out[6]: (284807, 31)

In [7]:
```
data.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
```

In [8]:
```
data.isnull().sum()
```

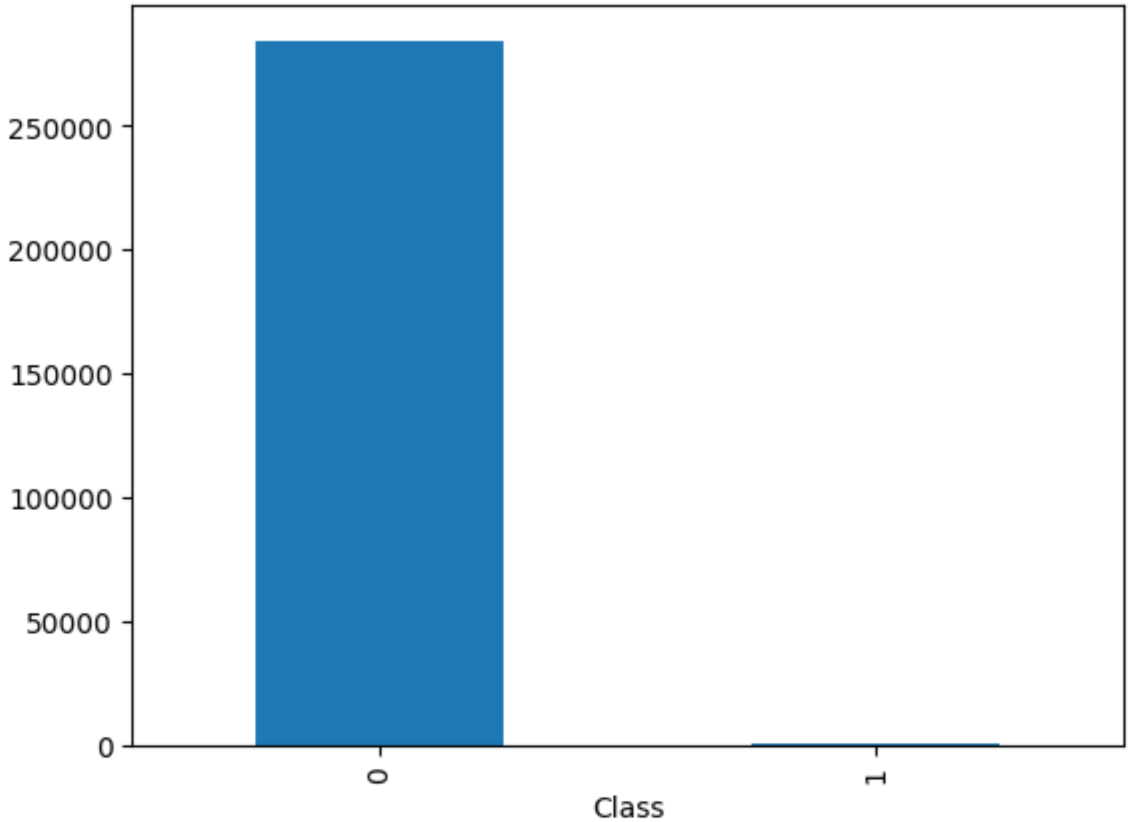
Out[8]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [9]:
```
data['Class'].value_counts()
```

Out[9]:
```
Class
0    284315
1       492
Name: count, dtype: int64
```

In [10]:
```
data['Class'].value_counts().plot(kind = 'bar')
```

Out[10]:
```
<AxesSubplot: xlabel='Class'>
```



we have a huge difference btwn fraud values or non fraud values means tha data is biased so we will split the target value into two categories and than take out a sample from that and concatenate that with the data having smaller values to make a new dataset so that we can reduce the biasedness in data

In [11]:
```
non_fraud = data[data.Class == 0]
fraud = data[data.Class == 1]
```

In [12]:
```
non_fraud.shape
```

Out[12]: (284315, 31)

In [13]:
```
fraud.shape
```

Out[13]: (492, 31)

In [14]:
```
non_fraud_sample = non_fraud.sample(600)
```

In [15]:
```
non_fraud_sample
```

Out[15]:

	Time	V1	V2	V3	V4	V5	V6	
128226	78641.0	1.203948	0.131052	0.598463	0.562670	-0.616091	-0.810741	-0.109
81009	58756.0	-2.319104	-1.556175	1.757399	-1.275513	-0.685819	0.348512	-0.754
282522	170957.0	-2.759096	3.027481	-2.699052	-0.681087	-0.957376	-0.951570	-0.985
67993	52784.0	1.133615	-0.086691	1.261303	1.156702	-0.983421	0.003024	-0.721
181361	124943.0	-0.585651	1.241902	-1.488338	-0.566437	1.278687	-0.879811	1.341
...	...	...	...	...	...	...	...	
27839	34727.0	1.005408	-1.120883	0.431941	-0.741640	-0.933930	0.380253	-0.791
83089	59685.0	1.278922	-0.688400	0.306704	-0.877167	-0.773223	-0.112205	-0.684
24651	33314.0	1.317910	-1.101923	-0.663724	-1.761183	0.965597	3.552032	-1.522
198922	132714.0	-5.203447	-7.087964	-0.061621	0.667184	3.751602	-0.096922	-0.834
70904	54070.0	1.257282	-1.121529	-1.369897	-1.543310	1.415319	3.406259	-0.891

600 rows × 31 columns

In [16]:
```
new_data = pd.concat([non_fraud_sample,fraud], axis =0)
```

In [17]:
```
new_data
```

Out[17]:

	Time	V1	V2	V3	V4	V5	V6	
128226	78641.0	1.203948	0.131052	0.598463	0.562670	-0.616091	-0.810741	-0.109
81009	58756.0	-2.319104	-1.556175	1.757399	-1.275513	-0.685819	0.348512	-0.754
282522	170957.0	-2.759096	3.027481	-2.699052	-0.681087	-0.957376	-0.951570	-0.985
67993	52784.0	1.133615	-0.086691	1.261303	1.156702	-0.983421	0.003024	-0.721
181361	124943.0	-0.585651	1.241902	-1.488338	-0.566437	1.278687	-0.879811	1.341
...	...	...	...	...	...	...	...	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223

1092 rows × 31 columns

values of x and y

In [18]:
```
x = new_data.drop(['Class'], axis = 1)
```

In [19]:
```
print(x)
```

```
             Time        V1        V2        V3        V4        V5        V6  \
128226   78641.0  1.203948  0.131052  0.598463  0.562670 -0.616091 -0.810741
81009    58756.0 -2.319104 -1.556175  1.757399 -1.275513 -0.685819  0.348512
282522  170957.0 -2.759096  3.027481 -2.699052 -0.681087 -0.957376 -0.951570
67993    52784.0  1.133615 -0.086691  1.261303  1.156702 -0.983421  0.003024
181361  124943.0 -0.585651  1.241902 -1.488338 -0.566437  1.278687 -0.879811
...          ...       ...       ...       ...       ...       ...       ...
279863  169142.0 -1.927883  1.125653 -4.518331  1.749293 -1.566487 -2.010494
280143  169347.0  1.378559  1.289381 -5.004247  1.411850  0.442581 -1.326536
280149  169351.0 -0.676143  1.126366 -2.213700  0.468308 -1.120541 -0.003346
281144  169966.0 -3.113832  0.585864 -5.399730  1.817092 -0.840618 -2.943548
281674  170348.0  1.991976  0.158476 -2.583441  0.408670  1.151147 -0.096695

              V7        V8        V9  ...       V20       V21       V22  \
128226 -0.109900 -0.011047 -0.067770  ... -0.158679 -0.205060 -0.680799
81009  -0.754404  0.950477 -0.814573  ...  0.834504  0.320837  0.218636
282522 -0.985091  2.241800 -0.126389  ...  0.081408 -0.228730 -0.912153
67993  -0.721792  0.273450  0.654784  ... -0.195585  0.029428  0.164201
181361  1.341948 -0.158087  0.133879  ...  0.014966  0.144172  0.802194
...          ...       ...       ...  ...       ...       ...       ...
279863 -0.882850  0.697211 -2.064945  ...  1.252967  0.778584 -0.319189
280143 -1.413170  0.248525 -1.127396  ...  0.226138  0.370612  0.028234
280149 -2.234739  1.210158 -0.652250  ...  0.247968  0.751826  0.834108
281144 -2.208002  1.058733 -1.632333  ...  0.306271  0.583276 -0.269209
281674  0.223050 -0.068384  0.577829  ... -0.017652 -0.164350 -0.295135

             V23       V24       V25       V26       V27       V28  Amount
128226  0.162836  0.501235  0.124477  0.068120 -0.039378  0.008476    0.89
81009   0.180391 -0.298655  0.481468 -0.293975  0.154894 -0.127781  199.73
282522  0.401224  0.626090 -0.115280  0.121893  0.124390  0.049659    9.03
67993   0.001280  0.308449  0.329003 -0.413555  0.060083  0.025442    1.00
181361 -0.340436 -1.027089 -0.203774 -0.116839  0.144424  0.054446   17.73
...          ...       ...       ...       ...       ...       ...     ...
279863  0.639419 -0.294885  0.537503  0.788395  0.292680  0.147968  390.00
280143 -0.145640 -0.081049  0.521875  0.739467  0.389152  0.186637    0.76
280149  0.190944  0.032070 -0.739695  0.471111  0.385107  0.194361   77.89
281144 -0.456108 -0.183659 -0.328168  0.606116  0.884876 -0.253700  245.00
281674 -0.072173 -0.450261  0.313267 -0.289617  0.002988 -0.015309   42.53

[1092 rows x 30 columns]
```

In [20]:
```
y = new_data["Class"]
```

In [21]:
```
print(y)
```

```
128226    0
81009     0
282522    0
67993     0
181361    0
         ..
279863    1
280143    1
280149    1
281144    1
281674    1
Name: Class, Length: 1092, dtype: int64
```

splitting of data into training and testing sets

In [22]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, random_state = 2, t
```

In [23]:
```
print(x.shape, x_train.shape, x_test.shape)
```

```
(1092, 30) (982, 30) (110, 30)
```

In [24]:
```
model = LogisticRegression()
```

In [25]:
```
model.fit(x_train, y_train)
```

```
/home/tamanna/.local/lib/python3.11/site-packages/sklearn/linear_model/_logis
tic.py:458: 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
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion
  n_iter_i = _check_optimize_result(
```

Out[25]:
```
▾ LogisticRegression

LogisticRegression()
```

accuracy on training data

In [26]:
```
x_train_prediction = model.predict(x_train)
training_data_accuracy = accuracy_score(x_train_prediction, y_train)
```

In [27]:
```
training_data_accuracy
```

Out[27]:
```
0.9439918533604889
```

accuracy on testing data

In [28]:
```
x_test_prediction = model.predict(x_test)
testing_data_accuracy = accuracy_score(x_test_prediction, y_test)
```

In [29]:
```
testing_data_accuracy
```

Out[29]: 0.9454545454545454

svm classifier

In [30]:
```
model2 = svm.SVC(kernel = "linear")
```

In [31]:
```
model2.fit(x_train, y_train)
```

Out[31]:
```
▾ SVC
SVC(kernel='linear')
```

In [32]:
```
x_train_prediction =model2.predict(x_train)
```

In [33]:
```
training_data_accuracy = accuracy_score(x_train_prediction, y_train)
```

In [34]:
```
training_data_accuracy
```

Out[34]: 0.9042769857433809

In [35]:
```
x_test_prediction = model2.predict(x_test)
```

In [36]:
```
testing_data_accuracy = accuracy_score(x_test_prediction, y_test)
testing_data_accuracy
```

Out[36]: 0.9272727272727272