Credit card fraud detection machine learning model

In [44]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import sklearn.metrics as metrics
from sklearn.metrics import classification_report, roc_auc_score, precision
from sklearn.metrics  import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [3]:
```
#loading data set using pandas
data = pd.read_csv("creditcard.csv")
```

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
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
...	...	...	...	...	...	...	...	...
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

284807 rows × 31 columns

In [4]:
```
#returns rows and columns in data set
```

Out[4]: (284807, 31)

In [5]:
```
data.describe
```

Out[5]:
```
<bound method NDFrame.describe of             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]>
```

In [6]:
```
#returns datatype of columns
```

Out[6]:
```
Time      float64
V1        float64
V2        float64
V3        float64
V4        float64
V5        float64
V6        float64
V7        float64
V8        float64
V9        float64
V10       float64
V11       float64
V12       float64
V13       float64
V14       float64
V15       float64
V16       float64
V17       float64
V18       float64
V19       float64
V20       float64
V21       float64
V22       float64
V23       float64
V24       float64
V25       float64
V26       float64
V27       float64
V28       float64
Amount    float64
Class       int64
dtype: object
```

In [7]:
```
data.head(10)
```

Out[7]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539

10 rows × 31 columns

In [8]:
```
data.tail(10)
```

Out[8]:

	Time	V1	V2	V3	V4	V5	V6	V7
284797	172782.0	-0.241923	0.712247	0.399806	-0.463406	0.244531	-1.343668	0.929369
284798	172782.0	0.219529	0.881246	-0.635891	0.960928	-0.152971	-1.014307	0.427126
284799	172783.0	-1.775135	-0.004235	1.189786	0.331096	1.196063	5.519980	-1.518185
284800	172784.0	2.039560	-0.175233	-1.196825	0.234580	-0.008713	-0.726571	0.017050
284801	172785.0	0.120316	0.931005	-0.546012	-0.745097	1.130314	-0.235973	0.812722
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

10 rows × 31 columns

In [9]:
```
#drop rows having null values
```

Out[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
...	...	...	...	...	...	...	...	...
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

284807 rows × 31 columns

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
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 [11]:
```
data["Class"].value_counts()#here class 0 indicates legit whereas 1 indicat
```

Out[11]:
```
Class
0    284315
1       492
Name: count, dtype: int64
```

In [12]:
```
#Classifying data into categories
genuine = data[data.Class == 0]
fraud = data[data.Class == 1]
```

In [13]:
```python
print(genuine)
```

```
            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

[284315 rows x 31 columns]
(284315, 31)
```

In [14]:
```
print(fraud.shape)
```

```
(492, 31)
```

In [15]:
```
genuine.Amount.describe()
```

Out[15]:
```
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
```

In [16]:
```
genuine.Time.describe()
```

Out[16]:
```
count    284315.000000
mean      94838.202258
std       47484.015786
min           0.000000
25%       54230.000000
50%       84711.000000
75%      139333.000000
max      172792.000000
Name: Time, dtype: float64
```

In [26]:
```
# Undersample the genuine class to match the number of fraud cases(Normalis
genuine_undersampled = genuine.sample(n=492)
```

In [27]:
```
undersampled_data = pd.concat([genuine_undersampled, fraud], axis=0)
```

In [28]:
```
#here is our normalisation of imbalanced dataset.
```

Out[28]:
```
Class
0    492
1    492
Name: count, dtype: int64
```

In [31]:
```
mean=undersampled_data.groupby("Class").mean()
```

```
                Time        V1        V2        V3        V4        V5  \
Class
0       95063.993902  0.073402  0.013656  0.012983 -0.078723  0.037778
1       80746.806911 -4.771948  3.623778 -7.033281  4.542029 -3.151225

              V6        V7        V8        V9  ...       V20       V21  \
Class                                           ...
0       0.040767 -0.075929 -0.013959  0.039811  ... -0.036242  0.026831
1      -1.397737 -5.568731  0.570636 -2.581123  ...  0.372319  0.713588

             V22       V23       V24       V25       V26       V27       V2
8  \
Class
0       0.001348 -0.007046 -0.006464  0.012918 -0.018738  0.003449  0.00568
2
1       0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575  0.07566
7

            Amount
Class
0        74.501118
1       122.211321

[2 rows x 30 columns]
```

In [19]:
```
undersampled_data = undersampled_data.sample(frac=1, random_state=42)
```

In [32]:
```
#spliting data
X_undersampled = undersampled_data.drop(columns=['Class'], axis=1)
y_undersampled = undersampled_data['Class']
```

In [21]:
```
X_train, X_test, y_train, y_test = train_test_split(X_undersampled, y_under
```

In [33]:
```
log_reg = LogisticRegression()
```

Out[33]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [40]:
```
y_pred_log_reg = log_reg.predict(X_test)
print("Logistic Regression Evaluation")
print("Classification Report:\n", classification_report(y_test, y_pred_log_
```

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

           0       0.89      0.99      0.94       110
           1       0.99      0.84      0.91        87

    accuracy                           0.92       197
   macro avg       0.94      0.91      0.92       197
weighted avg       0.93      0.92      0.92       197
```

In [52]:
```
#accuracy score of training data
X_train_prediction= log_reg.predict(X_train)
training_accuracy = accuracy_score(X_train_prediction,y_train)
```

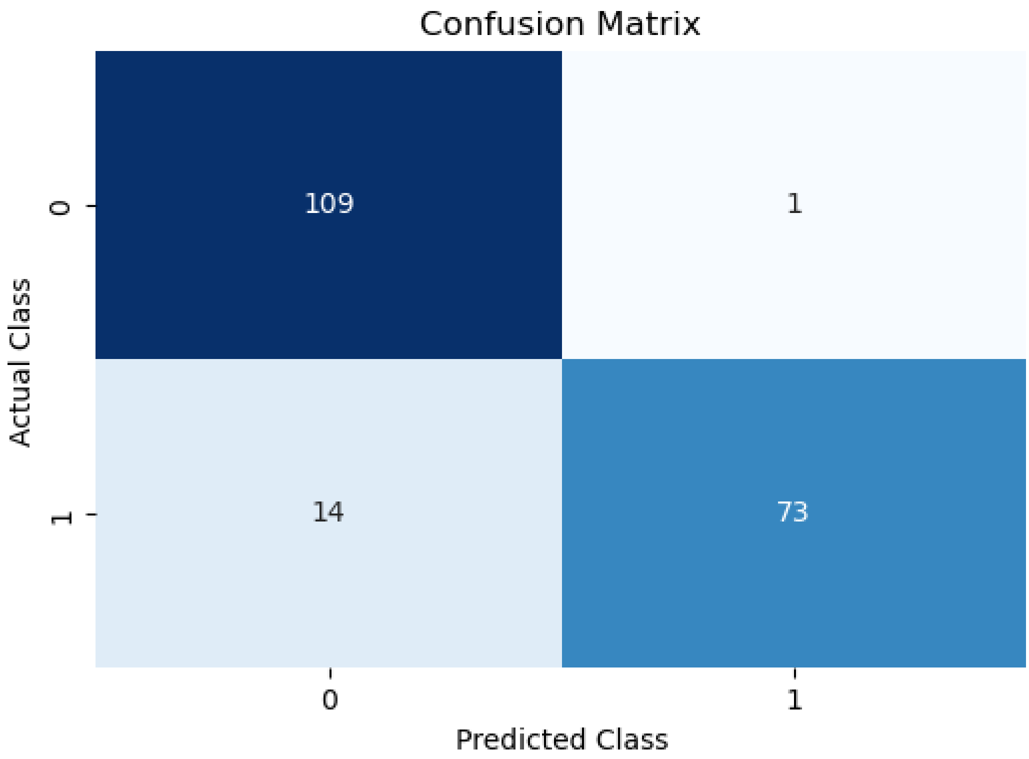
```
Accuracy: 0.9250317662007624
```

In [53]:
```
#accuracy score of test data
X_test_prediction= log_reg.predict(X_test)
testing_accuracy = accuracy_score(X_test_prediction,y_test)
```

```
Accuracy: 0.9238578680203046
```

In [58]:
```
y_pred_log_reg = log_reg.predict(X_test)
cm = confusion_matrix(y_test, y_pred_log_reg)

# Plotting the heatmap for the confusion matrix
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title('Confusion Matrix')
plt.ylabel('Actual Class')
plt.xlabel('Predicted Class')
```



In [ ]: