In [10]: # Import necessary libraries

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import classification_report, confusion_matrix

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.utils import resample

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U	u	L	LJ	LJ	LI	Ι.

	Time	V1	V2	V3	V4	V 5	V6	V 7	V8	V 9	 V21	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	 -0.018307	0.277
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	 -0.225775	-0.638
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	 0.247998	0.771
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	 -0.108300	0.005
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	 -0.009431	0.798
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	 0.213454	0.111
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	 0.214205	0.924
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	 0.232045	0.578
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	 0.265245	0.800
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	 0.261057	0.643

284807 rows × 31 columns

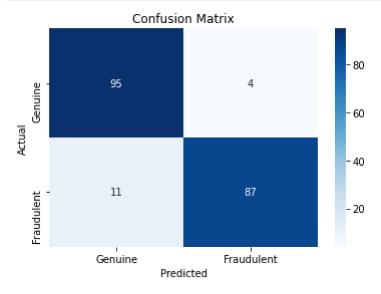
```
In [12]:
         data.head()
Out[12]:
             Time
                        V1
                                 V2
                                         V3
                                                  V4
                                                           V5
                                                                    V6
                                                                             V7
                                                                                      V8
                                                                                               V9 ...
                                                                                                          V21
                                                                                                                   V22
              0.0 -1.359807 -0.072781 2.536347
                                             1.378155 -0.338321
                                                               0.462388
                                                                        0.239599
                                                                                 0.098698
                                                                                          0.363787 ... -0.018307
                                                                                                               0.277838 -0.110
                  1.191857
                            0.266151 0.166480
                                                                                 0.085102 -0.255425 ... -0.225775
                                             0.448154
                                                      0.060018
                                                               -0.082361
                                                                        -0.078803
                                                                                                              -0.638672
                                                                                                                        0.101
              1.0 -1.358354 -1.340163 1.773209
                                             0.379780
                                                      -0.503198
                                                               1.800499
                                                                        0.791461
                                                                                 0.247676 -1.514654 ... 0.247998
                                                                                                                        0.909
                                                                                                               0.771679
              1.0 -0.966272 -0.185226 1.792993 -0.863291
                                                      -0.010309
                                                               1.247203
                                                                        0.237609
                                                                                 0.377436 -1.387024 ... -0.108300
                                                                                                               0.005274 -0.190
              0.095921
                                                                        0.592941 -0.270533  0.817739  ... -0.009431
                                                                                                               0.798278 -0.137
          5 rows × 31 columns
                                                                                                                         In [13]: X = data.drop('Class', axis=1)
          v = data['Class']
In [14]:
          scaler = StandardScaler()
         X[['Amount', 'Time']] = scaler.fit_transform(X[['Amount', 'Time']])
         data combined = pd.concat([X, y], axis=1)
In [15]:
         # Separate minority (fraudulent) and majority (genuine) classes
         fraudulent = data combined[data combined['Class'] == 1]
         genuine = data combined[data combined['Class'] == 0]
         genuine downsampled = resample(genuine, replace=False, n samples=len(fraudulent), random state=42)
In [17]:
         undersampled data = pd.concat([genuine downsampled, fraudulent])
         X_undersampled = undersampled_data.drop('Class', axis=1)
In [18]:
         y undersampled = undersampled data['Class']
         X_train, X_test, y_train, y_test = train_test_split(X_undersampled, y_undersampled, test_size=0.2, random_star
```

```
In [19]: model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [20]: print("Classification Report:\n", classification_report(y_test, y_pred))

Classification	•		_	
	precision	recall	f1-score	support
0	0.90	0.96	0.93	99
1	0.96	0.89	0.92	98
accuracy			0.92	197
macro avg	0.93	0.92	0.92	197
weighted avg	0.93	0.92	0.92	197

```
In [21]: # Confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Genuine', 'Fraudulent'], yticklabel
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()
```



In []: