```
In [12]: import numpy as np
   import pandas as pd
   import seaborn as sns
   import matplotlib.pyplot as plt
   from sklearn import metrics
   from sklearn.model_selection import GridSearchCV
   from sklearn.linear_model import LinearRegression
   from sklearn.ensemble import RandomForestClassifier
   from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve
   from sklearn.model_selection import train_test_split
```


Out[3]:

	id	V1	V2	V3	V4	V5	V6	V7	V8	V 9	 V21	V22	V23
0	0	-0.260648	-0.469648	2.496266	-0.083724	0.129681	0.732898	0.519014	-0.130006	0.727159	 -0.110552	0.217606	-0.134794
1	1	0.985100	-0.356045	0.558056	-0.429654	0.277140	0.428605	0.406466	-0.133118	0.347452	 -0.194936	-0.605761	0.079469
2	2	-0.260272	-0.949385	1.728538	-0.457986	0.074062	1.419481	0.743511	-0.095576	-0.261297	 -0.005020	0.702906	0.945045
3	3	-0.152152	-0.508959	1.746840	-1.090178	0.249486	1.143312	0.518269	-0.065130	-0.205698	 -0.146927	-0.038212	-0.214048
4	4	-0.206820	-0.165280	1.527053	-0.448293	0.106125	0.530549	0.658849	-0.212660	1.049921	 -0.106984	0.729727	-0.161666
5	5	0.025302	-0.140514	1.191138	-0.707979	0.430490	0.458973	0.611050	-0.092629	0.180811	 -0.187739	-0.538518	-0.050465
6	6	1.016482	-0.397181	0.497868	-0.144463	0.331022	0.629243	0.431262	-0.134007	0.796159	 -0.171137	-0.287017	-0.178197
7	7	-0.051306	-0.007194	1.139941	-0.877880	0.684668	0.714326	0.892615	-0.908409	0.901938	 0.620676	-0.920426	0.034660
8	8	-0.130680	-0.349547	0.425786	-0.760444	1.702777	2.324816	0.568968	0.049100	0.273118	 -0.132787	-0.284700	-0.227779
9	9	0.058419	-0.093507	1.117270	-0.735172	0.466111	0.332371	0.683425	-0.136674	0.096409	 -0.203634	-0.601581	-0.145082

10 rows × 31 columns

In [4]: ccdf.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 568630 entries, 0 to 568629 Data columns (total 31 columns): Column Non-Null Count Dtype ---id 568630 non-null int64 0 1 ٧1 568630 non-null float64 2 V2 568630 non-null float64 3 V3 568630 non-null float64 4 V4 568630 non-null float64 5 V5 568630 non-null float64 6 ۷6 568630 non-null float64 7 V7 568630 non-null float64 8 V8 568630 non-null float64 9 ۷9 568630 non-null float64 V10 10 568630 non-null float64 11 V11 568630 non-null float64 12 V12 568630 non-null float64 13 V13 568630 non-null float64 14 V14 568630 non-null float64 15 V15 568630 non-null float64 16 V16 568630 non-null float64 17 V17 568630 non-null float64 18 V18 568630 non-null float64 19 V19 568630 non-null float64 20 V20 568630 non-null float64 21 V21 568630 non-null float64 22 V22 568630 non-null float64 23 V23 568630 non-null float64 24 V24 568630 non-null float64 25 V25 568630 non-null float64 26 V26 568630 non-null float64 27 V27 568630 non-null float64 28 V28 568630 non-null float64 Amount 568630 non-null float64 30 Class 568630 non-null int64

dtypes: float64(29), int64(2)

memory usage: 134.5 MB

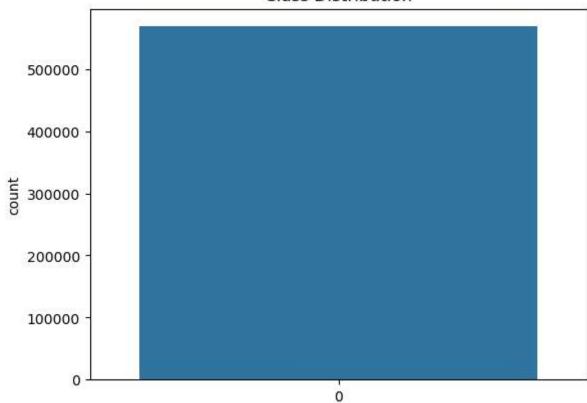
```
In [5]: ccdf.isnull().sum()
Out[5]: id
                  0
        V1
                  0
        V2
                  0
        ٧3
        ٧4
        V5
        ۷6
        V7
        V8
                   0
        V9
        V10
        V11
        V12
                   0
        V13
                   0
        V14
                   0
        V15
                   0
        V16
                  0
        V17
                   0
        V18
                  0
        V19
                   0
        V20
                  0
        V21
                  0
        V22
        V23
                  0
        V24
                  0
        V25
                  0
        V26
                  0
        V27
                  0
        V28
                  0
        Amount
        Class
```

dtype: int64

```
In [6]: sns.countplot(ccdf['Class'])
plt.title("Class Distribution")
```

Out[6]: Text(0.5, 1.0, 'Class Distribution')

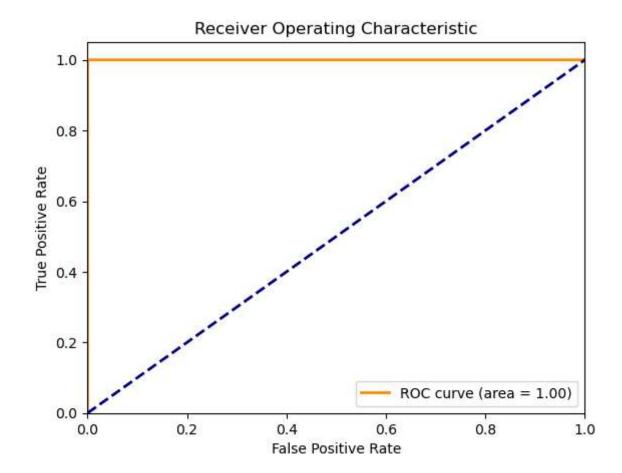




```
from sklearn.preprocessing import StandardScaler
In [7]:
         scaler = StandardScaler()
         ccdf['Amount'] = scaler.fit transform(ccdf['Amount'].values.reshape(-1, 1))
         ccdf.head(5)
Out[7]:
            id
                     V1
                              V2
                                       V3
                                                 V4
                                                         V5
                                                                  V6
                                                                           V7
                                                                                    V8
                                                                                              V9 ...
                                                                                                         V21
                                                                                                                  V22
                                                                                                                            V23
          0 0 -0.260648 -0.469648 2.496266 -0.083724 0.129681 0.732898 0.519014 -0.130006
                                                                                        0.727159 ... -0.110552
                                                                                                              0.217606 -0.134794
                0.985100 -0.356045 0.558056 -0.429654 0.277140 0.428605 0.406466 -0.133118 0.347452 ... -0.194936
                                                                                                              -0.605761
                                                                                                                        0.079469
          2 2 -0.260272 -0.949385 1.728538 -0.457986 0.074062 1.419481 0.743511 -0.095576 -0.261297 ... -0.005020
                                                                                                              0.702906
                                                                                                                        0.945045
          3 3 -0.152152 -0.508959 1.746840 -1.090178 0.249486 1.143312 0.518269 -0.065130 -0.205698 ... -0.146927
                                                                                                              -0.038212 -0.214048
            4 -0.206820 -0.165280 1.527053 -0.448293 0.106125 0.530549 0.658849 -0.212660 1.049921 ... -0.106984
                                                                                                              0.729727 -0.161666
         5 rows × 31 columns
In [8]:
         X = ccdf.drop(['Class','id'], axis=1)
         y = ccdf['Class']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
         random_forest_model = RandomForestClassifier()
In [9]:
         random_forest_model.fit(X_train, y_train)
Out[9]:
          ▼ RandomForestClassifier
          RandomForestClassifier()
```

```
In [11]:
         # Make predictions
         y pred = random forest model.predict(X test)
         # Print classification report
         print(classification report(y test, y pred))
         # Compute ROC curve and AUC
         y prob = random forest model.predict proba(X test)[:, 1]
         fpr, tpr, thresholds = roc curve(y test, y prob)
         roc auc = roc auc score(y test, y prob)
         plt.figure()
         plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc auc:.2f})')
         plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver Operating Characteristic')
         plt.legend(loc="lower right")
         plt.show()
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	85149
1	1.00	1.00	1.00	85440
accuracy			1.00	170589
macro avg	1.00	1.00	1.00	170589
weighted avg	1.00	1.00	1.00	170589



```
In [*]:
```