	0 1 2 3 4 6362615 6362616 6362617 6362618 6362619	step 1 1 1 1 1 743 743 743 743 743	TRANSFER CASH_OUT TRANSFER	11668.14 339682.13 6311409.28 6311409.28 850002.52	C1231006815 C1666544295 C1305486145 C840083671 C2048537720 C786484425 C1529008245		\	
	d \ 0 0	newba	- lanceOrig	nameDest		st newbalance	Dest	isFrau
			160296.36	M1979787155	0.	00	0.00	
	1 0		19384.72	M2044282225	0.	00	0.00	
	2		0.00	C553264065	0.	00	0.00	
	3		0.00	C38997010	21182.	00	0.00	
	4		29885.86	M1230701703	0.	00	0.00	
	6362615 1		0.00	C776919290	0.	00 33968	2.13	
	6362616		0.00	C1881841831	0.	00	0.00	
	6362617 1		0.00	C1365125890	68488.	84 637989	8.11	
	6362618		0.00	C2080388513	0.	00	0.00	
	6362619 1		0.00	C873221189	6510099.	11 736010	1.63	
	0 1 2 3 4 6362615 6362616 6362617 6362618 6362619	isFla	oggedFraud 0 0 0 0 0 0 0 0					
	[6362620 rows x 11 columns]							

[6362620 rows x 11 columns]

```
In [32]: # Step 2: Explore and preprocess the data
# ------
```

```
# Let's preprocess the data to prepare it for training the model.
        # Encode the 'type' column into numerical values (e.g., CASH-IN -> 0, PAYMEN
        df['type'] = df['type'].astype('category').cat.codes
        # Fill any missing values with 0 (common for balance columns)
        df.fillna(0, inplace=True)
In [34]: # Step 3: Define features (X) and the target (y)
        # X: Features we use to predict fraud (independent variables)
        # y: The target column ('isFraud'), indicating if a transaction is fraudulen
        X = df[['step', 'type', 'amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbal
        y = df['isFraud']
In [36]: # Step 4: Split the data into training and testing sets
        # Splitting the dataset into 70% training and 30% testing.
        # This ensures the model is evaluated on unseen data for reliability.
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ran
In [38]: # Step 5: Train the model
        # -----
        # Using a Random Forest Classifier because:
        # - It works well with imbalanced datasets
        # - It handles both categorical and numerical features well
        model = RandomForestClassifier(random_state=42)
        model.fit(X_train, y_train) # Train the model on the training data
Out[38]:
                                           (i) (?)
                RandomForestClassifier
        RandomForestClassifier(random_state=42)
```

```
In [40]: # Step 6: Make predictions
         # Predict the outcomes for the test data
         y_pred = model.predict(X_test) # Predicted class labels (0 or 1)
         y_prob = model.predict_proba(X_test)[:, 1] # Predicted probabilities for th
In [42]: # Step 7: Evaluate the model
         # Metrics are used to assess the model's performance
         print("=== Evaluation Metrics ===")
         accuracy = accuracy_score(y_test, y_pred) # Overall correctness
         precision = precision_score(y_test, y_pred) # Fraction of correct fraud pre
         recall = recall_score(y_test, y_pred) # Fraction of fraud cases detected
         f1 = f1_score(y_test, y_pred) # Harmonic mean of precision and recall
         conf_matrix = confusion_matrix(y_test, y_pred) # Breakdown of predictions (
         # Print the metrics
         print(f"Accuracy: {accuracy}")
         print(f"Precision: {precision}")
         print(f"Recall: {recall}")
         print(f"F1 Score: {f1}")
         print(f"Confusion Matrix:\n{conf_matrix}")
        === Evaluation Metrics ===
        Accuracy: 0.999705572023265
        Precision: 0.9785385794583547
        Recall: 0.7864476386036962
        F1 Score: 0.8720400728597449
        Confusion Matrix:
        [[1906309
                    42]
              520 1915]]
In [44]: # Step 8: Plot the ROC Curve
         # The ROC Curve shows the trade-off between the true positive rate (TPR) and
```

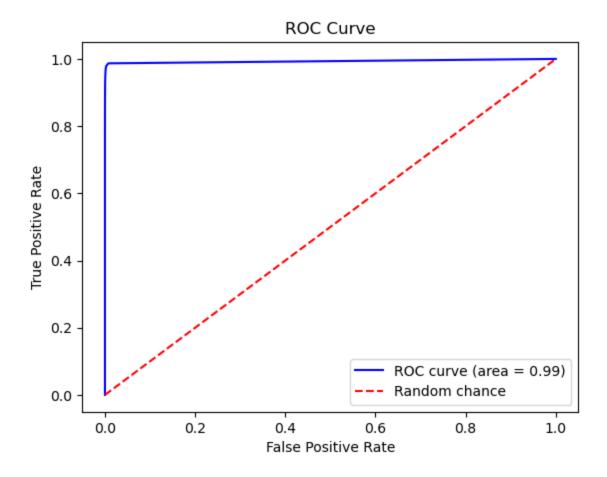
```
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr) # Area under the curve (AUC)

# Plot the ROC Curve

plt.figure()
plt.plot(fpr, tpr, label=f'ROC curve (area = {roc_auc:.2f})', color='blue')
plt.plot([0, 1], [0, 1], 'k--', label='Random chance', color='red')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```

/var/folders/1m/rzrgll2n2tbd654y_lgs97k40000gn/T/ipykernel_53275/295897862 4.py:19: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "k--" (-> color='k'). The keyword argument will take precedence.

plt.plot([0, 1], [0, 1], 'k--', label='Random chance', color='red')



```
In [46]: # Step 9: Analyze Feature Importance
         # Feature importance helps us understand which features contribute most to f
         importances = model.feature_importances_
         feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance': impor
         print("\n=== Feature Importance ===")
         print(feature_importance)
        === Feature Importance ===
                  Feature Importance
          newbalanceDest
        6
                             0.329721
            oldbalanceOrg
                             0.268478
        3
        2
                   amount
                             0.165631
                     step
                             0.092602
        5 oldbalanceDest
                             0.067778
                             0.047391
                     type
          newbalanceOrig
                             0.028399
In [48]: # Step 10: Save the cleaned data or model for future use
         # Save the cleaned data to a CSV file
```

```
df.to_csv("cleaned_fraud_data.csv", index=False) # Saves without the index
print("Cleaned data saved as 'cleaned_fraud_data.csv")

# ------
# Save the trained model for later use (e.g., deployment)
import joblib
joblib.dump(model, "fraud_detection_model.pkl") # Save the model as a .pkl
Cleaned data saved as 'cleaned_fraud_data.csv'
Out[48]: ['fraud_detection_model.pkl']
In [ ]:
```