```
# Step 1: Install the XGBoost Library
# XGBoost (Extreme Gradient Boosting) is a powerful library for building optimized gradient boosting models.
# It is widely used for classification and regression tasks in machine learning.
# The following command installs the XGBoost library if it is not already installed on your system.

!pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-packages (2.1.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from xgboost) (1.26.4)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.10/dist-packages (from xgboost) (2.23.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from xgboost) (1.13.1)
```

```
# Step 2: Import Standard Libraries
# Importing libraries that are essential for data analysis, visualization, and model evaluation.

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Step 3: Load the Dataset from GitHub Repository
url = "https://raw.githubusercontent.com/IndulekhaKP/credit-card-fraud-detection/main/data/creditcard.csv"
data = pd.read_csv(url)
print(f"Dataset shape: {data.shape}")
data.head(100)
```

```
Dataset shape: (284807, 31)
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
95	64.0	-0.658305	0.406791	2.037461	-0.291298	0.147910	-0.350857	0.945373	-0.172560	0.025133	...	-0.156096	-0.238805	0.089877
96	64.0	0.959602	0.370711	0.888613	2.343244	0.352491	1.365515	-0.277771	0.516053	-0.700929	...	-0.155547	-0.403239	0.356504
97	67.0	-0.653445	0.160225	1.592256	1.296832	0.997175	-0.343000	0.469937	-0.132470	-0.197794	...	0.038363	0.336449	-0.014883
98	67.0	-1.494668	0.837241	2.628211	3.145414	-0.609098	0.258495	-0.012189	0.102136	-0.286164	...	-0.140047	0.355044	0.332720
99	68.0	1.232996	0.189454	0.491040	0.633673	-0.511574	-0.990609	0.066240	-0.196940	0.075921	...	-0.251566	-0.770139	0.125998

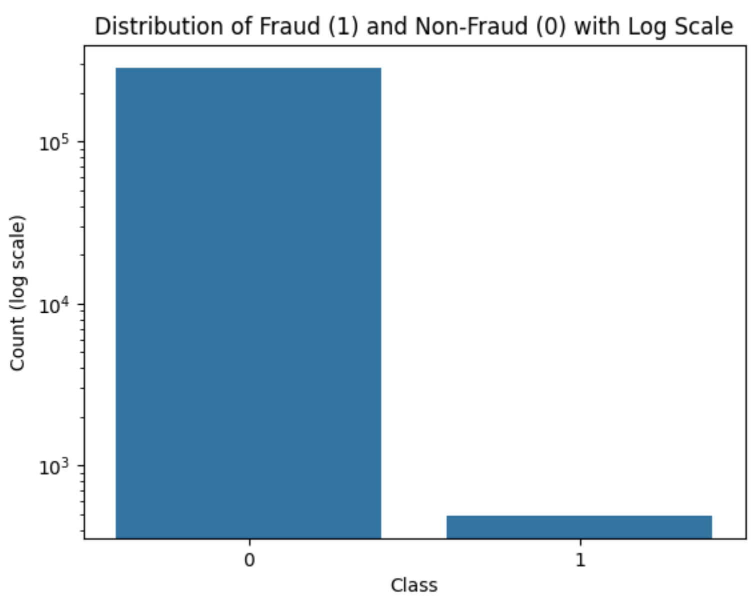
100 rows × 31 columns

```
# Step 4: Check for Missing Values
# Checking for any missing or null values in each column to ensure data completeness.

print("Missing values per column:\n", data.isnull().sum())
```

```
Missing values per column:
 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
```

```
# Step 5: Visualize the Class Distribution (Fraud and Non-Fraud)
# Plotting the distribution of Fraud (Class = 1) and Non-Fraud (Class = 0) cases.
# Using a log scale on the y-axis to handle the class imbalance and make the visualization clearer.

sns.countplot(x='Class', data=data)
plt.yscale('log')  # Log scale to view imbalance clearly
plt.title("Distribution of Fraud (1) and Non-Fraud (0) with Log Scale")
plt.xlabel("Class")
plt.ylabel("Count (log scale)")
plt.show()
```




```
# Step 6: Define Features and Target Variable
# Separating the dataset into features (X) and target variable (y).
# Features (X): All columns except 'Class', which will be used as input for the model.
# Target variable (y): The 'Class' column, indicating fraud (1) or non-fraud (0).

X = data.drop(columns=['Class'])  # Features
y = data['Class']  # Target variable (fraud or non-fraud)
```

```
# Step 7: Split the Data into Training and Test Sets
# Dividing the dataset into training and testing subsets to evaluate the model.
# Training set: 80% of the data used to train the model.
# Test set: 20% of the data used to test and validate the model's performance.

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Step 8: Calculate scale_pos_weight for Handling Imbalance
# Calculating the ratio of non-fraudulent (Class 0) to fraudulent (Class 1) cases in the training data.
# This weight helps the model handle the class imbalance by giving more importance to the minority class (fraud cases).

scale_pos_weight = y_train.value_counts()[0] / y_train.value_counts()[1]
```

```
# Step 9: Initialize and Train the XGBoost Classifier
# Initializing the XGBoost model with class weighting to handle the class imbalance effectively.
# Training the model on the training dataset (X_train, y_train).

from xgboost import XGBClassifier

# Initialize XGBoost with class weighting
model_xgb = XGBClassifier(scale_pos_weight=scale_pos_weight, random_state=42, use_label_encoder=False, eval_metric='logloss')

# Train the XGBoost model on the training data
model_xgb.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [09:46:30] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, random_state=42, ...)
```

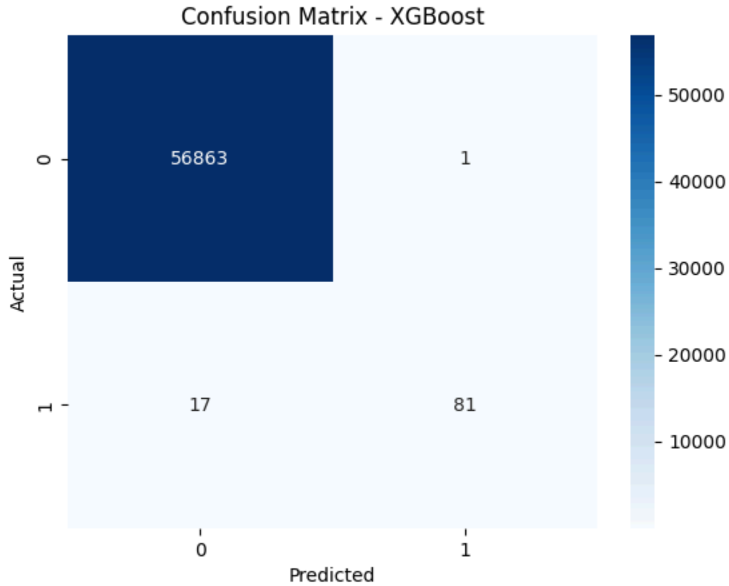
```
# Step 10: Make Predictions on the Test Data
# Using the trained XGBoost model to predict the class labels (fraud or non-fraud) for the test dataset (X_test).

y_pred = model_xgb.predict(X_test)
```

```
# Step 11: Evaluate the Model's Performance
# Printing the accuracy score to assess the overall correctness of the model's predictions.
# Generating a detailed classification report to evaluate metrics such as precision, recall, and F1-score for each class.

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

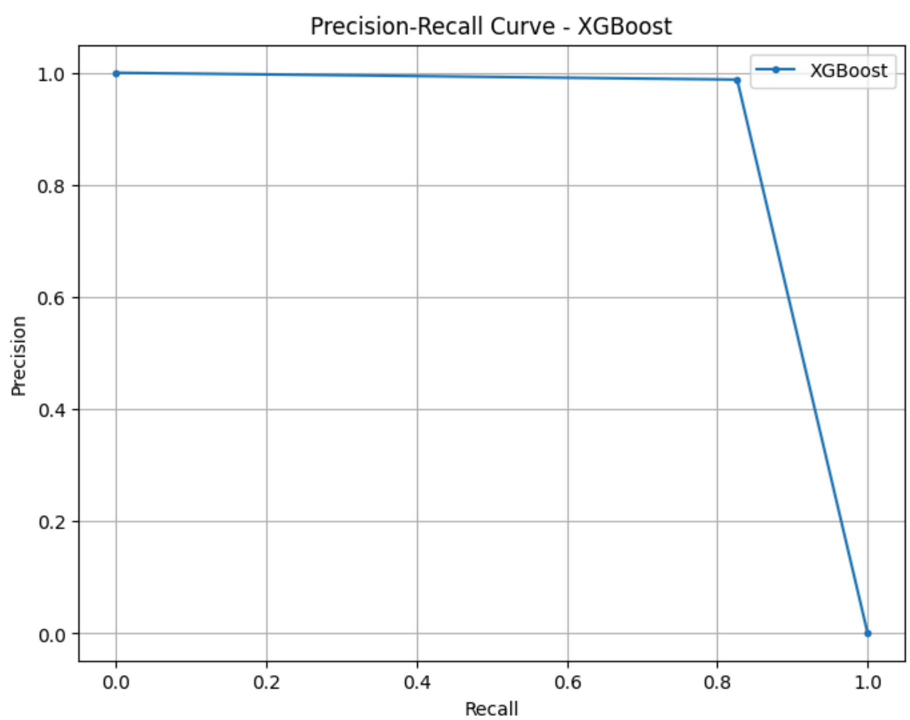
```
Accuracy: 0.9996839998595555
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.99      0.83      0.90        98

    accuracy                           1.00     56962
   macro avg       0.99      0.91      0.95     56962
weighted avg       1.00      1.00      1.00     56962
```

```
# Step 12: Plot the Confusion Matrix to Visualize Model Performance
# Creating a heatmap to display the confusion matrix, which shows the counts of true positives, true negatives,
# false positives, and false negatives. This helps visualize how well the model is distinguishing between classes.

sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix - XGBoost")
plt.xlabel("Predicted")
plt.ylabel("Actual")
```

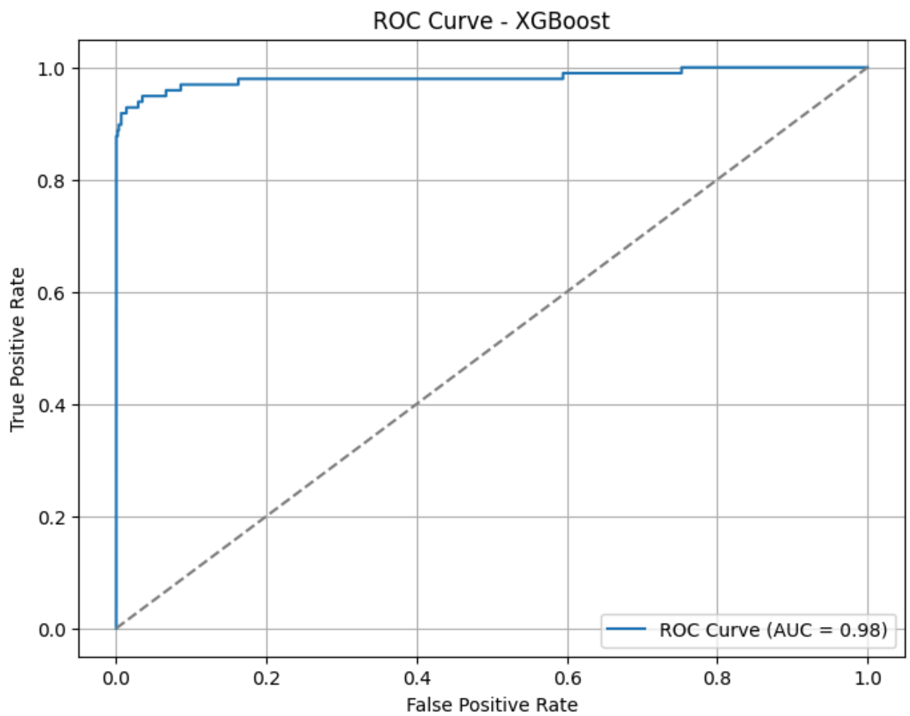
```
plt.show()
```




```
# Plot Precision-Recall Curve for XGBoost

from sklearn.metrics import precision_recall_curve


y_pred_xgb = model_xgb.predict(X_test)  # Predictions for test data
precision_xgb, recall_xgb, _ = precision_recall_curve(y_test, y_pred_xgb)

plt.figure(figsize=(8, 6))
plt.plot(recall_xgb, precision_xgb, marker='.', label='XGBoost')
plt.title("Precision-Recall Curve - XGBoost")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.legend()
plt.grid()
plt.show()
```



```python
# Plot ROC Curve for XGBoost
from sklearn.metrics import roc_curve, auc


y_pred_prob_xgb = model_xgb.predict_proba(X_test)[:, 1]  # Get probabilities for class 1
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_pred_prob_xgb)
roc_auc_xgb = auc(fpr_xgb, tpr_xgb)

plt.figure(figsize=(8, 6))
plt.plot(fpr_xgb, tpr_xgb, label=f'ROC Curve (AUC = {roc_auc_xgb:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')  # Baseline
plt.title("ROC Curve - XGBoost")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid()
plt.show()
```




```python
# Save the trained XGBoost model as .pkl
import pickle

with open("xgboost_model.pkl", "wb") as file:
    pickle.dump(model_xgb, file)

print("Trained XGBoost model saved as 'xgboost_model.pkl'.")
```

```
Trained XGBoost model saved as 'xgboost_model.pkl'.
```

```python
from google.colab import files

# Download each file locally
files.download("xgboost_model.pkl")
```