AI/ML Task

Develop a machine learning model to detect fraudulent transactions using a Kaggle dataset
Kaggle Credit Card Fraud Detection dataset with a focus on data handling, model training, evaluation, and explainability.

Task 1: Data Exploration and Preprocessing

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
```

```
data = pd.read_csv("creditcard.csv")
data
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	
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
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
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
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
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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111864	1
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924384	0
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578229	-0
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800049	-0
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643078	0

284807 rows × 31 columns

```
print("Dataset Info: ", data.info())
print("\nClass Distribution: ", data['Class'].value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
```

```
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
Dataset Info:  None

Class Distribution:  Class
0    284315
1       492
Name: count, dtype: int64
```

```
# Feature Scaling for 'Amount' (normalize)
scaler = StandardScaler()
data['Amount'] = scaler.fit_transform(data['Amount'].values.reshape(-1, 1))
```

```
# Split Features and Target
X = data.drop(columns=['Class'])
y = data['Class']
```

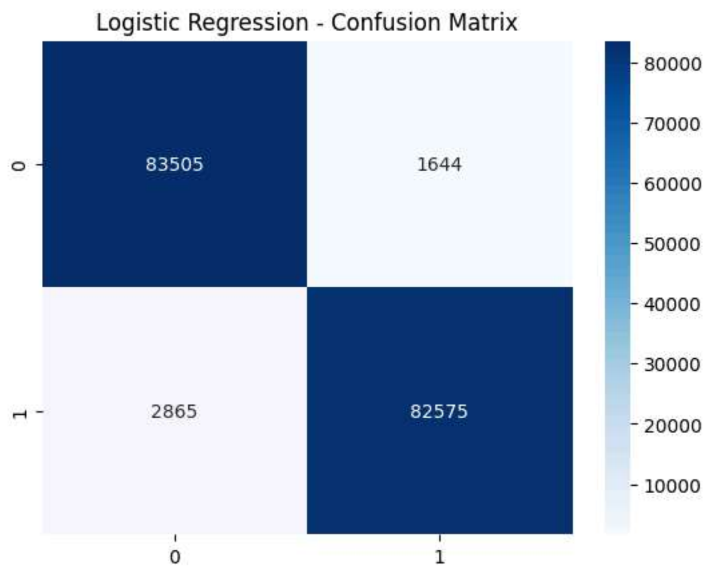
```
# Handle Class Imbalance using SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

Task 2: Supervised Model Development

```
# Importing necessary libraries for modeling
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve
from xgboost import XGBClassifier
```

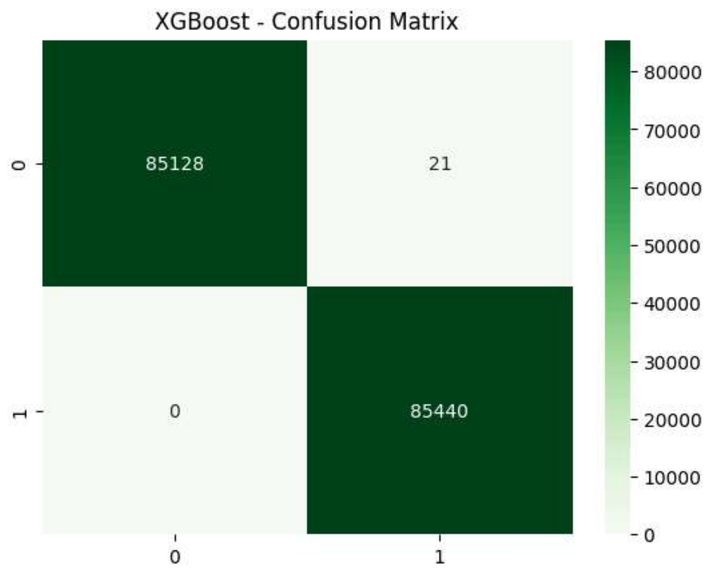
```
# Logistic Regression

# Spliting Data into Train-Test Sets
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.3, random_state=42)

# Training Logistic Regression (Baseline Model)
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)

# Evaluating Logistic Regression
print("Logistic Regression Performance:")
print(classification_report(y_test, y_pred_lr))

# Confusion Matrix for Logistic Regression
conf_matrix = confusion_matrix(y_test, y_pred_lr)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title("Logistic Regression - Confusion Matrix")
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:469: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
Logistic Regression Performance:
              precision    recall  f1-score   support

           0       0.97      0.98      0.97     85149
           1       0.98      0.97      0.97     85440

    accuracy                           0.97    170589
   macro avg       0.97      0.97      0.97    170589
weighted avg       0.97      0.97      0.97    170589
```

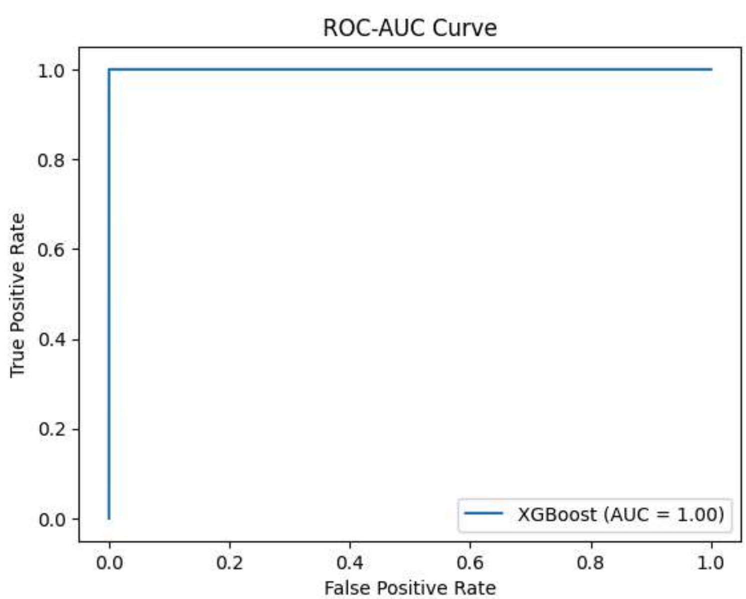



```
# XGBoost Model

# Training XGBoost Model
xgb_model = XGBClassifier(eval_metric='logloss', use_label_encoder=False)
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)

# Evaluating XGBoost Model
print("XGBoost Performance:")
print(classification_report(y_test, y_pred_xgb))

# Confusion Matrix for XGBoost
conf_matrix = confusion_matrix(y_test, y_pred_xgb)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Greens')
plt.title("XGBoost - Confusion Matrix")
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [14:52:03] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
XGBoost Performance:
              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
```




```
# ROC-AUC Curve for XGBoost
y_pred_prob = xgb_model.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc_auc = roc_auc_score(y_test, y_pred_prob)

plt.plot(fpr, tpr, label=f"XGBoost (AUC = {roc_auc:.2f})")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC-AUC Curve")
plt.legend()
plt.show()
```



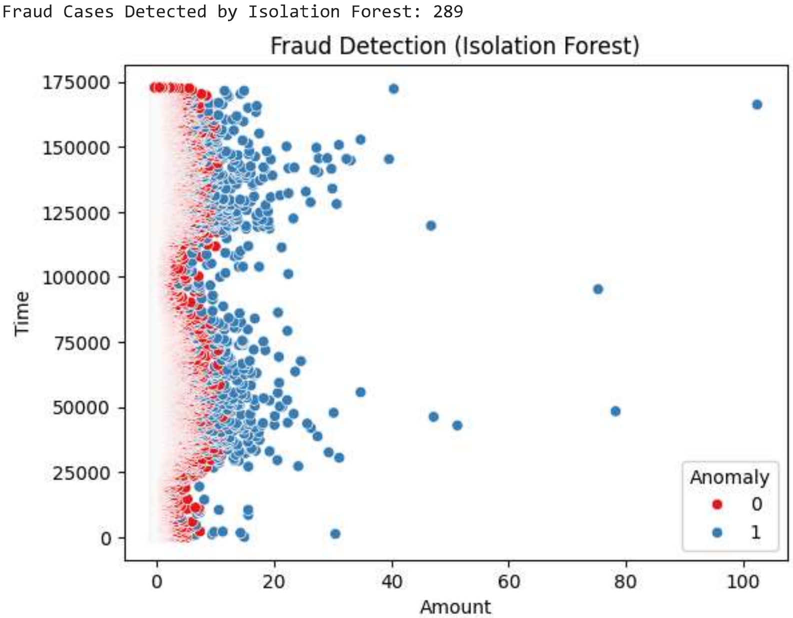
Task 3: Unsupervised Model Development

```
from sklearn.ensemble import IsolationForest


# Training Isolation Forest Model
isolation_forest = IsolationForest(contamination=0.01, random_state=42)
data['Anomaly'] = isolation_forest.fit_predict(X)
data['Anomaly'] = data['Anomaly'].apply(lambda x: 1 if x == -1 else 0)


# Evaluating Anomalies
anomalies_detected = data[data['Anomaly'] == 1]
print(f"Total Anomalies Detected: {len(anomalies_detected)}")
print("Sample Anomalies:", anomalies_detected.head())
```

```
Total Anomalies Detected: 2849
Sample Anomalies:        Time        V1         V2        V3        V4        V5        V6  \
164  103.0 -6.093248 -12.114213 -5.694973  3.294389 -1.413792  4.776000
362  266.0 -2.564961   2.470985  2.649417 -1.564256  1.794297 -0.614742
401  290.0 -5.166299  -5.449369  2.988498  2.658991  1.948152 -0.854470
455  333.0 -2.977214   0.781748  2.881724 -1.627798 -1.368067  1.656876
601  454.0 -3.133891   2.887394  2.178690 -1.576535  1.434510 -0.687313

           V7        V8        V9  ...       V22       V23       V24  \
164  4.808426 -0.228197 -0.525896  ... -2.264037 -3.553381  1.215279
362  4.185906 -3.855359  5.436633  ... -0.463149 -0.532466  0.306494
401 -0.326394 -1.017364  1.983901  ...  1.172278  3.150413  0.574081
455 -1.185053 -5.393736  1.719407  ... -1.929181  0.190843  0.533134
601  3.816056 -3.416915  5.459274  ... -0.498518 -0.476668  0.302196

          V25       V26       V27       V28     Amount  Class  Anomaly
164 -0.406073 -0.653384 -0.711222  0.672900  14.951604      0        1
362  0.226844 -0.365416 -0.936735 -2.733887  -0.311849      0        1
401  1.018394  0.987099  0.658283 -1.609716  -0.013392      0        1
455  0.296773  0.890104 -0.123225 -0.543750  -0.053373      0        1
601  0.299993 -0.359155 -0.958818 -2.735623  -0.314648      0        1

[5 rows x 32 columns]
```

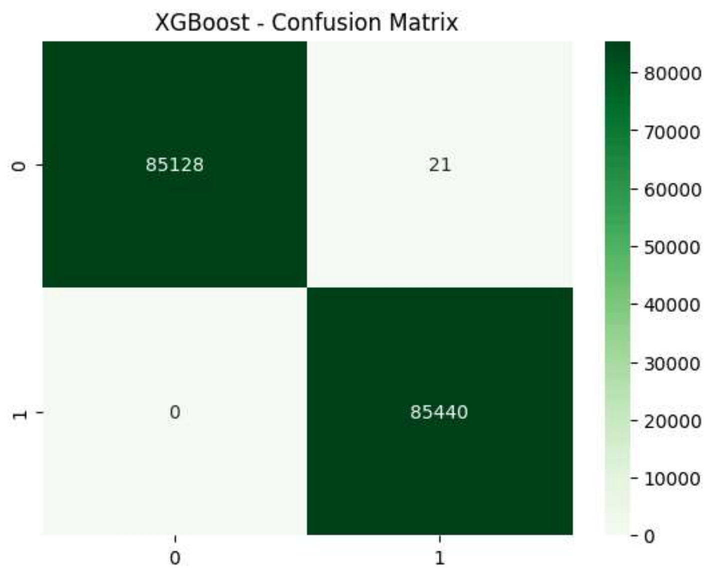
```
# Compare with Actual Fraudulent Transactions
fraud_data = data[data['Class'] == 1]
common_cases = fraud_data[fraud_data['Anomaly'] == 1]

print(f"Fraud Cases Detected by Isolation Forest: {len(common_cases)}")

# Visualize Anomalies
sns.scatterplot(data=data, x='Amount', y='Time', hue='Anomaly', palette='Set1')
plt.title("Fraud Detection (Isolation Forest)")
plt.show()
```

```
Fraud Cases Detected by Isolation Forest: 289
```

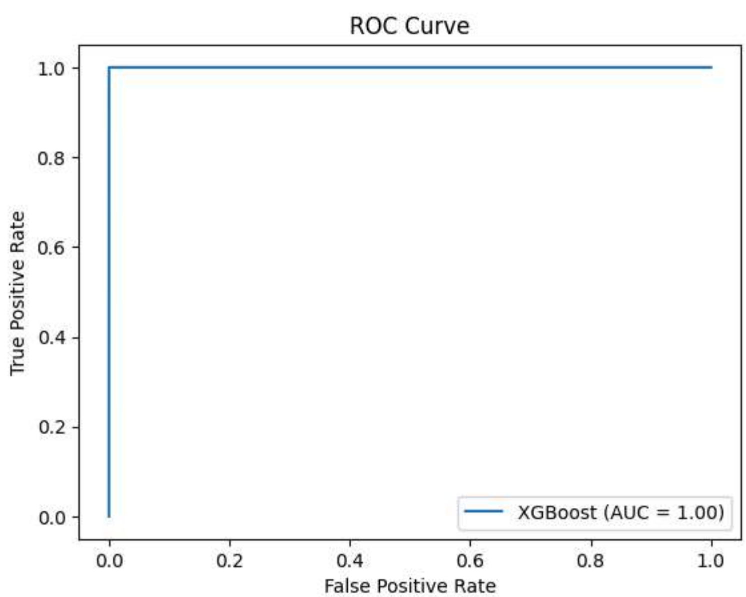


Task 4: Model Evaluation

```
from sklearn.metrics import confusion_matrix, roc_curve, auc


# Confusion Matrix for XGBoost
conf_matrix = confusion_matrix(y_test, y_pred_xgb)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Greens')
plt.title("XGBoost - Confusion Matrix")
plt.show()
```



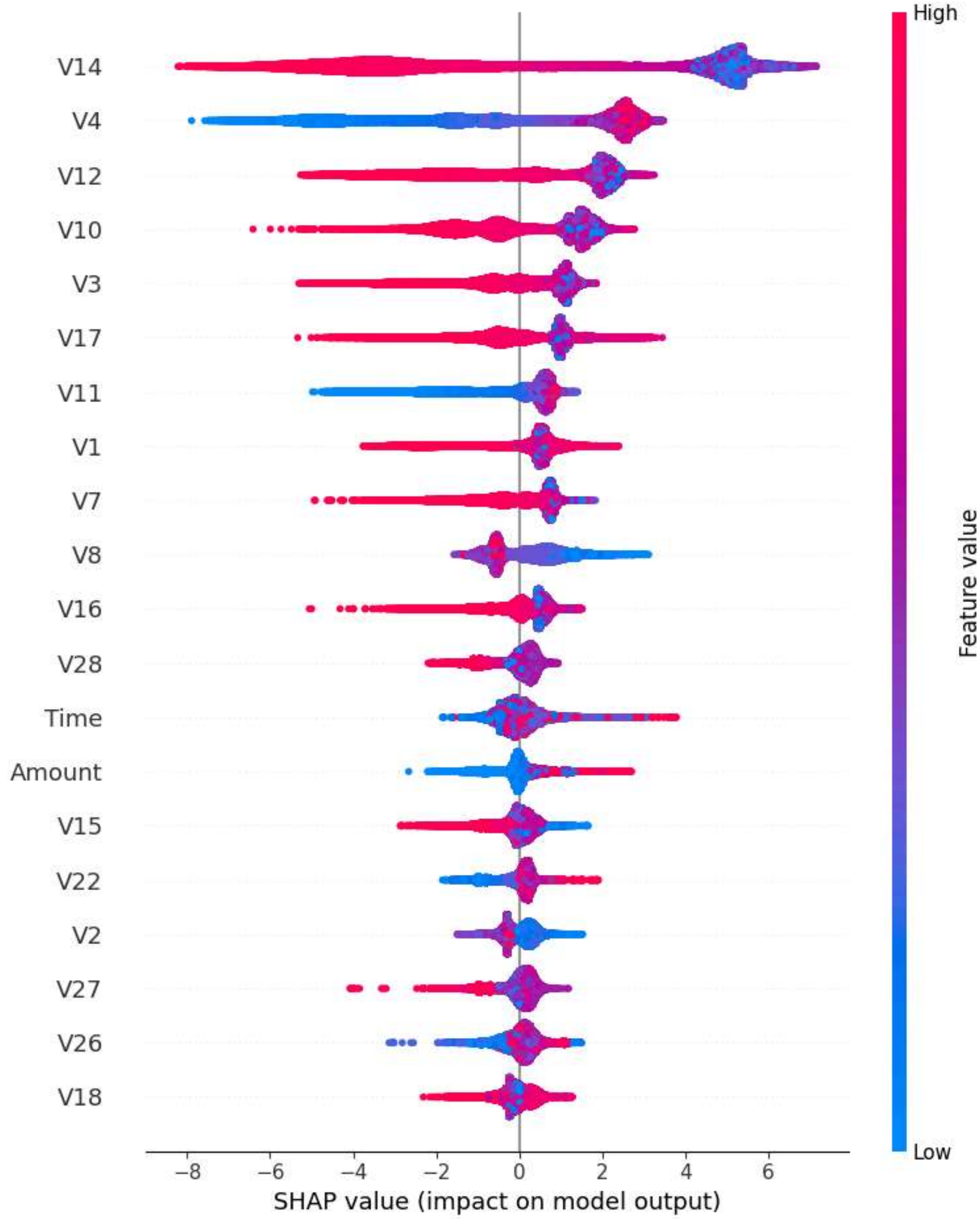

```
# ROC Curve for XGBoost
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, label=f'XGBoost (AUC = {roc_auc:.2f})')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```



Task 5: Model Explainability

```
import shap

# SHAP for XGBoost
explainer = shap.Explainer(xgb_model, X_test)
shap_values = explainer(X_test)

# Plotting SHAP Summary
shap.summary_plot(shap_values, X_test)
```

```
100%|===================| 170577/170589 [19:40<00:00]
```




```
# Feature Importance for XGBoost
```