```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, roc_auc_score, roc_curve
```

```
# Load the dataset
data = pd.read_csv('/content/Preprocessed_Missing_dataset.csv')
# Display the first few rows of the dataset
data.head()
```

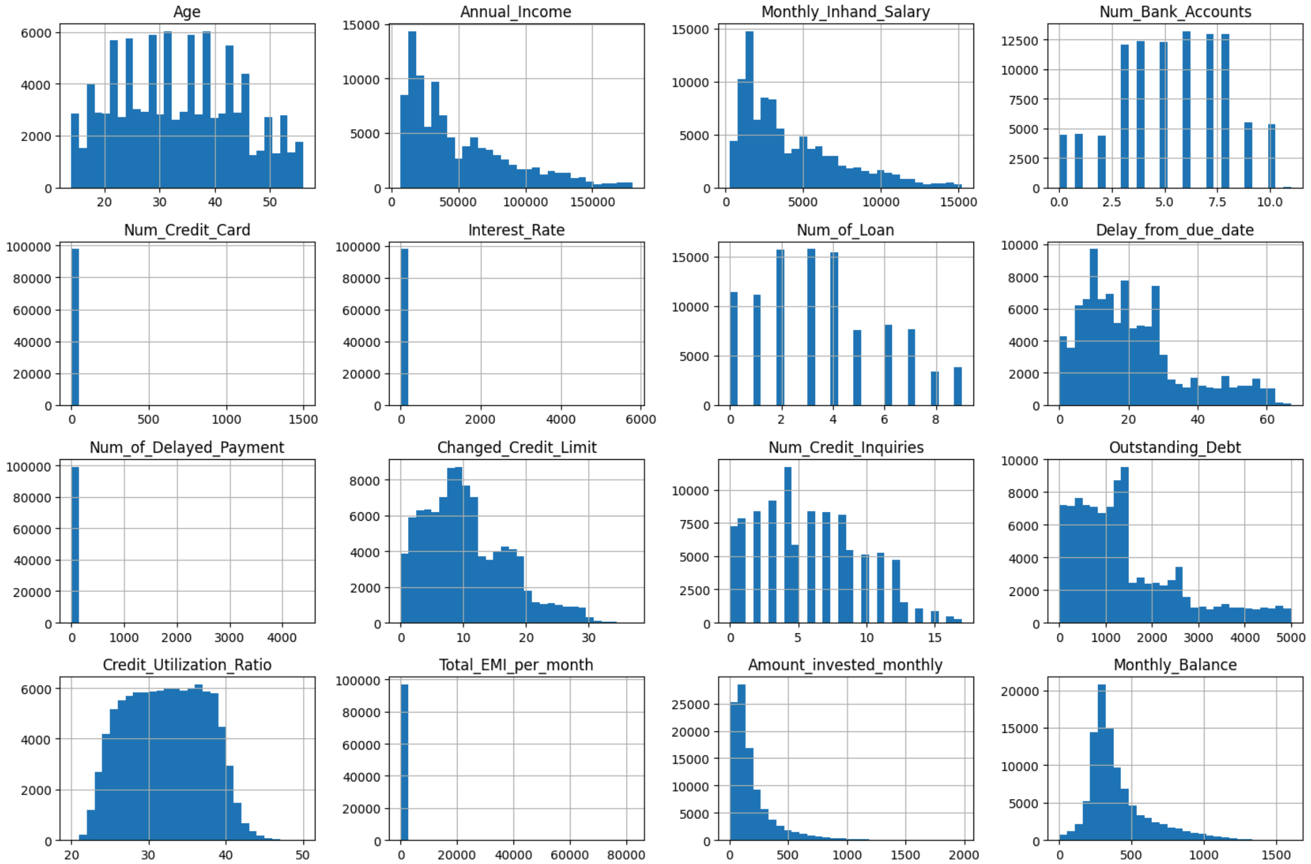
	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Nu
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	
2	0x1604	CUS_0xd40	March	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	

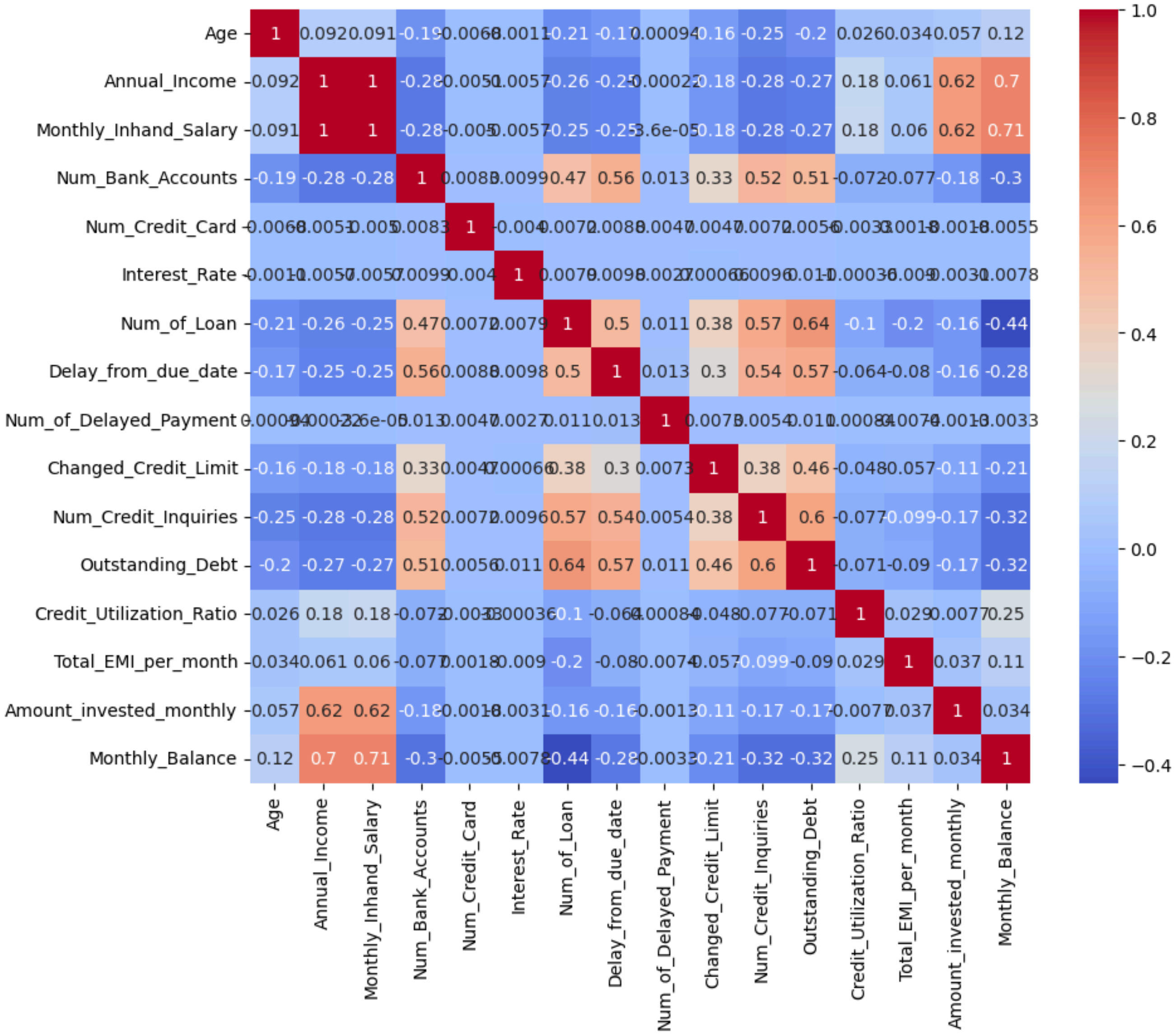
5 rows × 28 columns

```
# Display summary statistics
print(data.describe())

# Check data types and info
print(data.info())

# Check for unique values in each column
print(data.nunique())
```

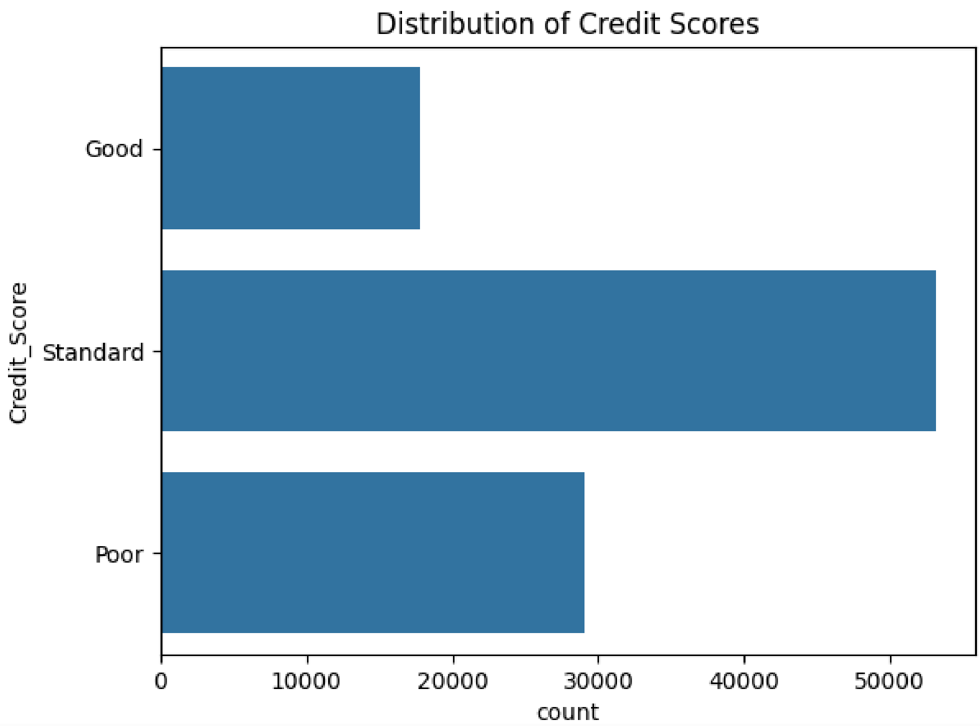
```
 22  Payment_of_Min_Amount     100000 non-null  object
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   100000 non-null  float64
 25  Payment_Behaviour         100000 non-null  object
 26  Monthly_Balance           100000 non-null  float64
 27  Credit_Score              100000 non-null  object
dtypes: float64(9), int64(7), object(12)
memory usage: 21.4+ MB
None
ID                          100000
Customer_ID                  12500
Month                            8
Name                         10139
Age                             43
SSN                          12500
Occupation                      15
Annual_Income                12488
Monthly_Inhand_Salary        13235
Num_Bank_Accounts               12
Num_Credit_Card               1179
Interest_Rate                 1750
Num_of_Loan                     10
Type_of_Loan                  6260
Delay_from_due_date             68
Num_of_Delayed_Payment         708
Changed_Credit_Limit          3716
Num_Credit_Inquiries            18
Credit_Mix                       3
Outstanding_Debt             12203
Credit_Utilization_Ratio    100000
Credit_History_Age             414
Payment_of_Min_Amount            3
Total_EMI_per_month          12191
Amount_invested_monthly      97607
Payment_Behaviour                6
Monthly_Balance              99759
Credit_Score                     3
dtype: int64
```

```
# Plotting histograms for all features
data.hist(bins=30, figsize=(15, 10))
plt.tight_layout()
plt.show()

# Correlation heatmap
numeric_data = data.select_dtypes(include=[np.number])
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
plt.show()
```


Age
Annual_Income
Monthly_Inhand_Salary
Num_Bank_Accounts
Num_Credit_Card
Interest_Rate
Num_of_Loan
Delay_from_due_date
Num_of_Delayed_Payment
Changed_Credit_Limit
Num_Credit_Inquiries
Outstanding_Debt
Credit_Utilization_Ratio
Total_EMI_per_month
Amount_invested_monthly
Monthly_Balance


Age
Annual_Income
Monthly_Inhand_Salary
Num_Bank_Accounts
Num_Credit_Card
Interest_Rate
Num_of_Loan
Delay_from_due_date
Num_of_Delayed_Payment
Changed_Credit_Limit
Num_Credit_Inquiries
Outstanding_Debt
Credit_Utilization_Ratio
Total_EMI_per_month
Amount_invested_monthly
Monthly_Balance
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

```
# Assuming 'Credit_Score' is the target column (adjust as needed)
sns.countplot(data['Credit_Score'])
plt.title('Distribution of Credit Scores')
plt.show()
```




```
# Identify categorical columns
categorical_columns = data.select_dtypes(include=['object']).columns
print("Categorical columns:", categorical_columns)
```

```
Categorical columns: Index(['ID', 'Customer_ID', 'Month', 'Name', 'SSN', 'Occupation',
       'Type_of_Loan', 'Credit_Mix', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Payment_Behaviour', 'Credit_Score'],
      dtype='object')
```

```
from sklearn.preprocessing import LabelEncoder

# Example of encoding multiple categorical columns
label_encoder = LabelEncoder()
for col in categorical_columns:
    data[col] = label_encoder.fit_transform(data[col])
```

```
from sklearn.preprocessing import LabelEncoder

# Encoding specific categorical columns
label_encoder = LabelEncoder()
for col in ['Occupation', 'Type_of_Loan', 'Credit_Mix', 'Payment_of_Min_Amount', 'Payment_Behaviour']:  # Repl
    data[col] = label_encoder.fit_transform(data[col])

# Continue with your analysis and modeling
print(data.head())
```

```
      ID  Customer_ID  Month  Name  Age    SSN  Occupation  Annual_Income  \
0  16406        12320      3    84   23  10204          12       19114.12
1  16417        12320      2    84   23  10204          12       19114.12
```

```
2  16428        12320      6    84   23  10204          12       19114.12
3  16441        12320      0    84   23  10204          12       19114.12
4  16452        12320      7    84   23  10204          12       19114.12

   Monthly_Inhand_Salary  Num_Bank_Accounts  ...  Credit_Mix  \
0            1824.843333                  3  ...           1
1            1824.843333                  3  ...           1
2            1824.843333                  3  ...           1
3            1824.843333                  3  ...           1
4            1824.843333                  3  ...           1

   Outstanding_Debt  Credit_Utilization_Ratio  Credit_History_Age  \
0            809.98                 26.822620                 186
1            809.98                 31.944960                 189
2            809.98                 28.609352                 190
3            809.98                 31.377862                 191
4            809.98                 24.797347                 192

   Payment_of_Min_Amount  Total_EMI_per_month  Amount_invested_monthly  \
0                      1            49.574949                80.415295
1                      1            49.574949               118.280222
2                      1            49.574949                81.699521
3                      1            49.574949               199.458074
4                      1            49.574949                41.420153

   Payment_Behaviour  Monthly_Balance  Credit_Score
0                  2       312.494089             0
1                  3       284.629162             0
2                  4       331.209863             0
3                  5       223.451310             0
4                  1       341.489231             0

[5 rows x 28 columns]
```

```
# Define the features (X) and target (y)
X = data.drop('Credit_Score', axis=1)  # All columns except the target
y = data['Credit_Score']  # The target column

# Check the shape of X and y to confirm the split
print(f'Shape of X: {X.shape}')
print(f'Shape of y: {y.shape}')
```

```
Shape of X: (100000, 27)
Shape of y: (100000,)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
# Initialize RandomForest Classifier
rf = RandomForestClassifier(random_state=42)

# Define hyperparameters grid for tuning
param_grid = {
    'n_estimators': [100, 300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [4, 6, 10],
    'criterion': ['gini', 'entropy']
}

# Setup GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1, scoring='accuracy')

# Fit the model
grid_search.fit(X_train, y_train)
```

```
# Print best parameters and best score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best accuracy: {grid_search.best_score_}")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:425: FitFailedWarning:
60 fits failed out of a total of 180.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
37 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 729, in _fi
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1145, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 638, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py", line 96, in validate
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestClassi

--------------------------------------------------------------------------------
23 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 729, in _fi
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1145, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 638, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py", line 96, in validate
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestClassi

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:979: UserWarning: One or more
        nan        nan 0.68964286 0.69231429 0.68578571 0.68507143
        nan        nan 0.7306     0.73062857 0.72905714 0.72962857
        nan        nan 0.65748571 0.65747143 0.65221429 0.6519
        nan        nan 0.68828571 0.68762857 0.67322857 0.67075714
        nan        nan 0.725      0.72568571 0.72592857 0.72552857]
  warnings.warn(
Best parameters: {'criterion': 'gini', 'max_depth': 10, 'max_features': 'sqrt', 'n_estimators': 300}
Best accuracy: 0.7306285714285713
```

```
# Initialize Gradient Boosting Classifier
gbc = GradientBoostingClassifier(random_state=42)

# Define hyperparameters grid for tuning
gbc_param_grid = {
    'n_estimators': [100, 150],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 4]
}

# Setup GridSearchCV for Gradient Boosting
# gbc_grid_search = GridSearchCV(estimator=gbc, param_grid=gbc_param_grid, cv=5, n_jobs=-1, scoring='accuracy
gbc_grid_search = GridSearchCV(
    estimator=gbc,
    param_grid=gbc_param_grid,
    cv=3,  # Reduce number of folds
    n_jobs=-1,
    scoring='accuracy'
)
# Fit the model
gbc_grid_search.fit(X_train, y_train)
```

```
# Print best parameters and best score for Gradient Boosting
print(f"Best parameters for GBC: {gbc_grid_search.best_params_}")
print(f"Best accuracy for GBC: {gbc_grid_search.best_score_}")
```

```
Best parameters for GBC: {'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 150}
Best accuracy for GBC: 0.729885666625124
```

```
# Predictions using the best RandomForest model
rf_best = grid_search.best_estimator_
y_pred_rf = rf_best.predict(X_test)

# Performance metrics for RandomForest
print("RandomForest Model Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
RandomForest Model Accuracy: 0.7298
Confusion Matrix:
 [[ 4044    82  1196]
 [  678  6030  2097]
 [ 2229  1824 11820]]
Classification Report:
               precision    recall  f1-score   support

           0       0.58      0.76      0.66      5322
           1       0.76      0.68      0.72      8805
           2       0.78      0.74      0.76     15873

    accuracy                           0.73     30000
   macro avg       0.71      0.73      0.71     30000
weighted avg       0.74      0.73      0.73     30000
```

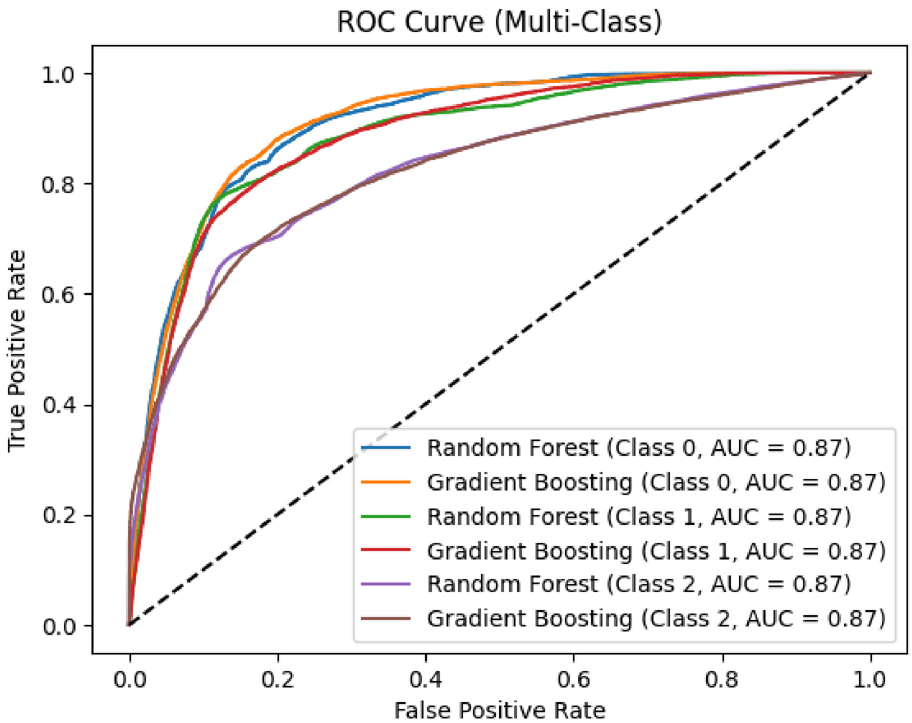
```
# Predictions using the best GradientBoosting model
gbc_best = gbc_grid_search.best_estimator_
y_pred_gbc = gbc_best.predict(X_test)

# Performance metrics for Gradient Boosting
print("Gradient Boosting Model Accuracy:", accuracy_score(y_test, y_pred_gbc))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_gbc))
print("Classification Report:\n", classification_report(y_test, y_pred_gbc))
```

```
Gradient Boosting Model Accuracy: 0.7317333333333333
Confusion Matrix:
 [[ 3763    86  1473]
 [  493  5982  2330]
 [ 1764  1902 12207]]
Classification Report:
               precision    recall  f1-score   support

           0       0.63      0.71      0.66      5322
           1       0.75      0.68      0.71      8805
           2       0.76      0.77      0.77     15873

    accuracy                           0.73     30000
   macro avg       0.71      0.72      0.71     30000
weighted avg       0.73      0.73      0.73     30000
```

```
from sklearn.metrics import roc_auc_score, roc_curve

# Calculate ROC-AUC using multi-class setting
rf_roc_auc = roc_auc_score(y_test, rf_best.predict_proba(X_test), multi_class='ovr')
gbc_roc_auc = roc_auc_score(y_test, gbc_best.predict_proba(X_test), multi_class='ovr')

print(f"Random Forest ROC-AUC: {rf_roc_auc}")
print(f"Gradient Boosting ROC-AUC: {gbc_roc_auc}")
```

```
# Since you are dealing with multi-class classification, plotting ROC curves separately for each class
for i in range(len(rf_best.classes_)):
    rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_best.predict_proba(X_test)[:, i], pos_label=rf_best.classes_[i])
    gbc_fpr, gbc_tpr, _ = roc_curve(y_test, gbc_best.predict_proba(X_test)[:, i], pos_label=gbc_best.classes_[

    plt.plot(rf_fpr, rf_tpr, label=f'Random Forest (Class {i}, AUC = {rf_roc_auc:.2f})')
    plt.plot(gbc_fpr, gbc_tpr, label=f'Gradient Boosting (Class {i}, AUC = {gbc_roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (Multi-Class)')
plt.legend(loc='lower right')
plt.show()
```

```
Random Forest ROC-AUC: 0.8728681390457836
Gradient Boosting ROC-AUC: 0.8739737432153131
```



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