```python
# Importing necessary libraries for data manipulation, model building, and evaluation
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt  # Ensure this is imported for plotting
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score
from sklearn.feature_selection import SelectKBest, f_classif
from imblearn.over_sampling import SMOTE

# Printing success message to confirm all libraries have been imported without errors
print("Libraries imported successfully.")
```

```
Libraries imported successfully.
```

```python
# Importing the pandas library, which provides data manipulation and analysis functions
import pandas as pd

# Loading the dataset from the specified file path into a DataFrame object called 'data'
data = pd.read_csv(r"C:\Users\teena\OneDrive\Desktop\healthcare-dataset-stroke-data.csv")
# Printing a confirmation message indicating the dataset is loaded successfully
print("Dataset loaded successfully.")
# Displaying the first few rows of the dataset using the head() function
print(data.head())
```

```
Dataset loaded successfully.
      id  gender   age  hypertension  heart_disease ever_married  \
0   9046    Male  67.0             0              1          Yes
1  51676  Female  61.0             0              0          Yes
2  31112    Male  80.0             0              1          Yes
3  60182  Female  49.0             0              0          Yes
4   1665  Female  79.0             1              0          Yes

       work_type Residence_type  avg_glucose_level   bmi
```

```
smoking_status  \
0        Private          Urban             228.69  36.6  formerly
smoked
1  Self-employed          Rural             202.21   NaN     never
smoked
2        Private          Rural             105.92  32.5     never
smoked
3        Private          Urban             171.23  34.4
smokes
4  Self-employed          Rural             174.12  24.0     never
smoked

   stroke
0       1
1       1
2       1
3       1
4       1
```

```python
# Selecting only the relevant features from the dataset for analysis
# Keeping features that are relevant to predicting stroke, based on
prior research or domain knowledge
data = data[['age', 'gender', 'hypertension', 'heart_disease',
'avg_glucose_level', 'bmi', 'smoking_status', 'stroke']]

# Displaying a message to indicate the selection of relevant features
has been done
print("Selected Relevant Features")

# Displaying the first few rows of the selected data to verify the
selected features
data.head()
```

```
Selected Relevant Features

    age  gender  hypertension  heart_disease  avg_glucose_level   bmi
\
0  67.0    Male             0              1             228.69  36.6

1  61.0  Female             0              0             202.21   NaN

2  80.0    Male             0              1             105.92  32.5

3  49.0  Female             0              0             171.23  34.4

4  79.0  Female             1              0             174.12  24.0


    smoking_status  stroke
0  formerly smoked       1
1     never smoked       1
```

```
2     never smoked       1
3           smokes       1
4     never smoked       1

# Creating a copy of the original dataset to prevent modifying the
original data directly
data = data.copy()

# Filling missing values in the 'bmi' column with the mean of the
'bmi' column
# This is using the 'fillna()' method to replace NaN values with the
mean
# Setting inplace=False to avoid potential warnings by modifying the
data in a copied version
data['bmi'] = data['bmi'].fillna(data['bmi'].mean())

# Checking if missing values in the 'bmi' column have been
successfully handled
# Using 'isnull().sum()' to verify that there are no remaining NaN
values in 'bmi'
print("Missing values in 'bmi' column handled successfully.")
print(data['bmi'].isnull().sum())

Missing values in 'bmi' column handled successfully.
0

# Encoding the 'gender' column by mapping categorical values to
numeric values
# Mapping 'Female' to 0 and 'Male' to 1
data['gender'] = data['gender'].map({'Female': 0, 'Male': 1})

# Encoding the 'smoking_status' column by mapping categorical values
to numeric values
data['smoking_status'] = data['smoking_status'].map({
    'never smoked': 0,
    'smokes': 1,
    'formerly smoked': 2
})

# Printing a message to confirm that the encoding of 'gender' and
'smoking_status' is complete
print("Encoded Categorical Variables 'gender' and 'smoking_status'")

# Displaying the first few rows of the dataset to verify the changes
data.head()

Encoded Categorical Variables 'gender' and 'smoking_status'

    age  gender  hypertension  heart_disease  avg_glucose_level
bmi  \
0  67.0     1.0             0              1             228.69
```

```
36.600000
1  61.0     0.0             0             0            202.21
28.893237
2  80.0     1.0             0             1            105.92
32.500000
3  49.0     0.0             0             0            171.23
34.400000
4  79.0     0.0             1             0            174.12
24.000000

   smoking_status  stroke
0             2.0       1
1             0.0       1
2             0.0       1
3             1.0       1
4             0.0       1
```

```
# Defining features and target
X = data.drop('stroke', axis=1)
y = data['stroke']
print("Separated features and target variable.")
print(X.head())
print(y.head())
```

```
Separated features and target variable.
    age  gender  hypertension  heart_disease  avg_glucose_level
bmi  \
0  67.0     1.0             0             1            228.69
36.600000
1  61.0     0.0             0             0            202.21
28.893237
2  80.0     1.0             0             1            105.92
32.500000
3  49.0     0.0             0             0            171.23
34.400000
4  79.0     0.0             1             0            174.12
24.000000

   smoking_status
0             2.0
1             0.0
2             0.0
3             1.0
4             0.0
0    1
1    1
2    1
3    1
4    1
Name: stroke, dtype: int64
```

```python
# Importing train_test_split function from sklearn library to split
data into training and testing sets
from sklearn.model_selection import train_test_split

# Splitting the dataset into training and testing sets, where X
represents features and y represents target variable
# Setting test_size to 0.2, which means 20% of the data will be used
for testing, and 80% will be used for training
# Setting random_state to 42 to ensure reproducibility of the split;
using the same seed will give the same split every time
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Printing a message indicating that the data has been split into
training and testing sets
print("Split Data into Training and Testing Sets")

# Printing the shape (number of samples and features) of the training
set to show its size
print("Training Set Size:", X_train.shape)

# Printing the shape (number of samples and features) of the testing
set to show its size
print("Testing Set Size:", X_test.shape)
```

```
Split Data into Training and Testing Sets
Training Set Size: (4088, 7)
Testing Set Size: (1022, 7)
```

```python
from sklearn.preprocessing import StandardScaler
import numpy as np

# To Ensure X_train and X_test have been split before this point

# Step 1: Scaling the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)  # Scale training data
X_test_scaled = scaler.transform(X_test)  # Scale testing data
print("Data scaled successfully.")

# Step 2: Checking for NaN values in scaled data
print("Checking for NaN values in scaled training data:")

# Summing up the count of NaN values for each column in X_train_scaled
# and storing it in 'nan_columns' to identify columns with NaN issues
nan_columns = np.isnan(X_train_scaled).sum(axis=0)
print("NaN counts per column:", nan_columns)

# Step 3: Replacing any NaN values with column means
if nan_columns.any():  # Check if there are any NaN values
    X_train_scaled = np.where(np.isnan(X_train_scaled),
```

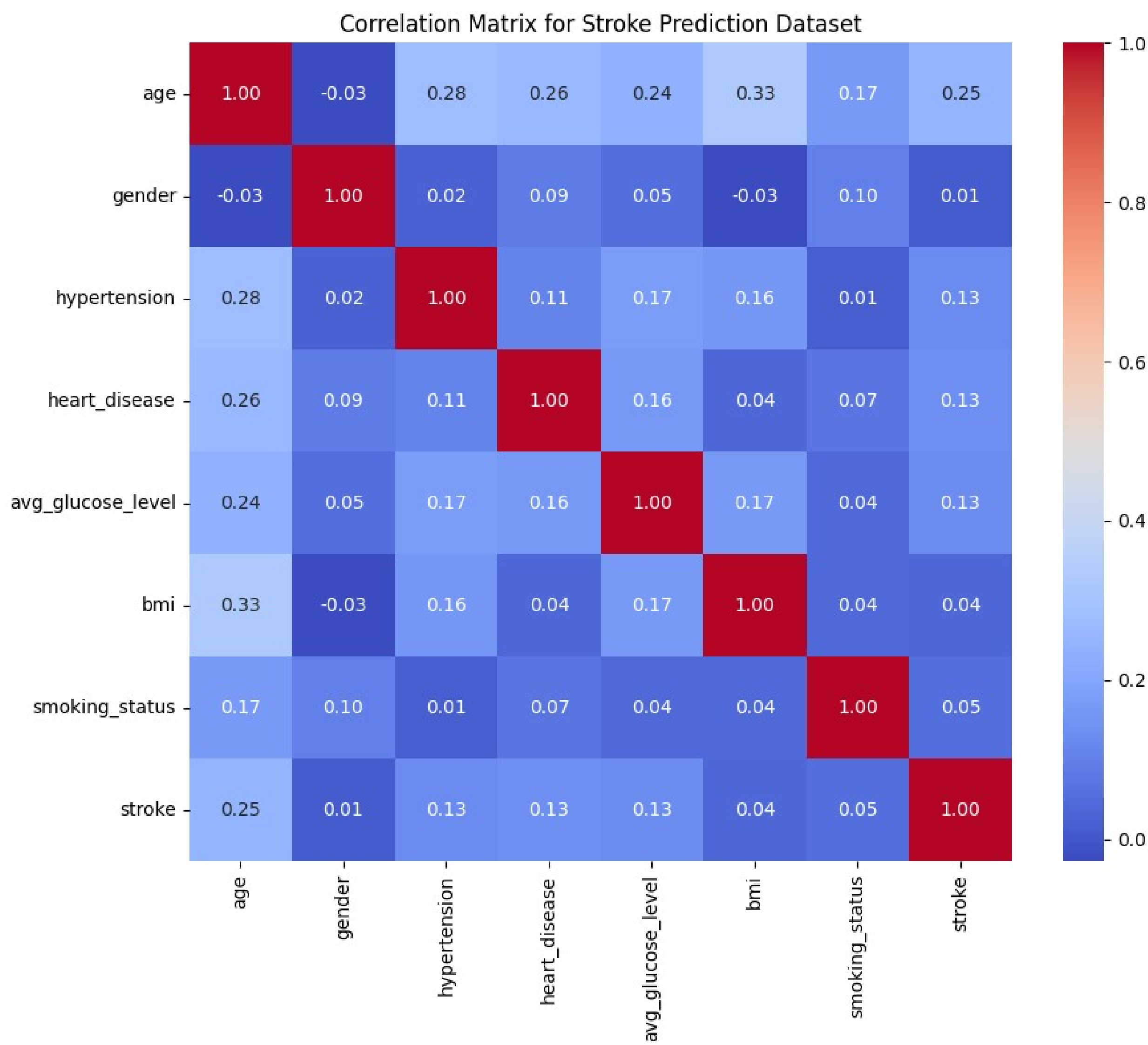
```
np.nanmean(X_train_scaled, axis=0), X_train_scaled)
    X_test_scaled = np.where(np.isnan(X_test_scaled),
np.nanmean(X_test_scaled, axis=0), X_test_scaled)
    print("Replaced NaN values with column means.")
else:
    print("No NaN values found in scaled data.")
```

```
Data scaled successfully.
Checking for NaN values in scaled training data:
NaN counts per column: [   0    0    0    0    0    0 1233]
Replaced NaN values with column means.
```

```
# Importing SMOTE from imbalanced-learn library to handle class
imbalance
smote = SMOTE(random_state=42)  # Creating an instance of SMOTE with a
fixed random state for reproducibility

# Applying SMOTE to the training data to balance the class
distribution
X_train_resampled, y_train_resampled =
smote.fit_resample(X_train_scaled, y_train)

# Printing a message to confirm that SMOTE has been successfully
applied for class balancing
print("SMOTE applied for class balancing successfully.")

# Displaying the distribution of classes after SMOTE to verify
balancing
print("Class distribution after SMOTE:\n",
pd.Series(y_train_resampled).value_counts())
```

```
SMOTE applied for class balancing successfully.
Class distribution after SMOTE:
 stroke
0    3901
1    3901
Name: count, dtype: int64
```

```
# Generating the correlation matrix
correlation_matrix = data.corr()

# Plotting the correlation matrix as a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f", cbar=True)
plt.title("Correlation Matrix for Stroke Prediction Dataset")
plt.show()
```




```
from sklearn.feature_selection import SelectKBest, f_classif

# Setting the number of top features to select
# 'k' is set to the lesser of 16 or 20, to ensure it doesn't exceed
the number of features available
k = min(16, data.shape[1] - 1)  # Adjusts k to the lesser of 16 or the
number of features

# Creating an instance of SelectKBest for feature selection
# SelectKBest is using the f_classif function to score features based
on their ANOVA F-value with the target
selector = SelectKBest(f_classif, k=k)

# Fitting the SelectKBest model on the resampled training data
X_train_selected = selector.fit_transform(X_train_resampled,
y_train_resampled)
```

```
# Transforming the scaled testing data to only include the selected
features
X_test_selected = selector.transform(X_test_scaled)

# Confirming the feature selection process
print("Top features selected successfully.")
# Printing the shape of the selected training features to verify the
expected number of features
print("Selected training features shape:", X_train_selected.shape)
# Printing the shape of the selected testing features to confirm
consistency with the training set
print("Selected testing features shape:", X_test_selected.shape)
```

```
Top features selected successfully.
Selected training features shape: (7802, 7)
Selected testing features shape: (1022, 7)
```

```
# Importing necessary libraries
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression

# Defining classifiers
classifiers = {
    'KNN': KNeighborsClassifier(),
    'MLP': MLPClassifier(max_iter=1000),
    'Random Forest': RandomForestClassifier(),
    'AdaBoost': AdaBoostClassifier(),
    'GaussianNB': GaussianNB(),
    'SVM (Linear)': SVC(kernel='linear', probability=True),
    'SVM (RBF)': SVC(kernel='rbf', probability=True),
    'SVM (Sigmoid)': SVC(kernel='sigmoid', probability=True),
    'XGBoost': XGBClassifier(use_label_encoder=False,
eval_metric='logloss'),
    'Logistic Regression': LogisticRegression(),

}

print("Classifiers defined successfully.")
```

```
Classifiers defined successfully.
```

```
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier,
RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, roc_auc_score,
```

```python
classification_report
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Defining classifiers with adjustments
classifiers = {
    'KNN': KNeighborsClassifier(),
    'MLP': MLPClassifier(max_iter=1000),
    'Random Forest': RandomForestClassifier(),
    'AdaBoost': AdaBoostClassifier(algorithm='SAMME'),
    'GaussianNB': GaussianNB(),
    'SVM (Linear)': SVC(kernel='linear', probability=True),
    'SVM (RBF)': SVC(kernel='rbf', probability=True),
    'SVM (Sigmoid)': SVC(kernel='sigmoid', probability=True),
    'XGBoost': XGBClassifier(eval_metric='logloss'),
    'Logistic Regression': LogisticRegression()
}

# Storing results
results = {
    "Classifier": [],
    "Accuracy": [],
    "AUC": [],
    "Precision": [],
    "Recall": [],
    "F1-score": []
}

# Training and evaluating classifiers
for name, clf in classifiers.items():
    clf.fit(X_train_selected, y_train_resampled)
    y_pred = clf.predict(X_test_selected)
    y_pred_proba = clf.predict_proba(X_test_selected)[:, 1] if
hasattr(clf, "predict_proba") else None

    accuracy = accuracy_score(y_test, y_pred)
    auc = roc_auc_score(y_test, y_pred_proba) if y_pred_proba is not
None else "N/A"
    report = classification_report(y_test, y_pred, output_dict=True)

    # Append results
    results["Classifier"].append(name)
    results["Accuracy"].append(accuracy)
    results["AUC"].append(auc)
    results["Precision"].append(report['weighted avg']['precision'])
    results["Recall"].append(report['weighted avg']['recall'])
    results["F1-score"].append(report['weighted avg']['f1-score'])

    print(f"\n{name} Classifier:")
```

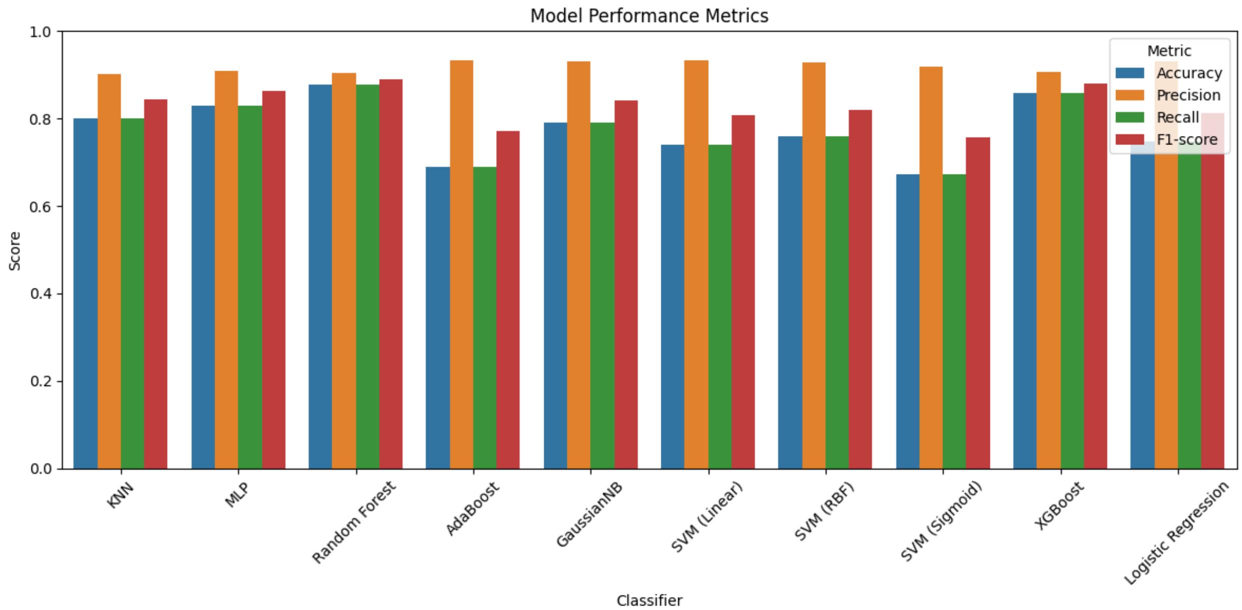
```python
    print(f"Accuracy: {accuracy:.4f}")
    print(f"AUC: {auc}")
    print("Classification Report:")
    print(classification_report(y_test, y_pred))

# Converting results to DataFrame
summary_df = pd.DataFrame(results)

# Displaying summary
print("\nSummary of Classifier Results:")
print(summary_df)

# Melting DataFrame for seaborn compatibility
summary_melted = summary_df.melt(id_vars="Classifier",
value_vars=["Accuracy", "Precision", "Recall", "F1-score"],
                                 var_name="Metric",
value_name="Score")

# Plotting with seaborn
plt.figure(figsize=(12, 6))
sns.barplot(data=summary_melted, x="Classifier", y="Score",
hue="Metric")

# Adding plot labels and title
plt.title("Model Performance Metrics")
plt.xlabel("Classifier")
plt.ylabel("Score")
plt.ylim(0, 1)  # Score range from 0 to 1 for better visibility
plt.legend(title="Metric")

# Displaying the plot
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
KNN Classifier:
Accuracy: 0.8014
AUC: 0.6745631720430108
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.83      0.89       960
           1       0.12      0.37      0.18        62

    accuracy                           0.80      1022
   macro avg       0.54      0.60      0.54      1022
weighted avg       0.90      0.80      0.84      1022


MLP Classifier:
```

```
Accuracy: 0.8288
AUC: 0.7763608870967742
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.86      0.90       960
           1       0.16      0.42      0.23        62

    accuracy                           0.83      1022
   macro avg       0.56      0.64      0.57      1022
weighted avg       0.91      0.83      0.86      1022


Random Forest Classifier:
Accuracy: 0.8787
AUC: 0.7661542338709678
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.92      0.93       960
           1       0.17      0.26      0.21        62

    accuracy                           0.88      1022
   macro avg       0.56      0.59      0.57      1022
weighted avg       0.90      0.88      0.89      1022


AdaBoost Classifier:
Accuracy: 0.6898
AUC: 0.8503864247311828
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.68      0.80       960
           1       0.14      0.84      0.25        62

    accuracy                           0.69      1022
   macro avg       0.56      0.76      0.53      1022
weighted avg       0.93      0.69      0.77      1022


GaussianNB Classifier:
Accuracy: 0.7906
AUC: 0.833921370967742
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.79      0.88       960
           1       0.19      0.73      0.30        62

    accuracy                           0.79      1022
```

```
   macro avg       0.58      0.76      0.59      1022
weighted avg       0.93      0.79      0.84      1022


SVM (Linear) Classifier:
Accuracy: 0.7407
AUC: 0.856292002688l721
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.74      0.84       960
           1       0.17      0.81      0.27        62

    accuracy                           0.74      1022
   macro avg       0.57      0.77      0.56      1022
weighted avg       0.93      0.74      0.81      1022


SVM (RBF) Classifier:
Accuracy: 0.7583
AUC: 0.7935315860215054
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.76      0.86       960
           1       0.17      0.74      0.27        62

    accuracy                           0.76      1022
   macro avg       0.57      0.75      0.56      1022
weighted avg       0.93      0.76      0.82      1022


SVM (Sigmoid) Classifier:
Accuracy: 0.6722
AUC: 0.7165658602150538
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.67      0.79       960
           1       0.12      0.69      0.20        62

    accuracy                           0.67      1022
   macro avg       0.55      0.68      0.50      1022
weighted avg       0.92      0.67      0.76      1022


XGBoost Classifier:
Accuracy: 0.8581
AUC: 0.7767641129032258
Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.95      0.89      0.92       960
           1       0.17      0.34      0.22        62

    accuracy                           0.86      1022
   macro avg       0.56      0.62      0.57      1022
weighted avg       0.91      0.86      0.88      1022


Logistic Regression Classifier:
Accuracy: 0.7476
AUC: 0.8551579301075268
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.75      0.85       960
           1       0.16      0.77      0.27        62

    accuracy                           0.75      1022
   macro avg       0.57      0.76      0.56      1022
weighted avg       0.93      0.75      0.81      1022


Summary of Classifier Results:
            Classifier  Accuracy       AUC  Precision    Recall  F1-
score
0                  KNN  0.801370  0.674563   0.902923  0.801370
0.844311
1                  MLP  0.828767  0.776361   0.909435  0.828767
0.862762
2        Random Forest  0.878669  0.766154   0.903099  0.878669
0.890085
3             AdaBoost  0.689824  0.850386   0.933954  0.689824
0.770853
4           GaussianNB  0.790607  0.833921   0.930143  0.790607
0.841767
5         SVM (Linear)  0.740705  0.856292   0.933668  0.740705
0.807698
6            SVM (RBF)  0.758317  0.793532   0.929235  0.758317
0.819719
7        SVM (Sigmoid)  0.672211  0.716566   0.919682  0.672211
0.757841
8              XGBoost  0.858121  0.776764   0.906591  0.858121
0.879614
9  Logistic Regression  0.747554  0.855158   0.931292  0.747554
0.812385
```



Model Performance Metrics
Metric
Accuracy
Precision
Recall
F1-score
Score
1.0
0.8
0.6
0.4
0.2
0.0
KNN
MLP
Random Forest
AdaBoost
GaussianNB
SVM (Linear)
SVM (RBF)
SVM (Sigmoid)
XGBoost
Logistic Regression
Classifier