In [ ]:
```
!pip install ISLP
!pip install catboost
```

```
Collecting ISLP
  Downloading ISLP-0.4.0-py3-none-any.whl.metadata (7.0 kB)
Requirement already satisfied: numpy>=1.7.1 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.26.4)
Requirement already satisfied: scipy>=0.9 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.13.1)
Requirement already satisfied: pandas>=0.20 in /usr/local/lib/python3.10/dist-packages (from ISLP) (2.2.2)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages (from ISLP) (5.3.0)
Requirement already satisfied: scikit-learn>=1.2 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.5.2)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.4.2)
Requirement already satisfied: statsmodels>=0.13 in /usr/local/lib/python3.10/dist-packages (from ISLP) (0.14.4)
Collecting lifelines (from ISLP)
  Downloading lifelines-0.30.0-py3-none-any.whl.metadata (3.2 kB)
Collecting pygam (from ISLP)
  Downloading pygam-0.9.1-py3-none-any.whl.metadata (7.1 kB)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (from ISLP) (2.5.1+cu121)
Collecting pytorch-lightning (from ISLP)
  Downloading pytorch_lightning-2.4.0-py3-none-any.whl.metadata (21 kB)
Collecting torchmetrics (from ISLP)
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Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20->ISLP) (2.
8.2)
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Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13->ISLP) (1.0.1)
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Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.10/dist-packages (from lifelines->ISLP) (3.8.0)
Requirement already satisfied: autograd>=1.5 in /usr/local/lib/python3.10/dist-packages (from lifelines->ISLP) (1.7.0)
Collecting autograd-gamma>=0.3 (from lifelines->ISLP)
  Downloading autograd-gamma-0.5.0.tar.gz (4.0 kB)
  Preparing metadata (setup.py) ... done
Collecting formulaic>=0.2.2 (from lifelines->ISLP)
  Downloading formulaic-1.0.2-py3-none-any.whl.metadata (6.8 kB)
Requirement already satisfied: progressbar2<5.0.0,>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from pygam->ISLP) (4.5.0)
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h-lightning->ISLP) (2024.10.0)
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P) (4.12.2)
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Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-packages (from torch->ISLP) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch->ISLP)
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Collecting interface-meta>=1.2.0 (from formulaic>=0.2.2->lifelines->ISLP)
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Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in /usr/local/lib/python3.10/dist-packages (from fsspec[http]>=2022.
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-lightning->ISLP) (75.1.0)
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>pygam->ISLP) (3.9.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas>=0.20->
ISLP) (1.16.0)
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Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.
0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP) (2.4.4)
Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.0a1->fs
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Requirement already satisfied: async-timeout<6.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.
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c[http]>=2022.5.0->pytorch-lightning->ISLP) (24.2.0)
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.0a1->f
sspec[http]>=2022.5.0->pytorch-lightning->ISLP) (1.5.0)
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>fsspec[http]>=2022.5.0->pytorch-lightning->ISLP) (6.1.0)
Requirement already satisfied: propcache>=0.2.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.0a1->fs
spec[http]>=2022.5.0->pytorch-lightning->ISLP) (0.2.1)
Requirement already satisfied: yarl<2.0,>=1.17.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp!=4.0.0a0,!=4.0.0a1->f
sspec[http]>=2022.5.0->pytorch-lightning->ISLP) (1.18.3)
Requirement already satisfied: idna>=2.0 in /usr/local/lib/python3.10/dist-packages (from yarl<2.0,>=1.17.0->aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP) (3.10)
Downloading ISLP-0.4.0-py3-none-any.whl (3.6 MB)
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Downloading pygam-0.9.1-py3-none-any.whl (522 kB)
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Downloading scipy-1.11.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (36.4 MB)
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Downloading pytorch_lightning-2.4.0-py3-none-any.whl (815 kB)
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Downloading torchmetrics-1.6.0-py3-none-any.whl (926 kB)
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Downloading formulaic-1.0.2-py3-none-any.whl (94 kB)
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Downloading lightning_utilities-0.11.9-py3-none-any.whl (28 kB)
Downloading interface_meta-1.3.0-py3-none-any.whl (14 kB)
Building wheels for collected packages: autograd-gamma
  Building wheel for autograd-gamma (setup.py) ... done
  Created wheel for autograd-gamma: filename=autograd_gamma-0.5.0-py3-none-any.whl size=4031 sha256=4f9e7490640d47feffb5257bb51
58ba92c129d664024a22c9b3f84708c5784dc
  Stored in directory: /root/.cache/pip/wheels/25/cc/e0/ef2969164144c899fedb22b338f6703e2b9cf46eeebf254991
Successfully built autograd-gamma
Installing collected packages: scipy, lightning-utilities, interface-meta, autograd-gamma, torchmetrics, pygam, formulaic, life
lines, pytorch-lightning, ISLP
  Attempting uninstall: scipy
    Found existing installation: scipy 1.13.1
    Uninstalling scipy-1.13.1:
      Successfully uninstalled scipy-1.13.1
Successfully installed ISLP-0.4.0 autograd-gamma-0.5.0 formulaic-1.0.2 interface-meta-1.3.0 lifelines-0.30.0 lightning-utilitie
s-0.11.9 pygam-0.9.1 pytorch-lightning-2.4.0 scipy-1.11.4 torchmetrics-1.6.0
Collecting catboost
  Downloading catboost-1.2.7-cp310-cp310-manylinux2014_x86_64.whl.metadata (1.2 kB)
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from catboost) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from catboost) (3.8.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.26.4)
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Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly->catboost) (9.0.0)
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Installing collected packages: catboost
Successfully installed catboost-1.2.7
```

In [ ]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.pyplot import subplots
import statsmodels.api as sm
from ISLP import load_data
from ISLP.models import (ModelSpec as MS,
summarize)

from ISLP import confusion_table
from ISLP.models import contrast
from sklearn.discriminant_analysis import \
(LinearDiscriminantAnalysis as LDA,
QuadraticDiscriminantAnalysis as QDA)
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from itertools import combinations

import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, f1_score, recall_score, balanced_accuracy_score,classification_report, confusion_m
from sklearn.model_selection import GridSearchCV
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.linear_model import LogisticRegression
```

In [ ]:
```
df = pd.read_csv("train.csv")
df.head(5)
```

Out[ ]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	PhysicalActivity	DietQuality	...	Memor
0	1	67	0	3	0	37.205177	0	12.215677	7.780544	6.433890	...	
1	2	65	1	0	0	35.141843	1	17.111404	6.645284	1.112379	...	
2	3	62	0	1	1	17.875103	0	13.525546	9.585769	4.266008	...	
3	4	67	0	0	1	37.503437	1	19.952014	1.953946	6.797333	...	
4	5	65	1	0	2	29.187863	1	0.533209	8.759570	6.364302	...	

5 rows × 35 columns

Exploratory Data Analysis (EDA)

In [ ]:
```
#Checking for NULL values
df.isna().sum()
```

Out[ ]:

	0
PatientID	0
Age	0
Gender	0
Ethnicity	0
EducationLevel	0
BMI	0
Smoking	0
AlcoholConsumption	0
PhysicalActivity	0
DietQuality	0
SleepQuality	0
FamilyHistoryAlzheimers	0
CardiovascularDisease	0
Diabetes	0
Depression	0
HeadInjury	0
Hypertension	0
SystolicBP	0
DiastolicBP	0
CholesterolTotal	0
CholesterolLDL	0
CholesterolHDL	0
CholesterolTriglycerides	0
MMSE	0
FunctionalAssessment	0
MemoryComplaints	0
BehavioralProblems	0
ADL	0
Confusion	0
Disorientation	0
PersonalityChanges	0
DifficultyCompletingTasks	0
Forgetfulness	0
Diagnosis	0
DoctorInCharge	0

dtype: int64

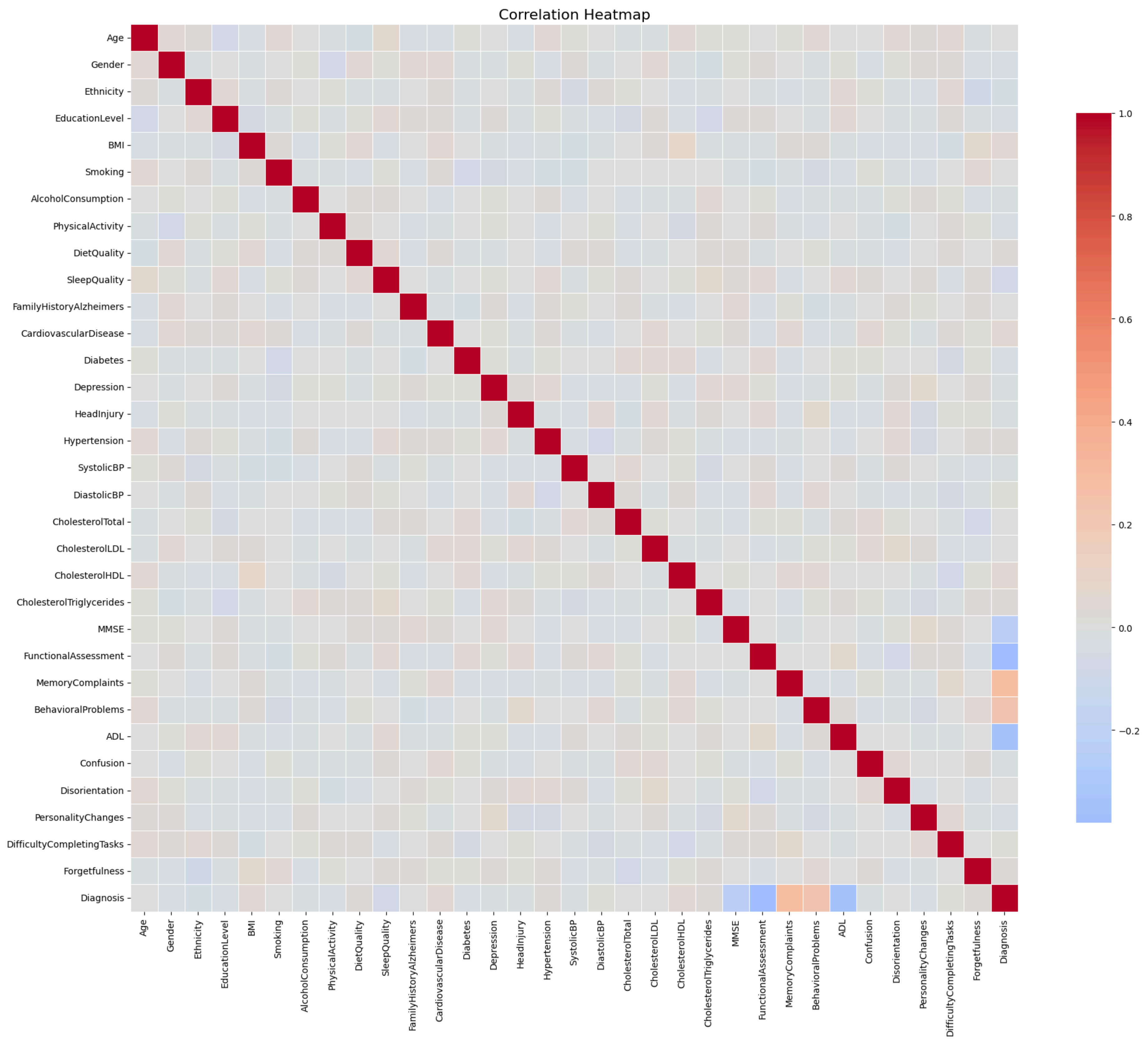
In [ ]:
```
#Checking for duplicates
duplicates = df[df[list(df.columns)].duplicated()].index
duplicates
```

Out[ ]:
```
Index([], dtype='int64')
```

The dataset got no duplicates and no null values

In [ ]:
```
def reset_df():
    # 0.8-0.2 Train-val split
    df_train, df_val = train_test_split(df, test_size=0.2, random_state=5, stratify=df['Diagnosis'])

    train_diagnosis = df_train['Diagnosis'].reset_index(drop = True)
    val_diagnosis = df_val['Diagnosis'].reset_index(drop = True)

    #Dropping Irrelevant columns
    df_train = df_train.drop(['PatientID', 'DoctorInCharge','Diagnosis'], axis=1)
    df_val = df_val.drop(['PatientID', 'DoctorInCharge','Diagnosis'], axis=1)
    #Standardizing every column except diagnosis
    scaler = StandardScaler()

    df_train = pd.DataFrame(scaler.fit_transform(df_train), columns=df_train.columns)
    df_val = pd.DataFrame(scaler.transform(df_val), columns = df_val.columns)

    #Adding diagnosis column which is not standardized
    df_train['Diagnosis'] = train_diagnosis
    df_val['Diagnosis'] = val_diagnosis
    return df_train, df_val, scaler
df_train, df_val, scaler = reset_df()
```

In [ ]:
```
#Plotting Correlation Matrix
correlation_matrix = df_train.corr()
plt.figure(figsize=(20, 16))
sns.heatmap(correlation_matrix, annot=False, cmap='coolwarm', center=0,
            square=True, linewidths=0.5, cbar_kws={"shrink": .8})
plt.title('Correlation Heatmap', fontsize=16)
plt.tight_layout()
plt.show()
```



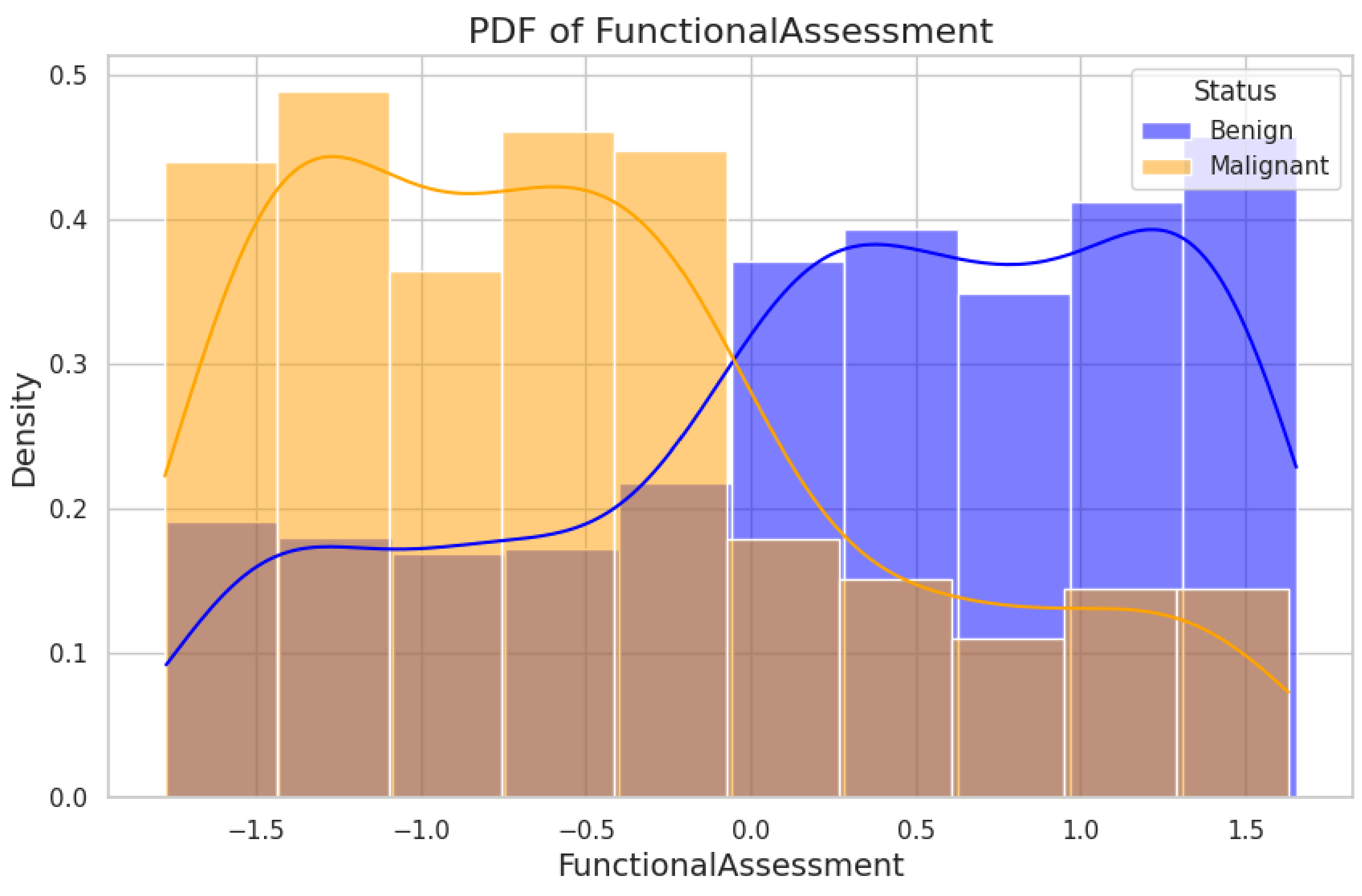
In [ ]:
```
def top_correlated_features(data, target_feature, top_n=10):
    # Identifies the top correlated features to a given target feature.

    # Calculate the correlation matrix
    correlation_matrix = data.corr()

    # Extract correlation values for the target feature
    target_correlation = correlation_matrix[target_feature].drop(labels=[target_feature])

    # Get the top N correlated features (absolute value to account for both positive and negative correlations)
    top_correlations = target_correlation.abs().sort_values(ascending=False).head(top_n)

    # Return the correlation values with original signs
    return target_correlation[top_correlations.index]
top_correlated_features(df_train,"BehavioralProblems")
```

Out[ ]:

	BehavioralProblems
Diagnosis	0.239710
HeadInjury	0.064203
PersonalityChanges	-0.060831
Forgetfulness	0.060083
Smoking	-0.058980
Age	0.054790
FamilyHistoryAlzheimers	-0.050267
CholesterolHDL	0.047882
CardiovascularDisease	-0.044209
DiastolicBP	0.041060

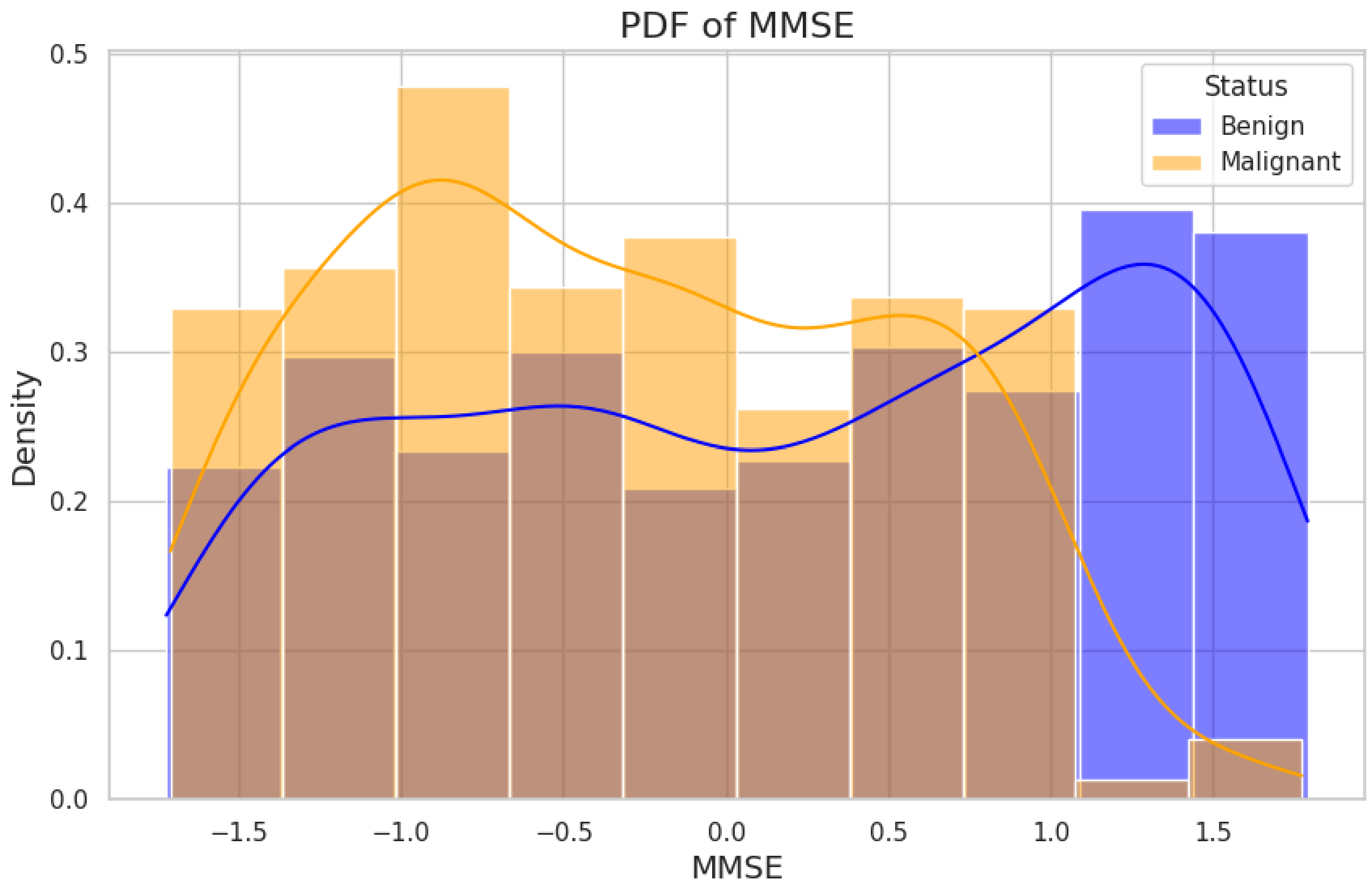
dtype: float64

In [ ]:
```python
def plot_pdf(df, col):
    #Plot two pdf: pdf of specific column given diagnosis = 0, pdf of specific column given diagnosis = 1
    sns.set(style="whitegrid")

    # Plot the PDF using Seaborn's kdeplot
    plt.figure(figsize=(10, 6))
    sns.histplot(df[df['Diagnosis'] == 0][col], kde=True, color='blue', label='Benign', stat="density", bins=10, alpha=0.5)
    sns.histplot(df[df['Diagnosis'] == 1][col], kde=True, color='orange', label='Malignant', stat="density", bins=10, alpha=0.

    plt.title(f"PDF of {col}", fontsize=16)
    plt.xlabel(f"{col}", fontsize=14)
    plt.ylabel("Density", fontsize=14)
    plt.legend(title="Status")
    plt.grid(True)

    plt.show()
plot_pdf(df_train,"FunctionalAssessment")
```



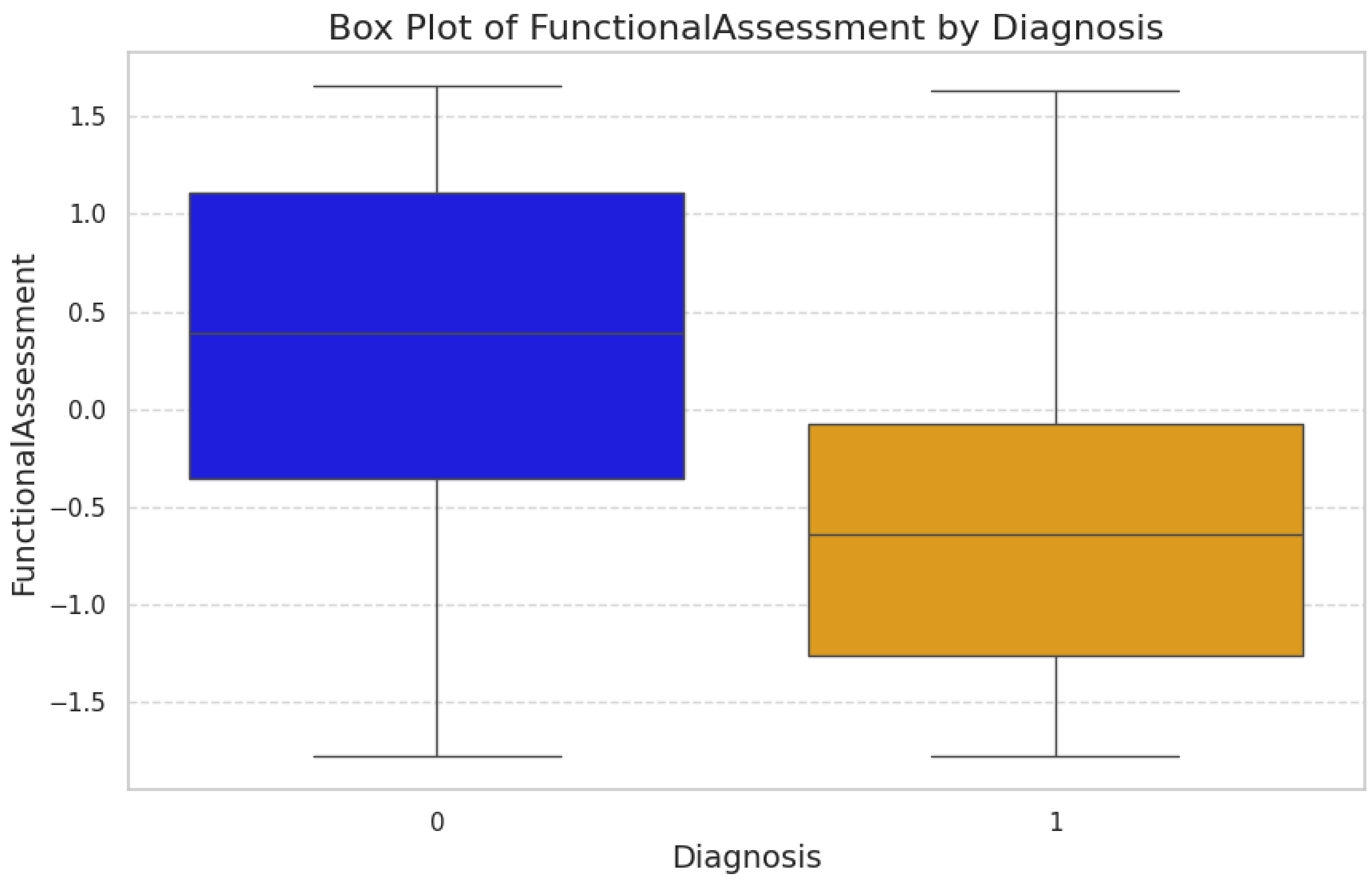
1. FunctionalAssessment > 0, tend to be Benign FunctionalAssessment < 0, tend to be Malignant
2. Graph overlaps, so additional features are needed to classify Benign/Malignant

In [ ]:
```python
plot_pdf(df_train,'MMSE')
```



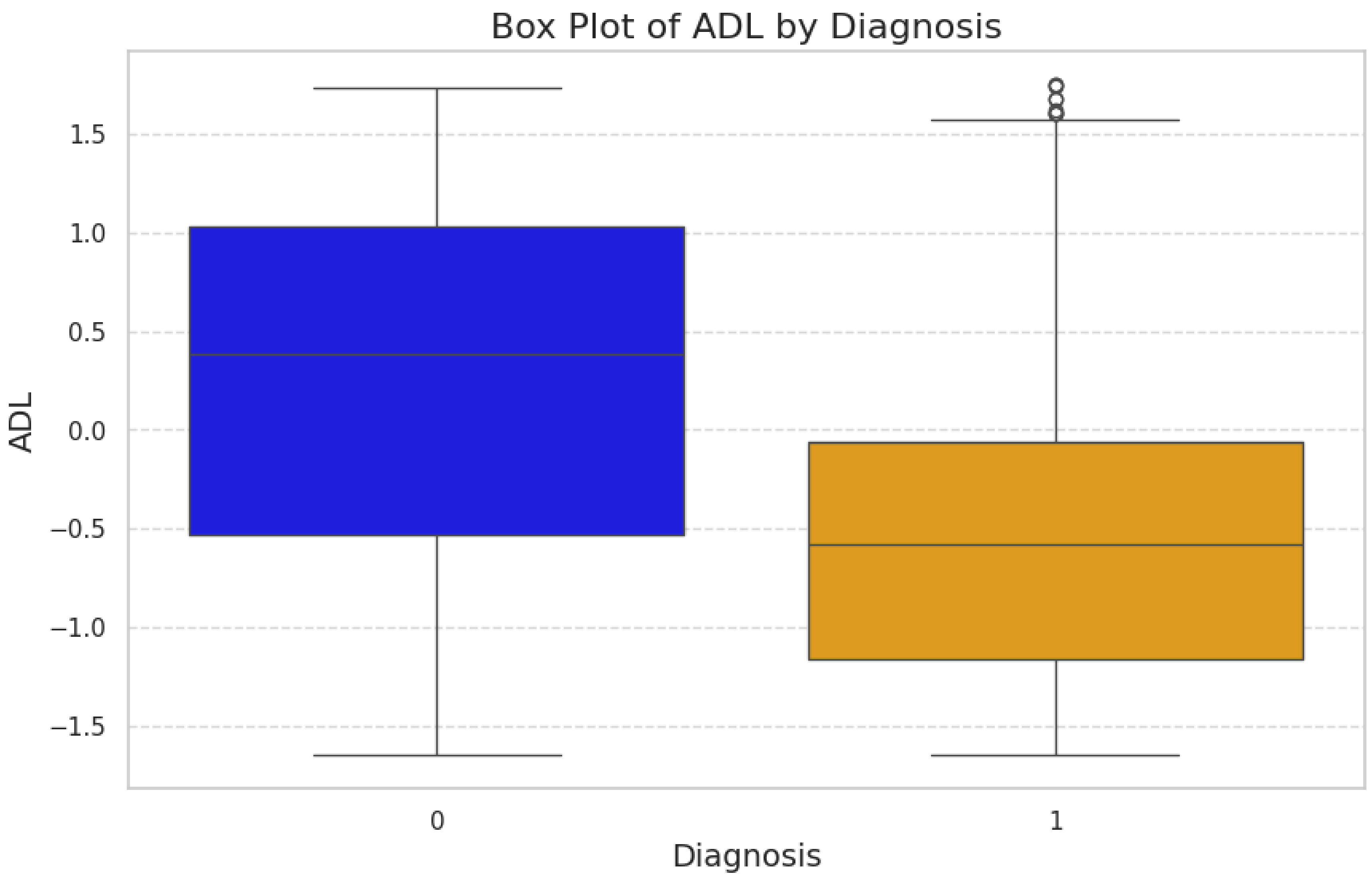
```
In [ ]: def plot_box(df,col):
            #Plotting box plot of specific column for diagnosis = 0, diagnosis = 1

            plt.figure(figsize=(10, 6))
            sns.boxplot(data=df, x='Diagnosis', y=col, palette={'0': 'blue', '1': 'orange'})

            plt.title(f'Box Plot of {col} by Diagnosis', fontsize=16)
            plt.xlabel('Diagnosis', fontsize=14)
            plt.ylabel(col, fontsize=14)

            plt.grid(axis='y', linestyle='--', alpha=0.7)
            plt.show()
        plot_box(df_train,"FunctionalAssessment")
```

```
<ipython-input-11-4e68a1b26e33>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(data=df, x='Diagnosis', y=col, palette={'0': 'blue', '1': 'orange'})
```



```
In [ ]: plot_box(df_train,"ADL")
```

```
<ipython-input-11-4e68a1b26e33>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(data=df, x='Diagnosis', y=col, palette={'0': 'blue', '1': 'orange'})
```



```
In [ ]: #Finding upper bound for group 1
        grouped = df_train.groupby('Diagnosis')['ADL']

        # For Diagnosis = 1 (orange box)
        Q1 = grouped.quantile(0.25).loc[1]
        Q3 = grouped.quantile(0.75).loc[1]
        IQR = Q3 - Q1
        upper_bound = Q3 + 1.5 * IQR

        # Print results for Diagnosis = 1
        print("For Diagnosis = 1:")
        print("Q1:", Q1)
        print("Q3:", Q3)
        print("IQR:", IQR)
        print("Upper Bound:", upper_bound)
```

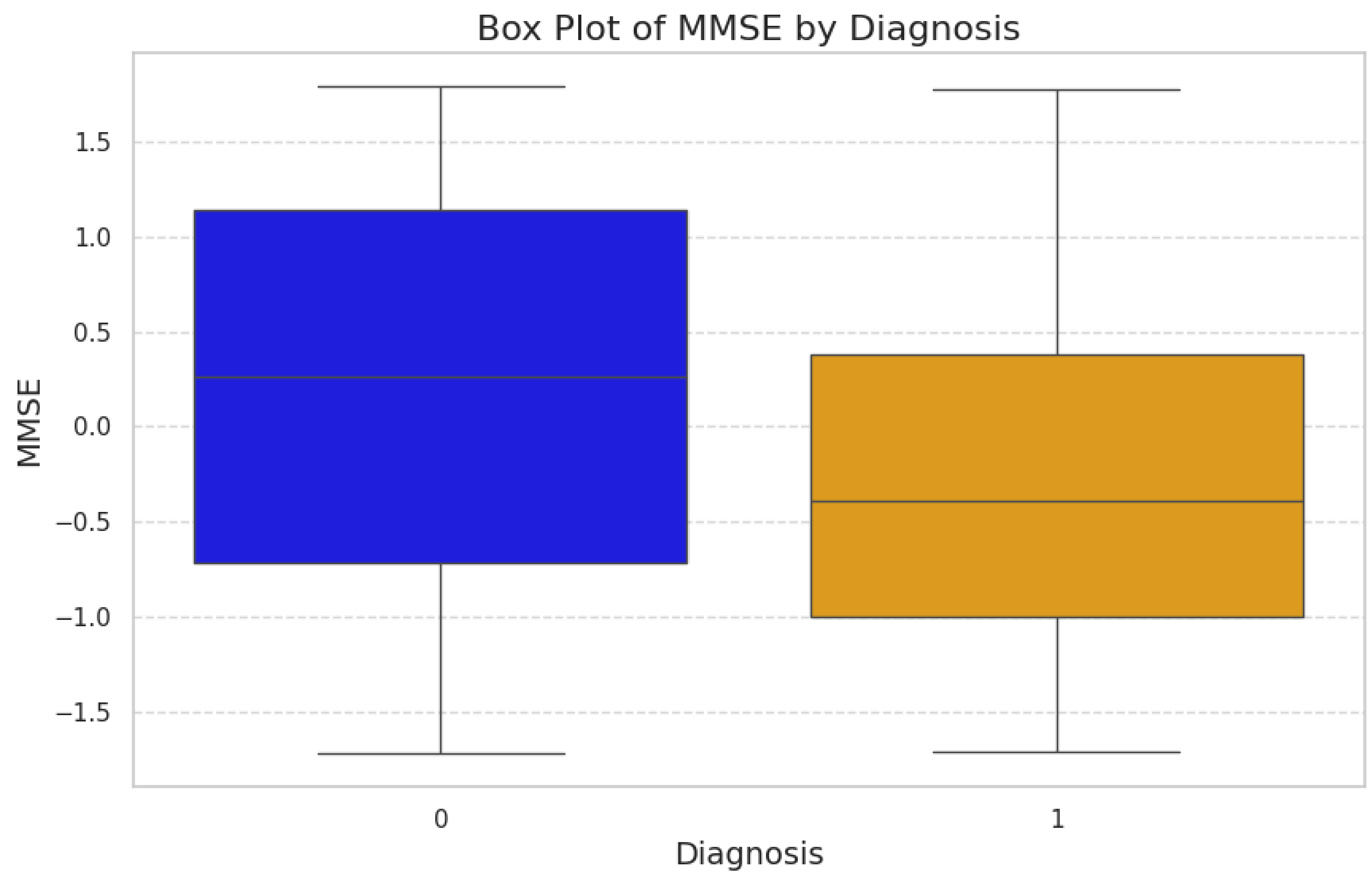
```
For Diagnosis = 1:
Q1: -1.1616764567839484
Q3: -0.059578148261666145
IQR: 1.1020983085222822
Upper Bound: 1.593569314521757
```

```
In [ ]: len(df_train[(df_train['ADL'] > upper_bound) & (df_train['Diagnosis'] == 1)])
```

```
Out[ ]: 9
```

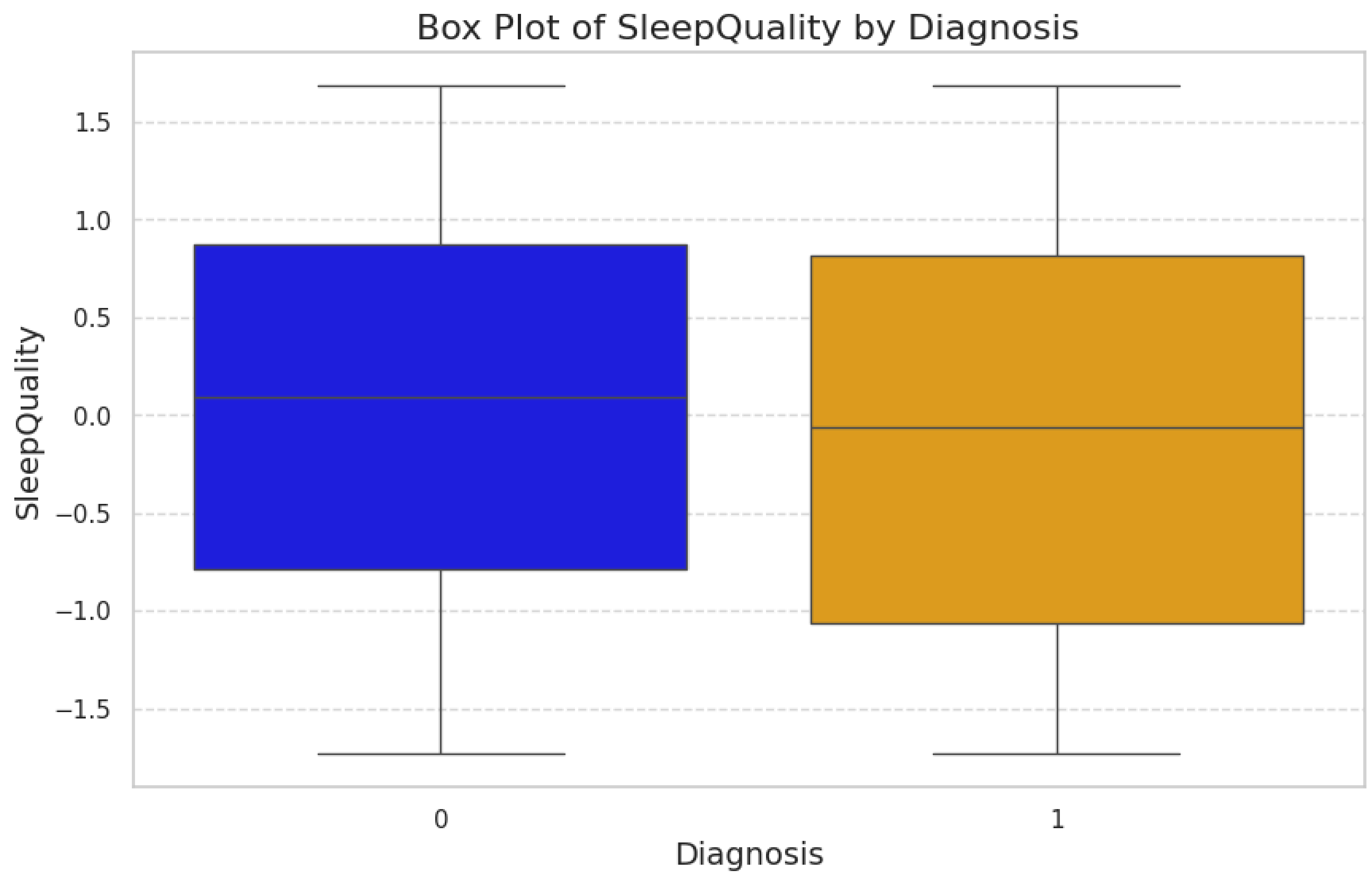
```
In [ ]: plot_box(df_train,"MMSE")
```

```
<ipython-input-11-4e68a1b26e33>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(data=df, x='Diagnosis', y=col, palette={'0': 'blue', '1': 'orange'})
```



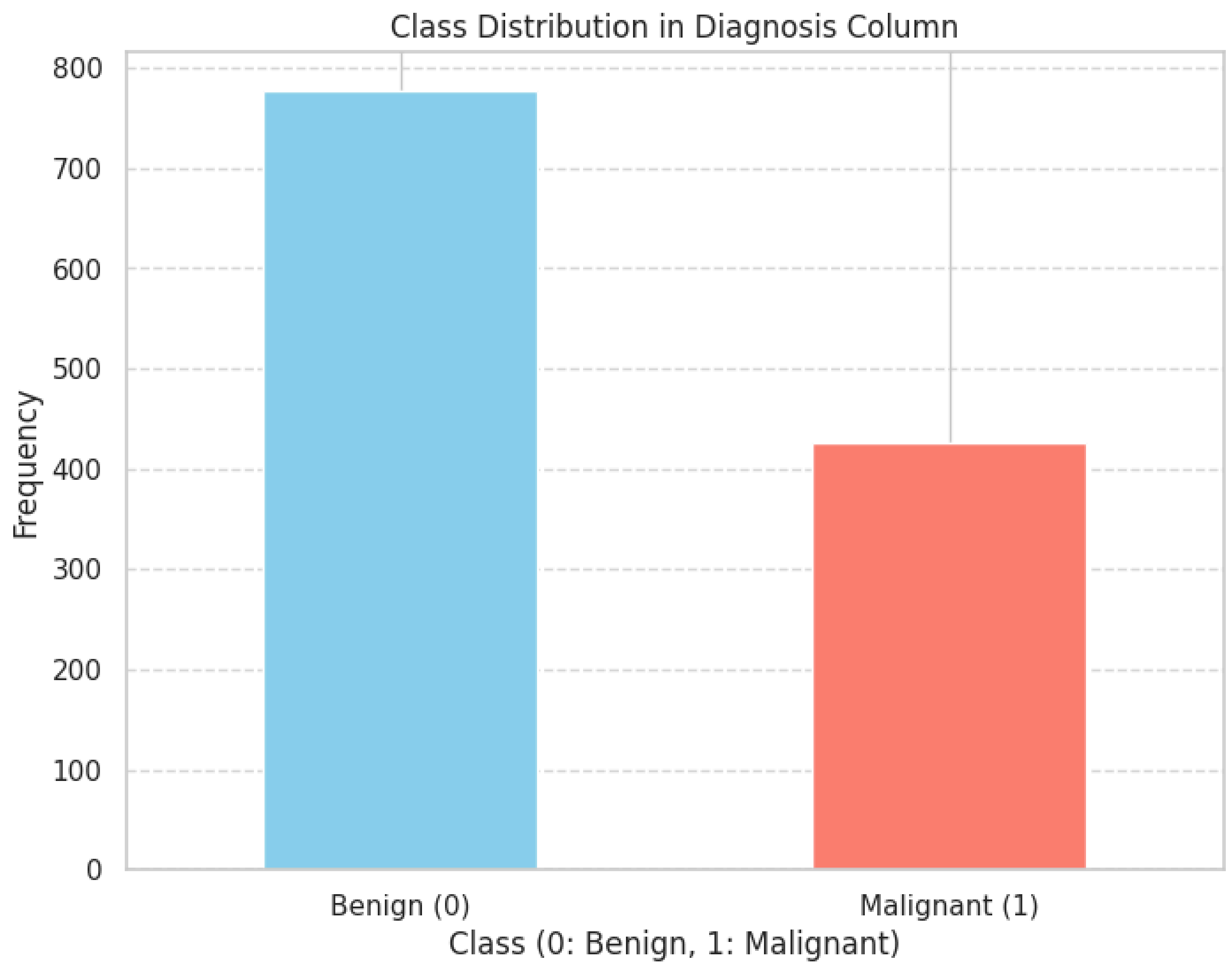
In [ ]:
```
plot_box(df_train,"SleepQuality")
```

```
<ipython-input-11-4e68a1b26e33>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(data=df, x='Diagnosis', y=col, palette={'0': 'blue', '1': 'orange'})
```



In [ ]:
```
class_counts = df_train['Diagnosis'].value_counts()

# Print the distribution
print("Class Distribution:")
print(class_counts)

# Plot the distribution
plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar', color=['skyblue', 'salmon'])
plt.title('Class Distribution in Diagnosis Column')
plt.xlabel('Class (0: Benign, 1: Malignant)')
plt.ylabel('Frequency')
plt.xticks([0, 1], ['Benign (0)', 'Malignant (1)'], rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
Class Distribution:
Diagnosis
0    777
1    426
Name: count, dtype: int64
```



Model

In [ ]:
```
def evaluate(model, X, y, class_report = True):
    y_pred = model.predict(X)
    accuracy = accuracy_score(y,y_pred)
    f1 = f1_score(y,y_pred, average='weighted')
    sensitivity = recall_score(y,y_pred,average='weighted')
    balanced_accuracy = balanced_accuracy_score(y,y_pred)
    if class_report:
        print(classification_report(y, y_pred, target_names=["Benign","Malignant"]))
    return accuracy, f1, sensitivity, balanced_accuracy
```

In [ ]:
```
def evaluate_model(model, X_train, y_train, X_val, y_val, class_report = True):
    train_accuracy, train_f1, train_sensitivity, train_balanced_accuracy = evaluate(model, X_train, y_train, class_report)
    validation_accuracy, validation_f1, validation_sensitivity, validation_balanced_accuracy = evaluate(model, X_val, y_val, c
    print(f"Training Metrics: Accuracy = {train_accuracy}, F1 score = {train_f1}, Sensitivity = {train_sensitivity}")
    print(f"Validation Metrics: Accuracy = {validation_accuracy}, F1 score = {validation_f1}, Sensitivity = {validation_sensit
```

In [ ]:
```
def prepare_X_y(X_col, resample = True):
    #prepare X, y given arbitrary training features with SMOTE resampling
    X_train = df_train[X_col]
    y_train = df_train['Diagnosis']

    X_val = df_val[X_col]
    y_val = df_val['Diagnosis']

    #Apply SMOTE resampling
    if resample == True:
        smote = SMOTE(random_state=0)
        X_train, y_train = smote.fit_resample(X_train, y_train)
    return X_train, y_train, X_val, y_val
```

Logistic Regression

In [ ]:
```
#Try using MMSE, FunctionalAssessment, MemoryComplaints, BehavioralProblems, ADL for fitting (5 most important features)
X_train, y_train, X_val, y_val = prepare_X_y(['MMSE', 'FunctionalAssessment', 'MemoryComplaints', 'BehavioralProblems', 'ADL',
lr_model = LogisticRegression(
    penalty='l2',  # L2 regularization (ridge)
    C=1.0,
    solver='liblinear',  # Good for small datasets
    random_state=42,
    max_iter=1000,
)

# Fit the model
lr_model.fit(X_train, y_train)
evaluate_model(lr_model, X_train, y_train, X_val, y_val)
```

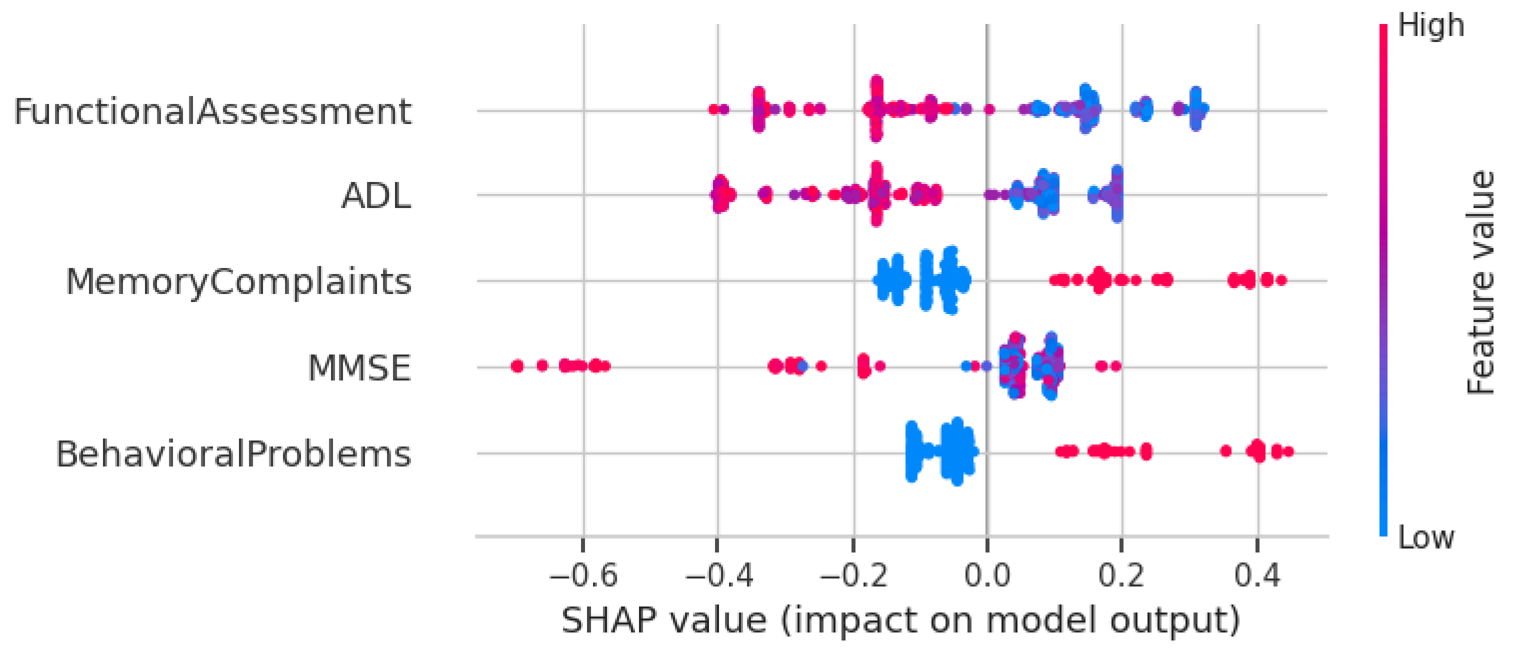
```
              precision    recall  f1-score   support

      Benign       0.84      0.82      0.83       777
   Malignant       0.82      0.84      0.83       777

    accuracy                           0.83      1554
   macro avg       0.83      0.83      0.83      1554
weighted avg       0.83      0.83      0.83      1554

              precision    recall  f1-score   support

      Benign       0.88      0.80      0.84       195
   Malignant       0.69      0.80      0.74       106

    accuracy                           0.80       301
   macro avg       0.78      0.80      0.79       301
weighted avg       0.81      0.80      0.80       301

Training Metrics: Accuracy = 0.832046332046332, F1 score = 0.8320262301382366, Sensitivity = 0.832046332046332
Validation Metrics: Accuracy = 0.8006644518272426, F1 score = 0.803641904264886, Sensitivity = 0.8006644518272426
```

Decision Tree

In [ ]:
```
#Decision Tree
clf = DecisionTreeClassifier(random_state=0, max_depth = 5, min_samples_split = 2)
clf.fit(X_train, y_train)
evaluate_model(clf, X_train, y_train, X_val, y_val)
```

```
              precision    recall  f1-score   support

      Benign       0.95      0.98      0.97       777
   Malignant       0.98      0.95      0.96       777

    accuracy                           0.96      1554
   macro avg       0.96      0.96      0.96      1554
weighted avg       0.96      0.96      0.96      1554

              precision    recall  f1-score   support

      Benign       0.96      0.92      0.94       195
   Malignant       0.87      0.93      0.90       106

    accuracy                           0.93       301
   macro avg       0.92      0.93      0.92       301
weighted avg       0.93      0.93      0.93       301

Training Metrics: Accuracy = 0.9646074646074646, F1 score = 0.9646010002174386, Sensitivity = 0.9646074646074646
Validation Metrics: Accuracy = 0.9269102990033222, F1 score = 0.927473865474596, Sensitivity = 0.9269102990033222
```

In [ ]:
```
import shap

# Initialize SHAP explainer
explainer = shap.TreeExplainer(clf)

# Get SHAP values for the entire dataset
shap_values = explainer.shap_values(X_val)

# Visualize SHAP values
shap.summary_plot(shap_values[:,:,1], X_val)  # For binary classification (class 1)
```



Random Forest

In [ ]:
```
#Random Forest using all features & Grid search
features = [col for col in df_train.columns if col != 'Diagnosis']
X_train, y_train, X_val, y_val = prepare_X_y(features)
```

In [ ]:
```
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2, 3],
    'max_features': ['log2','sqrt'],
    'bootstrap': [True]
}
```

In [ ]:
```
rf = RandomForestClassifier(random_state=42)
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='precision', verbose=1) #Accuracy
grid_search.fit(X_train, y_train)
```

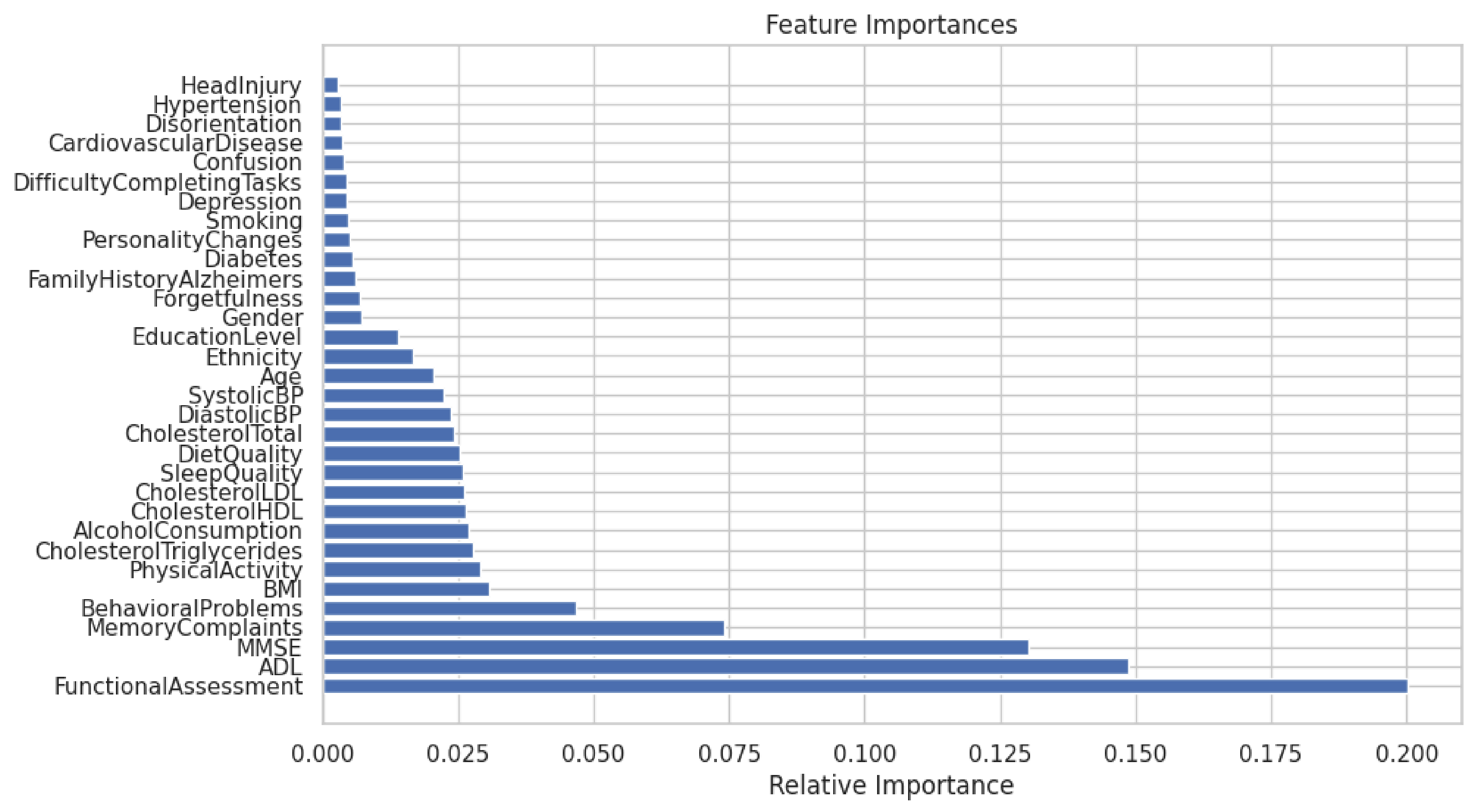
```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py:2820: RuntimeWarning: invalid value encountered in cast
  _data = np.array(data, dtype=dtype, copy=copy,
```

Out[ ]:
```
▸            GridSearchCV
▸ best_estimator_: RandomForestClassifier
      ▸ RandomForestClassifier
```

In [ ]:
```
print("Best Parameters:", grid_search.best_params_)
print("Best Accuracy:", grid_search.best_score_)
best_rf = grid_search.best_estimator_
```

```
Best Parameters: {'bootstrap': True, 'max_depth': None, 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split': 2,
'n_estimators': 100}
Best Accuracy: 0.9760440649975571
```

In [ ]:
```
#Feature importances from our Random Forest
importances = best_rf.feature_importances_

feature_names = X_train.columns

indices = np.argsort(importances)[::-1]

# Plot the feature importances
plt.figure(figsize=(10, 6))
plt.title("Feature Importances")
plt.barh(range(len(importances)), importances[indices], align="center")
plt.yticks(range(len(importances)), np.array(feature_names)[indices])
plt.xlabel("Relative Importance")
plt.show()
```



In [ ]:
```
validation_accuracy, validation_f1, validation_sensitivity, validation_balanced_accuracy = evaluate(best_rf, X_val, y_val)
print(f"Validation Metrics: Accuracy = {validation_accuracy}, F1 score = {validation_f1}, Sensitivity = {validation_sensitivit
              precision    recall  f1-score   support

      Benign       0.93      0.95      0.94       195
   Malignant       0.90      0.87      0.88       106

    accuracy                           0.92       301
   macro avg       0.92      0.91      0.91       301
weighted avg       0.92      0.92      0.92       301

Validation Metrics: Accuracy = 0.920265780730897, F1 score = 0.9199038477754095, Sensitivity = 0.920265780730897
```

XGBoost

```
In [ ]: #Fitting XGBoost on 30 most important features
        X_train, y_train, X_val, y_val = prepare_X_y(np.array(feature_names)[indices][:30])

        xgb_clf = xgb.XGBClassifier(
            objective='binary:logistic',
            random_state=42,
            n_jobs=-1,  # Use all available cores
        )

        xgb_clf.fit(X_train,y_train)
        evaluate_model(xgb_clf,X_train, y_train, X_val, y_val)
```

```
              precision    recall  f1-score   support

      Benign       1.00      1.00      1.00       777
   Malignant       1.00      1.00      1.00       777

    accuracy                           1.00      1554
   macro avg       1.00      1.00      1.00      1554
weighted avg       1.00      1.00      1.00      1554

              precision    recall  f1-score   support

      Benign       0.97      0.93      0.95       195
   Malignant       0.88      0.94      0.91       106

    accuracy                           0.93       301
   macro avg       0.92      0.94      0.93       301
weighted avg       0.94      0.93      0.93       301

Training Metrics: Accuracy = 1.0, F1 score = 1.0, Sensitivity = 1.0
Validation Metrics: Accuracy = 0.9335548172757475, F1 score = 0.9340671504314509, Sensitivity = 0.9335548172757475
```

```
In [ ]: #XGBoost with grid search
        param_grid = {
                      'n_estimators': [50, 100, 200],
                      'learning_rate': [0.01, 0.1, 1],
                      'max_depth': [3, 5, 7],
                      }
        # Create the XGBoost classifier
        xgb_clf = xgb.XGBClassifier(
            objective='binary:logistic',
            random_state=42,
            n_jobs=-1  # Use all available cores
        )

        grid_search = GridSearchCV(estimator=xgb_clf, param_grid=param_grid, cv=5, scoring='precision', verbose=1)

        grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

```
Out[ ]: ▸ GridSearchCV
        ▸ best_estimator_: XGBClassifier
              ▸ XGBClassifier
```

```
In [ ]: print("Best Parameters:", grid_search.best_params_)
        print("Best Accuracy:", grid_search.best_score_)
        best_xgb = grid_search.best_estimator_
```

```
Best Parameters: {'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 100}
Best Accuracy: 0.9735702856249894
```

```
In [ ]: validation_accuracy, validation_f1, validation_sensitivity, validation_balanced_accuracy = evaluate(best_xgb, X_val, y_val)
        print(f"Validation Metrics: Accuracy = {validation_accuracy}, F1 score = {validation_f1}, Sensitivity = {validation_sensitivit
              precision    recall  f1-score   support

      Benign       0.96      0.95      0.95       195
   Malignant       0.91      0.92      0.92       106

    accuracy                           0.94       301
   macro avg       0.93      0.94      0.93       301
weighted avg       0.94      0.94      0.94       301

Validation Metrics: Accuracy = 0.9401993355481728, F1 score = 0.9403246524815795, Sensitivity = 0.9401993355481728
```

In [ ]:
```python
#SKlearn gradient boosting + Grid search
from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier(random_state = 0)

grid_search = GridSearchCV(model, param_grid, cv = 5, scoring = 'precision')
grid_search.fit(X_train,y_train)
best_gb = grid_search.best_estimator_
```

In [ ]:
```python
print("Best Parameters:", grid_search.best_params_)
print("Best Accuracy:", grid_search.best_score_)
```

```
Best Parameters: {'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 50}
Best Accuracy: 0.9643439784819096
```

In [ ]:
```python
validation_accuracy, validation_f1, validation_sensitivity, validation_balanced_accuracy = evaluate(best_gb, X_val, y_val)
print(f"Validation Metrics: Accuracy = {validation_accuracy}, F1 score = {validation_f1}, Sensitivity = {validation_sensitivit
```

```
              precision    recall  f1-score   support

      Benign       0.96      0.93      0.94       195
   Malignant       0.88      0.92      0.90       106

    accuracy                           0.93       301
   macro avg       0.92      0.93      0.92       301
weighted avg       0.93      0.93      0.93       301

Validation Metrics: Accuracy = 0.9269102990033222, F1 score = 0.9273451072876345, Sensitivity = 0.9269102990033222
```

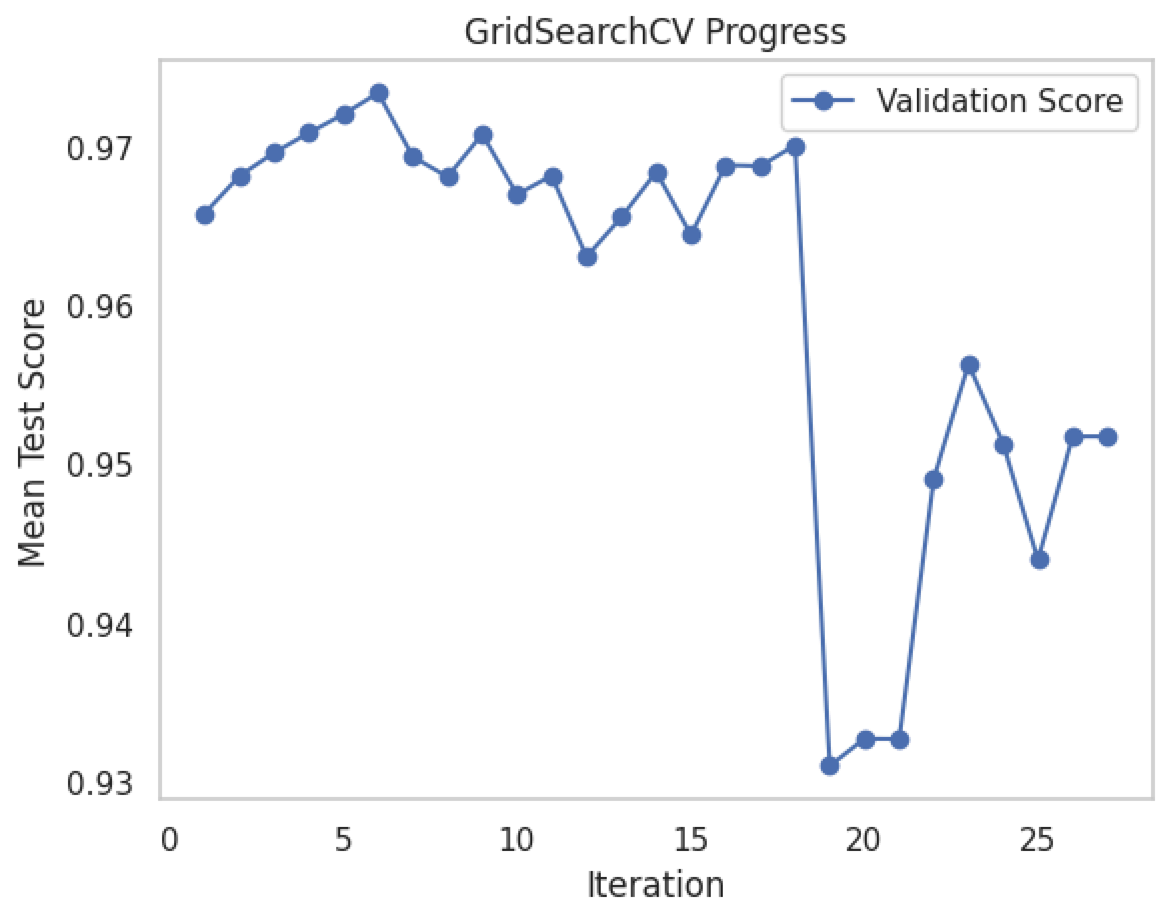
In [ ]:
```python
#CatBoost + Gridsearch
from catboost import CatBoostClassifier
cbc = CatBoostClassifier(verbose=0)
grid_search = GridSearchCV(estimator=cbc, param_grid=param_grid, cv=5, scoring='precision', verbose=1)

grid_search.fit(X_train,y_train)
best_cbc = grid_search.best_estimator_
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

Gridsearch Visualization (Edited)

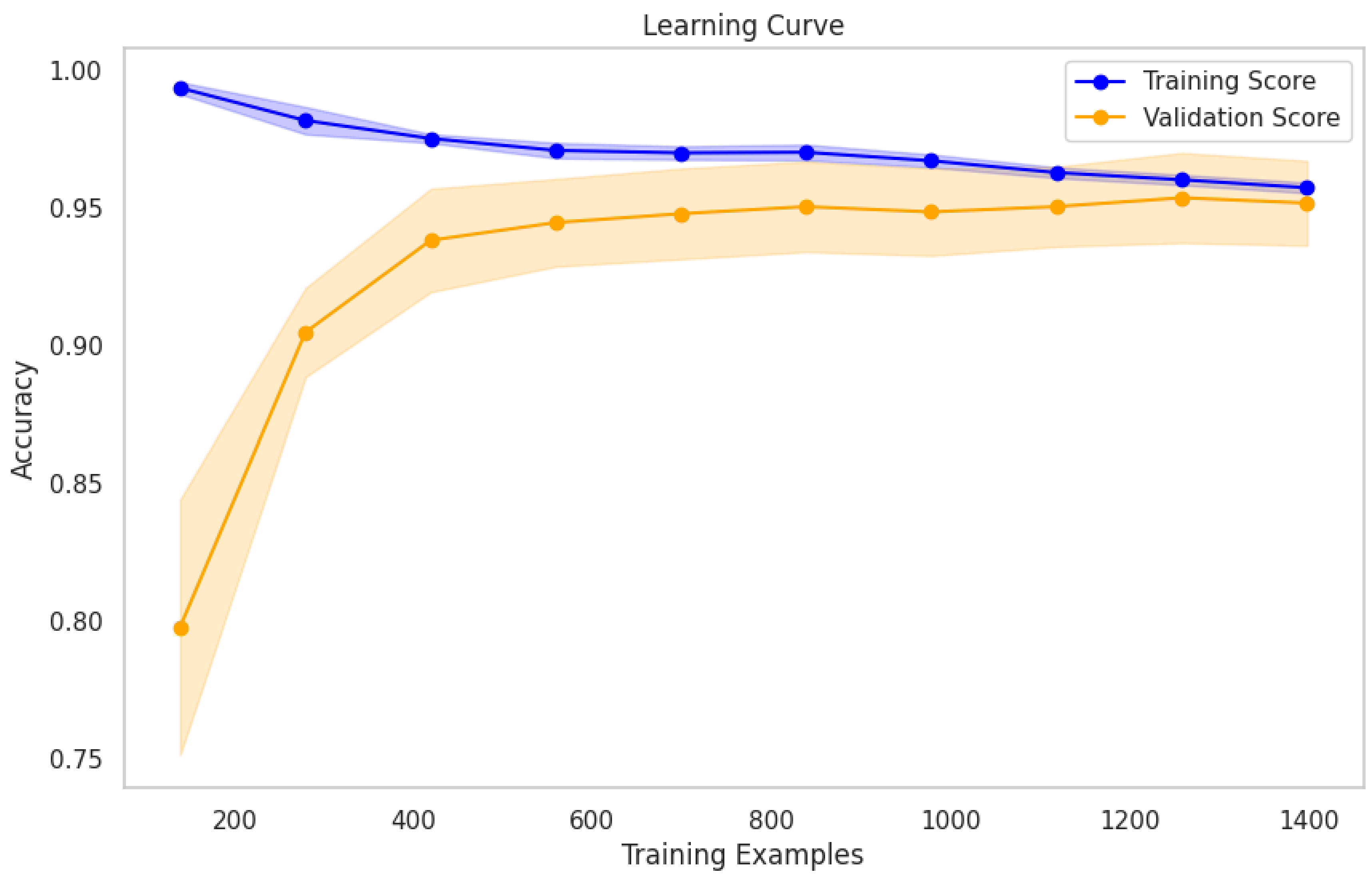
In [ ]:
```python
# taking results
results = grid_search.cv_results_

# checking result tables
results_df = pd.DataFrame(results)
print(results_df[['param_learning_rate', 'param_max_depth','param_n_estimators', 'mean_test_score']])

# compute score
scores = results['mean_test_score']
iterations = range(1, len(scores) + 1)

# line graph
plt.plot(iterations, scores, marker='o', label='Validation Score')
plt.xlabel('Iteration')
plt.ylabel('Mean Test Score')
plt.title('GridSearchCV Progress')
plt.grid()
plt.legend()
plt.show()
```

```
    param_learning_rate  param_max_depth  param_n_estimators  mean_test_score
0                  0.01                3                  50         0.965752
1                  0.01                3                 100         0.968102
2                  0.01                3                 200         0.969561
3                  0.01                5                  50         0.970811
4                  0.01                5                 100         0.971982
5                  0.01                5                 200         0.973323
6                  0.01                7                  50         0.969303
7                  0.01                7                 100         0.968049
8                  0.01                7                 200         0.970737
9                  0.10                3                  50         0.966932
10                 0.10                3                 100         0.968125
11                 0.10                3                 200         0.963040
12                 0.10                5                  50         0.965520
13                 0.10                5                 100         0.968360
14                 0.10                5                 200         0.964393
15                 0.10                7                  50         0.968784
16                 0.10                7                 100         0.968724
17                 0.10                7                 200         0.970035
18                 1.00                3                  50         0.931027
19                 1.00                3                 100         0.932732
20                 1.00                3                 200         0.932717
21                 1.00                5                  50         0.949115
22                 1.00                5                 100         0.956269
23                 1.00                5                 200         0.951239
24                 1.00                7                  50         0.943992
25                 1.00                7                 100         0.951719
26                 1.00                7                 200         0.951717
```



Learning curve (Edited)

In [ ]:
```python
from sklearn.model_selection import learning_curve
# define model
model = CatBoostClassifier(**best_cbc.get_params())

# calculating learning curve
train_sizes, train_scores, test_scores = learning_curve(
    model, X_train, y_train, cv=10, scoring='accuracy', n_jobs=-1, train_sizes=np.linspace(0.1, 1.0, 10)
)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# plot
plt.figure(figsize=(10, 6))
plt.plot(train_sizes, train_mean, 'o-', color='blue', label='Training Score')
plt.plot(train_sizes, test_mean, 'o-', color='orange', label='Validation Score')

# std area
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, alpha=0.2, color='blue')
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, alpha=0.2, color='orange')


plt.title('Learning Curve')
plt.xlabel('Training Examples')
plt.ylabel('Accuracy')
plt.legend(loc='best')
plt.grid()
plt.show()
```



In [ ]:
```
print("Best Parameters:", grid_search.best_params_)
print("Best Accuracy:", grid_search.best_score_)
```

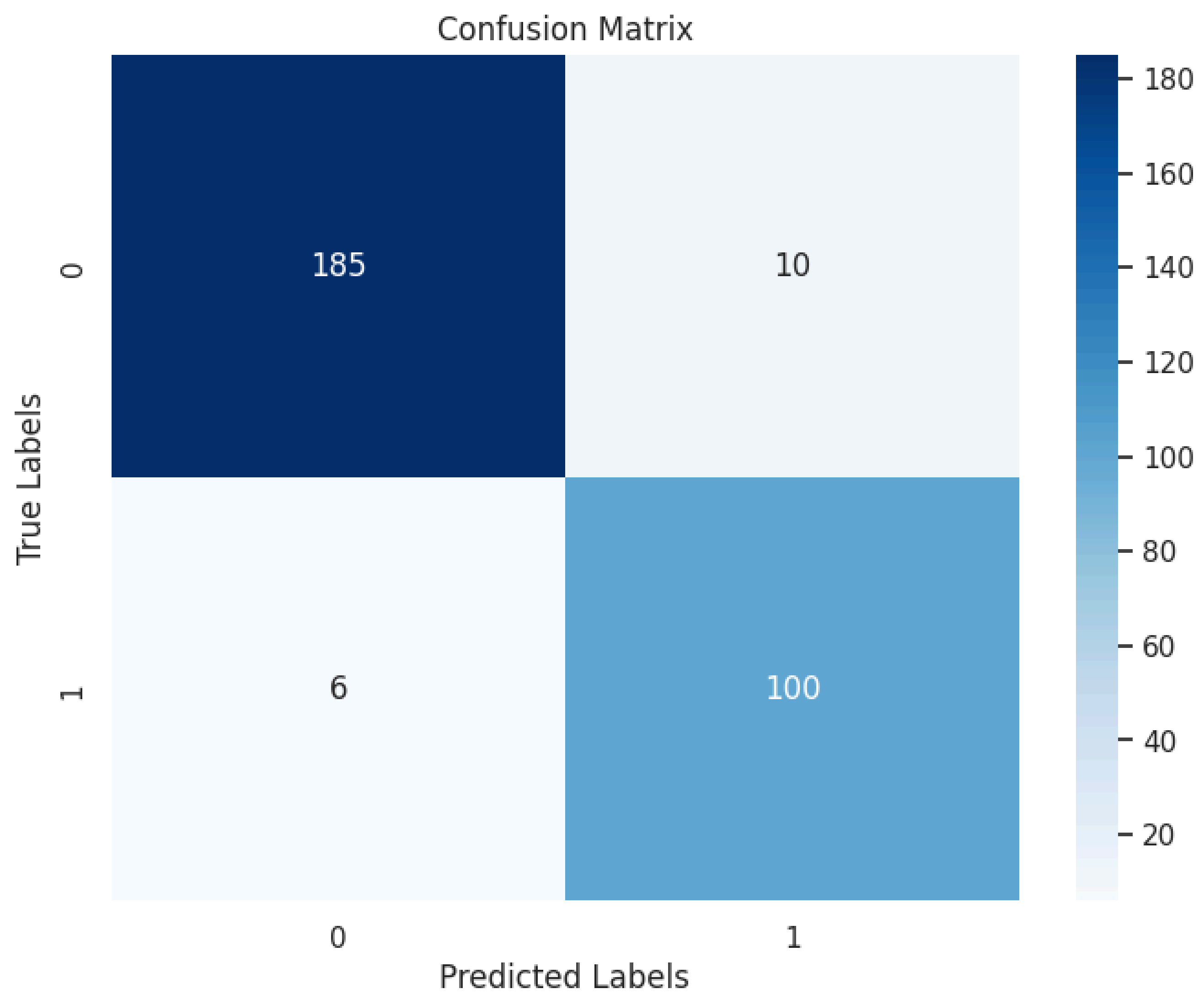
```
Best Parameters: {'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 200}
Best Accuracy: 0.9733232763028855
```

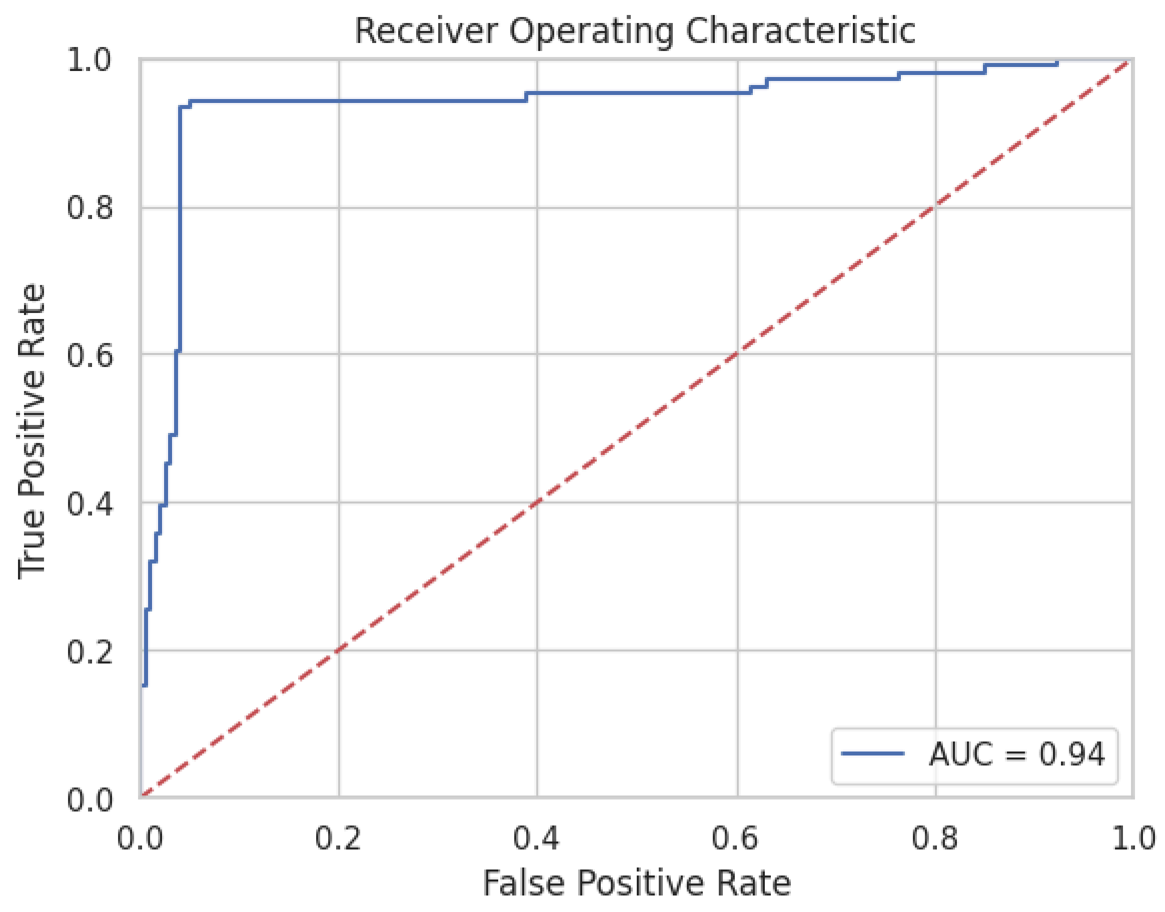
In [ ]:
```
validation_accuracy, validation_f1, validation_sensitivity, validation_balanced_accuracy = evaluate(best_cbc, X_val, y_val)
print(f"Validation Metrics: Accuracy = {validation_accuracy}, F1 score = {validation_f1}, Sensitivity = {validation_sensitivit
```

```
              precision    recall  f1-score   support

      Benign       0.97      0.95      0.96       195
   Malignant       0.91      0.94      0.93       106

    accuracy                           0.95       301
   macro avg       0.94      0.95      0.94       301
weighted avg       0.95      0.95      0.95       301

Validation Metrics: Accuracy = 0.946843853820598, F1 score = 0.9470606199127708, Sensitivity = 0.946843853820598
```

Confusion Matrix and AUC (Edited)

In [ ]:
```
#addded for confusion matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

y_true = y_val
y_pred = best_cbc.predict(X_val)

#compute
cm = confusion_matrix(y_true, y_pred)

#display
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()

#AUC
import sklearn.metrics as metrics
probs = best_cbc.predict_proba(X_val)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_true, preds)
roc_auc = metrics.auc(fpr, tpr)

#method: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```





```
In [ ]: #Refitting the model on whole data

        #Top 30 features
        features = list(X_train.columns)

        diag = df['Diagnosis'].reset_index(drop = True)

        #Drop Irrelevant Columns
        df_scaled = df.drop(['PatientID', 'DoctorInCharge','Diagnosis'], axis=1)

        #Standardizing every column except diagnosis
        df_scaled = pd.DataFrame(scaler.transform(df_scaled), columns=df_scaled.columns)

        #Adding unscaled diagnosis column back
        df_scaled['Diagnosis'] = diag

        #Get X,y
        X = df_scaled[features]
```

```
y = df_scaled['Diagnosis']
smote = SMOTE(random_state=20)

#Resample
X, y = smote.fit_resample(X, y)

#Refit the model on whole data
best_model = CatBoostClassifier(**best_cbc.get_params())
best_model.fit(X, y)
```

```
Out[ ]: <catboost.core.CatBoostClassifier at 0x7bedacefca30>
```

Ensembling

```
In [ ]: X_train, y_train, X_val, y_val = prepare_X_y(['MMSE', 'FunctionalAssessment', 'MemoryComplaints', 'BehavioralProblems', 'ADL',

#Logistic regression
lr_pred = lr_model.predict_proba(X_val)

#Decision Tree
dt_pred = clf.predict_proba(X_val)

#Random Forest
features = [col for col in df_train.columns if col != 'Diagnosis']
X_train, y_train, X_val, y_val = prepare_X_y(features)

rf_pred = best_rf.predict_proba(X_val)

#Tree Boosting
X_train, y_train, X_val, y_val = prepare_X_y(np.array(feature_names)[indices][:30])
xgb_pred = best_xgb.predict_proba(X_val)
gb_pred = best_gb.predict_proba(X_val)
cbc_pred = best_cbc.predict_proba(X_val)
```

```
In [ ]: #Weighted Averaging
y_pred_prob = (0.05*lr_pred + 0.05*dt_pred + 0.2*rf_pred + 0.2*xgb_pred + 0.2*gb_pred + 0.3*cbc_pred)
y_pred = np.argmax(y_pred_prob, axis=1)
print(f"Accuracy: {accuracy_score(y_val,y_pred)}")
print(f"Recall: {recall_score(y_val,y_pred, average='weighted')}")
```

```
Accuracy: 0.9435215946843853
Recall: 0.9435215946843853
```

Model Submission

```
In [ ]: df_bf = pd.read_csv('best_submission.csv')
df_test = pd.read_csv("test.csv")
```

```
In [ ]: def get_submission(model, features_used,scaler):
    df_test = pd.read_csv("test.csv")
    pat_ID = pd.DataFrame(df_test['PatientID'])
    df_test = df_test.drop(['PatientID', 'DoctorInCharge'], axis=1)
    df_test = pd.DataFrame(scaler.transform(df_test), columns=df_test.columns)

    X_t = df_test[features_used]
    y_test_pred = model.predict(X_t)
    pat_ID['Diagnosis'] = y_test_pred
    pat_ID.to_csv('submission.csv', index=False)

    accuracy, f1, sensitivity, _ = evaluate(model, X_t, df_bf['Diagnosis'])
    print(f"Comparing best result: Accuracy = {accuracy}, F1 score = {f1}, Sensitivity = {sensitivity}")

    print("Submission File Downloaded")
```

```
In [ ]: get_submission(best_model, list(X_train.columns), scaler)
```

```
              precision    recall  f1-score   support

      Benign       1.00      1.00      1.00       426
   Malignant       1.00      1.00      1.00       219

    accuracy                           1.00       645
   macro avg       1.00      1.00      1.00       645
weighted avg       1.00      1.00      1.00       645

Comparing best result: Accuracy = 1.0, F1 score = 1.0, Sensitivity = 1.0
Submission File Downloaded
```

```
In [ ]: %%shell
jupyter nbconvert --to html /content/Colab_downladed_file_name.ipynb
```