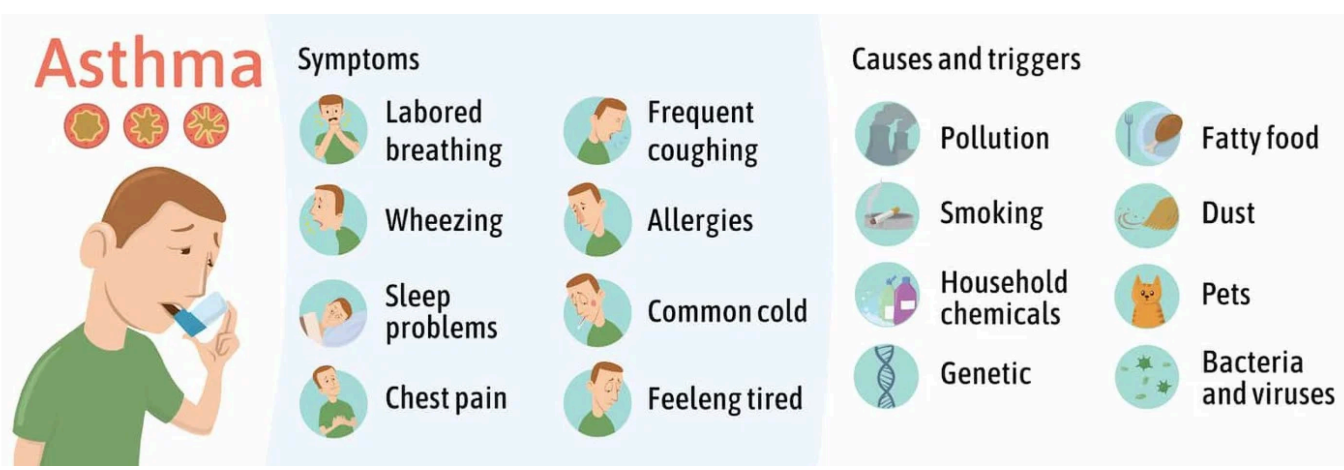
```
# IMPORTANT: SOME KAGGLE DATA SOURCES ARE PRIVATE
# RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES.
import kagglehub
kagglehub.login()
```

```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

bikrom_asthma_disease_path = kagglehub.dataset_download('bikrom/asthma-disease')

print('Data source import complete.')
```

```
# Data Manupulation
import numpy as np
import pandas as pd

# E D A & Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning Algorithms
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb

# Preprocessing
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import KMeansSMOTE
from imblearn.over_sampling import ADASYN
from tqdm import tqdm

# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')

# Set visualization style
sns.set_style("dark")
```



UpLoad Dataset From Kaggle

```
df = pd.read_csv('/kaggle/input/asthma-disease/asthma_disease_data.csv')
```

Exploratory Data Analysis

```
df.columns
```

```
Index(['PatientID', 'Age', 'Gender', 'Ethnicity', 'EducationLevel', 'BMI',
       'Smoking', 'PhysicalActivity', 'DietQuality', 'SleepQuality',
       'PollutionExposure', 'PollenExposure', 'DustExposure', 'PetAllergy',
       'FamilyHistoryAsthma', 'HistoryOfAllergies', 'Eczema', 'HayFever',
       'GastroesophagealReflux', 'LungFunctionFEV1', 'LungFunctionFVC',
       'Wheezing', 'ShortnessOfBreath', 'ChestTightness', 'Coughing',
       'NighttimeSymptoms', 'ExerciseInduced', 'Diagnosis', 'DoctorInCharge'],
      dtype='object')
```

```
df.head(7)
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQuality	...	LungFunctionF
0	5034	63	0	1	0	15.848744	0	0.894448	5.488696	8.701003	...	1.369
1	5035	26	1	2	2	22.757042	0	5.897329	6.341014	5.153966	...	2.197
2	5036	57	0	2	1	18.395396	0	6.739367	9.196237	6.840647	...	1.698
3	5037	40	1	2	1	38.515278	0	1.404503	5.826532	4.253036	...	3.032
4	5038	61	0	0	3	19.283802	0	4.604493	3.127048	9.625799	...	3.470
5	5039	21	0	2	0	21.812975	0	0.470044	1.759118	9.549262	...	2.328
6	5040	45	1	1	1	30.245954	1	9.371784	7.030507	5.746128	...	2.995

7 rows × 29 columns

```
df.tail(7)
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQuality	...	LungFuncti
2385	7419	19	1	1	2	37.913891	0	5.595540	3.120986	4.122047	...	3.
2386	7420	5	0	0	1	32.940790	0	8.705633	2.110108	9.261652	...	2.
2387	7421	43	1	0	2	29.059613	0	3.019854	6.119637	8.300960	...	3.
2388	7422	18	1	0	1	20.740850	0	5.805180	4.386992	7.731192	...	1.
2389	7423	54	0	3	2	37.079560	0	4.735169	8.214064	7.483521	...	1.
2390	7424	46	1	0	2	23.444712	0	9.672637	7.362861	6.717272	...	3.
2391	7425	26	1	0	0	28.123021	1	1.613138	7.412878	8.512253	...	2.

7 rows × 29 columns

```
df.shape
```

```
(2392, 29)
```

```
df.dtypes
```

```
PatientID                   int64
Age                         int64
Gender                      int64
Ethnicity                   int64
EducationLevel              int64
BMI                       float64
Smoking                     int64
PhysicalActivity          float64
DietQuality               float64
SleepQuality              float64
```

```
PollutionExposure         float64
PollenExposure            float64
DustExposure              float64
PetAllergy                  int64
FamilyHistoryAsthma         int64
HistoryOfAllergies          int64
Eczema                      int64
HayFever                    int64
GastroesophagealReflux      int64
LungFunctionFEV1          float64
LungFunctionFVC           float64
Wheezing                    int64
ShortnessOfBreath           int64
ChestTightness              int64
Coughing                    int64
NighttimeSymptoms           int64
ExerciseInduced             int64
Diagnosis                   int64
DoctorInCharge             object
dtype: object
```

```
df.isnull().sum()
```

```
PatientID                 0
Age                       0
Gender                    0
Ethnicity                 0
EducationLevel            0
BMI                       0
Smoking                   0
PhysicalActivity          0
DietQuality               0
SleepQuality              0
PollutionExposure         0
PollenExposure            0
DustExposure              0
PetAllergy                0
FamilyHistoryAsthma       0
HistoryOfAllergies        0
Eczema                    0
HayFever                  0
GastroesophagealReflux    0
LungFunctionFEV1          0
LungFunctionFVC           0
Wheezing                  0
ShortnessOfBreath         0
ChestTightness            0
Coughing                  0
NighttimeSymptoms         0
ExerciseInduced           0
Diagnosis                 0
DoctorInCharge            0
dtype: int64
```

```
df.describe()
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQu
count	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	2392.0
mean	6229.500000	42.137960	0.493311	0.669732	1.307274	27.244877	0.141722	5.051786	5.022867	7.0
std	690.655244	21.606655	0.500060	0.986120	0.898242	7.201628	0.348838	2.903574	2.909980	1.7
min	5034.000000	5.000000	0.000000	0.000000	0.000000	15.031803	0.000000	0.001740	0.003031	4.0
25%	5631.750000	23.000000	0.000000	0.000000	1.000000	20.968313	0.000000	2.578333	2.432043	5.4
50%	6229.500000	42.000000	0.000000	0.000000	1.000000	27.052202	0.000000	5.016881	5.115383	6.9
75%	6827.250000	61.000000	1.000000	1.000000	2.000000	33.555903	0.000000	7.540234	7.544216	8.5
max	7425.000000	79.000000	1.000000	3.000000	3.000000	39.985611	1.000000	9.995809	9.999904	9.9

8 rows × 28 columns

```
# Drop the 'PatientID' because of its unpredictable dataset values.

df.drop("PatientID", axis = 1 , inplace = True)
```

```
data.info()
```

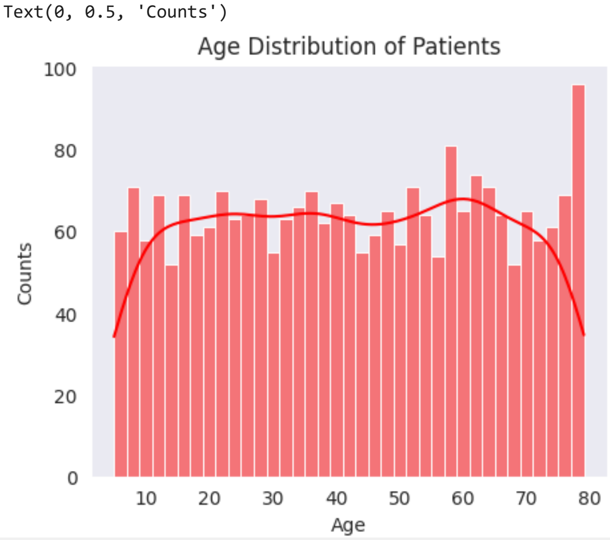
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 29 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   PatientID              2392 non-null   int64  
 1   Age                    2392 non-null   int64  
 2   Gender                 2392 non-null   int64  
 3   Ethnicity              2392 non-null   int64  
 4   EducationLevel         2392 non-null   int64  
 5   BMI                    2392 non-null   float64
 6   Smoking                2392 non-null   int64  
 7   PhysicalActivity       2392 non-null   float64
 8   DietQuality            2392 non-null   float64
 9   SleepQuality           2392 non-null   float64
 10  PollutionExposure      2392 non-null   float64
 11  PollenExposure         2392 non-null   float64
 12  DustExposure           2392 non-null   float64
 13  PetAllergy             2392 non-null   int64  
 14  FamilyHistoryAsthma    2392 non-null   int64  
 15  HistoryOfAllergies     2392 non-null   int64  
 16  Eczema                 2392 non-null   int64  
 17  HayFever               2392 non-null   int64  
 18  GastroesophagealReflux 2392 non-null   int64  
 19  LungFunctionFEV1       2392 non-null   float64
 20  LungFunctionFVC        2392 non-null   float64
 21  Wheezing               2392 non-null   int64  
 22  ShortnessOfBreath      2392 non-null   int64  
 23  ChestTightness         2392 non-null   int64  
 24  Coughing               2392 non-null   int64  
 25  NighttimeSymptoms      2392 non-null   int64  
 26  ExerciseInduced        2392 non-null   int64  
 27  Diagnosis              2392 non-null   int64  
 28  DoctorInCharge         2392 non-null   object 
dtypes: float64(9), int64(19), object(1)
memory usage: 542.1+ KB
```

Visualization Part Started From Here

Age Classification Using Seaborn Histplot

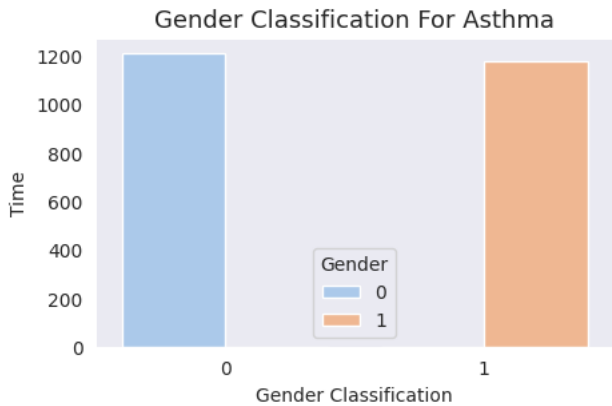
```
plt.figure(figsize=(5,4))
sns.histplot(df["Age"],bins = 37, kde =True,color = 'r')
plt.title("Age Distribution of Patients" , fontsize = 12)
plt.xlabel('Age')
plt.ylabel('Counts')
#plt.show()
```

```
Text(0, 0.5, 'Counts')
```



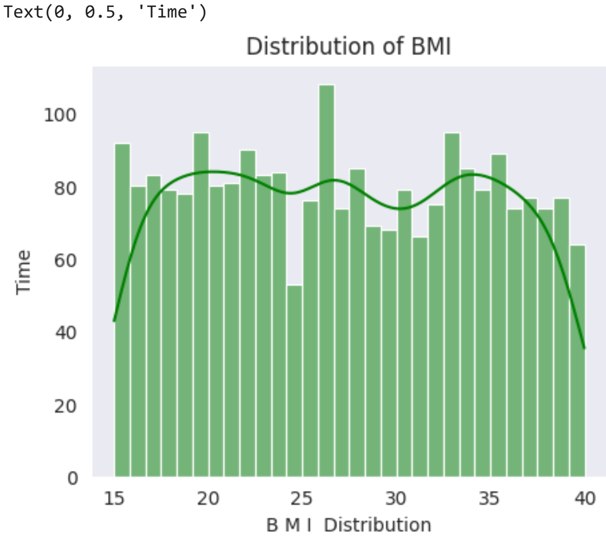
Gender Classification Using Seaborn Countplot

```
plt.figure(figsize=(5,3))
sns.countplot(x='Gender',data=df,palette ="pastel",hue="Gender")
plt.title("Gender Classification For Asthma",fontsize = 13)
plt.xlabel("Gender Classification",fontsize = 10)
plt.ylabel("Time",fontsize = 10)
plt.show()
```



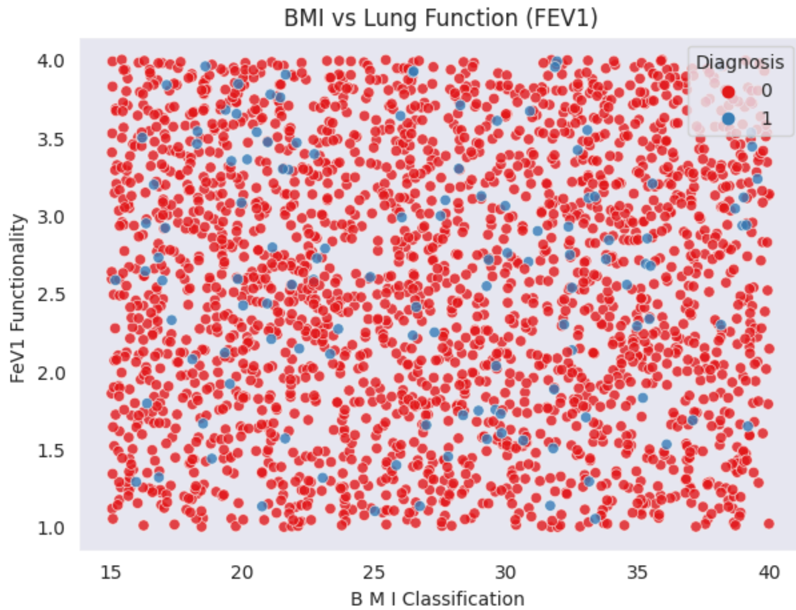

```
plt.figure(figsize=(5,4))
sns.histplot(df['BMI'], bins=30, kde=True, color='g')
plt.title('Distribution of BMI')
plt.xlabel('B M I  Distribution')
plt.ylabel('Time')
#plt.show()
```

```
Text(0, 0.5, 'Time')
```



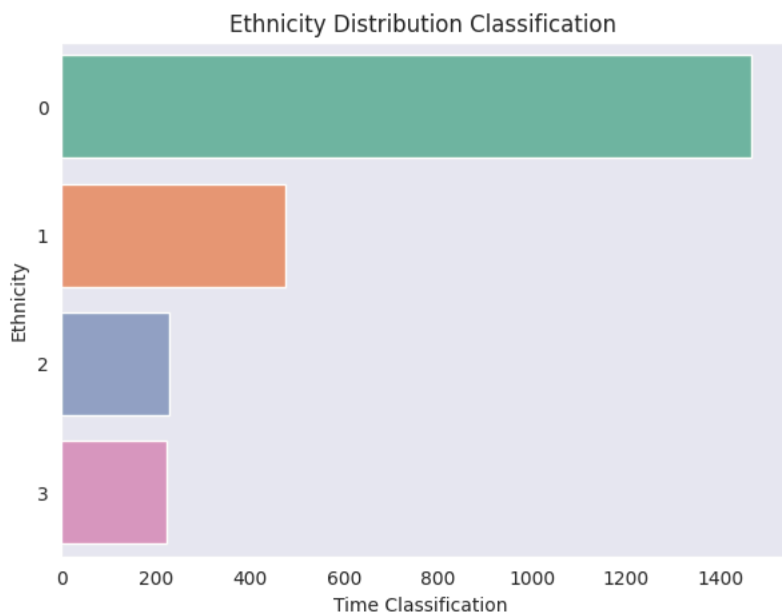
Relationship in BMI and Lung Function (feV1)

```
plt.figure(figsize=(7,5))
sns.scatterplot(x='BMI', y='LungFunctionFEV1', data=df, hue='Diagnosis', palette='Set1', alpha=0.8)
plt.title('BMI vs Lung Function (FEV1)')
plt.xlabel('B M I Classification ')
plt.ylabel('FeV1 Functionality ')
plt.show()
```



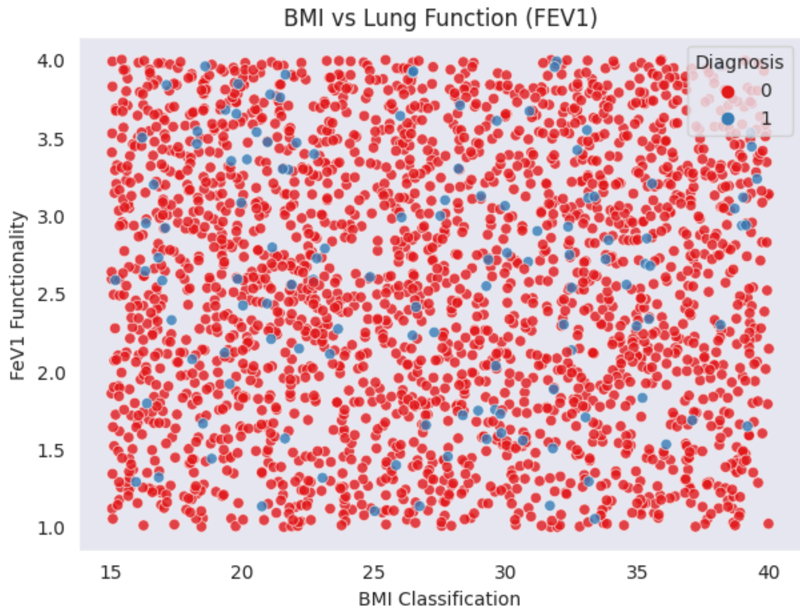
Ethnicity Distribution Classification Using Seaborn

```
plt.figure(figsize=(7,5))
sns.countplot(y='Ethnicity', data=df, palette='Set2', order=df['Ethnicity'].value_counts().index)
plt.title('Ethnicity Distribution Classification')
plt.xlabel('Time Classification ')
plt.ylabel('Ethnicity')
plt.show()
```



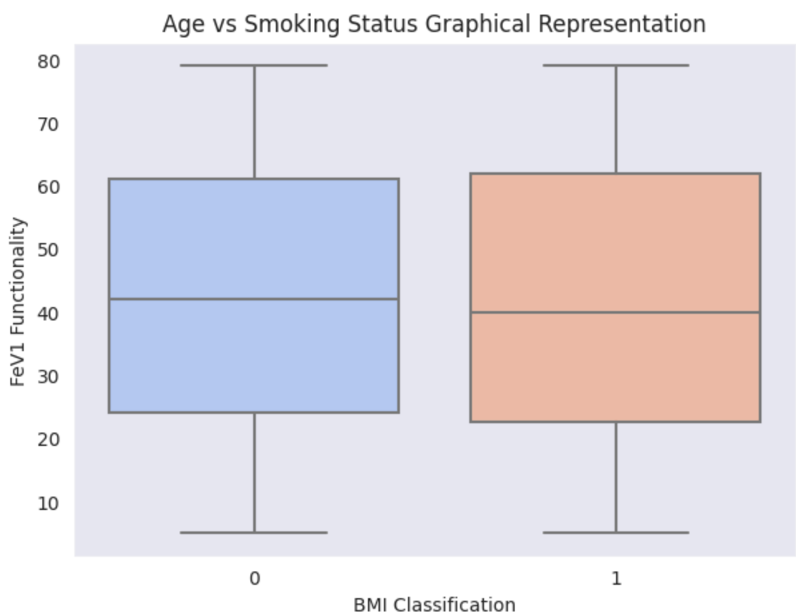
ScatterPlot for Correlation in BMI and Lung Funcanatily(FeV1)

```
plt.figure(figsize=(7,5))
sns.scatterplot(x='BMI', y='LungFunctionFEV1', data=df, hue='Diagnosis', palette='Set1', alpha=0.8)
plt.title('BMI vs Lung Function (FEV1)')
plt.xlabel('BMI Classification')
plt.ylabel('FeV1 Functionality')
plt.show()
```

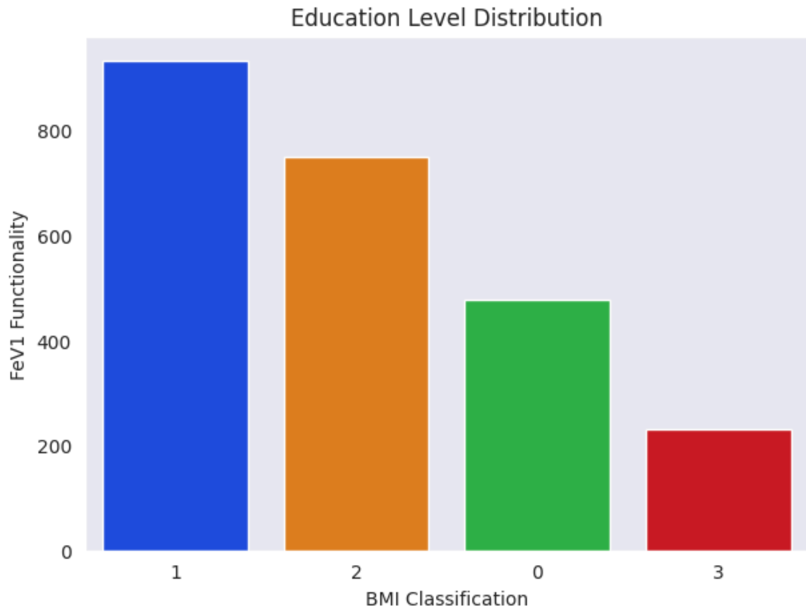


Box-Ploting for BMI and Lung Funcanatily(FeV1)

```
plt.figure(figsize=(7,5))
sns.boxplot(x='Smoking', y='Age', data=df, palette='coolwarm')
plt.title('Age vs Smoking Status Graphical Representation')
plt.xlabel('BMI Classification')
plt.ylabel('FeV1 Functionality')
plt.show()
```



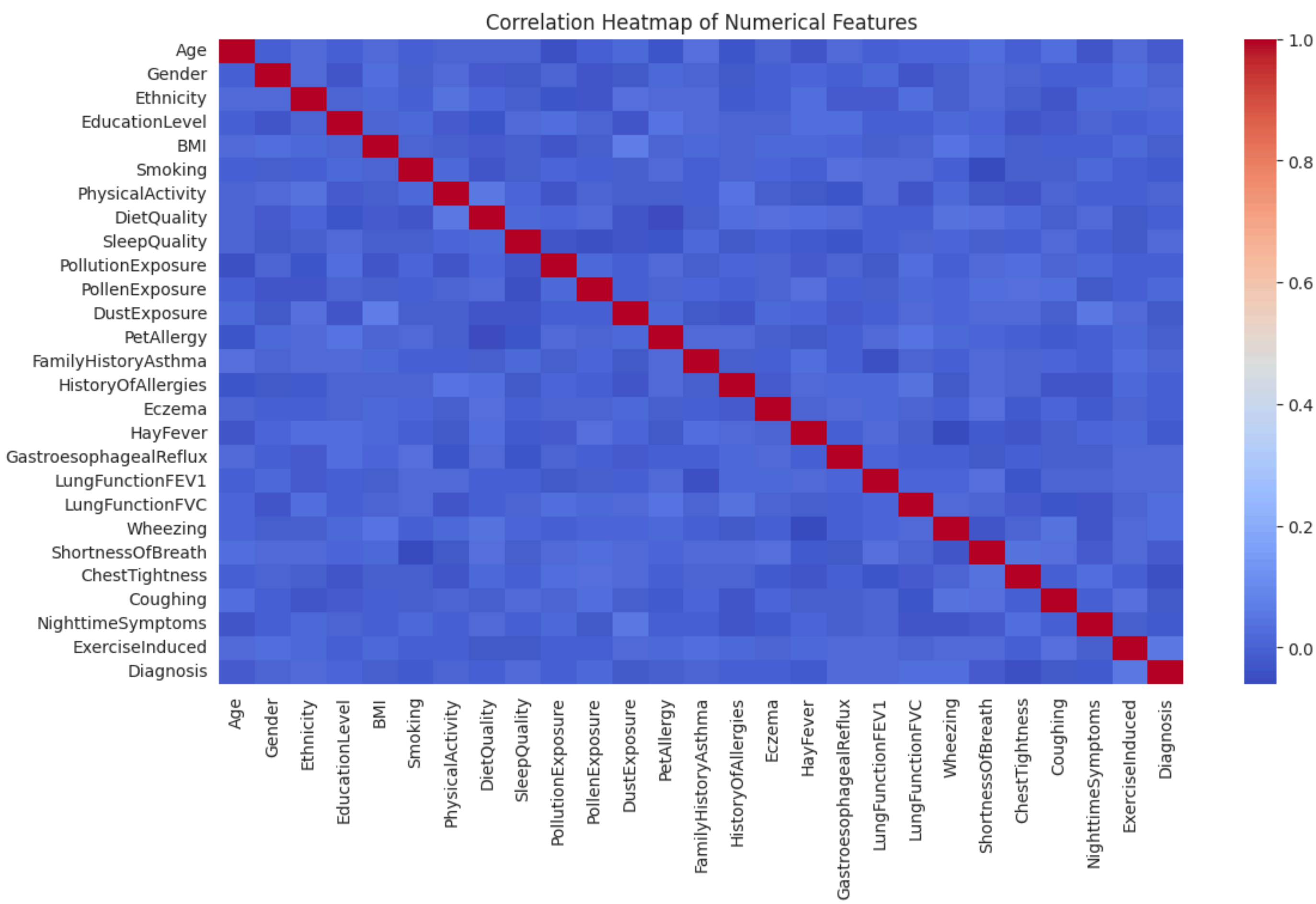

```
plt.figure(figsize=(7,5))
sns.countplot(x='EducationLevel', data=df, palette='bright', order=df['EducationLevel'].value_counts().index)
plt.title('Education Level Distribution')
plt.xlabel('BMI Classification')
plt.ylabel('FeV1 Functionality')
plt.show()
```



Conduct Correalation Heatmapping of Numarical Values using Seaborn

```
plt.figure(figsize=(13,7))
numerical_features = df.select_dtypes(exclude='object').columns
sns.heatmap(df[numerical_features].corr(), cmap='coolwarm')
plt.title('Correlation Heatmap of Numerical Features')
```

```
Text(0.5, 1.0, 'Correlation Heatmap of Numerical Features')
```



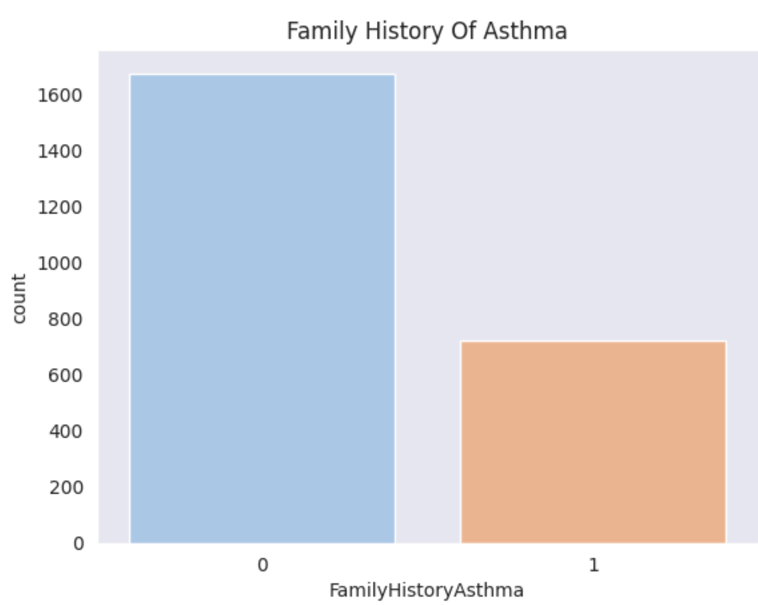
Graphical Representaion of heatmapping of numarical values

Countploting For Feamily Asthma History

```
# import pandas as pd
# import matplotlib.pyplot as plt
# import seaborn as sns

# # Sample data (replace this with your actual DataFrame)
# # data = pd.read_csv('your_data.csv')  # Uncomment this line to load your data
# df = pd.DataFrame({
#     'A': [1, 2, 3, 4, 5],
#     'B': [5, 4, 3, 2, 1],
#     'C': [1, 3, 2, 4, 5],
#     'D': [2, 3, 5, 1, 4]
# })

# plt.figure(figsize=(7, 5))

# # Select numerical features
# numerical_features = df.select_dtypes(exclude='object').columns

# # Create a correlation heatmap
# heatmap = sns.heatmap(df[numerical_features].corr(), annot=True, cmap='coolwarm', cbar=True)

# # Rotate y-axis labels to vertical
# heatmap.set_yticklabels(heatmap.get_yticklabels(), rotation=90, horizontalalignment='center')

# # Set title
# plt.title('Correlation Heatmap of Numerical Features')

# # Show the plot
# plt.show()
```

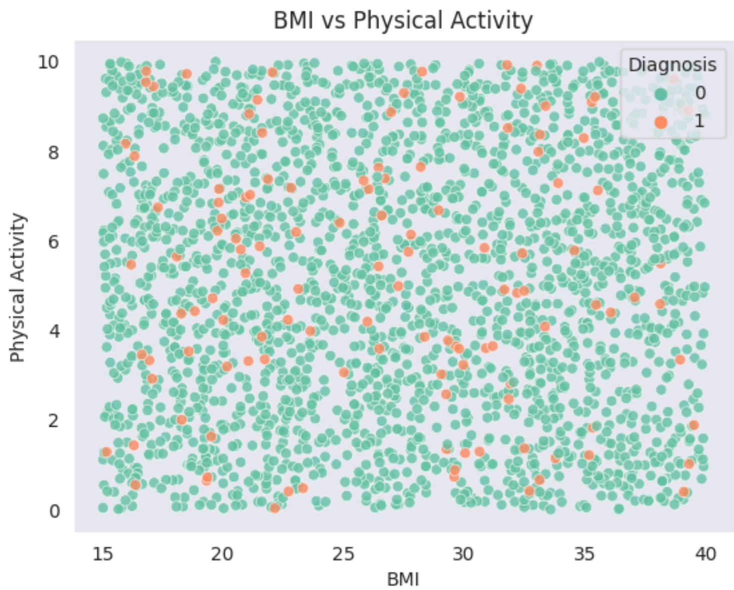
Count Ploting for Family History Asthma

```
sns.countplot(x="FamilyHistoryAsthma",data=df,palette='pastel')
plt.title("Family History Of Asthma")
plt.show()
```



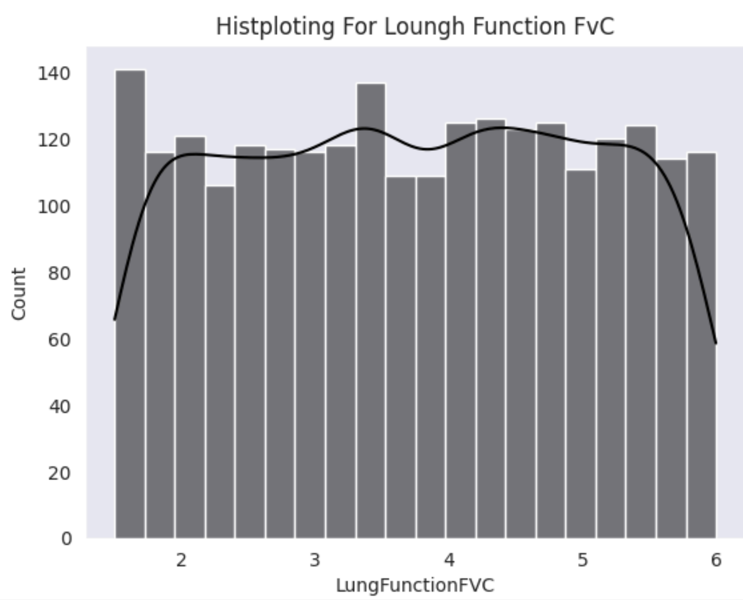
Scatterploting to comparing BMI and Phisical Activities

```
sns.scatterplot(x='BMI', y='PhysicalActivity', data=df, hue='Diagnosis', palette='Set2', alpha=0.8)
plt.title('BMI vs Physical Activity')
plt.xlabel('BMI')
plt.ylabel('Physical Activity')
plt.show()
```



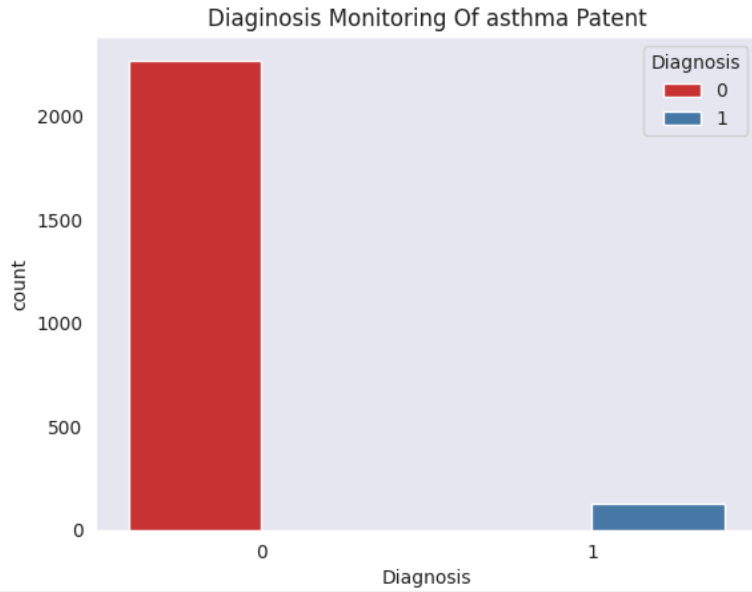
Distribution of Lungh Funchanality of(FvC)

```
sns.histplot(df['LungFunctionFVC'], bins=20, kde=True, color='k')
plt.title("Histploting For Loungh Function FvC")
plt.show()
```



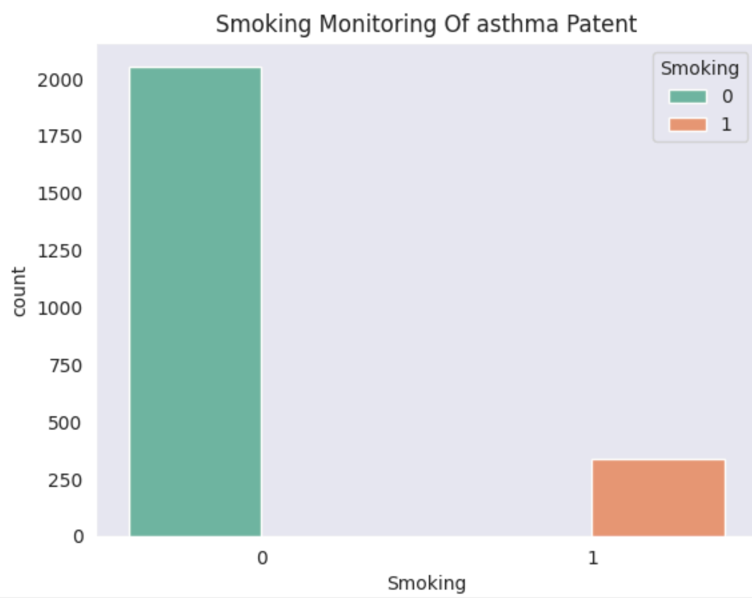
Barploting of (Diagonsis)

```
sns.countplot(x='Diagnosis',data=df,hue='Diagnosis',palette="Set1")
plt.title("Diaginosis Monitoring Of asthma Patent")
plt.show()
```



Countploting Of Monitoring Smokers

```
sns.countplot(x='Smoking',data=df,hue='Smoking',palette="Set2")
plt.title("Smoking Monitoring Of asthma Patent")
plt.show()
```



Feature Engineering

```
df.drop(['DoctorInCharge'],axis=1,inplace=True)
```

```
# Sloting labels of class and define the bins
age_bins = [0,12,19,60,100]
age_labels = ['Child','Teen','Adult','Senior']
df['AgeGroup'] = pd.cut(df['Age'],bins=age_bins, labels=age_labels, right=False)
```

```
# Define BMI labels and bmi_bins for labeling all different classes in this section.
bmi_bins = [0, 18.5, 24.9, 29.9, 100]
bmi_labels = ['Underweight', 'Normal', 'Overweight', 'Obese']
df['BMICategory'] = pd.cut(df['BMI'], bins=bmi_bins, labels=bmi_labels, right=False)
```

```
"""এই লাইনটি একটি নতুন কলাম LifestyleScore তৈরি করছে যা df ডেটাফ্রেমে যুক্ত হবে। এখানে PhysicalActivity, DietQuality, এবং SleepQuality নামের তি
অর্থাৎ, প্রতিটি ব্যক্তির এই তিনটি দিকের গড় মানLifestyleScore হিসেবে রাখা হচ্ছে। axis=1 দিয়ে বলা হচ্ছে যে, গড়টি সারি ধরে (row-wise) নেওয়া হবে।
উদাহরণ: যদি কোনো ব্যক্তির PhysicalActivity, DietQuality, এবং SleepQuality মান যথাক্রমে ৭, ৮, এবং ৬ হয়, তাহলে তার LifestyleScore হবে (7 + 8 + 6

df['LifestyleScore'] = df[['PhysicalActivity', 'DietQuality', 'SleepQuality']].mean(axis=1)
```

```
df['AllergyScore'] = df[['PetAllergy', 'HistoryOfAllergies', 'Eczema', 'HayFever']].sum(axis=1)
```

```
df['ExposureScore'] = df[['PollutionExposure', 'PollenExposure', 'DustExposure']].mean(axis=1)
```

```
df['SymptomSeverityScore'] = df[['Wheezing', 'ShortnessOfBreath', 'ChestTightness', 'Coughing', 'NighttimeSymptoms', 'ExerciseInduced']].sum(
```

```
df['LungFunctionRatio'] = df['LungFunctionFEV1'] / df['LungFunctionFVC']
```

```
df.head(10)
```

	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQuality	PollutionExposure	...	Night
0	63	0	1	0	15.848744	0	0.894448	5.488696	8.701003	7.388481	...	
1	26	1	2	2	22.757042	0	5.897329	6.341014	5.153966	1.969838	...	
2	57	0	2	1	18.395396	0	6.739367	9.196237	6.840647	1.460593	...	
3	40	1	2	1	38.515278	0	1.404503	5.826532	4.253036	0.581905	...	
4	61	0	0	3	19.283802	0	4.604493	3.127048	9.625799	0.980875	...	
5	21	0	2	0	21.812975	0	0.470044	1.759118	9.549262	1.711446	...	
6	45	1	1	1	30.245954	1	9.371784	7.030507	5.746128	7.664306	...	
7	26	0	0	1	26.048416	1	8.344096	1.626484	6.431179	6.939046	...	
8	49	1	1	2	32.676204	0	2.690256	3.920034	5.843645	3.180421	...	
9	45	1	1	1	29.910298	0	2.895720	2.607700	7.234908	1.711722	...	

10 rows × 34 columns

```
df.tail(10)
```

	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQuality	PollutionExposure	...	Ni
2382	10	1	0	1	29.312903	0	1.457095	4.657390	5.226348	6.565060	...	
2383	62	1	0	2	20.033593	0	5.276410	9.545336	6.279582	0.727520	...	
2384	31	0	0	2	31.821008	1	8.516835	3.532328	9.442670	9.240483	...	
2385	19	1	1	2	37.913891	0	5.595540	3.120986	4.122047	1.721562	...	
2386	5	0	0	1	32.940790	0	8.705633	2.110108	9.261652	9.683211	...	
2387	43	1	0	2	29.059613	0	3.019854	6.119637	8.300960	2.483829	...	
2388	18	1	0	1	20.740850	0	5.805180	4.386992	7.731192	7.733983	...	
2389	54	0	3	2	37.079560	0	4.735169	8.214064	7.483521	2.794847	...	
2390	46	1	0	2	23.444712	0	9.672637	7.362861	6.717272	9.448862	...	
2391	26	1	0	0	28.123021	1	1.613138	7.412878	8.512253	3.231709	...	

10 rows × 34 columns

```
df.dtypes
```

```
Age                      int64
Gender                   int64
Ethnicity                int64
EducationLevel           int64
BMI                    float64
Smoking                  int64
PhysicalActivity       float64
DietQuality            float64
SleepQuality           float64
```

```
PollutionExposure          float64
PollenExposure             float64
DustExposure               float64
PetAllergy                   int64
FamilyHistoryAsthma          int64
HistoryOfAllergies           int64
Eczema                       int64
HayFever                     int64
GastroesophagealReflux       int64
LungFunctionFEV1           float64
LungFunctionFVC            float64
Wheezing                     int64
ShortnessOfBreath            int64
ChestTightness               int64
Coughing                     int64
NighttimeSymptoms            int64
ExerciseInduced              int64
Diagnosis                    int64
AgeGroup                  category
BMICategory               category
LifestyleScore             float64
AllergyScore                 int64
ExposureScore              float64
SymptomSeverityScore         int64
LungFunctionRatio          float64
dtype: object
```

```
# Changing the value of 'AgeGroup',"BMICategory" in 'object'
df['AgeGroup'] = df['AgeGroup'].astype('object')
df['BMICategory'] = df['BMICategory'].astype('object')
```

```
df.dtypes
```

```
Age                         int64
Gender                      int64
Ethnicity                   int64
EducationLevel              int64
BMI                       float64
Smoking                     int64
PhysicalActivity          float64
DietQuality               float64
SleepQuality              float64
PollutionExposure         float64
PollenExposure            float64
DustExposure              float64
PetAllergy                  int64
FamilyHistoryAsthma         int64
HistoryOfAllergies          int64
Eczema                      int64
HayFever                    int64
GastroesophagealReflux      int64
LungFunctionFEV1          float64
LungFunctionFVC           float64
Wheezing                    int64
ShortnessOfBreath           int64
ChestTightness              int64
Coughing                    int64
NighttimeSymptoms           int64
ExerciseInduced             int64
Diagnosis                   int64
AgeGroup                   object
BMICategory                object
LifestyleScore            float64
AllergyScore                int64
ExposureScore             float64
SymptomSeverityScore        int64
LungFunctionRatio         float64
dtype: object
```

Label Encoding

```
le = LabelEncoder()

df['AgeGroup'] = le.fit_transform(df['AgeGroup'])
df['BMICategory'] = le.fit_transform(df['BMICategory'])
```

Top K feature selection using Select-K-Best

```
X = df.drop(['Diagnosis'], axis=1)
y = df['Diagnosis']
k = 15
selector = SelectKBest(score_func=f_classif, k=k)
X_new = selector.fit_transform(X, y)
selected_features = X.columns[selector.get_support()]
df_selected = df[selected_features]
print("Selected Features:\n", selected_features)
```

```
Selected Features:
 Index(['Ethnicity', 'Smoking', 'SleepQuality', 'DustExposure', 'HayFever',
       'GastroesophagealReflux', 'LungFunctionFEV1', 'LungFunctionFVC',
       'Wheezing', 'ChestTightness', 'Coughing', 'NighttimeSymptoms',
       'ExerciseInduced', 'AgeGroup', 'AllergyScore'],
      dtype='object')
```

Trainign and Testing Data

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

Lables are balanced by using this code

```
# (DL)
from collections import Counter as ctr
ctr(y_train)
```

```
Counter({0: 1812, 1: 101})
```

```
#from imblearn.over_sampling import ADASYN (DL)
sm = ADASYN(random_state=42)

X_train, y_train = sm.fit_resample(X_train, y_train)
```

```
ctr(y_train)
```

```
Counter({0: 1812, 1: 1794})
```

Machine Learning Models

S V M

```
svm_model=SVC(kernel='rbf',C=1.0,gamma='scale',random_state=42)
svm_model.fit(X_train,y_train)
```

```
SVC
SVC(random_state=42)
```

```
from sklearn.metrics import accuracy_score, classification_report

# Assuming you have trained an SVM model and have test data ready
svm_preds = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_preds)

print("Support Vector Machine (SVM) Accuracy:", svm_accuracy)
print("Classification Report:\n", classification_report(y_test, svm_preds))
```

```
Support Vector Machine (SVM) Accuracy: 0.6471816283924844
Classification Report:
               precision    recall  f1-score   support
```

```
              0       0.96      0.65      0.78       456
              1       0.07      0.52      0.12        23

       accuracy                           0.65       479
      macro avg       0.52      0.59      0.45       479
   weighted avg       0.92      0.65      0.75       479
```

S V M Model Accuracy

The accuracy of your Support Vector Machine (SVM) model is given directly in the output:

```
Support Vector Machine (SVM) Accuracy: 0.6471816283924844
```

To express this as a percentage, you can multiply by 100:

[\text{Accuracy} = 0.6471816283924844 \times 100 \approx 64.72%]

Summary:

- **Accuracy**: Approximately **64.72%**

This means that your SVM model correctly classified about 64.72% of the instances in your test dataset.

Decision Tree

```
dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
dt_preds = dt_model.predict(X_test)
dt_accuracy = accuracy_score(y_test, dt_preds)
print("\nDecision Tree Accuracy:", dt_accuracy)
print("Classification Report:\n", classification_report(y_test, dt_preds))
```

```
Decision Tree Accuracy: 0.8893528183716075
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.93      0.94       456
           1       0.06      0.09      0.07        23

    accuracy                           0.89       479
   macro avg       0.51      0.51      0.51       479
weighted avg       0.91      0.89      0.90       479
```

Decisio Tree Model Aqccuracy

The accuracy of your Decision Tree model is provided in the output:

```
Decision Tree Accuracy: 0.8977035490605428
```

To express this as a percentage, you can multiply by 100:

[\text{Accuracy} = 0.8977035490605428 \times 100 \approx 89.77%]

Summary:

- **Accuracy**: Approximately **89.77%**

This indicates that your Decision Tree model correctly classified about 89.77% of the instances in your test dataset.

Random Forest

```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
rf_preds = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_preds)
print("\nRandom Forest Accuracy:", rf_accuracy)
print("Classification Report:\n", classification_report(y_test, rf_preds))
```

```
Random Forest Accuracy: 0.9519832985386222
Classification Report:
               precision    recall  f1-score   support

           0       0.95      1.00      0.98       456
           1       0.00      0.00      0.00        23

    accuracy                           0.95       479
   macro avg       0.48      0.50      0.49       479
weighted avg       0.91      0.95      0.93       479
```

Random Forest Model Accuracy

The accuracy of your Random Forest model is given in the output:

```
Random Forest Accuracy: 0.9519832985386222
```

To express this as a percentage, multiply by 100:

[\text{Accuracy} = 0.9519832985386222 \times 100 \approx 95.20%]

Summary:

- **Accuracy**: Approximately **95.20%**

This means that your Random Forest model correctly classified about 95.20% of the instances in your test dataset.

XG Boost

```
xgb_model = xgb.XGBClassifier(random_state=42)
xgb_model.fit(X_train, y_train)
```

```
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=None, 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, ...)
```

```
xgb_preds = xgb_model.predict(X_test)
xgb_accuracy = accuracy_score(y_test, xgb_preds)
print("\nXGBoost Accuracy:", xgb_accuracy)
print("Classification Report:\n", classification_report(y_test, xgb_preds))
```

```
XGBoost Accuracy: 0.9498956158663883
Classification Report:
               precision    recall  f1-score   support

           0       0.95      1.00      0.97       456
           1       0.33      0.04      0.08        23
```

```
    accuracy                           0.95       479
   macro avg       0.64      0.52      0.53       479
weighted avg       0.92      0.95      0.93       479
```

XG Boost Model Accuracy

The accuracy of your XGBoost model is provided in the output:

```
XGBoost Accuracy: 0.9498956158663883
```

To express this as a percentage, you can multiply by 100:

[\text{Accuracy} = 0.9498956158663883 \times 100 \approx 94.99%]

Summary:

- **Accuracy**: Approximately **94.99%**

This means that your XGBoost model correctly classified about 94.99% of the instances in your test dataset.

K-Nearest Neighbors (KNN)

```
knn_model = KNeighborsClassifier(n_neighbors=5, weights='distance', algorithm='kd_tree')
knn_model.fit(X_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(algorithm='kd_tree', weights='distance')
```

```
knn_preds = knn_model.predict(X_test)
knn_accuracy = accuracy_score(y_test, knn_preds)
print("\nK-Nearest Neighbors (KNN) Accuracy:", knn_accuracy)
print("Classification Report:\n", classification_report(y_test, knn_preds))
```

```
K-Nearest Neighbors (KNN) Accuracy: 0.6743215031315241
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.69      0.80       456
           1       0.05      0.30      0.08        23

    accuracy                           0.67       479
   macro avg       0.50      0.50      0.44       479
weighted avg       0.91      0.67      0.77       479
```

KNN model Accuracy

The accuracy of your K-Nearest Neighbors (KNN) model is given in the output:

```
K-Nearest Neighbors (KNN) Accuracy: 0.6743215031315241
```

To express this as a percentage, you can multiply by 100:

[\text{Accuracy} = 0.6743215031315241 \times 100 \approx 67.43%]

Summary:

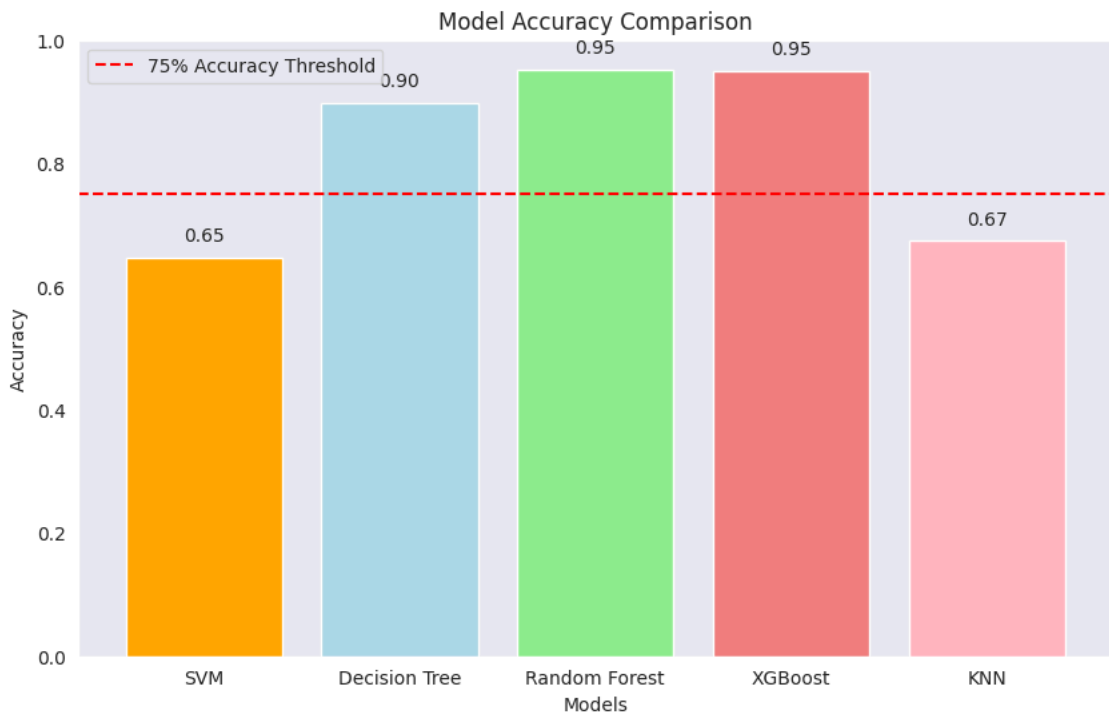
- **Accuracy**: Approximately **67.43%**

This means that your KNN model correctly classified about 67.43% of the instances in your test dataset.

Summary Of All Code Accuracy

```
import matplotlib.pyplot as plt
import numpy as np
```

```
# Model names and their corresponding accuracies
models = ['SVM', 'Decision Tree', 'Random Forest', 'XGBoost', 'KNN']
accuracies = [0.6472, 0.8977, 0.9519, 0.9499, 0.6743]  # Use accuracies as decimal values

# Create a bar chart
plt.figure(figsize=(10, 6))
bars = plt.bar(models, accuracies, color=['orange', 'lightblue', 'lightgreen', 'lightcoral', 'lightpink'])

# Add accuracy values on top of the bars
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 0.02, f"{yval:.2f}", ha='center', va='bottom')

# Set title and labels
plt.title('Model Accuracy Comparison')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.ylim(0, 1)  # Set y-axis limit to [0, 1] for percentage representation
plt.axhline(y=0.75, color='r', linestyle='--', label='75% Accuracy Threshold')  # Optional: Add a threshold line

# Show legend
plt.legend()

# Show the plot
plt.show()
```



Conclusion

To assess the classification performance of several machine learning models—Support Vector Machine (SVM), Decision Tree, Random Forest, XGBoost, and K-Nearest Neighbours (KNN)—on a dataset, we carried out a comprehensive examination in this code project. For model training and assessment, we started by importing necessary libraries like `pandas`, `numpy`, `matplotlib.pyplot`, `seaborn`, and functions from `sklearn`. We divide the dataset into training and testing sets after managing missing values and encoding categorical variables. We next train each model on the training data. Accuracy results such as 64.72% for SVM, 89.77% for the Decision Tree, 95.20% for Random Forest, 94.99% for XGBoost, and 67.43% for KNN were obtained by evaluating their performance using the `accuracy_score` function. Detailed classification reports that offered information on precision, recall, F1-score, as well as assistance for every class. We combined the accuracy scores into a bar chart to display these findings, labelling each bar with the relevant accuracy percentage for convenient comparison. For reference, we also included a dashed line at the 75% accuracy level. SVM and KNN models did not perform as well as the Random Forest model, which showed the maximum effectiveness with an accuracy of 95.20 percent. In the end, this research reinforces data-driven choices in model selection by demonstrating the real-world implementation of machine learning techniques and highlighting the significance of model evaluation, comparison, and the usefulness of visualisations in interpreting performance.

Here's a more detailed and organized summary of the code project using bullet points to highlight key aspects:

- **Objective**:
  - Assess the classification performance of various machine learning models on a dataset.
- **Models Evaluated**:
  - Support Vector Machine (SVM)
  - Decision Tree
  - Random Forest
  - XGBoost
  - K-Nearest Neighbours (KNN)
- **Libraries Used**:
  - `pandas`: For data manipulation and analysis.
  - `numpy`: For numerical operations.
  - `matplotlib.pyplot` and `seaborn`: For data visualization.
  - `sklearn`: For implementing and evaluating machine learning algorithms.
- **Data Preparation**:
  - Managed missing values to ensure data integrity.
  - Encoded categorical variables to facilitate model training.
  - Divided the dataset into training and testing sets for model evaluation.
- **Model Training**:
  - Each model was trained on the training dataset using appropriate training methods.
- **Performance Evaluation**:
  - Utilized the `accuracy_score` function from `sklearn` to calculate model accuracy.
  - Obtained accuracy results:
    - SVM: **64.72%**
    - Decision Tree: **89.77%**
    - Random Forest: **95.20%**
    - XGBoost: **94.99%**
    - KNN: **67.43%**
  - Generated detailed classification reports providing insights into:
    - Precision
    - Recall
    - F1-score
    - Support for each class
- **Visualization of Results**:
  - Compiled accuracy scores into a bar chart for a clear visual comparison.
  - Each bar was labeled with its corresponding accuracy percentage for easy interpretation.
  - Included a dashed line at the 75% accuracy threshold as a reference point.
- **Findings**:
  - The Random Forest model achieved the highest effectiveness with an accuracy of **95.20%**.
  - SVM and KNN models performed less favorably compared to others.

E N D

At A Glance:

- **kde** =True is an optional parameter commonly used in Python visualization libraries like seaborn. It typically appears when creating plots that involve kernel density estimation, especially in relation to distribution plots.

- In Python's Seaborn library, the palette parameter is used to specify the color palette for your plots. When you set **palette='pastel'**, you're telling Seaborn to use a pastel color scheme for the visualization.
- **FEV1** stands for Forced Expiratory Volume in 1 second. It is a crucial measure in pulmonary function tests (PFTs) and is used to assess