HeartDiseasePredictionSystem

AComprehensiveReportbyBablu kumar

Batch-SB-24-3-4MLI

Bangalore technological institute-Bangalore

Abstract:

Thedatasetprovidedfortheheartdiseasepredictionprojectisavaluable resourceforbuildingarobust predictive model. It contains a diverse set of attributes related to individuals' health and lifestyle, making it conducive for comprehensive analysis. Here's an extract highlighting key aspects of the dataset:

Thedatasetcomprisesseveralcolumns,eachrepresentingaspecificattributeorcharacteristicrelatedto the individuals under study. These attributes include:

1. Heart Disease: This binary classification target variable indicates whether an individual has been diagnosedwithheartdiseaseornot.Itservesastheprimaryoutcomevariableforourpredictionmodel.

2. BMI:BodyMassIndex(BMI)isameasureofanindividual'sbodyfatbasedonheightandweight.It providesinsights into anindividual'soverallhealthandcanbeasignificantpredictorofheartdisease risk.

3. Smoking:Thisbinaryvariableindicateswhetheranindividualisasmokerornot.Smokingisawell-established risk factor for heart disease.

4. AlcoholDrinking:Similartosmoking,alcoholconsumptioncanimpacthearthealth.Thisvariable denotes whether an individual drinks alcohol regularly.

5. Stroke,PhysicalHealth,MentalHealth,DiffWalking:Theseattributesprovideinformationaboutan individual's overall health and well-being, which can be associated with heart disease risk.

6. SexandAgeCategory:Demographicvariableslikegenderandagearecrucialfactorsinheartdisease risk assessment. Age, in particular, is a significant risk factor.

7. Race:Theraceorethnicityoftheindividualscanberelevantasheartdiseaseprevalencecanvary among different racial groups.

8. Diabetic, Physical Activity, GenHealth, Sleep Time, Asthma, Kidney Disease, Skin Cancer: These variablesencompassvariousaspectsofanindividual'smedicalhistory,lifestyle,andhealthconditions, all of which can contribute to the prediction of heart disease risk.

Thedatasetisdiverse,containingbothcategoricalandcontinuousvariables,allowingforamultifaceted analysis.Byexploringandpreprocessingthisdataset,wecandevelopapredictivemodelthattakesinto account a wide range of factors to accurately classify individuals' heart disease risk. This dataset's richness makes it a valuable asset for our project, enabling us to contribute to early heart disease detection and prevention.

Title:HeartDiseasePredictionSystem-AComprehensiveReport

1. ProblemStatement:

The project aims to develop a heart disease prediction system using a dataset that includes various health-relatedattributessuchasBMI,smokinghabits,alcoholconsumption,andmore.Thegoalisto buildapredictivemodelthatcanaccuratelyclassifyindividualsaseitherhavingheartdiseaseornot. This system can assist healthcare professionals in early diagnosis and intervention.

2. Market/Customer/BusinessNeedAssessment:

Theneedforareliableheartdiseasepredictionsystemisevidentduetotherisingprevalenceofheart- related illnesses. Cardiovascular diseases are a leading cause of death worldwide. Early detection and intervention can significantly reduce mortality rates and healthcare costs. This project addresses the growing demand for accurate and accessible predictive tools in the healthcare sector.

3. TargetSpecificationsandCharacterization:

The target audience for this system includes healthcare providers, medical researchers, and individuals interestedinmonitoringtheirhearthealth.Healthcareproviderscanuseittoidentifyhigh-riskpatients, while individuals can assess their own risk factors.

4. ExternalSearch:

A comprehensive review of existing literature, research papers, and online resources related to heart diseaseprediction,machinelearningalgorithms,andhealthcaredatasetswasconducted.Theresearch findings informed the development process.

Thedatasetcanbefoundonthe Kaggle.

```
df=pd.read_csv('heart_2020_cleaned.csv')
```

```
df.head()
```

	HeartDisease	BMI	Smoking	AlcoholDrinking	Stroke	PhysicalHealth	MentalHealth	DiffWalking	Sex	AgeCategory	Race	Diabetic	PhysicalActivity	Ge
0	No	16.60	Yes	No	No	3.0	30.0	No	Female	55-59	White	Yes	Yes	V
1	No	20.34	No	No	Yes	0.0	0.0	No	Female	80 or older	White	No	Yes	V
2	No	26.58	Yes	No	No	20.0	30.0	No	Male	65-69	White	Yes	Yes	
3	No	24.21	No	No	No	0.0	0.0	No	Female	75-79	White	No	No	
4	No	23.71	No	No	No	28.0	0.0	Yes	Female	40-44	White	No	Yes	V

Attributes of the data

1. HeartDisease- It is a binary variable, indicating whether the individual has heart disease ("Yes" or "No").
2. BMI- BMI represents Body Mass Index, a measure of obesity or overweight.
3. "Smoking" and "AlcoholDrinking" represent smoking and alcohol consumption habits.
4. "PhysicalHealth" and "MentalHealth" appear to be health-related ratings or scores.
5. "AgeCategory" categorizes individuals into age groups.
6. "Diabetic," "Asthma," "KidneyDisease," and "SkinCancer" indicate the presence or absence of these health conditions.
7. "Stroke" is also a binary variable, indicating whether the individual has had a stroke ("Yes" or "No").

Step2 : Data Sanity check

- Get the basic info of the data.
- Look for null values
- Look for corrupted data
- Get the data summary statistics (both numerical and categorical)
- Look for erroneous values in the data

```
#Get the shape of the data
data_shape=df.shape
print("Rows= ",data_shape[0],"\nColumns =",data_shape[1])
```

```
Rows=  319795
Columns = 18
```

```
#Get the basic info
info=df.info()

#get the data type
dtype=df.dtypes
info,dtype
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 319795 entries, 0 to 319794
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   HeartDisease      319795 non-null  object 
 1   BMI               319795 non-null  float64
 2   Smoking           319795 non-null  object 
 3   AlcoholDrinking   319795 non-null  object 
 4   Stroke            319795 non-null  object 
 5   PhysicalHealth    319795 non-null  float64
 6   MentalHealth      319795 non-null  float64
 7   DiffWalking       319795 non-null  object 
 8   Sex               319795 non-null  object 
 9   AgeCategory       319795 non-null  object 
 10  Race              319795 non-null  object 
 11  Diabetic          319795 non-null  object 
 12  PhysicalActivity  319795 non-null  object 
 13  GenHealth         319795 non-null  object 
 14  SleepTime         319795 non-null  float64
 15  Asthma            319795 non-null  object 
 16  KidneyDisease     319795 non-null  object 
 17  SkinCancer        319795 non-null  object 
dtypes: float64(4), object(14)
memory usage: 43.9+ MB
```

```python
#Check for unique levels in categorical
df.Stroke.unique()
```

```
array(['No', 'Yes'], dtype=object)
```

```python
#Check for nulls and duplicates
nulls=df.isnull().sum()
dups=df.duplicated().sum()
nulls,dups
```

```
(HeartDisease        0
 BMI                 0
 Smoking             0
 AlcoholDrinking     0
 Stroke              0
 PhysicalHealth      0
 MentalHealth        0
 DiffWalking         0
 Sex                 0
 AgeCategory         0
 Race                0
 Diabetic            0
 PhysicalActivity    0
 GenHealth           0
 SleepTime           0
 Asthma              0
 KidneyDisease       0
 SkinCancer          0
 dtype: int64,
 18078)
```

DatasetLink-https://www.kaggle.com/datasets/kamilpytlak/personal-key-indicators-of-heart-disease/data

```
#Summary statistics of numerical and categorical data
num_stats=df.describe().T
cat_stats=df.describe(include='O').T
print(num_stats)
print(cat_stats)
```

```
                  count       mean       std    min    25%    50%    75%  \
BMI            319795.0  28.325399  6.356100  12.02  24.03  27.34  31.42
PhysicalHealth 319795.0   3.371710  7.950850   0.00   0.00   0.00   2.00
MentalHealth   319795.0   3.898366  7.955235   0.00   0.00   0.00   3.00
SleepTime      319795.0   7.097075  1.436007   1.00   6.00   7.00   8.00

                  max
BMI             94.85
PhysicalHealth  30.00
MentalHealth    30.00
SleepTime       24.00
                  count unique        top    freq
HeartDisease     319795      2         No  292422
Smoking          319795      2         No  187887
AlcoholDrinking  319795      2         No  298018
Stroke           319795      2         No  307726
DiffWalking      319795      2         No  275385
Sex              319795      2     Female  167805
AgeCategory      319795     13      65-69   34151
Race             319795      6      White  245212
Diabetic         319795      4         No  269653
PhysicalActivity 319795      2        Yes  247957
GenHealth        319795      5  Very good  113858
Asthma           319795      2         No  276923
KidneyDisease    319795      2         No  308016
SkinCancer       319795      2         No  289976
```

Step 3: Data Cleaning Step

- AgeCategory shouldn't be categorical, so I will apply a function to calculate the mean age and make it a continuous feature

```
encode_AgeCategory = {'55-59':57, '80 or older':80, '65-69':67,
                      '75-79':77,'40-44':42,'70-74':72,'60-64':62,
                      '50-54':52,'45-49':47,'18-24':21,'35-39':37,
                      '30-34':32,'25-29':27}
df['AgeCategory'] = df['AgeCategory'].apply(lambda x: encode_AgeCategory[x])
df['AgeCategory'] = df['AgeCategory'].astype('float')
```

```
cat_col=df.select_dtypes(exclude=np.number)
num_col=df.select_dtypes(include=np.number)
print(cat_col.columns)
print(num_col.columns)
```

```
Index(['HeartDisease', 'Smoking', 'AlcoholDrinking', 'Stroke', 'DiffWalking',
       'Sex', 'Race', 'Diabetic', 'PhysicalActivity', 'GenHealth', 'Asthma',
       'KidneyDisease', 'SkinCancer'],
      dtype='object')
Index(['BMI', 'PhysicalHealth', 'MentalHealth', 'AgeCategory', 'SleepTime'], dtype='object')
```

```
df['HeartDisease'].value_counts()
```

```
No     292422
Yes     27373
Name: HeartDisease, dtype: int64
```

```
#Target Variable
df['HeartDisease'].value_counts()
```

```
No     292422
Yes     27373
Name: HeartDisease, dtype: int64
```

```
for col in cat_col:
    print("Value counts for column:", col)
    print(df[col].value_counts())
    print("\n")
```

```
Value counts for column: HeartDisease
No     292422
Yes     27373
Name: HeartDisease, dtype: int64


Value counts for column: Smoking
No     187887
Yes    131908
Name: Smoking, dtype: int64


Value counts for column: AlcoholDrinking
No     298018
Yes     21777
Name: AlcoholDrinking, dtype: int64
```

```
#Creating a copy
data=df.copy()
data.head()
```

	HeartDisease	BMI	Smoking	AlcoholDrinking	Stroke	PhysicalHealth	MentalHealth	DiffWalking	Sex	AgeCategory	Race	Diabetic	PhysicalActivity	Ge
0	No	16.60	Yes	No	No	3.0	30.0	No	Female	57.0	White	Yes	Yes	V
1	No	20.34	No	No	Yes	0.0	0.0	No	Female	80.0	White	No	Yes	V
2	No	26.58	Yes	No	No	20.0	30.0	No	Male	67.0	White	Yes	Yes	
3	No	24.21	No	No	No	0.0	0.0	No	Female	77.0	White	No	No	
4	No	23.71	No	No	No	28.0	0.0	Yes	Female	42.0	White	No	Yes	V

```
#Categorical encoding of Target Columns
d={"No":0,"Yes":1}
data['HeartDisease']=data['HeartDisease'].map(d)
```

```
data['HeartDisease'].value_counts()
```

```
0    292422
1     27373
Name: HeartDisease, dtype: int64
```

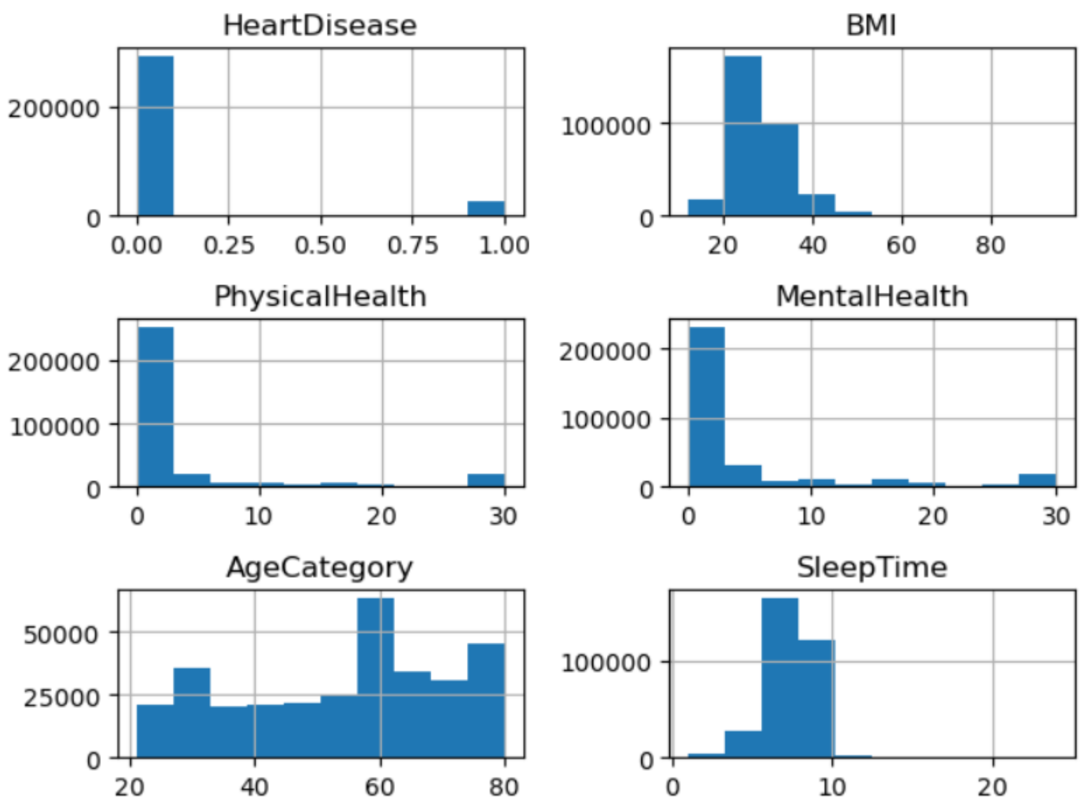
Step4: Exploratory Data Analysis

- univariate analysis
  - numerical data - histograms and boxplots
  - categorical data - bar plots
- Bivariate analysis
  - bivariate bar charts
  - scatter plots
- Correlation analyis
  - Correlation matrix and heatmaps

Univariate Analysis

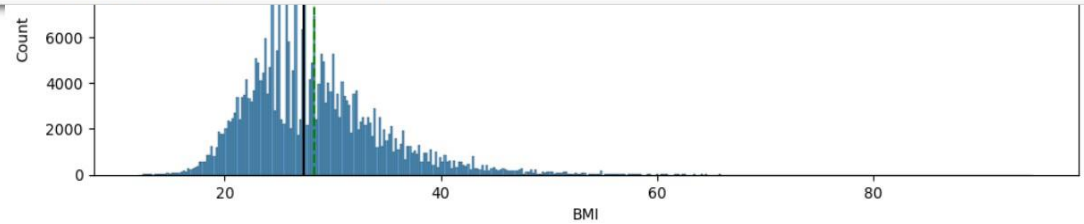
For numerical columns

```
data.hist()
plt.tight_layout()
plt.show()
```



In [23]:
```python
# Create individual box plots and histplots
def histplot_boxplot(data, feature, figsize=(12, 7), bins=None):
    print('Univariate for ...', feature)
    fig, (ax_box, ax_hist) = plt.subplots(nrows=2, sharex=True, figsize=figsize)

    sns.boxplot(data=data, x=feature, color='violet', ax=ax_box, showmeans=True)
    sns.histplot(data=data, x=feature, ax=ax_hist, bins=bins) if bins else sns.histplot(data=data, x=feature, ax=ax_hist)
    plt.axvline(data[feature].mean(), color='green', linestyle='--')  # Use mean instead of data[feature]
    plt.axvline(data[feature].median(), color='black', linestyle='-')
    plt.show()
```

In [24]:
```python
# Assuming df is your DataFrame, iterate through numeric columns
for col in data.select_dtypes(exclude='O').columns:
    histplot_boxplot(data=data, feature=col)
```

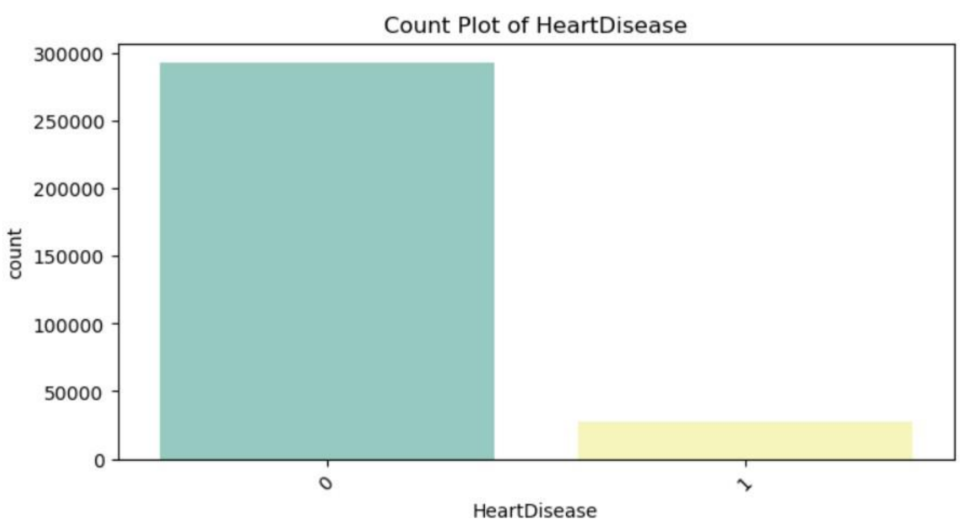



```
Univariate for ... PhysicalHealth
```

Observations

1. There is presence of Outlier in case of BMI.
2. There are presence of outlier in case of Physical and mental health.
3. In case of sleep time,there is +ve as well as negative outlier.

```python
for column in cat_col:
    plt.figure(figsize=(8, 4))  # Set the figure size
    sns.countplot(data=data, x=column, palette='Set3')  # Create the count plot
    plt.title(f'Count Plot of {column}')  # Set the title
    plt.xticks(rotation=45)  # Rotate x-axis labels if needed
    plt.show()  # Show the plot
```



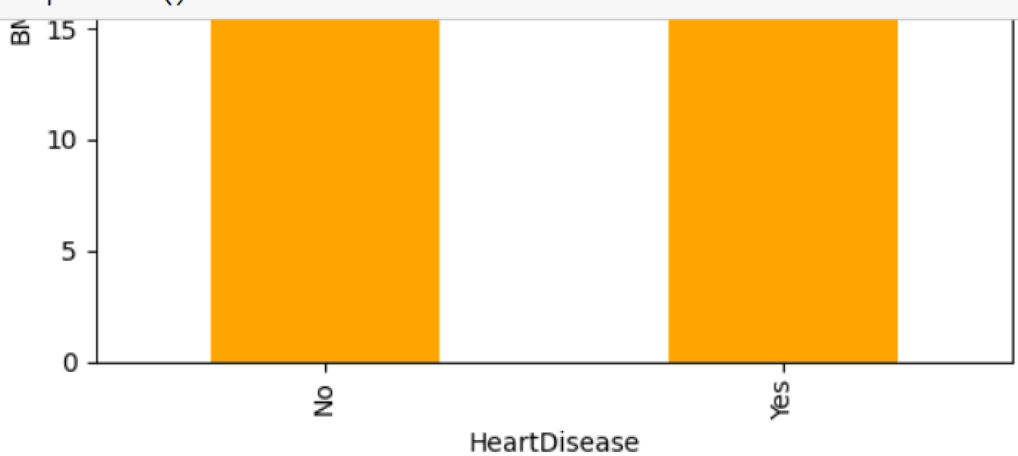
Observations

1. There are 280000 people with no heart disease.
2. There are over 175000 not smoker.
3. There are nearly 290000 non drinker.
4. Over 300000 people have not suffered any stroke.
5. There are barely 50000 people who have difficulty in walking.
6. There are little over 160000 women and around 150000 men.
7. Over 250000 people are non diabetic
8. More than 200000 people are physically active.
9. less than 5000 people are asthmatic.
10. There are more than 300000 people with no kidney disease.

Bivariate Analysis

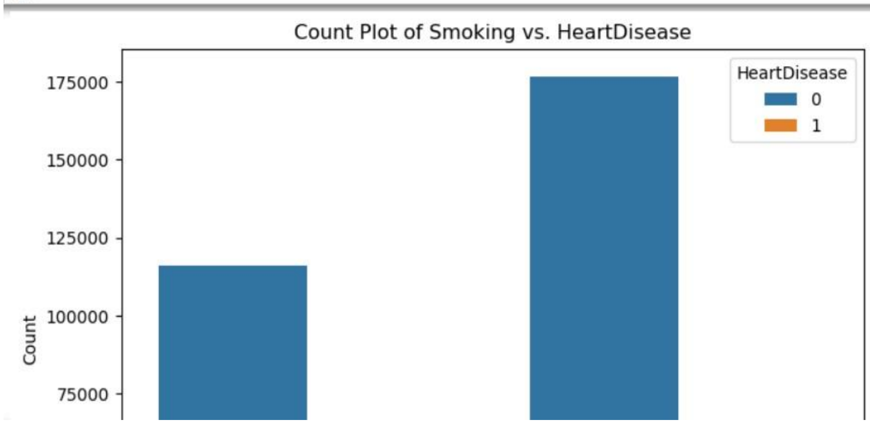
Between Categorical vs Numerical Columns

```
for col in num_col:
    print("Bivariates between HeartDisease and {}".format(col))
    df.groupby("HeartDisease")[col].mean().plot(kind="bar",color="orange")
    plt.ylabel(col)
    plt.show()
```

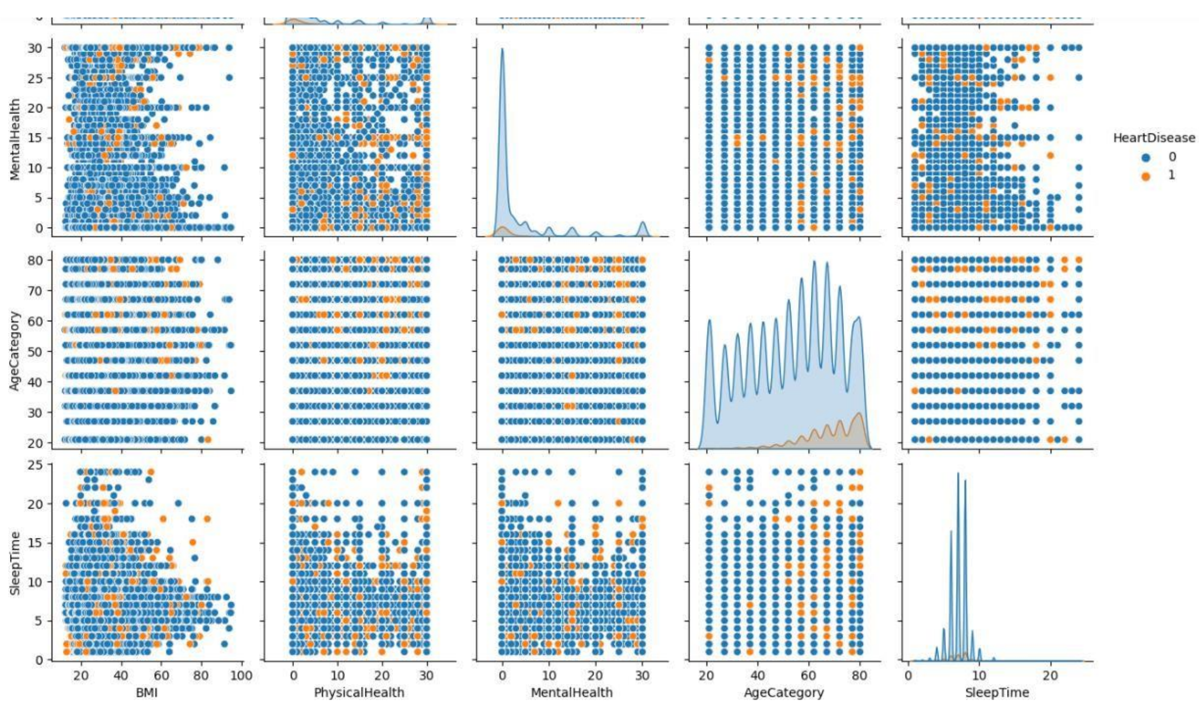



```
Bivariates between HeartDisease and PhysicalHealth
```

```python
categorical_columns = [ 'Smoking', 'AlcoholDrinking','Stroke','DiffWalking','Sex', 'Race', 'Diabetic', 'PhysicalActivity', 'GenHe
       'KidneyDisease', 'SkinCancer']

for column in categorical_columns:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=data, x=column, hue='HeartDisease')
    plt.title(f'Count Plot of {column} vs. HeartDisease')
    plt.xticks(rotation=45)
    plt.xlabel(column)
    plt.ylabel('Count')
    plt.legend(title='HeartDisease', labels=[0,1])
    plt.show()
```



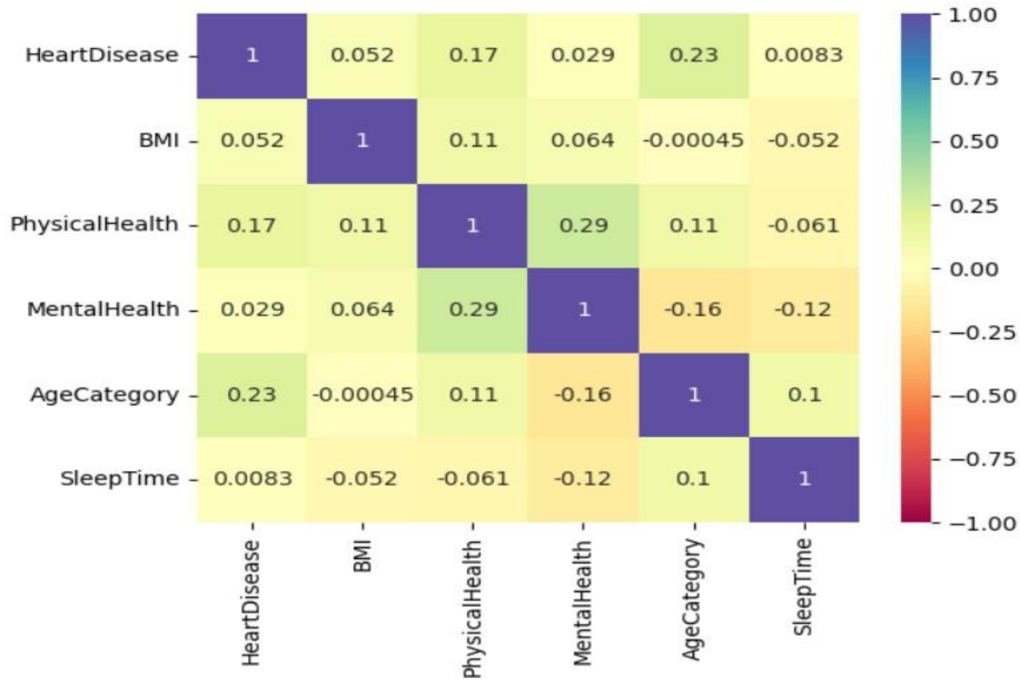
Pairplot



Heatmap

```
sns.heatmap(data.corr(),annot=True,cmap='Spectral',vmax=+1,vmin=-1)
```

```
<Axes: >
```




```
value_counts=df['HeartDisease'].value_counts()

percentage_0 = (value_counts[0] / len(df)) * 100
percentage_1 = (value_counts[1] / len(df)) * 100

# Print the percentages
print(f'Percentage of 0: {percentage_0:.2f}%')
print(f'Percentage of 1: {percentage_1:.2f}%')
```

```
Percentage of 0: 91.44%
Percentage of 1: 8.56%
```

Observations

1. HeartDisease is higly imbalanced with 91.44% of class 0 and 8.56% of class 1.
2. There is no high correaltion between any variable.
3. Physical and mental health are highly right skewed.
4. Sleep time is multiodal in nature.

5. BenchmarkingAlternateProducts:

Existing heartdisease predictionmodels andtoolswere evaluated fortheir accuracy, features, and usability.Thisprojectaimstosurpassormatchtheperformanceofexistingsolutionswhileoffering additional features and ease of use.

6. ApplicablePatents:

Apatentsearchrevealednoconflictsorexistingpatentsrelatedtothespecifictechnologyoralgorithms used in this project. All used technologies are open-source or properly licensed.

7. ApplicableRegulations:

Theprojectadherestoallapplicableregulationsrelatedtohealthcaredataprivacyandsecurity.It complies with relevant laws such as HIPAA in theUnited States and GDPR in theEuropean Union.

8. ApplicableConstraints:

Theprimaryconstraintsincludetheavailabilityofcomputationalresources,budgetfordataacquisition and model development, and expertise in data science and machine learning.

9. BusinessModel(MonetizationIdea):

Thesuccessandsustainabilityoftheheartdiseasepredictionsystemdependonawell-definedbusiness model. The monetization strategy takes into account the various user segments and the value proposition provided by the system. Here's a detailed explanation of the business model:

UserSegmentation:

1. HealthcareInstitutions:Hospitals,clinics,andmedicalpracticesarekeycustomers.Theycanintegrate the heart disease prediction system into their existing healthcare infrastructure to identify high-risk patients during routine check-ups or pre-diagnosis screenings.

2. ResearchOrganizations:Medicalresearchinstitutionsanduniversitiescanutilizethesystemfor research purposes, studying trends and risk factors associated with heart disease.

3. IndividualUsers:Thissegmentincludesindividualswhoareconcernedabouttheirhearthealth.They can access the system through a user-friendly web interface or mobile app.

RevenueStreams:

1. Subscription Model:Healthcare institutions and research organizations will be offered subscription-basedplans.Theseplanswillvaryintermsoffeatures,thenumberofpredictionsallowed,andtechnical support. Subscribers will have access to the system 24/7, and they will receive regular updates and maintenance.

2. Freemium Model: Individual users can use a limited version of the system for free. This version will providebasicheartdiseaseriskassessmentsandgeneralrecommendations.Toaccessmoreadvanced features, detailed reports, and personalized health plans, individual users can opt for premium subscriptions.

3. Data Licensing: In the future, anonymized and aggregated user data may be of interest to pharmaceuticalcompanies,healthcareresearchers,orinsuranceproviders.Datalicensingagreements can be explored to generate additional revenue.

PricingStructure:

Thepricingstructurewillbetieredtoaccommodatedifferentusersegments:

- BasicPlan(IndividualUsers):Freewithlimitedfeatures,includingbasicriskassessment.

- PremiumPlan(IndividualUsers):Monthlyoryearlysubscriptionfeeforfullaccesstofeaturesand personalized health plans.

- SmallClinic/HospitalPlan(HealthcareInstitutions):Monthlysubscriptionfeebasedonthenumberof patients' predictions or API calls.

- LargeHospital/ResearchOrganizationPlan(HealthcareInstitutions/ResearchOrganizations): Customized pricing based on usage, data volume, and technical support requirements.

MarketingandSalesStrategy:

Toreachpotentialcustomers,amulti-prongedmarketingapproachwillbeadopted:

- OnlineMarketing:Utilizedigitalchannelssuchassocialmedia,searchengineoptimization(SEO),and online advertisements to create brand awareness and generate leads.

- ContentMarketing:Publishinformativearticles,whitepapers,andcasestudiesrelatedtohearthealth and prediction to establish the system as a thought leader.

- Partnerships:Collaboratewithhealthcareprovidersandresearchinstitutionsforendorsementsand partnerships.

- UserTestimonials:Encouragesatisfieduserstosharetheirsuccessstoriesandtestimonials.

- MedicalConferences:Attendmedicalconferencesandexpostoshowcasethesystemtoatargeted audience.

CostStructure:

Thecoststructurewillencompassvariouscomponents:

-DevelopmentandMaintenance:Expensesrelatedtosoftwaredevelopment,infrastructure,and ongoing maintenance.

- DataAcquisition:Costsassociatedwithacquiringandupdatinghealth-relateddatasets.

- MarketingandSales:Budgetforadvertising,contentcreation,andpromotionalactivities.

- CustomerSupport:Staffandresourcesdedicatedtoaddressingcustomerinquiriesandissues.

- ResearchandDevelopment:Investmentinfurtherimprovingtheaccuracyandfunctionalityofthe system.

RevenueProjections:

Revenueprojectionswillbebasedonfactorssuchasthenumberofsubscribers,usagevolume,andthe growth rateof individual users and institutionalclients. Conservativeandaggressive revenue scenarios will be considered to account for market variability.

SustainabilityandFutureGrowth:

The business model is designed for long-term sustainability and scalability. Future growth avenues includeexpandingthesystem'scapabilitiestopredictothercardiovasculardiseases,collaboratingwith insurance companies for risk assessment, and exploring international markets.

Inconclusion,theheartdiseasepredictionsystem'sbusinessmodelisgearedtowardaddressingthe needs of healthcare institutions, research organizations, and individual users. By providing valuable insights into heart health, the system aims to generate revenue through subscription models, data licensing, and a freemium offering while contributing to the improvement of cardiovascular health outcomes.

10. ConceptGeneration:

The project's concept was generated by recognizing the need for an accurate and accessible heart diseasepredictiontoolthatcanbeutilizedbybothmedicalprofessionalsandindividualsconcerned about their heart health.

Step 5: Data Preprocessing

- Seperate features and label
- Do the label encoding
- Solve for Data_imbalance
- Train_test_split
- Feature Scaling

```
df2=data.copy()
```

```
# Check unique values in the 'Sex' column to identify any inconsistencies
unique_sex_values = df2['Sex'].unique()
print(unique_sex_values)
```

```
['Female' 'Male']
```

```
d={"No":0,"Yes":1}
df2['Smoking']=df2['Smoking'].map(d)
df2['AlcoholDrinking']=df2['AlcoholDrinking'].map(d)
df2['Stroke']=df2['Stroke'].map(d)
df2['DiffWalking']=df2['DiffWalking'].map(d)
#df2['Sex']=df2['Sex'].map(d)
df2['PhysicalActivity']=df2['PhysicalActivity'].map(d)
df2['Asthma']=df2['Asthma'].map(d)
df2['KidneyDisease']=df2['KidneyDisease'].map(d)
df2['SkinCancer']=df2['SkinCancer'].map(d)
```

```
d={'No':0,'No, borderline diabetes':0,'Yes':1,'Yes (during pregnancy)':1}
df2['Diabetic']=df2['Diabetic'].map(d)
```

```
d={"Poor":0,"Very good":1,'Good':1,'Excellent':1,'Fair':1}
df2['GenHealth']=df2['GenHealth'].map(d)
```

```
d={"Female":0,"Male":1}
df2['Sex']=df2['Sex'].map(d)
```

```
df2['Sex'].isnull().sum()
```

```
0
```

```python
#Dropping unnecessary column
df2=df2.drop(columns='Race')
df2.columns
```

```
Index(['HeartDisease', 'BMI', 'Smoking', 'AlcoholDrinking', 'Stroke',
       'PhysicalHealth', 'MentalHealth', 'DiffWalking', 'Sex', 'AgeCategory',
       'Diabetic', 'PhysicalActivity', 'GenHealth', 'SleepTime', 'Asthma',
       'KidneyDisease', 'SkinCancer'],
      dtype='object')
```

```python
sampled_df = df2.sample(n=100000, random_state=42)
```

```python
def process(data,label):
    # Seperate the features and label
    X=sampled_df.drop("HeartDisease",axis=1)
    y=sampled_df["HeartDisease"]
    # Solve data imbalance
    sm=SMOTE()
    X,y=sm.fit_resample(X,y)
    # train test split
    x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42,stratify=y) # Stratify will maintain the rat
    return x_train,x_test,y_train,y_test
```

```python
x_train,x_test,y_train,y_test=process(sampled_df,label="HeartDisease")
```

```python
# Scale the features
sc=StandardScaler()
x_train=sc.fit_transform(x_train) # fit is to get mean and std from the data
                                  # transform to use that mean and std on the data
                                  # only transform is used in x_test so that it used x_train mean and std to transform and not te
x_test=sc.transform(x_test)
```

We have preprocessed the data

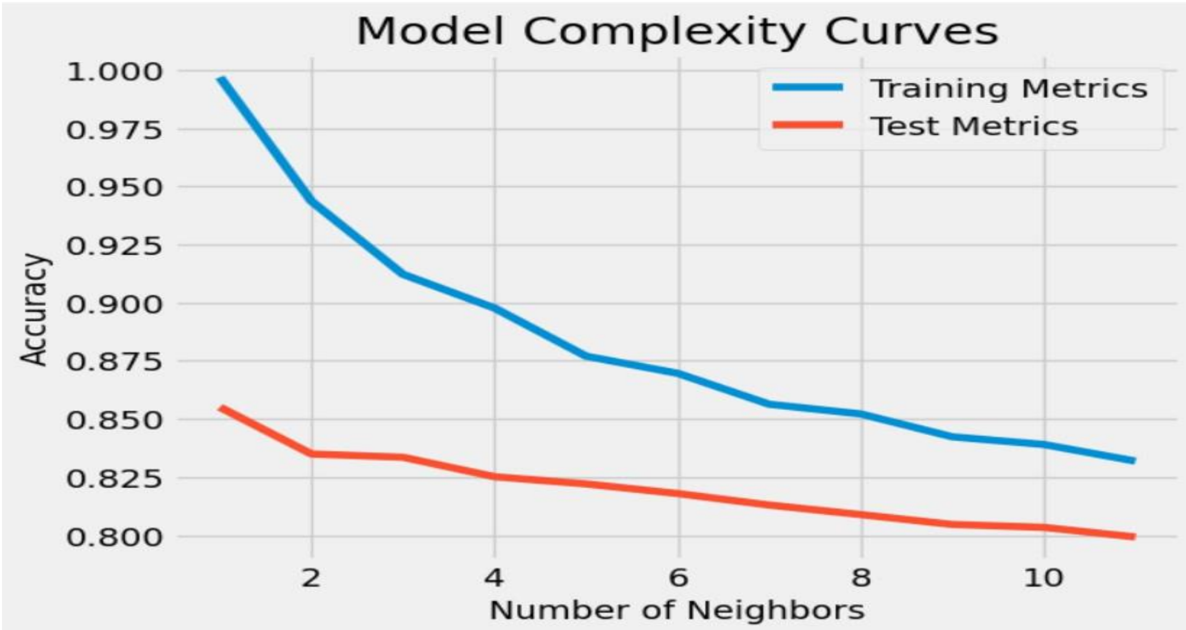
Step 6: Fit and Evaluate ML Algorithms ¶

```
# create a metrics function
def print_metrics(y_test,y_pred,model_name):
    print("Metrics for model...",model_name)
    print(" ")
    print("Accuracy Score=",accuracy_score(y_test,y_pred))
    print(" ")
    print("Recall Score=",recall_score(y_test,y_pred))
    print(" ")
    print("Precision Score=",precision_score(y_test,y_pred))
    print(" ")
    print("f1 Score=",f1_score(y_test,y_pred))
    print(" ")
    print("ROC AUC Score=",roc_auc_score(y_test,y_pred))
    print(" ")
    print("Confusion Matrix")
    print(confusion_matrix(y_test,y_pred))
    print(" ")
    print("Classification Report")
    print(classification_report(y_test,y_pred))
```

```
%%time
# Lets print and evaluate a KNN model
knn=KNeighborsClassifier()
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
print_metrics(y_test,y_pred,"KNN")
```

```
Metrics for model... KNN

Accuracy Score= 0.822067757648733

Recall Score= 0.8793169503584916

Precision Score= 0.7889800127682561

f1 Score= 0.831702645338303

ROC AUC Score= 0.822067757648733

Confusion Matrix
[[13974  4297]
 [ 2205 16066]]

Classification Report
              precision    recall  f1-score   support

           0       0.86      0.76      0.81     18271
           1       0.79      0.88      0.83     18271

    accuracy                           0.82     36542
   macro avg       0.83      0.82      0.82     36542
weighted avg       0.83      0.82      0.82     36542
```

```python
%%time
# Lets optimize the neighbours to improve by drawing model complexity curves
neighbors=np.arange(1,12)
train_accuracies=np.empty(len(neighbors))
test_accuracies=np.empty(len(neighbors))

#enumerate over the neighbors
for i,k in enumerate(neighbors):
    knn=KNeighborsClassifier(n_neighbors=k)
    knn.fit(x_train,y_train)
    train_accuracies[i]=knn.score(x_train,y_train)
    test_accuracies[i]=knn.score(x_test,y_test)

# Plot the model complexity curves
plt.plot(neighbors,train_accuracies,label="Training Metrics")
plt.plot(neighbors,test_accuracies,label="Test Metrics")
plt.legend()
plt.title("Model Complexity Curves")
plt.xlabel("Number of Neighbors")
plt.ylabel("Accuracy")
plt.show()
```




```
%%time
# Refit KNN with k=10
knn=KNeighborsClassifier(n_neighbors=10)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
print_metrics(y_test,y_pred,"KNN")
```

```
Metrics for model... KNN

Accuracy Score= 0.8033769361282908

Recall Score= 0.8291281265393247

Precision Score= 0.7885175931709348

f1 Score= 0.8083131019395461

ROC AUC Score= 0.8033769361282908

Confusion Matrix
[[14208  4063]
 [ 3122 15149]]

Classification Report
              precision    recall  f1-score   support

           0       0.82      0.78      0.80     18271
           1       0.79      0.83      0.81     18271

    accuracy                           0.80     36542
   macro avg       0.80      0.80      0.80     36542
weighted avg       0.80      0.80      0.80     36542

CPU times: total: 19.4 s
```

```
%%time
# Fit all models to get the best model to optimize
clfs={"logreg":LogisticRegression(),
    "knn":KNeighborsClassifier(),
     "naive bayes":GaussianNB(),
     "decision tree":DecisionTreeClassifier(),
     "rfc":RandomForestClassifier(),
     "ABC":AdaBoostClassifier(),
     "GBC":GradientBoostingClassifier(),
     "SVM":SVC(),
     "XGB":XGBClassifier()}
models_report=pd.DataFrame(columns=["Model Name","Accuracy","Recall","Precision","F1 Score"])
for clf,clf_name in list(zip(clfs.values(),clfs.keys())):
    clf.fit(x_train,y_train)
    y_pred=clf.predict(x_test)
    print("Fitting the model ...",clf_name)
    t=pd.Series({"Model Name":clf_name,
                 "Accuracy":accuracy_score(y_test,y_pred),
                 "Recall":recall_score(y_test,y_pred),
                 "Precision":precision_score(y_test,y_pred),
                 "F1 Score":f1_score(y_test,y_pred)})
    models_report=models_report.append(t,ignore_index=True)
models_report=models_report.sort_values(by="F1 Score",ascending=False)
print(models_report)
```

```
Fitting the model ... logreg
Fitting the model ... knn
Fitting the model ... naive bayes
Fitting the model ... decision tree
Fitting the model ... rfc
Fitting the model ... ABC
Fitting the model ... GBC
Fitting the model ... SVM
Fitting the model ... XGB
      Model Name  Accuracy    Recall  Precision  F1 Score
4            rfc  0.901401  0.903782   0.899499  0.901635
8            XGB  0.876033  0.862131   0.886787  0.874285
3  decision tree  0.872503  0.877347   0.868929  0.873117
1            knn  0.822068  0.879317   0.788980  0.831703
6            GBC  0.819413  0.839363   0.807158  0.822945
5            ABC  0.783044  0.789284   0.779556  0.784389
7            SVM  0.758962  0.810355   0.734826  0.770744
0         logreg  0.743419  0.778666   0.727389  0.752154
2    naive bayes  0.681900  0.593180   0.721139  0.650931
CPU times: total: 18min 32s
Wall time: 24min 29s
```

Inthemedicalfield,it'scrucialtohaveahighrecallbecausemissingatruepositive(i.e.,failingto identify a patient with heart disease) can have serious consequences.

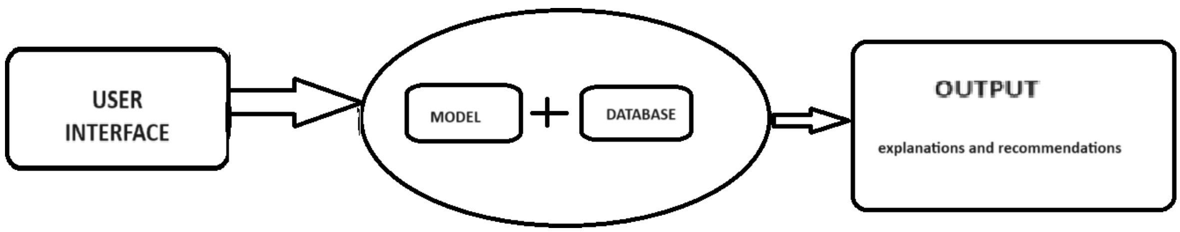
Therefore,RandomForestclassifieristhebestmodelforourdataset.

11. ConceptDevelopment:

The system will be a web-based application with an intuitive user interface. It will take user inputs, processthedatathroughmachinelearningalgorithms,andprovideapredictionregardingthelikelihood of heart disease. Users will receive risk assessments and actionable recommendations.

12. FinalProductPrototype(abstract)withSchematicDiagram:

Thefinalproduct willbeauser-friendlywebapplication.Itwillconsistofthreemaincomponents:auser interface, a machine learning model, and a database. Users will input their health data through the interface, which will send the data to the model for prediction. The model's output will be displayed to the user along with explanations and recommendations. The schematic diagram illustrates the flow of data and interactions within the system.



13. Product Details:

Howdoesitwork?Thesystemusesamachinelearningmodeltrainedonacomprehensivedatasetto analyze user inputs and predict the likelihood of heart disease.

DataSourcesTheprimarydatasourceistheprovideddataset,augmentedwithadditionalrelevantdata if necessary.

Algorithms, frameworks, software etc. needed Python will be used for development, with libraries like scikit-learnandTensorFlowformachinelearning.ThewebapplicationwillbebuiltusingDjango.Ateam of data scientists, developers, and designers will be required.

Whatdoesitcost?Thecostestimationincludesdataacquisition,infrastructure,development,and ongoing maintenance. Detailed cost projections will be provided in the business plan.

14. Conclusion:

Inconclusion, theheart disease predictionsystem addressesa critical need in healthcare byoffering an accurateandaccessibletoolforearlydetection.Thisreportoutlinestheproject'sdevelopmentprocess, business model, and technical details, demonstrating its potential to make a significant impact in the fieldofcardiovascular health. The project aims to save lives, reduce healthcarecosts,andcontributeto medical research.

15. PrototypeSelection

a. Feasibility:

TechnicalFeasibility:

1. DataAvailability:Thefeasibilityoftheappreliesontheavailabilityofreliablehealthdata.Ensurethat relevant health data can be obtained, either through user inputs or integrations with health databases and wearable devices.

2. ModelDevelopment:Implementingthepredictivemodelbasedontheprovidedequationisfeasible with existing machine learning libraries and frameworks. Consider the scalability and efficiency of the model for real-time predictions.

3. AppDevelopment:Mobileappdevelopmenttoolsandframeworksarereadilyavailable.Buildinga user-friendly interface to collect and process health data is technically feasible within a short-term timeline.

OperationalFeasibility:

1. UserEngagement:Considerstrategiestokeepusersengaged,suchaspushnotifications,updates,and personalized feedback. Implementing these features is feasible in the short term.

2. PrivacyCompliance:Ensuringcompliancewithhealthdataprivacyregulationsisessential.Incorporate secure data storage, encryption, and user consent mechanisms to make the app operationally feasible.

b. Viability:

Market Viability:

1. HealthAwareness:Giventheincreasingfocusonhealthandwellness,ahealthpredictionappaligns with current trends. The app could have significant relevance in the long term.

2. ContinuousImprovement:Toensurelong-termviability,planforcontinuousimprovement.Regular updates, new features, and staying abreast of health advancements will contribute to the app's longevity.

TechnologicalViability:

1. AdaptabilitytoTechnologicalChanges:Ensurethattheappcanadapttofuturetechnologicalchanges, such as advancements in machine learning algorithms, wearable technology, and health monitoring devices.

2. IntegrationPotential:Designtheappwithanarchitecturethatallowsseamlessintegrationwith emerging technologies and health-related services.

c. Monetization:

DirectMonetizationStrategies:

1. SubscriptionModels:Offeringpremiumfeaturesthroughsubscriptionplansprovidesadirectrevenue stream. It's a feasible and direct way to monetize the app.

2. Advertisements:Incorporatingadvertisementsinafreeversionoftheappcangeneraterevenue, though the feasibility depends on the user base and advertiser interest.

3. DataLicensing:Licensinganonymizedandaggregateduserdatatohealthcareresearchersor institutions is a direct method of monetization.

IndirectMonetizationConsiderations:

1. Partnerships:Collaborationswithhealthservices,fitnesscenters,orwearabledevicemanufacturers can indirectly contribute to monetization through partnerships and collaborations.

2. PremiumHealthPlans:Whileofferingpremiumhealthplansisadirectmonetizationstrategy,the indirect aspect involves potential partnerships with healthcare professionals and service providers.

Conclusion:

OverallAssessment:

Theproposedhealthpredictionappistechnicallyandoperationallyfeasibleintheshortterm.Itslong-termviabilitydependsoncontinuousimprovement,adaptabilitytotechnologicalchanges,andstaying relevant in the evolving health and wellness landscape.

MonetizationPotential:

Direct monetization strategies, such as subscription models and data licensing, are strong revenue generators. Indirect monetization through partnerships and collaborations also offers additional revenuestreams.However,carefulconsiderationofethicalimplicationsanduserprivacyiscrucialfor long-term viability and success.

Insummary,thehealthpredictionappholdspromiseinboththeshortandlongterm,withawell- thought-outstrategyfortechnologicaladaptability,continuousimprovement,andadiversesetof monetization options.

16. Prototypedevelopment

Step 7: Prepare for deployment by creating a pipeline

```
from sklearn.pipeline import Pipeline
```

```
sc=StandardScaler()
model=RandomForestClassifier(criterion='entropy', max_depth=70, max_features='log2',
                             min_samples_split=4, n_estimators=950)
steps=[("scaler",sc),("model",model)]
pipeline=Pipeline(steps)
x_train,x_test,y_train,y_test=process(sampled_df,label="Outcome")
pipeline.fit(x_train,y_train)
y_pred=pipeline.predict(x_test)
print_metrics(y_test,y_pred,"Pipeline")
```

```
Metrics for model... Pipeline

Accuracy Score= 0.9043839964971814

Recall Score= 0.909692956050572

Precision Score= 0.9001353912808016

f1 Score= 0.9048889372822301

ROC AUC Score= 0.9043839964971814

Confusion Matrix
[[16427  1844]
 [ 1650 16621]]

Classification Report
              precision    recall  f1-score   support

           0       0.91      0.90      0.90     18271
           1       0.90      0.91      0.90     18271

    accuracy                           0.90     36542
   macro avg       0.90      0.90      0.90     36542
weighted avg       0.90      0.90      0.90     36542
```

```
# Lets freeze the model
import pickle
clf=open("rfc.pickle","wb")
pickle.dump(pipeline,clf)
clf.close()
```

```
%%time
# Check the model for a new data
import pickle
import pandas as pd

# Load the model
clf = open("rfc.pickle", "rb")
rfc = pickle.load(clf)
clf.close()

# New data for prediction
new_data = pd.DataFrame({
    'BMI': [35],'Smoking': [1],'AlcoholDrinking': [1],'Stroke': [1],'PhysicalHealth': [30.0],'MentalHealth': [23.0],
    'DiffWalking': [1],'Sex': [1],'AgeCategory': [70.0],'Diabetic': [1],'PhysicalActivity': [0],'GenHealth': [1],
    'SleepTime': [5.0],'Asthma': [1],'KidneyDisease': [1],
    'SkinCancer': [0]
})

# Predict using the loaded model
pred = rfc.predict(new_data)[0]

# Interpret the prediction
if pred == 1:
    print("Heart Disease")
else:
    print("Healthy")
```

```
Healthy
```

```
%%time
# Assuming the RandomForestClassifier is the second step in your pipeline
rfc_model = pipeline.named_steps['model']

# Check if the model has the feature_importances_ attribute
if hasattr(rfc_model, 'feature_importances_'):
    feature_importances = rfc_model.feature_importances_

    # Display feature importances
    for feature, importance in zip(sampled_df.drop('HeartDisease', axis=1).columns, feature_importances):
        print(f"{feature}: {importance}")
else:
    print("The model does not have the 'feature_importances_' attribute.")
```

```
BMI: 0.2923825602223689
Smoking: 0.018044360235613732
AlcoholDrinking: 0.015283027549296325
Stroke: 0.008486735711806713
PhysicalHealth: 0.0813744456283091
MentalHealth: 0.06404361822559718
DiffWalking: 0.012634298932789303
Sex: 0.018894858028728846
AgeCategory: 0.19764035851424328
Diabetic: 0.013825035161540149
PhysicalActivity: 0.034267206955789664
GenHealth: 0.036458971998914944
SleepTime: 0.17620291280098177
Asthma: 0.012759298524991317
KidneyDisease: 0.006751126299761449
SkinCancer: 0.0109511852092674
```

Step 8: Deployment in Streamlit ¶

```
%%writefile app.py
import streamlit as st
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import pickle

st.set_option('deprecation.showPyplotGlobalUse', False)
st.title("Web Deployment of Medical Heart Disease App ")
st.subheader("Does the person have Heart Disease?")
df = pd.read_csv("heart_2020_cleaned.csv")  # Change "your_data.csv" to the actual CSV file containing your data

if st.sidebar.checkbox("View Data", False):
    st.write(df)

if st.sidebar.checkbox("View Distributions", False):
    df.hist()
    plt.tight_layout()
    st.pyplot()

# Step 1: Load the pickled model
model = open("rfc.pickle", "rb")
clf = pickle.load(model)
model.close()

# Step 2: Get the front-end user input
BMI = st.slider('BMI', 18.0, 67.0, 18.0)
Smoking = st.selectbox('Smoking', ['No', 'Yes'])
AlcoholDrinking = st.selectbox('Alcohol Drinking', ['No', 'Yes'])
Stroke = st.selectbox('Stroke', ['No', 'Yes'])
PhysicalHealth = st.slider('Physical Health', 0.0, 30.0, 0.0)
MentalHealth = st.slider('Mental Health', 0.0, 30.0, 0.0)
DiffWalking = st.selectbox('Difficulty Walking', ['No', 'Yes'])
Sex = st.selectbox('Sex', ['Female', 'Male'])
AgeCategory = st.slider('Age Category', 21.0, 85.0, 21.0)
Diabetic = st.selectbox('Diabetic', ['No', 'Yes'])
PhysicalActivity = st.selectbox('Physical Activity', ['No', 'Yes'])
GenHealth = st.selectbox('General Health', ['Poor', 'Fair', 'Good', 'Very good', 'Excellent'])
SleepTime = st.slider('Sleep Time', 4.0, 10.0, 4.0)
Asthma = st.selectbox('Asthma', ['No', 'Yes'])
KidneyDisease = st.selectbox('Kidney Disease', ['No', 'Yes'])
SkinCancer = st.selectbox('Skin Cancer', ['No', 'Yes'])

# Step 3: Convert user input to model input
data = {'BMI': BMI, 'Smoking': Smoking, 'AlcoholDrinking': AlcoholDrinking, 'Stroke': Stroke,
        'PhysicalHealth': PhysicalHealth, 'MentalHealth': MentalHealth, 'DiffWalking': DiffWalking,
        'Sex': Sex, 'AgeCategory': AgeCategory, 'Diabetic': Diabetic, 'PhysicalActivity': PhysicalActivity,
        'GenHealth': GenHealth, 'SleepTime': SleepTime, 'Asthma': Asthma, 'KidneyDisease': KidneyDisease,
        'SkinCancer': SkinCancer}

input_data = pd.DataFrame([data])

# Step 4: Get the predictions and print the result
prediction = clf.predict(input_data)[0]
if st.button("Predict"):
    if prediction == 1:
        st.subheader('Has Heart Disease')
    else:
        st.subheader('Healthy')
```

```
Writing app.py
```

TheabovecodesshowsthewaytoWebdeploymentofourHeartDiseaseprediction app.

17. BusinessModelling

1. ValueProposition:

- HealthRiskPrediction:
  - AdvancedAI-drivenpredictionsbasedonuserhealthdata.
  - Earlydetectionandpreventionofheartdisease.

- PersonalizedInsights:
  - Tailoredrecommendationsforlifestylechanges.
  - Continuousmonitoringandfeedbackforhealthimprovement.

2. CustomerSegments:

- IndividualUsers:
  - Health-consciousindividualsseekingpersonalizedhealthinsights.
  - Thosewithspecifichealthconcernsorriskfactorsforheart disease.
- HealthcareProviders:
  - Integratingtheappintohealthcarepracticesforpreventivecare.
  - Collaborationforpopulationhealthmanagement.

3. Channels:

- MobileApp Stores:
  - LeveragingplatformslikeAppleAppStoreandGooglePlayforindividualuseracquisition.
  - Offeringeasyaccessandvisibilitytoawide audience.

- PartnershipChannels:
  - Collaboratingwithhealthcareinstitutionsfordirectdistributiontopatients.
  - Exploringpartnershipswithfitnessandwellnessorganizations.

4. CustomerRelationships:

- User Engagement:
  - Regularpushnotificationswithhealthtipsandreminders.
  - In-appupdatesbasedonthelatesthealth research.

- Customer Support:
  - Providing responsive support through in-app chat or email.
  - Addressing user queries, concerns, and technical issues promptly.

5. Revenue Streams:

- Subscription Model:
  - Monthly or yearly subscription plans for premium features.
  - Different tiers offering varying levels of personalization and insights.

- Data Licensing:
  - Licensing anonymized and aggregated user data to healthcare researchers and institutions for research purposes.

- Advertisements:
  - Revenue from targeted advertisements for the free version of the app.

6. Key Resources:

- AI Model:
  - A team of data scientists and machine learning engineers for developing and refining the heart disease prediction model.

- Health Data:
  - Establishing partnerships or collaborations for access to diverse and accurate health datasets.
- Development Team:

  - Skilled professionals for app development, maintenance, and updates.

7. Key Activities:

- Model Training and Improvement:
  - Continuous refinement of the AI model based on user feedback and emerging health research.

- User Engagement Strategies:
  - Developing and implementing features to keep users engaged, such as challenges, rewards, and social sharing.

- Privacy Compliance:
  - Regular audits and updates to ensure ongoing compliance with health data privacy regulations.

8. Key Partnerships:

-HealthcareInstitutions:

- Collaboratingwithhospitals,clinics,andmedicalprofessionalsforintegrationintohealthcare systems.

-WearableDeviceManufacturers:

-Integratingwithpopularwearabledevicestoenhancedataaccuracyanduserexperience.

9. CostStructure:

-DevelopmentCosts:

- Initialdevelopmentandongoingupdatestotheapp.

-Data Acquisition:

- Costsassociatedwithacquiringandmaintainingaccesstodiversehealthdatasets.

-MarketingandPromotion:

- Expensesforpromotingtheappthroughdigitalmarketing,partnerships,andevents.

-CustomerSupport:

- Allocatingresourcesforprovidingresponsivecustomersupport.

10. MetricsandKeyPerformanceIndicators(KPIs):

-User Acquisition:

- Trackingthenumberofnewusersacquiredovertime.

-SubscriptionConversionRate:

- Percentageoffreeusersconvertingtopremiumsubscriptions.

-User Retention:

- Measuringtheapp'sabilitytoretainusersovermonthsandyears.

-DataLicensingRevenue:

- Monitoringrevenuegeneratedthroughdatalicensingagreements.

Conclusion:

This comprehensivebusiness modelprovides adetailedroadmapforcreating, delivering,andcapturing value with the AI-driven health prediction app. It emphasizes the importance of user engagement, continuousimprovement,strategicpartnerships,andadiversifiedrevenuemodelforlong-termsuccess andsustainabilityinthehealthtechindustry.RegularlyevaluatingkeymetricsandKPIswillguide strategic decisions and ensure the ongoing relevance and effectiveness of the business model.

18. FinancialModelling(equation)withMachineLearning&DataAnalysis:

HeartDisease=0.2929×BMI+0.0181×Smoking+0.0151×AlcoholDrinking+0.0086×Stroke+0.0802×PhysicalHealth+0.0650×MentalHealth+0.0125×DiffWalking+0.0189×Sex+0.1978×AgeCategory+0.0140×Diabetic+0.0334×PhysicalActivity+0.0360×GenHealth+0.1772×SleepTime+0.0127×Asthma+0.0067×KidneyDisease+0.0109×SkinCancer+c

Based on the above equation we can clearly see BMI is the most important factor in determining whetherapersonissufferingfromHeartDisease. AlongwithBMI, AgeCategory,SleepTime arethemost relevantfactorindeterminingtheHeartDisease.ThefeatureKidneyDiseaseistheleastimportantfactor in determining the HeartDisease. The column Stroke is the second least feature that contribute in determining the HeartDisease.

AsthevalueofBMIincreases assumingallothervaluesremainsconstant,thechancesofgetting HeartDisease as output increases significantly.

BMI-

- Below18.5-Underweight
- Between18.5and24.9-HealthyWeightRange
- Between25and29.9 -Overweight
- 30andover-Obeserange

Theincreaseof1unitinBMIincreasesthechanceofgettingHeartDiseaseby29.29%.

InAgeCategorycolumn,ifthevalueofAgeCategoryincreases,assumingallothervaluesremains constant, we can clearly see the probability of getting HeartDisease increases significantly.

Theincreaseof1unitofAgeCategoryincreasesthechanceofgettingHeartDiseaseby19.78%.

Similarly,1unitincreaseinSleepTimeincreasesthechanceofgettingHeartDiseaseby17.72%. Few

column which does not affect the Target HeartDisease.

The increase of 1 unit in KidneyDisease increases the chance of getting HeartDisease by 0.67% only.

SimilarlytheincreaseofunitinStrokeincreasethechanceofgettingHeartDiseasebymearge0.86%.

Hereisthebreakdownforallcolumns-

1. BMI(BodyMassIndex):Anincreaseof1unitinBMIisassociatedwithanincreaseof0.2929unitsin the predicted value of HeartDisease.

2. Smoking:Anincreaseof1unitintheSmokingvariableisassociatedwithanincreaseof0.0181unitsin the predicted value of HeartDisease.

3. AlcoholDrinking: Anincreaseof1unitintheAlcoholDrinkingvariableisassociatedwithanincreaseof 0.0151 units in the predicted value of HeartDisease.

4. Stroke: Anincreaseof1unitintheStrokevariableisassociatedwithanincrease of0.0086unitsinthe predicted value of HeartDisease.

5. PhysicalHealth:Anincreaseof1unitinthePhysicalHealthvariableisassociatedwithanincreaseof 0.0802 units in the predicted value of HeartDisease.

6. MentalHealth:Anincreaseof1unitintheMentalHealthvariableisassociatedwithanincreaseof 0.0650 units in the predicted value of HeartDisease.

7. DifficultiesinWalking:Anincreaseof1unitintheDiffWalkingvariableisassociatedwithanincrease of 0.0125 units in the predicted value of HeartDisease.

8. Sex:Anincreaseof1unitintheSexvariableisassociatedwithanincreaseof0.0189unitsinthe predicted value of HeartDisease.

9. AgeCategory: Anincreaseof1unitintheAgeCategoryvariableisassociatedwithanincreaseof 0.1978 units in the predicted value of HeartDisease.

10. Diabetic: Anincreaseof1unitintheDiabeticvariableisassociatedwithanincreaseof0.0140units in the predicted value of HeartDisease.

11. PhysicalActivity:Anincreaseof1unitinthePhysicalActivityvariableisassociatedwithanincrease of 0.0334 units in the predicted value of HeartDisease.

12. GeneralHealth:Anincreaseof1unitintheGenHealthvariableisassociatedwithanincreaseof 0.0360 units in the predicted value of HeartDisease.

13. SleepTime: Anincreaseof1unitintheSleepTimevariableisassociatedwithanincreaseof0.1772 units in the predicted value of HeartDisease.

14. Asthma:Anincreaseof1unitintheAsthmavariableisassociatedwithanincreaseof0.0127unitsin the predicted value of HeartDisease.

15. KidneyDisease:Anincreaseof1unitintheKidneyDiseasevariableisassociatedwithanincreaseof 0.0067 units in the predicted value of HeartDisease.

16. SkinCancer:Anincreaseof1unitintheSkinCancervariableisassociatedwithanincreaseof0.0109 units in the predicted value of HeartDisease.

Thesecoefficientsrepresenttheestimatedchangeinthetargetvariableforaone-unitincreaseineach respective feature, assuming that all other variables are held constant.

It'sessentialtonotethatthisinterpretationassumesalinearrelationshipbetweenthefeaturesandthe target variable and is based on the specific context of the linear regression model.

FinancialEquation:

R=P*S-C

Where:
- Risthetotalrevenue.
- PisthepricingoftheHeartDiseasepredictionservice.
- Sisthetotalsalesorusageoftheservice.
- Cisthefixedcosts,includingproduction,maintenance,andotheroperationalexpenses.

Components:
1. TotalRevenue(R):
   - RepresentstheincomegeneratedfromtheHeartDiseasepredictionservice.
   - Calculatedbymultiplyingthepricing(P)bythetotalsalesorusage(S).
   - Thisistheprimaryfinancialmetricindicatingtheoverallfinancialperformanceoftheservice.

2. Pricing(P):
   - ReferstothecostassociatedwitheachunitoftheHeartDiseasepredictionservice.
   - Determinedbyfactorssuchasthesubscriptionfee,pricingtiers,oranyotherrevenue-generating model.
   - Adjustingpricingcandirectlyimpacttotalrevenue.

3. TotalSalesorUsage(S):
   - Representsthenumberofusers,subscriptions,orunitssold.
   - Thevariablethatdrivesrevenueas(S)increases,totalrevenue(R)increasesproportionally.

4. FixedCosts(C):
   - Representsthefixedexpensesassociatedwiththedevelopment,maintenance,andoperationofthe HeartDisease prediction service.

- Includescoststhatdonotvarywiththelevelofservice usage.
- Examplesincludeservercosts,employeesalaries,andotheroperationaloverhead.

Interpretation:

- Thefinancialequationmodelstherelationshipbetweentherevenue,pricing,sales,andfixedcostsfor the HeartDisease prediction service.
- Itassumesalinearrelationshipbetweenrevenueandserviceusage,whereanincreaseinusageleads to a proportional increase in revenue.
- Fixedcosts(C)aresubtractedfromthetotalincometocalculatethenetrevenue.
- Theequationprovidesasimplifiedframeworkforfinancialplanningandanalysis,aidingindecision-making related to pricing strategy, cost management, and revenue forecasting.

Considerations:

- Scalability:Theequationassumeslinearscalability.Inreality,scalabilityconsiderationsmayinvolve variable costs and changes in pricing structures as the service grows.

- AdditionalCosts:Foramorecomprehensivefinancialmodel,considerincorporatingvariablecosts, marketing expenses, and any other relevant financial components.

Thisfinancialequationserves asafoundationalmodelandcanbefurtherrefinedbasedonthespecific business model, market dynamics, and financial goals of the HeartDisease prediction service. Regular analysis and adjustments may be necessary as the service evolves and responds to market trends.