Visualizing and Predicting Heart Diseases with an InteractiveDash Board

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Heart Disease Prediction using Machine Learning Approach

Heart Disease (including Coronary Heart Disease, Hypertension, and Stroke) remains the No. 1 cause of death in the US.The Heart Disease and Stroke Statistics—2019 Update from the American Heart Association indicates that:

- 116.4 million, or 46% of US adults are estimated to have hypertension. These are findings related to the new 2017 Hypertension Clinical Practice Guidelines.
- On average, someone dies of CVD every 38 seconds. About 2,303 deaths from CVD each day, based on 2016 data.
- On average, someone dies of a stroke every 3.70 minutes. About 389.4 deaths from stroke each day, based on 2016 data.

In this machine learning project, we have collected the dataset from Kaggle and we will be using Machine Learning to make predictions on whether a person is suffering from Heart Disease or not.

Problem Statement

- Complete analysis of Heart Disease UCI dataset.
- To predict whether a person has a heart disease or not based on the various biological and physical parameters.

Machine Learning Algorithms

- Random Forest Classifier
- K-Nearest Neighbors Classifier
- Decision Tree Classifier
- Naive Bayes Classifier

IMPORT LIBRARIES:

Let's first import all the necessary libraries. We will use numpy and pandas to start with. For visualization, we will use pyplot subpackage of matplotlib, use rcParams to add styling to the plots and rainbow for colors and seaborn. For implementing Machine Learning models and processing of data, we will use the sklearn library.

```
[1]  import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     from matplotlib import rcParams
     from matplotlib.cm import rainbow
     import seaborn as sns
     %matplotlib inline
```

For processing the data, we'll import a few libraries. To split the available dataset for testing and training, we'll use the train_test_split method. To scale the features, we are using StandardScaler.

```
[2]  from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.preprocessing import LabelEncoder
     from sklearn import tree
     from warnings import filterwarnings
     filterwarnings("ignore")
```

```
[3]  #model validation
     from sklearn.metrics import log_loss,roc_auc_score,precision_score,f1_score,recall_score,roc_curve,auc,plot_roc_curve
     from sklearn.metrics import classification_report, confusion_matrix,accuracy_score,fbeta_score,matthews_corrcoef
     from sklearn import metrics
     from mlxtend.plotting import plot_confusion_matrix
```

For model validation, we'll import a few libraries.

```
#extra
from sklearn.pipeline import make_pipeline, make_union
from sklearn.preprocessing import PolynomialFeatures
from sklearn.feature_selection import SelectFwe, f_regression
```

Next, we will import all the Machine Learning algorithms

- K-Nearest Neighbors Classifier
- Random Forest Classifier
- Decision Tree Classifier
- Naive Bayes Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
```

Import dataset

Now that we have all the libraries we will need, we can import the dataset and take a look at it. The dataset is stored in the file dataset.csv. We'll use the pandas read_csv method to read the dataset.

```
dataset = pd.read_csv('/content/Heart_Disease_Prediction.csv',sep=',',encoding="utf-8")
```

Data Preparation and Data Exploration

```
type(dataset)
```

```
pandas.core.frame.DataFrame
```

```
dataset.shape
```

```
(270, 14)
```

The dataset is now loaded into the variable dataset. We'll just take a glimpse of the data using the desribe() and info() methods before we actually start processing and visualizing it.

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270 entries, 0 to 269
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Age                      270 non-null    int64
 1   Sex                      270 non-null    int64
 2   Chest pain type          270 non-null    int64
 3   BP                       270 non-null    int64
 4   Cholesterol              270 non-null    int64
 5   FBS over 120             270 non-null    int64
 6   EKG results              270 non-null    int64
 7   Max HR                   270 non-null    int64
 8   Exercise angina          270 non-null    int64
 9   ST depression            270 non-null    float64
 10  Slope of ST              270 non-null    int64
 11  Number of vessels fluro  270 non-null    int64
 12  Thallium                 270 non-null    int64
 13  Heart Disease            270 non-null    object
dtypes: float64(1), int64(12), object(1)
memory usage: 29.7+ KB
```

Looks like the dataset has a total of 270 rows and there are no missing values. There are a total of 13 features along with one target value which we wish to find.

```
dataset.columns
```

```
Index(['Age', 'Sex', 'Chest pain type', 'BP', 'Cholesterol', 'FBS over 120',
       'EKG results', 'Max HR', 'Exercise angina', 'ST depression',
       'Slope of ST', 'Number of vessels fluro', 'Thallium', 'Heart Disease'],
      dtype='object')
```

```
[12] dataset.describe()
```

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.00000	270.000000	270.000000	270.000000
mean	54.433333	0.677778	3.174074	131.344444	249.659259	0.148148	1.022222	149.677778	0.329630	1.05000	1.585185	0.670370	4.696296
std	9.109067	0.468195	0.950090	17.861608	51.686237	0.355906	0.997891	23.165717	0.470952	1.14521	0.614390	0.943896	1.940659
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.00000	1.000000	0.000000	3.000000
25%	48.000000	0.000000	3.000000	120.000000	213.000000	0.000000	0.000000	133.000000	0.000000	0.00000	1.000000	0.000000	3.000000
50%	55.000000	1.000000	3.000000	130.000000	245.000000	0.000000	2.000000	153.500000	0.000000	0.80000	2.000000	0.000000	3.000000
75%	61.000000	1.000000	4.000000	140.000000	280.000000	0.000000	2.000000	166.000000	1.000000	1.60000	2.000000	1.000000	7.000000
max	77.000000	1.000000	4.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.20000	3.000000	3.000000	7.000000

The scale of each feature column is different and quite varied as well. While the maximum for age reaches 77, the maximum of chol (serum cholestoral) is 564.

```
dataset
```

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3	Presence
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7	Absence
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7	Presence
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7	Absence
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3	Absence
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
265	52	1	3	172	199	1	0	162	0	0.5	1	0	7	Absence
266	44	1	2	120	263	0	0	173	0	0.0	1	0	7	Absence
267	56	0	2	140	294	0	2	153	0	1.3	2	0	3	Absence
268	57	1	4	140	192	0	0	148	0	0.4	2	0	6	Absence
269	67	1	4	160	286	0	2	108	1	1.5	2	3	3	Presence

270 rows × 14 columns

```
dataset.head()
```

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3	Presence
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7	Absence
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7	Presence
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7	Absence
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3	Absence

```
dataset.isnull().sum()
```

```
Age                        0
Sex                        0
Chest pain type            0
BP                         0
Cholesterol                0
FBS over 120               0
EKG results                0
Max HR                     0
Exercise angina            0
ST depression              0
Slope of ST                0
Number of vessels fluro    0
Thallium                   0
Heart Disease              0
dtype: int64
```

So, we have no missing values

```
dataset.apply(lambda x:len(x.unique()))
```

```
Age                          41
Sex                           2
Chest pain type               4
BP                           47
Cholesterol                 144
FBS over 120                  2
EKG results                   3
Max HR                       90
Exercise angina               2
ST depression                39
Slope of ST                   3
Number of vessels fluro       4
Thallium                      3
Heart Disease                 2
dtype: int64
```

```
print('Chest pain type',dataset['Chest pain type'].unique())
print('FBS over 120',dataset['FBS over 120'].unique())
print('EKG results ',dataset['EKG results'].unique())
print('Exercise angina ',dataset['Exercise angina'].unique())
print('Slope of ST ',dataset['Slope of ST'].unique())
print('Number of vessels fluro ',dataset['Number of vessels fluro'].unique())
print('Thallium ',dataset['Thallium'].unique())
```

```
Chest pain type [4 3 2 1]
FBS over 120 [0 1]
EKG results  [2 0 1]
Exercise angina  [0 1]
Slope of ST  [2 1 3]
Number of vessels fluro  [3 0 1 2]
Thallium  [3 7 6]
```

Dataset Description:

This dataset consists of 13 features and a target variable. The detailed description of all the features are as follows:

1. **Age**: Patients Age in years (Numeric)

---

2. **Sex**: Gender of patient (Male - 1, Female - 0)(Nominal)

---

3. **Chest pain type**: Type of chest pain experienced by patient categorized into :(Nominal)

- Value 1: Typical angina
- Value 2: Atypical angina
- Value 3: Non-anginal pain
- Value 4: Asymptomatic

(Angina: Angina is caused when there is not enough oxygen-rich blood flowing to a certain part of the heart. The arteries of the heart become narrow due to fatty deposits in the artery walls. The narrowing of arteries means that blood supply to the heart is reduced, causing angina.)

---

4. **BP**: Level of blood pressure at resting mode in mm/HG (Numerical)

---

5. **Cholesterol**: Serum cholesterol in mg/dl (Numeric)

(Cholesterol means the blockage for blood supply in the blood vessels)

---

6. **FBS over 120**: Blood sugar levels on fasting > 120 mg/dl represents as 1 in case of true and 0 as false (Nominal)

(blood sugar taken after a long gap between a meal and the test. Typically, it's taken before any meal in the morning.)

---

7. **EKG results**: Result of electrocardiogram while at rest are represented in 3 distinct values: (Nominal)

- Value 0: Normal
- Value 1: Having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)
- Value 2: Showing probable or definite left ventricular hypertrophy by Estes' criteria.

(ECG values taken while person is on rest which means no exercise and normal functioning of heart is happening)

---

8. **ST depression**: Exercise induced ST-depression in comparison with the state of rest (Numeric)

(ST Depression is the difference between value of ECG at rest and after exercise. An electrocardiogram records the electrical signals in your heart. It's a common and painless test used to quickly detect heart problems and monitor your heart's health. Electrocardiograms — also called ECGs or EKGs — are often done in a doctor's office, a clinic or a hospital room. ECG machines are standard equipment in operating rooms and ambulances. Some personal devices, such as smart watches.)

---

9. **Slope of ST**: ST segment measured in terms of slope during peak exercise (Nominal)

- Value 1: Upsloping
- Value 2: Flat
- Value 3: Downsloping

---

10. **Number of vessels fluro**: Number of major blood vessels (0-3)(Numeric)

(Fluoroscopy is an imaging technique that uses X-rays to obtain real-time moving images of the interior of an object. In its primary application of medical imaging, a fluoroscope allows a physician to see the internal structure and function of a patient, so that the pumping action of the heart or the motion of swallowing, for example, can be watched)

---

11. **Exercise angina**: Exercise induced angina (1 = yes; 0 = no)

(is chest pain while exercising or doing any physical activity.)

---

12. **Thallium**: Thalium stress test

- Value 3: normal
- Value 6: fixed defect
- Value 7: reversibe defect

---

13. **Max HR**: Maximum heart rate achieved in bpm (Numeric)

---

14. **Heart Disease**: It is the target variable which we have to predict , that **Presence** means patient is suffering from heart risk and **Absence** means patient is normal.

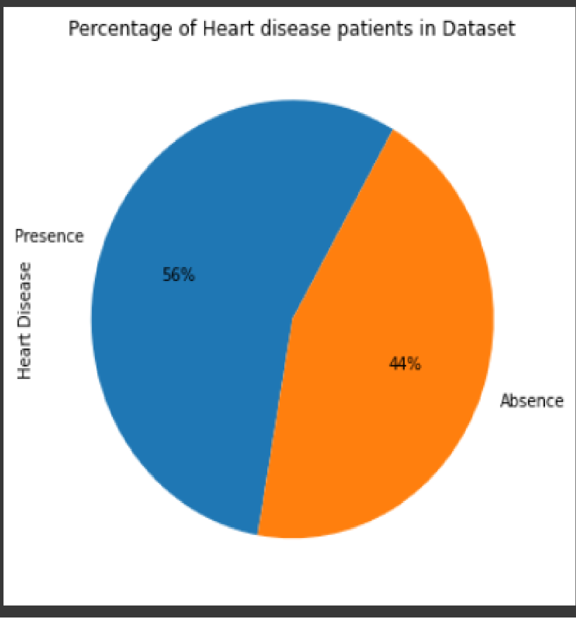
Data Visualization:

Now let's see various visual representations of the data to understand more about relationship between various features.

Distribution of Heart disease (Heart Disease)

It's always a good practice to work with a dataset where the target classes are of approximately equal size. Thus, let's check for the same.

```
fig, (ax1) = plt.subplots(nrows=1, ncols=1, sharey=False, figsize=(15,6))

ax1 = dataset['Heart Disease'].value_counts().plot.pie( x="Heart disease" ,y ="no.of patients",
                   autopct = "%1.0f%%",labels=["Presence","Absence"], startangle = 60,ax=ax1);
ax1.set(title = 'Percentage of Heart disease patients in Dataset')
plt.show()
```

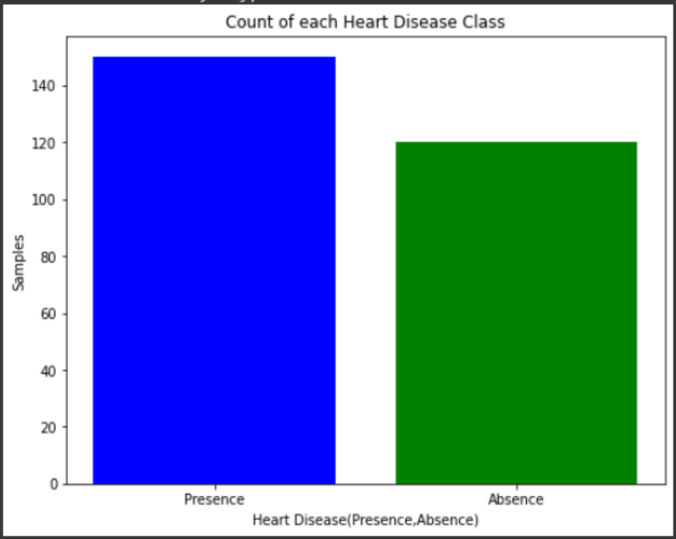


The two classes are not exactly 50% each but the ratio is good enough to continue without dropping/increasing our data.

```
[26] y = dataset["Heart Disease"]
```

```
[56] rcParams['figure.figsize'] = 8,6
     plt.bar(dataset['Heart Disease'].unique(), dataset['Heart Disease'].value_counts(), color = ['blue', 'green'])
     plt.xticks(["Presence","Absence"])
     plt.xlabel('Heart Disease(Presence,Absence)')
     plt.ylabel('Samples')
     plt.title('Count of each Heart Disease Class')
     target_temp = dataset['Heart Disease'].value_counts()
     print(target_temp)
```

```
Absence     150
Presence    120
Name: Heart Disease, dtype: int64
```

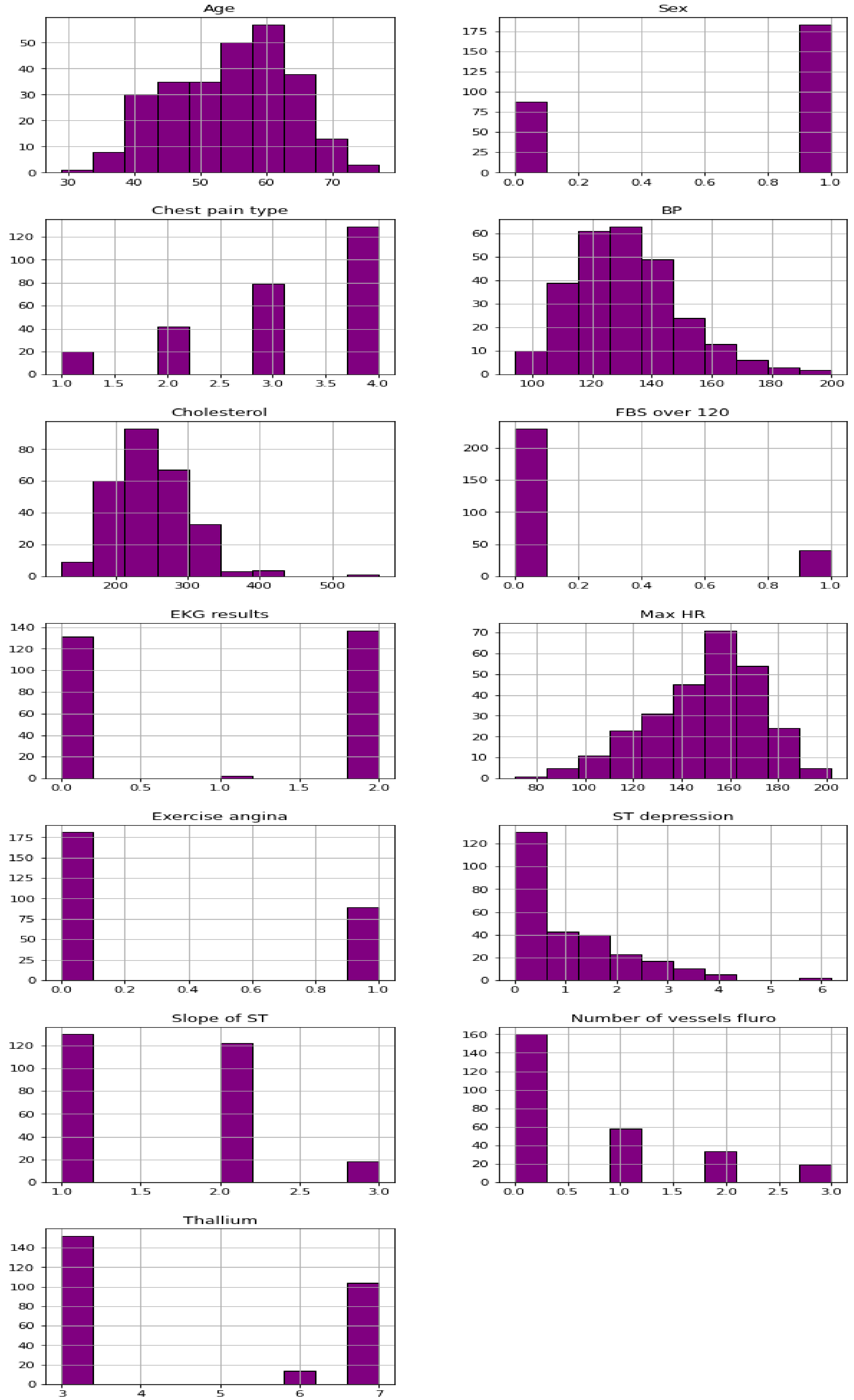


From the total dataset of 270 patients, 150 (56%) have a heart disease (Heart Disease=”Presence”)

Next, we'll take a look at the histograms for each variable.

```
dataset.hist(edgecolor='black',layout = (7, 2),
             figsize = (10, 30),
             color=['purple'])
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11aa39e10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11aa01550>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a9b6b50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a97b190>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a932790>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a8e8d90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a8ac450>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a863990>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a8639d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a826110>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a793c10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a758250>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a70bad0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fd11a736b10>]],
      dtype=object)
```

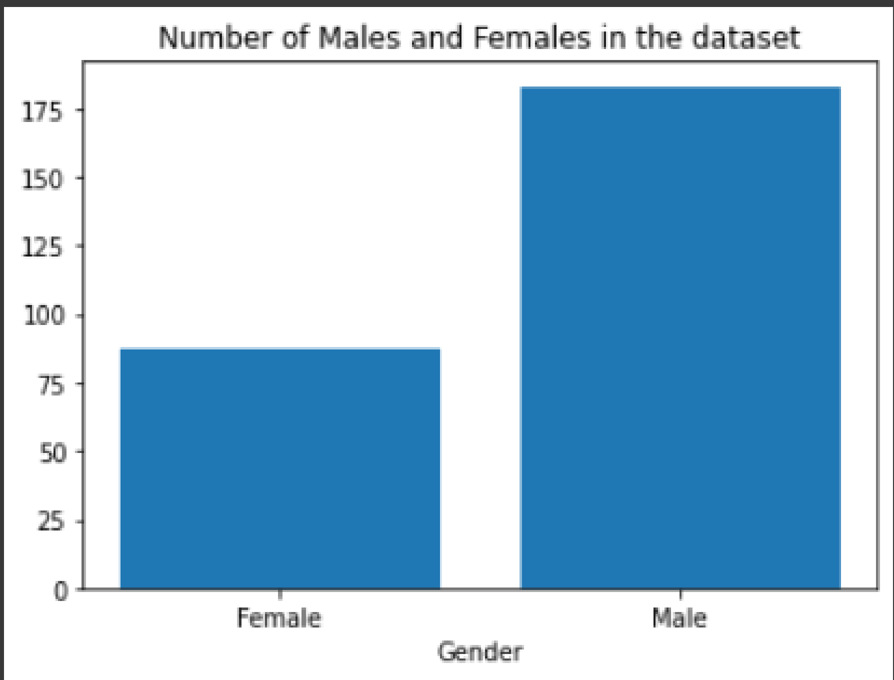

Age
0 10 20 30 40 50
30 40 50 60 70
Sex
0 25 50 75 100 125 150 175
0.0 0.2 0.4 0.6 0.8 1.0
Chest pain type
0 20 40 60 80 100 120
1.0 1.5 2.0 2.5 3.0 3.5 4.0
BP
0 10 20 30 40 50 60
100 120 140 160 180 200
Cholesterol
0 20 40 60 80
200 300 400 500
FBS over 120
0 50 100 150 200
0.0 0.2 0.4 0.6 0.8 1.0
EKG results
0 20 40 60 80 100 120 140
0.0 0.5 1.0 1.5 2.0
Max HR
0 10 20 30 40 50 60 70
80 100 120 140 160 180 200
Exercise angina
0 25 50 75 100 125 150 175
0.0 0.2 0.4 0.6 0.8 1.0
ST depression
0 20 40 60 80 100 120
0 1 2 3 4 5 6
Slope of ST
0 20 40 60 80 100 120
1.0 1.5 2.0 2.5 3.0
Number of vessels fluro
0 20 40 60 80 100 120 140 160
0.0 0.5 1.0 1.5 2.0 2.5 3.0
Thallium
0 20 40 60 80 100 120 140
3 4 5 6 7

Taking a look at the histograms above, I can see that each feature has a different range of distribution. Thus, using scaling before our predictions should be of great use. Also, the categorical features do stand out.

Exploratory Data Analysis (EDA)

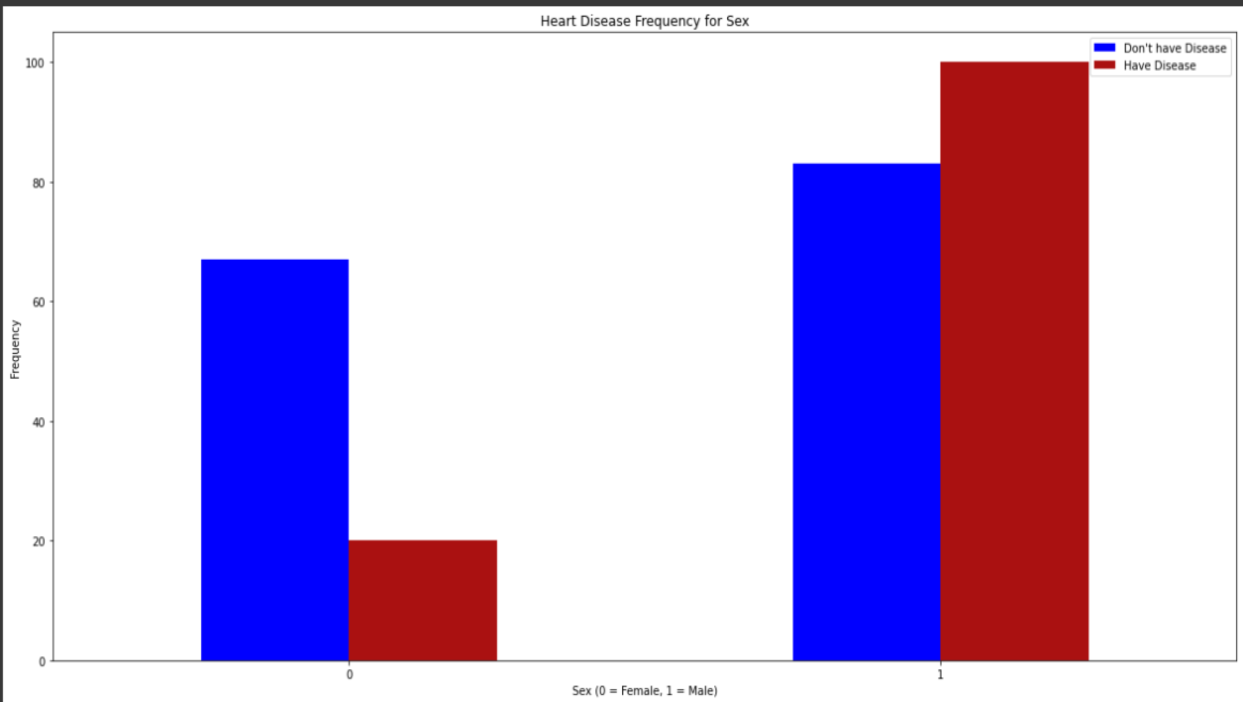
Gender distribution based on heart disease

```
[45] dataset["Sex"].unique()

     array([1, 0])

[46] # Number of males and females
     F = dataset[dataset["Sex"] == 0].count()["Heart Disease"]
     M = dataset[dataset["Sex"] == 1].count()["Heart Disease"]

     # Create a plot
     figure, ax = plt.subplots(figsize = (6, 4))
     ax.bar(x = ['Female', 'Male'], height = [F, M])
     plt.xlabel('Gender')
     plt.title('Number of Males and Females in the dataset')
     plt.show()
```



Heart Disease frequency for Gender:

```
pd.crosstab(dataset['Sex'],dataset['Heart Disease']).plot(kind="bar",figsize=(20,10),color=['blue','#AA1111' ])
plt.title('Heart Disease Frequency for Sex')
plt.xlabel('Sex (0 = Female, 1 = Male)')
plt.xticks(rotation=0)
plt.legend(["Don't have Disease", "Have Disease"])
plt.ylabel('Frequency')
plt.show()
```




```
countFemale = len(dataset[dataset.Sex == 0])
countMale = len(dataset[dataset.Sex == 1])
print("Percentage of Female Patients:{:.2f}%".format((countFemale)/(len(dataset.Sex))*100))
print("Percentage of Male Patients:{:.2f}%".format((countMale)/(len(dataset.Sex))*100))
```

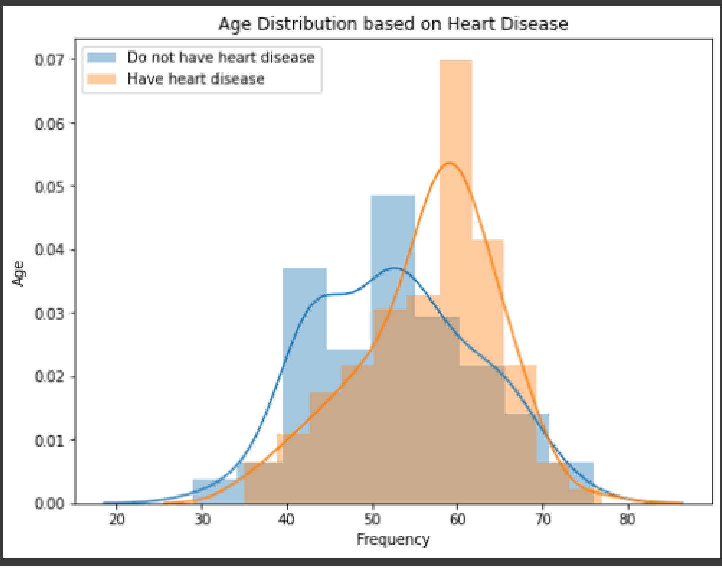
```
Percentage of Female Patients:32.22%
Percentage of Male Patients:67.78%
```

Here, we have calculated the frequency of heart disease based on the gender.

0➔ female
1➔ male

Age distribution based on heart disease:

```python
# Display age distribution based on heart disease
sns.distplot(dataset[dataset['Heart Disease'] == "Absence"]['Age'], label='Do not have heart disease')
sns.distplot(dataset[dataset['Heart Disease'] == "Presence"]['Age'], label = 'Have heart disease')
plt.xlabel('Frequency')
plt.ylabel('Age')
plt.title('Age Distribution based on Heart Disease')
plt.legend()
plt.show()
```



Get min, max and average of the age of the people **do not have heart disease**

```python
print('Min age of people who do not have heart disease: ', min(dataset[dataset['Heart Disease'] == "Absence"]['Age']))
print('Max age of people who do not have heart disease: ', max(dataset[dataset['Heart Disease'] == "Absence"]['Age']))
print('Average age of people who do not have heart disease: ', dataset[dataset['Heart Disease'] == "Absence"]['Age'].mean())
```

```
Min age of people who do not have heart disease:  29
Max age of people who do not have heart disease:  76
Average age of people who do not have heart disease:  52.70666666666666
```

Get min, max and average of the age of the people **have heart disease**

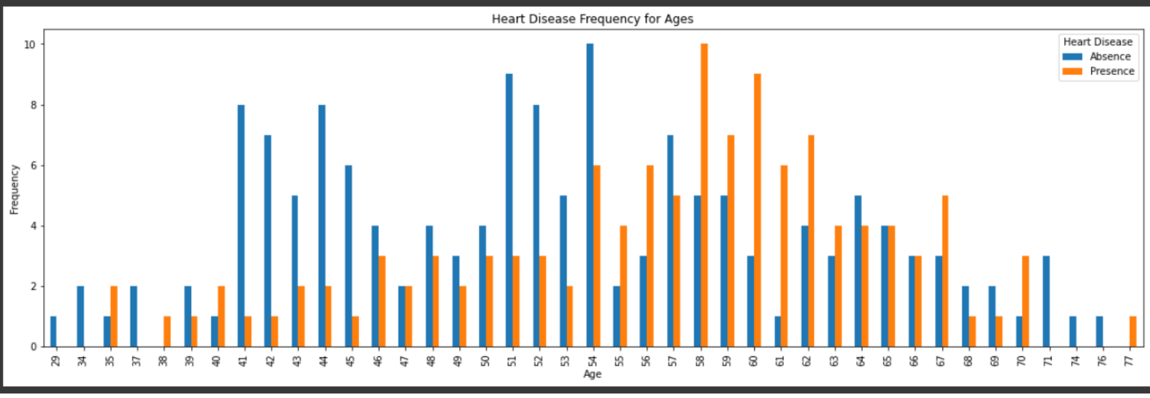
```python
print('Min age of people who have heart disease: ', min(dataset[dataset['Heart Disease'] == "Presence"]['Age']))
print('Max age of people who have heart disease: ', max(dataset[dataset['Heart Disease'] == "Presence"]['Age']))
print('Average age of people who have heart disease: ', dataset[dataset['Heart Disease'] == "Presence"]['Age'].mean())
```

```
Min age of people who have heart disease:  35
Max age of people who have heart disease:  77
Average age of people who have heart disease:  56.59166666666667
```

From the data, we can say that the heart disease infects the old and young people, and the probability of the old people te be infected is higher than young people.

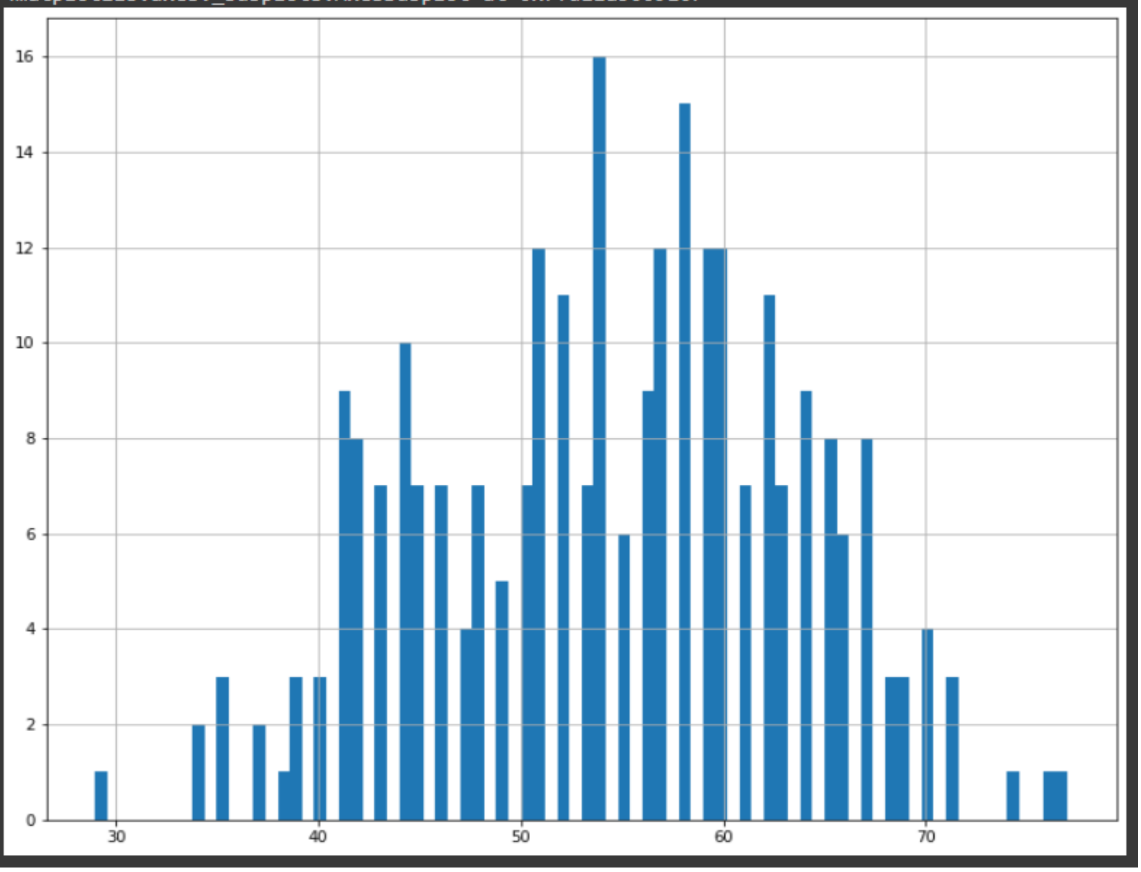
Heart Disease Frequency for ages:

```
pd.crosstab(dataset.Age,dataset['Heart Disease']).plot(kind="bar",figsize=(20,6))
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('heartDiseaseAndAges.png')
plt.show()
```




```
plt.figure(figsize=(12, 10))
dataset.Age.hist(bins=80)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd11a500910>
```



```
print(f"The most of the patients have a mean age of : {dataset.Age.mean()}")
```

```
The most of the patients have a mean age of : 54.43333333333333
```

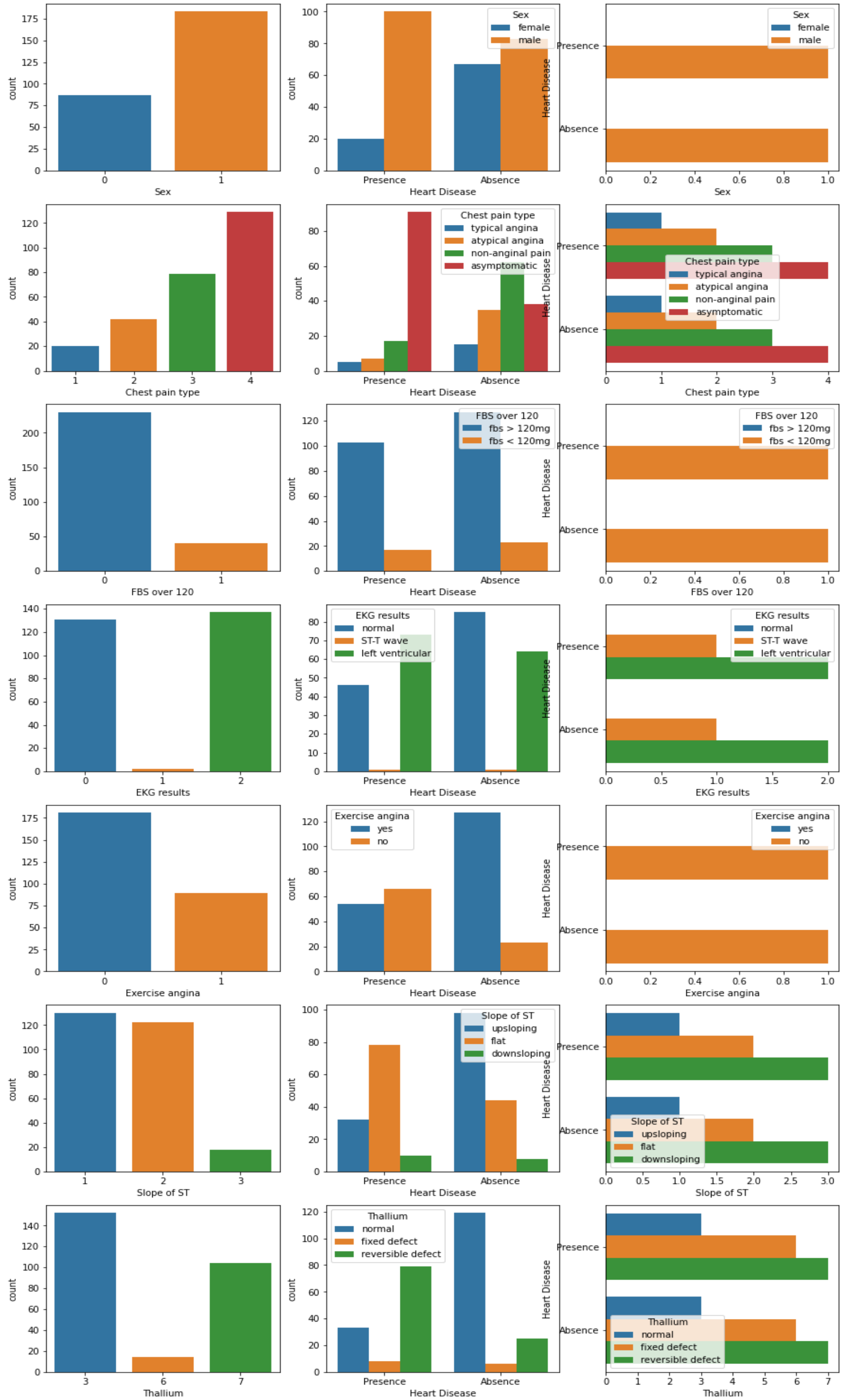
Distribution of Categorial features:

```
[34] categorial = [('Sex', ['female', 'male']),
                   ('Chest pain type', ['typical angina', 'atypical angina', 'non-anginal pain', 'asymptomatic']),
                   ('FBS over 120', ['fbs > 120mg', 'fbs < 120mg']),
                   ('EKG results', ['normal', 'ST-T wave', 'left ventricular']),
                   ('Exercise angina', ['yes', 'no']),
                   ('Slope of ST', ['upsloping', 'flat', 'downsloping']),
                   ('Thallium', ['normal', 'fixed defect', 'reversible defect'])]
```

```
[35] def plotGrid(isCategorial):
         if isCategorial:
             [plotCategorial(x[0], x[1], i) for i, x in enumerate(categorial)]
         else:
             [plotContinuous(x[0], x[1], i) for i, x in enumerate(continuous)]
```

```
[42] def plotCategorial(attribute, labels, ax_index):
         sns.countplot(x=attribute, data=dataset, ax=axes[ax_index][0])
         sns.countplot(x='Heart Disease', hue=attribute, data=dataset, ax=axes[ax_index][1])
         avg = dataset[[attribute, 'Heart Disease']].groupby([attribute], as_index=False).mean()
         sns.barplot(x=attribute, y='Heart Disease', hue=attribute, data=dataset, ax=axes[ax_index][2])

         for t, l in zip(axes[ax_index][1].get_legend().texts, labels):
             t.set_text(l)
         for t, l in zip(axes[ax_index][2].get_legend().texts, labels):
             t.set_text(l)
```

```
fig_categorial, axes = plt.subplots(nrows=len(categorial), ncols=3, figsize=(15, 30))
plotGrid(True)
```

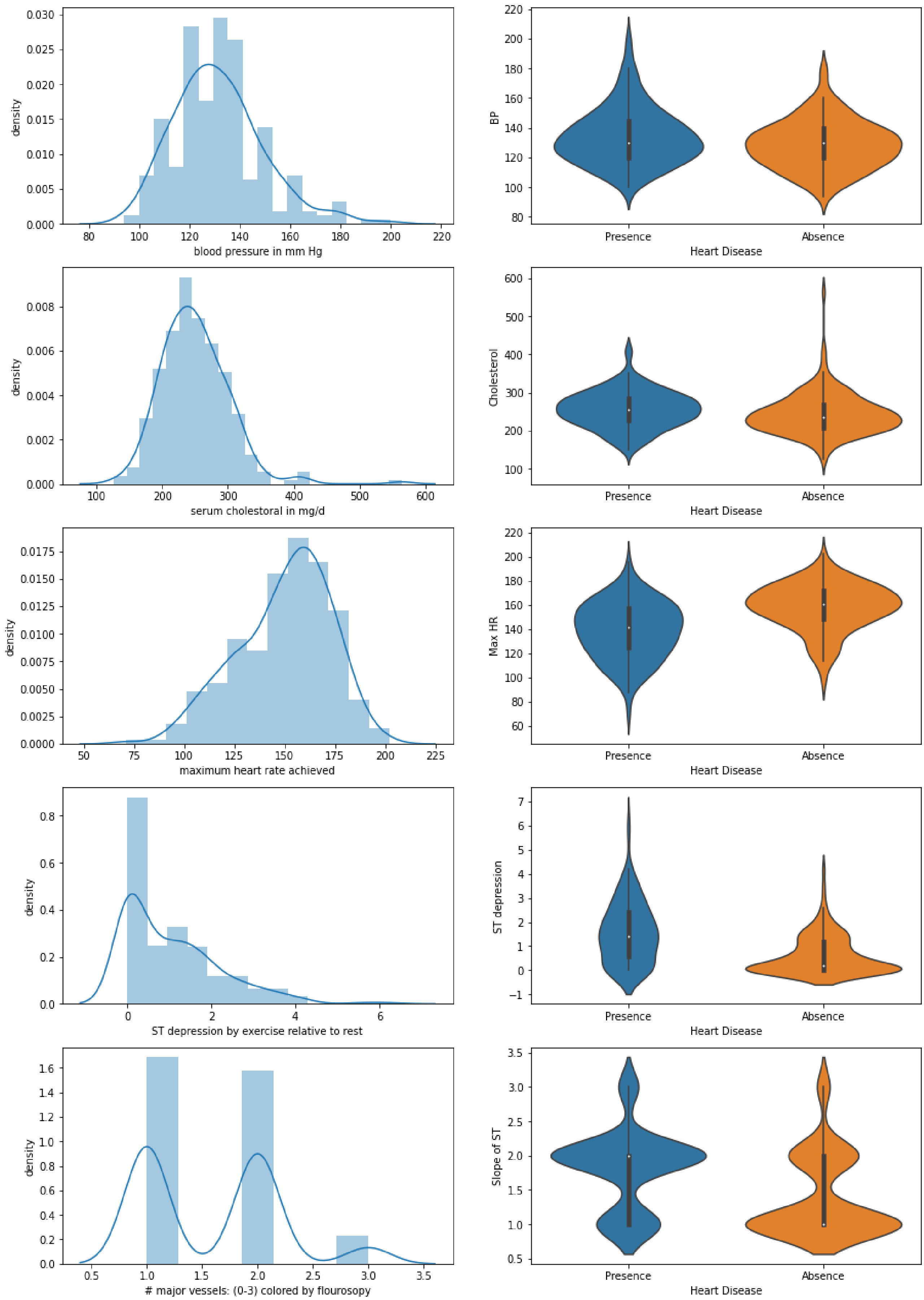

count
Sex
Heart Disease
Presence
Absence
Sex
female
male
Chest pain type
typical angina
atypical angina
non-anginal pain
asymptomatic
FBS over 120
fbs > 120mg
fbs < 120mg
EKG results
normal
ST-T wave
left ventricular
Exercise angina
yes
no
Slope of ST
upsloping
flat
downsloping
Thallium
normal
fixed defect
reversible defect

Distribution of Continuous features:

```
[44] continuous = [('BP', 'blood pressure in mm Hg'),
                  ('Cholesterol', 'serum cholestoral in mg/d'),
                  ('Max HR', 'maximum heart rate achieved'),
                  ('ST depression', 'ST depression by exercise relative to rest'),
                  ('Slope of ST', '# major vessels: (0-3) colored by flourosopy')]
```

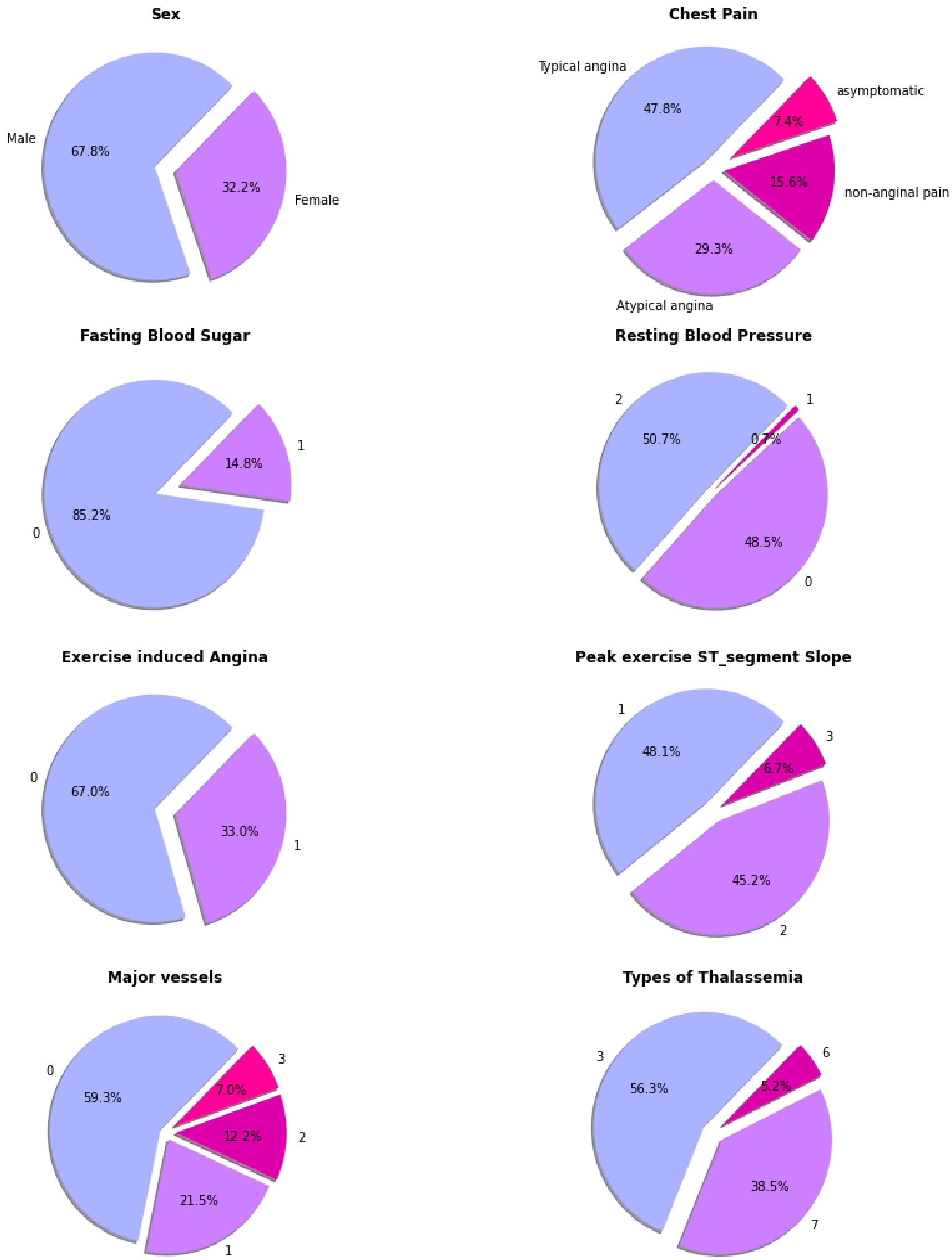
```
[46] def plotContinuous(attribute, xlabel, ax_index):
         sns.distplot(dataset[[attribute]], ax=axes[ax_index][0])
         axes[ax_index][0].set(xlabel=xlabel, ylabel='density')
         sns.violinplot(x='Heart Disease', y=attribute, data=dataset, ax=axes[ax_index][1])
```

```
fig_continuous, axes = plt.subplots(nrows=len(continuous), ncols=2, figsize=(15, 22))

plotGrid(isCategorial=False)
```


density
blood pressure in mm Hg
BP
Presence
Absence
Heart Disease
density
serum cholestoral in mg/d
Cholesterol
Presence
Absence
Heart Disease
density
maximum heart rate achieved
Max HR
Presence
Absence
Heart Disease
density
ST depression by exercise relative to rest
ST depression
Presence
Absence
Heart Disease
density
major vessels: (0-3) colored by flourosopy
Slope of ST
Presence
Absence
Heart Disease

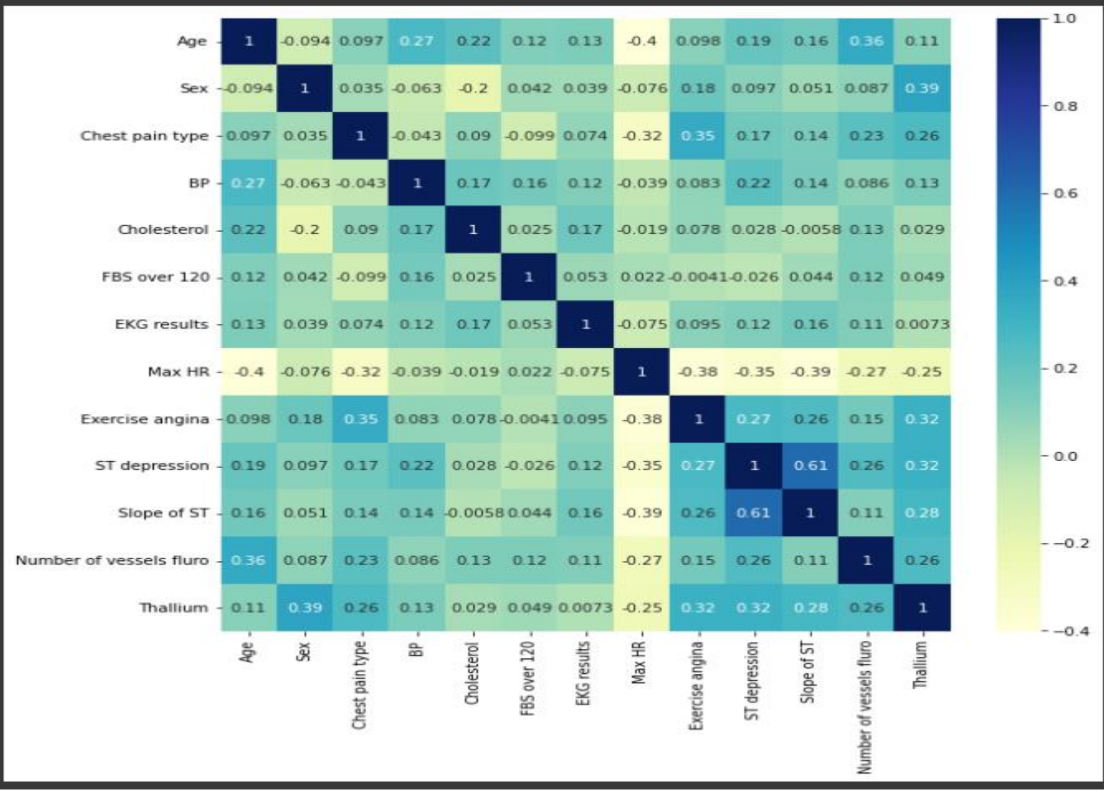
PiePlots:

```
fig, ax = plt.subplots(4,2, figsize = (14,14))
((ax1, ax2), (ax3, ax4), (ax5, ax6), (ax7, ax8)) = ax

labels = ["Male", "Female"]
values = dataset['Sex'].value_counts().tolist()[:2]
ax1.pie(x=values, labels=labels, autopct="%1.1f%%",colors=['#AAb3ff','#CC80FF'],shadow=True, startangle=45,explode=[0.1, 0.1])
ax1.set_title("Sex", fontdict={'fontsize': 12},fontweight ='bold')

labels = ["Typical angina", "Atypical angina","non-anginal pain","asymptomatic"]
values = dataset['Chest pain type'].value_counts().tolist()
ax2.pie(x=values, labels=labels, autopct="%1.1f%%",colors=['#AAb3ff','#CC80FF','#DD00AA','#FF0099'],shadow=True,startangle=45,explode=[0.1, 0.1, 0.1, 0.2])
ax2.set_title("Chest Pain", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['FBS over 120'].value_counts().index.tolist()[:2]
values = dataset['FBS over 120'].value_counts().tolist()
ax3.pie(x=values, labels=labels, autopct="%1.1f%%",colors=['#AAb3ff','#CC80FF'],shadow=True, startangle=45,explode=[0.1, 0.15])
ax3.set_title("Fasting Blood Sugar", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['EKG results'].value_counts().index.tolist()[:3]
values = dataset['EKG results'].value_counts().tolist()
ax4.pie(x=values, labels=labels, autopct="%1.1f%%", colors=['#AAb3ff','#CC80FF','#DD00AA'],shadow=True,startangle=45,explode=[ 0.05, 0.05, 0.05])
ax4.set_title("Resting Blood Pressure", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['Exercise angina'].value_counts().index.tolist()[:2]
values = dataset['Exercise angina'].value_counts().tolist()
ax5.pie(x=values, labels=labels, autopct="%1.1f%%", colors=['#AAb3ff','#CC80FF'],shadow=True, startangle=45,explode=[0.1, 0.1])
ax5.set_title("Exercise induced Angina", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['Slope of ST'].value_counts().index.tolist()[:3]
values = dataset['Slope of ST'].value_counts().tolist()
ax6.pie(x=values, labels=labels, autopct="%1.1f%%", colors=['#AAb3ff','#CC80FF','#DD00AA'],shadow=True,startangle=45,explode=[  0.1, 0.1, 0.1])
ax6.set_title("Peak exercise ST_segment Slope", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['Number of vessels fluro'].value_counts().index.tolist()[:4]
values = dataset['Number of vessels fluro'].value_counts().tolist()
ax7.pie(x=values, labels=labels, autopct="%1.1f%%", shadow=True, startangle=45,explode=[0.05, 0.07, 0.1, 0.1],colors=['#AAb3ff','#CC80FF','#DD00AA','#FF0099'])
ax7.set_title("Major vessels", fontdict={'fontsize': 12},fontweight ='bold')

labels = dataset['Thallium'].value_counts().index.tolist()[:3]
values = dataset['Thallium'].value_counts().tolist()
ax8.pie(x=values, labels=labels, autopct="%1.1f%%", shadow=True, startangle=45,explode=[0.1, 0.1, 0.1],colors=['#AAb3ff','#CC80FF','#DD00AA'])
ax8.set_title("Types of Thalassemia", fontdict={'fontsize': 12},fontweight ='bold')

plt.tight_layout()
plt.show()

plt.savefig("PiePlots.png")
```


Sex
Male
67.8%
32.2%
Female
Chest Pain
Typical angina
47.8%
asymptomatic
7.4%
15.6%
non-anginal pain
29.3%
Atypical angina
Fasting Blood Sugar
14.8%
1
85.2%
0
Resting Blood Pressure
2
50.7%
1
0.7%
48.5%
0
Exercise induced Angina
0
67.0%
33.0%
1
Peak exercise ST_segment Slope
1
48.1%
3
6.7%
45.2%
2
Major vessels
0
59.3%
3
7.0%
12.2%
2
21.5%
1
Types of Thalassemia
3
56.3%
6
5.2%
38.5%
7

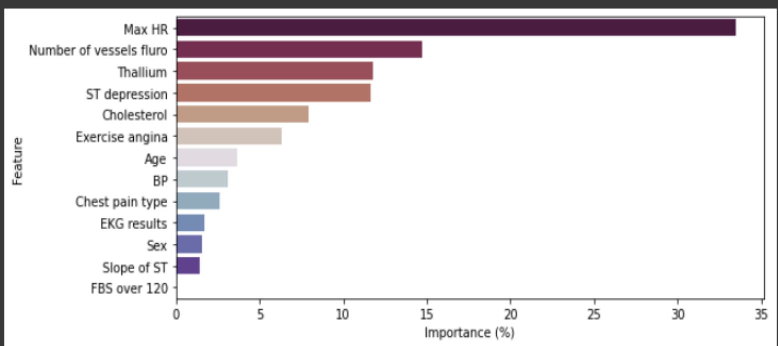
Dataset Correlations:

```python
plt.figure(figsize=(10,10))
sns.heatmap(pd.DataFrame(dataset.corr()), cmap="YlGnBu", annot=True);
plt.savefig("TargetCorrelations.png")
```



Feature Importance:

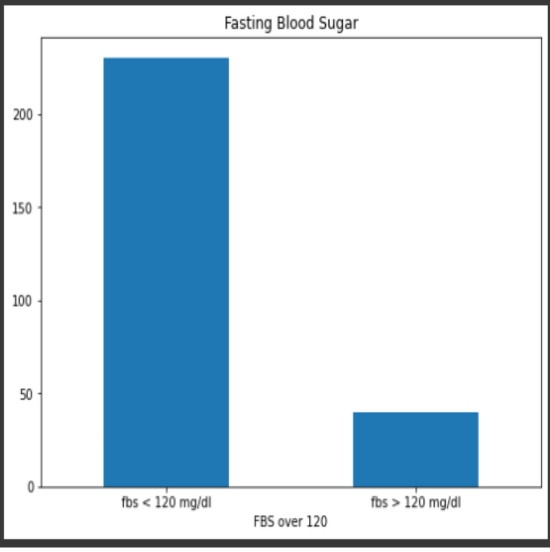
```python
X = dataset.drop('Heart Disease',axis=1)
Y = dataset['Heart Disease']
from sklearn.feature_selection import SelectKBest, chi2
fs = SelectKBest(score_func=chi2, k='all')
fs.fit(X, Y)
per = []
for i in fs.scores_:
    per.append(round(((i/sum(fs.scores_))*100),3))

features_data = pd.DataFrame({'Feature':X.columns,'Scores':fs.scores_,'Importance (%)':per}).sort_values(by=['Scores'],ascending=False)

plt.figure(figsize=(9,4))
sns.barplot( 'Importance (%)','Feature',orient='h',data=features_data,palette='twilight_shifted_r')
insignificant = features_data.loc[features_data['Importance (%)']<0.005]['Feature'].unique()
features_data = features_data.set_index('Feature')
features_data
plt.savefig("FeatureImportance.png")
```



Analyzing Fasting Blood sugar [FBS over 120]:\

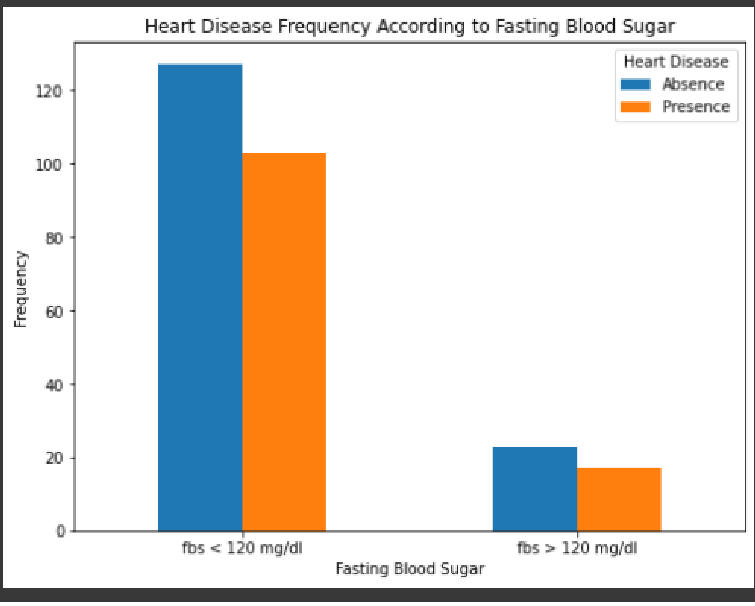
Heart disease according to Fasting Blood sugar

```python
# Display fasting blood sugar in bar chart
dataset.groupby(dataset['FBS over 120']).count()['Heart Disease'].plot(kind = 'bar', title = 'Fasting Blood Sugar', figsize = (8, 6))
plt.xticks(np.arange(2), ('fbs < 120 mg/dl', 'fbs > 120 mg/dl'), rotation = 0)
plt.show()
```



Display fasting blood sugar based on the Heart Disease:

```python
pd.crosstab(dataset['FBS over 120'],dataset['Heart Disease']).plot(kind = "bar", figsize = (8, 6))
plt.title('Heart Disease Frequency According to Fasting Blood Sugar')
plt.xlabel('Fasting Blood Sugar')
plt.xticks(np.arange(2), ('fbs < 120 mg/dl', 'fbs > 120 mg/dl'), rotation = 0)
plt.ylabel('Frequency')
plt.show()
```

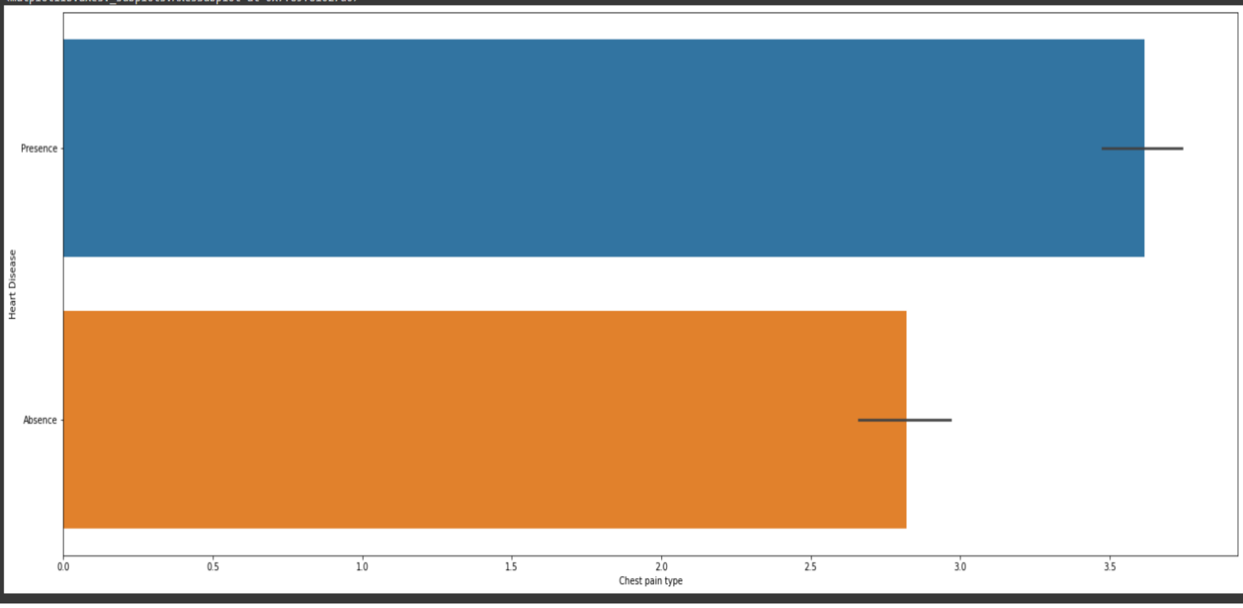


Analyzing the Chest Pain: [Chest pain type] (4 types of chest pain)

```
[68] dataset["Chest pain type"].unique()

array([4, 3, 2, 1])
```

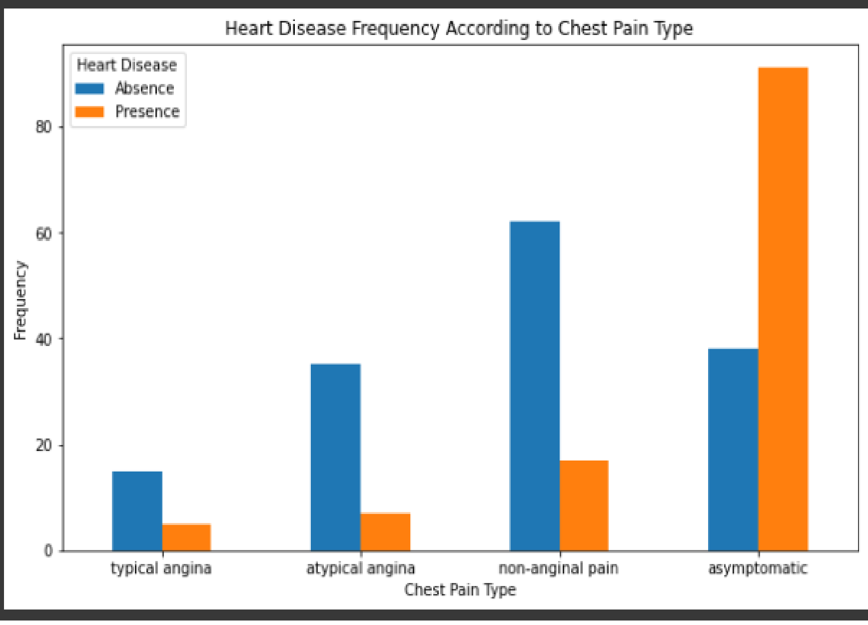
```
plt.figure(figsize=(26, 10))
sns.barplot(dataset["Chest pain type"],y)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89f81627d0>
```



Display chest pain types based on the Heart Disease:

```
pd.crosstab(dataset['Chest pain type'],dataset['Heart Disease']).plot(kind = "bar", figsize = (10, 6))
plt.title('Heart Disease Frequency According to Chest Pain Type')
plt.xlabel('Chest Pain Type')
plt.xticks(np.arange(4), ('typical angina', 'atypical angina', 'non-anginal pain', 'asymptomatic'), rotation = 0)
plt.ylabel('Frequency')
plt.show()
```



Analyzing Resting Blood Pressure [BP]

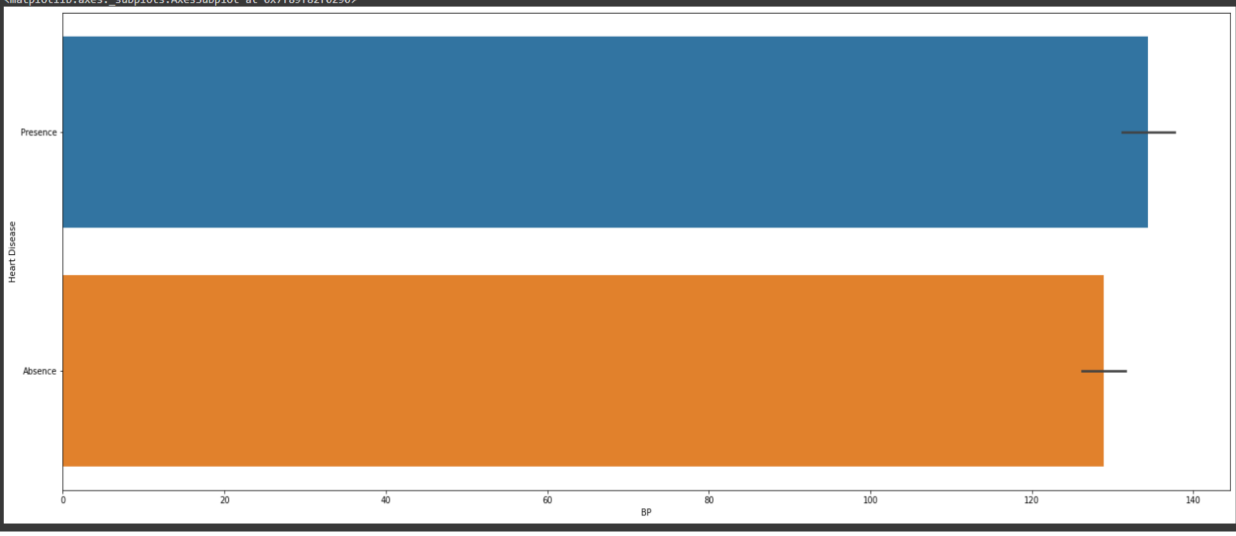
mm Hg on admission to the hospital

```
[72] dataset["BP"].unique()
```

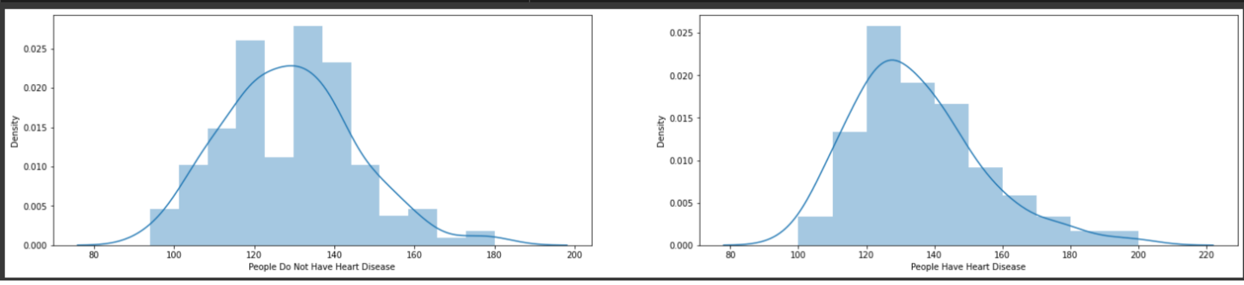
```
array([130, 115, 124, 128, 120, 110, 140, 150, 135, 142, 134, 112, 132,
       138, 160, 170, 144, 122, 152, 101, 126, 118, 136, 105, 174, 145,
       108, 156, 106, 104,  94, 146, 148, 178, 125, 100, 165, 180, 158,
       200, 117, 192, 123, 129, 102, 155, 172])
```

```
plt.figure(figsize=(26, 10))
sns.barplot(dataset["BP"],y)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89f82f0290>
```




```
fig, (axis1, axis2) = plt.subplots(1, 2,figsize=(25, 5))
ax = sns.distplot(dataset[dataset['Heart Disease'] == "Absence"]['BP'], label='Do not have heart disease', ax = axis1)
ax.set(xlabel='People Do Not Have Heart Disease')
ax = sns.distplot(dataset[dataset['Heart Disease'] == "Presence"]['BP'], label = 'Have heart disease', ax = axis2)
ax.set(xlabel='People Have Heart Disease')
plt.show()
```




```
[75] # Get min, max and average of the  blood pressure of the people do not have heart diseas
print('Min blood pressure of people who do not have heart disease: ', min(dataset[dataset['Heart Disease'] == "Absence"]['BP']))
print('Max blood pressure of people who do not have heart disease: ', max(dataset[dataset['Heart Disease'] == "Absence"]['BP']))
print('Average blood pressure of people who do not have heart disease: ', dataset[dataset['Heart Disease'] == "Absence"]['BP'].mean())
```

```
Min blood pressure of people who do not have heart disease:  94
Max blood pressure of people who do not have heart disease:  180
Average blood pressure of people who do not have heart disease:  128.86666666666667
```

```
# Get min, max and average of the blood pressure of the people have heart diseas
print('Min blood pressure of people who have heart disease: ', min(dataset[dataset['Heart Disease'] == "Presence"]['BP']))
print('Max blood pressure of people who have heart disease: ', max(dataset[dataset['Heart Disease'] == "Presence"]['BP']))
print('Average blood pressure of people who have heart disease: ', dataset[dataset['Heart Disease'] == "Presence"]['BP'].mean())
```

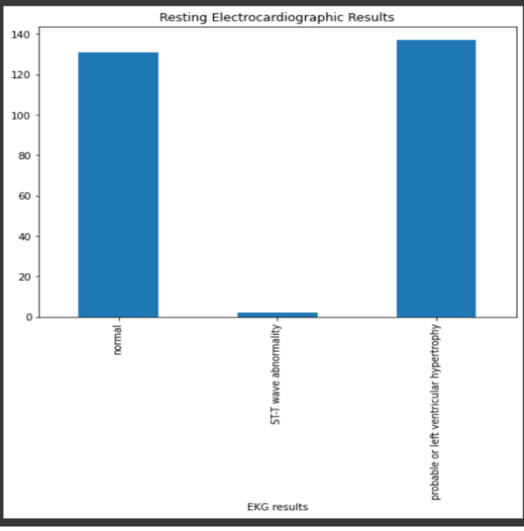
```
Min blood pressure of people who have heart disease:  100
Max blood pressure of people who have heart disease:  200
Average blood pressure of people who have heart disease:  134.44166666666666
```

Analyzing the Resting Electrocardiographic Measurement [EKG results]:

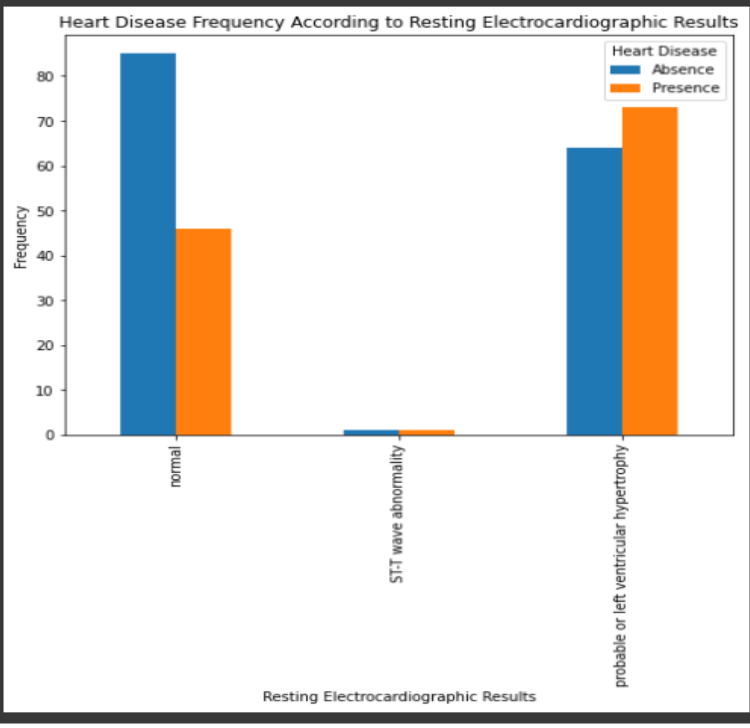
(0 = normal, 1 = having ST-T wave abnormality, 2 = showing probable or definite left ventricular hypertrophy by Estes' criteria)

```
[77] dataset["EKG results"].unique()

     array([2, 0, 1])
```

```
# Display electrocardiographic results in bar chart
dataset.groupby(dataset['EKG results']).count()['Heart Disease'].plot(kind = 'bar', title = 'Resting Electrocardiographic Results', figsize = (8, 6))
plt.xticks(np.arange(3), ('normal', 'ST-T wave abnormality', 'probable or left ventricular hypertrophy'))
plt.show()
```




```
# Display resting electrocardiographic results based on the target
pd.crosstab(dataset['EKG results'],dataset['Heart Disease']).plot(kind = "bar", figsize = (8, 6))
plt.title('Heart Disease Frequency According to Resting Electrocardiographic Results')
plt.xticks(np.arange(3), ('normal', 'ST-T wave abnormality', 'probable or left ventricular hypertrophy'))
plt.xlabel('Resting Electrocardiographic Results')
plt.ylabel('Frequency')
plt.show()
```

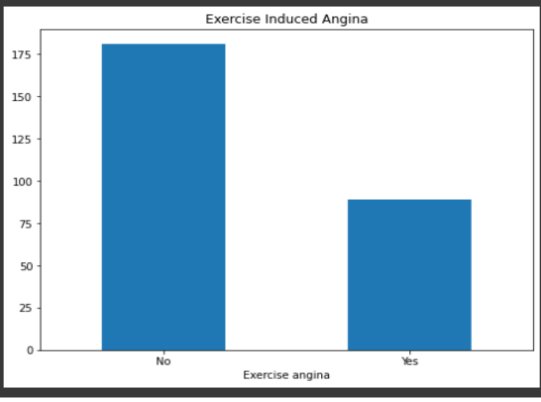


Usually, the people who do not have heart disease have normal electrocardiographic, whereas the people who have heart disease have probable or left ventricular hypertrophy.

Analyzing Exercise Induced Angina [Exercise angina]:

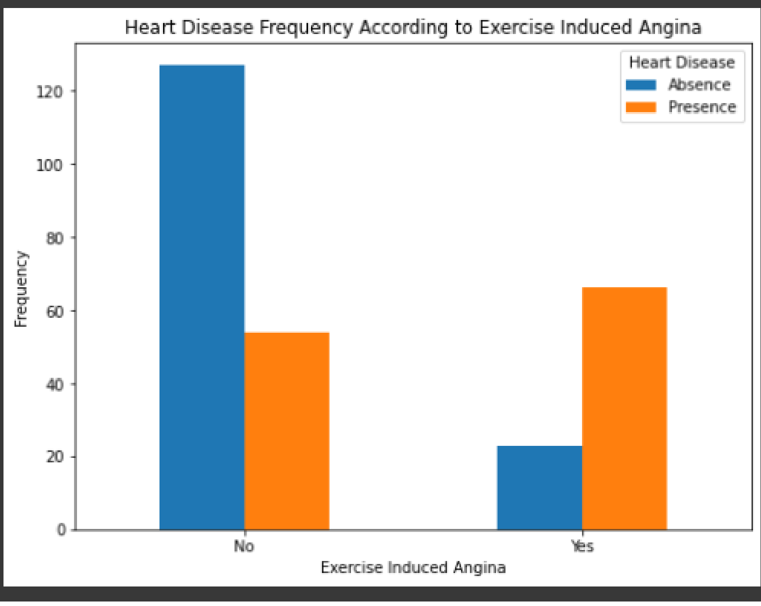
(1 = yes; 0 = no)

```
[80] dataset["Exercise angina"].unique()

array([0, 1])

[81] # Display exercise induced angina in bar chart
     dataset.groupby(dataset['Exercise angina']).count()['Heart Disease'].plot(kind = 'bar', title = 'Exercise Induced Angina',  figsize = (8, 6))
     plt.xticks(np.arange(2), ('No', 'Yes'), rotation = 0)
     plt.show()
```



Display exercise induced angina based on the Heart Disease:

```
pd.crosstab(dataset['Exercise angina'],dataset['Heart Disease']).plot(kind = "bar", figsize = (8, 6))
plt.title('Heart Disease Frequency According to Exercise Induced Angina')
plt.xlabel('Exercise Induced Angina')
plt.xticks(np.arange(2), ('No', 'Yes'), rotation = 0)
plt.ylabel('Frequency')
plt.show()
```



The people who suffer from exercise induced angina are more likely to be infected with the heart disease.

Analyzing the Slope of the peak exercise ST segment [Slope of ST]

(Value 1: upsloping, Value 2: flat, Value 3: downsloping)

```
dataset["Slope of ST"].unique()
```

```
array([2, 1, 3])
```

```
# Display slope of the peak exercise ST segment in bar chart
dataset.groupby(dataset['Slope of ST']).count()['Heart Disease'].plot(kind = 'bar', title = 'Slope of the Peak Exercise ST Segment', figsize = (8, 6))
plt.xticks(np.arange(3), ('upsloping', 'flat', 'downsloping'), rotation = 0)
plt.show()
```