Capstone-Heart-RBM-Final

April 7, 2023

[1]:
```
# Capstone Project - Heart Disease Prediction
# Dataset - data.xlsx in folder '1582800613_project3datadictionary' as␣
↪downloaded from website
```

[2]:
```
# Initial preparation to work on Python
# Import packages pandas, numpy and os

import pandas as pd
import numpy as np
import os
```

[3]:
```
# Get current working directory

os.getcwd()

# Current working directory will be used for this project
```

[3]:
```
'/home/labsuser/Capstone'
```

[4]:
```
os.chdir('/home/labsuser/Capstone')
```

[5]:
```
os.getcwd()
```

[5]:
```
'/home/labsuser/Capstone'
```

[6]:
```
# Read the dataset

heart = pd.read_excel('data.xlsx')
```

[7]:
```
# Output the dataset

heart

# dataset has 303 rows and 14 columns
```

[7]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0     63    1   3       145   233    1        0      150      0      2.3
```

```
1      37    1   2       130   250    0         1       187       0       3.5
2      41    0   1       130   204    0         0       172       0       1.4
3      56    1   1       120   236    0         1       178       0       0.8
4      57    0   0       120   354    0         1       163       1       0.6
..    …   …  ..      …   …   …      …      …    …      …
298    57    0   0       140   241    0         1       123       1       0.2
299    45    1   3       110   264    0         1       132       0       1.2
300    68    1   0       144   193    1         1       141       0       3.4
301    57    1   0       130   131    0         1       115       1       1.2
302    57    0   1       130   236    0         0       174       0       0.0

     slope  ca  thal  target
0        0   0     1       1
1        0   0     2       1
2        2   0     2       1
3        2   0     2       1
4        2   0     2       1
..     …  ..   …     …
298      1   0     3       0
299      1   0     3       0
300      1   2     3       0
301      1   1     3       0
302      1   1     2       0

[303 rows x 14 columns]
```

[8]:
```python
# Initial check of the data

heart.head()
```

[8]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   63    1   3       145   233    1        0      150      0      2.3      0
1   37    1   2       130   250    0        1      187      0      3.5      0
2   41    0   1       130   204    0        0      172      0      1.4      2
3   56    1   1       120   236    0        1      178      0      0.8      2
4   57    0   0       120   354    0        1      163      1      0.6      2

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

[9]:
```python
# Initial check of the data

heart.tail()
```

```
[9]:      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
298      1   0     3       0
299      1   0     3       0
300      1   2     3       0
301      1   1     3       0
302      1   1     2       0
```

```
[10]: # Check for Null values or missing data

heart.isna().sum()

# There are no null values
# There are Zero values whaich are important to the dataset for analysis
# They need to be retailed
```

```
[10]: age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```
[11]: # Check for data types

heart.dtypes

# Data is all integer except for the oldpeak which is float64
# Data to be retained in current format
```

```
[11]: age           int64
sex           int64
```

```
cp              int64
trestbps        int64
chol            int64
fbs             int64
restecg         int64
thalach         int64
exang           int64
oldpeak       float64
slope           int64
ca              int64
thal            int64
target          int64
dtype: object
```

[12]:

```
# Additional check for data integrity

heart.info()

# 303 non-null values in dataset with 14 columns - all integer except oldpeak␣
↪is float64
# 13 independent variables and 1 dependent variable - 'target' (which needs to␣
↪be predicted)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

[13]:

```
# Dataset structure - 13 variables as under:
# Categorical values - 7 - sex, cp, restecg, exang, slope, ca and thal
```

```
# Boolean values - 1 - fbs
# Numberic values - 5 - age, trestbps, chol, thalach, oldpeak
```

[14]:
```
# Check the value counts for the target variable

heart['target'].value_counts()

# Data indicates heart disease risk higher for 165 and low for 138
# There is good balance between positive and negative CVD cases
```

[14]:
```
1    165
0    138
Name: target, dtype: int64
```

[15]:
```
# Check the number of males and females in the dataset

heart['sex'].value_counts()

# There are 207 males and 96 females
```

[15]:
```
1    207
0     96
Name: sex, dtype: int64
```

[16]:
```
# Import the plot packges

import seaborn as sns
import matplotlib.pyplot as plt
```

[17]:
```
# Check the statistical output of all the variables

heart.describe()
```

[17]:

	age	sex	cp	trestbps	chol	fbs \
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000

	restecg	thalach	exang	oldpeak	slope	ca \
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373
std	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606

```
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.500000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  153.000000    0.000000    0.800000    1.000000    0.000000
75%      1.000000  166.000000    1.000000    1.600000    2.000000    1.000000
max      2.000000  202.000000    1.000000    6.200000    2.000000    4.000000

             thal      target
count  303.000000  303.000000
mean     2.313531    0.544554
std      0.612277    0.498835
min      0.000000    0.000000
25%      2.000000    0.000000
50%      2.000000    1.000000
75%      3.000000    1.000000
max      3.000000    1.000000
```

[18]:

```python
# Check the correlation between the variables to understand the relationship␣
↪between all the variables

heart.corr()
```

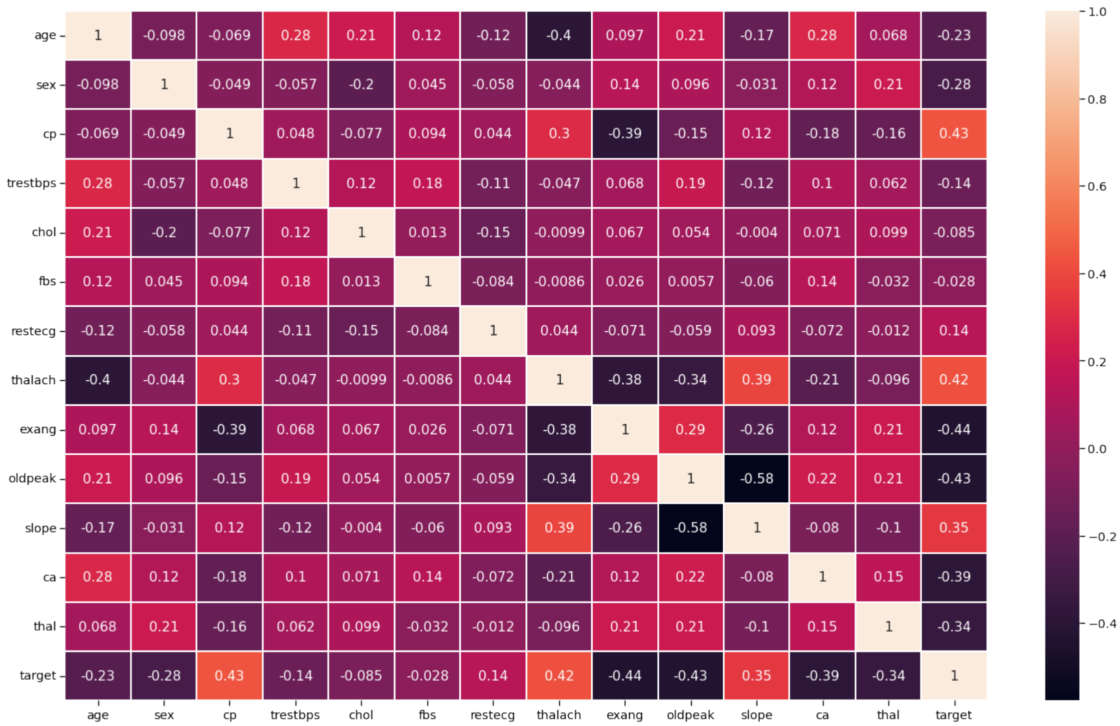
[18]:

```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.098447 -0.068653  0.279351  0.213678  0.121308
sex      -0.098447  1.000000 -0.049353 -0.056769 -0.197912  0.045032
cp       -0.068653 -0.049353  1.000000  0.047608 -0.076904  0.094444
trestbps  0.279351 -0.056769  0.047608  1.000000  0.123174  0.177531
chol      0.213678 -0.197912 -0.076904  0.123174  1.000000  0.013294
fbs       0.121308  0.045032  0.094444  0.177531  0.013294  1.000000
restecg  -0.116211 -0.058196  0.044421 -0.114103 -0.151040 -0.084189
thalach  -0.398522 -0.044020  0.295762 -0.046698 -0.009940 -0.008567
exang     0.096801  0.141664 -0.394280  0.067616  0.067023  0.025665
oldpeak   0.210013  0.096093 -0.149230  0.193216  0.053952  0.005747
slope    -0.168814 -0.030711  0.119717 -0.121475 -0.004038 -0.059894
ca        0.276326  0.118261 -0.181053  0.101389  0.070511  0.137979
thal      0.068001  0.210041 -0.161736  0.062210  0.098803 -0.032019
target   -0.225439 -0.280937  0.433798 -0.144931 -0.085239 -0.028046

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.116211 -0.398522  0.096801  0.210013 -0.168814  0.276326
sex      -0.058196 -0.044020  0.141664  0.096093 -0.030711  0.118261
cp        0.044421  0.295762 -0.394280 -0.149230  0.119717 -0.181053
trestbps -0.114103 -0.046698  0.067616  0.193216 -0.121475  0.101389
chol     -0.151040 -0.009940  0.067023  0.053952 -0.004038  0.070511
fbs      -0.084189 -0.008567  0.025665  0.005747 -0.059894  0.137979
restecg   1.000000  0.044123 -0.070733 -0.058770  0.093045 -0.072042
thalach   0.044123  1.000000 -0.378812 -0.344187  0.386784 -0.213177
exang    -0.070733 -0.378812  1.000000  0.288223 -0.257748  0.115739
```

```
oldpeak  -0.058770 -0.344187  0.288223  1.000000 -0.577537  0.222682
slope     0.093045  0.386784 -0.257748 -0.577537  1.000000 -0.080155
ca       -0.072042 -0.213177  0.115739  0.222682 -0.080155  1.000000
thal     -0.011981 -0.096439  0.206754  0.210244 -0.104764  0.151832
target    0.137230  0.421741 -0.436757 -0.430696  0.345877 -0.391724

              thal    target
age       0.068001 -0.225439
sex       0.210041 -0.280937
cp       -0.161736  0.433798
trestbps  0.062210 -0.144931
chol      0.098803 -0.085239
fbs      -0.032019 -0.028046
restecg  -0.011981  0.137230
thalach  -0.096439  0.421741
exang     0.206754 -0.436757
oldpeak   0.210244 -0.430696
slope    -0.104764  0.345877
ca        0.151832 -0.391724
thal      1.000000 -0.344029
target   -0.344029  1.000000
```

[19]:

```python
# For better visualization of the correlation, convert the above into a heat map

plt.figure(figsize=(20,12))
sns.set_context('notebook',font_scale = 1.3)
sns.heatmap(heart.corr(),annot=True,linewidth =2)
plt.tight_layout()

# The following can be inferred from the heat map:
# 1. cp, restecg, thalach and slope have a high positive correlation with the␣
↪target variable
# 2. exang - exercise induced angina and oldpeak - ST depression induced by␣
↪exercise relative to rest -
# - have high negative correlation to target indicating more stress/blood␣
↪requirement by heart during exercise
# Other variables are negatively correlated to the target variable
# 3. There is also a higher positive correlation between variables as below:
#    a. thalach and cp
#    b. slope and thalach
# thalach - highset heart rate achieved therefore needs further analysis
```



[20]:
```
# Carry out univariate analysis
# AGE
# Age distribution - min, max, median
# Age classification into young, middle and old ages
# Create various plots to analyse the data
# 1. Age distribution

min(heart.age)
```

[20]: 29

[21]:
```
max(heart.age)
```

[21]: 77

[22]:
```
heart.age.mean()
```

[22]: 54.366336633663366

[23]:
```
# Minimum age in the dataset is 29
# Maximum age in dataset is 77
# Mean age in the dataset is 54.36
```

[24]:
```python
# Grouping data to create bar plot

age_freq = heart.groupby('age').agg({'age':'count'})
age_freq
```

[24]:

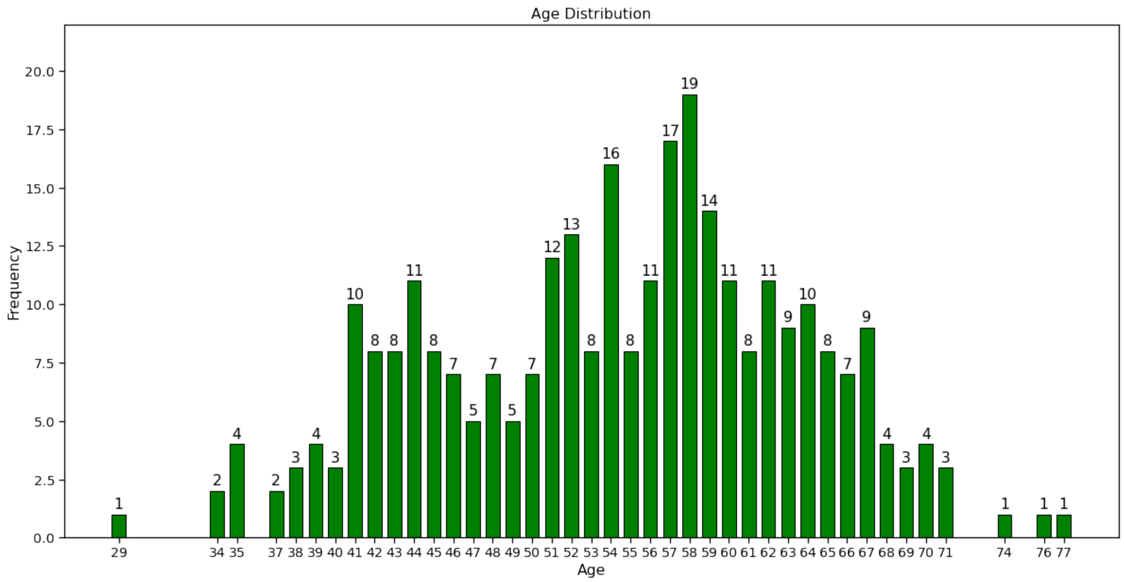
	age
age	
29	1
34	2
35	4
37	2
38	3
39	4
40	3
41	10
42	8
43	8
44	11
45	8
46	7
47	5
48	7
49	5
50	7
51	12
52	13
53	8
54	16
55	8
56	11
57	17
58	19
59	14
60	11
61	8
62	11
63	9
64	10
65	8
66	7
67	9
68	4
69	3
70	4
71	3
74	1
76	1

```
77     1
```

[25]:
```
# Create a bar plot for age distribution

plt.figure(figsize = (20,10))
barplot = plt.bar(age_freq.index, age_freq.age, fc = 'green', ec = 'black',␣
 ↪width = 0.7)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.ylim([0,22])
plt.xticks(age_freq.index)
plt.bar_label(barplot, labels = age_freq.age, label_type = 'edge', padding = 3)
```

[25]:
```
[Text(0, 3, '1'),
 Text(0, 3, '2'),
 Text(0, 3, '4'),
 Text(0, 3, '2'),
 Text(0, 3, '3'),
 Text(0, 3, '4'),
 Text(0, 3, '3'),
 Text(0, 3, '10'),
 Text(0, 3, '8'),
 Text(0, 3, '8'),
 Text(0, 3, '11'),
 Text(0, 3, '8'),
 Text(0, 3, '7'),
 Text(0, 3, '5'),
 Text(0, 3, '7'),
 Text(0, 3, '5'),
 Text(0, 3, '7'),
 Text(0, 3, '12'),
 Text(0, 3, '13'),
 Text(0, 3, '8'),
 Text(0, 3, '16'),
 Text(0, 3, '8'),
 Text(0, 3, '11'),
 Text(0, 3, '17'),
 Text(0, 3, '19'),
 Text(0, 3, '14'),
 Text(0, 3, '11'),
 Text(0, 3, '8'),
 Text(0, 3, '11'),
 Text(0, 3, '9'),
 Text(0, 3, '10'),
 Text(0, 3, '8'),
 Text(0, 3, '7'),
```

```
 Text(0, 3, '9'),
 Text(0, 3, '4'),
 Text(0, 3, '3'),
 Text(0, 3, '4'),
 Text(0, 3, '3'),
 Text(0, 3, '1'),
 Text(0, 3, '1'),
 Text(0, 3, '1')]
```



[26]:
```
# Categorizing the ages into 3 groups to understand the spread of data within␣
↪the dataset
# Categorize into 3 categories - Young (25-40 yrs), Middle (40-55 yrs) and Old␣
↪(>55 yrs)
# Create an additional column with the categorization

heart['Age_Category'] = np.where((heart.age >= 29) & (heart.age < 40),'Young␣
↪Age',
                                  np.where((heart.age >= 40) & (heart.age <␣
↪55),'Middle Age','Old Age'))
heart
```

[26]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0   63    1   3       145   233    1        0      150      0      2.3
1   37    1   2       130   250    0        1      187      0      3.5
2   41    0   1       130   204    0        0      172      0      1.4
3   56    1   1       120   236    0        1      178      0      0.8
4   57    0   0       120   354    0        1      163      1      0.6
```

```
..   ...  ...  ..        ...   ...  ...       ...       ...      ...        ...
298   57    0   0        140   241    0                1       123       1        0.2
299   45    1   3        110   264    0                1       132       0        1.2
300   68    1   0        144   193    1                1       141       0        3.4
301   57    1   0        130   131    0                1       115       1        1.2
302   57    0   1        130   236    0                0       174       0        0.0

     slope  ca  thal  target Age_Category
0        0   0     1       1      Old Age
1        0   0     2       1    Young Age
2        2   0     2       1   Middle Age
3        2   0     2       1      Old Age
4        2   0     2       1      Old Age
..     ...  ..   ...     ...          ...
298      1   0     3       0      Old Age
299      1   0     3       0   Middle Age
300      1   2     3       0      Old Age
301      1   1     3       0      Old Age
302      1   1     2       0      Old Age

[303 rows x 15 columns]
```

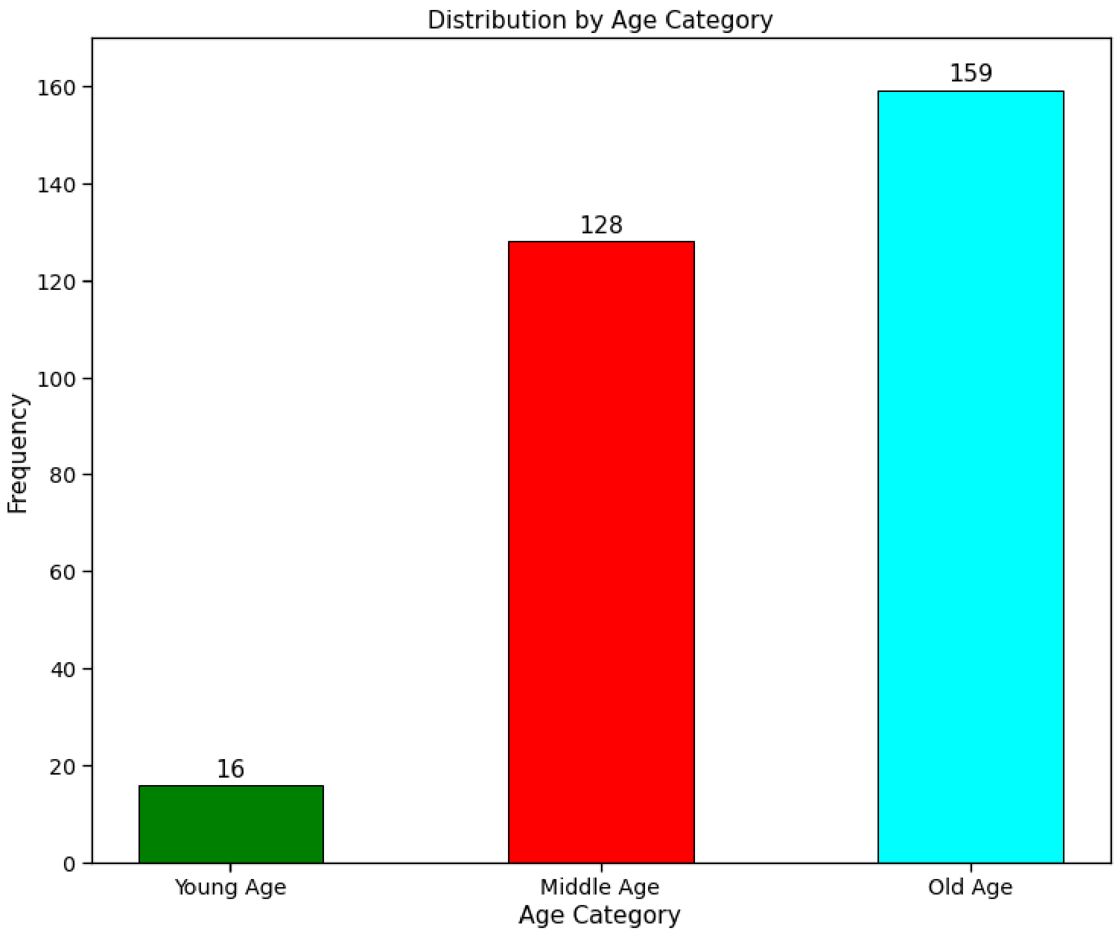
[27]:
```python
# Aggregate the data with the new categorization

age_category = heart.groupby('Age_Category').agg({'Age_Category' : 'count'}).
 ↪apply(lambda x: x.sort_values(ascending = True).head(3))
age_category
```

[27]:
```
              Age_Category
Age_Category
Young Age               16
Middle Age             128
Old Age                159
```

[28]:
```python
# Plot a barplot to see the distribution of samples in the dataset by age␣
 ↪category

plt.figure(figsize = (12,10))
barplot = plt.bar(age_category.index, age_category.Age_Category,
                  color = ['green', 'red', 'cyan'], ec = 'black', width = 0.5)
plt.title('Distribution by Age Category')
plt.xlabel('Age Category')
plt.ylabel('Frequency')
plt.ylim([0,170])
plt.xticks(age_category.index)
plt.bar_label(barplot, labels = age_category.Age_Category, label_type = 'edge',␣
 ↪padding = 3)
```

```
# It is seen that the dataset has maximum old age - 159, middle age - 128 and␣
↪young age - 16
```

[28]: [Text(0, 3, '16'), Text(0, 3, '128'), Text(0, 3, '159')]



[29]:
```
# Understand and check the relation between high risk CVD to the age group

age_group = heart.groupby('Age_Category')['target'].apply(lambda x: (x == 1).
↪sum()).reset_index(name = 'Total_CVD')
age_group

# In the Young age group, there are 12 cases with CVD
# In the Middle age group, there are 88 cases of CVD
# In the Old age group, there are 65 cases of CVD
```

[29]:

	Age_Category	Total_CVD
0	Middle Age	88

```
1       Old Age          65
2     Young Age          12
```

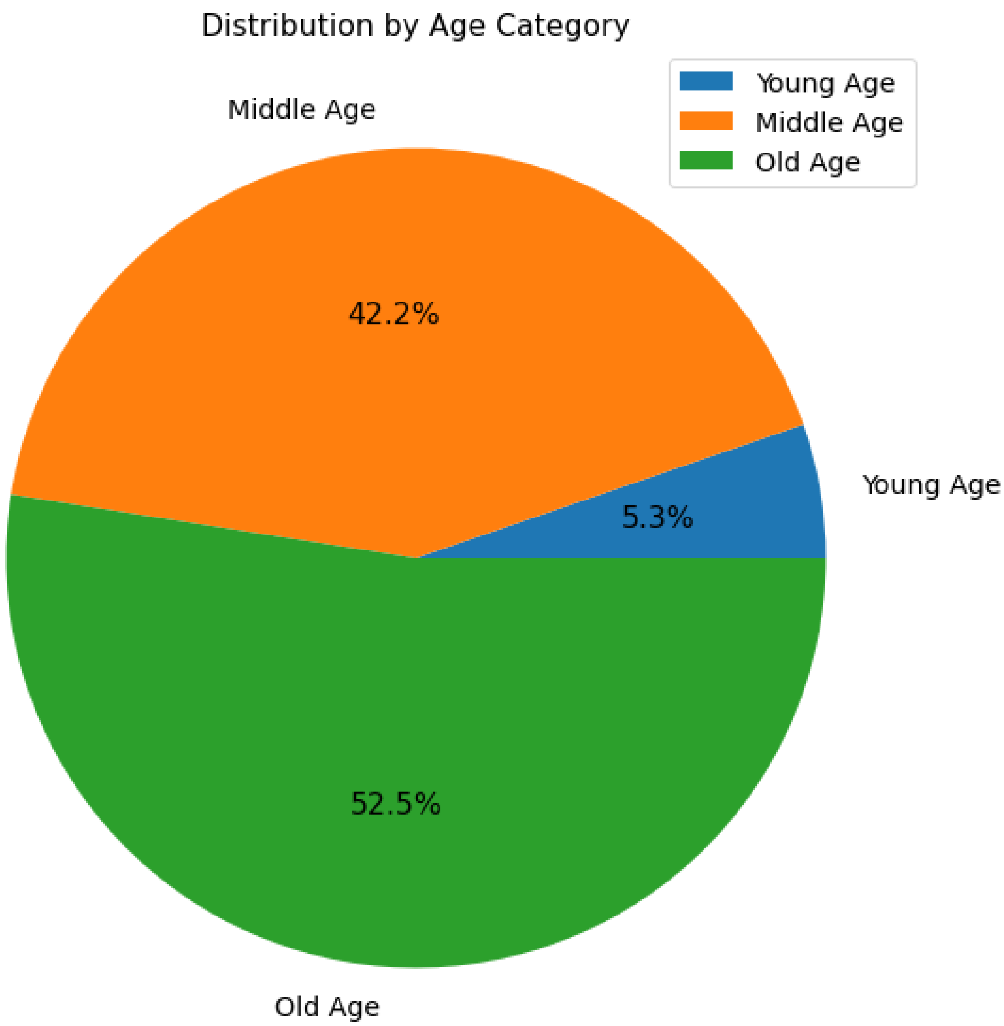
[30]:
```
# Create a new dataframe to display the overall statistics of CVD with respect␣
↪to age

age_grouptotal = pd.DataFrame({'Age_Category' : ['Young Age', 'Middle Age',␣
↪'Old Age'],
                               'Total_CVD' : [12, 88, 65], 'Total' : [16, 128,␣
↪159]})
age_grouptotal
```

[30]:

	Age_Category	Total_CVD	Total
0	Young Age	12	16
1	Middle Age	88	128
2	Old Age	65	159

[31]:
```
# Create a pie chart to understand the % distribution of the population

plt.figure(figsize = (10,10))
plt.pie(age_grouptotal.Total, labels = age_grouptotal.Age_Category, autopct =␣
↪'%.1f%%')
plt.title('Distribution by Age Category')
plt.legend()

# Population distribution is as follows:
# 1. Young age - 5.3% of the total 303
# 2. Middle age - 42.2% of the total 303
# 3. Old age - 52.5% of the total 303
```

[31]: <matplotlib.legend.Legend at 0x7f4aadfd0f10>



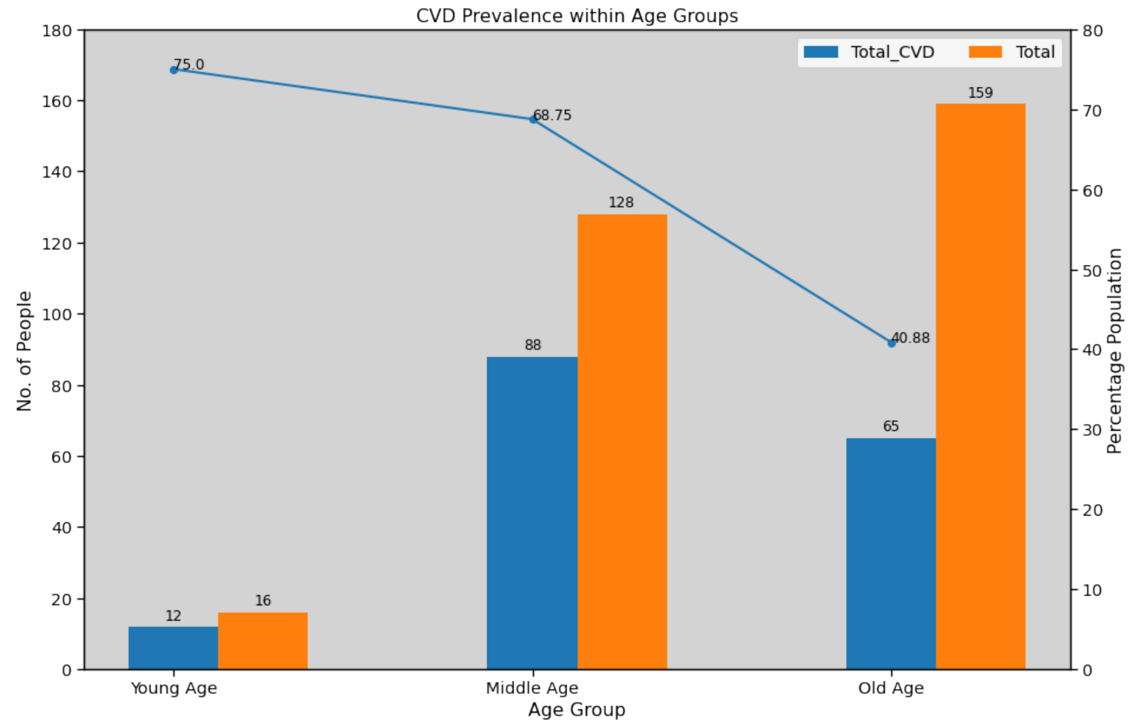
[32]:
```
# Add a % of the population column to the dataframe

age_grouptotal['Percent_Population'] = round((age_grouptotal['Total_CVD']/
                                        age_grouptotal['Total']) * 100, 2)
age_grouptotal
```

[32]:

	Age_Category	Total_CVD	Total	Percent_Population
0	Young Age	12	16	75.00
1	Middle Age	88	128	68.75
2	Old Age	65	159	40.88

[33]:
```
# Create a combined multiple bar plot and line plot to visualize the data of␣
↪CVD prevalence
```

```
age_cat = ('Young Age', 'Middle Age', 'Old Age') # Label location
cvd_means = {'Total_CVD' : (12, 88, 65),
            'Total' : (16, 128, 159)}            # Define the labels
pp_means = {'Percent_Population' : (75, 68.8, 40.9)}
x = np.arange(len(age_cat))
width = 0.25                        # Width of the bar
multiplier = 0                      # Multiplier
fig, ax = plt.subplots(figsize = (15, 10))
ax.set_ylim(0,180)
ax.set_facecolor('lightgray')
ax.grid(False)
ax.set_title('CVD Prevalence within Age Groups')
ax.set_xlabel('Age Group')
ax.set_ylabel('No. of People')
ax.set_xticks(x, age_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(age_grouptotal['Percent_Population'].values, linestyle = '-', marker =␣
 ↪'o', linewidth = 2.0)
ax2.set_ylim(0,80)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
for i, j in age_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



[34]:
```
# Inferences:
# Of the 165 total high risk CVD cases:
# 1. 12 out 16 Young age are CVD high risk - 75%
# 2. 88 out of 128 Middle age are CVD high risk - 68.75%
# 3. 65 out of 159 Old age are CVD high risk - 40.9%
# It is thus interesting to note the following:
# 1. maximum high risk of CVD is with the young population followed by middle age
# 2. Old age people seem to be at lesser risk of CVD
```

[35]:
```
# Refer Line 17
# cp - Chest Pain Type - it has a high positive correlation with the target variable
# Analysis of Chest Pain Type -
# 0 - Asympomatic, 1 - Non-anginal, 2 - Atypical Angina, 3 - Typical Angina
# 4 categorical variables
# Let us understand the distribution of the cp variable

cp_freq = heart.groupby('cp').agg({'cp':'count'})
cp_freq

# Inferences
# Of the 303 samples - 143 - asymptomatic, 50 - non-anginal pain, 87 - atypical angina & 23 - typical angina
```

[35]:

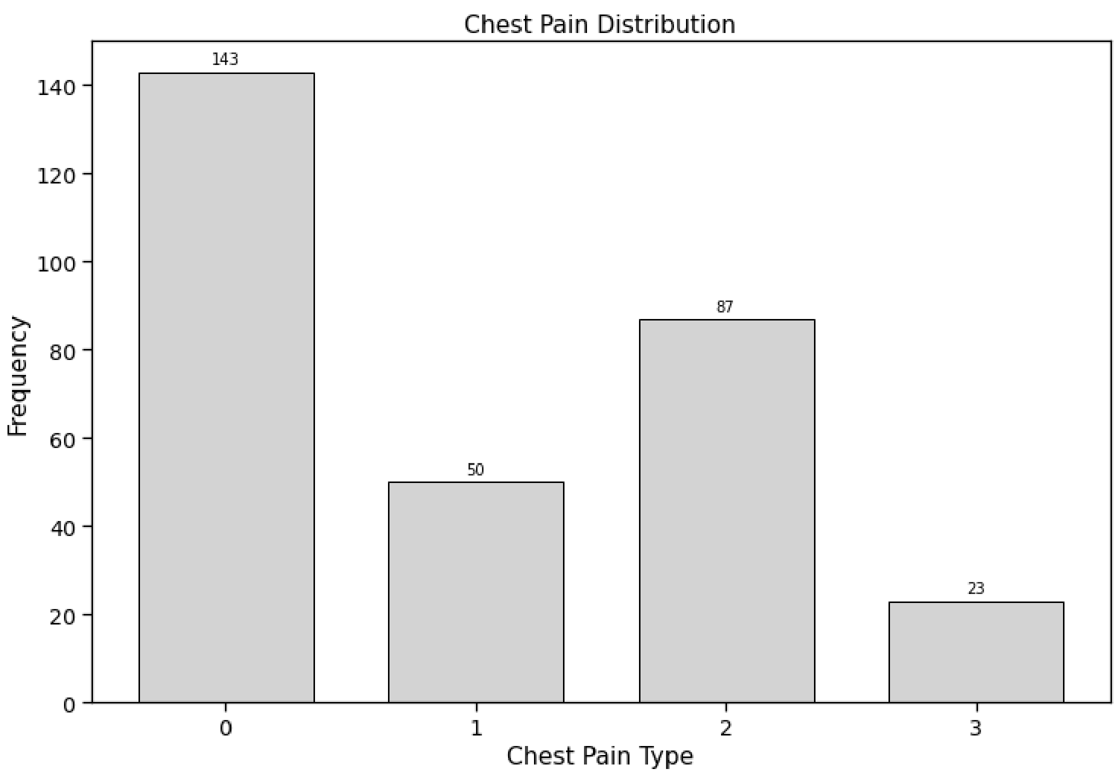
```
     cp
cp
0   143
1    50
2    87
3    23
```

[36]:

```
# Plot a barplot to see the distribution of samples in the dataset by type of␣
↪chest pain

plt.figure(figsize = (12,8))
barplot = plt.bar(cp_freq.index, cp_freq.cp, fc = 'lightgray', ec = 'black',␣
↪width = 0.7)
plt.title('Chest Pain Distribution')
plt.xlabel('Chest Pain Type')
plt.ylabel('Frequency')
plt.ylim([0,150])
plt.xticks(cp_freq.index)
plt.bar_label(barplot, labels = cp_freq.cp, label_type = 'edge', padding = 3,␣
↪fontsize = 10)
```

[36]:

```
[Text(0, 3, '143'), Text(0, 3, '50'), Text(0, 3, '87'), Text(0, 3, '23')]
```



[37]:
```
# Understand and check the relation between high risk CVD to the chest pain type

cp_group = heart.groupby('cp')['target'].apply(lambda x: (x == 1).sum()).
↪reset_index(name = 'Total_CVD')
cp_group
```

[37]:

	cp	Total_CVD
0	0	39
1	1	41
2	2	69
3	3	16

[38]:
```
# Create a new dataframe to display the overall statistics of CVD with type of␣
↪chest pain

cp_grouptotal = pd.DataFrame({'cp' : [0, 1, 2 ,3],
                              'Total_CVD' : [39, 41, 69, 16], 'Total' : [143,␣
↪50, 87, 23]})
cp_grouptotal
```

[38]:

	cp	Total_CVD	Total
0	0	39	143
1	1	41	50
2	2	69	87
3	3	16	23

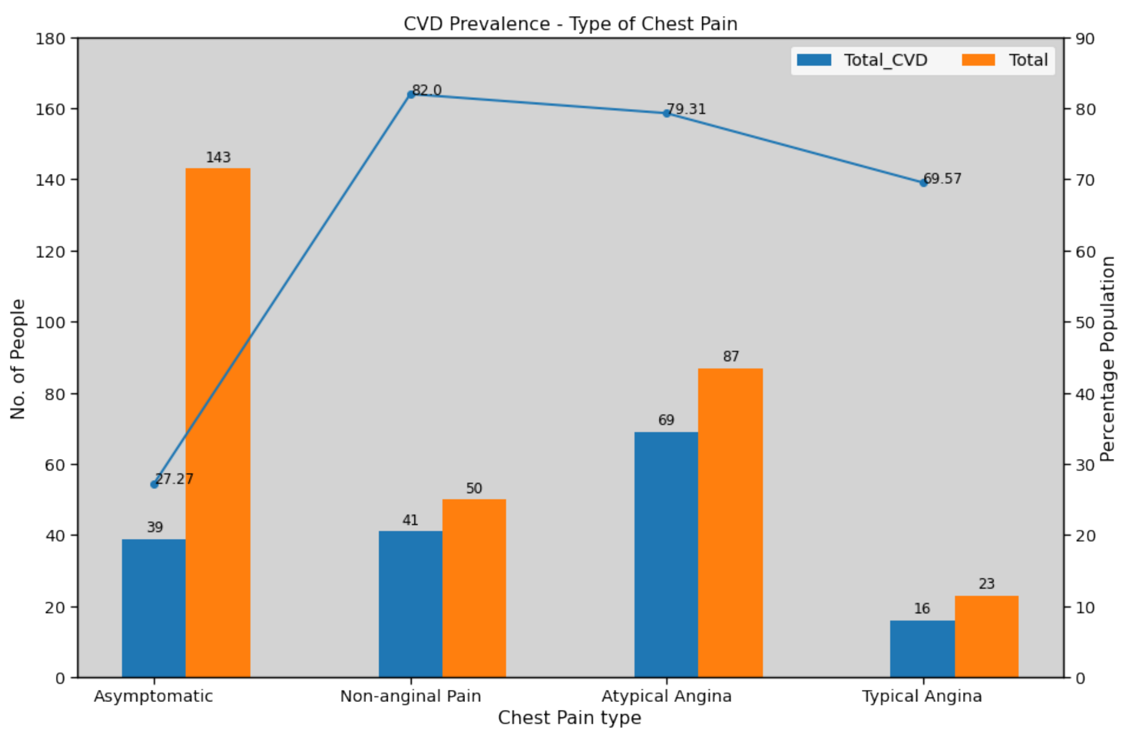
[39]:
```
# Add a % of the population column to the dataframe

cp_grouptotal['Percent_Population'] = round((cp_grouptotal['Total_CVD']/
                                        cp_grouptotal['Total']) * 100, 2)
cp_grouptotal
```

[39]:

	cp	Total_CVD	Total	Percent_Population
0	0	39	143	27.27
1	1	41	50	82.00
2	2	69	87	79.31
3	3	16	23	69.57

[40]:
```
# Create a combined multiple bar plot and line plot to visualize the data of␣
↪CVD prevalence

cp_cat = ('Asymptomatic', 'Non-anginal Pain', 'Atypical Angina', 'Typical␣
↪Angina') # Label location
cvd_means = {'Total_CVD' : (39, 41, 69, 16),
            'Total' : (143, 50, 87, 23)}            # Define the labels
pp_means = {'Percent_Population' : (27.3, 82.0, 79.3, 69.6)}
x = np.arange(len(cp_cat))
```

```
width = 0.25                    # Width of the bar
multiplier = 0                  # Multiplier
fig, ax = plt.subplots(figsize = (15, 10))
ax.set_ylim(0,180)
ax.set_facecolor('lightgray')
ax.grid(False)
ax.set_title('CVD Prevalence - Type of Chest Pain')
ax.set_xlabel('Chest Pain type')
ax.set_ylabel('No. of People')
ax.set_xticks(x, cp_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(cp_grouptotal['Percent_Population'].values, linestyle = '-', marker =␣
 ↪'o', linewidth = 2.0)
ax2.set_ylim(0,90)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
for i, j in cp_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



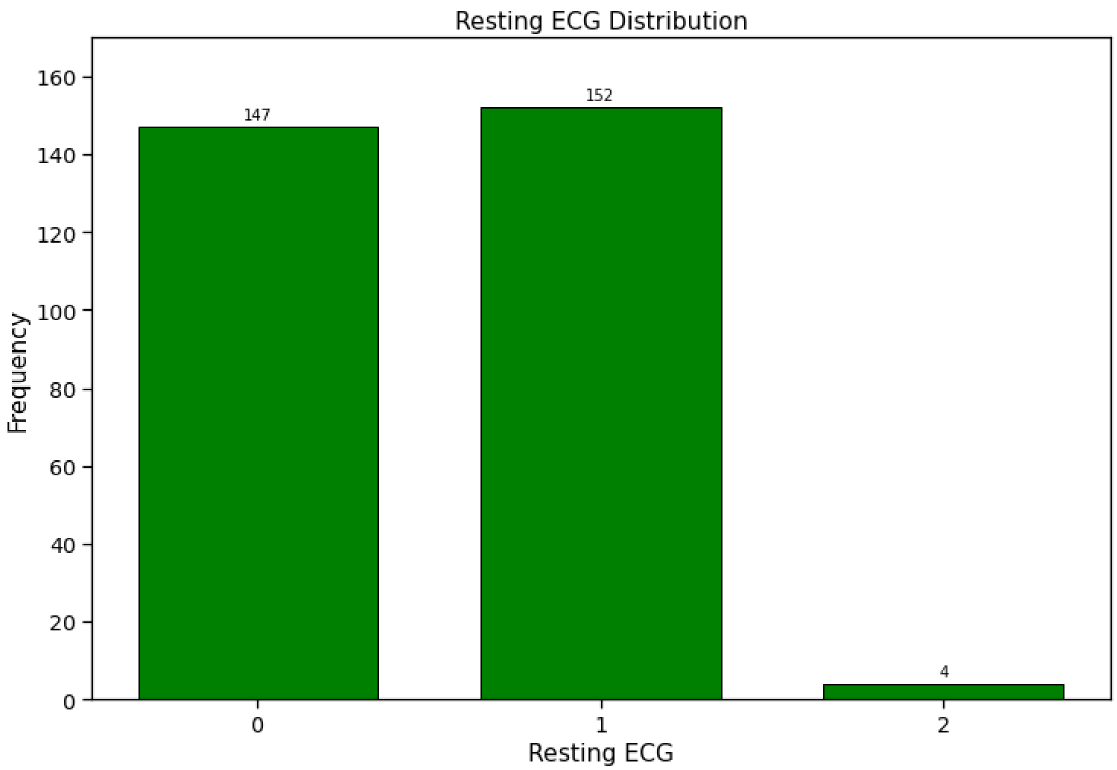
[41]:
```
# Inferences:
# Of the 143 total asymptomatic cases, only 39 are high risk CVD cases - 27.3%
# Of the 50 total non-angina pain cases, 41 are high risk CVD cases - 82.0%
# Of the 87 total atypical angina cases, 69 are high risk CVD cases - 79.3%
# Of the 23 total typical angina cases, 23 are high risk CVD cases - 69.8%
# It may be noted that:
# 69.6% to 82.0% of the reported CVD cases are either non-anginal pain,␣
↪atypical and typical angina
# Non-anginal pain at 82% has the highest % of positive CVD cases
```

[42]:
```
# Refer Line 17
# restecg - resting ecg has a high positive correlation with the target variable
# Analysis of resting ecg - categorical variable with 3 values
# 0 - normal, 1 - having ST-T, 2 - hypertrophy
# Let us understand the distribution of the resting ecg variable

restecg_freq = heart.groupby('restecg').agg({'restecg':'count'})
restecg_freq

# Inferences
# Of the 303 samples - 147 - normal, 152 - have ST-T and 4 - have hypertrophy
```

[42]:
```
         restecg
restecg
0            147
1            152
2              4
```

[43]:
```
# Create a barplot to visualize the distribution of the resting ECG data

plt.figure(figsize = (12,8))
barplot = plt.bar(restecg_freq.index, restecg_freq.restecg, fc = 'green', ec =␣
↪'black', width = 0.7)
plt.title('Resting ECG Distribution')
plt.xlabel('Resting ECG')
plt.ylabel('Frequency')
plt.ylim([0,170])
plt.xticks(restecg_freq.index)
plt.bar_label(barplot, labels = restecg_freq.restecg, label_type = 'edge',␣
↪padding = 3, fontsize = 10)
```

[43]:
```
[Text(0, 3, '147'), Text(0, 3, '152'), Text(0, 3, '4')]
```



[44]:
```python
# Understand and check the relation between high risk CVD to resting ECG

restecg_group = heart.groupby('restecg')['target'].apply(lambda x: (x == 1).
    ↪sum()).reset_index(name = 'Total_CVD')
restecg_group
```

[44]:

	restecg	Total_CVD
0	0	68
1	1	96
2	2	1

[45]:
```python
# Create a new dataframe to display the overall statistics of CVD with resting␣
    ↪ECG

restecg_grouptotal = pd.DataFrame({'restecg' : [0, 1, 2],
                                   'Total_CVD' : [68, 96, 1], 'Total' : [147, 152,␣
    ↪4]})
restecg_grouptotal
```

[45]:

	restecg	Total_CVD	Total
0	0	68	147
1	1	96	152

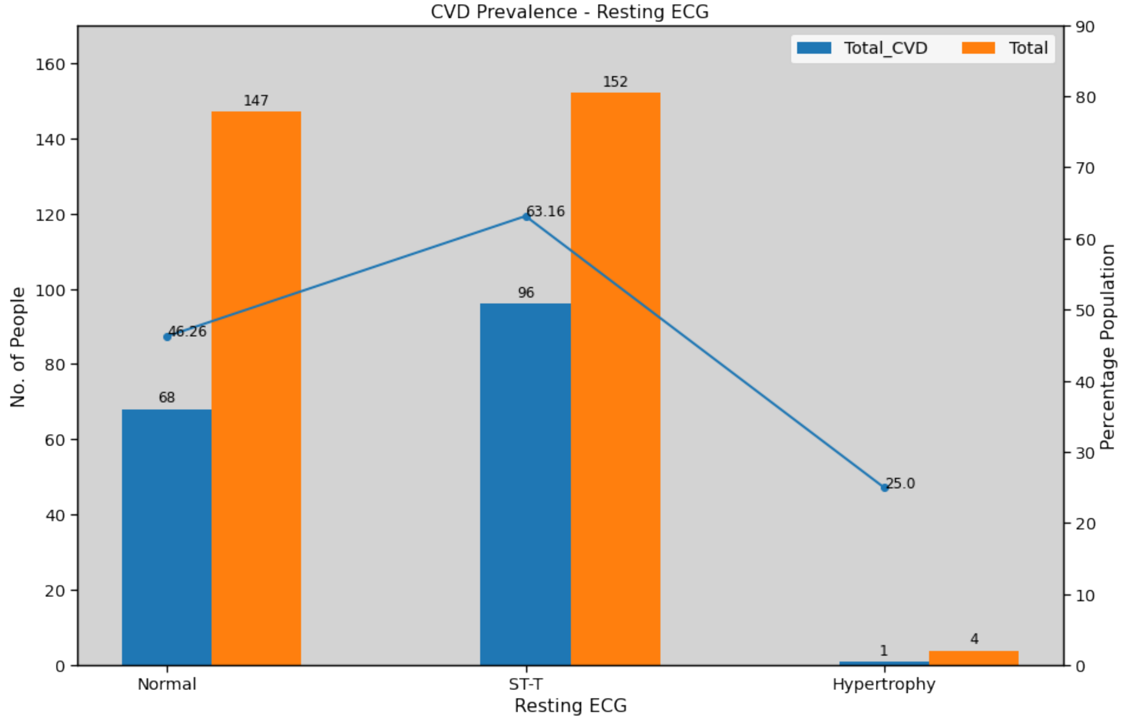
2 2 1 4

[46]:
```
# Add a % of the population column to the dataframe

restecg_grouptotal['Percent_Population'] =␣
↪round((restecg_grouptotal['Total_CVD']/
                                        restecg_grouptotal['Total']) * 100, 2)
restecg_grouptotal
```

[46]:

	restecg	Total_CVD	Total	Percent_Population
0	0	68	147	46.26
1	1	96	152	63.16
2	2	1	4	25.00

[47]:
```
# Create a combined multiple bar plot and line plot to visualize the data of␣
↪CVD prevalence

restecg_cat = ('Normal', 'ST-T', 'Hypertrophy') # Label location
cvd_means = {'Total_CVD' : (68, 96, 1),
            'Total' : (147, 152, 4)}            # Define the labels
pp_means = {'Percent_Population' : (46.3, 63.2, 25.0)}
x = np.arange(len(restecg_cat))
width = 0.25                      # Width of the bar
multiplier = 0                    # Multiplier
fig, ax = plt.subplots(figsize = (15, 10))
ax.set_ylim(0,170)
ax.set_facecolor('lightgray')
ax.grid(False)
ax.set_title('CVD Prevalence - Resting ECG')
ax.set_xlabel('Resting ECG')
ax.set_ylabel('No. of People')
ax.set_xticks(x, restecg_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(restecg_grouptotal['Percent_Population'].values, linestyle = '-',␣
↪marker = 'o', linewidth = 2.0)
ax2.set_ylim(0,90)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
for i, j in restecg_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



[48]:
```
# Inferences:
# Of the 147 normal ECG cases, 68 are high risk CVD cases - 46.3%
# Of the 152 cases having ST-T, 96 are high risk CVD cases - 63.2%
# Of the 4 cases with Hypertrophy, 1 case is high risk CVD - 25.0%
# It may thus be noted that:
# 1. Maximum high risk of CVD are the ones with ST-T
# 2. The normal resting ecg cases also need to be monitored regularly for␣
↪inconsistencies
# 3. 46.3% of normal ECG cases also show signs of high risk CVD
```

[49]:
```
# Understanding the CVD cases in relation to the sex of the individual

sex_group = heart.groupby('sex')['target'].apply(lambda x: (x == 1).sum()).
↪reset_index(name = 'Total_CVD')
sex_group
```

[49]:

	sex	Total_CVD
0	0	72
1	1	93

[50]:
```
# Create a dataframe to analyze the datset further

sex_grouptotal = pd.DataFrame({'sex' : [0, 1],
                               'Total_CVD' : [72, 93], 'Total' : [96, 207]})
```

```
sex_grouptotal
```

[50]:

	sex	Total_CVD	Total
0	0	72	96
1	1	93	207

[51]:

```
# Add a pecentage of population column to the dataframe

sex_grouptotal['Percent_Population'] = round((sex_grouptotal['Total_CVD']/
                                        sex_grouptotal['Total']) * 100, 2)
sex_grouptotal
```

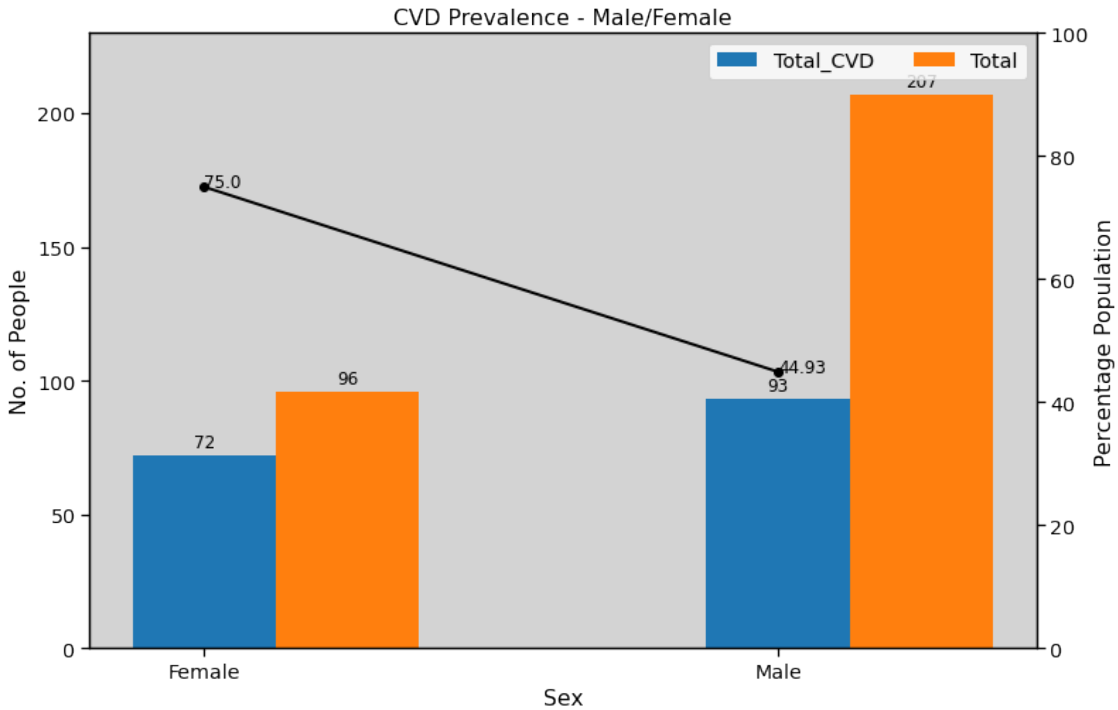
[51]:

	sex	Total_CVD	Total	Percent_Population
0	0	72	96	75.00
1	1	93	207	44.93

[52]:

```
# Create a combined multiple bar plot and line plot to visualize the data of␣
↪CVD prevalence

sex_cat = ('Female', 'Male') # Label location
cvd_means = {'Total_CVD' : (72, 93),
            'Total' : (96, 207)}            # Define the labels
pp_means = {'Percent_Population' : (75.0, 44.9)}
x = np.arange(len(sex_cat))
width = 0.25                    # Width of the bar
multiplier = 0                  # Multiplier
fig, ax = plt.subplots(figsize = (12, 8))
ax.set_ylim(0,230)
ax.set_facecolor('lightgray')
ax.grid(False)
ax.set_title('CVD Prevalence - Male/Female')
ax.set_xlabel('Sex')
ax.set_ylabel('No. of People')
ax.set_xticks(x, sex_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(sex_grouptotal['Percent_Population'].values, linestyle = '-', marker =␣
↪'o',
         linewidth = 2.0, color = 'black')
ax2.set_ylim(0,100)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
```

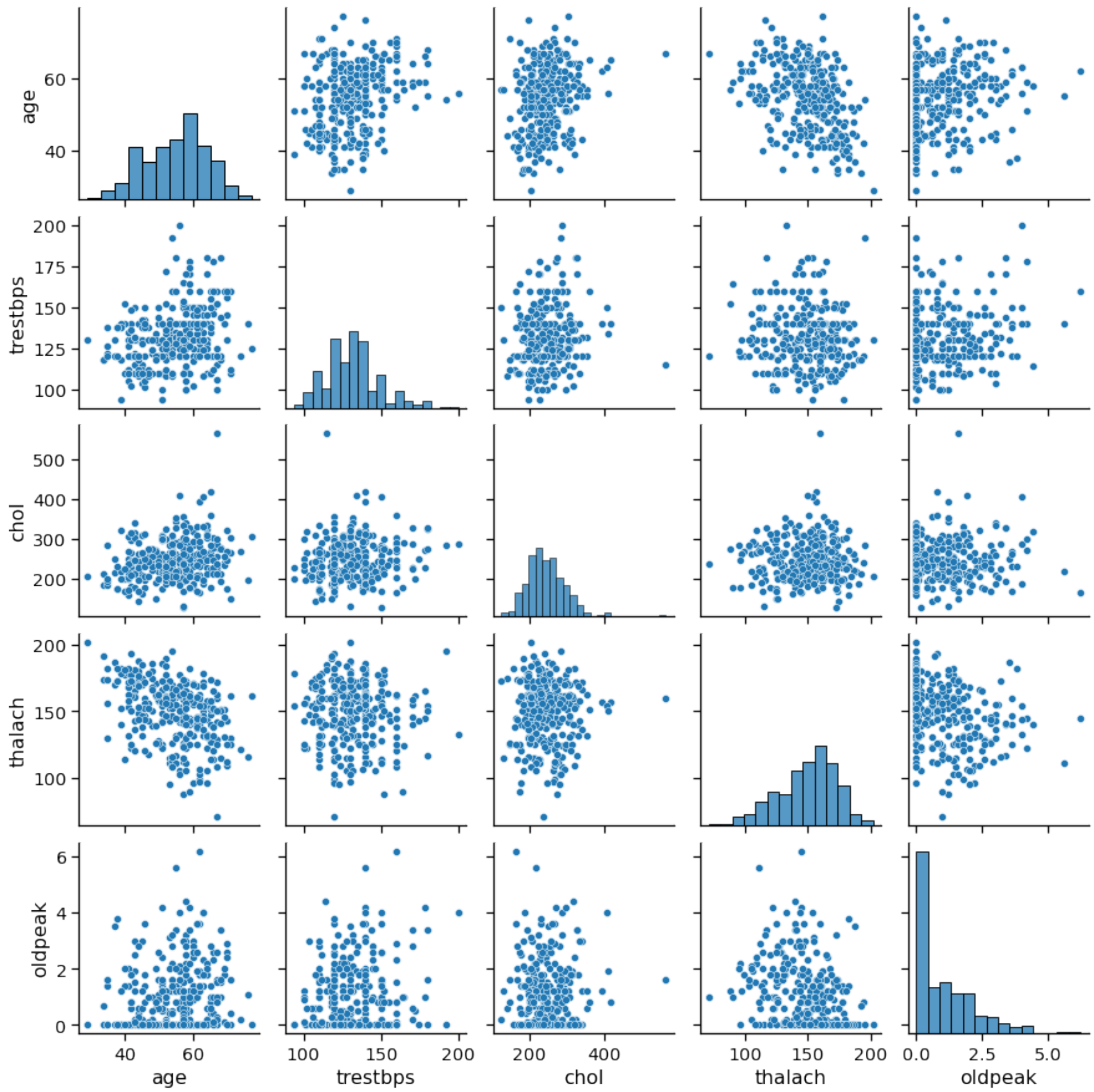
```
for i, j in sex_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



[53]:
```
# Inferences:
# 75% of the Female population are high risk CVD cases
# 44.6% of the Male population are high risk CVD cases
```

[54]:
```
# Create a pair plot to study the correlation of continuous variables

sub_data = heart[['age', 'trestbps', 'chol', 'thalach', 'oldpeak']]
sns.pairplot(sub_data)
```

[54]: <seaborn.axisgrid.PairGrid at 0x7f4aac26b2d0>



[55]:
```
# Refer Line 17
# slope - slope of the peak exercise segment has a high positive correlation␣
↪with the target variable
# Analysis of slope - categorical variable with 3 values
# 0 - upslope, 1 - flat, 2 - downslope
# Let us understand the distribution of the slope variable

slope_freq = heart.groupby('slope').agg({'slope':'count'})
slope_freq

# Inferences
# Of the 303 samples - 21 - upslope, 140 - have flat and 142 - downslope
```

[55]:
```
       slope
slope
0         21
1        140
2        142
```

[56]:
```
# Understanding the CVD cases in relation to the ST depression slope

slope_group = heart.groupby('slope')['target'].apply(lambda x: (x == 1).sum()).
 ↪reset_index(name = 'Total_CVD')
slope_group
```

[56]:
```
   slope  Total_CVD
0      0          9
1      1         49
2      2        107
```

[57]:
```
# Create a dataframe to analyse the data of ST depression slope further

slope_grouptotal = pd.DataFrame({'slope' : [0, 1, 2],
                                'Total_CVD' : [9, 49, 107], 'Total' : [21, 140,␣
 ↪142]})
slope_grouptotal
```

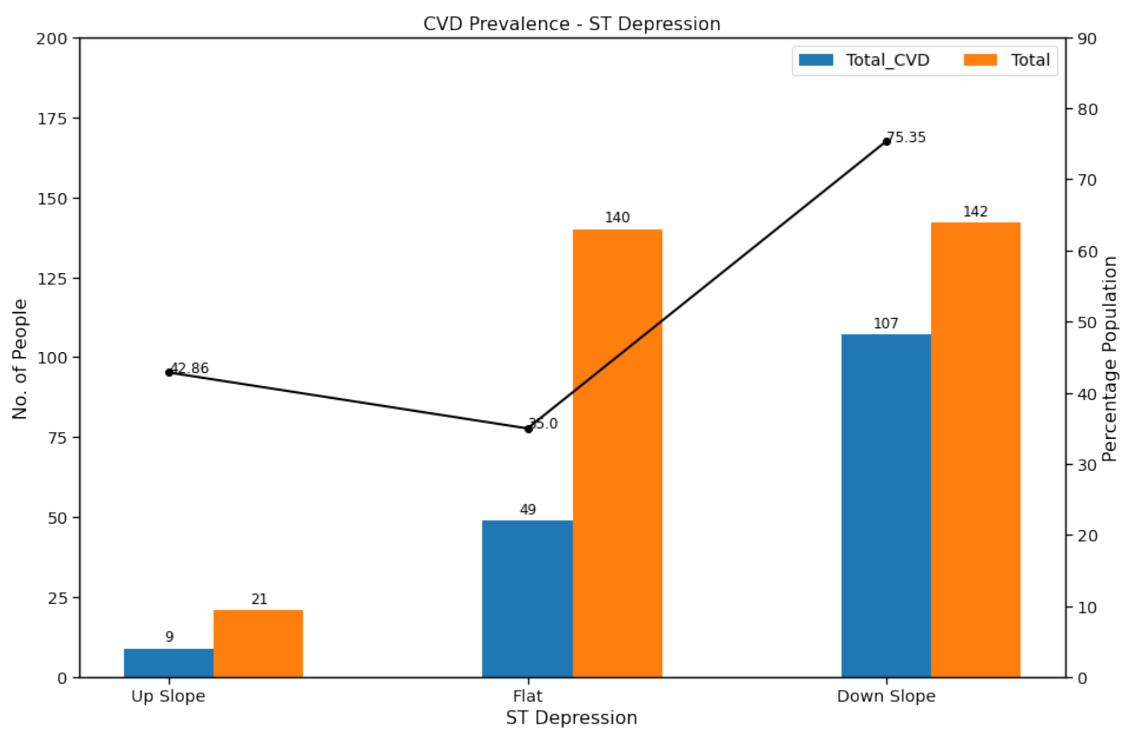
[57]:
```
   slope  Total_CVD  Total
0      0          9     21
1      1         49    140
2      2        107    142
```

[58]:
```
# Add percentage of population column to the dataframe

slope_grouptotal['Percent_Population'] = round((slope_grouptotal['Total_CVD']/
                                        slope_grouptotal['Total']) * 100, 2)
slope_grouptotal
```

[58]:
```
   slope  Total_CVD  Total  Percent_Population
0      0          9     21               42.86
1      1         49    140               35.00
2      2        107    142               75.35
```

[59]:
```
# Create a combined multiple bar plot and line plot to visualize the data of␣
 ↪CVD prevalence

slope_cat = ('Up Slope', 'Flat', 'Down Slope') # Label location
cvd_means = {'Total_CVD' : (9, 49, 107),
            'Total' : (21, 140, 142)}            # Define the labels
pp_means = {'Percent_Population' : (42.9, 35.0, 75.4)}
```

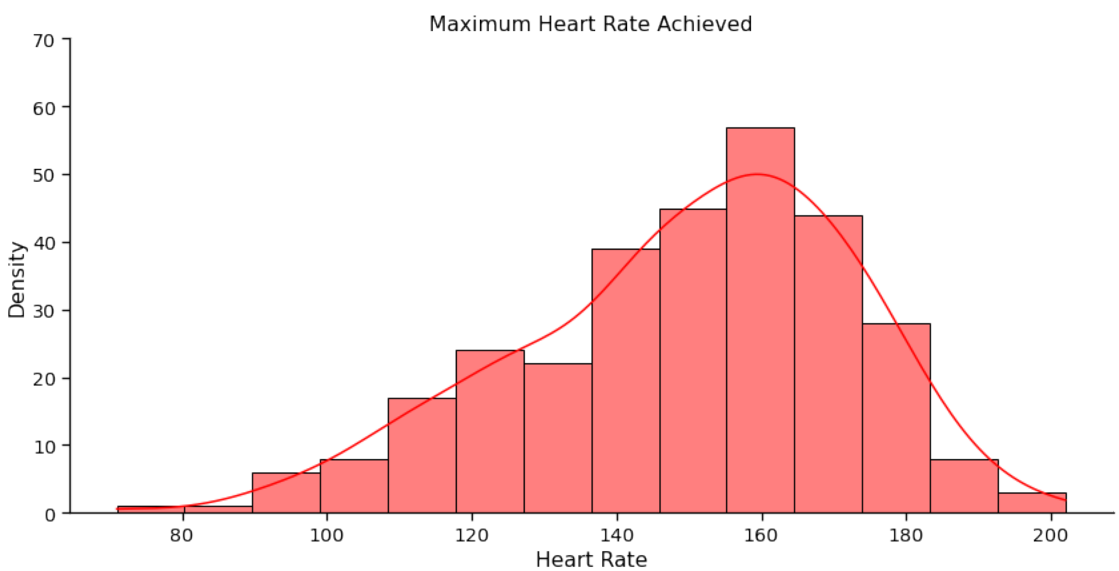
```
x = np.arange(len(slope_cat))
width = 0.25                    # Width of the bar
multiplier = 0                  # Multiplier
fig, ax = plt.subplots(figsize = (15, 10))
ax.set_ylim(0,200)
ax.set_facecolor('white')
ax.grid(False)
ax.set_title('CVD Prevalence - ST Depression')
ax.set_xlabel('ST Depression')
ax.set_ylabel('No. of People')
ax.set_xticks(x, slope_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(slope_grouptotal['Percent_Population'].values, linestyle = '-', marker␣
 ↪= 'o',
         linewidth = 2.0, color = 'black')
ax2.set_ylim(0,90)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
for i, j in slope_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



[60]:
```
# Inferences
# slope - CVD instances are highest for ST depression down slope cases at 75.4%␣
↪of the cases
# slope - CVD instances are below 50% for ST depression up slope and and flat
```

[61]:
```
# Refer Line 17
# thalach - maximum heart rate achieved has a high positive correlation with␣
↪the target variable
# Analysis of thalach variable
# Let us understand the distribution of the maximum heart rate achieved variable

sns.displot(heart.thalach, color = 'red', kde = True, height = 6, aspect = 2)
plt.title('Maximum Heart Rate Achieved')
plt.xlabel('Heart Rate')
plt.ylabel('Density')
plt.ylim(0, 70)
```

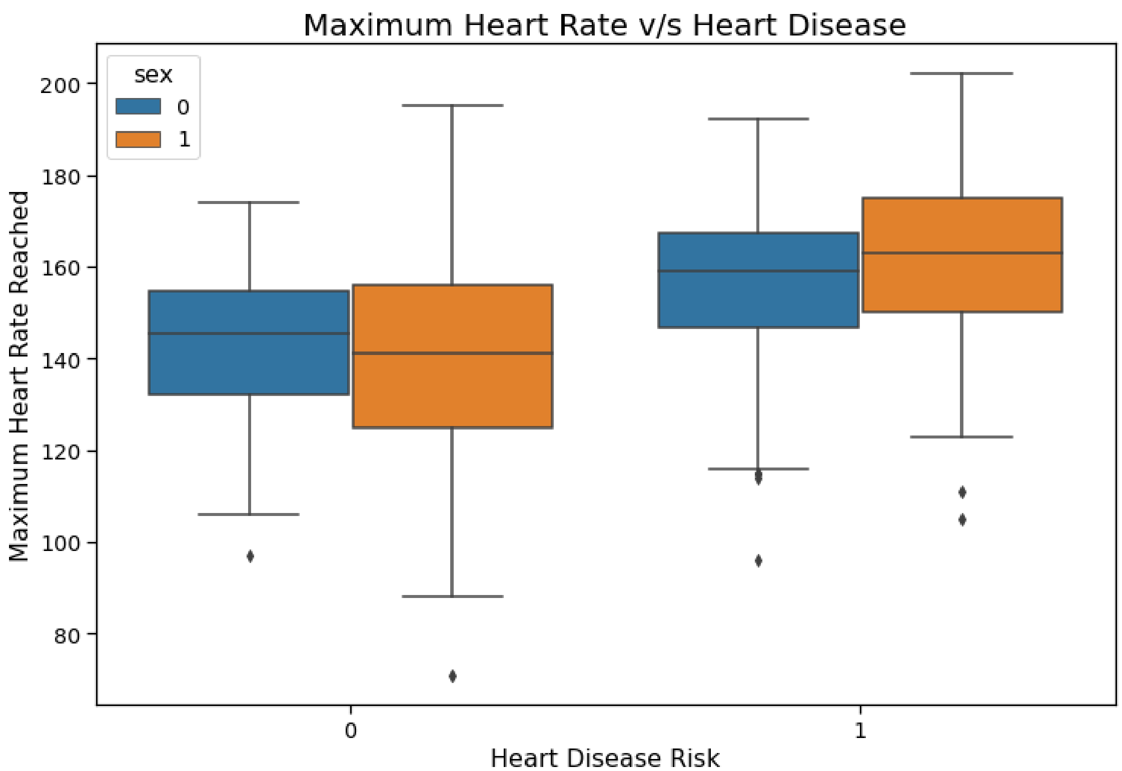
[61]: (0.0, 70.0)



[62]:
```
# Understand the distribution of the data of highest heart rate achieved
# Study the data in relation to the target variable and sex of the individual
# Use a box plot to understand the min, max, median and outliers in the dataset

plt.figure(figsize = (12, 8))
sns.boxplot(x = 'target', y = 'thalach', hue = 'sex', data = heart)
plt.title('Maximum Heart Rate v/s Heart Disease', fontsize = 20)
```

```
plt.xlabel('Heart Disease Risk', fontsize = 16)
plt.ylabel('Maximum Heart Rate Reached', fontsize = 16)
```

[62]: Text(0, 0.5, 'Maximum Heart Rate Reached')



[63]:
```
# Inferences
# High risk CVD (positive patients) shows a higher median
# The median values for male and female is not very different in bith cases
# Males have a higher range of maximum heart rate reached than females
```

[64]:
```
# Refer Line 17
# There are 2 variables which have a high negative correlation to the target␣
↪variable
# exang - exercise induced angina - (-) 0.44
# oldpeak - ST depression induced by exercise - (-) 0.43
# We need to analyze these 2 variables in more detail
# 1. exang - 1 - yes, 0 - no

exang_freq = heart.groupby('exang').agg({'exang':'count'})
exang_freq

# Inferences
```

```
# Of the 303 samples - 204 - No exercise induced angina, 99 - Yes to exercise␣
↪induced angina
```

[64]:

```
       exang
exang
0        204
1         99
```

[65]:

```
# Understanding the CVD cases in relation to the exercise induced angina

exang_group = heart.groupby('exang')['target'].apply(lambda x: (x == 1).sum()).
↪reset_index(name = 'Total_CVD')
exang_group
```

[65]:

	exang	Total_CVD
0	0	142
1	1	23

[66]:

```
# Create a dataframe to analyse the data of exercise induced angina further

exang_grouptotal = pd.DataFrame({'exang' : [0, 1],
                               'Total_CVD' : [142, 23], 'Total' : [204, 99]})
exang_grouptotal
```

[66]:

	exang	Total_CVD	Total
0	0	142	204
1	1	23	99

[67]:

```
# Add percentage of population column to the dataframe

exang_grouptotal['Percent_Population'] = round((exang_grouptotal['Total_CVD']/
                                        exang_grouptotal['Total']) * 100, 2)
exang_grouptotal
```

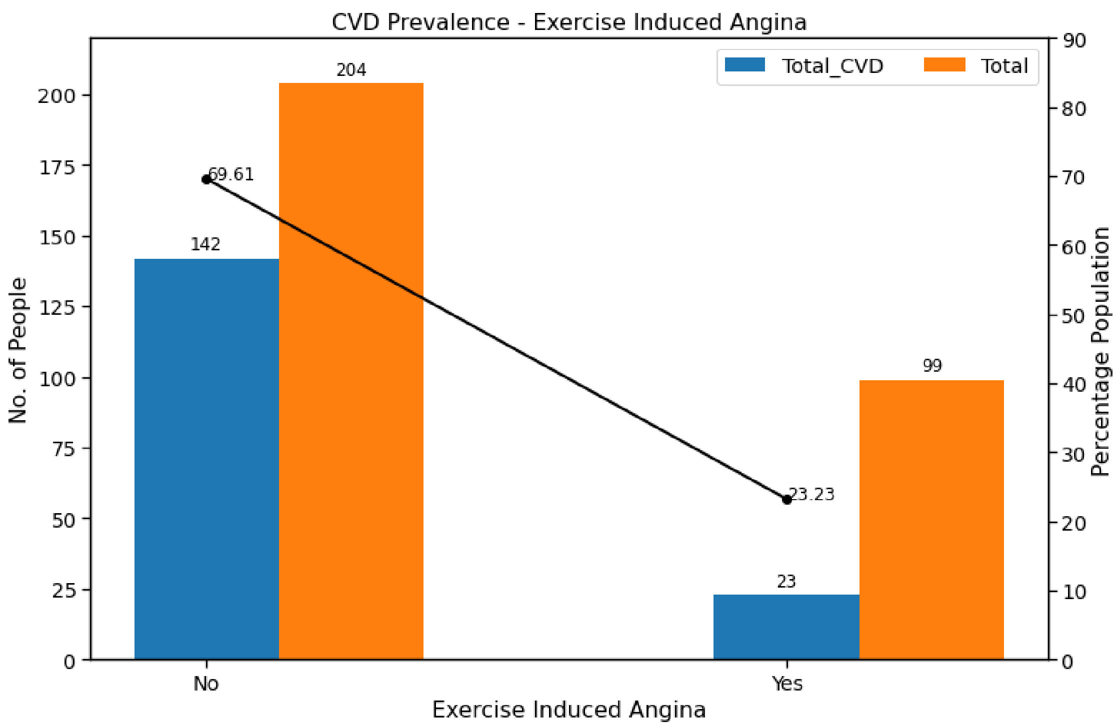
[67]:

	exang	Total_CVD	Total	Percent_Population
0	0	142	204	69.61
1	1	23	99	23.23

[68]:

```
# Create a combined multiple bar plot and line plot to visualize the data of␣
↪CVD prevalence

exang_cat = ('No', 'Yes') # Label location
cvd_means = {'Total_CVD' : (142, 23),
            'Total' : (204, 99)}            # Define the labels
pp_means = {'Percent_Population' : (42.9, 35.0, 75.4)}
x = np.arange(len(exang_cat))
width = 0.25                  # Width of the bar
```

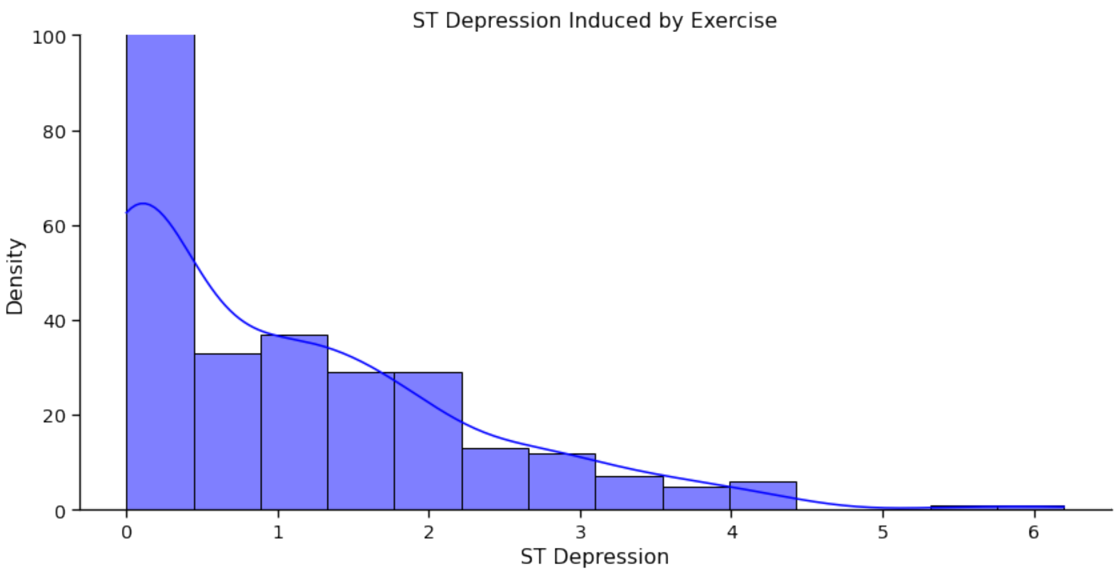
```
multiplier = 0                  # Multiplier
fig, ax = plt.subplots(figsize = (12, 8))
ax.set_ylim(0,220)
ax.set_facecolor('white')
ax.grid(False)
ax.set_title('CVD Prevalence - Exercise Induced Angina')
ax.set_xlabel('Exercise Induced Angina')
ax.set_ylabel('No. of People')
ax.set_xticks(x, exang_cat, rotation = 0)
for attribute, measurement in cvd_means.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label = attribute)
    ax.bar_label(rects, padding=3, fontsize = 12)
    multiplier += 1
ax.legend(loc = 'upper right', ncol = 2)
ax2 = ax.twinx()
ax2.plot(exang_grouptotal['Percent_Population'].values, linestyle = '-', marker␣
 ↪= 'o',
         linewidth = 2.0, color = 'black')
ax2.set_ylim(0,90)
ax2.grid(False)
ax2.set_ylabel('Percentage Population')
for i, j in exang_grouptotal.Percent_Population.items():
    ax2.annotate(str(j), xy = (i,j), fontsize = 12)
```



[69]:
```
# Inferences
# Of the total positive cases, there are only 23.2% of cases where there has␣
↪been exercise induced angina
```

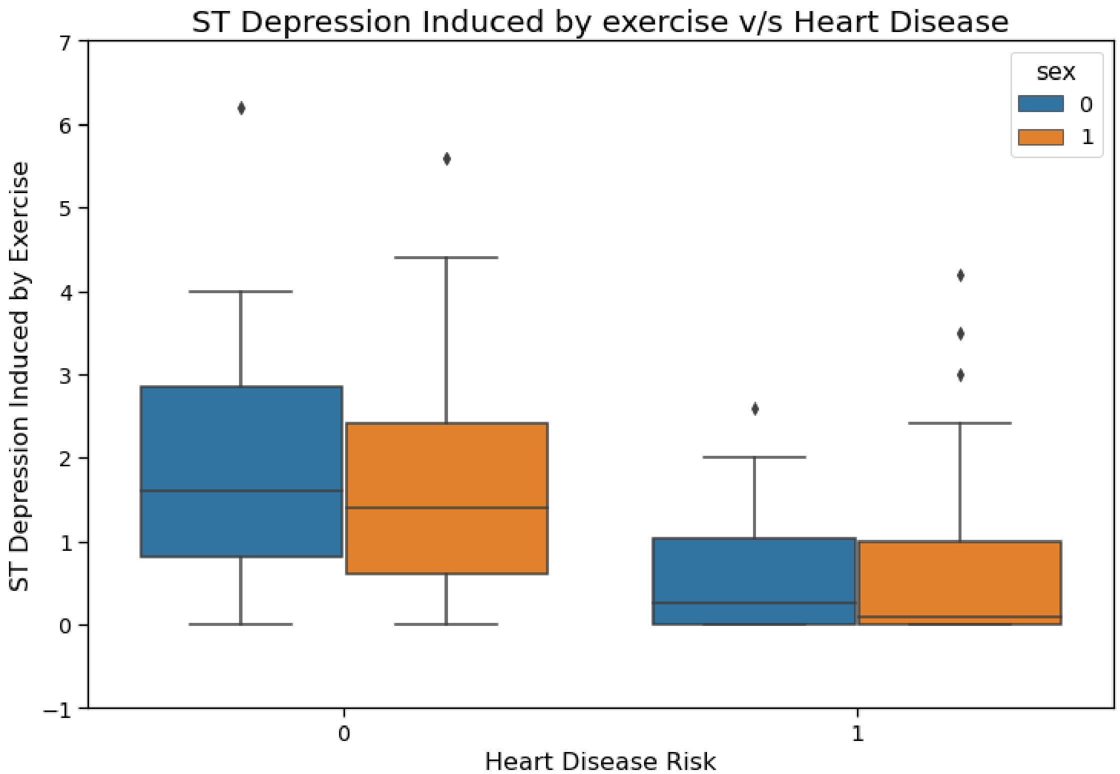
[70]:
```
# Refer Line 64
# 2. oldpeak - ST depression induced by exercise relative to rest - (-) 0.43
# Continuous variable
# Let us understand the distribution of the maximum oldpeak variable

sns.displot(heart.oldpeak, color = 'blue', kde = True, height = 6, aspect = 2)
plt.title('ST Depression Induced by Exercise')
plt.xlabel('ST Depression')
plt.ylabel('Density')
plt.ylim(0, 100)
```

[70]: (0.0, 100.0)



[71]:
```
# Understand the distribution of the data of ST depression induced by exercise
# Study the data in relation to the target variable and sex of the individual
# Use a box plot to understand the min, max, median and outliers in the dataset

plt.figure(figsize = (12, 8))
sns.boxplot(x = 'target', y = 'oldpeak', hue = 'sex', data = heart)
plt.title('ST Depression Induced by exercise v/s Heart Disease', fontsize = 20)
plt.xlabel('Heart Disease Risk', fontsize = 16)
plt.ylabel('ST Depression Induced by Exercise', fontsize = 16)
plt.ylim(-1, 7)
```

[71]: (-1.0, 7.0)



[72]:
```
# Inferences
# In positive CVD cases, the median of ST depression induced by exercise is␣
↪much low
# Lower ST depression induced by exercise median is indicative of heart disease
# In negative CVD cases, the median of ST depression induced by exercise for␣
↪males and females is almost same
```

[73]:
```
# filter CVD positive cases for further analysis

pos_data = heart[heart['target'] == 1]
pos_data.describe()
```

[73]:

	age	sex	cp	trestbps	chol	fbs \
count	165.000000	165.000000	165.000000	165.000000	165.000000	165.000000
mean	52.496970	0.563636	1.375758	129.303030	242.230303	0.139394
std	9.550651	0.497444	0.952222	16.169613	53.552872	0.347412
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000
25%	44.000000	0.000000	1.000000	120.000000	208.000000	0.000000
50%	52.000000	1.000000	2.000000	130.000000	234.000000	0.000000
75%	59.000000	1.000000	2.000000	140.000000	267.000000	0.000000

```
max     76.000000    1.000000    3.000000  180.000000  564.000000    1.000000

        restecg     thalach       exang     oldpeak       slope          ca  \
count  165.000000  165.000000  165.000000  165.000000  165.000000  165.000000
mean     0.593939  158.466667    0.139394    0.583030    1.593939    0.363636
std      0.504818   19.174276    0.347412    0.780683    0.593635    0.848894
min      0.000000   96.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  149.000000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  161.000000    0.000000    0.200000    2.000000    0.000000
75%      1.000000  172.000000    0.000000    1.000000    2.000000    0.000000
max      2.000000  202.000000    1.000000    4.200000    2.000000    4.000000

             thal  target
count  165.000000   165.0
mean     2.121212     1.0
std      0.465752     0.0
min      0.000000     1.0
25%      2.000000     1.0
50%      2.000000     1.0
75%      2.000000     1.0
max      3.000000     1.0
```

[74]:
```
# filter CVD positive cases for further analysis

neg_data = heart[heart['target'] == 0]
neg_data.describe()
```

[74]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  138.000000  138.000000  138.000000  138.000000  138.000000  138.000000
mean    56.601449    0.826087    0.478261  134.398551  251.086957    0.159420
std      7.962082    0.380416    0.905920   18.729944   49.454614    0.367401
min     35.000000    0.000000    0.000000  100.000000  131.000000    0.000000
25%     52.000000    1.000000    0.000000  120.000000  217.250000    0.000000
50%     58.000000    1.000000    0.000000  130.000000  249.000000    0.000000
75%     62.000000    1.000000    0.000000  144.750000  283.000000    0.000000
max     77.000000    1.000000    3.000000  200.000000  409.000000    1.000000

        restecg     thalach       exang     oldpeak       slope          ca  \
count  138.000000  138.000000  138.000000  138.000000  138.000000  138.000000
mean     0.449275  139.101449    0.550725    1.585507    1.166667    1.166667
std      0.541321   22.598782    0.499232    1.300340    0.561324    1.043460
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  125.000000    0.000000    0.600000    1.000000    0.000000
50%      0.000000  142.000000    1.000000    1.400000    1.000000    1.000000
75%      1.000000  156.000000    1.000000    2.500000    1.750000    2.000000
max      2.000000  195.000000    1.000000    6.200000    2.000000    4.000000
```

	thal	target
count	138.000000	138.0
mean	2.543478	0.0
std	0.684762	0.0
min	0.000000	0.0
25%	2.000000	0.0
50%	3.000000	0.0
75%	3.000000	0.0
max	3.000000	0.0

[75]:
```
heart.columns
```

[75]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target', 'Age_Category'],
      dtype='object')
```

[76]:
```
# Creating a dataframe to compare the mean of the positive CVD and negative CVD␣
↪filtered data above

compare_data = pd.DataFrame({'Health Varaiable' : ['trestbps', 'chol',␣
↪'thalach', 'oldpeak'],
                             'Pos_CVD_Mean' : [129.3, 242.2, 158.5, 0.58],
                             'Neg_CVD_Mean' : [134.4, 251.1, 139.1, 1.58]})
compare_data
```

[76]:

	Health Varaiable	Pos_CVD_Mean	Neg_CVD_Mean
0	trestbps	129.30	134.40
1	chol	242.20	251.10
2	thalach	158.50	139.10
3	oldpeak	0.58	1.58

[77]:
```
# Inferences
# In positive cases, the highest heart rate achieved is much higher than␣
↪negative cases
# In positive cases, the ST depression induced by exercise is very low compared␣
↪to negative cases
# Ratio is almost 1/3rd for positive cases in terms of ST depression induced by␣
↪exercise
```

[78]:
```
heart1 = heart.drop(['Age_Category'], axis = 1)
heart1
```

[78]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
0	63	1	3	145	233	1	0	150	0	2.3	
1	37	1	2	130	250	0	1	187	0	3.5	
2	41	0	1	130	204	0	0	172	0	1.4	
3	56	1	1	120	236	0	1	178	0	0.8	

```
4      57    0   0       120   354    0        1      163      1      0.6
..    …   …   ..        …     …   …       …        …     …      …
298    57    0   0       140   241    0        1      123      1      0.2
299    45    1   3       110   264    0        1      132      0      1.2
300    68    1   0       144   193    1        1      141      0      3.4
301    57    1   0       130   131    0        1      115      1      1.2
302    57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
0        0   0     1       1
1        0   0     2       1
2        2   0     2       1
3        2   0     2       1
4        2   0     2       1
..     …  ..    …      …
298      1   0     3       0
299      1   0     3       0
300      1   2     3       0
301      1   1     3       0
302      1   1     2       0

[303 rows x 14 columns]
```

[79]:
```python
# Model building - Logistic Regression
# Import packages

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
```

[80]:
```python
# Assigning the 13 variables to X and the last column to Predictor Y

x = heart.drop(['target', 'Age_Category'], axis = 1)
x
```

[80]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0     63    1   3       145   233    1        0      150      0      2.3
1     37    1   2       130   250    0        1      187      0      3.5
2     41    0   1       130   204    0        0      172      0      1.4
3     56    1   1       120   236    0        1      178      0      0.8
4     57    0   0       120   354    0        1      163      1      0.6
..    …   …   ..        …     …   …       …        …     …      …
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0
```

```
     slope  ca  thal
0        0   0     1
1        0   0     2
2        2   0     2
3        2   0     2
4        2   0     2
..     ...  ..   ...
298      1   0     3
299      1   0     3
300      1   2     3
301      1   1     3
302      1   1     2

[303 rows x 13 columns]
```

[81]:
```
y = heart.target
y
```

[81]:
```
0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: target, Length: 303, dtype: int64
```

[82]:
```
x_train, x_test, y_train, y_test =  train_test_split(x,y,test_size=0.2,␣
 ↪random_state = 1)
```

[83]:
```
df_train = pd.concat([x_train, y_train], axis = 1)
df_train
```

[83]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
62    52    1   3       118   186    0        0      190      0      0.0
127   67    0   2       152   277    0        1      172      0      0.0
111   57    1   2       150   126    1        1      173      0      0.2
287   57    1   1       154   232    0        0      164      0      0.0
108   50    0   1       120   244    0        1      162      0      1.1
..   ...  ...  ..       ...   ...  ...      ...      ...    ...      ...
203   68    1   2       180   274    1        0      150      1      1.6
255   45    1   0       142   309    0        0      147      1      0.0
```

```
72    29   1   1        130  204    0        0      202      0      0.0
235   51   1   0        140  299    0        1      173      1      1.6
37    54   1   2        150  232    0        0      165      0      1.6

     slope  ca  thal  target
62       1   0     1       1
127      2   1     2       1
111      2   1     3       1
287      2   1     2       0
108      2   0     2       1
..     …   ..    …       …
203      1   0     3       0
255      1   3     3       0
72       2   0     2       1
235      2   0     3       0
37       2   0     3       1

[242 rows x 14 columns]
```

[84]:
```python
df_test = pd.concat([x_test, y_test], axis = 1)
df_test
```

[84]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
204   62    0   0       160   164    0        0      145      0      6.2
159   56    1   1       130   221    0        0      163      0      0.0
219   48    1   0       130   256    1        0      150      1      0.0
174   60    1   0       130   206    0        0      132      1      2.4
184   50    1   0       150   243    0        0      128      0      2.6
..   …  …  ..       …   …  …      …      …      …
0     63    1   3       145   233    1        0      150      0      2.3
288   57    1   0       110   335    0        1      143      1      3.0
259   38    1   3       120   231    0        1      182      1      3.8
179   57    1   0       150   276    0        0      112      1      0.6
110   64    0   0       180   325    0        1      154      1      0.0

     slope  ca  thal  target
204      0   3     3       0
159      2   0     3       1
219      2   2     3       0
174      1   2     3       0
184      1   0     3       0
..     …   ..    …       …
0        0   0     1       1
288      1   1     3       0
259      1   0     3       0
179      1   1     1       0
110      2   0     2       1
```

```
[61 rows x 14 columns]
```

[85]:
```python
x_train.shape
```

[85]:
```
(242, 13)
```

[86]:
```python
y_train.shape
```

[86]:
```
(242,)
```

[87]:
```python
x_test.shape
```

[87]:
```
(61, 13)
```

[88]:
```python
y_test.shape
```

[88]:
```
(61,)
```

[89]:
```python
# Normalize the train and test data prior to regression
# Import the package StandardScaler from sklearn

from sklearn.preprocessing import StandardScaler
```

[90]:
```python
# Normalize the x_train and x_test data

sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

[91]:
```python
# Logistic Regression
# Get instance of the model & fit the train model

model1 = LogisticRegression(random_state = 1)
model1.fit(x_train, y_train)
```

[91]:
```
LogisticRegression(random_state=1)
```

[92]:
```python
# Get the y predictions
# print the model accuracy classification report

y_pred1 = model1.predict(x_test)
print(classification_report(y_test, y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.77      0.67      0.71        30
```

```
           1       0.71      0.81      0.76        31

    accuracy                           0.74        61
   macro avg       0.74      0.74      0.74        61
weighted avg       0.74      0.74      0.74        61
```

[93]:
```python
# Logistic Regression accuracy is 74%
```

[94]:
```python
# K-NN - K-Nearest Neighbors
# Import package

from sklearn.neighbors import KNeighborsClassifier
```

[95]:
```python
# Get instance of the model & fit the train model

model2 = KNeighborsClassifier()
model2.fit(x_train, y_train)
```

[95]: KNeighborsClassifier()

[96]:
```python
# Get the y predictions
# print the model accuracy classification report

y_pred2 = model2.predict(x_test)
print(classification_report(y_test, y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.78      0.70      0.74        30
           1       0.74      0.81      0.77        31

    accuracy                           0.75        61
   macro avg       0.76      0.75      0.75        61
weighted avg       0.76      0.75      0.75        61
```

[97]:
```python
# K-NN - K-Nearest Neighbors accuracy - 75%
```

[98]:
```python
# Support Vector Machine
# Import package

from sklearn.svm import SVC
```

[99]:
```python
# Get instance of the model & fit the train model

model3 = SVC(random_state = 1)
```

```
model3.fit(x_train, y_train)
```

[99]: SVC(random_state=1)

[100]:
```
# Get the y predictions
# print the model accuracy classification report

y_pred3 = model3.predict(x_test)
print(classification_report(y_test, y_pred3))
```

```
              precision    recall  f1-score   support

           0       0.80      0.67      0.73        30
           1       0.72      0.84      0.78        31

    accuracy                           0.75        61
   macro avg       0.76      0.75      0.75        61
weighted avg       0.76      0.75      0.75        61
```

[101]:
```
# Support Vector Machine SVC accuracy is 75%
```

[102]:
```
# Naives Bayer Classifier
# Import package

from sklearn.naive_bayes import GaussianNB
```

[103]:
```
# Get instance of the model & fit the train model

model4 = GaussianNB()
model4.fit(x_train, y_train)
```

[103]: GaussianNB()

[104]:
```
# Get the y predictions
# print the model accuracy classification report

y_pred4 = model4.predict(x_test)
print(classification_report(y_test, y_pred4))
```

```
              precision    recall  f1-score   support

           0       0.79      0.73      0.76        30
           1       0.76      0.81      0.78        31

    accuracy                           0.77        61
   macro avg       0.77      0.77      0.77        61
```

```
weighted avg       0.77      0.77      0.77        61
```

[105]:
```python
# Naives Bayer Classifier accuracy - 77%
```

[106]:
```python
# Decision Tree
# Import package

from sklearn.tree import DecisionTreeClassifier
```

[107]:
```python
# Get instance of the model & fit the train model

model5 = DecisionTreeClassifier(random_state = 1)
model5.fit(x_train, y_train)
```

[107]:
```
DecisionTreeClassifier(random_state=1)
```

[108]:
```python
# Get the y predictions
# print the model accuracy classification report

y_pred5 = model5.predict(x_test)
print(classification_report(y_test, y_pred5))
```

```
              precision    recall  f1-score   support

           0       0.68      0.70      0.69        30
           1       0.70      0.68      0.69        31

    accuracy                           0.69        61
   macro avg       0.69      0.69      0.69        61
weighted avg       0.69      0.69      0.69        61
```

[109]:
```python
# Decision Tree Classifier accuracy is 69%
```

[110]:
```python
# Random Forest
# Import package

from sklearn.ensemble import RandomForestClassifier
```

[111]:
```python
# Get instance of the model & fit the train model

model6 = RandomForestClassifier(random_state = 1)
model6.fit(x_train, y_train)
```

[111]:
```
RandomForestClassifier(random_state=1)
```

[112]:
```
# Get the y predictions
# print the model accuracy classification report

y_pred6 = model6.predict(x_test)
print(classification_report(y_test, y_pred6))
```

```
              precision    recall  f1-score   support

           0       0.88      0.70      0.78        30
           1       0.76      0.90      0.82        31

    accuracy                           0.80        61
   macro avg       0.82      0.80      0.80        61
weighted avg       0.81      0.80      0.80        61
```

[113]:
```
# Random Forest Classifier accuracy is 80%
```

[114]:
```
# Random Forest Classifier accuracy is the highest of all models - 80%
```

[115]:
```
# Confusion Matrix
# Import package

from sklearn.metrics import confusion_matrix, accuracy_score
```

[116]:
```
cm = confusion_matrix(y_test, y_pred6)
cm
```

[116]:
```
array([[21,  9],
       [ 3, 28]])
```

[117]:
```
accuracy_score(y_test, y_pred6)
```

[117]:
```
0.8032786885245902
```

[118]:
```
# Accuracy of 80.32% is good as any accuracy > 70% is good to deploy a model
# Inferences from Confusion Matrix
# True Positives (TP) - 21
# True Negatives (TN) - 28
# No. of errors - 9 & 3
# Type 1 error - False Positives (FP) - 9 - Predicted positive and its false
# Type 2 error - False Negatives (FN) - 3 - Predicted negative and its false
# Calculate accuracy - (TP + TN)/ (TP + TN + FP + FN) - Correct Predicted /␣
↪Total
# Accuracy = (21 + 28) / (21 + 28 + 9 + 3)
# Accuracy - 49 / 61 = 80.32%
```

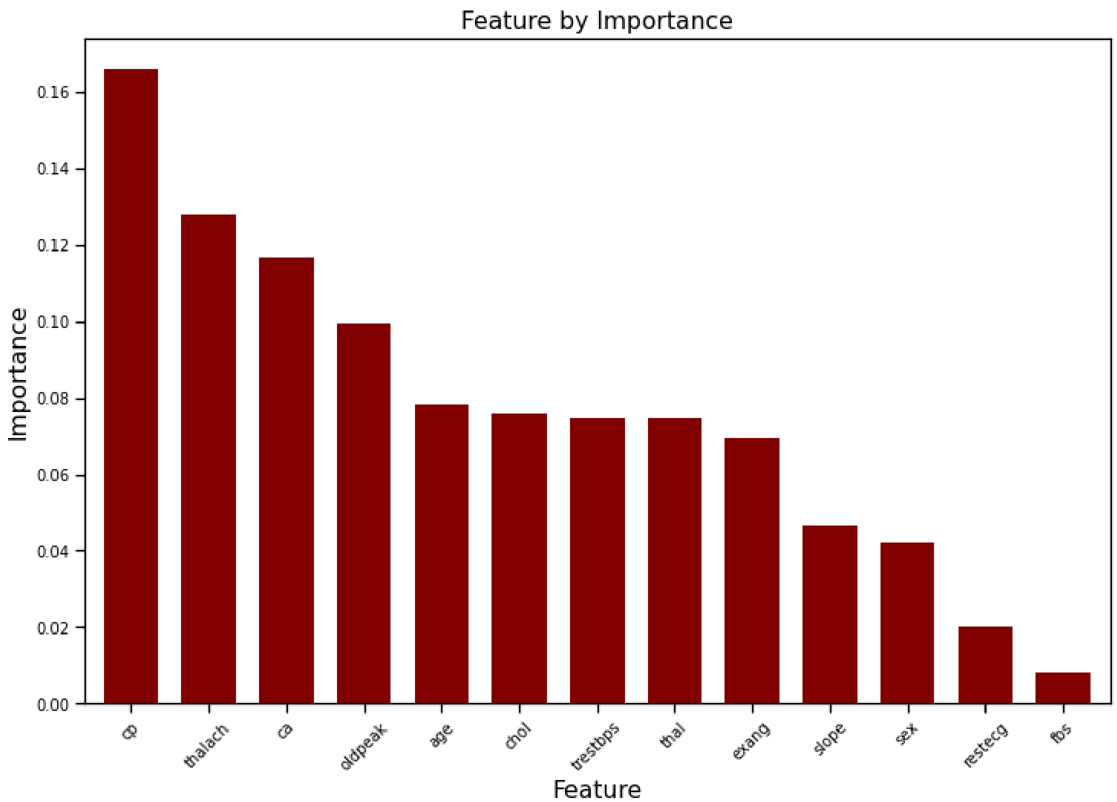
[119]:
```python
# Feature Importance

importance = model6.feature_importances_
```

[120]:
```python
# Summarize feature importance

for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))
```

```
Feature: 0, Score: 0.07814
Feature: 1, Score: 0.04206
Feature: 2, Score: 0.16580
Feature: 3, Score: 0.07477
Feature: 4, Score: 0.07587
Feature: 5, Score: 0.00828
Feature: 6, Score: 0.02014
Feature: 7, Score: 0.12772
Feature: 8, Score: 0.06950
Feature: 9, Score: 0.09957
Feature: 10, Score: 0.04677
Feature: 11, Score: 0.11667
Feature: 12, Score: 0.07473
```

[121]:
```python
index = x.columns
importance = pd.Series(model6.feature_importances_, index = index)
importance.nlargest(13).plot(kind = 'bar', color = 'maroon', width = 0.7,␣
 ↪figsize = (12, 8))
plt.title('Feature by Importance')
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.xticks(fontsize = 10, rotation = 45)
plt.yticks(fontsize = 10)
```

[121]:
```
(array([0.  , 0.02, 0.04, 0.06, 0.08, 0.1 , 0.12, 0.14, 0.16, 0.18]),
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```



[122]:
```
# Inferences
# The top 4 significant features that determine/predict CVD positivity are:
# 1. cp - Chest Pain type
# 2. thalach - maximum heart rate achieved
# 3. ca - number of major vessels coloured by flouroscopy
# 4. oldpeak - ST depression induced by exercise relative to rest
```

[123]:
```
# Run the model on the test data to check the accuracy of the predictions

pred_array = model6.predict(x_test)
pred_array
```

[123]:
```
array([0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1])
```

[124]:
```
# Create a dataframe to combine the predictions with the test data

pd.DataFrame(pred_array, columns = ['Pred_CVD'])
```

[124]:

```
    Pred_CVD
0          0
1          1
2          0
3          0
4          0
..       ...
56         1
57         0
58         1
59         0
60         1

[61 rows x 1 columns]
```

[125]:

```python
# Create the new test data with the predicted values column

test_final = pd.concat([df_test.reset_index(drop = True),
                        pd.DataFrame(pred_array, columns = ['Pred_CVD'])], axis␣
 ↪= 1)
test_final
```

[125]:

```
    age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0    62    0   0       160   164    0        0      145      0      6.2
1    56    1   1       130   221    0        0      163      0      0.0
2    48    1   0       130   256    1        0      150      1      0.0
3    60    1   0       130   206    0        0      132      1      2.4
4    50    1   0       150   243    0        0      128      0      2.6
..  ...  ...  ..       ...   ...  ...      ...      ...    ...      ...
56   63    1   3       145   233    1        0      150      0      2.3
57   57    1   0       110   335    0        1      143      1      3.0
58   38    1   3       120   231    0        1      182      1      3.8
59   57    1   0       150   276    0        0      112      1      0.6
60   64    0   0       180   325    0        1      154      1      0.0

    slope  ca  thal  target  Pred_CVD
0       0   3     3       0         0
1       2   0     3       1         1
2       2   2     3       0         0
3       1   2     3       0         0
4       1   0     3       0         0
..    ...  ..   ...     ...       ...
56      0   0     1       1         1
57      1   1     3       0         0
58      1   0     3       0         1
59      1   1     1       0         0
60      2   0     2       1         1
```

```
[61 rows x 15 columns]
```

[126]:
```
# The predictions and the target variables are binary
# Will therefore create a new Boolean column with True and False
# This will help to calculate the accuracy of the predictions

test_final['Predicted'] = np.where((test_final.target == test_final.Pred_CVD),
 'True', 'False')
test_final
```

[126]:
```
    age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0    62    0   0       160   164    0        0      145      0      6.2
1    56    1   1       130   221    0        0      163      0      0.0
2    48    1   0       130   256    1        0      150      1      0.0
3    60    1   0       130   206    0        0      132      1      2.4
4    50    1   0       150   243    0        0      128      0      2.6
..  …   …  ..       …     …   …       …      …      …       …
56   63    1   3       145   233    1        0      150      0      2.3
57   57    1   0       110   335    0        1      143      1      3.0
58   38    1   3       120   231    0        1      182      1      3.8
59   57    1   0       150   276    0        0      112      1      0.6
60   64    0   0       180   325    0        1      154      1      0.0

    slope  ca  thal  target  Pred_CVD Predicted
0       0   3     3       0         0      True
1       2   0     3       1         1      True
2       2   2     3       0         0      True
3       1   2     3       0         0      True
4       1   0     3       0         0      True
..    …  ..   …     …       …       …
56      0   0     1       1         1      True
57      1   1     3       0         0      True
58      1   0     3       0         1     False
59      1   1     1       0         0      True
60      2   0     2       1         1      True

[61 rows x 16 columns]
```

[127]:
```
# Total the True and False in the predicted values

test_final.Predicted.value_counts()

# There are 49 True (which is 21 (TP) + 28 (TN) as per confusion matrix)
# The false predictions are 12 (which is 9 (FP) and 3 (FN) as per confusion
 matrix)
```

[127]:
```
True     49
False    12
Name: Predicted, dtype: int64
```

[128]:
```
# Calculate the error False/Total

12/61

# Error in prediction is 19.67%
```

[128]:
```
0.19672131147540983
```

[129]:
```
# Accuracy of prediction is 1 - Error

1 - 12/61

# Accuracy of prediction is 80.32%
# this matches with the train data accuracy of 80.32%
```

[129]:
```
0.8032786885245902
```

[130]:
```
# Our model is therefore accurate in predition of the heart condition and can␣
 ↪be used
```

[131]:
```
# Check the Coefficient of Determination - R-Squared value of the model on the␣
 ↪test data

from sklearn.metrics import r2_score
```

[132]:
```
# Coefficient of Determination - R-Squared

r2_score(test_final.target,test_final.Pred_CVD)
```

[132]:
```
0.2129032258064516
```

[133]:
```
# Since the number of variables are 13, we would need to arrive at the adjusted␣
 ↪R-Squared

1 - r2_score(test_final.target,test_final.Pred_CVD)
```

[133]:
```
0.7870967741935484
```

[134]:
```
# The Adjusted R_Squared value is 78.71%
# This value is very close to the accuracy of the model
# The model can thus be deployed for accurate predictions of heart disease
```

[135]:

```
# Final Conclusions

# The top 4 significant features (out of the 13) that helped predict a positive/
↪negative diagnosis are:
# 1. cp - chest pain type
# 2. thalach - maximum heart rate achieved
# 3. ca - number of major vessels and
# 4. oldpeak - ST depression induced by exercise relative to rest

# Random Forest algorithm yields the maximum accuracy of 80.32%
# The model worked well on the test data and thus assumed to be accurate for use
# Coefficient of Determination - R-Squared is 0.213
# Adjsuted R-Squared is 78.70
# The model is thus well suited to be deployed in predicting heart conditions
```