Examining Factors Responsible for Heart Attacks

Data Analysis is the process of creating a story using the data for easy and effective communication. It mostly utilizes visualization methods like plots, charts, and tables to convey what the data holds beyond the formal modeling or hypothesis testing task.

Domain: Healthcare

Cardiovascular diseases are the leading cause of death globally. To identify the causes and to develop a system to predict heart attack in an effective manner is necessary. The presented data has all the information about all the relevant factors that might have an impact on heart health. The data needs to be explained in detail for any further analysis.

Objective: The objective was to create a model that would correctly classify patients with a high risk of heart attack

Perform preliminary data inspection and report the findings as the structure of the data, missing values, duplicates, etc.

In [1]:

```
## Data Analysis and Wrangling
import pandas as pd
import numpy as np
## Visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
# Standardization and Classification
from sklearn.preprocessing import StandardScaler
from sklearn.linear model import LogisticRegression
from sklearn.model selection import train test split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import classification report
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import plot_confusion_matrix
```

In [2]:

```
## Reading data
df_vardesc=pd.read_excel("C:/Users/nawin/variable_description1.xlsx")
df_vardesc.head(14)
```

Out[2]:

	variable	description
0	age	age in years
1	sex	(1 = male; 0 = female)
2	ср	chest pain type
3	trestbps	resting blood pressure (in mm Hg on admission
4	chol	serum cholestoral in mg/dl
5	fbs	(fasting blood sugar > 120 mg/dl) (1 = true;
6	restecg	resting electrocardiographic results
7	thalach	maximum heart rate achieved
8	exang	exercise induced angina (1 = yes; 0 = no)
9	oldpeak	ST depression induced by exercise relative to
10	slope	the slope of the peak exercise ST segment
11	ca	number of major vessels (0-3) colored by flou
12	thal	3 = normal; 6 = fixed defect; 7 = reversable
13	target	1 or 0

In [3]:

```
## Reading data
df_hea=pd.read_excel("C:/Users/nawin/data_heart.xlsx")
df_hea.head()
```

Out[3]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal	tar
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	
													_	

```
In [4]:
```

[303 rows x 14 columns]

```
# Printing Variables names
print("The number of rows and columns are:",df_hea.shape)
print("The name of columns in dataset are :",df_hea.columns)
The number of rows and columns are: (303, 14)
The name of columns in dataset are : Index(['age', 'sex', 'cp', 'trestbp
s', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
In [5]:
# Printing Variables names
print("The number of rows and columns are:",df_vardesc.shape)
print("The name of columns in dataset are :",df_vardesc.columns)
The number of rows and columns are: (14, 2)
The name of columns in dataset are : Index(['variable', 'description'], d
type='object')
In [6]:
# Structure of data
print("The structure of dataframe of Country-code is:\n",str(df hea))
The structure of dataframe of Country-code is:
      age sex cp trestbps chol fbs restecg thalach exang oldpeak
\
0
      63
                 3
                                233
                                                 0
                                                                  0
                                                                         2.3
            1
                         145
                                       1
                                                        150
                 2
                                250
1
      37
            1
                         130
                                       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
                                                                  1
                                                        163
                                                                         0.6
                         . . .
                . .
                                . . .
                                               . . .
                                                        . . .
                                                                          . . .
                 0
                                                                         0.2
298
      57
            0
                         140
                                241
                                       0
                                                 1
                                                        123
                                                                  1
299
      45
            1
                 3
                         110
                                264
                                       0
                                                 1
                                                        132
                                                                  0
                                                                         1.2
                                193
                                                 1
                                                                  0
300
      68
                0
                         144
                                       1
                                                        141
                                                                         3.4
            1
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
         0
             0
                    2
                            1
1
         2
                    2
2
             0
                            1
         2
3
             0
                    2
                            1
4
         2
             0
                    2
                            1
       . . .
             . .
                  . . .
                           . . .
         1
             0
                    3
298
                            0
299
         1
             0
                    3
                            0
             2
                    3
300
         1
                            0
         1
             1
301
                    3
                            0
302
         1
             1
                    2
```

Based on the findings from the previous question, remove duplicates (if any) and treat missing values using an appropriate strategy.

In [7]:

```
# Missing values
df_hea.isnull().sum()
## no missing value in dataset
```

Out[7]:

0 age 0 sex 0 ср trestbps 0 chol 0 fbs 0 restecg 0 thalach 0 exang 0 oldpeak 0 slope 0 ca 0 thal 0 target 0 dtype: int64

In [8]:

```
df_hea.info()
# no missing values
```

```
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
             Non-Null Count Dtype
    Column
#
             -----
---
    ----
                             ----
              303 non-null
                             int64
0
    age
1
    sex
              303 non-null
                             int64
2
              303 non-null
                             int64
    ср
3
    trestbps 303 non-null
                             int64
4
              303 non-null
    chol
                             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
              303 non-null
                             int64
11 ca
12
    thal
              303 non-null
                             int64
    target
              303 non-null
                             int64
13
dtypes: float64(1), int64(13)
```

<class 'pandas.core.frame.DataFrame'>

memory usage: 33.3 KB

In [9]: ## Checking duplicated values df_hea[df_hea.duplicated()] ## one row duplicate value Out[9]: cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal 1 2 138 175 0 1 0 0.0 2 4 2 164 38 173

In [10]:

```
# Dropping duplicate values
df_heart = df_hea.drop_duplicates()
```

In [11]:

```
## Rechecking duplicated values
df_heart[df_heart.duplicated()]
## No duplicate value
```

Out[11]:



Get a preliminary statistical summary of the data. Explore the measures of central tendencies and the spread of the data overall.

In [12]:

```
print("The Basic Statistical Summary:\n",df_hea.describe().T)
```

The Basic Statistical Summary:								
	count	mean	std	min	25%	50%	75%	ma
X								
age	303.0	54.366337	9.082101	29.0	47.5	55.0	61.0	77.0
sex	303.0	0.683168	0.466011	0.0	0.0	1.0	1.0	1.0
ср	303.0	0.966997	1.032052	0.0	0.0	1.0	2.0	3.0
trestbps	303.0	131.623762	17.538143	94.0	120.0	130.0	140.0	200.0
chol	303.0	246.264026	51.830751	126.0	211.0	240.0	274.5	564.0
fbs	303.0	0.148515	0.356198	0.0	0.0	0.0	0.0	1.0
restecg	303.0	0.528053	0.525860	0.0	0.0	1.0	1.0	2.0
thalach	303.0	149.646865	22.905161	71.0	133.5	153.0	166.0	202.0
exang	303.0	0.326733	0.469794	0.0	0.0	0.0	1.0	1.0
oldpeak	303.0	1.039604	1.161075	0.0	0.0	0.8	1.6	6.2
slope	303.0	1.399340	0.616226	0.0	1.0	1.0	2.0	2.0
ca	303.0	0.729373	1.022606	0.0	0.0	0.0	1.0	4.0
thal	303.0	2.313531	0.612277	0.0	2.0	2.0	3.0	3.0
target	303.0	0.544554	0.498835	0.0	0.0	1.0	1.0	1.0

Identify the data variables which might be categorical in nature. Describe and explore these variables using appropriate tools. For example: count plot.

In [13]:

```
## Checking datatypes
df_heart.dtypes
```

Out[13]:

int64
int64
int64
s int64
int64
int64
int64
int64
int64
float64
int64
int64
int64
int64
object

In [14]:

```
# Conversion of datatypes of sex, cp, fbs, restecg,exang, thal, target
df_heart['sex'] = df_heart['sex'].astype('string')
df_heart['cp'] = df_heart['cp'].astype('string')
df_heart['fbs'] = df_heart['fbs'].astype('string')
df_heart['thal'] = df_heart['thal'].astype('string')
df_heart['exang'] = df_heart['exang'].astype('string')
df_heart['restecg'] = df_heart['restecg'].astype('string')
df_heart['target'] = df_heart['target'].astype('string')
```

In [15]:

```
## Checking datatypes
df_heart.dtypes
```

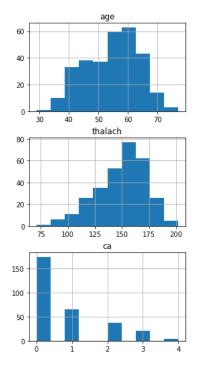
Out[15]:

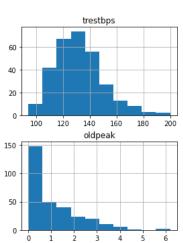
int64 age string sex ср string trestbps int64 chol int64 fbs string restecg string thalach int64 string exang oldpeak float64 slope int64 int64 ca thal string target string dtype: object

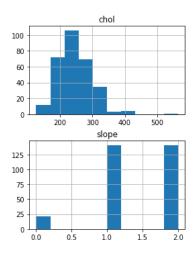
In [16]:

```
df_heart.hist(figsize=(15,15),layout=(5,3))
# Observation
# ca , age is left skewed
# trestbps,oldpeak ,chol are right skewed
```

Out[16]:







In [17]:

```
# count of patients by gender
df_heart["sex"].value_counts()
# There are 206 males and 96 females
```

Out[17]:

206
 96

Name: sex, dtype: Int64

In [18]:

```
df_heart["target"].value_counts()
# Heart disease (0 = no, 1 = yes)
# There are 164 persons reported heart disease
# There are 138 persons reported no heart disease
```

Out[18]:

1 164
 0 138

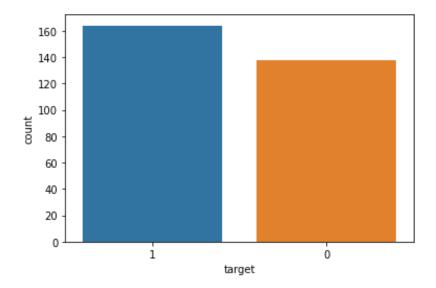
Name: target, dtype: Int64

In [19]:

```
# count plot on single categorical variable "target"
sns.countplot(x = 'target', data = df_heart)
# its a balanced dataset
```

Out[19]:

<AxesSubplot:xlabel='target', ylabel='count'>



In [20]:

```
df_heart["cp"].value_counts()
# Value 1: typical angina, Value 2: atypical angina, Value 3: non-anginal pain, Value 4.
```

Out[20]:

0 1432 861 503 23

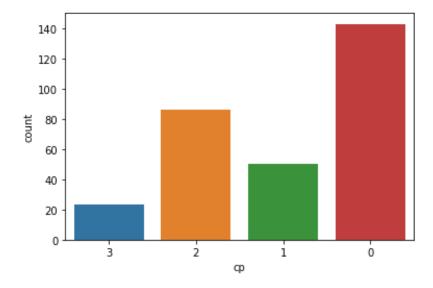
Name: cp, dtype: Int64

In [21]:

```
# count plot on single categorical variable 'cp'
sns.countplot(x = 'cp', data = df_heart)
```

Out[21]:

<AxesSubplot:xlabel='cp', ylabel='count'>



In [22]:

```
df_heart["exang"].value_counts()
# Exercise-induced angina (1 = yes; 0 = no)
```

Out[22]:

0 2031 99

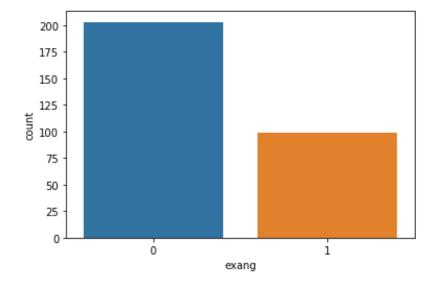
Name: exang, dtype: Int64

In [23]:

```
# count plot on single categorical variable 'exang'
sns.countplot(x = 'exang', data = df_heart)
```

Out[23]:

<AxesSubplot:xlabel='exang', ylabel='count'>



In [24]:

```
df_heart["restecg"].value_counts()
# Resting electrocardiographic measurement (0 = normal, 1 = having ST-T wave abnormality
```

Out[24]:

1 151
 0 147
 2 4

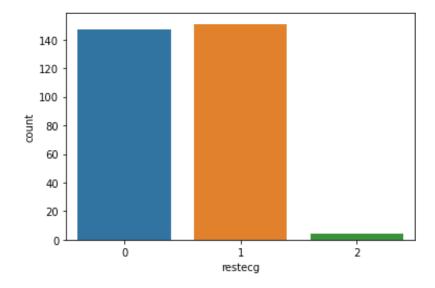
Name: restecg, dtype: Int64

In [25]:

```
# count plot on single categorical variable 'restecg'
sns.countplot(x = 'restecg', data = df_heart)
```

Out[25]:

<AxesSubplot:xlabel='restecg', ylabel='count'>



In [26]:

```
df_heart["fbs"].value_counts()
# The person's fasting blood sugar (> 120 mg/dl, 1 = true; 0 = false)
```

Out[26]:

0 2571 45

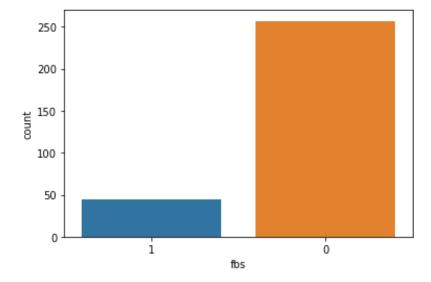
Name: fbs, dtype: Int64

In [27]:

```
# count plot on single categorical variable 'fbs'
sns.countplot(x = 'fbs', data = df_heart)
```

Out[27]:

<AxesSubplot:xlabel='fbs', ylabel='count'>



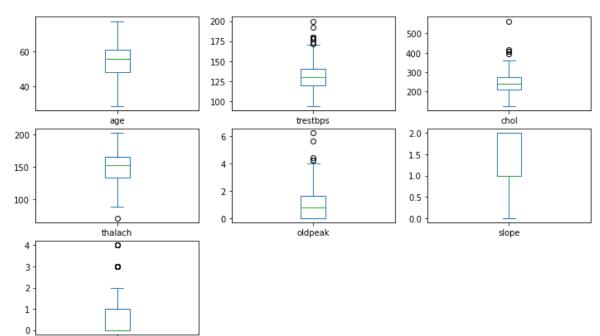
In [28]:

```
df_heart.plot(kind='box',subplots=True, layout=(5,3),figsize=(12,12))
# Observation:
# No outliers in age, slope, thalach
# Upper outliers in trestbps,chol,ca,oldpeak
```

Out[28]:

age AxesSubplot(0.125,0.749828;0.227941x0.130172)
trestbps AxesSubplot(0.398529,0.749828;0.227941x0.130172)
chol AxesSubplot(0.672059,0.749828;0.227941x0.130172)
thalach AxesSubplot(0.125,0.593621;0.227941x0.130172)
oldpeak AxesSubplot(0.398529,0.593621;0.227941x0.130172)
slope AxesSubplot(0.672059,0.593621;0.227941x0.130172)
ca AxesSubplot(0.125,0.437414;0.227941x0.130172)

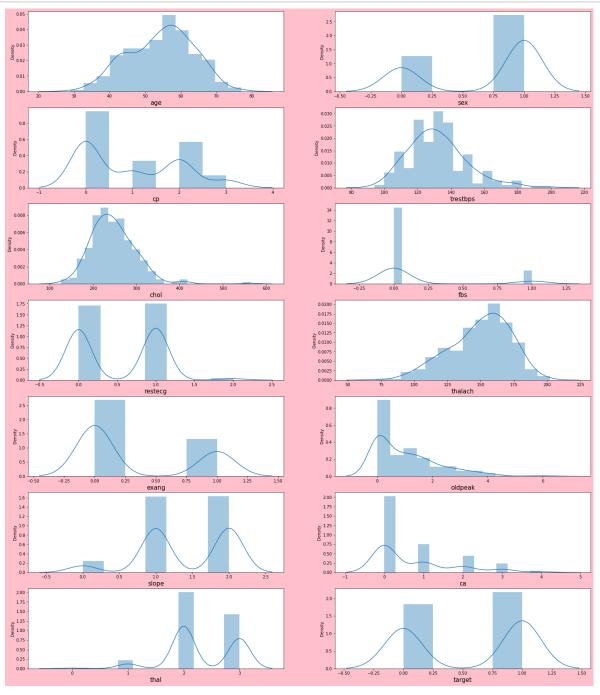
dtype: object



In [29]:

```
## Distribution of data
plt.figure(figsize=(25,30),facecolor='pink')
columnnumber=1

for column in df_heart:
    if columnnumber<=14:
        ax=plt.subplot(7,2,columnnumber)
        sns.distplot(df_heart[column])
        plt.xlabel(column,fontsize=15)
        columnnumber+=1
plt.show()</pre>
```



Study the occurrence of CVD across different ages.

In [30]:

```
# Distribution of heart disease/No heart disease by ages
tab2 =pd.crosstab(df_heart['age'],df_heart['target'])
tab2
```

Out[30]:

	4	
target	0	1
age		
29	0	1
34	0	2
35	2	2
37	0	2
38	1	1
39	1	3
40	2	1
41	1	9
42	1	7
43	3	5
44	3	8
45	2	6
46	3	4
47	2	3
48	3	4
49	2	3
50	3	4
51	3	9
52	4	9
53	2	6
54	6	10
55	5	3
56	6	5
57	10	7
58	12	7
59	9	5
60	8	3
61	7	1
62	7	4
63	6	3
64	4	6
65	4	4
66	3	4
67	6	3
68	2	2

```
target 0 1

age

69 1 2

70 3 1

71 0 3

74 0 1

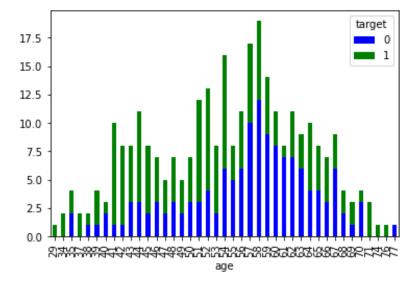
In [31]:

77 1 0

# Stacked plot for Distribution of heart disease/No heart disease by ages
tab2.plot(kind='bar', stacked='True', color=['blue','green'],grid=False)
```

Out[31]:

<AxesSubplot:xlabel='age'>

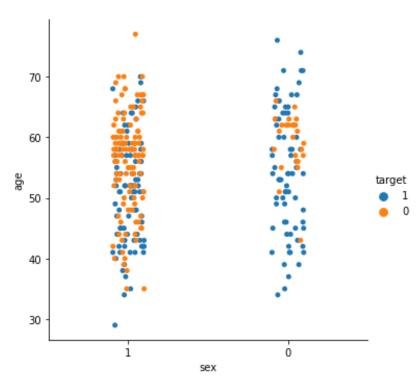


In [32]:

```
sns.catplot(data=df_heart, x='sex', y='age', hue='target')
```

Out[32]:

<seaborn.axisgrid.FacetGrid at 0x1cfe3ae6e20>



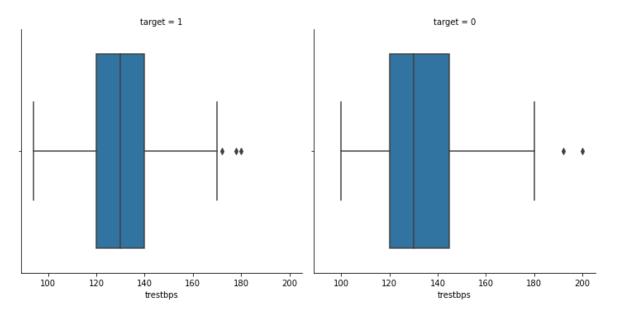
Can we detect heart attack based on anomalies in resting blood pressure of the patient?

In [33]:

```
# A boxplot of the resting blood pressure of patients in categories
sns.factorplot(x = 'trestbps', data = df_heart, col = 'target', kind = 'box')
```

Out[33]:

<seaborn.axisgrid.FacetGrid at 0x1cff5226940>

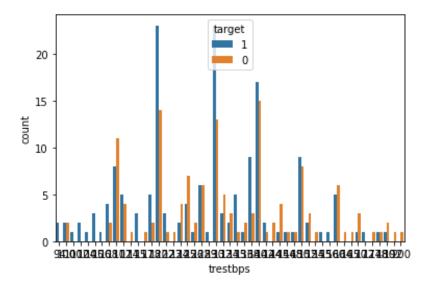


In [34]:

```
sns.countplot(x ='trestbps',hue='target', data = df_heart)
```

Out[34]:

<AxesSubplot:xlabel='trestbps', ylabel='count'>



Study the composition of overall patients w.r.t . gender.

In [35]:

```
# Distribution of heart disease/No heart disease by gender
tab1 =pd.crosstab(df_heart['sex'],df_heart['target'])
tab1
# Heart disease (0 = no, 1 = yes)
# There are 24 females with no Heart Disease
# There are 72 females with Heart Disease
# There are 92 males with Heart Disease
# There are 114 males with no Heart Disease
```

Out[35]:

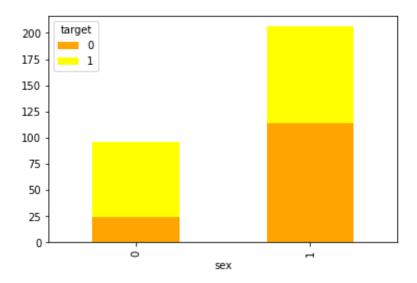
target	0	1
sex		
0	24	72
1	114	92

In [36]:

```
# Stacked plot for Distribution of heart disease/No heart disease by gender
tab1.plot(kind='bar', stacked='True', color=['orange','yellow'],grid=False)
```

Out[36]:

<AxesSubplot:xlabel='sex'>



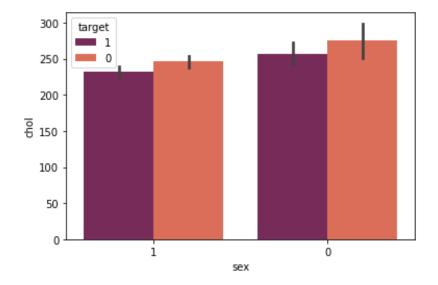
Describe the relationship between cholesterol levels and our target variable.

In [37]:

```
sns.barplot(data=df_heart, x='sex', y='chol', hue='target', palette='rocket')
```

Out[37]:

<AxesSubplot:xlabel='sex', ylabel='chol'>



What can be concluded about the relationship between peak exercising and occurrence of heart attack?

In [38]:

```
# Distribution of heart disease/No heart disease by exang(Exercise induced angina :1 = y
tab3 =pd.crosstab(df_heart['exang'],df_heart['target'])
tab3
# 23 cases of Heart Disease induced by angina(exang)
```

Out[38]:

target	0	1
exang		
0	62	141
1	76	23

In [39]:

```
# Distribution of heart disease/No heart disease by slope(Peak exercise ST segment)
tab4 =pd.crosstab(df_heart['slope'],df_heart['target'])
tab4
# 44 cases heart diseases of flat, Peak exercise ST segment
# 106 cases heart diseases of downsloping, Peak exercise ST segment
```

Out[39]:

target	0	1
slope		
0	12	9
1	91	49
2	35	106

In [40]:

Distribution of heart disease/No heart disease by oldpeak(displays the value which is
tab5 =pd.crosstab(df_heart['oldpeak'],df_heart['target'])
tab5

Out[40]:

out[40].		
target	0	1
oldpeak		
0.0	25	73
0.1	3	4
0.2	3	9
0.3	1	2
0.4	1	8
0.5	1	4
0.6	4	10
0.7	0	1
0.8	6	7
0.9	2	1
1.0	10	4
1.1	0	2
1.2	10	7
1.3	0	1
1.4	7	6
1.5	1	4
1.6	4	7
1.8	7	3
1.9	3	2
2.0	7	2
2.1	1	0
2.2	4	0
2.3	0	2
2.4	2	1
2.5	2	0
2.6	5	1
2.8	6	0
2.9	1	0
3.0	4	1
3.1	1	0
3.2	2	0
3.4	3	0
3.5	0	1
3.6	4	0
3.8	1	0

```
target
oldpeak
             0
    4.0
         3
    4.2
             1
    4.4
             0
    5.6
Is thalassemia a major cause of CVD? How are the other factors determining the occurrence of CVD?
    6.2 1 0
In [41]:
# Distribution of heart disease/No heart disease by thal(Peak exercise ST segment)
tab6 =pd.crosstab(df_heart['thal'],df_heart['target'])
tab6
# 129 cases of heart diseases of fixed defect
# 28 cases of heart diseases of reversible defect
Out[41]:
target
      0
  thal
    0
       1
            1
    1 12
            6
    2 36
          129
    3 89
           28
In [42]:
# Distribution of heart disease/No heart disease by ca
tab7 =pd.crosstab(df_heart['ca'],df_heart['target'])
tab7
Out[42]:
target
            1
   ca
    0 45
          130
    1 44
           21
    2 31
            7
    3 17
            3
            3
       1
```

```
In [43]:
```

```
# Distribution of heart disease/No heart disease by fbs
tab8 =pd.crosstab(df_heart['fbs'],df_heart['target'])
tab8
```

Out[43]:

In [44]:

```
# Distribution of heart disease/No heart disease by restecg
tab9 =pd.crosstab(df_heart['restecg'],df_heart['target'])
tab9
```

Out[44]:

In [45]:

```
# Distribution of heart disease/No heart disease by thalach
tab10 =pd.crosstab(df_heart['thalach'],df_heart['target'])
tab10
```

Out[45]:

target	0	1
thalach		
71	1	0
88	1	0
90	1	0
95	1	0
96	1	1
190	0	1
192	0	1
194	0	1
195	1	0
202	0	1

91 rows × 2 columns

In [46]:

```
# Distribution of heart disease/No heart disease by cp
tab11 =pd.crosstab(df_heart['cp'],df_heart['target'])
tab11
```

Out[46]:

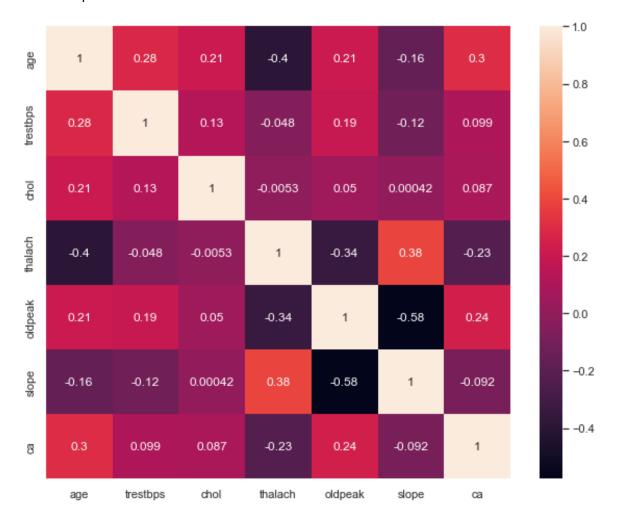
target	0	1
ср		
0	104	39
1	9	41
2	18	68
3	7	16

In [47]:

```
## Plotting heatmap to
sns.set(rc={'figure.figsize':(10,8)})
sns.heatmap(df_heart.corr(),annot=True)
```

Out[47]:

<AxesSubplot:>



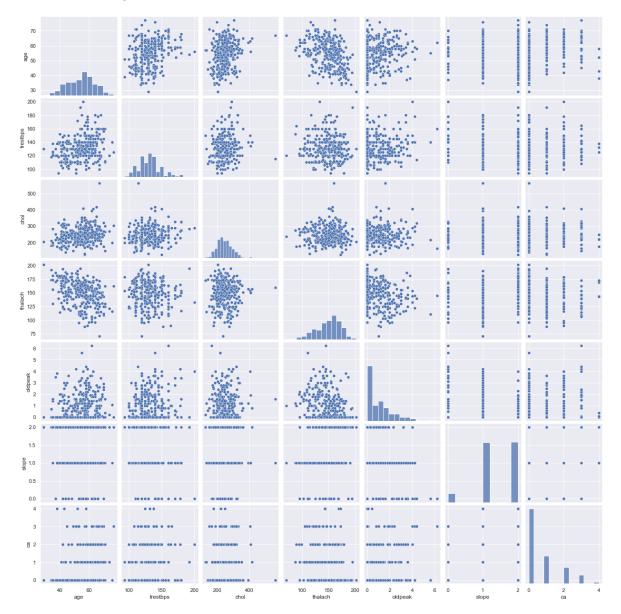
Use a pair plot to understand the relationship between all the given variables.

In [48]:

Plotting pair plot to visualize graphically
sns.pairplot(df_heart)

Out[48]:

<seaborn.axisgrid.PairGrid at 0x1cff5564f70>



Perform logistic regression, predict the outcome for test data, and validate the results by using the confusion matrix.

In [49]:

from sklearn.impute import SimpleImputer

```
In [50]:
```

```
# Segretating X and y values
X = df_heart.iloc[:, :-1].values
Y = df_heart.iloc[:, 13].values
```

In [51]:

```
# Standardization of Data
scale = StandardScaler()
```

In [52]:

```
# Training the data
X = scale.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=10)
```

In [53]:

```
# logistic_model is name of object
logistic_model = LogisticRegression()
```

In [54]:

```
# Fitting of train
logistic_model.fit(X_train, y_train)
```

Out[54]:

LogisticRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [55]:

```
## printing coefficient of model
print(logistic_model.coef_)
```

```
[[-0.16186905 -0.64177319 0.98651948 -0.17311117 -0.00625313 0.15570226 0.24102167 0.08948139 -0.46814646 -0.74259952 0.27365405 -0.5988354 -0.53422449]]
```

In [56]:

```
## printing intercept of model
print(logistic_model.intercept_)
```

[0.24368175]

```
In [57]:
## Printing Training Score
print('The Training Score is:',logistic_model.score(X_train,y_train))
The Training Score is: 0.8436018957345972
In [58]:
## Printing Test Score
print('The Test Score is:',logistic_model.score(X_test,y_test))
The Test Score is: 0.8681318681318682
In [59]:
```

```
# Predicted values
logistic_predictions = logistic_model.predict(X_test)
logistic_predictions
```

Out[59]:

```
'0',
array(['1', '1', '1', '1', '0', '1', '1', '0',
                                         '0', '1',
              '1', '1', '1', '1',
                                '0', '0',
                                         '0', '1',
                                '1',
                                     '0',
                                                       '1',
                        '0', '1',
                                                   '1',
      '0', '1',
               '0', '1',
                                         '1', '1',
              '1',
                   '1',
                       '1',
                            '0',
                                '1',
                                    '0',
                                         '1',
                                             '1',
                                                  '0',
                                                       '1',
              '1', '0', '0', '1', '1', '0', '1', '1',
                                                  '0',
                                             '1',
               '1', '1', '1',
                           '1', '0', '1', '0',
                                                      '0',
          '1',
                                                  '0',
              '1', '1',
     dtype=object)
```

In [60]:

```
# Confusion Matrix
conf_matrix=confusion_matrix(y_test, logistic_predictions)
```

In [61]:

```
print("The confusion matrix is :'\n")
print(confusion_matrix(y_test, logistic_predictions))
```

The confusion matrix is:'

```
[[35 8]
[ 4 44]]
```

In [62]:

```
## Computing True positive
True_positive=conf_matrix[0][0]
True_positive
```

Out[62]:

```
In [63]:
## Computing False positive
False_positive =conf_matrix[0][1]
False_positive
Out[63]:
8
In [64]:
## Computing False negative
False_negative =conf_matrix[1][0]
False_negative
Out[64]:
In [65]:
## Computing True Negative
True_negative=conf_matrix[1][1]
True_negative
Out[65]:
44
In [66]:
## Computing Precision
Precision= True_positive/(True_positive+False_positive)
Precision
Out[66]:
0.813953488372093
In [67]:
## Computing Recall
Recall= True_positive/(True_positive+False_negative)
Recall
Out[67]:
0.8974358974358975
In [68]:
## Computing F1 Score
f1_Score=2*(Precision*Recall)/(Recall+Precision)
```

In [69]:

```
## Printing Classification Report
Classification_Report= classification_report(y_test,logistic_predictions)
print(Classification_Report)
```

	precision	recall	f1-score	support
0	0.90	0.81	0.85	43
1	0.85	0.92	0.88	48
accuracy			0.87	91
macro avg	0.87	0.87	0.87	91
weighted avg	0.87	0.87	0.87	91

In [70]:

```
print('Accuracy of logistic regression classifier {}'.format(logistic_model.score(X_test))
```

Accuracy of logistic regression classifier 0.8681318681318682

Result:

The model correctly classifys patients with the risk of having a heart attack 87% accuracy.

Concerns:

Even though the logistic model was able to classify with 87% accuracy the amount of miscalculatoin is concerning especially in regards to the type 2 errors.

Model Performance Summary

The logistic regression model has accuracy with 87 percent to predict the examining Factors Responsible for Heart Attacks.