HEALTH CARE DOMAIN (Heart Disease)

Extensive Analysis + Visualization with Python

TABLE OF CONTENTS

The table of contents for this project are as follows: -

In [1]:
```
# import required libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as st
%matplotlib inline

import os
os.getcwd()
```

Out[1]:
```
'C:\\Users\\Hanshu\\basics'
```

In [2]:
```
sns.set(style = 'whitegrid')
```

In [3]:
```python
# ignore warnings

import warnings
warnings.filterwarnings('ignore')
```

i have imported the required libraries. now ,next stp is import the dataset

IMPORT DATASET

In [4]:
```python
df = pd.read_csv(r'C:\Users\Hanshu\Desktop\excel data\heart.csv')
df
```

Out[4]:

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

303 rows × 14 columns

EXPLORATORY DATA ANALYSIS

In [5]:
```python
# check the shape of the dataset
# print the shape

print('the shape of the dataset :' , df.shape)

# dataset contain 303 instance(rows/records), and 14(columns/attributes) variabl
```

```
the shape of the dataset : (303, 14)
```

In [6]:
```python
df.shape
```

Out[6]:
```
(303, 14)
```

preview the dataset

preview the dataset

In [7]:
```
# preview the dataset
df.head()
```

Out[7]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
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 [8]:
```
# summary of dataset
df.info()
```

```
<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
```

In [9]:
```
# check the data type of a particular column      # sex -->  (1 - male, 0- femal

df.dtypes
```

```
Out[9]: 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
```

```
In [10]: # statistical properties of dataset

         df.describe()
```

Out[10]:

	age	sex	cp	trestbps	chol	fbs	reste
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.5280
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.5258
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.0000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.0000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.0000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.0000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.0000

Important points to note

- The above command `df.describe()` helps us to view the statistical properties of numerical variables. It excludes character variables.
- If we want to view the statistical properties of character variables, we should run the following command -

  `df.describe(include=['object'])`

- If we want to view the statistical properties of all the variables, we should run the following command -

  `df.describe(include='all')`

```
In [11]: # view column names

         df.columns
```

Out[11]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

7. UNIVARIATE ANALYSIS

Analysis of `target` feature variable

- Our feature variable of interest is `target`.
- It refers to the presence of heart disease in the patient.
- It is integer valued as it contains two integers 0 and 1 - (0 stands for absence of heart disease and 1 for presence of heart disease).
- So, in this section, I will analyze the `target` variable.

Check the no.of unique values in TARGET Variable

In [12]:
```
df['target'].nunique()      # means count of unique values
```

Out[12]:
```
2
```

We can see that there are 2 unique values in the `target` variable.

View the unique values in `target` variable

In [13]:
```
df['target'].unique()       # means original unique values displyed (1,0)
```

Out[13]:
```
array([1, 0], dtype=int64)
```

Comment

So, the unique values are 1 and 0. (1 stands for presence of heart disease and 0 for absence of hear disease).

Frequency Distribution of TARGET Variable

In [14]:
```
df['target'].value_counts()     # it means  1- heart disease  ,0 - no heart dise
```

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

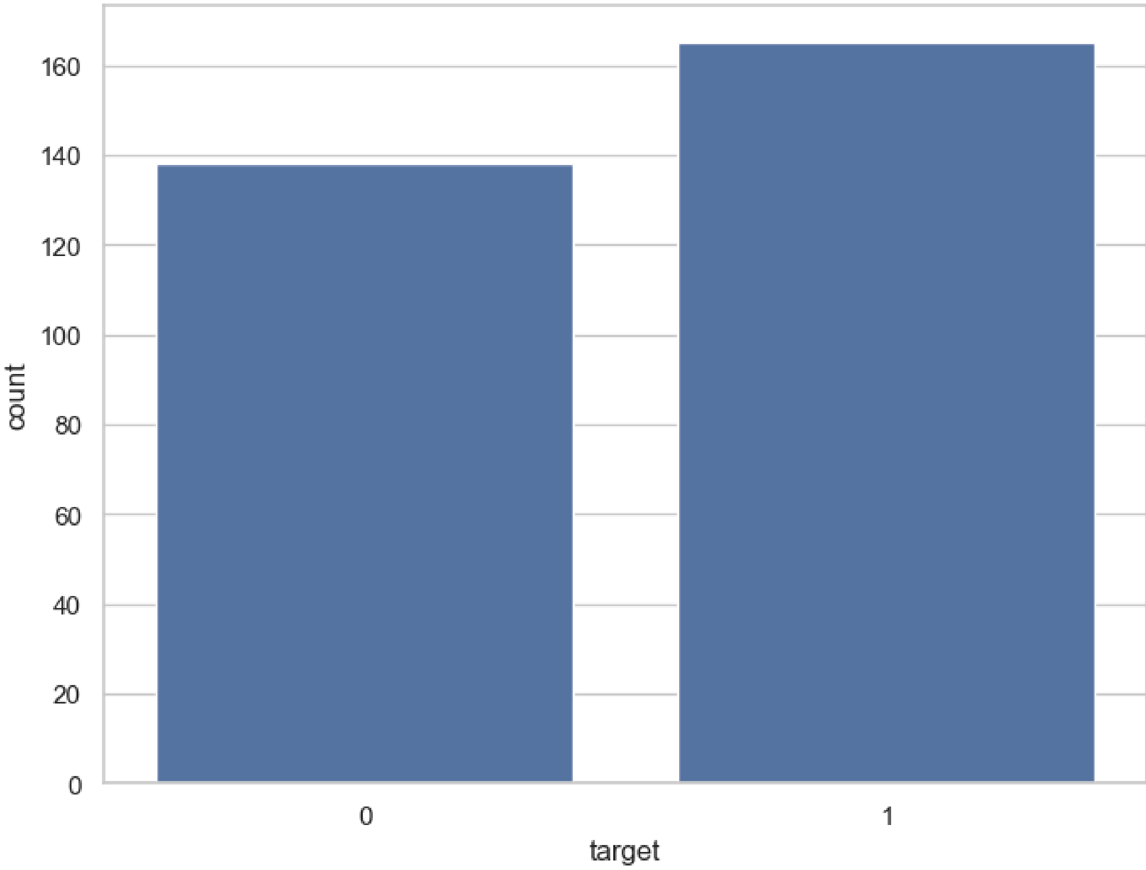
In [ ]:
```

```

COMMENTS

- `1` stands for presence of heart disease. So, there are 165 patients suffering from heart disease.
- Similarly, `0` stands for absence of heart disease. So, there are 138 patients who do not have any heart disease.
- We can visualize this information below.

Visualize frequency distribution of TARGET Variable

In [15]:
```
f , ax = plt.subplots(figsize = (8,6))
ax = sns.countplot( x= 'target', data = df)
plt.show()
```



In [ ]:
```

```

INTERPRETATION

- The above plot confirms the findings that -
  - There are 165 patients suffering from heart disease, and
  - There are 138 patients who do not have any heart disease.

Frequency distribution of `target` variable wrt `sex`

In [16]:
```
df.groupby('sex')['target'].value_counts()
```

Out[16]:
```
sex  target
0    1          72
     0          24
1    0         114
     1          93
Name: count, dtype: int64
```

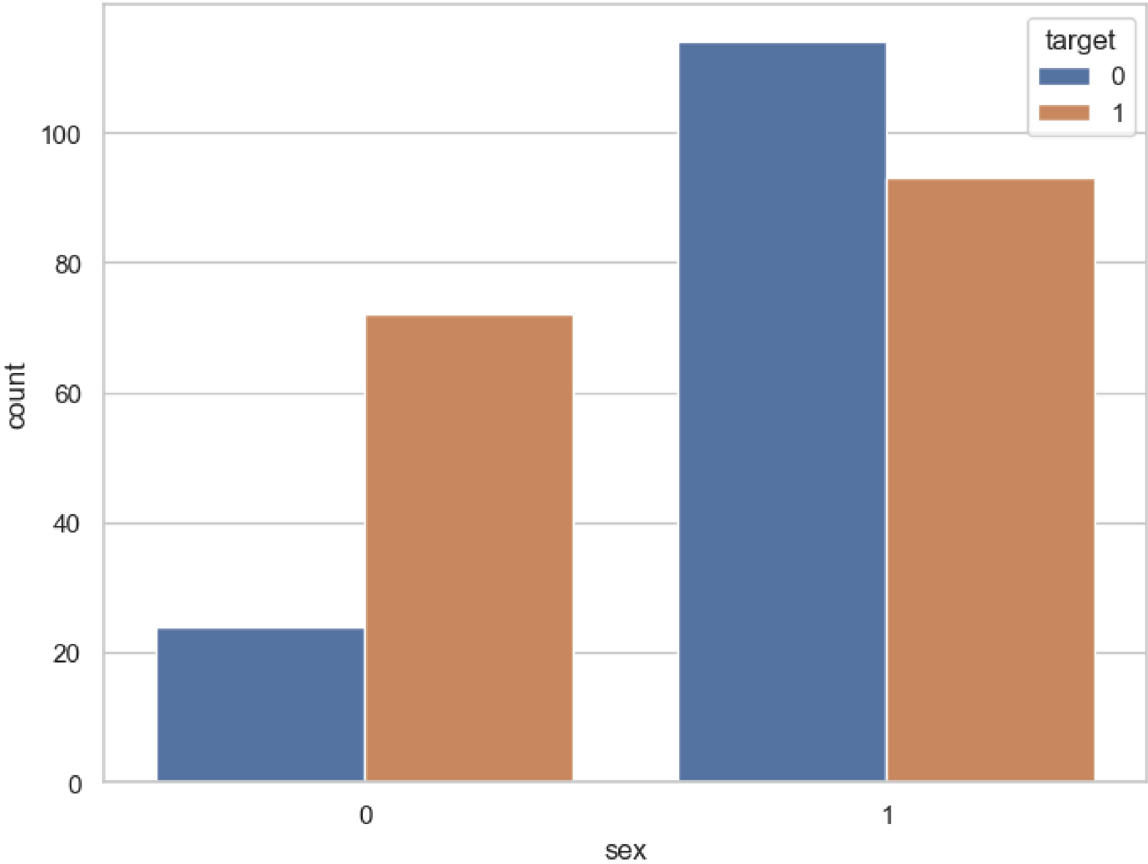
In [ ]:

COMMENT

- `sex` variable contains two integer values 1 and 0 : (1 = male; 0 = female).
- `target` variable also contains two integer values 1 and 0 : (1 = Presence of heart disease; 0 = Absence of heart disease)
- So, out of 96 females - 72 have heart disease and 24 do not have heart disease.
- Similarly, out of 207 males - 93 have heart disease and 114 do not have heart disease.
- We can visualize this information below.

We can visualize the value counts of the `sex` variable wrt `target` as follows

In [17]:
```
f, ax = plt.subplots(figsize=(8,6))
ax = sns.countplot(x ='sex' , hue= 'target' , data = df)
plt.show()
```



INTERPRETATION

- We can see that the values of `target` variable are plotted wrt `sex` : (1 = male; 0 = female).
- `target` variable also contains two integer values 1 and 0 : (1 = Presence of heart disease; 0 = Absence of heart disease)
- The above plot confirms our findings that -
  - Out of 96 females - 72 have heart disease and 24 do not have heart disease.
  - Similarly, out of 207 males - 93 have heart disease and 114 do not have heart disease.

COMMENT

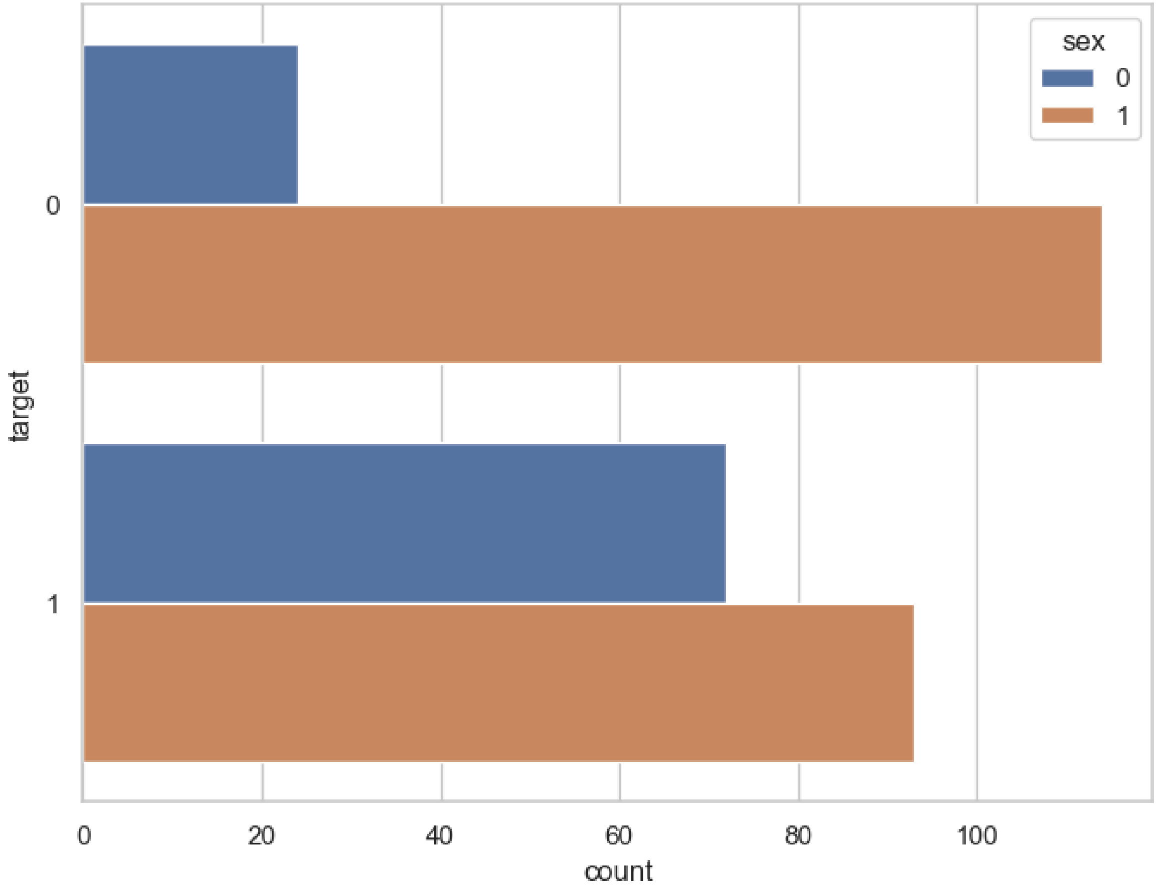
The above plot segregate the values of `target` variable and plot on two different columns labelled as (sex = 0, sex = 1).

- I think it is more convinient way of interpret the plots.

We can PLOT the BARS horizontally as follows:

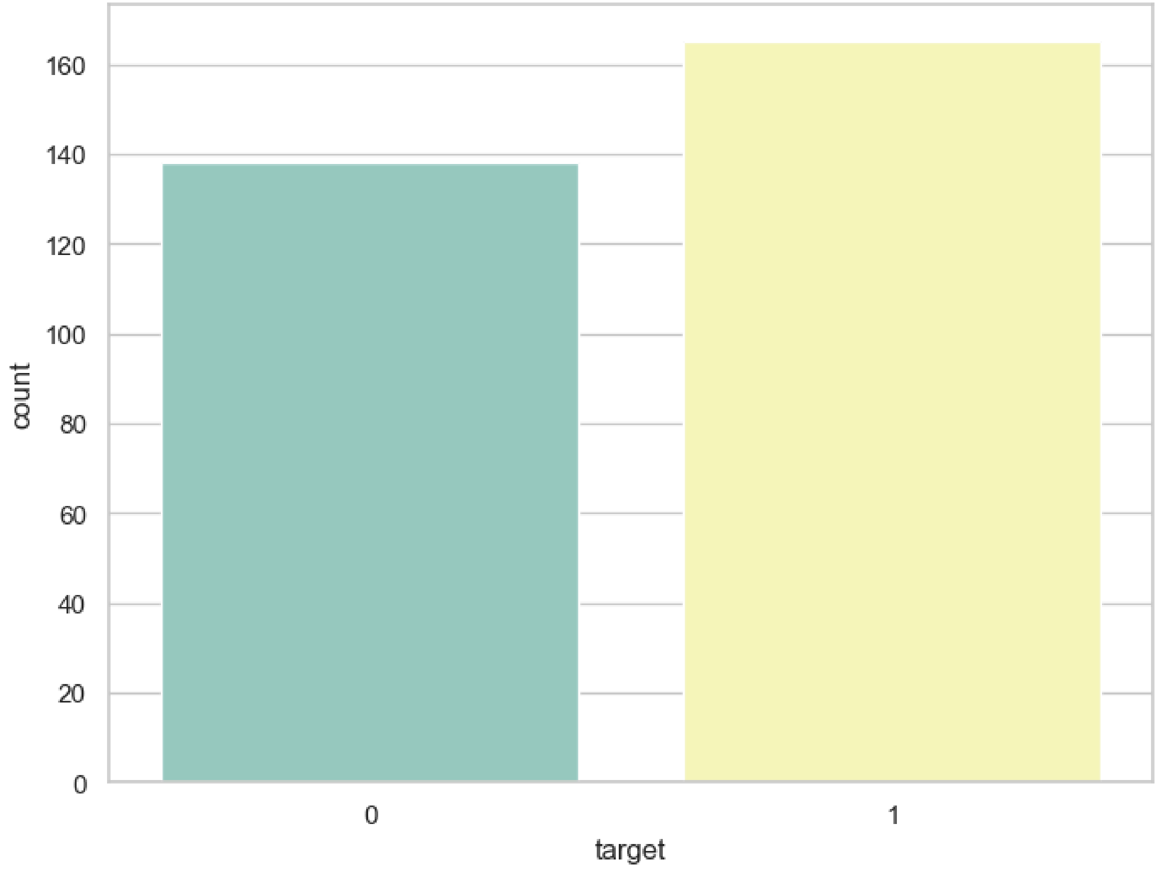
In [18]:
```
f, ax = plt.subplots(figsize= (8,6))
ax = sns.countplot(y ='target' , hue ='sex', data = df)
```

```
plt.show()
```



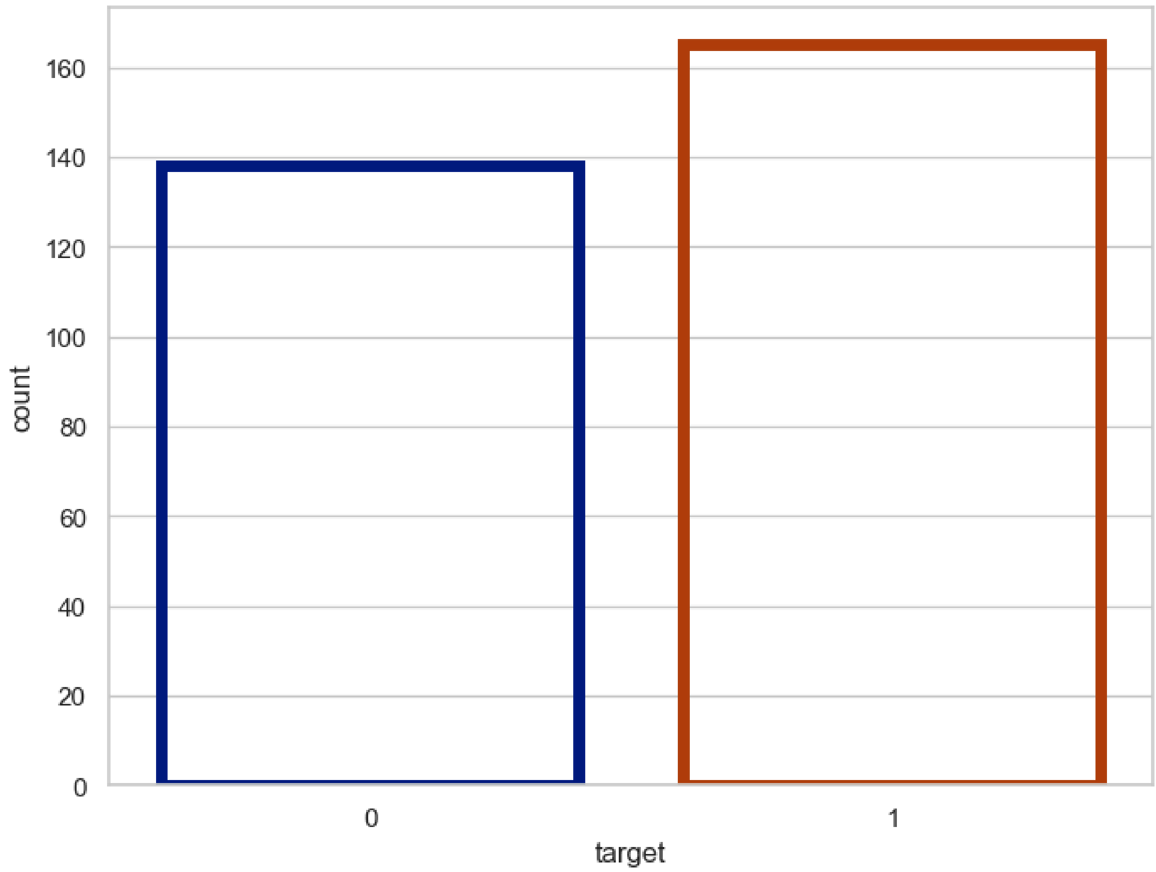
WE CAN USE A DIFFERENT COLOR PALETTE AS FOLLOWS:

In [19]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", data=df, palette="Set3")
plt.show()
```



We can use `plt.bar` keyword arguments for a different look :

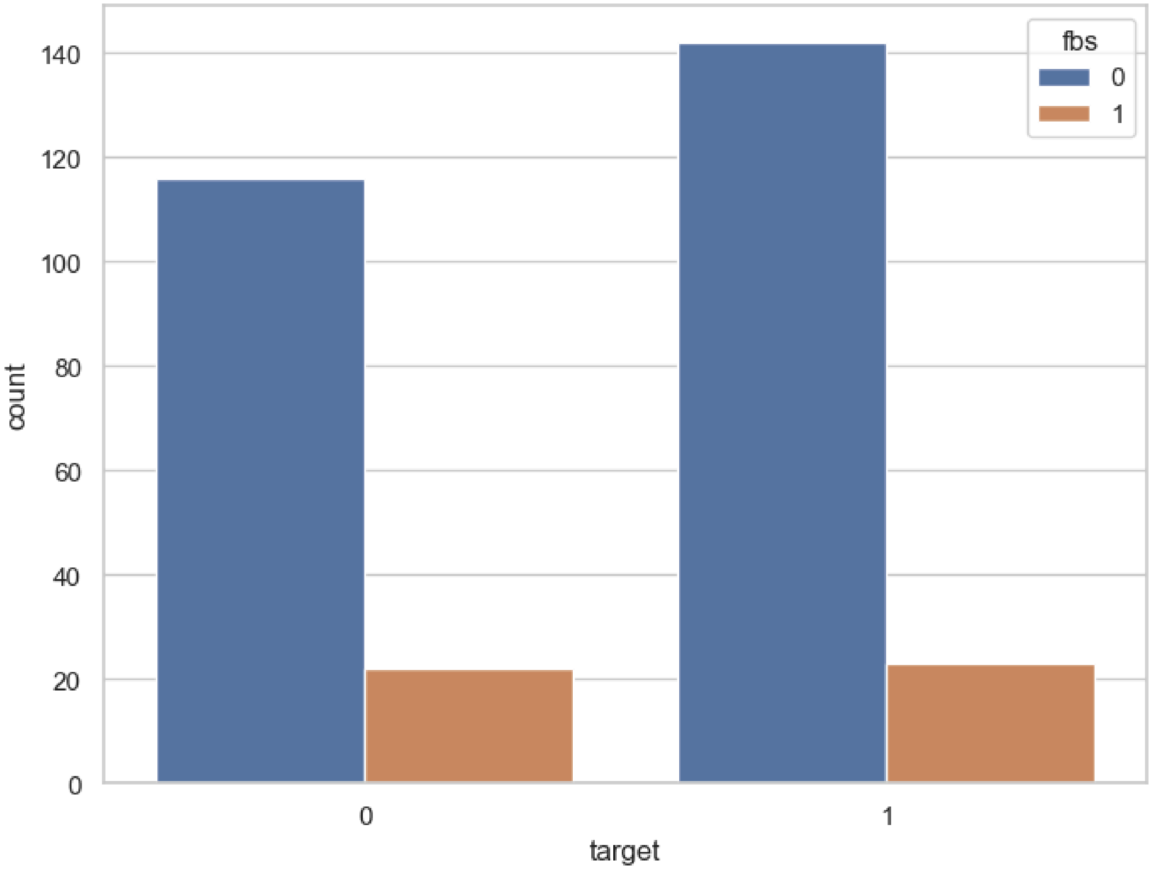
In [20]:
```
f ,ax = plt.subplots(figsize = (8,6))
ax = sns.countplot(x='target',data = df, facecolor = (0,0,0,0), linewidth = 5, e
plt.show()
```



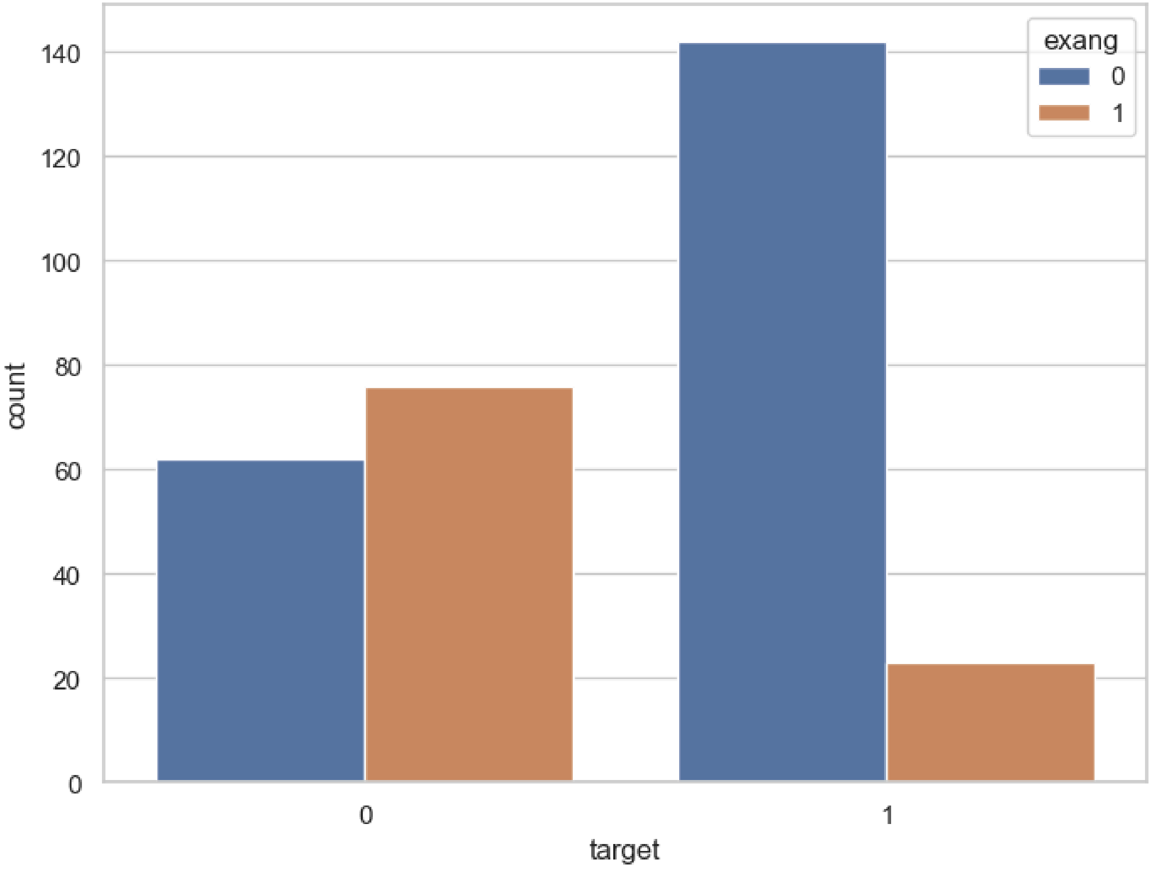
COMMENT

- I have visualize the `target` values distribution wrt `sex`.
- We can follow the same principles and visualize the `target` values distribution wrt `fbs (fasting blood sugar)` and `exang (exercise induced angina)`.

In [21]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", hue="fbs", data=df)
plt.show()
```



In [22]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", hue="exang", data=df)
plt.show()
```



Findings of Univariate Analysis

Findings of univariate analysis are as follows:-

- Our feature variable of interest is `target`.
- It refers to the presence of heart disease in the patient.
- It is integer valued as it contains two integers 0 and 1 - (0 stands for absence of heart disease and 1 for presence of heart disease).
- `1` stands for presence of heart disease. So, there are 165 patients suffering from heart disease.
- Similarly, `0` stands for absence of heart disease. So, there are 138 patients who do not have any heart disease.
- There are 165 patients suffering from heart disease, and
- There are 138 patients who do not have any heart disease.
- Out of 96 females - 72 have heart disease and 24 do not have heart disease.
- Similarly, out of 207 males - 93 have heart disease and 114 do not have heart disease.

```
In [ ]:
```

8. BIVARIATE ANALYSIS

Estimate correlation coefficients

Our dataset is very small. So, I will compute the standard correlation coefficient (also called Pearson's r) between every pair of attributes. I will compute it using the `df.corr()` method as follows:-

In [23]:
```
correlation = df.corr()
```

The target variable is `target`. So, we should check how each attribute correlates with the `target` variable. We can do it as follows:-

In [24]:
```
correlation['target'].sort_values(ascending = False)
```

Out[24]:
```
target      1.000000
cp          0.433798
thalach     0.421741
slope       0.345877
restecg     0.137230
fbs        -0.028046
chol       -0.085239
trestbps   -0.144931
age        -0.225439
sex        -0.280937
thal       -0.344029
ca         -0.391724
oldpeak    -0.430696
exang      -0.436757
Name: target, dtype: float64
```

In [ ]:
```

```

Interpretation of correlation coefficient

- The correlation coefficient ranges from -1 to +1.
- When it is close to +1, this signifies that there is a strong positive correlation. So, we can see that there is no variable which has strong positive correlation with `target` variable.
- When it is clsoe to -1, it means that there is a strong negative correlation. So, we can see that there is no variable which has strong negative correlation with `target` variable.
- When it is close to 0, it means that there is no correlation. So, there is no correlation between `target` and `fbs`.
- We can see that the `cp` and `thalach` variables are mildly positively correlated with `target` variable. So, I will analyze the interaction between these features and `target` variable.

Analysis of `target` and `cp` variable

Explore `cp` variable

- `cp` stands for chest pain type.
- First, I will check number of unique values in `cp` variable.

In [25]:
```
df['cp'].nunique()
```

Out[25]:
```
4
```

So, there are 4 unique values in `cp` variable. Hence, it is a categorical variable.

In [26]:
```
df['cp'].value_counts()
```

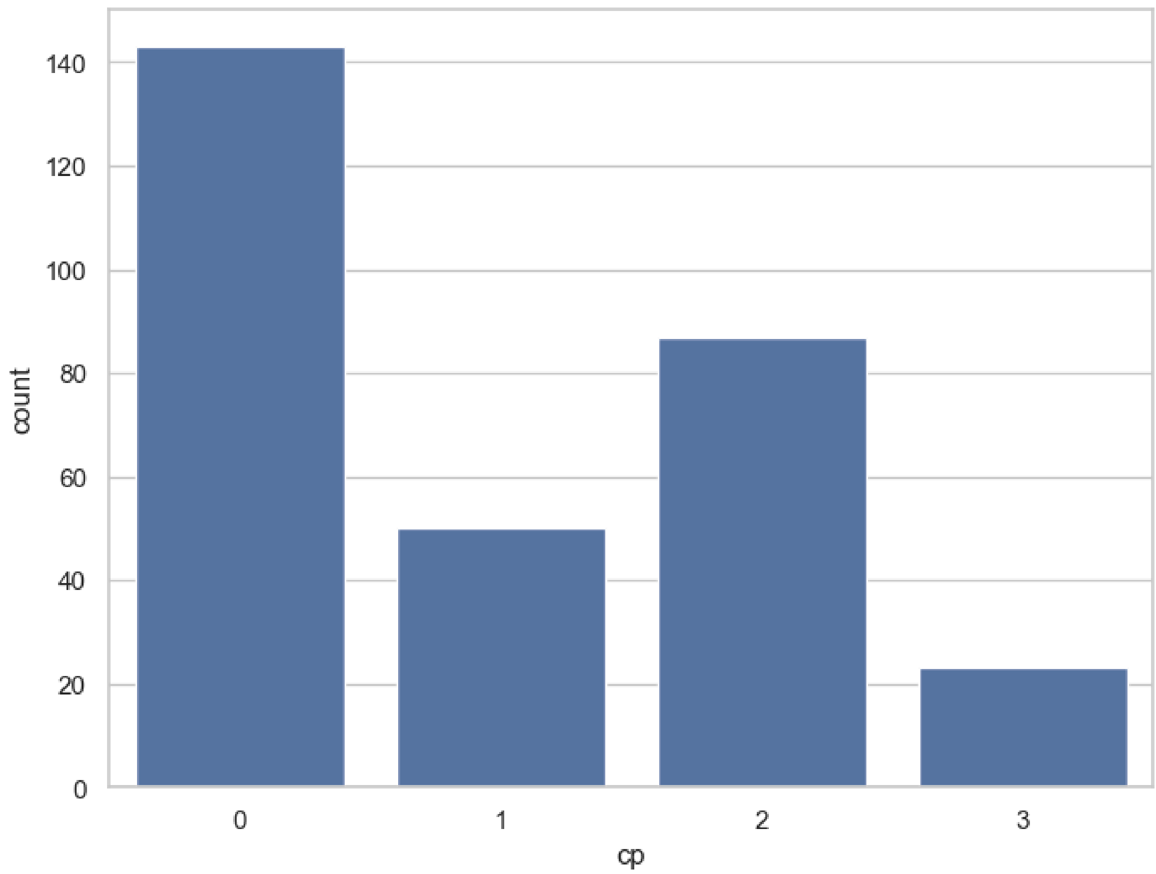
Out[26]:
```
cp
0    143
2     87
1     50
3     23
Name: count, dtype: int64
```

COMMENTS

- It can be seen that `cp` is a categorical variable and it contains 4 types of values - 0, 1, 2 and 3.

Visualize the frequency distribution of `cp` variable

In [31]:
```
f , ax = plt.subplots(figsize=(8,6))
ax = sns.countplot(x = 'cp' , data = df)
plt.show()
```



Frequency distribution of `target` variable wrt `cp`

In [29]:
```
df.groupby('cp')['target'].value_counts()
```

Out[29]:
```
cp  target
0   0         104
    1          39
1   1          41
    0           9
2   1          69
    0          18
3   1          16
    0           7
Name: count, dtype: int64
```

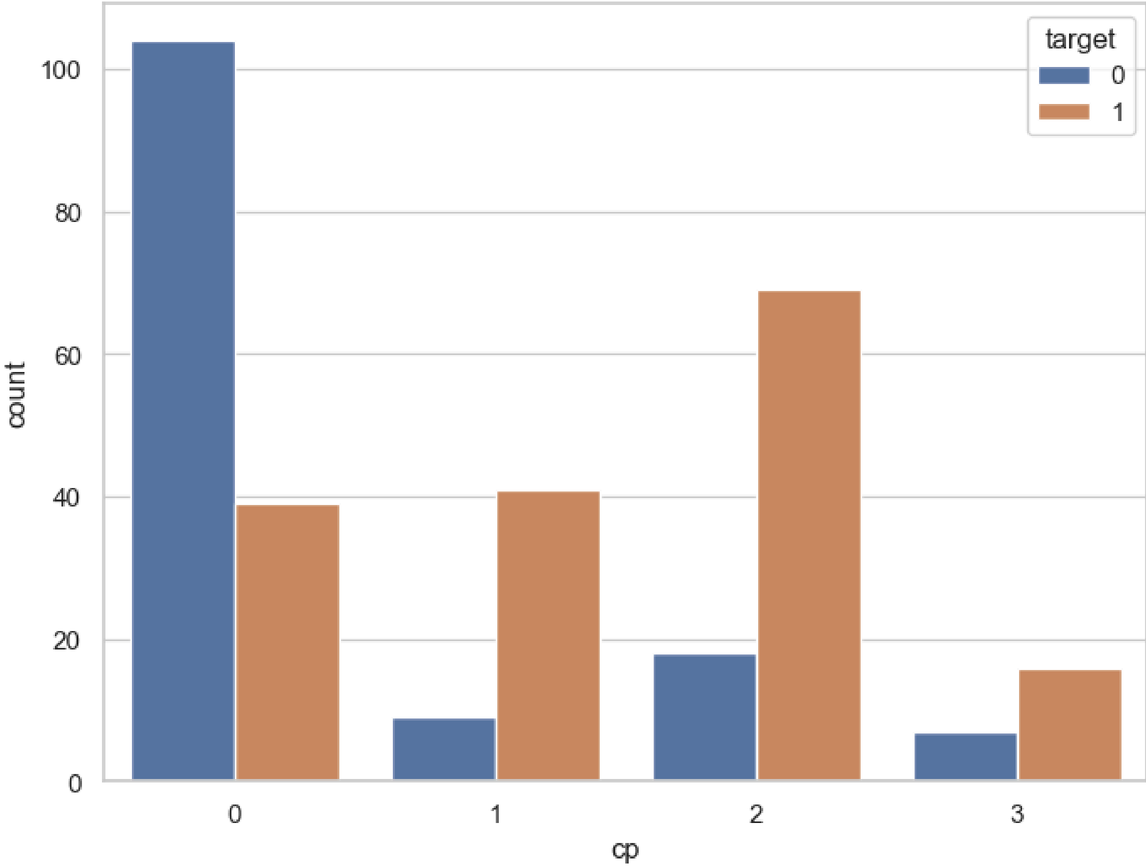
COMMENTS

- `cp` variable contains four integer values 0, 1, 2 and 3.
- `target` variable contains two integer values 1 and 0 : (1 = Presence of heart disease; 0 = Absence of heart disease)
- So, the above analysis gives `target` variable values categorized into presence and absence of heart disease and groupby `cp` variable values.

- We can visualize this information below.

We can visualize the value counts of the `cp` variable wrt `target` as follows -

In [32]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="cp", hue="target", data=df)
plt.show()
```

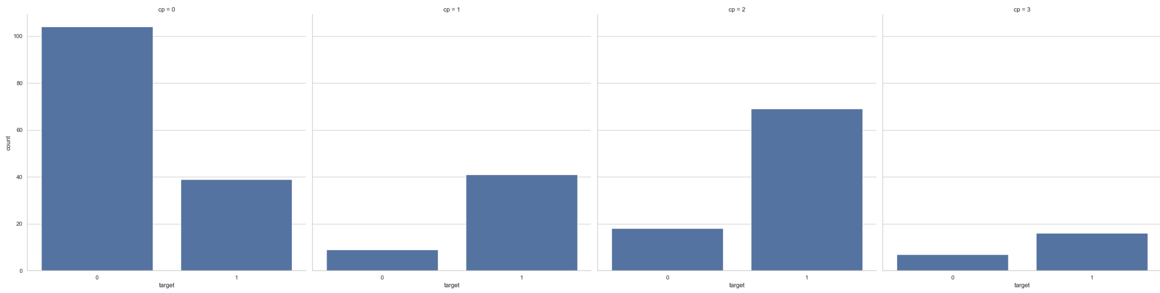


INTERCEPTION

- We can see that the values of `target` variable are plotted wrt `cp`.
- `target` variable contains two integer values 1 and 0 : (1 = Presence of heart disease; 0 = Absence of heart disease)
- The above plot confirms our above findings,

Alternatively, we can visualize the same information as follows :

In [35]:
```
ax = sns.catplot(x="target", col="cp", data=df, kind="count", height=8, aspect=1
plt.show()
```



Analysis of `target` and `thalach` variable

Explore `thalach` variable

- `thalach` stands for maximum heart rate achieved.
- I will check number of unique values in `thalach` variable as follows :

In [36]:
```
df['thalach'].nunique()
```

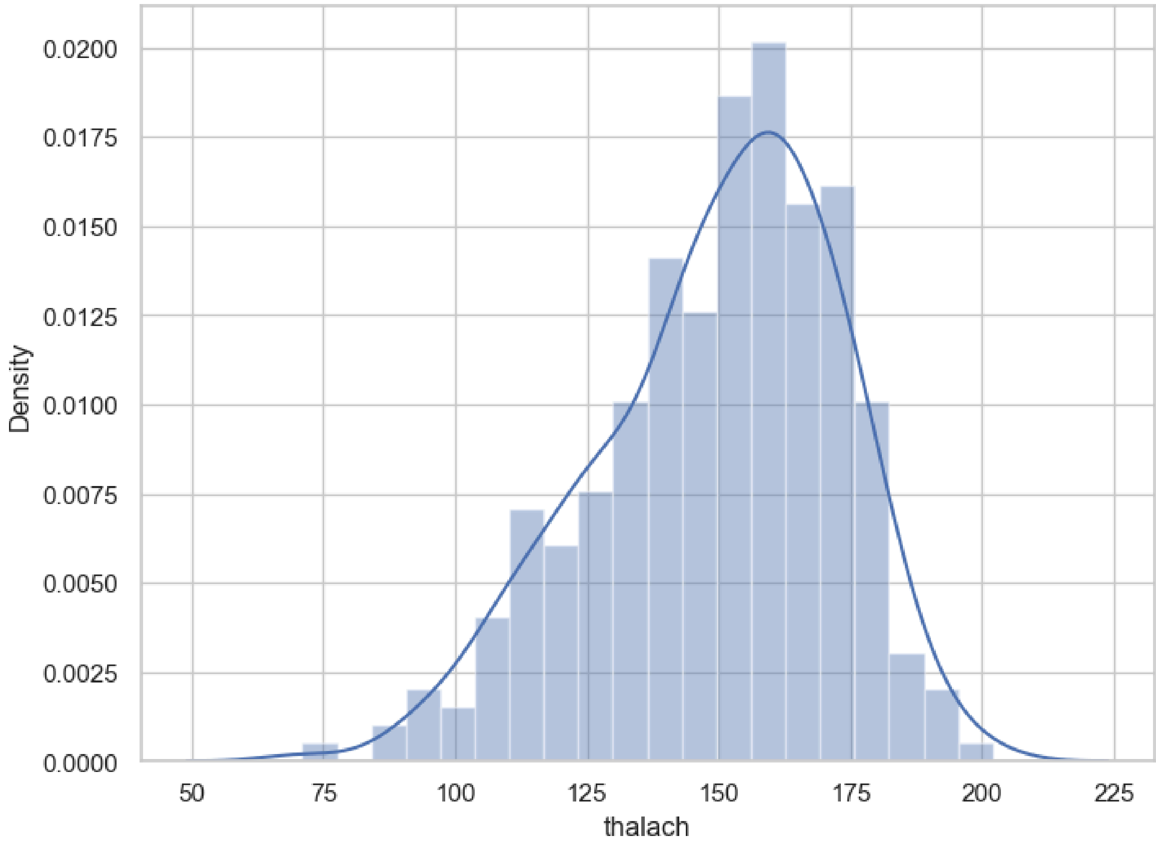
Out[36]: 91

- So, number of unique values in `thalach` variable is 91. Hence, it is numerical variable.

- I will visualize its frequency distribution of values as follows :

Visualize the frequency distribution of `thalach` variable

In [38]:
```
f ,ax = plt.subplots(figsize= (8,6))
x = df['thalach']
ax = sns.distplot(x, bins=20)
plt.show()
```

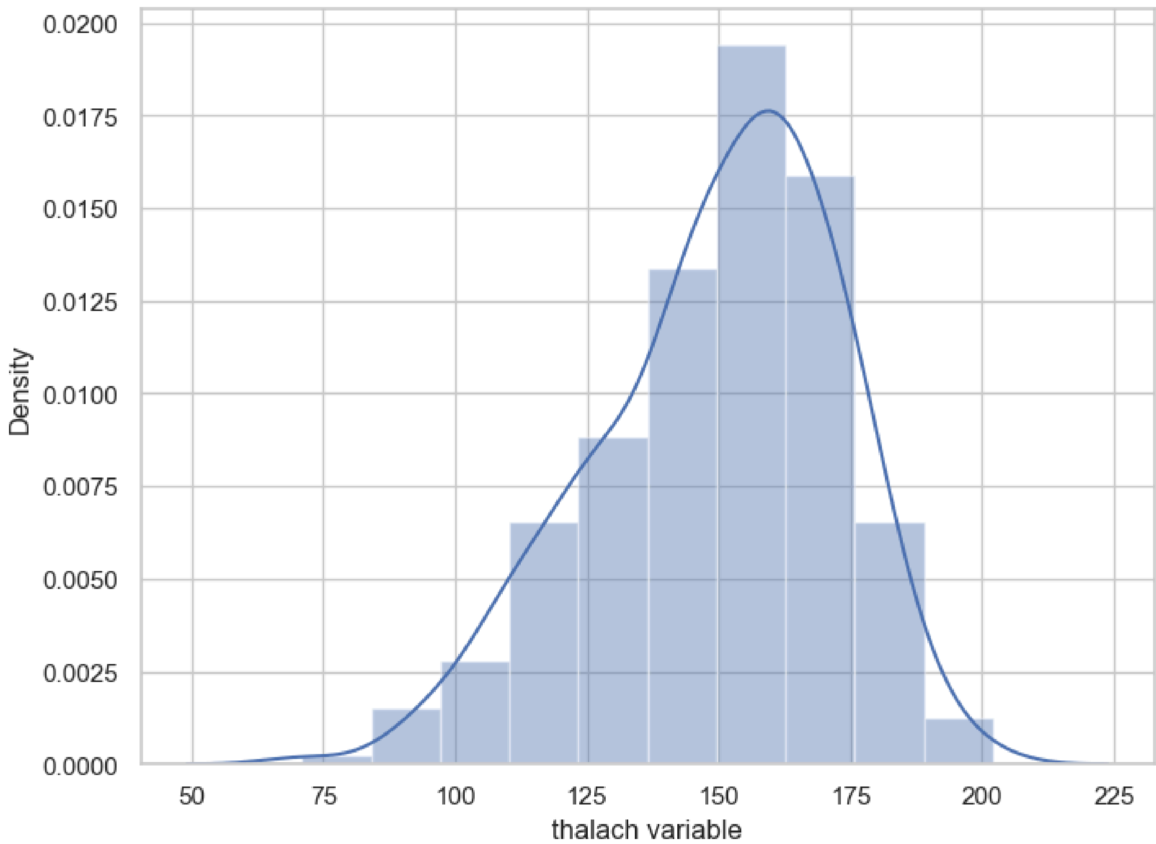


#COMMENTS

- We can see that the `thalach` variable is slightly negatively skewed.

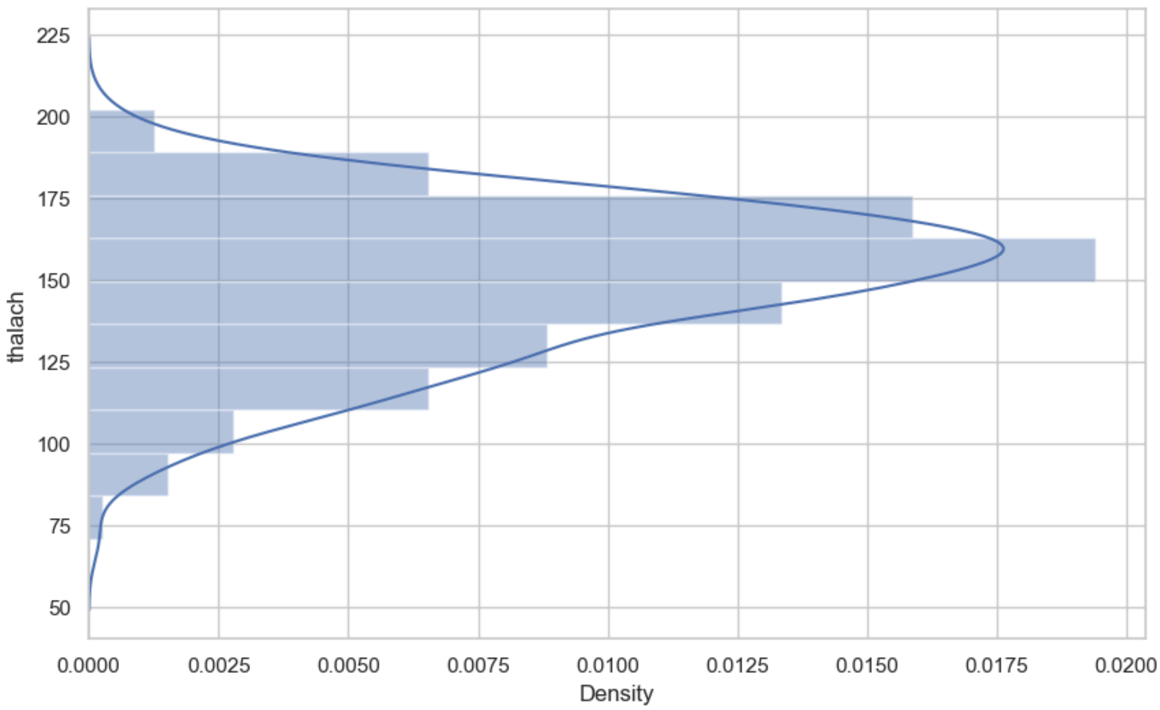
We can use Pandas series object to get an informative axis label as follows :

In [46]:
```
f ,ax = plt.subplots(figsize= (8,6))
x = df['thalach']
x = pd.Series(x, name="thalach variable")
ax = sns.distplot(x, bins=10)
plt.show()
```



We can plot the distribution on the vertical axis as follows:-

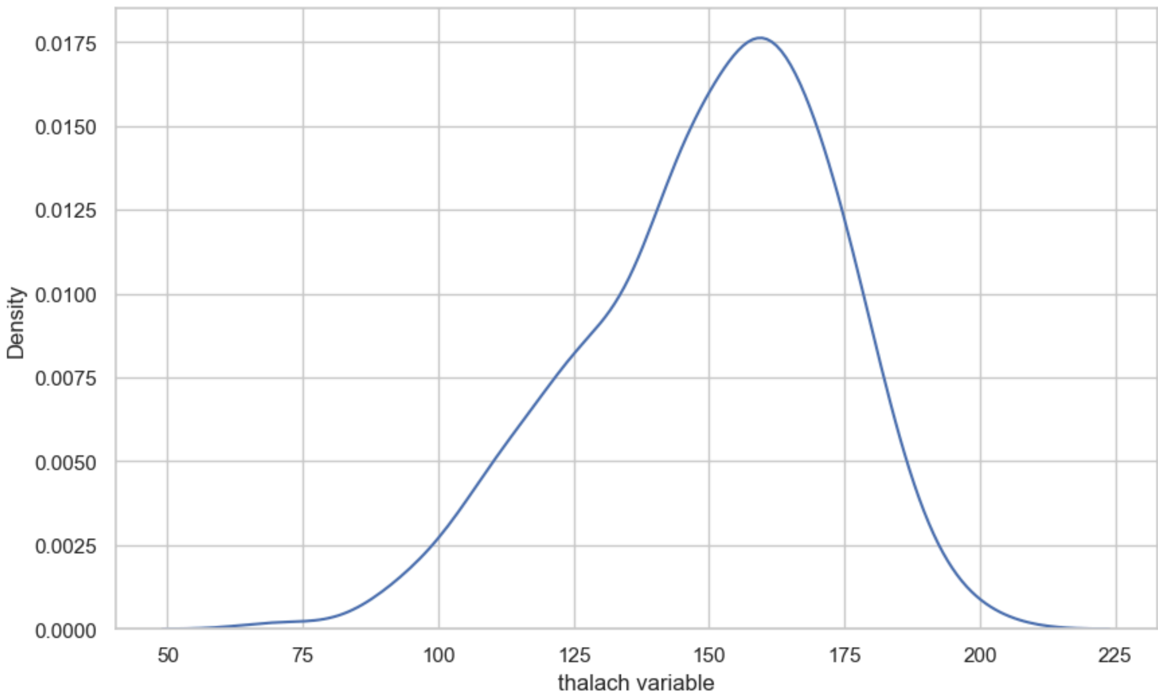
In [47]:
```
f, ax = plt.subplots(figsize=(10,6))
x = df['thalach']
ax = sns.distplot(x, bins=10, vertical=True)
plt.show()
```



Seaborn Kernel Density Estimation (KDE) Plot

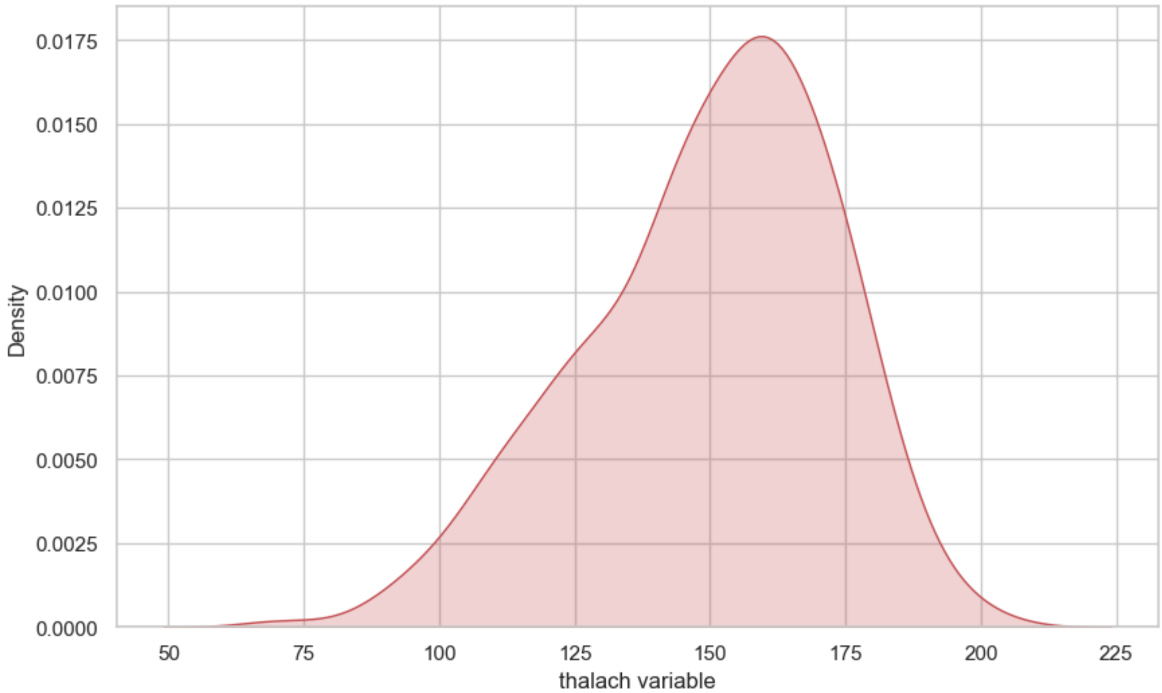
- The kernel density estimate (KDE) plot is a useful tool for plotting the shape of a distribution.
- The KDE plot plots the density of observations on one axis with height along the other axis.
- We can plot a KDE plot as follows :

In [48]:
```
f , ax = plt.subplots(figsize=(10,6))
x = df['thalach']
x = pd.Series(x , name= 'thalach variable')
ax = sns.kdeplot(x)
plt.show()
```



We can shade under the density curve and use a different color as follows:

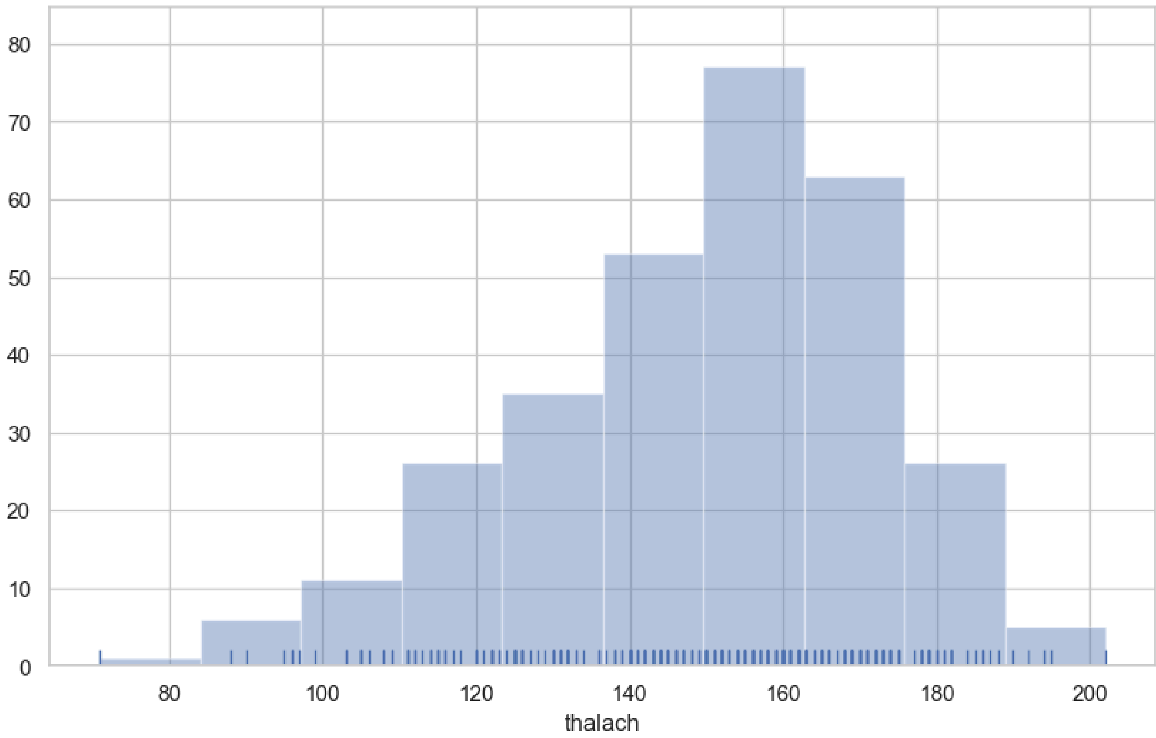
In [52]:
```
f ,ax = plt.subplots(figsize=(10,6))
x = df['thalach']
x = pd.Series(x , name='thalach variable')
ax = sns.kdeplot(x, shade = True, color = 'r')
plt.show()
```



Histogram

- A histogram represents the distribution of data by forming bins along the range of the data and then drawing bars to show the number of observations that fall in each bin.
- We can plot a histogram as follows :

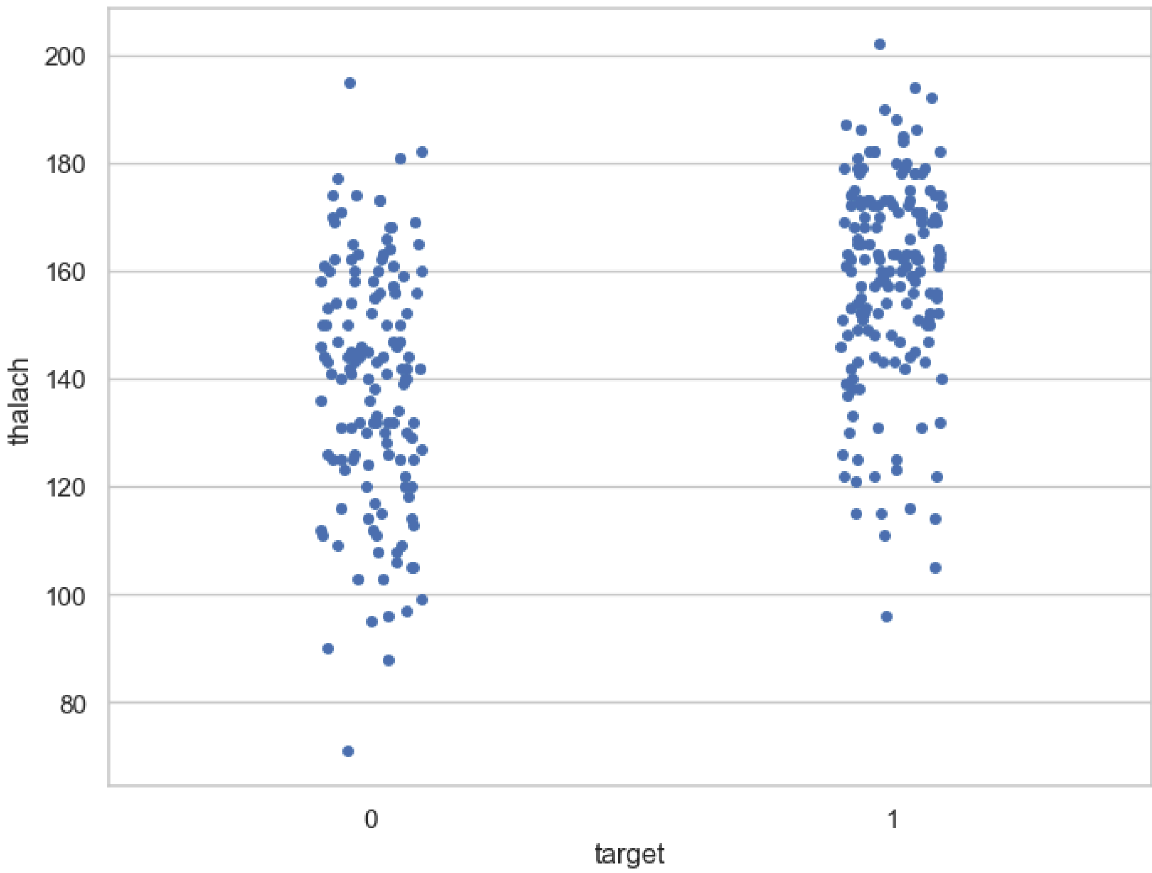
In [53]:
```
f ,ax = plt.subplots(figsize = (10,6))
x = df['thalach']
ax = sns.distplot(x, kde = False, rug = True , bins = 10)
plt.show()
```



Visualize frequency distribution of `thalach` variable wrt `target`

In [54]:

```
f , ax = plt.subplots(figsize= (8,6))
sns.stripplot(x = 'target', y = 'thalach', data = df)
plt.show()
```

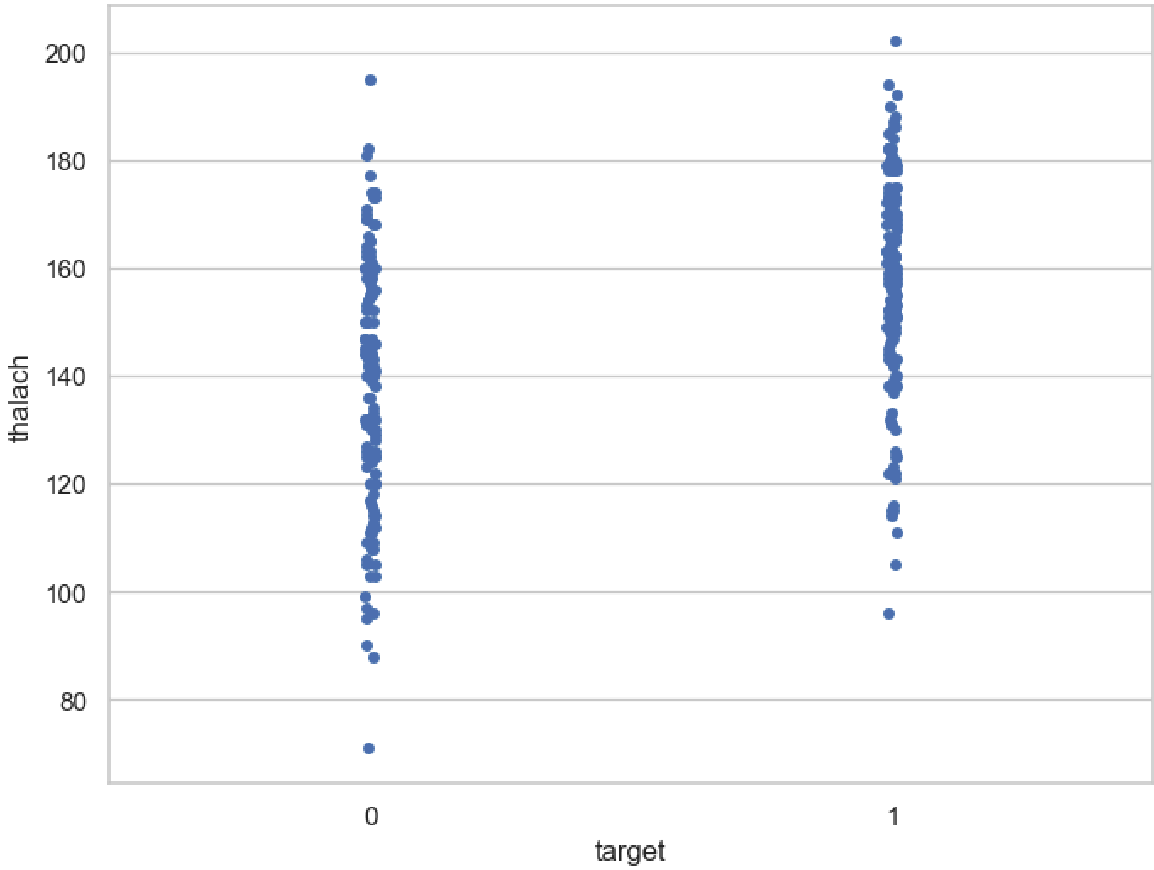


Interpretation

- We can see that those people suffering from heart disease (target = 1) have relatively higher heart rate (thalach) as compared to people who are not suffering from heart disease (target = 0).

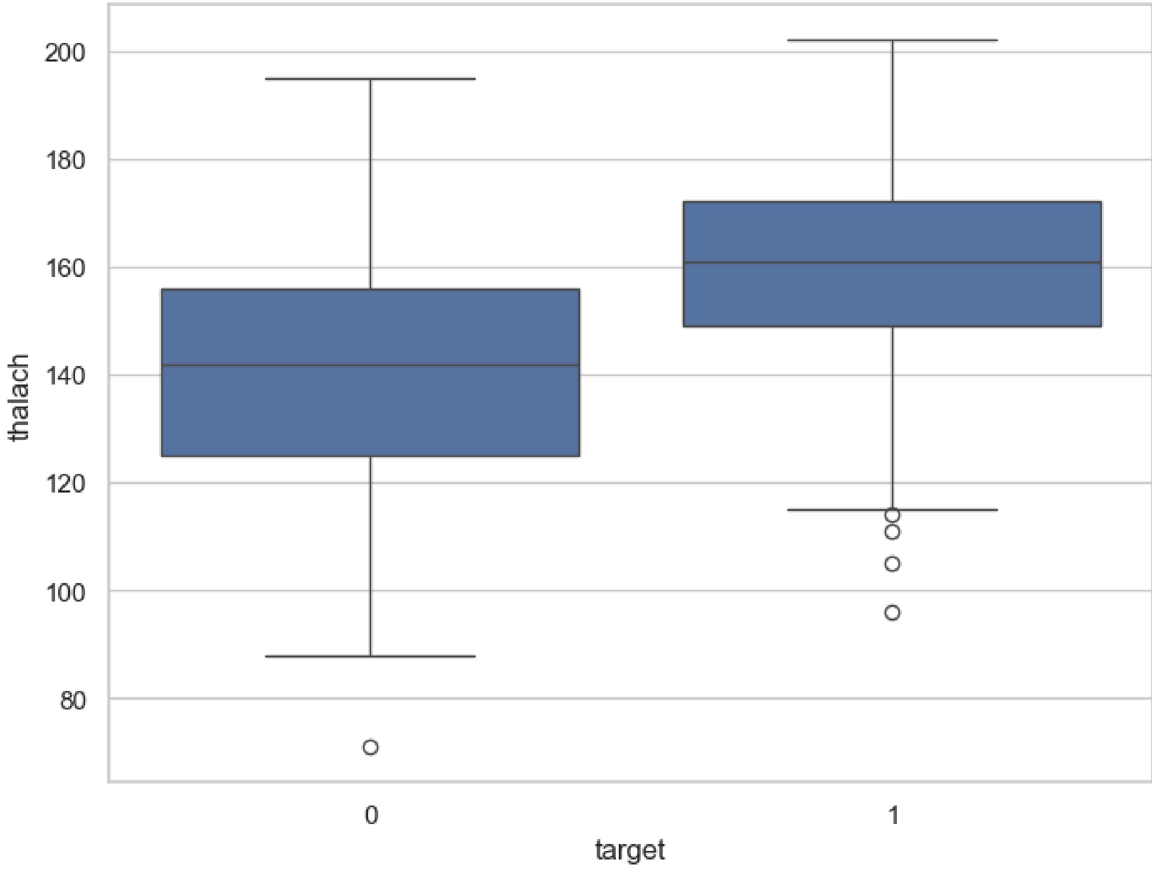
We can add jitter to bring out the distribution of values as follows :

In [55]:
```
f , ax = plt.subplots(figsize = (8,6))
sns.stripplot(x ='target', y = 'thalach', data = df, jitter = 0.01)
plt.show()
```



Visualize distribution of `thalach` variable wrt `target` with boxplot

In [56]:
```
f,ax = plt.subplots(figsize=(8,6))
sns.boxplot(x='target', y = 'thalach',data = df)
plt.show()
```



Interpretation

The above boxplot confirms our finding that people suffering from heart disease (target = 1) have relatively higher heart rate (thalach) as compared to people who are not suffering from heart disease (target = 0).

Findings of Bivariate Analysis

Findings of Bivariate Analysis are as follows –

- There is no variable which has strong positive correlation with `target` variable.
- There is no variable which has strong negative correlation with `target` variable.
- There is no correlation between `target` and `fbs` .
- The `cp` and `thalach` variables are mildly positively correlated with `target` variable.
- We can see that the `thalach` variable is slightly negatively skewed.
- The people suffering from heart disease (target = 1) have relatively higher heart rate (thalach) as compared to people who are not suffering from heart disease (target = 0).
- The people suffering from heart disease (target = 1) have relatively higher heart rate (thalach) as compared to people who are not suffering from heart disease (target =

0).

9. Multivariate analysis

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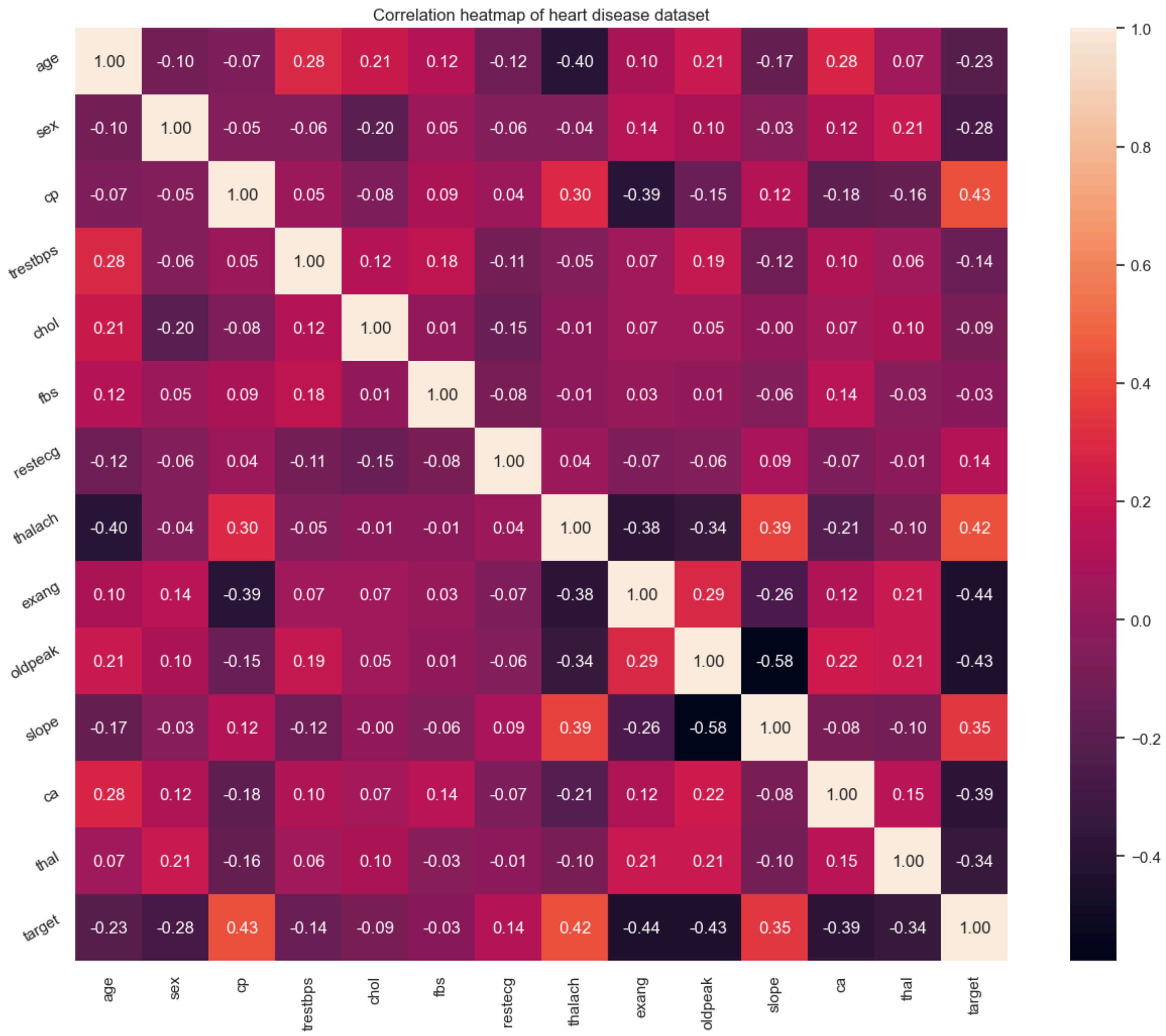
- The objective of the multivariate analysis is to discover patterns and relationships in the dataset.

Discover patterns and relationships

- An important step in EDA is to discover patterns and relationships between variables in the dataset.
- I will use `heat map` and `pair plot` to discover the patterns and relationships in the dataset.
- First of all, I will draw a `heat map`.

Heat Map

In [59]:
```
plt.figure(figsize=(16,12))
plt.title('Correlation heatmap of heart disease dataset')
a = sns.heatmap(correlation , square=True, annot=True , fmt='.2f', linecolor = '
a.set_xticklabels(a.get_xticklabels(), rotation=90)
a.set_yticklabels(a.get_yticklabels(), rotation=30)
plt.show()
```



Interpretation

From the above correlation heat map, we can conclude that :-

- `target` and `cp` variable are mildly positively correlated (correlation coefficient = 0.43).
- `target` and `thalach` variable are also mildly positively correlated (correlation coefficient = 0.42).
- `target` and `slope` variable are weakly positively correlated (correlation coefficient = 0.35).
- `target` and `exang` variable are mildly negatively correlated (correlation coefficient = -0.44).
- `target` and `oldpeak` variable are also mildly negatively correlated (correlation coefficient = -0.43).
- `target` and `ca` variable are weakly negatively correlated (correlation coefficient = -0.39).

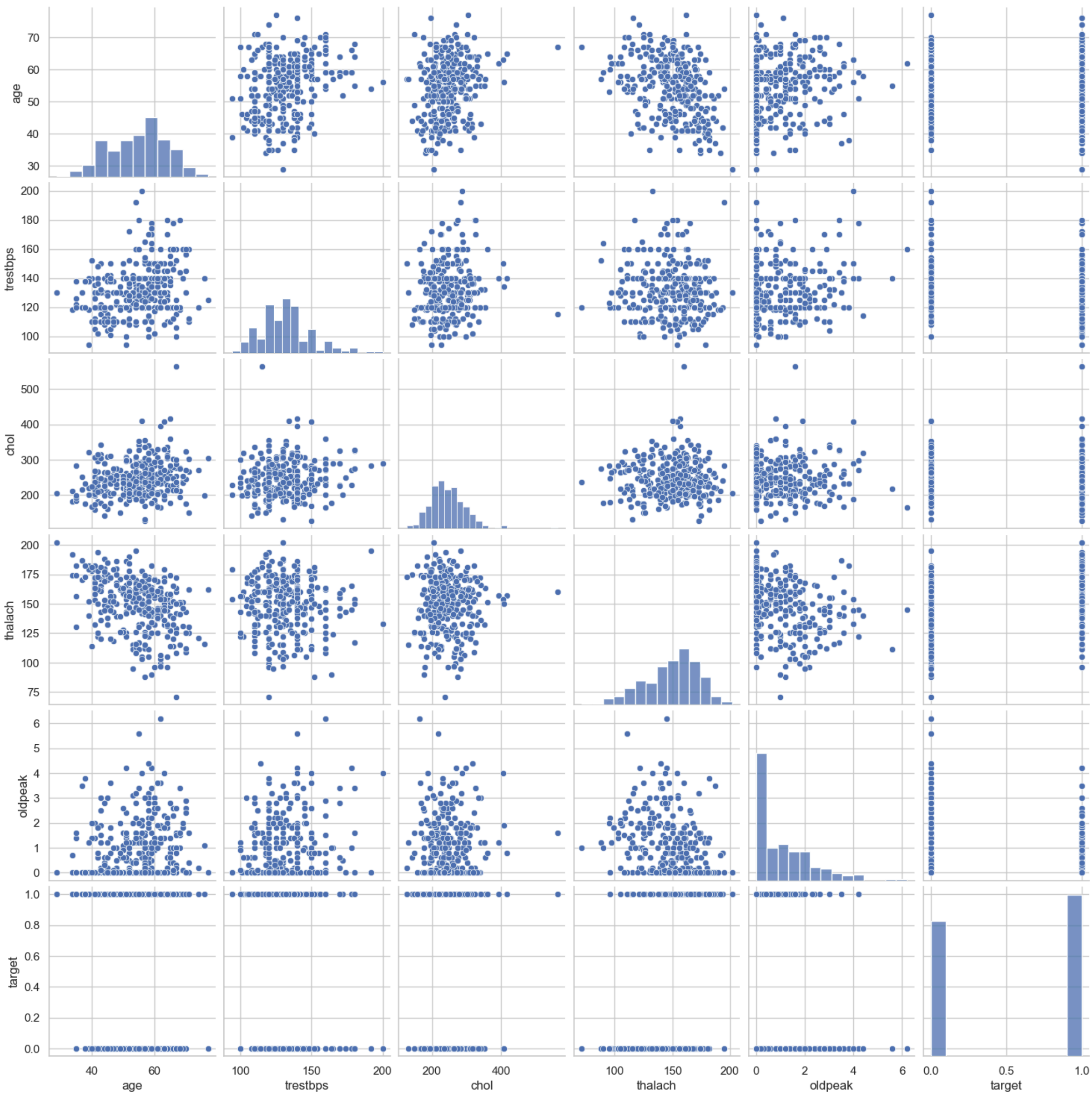
- `target` and `thal` variable are also waekly negatively correlated (correlation coefficient = -0.34).

Pair Plot

In [61]:
```
df.columns
```

Out[61]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

In [62]:
```
num_var = ['age','trestbps','chol','thalach','oldpeak','target']
sns.pairplot(df[num_var], kind='scatter',diag_kind='hist')
plt.show()
```



Comment

- I have defined a variable `num_var` . Here `age` , `trestbps` , `chol`, `thalach` and `oldpeak` are numerical variables and `target` is the categorical variable.

- So, I wll check relationships between these variables.

Analysis of `age` and other variables

Check the number of unique values in `age` variable

In [63]:
```
df['age'].nunique()
```

Out[63]:
```
41
```

View statistical summary of `age` variable

In [64]:
```
df['age'].describe()
```

Out[64]:
```
count    303.000000
mean      54.366337
std        9.082101
min       29.000000
25%       47.500000
50%       55.000000
75%       61.000000
max       77.000000
Name: age, dtype: float64
```

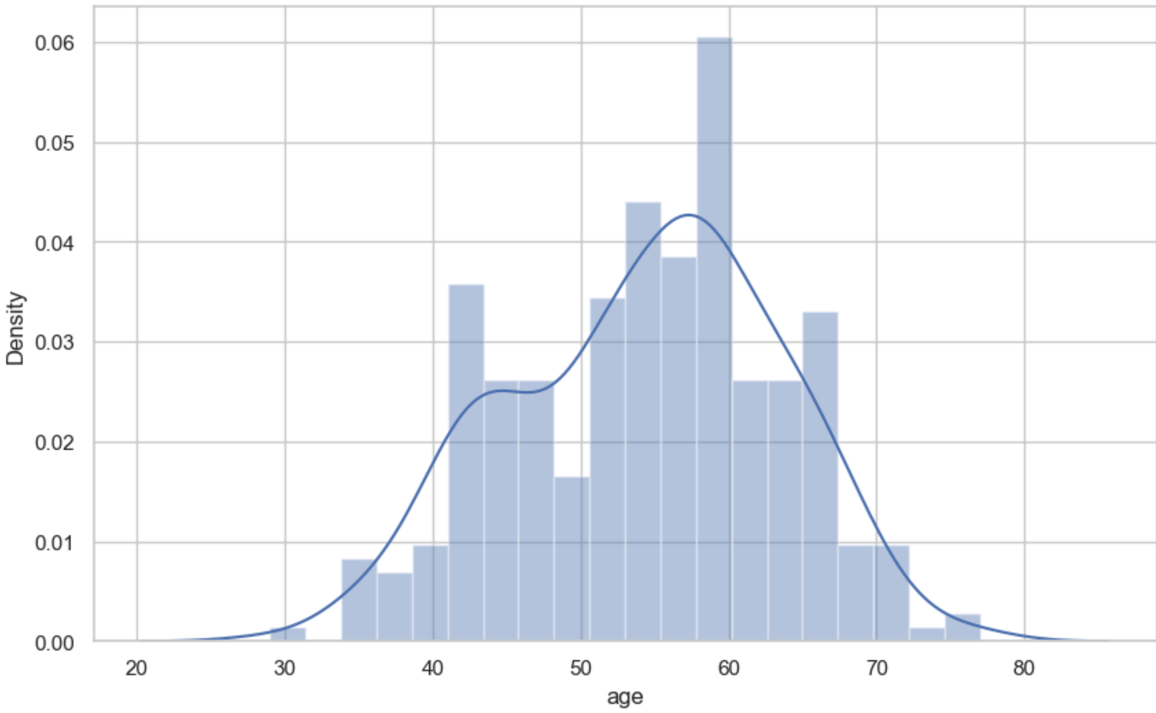
Interpretation

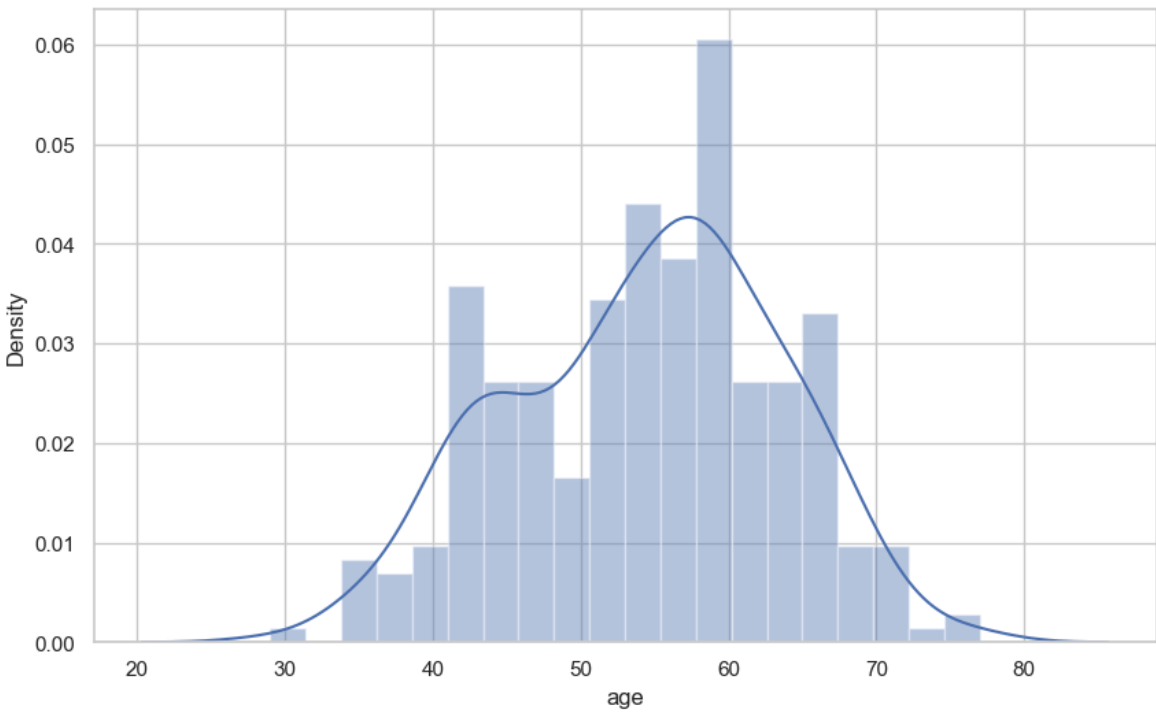
- The mean value of the `age` variable is 54.37 years.
- The minimum and maximum values of `age` are 29 and 77 years.

Plot the distribution of `age` variable

Now, I will plot the distribution of `age` variable to view the statistical properties.

In [66]:
```
x,ax = plt.subplots(figsize=(10,6))
x = df['age']
ax = sns.distplot(x, bins=20)
plt.show()
```





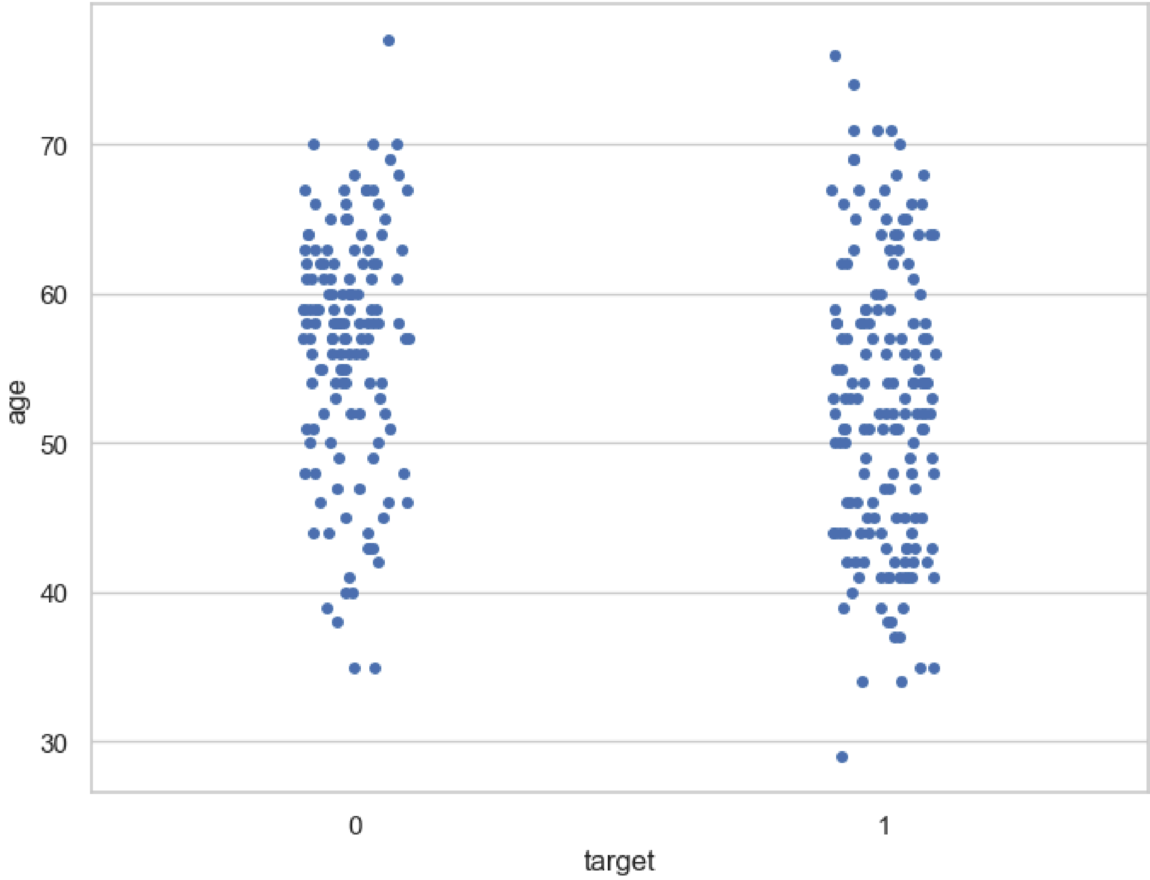
Interpretation

- The `age` variable distribution is approximately normal.

Analyze `age` and `target` variable

Visualize frequency distribution of `age` variable wrt `target`

In [67]:
```
f,ax = plt.subplots(figsize=(8,6))
sns.stripplot(x='target', y='age',data=df)
plt.show()
```

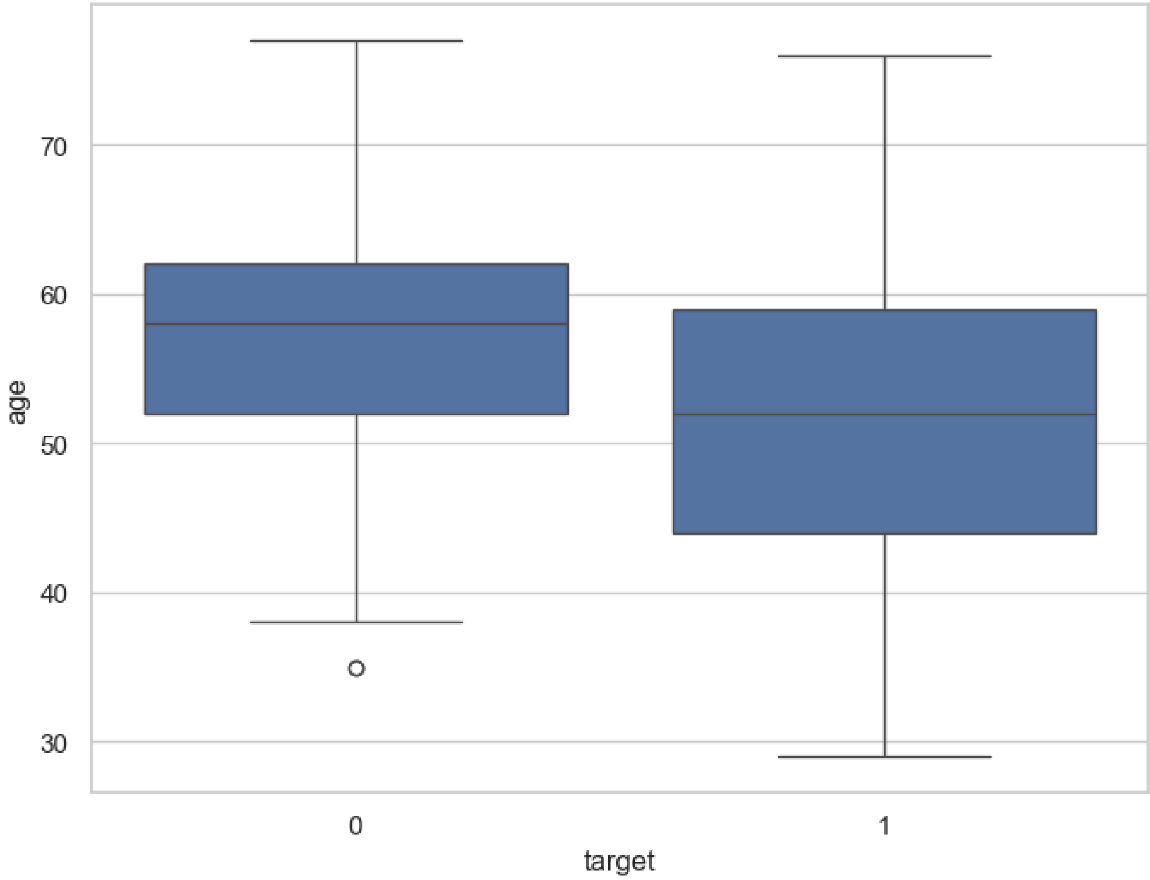


Interpretation

- We can see that the people suffering from heart disease (target = 1) and people who are not suffering from heart disease (target = 0) have comparable ages.

Visualize distribution of `age` variable wrt `target` with boxplot

In [68]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x="target", y="age", data=df)
plt.show()
```



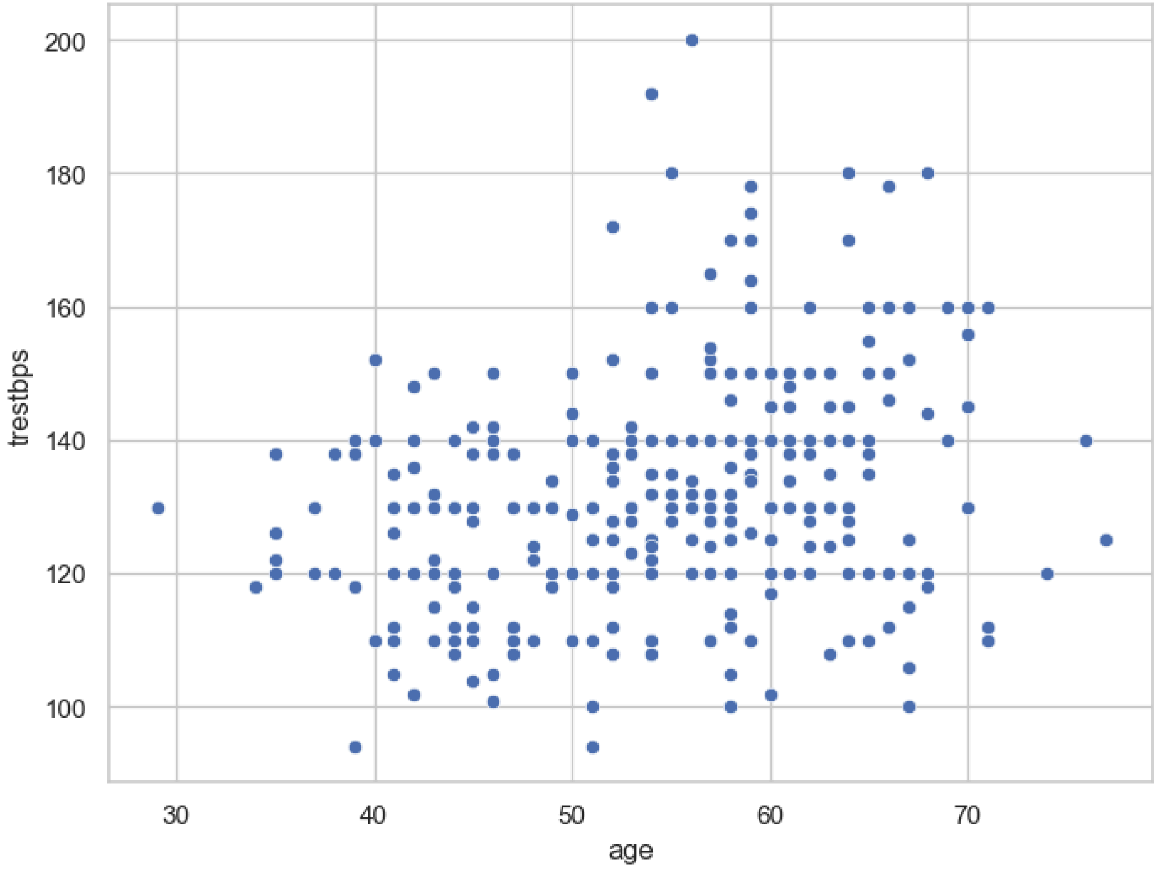
Interpretation

- The above boxplot tells two different things :
  - The mean age of the people who have heart disease is less than the mean age of the people who do not have heart disease.
  - The dispersion or spread of age of the people who have heart disease is greater than the dispersion or spread of age of the people who do not have heart disease.

Analyze `age` and `trestbps` variable

I will plot a scatterplot to visualize the relationship between `age` and `trestbps` variable.

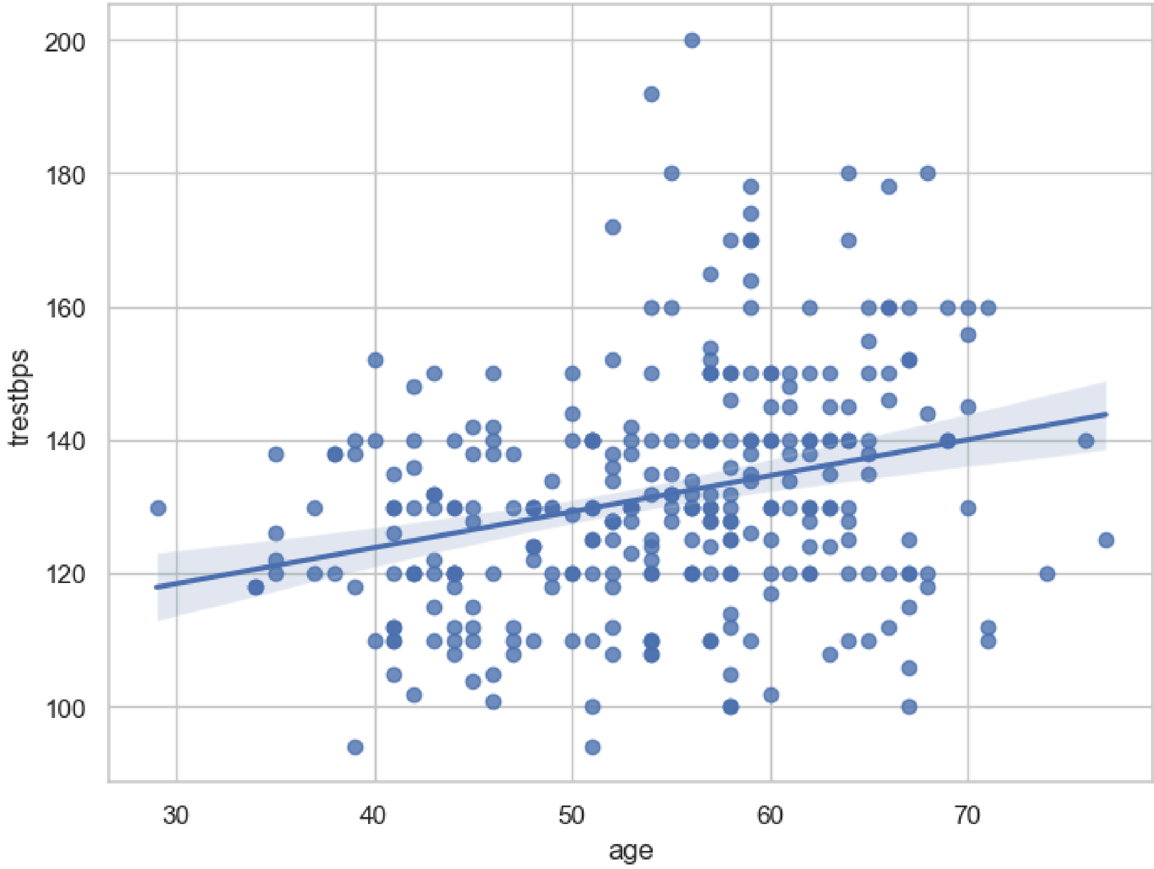
In [70]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.scatterplot(x="age", y="trestbps", data=df)
plt.show()
```



Interpretation

- The above scatter plot shows that there is no correlation between `age` and `trestbps` variable.

In [71]:
```
f,ax = plt.subplots(figsize=(8,6))
ax = sns.regplot(x='age', y='trestbps',data=df)
plt.show()
```

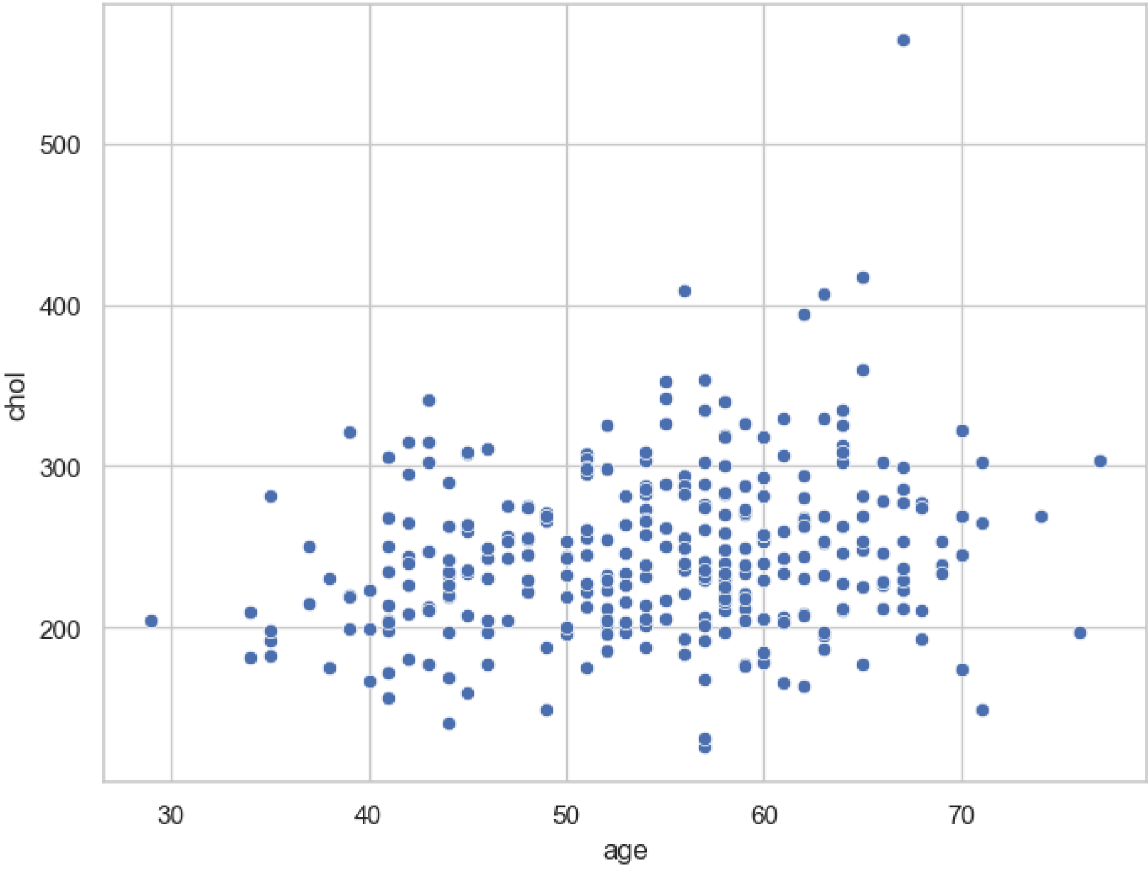


Interpretation

- The above line shows that linear regression model is not good fit to the data.

Analyze `age` and `chol` variable

In [72]:
```
f,ax= plt.subplots(figsize=(8,6))
ax=sns.scatterplot(x='age',y='chol',data=df)
plt.show()
```

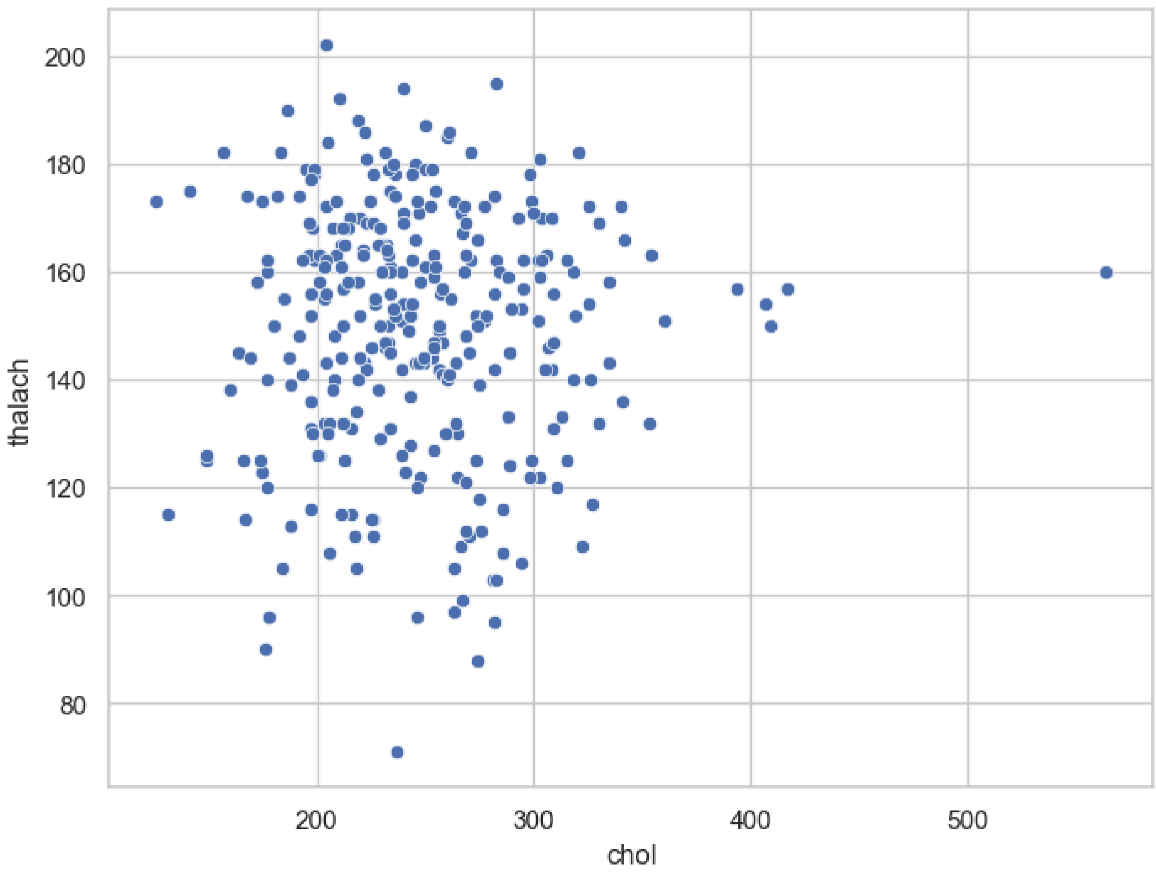


Interpretation

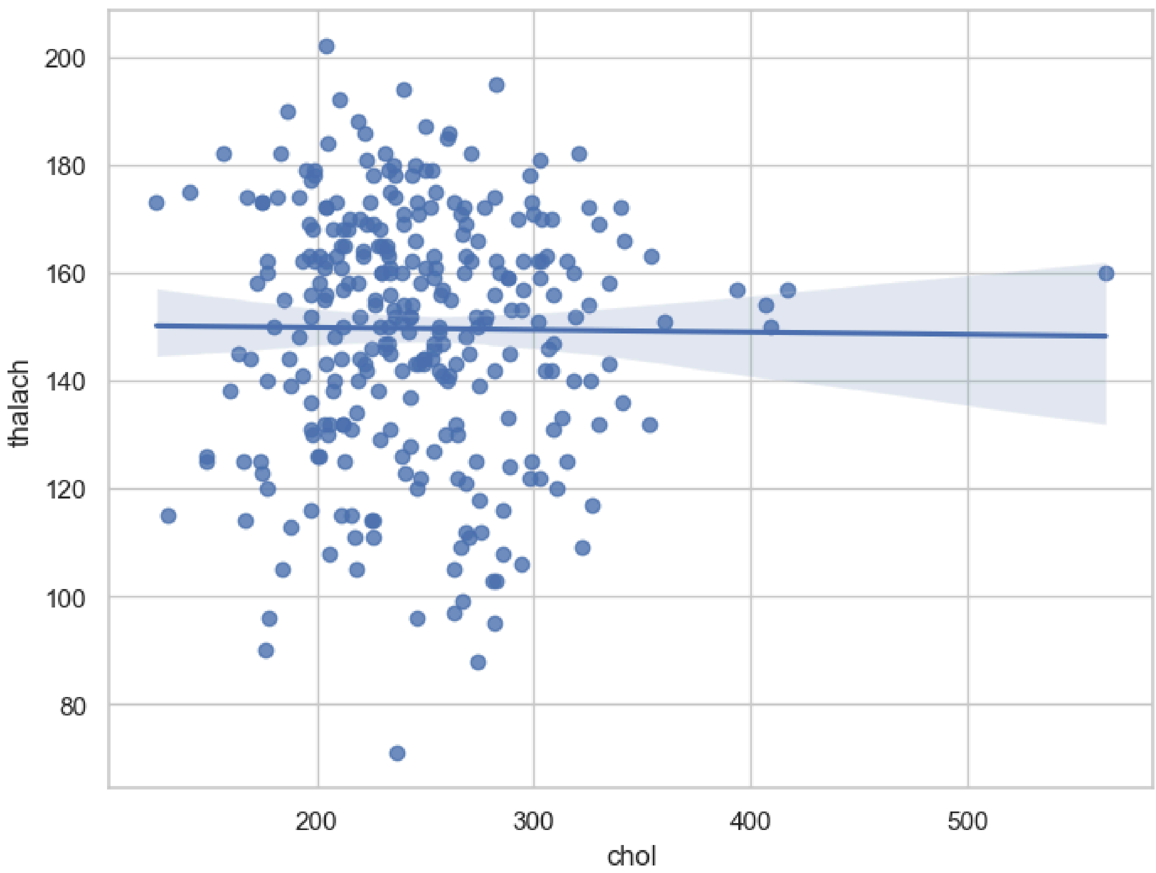
- The above plot confirms that there is a slighly positive correlation between `age` and `chol` variables.

Analyze `chol` and `thalach` variable

In [73]:
```
f,ax = plt.subplots(figsize=(8,6))
ax = sns.scatterplot(x='chol', y='thalach',data=df)
plt.show()
```



In [74]:
```
f, ax= plt.subplots(figsize=(8,6))
ax = sns.regplot(x='chol',y='thalach',data=df)
plt.show()
```



Interpretation

- The above plot shows that there is no correlation between `chol` and `thalach` variable.

10. Dealing with missing values

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- In Pandas missing data is represented by two values:
  - **None**: None is a Python singleton object that is often used for missing data in Python code.
  - **NaN** : NaN (an acronym for Not a Number), is a special floating-point value recognized by all systems that use the standard IEEE floating-point representation.
- There are different methods in place on how to detect missing values.

Pandas isnull() and notnull() functions

- Pandas offers two functions to test for missing data - `isnull()` and `notnull()`. These are simple functions that return a boolean value indicating whether the passed in argument value is in fact missing data.
- Below, I will list some useful commands to deal with missing values.

Useful commands to detect missing values

- **df.isnull()**

The above command checks whether each cell in a dataframe contains missing values or not. If the cell contains missing value, it returns True otherwise it returns False.

- **df.isnull().sum()**

The above command returns total number of missing values in each column in the dataframe.

- **df.isnull().sum().sum()**

It returns total number of missing values in the dataframe.

- **df.isnull().mean()**

It returns percentage of missing values in each column in the dataframe.

- **df.isnull().any()**

It checks which column has null values and which has not. The columns which has null values returns TRUE and FALSE otherwise.

- **df.isnull().any().any()**

It returns a boolean value indicating whether the dataframe has missing values or not. If dataframe contains missing values it returns TRUE and FALSE otherwise.

- **df.isnull().values.any()**

It checks whether a particular column has missing values or not. If the column contains missing values, then it returns TRUE otherwise FALSE.

- **df.isnull().values.sum()**

It returns the total number of missing values in the dataframe.

In [75]:
```
# check for missing values

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

Out[75]:
```
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
```

Interpretation

We can see that there are no missing values in the dataset.

11. Check with ASSERT statement

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- We must confirm that our dataset has no missing values.
- We can write an **assert statement** to verify this.
- We can use an assert statement to programmatically check that no missing, unexpected 0 or negative values are present.
- This gives us confidence that our code is running properly.
- **Assert statement** will return nothing if the value being tested is true and will throw an AssertionError if the value is false.

- **Asserts**

    - assert 1 == 1 (return Nothing if the value is True)

    - assert 1 == 2 (return AssertionError if the value is False)

In [76]:
```
# assert that there are no missing values in the dataframe

assert pd.notnull(df).all().all()
```

In [77]:
```
# assert all values are greater than or equal to 0

assert (df >= 0).all().all()
```

Interpretation

- The above two commands do not throw any error. Hence, it is confirmed that there are no missing or negative values in the dataset.

- All the values are greater than or equal to zero.

12. Outlier detection

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I will make boxplots to visualise outliers in the continuous numerical variables : -

`age`, `trestbps`, `chol`, `thalach` and `oldpeak` variables.

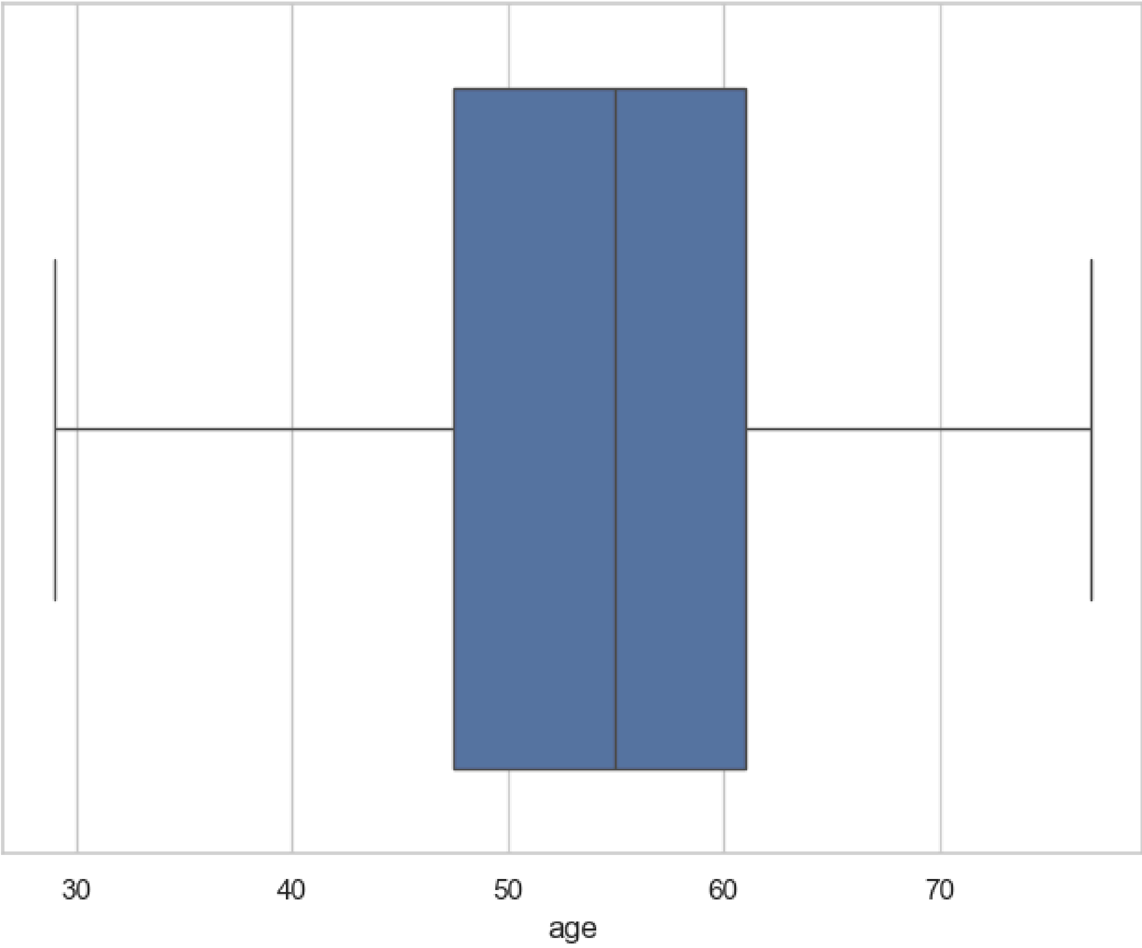
`age` variable

In [78]:
```
df['age'].describe()
```

Out[78]:
```
count    303.000000
mean      54.366337
std        9.082101
min       29.000000
25%       47.500000
50%       55.000000
75%       61.000000
max       77.000000
Name: age, dtype: float64
```

Box-plot of `age` variable

In [79]:
```
f,ax = plt.subplots(figsize = (8,6))
sns.boxplot(x=df['age'])
plt.show()
```



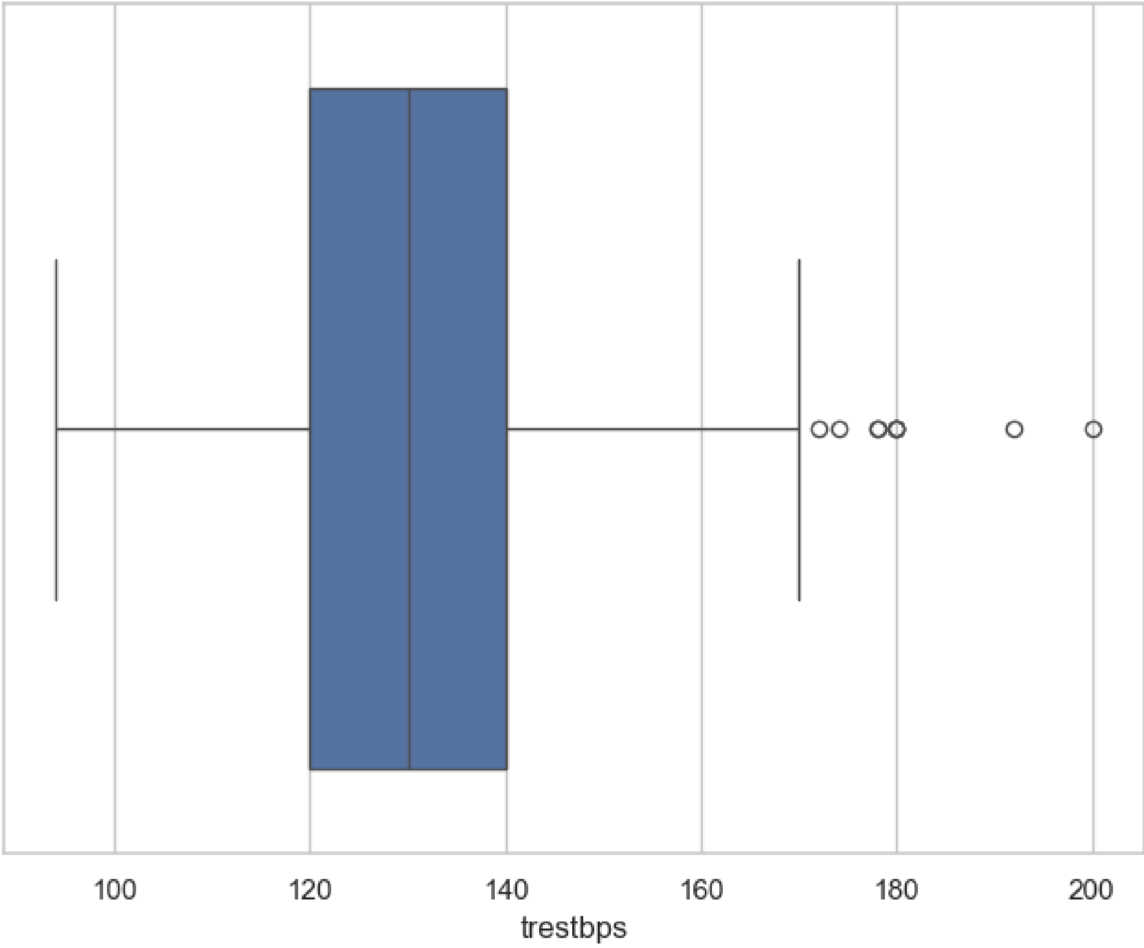
`trestbps` variable

In [80]:
```
df['trestbps'].describe()
```

Out[80]:
```
count    303.000000
mean     131.623762
std       17.538143
min       94.000000
25%      120.000000
50%      130.000000
75%      140.000000
max      200.000000
Name: trestbps, dtype: float64
```

Box-plot of `trestbps` variable

In [81]:
```
f,ax = plt.subplots(figsize = (8,6))
sns.boxplot(x=df['trestbps'])
plt.show()
```



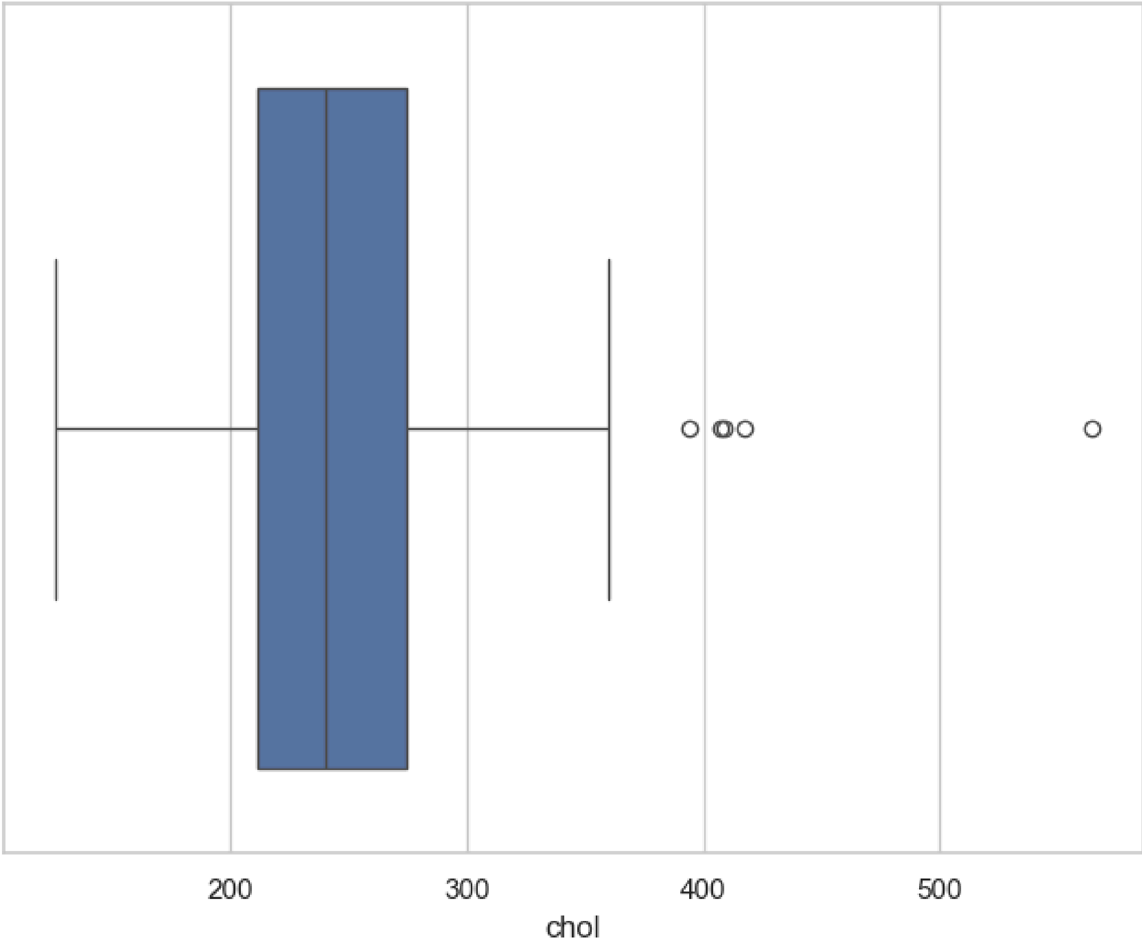
`chol` variable

In [82]:
```
df['chol'].describe()
```

Out[82]:
```
count    303.000000
mean     246.264026
std       51.830751
min      126.000000
25%      211.000000
50%      240.000000
75%      274.500000
max      564.000000
Name: chol, dtype: float64
```

Box-plot of `chol` variable

In [83]:
```
f,ax= plt.subplots(figsize =(8,6))
sns.boxplot(x = df['chol'])
plt.show()
```



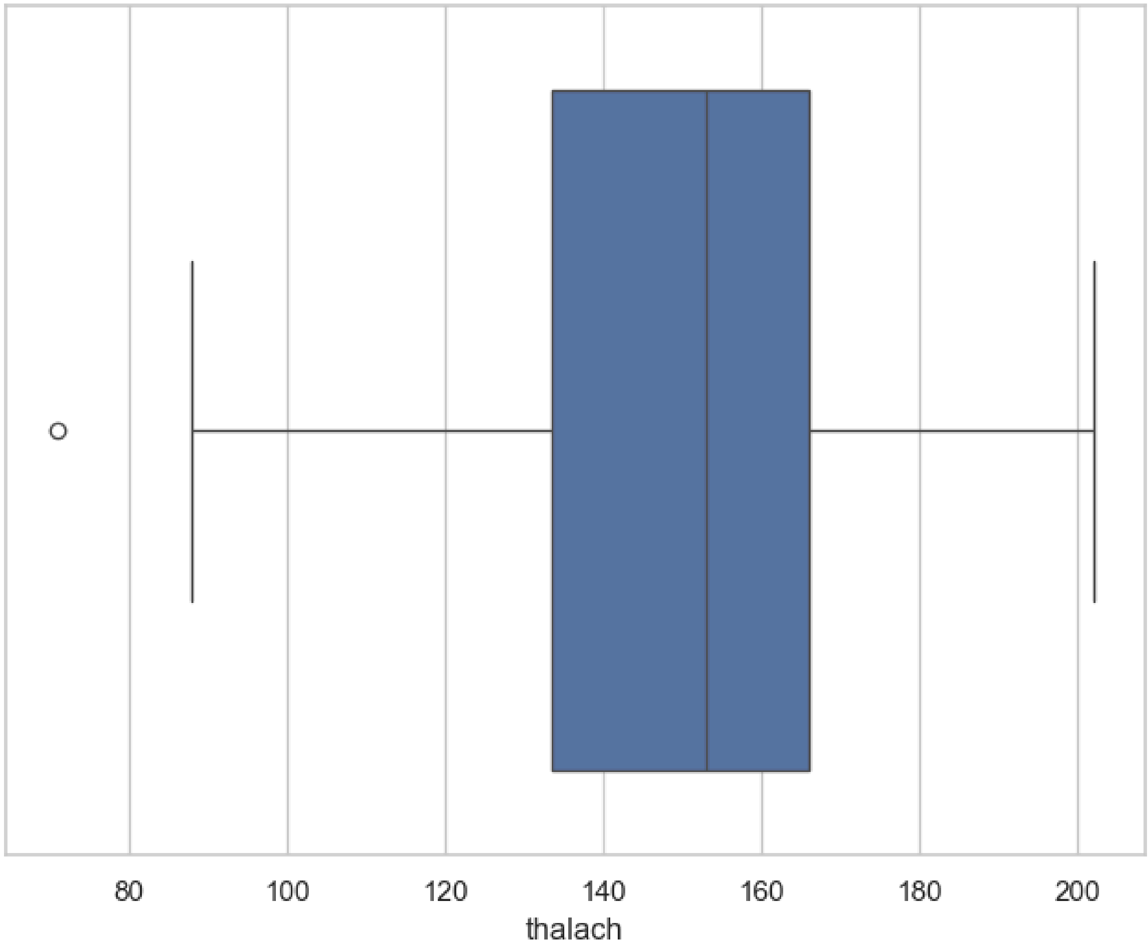
`thalach` variable

In [84]:
```
df['thalach'].describe()
```

Out[84]:
```
count    303.000000
mean     149.646865
std       22.905161
min       71.000000
25%      133.500000
50%      153.000000
75%      166.000000
max      202.000000
Name: thalach, dtype: float64
```

Box-plot of `thalach` variable

In [85]:
```
f,ax = plt.subplots(figsize=(8,6))
sns.boxplot(x=df['thalach'])
plt.show()
```



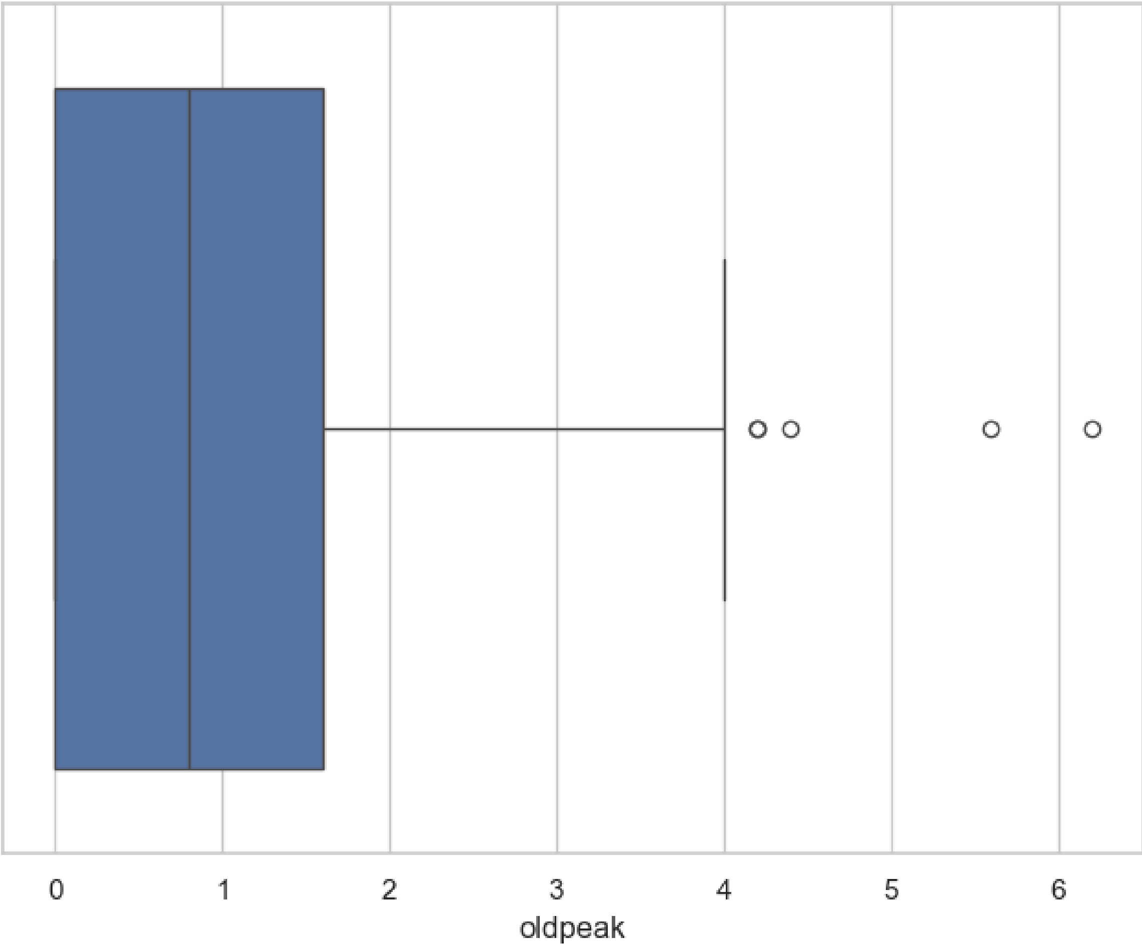
oldpeak variable

In [86]:
```
df['oldpeak'].describe()
```

Out[86]:
```
count    303.000000
mean       1.039604
std        1.161075
min        0.000000
25%        0.000000
50%        0.800000
75%        1.600000
max        6.200000
Name: oldpeak, dtype: float64
```

Box-plot of `oldpeak` variable

In [87]:
```
f,ax = plt.subplots(figsize=(8,6))
sns.boxplot(x=df['oldpeak'])
plt.show()
```



Findings

- The `age` variable does not contain any outlier.
- `trestbps` variable contains outliers to the right side.
- `chol` variable also contains outliers to the right side.
- `thalach` variable contains a single outlier to the left side.
- `oldpeak` variable contains outliers to the right side.
- Those variables containing outliers needs further investigation.

13. Conclusion

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so, our EDA journey has come to an end.

In this kernel, we have explored the heart disease dataset. In this kernel, we have implemented many of the strategies presented in the book **Think Stats - Exploratory Data Analysis in Python by Allen B Downey** . The feature variable of interest is `target` variable. We have analyzed it alone and check its interaction with other variables. We have also discussed how to detect missing data and outliers.