```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

pd.set_option('display.max_rows', 20)
pd.set_option('display.max_columns', None)

import warnings
warnings.filterwarnings('ignore')

# data dictionary
df_dict = pd.read_excel('variable description.xlsx')
df_dict
```

```
     variable                                        description
0         age                                       age in years
1         sex                              (1 = male; 0 = female)
2          cp                                    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
```

```python
# import the data
df = pd.read_excel('data.xlsx')

df.head()
```

```
   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
```

```python
df.tail()
```

```
     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
```

```
# finding the structure of the data
df.shape
```

```
(303, 14)
```

```
# the findings on the missing values
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
```

```
# cheking the null values
df.isna().sum()

# Observation: From the result below, we can conclude that there are no null values in the dataset.
```

```
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
```

```
# we can assume a column to be categorical if number of unique value is below 10.
df.nunique()
```

```
age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
dtype: int64
```

```python
# findings the duplicate value in the data
df.duplicated().sum()

# There is 1 duplicated value in the data.
```

```
1
```

```python
# removing the duplicate value
df.drop_duplicates(inplace=True)
```

```python
df.duplicated().sum()
```

```
0
```

```python
df.describe()
```

```
             age         sex          cp    trestbps        chol         fbs  \
count  302.00000  302.000000  302.000000  302.000000  302.000000  302.000000
mean    54.42053    0.682119    0.963576  131.602649  246.500000    0.149007
std      9.04797    0.466426    1.032044   17.563394   51.753489    0.356686
min     29.00000    0.000000    0.000000   94.000000  126.000000    0.000000
25%     48.00000    0.000000    0.000000  120.000000  211.000000    0.000000
50%     55.50000    1.000000    1.000000  130.000000  240.500000    0.000000
75%     61.00000    1.000000    2.000000  140.000000  274.750000    0.000000
max     77.00000    1.000000    3.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  302.000000  302.000000  302.000000  302.000000  302.000000  302.000000
mean     0.526490  149.569536    0.327815    1.043046    1.397351    0.718543
std      0.526027   22.903527    0.470196    1.161452    0.616274    1.006748
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.250000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  152.500000    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  302.000000  302.000000
mean     2.314570    0.543046
std      0.613026    0.498970
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
```

```python
# we can assume a column to be categorical if number of unique value is 5 or less.
df.nunique().sort_values()
```

```
sex           2
fbs           2
exang         2
target        2
restecg       3
slope         3
cp            4
thal          4
ca            5
oldpeak      40
age          41
trestbps     49
thalach      91
chol        152
dtype: int64
```

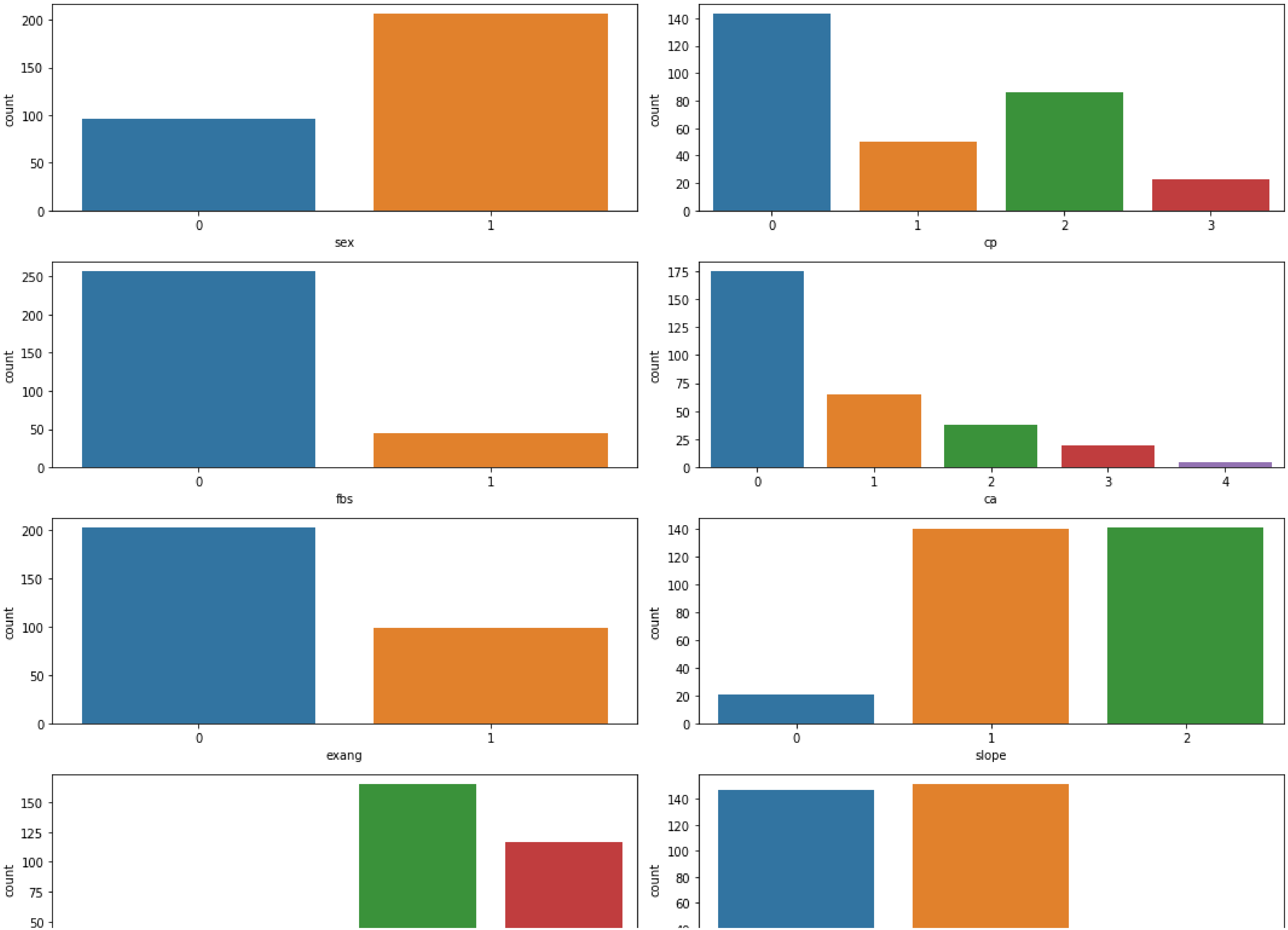
```python
print(df.sex.value_counts()),
print(df.sex.value_counts(normalize=True)*100)
```

```
1    206
0     96
Name: sex, dtype: int64
1    68.211921
0    31.788079
Name: sex, dtype: float64
```

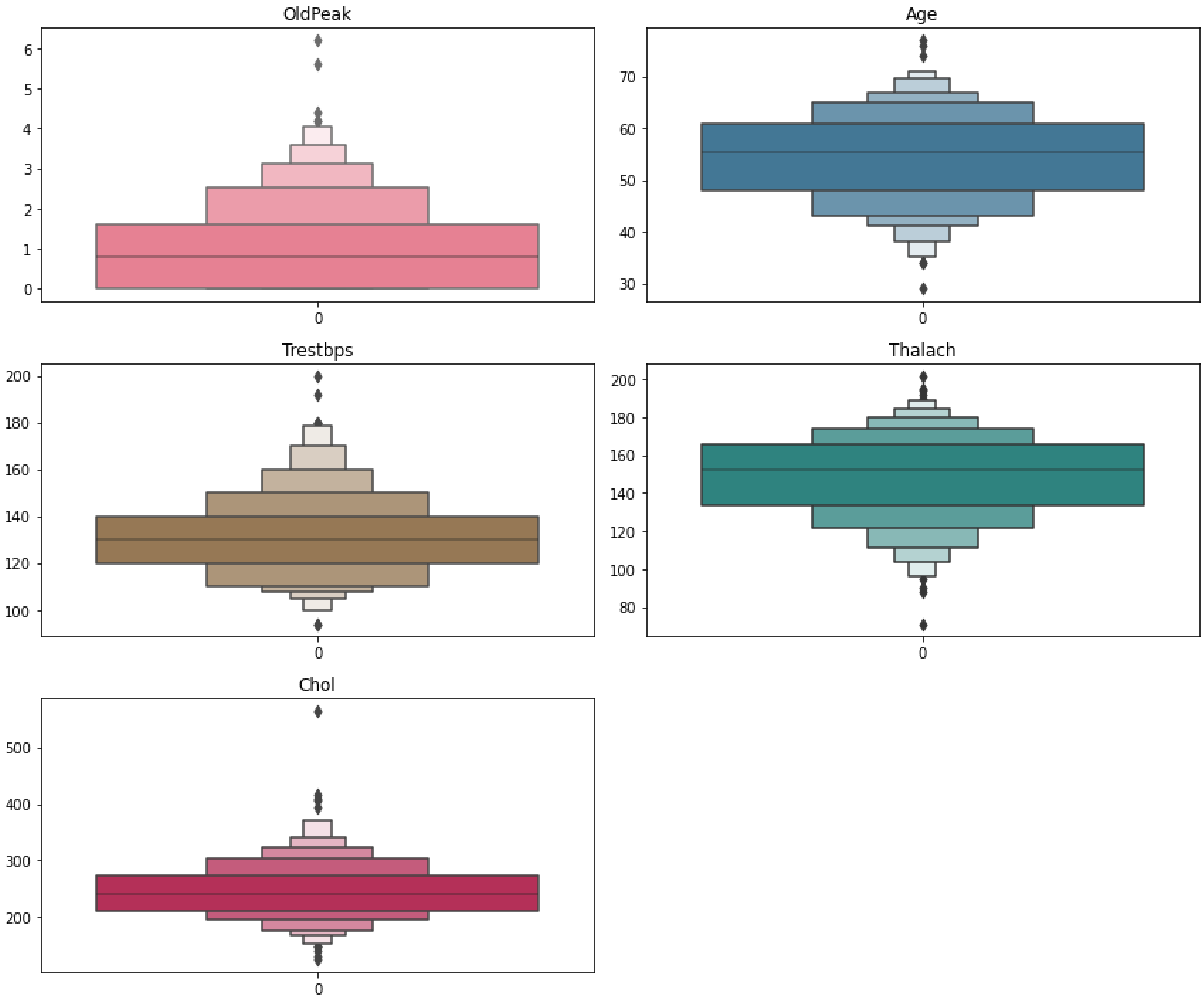
```python
for i in ['sex', 'cp', 'fbs', 'ca', 'restecg', 'exang', 'slope', 'thal']:

    print(i,"\n",df[i].value_counts(normalize=True)*100, "\n")
```

```
sex
 1    68.211921
0    31.788079
Name: sex, dtype: float64

cp
 0    47.350993
2    28.476821
1    16.556291
3     7.615894
Name: cp, dtype: float64

fbs
 0    85.099338
1    14.900662
Name: fbs, dtype: float64

ca
 0    57.947020
1    21.523179
2    12.582781
3     6.622517
4     1.324503
Name: ca, dtype: float64

restecg
 1    50.000000
```

```
0    48.675497
2     1.324503
Name: restecg, dtype: float64

exang
 0    67.218543
1    32.781457
Name: exang, dtype: float64

slope
 2    46.688742
1    46.357616
0     6.953642
Name: slope, dtype: float64

thal
 2    54.635762
3    38.741722
1     5.960265
0     0.662252
Name: thal, dtype: float64


# Plotting the categorical variable
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(15,12))
sns.countplot(x='sex', data=df, ax=axes[0][0])
sns.countplot(x='cp', data=df, ax=axes[0][1])
sns.countplot(x='fbs', data=df, ax=axes[1][0])
sns.countplot(x='ca', data=df, ax=axes[1][1])
sns.countplot(x='exang', data=df, ax=axes[2][0])
sns.countplot(x='slope', data=df, ax=axes[2][1])
sns.countplot(x='thal', data=df, ax=axes[3][0])
sns.countplot(x='restecg', data=df, ax=axes[3][1])

plt.tight_layout()
plt.show()
```


count
sex
0
1
count
cp
0
1
2
3
count
fbs
0
1
count
ca
0
1
2
3
4
count
exang
0
1
count
slope
0
1
2
count
count

```python
## Plotting box plot of continuous features

fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(12,10))
sns.boxenplot(df['oldpeak'], palette='husl', ax=axes[0][0]).set_title('OldPeak', fontsize=12)
sns.boxenplot(df['age'], palette='mako', ax=axes[0][1]).set_title('Age', fontsize=12)
sns.boxenplot(df['trestbps'], palette='cubehelix', ax=axes[1][0]).set_title('Trestbps', fontsize=12)
sns.boxenplot(df['thalach'], palette='viridis', ax=axes[1][1]).set_title('Thalach', fontsize=12)
sns.boxenplot(df['chol'], palette='rocket_r', ax=axes[2][0]).set_title('Chol', fontsize=12)

fig.delaxes(axes[2][1])
plt.tight_layout()
plt.show()
```



Observations:

- There are certain outliers in all the continuous features.

```
# Study the occurence of CVD across the Age category

# pd.cut --> creates bucket of the values of that columns, analyzing the CVD columns using age

df.groupby([pd.cut(df['age'], 5)])['target'].mean()
```

```
age
(28.952, 38.6]    0.727273
(38.6, 48.2]      0.704225
(48.2, 57.8]      0.577320
(57.8, 67.4]      0.377358
(67.4, 77.0]      0.588235
Name: target, dtype: float64
```

```
df.groupby([pd.cut(df['age'], 5)])['target'].describe()
```

age	count	mean	std	min	25%	50%	75%	max
(28.952, 38.6]	11.0	0.727273	0.467099	0.0	0.5	1.0	1.0	1.0
(38.6, 48.2]	71.0	0.704225	0.459639	0.0	0.0	1.0	1.0	1.0
(48.2, 57.8]	97.0	0.577320	0.496552	0.0	0.0	1.0	1.0	1.0
(57.8, 67.4]	106.0	0.377358	0.487029	0.0	0.0	0.0	1.0	1.0
(67.4, 77.0]	17.0	0.588235	0.507300	0.0	0.0	1.0	1.0	1.0

Observations:

- The above output provides insights into how CVD is distributed across different age groups.
- The age group (28.952, 38.6] has a mean of 0.75, indicating that 75% of individuals in this age group have CVD. This group has the highest mean CVD probability among the age groups.
- The age group (38.6, 48.2] also has a relatively high mean CVD probability of 0.704, with a similar pattern of 75% of individuals having CVD.
- As age increases, the mean CVD probability decreases:
  - The age group (48.2, 57.8] has a mean of 0.577.
  - The age group (57.8, 67.4] has a lower mean of 0.377.
  - The age group (67.4, 77.0] sees a slight increase in the mean to 0.588.

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

df.sex.value_counts(normalize=True)*100

# Observations: from the below result we see 68.21% are male and 31.79% are female.
```

```
1    68.211921
0    31.788079
Name: sex, dtype: float64
```

```
print(df.groupby(['sex'])['target'].mean(),'\n')

# more detailed
print(df.groupby(['sex'])['target'].describe())

# Observations:
# 1. From the below result, we see that out of 96 female, 75% have Heart diseases.
# 2. And Out of 206 male, 44.66% have heart diseases.
```

```
sex
0    0.750000
1    0.446602
Name: target, dtype: float64
```

```
     count      mean       std  min   25%  50%  75%  max
sex
0     96.0  0.750000  0.435286  0.0  0.75  1.0  1.0  1.0
1    206.0  0.446602  0.498352  0.0  0.00  0.0  1.0  1.0
```

```
## Heart attack based on anomalies in the resting blood pressure of the patient.

df.groupby([pd.cut(df['trestbps'], 5)])['target'].mean()
```

```
trestbps
(93.894, 115.2]    0.615385
(115.2, 136.4]     0.560284
(136.4, 157.6]     0.530120
(157.6, 178.8]     0.380952
(178.8, 200.0]     0.200000
Name: target, dtype: float64
```

```
## more detailed view of the above

df.groupby([pd.cut(df['trestbps'], 5)])['target'].describe()
```

```
                 count      mean       std  min  25%  50%  75%  max
trestbps
(93.894, 115.2]   52.0  0.615385  0.491251  0.0  0.0  1.0  1.0  1.0
(115.2, 136.4]   141.0  0.560284  0.498122  0.0  0.0  1.0  1.0  1.0
(136.4, 157.6]    83.0  0.530120  0.502126  0.0  0.0  1.0  1.0  1.0
(157.6, 178.8]    21.0  0.380952  0.497613  0.0  0.0  0.0  1.0  1.0
(178.8, 200.0]     5.0  0.200000  0.447214  0.0  0.0  0.0  0.0  1.0
```

Observations:

- On the basis of above result, it appears that as blood pressure ('trestbps') increases, the mean of the 'target' variable decreases. This suggests that there may be a trend where lower blood pressure values are associated with a higher probability of the target event (higher likelihood of a heart disease diagnosis) or vice-versa.

However, it's important to note that these findings are based on the data provided and may not necessarily imply causation. Further analysis and domain knowledge may be needed to draw meaningful conclusions.

```
## describing the relationship between Cholesterol levels and our target variable.

df.groupby([pd.cut(df['chol'], 5)])['target'].describe()
```

```
                  count      mean       std  min  25%  50%  75%  max
chol
(125.562, 213.6]   84.0  0.607143  0.491319  0.0  0.0  1.0  1.0  1.0
(213.6, 301.2]    175.0  0.514286  0.501230  0.0  0.0  1.0  1.0  1.0
(301.2, 388.8]     38.0  0.526316  0.506009  0.0  0.0  1.0  1.0  1.0
(388.8, 476.4]      4.0  0.500000  0.577350  0.0  0.0  0.5  1.0  1.0
(476.4, 564.0]      1.0  1.000000       NaN  1.0  1.0  1.0  1.0  1.0
```

Observations:

On the basis of above result,

- The mean value of the 'target' variable tends to decrease as cholesterol levels ('chol') increase. This suggests that lower cholesterol levels are associated with a higher probability of the target event (higher likelihood of a heart disease diagnosis).
- There is variability in the 'target' values within each cholesterol range, as indicated by the standard deviation ('std').
- It's interesting to note that the highest mean value (1.0) is in the (476.4, 564.0] cholesterol range, but this range has only one data point, which means it may not be representative and should be interpreted with caution. The high mean could be due to the presence of a single individual with a heart disease diagnosis in this range.

However, it's important to note that these findings are based on the data provided and may not necessarily imply causation. Further analysis and domain knowledge may be needed to draw meaningful conclusions.

```
df.corr()
```

```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.094962 -0.063107  0.283121  0.207216  0.119492
sex      -0.094962  1.000000 -0.051740 -0.057647 -0.195571  0.046022
cp       -0.063107 -0.051740  1.000000  0.046486 -0.072682  0.096018
trestbps  0.283121 -0.057647  0.046486  1.000000  0.125256  0.178125
chol      0.207216 -0.195571 -0.072682  0.125256  1.000000  0.011428
fbs       0.119492  0.046022  0.096018  0.178125  0.011428  1.000000
restecg  -0.111590 -0.060351  0.041561 -0.115367 -0.147602 -0.083081
thalach  -0.395235 -0.046439  0.293367 -0.048023 -0.005308 -0.007169
exang     0.093216  0.143460 -0.392937  0.068526  0.064099  0.024729
oldpeak   0.206040  0.098322 -0.146692  0.194600  0.050086  0.004514
slope    -0.164124 -0.032990  0.116854 -0.122873  0.000417 -0.058654
ca        0.302261  0.113060 -0.195356  0.099248  0.086878  0.144935
thal      0.065317  0.211452 -0.160370  0.062870  0.096810 -0.032752
target   -0.221476 -0.283609  0.432080 -0.146269 -0.081437 -0.026826

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.111590 -0.395235  0.093216  0.206040 -0.164124  0.302261
sex      -0.060351 -0.046439  0.143460  0.098322 -0.032990  0.113060
cp        0.041561  0.293367 -0.392937 -0.146692  0.116854 -0.195356
trestbps -0.115367 -0.048023  0.068526  0.194600 -0.122873  0.099248
chol     -0.147602 -0.005308  0.064099  0.050086  0.000417  0.086878
fbs      -0.083081 -0.007169  0.024729  0.004514 -0.058654  0.144935
restecg   1.000000  0.041210 -0.068807 -0.056251  0.090402 -0.083112
thalach   0.041210  1.000000 -0.377411 -0.342201  0.384754 -0.228311
exang    -0.068807 -0.377411  1.000000  0.286766 -0.256106  0.125377
oldpeak  -0.056251 -0.342201  0.286766  1.000000 -0.576314  0.236560
slope     0.090402  0.384754 -0.256106 -0.576314  1.000000 -0.092236
ca       -0.083112 -0.228311  0.125377  0.236560 -0.092236  1.000000
thal     -0.010473 -0.094910  0.205826  0.209090 -0.103314  0.160085
target    0.134874  0.419955 -0.435601 -0.429146  0.343940 -0.408992

              thal    target
age       0.065317 -0.221476
sex       0.211452 -0.283609
cp       -0.160370  0.432080
trestbps  0.062870 -0.146269
chol      0.096810 -0.081437
fbs      -0.032752 -0.026826
restecg  -0.010473  0.134874
thalach  -0.094910  0.419955
exang     0.205826 -0.435601
oldpeak   0.209090 -0.429146
slope    -0.103314  0.343940
ca        0.160085 -0.408992
thal      1.000000 -0.343101
target   -0.343101  1.000000
```

Observations:

Correlation with the 'target' feature:

- The most relevant feature to predict the 'target' (heart disease) is 'cp' (chest pain type) with a positive correlation of 0.432080. This suggests that as the value of 'cp' increases, the likelihood of having heart disease (positive 'target') also increases. Chest pain type may be a strong indicator of heart disease.

- 'thalach' (maximum heart rate achieved) is positively correlated with 'target' at 0.419955. This indicates that as 'thalach' increases, the likelihood of having heart disease increases. A higher maximum heart rate achieved may be associated with a higher risk of heart disease.

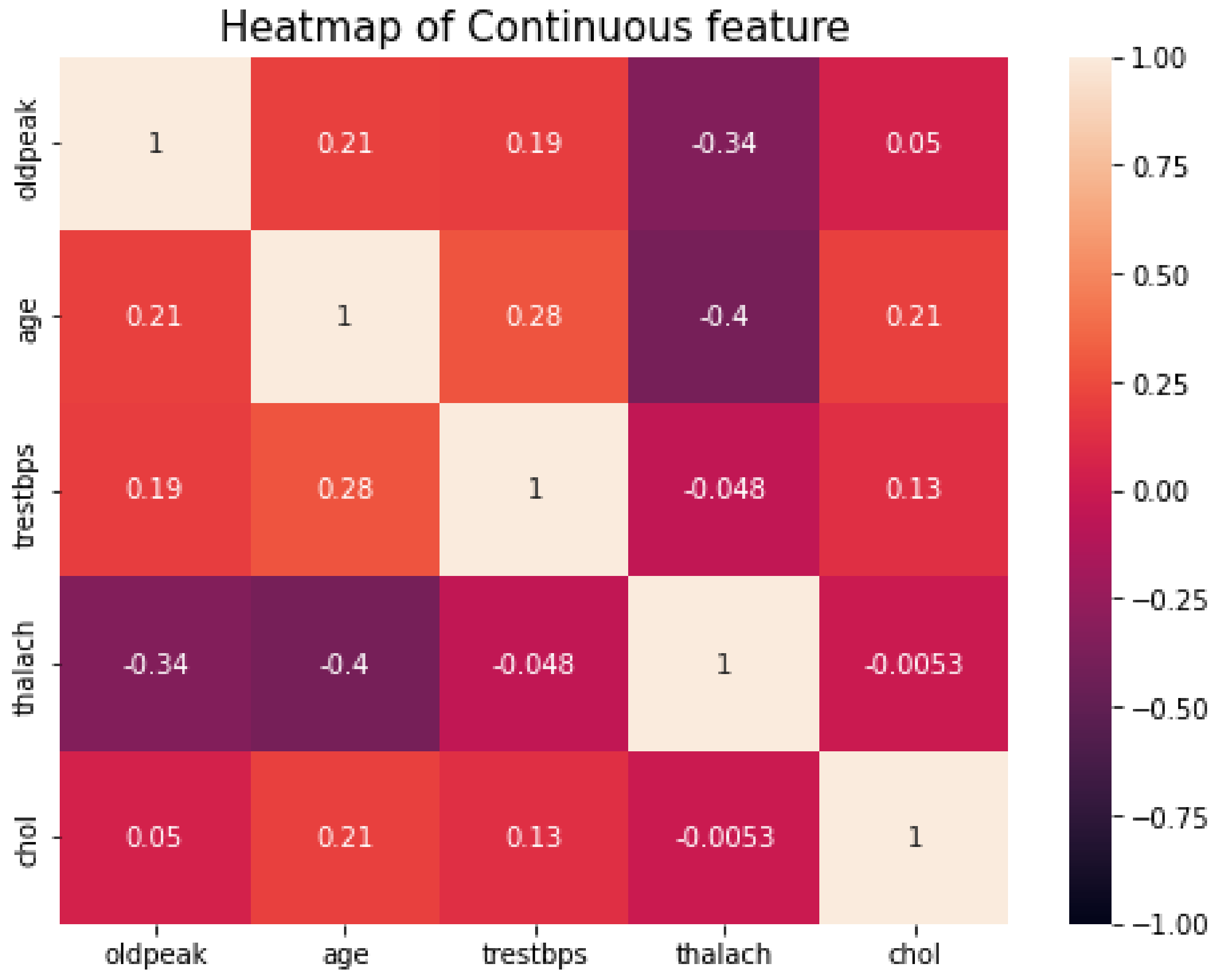
- 'exang' (exercise-induced angina) has a negative correlation of -0.435601 with 'target,' suggesting that the presence of exercise-induced angina is associated with a lower likelihood of having heart disease.

Features with notable correlations:

- 'slope' and 'restecg' (resting electrocardiographic results) have positive correlations with 'target' but are relatively weaker compared to 'cp' and 'thalach.' This suggests that it may be associated with a slightly increased likelihood of heart disease.
- 'oldpeak' (ST depression induced by exercise relative to rest) has a negative correlation with 'target,' indicating that as 'oldpeak' increases, the likelihood of heart disease decreases.
- 'ca' (number of major vessels colored by fluoroscopy) is negatively correlated with 'target,' meaning that as the number of major vessels increases, the likelihood of heart disease decreases.

Above findings suggest that 'cp,' 'thalach,' 'exang,' 'ca,' and 'oldpeak' are among the most important features for predicting heart disease in this dataset. The correlations provide insights into the relationships between these features and the likelihood of heart disease, but it's important to remember that correlation does not imply causation. Further analysis, including machine learning models, may be necessary to make accurate predictions and draw actionable conclusions.

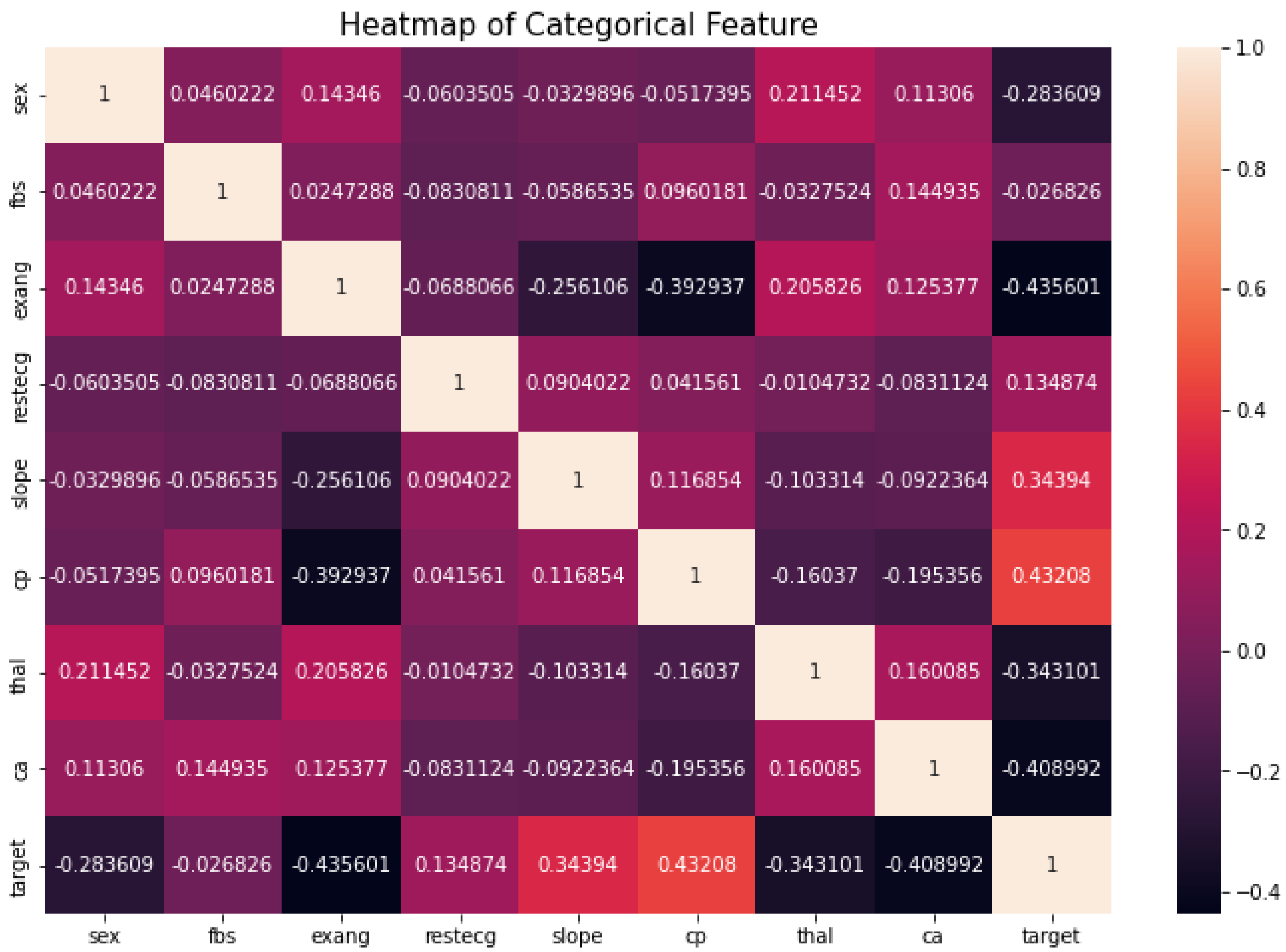
```
## Heatmap of continuous feature

plt.figure(figsize=(8,6))
sns.heatmap(df[['oldpeak', 'age', 'trestbps', 'thalach', 'chol']].corr(), vmin=-1, vmax=1, annot=True)
plt.title('Heatmap of Continuous feature', fontsize=15)
plt.show()
```



Observations:

- The heatmap of continuous variable do show some correlations, but these correlations are generally weak to moderate.
- The heatmap indicates that there are no strong linear correlations (either positive or negative) between these variables. The correlation coefficients are all relatively close to zero, which suggests that there are no prominent linear patterns or strong linear relationships among these variables.

```python
## Heatmap of Categorical features.
plt.figure(figsize=(12,8))
sns.heatmap(df[['sex', 'fbs', 'exang', 'restecg', 'slope', 'cp', 'thal', 'ca', 'target']].corr(), fmt='g', annot=True)
plt.title('Heatmap of Categorical Feature', fontsize=15)
plt.show()
```




```python
## describing the relationship between peak exercising and the occurrence of a heart attack.

df.groupby([pd.cut(df['slope'],3)])['target'].describe()
```

```
                 count      mean       std  min  25%  50%  75%  max
slope
(-0.002, 0.667]   21.0  0.428571  0.507093  0.0  0.0  0.0  1.0  1.0
(0.667, 1.333]   140.0  0.350000  0.478682  0.0  0.0  0.0  1.0  1.0
(1.333, 2.0]     141.0  0.751773  0.433524  0.0  1.0  1.0  1.0  1.0
```

Observations:

CVD probability varies among the 'slope' categories:

- The 'slope' category (-0.002, 0.667] has a mean CVD probability of approximately 0.429.

- The 'slope' category (0.667, 1.333] has a lower mean CVD probability of approximately 0.350.
- The 'slope' category (1.333, 2.0] has the highest mean CVD probability of approximately 0.752.
- Standard deviation (std) values indicate the variability of CVD prevalence within each 'slope' category.

The 'slope' variable appears to be associated with the likelihood of cardiovascular disease, with higher 'slope' values indicating a higher probability of CVD.

```
## Is thalassemia a major cause of CVD?

df.groupby(['thal'])['target'].describe()
```

thal	count	mean	std	min	25%	50%	75%	max
0	2.0	0.500000	0.707107	0.0	0.25	0.5	0.75	1.0
1	18.0	0.333333	0.485071	0.0	0.00	0.0	1.00	1.0
2	165.0	0.781818	0.414269	0.0	1.00	1.0	1.00	1.0
3	117.0	0.239316	0.428501	0.0	0.00	0.0	0.00	1.0

Obseravtions:

- The 'mean' values represent the average probability of having cardiovascular disease (CVD) within each 'thal' category.
- The first category, with 'thal' values 0, has a mean of approximately 0.50, indicating a relatively moderate likelihood of CVD.
- The second category, with 'thal' values 1, has a mean of approximately 0.33, indicating a relatively lower likelihood of CVD.
- The third category, with 'thal' values 2, has the highest mean of about 0.78, suggesting a higher likelihood of CVD.
- The fourth category, with 'thal' values 3, has a lower mean of approximately 0.24, indicating a lower likelihood of CVD.

In summary, the 'thal' variable appears to be associated with the likelihood of cardiovascular disease, with 'thal' values of 2, having the highest probability of CVD and values 3.0, having the lowest probability.

```
## checking relationship between chest pain type('cp') and the occurrence of a heart attack.
df.groupby(['cp'])['target'].describe()
```

cp	count	mean	std	min	25%	50%	75%	max
0	143.0	0.272727	0.446927	0.0	0.0	0.0	1.0	1.0
1	50.0	0.820000	0.388088	0.0	1.0	1.0	1.0	1.0
2	86.0	0.790698	0.409197	0.0	1.0	1.0	1.0	1.0
3	23.0	0.695652	0.470472	0.0	0.0	1.0	1.0	1.0

```
## checking relationship between number of major vessels('ca') and the occurrence of a heart attack.
df.groupby(['ca'])['target'].describe()
```

ca	count	mean	std	min	25%	50%	75%	max
0	175.0	0.742857	0.438313	0.0	0.00	1.0	1.0	1.0
1	65.0	0.323077	0.471291	0.0	0.00	0.0	1.0	1.0
2	38.0	0.184211	0.392859	0.0	0.00	0.0	0.0	1.0
3	20.0	0.150000	0.366348	0.0	0.00	0.0	0.0	1.0
4	4.0	0.750000	0.500000	0.0	0.75	1.0	1.0	1.0

```
## checking relationship between maximum heart rate achieved('thalach') and the occurrence of a heart attack.

df.groupby([pd.cut(df['thalach'], 5)])['target'].describe()
```

thalach	count	mean	std	min	25%	50%	75%	max
(70.869, 97.2]	7.0	0.142857	0.377964	0.0	0.0	0.0	0.0	1.0
(97.2, 123.4]	37.0	0.297297	0.463373	0.0	0.0	0.0	1.0	1.0
(123.4, 149.6]	88.0	0.352273	0.480416	0.0	0.0	0.0	1.0	1.0
(149.6, 175.8]	139.0	0.676259	0.469595	0.0	0.0	1.0	1.0	1.0
(175.8, 202.0]	31.0	0.870968	0.340777	0.0	1.0	1.0	1.0	1.0

Observations:

On the basis of above result,

- It appears that as maximum heart rate (thalach) increases, the likelihood of the presence of cardiovascular disease ('target' = 1) also tends to increase.
- The trend is evident as you move from lower thalach ranges to higher ones. For example, the group with thalach in the range of (175.8, 202.0] has the highest mean target value (0.871), indicating a relatively high presence of cardiovascular disease.
- This suggests that maximum heart rate achieved (thalach) is a potential factor associated with cardiovascular disease, and higher heart rates may be correlated with a higher risk of the disease.

```
## relationship between ('oldpeak') and the occurrence of a heart attack.

df.groupby([pd.cut(df['oldpeak'], 3)])['target'].describe()
```

oldpeak	count	mean	std	min	25%	50%	75%	max
(-0.0062, 2.067]	252.0	0.623016	0.485595	0.0	0.0	1.0	1.0	1.0
(2.067, 4.133]	45.0	0.133333	0.343776	0.0	0.0	0.0	0.0	1.0
(4.133, 6.2]	5.0	0.200000	0.447214	0.0	0.0	0.0	0.0	1.0

```
## relationship between exercise induced angina('exang') and the occurrence of a heart attack.

df.groupby(['exang'])['target'].describe()
```

exang	count	mean	std	min	25%	50%	75%	max
0	203.0	0.694581	0.461723	0.0	0.0	1.0	1.0	1.0
1	99.0	0.232323	0.424463	0.0	0.0	0.0	0.0	1.0

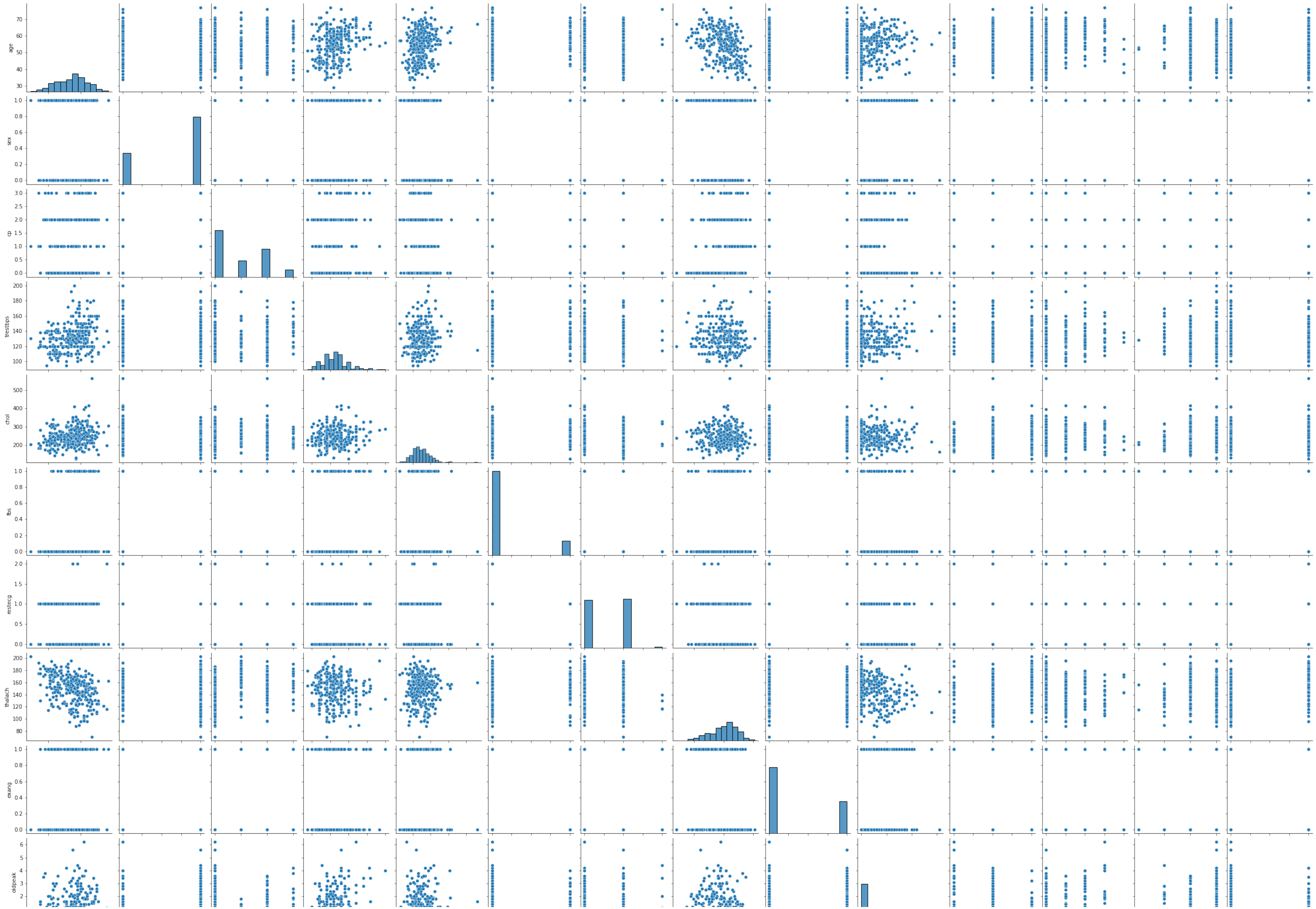
Observations:

- People with no exercise induced angina i.e. (exang=0) has the highest mean of about 0.694, indicating the higher chance of heart attacks.

```
## checking relationship between fasting blood sugar('fbs') and the occurrence of a heart attack.

df.groupby([pd.cut(df['fbs'], 2)])['target'].describe()
```

fbs	count	mean	std	min	25%	50%	75%	max
(-0.001, 0.5]	257.0	0.548638	0.498600	0.0	0.0	1.0	1.0	1.0
(0.5, 1.0]	45.0	0.511111	0.505525	0.0	0.0	1.0	1.0	1.0

```
## pair plot to understand the relationship between all the given variables.

sns.pairplot(df)
plt.show()
```


age
sex
cp
trestbps
chol
fbs
restecg
thalach
exang
oldpeak

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

```
from sklearn.model_selection import train_test_split

df.columns

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

# Split the data features & Label.
X = df.drop('target', axis=1) # feature
y = df[['target']]            # Label

X.head(2)

   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

   ca  thal
0   0     1
1   0     2

y.head(2)

   target
0       1
1       1

# Split into training & testing data
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.20, random_state=42)
```

Logistic Regression:

```
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression()

# fit the model
lr_model.fit(X_train, y_train)

LogisticRegression()

# predict the model
y_pred = lr_model.predict(X_test)
y_pred

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

lr_model.score(X_test, y_test)

0.8524590163934426

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
lr_accuracy = accuracy_score(y_test, y_pred)
lr_accuracy

0.8524590163934426
```

```python
# Confusion Matrix
lr_cm = confusion_matrix(y_test, y_pred)
lr_cm
```

```
array([[24,  5],
       [ 4, 28]])
```

```python
# plot the confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(lr_cm, annot=True, cmap='RdYlGn')
plt.title('Confusion Matrix (Logistic Regression)', fontsize=15)
plt.show()
```


```python
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.83      0.84        29
           1       0.85      0.88      0.86        32

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.85      0.85      0.85        61
```

```python
# Using Random forest classifier

from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators=50, max_depth=5, criterion='gini',random_state=42)
print(rfc)
rfc.fit(X_train, y_train)

print('\nScore:',rfc.score(X_test, y_test))
```

```python
rfc_pred = rfc.predict(X_test)
print('\nPredictions:', rfc_pred)

rfc_accuracy = accuracy_score(y_test, rfc_pred)
print('\nAccuracy Score:', rfc_accuracy)

rfc_cm = confusion_matrix(y_test, rfc_pred)
print('\nConfusion Matrix:\n', rfc_cm)

print('\n\nClassification Report:\n\n', classification_report(y_test, rfc_pred))
```

```
RandomForestClassifier(max_depth=5, n_estimators=50, random_state=42)

Score: 0.9180327868852459

Predictions: [0 0 1 0 1 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 0 1 1 1 1 0 1 0 1 0 0 0 0 1 0 1
 1 1 1 1 1 1 1 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0]

Accuracy Score: 0.9180327868852459

Confusion Matrix:
 [[27  2]
 [ 3 29]]


Classification Report:

               precision    recall  f1-score   support

           0       0.90      0.93      0.92        29
           1       0.94      0.91      0.92        32

    accuracy                           0.92        61
   macro avg       0.92      0.92      0.92        61
weighted avg       0.92      0.92      0.92        61
```