Project-1

December 20, 2023

1 Course End Project : HealthCare

[1]:
```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 1. Data preprocessing and Visualisation

[2]:
```
df = pd.read_csv("1645792390_cep1_dataset.csv")
```

[3]:
```
df.head()
```

[3]:
```
   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
```

[4]:
```
df.tail()
```

[4]:
```
     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
```

[5]:

```
df.dtypes
```

[5]:

```
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
```

[6]:

```
df.shape
```

[6]:

```
(303, 14)
```

[7]:

```
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
```

[8]:
```python
df.isnull().sum()   # there is no null values
```

[8]:
```
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
```

[9]:
```python
df[df.duplicated()]   # row number 164 is a duplicate row
```

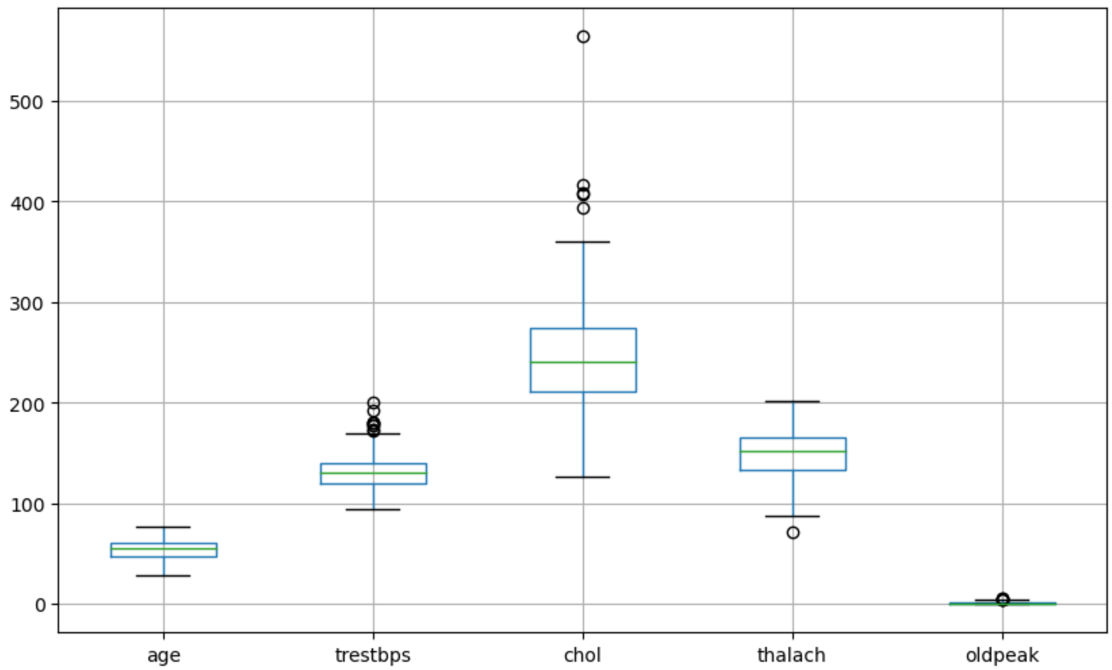
[9]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
164   38    1   2       138   175    0        1      173      0      0.0

     slope  ca  thal  target
164      2   4     2       1
```

[10]:
```python
df.drop_duplicates(inplace=True)
df.reset_index(drop=True, inplace=True)    # removing the duplicate row
df.shape
```

[10]: (302, 14)

[11]:
```python
# checking for outliers
plt.figure(figsize=(10,6))
df.boxplot(column=['age','trestbps','chol','thalach','oldpeak'])
```

[11]: <Axes: >



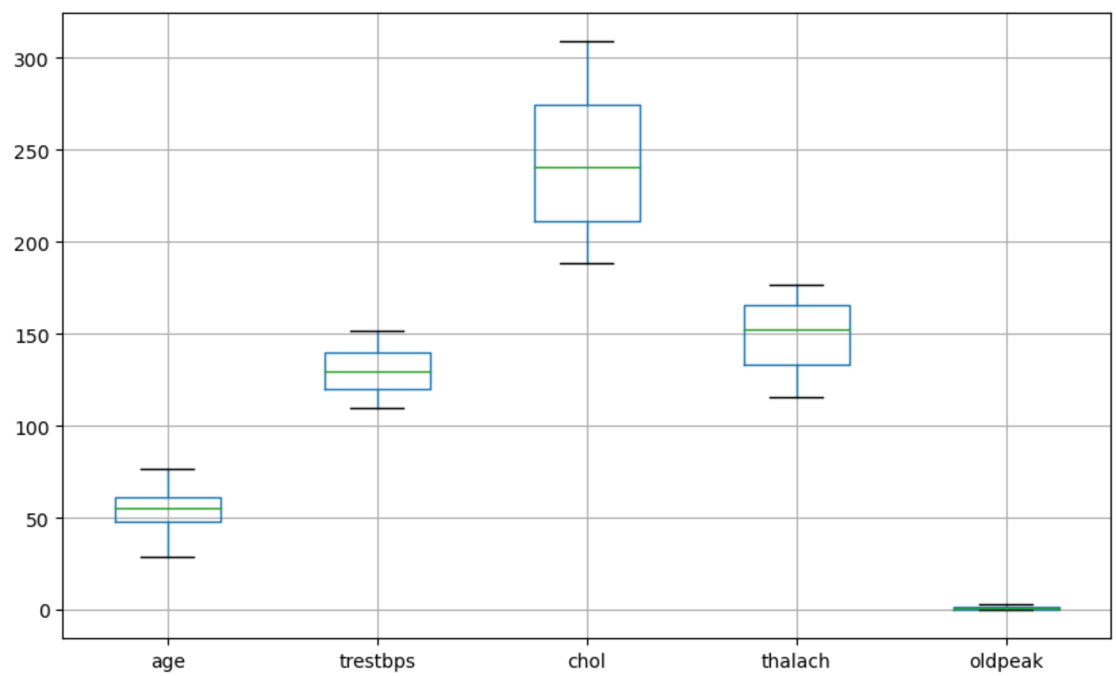
[12]:
```
# there are outliers in the numerical columns except "age"
```

[13]:
```
# Finding values of outliers(IQR method)

def detect_outliers_iqr(data):
    outlier_list = []
    data = sorted(data)
    q1 = np.percentile(data, 25)
    q3 = np.percentile(data, 75)
    #print("The Val of Q1 and Q2",q1, q3)
    IQR = q3-q1
    lwr_bound = q1-(1.5*IQR)
    upr_bound = q3+(1.5*IQR)
    #print("The lower & Upper Bound",lwr_bound, upr_bound)

    for i in data:
        if (i<lwr_bound or i>upr_bound):
            outlier_list.append(i)
    return outlier_list # Driver code



for i in ['age','trestbps','chol','thalach','oldpeak']:
    outliers = detect_outliers_iqr(df[i])
    print("Outliers in",i,"attribute :", outliers)
```

```
Outliers in age attribute : []
Outliers in trestbps attribute : [172, 174, 178, 178, 180, 180, 180, 192, 200]
Outliers in chol attribute : [394, 407, 409, 417, 564]
Outliers in thalach attribute : [71]
Outliers in oldpeak attribute : [4.2, 4.2, 4.4, 5.6, 6.2]
```

[14]:
```python
# Handling outliers using Quantile based flooring and capping method.
#the outlier is capped at a certain value above the 90th percentile value or␣
↪floored at a factor below the 10th percentile value
# Computing 10th, 90th percentiles and replacing the outliers

def handle_outliers(data):

    tenth_percentile = np.percentile(data, 10)
    ninetieth_percentile = np.percentile(data, 90)

    b = np.where(data<tenth_percentile, tenth_percentile, data)

    b1 = np.where(b>ninetieth_percentile, ninetieth_percentile, b)
    return b1


for i in ['trestbps','chol','thalach','oldpeak']:
    df[i]=handle_outliers(df[i])
```

[15]:
```python
# verifying again with boxplot
plt.figure(figsize=(10,6))
df.boxplot(column=['age','trestbps','chol','thalach','oldpeak']);
```



[16]:
```
# now there are no outliers
```

[17]:
```
df.describe().T
```

[17]:

	count	mean	std	min	25%	50%	75%	max
age	302.0	54.420530	9.047970	29.0	48.00	55.5	61.00	77.0
sex	302.0	0.682119	0.466426	0.0	0.00	1.0	1.00	1.0
cp	302.0	0.963576	1.032044	0.0	0.00	1.0	2.00	3.0
trestbps	302.0	130.523179	13.620063	110.0	120.00	130.0	140.00	152.0
chol	302.0	244.696358	39.237586	188.4	211.00	240.5	274.75	308.9
fbs	302.0	0.149007	0.356686	0.0	0.00	0.0	0.00	1.0
restecg	302.0	0.526490	0.526027	0.0	0.00	1.0	1.00	2.0
thalach	302.0	149.992715	19.608496	116.0	133.25	152.5	166.00	176.8
exang	302.0	0.327815	0.470196	0.0	0.00	0.0	1.00	1.0
oldpeak	302.0	0.966556	0.976726	0.0	0.00	0.8	1.60	2.8
slope	302.0	1.397351	0.616274	0.0	1.00	1.0	2.00	2.0
ca	302.0	0.718543	1.006748	0.0	0.00	0.0	1.00	4.0
thal	302.0	2.314570	0.613026	0.0	2.00	2.0	3.00	3.0
target	302.0	0.543046	0.498970	0.0	0.00	1.0	1.00	1.0

[18]:
```
mean_value = df.mean()
median_value = df.median()

std_deviation = df.std()
interquartile_range = df.quantile(0.75) - df.quantile(0.25)

print("Mean:\n", mean_value)
```

```
Mean:
 age          54.420530
sex           0.682119
cp            0.963576
trestbps    130.523179
chol        244.696358
fbs           0.149007
restecg       0.526490
thalach     149.992715
exang         0.327815
oldpeak       0.966556
slope         1.397351
ca            0.718543
thal          2.314570
target        0.543046
dtype: float64
```

[19]:
```
print("\nMedian:\n", median_value)
```

```
Median:
 age          55.5
sex          1.0
cp           1.0
trestbps   130.0
chol       240.5
fbs          0.0
restecg      1.0
thalach    152.5
exang        0.0
oldpeak      0.8
slope        1.0
ca           0.0
thal         2.0
target       1.0
dtype: float64
```

[20]:
```
print("\nStandard Deviation:\n", std_deviation)
```

```
Standard Deviation:
 age          9.047970
sex         0.466426
cp          1.032044
trestbps   13.620063
chol       39.237586
fbs         0.356686
restecg     0.526027
thalach    19.608496
exang       0.470196
oldpeak     0.976726
slope       0.616274
ca          1.006748
thal        0.613026
target      0.498970
dtype: float64
```

[21]:
```
print("\nInterquartile Range:\n", interquartile_range)
```

```
Interquartile Range:
 age         13.00
sex         1.00
cp          2.00
trestbps   20.00
```

```
chol         63.75
fbs           0.00
restecg       1.00
thalach      32.75
exang         1.00
oldpeak       1.60
slope         1.00
ca            1.00
thal          1.00
target        1.00
dtype: float64
```

3 Exploring categorical features:

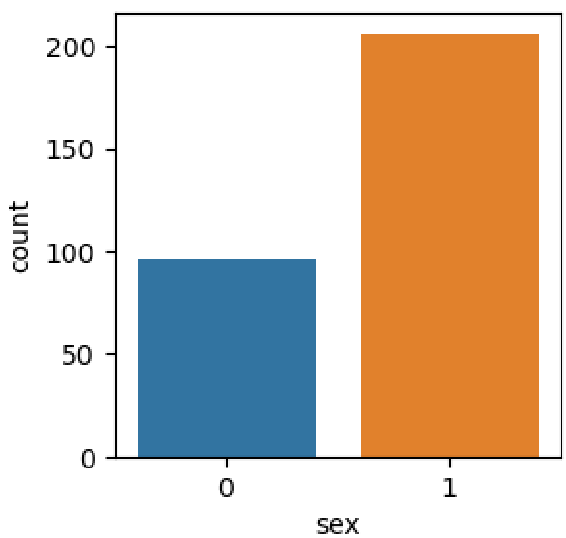
Various types of categorical structures are :

['sex','cp','fbs','restecg',"exang","slope",'ca',"thal",'target']

[22]:
```
df["sex"].value_counts()
```

[22]:
```
1    206
0     96
Name: sex, dtype: int64
```

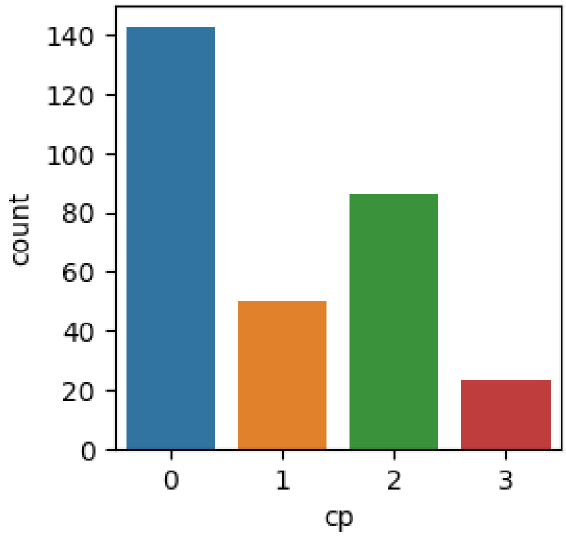
[23]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "sex",data = df)  # countplot
plt.show()
```



[24]:
```
df["cp"].value_counts()
```

[24]:
```
0    143
2     86
1     50
3     23
Name: cp, dtype: int64
```

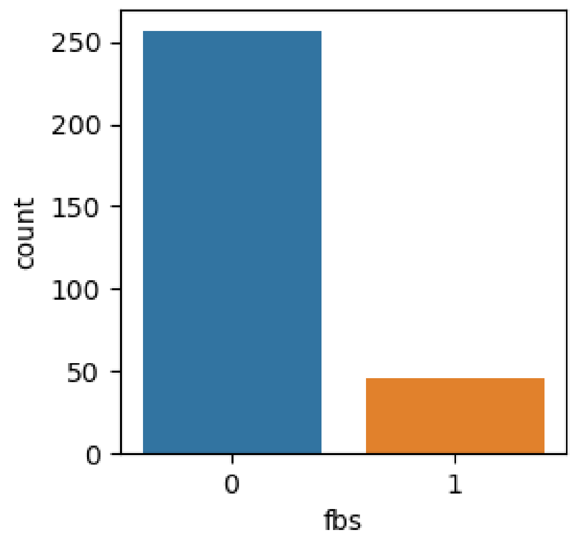
[25]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "cp",data = df)
plt.show()
```



[26]:
```
df["fbs"].value_counts()
```

[26]:
```
0    257
1     45
Name: fbs, dtype: int64
```

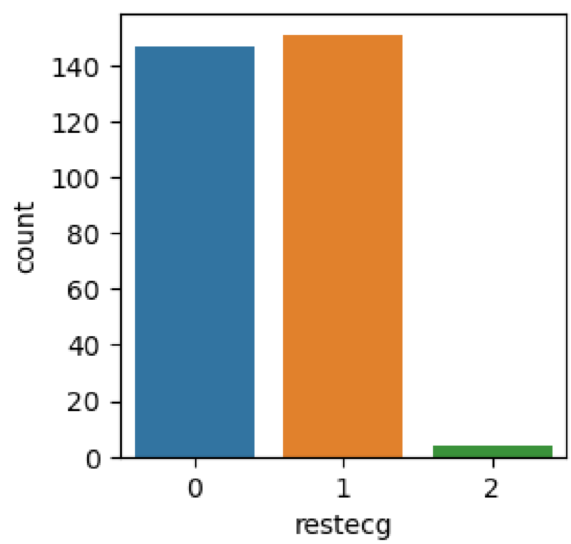
[27]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "fbs",data = df)
plt.show()
```



[28]:
```
df["restecg"].value_counts()
```

[28]:
```
1    151
0    147
2      4
Name: restecg, dtype: int64
```

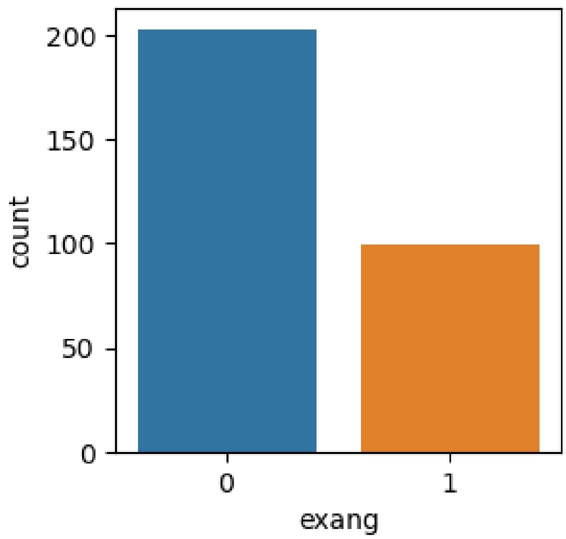
[29]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "restecg",data = df)
plt.show()
```



[30]:
```
df["exang"].value_counts()
```

[30]:
```
0    203
1     99
Name: exang, dtype: int64
```

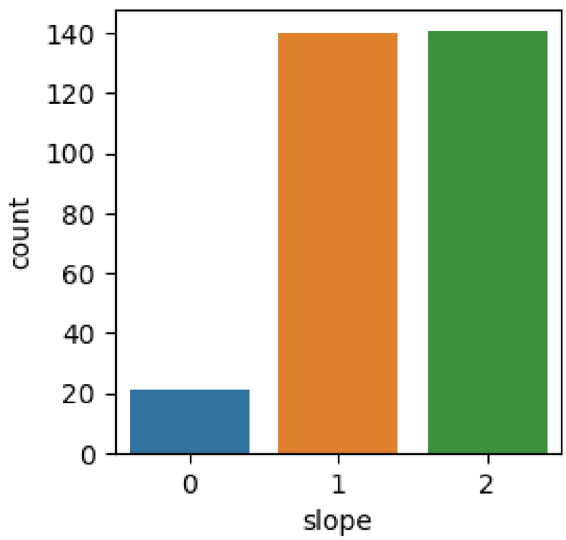
[31]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "exang",data = df)
plt.show()
```



[32]:
```
df["slope"].value_counts()
```

[32]:
```
2    141
1    140
0     21
Name: slope, dtype: int64
```

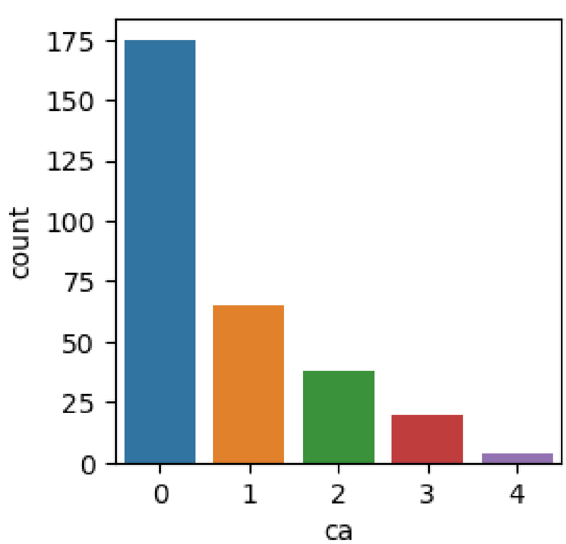
[33]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "slope",data = df)
plt.show()
```



[34]:
```
df["ca"].value_counts()
```

[34]:
```
0    175
1     65
2     38
3     20
4      4
Name: ca, dtype: int64
```

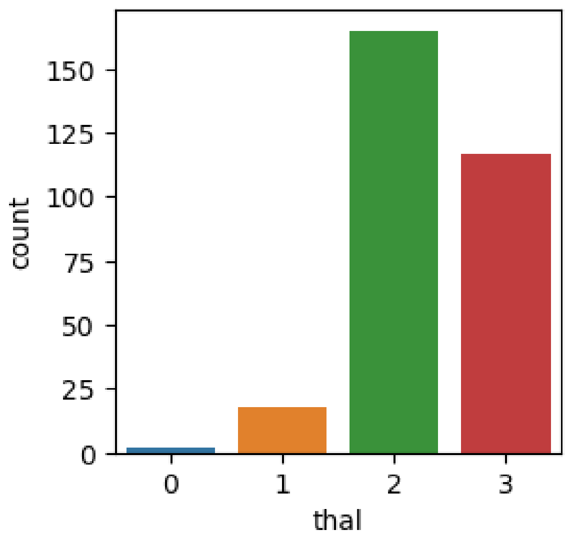
[35]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "ca",data = df)
plt.show()
```



[36]:
```
df["thal"].value_counts()
```

[36]:
```
2    165
3    117
1     18
0      2
Name: thal, dtype: int64
```

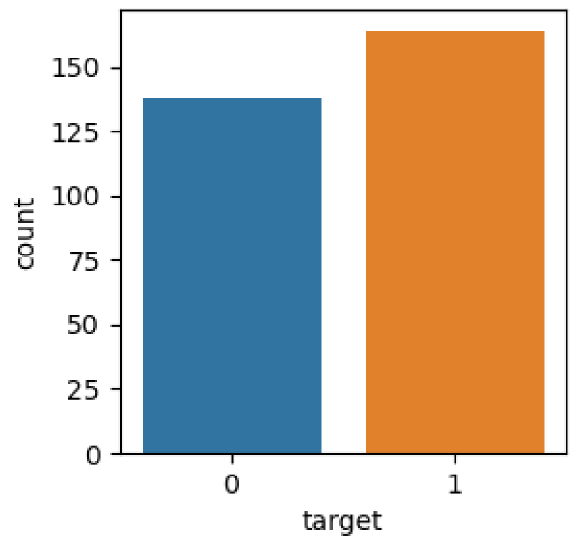
[37]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "thal",data = df)
plt.show()
```



[38]:
```
df["target"].value_counts()
```

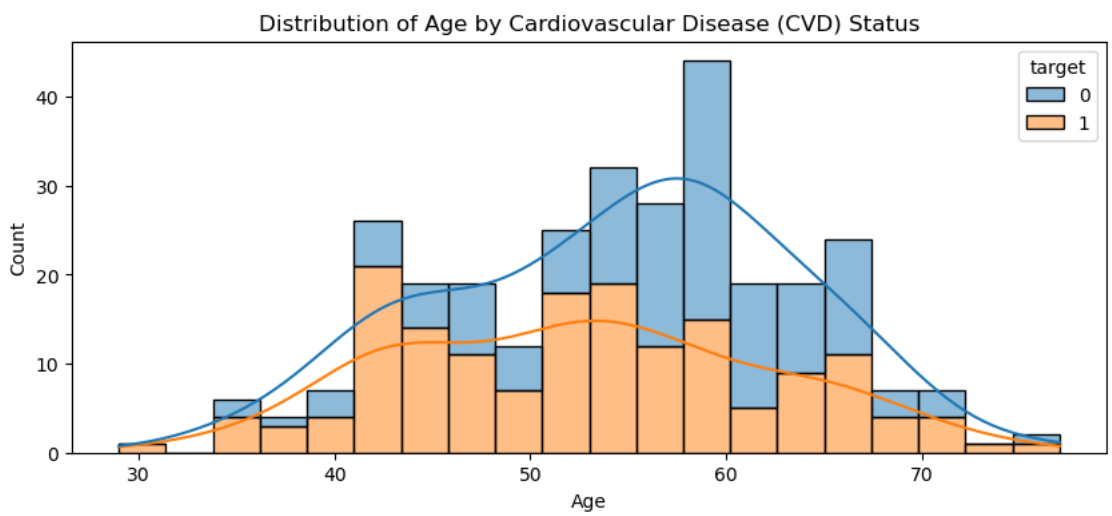
[38]:
```
1    164
0    138
Name: target, dtype: int64
```

[39]:
```
plt.figure(figsize=(3,3))
sns.countplot(x = "target",data = df)
plt.show()
```



[40]:

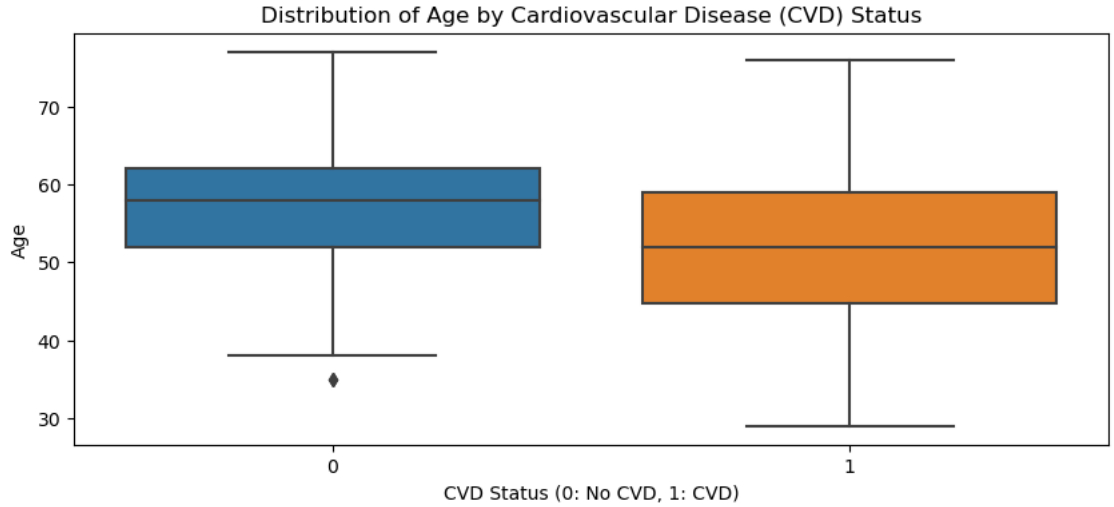
```
# Example: Histogram of Age, separated by CVD status
plt.figure(figsize=(10, 4))
sns.histplot(df, x='age', hue='target', bins=20, kde=True, multiple='stack')
plt.title('Distribution of Age by Cardiovascular Disease (CVD) Status')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



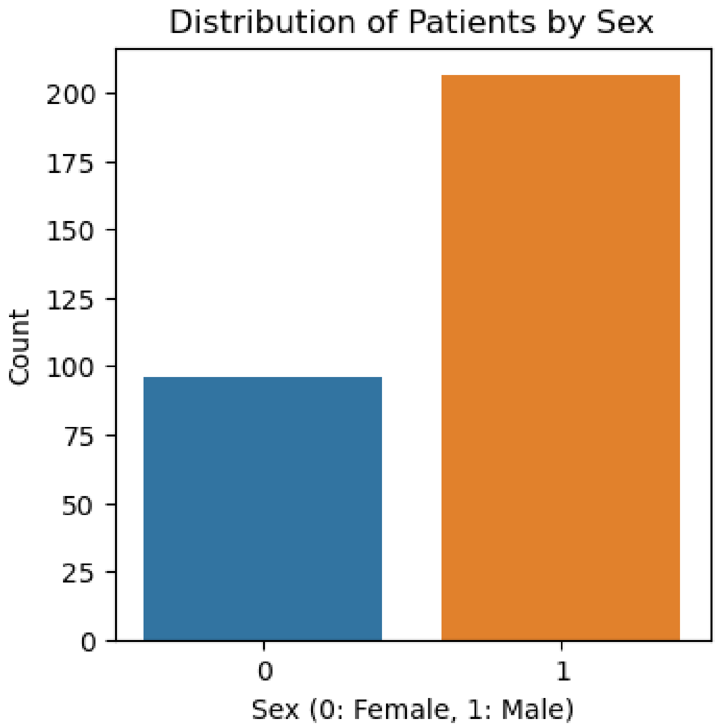
[41]:

```
# Example: Boxplot of Age vs. Target (CVD)
plt.figure(figsize=(10, 4))
sns.boxplot(x='target', y='age', data=df)
```

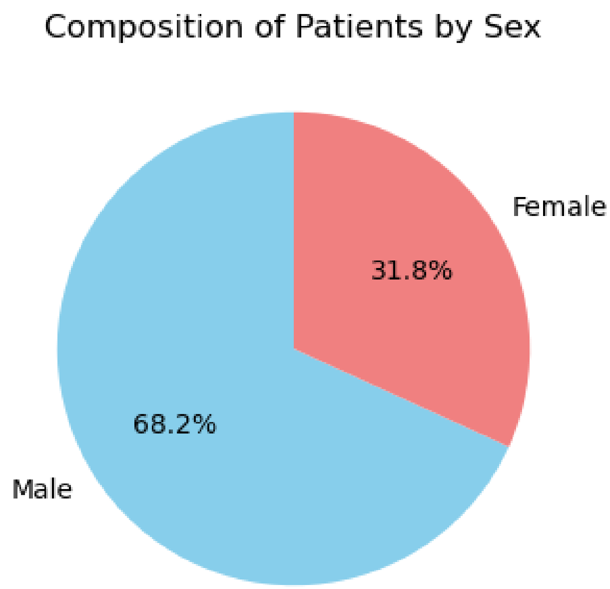
```
plt.title('Distribution of Age by Cardiovascular Disease (CVD) Status')
plt.xlabel('CVD Status (0: No CVD, 1: CVD)')
plt.ylabel('Age')
plt.show()
```



[42]:
```
# Countplot of Sex
plt.figure(figsize=(4, 4))
sns.countplot(x='sex', data=df)
plt.title('Distribution of Patients by Sex')
plt.xlabel('Sex (0: Female, 1: Male)')
plt.ylabel('Count')
plt.show()
```



[43]:
```
sex_distribution = df['sex'].value_counts()
labels = ['Male', 'Female']

plt.figure(figsize=(4, 4))
plt.pie(sex_distribution, labels=labels, autopct='%1.1f%%', startangle=90,␣
  ↪colors=['skyblue', 'lightcoral'])
plt.title('Composition of Patients by Sex')
plt.show()
```



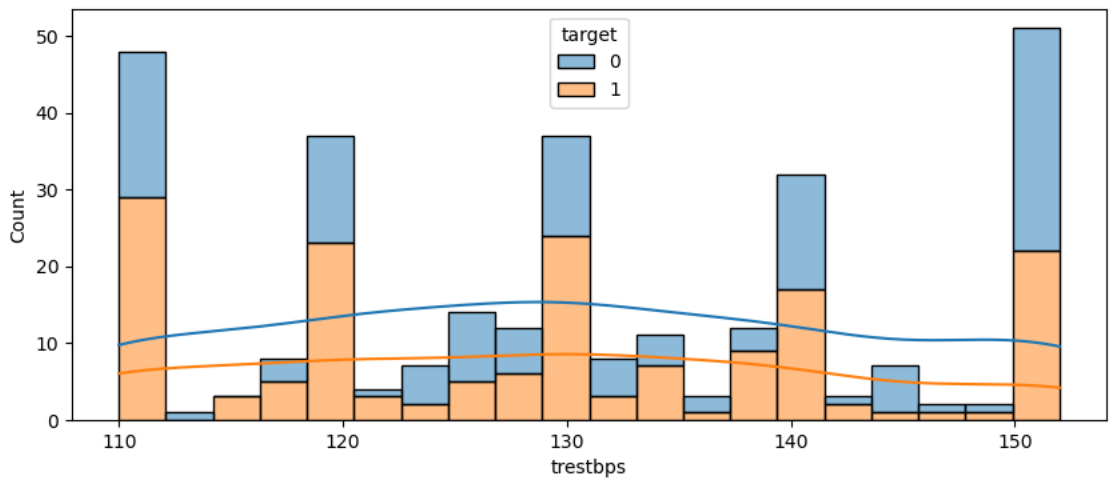
Composition of all patients with respect to the Sex category : From the count plot and histogram we can conclude that There is more number of male patient present compared to female patients.

[44]:
```
df_new = df[["trestbps","target"]].groupby(["trestbps","target"]).size().
  ↪reset_index().rename(columns = {0:"number"})
df_new.head()
```

[44]:

	trestbps	target	number
0	110.0	0	15
1	110.0	1	24
2	112.0	0	4
3	112.0	1	5
4	114.0	0	1

[45]:
```
# Example: Histogram of trestbps, separated by CVD status
plt.figure(figsize=(10, 4))
sns.histplot(df, x='trestbps',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```



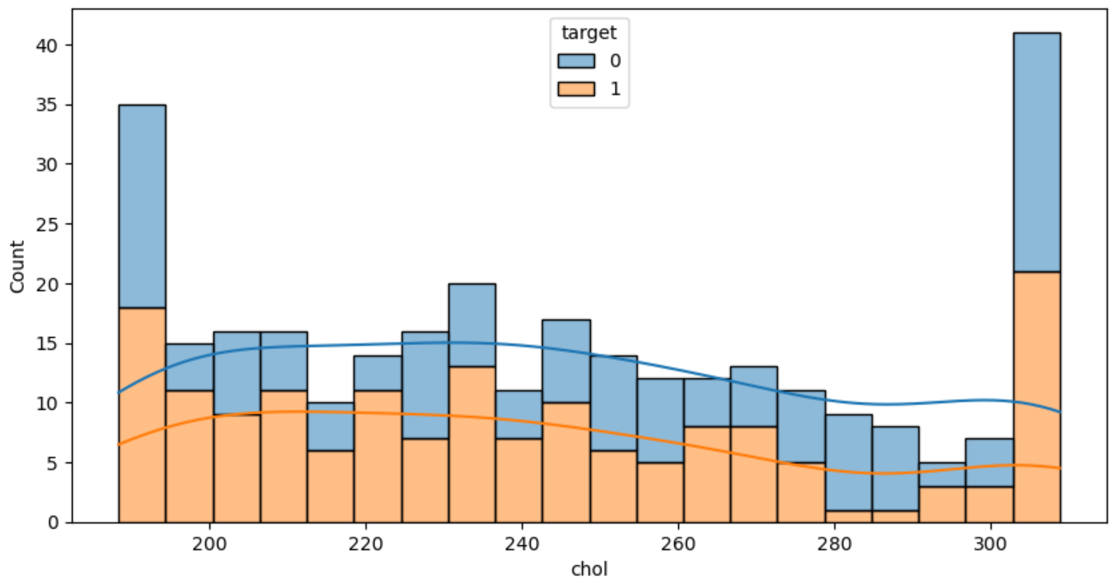
Relatiobnship between resting blood sugar level and target variable : From the histplot we can conclude that a high amount of patient count present in ”resting blood sugar level:110”,”resting blood sugar level:120”,”resting blood sugar level:130”,”resting blood sugar level:140” and ”resting blood sugar level:150” and hence there is also high amount of share of ”occurance of CVD” is present in the same ”resting blood sugar level” also.

[46]:
```
df_new_one = df[["chol","target"]].groupby(["chol","target"]).size().
↪reset_index().rename(columns = {0:"number"})
df_new_one.head(10)
```

[46]:

	chol	target	number
0	188.4	0	16
1	188.4	1	15
2	192.0	1	2
3	193.0	0	1
4	193.0	1	1
5	195.0	1	1
6	196.0	1	2
7	197.0	0	2
8	197.0	1	4
9	198.0	0	1

[47]:
```
# Example: Histogram of chol, separated by CVD status
plt.figure(figsize=(10, 5))
sns.histplot(df, x='chol',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```



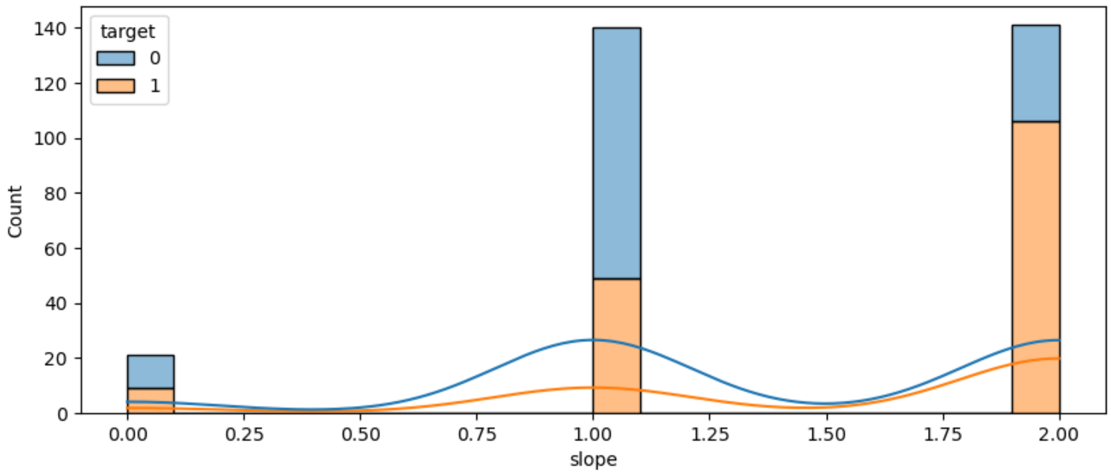
Relatiobnship between cholestrol level and target variable : From the histplot we can conclude that all ranges of cholestrol level hava an approximately equal sharing of ”occurance of CVD” though the ”occurance of CVD” is minimum between the range ”270 to 305”.

[48]:
```
df_new_one = df[["slope","target"]].groupby(["slope","target"]).size().
    ↪reset_index().rename(columns = {0:"number"})
df_new_one.head()
```

[48]:

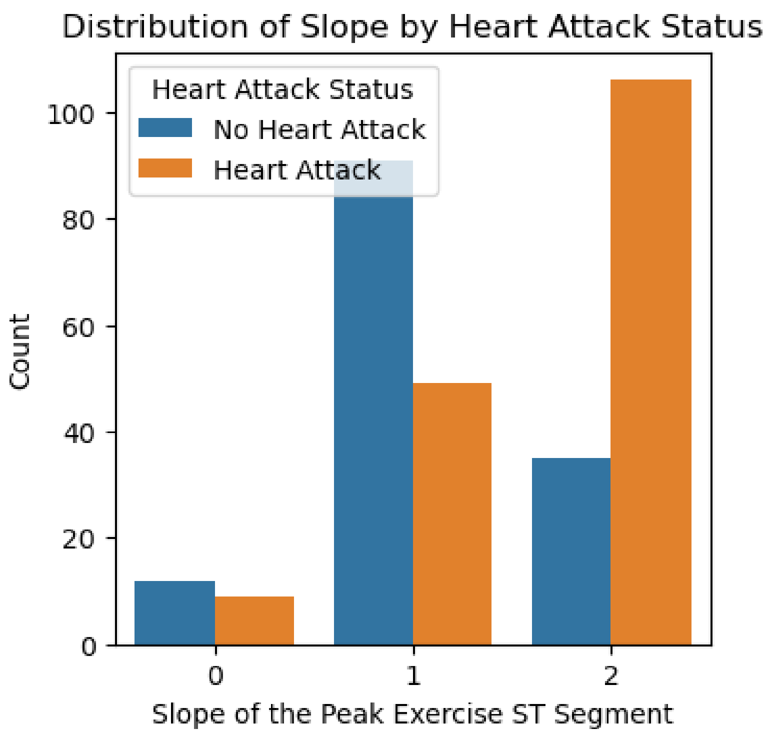
	slope	target	number
0	0	0	12
1	0	1	9
2	1	0	91
3	1	1	49
4	2	0	35

[49]:
```
plt.figure(figsize=(10, 4))
sns.histplot(df, x='slope',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```

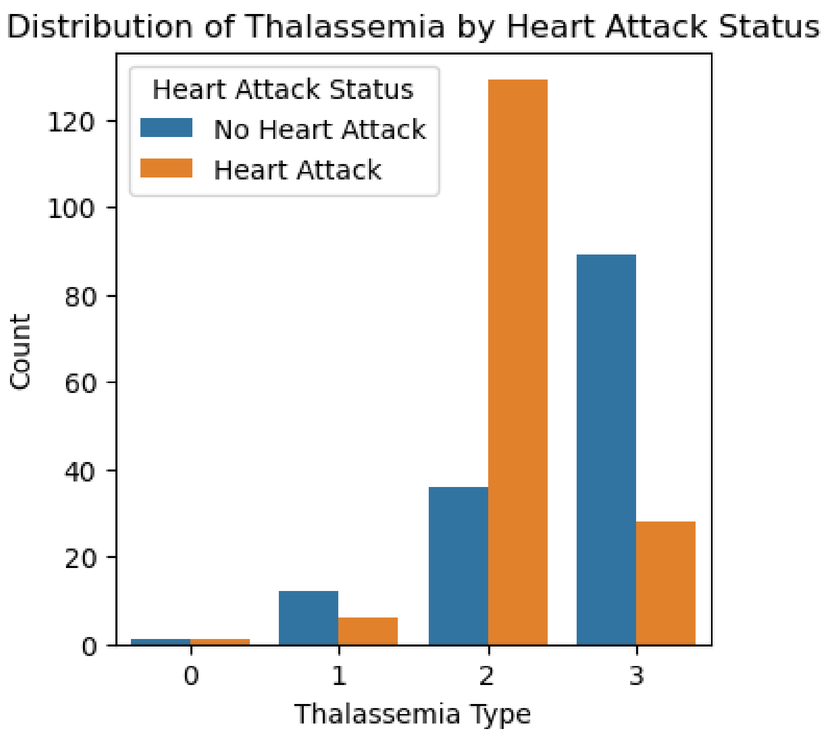


Relationship between peak exercising and occurance of a heart attack : The variable "slope" which denotes the the peak exercising which contains three classes 0 ,1 ,2 . The class 0 has an approximate share of "occurance of CVD" . The class 1 has maximum share of "non occurance of CVD" and the calss 2 has a maximum share of "occurance of CVD".

[50]:
```
# Countplot of slope vs. Target (heart attack)
plt.figure(figsize=(4, 4))
sns.countplot(x='slope', hue='target', data=df)
plt.title('Distribution of Slope by Heart Attack Status')
plt.xlabel('Slope of the Peak Exercise ST Segment')
plt.ylabel('Count')
plt.legend(title='Heart Attack Status', labels=['No Heart Attack', 'Heart␣
↪Attack'])
plt.show()
```



[51]:
```
# Countplot of thal vs. Target (heart attack)
plt.figure(figsize=(4, 4))
sns.countplot(x='thal', hue='target', data=df)
plt.title('Distribution of Thalassemia by Heart Attack Status')
plt.xlabel('Thalassemia Type')
plt.ylabel('Count')
plt.legend(title='Heart Attack Status', labels=['No Heart Attack', 'Heart␣
↪Attack'])
plt.show()
```



Relationship between thalassemia type and occurance of a heart attack : Type 2 and type 3 thalssemia has the majority share of the count . We can conclude from the count plot is that type 2 thalssemia patients have a high number of CVD affected patients with respect to type 3 patients which has a low number of CVD affected patients.

[52]:
```
df_tt = df[["target","thal"]].groupby(["thal"]).value_counts().reset_index().
↪rename(columns = {0:"number"})
df_tt
```

[52]:

	thal	target	number
0	0	0	1
1	0	1	1
2	1	0	12
3	1	1	6
4	2	1	129
5	2	0	36
6	3	0	89
7	3	1	28

[53]:
```
df.head()
```

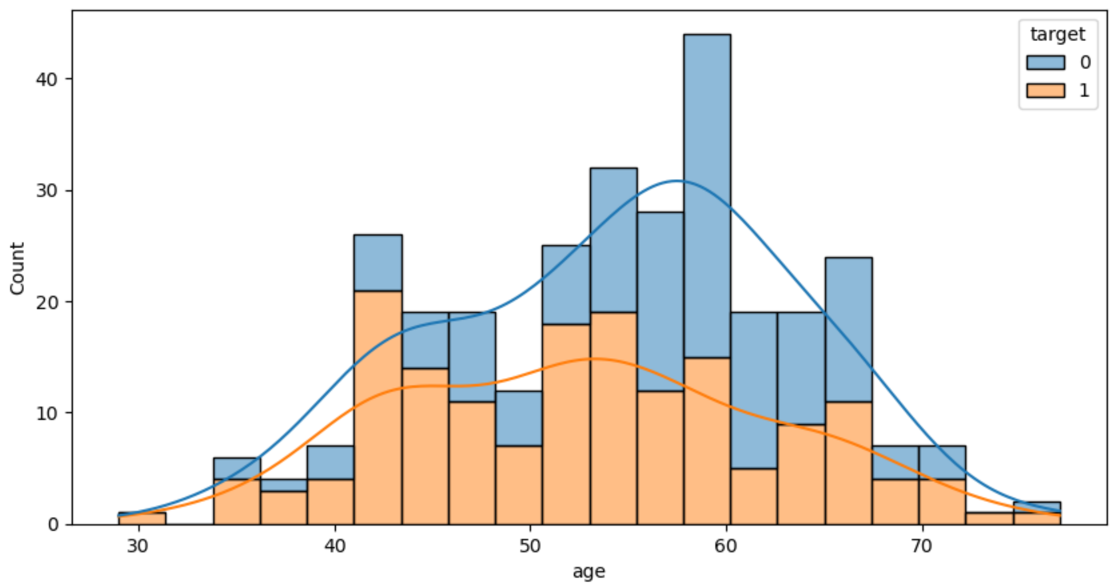
[53]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
0	63	1	3	145.0	233.0	1	0	150.0	0	2.3	
1	37	1	2	130.0	250.0	0	1	176.8	0	2.8	
2	41	0	1	130.0	204.0	0	0	172.0	0	1.4	

```
3   56    1   1     120.0  236.0    0         1    176.8       0        0.8
4   57    0   0     120.0  308.9    0         1    163.0       1        0.6

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

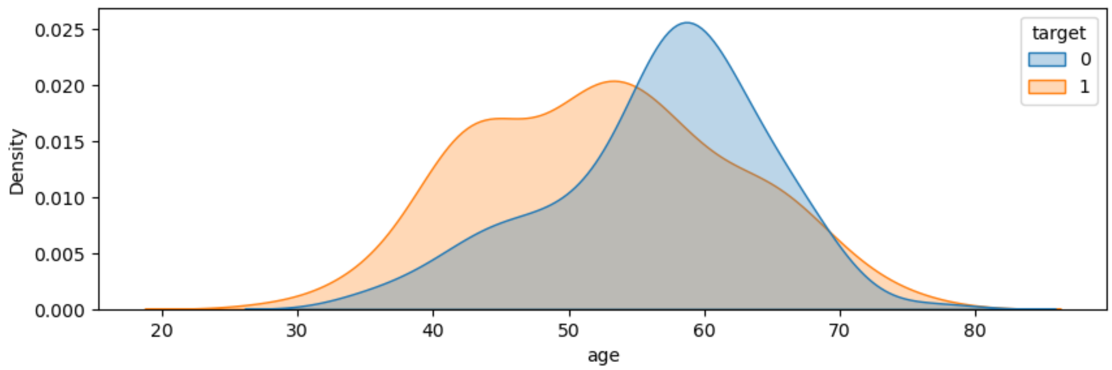
[54]:
```
## Other factors determining the occurance of heart attack
```

[99]:
```
#for age
plt.figure(figsize=(10, 5))
sns.histplot(df, x='age',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```



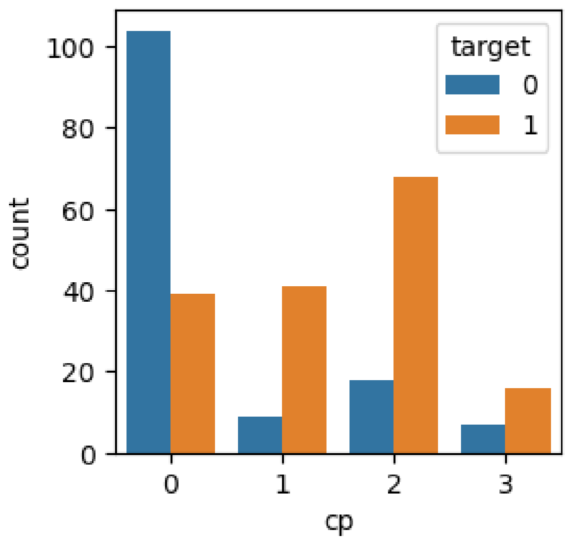
[56]:
```
plt.figure(figsize=(10,3))
sns.kdeplot(x='age', data=df, color='red',hue = "target", fill=True, alpha=0.3)
```

[56]:
```
<Axes: xlabel='age', ylabel='Density'>
```



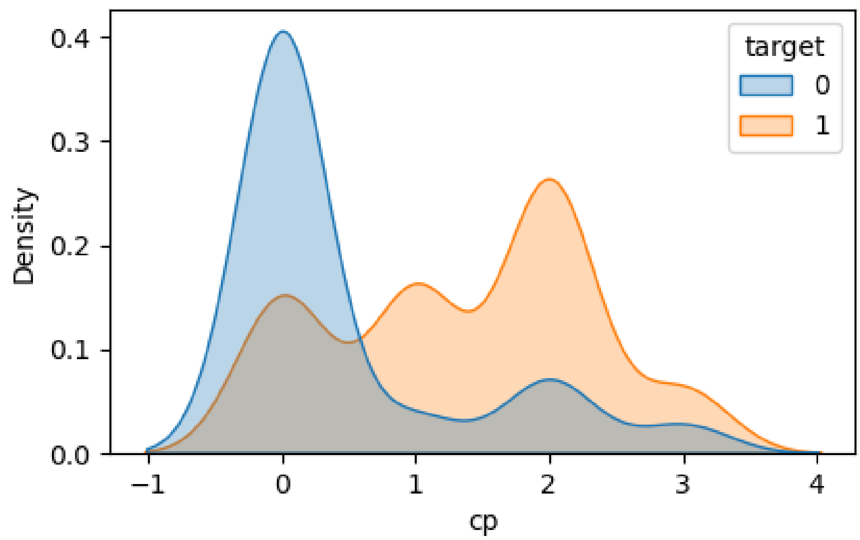
Relationship of age and the target variable : patients with the age 41 to 68 have the heighter number of counts and patients with the age 51 to 68 have the maximum number of share of patients with CVD.

[57]:
```
# for cp
plt.figure(figsize=(3,3))
sns.countplot(x = "cp",data = df,hue = "target")
plt.show()
```



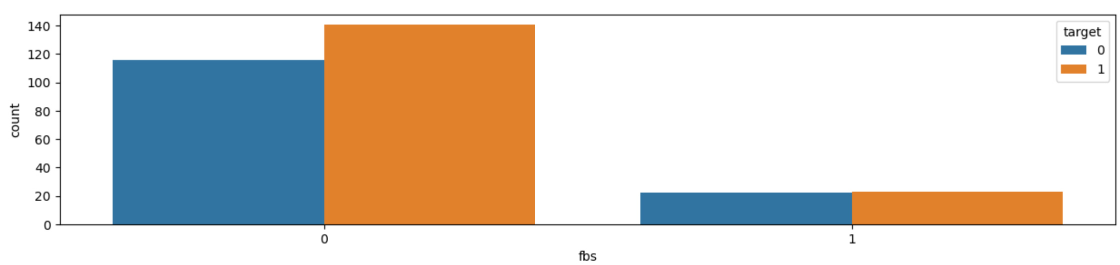
[58]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(x='cp', data=df, color='red',hue = "target", fill=True, alpha=0.3)
```

[58]: <Axes: xlabel='cp', ylabel='Density'>

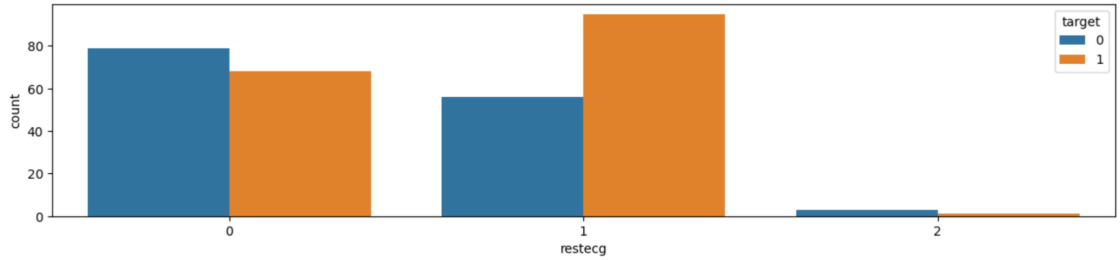


Relationship between chest pain type and the target variable : chest pain type 0 has the heighest number of patients and a maximum share of patients without CVD and chest pain type 1 , chest pain type 2, chest pain type 3 has a maximum share of patients with CVD.

[59]:
```
## for fbs
plt.figure(figsize=(15,3))
sns.countplot(x = "fbs",data = df,hue = "target")
plt.show()
```

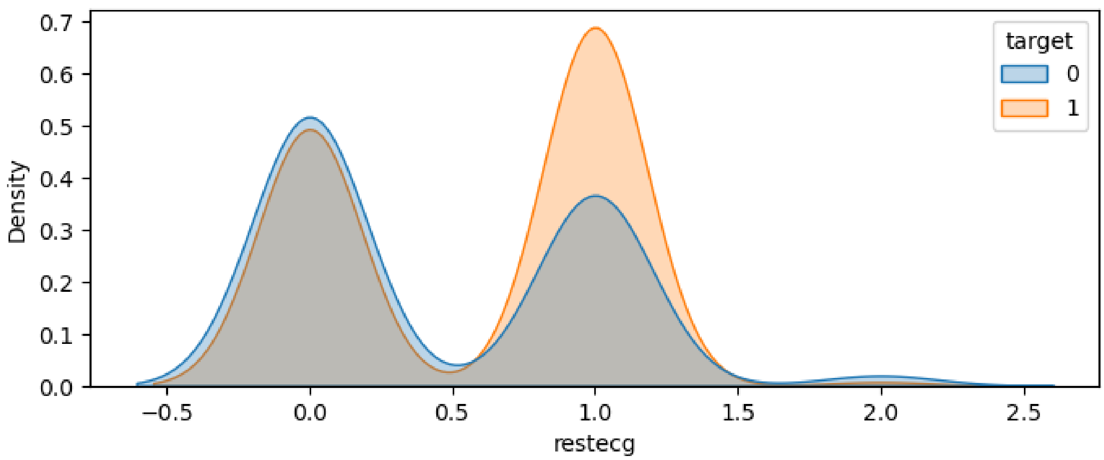


[60]:
```
## for rest ecg

plt.figure(figsize=(15,3))
sns.countplot(x = "restecg",data = df,hue = "target")
plt.show()
```

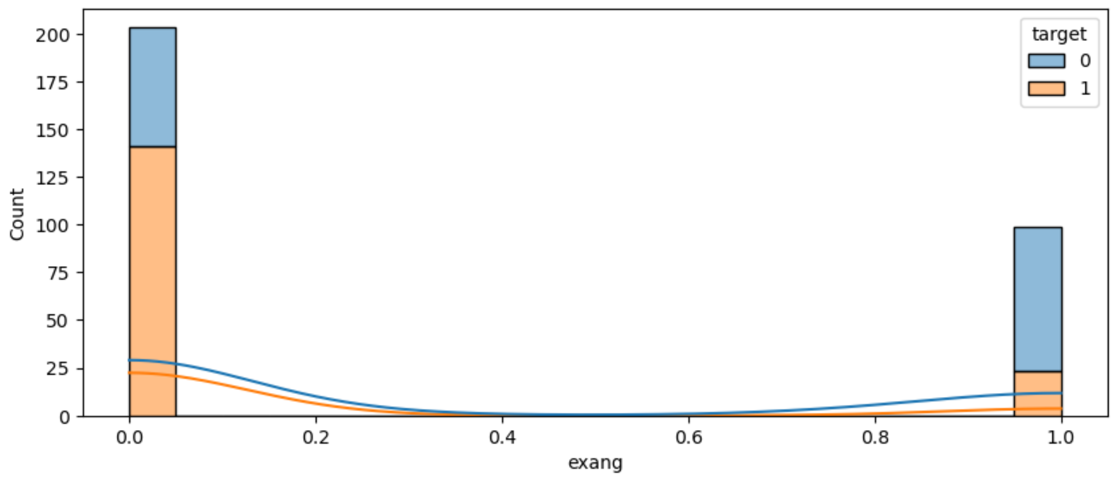


[61]:
```
plt.figure(figsize=(8,3))
sns.kdeplot(x='restecg', data=df, color='red',hue = "target", fill=True,␣
  ↪alpha=0.3)
```

[61]: <Axes: xlabel='restecg', ylabel='Density'>

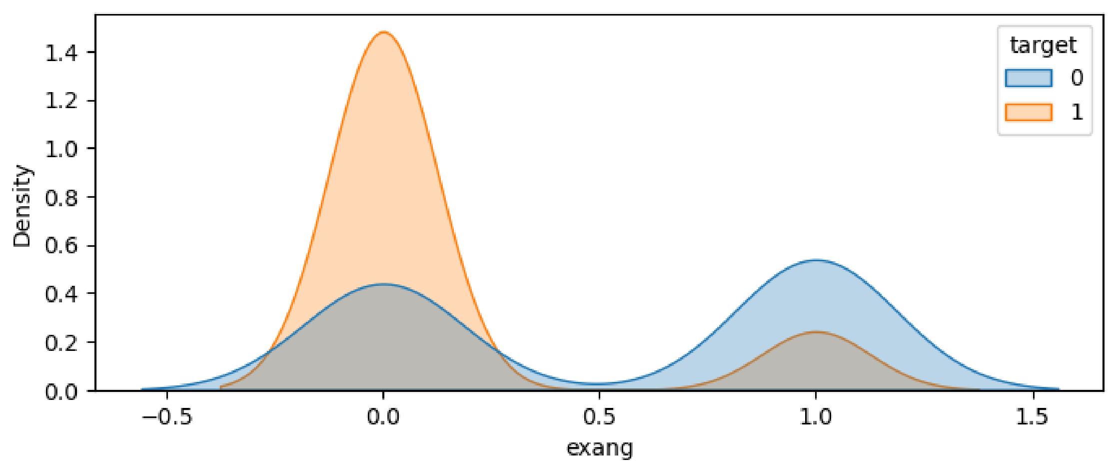


[101]:
```
# for exang
plt.figure(figsize=(10, 4))
sns.histplot(df, x='exang',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```

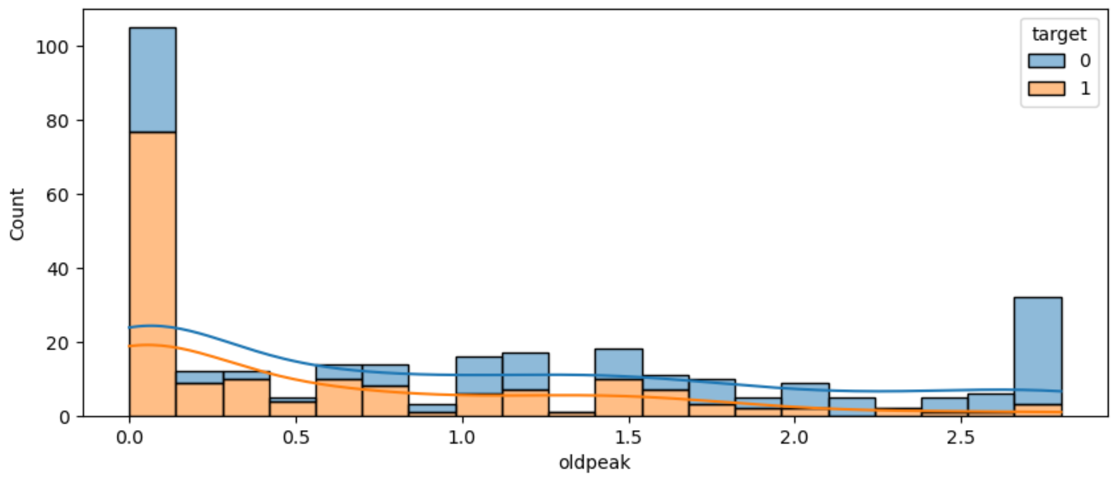


[65]:
```
plt.figure(figsize=(8,3))
sns.kdeplot(x='exang', data=df, color='red',hue = "target", fill=True, alpha=0.
 ↪3)
```

[65]: <Axes: xlabel='exang', ylabel='Density'>

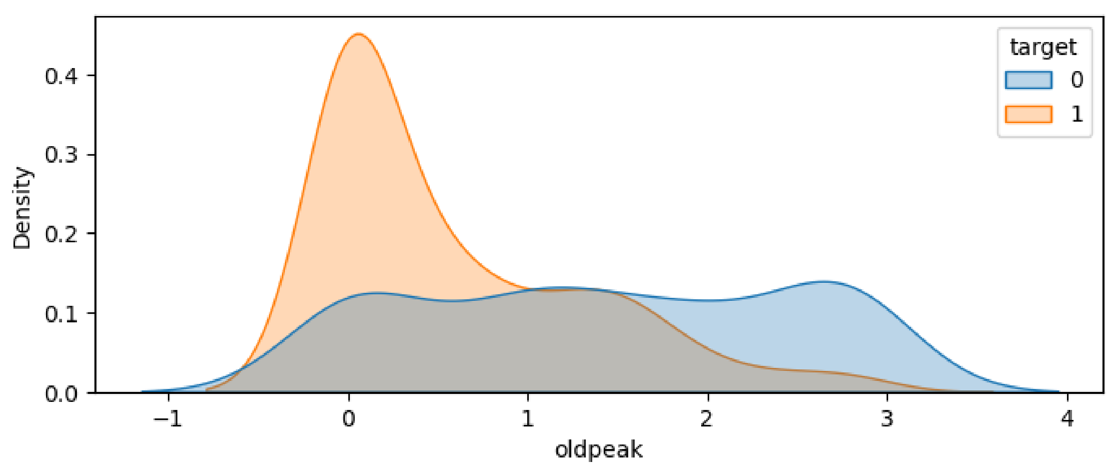


[102]:
```
# for oldpeak

plt.figure(figsize=(10, 4))
sns.histplot(df, x='oldpeak',hue='target', bins=20, kde=True, multiple='stack')
plt.show()
```



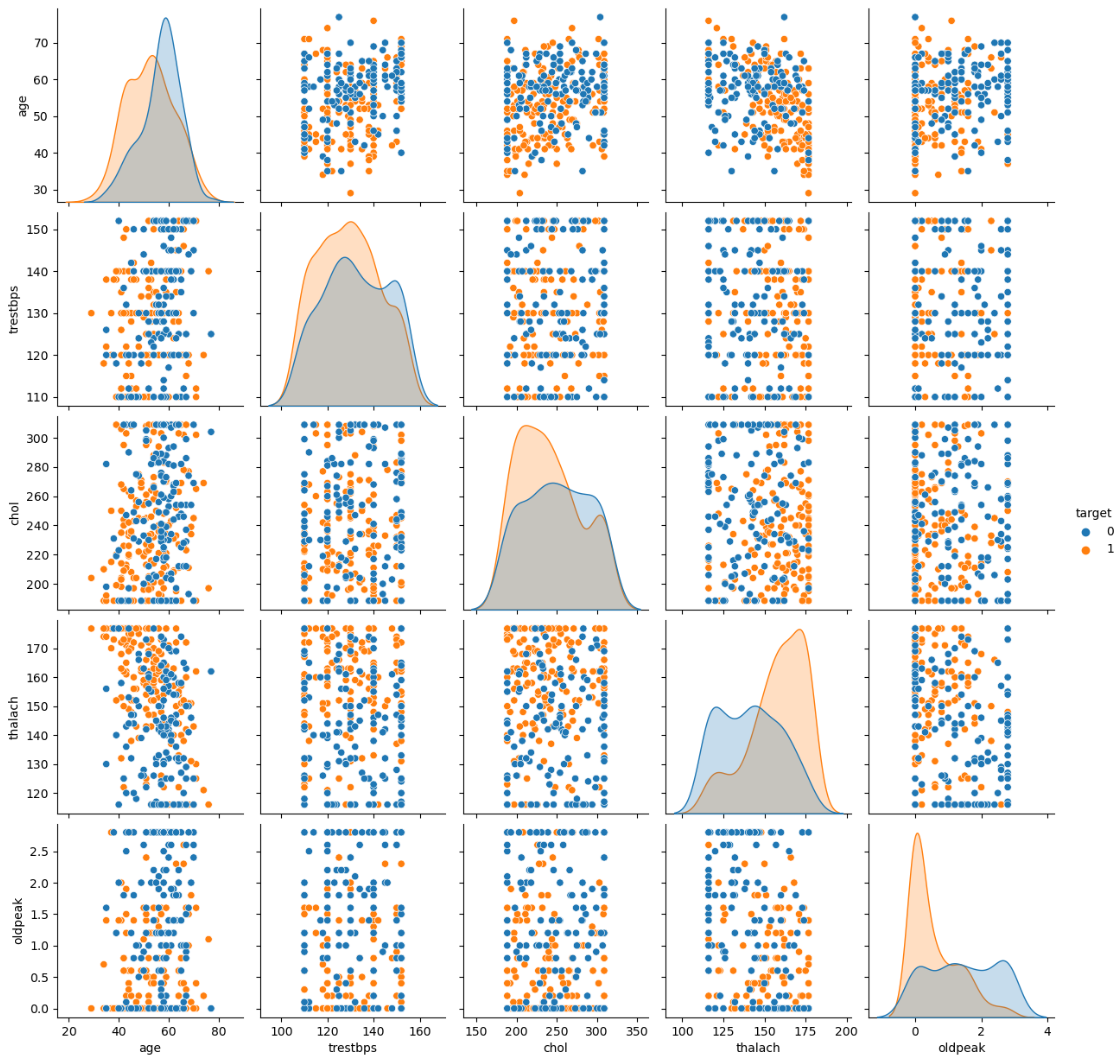
[67]:
```
plt.figure(figsize=(8,3))
sns.kdeplot(x='oldpeak', data=df,hue = "target", fill=True, alpha=0.3)
```

[67]: <Axes: xlabel='oldpeak', ylabel='Density'>



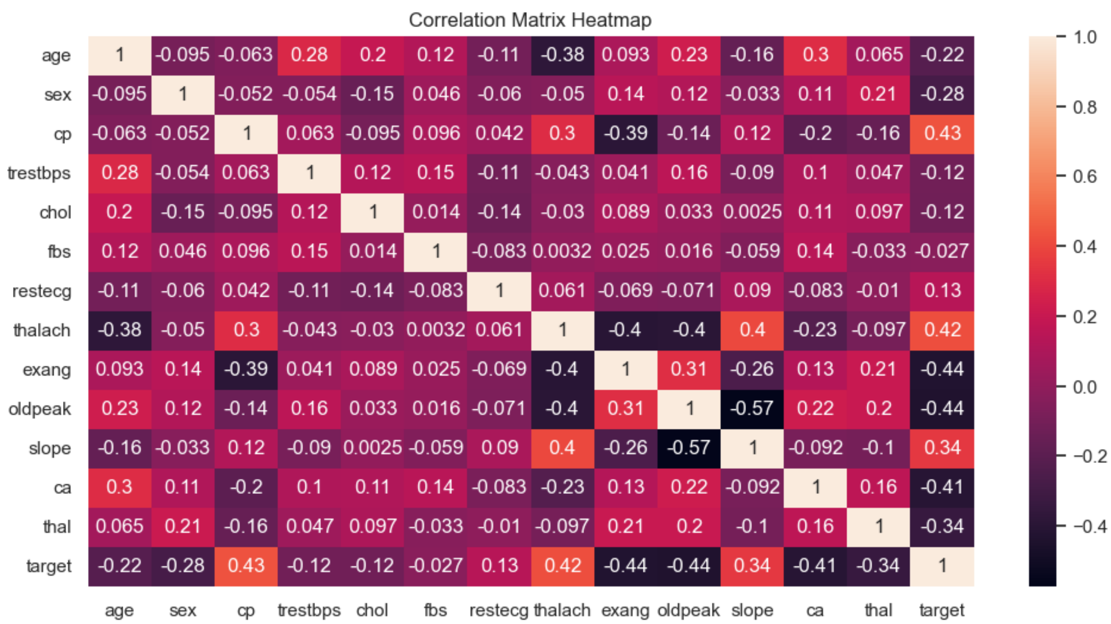
[105]:
```
## pairplot
# pairplot for numeric columns
sns.
↪pairplot(df[['age','trestbps','chol','thalach','oldpeak','target']],hue='target')
```

[105]: <seaborn.axisgrid.PairGrid at 0x1a604a72bc0>



3.1 Correlation analysis

[129]:
```python
# Compute the correlation matrix
correlation_matrix = df.corr()

# Create a heatmap using Seaborn
plt.figure(figsize=(12, 6))  # Set the figure size
# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(correlation_matrix,annot=True)

plt.title("Correlation Matrix Heatmap")
plt.show()
```



3.2 Feature Scaling

[71]:
```
## Feature Scaling
```

[108]:
```
from sklearn.preprocessing import StandardScaler
# -infinity to infinity
# z = (X - mean)/std deviation

scale = StandardScaler()
df[['age','trestbps','chol','thalach']]=scale.
↪fit_transform(df[['age','trestbps','chol','thalach']])
```

3.3 Preaparing The data

[109]:
```
x = df.drop(["target"],axis = 1)
y_init = df["target"]
```

[110]:
```
y = y_init.to_numpy()
```

[111]:
```
from sklearn.model_selection import train_test_split
```

[112]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.
↪2,random_state = 1) # 80 : 20
```

[113]:
```
x_train.shape
```

[113]: (241, 13)

[114]:
```
y_train.shape
```

[114]: (241,)

4 2. Model building

4.1 Apply logistic regression and evaluting performance

[115]:
```
from sklearn.linear_model import LogisticRegression
```

[116]:
```
LR_model = LogisticRegression()
```

[117]:
```
LR_model.fit(x_train,y_train)
```

[117]: LogisticRegression()

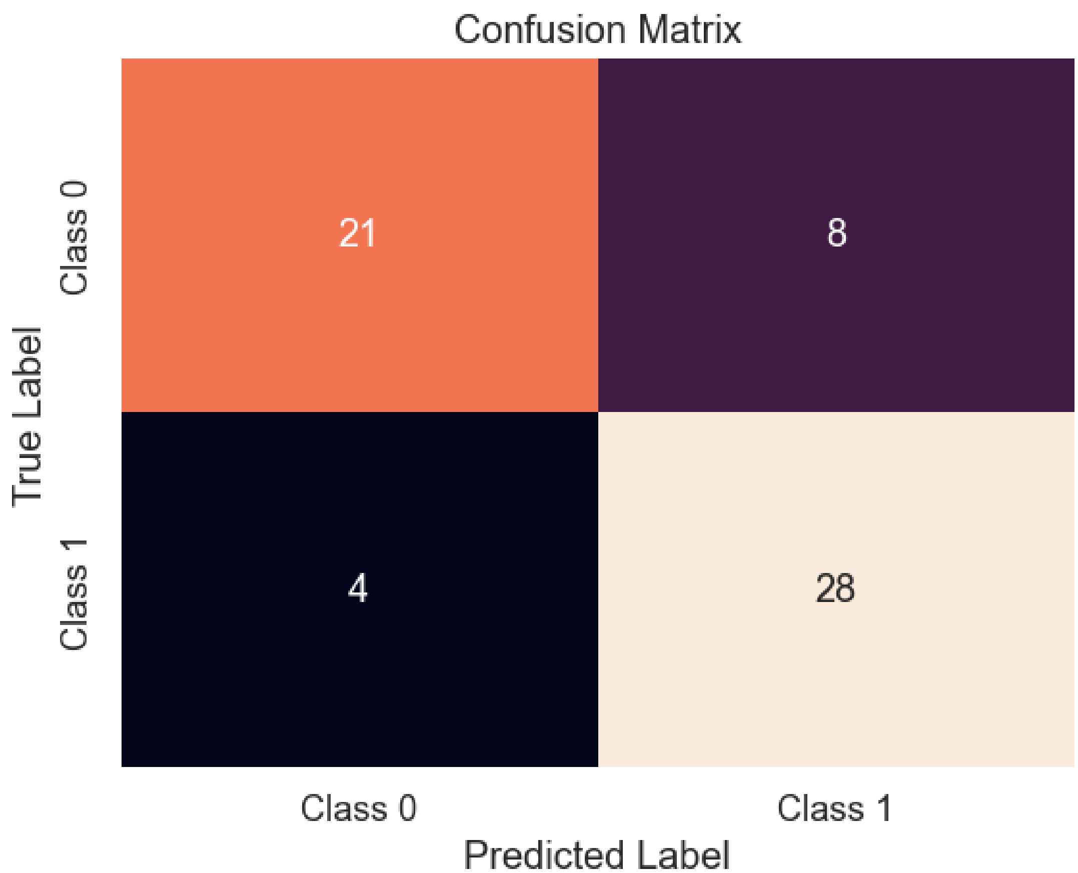
[118]:
```
y_pred = LR_model.predict(x_test)
```

[119]:
```
from sklearn.metrics import accuracy_score, classification_report ,␣
↪confusion_matrix
accuracy_logreg = accuracy_score(y_test, y_pred) * 100
print(f'Accuracy of Logistic Regression: {accuracy_logreg:.4f}')

print("\n")

# Additional evaluation metrics
print(classification_report(y_test, y_pred))
```

```
Accuracy of Logistic Regression: 80.3279


              precision    recall  f1-score   support

           0       0.84      0.72      0.78        29
           1       0.78      0.88      0.82        32

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

[121]:
```
# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Visualize the confusion matrix using Seaborn
sns.set(font_scale=1.2)  # Adjust font size for better readability
```

```
sns.heatmap(cm, annot=True, fmt="d", cbar=False,
            xticklabels=["Class 0", "Class 1"],
            yticklabels=["Class 0", "Class 1"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```



[122]:
```
import statsmodels.api as sm

# Add a constant term to the features matrix
X_train_with_const = sm.add_constant(x_train)

# Fit logistic regression using statsmodels
logit_model = sm.Logit(y_train, X_train_with_const)
result = logit_model.fit()

# Display summary including coefficients and p-values
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.337416
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  241
Model:                          Logit   Df Residuals:                      227
Method:                           MLE   Df Model:                           13
Date:                Wed, 20 Dec 2023   Pseudo R-squ.:                  0.5100
Time:                        11:49:51   Log-Likelihood:                -81.317
converged:                       True   LL-Null:                       -165.95
Covariance Type:            nonrobust   LLR p-value:                 2.605e-29
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.3485      1.111      3.013      0.003       1.170       5.526
age            0.0351      0.234      0.150      0.881      -0.424       0.494
sex           -1.9547      0.552     -3.543      0.000      -3.036      -0.873
cp             0.9485      0.208      4.558      0.000       0.541       1.356
trestbps      -0.2696      0.207     -1.302      0.193      -0.676       0.136
chol          -0.4675      0.243     -1.928      0.054      -0.943       0.008
fbs            0.2282      0.621      0.367      0.713      -0.989       1.445
restecg        0.1490      0.399      0.374      0.709      -0.633       0.931
thalach        0.5510      0.262      2.104      0.035       0.038       1.064
exang         -0.8479      0.478     -1.774      0.076      -1.785       0.089
oldpeak       -0.6882      0.270     -2.553      0.011      -1.217      -0.160
slope          0.4790      0.406      1.179      0.238      -0.317       1.275
ca            -0.9820      0.248     -3.956      0.000      -1.468      -0.495
thal          -0.8409      0.328     -2.562      0.010      -1.484      -0.198
==============================================================================
```

4.2 Applying Random Forest and evaluting performance

[130]:
```
from sklearn.ensemble import RandomForestClassifier
my_rf_classifier = RandomForestClassifier()
```

[131]:
```
my_rf_classifier.fit(x_train, y_train)
```

[131]:
```
RandomForestClassifier()
```

[132]:
```
my_predictions = my_rf_classifier.predict(x_test)
```

[135]:
```
print(accuracy_score(y_test, my_predictions)*100)
```

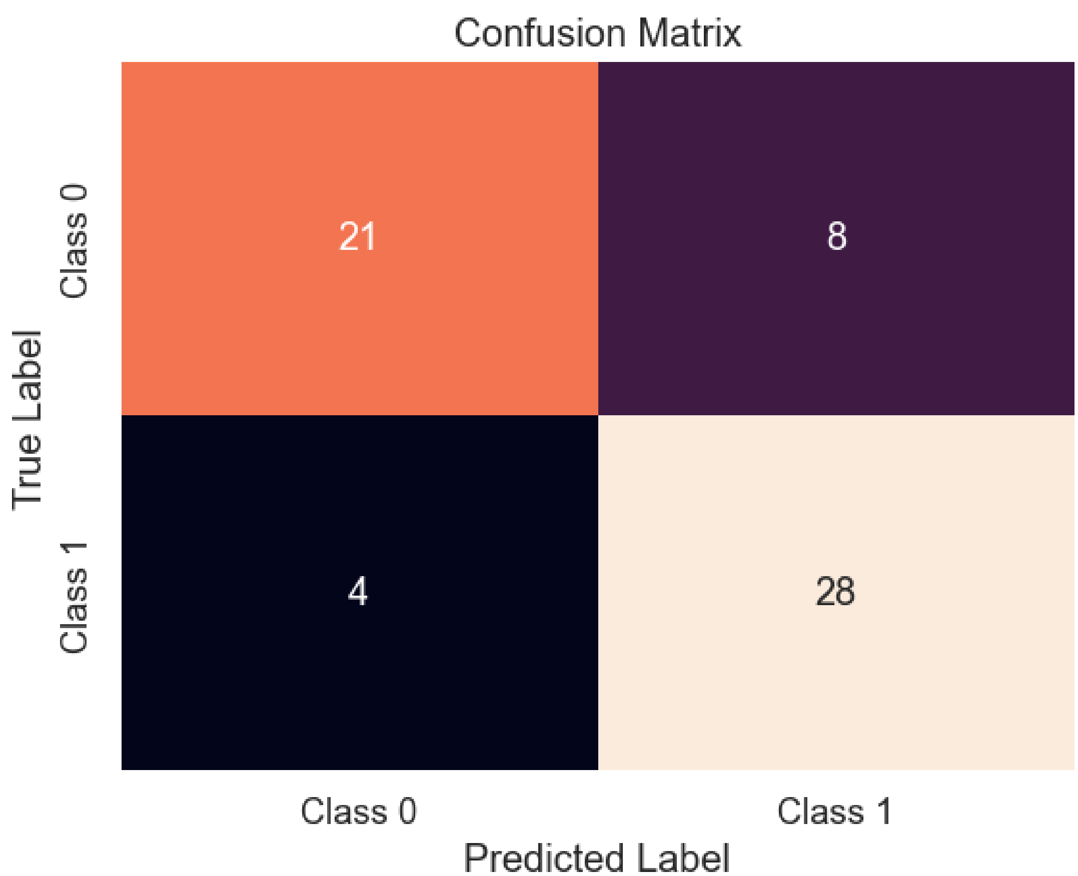
```
80.32786885245902
```

[136]:
```
print(classification_report(y_test, my_predictions))
```

```
              precision    recall  f1-score   support

           0       0.84      0.72      0.78        29
           1       0.78      0.88      0.82        32

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

[137]:

```
# Compute the confusion matrix
cm = confusion_matrix(y_test, my_predictions)
# Visualize the confusion matrix using Seaborn
sns.set(font_scale=1.2)  # Adjust font size for better readability
sns.heatmap(cm, annot=True, fmt="d", cbar=False,
            xticklabels=["Class 0", "Class 1"],
            yticklabels=["Class 0", "Class 1"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```



4.2.1 Hyperparameter tunning:

[175]:
```
my_rf_classifier1 = RandomForestClassifier(n_estimators=50,criterion='entropy')
my_rf_classifier1.fit(x_train, y_train)
my_predictions1 = my_rf_classifier1.predict(x_test)
print(accuracy_score(y_test, my_predictions1))
```

```
0.819672131147541
```

[176]:
```
print(classification_report(y_test, my_predictions1))
```

```
              precision    recall  f1-score   support

           0       0.85      0.76      0.80        29
           1       0.80      0.88      0.84        32

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

[ ]: