Github2

February 9, 2024

1 1. Data Wrangling

[2]:
```python
import pandas as pd
import numpy as np
```

[3]:
```python
df=pd.read_excel('Healthcare_dataset.xlsx')
```

[4]:
```python
df.shape
```

[4]:
```
(303, 14)
```

[5]:
```python
df.head()
```

[5]:
```
   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
```

[6]:
```python
df.isna().sum()
```

[6]:
```
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
```

No Null values detected

[7]:
```
df.duplicated().sum()
```

[7]:
```
1
```

[8]:
```
duplicate_rows = df[df.duplicated(keep=False)]
duplicate_rows
```

[8]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
163   38    1   2       138   175    0        1      173      0      0.0
164   38    1   2       138   175    0        1      173      0      0.0

     slope  ca  thal  target
163      2   4     2       1
164      2   4     2       1
```

One duplicate row detected

[9]:
```
df= df.drop_duplicates()
```

[10]:
```
df.shape
```

[10]:
```
(302, 14)
```

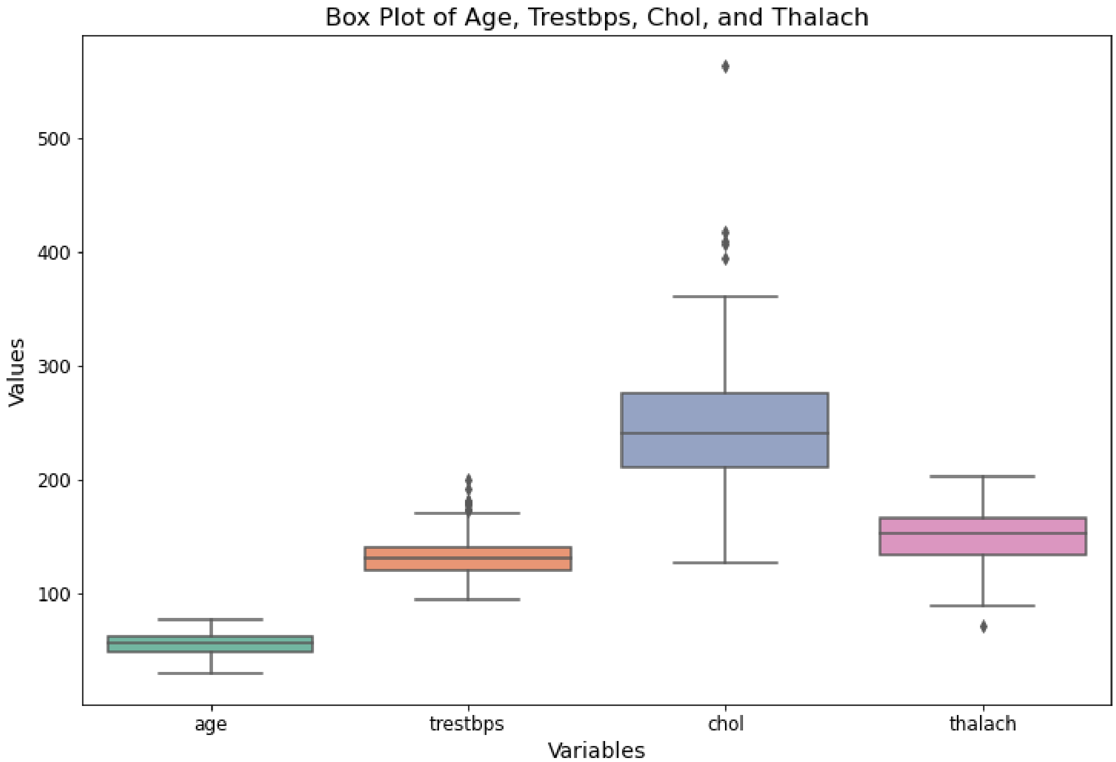
One duplicate row dropped.

[11]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[12]:
```
# Selecting the variables of interest as the spread of other variables is not␣
↪enough to accurately detect outliers
selected_variables = ['age', 'trestbps', 'chol', 'thalach']
data_selected = df[selected_variables]

# Creating the box plots
plt.figure(figsize=(12, 8))
sns.boxplot(data=data_selected, orient="v", palette="Set2")
plt.title('Box Plot of Age, Trestbps, Chol, and Thalach', fontsize=16)
plt.ylabel('Values', fontsize=14)
```

```
plt.xlabel('Variables', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.show()
```



Checked outlier in only four variables. Outliers detected in trestbps, chol and thalach.

[13]:
```
# Calculate the IQR for each variable
Q1 = df[selected_variables].quantile(0.25)
Q3 = df[selected_variables].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outlier detection
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out rows with outliers for each variable
outliers_removed = df[
    (df['age'] >= lower_bound['age']) & (df['age'] <= upper_bound['age']) &
    (df['trestbps'] >= lower_bound['trestbps']) & (df['trestbps'] <=␣
 ↪upper_bound['trestbps']) &
    (df['chol'] >= lower_bound['chol']) & (df['chol'] <= upper_bound['chol']) &
```

```
    (df['thalach'] >= lower_bound['thalach']) & (df['thalach'] <=
 ↪upper_bound['thalach'])
]

# Display the shape of the DataFrame before and after removing outliers
print("Shape of DataFrame before removing outliers:", df.shape)
print("Shape of DataFrame after removing outliers:", outliers_removed.shape)
```

```
Shape of DataFrame before removing outliers: (302, 14)
Shape of DataFrame after removing outliers: (287, 14)
```

2 2. EDA

2.1 Preliminary statistical summary of the data and the measures of central tendencies

[14]:
```
outliers_removed.describe()
```

[14]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  287.000000  287.000000  287.000000  287.000000  287.000000  287.000000
mean    54.083624    0.700348    0.972125  130.003484  242.411150    0.139373
std      9.081217    0.458906    1.030610   15.434612   44.951702    0.346940
min     29.000000    0.000000    0.000000   94.000000  126.000000    0.000000
25%     47.000000    0.000000    0.000000  120.000000  210.500000    0.000000
50%     55.000000    1.000000    1.000000  130.000000  239.000000    0.000000
75%     60.000000    1.000000    2.000000  140.000000  271.000000    0.000000
max     77.000000    1.000000    3.000000  170.000000  360.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  287.000000  287.000000  287.000000  287.000000  287.000000  287.000000
mean     0.529617  149.675958    0.320557    1.009756    1.411150    0.717770
std      0.520551   22.717855    0.467506    1.133891    0.613041    1.007211
min      0.000000   88.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  132.500000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  152.000000    0.000000    0.600000    1.000000    0.000000
75%      1.000000  167.500000    1.000000    1.600000    2.000000    1.000000
max      2.000000  202.000000    1.000000    6.200000    2.000000    4.000000

             thal      target
count  287.000000  287.000000
mean     2.299652    0.550523
std      0.615164    0.498310
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
```

2.2 Univariate Analysis of categorical variables

[15]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[17]:
```
df=outliers_removed
```

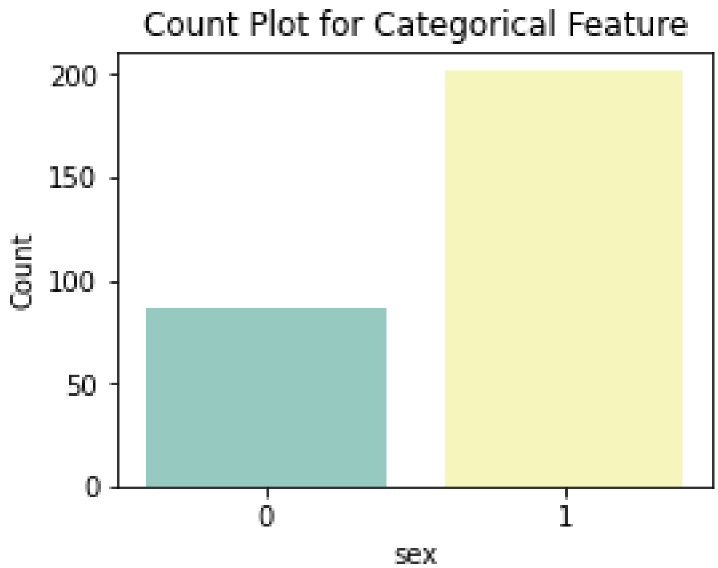
[18]:
```
df.dtypes
```

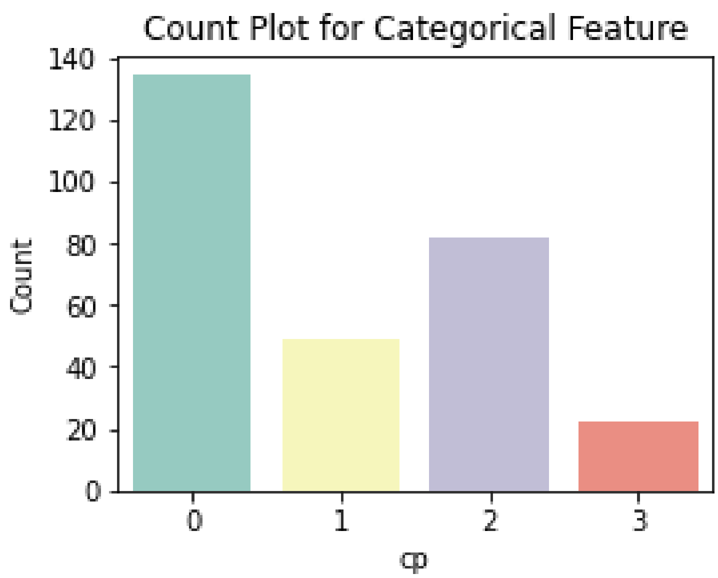
[18]:
```
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca            int64
thal          int64
target        int64
dtype: object
```

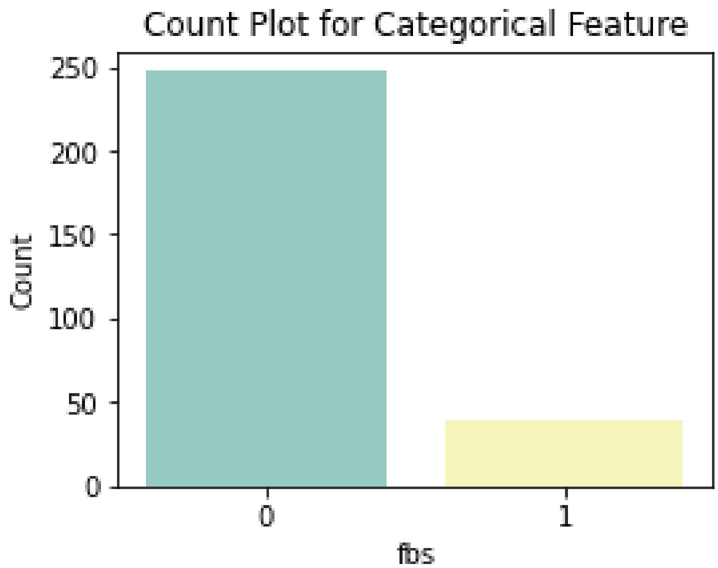
[19]:
```
for feature in df.columns:
    if len(df[feature].unique()) < 10:
        print(feature)
```

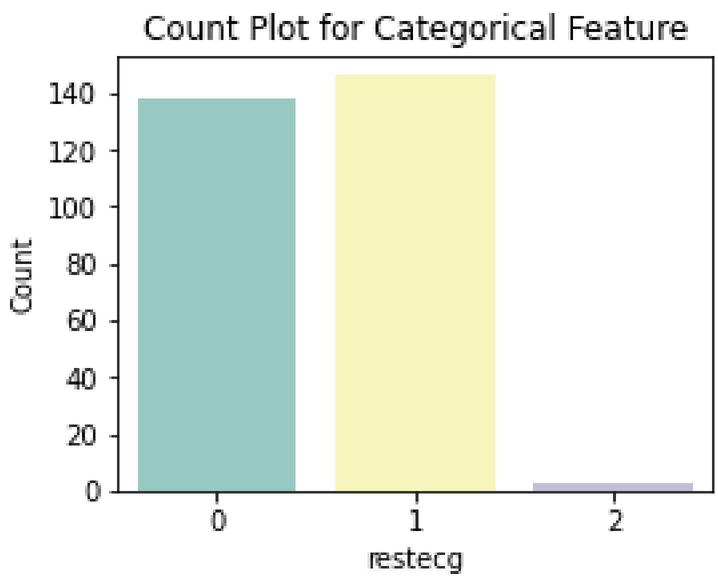
```
sex
cp
fbs
restecg
exang
slope
ca
thal
target
```

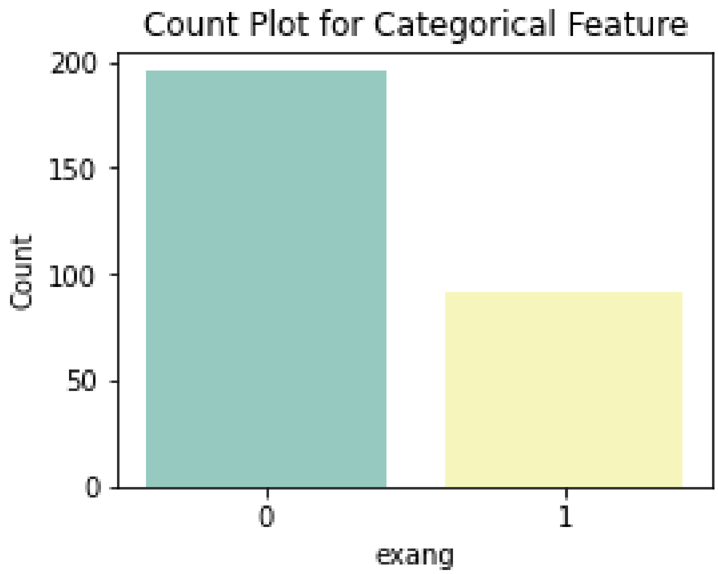
[20]:
```
for feature in df.columns:
    if len(df[feature].unique()) < 10:
        plt.figure(figsize=(4, 3))
        sns.countplot(x=feature, data=df, palette='Set3')
        plt.xlabel(feature)
        plt.ylabel('Count')
        plt.title('Count Plot for Categorical Feature')
        plt.show()
```

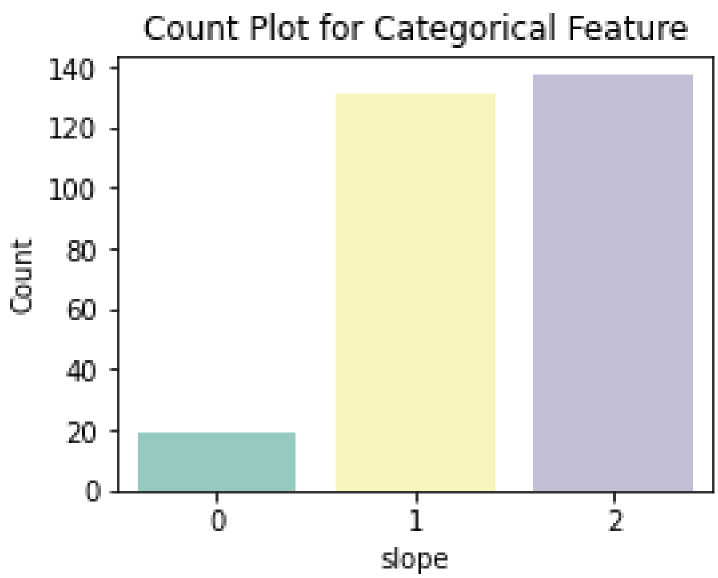

Count Plot for Categorical Feature
200
150
100
50
0
Count
0
1
sex

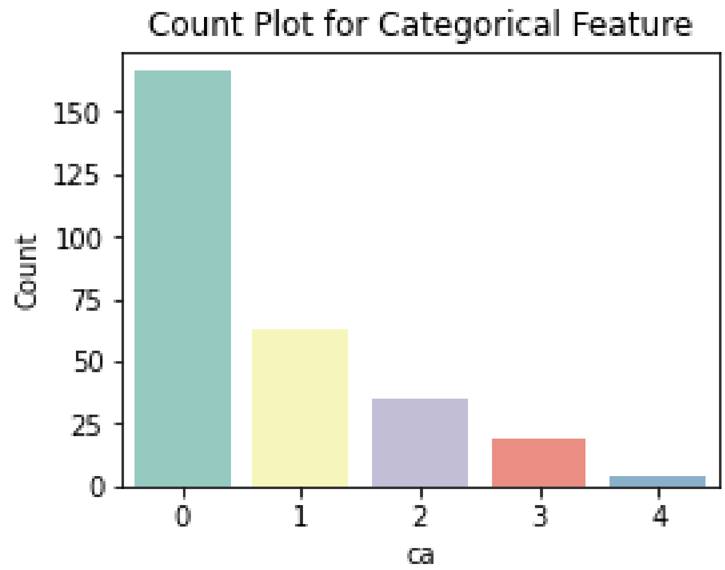

Count Plot for Categorical Feature
140
120
100
80
60
40
20
0
Count
0
1
2
3
cp

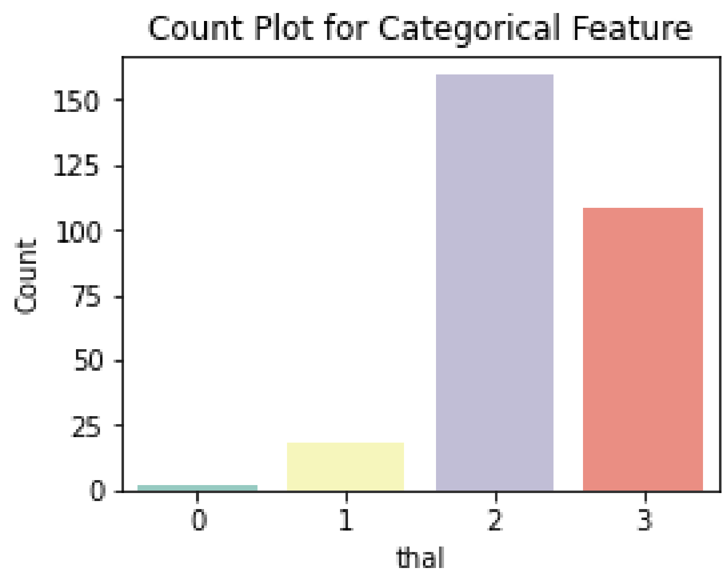

Count Plot for Categorical Feature
Count
250
200
150
100
50
0
0
1
fbs

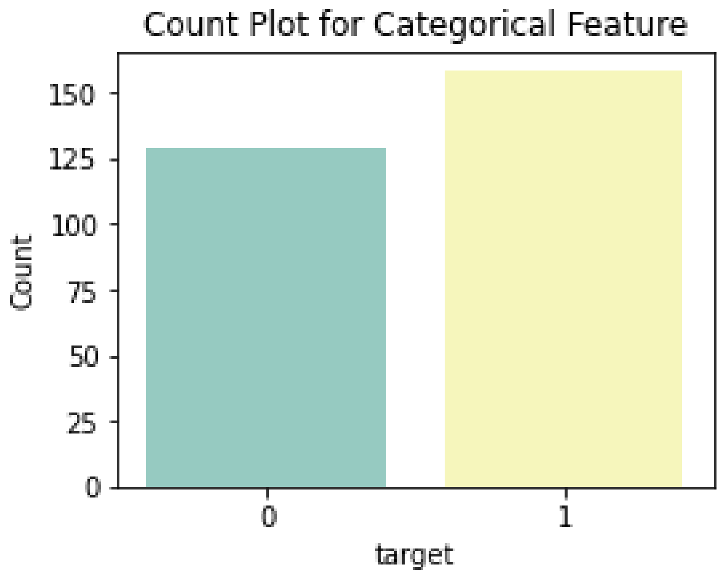

Count Plot for Categorical Feature
Count
140
120
100
80
60
40
20
0
0
1
2
restecg


Count Plot for Categorical Feature
200
150
100
50
0
Count
0
1
exang


Count Plot for Categorical Feature
140
120
100
80
60
40
20
0
Count
0
1
2
slope


Count Plot for Categorical Feature
150
125
100
75
50
25
0
Count
0
1
2
3
4
ca


Count Plot for Categorical Feature
150
125
100
75
50
25
0
Count
0
1
2
3
thal



3 Bivariate Analysis

3.1 Study the occurrence of CVD across the Age category

[21]:
```
mean_age_by_group = df.groupby('target')['age'].mean()

print(mean_age_by_group)
```

```
target
0    56.333333
1    52.246835
Name: age, dtype: float64
```

Average age where patients have CVD is 52 years aprox

3.2 Composition of all patients with respect to the Sex category

[22]:
```
count_sex = df.groupby('target')['sex'].count()

print(count_sex)
```

```
target
0    129
1    158
Name: sex, dtype: int64
```

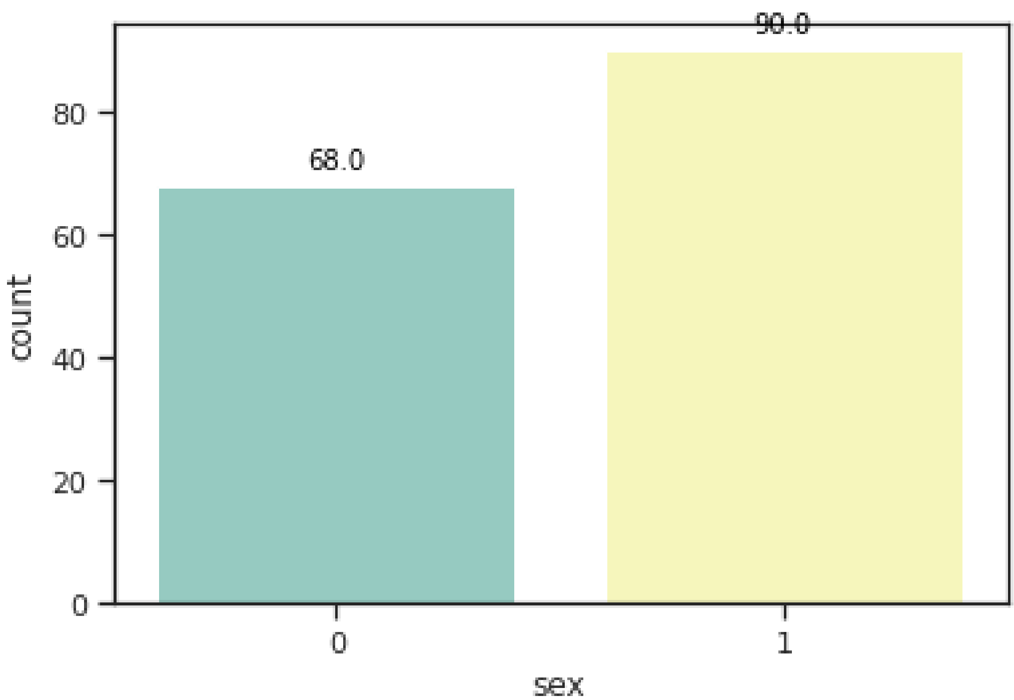
158 male patients, 129 female patients have CVD

[46]:
```python
patient_sex = df[df['target'] == 1]

# Create the count plot
ax = sns.countplot(x='sex', data=patient_sex, palette='Set3')

# Display count on each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()), ha='center', va='bottom', fontsize=10, color='black',␣
 ↪xytext=(0, 5), textcoords='offset points')

plt.show()
```



Out of 158 CVD patients, , 68 are female and 90 are male.

3.3 Multivariate analysis

3.4 Detecting heart attacks based on anomalies in the resting blood pressure, Cholestrol level and Peak Exercising of a patient

[24]:
```python
plt.figure(figsize=(15, 11))
sns.heatmap(df.corr(),annot=True)
plt.show()
```

Correlation score of Resting BP wrt target is very low (-0.12),so the anomalies in Resting BP are not a strong indicator for heart attacks

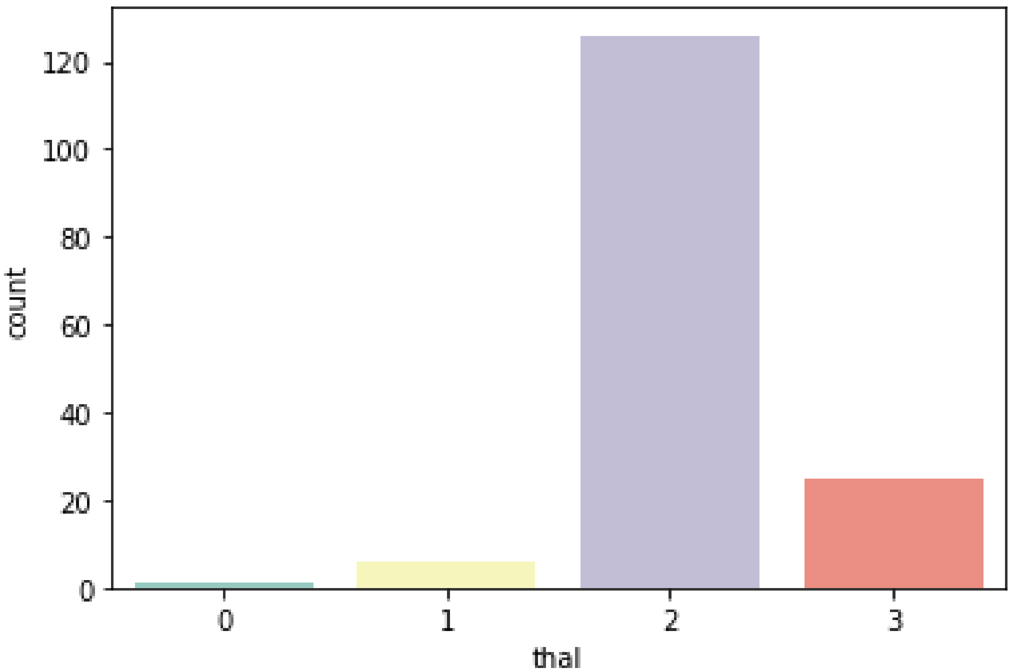
Corr score of Cholestrol level wrt target is vey low (-0.11), no conclusive relationship can be established between cholestrol level and Heart Attack as per the given dataset.

lower mean cholestrol value for confirmed Heat Attack cases

3.5 Checking if thalassemia is a major cause of CVD

[26]:
```
patient_thal = df[df['target'] == 1]
sns.countplot(x='thal', data=patient_thal, palette='Set3')
```

[26]:
```
<AxesSubplot: xlabel='thal', ylabel='count'>
```



Corr score of thal wrt target is good (-0.3), we can deduce that thal is a major cause of CVD

3.6 Other factors determine the occurrence of CVD

[27]:
```
corr_mat= df.corr()
corr_mat
```

[27]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.067799 -0.061766  0.283156  0.163933  0.105046
sex      -0.067799  1.000000 -0.091652 -0.002320 -0.106723  0.065578
cp       -0.061766 -0.091652  1.000000  0.074521 -0.080810  0.089133
trestbps  0.283156 -0.002320  0.074521  1.000000  0.096022  0.122665
chol      0.163933 -0.106723 -0.080810  0.096022  1.000000  0.012007
fbs       0.105046  0.065578  0.089133  0.122665  0.012007  1.000000
restecg  -0.107775 -0.065177  0.066719 -0.148194 -0.112741 -0.081017
thalach  -0.407455 -0.048922  0.293362 -0.076869 -0.022871 -0.018205
exang     0.088375  0.188530 -0.387777  0.006144  0.078394  0.003831
oldpeak   0.204472  0.138685 -0.157746  0.164722 -0.014519 -0.007024
slope    -0.155047 -0.057682  0.117817 -0.094012  0.039775 -0.056651
ca        0.318344  0.141673 -0.186129  0.112296  0.088448  0.142977
thal      0.054333  0.232480 -0.179806  0.009833  0.072407 -0.065303
target   -0.224237 -0.315818  0.424868 -0.122086 -0.105670 -0.020647

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.107775 -0.407455  0.088375  0.204472 -0.155047  0.318344
```

```
sex      -0.065177 -0.048922  0.188530  0.138685 -0.057682  0.141673
cp        0.066719  0.293362 -0.387777 -0.157746  0.117817 -0.186129
trestbps -0.148194 -0.076869  0.006144  0.164722 -0.094012  0.112296
chol     -0.112741 -0.022871  0.078394 -0.014519  0.039775  0.088448
fbs      -0.081017 -0.018205  0.003831 -0.007024 -0.056651  0.142977
restecg   1.000000  0.074288 -0.096618 -0.043143  0.082233 -0.067362
thalach   0.074288  1.000000 -0.394461 -0.348637  0.384432 -0.255380
exang    -0.096618 -0.394461  1.000000  0.300790 -0.254073  0.125975
oldpeak  -0.043143 -0.348637  0.300790  1.000000 -0.559600  0.229587
slope     0.082233  0.384432 -0.254073 -0.559600  1.000000 -0.088887
ca       -0.067362 -0.255380  0.125975  0.229587 -0.088887  1.000000
thal      0.015865 -0.119626  0.211936  0.191791 -0.086772  0.148256
target    0.152595  0.429382 -0.429975 -0.443331  0.343812 -0.406897

              thal    target
age       0.054333 -0.224237
sex       0.232480 -0.315818
cp       -0.179806  0.424868
trestbps  0.009833 -0.122086
chol      0.072407 -0.105670
fbs      -0.065303 -0.020647
restecg   0.015865  0.152595
thalach  -0.119626  0.429382
exang     0.211936 -0.429975
oldpeak   0.191791 -0.443331
slope    -0.086772  0.343812
ca        0.148256 -0.406897
thal      1.000000 -0.346123
target   -0.346123  1.000000
```

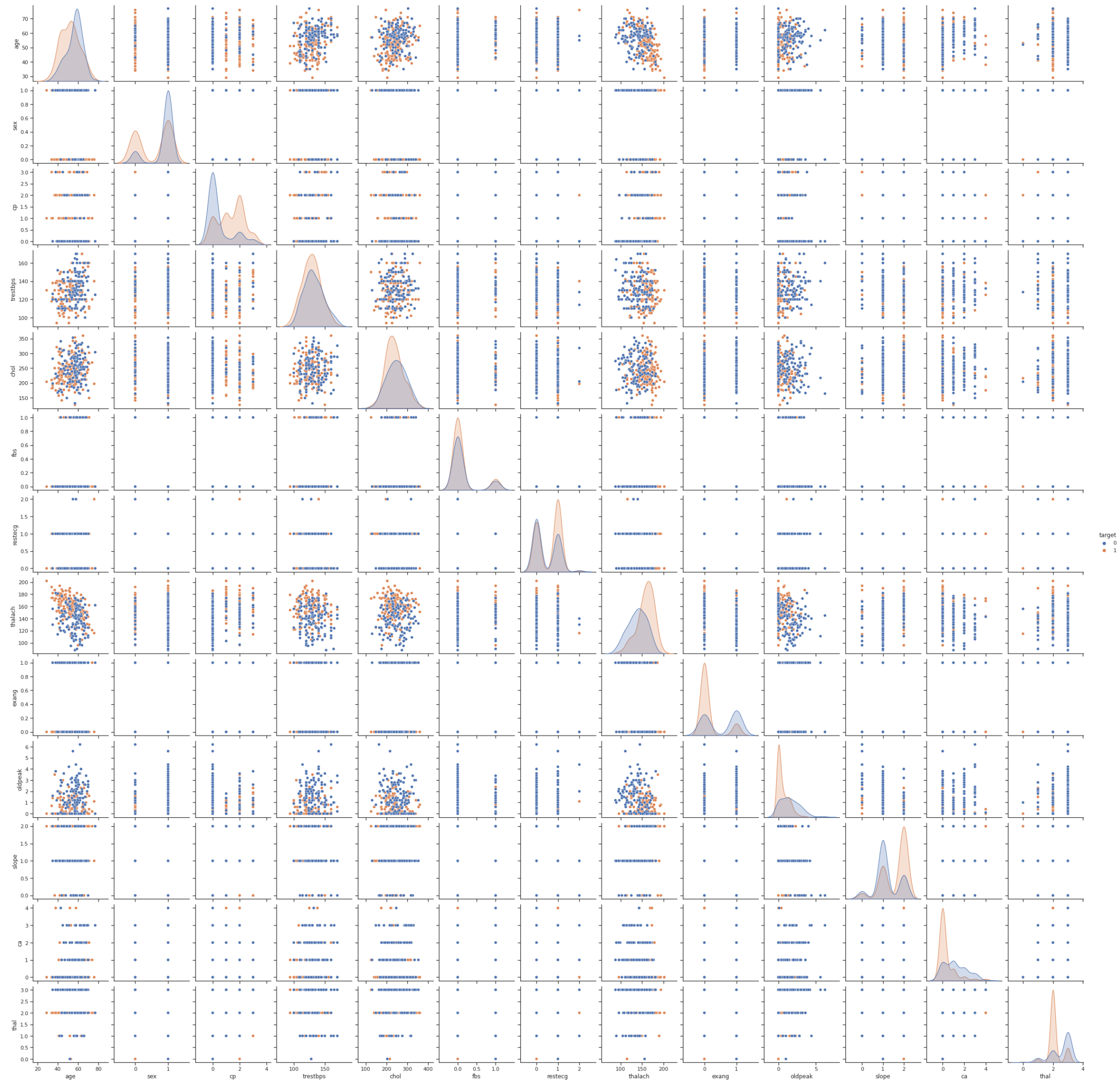
Considering variables with corr score with target > 0.2 as siggnificant, variables age,sex,cp,thalach,exang,oldpeak,slope,ca & thal impact the occurance of CVD the most.

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

[28]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

[29]:
```
sns.set(style="ticks")
sns.pairplot(df,hue='target')

plt.show()
```



3.8 3. ML Models

[30]:
```
X=df.drop('target', axis = 1)
y=df['target']
```

[31]:
```
X.shape
```

[31]: (287, 13)

[32]:
```
y.shape
```

[32]: (287,)

```
[33]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪25,random_state=32,stratify=y)
```

(i) Logistic Regression

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

logistic_reg = LogisticRegression()

logistic_reg.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:460:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[34]: LogisticRegression()
```

```
[35]: y_pred=logistic_reg.predict(X_test)
y_pred
```

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

```
[36]: from sklearn.metrics import confusion_matrix

confusion = confusion_matrix(y_test, y_pred)

print("Confusion Matrix:")
print(confusion)
```

```
Confusion Matrix:
[[24  8]
 [ 8 32]]
```

```
[37]: from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score

accuracy = accuracy_score(y_test, y_pred)
```

```python
precision = precision_score(y_test, y_pred)

recall = recall_score(y_test, y_pred)

f1 = f1_score(y_test, y_pred)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.7777777777777778
Precision: 0.8
Recall: 0.8
F1 Score: 0.8000000000000002
```

(ii) KNN model

[38]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn_clf=KNeighborsClassifier(n_neighbors=5, metric = 'euclidean')
knn_clf.fit(X_train,y_train)
```

[38]:
```
KNeighborsClassifier(metric='euclidean')
```

[39]:
```python
y_pred_knn=knn_clf.predict(X_test)
y_pred_knn
```

[39]:
```
array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 0, 1, 0, 0])
```

[40]:
```python
accuracy_knn = accuracy_score(y_test, y_pred_knn)

precision_knn = precision_score(y_test, y_pred_knn)

recall_knn = recall_score(y_test, y_pred_knn)

f1_knn = f1_score(y_test, y_pred_knn)

print("Accuracy:", accuracy_knn)
print("Precision:", precision_knn)
print("Recall:", recall_knn)
print("F1 Score:", f1_knn)
```

```
Accuracy: 0.6111111111111112
```

```
Precision: 0.6764705882352942
Recall: 0.575
F1 Score: 0.6216216216216216
```

(iii) SVM Model

[41]:
```python
from sklearn.svm import SVC
```

[42]:
```python
svm=SVC()
svm.fit(X_train,y_train)
```

[42]:
```
SVC()
```

[43]:
```python
y_pred_svm=svm.predict(X_test)
y_pred_svm
```

[43]:
```
array([1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1,
       0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       0, 1, 0, 1, 0, 1])
```

[44]:
```python
accuracy_svm = accuracy_score(y_test, y_pred_svm)

precision_svm = precision_score(y_test, y_pred_svm)

recall_svm = recall_score(y_test, y_pred_svm)

f1_svm = f1_score(y_test, y_pred_svm)

print("Accuracy:", accuracy_svm)
print("Precision:", precision_svm)
print("Recall:", recall_svm)
print("F1 Score:", f1_svm)
```

```
Accuracy: 0.5555555555555556
Precision: 0.5869565217391305
Recall: 0.675
F1 Score: 0.627906976744186
```

Out of three models, Logistic Regression gives best results.

[ ]:
```

```