Heart Attack Risk Prediction: A Case Study

This Data is regarding the Heart Attack Risk Prediction where we having the multiple features to check the Heart Attack Risk. Now we'll perform a lot of analysis to our dataset also we'll create a ML model which will help us to get to know which Data consist to more heart attack risk.

About the Dataset:

- **Age-:** Age of the Patient
- **Sex-:** Gender of the Patient
- **CP-:** Type of Chest Pain
    - Value 1: typical angina
    - Value 2: A-typical angina
    - Value 3: non-anginal pain
    - Value 4: asymptomatic
- **trtbps-:** trestbps (Resting Blood Pressure)
- **Chol-:** Cholesterol
- **FBS-:** Fasting Blood Sugar
- **rest_ecg-:** Resting Electrocardiographic Results
    - Value 0: normal
    - Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)
    - Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
- **exang-:** Exercise Induced Angina (1 - Yes; 0 - No)
- **OldPeak-:** Previous Peak
- **SLP-:** Slope
- **caa-:** Number of Major Vessels
- **thall-:** Thallium Stress Test Result (0-3)
- **Output-:** Whether the Patient Has Heart Attack Risk or Not
    - 1 - The Person Has Heart Attack Risk
    - 2 - The Person Does Not Have Heart Attack Risk

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Loading the Standard Libraries

In [190…

```
import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as sts
```

Loading the Dataset

In [191…

```
df = pd.read_csv('Dataset/heart.csv')
df.head()
```

Out[191…

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Fetching some information with data

In [192…

```
df.shape
```

Out[192…

```
(303, 14)
```

In [193…

```
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   trtbps    303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   restecg   303 non-null    int64  
 7   thalachh  303 non-null    int64  
 8   exng      303 non-null    int64  
 9   oldpeak   303 non-null    float64
 10  slp       303 non-null    int64  
 11  caa       303 non-null    int64  
 12  thall     303 non-null    int64  
 13  output    303 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

Observation-: There having only **303** Record with **14** Features also there is no as such object or any irrelevant data type format which we need to transform all data are in the form of **int** and **float**

In [194…

```
df.describe().T
```

Out[194…

	count	mean	std	min	25%	50%	75%	max
age	303.0	54.366337	9.082101	29.0	47.5	55.0	61.0	77.0
sex	303.0	0.683168	0.466011	0.0	0.0	1.0	1.0	1.0
cp	303.0	0.966997	1.032052	0.0	0.0	1.0	2.0	3.0
trtbps	303.0	131.623762	17.538143	94.0	120.0	130.0	140.0	200.0
chol	303.0	246.264026	51.830751	126.0	211.0	240.0	274.5	564.0
fbs	303.0	0.148515	0.356198	0.0	0.0	0.0	0.0	1.0
restecg	303.0	0.528053	0.525860	0.0	0.0	1.0	1.0	2.0
thalachh	303.0	149.646865	22.905161	71.0	133.5	153.0	166.0	202.0
exng	303.0	0.326733	0.469794	0.0	0.0	0.0	1.0	1.0
oldpeak	303.0	1.039604	1.161075	0.0	0.0	0.8	1.6	6.2
slp	303.0	1.399340	0.616226	0.0	1.0	1.0	2.0	2.0
caa	303.0	0.729373	1.022606	0.0	0.0	0.0	1.0	4.0
thall	303.0	2.313531	0.612277	0.0	2.0	2.0	3.0	3.0
output	303.0	0.544554	0.498835	0.0	0.0	1.0	1.0	1.0

Observation:-

- Age :-
  - The Maximum Age of Our Patient is :- 77
  - The Miniumu Age of Our Patient is :- 29
  - The Average Age of Our Patient is :- 55
- trtbps : - **Resting Blood Presure**

Our Resing Blood presure reading should be between 120 / 180. if it's more than 180 it's very critical condition we should immediate seek for medical treatment * The Maximum trtbps of Our Patient is :- 200 which is very critical condition for our patients * The Minimum trtbs of Our

Patient is :- 94 which is low blood presure which is not critical but it's not that much good for our health * The Agerage trtbs of Our Patients is :- 131 which is preety normal

- Chol :- **Cholesterol**

Our Cholerterol Level should under 200-240 * The Maximum Cholerterol of Our Patient is :- 564 which can significantly increase the risk of heat attack * The minimum cholerterol of Our Patient is :- 211 which can also signficat increse the risk of heat attack * The Average Cholerterol of Our Patient is :- 246 which is preety normal

Let's do some Sainity of the Data

In [195...
```
df.duplicated().sum()
```

Out[195...
```
1
```

In [196...
```
df[df.duplicated()]
```

Out[196...

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
164	38	1	2	138	175	0	1	173	0	0.0	2	4	2	1

Observation-: Our Data is containing only 1 duplicates values let's drop it out

In [197...
```
df = df.drop_duplicates()
```

Let's Check the Unique Value in our dataset

In [198...
```
df.nunique()
```

Out[198…

```
age          41
sex           2
cp            4
trtbps       49
chol        152
fbs           2
restecg       3
thalachh     91
exng          2
oldpeak      40
slp           3
caa           5
thall         4
output        2
dtype: int64
```

Let's Check the Null Value From Our Dataset

In [199…

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

Out[199…

```
age         0
sex         0
cp          0
trtbps      0
chol        0
fbs         0
restecg     0
thalachh    0
exng        0
oldpeak     0
slp         0
caa         0
thall       0
output      0
dtype: int64
```

Observation:- There are no as such missing values in our dataset

EDA

In [200…

```
df['sex'].value_counts()
```

Out[200…

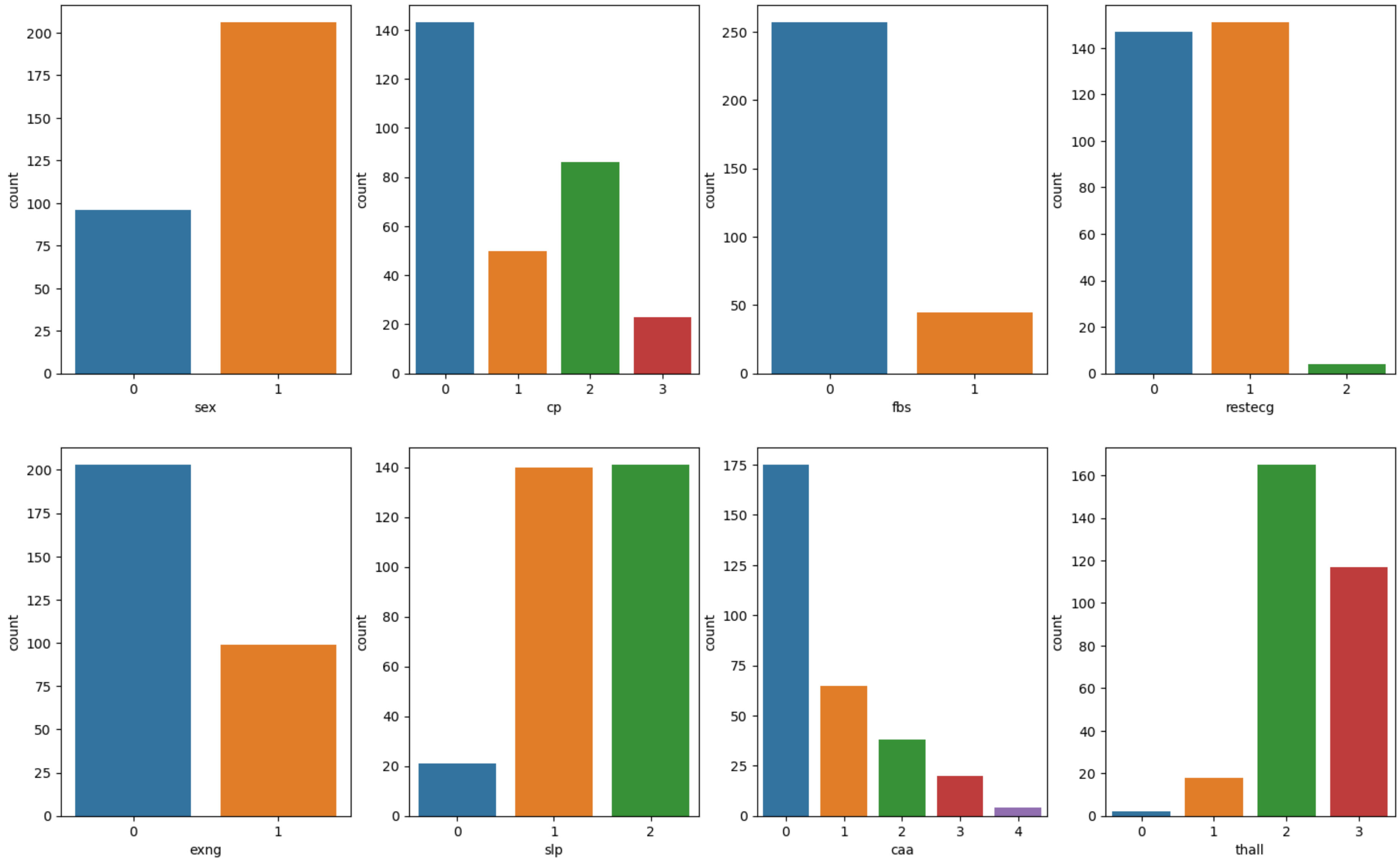
```
sex
1    206
0     96
Name: count, dtype: int64
```

In [201…

```
cate_value = ['sex', 'cp', 'fbs', 'restecg', 'exng', 'slp', 'caa', 'thall']
```

In [202…

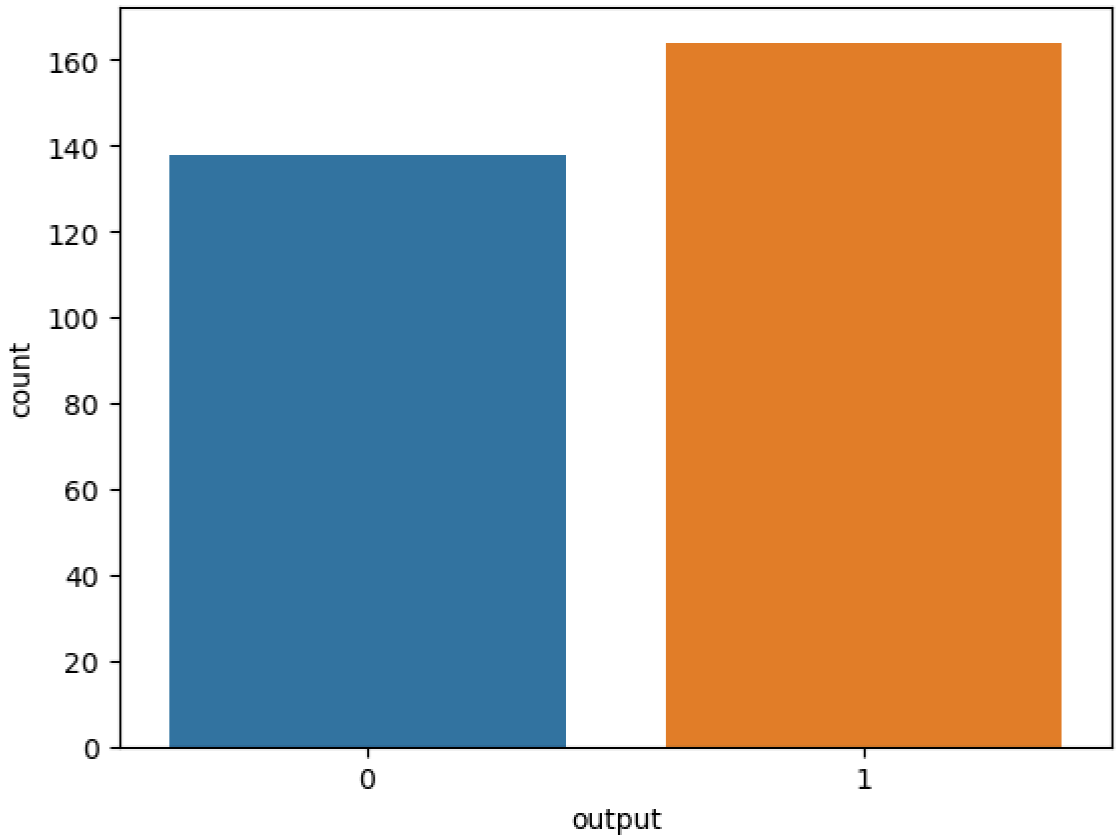
```
fig , axes = plt.subplots(2,4,figsize = (18,11))
axes = axes.flatten()
for i in range(len(cate_value)):
    sns.countplot(data = df , x = cate_value[i], ax = axes[i])
```



Countplot of Target

In [203…

```
sns.countplot(data = df , x = 'output')
plt.show()
```



Let's See the Correleation on the matrix

In [204…

```
num_col = ['age', 'trtbps', 'chol', 'thalachh', 'oldpeak']
df_corr = df[num_col].corr().T
df_corr
```

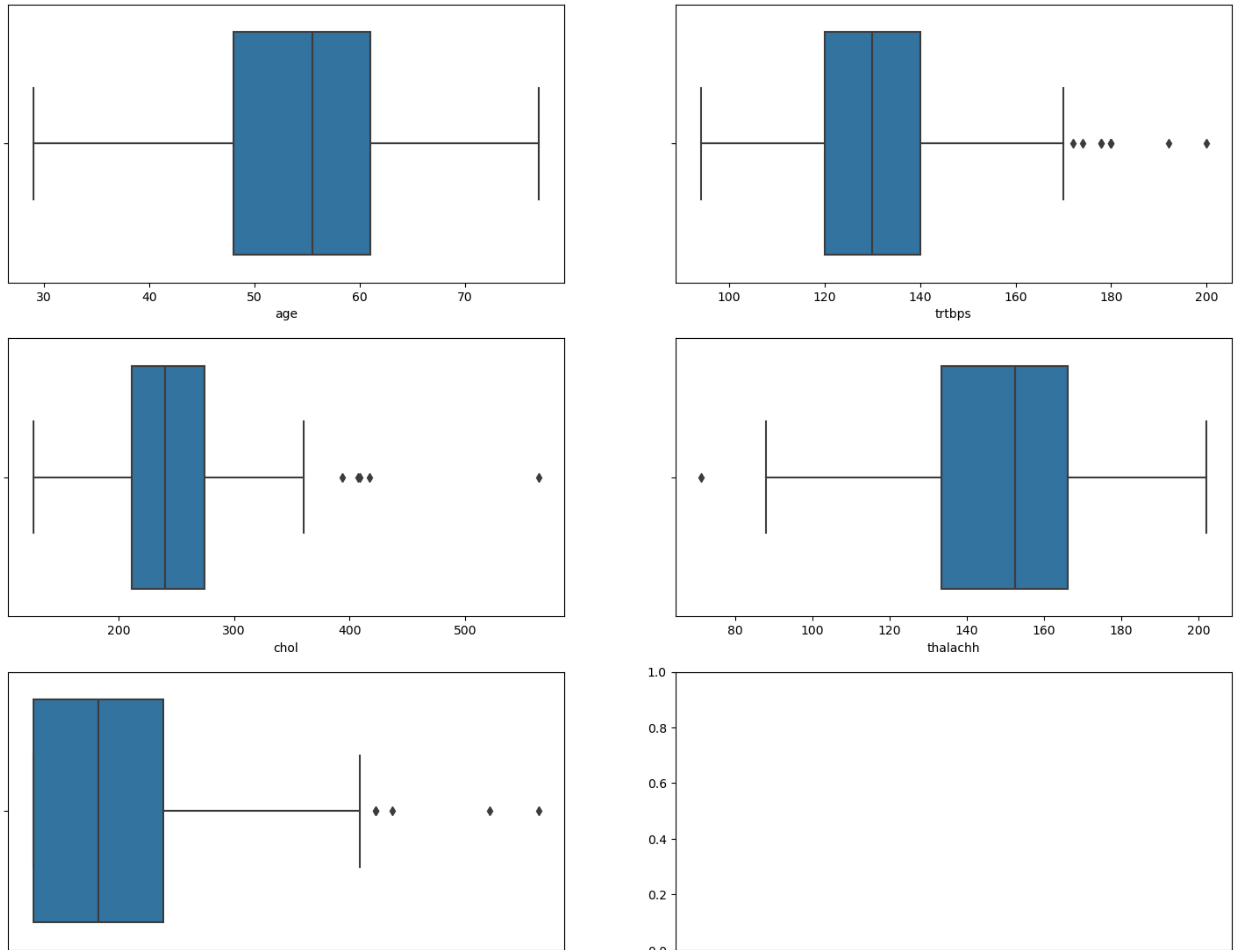
Out[204…

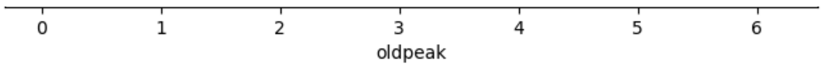
	age	trtbps	chol	thalachh	oldpeak
age	1.000000	0.283121	0.207216	-0.395235	0.206040
trtbps	0.283121	1.000000	0.125256	-0.048023	0.194600
chol	0.207216	0.125256	1.000000	-0.005308	0.050086
thalachh	-0.395235	-0.048023	-0.005308	1.000000	-0.342201
oldpeak	0.206040	0.194600	0.050086	-0.342201	1.000000

Outliers

In [205…

```
fig , axes = plt.subplots(3,2 , figsize = (18,14))
axes = axes.flatten()
for i in range(len(num_col)):
    sns.boxplot(data = df , x = num_col[i], ax = axes[i])
plt.show()
```


30
40
50
60
70
age
100
120
140
160
180
200
trtbps
200
300
400
500
chol
80
100
120
140
160
180
200
thalachh
1.0
0.8
0.6
0.4
0.2



Obsevation-: As we can see there are some outliers in out dataset we can remove this if we don't lost lot of data

Removing the Outliers

In [206…

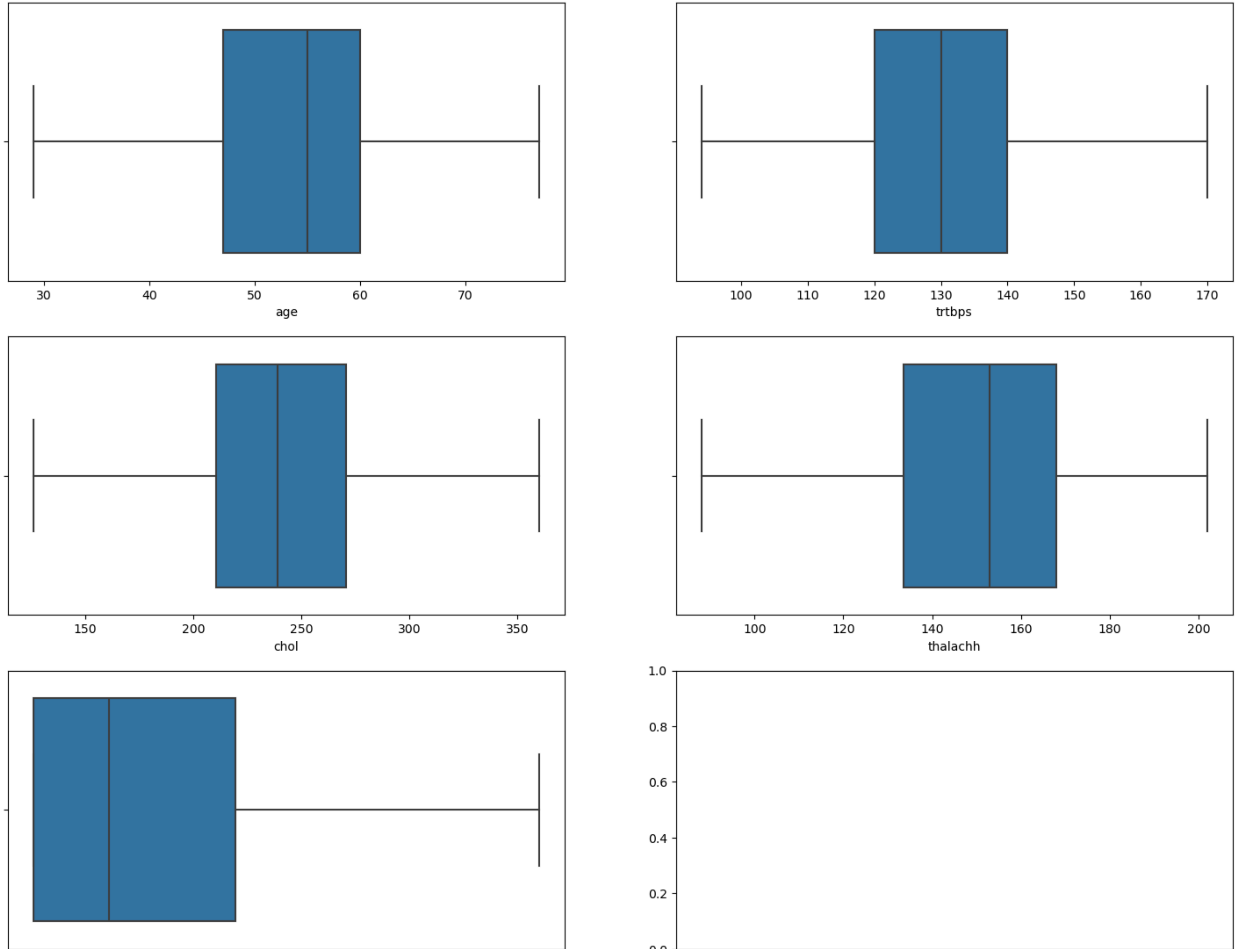
```
s = set()
for i in df[num_col]:
    q1 = df[i].quantile(0.25)
    q3 = df[i].quantile(0.75)
    iqr = q3-q1
    lower_bond = q1 - 1.5 * (iqr)
    upper_bond = q3 + 1.5 * (iqr)
    index_ = df[(df[i] < lower_bond ) | (df[i] >upper_bond)].index.tolist()
    s.update(index_)
print(f"The Index Where We Have the Outliers : {s}")
print(f"The Number of Data Which we lost : {len(s)}")
df = df.drop(s)
```

```
The Index Where We Have the Outliers : {260, 8, 266, 272, 28, 291, 203, 204, 85, 220, 221, 223, 96, 101, 110, 241, 246, 248, 25
0}
The Number of Data Which we lost : 19
```

Observation:- We have lost almost 19 records which was treated as outliers now if we check that are still dataset is contating the outliers after applying method of removing the outliers

In [207…

```
fig , axes = plt.subplots(3,2 , figsize = (18,14))
axes = axes.flatten()
for i in range(len(num_col)):
    sns.boxplot(data = df , x = num_col[i], ax = axes[i])
plt.show()
```

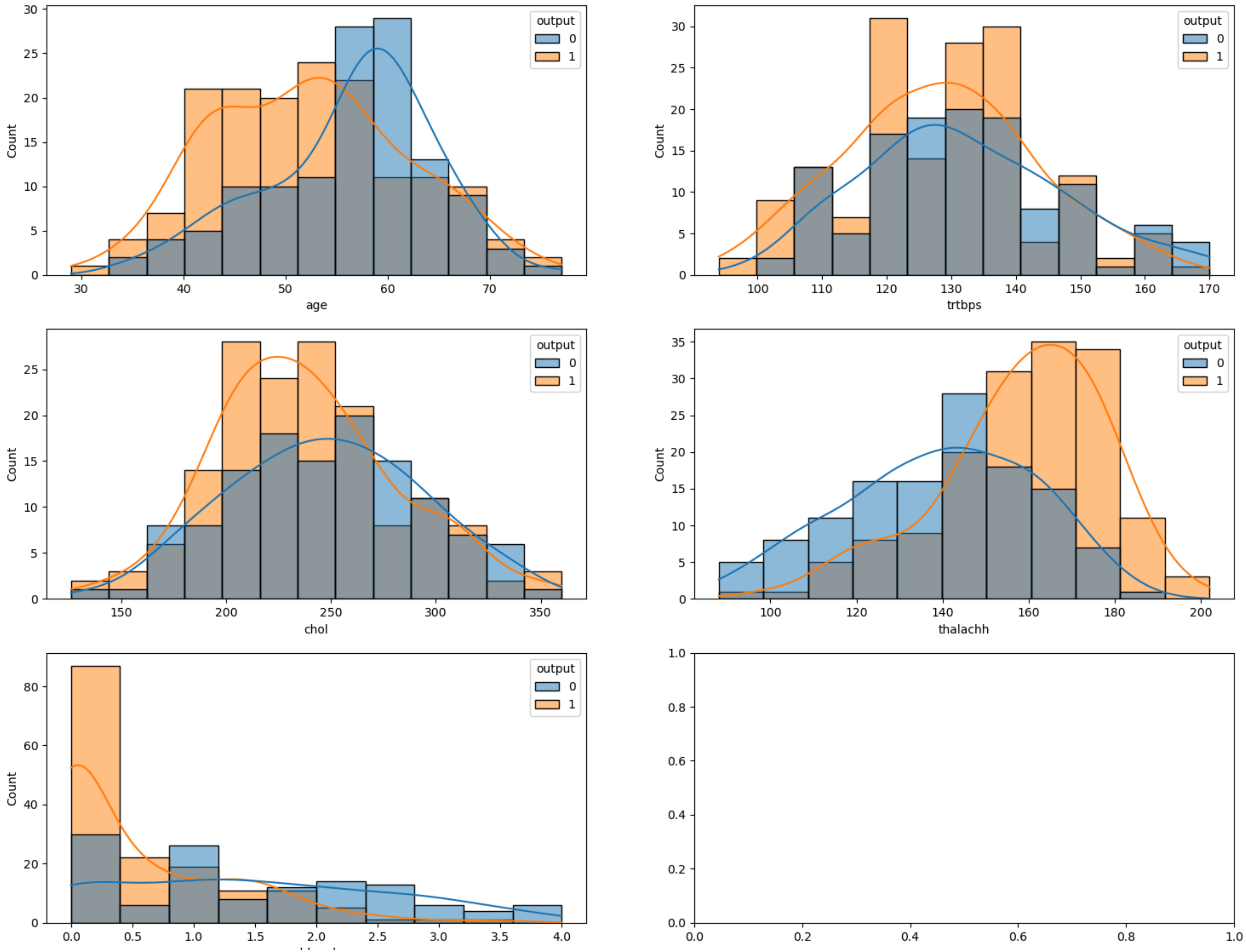

30
40
50
60
70
age
100
110
120
130
140
150
160
170
trtbps
150
200
250
300
350
chol
100
120
140
160
180
200
thalachh
1.0
0.8
0.6
0.4
0.2

Observation:- As you can see there are no as such outliers is our dataset

Now We'll See the Distribution of the Continues Column

In [208…

```
fig , axes = plt.subplots(3,2,figsize = (18,14))
axes = axes.flatten()
for i in range(len(num_col)):
    sns.histplot(data = df , x = num_col[i], hue = 'output', ax = axes[i], fill = True, kde = True)
```


output
0
1
Count
age
trtbps
chol
thalachh

oldpeak

Observation-: As we can see our age , trtbp , chol are normally distributed whereas oldpeak is left-skewed distribution and thalachh is a bit right skewed distributed.

- **Age:-**
  - More Risk of Heart Attack is between to Age Group of 40-55
  - Whereas is the Less Risk of Heart Attack is Between Age Group of 55-65
- **trtbps:- trestbps (Resting Blood Pressure).**
  - More Risk of Heart Attack Patient with low BP 95- 105 also with high BP of 120-140 some there is some patient is also there with the BP of 145-155.
  - Where as Less Risk of Heart Attack Patient **Resting Blood Pressure** is 140-145 also there some patient has been observed with low Risk of Heart Attack with the BP of 155-170
- **Chol (Cholesterol) :-**.
  - Cholesterol Level Make Huges impact of Heart Attack Risk. More People Having Heart Attack Risk with the Cholesterol Level of 145-250. but few people also have been observed with Heart Attack Risk at Cholesterol Level 350.
  - Where Less Risk of Heart Attack Risk of Patient has been observed 260 - 300.
- **thalachh (The Person Heart Rate Achieved) :-**
  - The Higher Risk of Heart Attack Patinent is 150-200
  - The Low Risk of Heart Attack Patient is 90 - 140

Data Preprocessing

1) Seperating the Dependent and Independent Features

In [209…
```
df_ = df.copy()
x = df_.drop('output', axis = 1)
y = df_[['output']]
```

2) Spliting the Dataset

In [210…
```
from sklearn.model_selection import train_test_split
```

In [211…
```
x_train , x_test , y_train,  y_test = train_test_split(x,y,random_state = 42 , test_size = 0.25)
```

In [212…
```
x_train.shape , y_train.shape , x_test.shape , y_test.shape
```

Out[212…
```
((212, 13), (212, 1), (71, 13), (71, 1))
```

Feature Engineering

1) Numerical Data Encoding

In [213…
```
from sklearn.preprocessing import StandardScaler
```

In [214…
```
ss = StandardScaler()
ss
```

Out[214…
```
▾ StandardScaler
StandardScaler()
```

In [215…
```
x_train[['age','trtbps','chol','thalachh']] = ss.fit_transform(x_train[['age','trtbps','chol','thalachh']])
```

In [216…
```
def transform(x_test):
    x_test[['age','trtbps','chol','thalachh']] = ss_new.transform(x_test[['age','trtbps','chol','thalachh']])
    return x_test
```

In [217…
```
import pickle
f = open("Feature Scaler File\\StandardScaler.pkl", "wb")
pickle.dump(ss, f)
f.close()
```

Modeling

1) LogisticRegression

In [218…
```
from sklearn.linear_model import LogisticRegression
```

In [219…
```
lr = LogisticRegression()
lr
```

Out[219…
```
▾ LogisticRegression
LogisticRegression()
```

In [220…
```
lr.fit(x_train , y_train)
```

Out[220…
```
▾ LogisticRegression
LogisticRegression()
```

In [221…
```
lr.coef_
```

Out[221…
```
array([[ 0.02512152, -1.30496145,  0.67026635, -0.28378598, -0.35751672,
        -0.28348342,  0.63866043,  0.74933245, -0.74104964, -0.54843962,
         0.49907719, -0.5671385 , -1.08789224]])
```

In [222…
```
lr.intercept_
```

Out[222…
```
array([3.1373863])
```

In [223…
```
import pickle
```

In [224…
```
file = open("Feature Scaler File\\StandardScaler.pkl", "rb")
ss_new = pickle.load(file)
```

In [225…
```
def transform(x_test):
    x_test[['age','trtbps','chol','thalachh']] = ss_new.transform(x_test[['age','trtbps','chol','thalachh']])
    return x_test

x_test_ = transform(x_test)
```

In [226…
```
y_pred_test = lr.predict(x_test_)
```

In [227…
```
pd.DataFrame({"predicted":y_pred_test, "actual":y_test['output']}).head()
```

Out[227…

	predicted	actual
10	1	1
263	1	0
145	1	1
216	0	0
77	1	1

In [228…
```
lr.score(x_train, y_train)
```

Out[228…
```
0.8632075471698113
```

Accuracy

In [229…
```
from sklearn.metrics import classification_report , accuracy_score , confusion_matrix
```

In [230…
```
print(classification_report(y_test ,y_pred_test ))
print(confusion_matrix(y_test, y_pred_test))
print(f"Accuracy Score of the Test Data-: {round(accuracy_score(y_test , y_pred_test)*100,3)} %")
```

```
              precision    recall  f1-score   support

           0       0.81      0.70      0.75        30
           1       0.80      0.88      0.84        41

    accuracy                           0.80        71
   macro avg       0.80      0.79      0.79        71
weighted avg       0.80      0.80      0.80        71

[[21  9]
 [ 5 36]]
Accuracy Score of the Test Data-: 80.282 %
```

Observation:- We got Test Accuracy as 83.099 we'll perform the hyperpermeter tunning to see weather we can improve the accuracy of the model or not

Hyperperameter Tunning

In [231…
```
from sklearn.model_selection import GridSearchCV
```

In [232…
```
parameter = {"penalty":["l1","l2","elasticnet"], "C" : [10,50,100, 500], "random_state" : [42], "solver":["liblinear","saga"]}
```

In [233…
```
gsv = GridSearchCV(lr , param_grid = parameter, cv = 10)
```

In [234…
```
gsv
```

Out[234…
```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [235…
```
np.ravel(y_train).shape
```

Out[235…
```
(212,)
```

In [236…
```
import warnings
warnings.filterwarnings('ignore')
gsv.fit(x_train ,y_train['output'])
```

Out[236…
```
GridSearchCV
estimator: LogisticRegression
LogisticRegression
```

In [237…
```
gsv.best_params_
```

Out[237…
```
{'C': 10, 'penalty': 'l2', 'random_state': 42, 'solver': 'liblinear'}
```

In [238…
```
gsv.best_estimator_
```

Out[238…
```
LogisticRegression
LogisticRegression(C=10, random_state=42, solver='liblinear')
```

In [239…
```
lr_ = LogisticRegression(C= 10, penalty='l2', random_state= 42, solver='liblinear')
```

Observation-: We have Added the Best Predicted Perameter into Logistic Regression. Now We'll See is there any changes in Accuracy Score

In [240…
```
lr_.fit(x_train, y_train)
```

Out[240…
```
LogisticRegression
LogisticRegression(C=10, random_state=42, solver='liblinear')
```

In [241…
```
lr_.coef_
```

Out[241…
```
array([[ 0.05318007, -1.60969064,  0.72833798, -0.32335647, -0.40054777,
        -0.36606581,  0.7601775 ,  0.82466617, -0.84674224, -0.52783103,
         0.6169009 , -0.58740307, -1.16395227]])
```

In [242…
```
lr_.intercept_
```
Out[242…
```
array([3.27403243])
```
In [243…
```
y_pred_test_ = lr_.predict(x_test)
```
In [244…
```
print(f"The Training Score : {lr_.score(x_train , y_train)*100}")
```
```
The Training Score : 86.79245283018868
```

Now we'll check the score of accuracy

In [245…
```
print(classification_report(y_test ,y_pred_test_ ))
print(confusion_matrix(y_test, y_pred_test_))
print(f"Accuracy Score of the Test Data-: {round(accuracy_score(y_test , y_pred_test_)*100,3)} %")
```
```
              precision    recall  f1-score   support

           0       0.75      0.70      0.72        30
           1       0.79      0.83      0.81        41

    accuracy                           0.77        71
   macro avg       0.77      0.76      0.77        71
weighted avg       0.77      0.77      0.77        71

[[21  9]
 [ 7 34]]
Accuracy Score of the Test Data-: 77.465 %
```

As we can see we have impovement of 1% of the Model

In [246…
```
f = open("ML Model//Logistic_Regression.pkl", "wb")
pickle.dump(lr_, f)
f.close()
```

DecisionTree Classifier

Now We'll Try Another Algorithym Which is know as Decision

In [247…
```
from sklearn.tree import DecisionTreeClassifier
```

In [248…
```
dtc = DecisionTreeClassifier()
dtc
```

Out[248…
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [249…
```
dtc.fit(x_train , y_train)
```

Out[249…
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [250…
```
dtc_y_pred = dtc.predict(x_test)
```

In [251…
```
print(classification_report(y_test ,dtc_y_pred ))
print(confusion_matrix(y_test, dtc_y_pred))
print(f"Accuracy Score of the Test Data-: {round(accuracy_score(y_test ,dtc_y_pred)*100,3)} %")
```

```
              precision    recall  f1-score   support

           0       0.60      0.70      0.65        30
           1       0.75      0.66      0.70        41

    accuracy                           0.68        71
   macro avg       0.68      0.68      0.67        71
weighted avg       0.69      0.68      0.68        71

[[21  9]
 [14 27]]
Accuracy Score of the Test Data-: 67.606 %
```

In [252...
```
dtc.get_depth()
```

Out[252... 9

In [253...
```
dtc = DecisionTreeClassifier(max_depth = 3)
dtc.fit(x_train , y_train)
```

Out[253...
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3)
```

In [254...
```
print(f"The Accuracy of Train Dataset is -: {dtc.score(x_train , y_train) * 100}")
```

```
The Accuracy of Train Dataset is -: 85.84905660377359
```

In [255...
```
dtc_y_pred_test = dtc.predict(x_test)
dtc_y_pred_test
```

Out[255...
```
array([1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,
       1, 1, 0, 1, 1], dtype=int64)
```

In [256...
```
print(classification_report(y_test ,dtc_y_pred_test ))
print(confusion_matrix(y_test, dtc_y_pred_test))
print(f"Accuracy Score of the Test Data-: {round(accuracy_score(y_test ,dtc_y_pred_test)*100,3)} %")
```

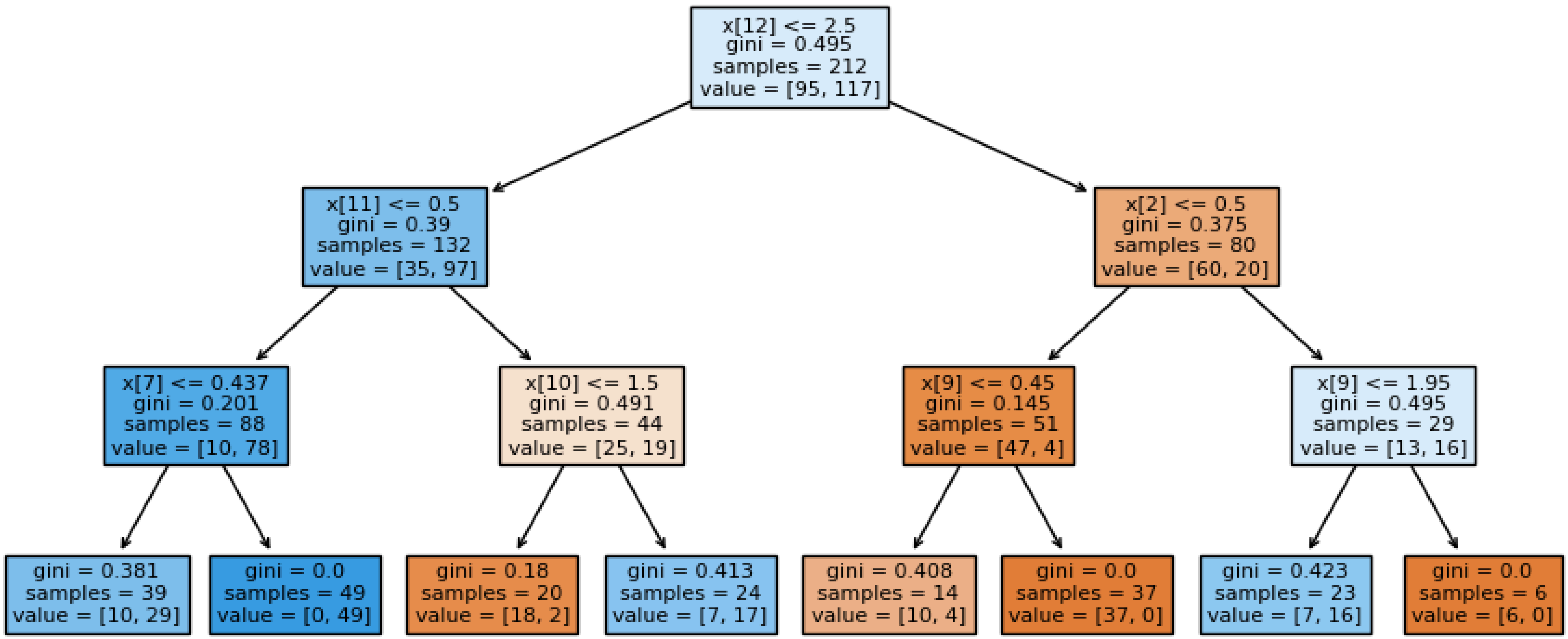
```
              precision    recall  f1-score   support

           0       0.79      0.73      0.76        30
           1       0.81      0.85      0.83        41

    accuracy                           0.80        71
   macro avg       0.80      0.79      0.80        71
weighted avg       0.80      0.80      0.80        71

[[22  8]
 [ 6 35]]
Accuracy Score of the Test Data-: 80.282 %
```

In [257…

```
from sklearn.tree import plot_tree
```

In [258…

```
plt.figure(figsize = (11,5))
plot_tree(dtc, filled =True)
plt.show()
```



In [264…

```
f = open("ML Model/DecisionTree_Model.yml", "wb")
pickle.dump(dtc ,f )
f.close()
```

Accuracy

- **LogisticRegression-:** We get accuracy with using LogisticRegression of Training Dataset is :- **86.73%** and test Dataset with score of **77.46%**
- **DecisionTree Classifier-:** We Get Accuracy With Using DecisionTree Classifier of Training Dataset is :- **85.84%** and test Dataset with score of **80.28%**

So we use **DecisionTree Classifier** for model **DecisionTree Classifier.**