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Batch:- DS22OCT7

Implementation of ML Algorithm on heart_disease_dataset

EDA and Feature Engineering

1. Data Cleaning
2. Graphical Analysis
3. Outliers Detection
4. Removal of Outliers

Algorithms

1. Logistic Regression, Accuracy got - 82.60%
2. Support Vector Classifier, Accuracy got - 80.43%
3. Decision Tree, Accuracy got - 69.56%
4. Random Forest, Accuracy got - 80.43%
5. Bagging Classifier, Accuracy got - 76.08%
6. Adaboost Classifier, Accuracy got - 76.08%
7. Gradient Boosting Classfier, Accuracy got - 80.43%
8. XGBoost Classifier, Accuracy got - 76.08%

Importing the Libraries for Data Cleaning , Preprocessing , Feature Engineering

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Importing the dataset

In [2]:

```
df=pd.read_csv("h.csv")
df.head()
```

Out[2]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | targe |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 63 | 1 | 3 | 145 | 233 | 1 | 0 | 150 | 0 | 2.3 | 0 | 0 | 1 | |
| **1** | 37 | 1 | 2 | 130 | 250 | 0 | 1 | 187 | 0 | 3.5 | 0 | 0 | 2 | |
| **2** | 41 | 0 | 1 | 130 | 204 | 0 | 0 | 172 | 0 | 1.4 | 2 | 0 | 2 | |
| **3** | 56 | 1 | 1 | 120 | 236 | 0 | 1 | 178 | 0 | 0.8 | 2 | 0 | 2 | |
| **4** | 57 | 0 | 0 | 120 | 354 | 0 | 1 | 163 | 1 | 0.6 | 2 | 0 | 2 | |

In [3]:

```
df.columns

```

Out[3]:

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

Checking the null values

In [4]:

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

```

Out[4]:

```
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 have zero null values in our dataset

Statistical Analysis

In [5]:

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

Out[5]:

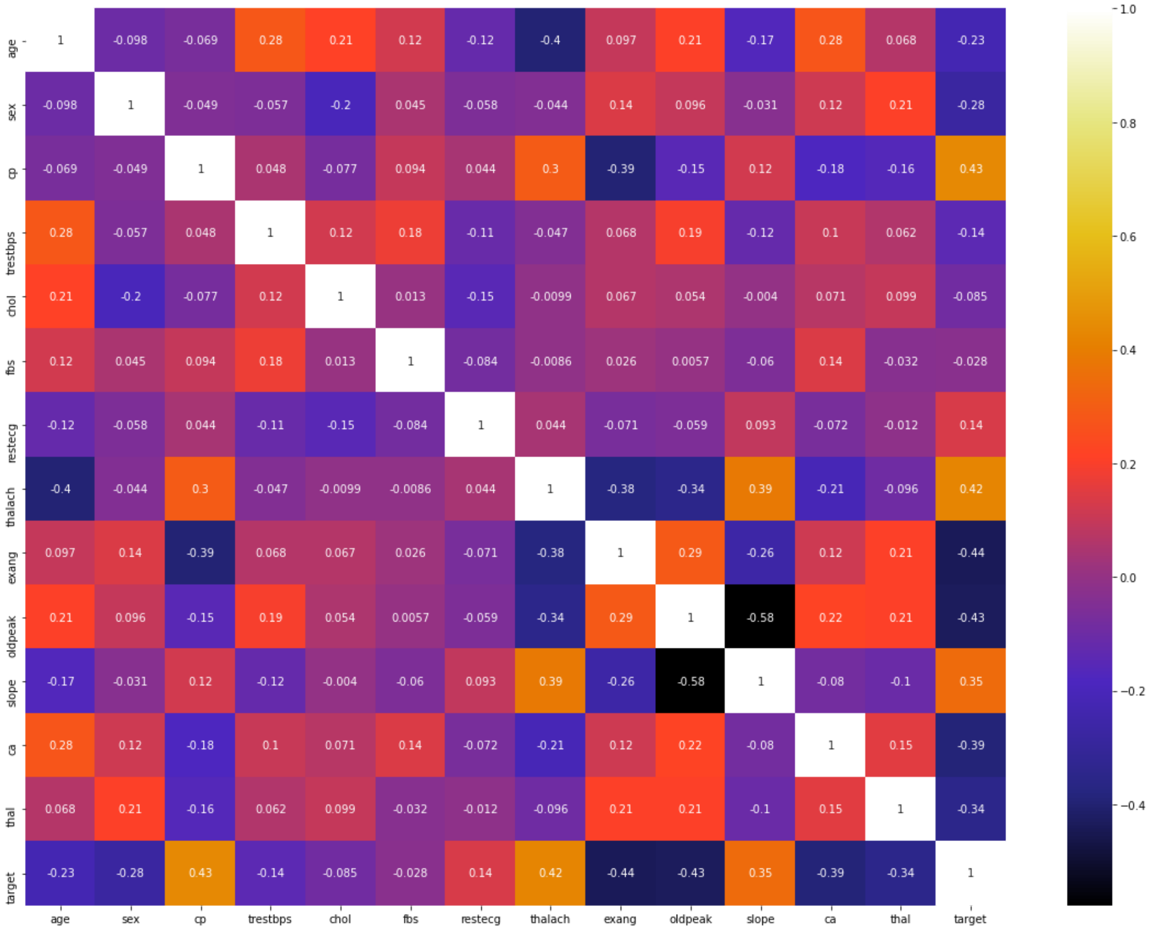
| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **age** | 303.0 | 54.366337 | 9.082101 | 29.0 | 47.5 | 55.0 | 61.0 | 77.0 |
| **sex** | 303.0 | 0.683168 | 0.466011 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| **cp** | 303.0 | 0.966997 | 1.032052 | 0.0 | 0.0 | 1.0 | 2.0 | 3.0 |
| **trestbps** | 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 |
| **thalach** | 303.0 | 149.646865 | 22.905161 | 71.0 | 133.5 | 153.0 | 166.0 | 202.0 |
| **exang** | 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 |
| **slope** | 303.0 | 1.399340 | 0.616226 | 0.0 | 1.0 | 1.0 | 2.0 | 2.0 |
| **ca** | 303.0 | 0.729373 | 1.022606 | 0.0 | 0.0 | 0.0 | 1.0 | 4.0 |
| **thal** | 303.0 | 2.313531 | 0.612277 | 0.0 | 2.0 | 2.0 | 3.0 | 3.0 |
| **target** | 303.0 | 0.544554 | 0.498835 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |

In [6]:

```
plt.figure(figsize=(20,15))
sns.heatmap(df.corr(),cmap="CMRmap",annot=True)
```

Out[6]:

<AxesSubplot:>



In [7]:

```
1 df.cov()
```

Out[7]:

| | age | sex | cp | trestbps | chol | fbs | restecg | |
|---|---|---|---|---|---|---|---|---|
| **age** | 82.484558 | -0.416661 | -0.643499 | 44.495902 | 100.585076 | 0.392433 | -0.555013 | -82 |
| **sex** | -0.416661 | 0.217166 | -0.023736 | -0.463970 | -4.780309 | 0.007475 | -0.014261 | -0 |
| **cp** | -0.643499 | -0.023736 | 1.065132 | 0.861714 | -4.113774 | 0.034719 | 0.024108 | 6 |
| **trestbps** | 44.495902 | -0.463970 | 0.861714 | 307.586453 | 111.967215 | 1.109042 | -1.052324 | -18 |
| **chol** | 100.585076 | -4.780309 | -4.113774 | 111.967215 | 2686.426748 | 0.245427 | -4.116703 | -11 |
| **fbs** | 0.392433 | 0.007475 | 0.034719 | 1.109042 | 0.245427 | 0.126877 | -0.015769 | -0 |
| **restecg** | -0.555013 | -0.014261 | 0.024108 | -1.052324 | -4.116703 | -0.015769 | 0.276528 | 0 |
| **thalach** | -82.903318 | -0.469871 | 6.991618 | -18.759131 | -11.800494 | -0.069897 | 0.531462 | 524 |
| **exang** | 0.413022 | 0.031014 | -0.191168 | 0.557111 | 1.631991 | 0.004295 | -0.017474 | -4 |
| **oldpeak** | 2.214583 | 0.051993 | -0.178821 | 3.934486 | 3.246794 | 0.002377 | -0.035883 | -9 |
| **slope** | -0.944791 | -0.008819 | 0.076137 | -1.312832 | -0.128964 | -0.013147 | 0.030151 | 5 |
| **ca** | 2.566356 | 0.056357 | -0.191080 | 1.818373 | 3.737252 | 0.050259 | -0.038741 | -4 |
| **thal** | 0.378139 | 0.059930 | -0.102201 | 0.668022 | 3.135488 | -0.006983 | -0.003858 | -1 |
| **target** | -1.021343 | -0.065307 | 0.223330 | -1.267950 | -2.203855 | -0.004983 | 0.035998 | 4 |

In [8]:

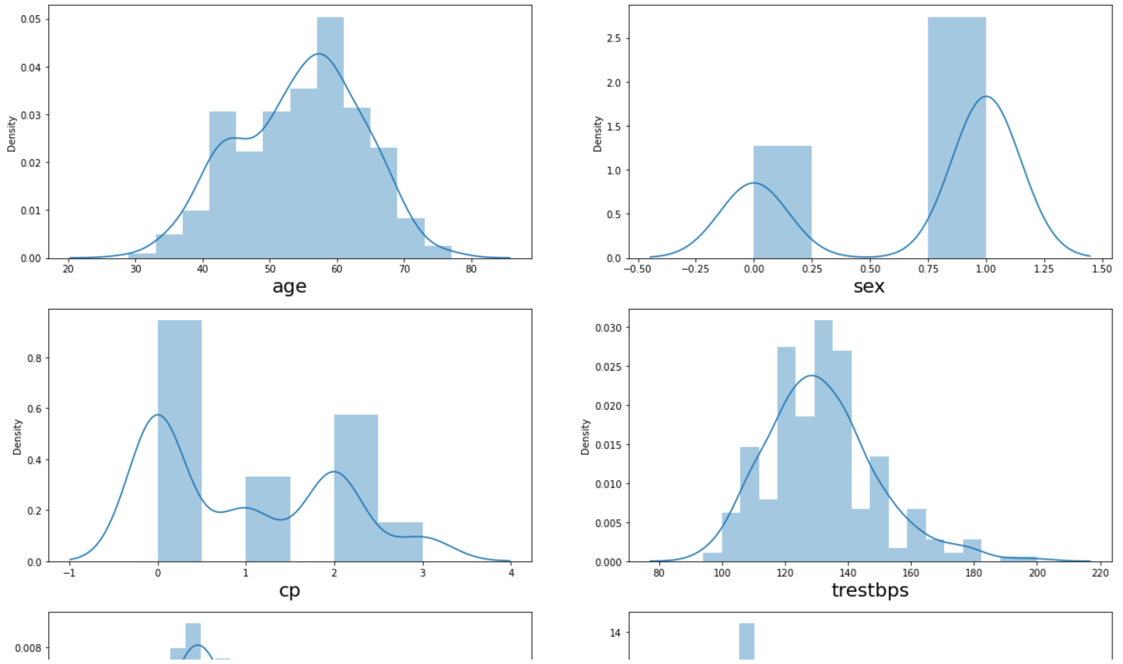
```
1 df.info()
```

```
<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
```

Checking the distribution of the features

In [9]:

```
plt.figure(figsize=(20,40),facecolor='White')
pltnumber=1
for column  in df:
    if pltnumber<15:
     ax=plt.subplot(7,2,pltnumber)
     sns.distplot(df[column])
     plt.xlabel(column,fontsize=20)
     pltnumber+=1
plt.show()

```




Here we can see some outliers in some features

Outliers Detection and Removal Approaches

Identifying outliers with visualization

Z-score method

Interquartile Range Method( IQR ) method

Compare Skewness

Z-score:

The number of standard deviations away from the mean that a particular observation is.

A negative Z-score means an observation is below the mean.

while a positive Z-score means means it above the mean.

The further away from 0 the Z-Score is, the further away from the mean your observation is.

Function to detect outliers

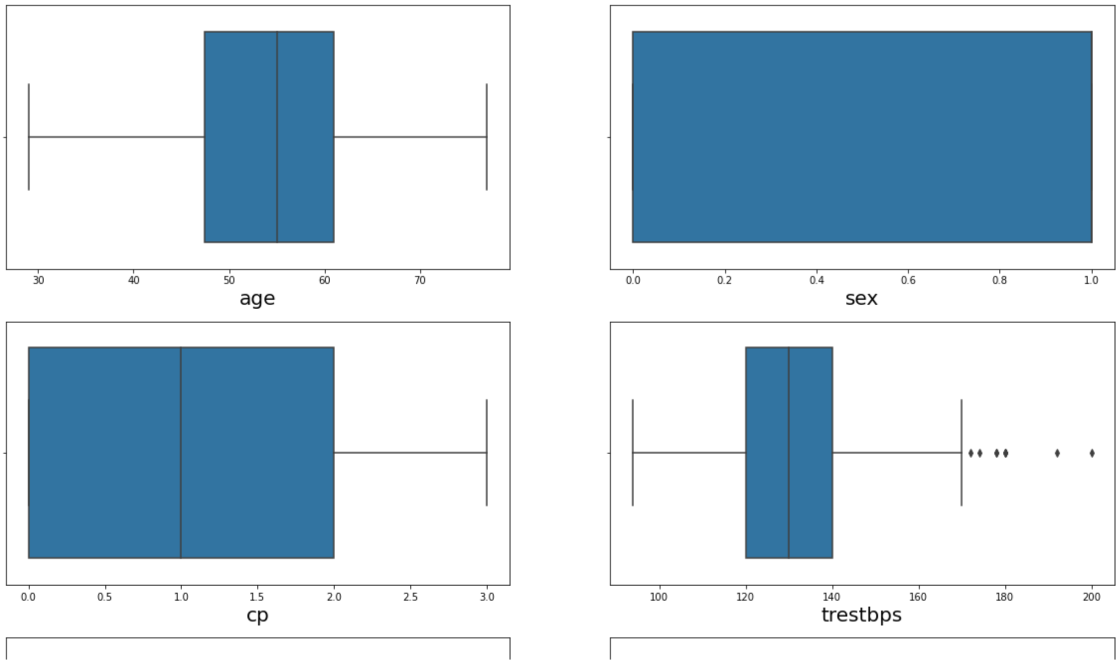
In [10]:

```
def outlier_thresholds(dataframe,variable):
    quartile1=dataframe[variable].quantile(0.25)
    quartile3=dataframe[variable].quantile(0.75)
    interquartile_range=quartile3-quartile1
    up_limit=quartile3+1.5*interquartile_range
    low_limit=quartile1-1.5*interquartile_range
    return low_limit,up_limit



for i in df.columns:
    print("lower limit and upper limit of {} is {}".format(i,outlier_thresholds(df,i)
```

```
lower limit and upper limit of age is (27.25, 81.25)
lower limit and upper limit of sex is (-1.5, 2.5)
lower limit and upper limit of cp is (-3.0, 5.0)
lower limit and upper limit of trestbps is (90.0, 170.0)
lower limit and upper limit of chol is (115.75, 369.75)
lower limit and upper limit of fbs is (0.0, 0.0)
lower limit and upper limit of restecg is (-1.5, 2.5)
lower limit and upper limit of thalach is (84.75, 214.75)
lower limit and upper limit of exang is (-1.5, 2.5)
lower limit and upper limit of oldpeak is (-2.4000000000000004, 4.0)
lower limit and upper limit of slope is (-0.5, 3.5)
lower limit and upper limit of ca is (-1.5, 2.5)
lower limit and upper limit of thal is (0.5, 4.5)
lower limit and upper limit of target is (-1.5, 2.5)
```

In [11]:

```
plt.figure(figsize=(20,40))
pltnumber=1

for column in df:
    if pltnumber<=14:
        ax=plt.subplot(7,2,pltnumber)
        sns.boxplot(df[column])
        plt.xlabel(column,fontsize=20)
    pltnumber+=1
plt.show()
```

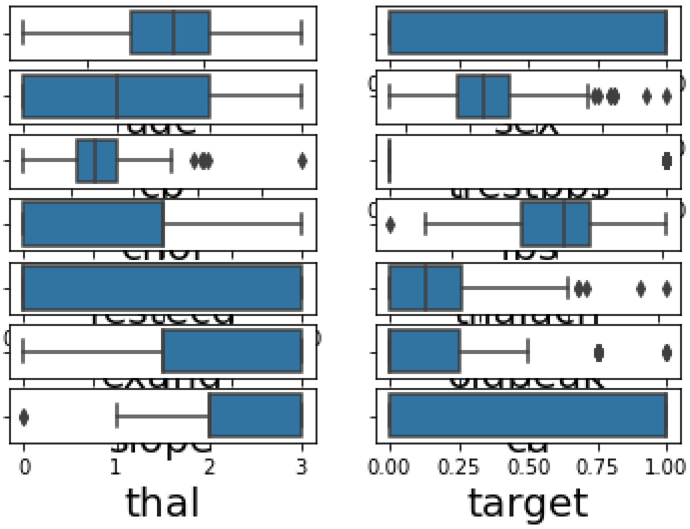



So , we got outliers in trestbps,chol,fbs,thalach,oldpeak,ca,thal

function to remove outliers

In [12]:

```python
def replace_with_thresholds(dataframe,columns):
    for variable in column:
        low_limit,up_limit=outlier_thresholds(dataframe,variable)
        dataframe.loc[(dataframe[variable]<low_limit),variable]=low_limit
        dataframe.loc[(dataframe[variable]>up_limit),variable]=lup_limit
    replace_with_thresholds(df,df.column)
    plt.figure(figsize=(20,40))
pltnumber=1

for column in df:
    if pltnumber<=14:
        ax=plt.subplot(7,2,pltnumber)
        sns.boxplot(df[column])
        plt.xlabel(column,fontsize=20)
    pltnumber+=1
plt.show()
```




As we can see from above boxplots outliers are not removed properly

Interquartile Range Method( IQR ) method

In [13]:

```python
df1=df.copy()
def remove_outliers_IQR(col):
    percentile25=df1[col].quantile(.25)
    percentile75=df1[col].quantile(.75)
    print("percentile25",percentile25)
    print("percentile75",percentile75)
    iqr=percentile75-percentile25
    upper_limit=percentile75+1.5*iqr
    lower_limit=percentile25-1.5*iqr
    print("upper limit",upper_limit)
    print("lower limit",lower_limit)
    df1[col]=np.where(df1[col]>upper_limit,upper_limit,np.where(df1[col]<lower_limit,
    return df1[df1[col]>upper_limit]

remove_outliers_IQR('trestbps')
```

```
percentile25 120.0
percentile75 140.0
upper limit 170.0
lower limit 90.0
```

Out[13]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [14]:

```python
remove_outliers_IQR("chol")
```

```
percentile25 211.0
percentile75 274.5
upper limit 369.75
lower limit 115.75
```

Out[14]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [15]:

```python
remove_outliers_IQR("fbs")
```

```
percentile25 0.0
percentile75 0.0
upper limit 0.0
lower limit 0.0
```

Out[15]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [16]:

```
remove_outliers_IQR("thalach")
```

```
percentile25 133.5
percentile75 166.0
upper limit 214.75
lower limit 84.75
```

Out[16]:

| age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [17]:

```
remove_outliers_IQR("oldpeak")
```

```
percentile25 0.0
percentile75 1.6
upper limit 4.0
lower limit -2.4000000000000004
```

Out[17]:

| age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [18]:

```
remove_outliers_IQR("ca")
```

```
percentile25 0.0
percentile75 1.0
upper limit 2.5
lower limit -1.5
```

Out[18]:

| age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

In [19]:

```
remove_outliers_IQR("thal")
```

```
percentile25 2.0
percentile75 3.0
upper limit 4.5
lower limit 0.5
```

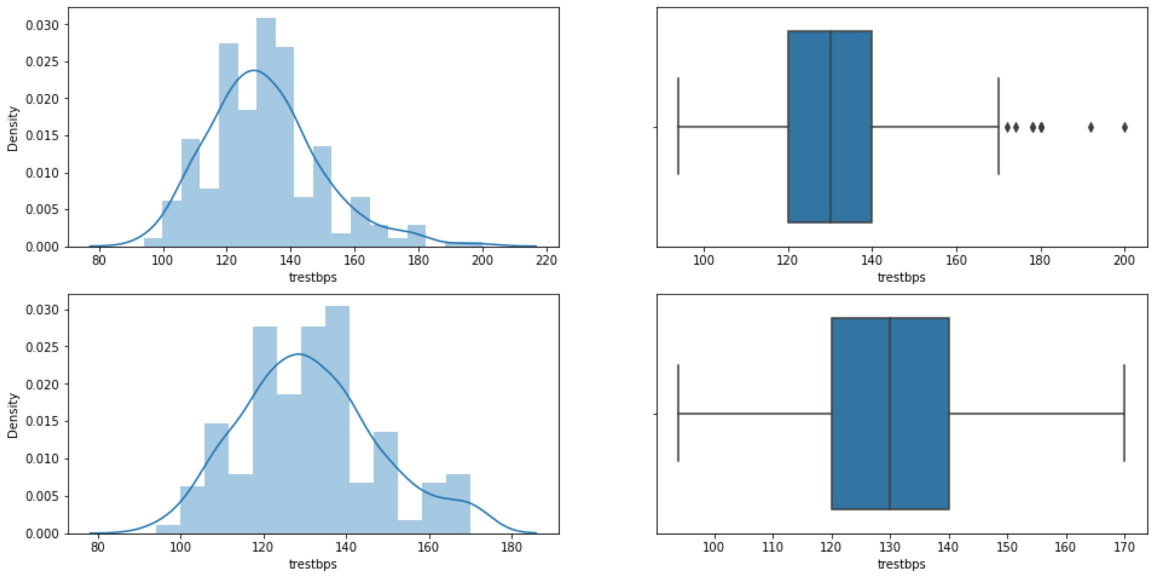
Out[19]:

| age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

Comparing

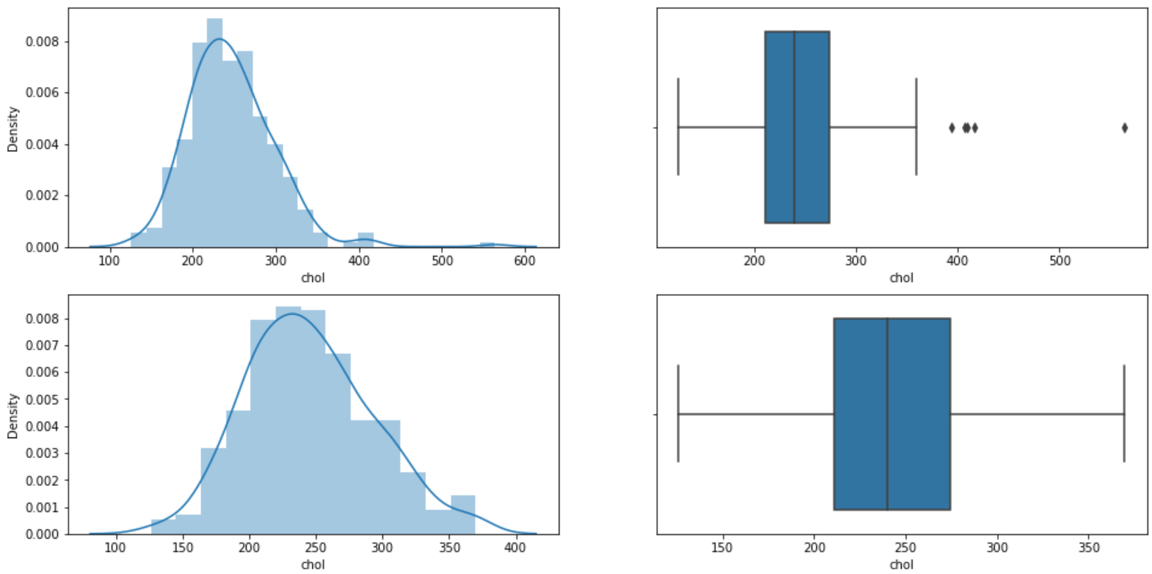
In [20]:

```python
def create_comparision_plot(df,df1,column):
    plt.figure(figsize=(16,8))
    plt.subplot(2,2,1)
    sns.distplot(df[column])

    plt.subplot(2,2,2)
    sns.boxplot(df[column])

    plt.subplot(2,2,3)
    sns.distplot(df1[column])

    plt.subplot(2,2,4)
    sns.boxplot(df1[column])

    plt.show()

create_comparision_plot(df,df1,'trestbps')
```



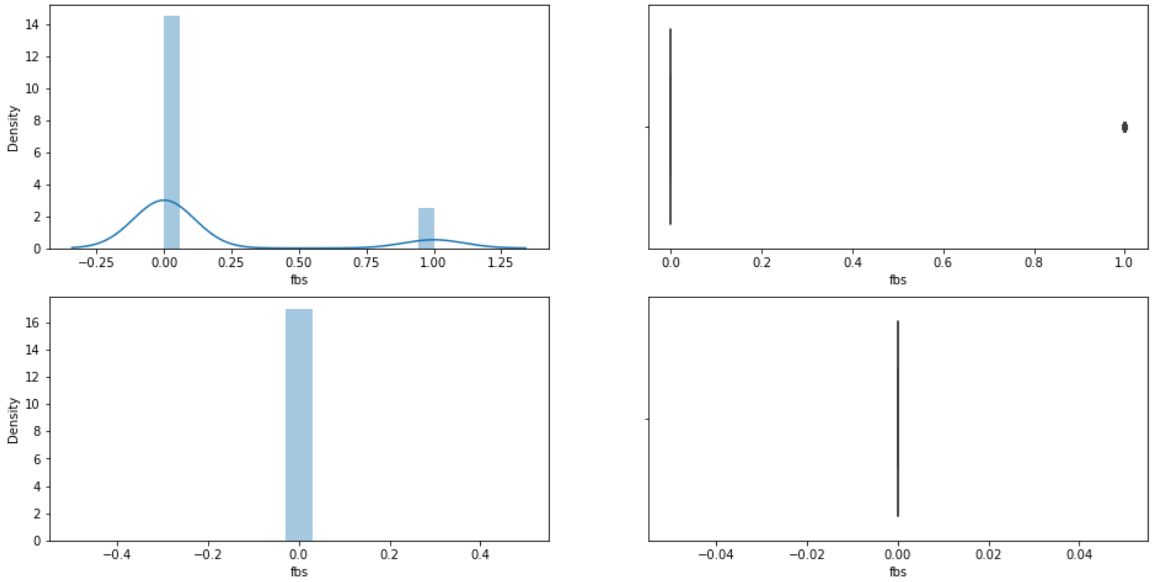

In [21]:

```python
create_comparision_plot(df,df1,'chol')
```



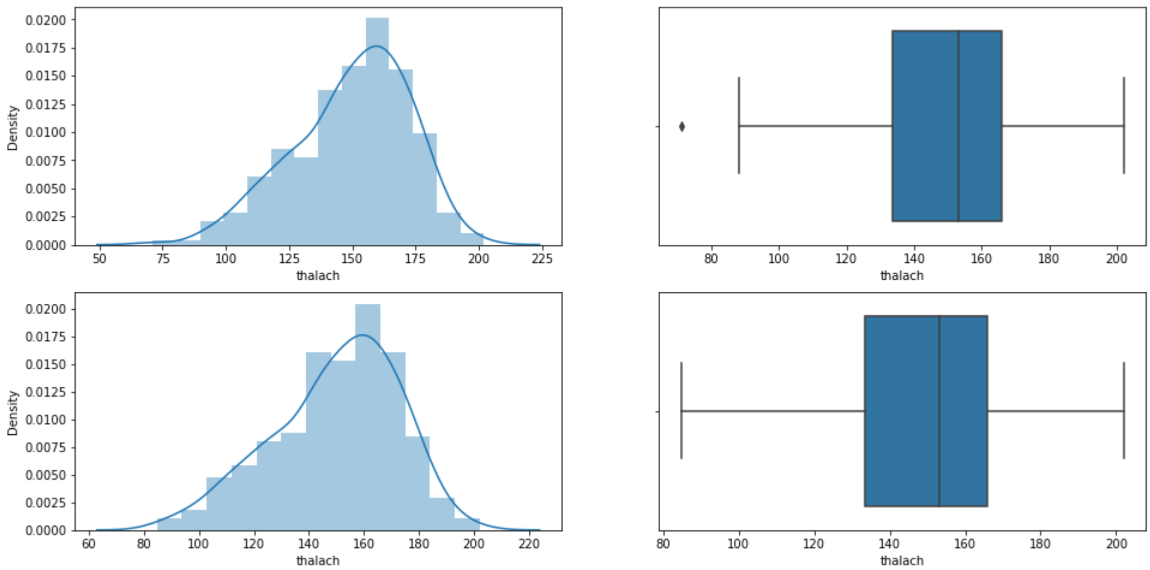
In [22]:

```
1 create_comparision_plot(df,df1,'fbs')
```



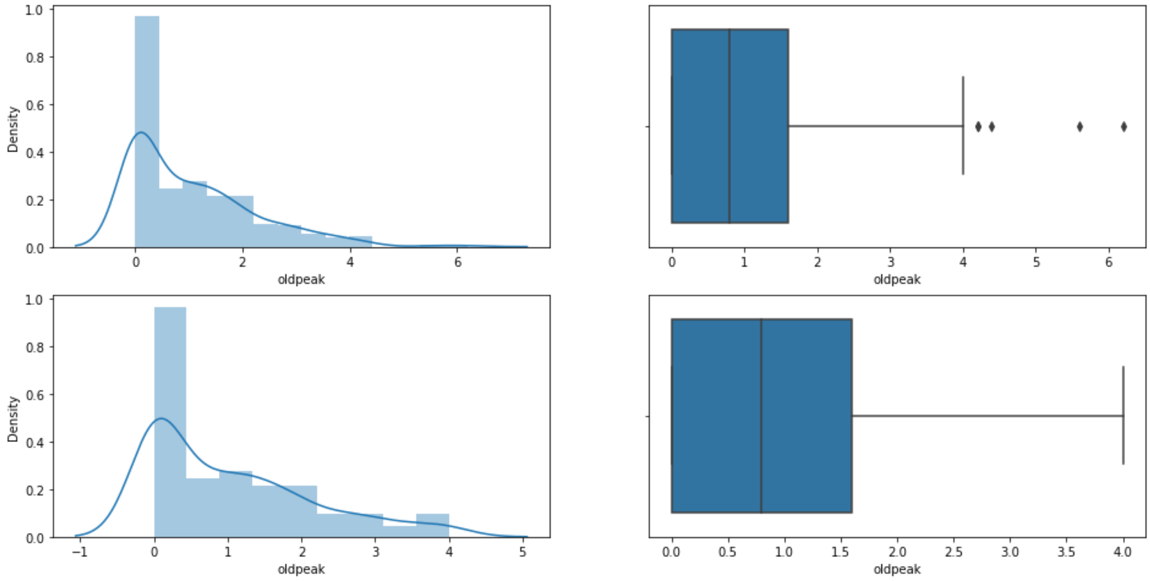

In [23]:

```
1 create_comparision_plot(df,df1,'thalach')
```



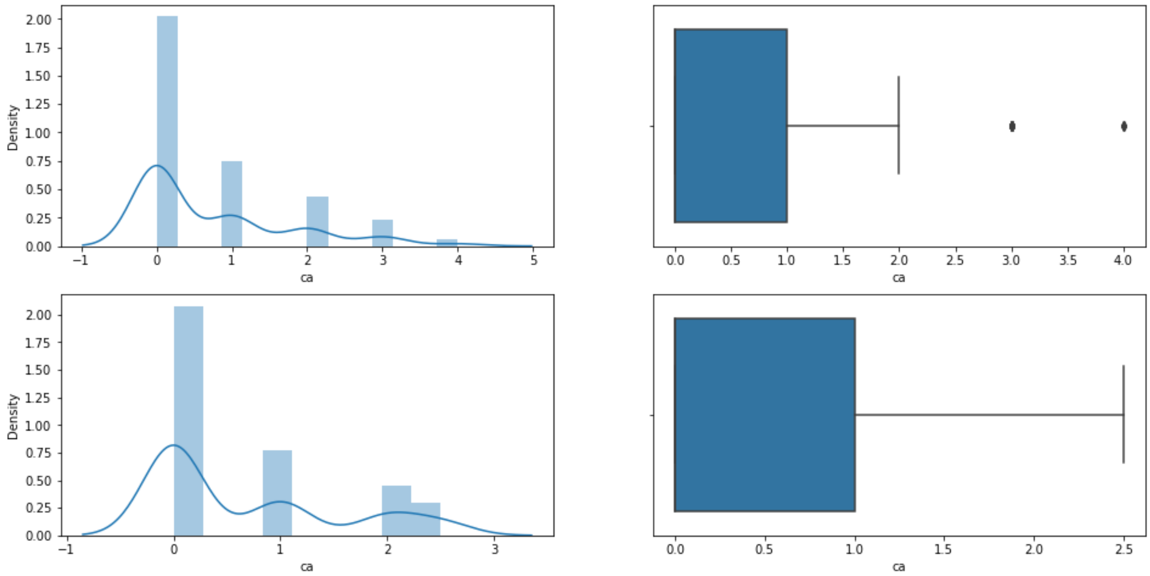
In [24]:

```
create_comparision_plot(df,df1,'oldpeak')
```



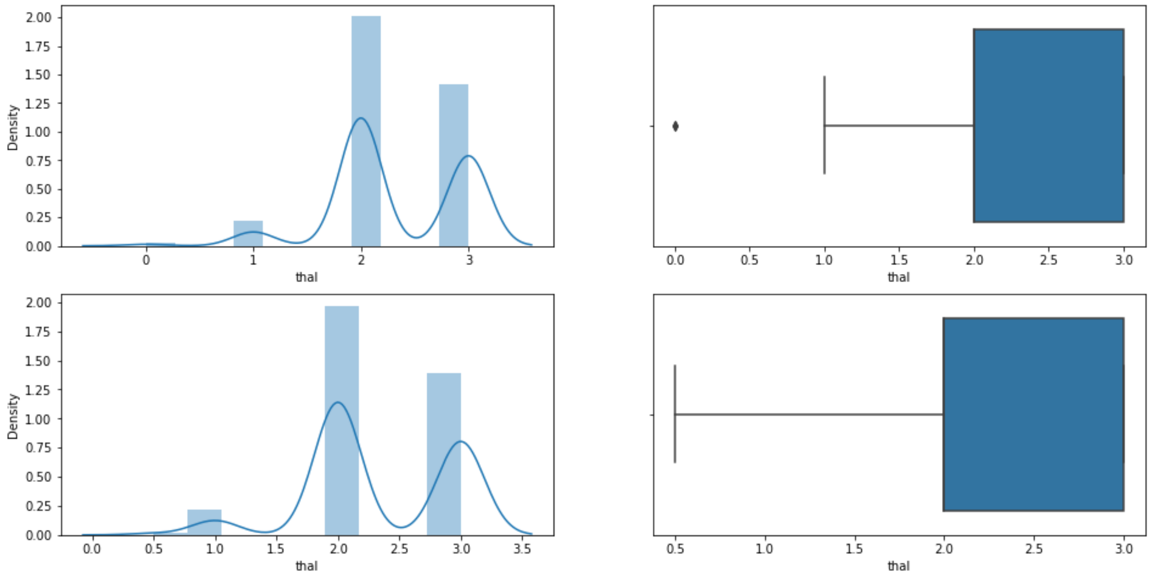

In [25]:

```
create_comparision_plot(df,df1,'ca')
```



In [26]:

```
create_comparision_plot(df,df1,'thal')
```




Compare skewness

In [27]:

```
df.skew()
```

Out[27]:

```
age         -0.202463
sex         -0.791335
cp           0.484732
trestbps     0.713768
chol         1.143401
fbs          1.986652
restecg      0.162522
thalach     -0.537410
exang        0.742532
oldpeak      1.269720
slope       -0.508316
ca           1.310422
thal        -0.476722
target      -0.179821
dtype: float64
```

In [28]:

```
df1.skew()
```

Out[28]:

```
age        -0.202463
sex        -0.791335
cp          0.484732
trestbps    0.386367
chol        0.333267
fbs         0.000000
restecg     0.162522
thalach    -0.493392
exang       0.742532
oldpeak     0.997885
slope      -0.508316
ca          0.919045
thal       -0.323530
target     -0.179821
dtype: float64
```

Skewness is reduced after we have removed ouliers using IQR Method

Splitting the Dataset into dependent and independent features

In [29]:

```
x=df1.drop(columns=['target'])
y=df1['target']
```

In [30]:

```
y
```

Out[30]:

```
0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: target, Length: 303, dtype: int64
```

In [31]:

```
x
```

Out[31]:

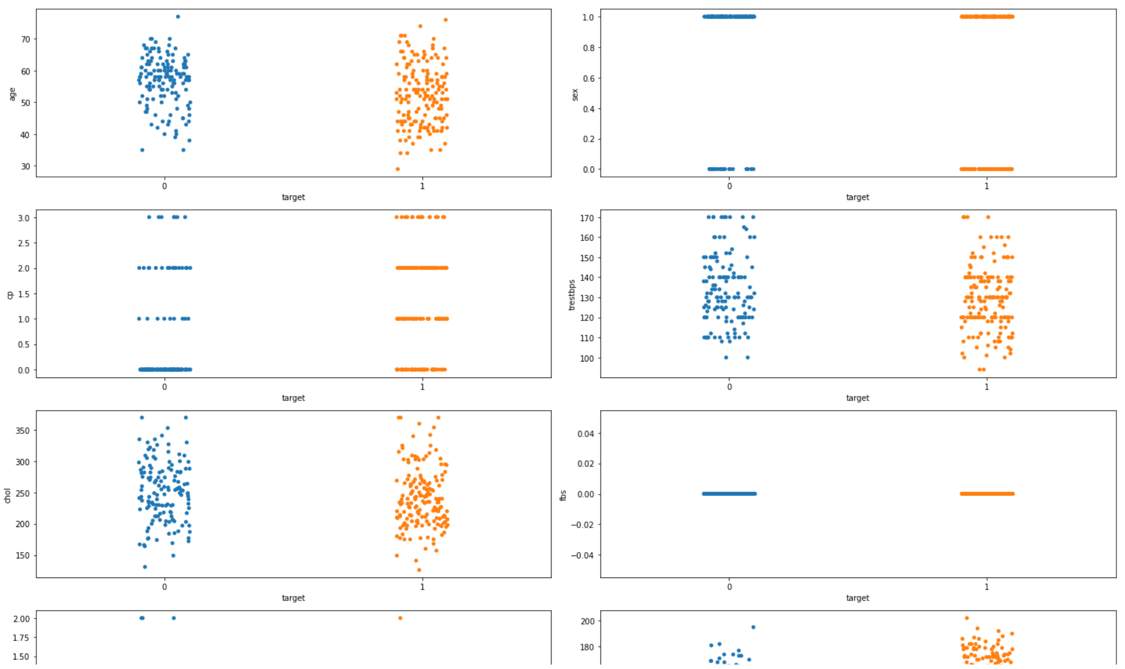
| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 63 | 1 | 3 | 145.0 | 233.0 | 0.0 | 0 | 150.0 | 0 | 2.3 | 0 | 0.0 | 1.0 |
| **1** | 37 | 1 | 2 | 130.0 | 250.0 | 0.0 | 1 | 187.0 | 0 | 3.5 | 0 | 0.0 | 2.0 |
| **2** | 41 | 0 | 1 | 130.0 | 204.0 | 0.0 | 0 | 172.0 | 0 | 1.4 | 2 | 0.0 | 2.0 |
| **3** | 56 | 1 | 1 | 120.0 | 236.0 | 0.0 | 1 | 178.0 | 0 | 0.8 | 2 | 0.0 | 2.0 |
| **4** | 57 | 0 | 0 | 120.0 | 354.0 | 0.0 | 1 | 163.0 | 1 | 0.6 | 2 | 0.0 | 2.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **298** | 57 | 0 | 0 | 140.0 | 241.0 | 0.0 | 1 | 123.0 | 1 | 0.2 | 1 | 0.0 | 3.0 |
| **299** | 45 | 1 | 3 | 110.0 | 264.0 | 0.0 | 1 | 132.0 | 0 | 1.2 | 1 | 0.0 | 3.0 |
| **300** | 68 | 1 | 0 | 144.0 | 193.0 | 0.0 | 1 | 141.0 | 0 | 3.4 | 1 | 2.0 | 3.0 |
| **301** | 57 | 1 | 0 | 130.0 | 131.0 | 0.0 | 1 | 115.0 | 1 | 1.2 | 1 | 1.0 | 3.0 |
| **302** | 57 | 0 | 1 | 130.0 | 236.0 | 0.0 | 0 | 174.0 | 0 | 0.0 | 1 | 1.0 | 2.0 |

303 rows × 13 columns

Relationship between dependent and independent features

In [32]:

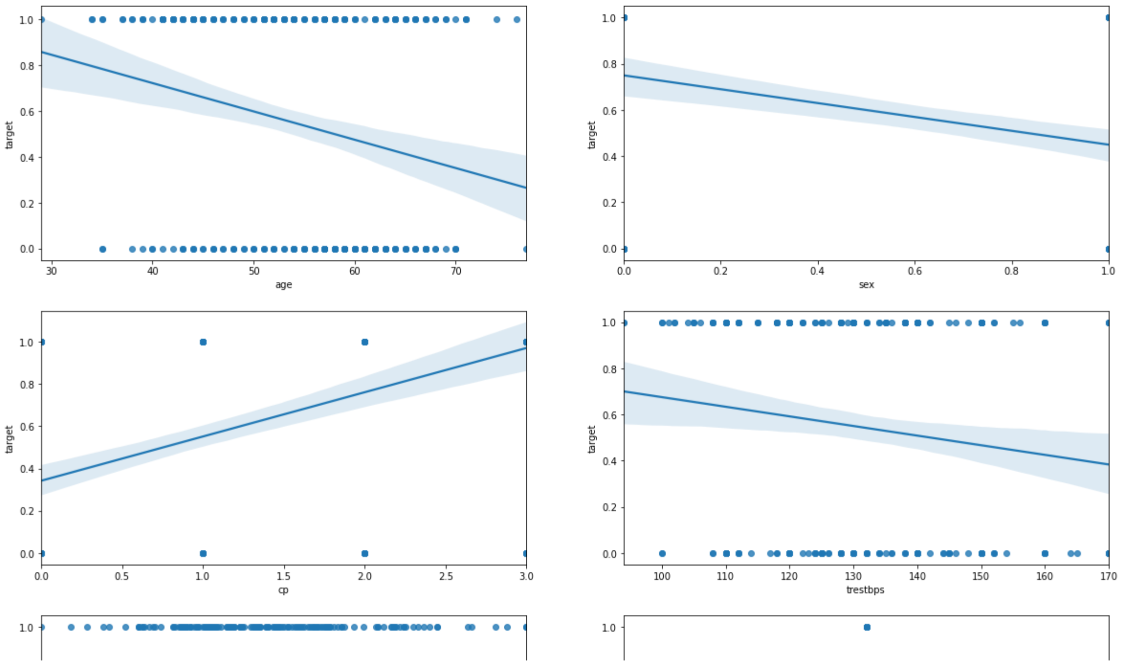
```
plt.figure(figsize=(20,25),facecolor='White')
plotnumber=1

for column in x:
    if plotnumber<14:
     ax=plt.subplot(7,2,plotnumber)
     sns.stripplot(y,x[column])
    plotnumber+=1
plt.tight_layout()

```




Graphical Analysis between dependent and independent features

In [33]:

```python
plt.figure(figsize=(20,40))
for i in enumerate(x.columns):
    plt.subplot(7,2,i[0]+1)
    sns.regplot(x=df1[i[1]],y=df1['target'])
```




Train Test Split

In [34]:

```python
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.15,random_state=16)
```

In [35]:

```
x_train
```

Out[35]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **220** | 63 | 0 | 0 | 150.0 | 369.75 | 0.0 | 0 | 154.0 | 0 | 4.0 | 1 | 2.5 | 3.0 |
| **179** | 57 | 1 | 0 | 150.0 | 276.00 | 0.0 | 0 | 112.0 | 1 | 0.6 | 1 | 1.0 | 1.0 |
| **135** | 49 | 0 | 0 | 130.0 | 269.00 | 0.0 | 1 | 163.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **64** | 58 | 1 | 2 | 140.0 | 211.00 | 0.0 | 0 | 165.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **276** | 58 | 1 | 0 | 146.0 | 218.00 | 0.0 | 1 | 105.0 | 0 | 2.0 | 1 | 1.0 | 3.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **123** | 54 | 0 | 2 | 108.0 | 267.00 | 0.0 | 0 | 167.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **69** | 62 | 0 | 0 | 124.0 | 209.00 | 0.0 | 1 | 163.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **121** | 59 | 1 | 0 | 138.0 | 271.00 | 0.0 | 0 | 182.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **238** | 77 | 1 | 0 | 125.0 | 304.00 | 0.0 | 0 | 162.0 | 1 | 0.0 | 2 | 2.5 | 2.0 |
| **169** | 53 | 1 | 0 | 140.0 | 203.00 | 0.0 | 0 | 155.0 | 1 | 3.1 | 0 | 0.0 | 3.0 |

257 rows × 13 columns

In [36]:

```
y_train
```

Out[36]:

```
220    0
179    0
135    1
64     1
276    0
      ..
123    1
69     1
121    1
238    0
169    0
Name: target, Length: 257, dtype: int64
```

In [37]:

```
x_test
```

Out[37]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **59** | 57 | 0 | 0 | 128.0 | 303.00 | 0.0 | 0 | 159.0 | 0 | 0.0 | 2 | 1.0 | 2.0 |
| **282** | 59 | 1 | 2 | 126.0 | 218.00 | 0.0 | 1 | 134.0 | 0 | 2.2 | 1 | 1.0 | 1.0 |
| **183** | 58 | 1 | 2 | 112.0 | 230.00 | 0.0 | 0 | 165.0 | 0 | 2.5 | 1 | 1.0 | 3.0 |
| **0** | 63 | 1 | 3 | 145.0 | 233.00 | 0.0 | 0 | 150.0 | 0 | 2.3 | 0 | 0.0 | 1.0 |
| **262** | 53 | 1 | 0 | 123.0 | 282.00 | 0.0 | 1 | 95.0 | 1 | 2.0 | 1 | 2.0 | 3.0 |
| **126** | 47 | 1 | 0 | 112.0 | 204.00 | 0.0 | 1 | 143.0 | 0 | 0.1 | 2 | 0.0 | 2.0 |
| **289** | 55 | 0 | 0 | 128.0 | 205.00 | 0.0 | 2 | 130.0 | 1 | 2.0 | 1 | 1.0 | 3.0 |
| **240** | 70 | 1 | 2 | 160.0 | 269.00 | 0.0 | 1 | 112.0 | 1 | 2.9 | 1 | 1.0 | 3.0 |
| **237** | 60 | 1 | 0 | 140.0 | 293.00 | 0.0 | 0 | 170.0 | 0 | 1.2 | 1 | 2.0 | 3.0 |
| **173** | 58 | 1 | 2 | 132.0 | 224.00 | 0.0 | 0 | 173.0 | 0 | 3.2 | 2 | 2.0 | 3.0 |
| **83** | 52 | 1 | 3 | 152.0 | 298.00 | 0.0 | 1 | 178.0 | 0 | 1.2 | 1 | 0.0 | 3.0 |
| **191** | 58 | 1 | 0 | 128.0 | 216.00 | 0.0 | 0 | 131.0 | 1 | 2.2 | 1 | 2.5 | 3.0 |
| **222** | 65 | 1 | 3 | 138.0 | 282.00 | 0.0 | 0 | 174.0 | 0 | 1.4 | 1 | 1.0 | 2.0 |
| **30** | 41 | 0 | 1 | 105.0 | 198.00 | 0.0 | 1 | 168.0 | 0 | 0.0 | 2 | 1.0 | 2.0 |
| **182** | 61 | 0 | 0 | 130.0 | 330.00 | 0.0 | 0 | 169.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **12** | 49 | 1 | 1 | 130.0 | 266.00 | 0.0 | 1 | 171.0 | 0 | 0.6 | 2 | 0.0 | 2.0 |
| **105** | 68 | 0 | 2 | 120.0 | 211.00 | 0.0 | 0 | 115.0 | 0 | 1.5 | 1 | 0.0 | 2.0 |
| **246** | 56 | 0 | 0 | 134.0 | 369.75 | 0.0 | 0 | 150.0 | 1 | 1.9 | 1 | 2.0 | 3.0 |
| **275** | 52 | 1 | 0 | 125.0 | 212.00 | 0.0 | 1 | 168.0 | 0 | 1.0 | 2 | 2.0 | 3.0 |
| **7** | 44 | 1 | 1 | 120.0 | 263.00 | 0.0 | 1 | 173.0 | 0 | 0.0 | 2 | 0.0 | 3.0 |
| **230** | 47 | 1 | 2 | 108.0 | 243.00 | 0.0 | 1 | 152.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **140** | 51 | 0 | 2 | 120.0 | 295.00 | 0.0 | 0 | 157.0 | 0 | 0.6 | 2 | 0.0 | 2.0 |
| **187** | 54 | 1 | 0 | 124.0 | 266.00 | 0.0 | 0 | 109.0 | 1 | 2.2 | 1 | 1.0 | 3.0 |
| **20** | 59 | 1 | 0 | 135.0 | 234.00 | 0.0 | 1 | 161.0 | 0 | 0.5 | 1 | 0.0 | 3.0 |
| **157** | 35 | 1 | 1 | 122.0 | 192.00 | 0.0 | 1 | 174.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **87** | 46 | 1 | 1 | 101.0 | 197.00 | 0.0 | 1 | 156.0 | 0 | 0.0 | 2 | 0.0 | 3.0 |
| **253** | 67 | 1 | 0 | 100.0 | 299.00 | 0.0 | 0 | 125.0 | 1 | 0.9 | 1 | 2.0 | 2.0 |
| **137** | 62 | 1 | 1 | 128.0 | 208.00 | 0.0 | 0 | 140.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **292** | 58 | 0 | 0 | 170.0 | 225.00 | 0.0 | 0 | 146.0 | 1 | 2.8 | 1 | 2.0 | 1.0 |
| **265** | 66 | 1 | 0 | 112.0 | 212.00 | 0.0 | 0 | 132.0 | 1 | 0.1 | 2 | 1.0 | 2.0 |
| **250** | 51 | 1 | 0 | 140.0 | 298.00 | 0.0 | 1 | 122.0 | 1 | 4.0 | 1 | 2.5 | 3.0 |
| **103** | 42 | 1 | 2 | 120.0 | 240.00 | 0.0 | 1 | 194.0 | 0 | 0.8 | 0 | 0.0 | 3.0 |
| **35** | 46 | 0 | 2 | 142.0 | 177.00 | 0.0 | 0 | 160.0 | 1 | 1.4 | 0 | 0.0 | 2.0 |
| **204** | 62 | 0 | 0 | 160.0 | 164.00 | 0.0 | 0 | 145.0 | 0 | 4.0 | 0 | 2.5 | 3.0 |
| **302** | 57 | 0 | 1 | 130.0 | 236.00 | 0.0 | 0 | 174.0 | 0 | 0.0 | 1 | 1.0 | 2.0 |
| **96** | 62 | 0 | 0 | 140.0 | 369.75 | 0.0 | 0 | 157.0 | 0 | 1.2 | 1 | 0.0 | 2.0 |
| **139** | 64 | 1 | 0 | 128.0 | 263.00 | 0.0 | 1 | 105.0 | 1 | 0.2 | 1 | 1.0 | 3.0 |

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **71** | 51 | 1 | 2 | 94.0 | 227.00 | 0.0 | 1 | 154.0 | 1 | 0.0 | 2 | 1.0 | 3.0 |
| **273** | 58 | 1 | 0 | 100.0 | 234.00 | 0.0 | 1 | 156.0 | 0 | 0.1 | 2 | 1.0 | 3.0 |
| **18** | 43 | 1 | 0 | 150.0 | 247.00 | 0.0 | 1 | 171.0 | 0 | 1.5 | 2 | 0.0 | 2.0 |
| **294** | 44 | 1 | 0 | 120.0 | 169.00 | 0.0 | 1 | 144.0 | 1 | 2.8 | 0 | 0.0 | 1.0 |
| **244** | 56 | 1 | 0 | 132.0 | 184.00 | 0.0 | 0 | 105.0 | 1 | 2.1 | 1 | 1.0 | 1.0 |
| **221** | 55 | 1 | 0 | 140.0 | 217.00 | 0.0 | 1 | 111.0 | 1 | 4.0 | 0 | 0.0 | 3.0 |
| **280** | 42 | 1 | 0 | 136.0 | 315.00 | 0.0 | 1 | 125.0 | 1 | 1.8 | 1 | 0.0 | 1.0 |
| **54** | 63 | 0 | 2 | 135.0 | 252.00 | 0.0 | 0 | 172.0 | 0 | 0.0 | 2 | 0.0 | 2.0 |
| **255** | 45 | 1 | 0 | 142.0 | 309.00 | 0.0 | 0 | 147.0 | 1 | 0.0 | 1 | 2.5 | 3.0 |

In [38]:

```
1 y_test
```

Out[38]:

```
59     1
282    0
183    0
0      1
262    0
126    1
289    0
240    0
237    0
173    0
83     1
191    0
222    0
30     1
182    0
12     1
105    1
246    0
275    0
7      1
230    0
140    1
187    0
20     1
157    1
87     1
253    0
137    1
292    0
265    0
250    0
103    1
35     1
204    0
302    0
96     1
139    1
71     1
273    0
18     1
294    0
244    0
221    0
280    0
54     1
255    0
Name: target, dtype: int64
```

Scaling

In [39]:

```
from sklearn.preprocessing import StandardScaler
scalar=StandardScaler()
x_train=scalar.fit_transform(x_train)
x_train

```

Out[39]:

```
array([[ 0.94139029, -1.44789003, -0.96097186, ..., -0.70591946,
         2.1056781 ,  1.18646406],
       [ 0.2904379 ,  0.69066019, -0.96097186, ..., -0.70591946,
         0.40391938, -2.25897395],
       [-0.57749862, -1.44789003, -0.96097186, ...,  0.95849615,
        -0.73058643, -0.53625494],
       ...,
       [ 0.50742203,  0.69066019, -0.96097186, ...,  0.95849615,
        -0.73058643, -0.53625494],
       [ 2.46027919,  0.69066019, -0.96097186, ...,  0.95849615,
         2.1056781 , -0.53625494],
       [-0.14353036,  0.69066019, -0.96097186, ..., -2.37033508,
        -0.73058643,  1.18646406]])
```

In [40]:

```
x_test=scalar.transform(x_test)
x_test
```

Out[40]:

```
array([[ 2.90437901e-01, -1.44789003e+00, -9.60971864e-01,
        -2.26470782e-01,  1.23322668e+00,  0.00000000e+00,
        -1.01374047e+00,  4.01349267e-01, -6.78400525e-01,
        -9.03547319e-01,  9.58496152e-01,  4.03919384e-01,
        -5.36254944e-01],
       [ 5.07422030e-01,  6.90660187e-01,  9.76045933e-01,
        -3.47098742e-01, -5.65790788e-01,  0.00000000e+00,
         9.01930860e-01, -7.06207500e-01, -6.78400525e-01,
         1.13015353e+00, -7.05919463e-01,  4.03919384e-01,
        -2.25897395e+00],
       [ 3.98929965e-01,  6.90660187e-01,  9.76045933e-01,
        -1.19149447e+00, -3.11811851e-01,  0.00000000e+00,
        -1.01374047e+00,  6.67162891e-01, -6.78400525e-01,
         1.40747638e+00, -7.05919463e-01,  4.03919384e-01,
         1.18646406e+00],
       [ 9.41390288e-01,  6.90660187e-01,  1.94455483e+00,
         7.98866882e-01, -2.48317117e-01,  0.00000000e+00,
        -1.01374047e+00,  2.62883124e-03, -6.78400525e-01,
```

Logistic Regression Model Training

In [41]:

```
from sklearn.linear_model import LogisticRegression
classifier=LogisticRegression()
classifier.fit(x_train,y_train)
LogisticRegression()
```

Out[41]:

```
LogisticRegression()
```

Prediction

In [42]:

```
y_pred=classifier.predict(x_test)
y_pred
```

Out[42]:

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

In [43]:

```
from sklearn.metrics import accuracy_score,classification_report
score=accuracy_score(y_pred,y_test)
print(score)
```

```
0.8260869565217391
```

In [44]:

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

```

```
              precision    recall  f1-score   support

           0       0.77      0.91      0.83        22
           1       0.90      0.75      0.82        24

    accuracy                           0.83        46
   macro avg       0.83      0.83      0.83        46
weighted avg       0.84      0.83      0.83        46
```

Support Vector Classification model Fitting Kernel SVM to the Training set

In [45]:

```
from sklearn.svm import SVC
classifier=SVC(kernel='linear',random_state=0)
classifier.fit(x_train,y_train)
SVC(kernel='linear',random_state=0)
```

Out[45]:

```
SVC(kernel='linear', random_state=0)
```

Predicting the Test set results

In [46]:

```
y_pred=classifier.predict(x_test)
y_pred
```

Out[46]:

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

In [47]:

```
score=accuracy_score(y_pred,y_test)
score
```

Out[47]:

```
0.8043478260869565
```

In [48]:

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

```
              precision    recall  f1-score   support

           0       0.73      0.90      0.81        21
           1       0.90      0.72      0.80        25

    accuracy                           0.80        46
   macro avg       0.82      0.81      0.80        46
weighted avg       0.82      0.80      0.80        46
```

Predicting the Test set results

In [49]:

```
from sklearn.tree import DecisionTreeClassifier
treemodel=DecisionTreeClassifier()
treemodel.fit(x_train,y_train)
DecisionTreeClassifier()
```

Out[49]:

```
DecisionTreeClassifier()
```

In [50]:

```python
from sklearn import tree
plt.figure(figsize=(20,17))
tree.plot_tree(treemodel,filled=True)
```

Out[50]:

```
[Text(592.875, 885.6150000000001, 'X[12] <= 0.325\ngini = 0.492\nsamples
= 257\nvalue = [112, 145]'),
 Text(341.775, 808.6050000000001, 'X[11] <= -0.163\ngini = 0.359\nsamples
= 162\nvalue = [38, 124]'),
 Text(209.25, 731.5950000000001, 'X[9] <= 1.685\ngini = 0.181\nsamples =
109\nvalue = [11, 98]'),
 Text(139.5, 654.585, 'X[0] <= 0.345\ngini = 0.142\nsamples = 104\nvalue
= [8, 96]'),
 Text(83.69999999999999, 577.575, 'X[12] <= -2.69\ngini = 0.026\nsamples
= 75\nvalue = [1, 74]'),
 Text(55.8, 500.5650000000001, 'X[7] <= -0.64\ngini = 0.5\nsamples = 2\nv
alue = [1, 1]'),
 Text(27.9, 423.55500000000006, 'gini = 0.0\nsamples = 1\nvalue = [0,
1]'),
 Text(83.69999999999999, 423.55500000000006, 'gini = 0.0\nsamples = 1\nva
lue = [1, 0]'),
 Text(111.6, 500.5650000000001, 'gini = 0.0\nsamples = 73\nvalue = [0, 7
3]'),
```

In [51]:

```python
y_pred=treemodel.predict(x_test)
y_pred
```

Out[51]:

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

In [52]:

```python
score=accuracy_score(y_pred,y_test)
score
```

Out[52]:

```
0.6956521739130435
```

In [53]:

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

```
              precision    recall  f1-score   support

           0       0.65      0.77      0.71        22
           1       0.75      0.62      0.68        24

    accuracy                           0.70        46
   macro avg       0.70      0.70      0.70        46
weighted avg       0.70      0.70      0.69        46
```

Random forest Classification

In [54]:

```
from sklearn.ensemble import RandomForestClassifier
classifier=RandomForestClassifier(n_estimators=50)
classifier.fit(x_train,y_train)
RandomForestClassifier(n_estimators=50)
```

Out[54]:

```
RandomForestClassifier(n_estimators=50)
```

In [55]:

```
y_pred=classifier.predict(x_test)
y_pred
```

Out[55]:

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

In [56]:

```
score=accuracy_score(y_pred,y_test)
score
```

Out[56]:

```
0.7608695652173914
```

In [57]:

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

```
              precision    recall  f1-score   support

           0       0.73      0.83      0.78        23
           1       0.80      0.70      0.74        23

    accuracy                           0.76        46
   macro avg       0.77      0.76      0.76        46
weighted avg       0.77      0.76      0.76        46
```

Bagging Classifier

In [58]:

```
from sklearn.ensemble import BaggingClassifier
BC=BaggingClassifier(base_estimator=None,n_estimators=10,max_samples=1.0,max_feature
```

In [59]:

```
BC.fit(x_train,y_train)
BaggingClassifier()
```

Out[59]:

```
BaggingClassifier()
```

In [60]:

```
y_pred=BC.predict(x_test)
y_pred
```

Out[60]:

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

In [61]:

```
score=accuracy_score(y_pred,y_test)
score
```

Out[61]:

```
0.6956521739130435
```

In [62]:

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

```
              precision    recall  f1-score   support

           0       0.73      0.73      0.73        26
           1       0.65      0.65      0.65        20

    accuracy                           0.70        46
   macro avg       0.69      0.69      0.69        46
weighted avg       0.70      0.70      0.70        46
```

Adaboost Classifier model

In [63]:

```
from sklearn.ensemble import AdaBoostClassifier
classifier=AdaBoostClassifier(n_estimators=100,random_state=0)
```

In [64]:

```
classifier.fit(x_train,y_train)
AdaBoostClassifier(n_estimators=100,random_state=0)
```

Out[64]:

```
AdaBoostClassifier(n_estimators=100, random_state=0)
```

In [65]:

```
y_pred=classifier.predict(x_test)
y_pred
```

Out[65]:

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

In [66]:

```
score=accuracy_score(y_pred,y_test)
score
```

Out[66]:

```
0.7608695652173914
```

In [67]:

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

```
              precision    recall  f1-score   support

           0       0.73      0.83      0.78        23
           1       0.80      0.70      0.74        23

    accuracy                           0.76        46
   macro avg       0.77      0.76      0.76        46
weighted avg       0.77      0.76      0.76        46
```

Gradient Boosting Classifier

In [68]:

```
from sklearn.ensemble import GradientBoostingClassifier
classifier=GradientBoostingClassifier(n_estimators=100,learning_rate=       1.0,max_(
```

In [69]:

```
classifier.fit(x_train,y_train)
GradientBoostingClassifier(n_estimators=100,learning_rate=1.0,max_depth=1,random_stat
```

Out[69]:

```
GradientBoostingClassifier(learning_rate=1.0, max_depth=1, random_state=0)
```

In [70]:

```
y_pred=classifier.predict(x_test)
y_pred
```

Out[70]:

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

In [71]:

```
score=accuracy_score(y_pred,y_test)
score
```

Out[71]:

```
0.8043478260869565
```

In [72]:

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

```
              precision    recall  f1-score   support

           0       0.81      0.84      0.82        25
           1       0.80      0.76      0.78        21

    accuracy                           0.80        46
   macro avg       0.80      0.80      0.80        46
weighted avg       0.80      0.80      0.80        46
```

XGBoost Classifier

In [73]:

```
import sys
!{sys.executable} -m pip install xgboost

```

```
Requirement already satisfied: xgboost in c:\users\hp\anaconda3\lib\site-p
ackages (1.7.4)
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\site-pac
kages (from xgboost) (1.6.2)
Requirement already satisfied: numpy in c:\users\hp\anaconda3\lib\site-pac
kages (from xgboost) (1.20.1)
```

In [74]:

```python
from xgboost import XGBClassifier
model=XGBClassifier()
model.fit(x_train,y_train)

```

Out[74]:

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=No
ne,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=N
one,
              interaction_constraints=None, learning_rate=None, max_bin=No
ne,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=Non
e,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [75]:

```python
y_pred=model.predict(x_test)
y_pred
```

Out[75]:

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

In [76]:

```python
score=accuracy_score(y_pred,y_test)
score
```

Out[76]:

```
0.7608695652173914
```

In [ ]:

```python

```