IMPORT NECESSARY LIBRARIES

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

IMPORT MODULES

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import
accuracy_score,classification_report,confusion_matrix,r2_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
```

LOAD THE DATASET

data=pd.read csv(r"C:\Users\Admin\Downloads\processed cleveland.csv") data.head() restecg thalach exang age sex cp trestbps chol fbs slope \ 2.3 1.5 2.6 3.5 1.4 ca thal num

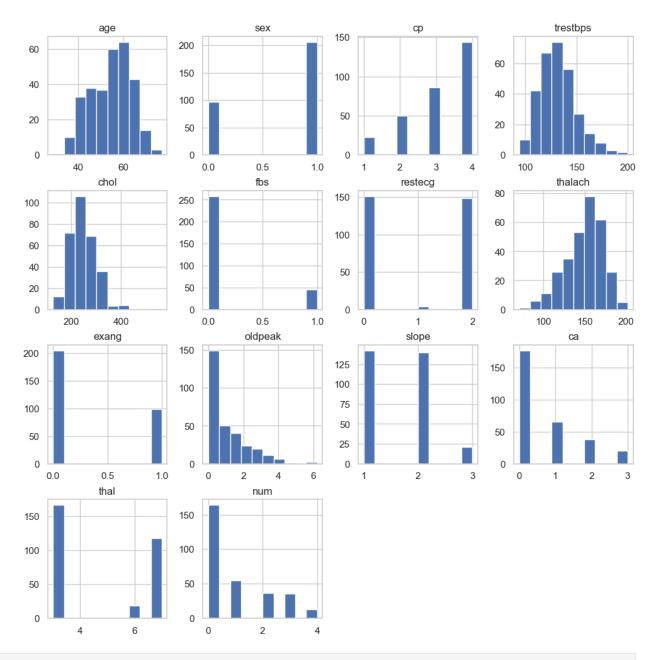
```
3 0
        3
             0
4 0
        3
             0
data.shape
(303, 14)
data.duplicated().sum()
data.isnull().sum()
            0
age
            0
sex
            0
ср
            0
trestbps
            0
chol
fbs
            0
            0
resteca
thalach
            0
            0
exang
            0
oldpeak
            0
slope
            0
ca
thal
            0
num
dtype: int64
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
#
               Non-Null Count Dtype
     Column
0
               303 non-null
                                int64
     age
1
               303 non-null
                                int64
     sex
 2
               303 non-null
                                int64
     ср
3
     trestbps
               303 non-null
                                int64
 4
     chol
               303 non-null
                                int64
 5
               303 non-null
     fbs
                                int64
 6
     restecg
               303 non-null
                                int64
 7
     thalach
               303 non-null
                                int64
 8
               303 non-null
                                int64
     exang
 9
     oldpeak
               303 non-null
                                float64
 10
     slope
               303 non-null
                                int64
 11
     ca
               303 non-null
                                object
 12
     thal
               303 non-null
                                object
 13
               303 non-null
                                int64
     num
```

```
dtypes: float64(1), int64(11), object(2)
memory usage: 33.3+ KB
data['ca']=pd.to numeric(data['ca'],errors='coerce')
data['thal']=pd.to numeric(data['thal'],errors='coerce')
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
               Non-Null Count
#
     Column
                                Dtype
- - -
     -----
 0
               303 non-null
                                int64
     age
 1
     sex
               303 non-null
                                int64
 2
               303 non-null
     ср
                                int64
 3
               303 non-null
     trestbps
                                int64
 4
               303 non-null
                                int64
     chol
 5
               303 non-null
     fbs
                                int64
 6
     restecg
               303 non-null
                                int64
 7
     thalach
               303 non-null
                                int64
 8
               303 non-null
     exang
                                int64
 9
     oldpeak
               303 non-null
                                float64
               303 non-null
 10
    slope
                                int64
 11
               299 non-null
                                float64
     ca
 12
     thal
               301 non-null
                                float64
13
               303 non-null
                                int64
     num
dtypes: float64(3), int64(11)
memory usage: 33.3 KB
data.describe()
                                              trestbps
                                                               chol
                           sex
                                        ср
              age
fbs \
count 303.000000
                   303.000000
                                303.000000
                                            303.000000 303.000000
303.000000
        54.438944
                     0.679868
                                  3.158416
                                            131.689769 246.693069
mean
0.148515
                     0.467299
                                  0.960126
                                             17.599748
std
         9.038662
                                                          51.776918
0.356198
        29.000000
                     0.000000
                                  1.000000
                                             94.000000
                                                        126.000000
min
0.000000
25%
        48.000000
                     0.000000
                                  3.000000
                                            120.000000
                                                        211.000000
0.000000
50%
                                            130.000000
                                                        241.000000
        56.000000
                     1.000000
                                  3.000000
0.000000
75%
        61.000000
                     1.000000
                                  4.000000
                                            140.000000
                                                         275.000000
0.000000
        77,000000
                     1.000000
                                            200.000000
                                                         564.000000
max
                                  4.000000
1.000000
```

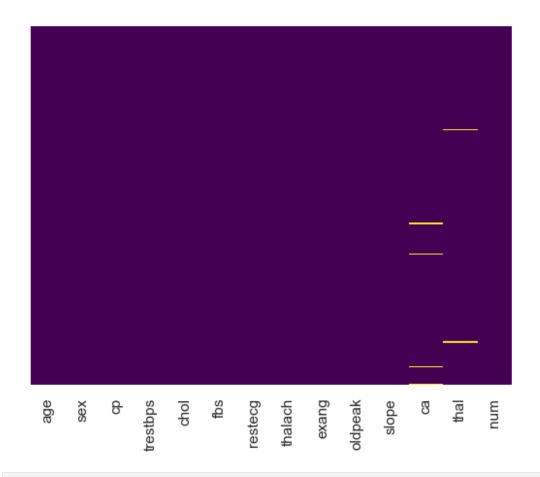
	restecg	thalach	exang	oldpeak	slope
ca \ count 303.	. 000000	303.000000	303.000000	303.000000	303.000000
299.000000		303100000	303100000	303100000	303100000
	990099	149.607261	0.326733	1.039604	1.600660
0.672241 std 0.	994971	22.875003	0.469794	1.161075	0.616226
0.937438	. 3343/1	22.073003	0.409/94	1.1010/3	0.010220
	.000000	71.000000	0.000000	0.000000	1.000000
0.000000 25% 0.	. 000000	133.500000	0.000000	0.000000	1.000000
0.000000	. 000000	133.36666	0.00000	0.00000	1.000000
50% 1.	.000000	153.000000	0.000000	0.800000	2.000000
0.000000 75% 2.	. 000000	166.000000	1.000000	1.600000	2.000000
1.000000	. 000000	100.000000	1.000000	1.000000	2.000000
	.000000	202.000000	1.000000	6.200000	3.000000
3.000000					
	thal	num			
		303.000000			
	.734219 .939706	0.937294 1.228536			
	.000000	0.000000			
	.000000	0.000000			
	. 000000 . 000000	0.000000 2.000000			
_	. 000000	4.000000			

VISUALIZING THE DATA

```
data.hist(figsize=(12,12))
plt.show()
```

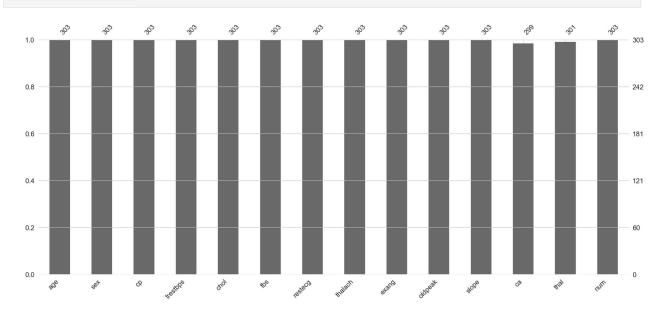


sns.heatmap(data.isnull(),yticklabels=False,cbar=False,cmap='viridis')
plt.show()

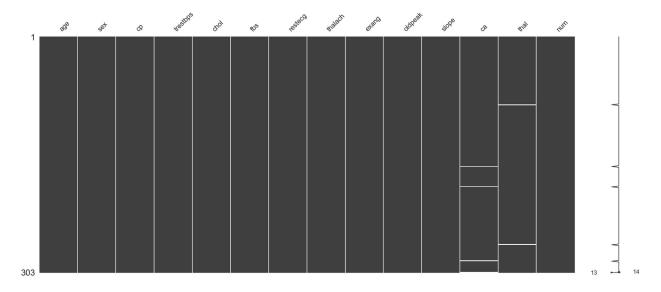


msno.bar(data)

<AxesSubplot:>



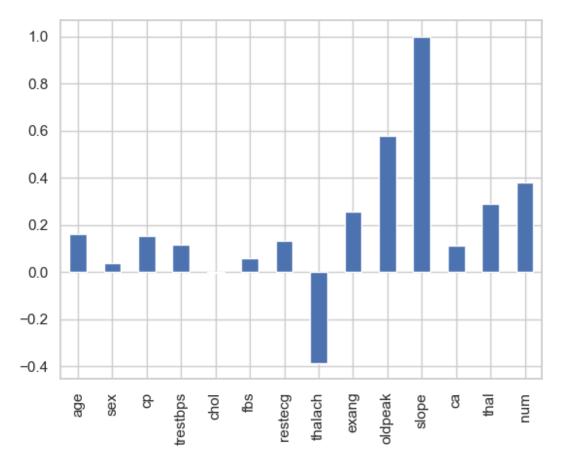
msno.matrix(data) plt.show()



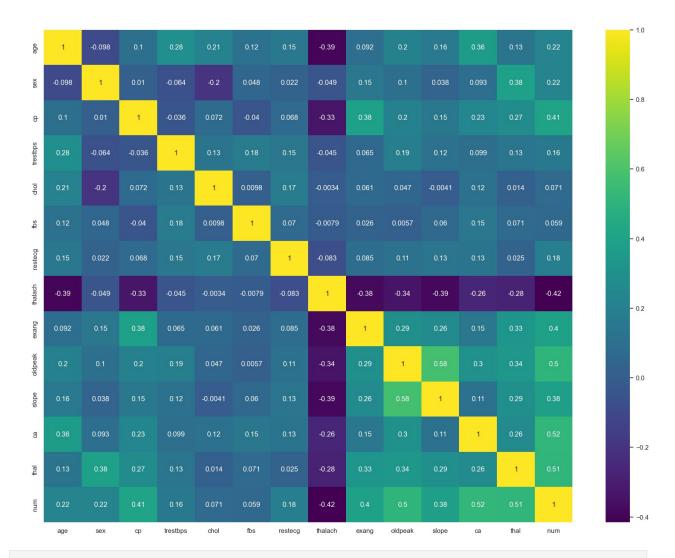
data.corr	()					
fbs \	age	sex	ср	trestbps	chol	
age	1.000000	-0.097542	0.104139	0.284946	0.208950	0.118530
sex	-0.097542	1.000000	0.010084	-0.064456	-0.199915	0.047862
ср	0.104139	0.010084	1.000000	-0.036077	0.072319	-0.039975
trestbps	0.284946	-0.064456	-0.036077	1.000000	0.130120	0.175340
chol	0.208950	-0.199915	0.072319	0.130120	1.000000	0.009841
fbs	0.118530	0.047862	-0.039975	0.175340	0.009841	1.000000
restecg	0.148868	0.021647	0.067505	0.146560	0.171043	0.069564
thalach	-0.393806	-0.048663	-0.334422	-0.045351	-0.003432	-0.007854
exang	0.091661	0.146201	0.384060	0.064762	0.061310	0.025665
oldpeak	0.203805	0.102173	0.202277	0.189171	0.046564	0.005747
slope	0.161770	0.037533	0.152050	0.117382	-0.004062	0.059894
ca	0.362605	0.093185	0.233214	0.098773	0.119000	0.145478
thal	0.127389	0.380936	0.265246	0.133554	0.014214	0.071358

num							
ca age	num	0.222853	0.224469	0.407075	0.157754	0.070909	0.059186
age 0.148868 -0.393806 0.091661 0.203805 0.161770 0.362605 sex 0.021647 -0.048663 0.146201 0.102173 0.037533 0.093185 cp 0.067505 -0.334422 0.384060 0.202277 0.152050 0.233214 trestbps 0.146560 -0.045351 0.064762 0.189171 0.117382 0.098773 chol 0.171043 -0.003432 0.061310 0.046564 -0.004062 0.119000 fbs 0.069564 -0.007854 0.025665 0.005747 0.059894 0.145478 restecg 1.000000 -0.083389 0.084867 0.114133 0.133946 0.128343 thalach -0.083389 1.000000 -0.378103 -0.343085 -0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal 0.127389 0.222469 cp 0.265246 0.407075 0.133554 0.157754 0.133554 0.157754 0.133554 0.157754 0.133554 0.157754 0.133554 0.157754 0.133696 0.024431 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.024531 0.183696 0.329680 0.397057 0.504092 0.377957 0.518909 0.287232 0.279631 0.415040 0.397057 0.504092 0.327325 0.37957 0.415040 0.397057 0.504092 0.327325 0.37957 0.415040 0.397057 0.504092 0.32680 0.397057 0.29680 0.397057 0.256382 0.518909 0.32680 0.32680 0.397057 0.256382 0.518909 0.32680 0.32680 0.397057 0.256382 0.518909 0.32680 0.397057 0.256382 0.518909 0.32680 0.32680 0.397057 0.256382 0.518909 0.32680 0.3	62.	restecg	thalach	exang	oldpeak	slope	
cp 0.067505 -0.334422 0.384060 0.202277 0.152050 0.233214 trestbps 0.146560 -0.045351 0.064762 0.189171 0.117382 0.098773 chol 0.171043 -0.003432 0.061310 0.046564 -0.04062 0.119000 fbs 0.069564 -0.007854 0.025665 0.005747 0.059894 0.145478 restecg 1.000000 -0.88389 0.084867 0.114133 0.133946 0.128343 thalach -0.083389 1.000000 -0.378103 1.000000 0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal num	•	0.148868	-0.393806	0.091661	0.203805	0.161770	0.362605
trestbps 0.146560 -0.045351 0.064762 0.189171 0.117382 0.098773 chol 0.171043 -0.003432 0.061310 0.046564 -0.004062 0.119000 fbs 0.069564 -0.007854 0.025665 0.005747 0.059894 0.145478 restecg 1.000000 -0.083389 0.084867 0.114133 0.133946 0.128343 thalach -0.083389 1.000000 -0.378103 -0.343085 -0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal num age 0.127389 0.222453	sex	0.021647	-0.048663	0.146201	0.102173	0.037533	0.093185
chol 0.171043 -0.003432 0.061310 0.046564 -0.004062 0.119000 fbs 0.069564 -0.007854 0.025665 0.005747 0.059894 0.145478 restecg 1.000000 -0.083389 0.084867 0.114133 0.133946 0.128343 thalach -0.083389 1.000000 -0.378103 -0.343085 -0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.24531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	ср	0.067505	-0.334422	0.384060	0.202277	0.152050	0.233214
fbs	trestbps	0.146560	-0.045351	0.064762	0.189171	0.117382	0.098773
restecg 1.000000 -0.083389 0.084867 0.114133 0.133946 0.128343 thalach -0.083389 1.000000 -0.378103 -0.343085 -0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal num age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.0709099 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 0.504092 0.377957 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	chol	0.171043	-0.003432	0.061310	0.046564	-0.004062	0.119000
thalach -0.083389 1.000000 -0.378103 -0.343085 -0.385601 -0.264246 exang 0.084867 -0.378103 1.000000 0.288223 0.257748 0.145570 oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909	fbs	0.069564	-0.007854	0.025665	0.005747	0.059894	0.145478
exang	restecg	1.000000	-0.083389	0.084867	0.114133	0.133946	0.128343
oldpeak 0.114133 -0.343085 0.288223 1.000000 0.577537 0.295832 slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909	thalach	-0.083389	1.000000	-0.378103	-0.343085	-0.385601	-0.264246
slope 0.133946 -0.385601 0.257748 0.577537 1.000000 0.110119 ca 0.128343 -0.264246 0.145570 0.295832 0.110119 1.000000 thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal num age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	exang	0.084867	-0.378103	1.000000	0.288223	0.257748	0.145570
ca	oldpeak	0.114133	-0.343085	0.288223	1.000000	0.577537	0.295832
thal 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal num age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	slope	0.133946	-0.385601	0.257748	0.577537	1.000000	0.110119
num 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 thal num age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	ca	0.128343	-0.264246	0.145570	0.295832	0.110119	1.000000
thal num age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	thal	0.024531	-0.279631	0.329680	0.341004	0.287232	0.256382
age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000	num	0.183696	-0.415040	0.397057	0.504092	0.377957	0.518909
age 0.127389 0.222853 sex 0.380936 0.224469 cp 0.265246 0.407075 trestbps 0.133554 0.157754 chol 0.014214 0.070909 fbs 0.071358 0.059186 restecg 0.024531 0.183696 thalach -0.279631 -0.415040 exang 0.329680 0.397057 oldpeak 0.341004 0.504092 slope 0.287232 0.377957 ca 0.256382 0.518909 thal 1.000000 0.509923 num 0.509923 1.000000		# la = 1					
data.corr()['chol']	sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal num	0.127389 0.380936 0.265246 0.133554 0.014214 0.071358 0.024531 -0.279631 0.329680 0.341004 0.287232 0.256382 1.000000 0.509923	0.222853 0.224469 0.407075 0.157754 0.070909 0.059186 0.183696 -0.415040 0.397057 0.504092 0.377957 0.518909 0.509923 1.000000				
	data.corr	()['chol']					

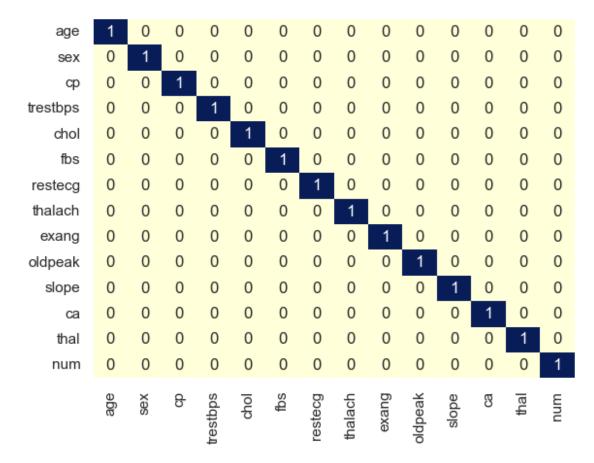
```
0.208950
age
           -0.199915
sex
            0.072319
ср
trestbps
            0.130120
chol
            1.000000
fbs
            0.009841
restecg
            0.171043
thalach
           -0.003432
            0.061310
exang
oldpeak
            0.046564
slope
           -0.004062
ca
            0.119000
thal
            0.014214
            0.070909
num
Name: chol, dtype: float64
data.corr()['slope']
            0.161770
age
            0.037533
sex
            0.152050
ср
trestbps
            0.117382
chol
           -0.004062
fbs
            0.059894
restecq
            0.133946
           -0.385601
thalach
            0.257748
exang
            0.577537
oldpeak
slope
            1.000000
            0.110119
ca
thal
            0.287232
            0.377957
num
Name: slope, dtype: float64
data.corr()['slope'].plot(kind='bar')
<AxesSubplot:>
```



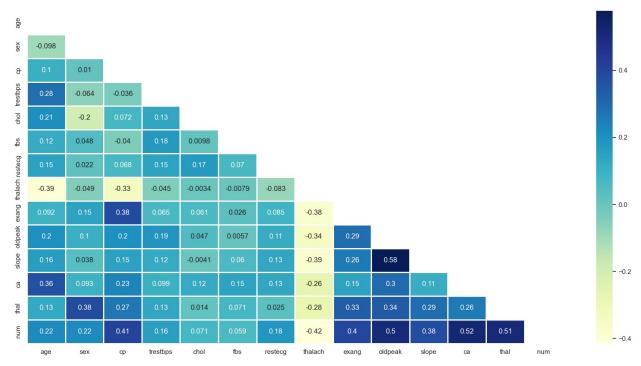
```
plt.figure(figsize=(20,15))
corr = data.corr()
sns.heatmap(data.corr(), cmap="viridis", annot=True)
plt.show()
```



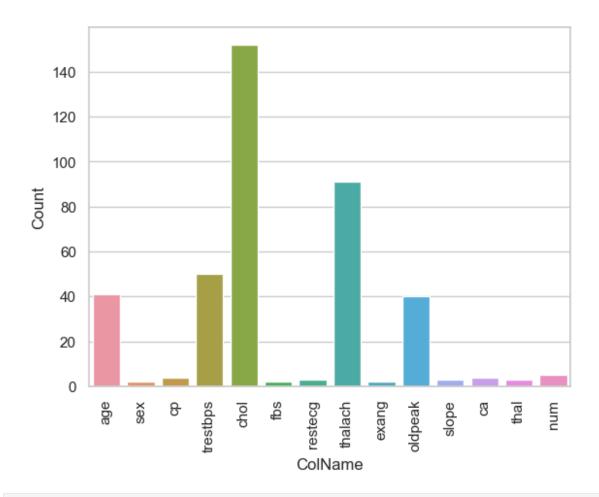
sns.heatmap(data.corr() > 0.9, annot=True, cbar=False,cmap="YlGnBu") plt.show()



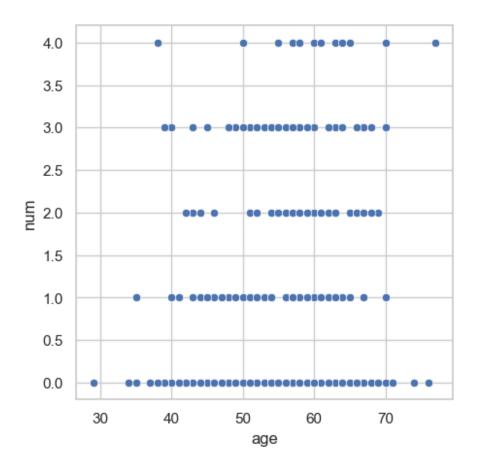
```
plt.figure(figsize=(20,10))
corr = data.corr()
mask=np.triu(np.ones_like(corr,dtype=bool))
sns.heatmap(data=corr, mask=mask,
cmap="YlGnBu",annot=True,linewidth=2)
plt.show()
```



```
unique=data.nunique().to_frame()
unique.columns=['Count']
unique.index.names=['ColName']
unique=unique.reset_index()
sns.set(style='whitegrid',color_codes='True')
sns.barplot(x='ColName', y = 'Count', data = unique)
plt.xticks(rotation=90)
plt.show()
```

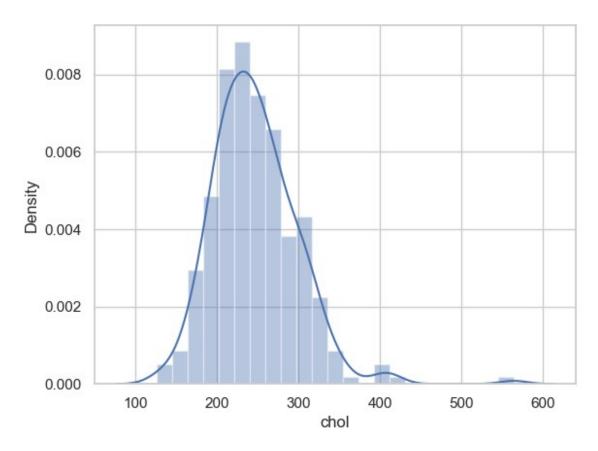


```
plt.figure(figsize=(5,5))
sns.scatterplot(x=data['age'],y=data['num'])
plt.show()
```



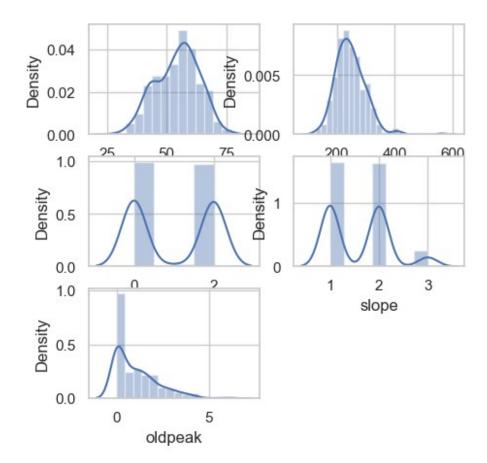
sns.distplot(data['chol'])

<AxesSubplot:xlabel='chol', ylabel='Density'>



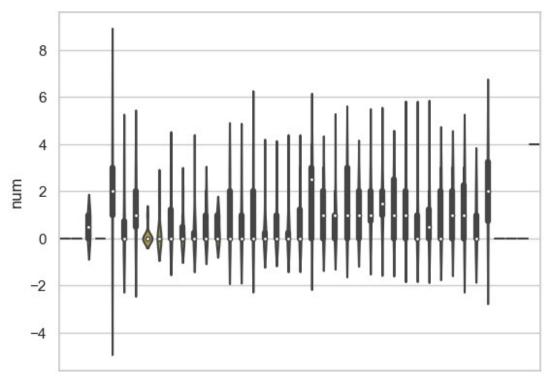
```
features = ['age','chol','restecg','slope', 'oldpeak']
plt.subplots(figsize=(5,5))

for i, col in enumerate(features):
   plt.subplot(3,2,i+1)
   sns.distplot(data[col])
plt.show()
```



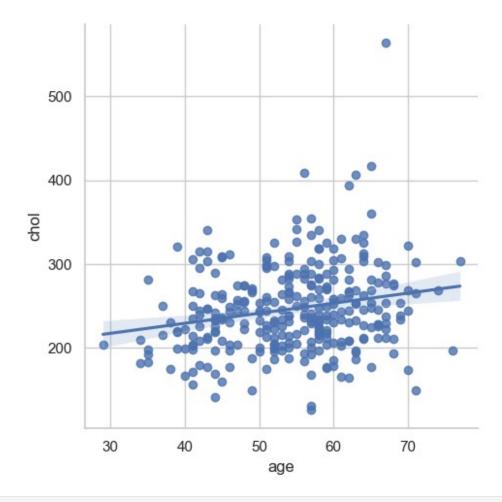
sns.violinplot(x='age', y='num', data=data)

<AxesSubplot:xlabel='age', ylabel='num'>



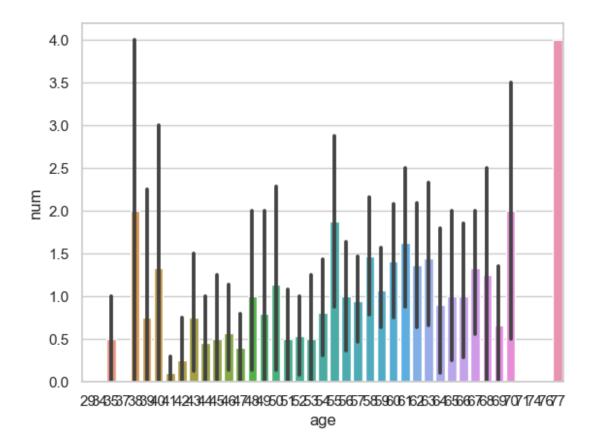
2934537383940414243444546474849505152354556575859506162636465666768697071747677 age

sns.lmplot(x='age',y='chol',data=data)
<seaborn.axisgrid.FacetGrid at 0x17845117a00>



sns.barplot(x='age',y='num',data=data)

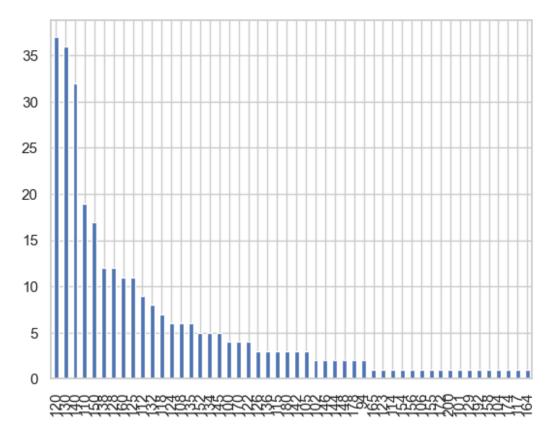
<AxesSubplot:xlabel='age', ylabel='num'>



data	.valu	e_co	unts()							
age slop	sex e ca		trestbps hal num	chol	fbs	restecg	thalach	exang	oldpeak	
29	1	2	130	204	0	2	202	0	0.0	1
0.0 59 2.0	3.0 1 6.0	0 4 3	1 164 1	176	1	2	90	0	1.0	2
			138	271	0	2	182	0	0.0	1
0.0	3.0	0	1 135	234	Θ	0	161	0	0.5	2
0.0	7.0	0	1 110	239	Θ	2	142	1	1.2	2
1.0	7.0	2	1	233	Ū	_	1.2	•	112	_
51 0.0	1 3.0	3 0	110 1	175	0	0	123	0	0.6	1
			100	222	0	0	143	1	1.2	2
0.0	3.0	0	1 94	227	0	0	154	1	0.0	1
1.0	7.0	0 1	1 125	213	0	2	125	1	1.4	1
1.0	3.0	0	1	213	J	_	123	_		-

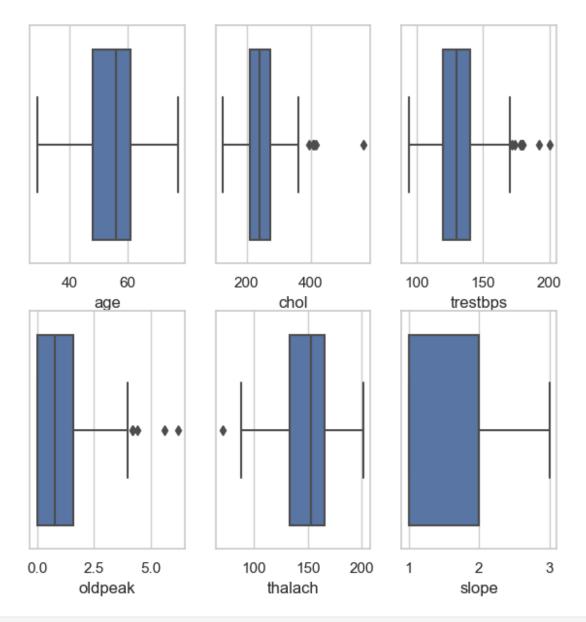
```
77
     1
                         304
                                                              0.0
              125
                               0
                                    2
                                              162
                                                       1
                                                                        1
           4
3.0 3.0
                  1
Length: 297, dtype: int64
data['chol'].value_counts()
204
       6
197
       6
234
       6
       5
269
212
       5
340
       1
160
       1
394
       1
184
       1
131
       1
Name: chol, Length: 152, dtype: int64
data['trestbps'].value_counts()
120
       37
130
       36
       32
140
110
       19
150
       17
138
       12
128
       12
160
       11
125
       11
112
        9
132
        8
118
        7
124
        6
108
        6
        6
135
        5
152
        5
134
        5
145
        4
100
170
        4
        4
122
126
        3
        3 3 3 3 2
136
115
180
142
105
102
146
        2
```

```
2
144
148
       2
178
       2
94
       1
165
123
       1
114
        1
154
        1
       1
156
       1
106
155
       1
       1
172
200
       1
101
        1
129
       1
192
       1
       1
158
       1
104
174
       1
117
        1
164
        1
Name: trestbps, dtype: int64
data['trestbps'].value_counts().plot(kind='bar')
<AxesSubplot:>
```

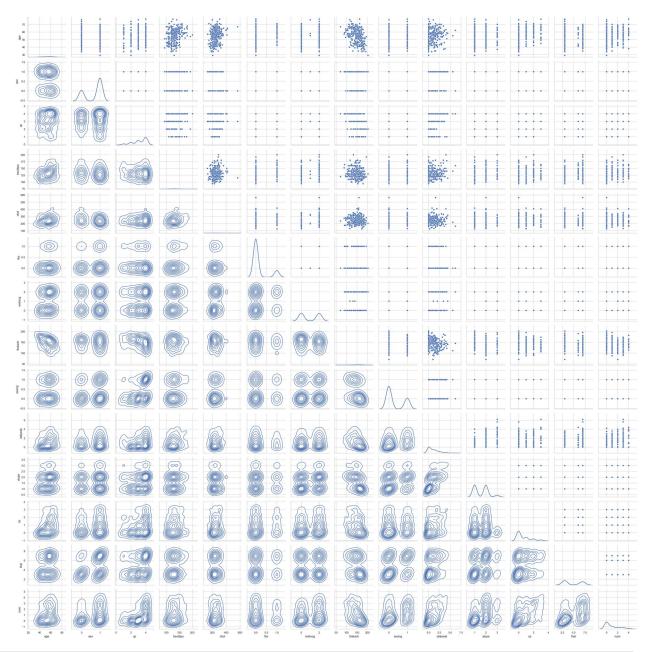


```
features = ['age','chol','trestbps','oldpeak','thalach','slope']
plt.subplots(figsize=(7,7))

for i, col in enumerate(features):
   plt.subplot(2,3,i+1)
   sns.boxplot(data[col])
plt.show()
```



```
graph=sns.PairGrid(data)
graph=graph.map_upper(sns.scatterplot)
graph=graph.map_lower(sns.kdeplot)
graph=graph.map_diag(sns.kdeplot,lw=2)
plt.show()
```



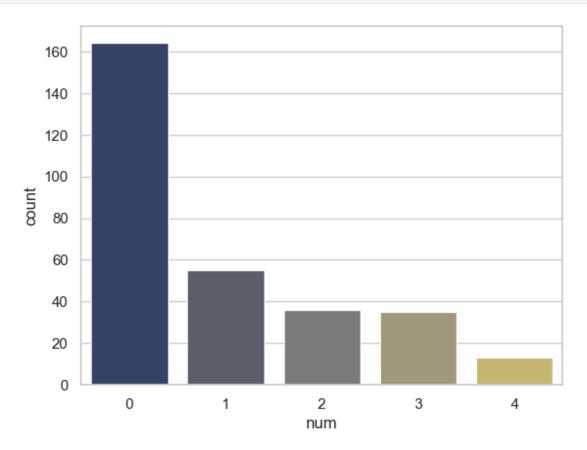
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```
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sns.countplot(x='num',data=data,palette='cividis')
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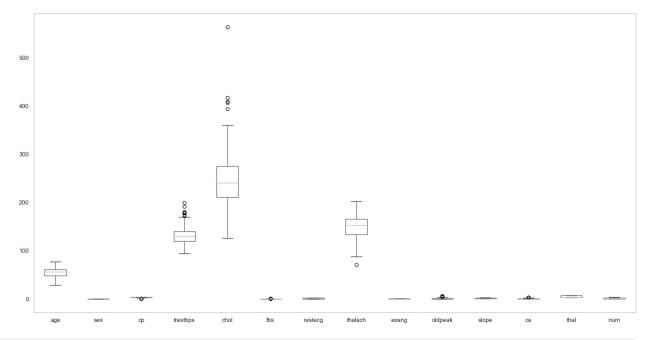


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74,54,54,56,46,49,42,41,41,49,61,60,67,58,47,52,62,57,58,64,51,43,42,6
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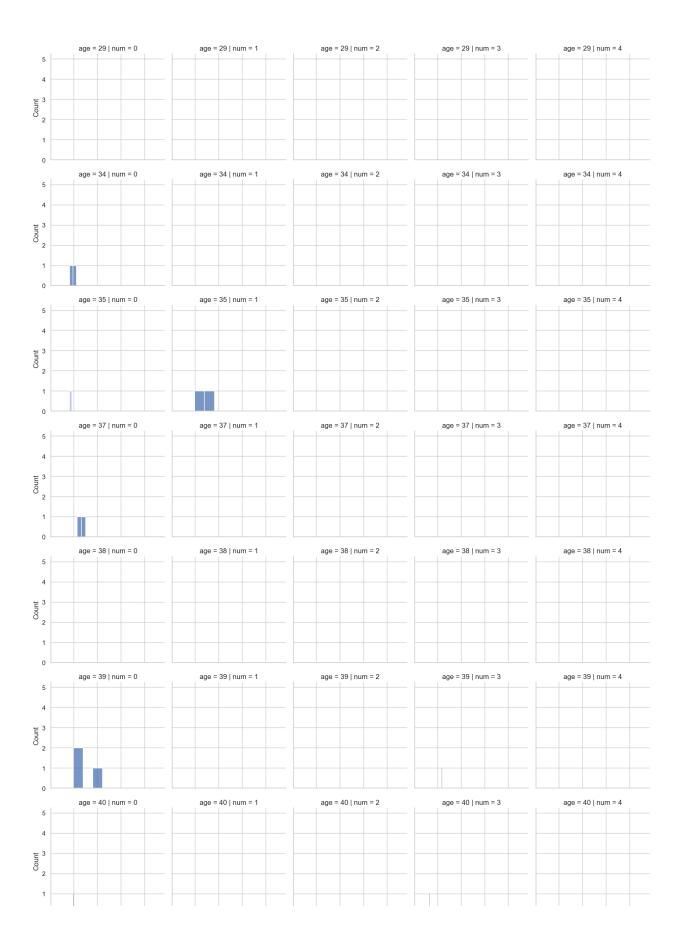
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data.nunique().sort values()
ColName
               2
sex
               2
fbs
               2
exang
```

```
restecg
               3 3
slope
thal
ср
               4
ca
               5
num
oldpeak
              40
age
              41
trestbps
              50
thalach
              91
chol
             152
dtype: int64
plt.figure(figsize=(20,10))
data.boxplot(grid=False)
plt.show()
```



```
a=sns.FacetGrid(data,row='age',col='num')
a.map(sns.histplot,'chol')
plt.show()
```



```
data.replace('?',' ',inplace=True)
data
         age sex cp trestbps chol fbs
ColName
                                                restecg thalach exang
oldpeak \
                              145
                                     233
                                                              150
                                                                        0
           63
                 1
                                            1
2.3
1
           67
                 1
                     4
                              160
                                     286
                                             0
                                                      2
                                                              108
                                                                        1
1.5
2
                              120
                                     229
                                                      2
                                                              129
           67
                 1
                    4
                                             0
                                                                        1
2.6
                              130
                                                              187
3
           37
                 1
                     3
                                     250
                                             0
                                                      0
                                                                        0
3.5
4
           41
               0
                     2
                              130
                                     204
                                             0
                                                      2
                                                              172
                                                                        0
1.4
. .
. . .
298
                              110
                                     264
                                             0
                                                              132
           45
                 1
                                                      0
                                                                        0
1.2
                                                              141
299
           68
                 1
                              144
                                     193
                                             1
                                                      0
                                                                        0
3.4
300
           57
                 1
                     4
                              130
                                     131
                                             0
                                                      0
                                                              115
                                                                        1
1.2
301
                              130
                                                              174
           57
                 0
                     2
                                     236
                                             0
                                                      2
                                                                        0
0.0
302
           38
                 1
                     3
                              138
                                     175
                                             0
                                                      0
                                                              173
                                                                        0
0.0
ColName
          slope
                       thal
                  ca
                             num
0
              3
                 0.0
                        6.0
                               0
              2
                 3.0
                               2
1
                        3.0
              2
2
                        7.0
                 2.0
                               1
3
              3
                 0.0
                        3.0
                               0
4
              1
                 0.0
                        3.0
                               0
              2
298
                 0.0
                        7.0
                               1
              2
299
                 2.0
                        7.0
                               2
              2
                 1.0
                        7.0
                               3
300
              2
301
                 1.0
                        3.0
                               1
              1
302
                 NaN
                        3.0
                               0
[303 rows x 14 columns]
data['ca'].replace('',np.nan, inplace=True)
data['thal'].replace('',np.nan, inplace=True)
data.dropna(subset=['ca'],inplace=True)
data.dropna(subset=['thal'],inplace=True)
```

TRAINING AND TESTING DATA

```
cat val=[]
count val=[]
for col in data.columns:
    if data[col].nunique()<=10:</pre>
        cat val.append(col)
        count val.append(col)
cat val
['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'num']
count val
['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
data=pd.get_dummies(data,columns=['cp','fbs','restecg','exang','slope'
,'ca','thal'])
data.head()
   age sex trestbps chol thalach oldpeak num cp 1 cp 2
cp_3 ... \
0
    63
          1
                   145
                          233
                                   150
                                             2.3
                                                           1
                                                                  0
0
1
    67
          1
                   160
                          286
                                   108
                                             1.5
                                                     2
                                                           0
0
   . . .
2
    67
                   120
                          229
                                   129
                                             2.6
                                                                  0
           1
                                                     1
                                                           0
0
   . . .
3
                   130
                          250
                                             3.5
    37
           1
                                   187
                                                     0
                                                           0
                                                                  0
1
   . . .
4
    41
          0
                   130
                          204
                                   172
                                             1.4
                                                     0
0
   . . .
   slope_1 slope_2 slope_3 ca_0.0 ca_1.0 ca_2.0 ca_3.0 thal_3.0
/
0
         0
                             1
                                      1
                                              0
                                                       0
                                                                          0
1
         0
                             0
                                      0
                                              0
                                                       0
                                                                          1
2
         0
                             0
                                      0
                                              0
                                                       1
                                                                          0
         0
                   0
                                                                          1
3
                             1
                                      1
                                              0
                                                       0
                                                                0
         1
                                      1
                                                                          1
   thal_6.0 thal_7.0
0
          1
```

```
1
          0
                     0
2
          0
                     1
3
          0
                     0
          0
[5 rows x 28 columns]
x=data.drop(['num'],axis=1)
y=data['num']
x train,x test,y train,y test=train test split(x,y,test size=0.2,rando
m state=1)
ss=StandardScaler()
x_train=ss.fit_transform(x_train)
x test=ss.transform(x test)
```

Random Forest

```
clfr=RandomForestClassifier(n estimators=10,criterion='entropy',random
state=0)
clfr.fit(x train,y train)
RandomForestClassifier(criterion='entropy', n estimators=10,
random state=0)
clfr1=RandomForestClassifier(n estimators=10,criterion='gini',random s
tate=0)
clfr1.fit(x_train,y_train)
RandomForestClassifier(n estimators=10, random state=0)
ypre1=clfr.predict(x test)# entropy ypre calculation
ypre2=clfr1.predict(x test)# gini ypre calculation
print('entropy Accuracy Score:')
accuracy score(y test,ypre1)*100
entropy Accuracy Score:
55.000000000000001
print('gini Accuracy Score:')
accuracy_score(y_test,ypre2)*100
gini Accuracy Score:
```

```
53.3333333333333
print('entropy - confusion matrix\n-----\n')
print(confusion matrix(y test,yprel))
print('gini - confusion matrix\n----\n')
print(confusion matrix(y test,ypre2))
entropy - confusion matrix
[[27 3 0 0 0]
 [35110]
 [5 3 0 3 0]
 [2 3 1 1
            11
 [0 \ 0 \ 0 \ 1]
             011
gini - confusion matrix
[[26 3 0 1 0]
[5 3 1 0 1]
 [6 2 0 3 0]
 [2 1 1 3 1]
 [1 0 0 0 0]
print('entropy result\n----')
print(classification_report(y_test,yprel))
print('gini index result\n-----')
print(classification report(y test,ypre2))
entropy result
             precision
                        recall f1-score
                                          support
          0
                 0.73
                          0.90
                                   0.81
                                               30
          1
                          0.50
                 0.36
                                   0.42
                                              10
          2
                 0.00
                          0.00
                                   0.00
                                               11
          3
                                   0.14
                                               8
                 0.17
                          0.12
          4
                 0.00
                          0.00
                                   0.00
                                               1
                                   0.55
                                              60
   accuracy
                 0.25
                          0.30
                                   0.27
                                              60
  macro avg
weighted avg
                 0.45
                          0.55
                                   0.49
                                              60
gini index result
            precision recall f1-score
                                          support
          0
                          0.87
                                   0.74
                                              30
                 0.65
                 0.33
                          0.30
                                   0.32
          1
                                              10
          2
                                   0.00
                                              11
                 0.00
                          0.00
          3
                 0.43
                          0.38
                                   0.40
                                               8
```

4	0.00	0.00	0.00	1
accuracy macro avg weighted avg	0.28 0.44	0.31 0.53	0.53 0.29 0.48	60 60 60

Decision Tree

```
dtree = DecisionTreeClassifier(max depth=6, random state=1)
dtree.fit(x_train,y_train)
DecisionTreeClassifier(max depth=6, random state=1)
y_pre3=dtree.predict(x test)
from sklearn.metrics import
classification report, confusion matrix, accuracy score, mean squared err
print(classification_report(y_test,y_pre3))
              precision
                           recall f1-score
                                              support
           0
                   0.76
                             0.83
                                                   30
                                       0.79
           1
                   0.18
                             0.20
                                       0.19
                                                   10
           2
                   0.33
                             0.27
                                       0.30
                                                   11
           3
                   0.00
                             0.00
                                       0.00
                                                    8
                   0.00
                             0.00
                                       0.00
                                                    1
                                       0.50
                                                   60
    accuracy
   macro avg
                   0.25
                             0.26
                                       0.26
                                                   60
weighted avg
                   0.47
                             0.50
                                       0.48
                                                   60
print(confusion matrix(y test,y pre3))
print("Training Score: ",dtree.score(x train,y train)*100)
[[25 3
        0 2 01
 [32311]
 [4331
               01
     2
        3
 [ 1
            0
               21
     1
 [ 0
        0
            0
              011
Training Score: 82.70042194092827
print(accuracy score(y test,y pre3)*100)
50.0
data = pd.DataFrame({'Actual': y_test, 'Predicted': y_pre3})
data.head()
```

	Actual	Predicted
139	0	0
236	2	1
51	0	1
295	0	Θ
295 245	2	0

Logistic Regression

```
reg = LogisticRegression()
reg.fit(x_train,y_train)
LogisticRegression()
y pre4=reg.predict(x test)
y_pre4
array([0, 3, 0, 0, 1, 1, 0, 4, 0, 2, 3, 2, 0, 1, 1, 1, 3, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 3, 1, 0, 0, 1, 0, 4, 2, 0, 0, 0, 0, 4, 0, 0, 0,
1,
       0, 0, 0, 1, 3, 4, 0, 1, 3, 1, 4, 3, 4, 4, 0, 1], dtype=int64)
print(classification_report(y_test,y_pre4))
print(confusion matrix(y test,y pre4))
print("Training Score: ",reg.score(x_train,y_train)*100)
                           recall f1-score
              precision
                                              support
           0
                             0.80
                   0.80
                                       0.80
                                                    30
           1
                   0.23
                             0.30
                                       0.26
                                                    10
           2
                   0.00
                             0.00
                                       0.00
                                                    11
           3
                   0.14
                             0.12
                                       0.13
                                                    8
           4
                   0.00
                             0.00
                                                    1
                                       0.00
                                       0.47
    accuracy
                                                    60
                   0.23
                             0.25
                                       0.24
                                                    60
   macro avq
                   0.46
weighted avg
                             0.47
                                       0.46
                                                    60
[[24 3
        0 1 2]
 [4301
               2]
 [2404
              1]
 [ 0 3 2 1
               2]
      0
        1
 [ 0
            0
              0]]
Training Score: 73.83966244725738
data = pd.DataFrame({'Actual': y_test, 'Predicted': y_pre4})
data.head()
```

```
Actual Predicted
139
          0
236
          2
                     3
                     0
51
          0
                     0
295
          0
          2
                     1
245
print(accuracy score(y test,y pre4)*100)
46.6666666666664
from sklearn.model selection import GridSearchCV
param = {
          penalty':['l1','l2'],
         'C':[0.001, 0.01, 0.1, 1, 10, 20,100, 1000]
lr= LogisticRegression(penalty='l1')
cv=GridSearchCV(reg,param,cv=5,n jobs=-1)
cv.fit(x_train,y_train)
cv.predict(x_test)
array([0, 3, 0, 0, 0, 1, 0, 4, 0, 2, 3, 2, 0, 1, 1, 0, 3, 0, 0, 0, 1,
0,
       0, 0, 0, 0, 0, 3, 1, 0, 0, 0, 0, 4, 2, 0, 0, 0, 0, 4, 0, 0, 0,
1,
       0, 0, 0, 1, 0, 4, 0, 1, 3, 1, 4, 3, 4, 4, 0, 1], dtype=int64)
print("Best CV score", cv.best score *100)
Best CV score 59.9290780141844
```

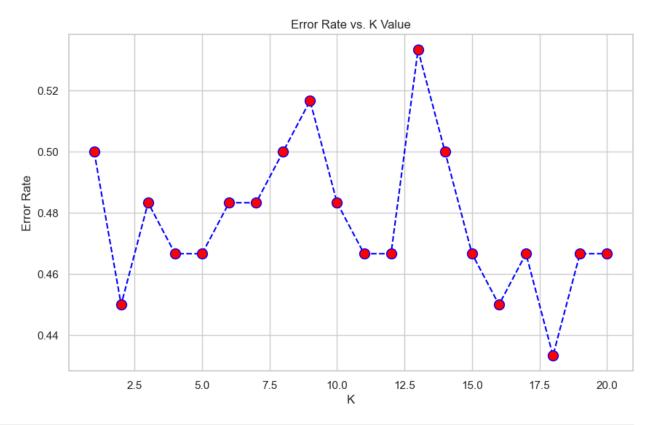
KNN

```
knn=KNeighborsClassifier(n neighbors=7)
knn.fit(x train,y train)
KNeighborsClassifier(n neighbors=7)
y_pre5=knn.predict(x_test)
data = pd.DataFrame({'Actual': y test, 'Predicted': y pre5})
data.head()
             Predicted
     Actual
139
          0
                     2
          2
236
51
          0
                     0
```

```
295
          0
          2
                     0
245
from sklearn.metrics import
classification report, confusion matrix, accuracy score, mean squared err
or, r2 score
print(classification_report(y_test,y_pre5))
              precision
                            recall f1-score
                                               support
                   0.64
                              0.93
                                        0.76
                                                     30
           0
           1
                   0.25
                              0.20
                                        0.22
                                                     10
           2
                   0.25
                              0.09
                                        0.13
                                                     11
           3
                   0.00
                              0.00
                                        0.00
                                                      8
           4
                                                      1
                   0.00
                              0.00
                                        0.00
                                        0.52
                                                     60
    accuracy
                   0.23
                              0.24
                                        0.22
                                                     60
   macro avg
                   0.41
                              0.52
                                        0.44
                                                     60
weighted avg
print(confusion_matrix(y_test,y_pre5))
[[28 2
            0
               0]
         0
 [ 6 2
        0 1 11
 [6 \ 3 \ 1 \ 1 \ 0]
 [ 3
     1
        3 0
               1]
 [ 1 0
            0
               011
print("Training Score: ",knn.score(x_train,y_train)*100)
print(knn.score(x_test,y_test))
Training Score: 66.6666666666666
0.516666666666667
accuracy score(y test,y pre5)
0.5166666666666667
t=1-accuracy_score(y_test,y_pre5)
0.483333333333333
error rate = []
for i in range(1,21):
    knn = KNeighborsClassifier(n neighbors=i)
    knn.fit(x_train,y_train)
    pred i = knn.predict(x test)
```

```
t=1-accuracy_score(y_test,pred_i)
error_rate.append(t)

plt.figure(figsize=(10,6))
plt.plot(range(1,21),error_rate,color='blue', linestyle='dashed',
marker='o',markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
Text(0, 0.5, 'Error Rate')
```



```
data=pd.DataFrame({'Models':
['Rf(Entropy)','Rf(Gini)','DT','Logreg','Knn'],
                'Accuracy':
[accuracy_score(y_test,ypre1)*100,accuracy_score(y_test,ypre2)*100,
accuracy score(y test,y pre3)*100, accuracy score(y test,y pre4)*100,
                             accuracy score(y test,y pre5)*100]})
data
        Models
                 Accuracy
   Rf(Entropy)
                55.000000
0
                53.333333
1
      Rf(Gini)
2
                50.000000
```

```
3 Logreg 46.666667
4 Knn 51.666667
sns.barplot(data['Models'],data['Accuracy'])
plt.xticks(rotation=90)
plt.show()
```

