Healthcare : Cardiovascular diseases Prediction

Course-end Project 5

Problem statement:

Cardiovascular diseases are the leading cause of death globally. It is therefore necessary to identify the causes and develop a system to predict heart attacks in an effective manner. The data below has the information about the factors that might have an impact on cardiovascular health.

Dataset description:

Variable Description Age Age in years Sex 1 = male; 0 = female cp| Chest pain type Trestbps Resting blood pressure (in mm Hg on admission to the hospital) Chol Serum cholesterol in mg/dl Fbs Fasting blood sugar > 120 mg/dl (1 = true; 0 = false) Restecg Resting electrocardiographic results Thalach Maximum heart rate achieved Exang Exercise induced angina (1 = yes; 0 = no) Oldpeak ST depression induced by exercise relative to rest slope Slope of the peak exercise ST segment ca Number of major vessels (0-3) colored by fluoroscopy thal 3 = normal; 6 = fixed defect; 7 = reversible defect Target 1 or 0

Note:

Download CEP 1_ Dataset.xlsx using the link given in the Healthcare project problem statement

Task to be performed:

1. Preliminary analysis:

a. Perform preliminary data inspection and report the findings on the structure of the data, missing values, duplicates, etc.

b. Based on these findings, remove duplicates (if any) and treat missing values using an appropriate strategy

1. Prepare a report about the data explaining the distribution of the disease and the related factors using the steps listed below:

a. Get a preliminary statistical summary of the data and explore the measures of central tendencies and spread of the data

b. Identify the data variables which are categorical and describe and explore these variables using the appropriate tools, such as count plot

c. Study the occurrence of CVD across the Age category

d. Study the composition of all patients with respect to the Sex category

e. Study if one can detect heart attacks based on anomalies in the resting blood pressure (trestbps) of a patient

f. Describe the relationship between cholesterol levels and a target variable

g. State what relationship exists between peak exercising and the occurrence of a heart attack

h. Check if thalassemia is a major cause of CVD

i. List how the other factors determine the occurrence of CVD

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

1. Build a baseline model to predict the risk of a heart attack using a logistic regression and random forest and explore the results while using correlation analysis and logistic regression (leveraging standard error and p-values from statsmodels) for feature selection

DESCRIPTION

Cardiovascular diseases are the leading cause of death globally. It is therefore necessary to identify the causes and develop a system to predict heart attacks in an effective manner. The data below has the information about the factors that might have an impact on cardiovascular health.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from google.colab import files
uploaded=files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving 1645792390_cep1_dataset.csv to 1645792390_cep1_dataset (1).csv
```

```
data=pd.read_csv('1645792390_cep1_dataset.csv')
```

```
data.head()
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  
slope  \
0   63    1   3       145   233    1        0      150      0      2.3   
0  
1   37    1   2       130   250    0        1      187      0      3.5   
0  
2   41    0   1       130   204    0        0      172      0      1.4   
2  
3   56    1   1       120   236    0        1      178      0      0.8   
```

```
2
4   57    0   0       120   354    0         1      163       1      0.6
2

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

```
data.tail()
```

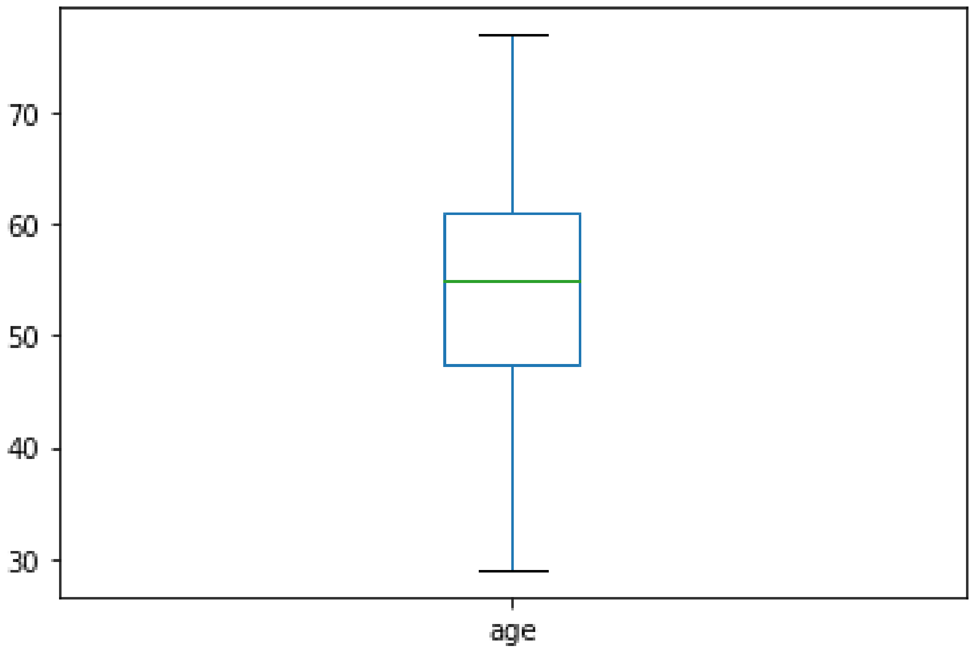
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang
oldpeak  \
298   57    0   0       140   241    0        1      123      1
0.2
299   45    1   3       110   264    0        1      132      0
1.2
300   68    1   0       144   193    1        1      141      0
3.4
301   57    1   0       130   131    0        1      115      1
1.2
302   57    0   1       130   236    0        0      174      0
0.0

     slope  ca  thal  target
298      1   0     3       0
299      1   0     3       0
300      1   2     3       0
301      1   1     3       0
302      1   1     2       0
```

REMOVAL OF OUTLIERS USING BOXPLOT

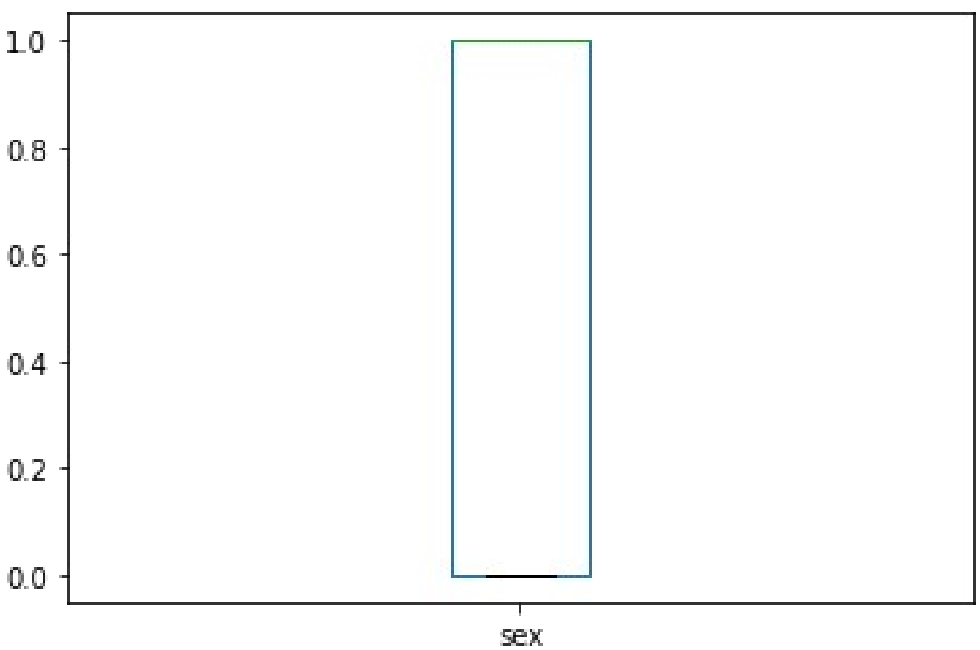
```
data.shape
```

```
(303, 14)
```

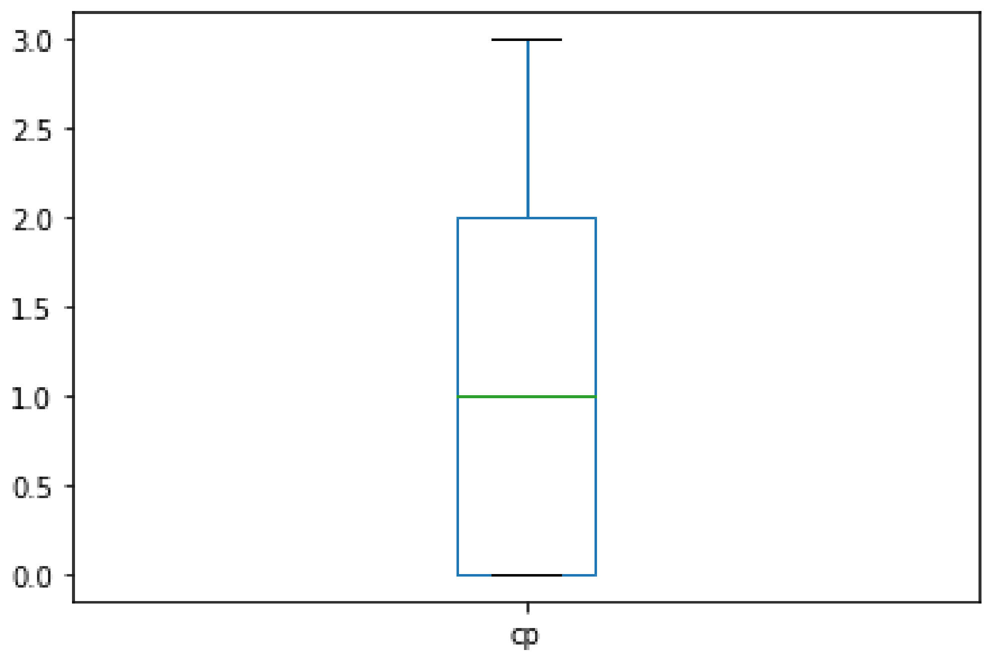
```
def plot_boxplot(df,ft):
  df.boxplot(column=[ft])
  plt.grid(False)
  plt.show()


plot_boxplot(data,'age')
```



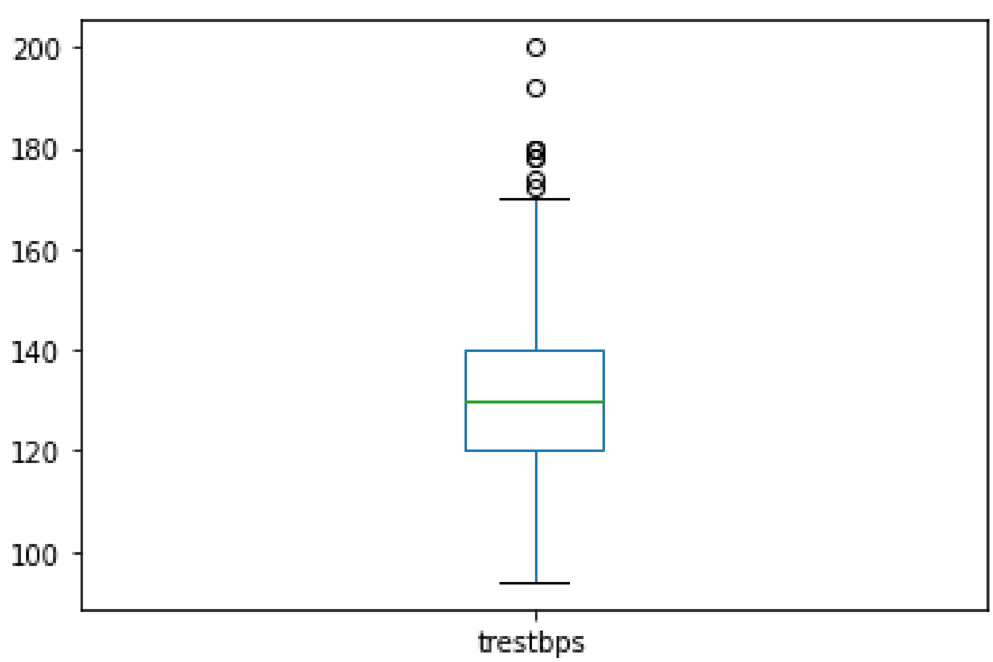

```
plot_boxplot(data,'sex')
```



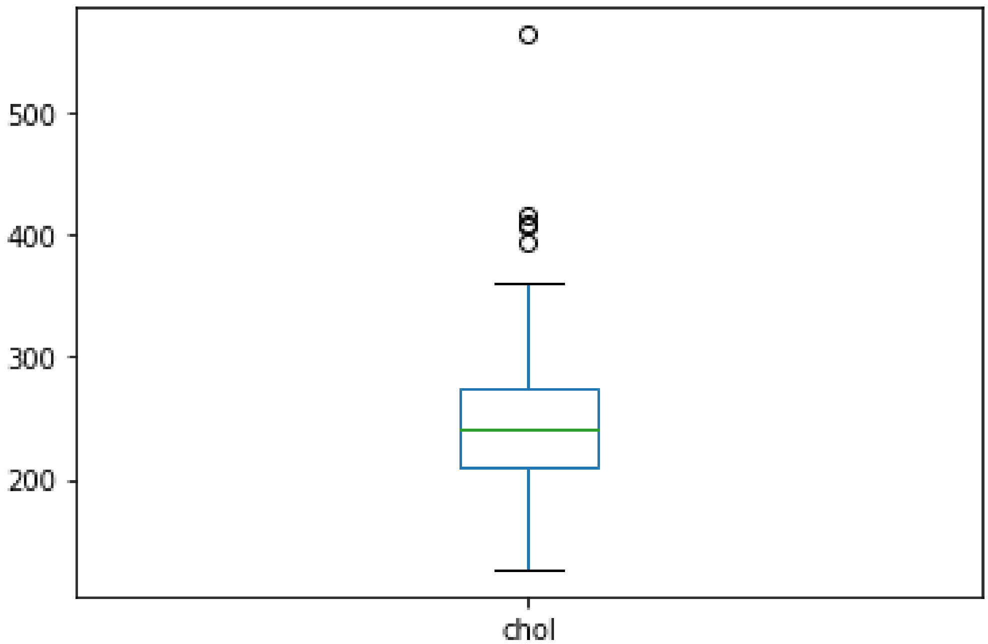

```
plot_boxplot(data,'cp')
```



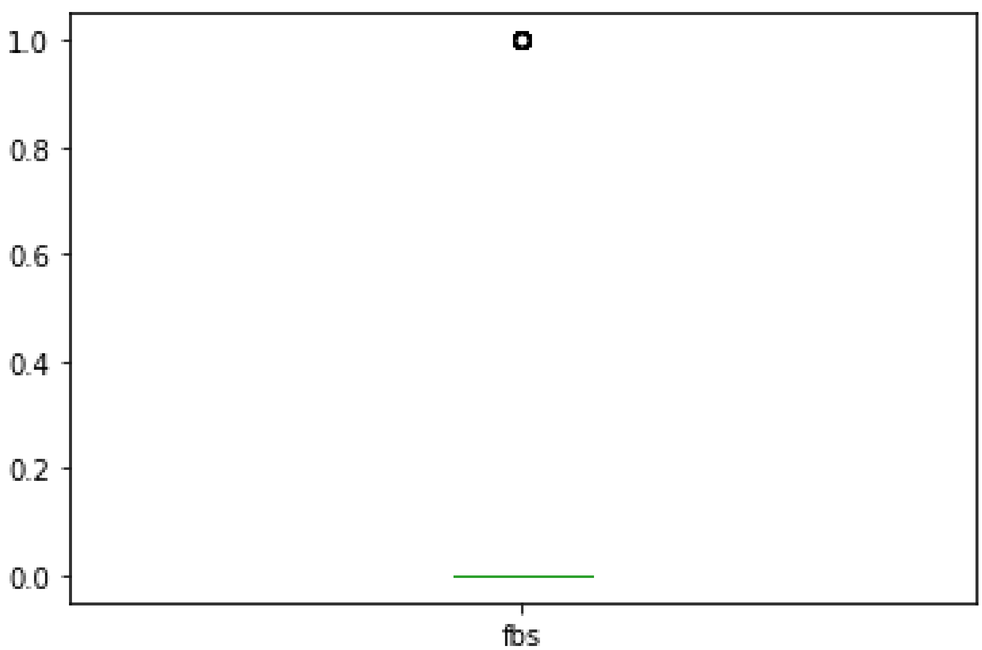

```
plot_boxplot(data,'trestbps')
```



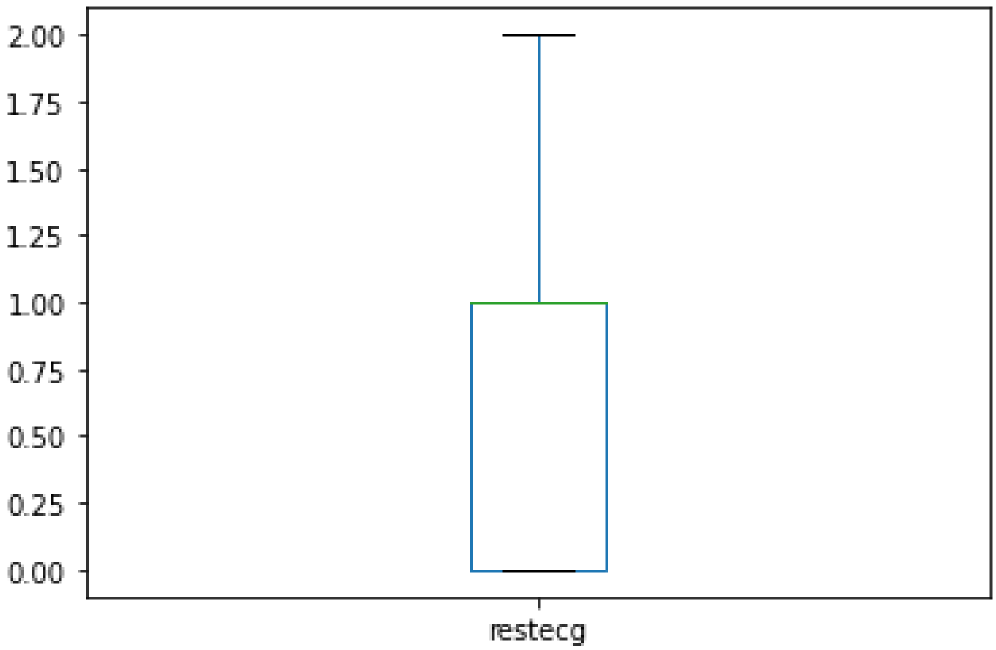

```
plot_boxplot(data,'chol')
```



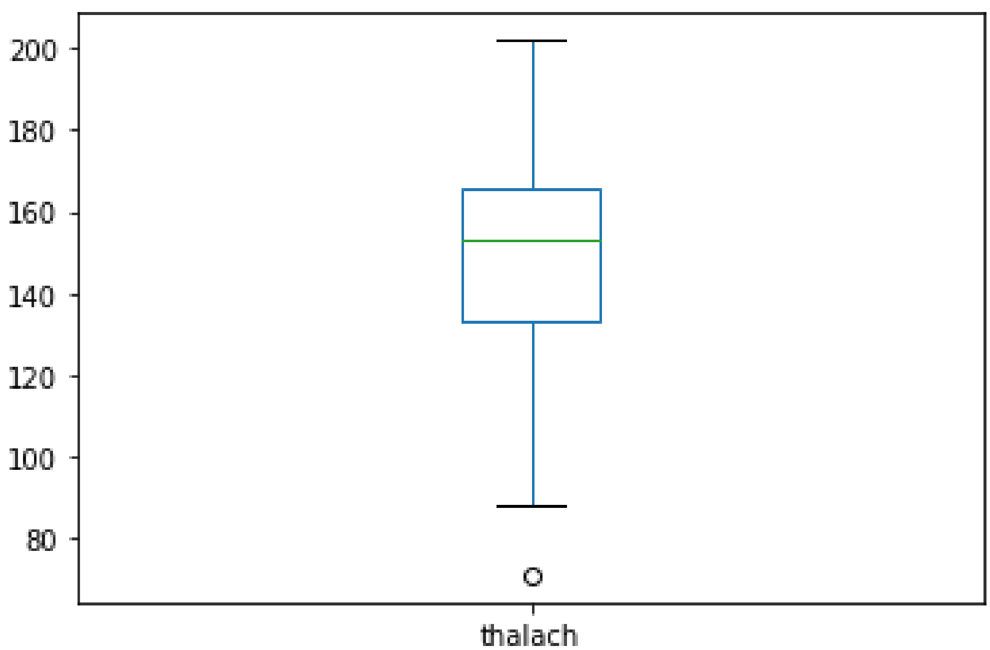

```
plot_boxplot(data,'fbs')
```



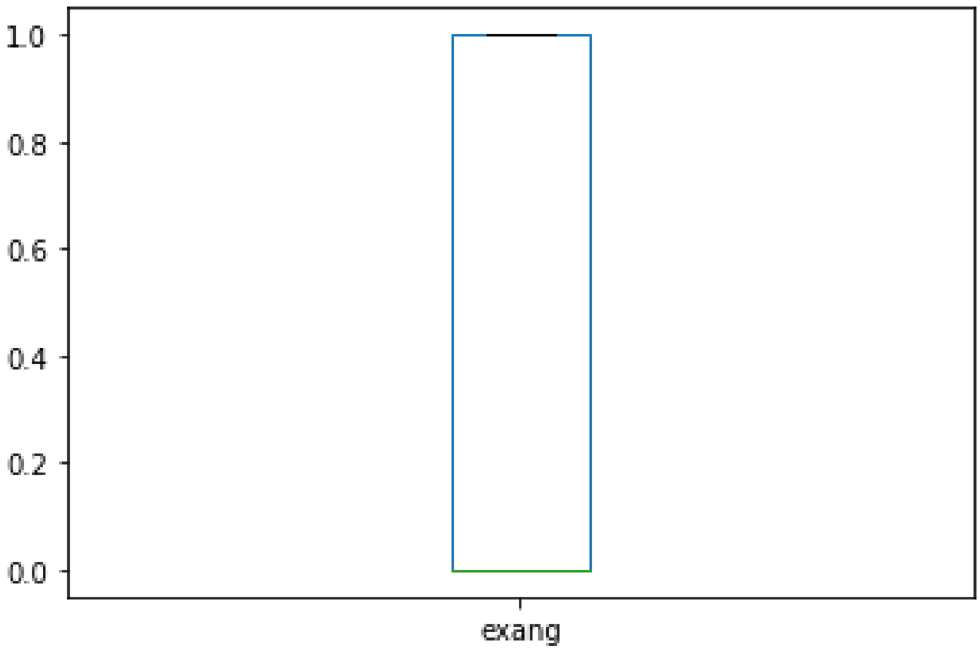

```
plot_boxplot(data,'restecg')
```



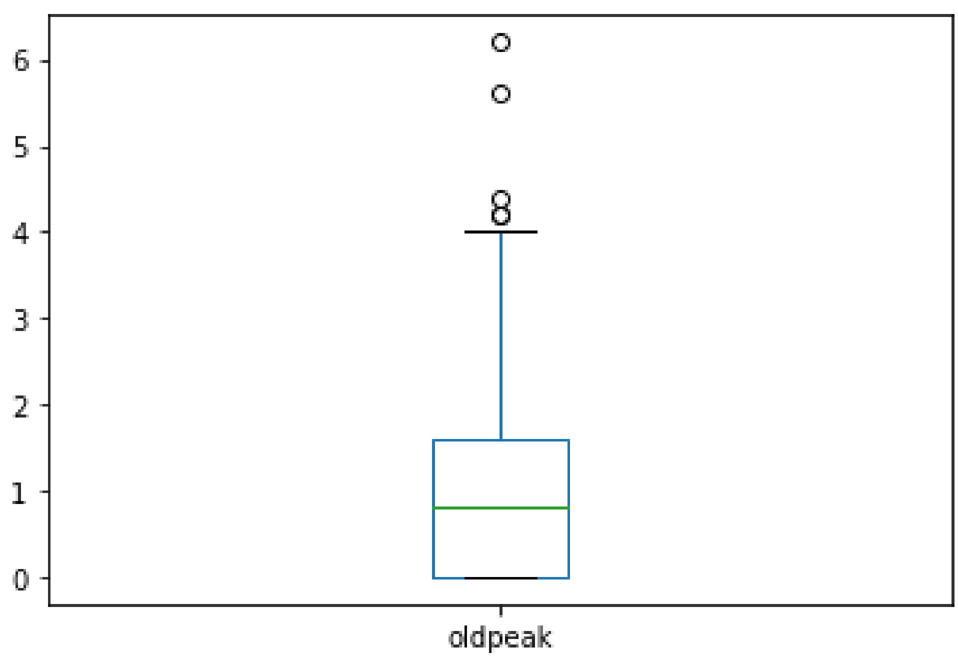

```
plot_boxplot(data,'thalach')
```



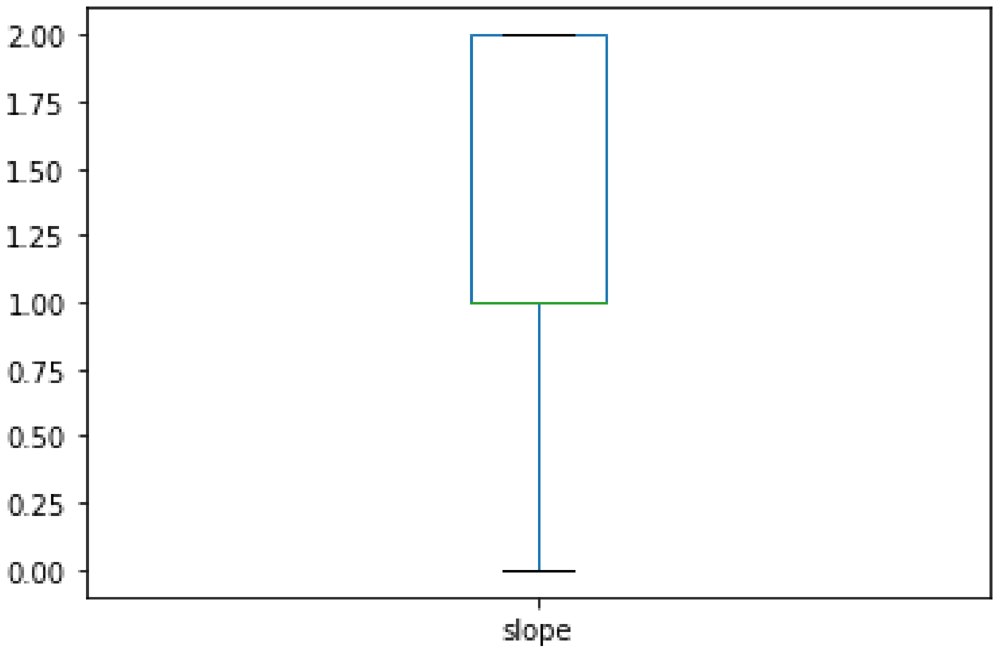

```
plot_boxplot(data,'exang')
```



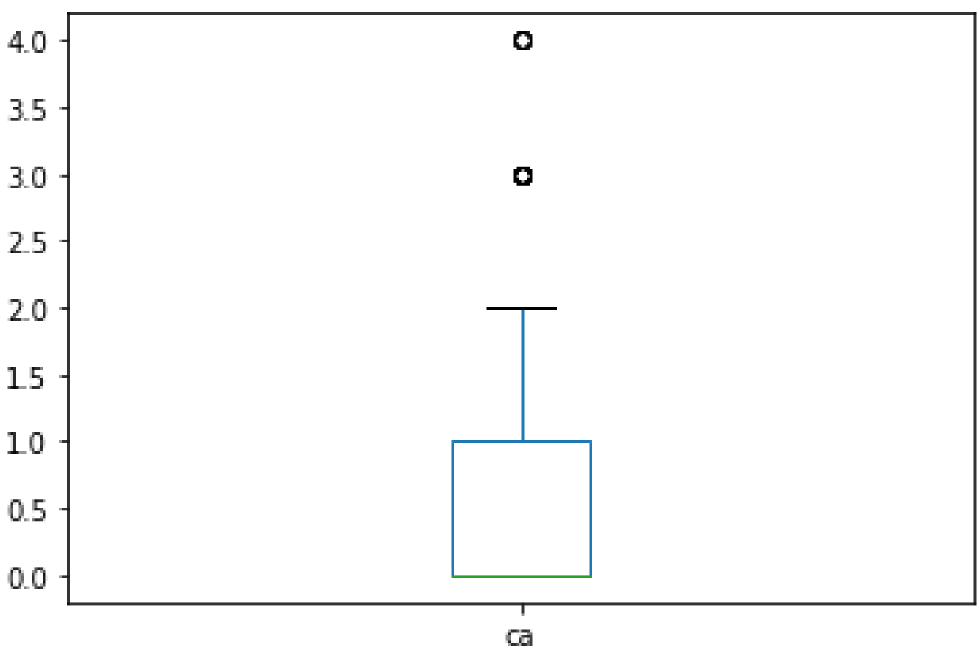
```
plot_boxplot(data,'oldpeak')
```



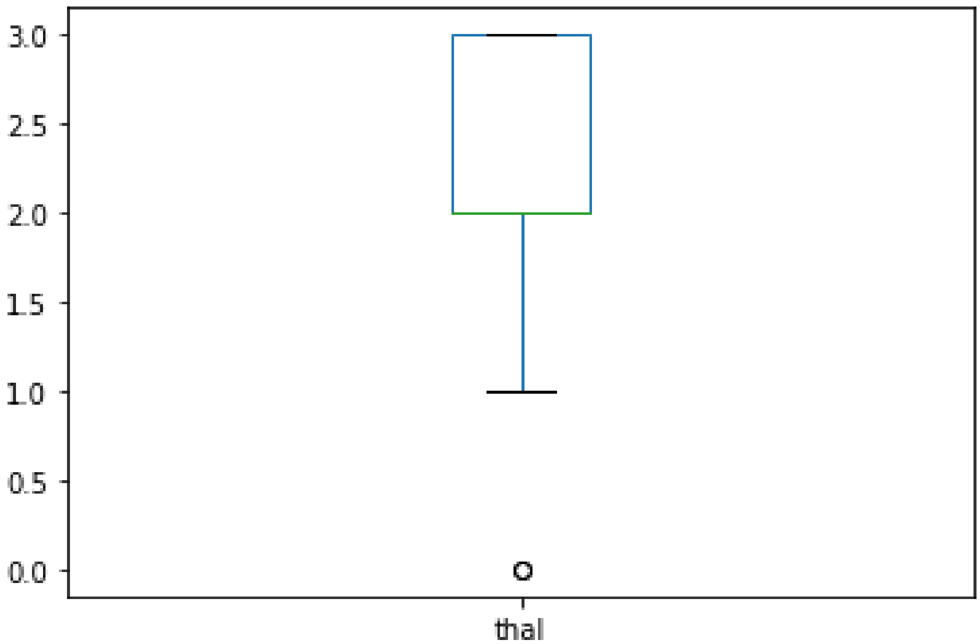
```
plot_boxplot(data,'slope')
```



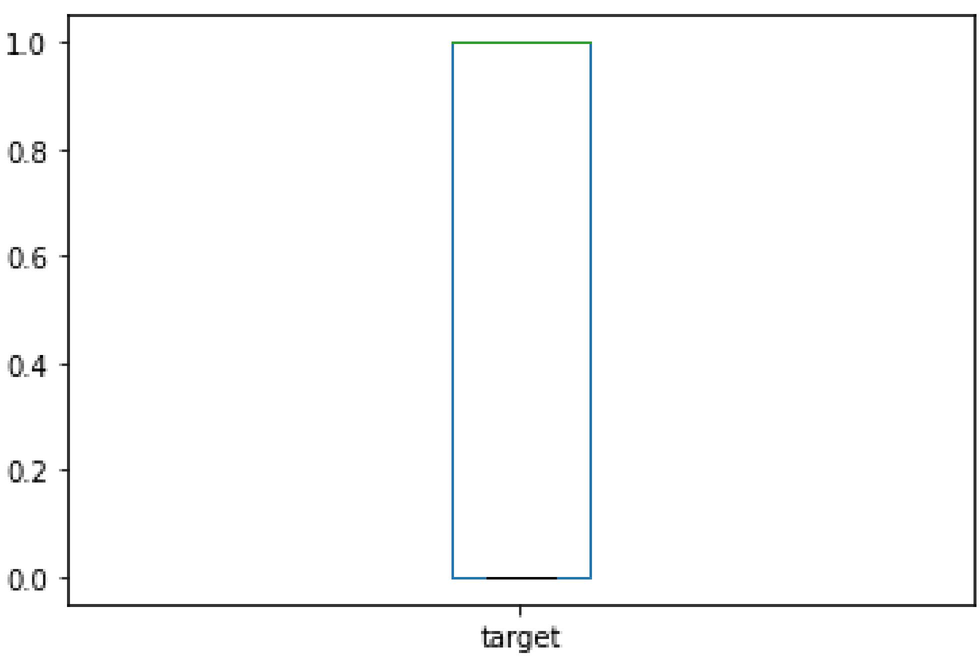

```
plot_boxplot(data,'ca')
```




```
plot_boxplot(data,'thal')
```

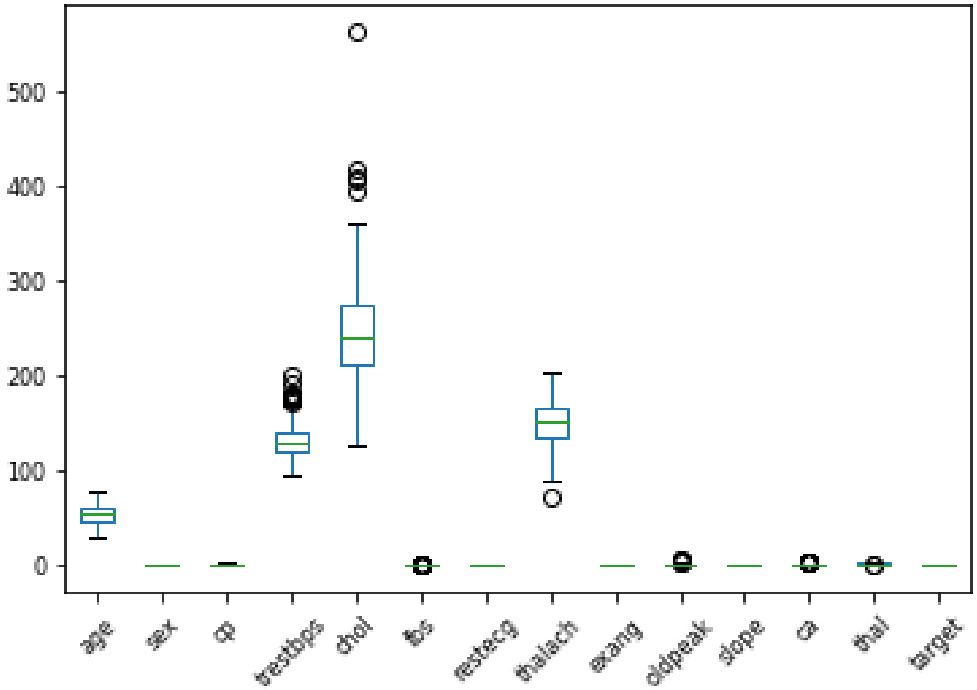



```
plot_boxplot(data,'target')
```




```
data.boxplot(grid=False,rot=45,fontsize=8)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fda9d9720d0>
```




```
def Outlier(df,ft):
  Q1=df[ft].quantile(0.25)
  Q3=df[ft].quantile(0.75)
  IQR=Q3-Q1
  lower_bound=Q1-1.5*IQR
  upper_bound=Q3+1.5*IQR
  lt=df.index[(df[ft]<lower_bound)|(df[ft]>upper_bound)]
  return lt

index_list=[]
for feature in data.columns:
  index_list.extend(Outlier(data,feature))

index_list
```

```
[8,
 101,
 110,
 203,
 223,
 241,
 248,
 260,
 266,
 28,
 85,
 96,
 220,
 246,
```

0,
8,
14,
23,
26,
28,
29,
36,
60,
64,
76,
78,
83,
87,
90,
93,
97,
99,
103,
106,
111,
136,
137,
169,
170,
176,
197,
203,
214,
215,
217,
219,
222,
223,
231,
251,
252,
260,
269,
278,
281,
282,
292,
297,
300,
272,
101,
204,
221,
250,

```
 291,
 52,
 92,
 97,
 99,
 158,
 163,
 164,
 165,
 181,
 191,
 204,
 208,
 217,
 220,
 231,
 234,
 238,
 247,
 249,
 250,
 251,
 252,
 255,
 267,
 291,
 48,
 281]
```

```
def remove(df,lt):
  lt=sorted(set(lt))
  df=df.drop(lt)
  return df
```

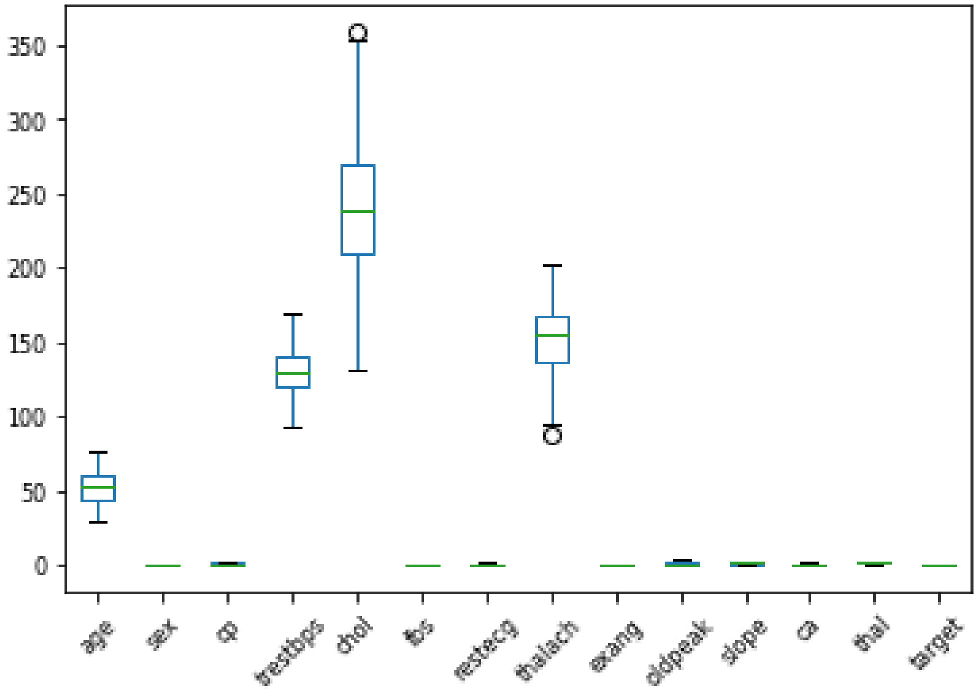
```
data=remove(data,index_list)
```

```
data.shape
```

```
(228, 14)
```

```
data.boxplot(grid=False,rot=45,fontsize=8)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fda9da40310>
```

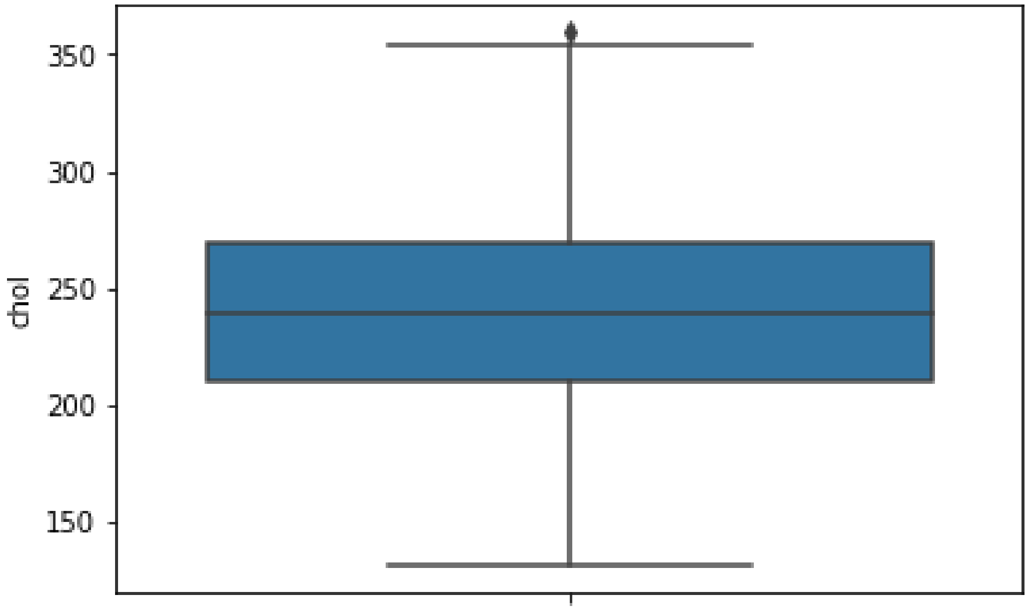



```
data.columns
```

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

```
sns.boxplot(y='chol', data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fda9dd139a0>
```



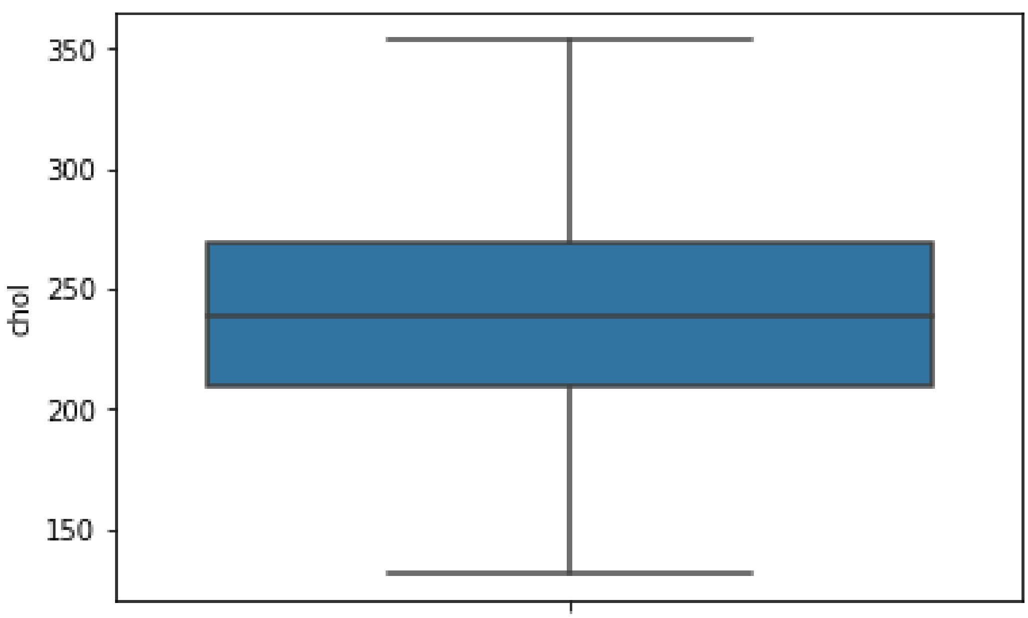

```
data['chol'].mean()
```

242.37280701754386

```
data= data[data['chol']<360]
```

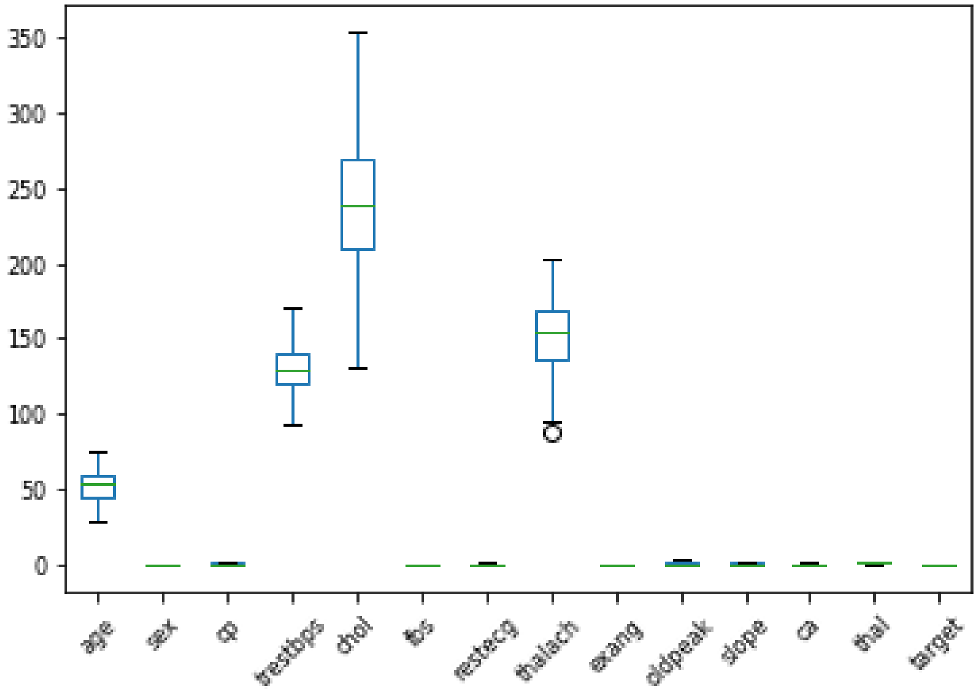
```
sns.boxplot(y='chol', data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fda9dd8a610>




```
data.boxplot(grid=False,rot=45,fontsize=8)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fdaa1cc27c0>

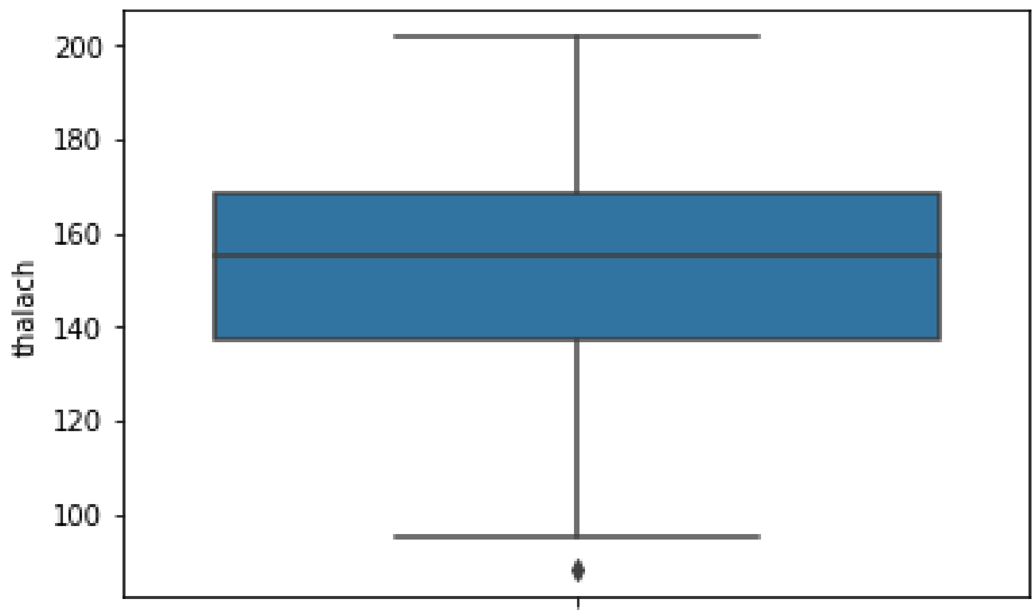



```
data.columns
```

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

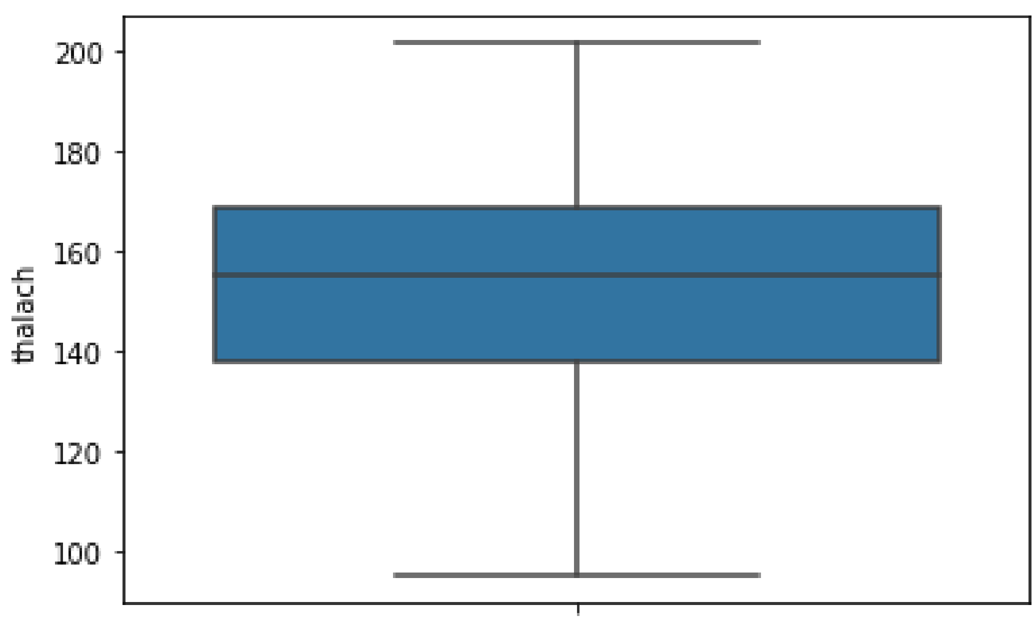
```
sns.boxplot(y='thalach', data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdaa2544d90>
```



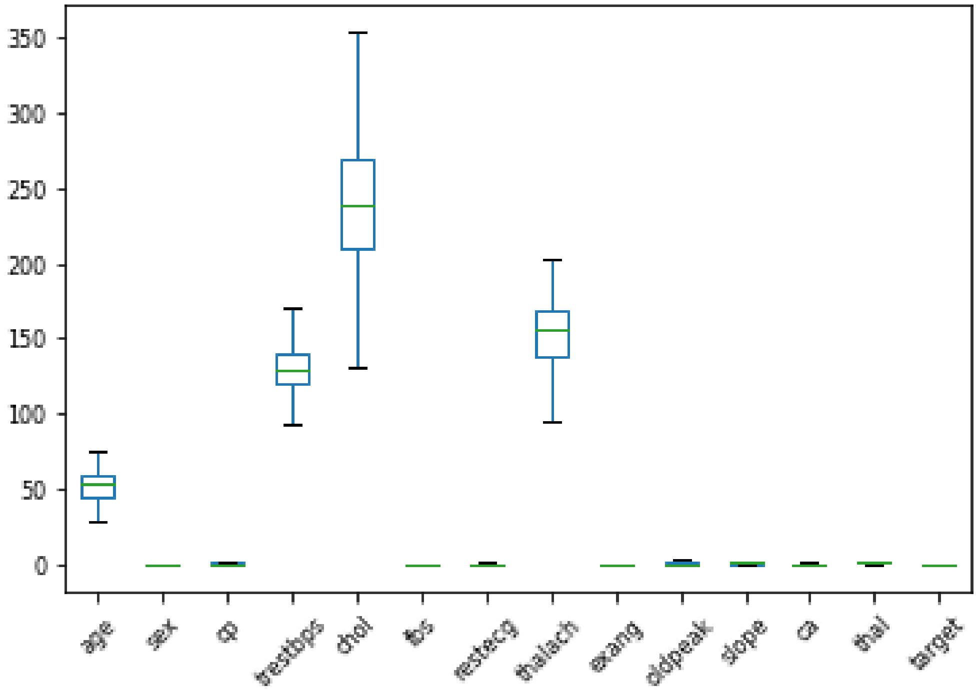

```
data= data[data['thalach']>90]
sns.boxplot(y='thalach', data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fda9ddd1f10>




```
data.boxplot(grid=False,rot=45,fontsize=8)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fda9dc23220>



HANDLING MISSING VALUES

```
data.isnull().sum()

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

data.head()

   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  
slope  \
1   37    1   2       130   250    0        1      187      0      3.5  
0
2   41    0   1       130   204    0        0      172      0      1.4  
2
```

```
3   56    1   1       120   236    0        1      178      0      0.8
2
4   57    0   0       120   354    0        1      163      1      0.6
2
5   57    1   0       140   192    0        1      148      0      0.4
1

   ca  thal  target
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
5   0     1       1
```

Data Balnacing using Synthetic Minority Over-sampling Technique(SMOTE)

```
data.target.value_counts()
```

```
1    131
0     95
Name: target, dtype: int64
```

```
x=data.drop(['target'],axis=1)
y=data.target
x.head()
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak
slope  \
1   37    1   2       130   250    0        1      187      0      3.5
0
2   41    0   1       130   204    0        0      172      0      1.4
2
3   56    1   1       120   236    0        1      178      0      0.8
2
4   57    0   0       120   354    0        1      163      1      0.6
2
5   57    1   0       140   192    0        1      148      0      0.4
1

   ca  thal
1   0     2
2   0     2
3   0     2
4   0     2
5   0     1
```

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test=train_test_split(x,y,test_size=0.2)
print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
```

```
(180, 13) (180,)
(46, 13) (46,)
```

Model Building

```
from sklearn.neighbors import KNeighborsClassifier
```

```
model=KNeighborsClassifier()
```

```
model.fit(x_train,y_train)
y_predict=model.predict(x_test)
```

```
pip install imblearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: imblearn in
/usr/local/lib/python3.8/dist-packages (0.0)
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.8/dist-packages (from imblearn) (0.8.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.2.0)
Requirement already satisfied: numpy>=1.13.3 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.21.6)
Requirement already satisfied: scikit-learn>=0.24 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.0.2)
Requirement already satisfied: scipy>=0.19.1 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.7.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.24-
>imbalanced-learn->imblearn) (3.1.0)
```

```
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test,y_predict))
pd.crosstab(y_test,y_predict)
```

```
0.717391304347826
```

```
col_0    0   1
target
0       12   6
1        7  21
```

```
pip install imblearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: imblearn in
/usr/local/lib/python3.8/dist-packages (0.0)
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.8/dist-packages (from imblearn) (0.8.1)
Requirement already satisfied: scipy>=0.19.1 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.7.3)
Requirement already satisfied: scikit-learn>=0.24 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.0.2)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.2.0)
Requirement already satisfied: numpy>=1.13.3 in
/usr/local/lib/python3.8/dist-packages (from imbalanced-learn-
>imblearn) (1.21.6)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.24-
>imbalanced-learn->imblearn) (3.1.0)
```

```
from imblearn.over_sampling import SMOTE
smote=SMOTE()
```

```
x_smote_train,y_smote_train=smote.fit_resample(x_train.astype('float')
,y_train)
```

```
from collections import Counter
print("Before applying SMOTE:",Counter(y_train))
print("After applying SMOTE:",Counter(y_smote_train))
```

```
Before applying SMOTE: Counter({1: 103, 0: 77})
After applying SMOTE: Counter({0: 103, 1: 103})
```

FEATURE SELECTION

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

```
important_features = SelectKBest(score_func=chi2, k=13)
fit = important_features.fit(x,y)
data_scores = pd.DataFrame(fit.scores_)
data_columns = pd.DataFrame(x.columns)
features_Scores = pd.concat([data_columns,data_scores],axis=1)
features_Scores.columns = ['Attributes','Score']
```

```
featureScores =
features_Scores.sort_values(by='Score',ascending=False)
featureScores
```

```
   Attributes       Score
7     thalach  124.640161
9     oldpeak   49.698923
11         ca   45.498266
2          cp   33.241387
8       exang   25.869274
0         age   17.379361
4        chol   10.081915
1         sex    9.366036
12       thal    6.220528
10      slope    5.453146
3    trestbps    3.584890
6     restecg    2.184383
5         fbs         NaN
```

```
data=data[['thalach','oldpeak','ca','cp','target']]
```

```
data.head()
```

```
   thalach  oldpeak  ca  cp  target
1      187      3.5   0   2       1
2      172      1.4   0   1       1
3      178      0.8   0   1       1
4      163      0.6   0   0       1
5      148      0.4   0   0       1
```

```
from sklearn.model_selection import train_test_split
```

```
y=data['target']
X=data.drop(['target'],axis=1)
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)
```

```
print(X_train.shape,y_train.shape)
print(X_test.shape,y_test.shape)
```

```
(180, 4) (180,)
(46, 4) (46,)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn import datasets, linear_model
from imblearn.pipeline import Pipeline
from sklearn.svm import SVC
from imblearn.pipeline import Pipeline
from sklearn.model_selection import RepeatedStratifiedKFold
# decision tree  on imbalanced dataset with SMOTE oversampling and
random undersampling
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
```

```python
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
import sklearn.linear_model as lm
```

```python
# fit a model
lm = lm.LogisticRegression()
model = lm.fit(X_train, y_train)
over = SMOTE(sampling_strategy=0.1)
steps = [('over', over), ('model', model)]
pipeline = Pipeline(steps=steps)
X, y = make_classification(n_samples=10000, n_features=5,
n_redundant=0,
n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
scores = cross_val_score(pipeline, X, y, scoring='roc_auc', cv=cv,
n_jobs=-1)
#model.score(X_test, y_test)
print('Mean ROC AUC: %.3f' % mean(scores))
```

```
Mean ROC AUC: 0.942
```

```python
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, y_pred, normalize=True)
)
```

```
0.782608695652174
```

```python
import pandas
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier

kfold = model_selection.KFold(n_splits=5)
# create the sub models
estimators = []
model1 = LogisticRegression().fit(x_test,y_test)
estimators.append(('logistic', model1))
model2 = KNeighborsClassifier(n_neighbors=3)
```

```python
estimators.append(('cart', model2))

# create the ensemble model
ensemble = VotingClassifier(estimators)

over = SMOTE(sampling_strategy=0.1)
steps = [('over', over), ('model', ensemble)]
pipeline = Pipeline(steps=steps)


results = model_selection.cross_val_score(pipeline, X, y, cv=kfold)
print(results.mean())
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/
_logistic.py:814: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
0.9917999999999999
```

```python
from sklearn.impute import SimpleImputer
```

```python
imputer = SimpleImputer(missing_values=np.nan,
strategy='most_frequent')
```

```python
X_train = imputer.fit_transform(X_train)
X_test = imputer.fit_transform(X_test)
```

```python
my_DT_model = DecisionTreeClassifier(criterion='entropy',
random_state=2)
```

```python
my_DT_model.fit(X_train,y_train)
```

```
DecisionTreeClassifier(criterion='entropy', random_state=2)
```

```python
my_DT_model.feature_importances_
```

```
array([0.41264523, 0.32160713, 0.0880592 , 0.17768844])
```

```python
from sklearn.model_selection import GridSearchCV
```

```python
params = {'criterion':['gini', 'entropy'], 'max_depth':[1,2,3,10],
'splitter' :['best', 'random']}
```

```
grid_search = GridSearchCV(my_DT_model, params, cv = 3, n_jobs = -1)
```

```
grid_search.fit(X_train, y_train)
```

```
GridSearchCV(cv=3,
             estimator=DecisionTreeClassifier(criterion='entropy',
                                              random_state=2),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [1, 2, 3, 10],
                         'splitter': ['best', 'random']})
```

```
grid_search.best_params_
```

```
{'criterion': 'gini', 'max_depth': 3, 'splitter': 'best'}
```

```
my_DT_model = DecisionTreeClassifier(criterion='gini', random_state=2,
max_depth = 3, splitter = 'best')
```

```
my_DT_model.fit(X_train, y_train)
```

```
DecisionTreeClassifier(max_depth=3, random_state=2)
```

```
my_preds = my_DT_model.predict(X_test)
```

```
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, precision_score
```

```
accuracy_score(y_test, my_preds)
```

```
0.8260869565217391
```

Project Completed By : Santhosh TN.