1. **Importing libraries and dataset**

In [70]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
import warnings
import copy
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 confusion_matrix, accuracy_score
warnings.filterwarnings('ignore')
```

In [71]:

```
dataset = pd.read_excel('1645792390_cep1_dataset.xlsx')
dataset.head()
```

Out[71]:

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

1. **Preliminary analysis**

In [72]:

```
print('Dataset Dimentions: ',dataset.shape)
```

```
Dataset Dimentions:  (303, 14)
```

In [73]:

```
print('Null value check:\n',dataset.isnull().any())
```

```
Null value check:
 age          False
sex          False
cp           False
trestbps     False
chol         False
fbs          False
restecg      False
thalach      False
exang        False
oldpeak      False
slope        False
ca           False
thal         False
target       False
dtype: bool
```

In [74]:

```
print('\nUnique value check:\n',dataset.nunique())
```

```
Unique value check:
 age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
dtype: int64
```

In [75]:

```
dataset.drop_duplicates(keep=False)
```

Out[75]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

301 rows × 14 columns

1. **EDA**

a&b.

In [76]:

```
#idetifying the numerical and categorical features
numerical_features=['age','trestbps','chol','thalach','oldpeak']
cols = dataset.columns.values.tolist()
for feature in numerical_features:
    cols.remove(feature)
categorical_features = copy.copy(cols)
```

In [77]:

```
#statistical summary of numerical features
dataset.drop(columns=categorical_features).describe()
```

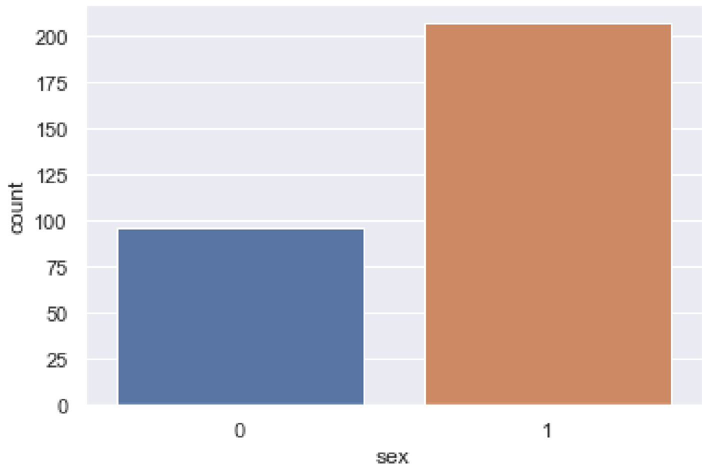
Out[77]:

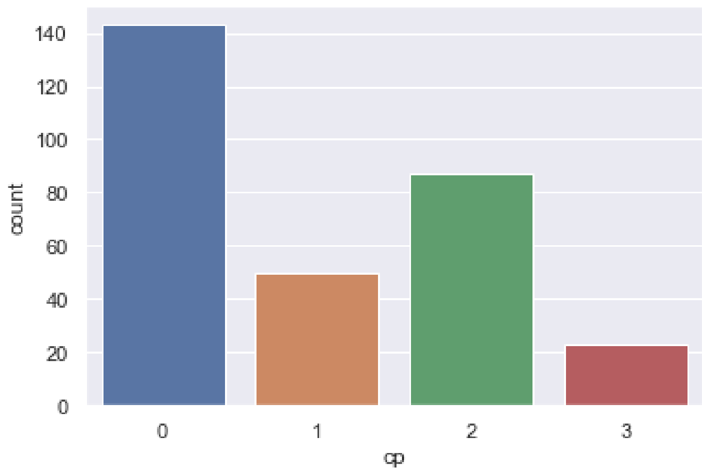
	age	trestbps	chol	thalach	oldpeak

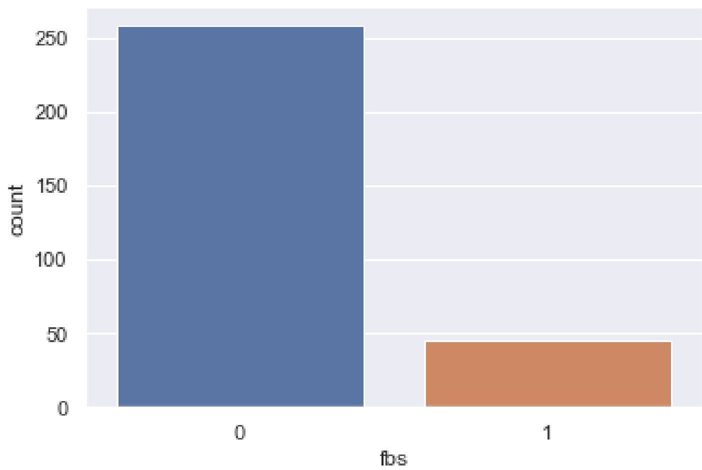
	age	trestbps	chol	thalach	oldpeak
count	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	131.623762	246.264026	149.646865	1.039604
std	9.082101	17.538143	51.830751	22.905161	1.161075
min	29.000000	94.000000	126.000000	71.000000	0.000000
25%	47.500000	120.000000	211.000000	133.500000	0.000000
50%	55.000000	130.000000	240.000000	153.000000	0.800000
75%	61.000000	140.000000	274.500000	166.000000	1.600000
max	77.000000	200.000000	564.000000	202.000000	6.200000

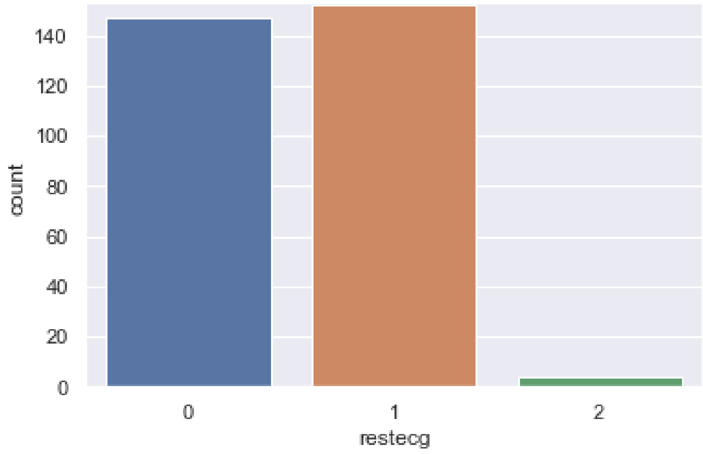
In [78]:

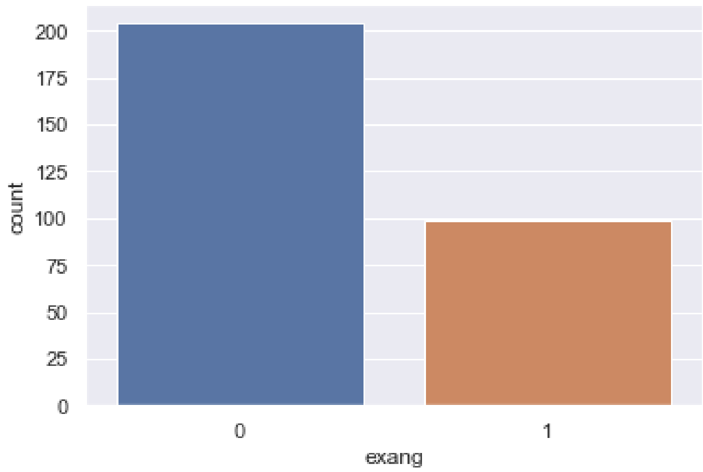
```
#count plots for categorical variables
sns.set()
for f in categorical_features:
    sns.countplot(dataset[f])
    plt.show()
```

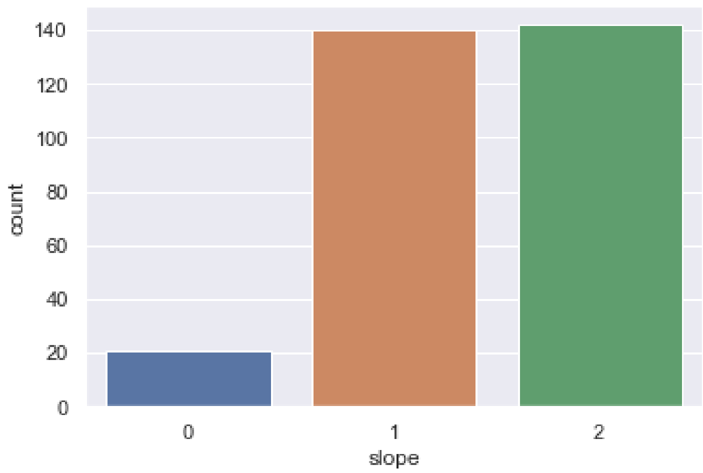


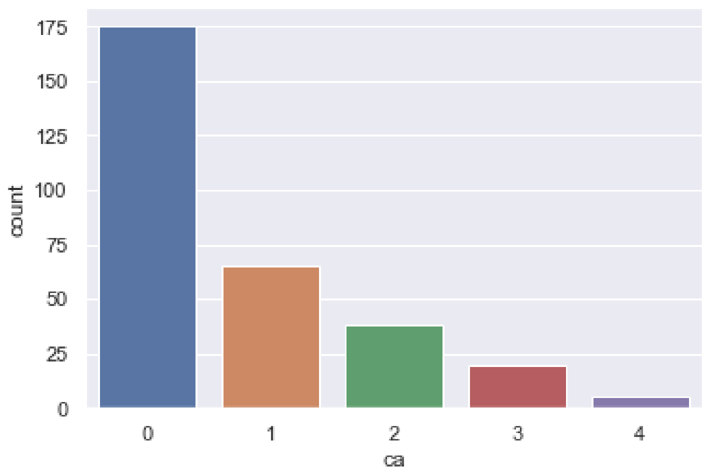


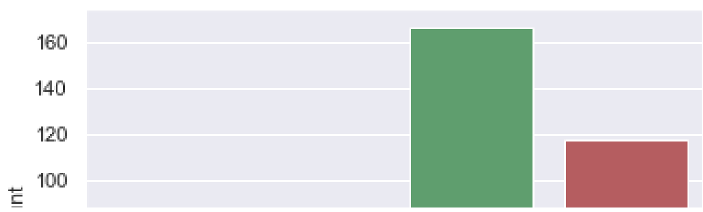


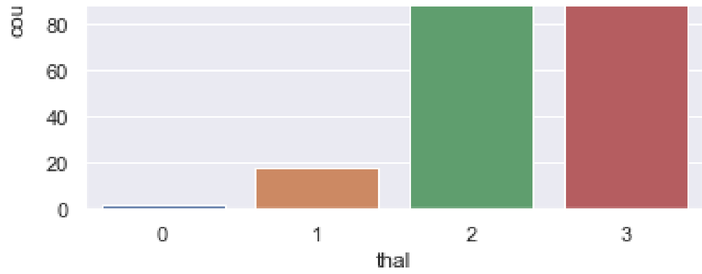

count
0
20
40
60
80
100
120
140
0
1
2
restecg

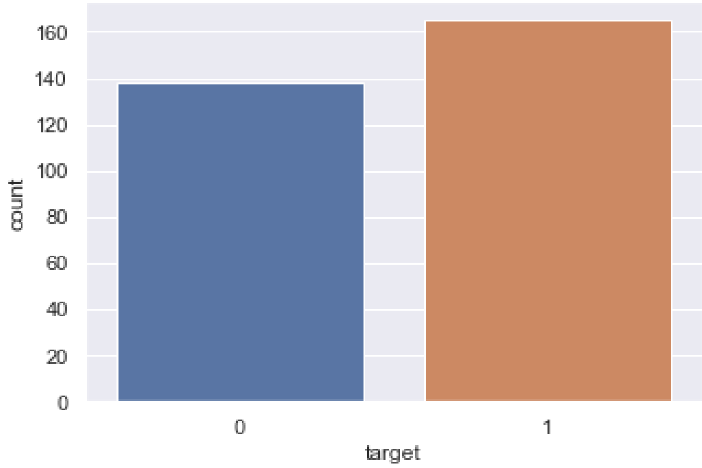

count
0
25
50
75
100
125
150
175
200
0
1
exang


count
0
20
40
60
80
100
120
140
0
1
2
slope


count
0
25
50
75
100
125
150
175
0
1
2
3
4
ca


100
120
140
160





In [79]:

```
#correlation analysis for numerical variables
f = plt.figure(figsize=(20,20))
corr = dataset.drop(columns=categorical_features).corr()
corr.style.background_gradient(cmap='coolwarm',vmin=-1,vmax=1)
```

Out[79]:

	age	trestbps	chol	thalach	oldpeak
age	1.000000	0.279351	0.213678	-0.398522	0.210013
trestbps	0.279351	1.000000	0.123174	-0.046698	0.193216
chol	0.213678	0.123174	1.000000	-0.009940	0.053952
thalach	-0.398522	-0.046698	-0.009940	1.000000	-0.344187
oldpeak	0.210013	0.193216	0.053952	-0.344187	1.000000

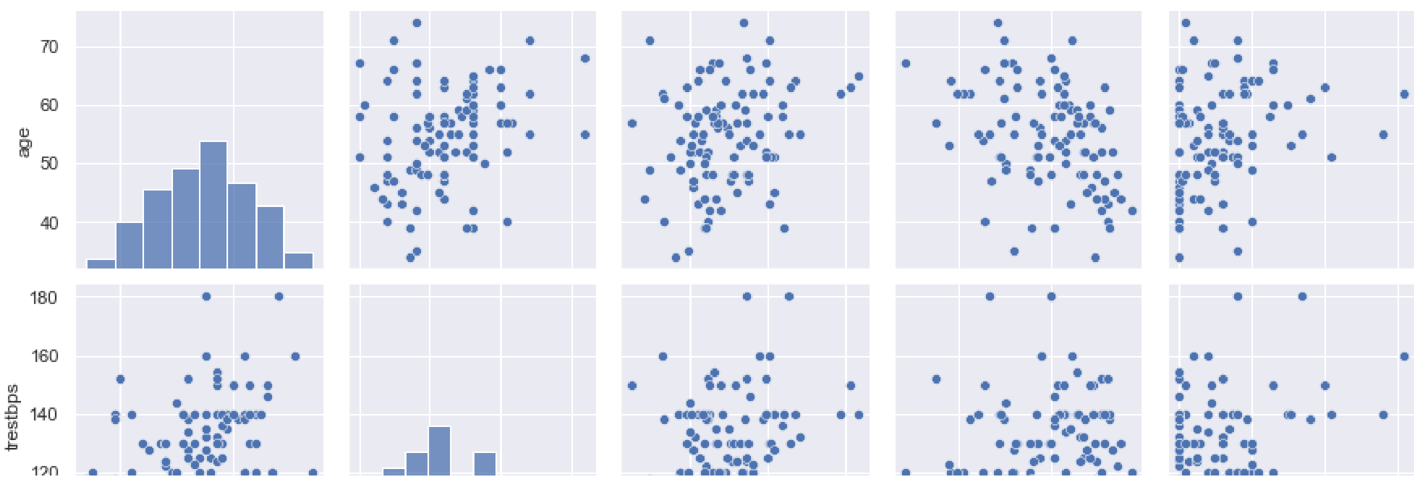
```
<Figure size 1440x1440 with 0 Axes>
```

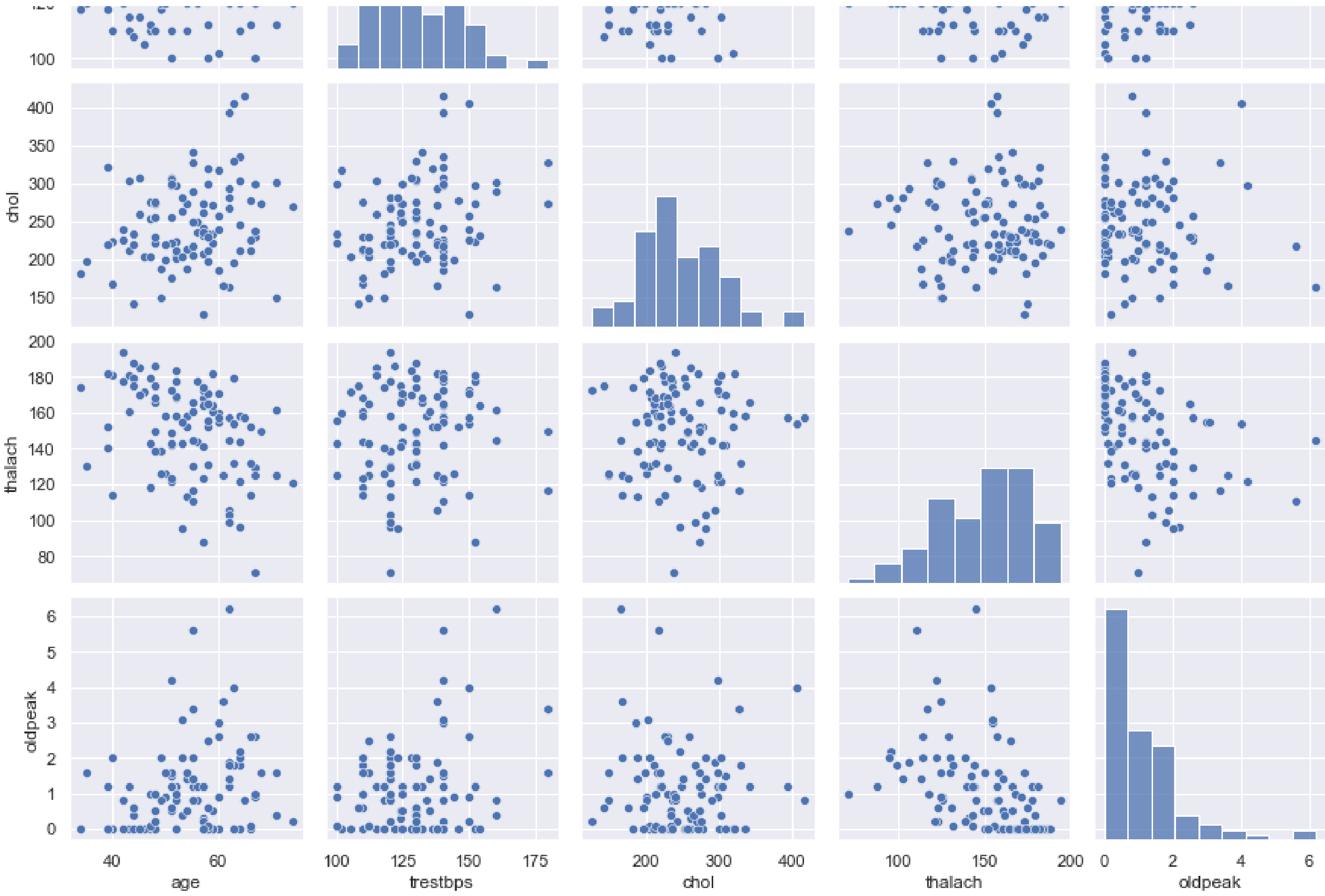
In [80]:

```
#distributions of numerical variables and scatter plots between variables
sns.pairplot(dataset.drop(columns=categorical_features).sample(100))
```

Out[80]:

```
<seaborn.axisgrid.PairGrid at 0x260deb8b820>
```



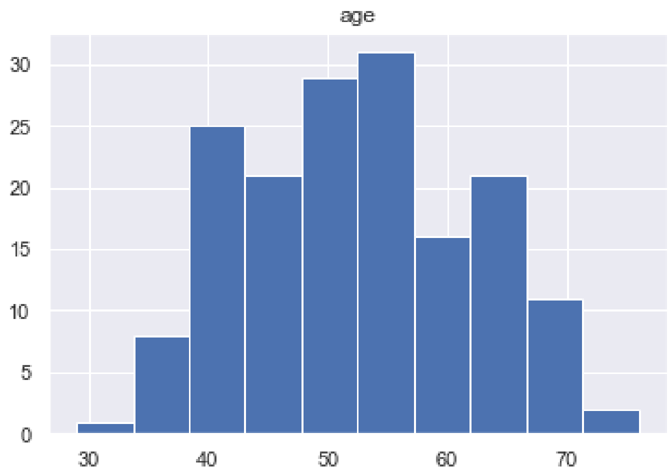


In [81]:

```
#Showing a histogram of CVD patients distributed by age
patients_by_age = dataset[['age','target']][dataset.target==1].drop(columns='target')
patients_by_age.hist()
```

Out[81]:

```
array([[<AxesSubplot:title={'center':'age'}>]], dtype=object)
```

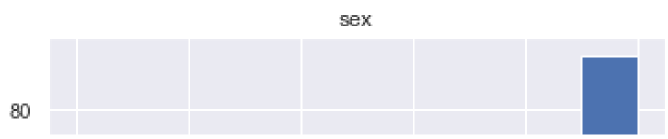


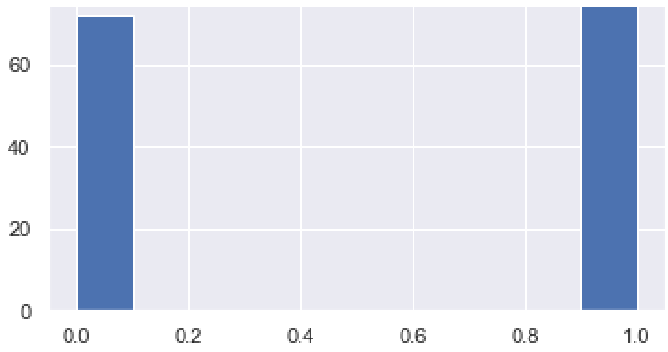
In [82]:

```
#Showing a histogram of CVD patients distributed by sex
patients_by_sex = dataset[['sex','target']][dataset.target==1].drop(columns='target')
patients_by_sex.hist()
```

Out[82]:

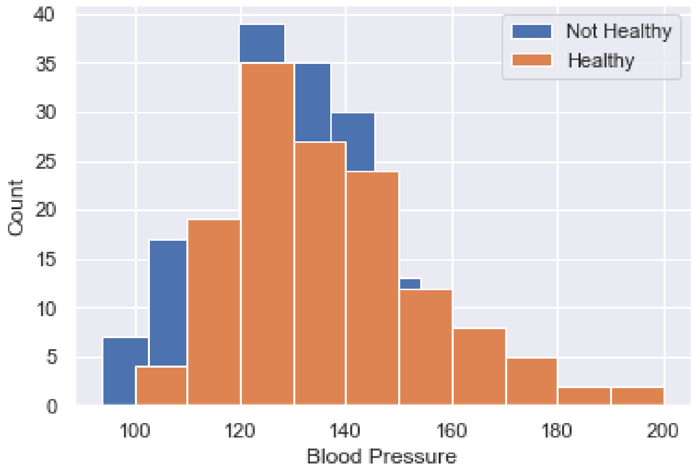
```
array([[<AxesSubplot:title={'center':'sex'}>]], dtype=object)
```





In [83]:

```
#Showing a histogram of CVD patients distributed by bloodpressure
patients_by_trestbps = dataset[['trestbps','target']][dataset.target==1].drop(columns='t
arget')
healthy_patients_by_trestbps = dataset[['trestbps','target']][dataset.target==0].drop(co
lumns='target')
plt.hist(patients_by_trestbps, label='Not Healthy')
plt.hist(healthy_patients_by_trestbps,label='Healthy')
plt.legend(loc='upper right')
plt.xlabel('Blood Pressure')
plt.ylabel('Count')
plt.show()
```



In [84]:

```
#Pateints of CVD have
healthy_patients_by_trestbps.describe()
```

Out[84]:

	trestbps
count	138.000000
mean	134.398551
std	18.729944
min	100.000000
25%	120.000000
50%	130.000000
75%	144.750000
max	200.000000

In [85]:

```
patients_by_trestbps.describe()
```

Out[85]:

	trestbps
count	165.000000
mean	129.303030
std	16.169613
min	94.000000
25%	120.000000
50%	130.000000
75%	140.000000
max	180.000000

In [86]:

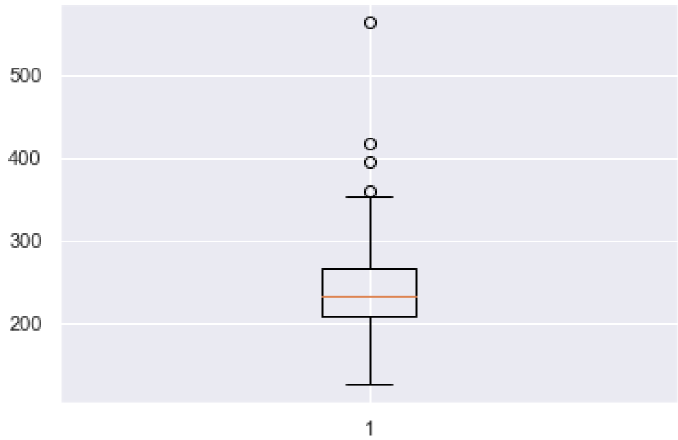
```
#The relationship between Cholesterol and the target
patients_by_chol = dataset[['chol','target']][dataset.target==1].drop(columns='target')
healthy_patients_by_chol = dataset[['chol','target']][dataset.target==0].drop(columns='t
arget')
```

In [87]:

```
plt.boxplot(patients_by_chol)
```

Out[87]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x260df6e83d0>,
  <matplotlib.lines.Line2D at 0x260df6e86a0>],
 'caps': [<matplotlib.lines.Line2D at 0x260df6e8970>,
  <matplotlib.lines.Line2D at 0x260df6e8c40>],
 'boxes': [<matplotlib.lines.Line2D at 0x260df6e8100>],
 'medians': [<matplotlib.lines.Line2D at 0x260df6e8f10>],
 'fliers': [<matplotlib.lines.Line2D at 0x260df6e91e0>],
 'means': []}
```

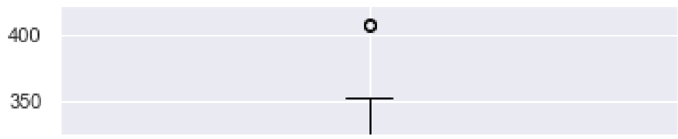


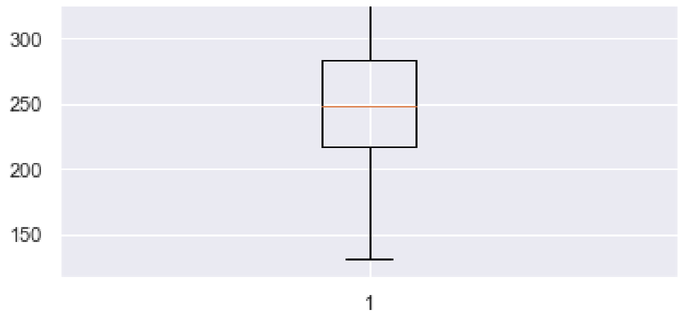
In [88]:

```
plt.boxplot(healthy_patients_by_chol)
```

Out[88]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x260dfa35390>,
  <matplotlib.lines.Line2D at 0x260dfa35660>],
 'caps': [<matplotlib.lines.Line2D at 0x260dfa35930>,
  <matplotlib.lines.Line2D at 0x260dfa35c00>],
 'boxes': [<matplotlib.lines.Line2D at 0x260dfa351e0>],
 'medians': [<matplotlib.lines.Line2D at 0x260dfa35ed0>],
 'fliers': [<matplotlib.lines.Line2D at 0x260dfa361a0>],
 'means': []}
```





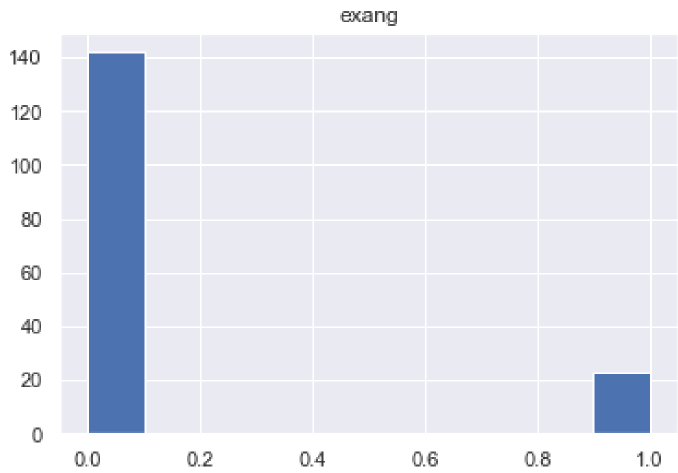
The CVD patients seem to have many more outliers with a high colesterol

In [93]:

```
patients_by_exang = dataset[['exang','target']][dataset.target==1].drop(columns='target'
)
patients_by_exang.hist()
```

Out[93]:

```
array([[<AxesSubplot:title={'center':'exang'}>]], dtype=object)
```



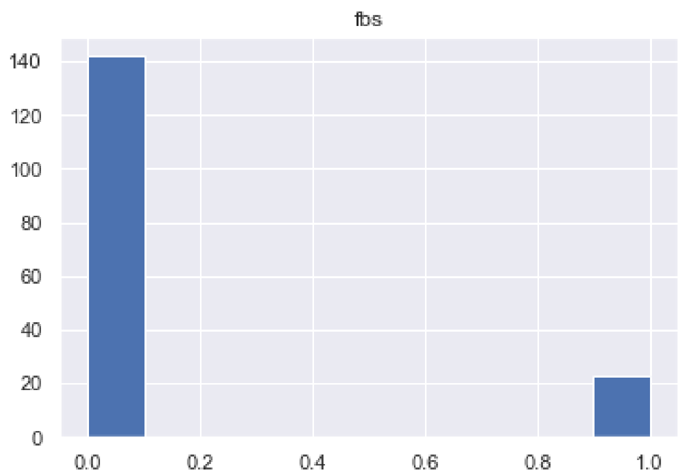
Diabetes is a significant complication of b-thalassaemia major. The aetiology includes iron overload causing b-cell destruction, autoimmunity, insulin resistance secondary to liver disease and development of type 1 or 2 diabetes. therefore, fasting blood sugar levels can give us a good indication to wether or not the patient has thalassaemia

In [92]:

```
patients_by_bloodSugar = dataset[['fbs','target']][dataset.target==1].drop(columns='targ
et')
patients_by_bloodSugar.hist()
```

Out[92]:

```
array([[<AxesSubplot:title={'center':'fbs'}>]], dtype=object)
```



This graph indicates a negative coorelation between blood sugar and CVD. Knowing this, it is possible to collect more data on the effects of thalassaemia on Cardio vascular health

How the other factors determine the occurance of CVD:

1. **cp: the type of chest pain can determine the Pressure, fullness, burning or tightness in the patient's chest**
2. **restecg: it determines if there is an abnormality in the rythym of the heart activity**

1. **Model Building**

In [89]:

```
#preprocessing features
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
= 0)
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [90]:

```
#Logistic regression model building and evaluation
LR_classifier = LogisticRegression()
LR_classifier.fit(X_train, y_train)
LR_y_pred = LR_classifier.predict(X_test)
LR_cm = confusion_matrix(y_test, LR_y_pred)
print('Confusion Matrix:\n',LR_cm,'\n','Model Accuracy: ',accuracy_score(y_test, LR_y_pr
ed)*100,'%')
```

```
Confusion Matrix:
 [[24  9]
 [ 4 39]]
 Model Accuracy:  82.89473684210526 %
```

In [91]:

```
#Random Forest model building and evaluation
RF_classifier = RandomForestClassifier(n_estimators = 100, criterion = 'entropy')
RF_classifier.fit(X_train, y_train)
RF_y_pred = RF_classifier.predict(X_test)
RF_cm = confusion_matrix(y_test, RF_y_pred)
print('Confusion Matrix:\n',RF_cm,'\n','Model Accuracy: ',accuracy_score(y_test, RF_y_pr
ed)*100,'%')
```

```
Confusion Matrix:
 [[26  7]
 [ 4 39]]
 Model Accuracy:  85.52631578947368 %
```