Heart disease diagnosis:

Problem statement

Chloe is hypochondriac. She has an intense fearof having a serious condition and worriesthat minor symptoms will indicate something serious.Her parents are really worried about herand decided to consult Dr. Will for the same. Dr.Will is a psychiatrist. Help Dr. Will to diagnoseChloe. Dr. Will needs to first determine if Chloeis really suffering from any heart andcardiovascular disease as she complains. Furtherthe doctor needs to check if the patient isdiabetic. Help Dr. Will to perform these three diagnosesso that we can help him save Chloe.

Loading Libraries

In [149]:

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

Reading the csv file

In [150]:

```
df = pd.read_csv('heart.csv')
```

In [151]:

```
df.head()
```

Out[151]:

	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

Examining the Data set

In [152]:

```
df.shape
```

Out[152]:

```
(303, 14)
```

In [153]:

```
df.columns
```

Out[153]:

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

In [154]:

```
df.describe()
```

Out[154]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpe
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.0396
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.1610
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.0000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.0000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.8000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.6000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.2000

In [155]:

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

Out[155]:

```
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
```

In [156]:

```
print(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
None
```

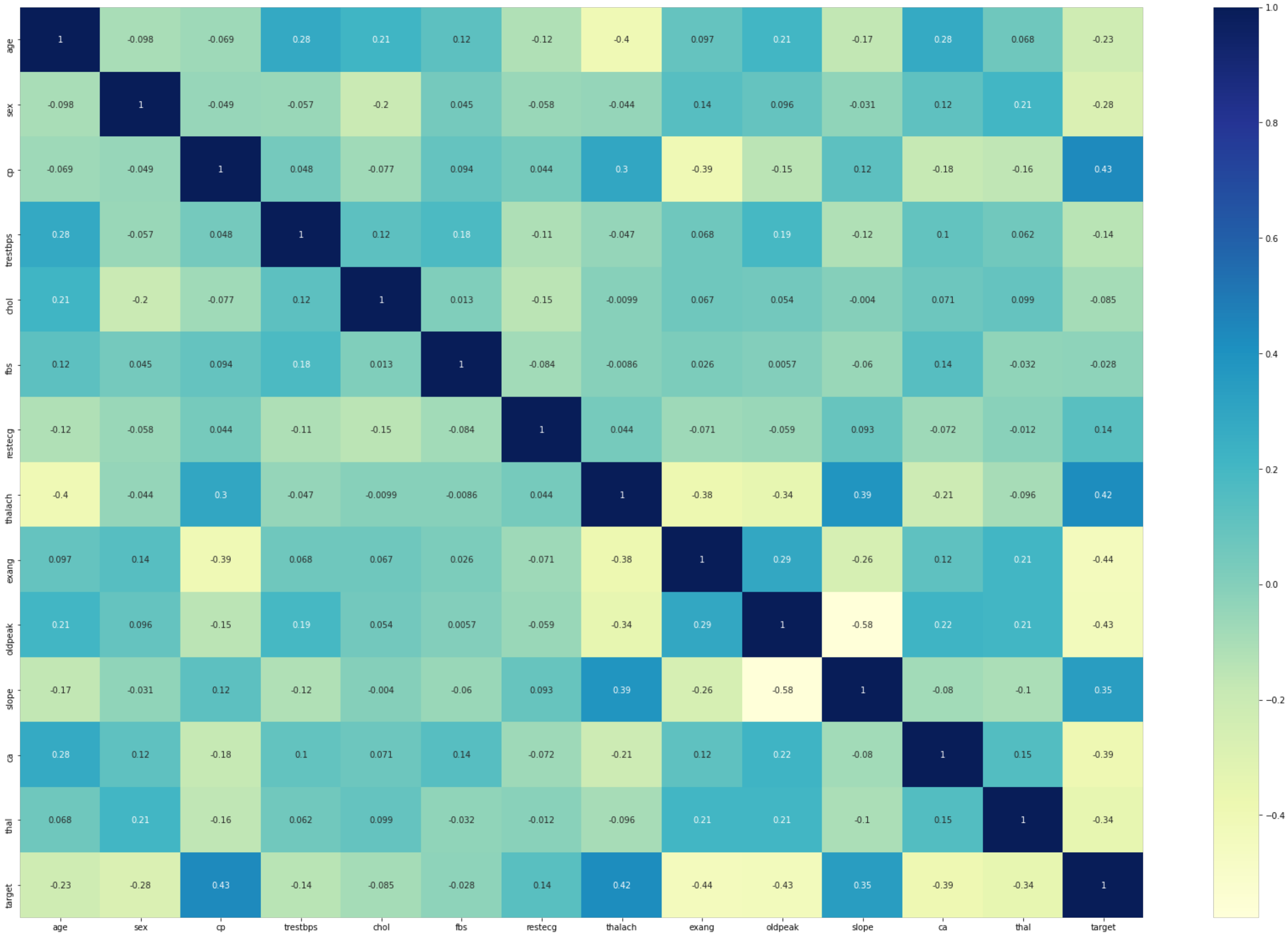
Correlation among the attributes

In [157]:

```
plt.figure(figsize=(30,20))
sns.heatmap(df.corr(), annot=True, cmap='YlGnBu')
```

Out[157]:

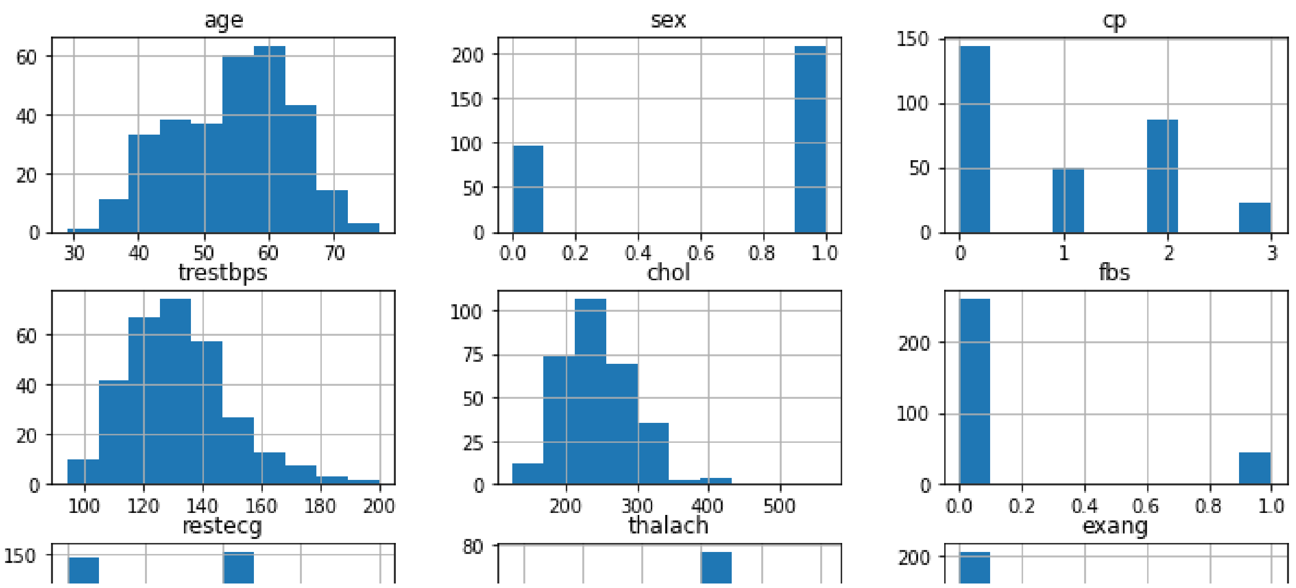
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc9291e6b10>
```

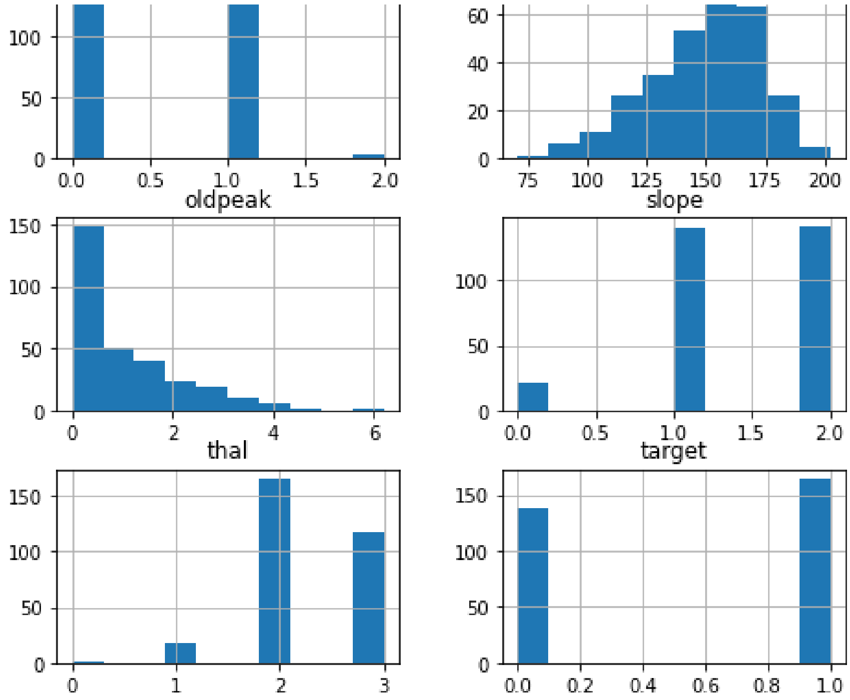


Here, We observe positive correlation between target and cp, thalach,slope and also negative correlation between target and sex, exang,ca,thai,oldpeak

In [158]:

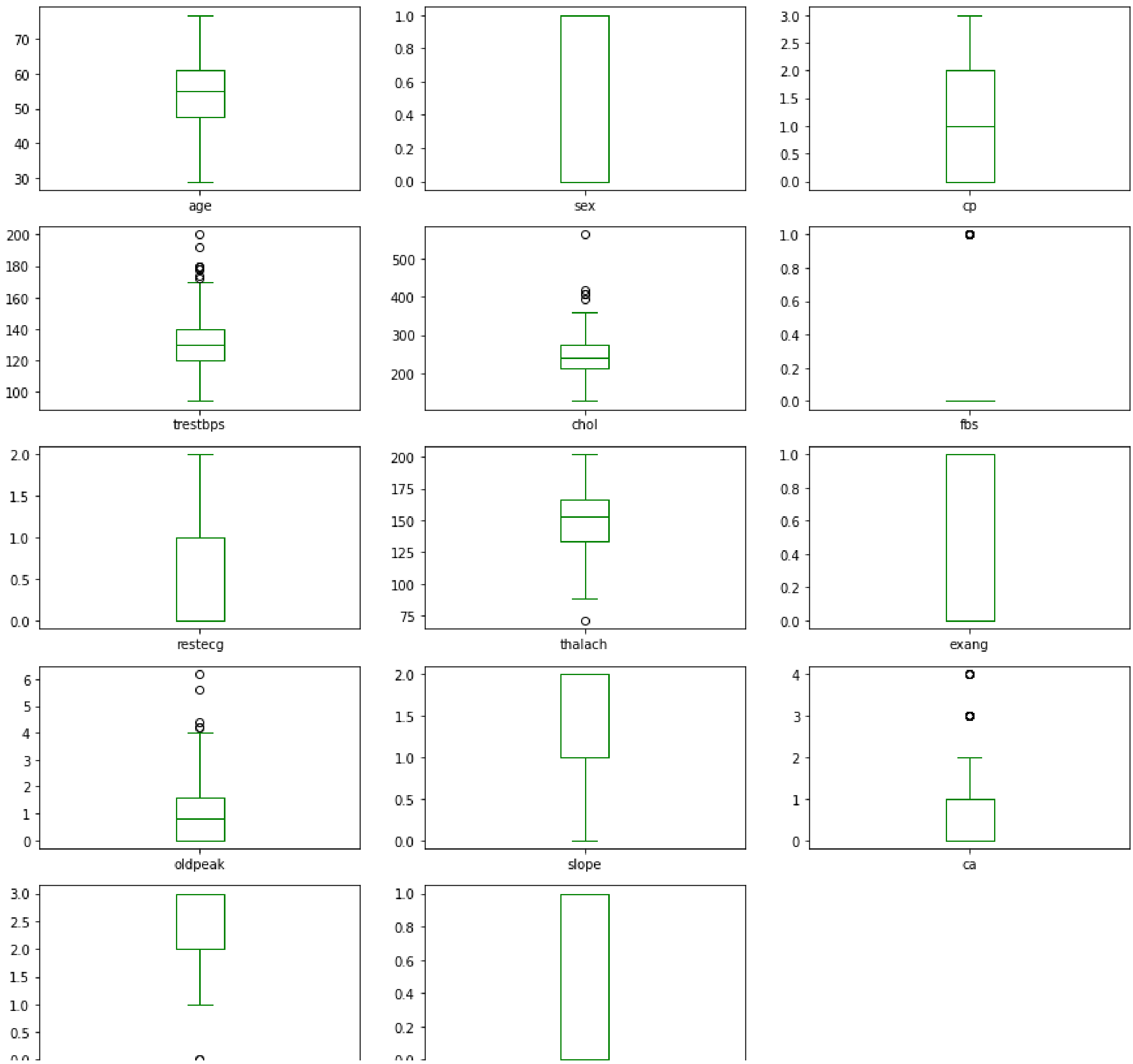
```
df.hist(figsize=(12,12), layout=(5,3));
```





In [159]:

```
df.plot(kind='box', subplots=True, layout=(5,3), figsize=(15,15),color = 'green')
plt.show()
```



In [160]:

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

Out[160]:

```
1    207
0     96
Name: sex, dtype: int64
```

In [161]:

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

Out[161]:

```
1    165
0    138
Name: target, dtype: int64
```

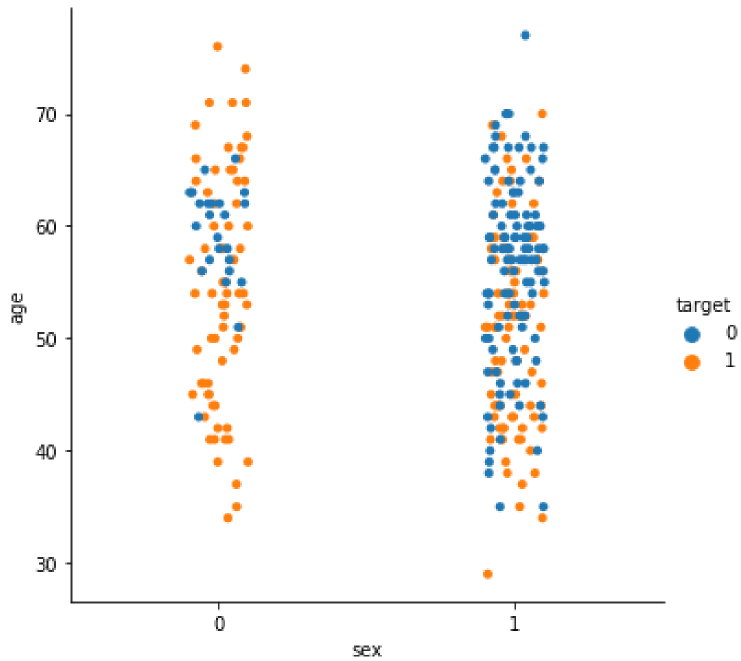
This means, there are 207 males and 96 females and 165 cases of heart diseases and 138 cases of no heart diseases

In [162]:

```
sns.catplot(data=df, x='sex', y='age', hue='target', palette='tab10')
```

Out[162]:

```
<seaborn.axisgrid.FacetGrid at 0x7fc92882bc90>
```

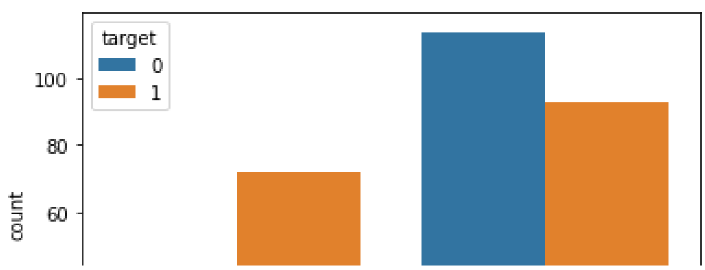


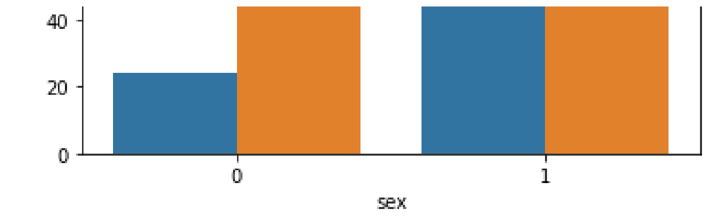
In [163]:

```
sns.countplot(x='sex', data=df, palette='tab10', hue='target')
```

Out[163]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc9287f41d0>
```





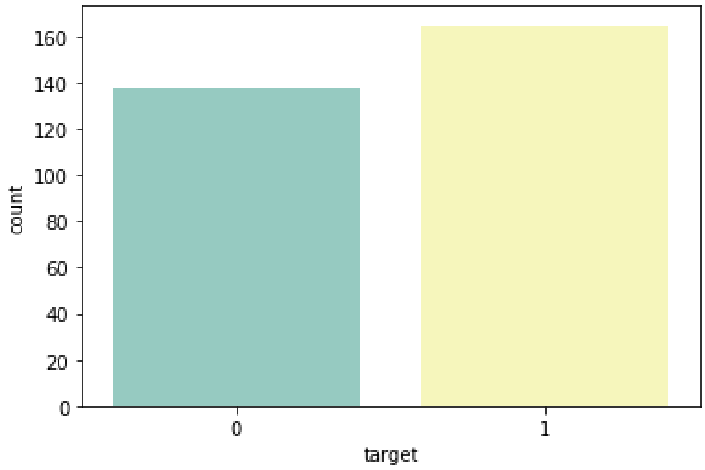
Here, 1 means male and 0 denotes female. we observe female having heart disease are comparatively less when compared to males Males have low heart diseases as compared to females in the given dataset.

In [164]:

```
sns.countplot(x='target',palette='Set3', data=df)
```

Out[164]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc929ae7c10>
```



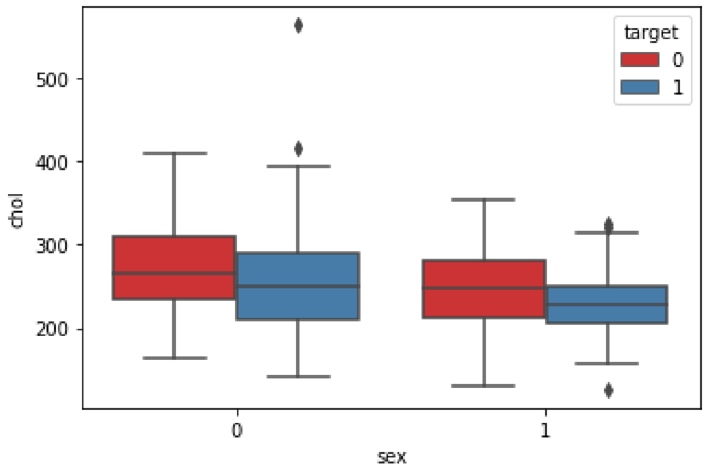
Here, We observe the count for not having heart disease and having heart disease are almost balanced not having frequency count is 140 and those having heart disease the count is 160.

In [165]:

```
sns.boxplot(x='sex', y='chol', hue='target', palette='Set1', data=df)
```

Out[165]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc929a5a790>
```



Here,We observe the outliers with the help of boxplot. outliers are values that are very small or large in the given data set.

Preparation of data for Model

In [166]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
StandardScaler = StandardScaler()
columns_to_scale = ['age','trestbps','chol','thalach','oldpeak']
df[columns_to_scale] = StandardScaler.fit_transform(df[columns_to_scale])
```

In [167]:

```
df.head()
```

Out[167]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	0.952197	1	3	0.763956	-0.256334	1	0	0.015443	0	1.087338	0	0	1	1
1	-1.915313	1	2	-0.092738	0.072199	0	1	1.633471	0	2.122573	0	0	2	1
2	-1.474158	0	1	-0.092738	-0.816773	0	0	0.977514	0	0.310912	2	0	2	1
3	0.180175	1	1	-0.663867	-0.198357	0	1	1.239897	0	-0.206705	2	0	2	1
4	0.290464	0	0	-0.663867	2.082050	0	1	0.583939	1	-0.379244	2	0	2	1

In [168]:

```
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    float64
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 3   trestbps  303 non-null    float64
 4   chol      303 non-null    float64
 5   fbs       303 non-null    int64  
 6   restecg   303 non-null    int64  
 7   thalach   303 non-null    float64
 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(5), int64(9)
memory usage: 33.3 KB
```

In [169]:

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

In [170]:

```
X_train, X_test,y_train, y_test=train_test_split(X,y,test_size=0.3,random_state=40)
```

Sample Size Check

In [171]:

```
print('X_train-', X_train.size)
print('X_test-',X_test.size)
print('y_train-', y_train.size)
print('y_test-', y_test.size)
```

```
X_train- 2756
X_test- 1183
y_train- 212
y_test- 91
```

y_test 91

Training with Different Models

Decision Tree

In [172]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
dtc=DecisionTreeClassifier()
model2=dtc.fit(X_train,y_train)
prediction2=model2.predict(X_test)
cm2= confusion_matrix(y_test,prediction2)
```

In [173]:

```
cm2
```

Out[173]:

```
array([[33,  7],
       [12, 39]])
```

In [174]:

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,prediction2)
```

Out[174]:

```
0.7912087912087912
```

In [175]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, prediction2))
```

```
              precision    recall  f1-score   support

           0       0.73      0.82      0.78        40
           1       0.85      0.76      0.80        51

    accuracy                           0.79        91
   macro avg       0.79      0.79      0.79        91
weighted avg       0.80      0.79      0.79        91
```

Logistic Regression

In [176]:

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()

model1=lr.fit(X_train,y_train)
prediction1=model1.predict(X_test)
```

In [177]:

```
cm=confusion_matrix(y_test,prediction1)
cm
```

Out[177]:

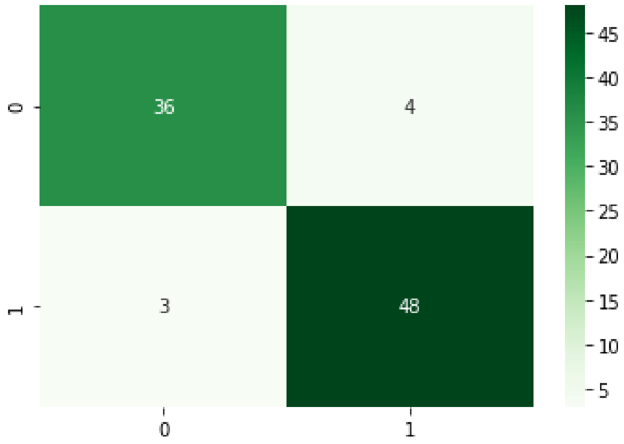
```
array([[36,  4],
       [ 3, 48]])
```

In [178]:

```
sns.heatmap(cm, annot=True,cmap='Greens')
```

Out[178]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc9296c01d0>
```



In [179]:

```
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]
print('Testing Accuracy:',(TP+TN)/(TP+TN+FN+FP))
```

```
Testing Accuracy: 0.9230769230769231
```

In [180]:

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,prediction1)
```

Out[180]:

```
0.9230769230769231
```

In [181]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, prediction1))
```

```
              precision    recall  f1-score   support

           0       0.92      0.90      0.91        40
           1       0.92      0.94      0.93        51

    accuracy                           0.92        91
   macro avg       0.92      0.92      0.92        91
weighted avg       0.92      0.92      0.92        91
```

Random Forest

In [182]:

```
from sklearn.ensemble import RandomForestClassifier

rfc=RandomForestClassifier()
model3 = rfc.fit(X_train, y_train)
prediction3 = model3.predict(X_test)
confusion_matrix(y_test, prediction3)
```

Out[182]:

```
array([[34,  6],
       [ 4, 47]])
```

In [183]:

```
accuracy_score(y_test, prediction3)
```

Out[183]:

```
0.8901098901098901
```

In [184]:

```
print(classification_report(y_test, prediction3))
```

```
              precision    recall  f1-score   support

           0       0.89      0.85      0.87        40
           1       0.89      0.92      0.90        51

    accuracy                           0.89        91
   macro avg       0.89      0.89      0.89        91
weighted avg       0.89      0.89      0.89        91
```

SVC

In [185]:

```
from sklearn.svm import SVC

svm=SVC()
model4=svm.fit(X_train,y_train)
prediction4=model4.predict(X_test)
cm4= confusion_matrix(y_test,prediction4)
cm4
```

Out[185]:

```
array([[33,  7],
       [ 2, 49]])
```

In [186]:

```
accuracy_score(y_test, prediction4)
```

Out[186]:

```
0.9010989010989011
```

Predicting for the given data

In [187]:

```
data= {'age' : 25, 'sex' : 0, 'cp': 1, 'trestbps' : 110, 'chol' : 162, 'fbs' : 0, 'reste
cg': 0, 'thalach' : 150, 'exang' : 1, 'oldpeak' : 0.8, 'ca' : 0, 'slope' : 1, 'thal' : 1
}
```

In [188]:

```
df1=pd.DataFrame(data, index=[0])
```

In [189]:

```
df1
```

Out[189]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	ca	slope	thal
0	25	0	1	110	162	0	0	150	1	0.8	0	1	1

Preidicting Outcome for the given, using different models

In [190]:

```
result=model1.predict(df1)
print(result)
```

```
[1]
```

In [191]:

```
result=model2.predict(df1)
print(result)
```

```
[1]
```

In [192]:

```
result=model3.predict(df1)
print(result)
```

```
[0]
```

In [193]:

```
result=model4.predict(df1)
print(result)
```

```
[1]
```

Out of the 4, Logistic Regression has highest Accuracy. So the Outcome using it is :

In [194]:

```
Predicted_Result=model1.predict(df1)
print(Predicted_Result)
```

```
[1]
```

In [195]:

```
if Predicted_Result:
    print("This Patient is likely to have a Heart Disease")
else:
    print("This Patient is not likely to have a Heart Disease")
```

```
This Patient is likely to have a Heart Disease
```