heart-disease-classification

September 10, 2023

1 Prediction Heart Disease using Machine Learning

This notebook uses various ML and Data Science libraries in an attempt to build a model that can classify whether a patient has a heart disease or not based on their medical attributes.

Steps 1. Problem Definition. 2. Data - Gathering and exploring the data 3. Evaluation - What is the goal of the project 4. Features 5. Modelling 6. Experimentaion

1.1 1. Problem Definition

> Given clinical parameters of a patient, we have to predict whether the patient has heart disease or not.

1.2 2. Data

Excerpt from UCI - This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to date. The "goal" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4. Experiments with the Cleveland database have concentrated on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).

UCI Machine Learning Repo - https://archive.ics.uci.edu/dataset/45/heart+disease Kaggle - https://www.kaggle.com/datasets/redwankarimsony/heart-disease-data

1.3 3. Evaluation

> The model should achieve atleast 85% accuracy in predicting whether a patient has a heart disease or not.

1.4 4. Features

Columns -

1. `age`: age in years

2. `sex`: sex (1 = male; 0 = female)

3. `cp`: chest pain type
    1. Value 0: typical angina

2. Value 1: atypical angina
3. Value 2: non-anginal pain
4. Value 3: asymptomatic

4. `trestbps`: resting blood pressure (in mm Hg on admission to the hospital)
5. `chol`: serum cholestoral in mg/dl
6. `fbs`: (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
7. `restecg`: resting electrocardiographic results
    1. Value 0: normal
    2. Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)
    3. Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
8. `thalach`: maximum heart rate achieved
9. `exang`: exercise induced angina (1 = yes; 0 = no)
10. `oldpeak`: ST depression induced by exercise relative to rest
11. `slope`: the slope of the peak exercise ST segment
    1. Value 0: upsloping
    2. Value 1: flat
    3. Value 2: downsloping
12. `ca`: number of major vessels (0-3) colored by flourosopy
13. `thal`: 0 = normal; 1 = fixed defect; 2 = reversable defect
14. `target`: predicted label, 0 = no disease, 1 = disease

1.5 Preparing the tools

[1]:
```python
# EDA (Exploratory Data Analysis) and plotting libs
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Models from Scikit-Learn
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

# Model Evaluations
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, f1_score, recall_score
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import RocCurveDisplay
```

1.6 Load Data

[2]:
```
df = pd.read_csv("heart-disease.csv")
df.shape
```

[2]:
```
(303, 14)
```

1.7 Data Exploration (EDA - Exploratory Data Analysis)

[3]:
```
df.head()
```

[3]:
```
   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
```

[4]:
```
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
```

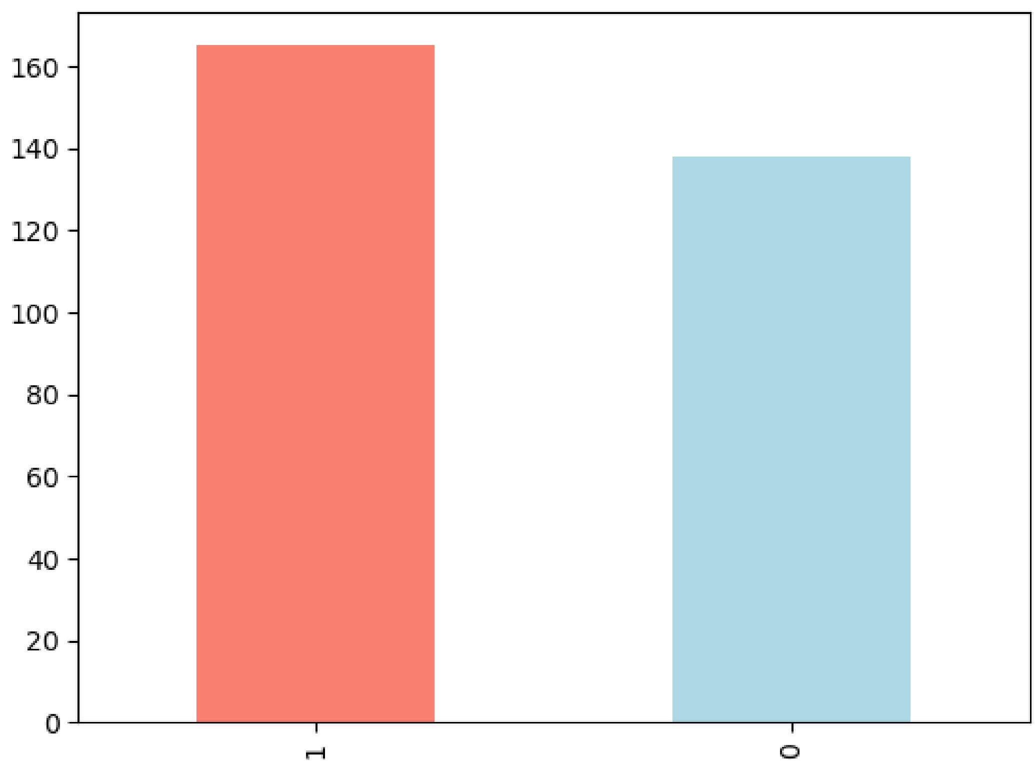
[5]:
```
df.isna().sum()
```

[5]:
```
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
```

[6]:
```
df["target"].value_counts()
```

[6]:
```
1    165
0    138
Name: target, dtype: int64
```

[7]:
```
df["target"].value_counts().plot(kind="bar", color = ["salmon", "lightblue"]);
```



This is a relatively balanced classification problem as the patients having heart disease (165) and patients not having heart disease (138) are relatively similar.

1.7.1 Heart Disease according to sex of the patient

[8]:
```
df["sex"].value_counts()
```

[8]:
```
1    207
0     96
Name: sex, dtype: int64
```

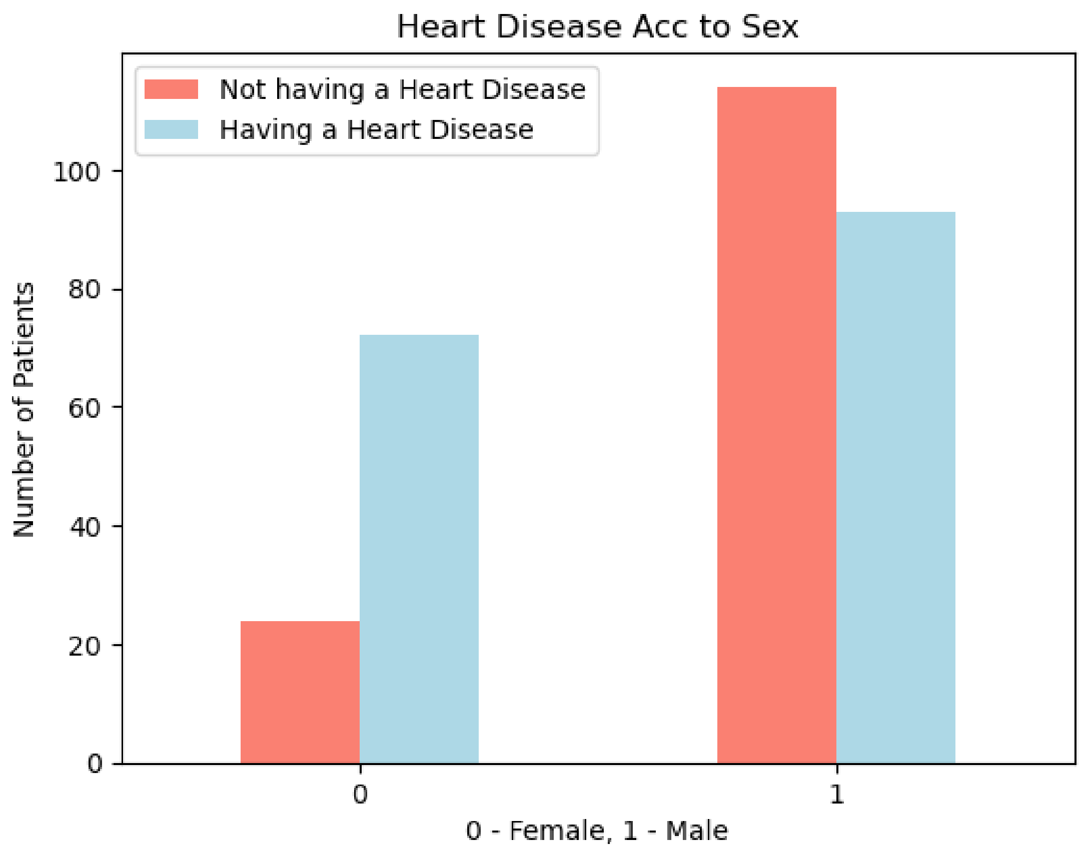
There are far more male patients than female patients

[9]:
```
pd.crosstab(df["sex"], df["target"])
```

[9]:
```
target    0   1
sex
0        24  72
1       114  93
```

From the crosstab we can see that of the 96 female patients, 72 have heart disease.
This means that for a female patient there's a 75% chance that she would have a heart disease based on our dataset.
However, for males this is more balanced - 93 out of 207 - 44%.

[10]:
```
pd.crosstab(df["sex"], df["target"]).plot(kind = "bar", color = ["salmon",␣
 ↪"lightblue"])
plt.title("Heart Disease Acc to Sex")
plt.xlabel("0 - Female, 1 - Male")
plt.ylabel("Number of Patients")
plt.legend(["Not having a Heart Disease", "Having a Heart Disease"])
plt.xticks(rotation = 0);
```



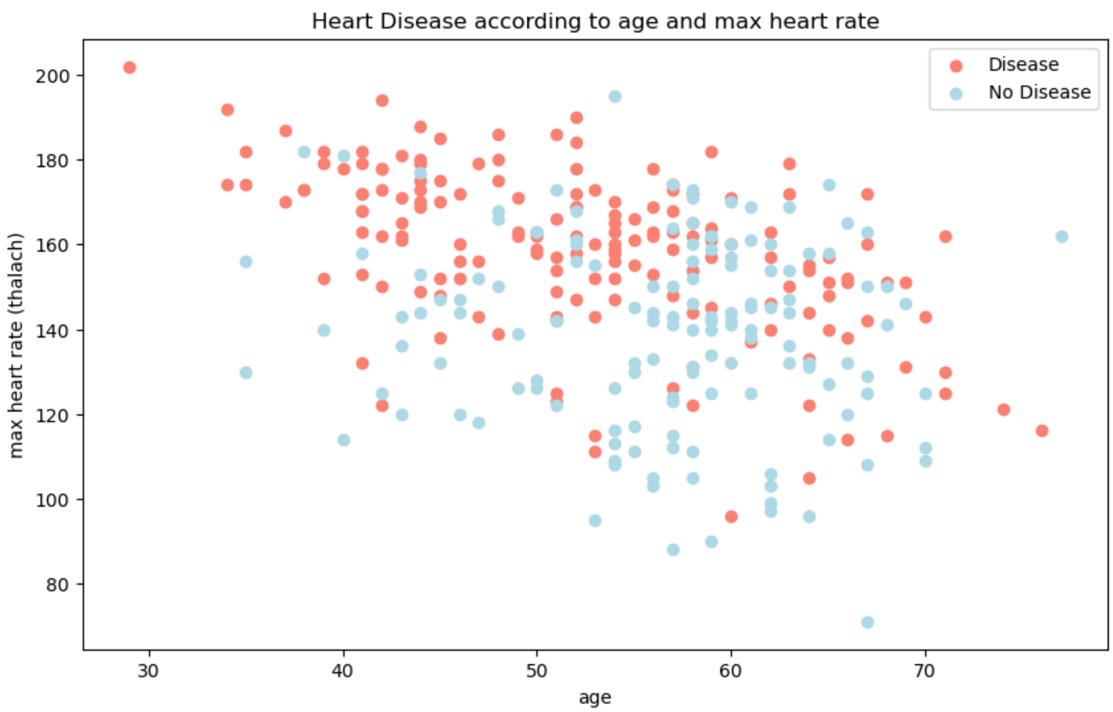
1.7.2 Heart Disease acc to Age and Thalach (Max Heart Rate)

[11]:
```
df["thalach"].value_counts()
```

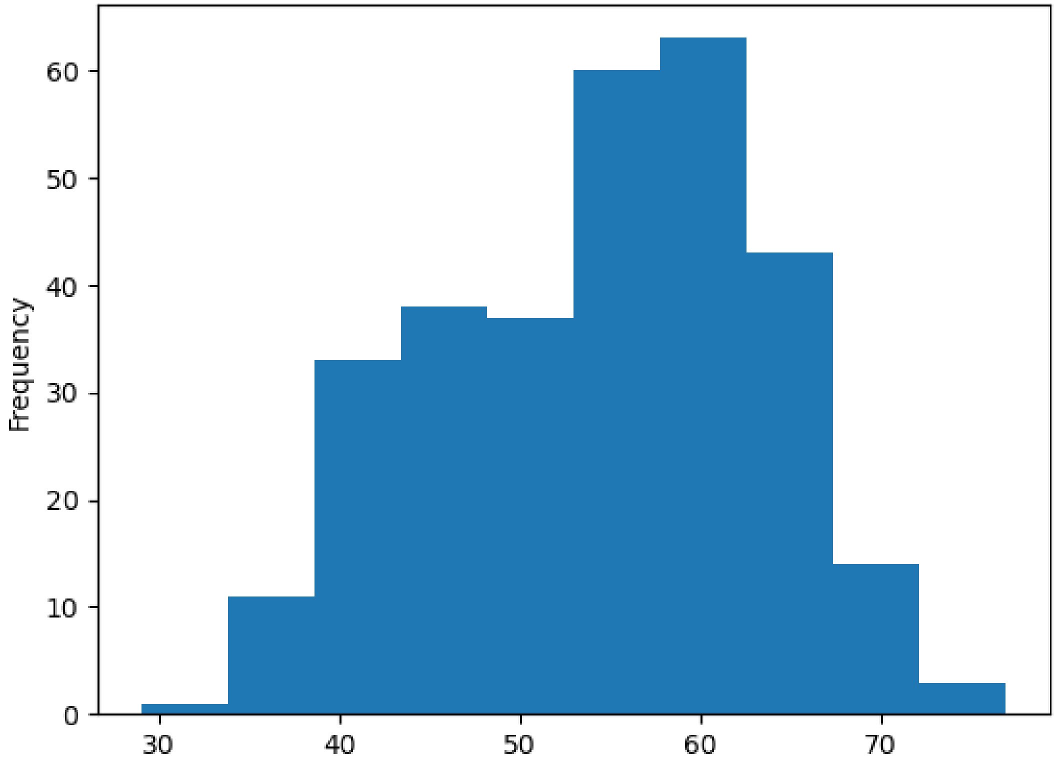
[11]:
```
162    11
160     9
163     9
152     8
173     8
       ..
202     1
184     1
121     1
192     1
90      1
Name: thalach, Length: 91, dtype: int64
```

There are 91 unique values for thalach. In such a diverse feature, scatter plots would be better than bar plots

[12]:
```
plt.figure(figsize=(10,6))

# Positive Examples (with heart disease)
plt.scatter(df.age[df.target == 1],
            df.thalach[df.target == 1],
            c = "salmon")

# Negative Examples (no heart disease)
plt.scatter(df.age[df.target == 0],
            df.thalach[df.target == 0],
            c = "lightblue")

# Extra information
plt.title("Heart Disease according to age and max heart rate")
plt.xlabel("age")
plt.ylabel("max heart rate (thalach)")
plt.legend(["Disease", "No Disease"]);
```



[13]:
```
# Distribution of age
df.age.plot.hist();
```



The graph is a normal distribution leaning towards the 60 age mark. There are not any outliers based on age.

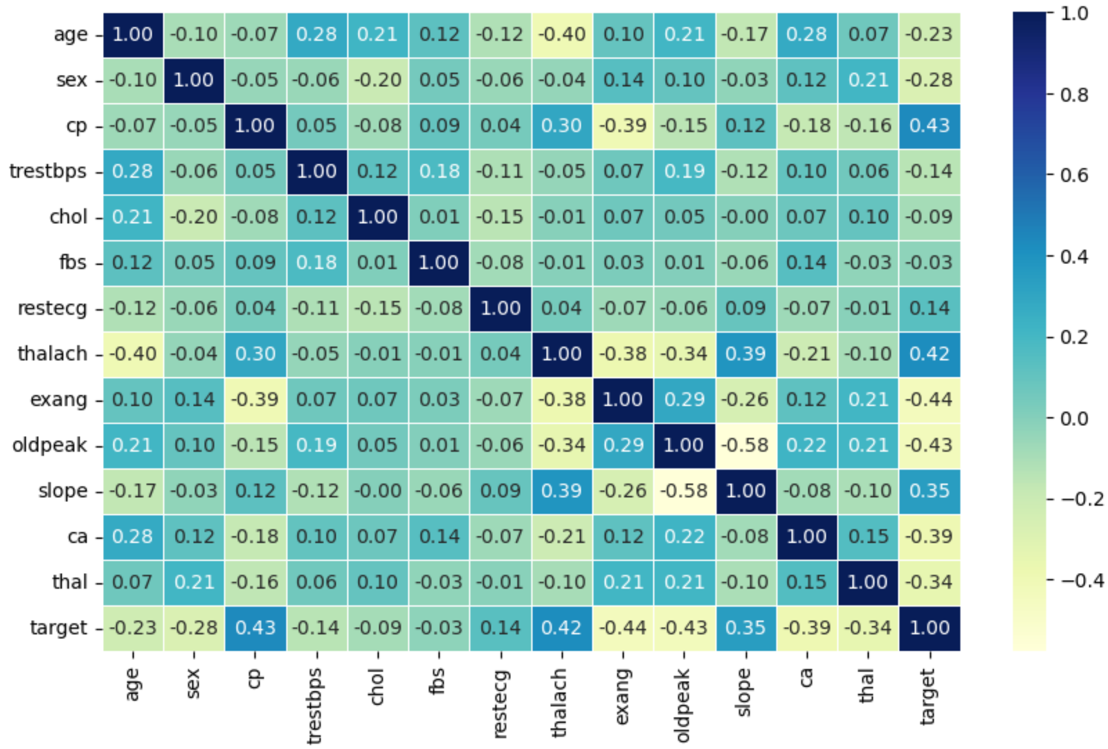
1.7.3 Correlation Matrix

[14]:
```
corr_matrix = df.corr()
corr_matrix
```

[14]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.098447 -0.068653  0.279351  0.213678  0.121308
sex      -0.098447  1.000000 -0.049353 -0.056769 -0.197912  0.045032
cp       -0.068653 -0.049353  1.000000  0.047608 -0.076904  0.094444
trestbps  0.279351 -0.056769  0.047608  1.000000  0.123174  0.177531
chol      0.213678 -0.197912 -0.076904  0.123174  1.000000  0.013294
fbs       0.121308  0.045032  0.094444  0.177531  0.013294  1.000000
restecg  -0.116211 -0.058196  0.044421 -0.114103 -0.151040 -0.084189
thalach  -0.398522 -0.044020  0.295762 -0.046698 -0.009940 -0.008567
exang     0.096801  0.141664 -0.394280  0.067616  0.067023  0.025665
oldpeak   0.210013  0.096093 -0.149230  0.193216  0.053952  0.005747
slope    -0.168814 -0.030711  0.119717 -0.121475 -0.004038 -0.059894
ca        0.276326  0.118261 -0.181053  0.101389  0.070511  0.137979
thal      0.068001  0.210041 -0.161736  0.062210  0.098803 -0.032019
```

```
target   -0.225439 -0.280937  0.433798 -0.144931 -0.085239 -0.028046

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.116211 -0.398522  0.096801  0.210013 -0.168814  0.276326
sex      -0.058196 -0.044020  0.141664  0.096093 -0.030711  0.118261
cp        0.044421  0.295762 -0.394280 -0.149230  0.119717 -0.181053
trestbps -0.114103 -0.046698  0.067616  0.193216 -0.121475  0.101389
chol     -0.151040 -0.009940  0.067023  0.053952 -0.004038  0.070511
fbs      -0.084189 -0.008567  0.025665  0.005747 -0.059894  0.137979
restecg   1.000000  0.044123 -0.070733 -0.058770  0.093045 -0.072042
thalach   0.044123  1.000000 -0.378812 -0.344187  0.386784 -0.213177
exang    -0.070733 -0.378812  1.000000  0.288223 -0.257748  0.115739
oldpeak  -0.058770 -0.344187  0.288223  1.000000 -0.577537  0.222682
slope     0.093045  0.386784 -0.257748 -0.577537  1.000000 -0.080155
ca       -0.072042 -0.213177  0.115739  0.222682 -0.080155  1.000000
thal     -0.011981 -0.096439  0.206754  0.210244 -0.104764  0.151832
target    0.137230  0.421741 -0.436757 -0.430696  0.345877 -0.391724

              thal    target
age       0.068001 -0.225439
sex       0.210041 -0.280937
cp       -0.161736  0.433798
trestbps  0.062210 -0.144931
chol      0.098803 -0.085239
fbs      -0.032019 -0.028046
restecg  -0.011981  0.137230
thalach  -0.096439  0.421741
exang     0.206754 -0.436757
oldpeak   0.210244 -0.430696
slope    -0.104764  0.345877
ca        0.151832 -0.391724
thal      1.000000 -0.344029
target   -0.344029  1.000000
```

[15]:
```
fig, ax = plt.subplots(figsize = (10, 6))
ax = sns.heatmap(corr_matrix,
                 annot = True,
                 linewidths = 0.5,
                 fmt = ".2f",
                 cmap = "YlGnBu");
```



From the Correlation Matrix we can see that higher values of features like cp(chest pain) and thalach(max heart beat) result in positive correlation with the target label (i.e. target is positive for higher values) while for features like exang, oldpeak, the relationship is inverse (i.e. lower values result in positive target).

1.8 5. Modelling

[16]:
```
df.head()
```

[16]:
```
   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
```

[17]:
```python
# Splitting data into X (features) and y (label)
X = df.drop("target", axis=1)
y = df["target"]
```

[18]:
```python
X
```

[18]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0     63    1   3       145   233    1        0      150      0      2.3
1     37    1   2       130   250    0        1      187      0      3.5
2     41    0   1       130   204    0        0      172      0      1.4
3     56    1   1       120   236    0        1      178      0      0.8
4     57    0   0       120   354    0        1      163      1      0.6
..   ...  ...  ..       ...   ...  ...      ...      ...    ...      ...
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
0        0   0     1
1        0   0     2
2        2   0     2
3        2   0     2
4        2   0     2
..     ...  ..   ...
298      1   0     3
299      1   0     3
300      1   2     3
301      1   1     3
302      1   1     2

[303 rows x 13 columns]
```

[19]:
```python
y
```

[19]:
```
0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
```

```
Name: target, Length: 303, dtype: int64
```

[20]:
```
# Splitting the data into training and test splits
np.random.seed(0)

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

[21]:
```
X_train
```

[21]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
74    43    0   2       122   213    0        1      165      0      0.2
153   66    0   2       146   278    0        0      152      0      0.0
64    58    1   2       140   211    1        0      165      0      0.0
296   63    0   0       124   197    0        1      136      1      0.0
287   57    1   1       154   232    0        0      164      0      0.0
..   …   …  ..       …   …   …       …      …     …      …
251   43    1   0       132   247    1        0      143      1      0.1
192   54    1   0       120   188    0        1      113      0      1.4
117   56    1   3       120   193    0        0      162      0      1.9
47    47    1   2       138   257    0        0      156      0      0.0
172   58    1   1       120   284    0        0      160      0      1.8

     slope  ca  thal
74       1   0     2
153      1   1     2
64       2   0     2
296      1   0     2
287      2   1     2
..     …  ..   …
251      1   4     3
192      1   1     3
117      1   0     3
47       2   0     2
172      1   0     2

[242 rows x 13 columns]
```

[22]:
```
y_train
```

[22]:
```
74     1
153    1
64     1
296    0
287    0
      ..
251    0
192    0
```

```
117    1
47     1
172    0
Name: target, Length: 242, dtype: int64
```

[23]:
```
len(X_train), len(y_train), len(X_test), len(y_test)
```

[23]:
```
(242, 242, 61, 61)
```

We're going to be using 3 classification models - 1. Logistic Regression 2. K-Nearest Neighbors Classifier 3. Random Forest Classifier

[24]:
```
import warnings
warnings.filterwarnings('ignore')
```

[25]:
```
# Let's make a function for fittting and evaluating models
def model_fit_and_score(models, X_train, X_test, y_train, y_test):
    '''
    Fits the data (X_train, X_test, y_train, y_test) into all the models in the␣
 ↪dictionary (models)
    and returns evaluation scores (default of each model) for them.
    models : dictionary containing models.
    '''
    np.random.seed(0)
    model_score = {}
    for name, model in models.items():
        model.fit(X_train, y_train)
        model_score[name] = model.score(X_test, y_test)
    return model_score
```

[26]:
```
models = {
    "Logistic Regression" : LogisticRegression(),
    "KNN" : KNeighborsClassifier(),
    "Random Forest" : RandomForestClassifier()
}

baseline_scores = model_fit_and_score(models, X_train, X_test, y_train, y_test)
baseline_scores
```

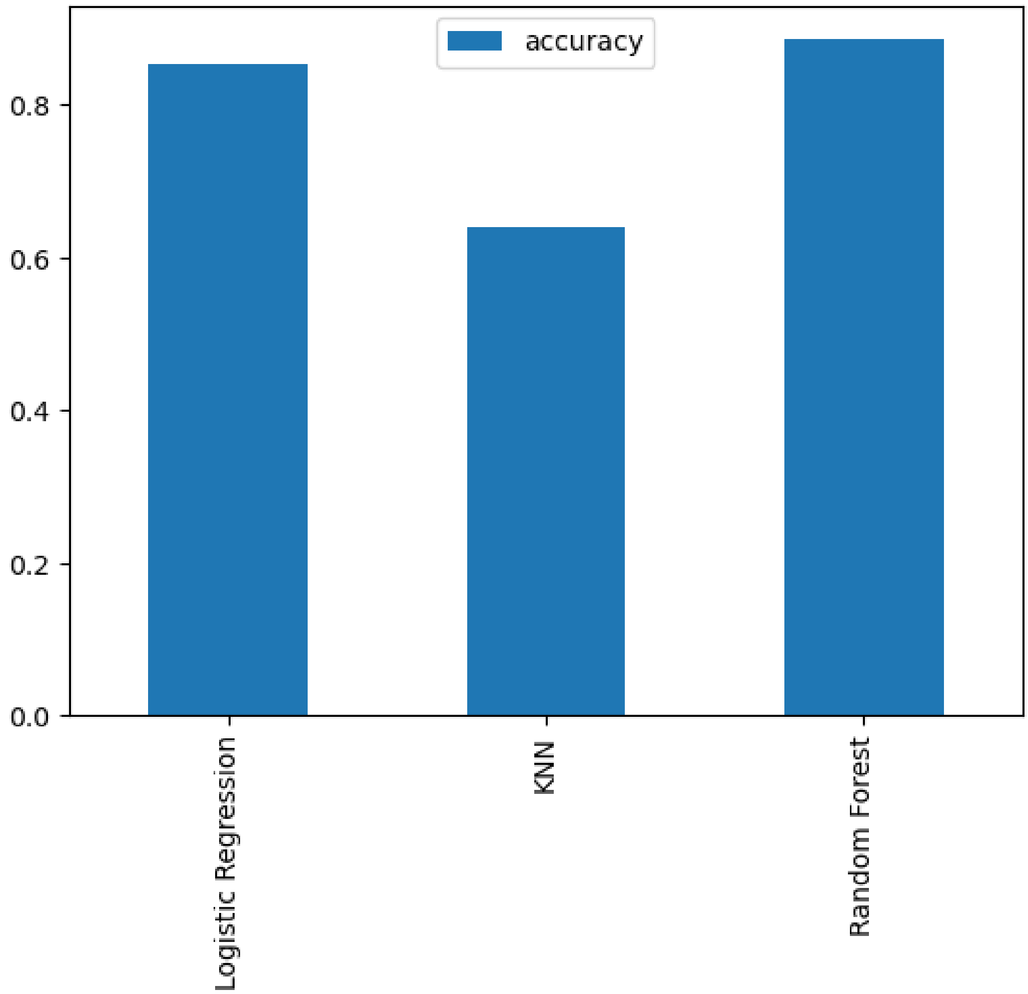
[26]:
```
{'Logistic Regression': 0.8524590163934426,
 'KNN': 0.639344262295082,
 'Random Forest': 0.8852459016393442}
```

[27]:
```
baseline_compare = pd.DataFrame(baseline_scores, index = ["accuracy"])
baseline_compare
```

[27]:

	Logistic Regression	KNN	Random Forest
accuracy	0.852459	0.639344	0.885246

[28]:
```
baseline_compare.T.plot.bar();
```



Now that we have baseline model predictions, let's move on to - * Hyperparameter Tuning * Feature importance * Confusion matrix * Cross - validation * Precision * F1 score * Recall * Classification report * ROC Curve * AUC Score

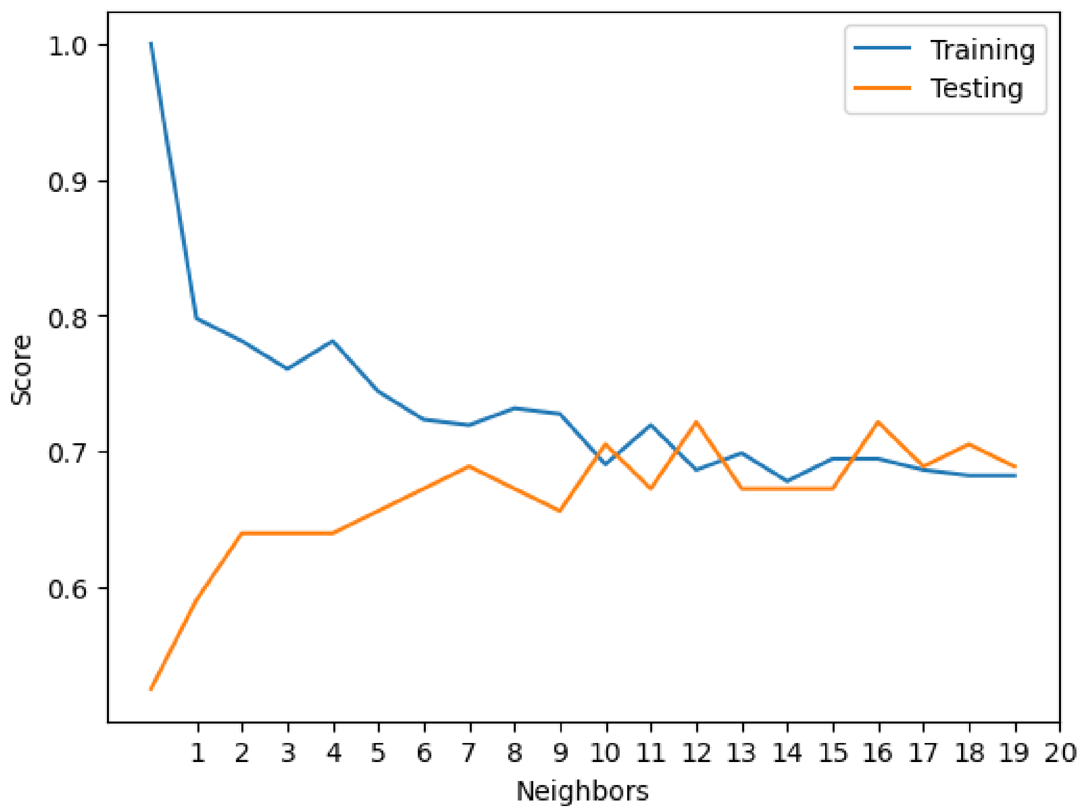
1.8.1 Hyperparameter Tuning (by hand)

KNN

[29]:
```
# Let's tune the knn classifier

knn = KNeighborsClassifier()
neighbors = range(1,21) # Range of neighbors from 1 to 20
train_score = []
test_score = []
```

```
for neighbor_amount in neighbors:
    knn.set_params(n_neighbors = neighbor_amount)
    knn.fit(X_train, y_train)
    train_score.append(knn.score(X_train, y_train))
    test_score.append(knn.score(X_test, y_test))
```

[30]:
```
plt.plot(train_score)
plt.plot(test_score)
plt.xlabel("Neighbors")
plt.ylabel("Score")
plt.legend(["Training", "Testing"])
plt.xticks(ticks = np.arange(1,21));
```



[31]:
```
print(f"Max KNN Score : {max(test_score) * 100 :.2f}%")
```

```
Max KNN Score : 72.13%
```

The KNN Classifier is worse than the other two models even after tuning number of neighbors so it's better to churn the KNN Classifier and focus on the other two models

1.8.2 Hyperparameter Tuning (using RandomizedSearchCV)

[32]:
```
# Grid for Logistic regression
logreg_grid = {"C" : np.logspace(-4, 4, 20),
              "penalty": ['l1', 'l2', 'elasticnet', None],
              "solver" : ["liblinear", 'newton-cholesky']}

# Grid for Random Forest Classifier
randfor_grid  = {"n_estimators" : np.arange(0,1000,50),
                "max_depth" : [None, 3, 5, 10],
                "min_samples_split": np.arange(0,10,2),
                "min_samples_leaf" : np.arange(0, 10, 2)}
```

[33]:
```
# Tuning Logistic Regression Classifier
np.random.seed(10)
rs_log_reg = RandomizedSearchCV(LogisticRegression(),
                               param_distributions = logreg_grid,
                               cv = 5,
                               n_iter = 20,
                               verbose = True)
rs_log_reg.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

[33]:
```
RandomizedSearchCV(cv=5, estimator=LogisticRegression(), n_iter=20,
                   param_distributions={'C': array([1.00000000e-04,
2.63665090e-04, 6.95192796e-04, 1.83298071e-03,
       4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
       2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
       1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
       5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),
                                        'penalty': ['l1', 'l2', 'elasticnet',
                                                    None],
                                        'solver': ['liblinear',
                                                   'newton-cholesky']},
                   verbose=True)
```

[34]:
```
rs_log_reg.best_params_
```

[34]:
```
{'solver': 'newton-cholesky', 'penalty': 'l2', 'C': 0.23357214690901212}
```

[35]:
```
baseline_scores
```

[35]:
```
{'Logistic Regression': 0.8524590163934426,
 'KNN': 0.639344262295082,
 'Random Forest': 0.8852459016393442}
```

[36]:
```
rs_log_reg.score(X_test, y_test)
```

[36]: 0.8524590163934426

[37]:
```
# now lets tune random forest classifier
np.random.seed(100)
rs_rand_for = RandomizedSearchCV(RandomForestClassifier(),
                                param_distributions = randfor_grid,
                                cv = 5,
                                n_iter = 20,
                                verbose = True)
rs_rand_for.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

[37]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=20,
                   param_distributions={'max_depth': [None, 3, 5, 10],
                                        'min_samples_leaf': array([0, 2, 4, 6,
8]),
                                        'min_samples_split': array([0, 2, 4, 6,
8]),
                                        'n_estimators': array([  0,  50, 100,
150, 200, 250, 300, 350, 400, 450, 500, 550, 600,
       650, 700, 750, 800, 850, 900, 950])},
                   verbose=True)
```

[38]:
```
rs_rand_for.best_params_
```

[38]:
```
{'n_estimators': 950,
 'min_samples_split': 6,
 'min_samples_leaf': 2,
 'max_depth': 10}
```

[39]:
```
rs_rand_for.score(X_test, y_test)
```

[39]: 0.8688524590163934

1.8.3 Hyperparameter Tuning (using GridSearchCV)

[40]:
```
logreg_grid
```

[40]:
```
{'C': array([1.00000000e-04, 2.63665090e-04, 6.95192796e-04, 1.83298071e-03,
        4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
        2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
        1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
        5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),
 'penalty': ['l1', 'l2', 'elasticnet', None],
 'solver': ['liblinear', 'newton-cholesky']}
```

[41]:
```
np.random.seed(0)
gs_logreg = GridSearchCV(LogisticRegression(),
                        param_grid = logreg_grid,
                        cv = 5,
                        verbose = True)
gs_logreg.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 160 candidates, totalling 800 fits
```

[41]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(),
             param_grid={'C': array([1.00000000e-04, 2.63665090e-04,
6.95192796e-04, 1.83298071e-03,
       4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
       2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
       1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
       5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2', 'elasticnet', None],
                         'solver': ['liblinear', 'newton-cholesky']},
             verbose=True)
```

[42]:
```
gs_logreg.best_params_
```

[42]:
```
{'C': 1.623776739188721, 'penalty': 'l2', 'solver': 'liblinear'}
```

[43]:
```
gs_logreg.score(X_test, y_test)
```

[43]:
```
0.8524590163934426
```

1.8.4 Model Evaluations

- Confusion matrix
- Precision
- F1 score
- Recall
- Classification report
- ROC Curve
- AUC Score

[46]:
```
y_preds = gs_logreg.predict(X_test)
y_preds
```

[46]:
```
array([0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1])
```

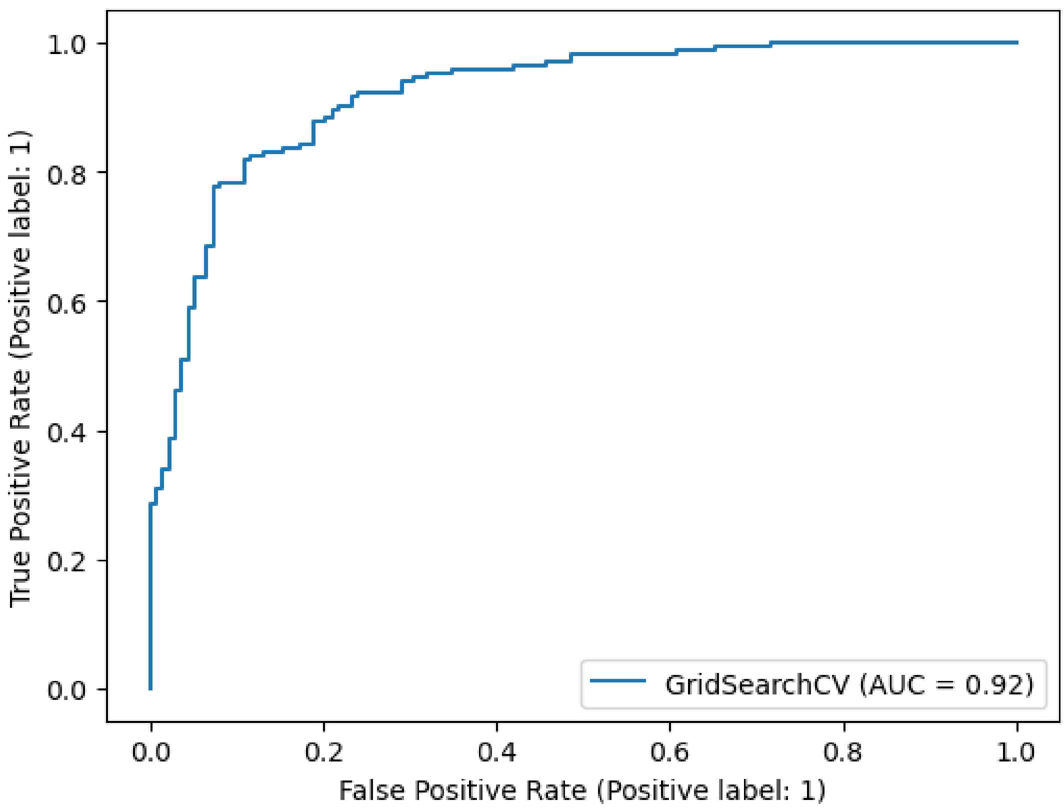
[45]:
```
y_test
```

[45]:
```
225    0
152    1
```

```
228    0
201    0
52     1
      ..
146    1
302    0
26     1
108    1
89     1
Name: target, Length: 61, dtype: int64
```

[52]:

```
# ROC Curve and AUC Score
RocCurveDisplay.from_estimator(gs_logreg, X, y);
```



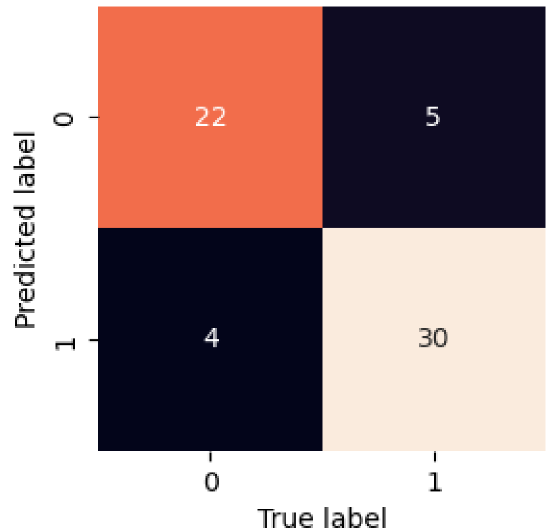
[53]:

```
# confusion matrix
confusion_matrix(y_test, y_preds)
```

[53]:

```
array([[22,  5],
       [ 4, 30]])
```

[57]:
```
fig, ax = plt.subplots(figsize = (3,3))
ax = sns.heatmap(confusion_matrix(y_test, y_preds),
                annot = True,
                cbar= False)
plt.xlabel("True label")
plt.ylabel("Predicted label");
```



[60]:
```
# Classification report (on train test split)
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.85      0.81      0.83        27
           1       0.86      0.88      0.87        34

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.85      0.85      0.85        61
```

[61]:
```
# Evaluating accuracy, precision, recall, f1 using cross validation
gs_logreg.best_params_
```

[61]:
```
{'C': 1.623776739188721, 'penalty': 'l2', 'solver': 'liblinear'}
```

[63]:
```
clf = LogisticRegression(C = 1.623776739188721,
                        penalty = "l2",
                        solver = "liblinear")
```

[64]:
```
# Accuracy
cv_acc = cross_val_score(clf, X, y, cv = 5, scoring = "accuracy")
cv_acc = np.mean(cv_acc)
cv_acc
```

[64]: 0.8182513661202186

[65]:
```
# Precision
cv_prec = cross_val_score(clf, X, y, cv =5 , scoring = "precision")
cv_prec = np.mean(cv_prec)
cv_prec
```

[65]: 0.8122549019607843

[66]:
```
# Recall
cv_recall = cross_val_score(clf, X, y, cv = 5, scoring = "recall")
cv_recall = np.mean(cv_recall)
cv_recall
```

[66]: 0.8727272727272727

[67]:
```
# f1 score
cv_f1 = cross_val_score(clf, X, y, cv = 5, scoring = "f1")
cv_f1 = np.mean(cv_f1)
cv_f1
```

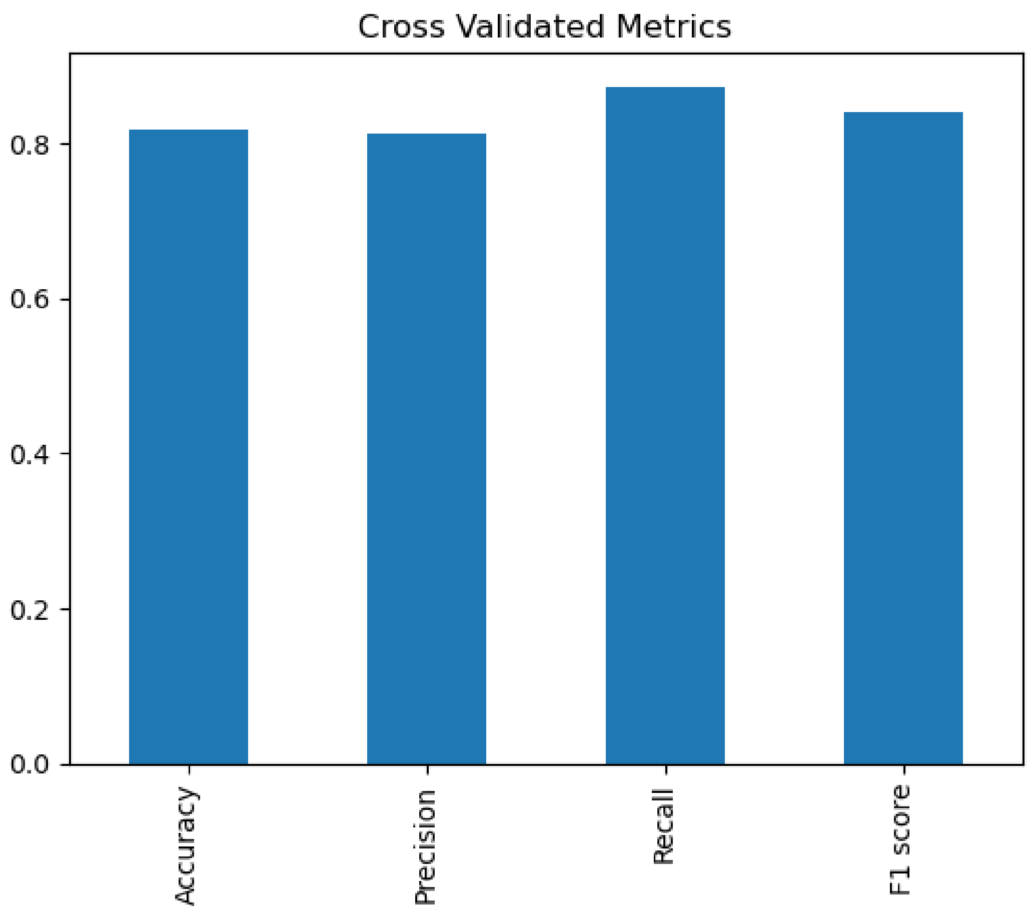
[67]: 0.8404818247075424

[68]:
```
cross_val_metrics = pd.DataFrame({"Accuracy": cv_acc,
                                  "Precision": cv_prec,
                                  "Recall": cv_recall,
                                  "F1 score": cv_f1},
                                 index = [0])
cross_val_metrics
```

[68]:

	Accuracy	Precision	Recall	F1 score
0	0.818251	0.812255	0.872727	0.840482

[71]:
```
cross_val_metrics.T.plot.bar(title= "Cross Validated Metrics" ,legend = False);
```



1.8.5 Feature Importance

[72]:
```
clf
```

[72]:
```
LogisticRegression(C=1.623776739188721, solver='liblinear')
```

[73]:
```
clf.fit(X_train, y_train)
```

[73]:
```
LogisticRegression(C=1.623776739188721, solver='liblinear')
```

[74]:
```
clf.coef_
```

[74]:
```
array([[ 0.00655176, -1.62134806,  0.75945315, -0.0084671 , -0.00404966,
        -0.3434305 ,  0.23128621,  0.02940965, -0.88063443, -0.54161158,
         0.2134618 , -0.87123514, -0.6927829 ]])
```

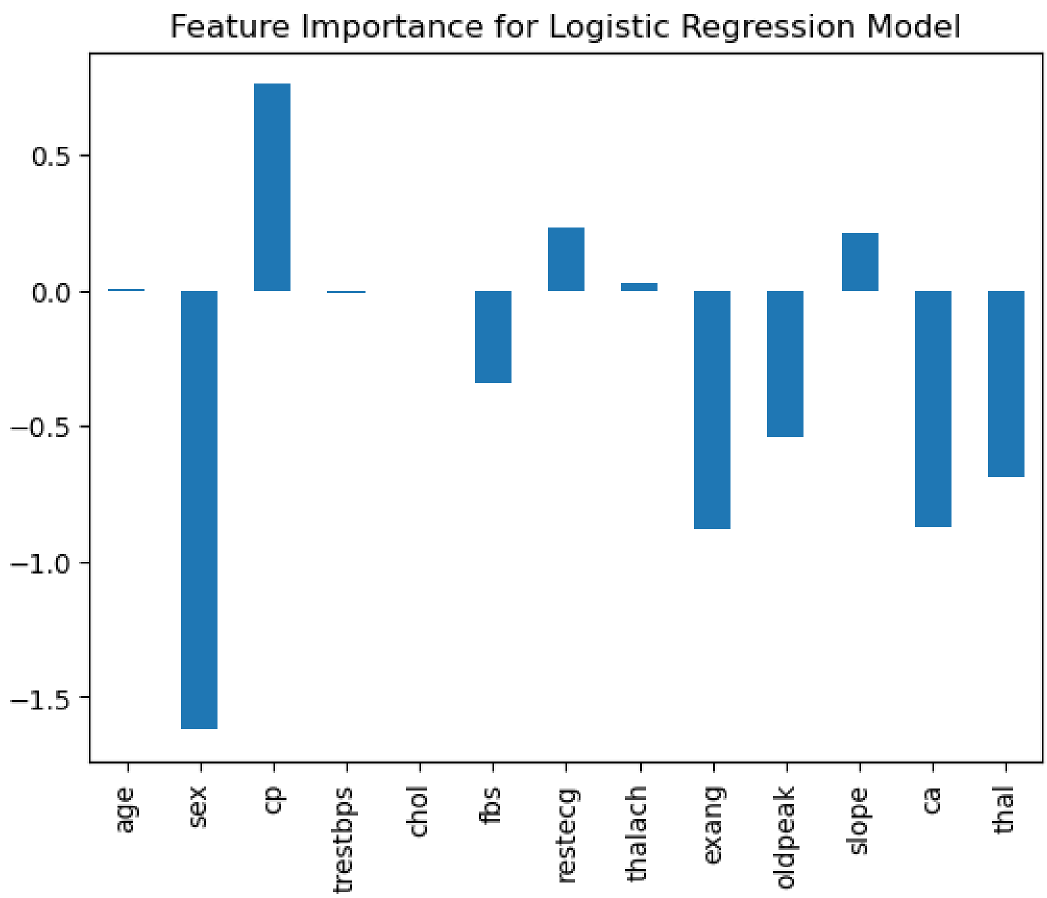
[76]:
```
feature_coef = dict(zip(df.columns, clf.coef_[0]))
feature_coef
```

[76]: {'age': 0.0065517585624253975,
 'sex': -1.6213480585313702,
 'cp': 0.7594531514538636,
 'trestbps': -0.008467101683917223,
 'chol': -0.004049664833738469,
 'fbs': -0.34343049664745534,
 'restecg': 0.2312862052685433,
 'thalach': 0.029409650316247673,
 'exang': -0.8806344289114787,
 'oldpeak': -0.5416115849299789,
 'slope': 0.21346179823107966,
 'ca': -0.8712351436972039,
 'thal': -0.6927828988569131}

[77]:
```
feature_importance = pd.DataFrame(feature_coef, index = [0])
feature_importance
```

[77]:
```
        age       sex        cp  trestbps     chol      fbs   restecg  \
0  0.006552 -1.621348  0.759453 -0.008467 -0.00405 -0.34343  0.231286

   thalach     exang   oldpeak     slope        ca      thal
0  0.02941 -0.880634 -0.541612  0.213462 -0.871235 -0.692783
```

[78]:
```
feature_importance.T.plot.bar(title = "Feature Importance for Logistic␣
 ↪Regression Model", legend = False);
```



We see that sex is really important and inversally related (sex = 0 -> target = 1), while cp is directly related (cp = higher -> target = 1)

[79]:
```
pd.crosstab(df["sex"], df["target"])
```

[79]:
```
target    0   1
sex
0        24  72
1       114  93
```

[80]:
```
pd.crosstab(df["cp"], df["target"])
```

[80]:
```
target    0   1
cp
0       104  39
1         9  41
2        18  69
3         7  16
```

[81]:
```python
pd.crosstab(df["ca"], df["target"])
```

[81]:

target	0	1
ca		
0	45	130
1	44	21
2	31	7
3	17	3
4	1	4

1.9 Verdict

To improve the model, we need to collect more data. We explored feature importance and need to collect data more focused on the features which are important for the model (sex, ca, cp, etc).