heart-disease-classification

July 2, 2024

1 Predicting heart disease using machine learning

This notebook looks into using various Python-based machine learning and data science libraries in an attempt to build a machine learning model capable of predicting whether or not someone has heart disease based on their medical attributes.

We're going to take the following approach: 1. Problem definition 2. Data 3. Evaluation 4. Features 5. Modelling 6. Experimentation

1.1 1. Problem Definition

In a statement, > Given clinical parameters about a patient, can we predict whether or not they have heart disease?

1.2 2. Data

The original data came from Cleveland data from the UCI Machine Learning Repository. https://archive.ics.uci.edu/dataset/45/heart+disease

There is also a version of it available on Kaggle. https://www.kaggle.com/datasets/redwankarimsony/heart-disease-data

1.3 3. Evaluation

> If we can reach 95% accuracy at predicting whether or not a patient has heart disease during the proof of concept, we'll pursue the project.

1.4 4. Features

Data dictionary

1. `age` Age of the patient in years
2. `sex` Male/Female
3. `cp` chest pain type
    - 0: Typical angina - chest pain related decrease blood supply to the heart
    - 1: Atypical angina - chest pain not related to heart
    - 2: Non-anginal pain - typically esophageal spasms (non heart related)
    - 3: Asymptomatic - chest pain not showing signs of disease
4. `trestbps` resting blood pressure (in mm Hg on admission to the hospital)
5. `chol` serum cholesterol in mg/dl
6. `fbs` (if fasting blood sugar > 120 mg/dl) (1 = True; 0 = False)

- (blood sugar > 126 mg/dl) signals diabetes

7. `restecg` resting electrocardiographic results
    - 0: Normal
    - 1: ST-T Wave Abnormality
        - Can range from mild symptoms to severe problems
        - Signals non-normal heart beat
    - 2: Left ventricular hypertrophy
        - Enlarged heart's main pumping chamber
8. `thalach` maximum heart rate achieved
9. `exang` exercise induced angina (1 = True; 0 = False)
10. `oldpeak` ST depression induced by exercise relative to rest
11. `slope` the slope of the peak exercise ST segment
    - 0: Upsloping - better heart rate with exercise (uncommon)
    - 1: Flatsloping - minimal change (typical healthy heart)
    - 2: Downsloping - signs of unhealthy heart
12. `ca` number of major vessels (0-3) colored by fluoroscopy
    - colored vessels means the doctor can see the blood passing through.
    - the more blood movement the better (no clots)
13. `thal` thalium stress result
    - 1, 3: normal
    - 6: fixed defect - used to be defect but ok now
    - 7: reversible defect - no proper blood movement when exercising
14. `num` have disease or not (1 = Yes; 0 = No) (the predicted attribute)

1.5 Preparing the tools

Using Pandas, Matplotlib and Numpy for data analysis and manipulation.

[1]:
```
# Import all the required tools

# Regular EDA and plotting libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# For plots to appear inside the notebook
%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 confusion_matrix, classification_report
```

```
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import RocCurveDisplay
```

1.6 Load data

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

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

1.7 Data Exploration (EDA)

The goal here is to find out more about the data and become a subject matter expert on the dataset we're working with.

1. What question(s) are we trying to solve?
2. What kind of data do we have and how do we treat different types?
3. What's missing from the data and how do we deal with it?
4. Where are the outliers and why should we care about them?
5. How can we add, change or remove features to get more out of the data?

[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.tail()
```

[4]:
```
     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
```

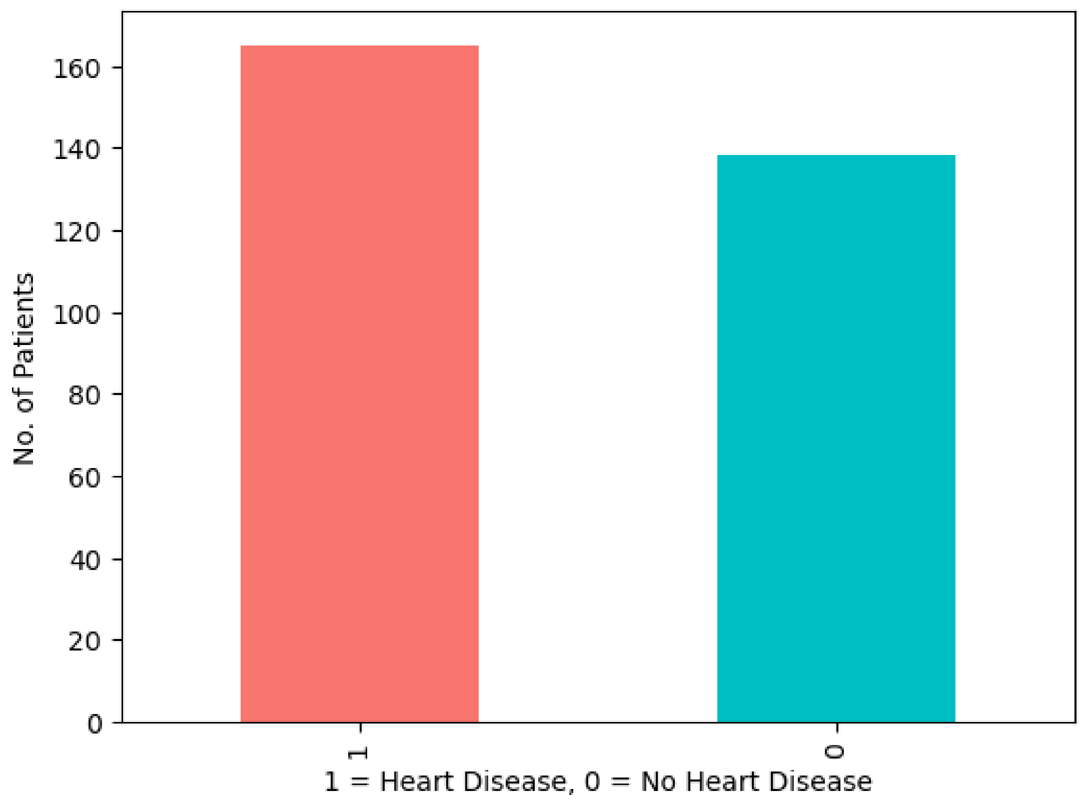
```
299        1   0     3       0
300        1   2     3       0
301        1   1     3       0
302        1   1     2       0
```

[5]:
```
# Let's find out how many of each class there are
df["target"].value_counts()
```

[5]:
```
target
1    165
0    138
Name: count, dtype: int64
```

[6]:
```
df["target"].value_counts().plot(kind="bar", color=["#F8766D", "#00BFC4"])

plt.xlabel("1 = Heart Disease, 0 = No Heart Disease")
plt.ylabel("No. of Patients")
```

[6]:
```
Text(0, 0.5, 'No. of Patients')
```



[7]:
```
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
```

[8]:
```
# Are there any missing values?
df.isna().sum()
```

[8]:
```
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
```

[9]:
```
df.describe()
```

[9]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean    54.366337    0.683168    0.966997  131.623762  246.264026    0.148515
std      9.082101    0.466011    1.032052   17.538143   51.830751    0.356198
```

```
min      29.000000     0.000000     0.000000    94.000000   126.000000     0.000000
25%      47.500000     0.000000     0.000000   120.000000   211.000000     0.000000
50%      55.000000     1.000000     1.000000   130.000000   240.000000     0.000000
75%      61.000000     1.000000     2.000000   140.000000   274.500000     0.000000
max      77.000000     1.000000     3.000000   200.000000   564.000000     1.000000

          restecg      thalach        exang      oldpeak        slope           ca  \
count  303.000000   303.000000   303.000000   303.000000   303.000000   303.000000
mean     0.528053   149.646865     0.326733     1.039604     1.399340     0.729373
std      0.525860    22.905161     0.469794     1.161075     0.616226     1.022606
min      0.000000    71.000000     0.000000     0.000000     0.000000     0.000000
25%      0.000000   133.500000     0.000000     0.000000     1.000000     0.000000
50%      1.000000   153.000000     0.000000     0.800000     1.000000     0.000000
75%      1.000000   166.000000     1.000000     1.600000     2.000000     1.000000
max      2.000000   202.000000     1.000000     6.200000     2.000000     4.000000

             thal       target
count  303.000000   303.000000
mean     2.313531     0.544554
std      0.612277     0.498835
min      0.000000     0.000000
25%      2.000000     0.000000
50%      2.000000     1.000000
75%      3.000000     1.000000
max      3.000000     1.000000
```

1.7.1 Heart Disease Frequency according to Sex

[10]:
```
df.sex.value_counts()
```

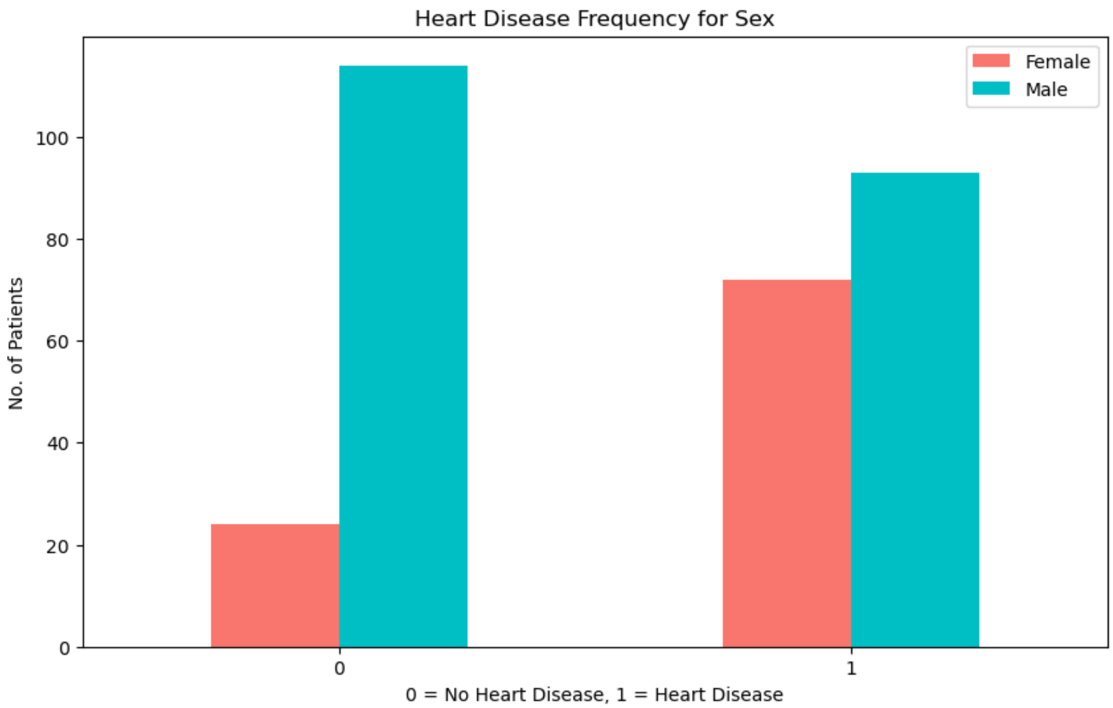
[10]:
```
sex
1    207
0     96
Name: count, dtype: int64
```

[11]:
```
# Compare target column with sex column
pd.crosstab(df.target, df.sex)
```

[11]:
```
sex      0    1
target
0       24  114
1       72   93
```

[12]:
```
# Create a plot of crosstab
pd.crosstab(df.target, df.sex).plot(kind="bar",
                                    figsize=(10, 6),
                                    color=["#F8766D", "#00BFC4"])
```

```
plt.title("Heart Disease Frequency for Sex")
plt.xlabel("0 = No Heart Disease, 1 = Heart Disease")
plt.ylabel("No. of Patients")
plt.legend(["Female", "Male"]);
plt.xticks(rotation=0);
```

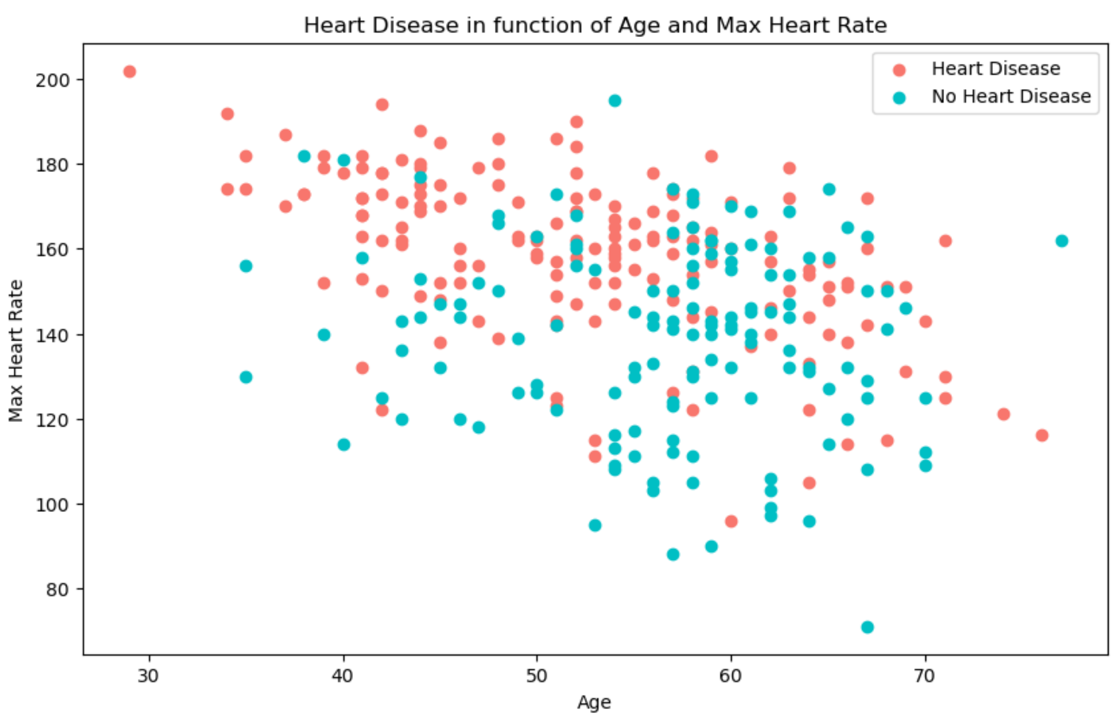


[13]:
```
df["thalach"].value_counts()
```

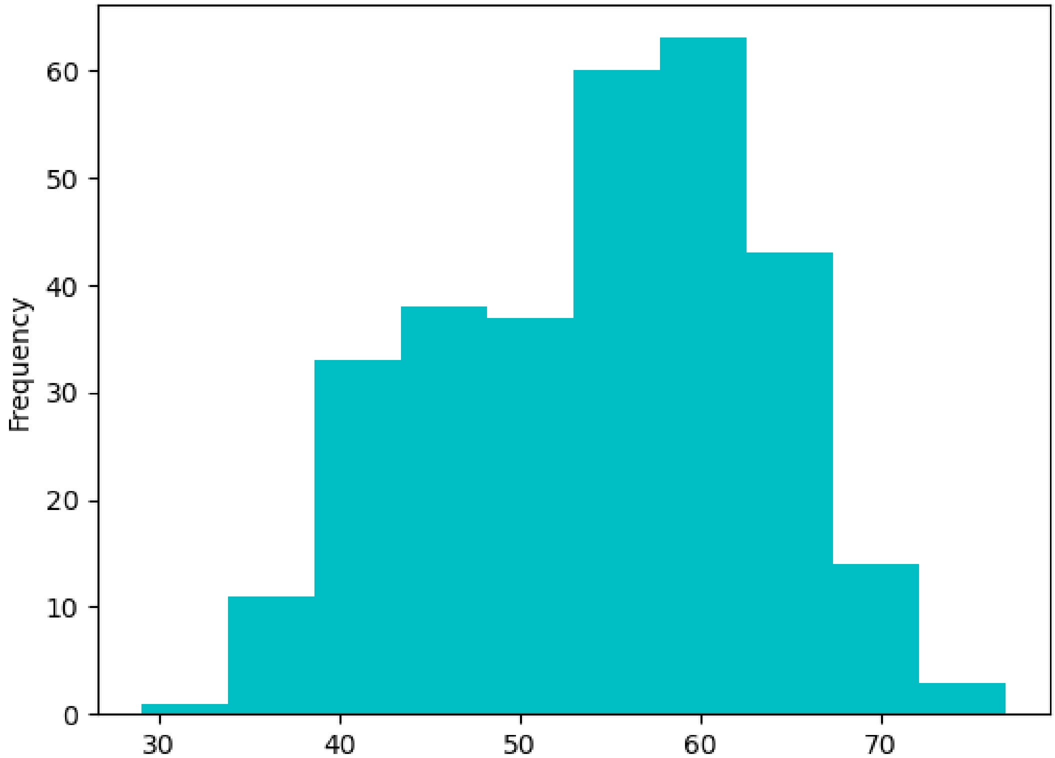
[13]:
```
thalach
162    11
160     9
163     9
152     8
173     8
       ..
202     1
184     1
121     1
192     1
90      1
Name: count, Length: 91, dtype: int64
```

1.7.2 Age vs. Max Heart Rate for Heart Disease

[14]:
```
# Create another figure
plt.figure(figsize=(10, 6))

# Scatter with positive examples
plt.scatter(df.age[df.target==1],
            df.thalach[df.target==1],
            c="#F8766D")

# Scatter with negative examples
plt.scatter(df.age[df.target==0],
            df.thalach[df.target==0],
            c="#00BFC4");

# Add some helpful info
plt.title("Heart Disease in function of Age and Max Heart Rate")
plt.xlabel("Age")
plt.ylabel("Max Heart Rate")
plt.legend(["Heart Disease", "No Heart Disease"]);
```



[15]:
```
# Check the distribution of the age column with a histogram
df.age.plot.hist(color="#00BFC4");
```

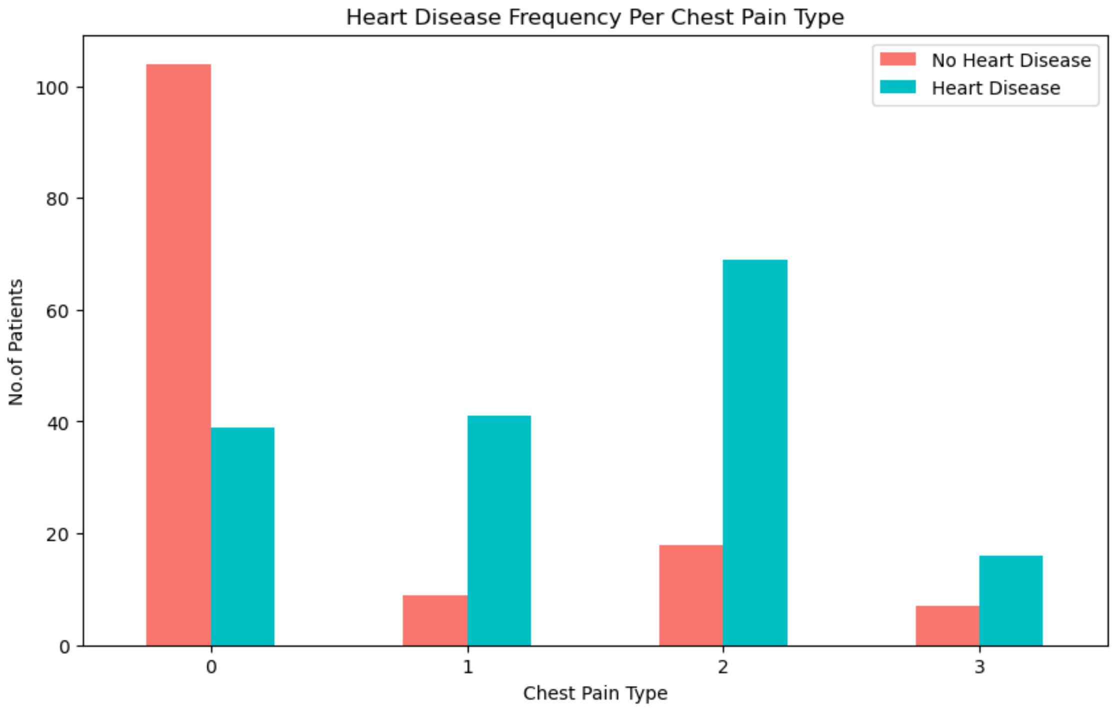


1.7.3 Heart Disease Frequency per Chest Pain Type

[16]:
```
pd.crosstab(df.cp, df.target)
```

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

[17]:
```
# Make the crosstab more visual
pd.crosstab(df.cp, df.target).plot(kind="bar",
                                   figsize=(10, 6),
                                    color=["#F8766D", "#00BFC4"])
# Add some communication
plt.title("Heart Disease Frequency Per Chest Pain Type")
plt.xlabel("Chest Pain Type")
plt.ylabel("No.of Patients")
plt.legend(["No Heart Disease", "Heart Disease"])
plt.xticks(rotation=0);
```



[18]:
```
df.head()
```

[18]:

	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

[19]:
```
# Make a correlation matrix
df.corr()
```

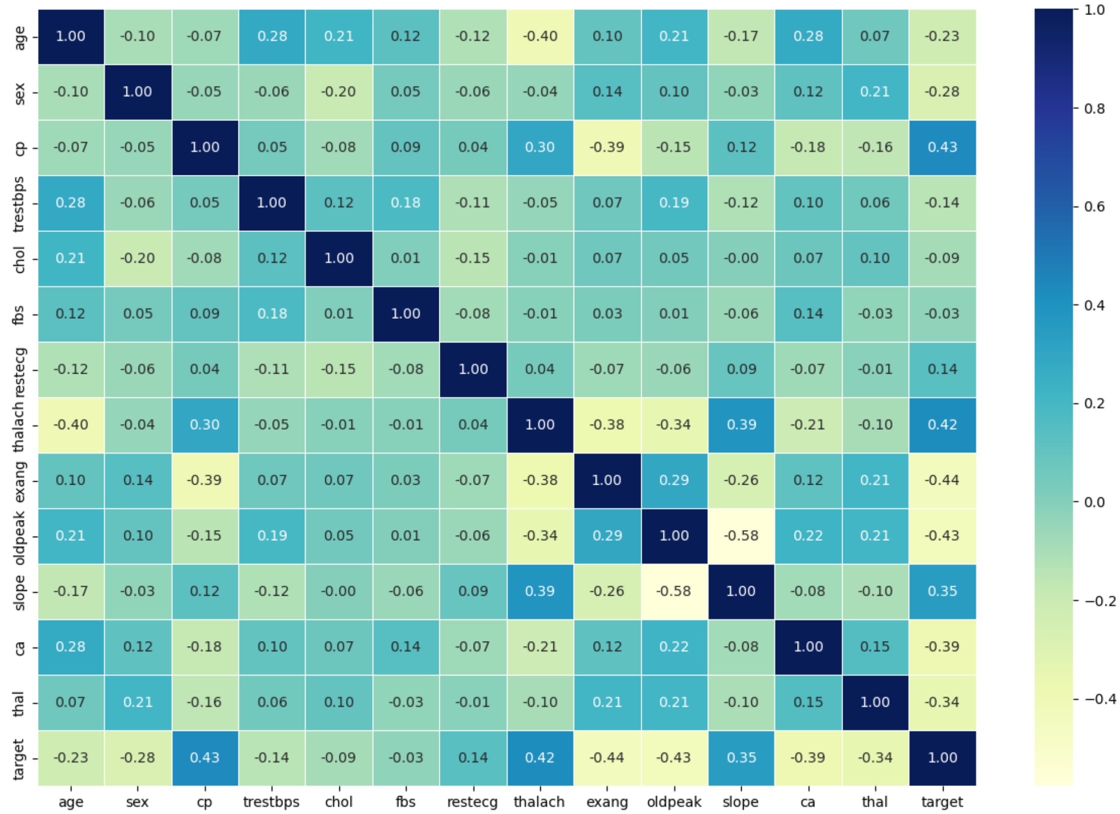
[19]:

	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
```

[20]:
```
# Let's make our correlation matrix a little prettier
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize=(15, 10))
ax = sns.heatmap(corr_matrix,
```

```
                    annot=True,
                    linewidths=0.5,
                    fmt=".2f",
                    cmap="YlGnBu");
```



1.8 5. Modelling

[21]:
```
df.head()
```

[21]:

	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
```

[22]:
```python
# Split data into X and y
X = df.drop("target", axis=1)
y = df["target"]
```

[23]:
```python
X
```

[23]:
```
     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]
```

[24]:
```python
y
```

[24]:
```
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
```

[25]:
```
# Split data into train and test sets
np.random.seed(42)

# Split into train & test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[26]:
```
X_train
```

[26]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
132   42    1   1       120   295    0        1      162      0      0.0
202   58    1   0       150   270    0        0      111      1      0.8
196   46    1   2       150   231    0        1      147      0      3.6
75    55    0   1       135   250    0        0      161      0      1.4
176   60    1   0       117   230    1        1      160      1      1.4
..   …    …  ..       …    …    …        …      …      …        …
188   50    1   2       140   233    0        1      163      0      0.6
71    51    1   2        94   227    0        1      154      1      0.0
106   69    1   3       160   234    1        0      131      0      0.1
270   46    1   0       120   249    0        0      144      0      0.8
102   63    0   1       140   195    0        1      179      0      0.0

     slope  ca  thal
132      2   0     2
202      2   0     3
196      1   0     2
75       1   0     2
176      2   2     3
..     …  ..   …
188      1   1     3
71       2   1     3
106      1   1     2
270      2   0     3
102      2   2     2

[242 rows x 13 columns]
```

[27]:
```
y_train, len(y_train)
```

[27]:
```
(132    1
 202    0
 196    0
 75     1
 176    0
```

```
       ..
188    0
71     1
106    1
270    0
102    1
Name: target, Length: 242, dtype: int64,
242)
```

Now we've got our data split into training and test sets, it's time to build a machine learning model.

We'll train it (find the patterns) on the training set.

And we'll test it (use the patterns) on the test set.

We're going to try 3 different machine learning models: 1. Logistic Regression 2. K-Nearest Neighbors Classifier 3. Random Forest Classifier

[28]:

```
# Put models in a dictionary
models = {"Logistic Regression": LogisticRegression(),
          "KNN": KNeighborsClassifier(),
          "Random Forest": RandomForestClassifier()}

# Create a function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models: a dictionary of different Scikit-Learn machine learning models
    X_train: training data (no labels)
    X_test: testing data (no labels)
    y_train: training labels
    y_test: testing labels
    """
    # Set random seed
    np.random.seed(42)
    # Make a dictionary to keep model scores
    model_scores = {}
    # Loop through models
    for name, model in models.items():
        # Fit the model to the data
        model.fit(X_train, y_train)
        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test, y_test)
    return model_scores
```

[29]:

```
model_scores = fit_and_score(models=models,
                             X_train=X_train,
                             X_test=X_test,
                             y_train=y_train,
```

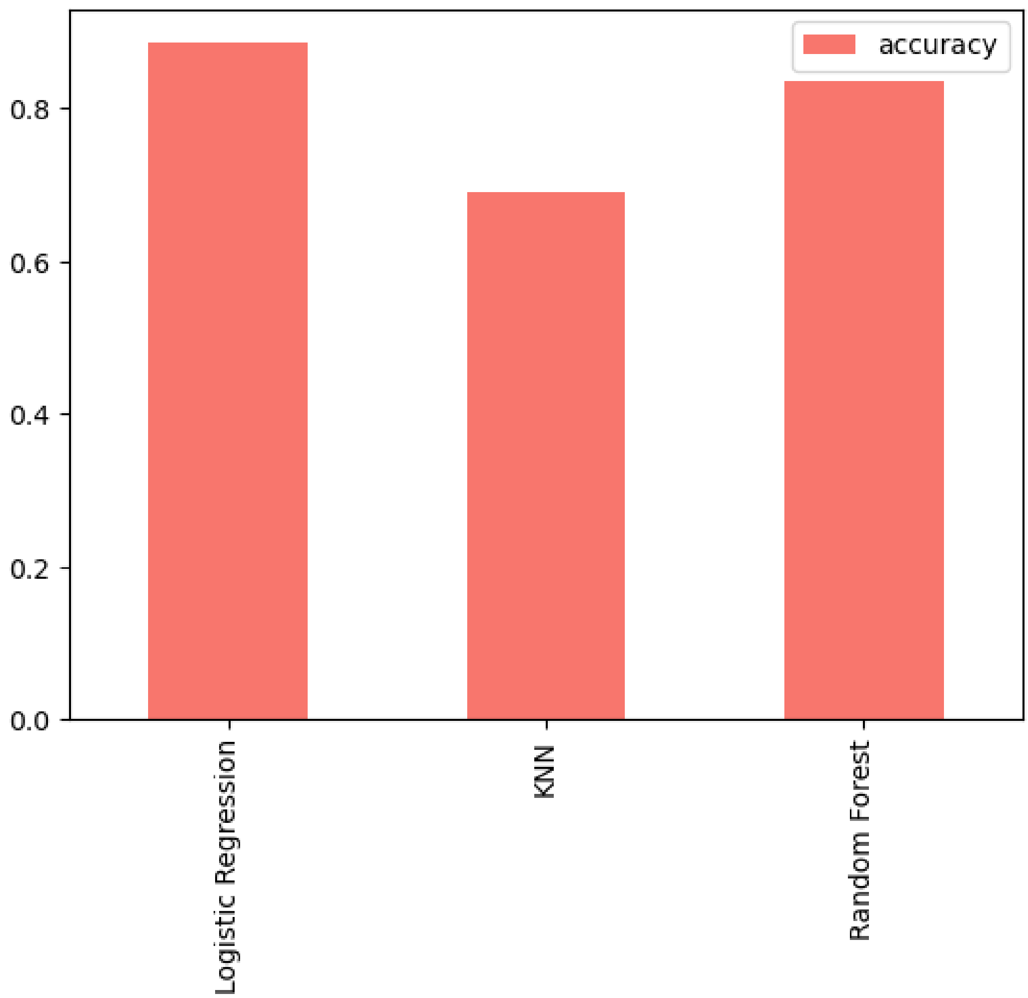
```
                                 y_test=y_test)
model_scores
```

```
D:\Developer\Portfolio_Project\heart-disease-project\env\Lib\site-
packages\sklearn\linear_model\_logistic.py:469: 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(
```

[29]:
```
{'Logistic Regression': 0.8852459016393442,
 'KNN': 0.6885245901639344,
 'Random Forest': 0.8360655737704918}
```

1.8.1 Model Comparison

[30]:
```
model_compare = pd.DataFrame(model_scores, index=["accuracy"])
model_compare.T.plot.bar(color="#F8766D"); # T: Transpose
```



Now we've got a baseline model… and we know a model's first predictions aren't always what we should base our next steps off. What should we do?

Let's look at the following: * For both classification & regression problems: * Hyperparameter tuning * Feature importance * Specific to classification problems: * Confusion matrix * Cross-validation * Precision * Recall * F1 score * Classification report * ROC curve * Area under the curve (AUC)

1.9 Hyperparameter tuning (by hand)

[31]:
```
# Let's tune KNN

train_scores = []
test_scores = []

# Create a list of different values for n_neighbors
```

```
neighbors = range(1, 21)

# Setup KNN instance
knn = KNeighborsClassifier()

# Loop through different n_neighbors
for i in neighbors:
    knn.set_params(n_neighbors=i)
    # Fit the algorithm
    knn.fit(X_train, y_train)
    # Update the training scores list
    train_scores.append(knn.score(X_train, y_train))
    # Update the test scores list
    test_scores.append(knn.score(X_test, y_test))
```

[32]:
```
train_scores
```

[32]:
```
[1.0,
 0.8099173553719008,
 0.7727272727272727,
 0.743801652892562,
 0.7603305785123967,
 0.7520661157024794,
 0.743801652892562,
 0.7231404958677686,
 0.71900826446281,
 0.6942148760330579,
 0.7272727272727273,
 0.6983471074380165,
 0.6900826446280992,
 0.6942148760330579,
 0.6859504132231405,
 0.6735537190082644,
 0.6859504132231405,
 0.6652892561983471,
 0.6818181818181818,
 0.6694214876033058]
```

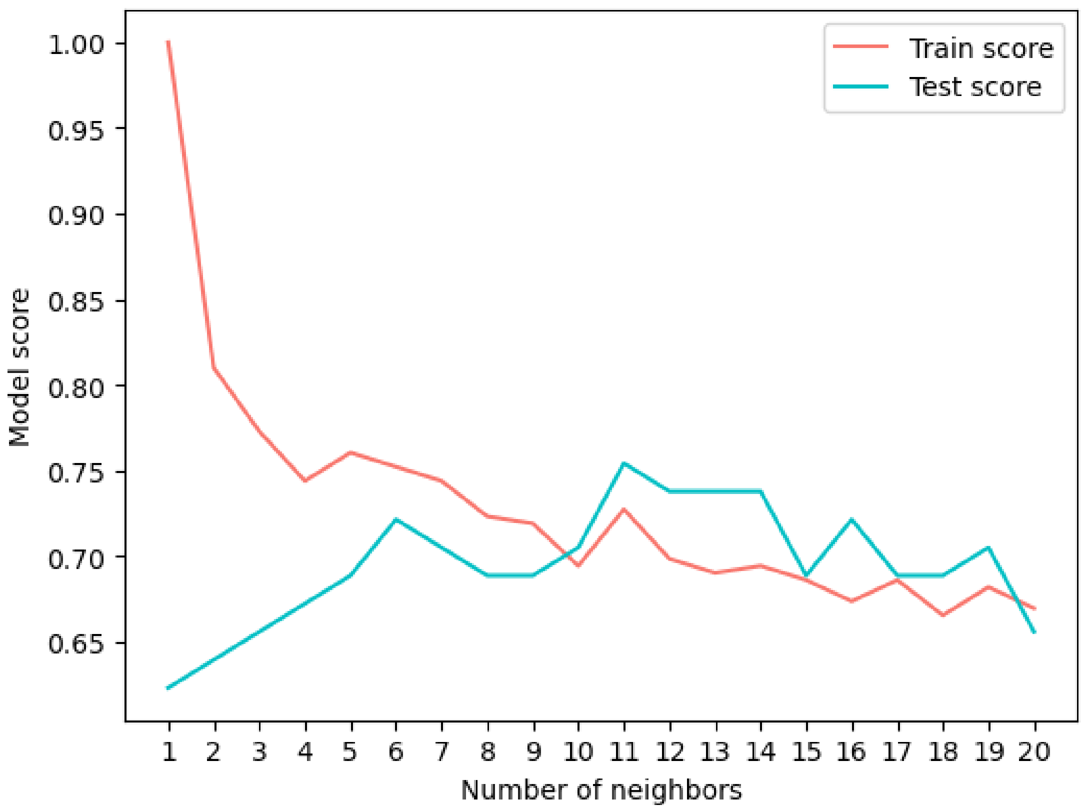
[33]:
```
test_scores
```

[33]:
```
[0.6229508196721312,
 0.639344262295082,
 0.6557377049180327,
 0.6721311475409836,
 0.6885245901639344,
 0.7213114754098361,
 0.7049180327868853,
```

```
 0.6885245901639344,
 0.6885245901639344,
 0.7049180327868853,
 0.7540983606557377,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.6885245901639344,
 0.7213114754098361,
 0.6885245901639344,
 0.6885245901639344,
 0.7049180327868853,
 0.6557377049180327]
```

[34]:
```python
plt.plot(neighbors, train_scores, label="Train score", color="#F8766D")
plt.plot(neighbors, test_scores, label="Test score", color="#00BFC4")
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(test_scores)*100:.2f}%")
```

```
Maximum KNN score on the test data: 75.41%
```



1.10 Hyperparameter tuning with RandomizedSearchCV

We're going to tune: * LogisticRegression() * RandomForestClassifier()

… using RandomizedSearchCV

[35]:
```
# Create a hyperparameter grid for LogisticRegression
log_reg_grid = {"C": np.logspace(-4, 4, 20),
                "solver": ["liblinear"]}

# Create a hyperparameter grid for RandomForestClassifier
rf_grid = {"n_estimators": np.arange(10, 1000, 50),
           "max_depth": [None, 3, 5, 10],
           "min_samples_split": np.arange(2, 20, 2),
           "min_samples_leaf": np.arange(1, 20, 2)}
```

[36]:
```
# What is?
np.logspace(-4, 4, 20)
```

[36]:
```
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])
```

[37]:
```
# What is?
np.arange(10, 1000, 50)
```

[37]:
```
array([ 10,  60, 110, 160, 210, 260, 310, 360, 410, 460, 510, 560, 610,
       660, 710, 760, 810, 860, 910, 960])
```

Now we've got hyperparameter grids setup for each of our models, let's tune them using RandomizedSearchCV…

[38]:
```
# Tune LogisticRegression

np.random.seed(42)

# Setup random hyperparameter search for LogisticRegression
rs_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions=log_reg_grid,
                                cv=5,
                                n_iter=20,
                                verbose=True)

# Fit random hyperparameter search model for LogisticRegression
```

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

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

[38]:
```
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]),
                                        'solver': ['liblinear']},
                   verbose=True)
```

[39]:
```
# Find the best hyperparameters
rs_log_reg.best_params_
```

[39]:
```
{'solver': 'liblinear', 'C': 0.23357214690901212}
```

[40]:
```
# Evaluate the randomized search LogisticRegression model
rs_log_reg.score(X_test, y_test)
```

[40]:
```
0.8852459016393442
```

Now we've tuned LogisticRegression(), let's do the same for RandomForestClassifier()…

[41]:
```
# Setup random seed
np.random.seed(42)

# Setup random hyperparameter search for RandomForestCLassifier
rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=rf_grid,
                           cv=5,
                           n_iter=20,
                           verbose=True)

# Fit random hyperparameter search model for RandomForestClassifier()
rs_rf.fit(X_train, y_train)
```

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

[41]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=20,
                   param_distributions={'max_depth': [None, 3, 5, 10],
                                        'min_samples_leaf': array([ 1,  3,  5,
7,  9, 11, 13, 15, 17, 19]),
                                        'min_samples_split': array([ 2,  4,  6,
8, 10, 12, 14, 16, 18]),
                                        'n_estimators': array([ 10,  60, 110,
```

```
160, 210, 260, 310, 360, 410, 460, 510, 560, 610,
       660, 710, 760, 810, 860, 910, 960])},
                   verbose=True)
```

[42]:
```python
# Find the best hyperparameters
rs_rf.best_params_
```

[42]:
```
{'n_estimators': 210,
 'min_samples_split': 4,
 'min_samples_leaf': 19,
 'max_depth': 3}
```

[43]:
```python
# Evaluate the randomized search RandomForestClassifier model
rs_rf.score(X_test, y_test)
```

[43]:
```
0.8688524590163934
```

[44]:
```python
# Comparing with the base results
model_scores
```

[44]:
```
{'Logistic Regression': 0.8852459016393442,
 'KNN': 0.6885245901639344,
 'Random Forest': 0.8360655737704918}
```

1.11 Hyperparameter Tuning with GridSearchCV

Since our LogisticRegression model provides the best scores so far, we'll try and improve them again using GridSearchCV…

[45]:
```python
# Different hyperparameters for our LogisticRegression model
log_reg_grid = {"C": np.logspace(-4, 4, 30),
                "solver": ["liblinear"]}

# Setup grid hyperparameter search for LogisticRegression
gs_log_reg = GridSearchCV(LogisticRegression(),
                          param_grid=log_reg_grid,
                          cv=5,
                          verbose=True)

# Fit grid hyperparameter search model
gs_log_reg.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
```

[46]:
```python
# Check the best hyperparameters
gs_log_reg.best_params_
```

[46]: {'C': 0.20433597178569418, 'solver': 'liblinear'}

[47]:
```
# Evaluate the grid search LogisticRegression model
gs_log_reg.score(X_test, y_test)
```

[47]: 0.8852459016393442

1.12 Evaluating our tuned machine learning classifier, beyond accuracy

- ROC curve and AUC score
- Confusion matrix
- Classification report
- Precision
- Recall
- F1-score

… and it would be great if cross-validation was used where possible.

To make comparisons and evaluate our trained model, first we need to make predictions.

[48]:
```
# Make predictions with tuned model
y_preds = gs_log_reg.predict(X_test)
```

[49]:
```
y_preds
```

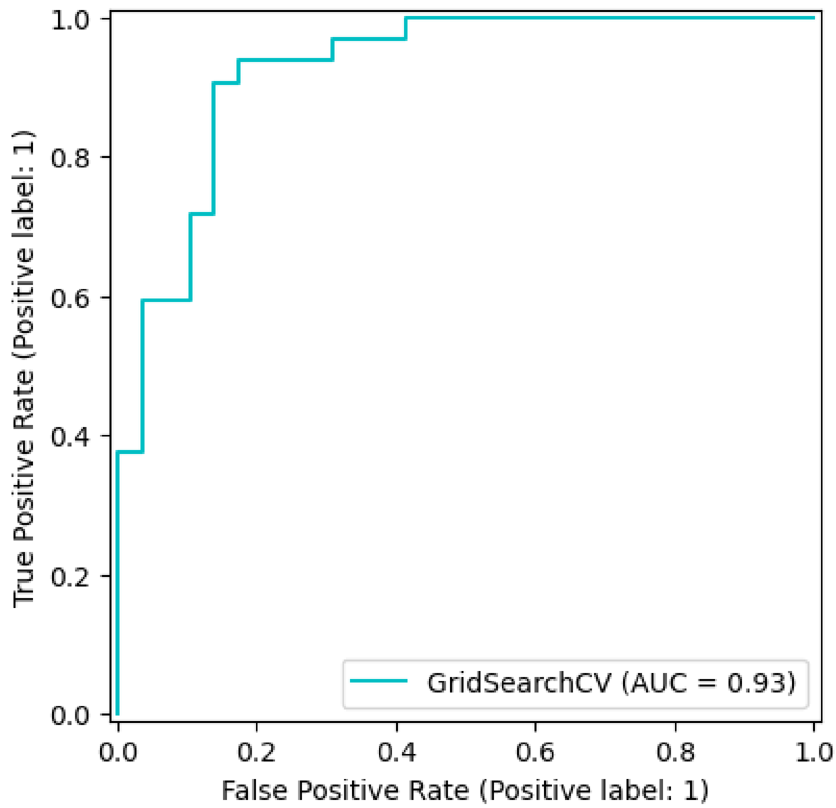
[49]:
```
array([0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
```

[50]:
```
y_test
```

[50]:
```
179    0
228    0
111    1
246    0
60     1
      ..
249    0
104    1
300    0
193    0
184    0
Name: target, Length: 61, dtype: int64
```

[51]:
```
# Plot ROC curve and calculate AUC metric
RocCurveDisplay.from_estimator(estimator=gs_log_reg, X=X_test, y=y_test,␣
 ↪color="#00BFC4")
```

[51]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1de7724a480>

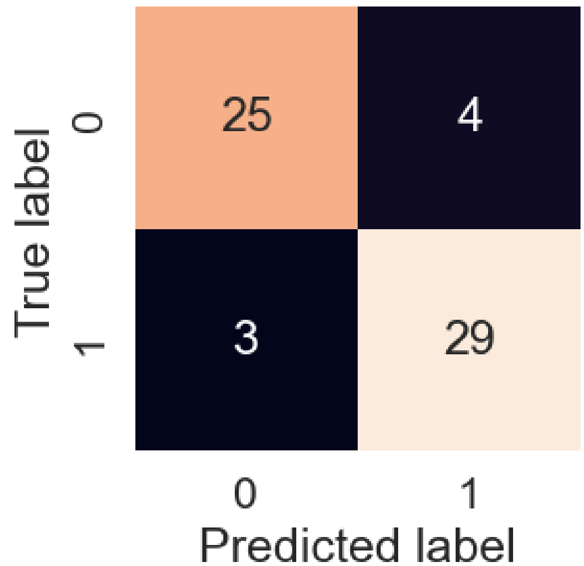


[52]:
```
# Confusion matrix
print(confusion_matrix(y_test, y_preds))
```

```
[[25  4]
 [ 3 29]]
```

[53]:
```
sns.set(font_scale=1.5)

def plot_conf_mat(y_test, y_preds):
    """
    Plots a nice looking confusion matrix using Seaborn's heatmap()
    """
    fig, ax = plt.subplots(figsize=(3, 3))
    ax = sns.heatmap(confusion_matrix(y_test, y_preds),
                     annot=True,
                     cbar=False)
    plt.xlabel("Predicted label")
    plt.ylabel("True label")
```

```
plot_conf_mat(y_test, y_preds)
```



Now we've got a ROC curve, an AUC metric and a confusion matrix, let's get a classification report as well as cross-validated precision, recall, and f1-score.

[54]:
```
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.89      0.86      0.88        29
           1       0.88      0.91      0.89        32

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.89        61
```

1.12.1 Calculate evaluation metrics using cross-validation

We're going to calculate accuracy, precision, recall, and f1-score of our model using cross-validation and to do so we'll be using `cross_val_score()`.

[55]:
```
# Check the best hyperparameters
gs_log_reg.best_params_
```

[55]: `{'C': 0.20433597178569418, 'solver': 'liblinear'}`

[56]:
```
# Create a new classifier with best parameters
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")
```

[57]:
```
# Cross-validated accuracy
cv_acc = cross_val_score(clf,
                         X,
                         y,
                         cv=5,
                         scoring="accuracy")
cv_acc
```

[57]:
```
array([0.81967213, 0.90163934, 0.86885246, 0.88333333, 0.75      ])
```

[58]:
```
cv_acc = np.mean(cv_acc)
cv_acc
```

[58]:
```
0.8446994535519124
```

[59]:
```
# Cross-validated precision
cv_precision = cross_val_score(clf,
                               X,
                               y,
                               cv=5,
                               scoring="precision")
cv_precision = np.mean(cv_precision)
cv_precision
```

[59]:
```
0.8207936507936507
```

[60]:
```
# Cross-validated recall
cv_recall = cross_val_score(clf,
                            X,
                            y,
                            cv=5,
                            scoring="recall")
cv_recall = np.mean(cv_recall)
cv_recall
```

[60]:
```
0.9212121212121213
```

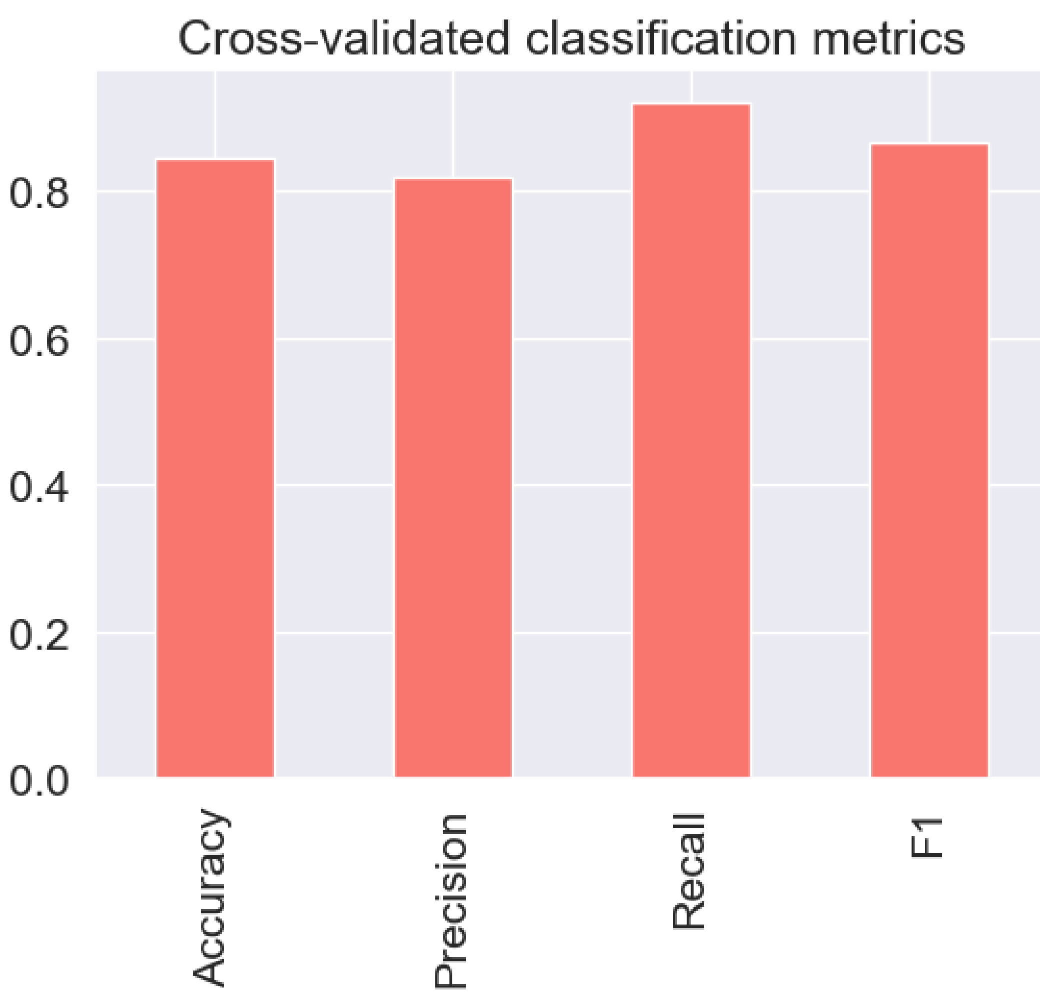
[61]:
```
# Cross-validated f1-score
cv_f1 = cross_val_score(clf,
                              X,
                              y,
                              cv=5,
                              scoring="f1")
```

```
cv_f1 = np.mean(cv_f1)
cv_f1
```

[61]: 0.8673007976269721

[62]:
```
# Visualize cross-validated metrics
cv_metrics = pd.DataFrame({"Accuracy": cv_acc,
                           "Precision": cv_precision,
                           "Recall": cv_recall,
                           "F1": cv_f1},
                          index=[0])
cv_metrics.T.plot.bar(title="Cross-validated classification metrics",
                      legend=False,
                      color="#F8766D")
```

[62]: <Axes: title={'center': 'Cross-validated classification metrics'}>



1.12.2 Feature Importance

Feature importance is another as asking, "which features contributed most to the outcomes of the model and how did they contribute?"

Finding feature importance is different for each machine learning model.

Let's find the feature importance for our LogisticRegression model...

[63]:
```
gs_log_reg.best_params_
```

[63]:
```
{'C': 0.20433597178569418, 'solver': 'liblinear'}
```

[64]:
```
# Fit an instance of LogisticRegression
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")

clf.fit(X_train, y_train);
```

[65]:
```
df.head()
```

[65]:
```
   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
```

[66]:
```
# Check coef_
clf.coef_
```

[66]:
```
array([[ 0.00316728, -0.86044651,  0.66067041, -0.01156993, -0.00166374,
         0.04386107,  0.31275847,  0.02459361, -0.6041308 , -0.56862804,
         0.45051628, -0.63609897, -0.67663373]])
```

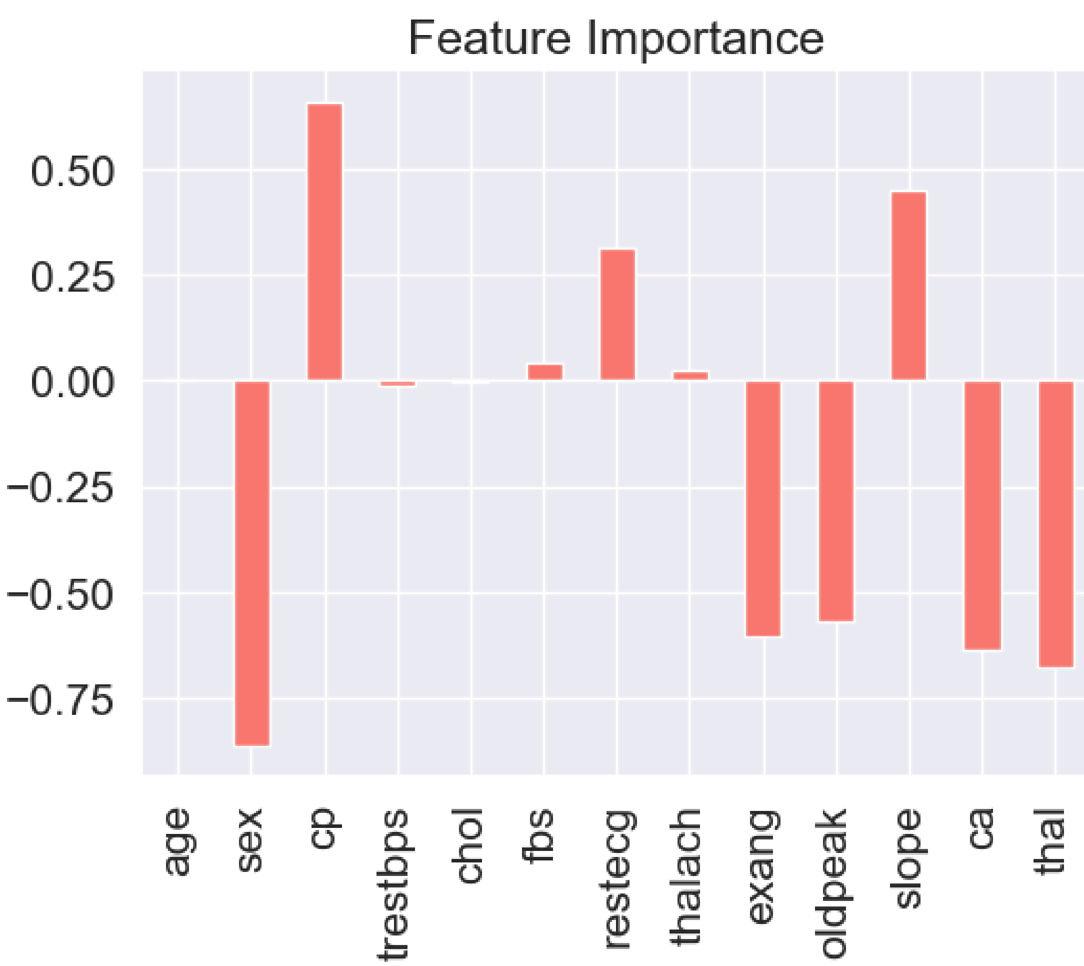
[67]:
```
# Match coef's of features to columns
feature_dict = dict(zip(df.columns, list(clf.coef_[0])))
feature_dict
```

[67]:
```
{'age': 0.0031672801993431563,
 'sex': -0.8604465072345515,
 'cp': 0.6606704082033799,
```

```
'trestbps': -0.011569931680808075,
'chol': -0.0016637445047768871,
'fbs': 0.04386107165246964,
'restecg': 0.31275846822418324,
'thalach': 0.024593613737779126,
'exang': -0.6041308000615746,
'oldpeak': -0.5686280368396555,
'slope': 0.4505162797258308,
'ca': -0.6360989676086223,
'thal': -0.6766337263029825}
```

[68]:

```
# Visualize feature importance
feature_df = pd.DataFrame(feature_dict, index=[0])
feature_df.T.plot.bar(title="Feature Importance", legend=False,␣
↪color="#F8766D");
```



[69]:

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

[69]:

target	0	1
sex		
0	24	72
1	114	93

[70]:
```
pd.crosstab(df["slope"], df["target"])
```

[70]:

target	0	1
slope		
0	12	9
1	91	49
2	35	107

1.13 Future Improvements

Since we haven't hit our evaluation metric yet… potential improvements could be: * Collect more data * Try a better model (Like CatBoost or XGBoost)