Predict Heart Disease

In [8]: #Check NAs

heart_data.isnull().sum()

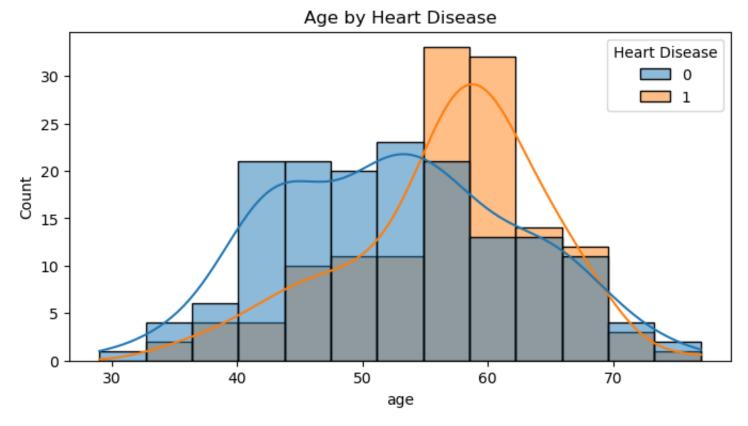
```
In [1]: #Packages
         #Data
         from ucimlrepo import fetch_ucirepo
         import pandas as pd
         import numpy as np
         #Graphs
         import matplotlib.pyplot as plt
         import seaborn as sns
         # Models
         from sklearn.model_selection import train_test_split, GridSearchCV
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear_model import LogisticRegression
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import classification_report, accuracy_score, ConfusionMatrixDisplay
         Upload data
In [2]: # Import code from Datasource
         # fetch dataset
         heart_disease = fetch_ucirepo(id=45)
         # data (as pandas dataframes)
         X = heart_disease.data.features
         y1 = heart_disease.data.targets
         Clean and EDA
In [3]: # Copy date
         heart_data = X.copy()
In [4]: # If they have heart disease
         y1.head(5)
Out[4]:
           num
         0
              0
              2
              1
              0
In [5]: # Check unique values
         y1.value_counts()
        num
Out[5]:
                164
                 55
         1
         2
                 36
                 35
                 13
         Name: count, dtype: int64
In [6]: # Change all levels of heart disease to binary
         heart_data['Heart Disease'] = y1['num'].replace([1,2,3,4], 1)
In [7]: # Check Values
         heart_data
              age sex cp trestbps chol fbs restecg thalach exang oldpeak slope
Out[7]:
                                                                                   ca thal Heart Disease
           0
              63
                    1 1
                               145 233
                                          1
                                                  2
                                                        150
                                                                 0
                                                                        2.3
                                                                               3
                                                                                  0.0
                                                                                       6.0
                                                                                                      0
                                                  2
                                                        108
               67
                    1 4
                               160
                                    286
                                          0
                                                                        1.5
                                                                               2
                                                                                   3.0
                                                                                       3.0
                                                                                                       1
                               120 229
                                                  2
           2
               67
                    1
                       4
                                          0
                                                        129
                                                                 1
                                                                       2.6
                                                                               2
                                                                                  2.0
                                                                                       7.0
                                                                                                       1
                                                  0
           3
               37
                               130
                                                        187
                                                                 0
                                                                        3.5
                                                                                                      0
                        3
                                    250
                                          0
                                                                               3
                                                                                   0.0
                                                                                        3.0
                                                  2
                                                        172
                                                                 0
                                                                                                      0
           4
               41
                    0
                        2
                               130
                                    204
                                          0
                                                                        1.4
                                                                               1
                                                                                   0.0
                                                                                       3.0
         298
               45
                    1
                       1
                               110
                                   264
                                          0
                                                  0
                                                        132
                                                                 0
                                                                        1.2
                                                                               2
                                                                                   0.0
                                                                                        7.0
                                                                                                       1
                                                  0
         299
              68
                               144
                                                        141
                                                                 0
                                                                               2
                                                                                        7.0
                                                                                                       1
                    1 4
                                    193
                                          1
                                                                       3.4
                                                                                  2.0
                                                  0
         300
                               130
                                          0
                                                        115
                                                                 1
                                                                               2
                                                                                        7.0
                                                                                                      1
               57
                       4
                                    131
                                                                        1.2
                                                                                   1.0
                    1
         301
                                                        174
                               130
                                                                 0
                                                                        0.0
                                                                                       3.0
               57
                                    236
                                                                                   1.0
         302
               38
                    1 3
                               138
                                    175
                                          0
                                                  0
                                                        173
                                                                 0
                                                                        0.0
                                                                               1 NaN
                                                                                       3.0
                                                                                                      0
        303 \text{ rows} \times 14 \text{ columns}
```

```
age
Out[8]:
         ср
         trestbps
         chol
         fbs
         restecg
                          0
         thalach
                          0
         exang
         oldpeak
         slope
         ca
         thal
                          2
         Heart Disease
                          0
         dtype: int64
In [9]: # Not many NAs, but drop for model
         heart_data = heart_data.dropna()
In [10]: #Figure Size
         plt.figure(figsize=(4,4))
         # Bar chart of people with and without heart disease
         sns.countplot(x='Heart Disease', data=heart_data)
         # Title
         plt.title('Heart Disease Presence')
         # Show graph
         plt.show()
```

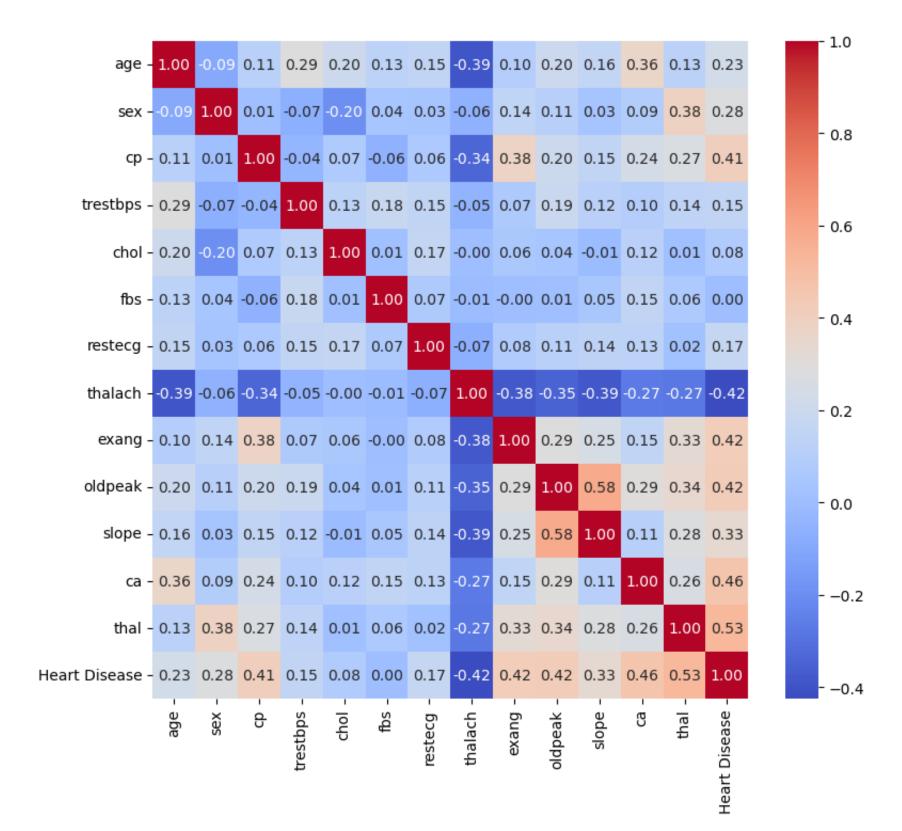
Heart Disease Presence 160 140 120 100 80 60 40 20 0 0 **Heart Disease**

0

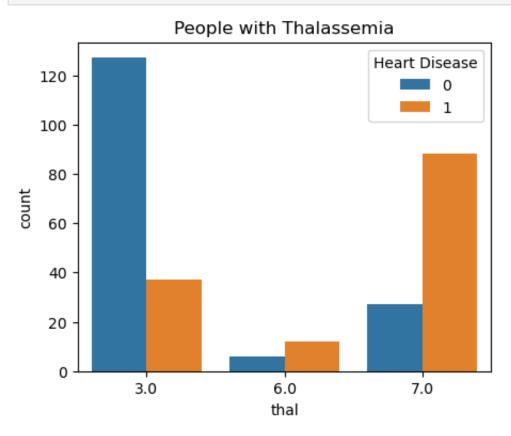
```
In [11]: # Figure size
         plt.figure(figsize=(8,4))
         # Check the ranges of ages to know if it is distributed
         sns.histplot(data=heart_data, x='age', hue='Heart Disease', kde=True)
         # Title
         plt.title('Age by Heart Disease')
         #Show Graph
         plt.show()
```



```
In [12]: # Figure Size
         plt.figure(figsize=(9,8))
         # Heatmap to find what correlates with heart disease. Round. Change color to an easy to read color.
         sns.heatmap(heart_data.corr(), annot=True, fmt=".2f", cmap='coolwarm')
         #Show results
         plt.show()
```



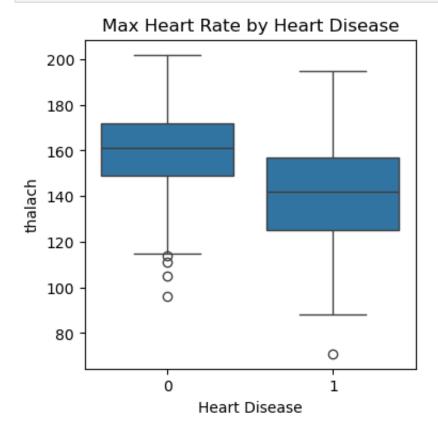
```
In [13]: # Figure size
    plt.figure(figsize=(5,4))
    # Count of the number of major blood vessels visible during imaging
    sns.countplot(x='thal', hue='Heart Disease', data=heart_data)
# Title
    plt.title('People with Thalassemia')
# Show Graph
    plt.show()
```



```
In [14]: # Figure Size
    plt.figure(figsize=(4,4))
    # Check
    sns.boxplot(x='Heart Disease', y='oldpeak', data=heart_data)
# Title
    plt.title('Stress Test by Heat Disease')
# Show Graph
    plt.show()
```

Stress Test by Heat Disease 0 6 0 5 0 4 0 0 2 1 0 1 **Heart Disease**

```
In [15]: # Figure Size
         plt.figure(figsize=(4,4))
         # Max Heart RateBox Plot
         sns.boxplot(x='Heart Disease', y='thalach', data=heart_data)
         plt.title('Max Heart Rate by Heart Disease')
         # Show Results
         plt.show()
```



Train Model and Results

Logistic Regression

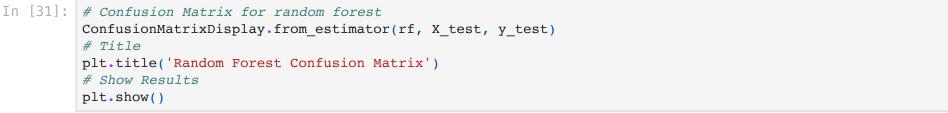
```
In [16]: #Split y
         y = heart_data['Heart Disease']
         X = heart_data.drop(columns = ['Heart Disease'])
In [17]:  # Split data
         X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
In [18]: # Allow scaler
         scaler = StandardScaler()
In [19]: # Fit and transform only training data
         X_train_s = scaler.fit_transform(X_train)
         # Transform test data
         X_test_s = scaler.transform(X_test)
In [20]: # Allow Logistic Regression
         lg = LogisticRegression(max_iter=1000)
In [21]: # Fit Model
         lg.fit(X_train_s, y_train)
Out[21]:
         ▼ LogisticRegression
         ▶ Parameters
In [22]: # Logistic Regression Predict
         y_pred_lr = lg.predict(X_test_s)
In [23]: # Print results
         print("Logistic Regression:\n", classification_report(y_test, y_pred_lr))
```

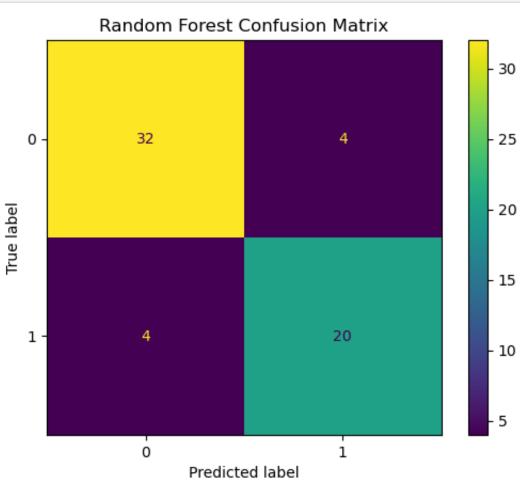
```
Logistic Regression:
              precision recall f1-score
                                              support
           0
                  0.89
                            0.89
                                      0.89
                                                   36
                                                   24
          1
                   0.83
                            0.83
                                      0.83
                                       0.87
                                                   60
   accuracy
                   0.86
                             0.86
                                                   60
  macro avg
                                       0.86
                   0.87
                             0.87
                                       0.87
                                                   60
weighted avg
```

Results are good, but see if random forest does better.

Random Forest

```
In [24]: # Allow Random Forest
         rf = RandomForestClassifier(random_state=42, max_depth=5)
In [25]: # Fit model
         rf.fit(X_train, y_train)
Out[25]:
          RandomForestClassifier
         ▶ Parameters
In [26]: # Predict results
         y_pred_rf= rf.predict(X_test)
In [27]: # Print Results
         print("Random Forest:\n", classification_report(y_test, y_pred_rf))
         Random Forest:
                        precision recall f1-score support
                    0
                            0.89
                                      0.89
                                                0.89
                                                             36
                            0.83
                                      0.83
                                                0.83
                    1
                                                             24
                                                0.87
                                                             60
             accuracy
                            0.86
                                      0.86
            macro avg
                                                0.86
                                                             60
         weighted avg
                            0.87
                                      0.87
                                                0.87
                                                             60
In [28]: # Predict the train and test results
         y_train_pred = rf.predict(X_train)
         y_test_pred = rf.predict(X_test)
In [29]: # Test train accuracy score
         train_accuracy = accuracy_score(y_train, y_train_pred)
         test_accuracy = accuracy_score(y_test, y_test_pred)
In [30]: # Print results
         print("Training Accuracy:", train_accuracy)
         print("Test Accuracy:", test_accuracy)
         Training Accuracy: 0.9240506329113924
         Test Accuracy: 0.866666666666667
         Results improved a little, but see if they can imporve more.
In [31]: # Confusion Matrix for random forest
```





Random Forest - GridSearch

```
In [32]: #Split y
y = heart_data['Heart Disease']
X = heart_data.drop(columns = ['Heart Disease'])
```

```
In [33]: # Test different param
         param_grid = {'n_estimators': [25, 50, 100],
                        'max depth': [None, 5, 10, 15],
                        'max_features': ['sqrt', 'log2'],
                        'min_samples_split': [2, 5, 10]}
In [34]: # Grid search
         grid_search = GridSearchCV(estimator=rf,
                                     param_grid=param_grid,
                                     cv=5,
                                     scoring='accuracy')
In [36]: # Fit on training data
         grid_search.fit(X_train, y_train);
In [37]: print("Best Parameters: ", grid_search.best_params_)
         Best Parameters: {'max_depth': 5, 'max_features': 'sqrt', 'min_samples_split': 2, 'n_estimators': 25}
In [38]: # Save the best model
         best_rf = grid_search.best_estimator_
In [39]: # Predict results
         y_pred = best_rf.predict(X_test)
In [40]: print("Random Forest - GridSearch \nClassfication Report:\n", classification_report(y_test, y_pred))
         Random Forest - GridSearch
         Classfication Report:
                        precision
                                      recall f1-score
                                                         support
                    0
                            0.89
                                      0.94
                                                 0.92
                                                             36
                    1
                            0.91
                                       0.83
                                                 0.87
                                                             24
                                                 0.90
                                                             60
             accuracy
                            0.90
            macro avg
                                       0.89
                                                 0.89
                                                             60
                            0.90
                                       0.90
                                                             60
         weighted avg
                                                 0.90
         Gridsearch decreased the results. Best results, first random forest.
In [41]: # Pull the features with the largest impact
         importances = rf.feature_importances_
In [42]: # Rename to read graph
         r_dict = {'age': 'Age',
                    'sex': 'Sex (1=Male)',
                    'cp': 'Chest Pain Type',
                    'trestbps': 'Resting BP',
                    'chol': 'Cholesterol',
                    'fbs': 'Fasting Blood Sugar',
                    'restecg': 'Resting ECG Results',
                    'thalach': 'Max Heart Rate',
                    'exang': 'Exercise Induced Angina',
                    'oldpeak': 'ST Depression (Oldpeak)',
                    'slope': 'Slope of ST Segment',
                    'ca': 'Major Vessels Colored',
                    'thal': 'Thalassemia Type'}
In [43]: # Save list of column names
         feat_names = X.columns
In [44]: # Make values into a series in order from highest to lowest
         feat_imp = pd.Series(importances, index=feat_names).sort_values(ascending=False)
In [45]: | # Rename columns
         feat_imp_r = feat_imp.rename(index=r_dict)
In [46]: # Figure size
         plt.figure(figsize=(8,6))
         # bar graph of top 10 features
         feat_imp_r.head(10).plot(kind='bar')
         # Turn labels and align
         plt.xticks(rotation=40, ha='right')
         # Title
         plt.title('Random Forest: Top 10 Feature Importances')
         # Show Results
         plt.show()
```

