Heart Disease Prediction Using Machine Learning Models

Importing the required libreries

In [2]:
```
# Importing the required libreries

#Importing the EDA - Exploratory Data Analysis and plotting libreries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

#importing the Models from Sci-kit Learn

from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.model_selection import RandomizedSearchCV,GridSearchCV
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

#Importing the Models for Evaluation

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.metrics import precision_score,recall_score,f1_score,make_scorer
from sklearn.metrics import RocCurveDisplay

#Importing the warning ignorner
import warnings
warnings.filterwarnings("ignore")
```

Starting with Data Cleaning Process

Reading CSV file using `.read_csv()` method in pandas and getting started with data cleaning process

In [3]:
```
df = pd.read_csv("Data/heart_disease.csv")
```

Displaying the first 5 Rows of the dataset using `.head()` method

In [4]:
```
df.head()
```

Out[4]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

Using the `.info()` method, we can obtain information about a dataset, including the data types of each column, column names, and the number of non-null values in each column.

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1025 non-null   int64
 1   sex       1025 non-null   int64
 2   cp        1025 non-null   int64
 3   trestbps  1025 non-null   int64
 4   chol      1025 non-null   int64
 5   fbs       1025 non-null   int64
 6   restecg   1025 non-null   int64
 7   thalach   1025 non-null   int64
 8   exang     1025 non-null   int64
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64
 11  ca        1025 non-null   int64
 12  thal      1025 non-null   int64
 13  target    1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

`.isnull().sum()` gives the total sum of NaN values in each column respectively

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
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
```

The `.describe()` method give the idea about the dataframe with mean, standard devitation etc...

In [7]:
```
df.describe()
```

Out[7]:

	age	sex	cp	trestbps	chol	fbs	restecg	t
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.00000	1025.000000	1025.000000	1025.(
mean	54.434146	0.695610	0.942439	131.611707	246.00000	0.149268	0.529756	149.'
std	9.072290	0.460373	1.029641	17.516718	51.59251	0.356527	0.527878	23.(
min	29.000000	0.000000	0.000000	94.000000	126.00000	0.000000	0.000000	71.(
25%	48.000000	0.000000	0.000000	120.000000	211.00000	0.000000	0.000000	132.(
50%	56.000000	1.000000	1.000000	130.000000	240.00000	0.000000	1.000000	152.(
75%	61.000000	1.000000	2.000000	140.000000	275.00000	0.000000	1.000000	166.(
max	77.000000	1.000000	3.000000	200.000000	564.00000	1.000000	2.000000	202.(

Checking for duplicates in the dataframe using `.duplicated()` method

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
723
```

Removing 723 duplicated values or repeated rows using `.drop_duplicates()`

In [9]:
```
df = df.drop_duplicates()
```

In [10]:
```
#Re-checking for deplicates
df.duplicated().sum()
```

Out[10]:
```
0
```

In [11]:
```
# Getting info of cleaned DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 302 entries, 0 to 878
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       302 non-null    int64  
 1   sex       302 non-null    int64  
 2   cp        302 non-null    int64  
 3   trestbps  302 non-null    int64  
 4   chol      302 non-null    int64  
 5   fbs       302 non-null    int64  
 6   restecg   302 non-null    int64  
 7   thalach   302 non-null    int64  
 8   exang     302 non-null    int64  
 9   oldpeak   302 non-null    float64
 10  slope     302 non-null    int64  
 11  ca        302 non-null    int64  
 12  thal      302 non-null    int64  
 13  target    302 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 35.4 KB
```

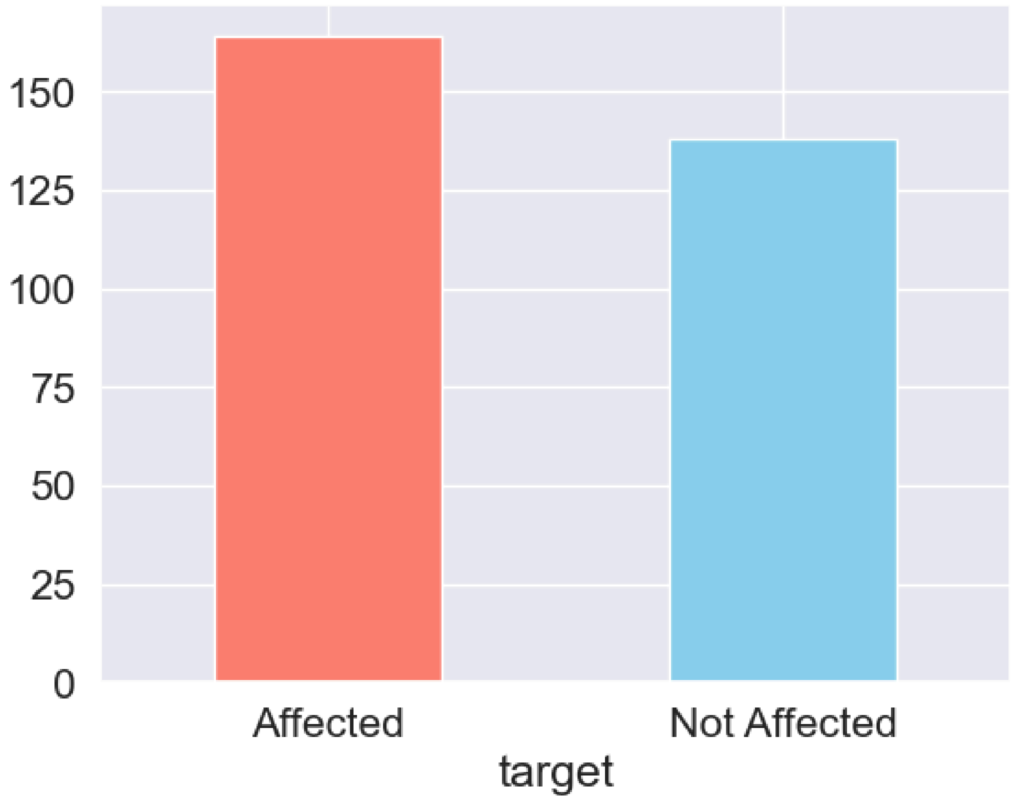
EDA - Exploratory Data Analysis with the cleaned data

Let's see the distribution of heart disease cases (affected and non-affected) using `.value_counts()`

In [12]:
```
df['target'].value_counts()
```

Out[12]:
```
target
1    164
0    138
Name: count, dtype: int64
```

In [67]:
```
ax = df['target'].value_counts().plot(kind='bar',color = ['salmon','skyblue']
ax.set_xticklabels(['Affected', 'Not Affected'], rotation=0)

plt.show()
```



Heart diseases frequency with sex

In [14]:
```
df['sex'].value_counts()
```

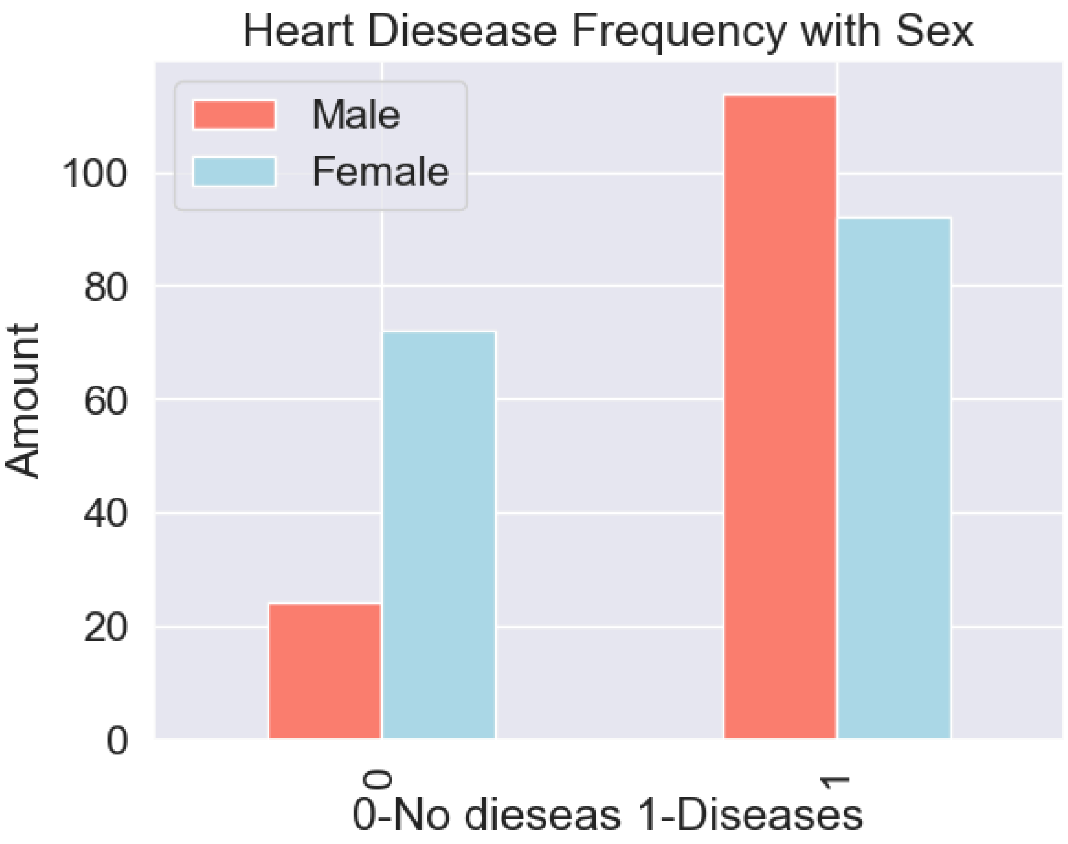
Out[14]:
```
sex
1    206
0     96
Name: count, dtype: int64
```

In [15]:
```
#using crosstab for comparision
pd.crosstab(df.sex,df.target)
```

Out[15]:

target	0	1
sex		
0	24	72
1	114	92

In [69]:
```
pd.crosstab(df.sex,df.target).plot(kind='bar',color=['salmon','lightblue'])
plt.title("Heart Diesease Frequency with Sex")
plt.legend(['Male','Female'])
plt.xlabel('0-No dieseas 1-Diseases')
plt.ylabel('Amount')
plt.show()
```

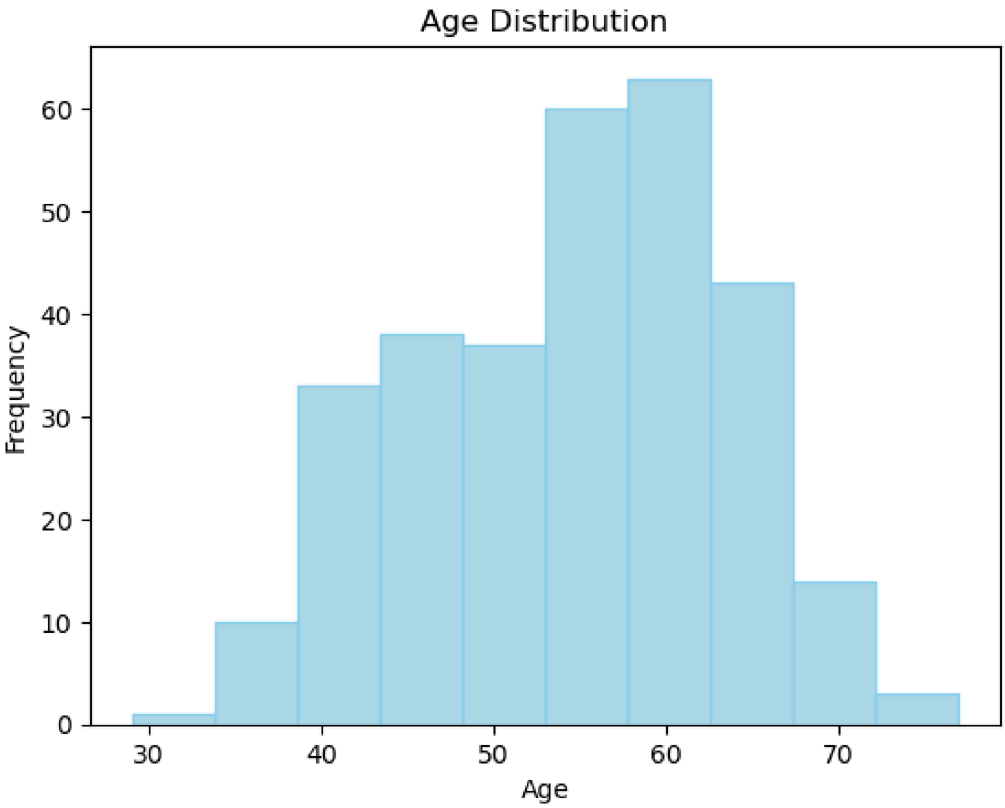


Age vs Heart Rate for Heart disease

In [17]:
```
plt.figure(figsize=(10,6))

plt.scatter(df.age[df.target==1],df.thalach[df.target==1],color='salmon')

plt.scatter(df.age[df.target==0],df.thalach[df.target==0],color='lightblue')

plt.title("Heart Diseases with relation to Age and Heart Rate")
plt.xlabel("Age")
plt.ylabel("Heart Rate")
plt.legend(['Disease','No Disease']);
```

Lets see the age distribution using histrogram

In [18]:
```
df.age.plot(kind='hist',color='lightblue',edgecolor='skyblue')
plt.title("Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



Chest pain related to Heart Diesease

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

In [19]:
```
df.cp.value_counts()
```

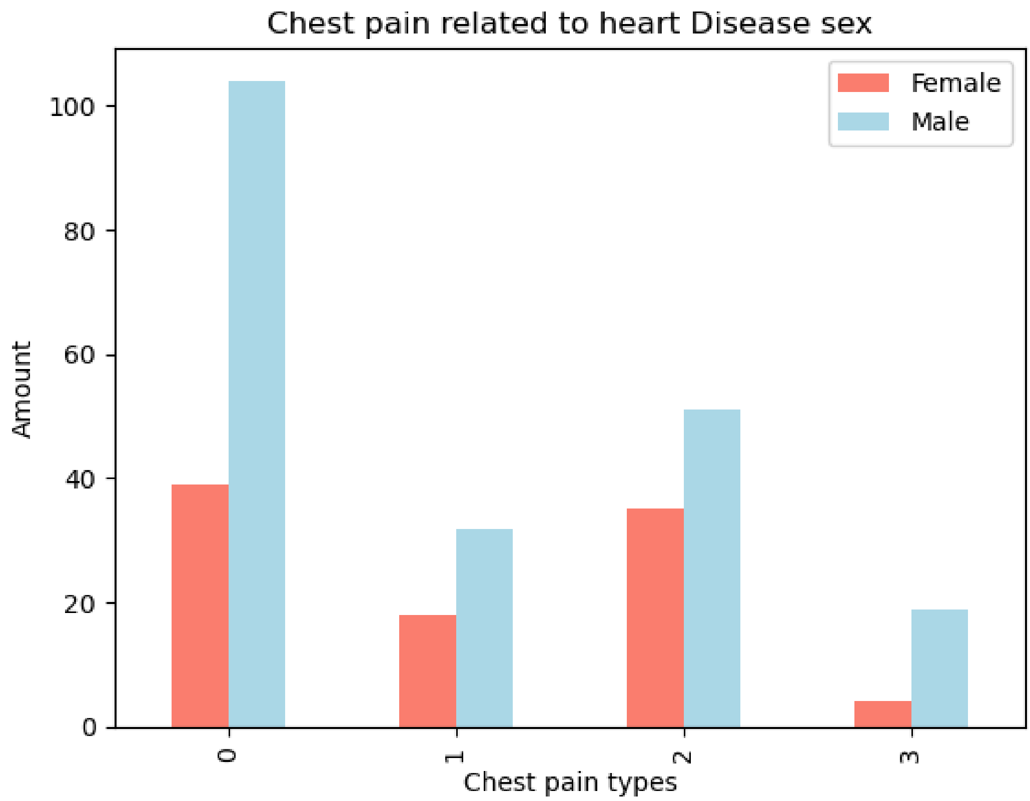
Out[19]:
```
cp
0    143
2     86
1     50
3     23
Name: count, dtype: int64
```

In [20]:
```
pd.crosstab(df.sex,df.cp)
```

Out[20]:

cp	0	1	2	3
sex				
0	39	18	35	4
1	104	32	51	19

In [21]:
```
pd.crosstab(df.cp,df.sex).plot(kind='bar',color=['salmon','lightblue'])
plt.title("Chest pain related to heart Disease sex")
plt.xlabel("Chest pain types")
plt.ylabel("Amount")
plt.legend(['Female','Male']);
```



Seeing the correlation

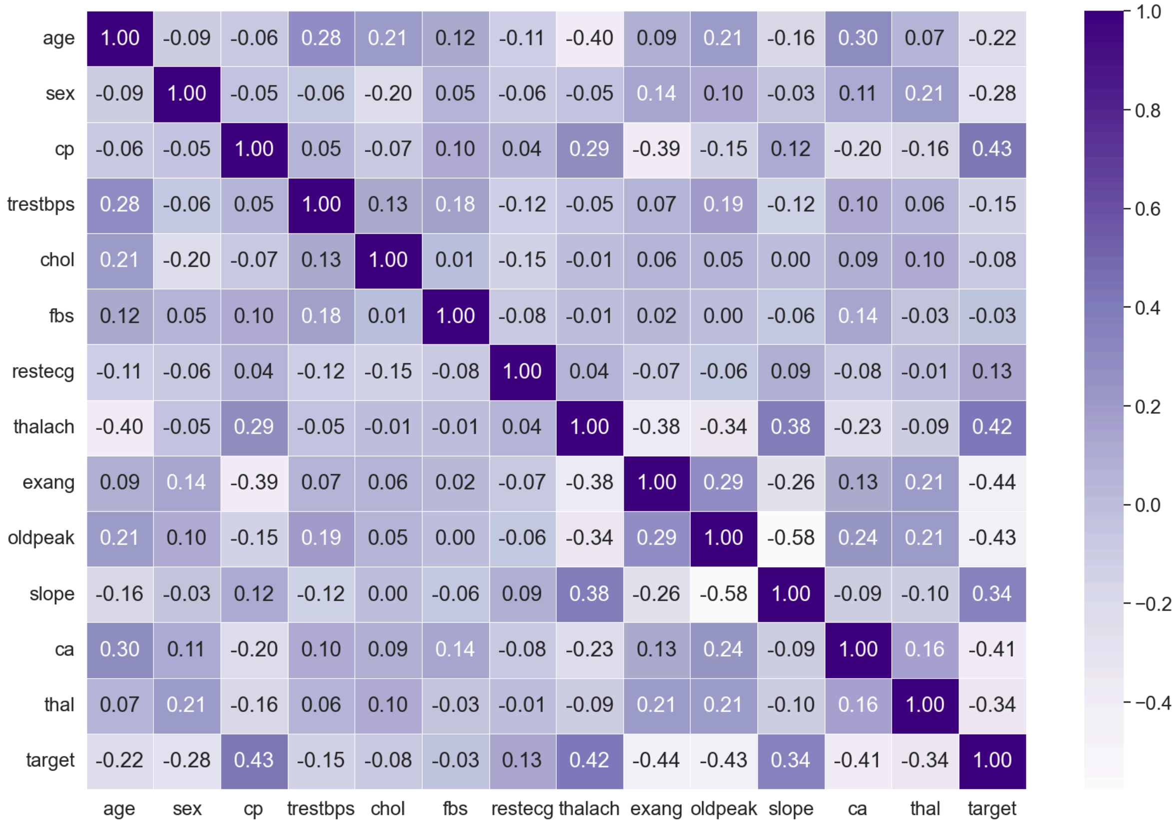
In [22]:
```
df.corr()
```

Out[22]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang
age	1.000000	-0.094962	-0.063107	0.283121	0.207216	0.119492	-0.111590	-0.395235	0.09321
sex	-0.094962	1.000000	-0.051740	-0.057647	-0.195571	0.046022	-0.060351	-0.046439	0.14346
cp	-0.063107	-0.051740	1.000000	0.046486	-0.072682	0.096018	0.041561	0.293367	-0.39293
trestbps	0.283121	-0.057647	0.046486	1.000000	0.125256	0.178125	-0.115367	-0.048023	0.06852
chol	0.207216	-0.195571	-0.072682	0.125256	1.000000	0.011428	-0.147602	-0.005308	0.06409
fbs	0.119492	0.046022	0.096018	0.178125	0.011428	1.000000	-0.083081	-0.007169	0.02472
restecg	-0.111590	-0.060351	0.041561	-0.115367	-0.147602	-0.083081	1.000000	0.041210	-0.06880
thalach	-0.395235	-0.046439	0.293367	-0.048023	-0.005308	-0.007169	0.041210	1.000000	-0.37741
exang	0.093216	0.143460	-0.392937	0.068526	0.064099	0.024729	-0.068807	-0.377411	1.00000
oldpeak	0.206040	0.098322	-0.146692	0.194600	0.050086	0.004514	-0.056251	-0.342201	0.28676
slope	-0.164124	-0.032990	0.116854	-0.122873	0.000417	-0.058654	0.090402	0.384754	-0.25610
ca	0.302261	0.113060	-0.195356	0.099248	0.086878	0.144935	-0.083112	-0.228311	0.12537
thal	0.065317	0.211452	-0.160370	0.062870	0.096810	-0.032752	-0.010473	-0.094910	0.20582
target	-0.221476	-0.283609	0.432080	-0.146269	-0.081437	-0.026826	0.134874	0.419955	-0.43560

Correlation Matrix

In [89]:
```
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize=(18,12),dpi=120)
ax = sns.heatmap(corr_matrix,annot=True,linewidths=0.5,fmt='.2f',cmap="Purple
plt.show()
```



Training the Machine Learning models

Spliting the `Features variables and Target variables`

In [24]:
```
x = df.drop('target',axis=1)

y = df['target']
```

Spliting the dataset for training and testing purpose

In [25]:
```
np.random.seed(42)
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)
```

Traing the Model

In [26]:
```
rfclf = RandomForestClassifier()
rfclf.fit(x_train,y_train)
```

Out[26]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

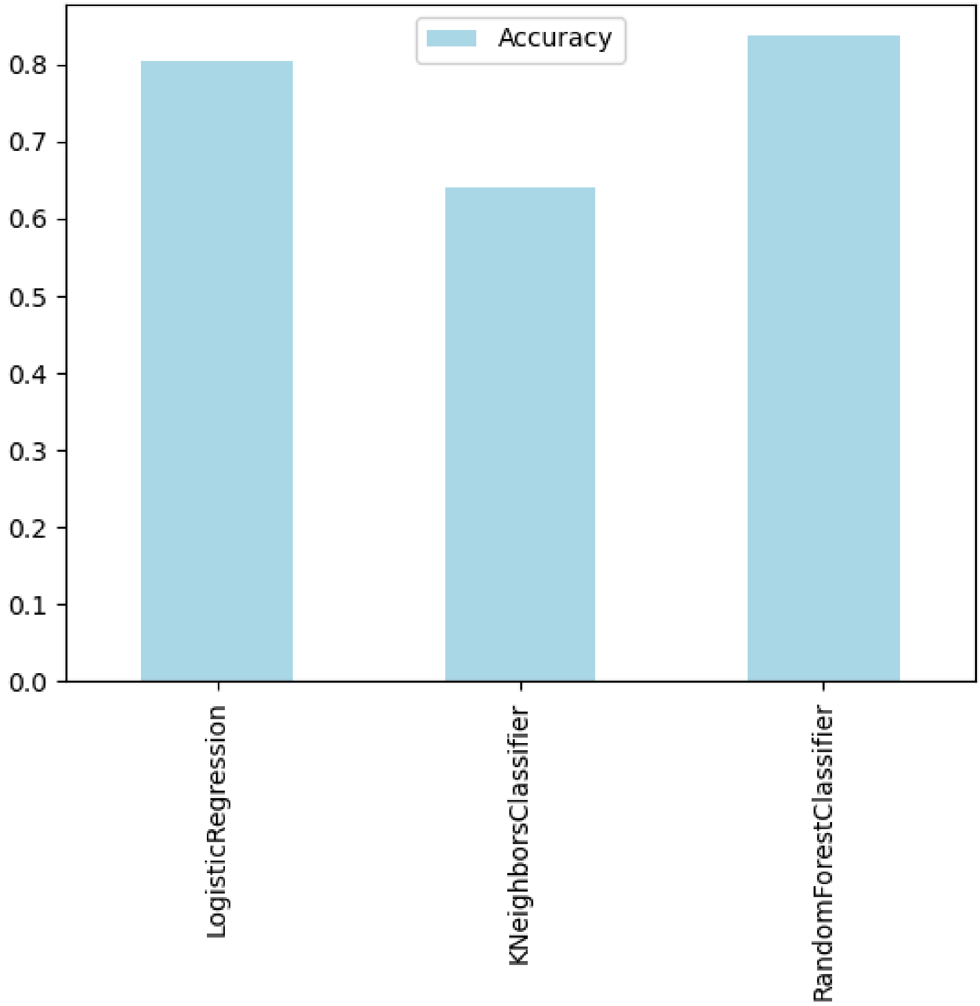
In [27]:
```
rfclf.score(x_test,y_test)*100
```

Out[27]:
```
83.60655737704919
```

In [28]:
```
# Testing all Three models together

models = {'LogisticRegression':LogisticRegression(),
          'KNeighborsClassifier':KNeighborsClassifier(),
          'RandomForestClassifier':RandomForestClassifier()}

def fit_score_models(models,x_train,x_test,y_train,y_test):
    np.random.seed(42)
    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

model_scores = fit_score_models(models,x_train,x_test,y_train,y_test)
model_scores
```

Out[28]:
```
{'LogisticRegression': 0.8032786885245902,
 'KNeighborsClassifier': 0.639344262295082,
 'RandomForestClassifier': 0.8360655737704918}
```

In [29]:
```
model_comparision = pd.DataFrame(model_scores,index=["Accuracy"])
model_comparision.T.plot(kind='bar',color='lightblue');
```



In [30]:
```
model_scores
```

Out[30]:
```
{'LogisticRegression': 0.8032786885245902,
 'KNeighborsClassifier': 0.639344262295082,
 'RandomForestClassifier': 0.8360655737704918}
```

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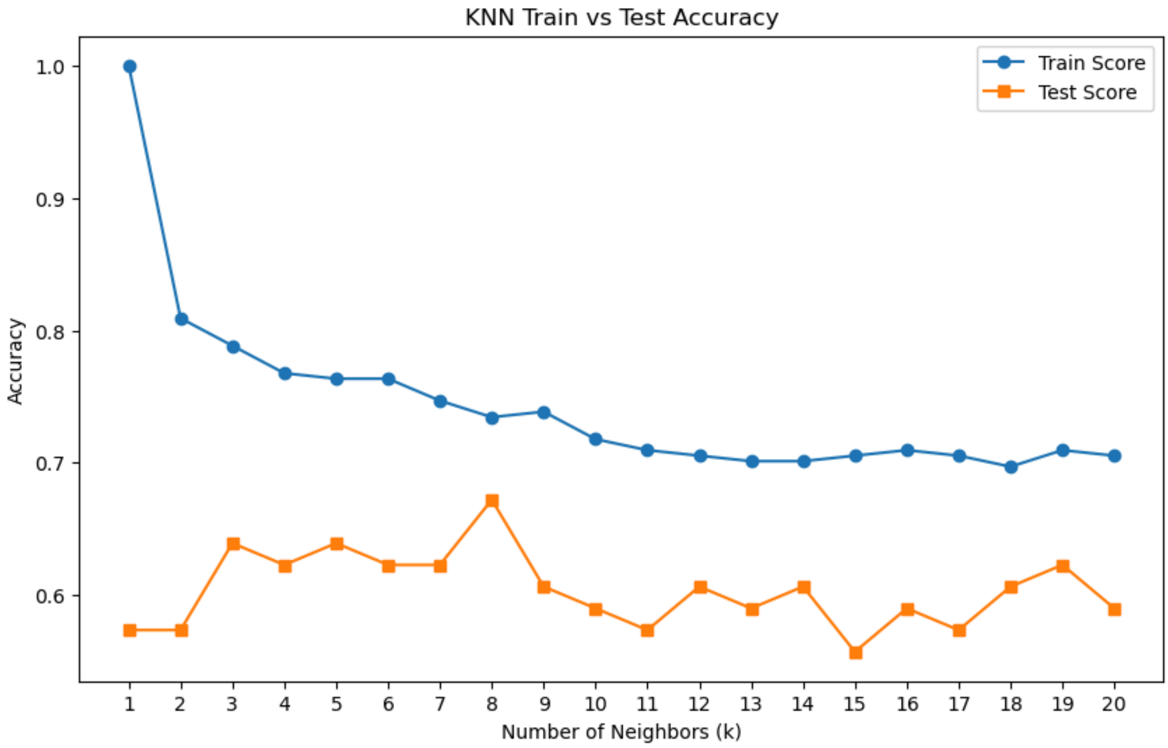
Hyperparameter Tuning

For imporving the model accuracy and to make model faster with more efficiency

In [31]:
```
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt

train_scores = []
test_scores = []

neighbours = range(1, 21)
knn = KNeighborsClassifier()

for i in neighbours:
    knn.set_params(n_neighbors=i)
    knn.fit(x_train, y_train)
    train_scores.append(knn.score(x_train, y_train))
    test_scores.append(knn.score(x_test, y_test))


print(f"The maximum Score of the KNN model is {max(test_scores)*100:.2f}")
plt.figure(figsize=(10, 6))
plt.plot(neighbours, train_scores, label="Train Score", marker='o')
plt.plot(neighbours, test_scores, label="Test Score", marker='s')
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Accuracy")
plt.grid(False)
plt.xticks(np.arange(1,21,1))
plt.legend()
plt.title("KNN Train vs Test Accuracy")
plt.show()
```

```
The maximum Score of the KNN model is 67.21
```



Now let we tune the other two models

```
* LogisticRegression
* RandomForestClassification
```

using RandomizedsearchCV

In [32]:
```
log_reg_grid = {
    'solver': ['liblinear', 'lbfgs'],
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'max_iter': [100, 200, 300]
}

ran_clf_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)}
```

Now we have done the grid setup for tuning the models using RandomizedSearchCV

lets start tuning for LogisticRegression()

In [33]:
```
np.random.seed(42)
#setting up random hyperparametric search for LogisticRegression()
rsc_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions=log_reg_grid,
                                 cv = 5,
                                n_iter=20,
                                verbose=True)

#Fitting the training Data to thr model
rsc_log_reg.fit(x_train,y_train)
```

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

Out[33]:
```
▸ RandomizedSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [34]:
```
rsc_log_reg.score(x_test,y_test)
```

Out[34]:
```
0.8032786885245902
```

In [35]:
```
rsc_log_reg.best_params_
```

Out[35]:
```
{'solver': 'lbfgs', 'max_iter': 100, 'C': 1}
```

let Start tuning for RandomForestClassifier()

In [36]:
```
np.random.seed(42)
#setting up random hyperparametric search for RandomForestClassifier()
rsc_rf_clf = RandomizedSearchCV(RandomForestClassifier(),
                               param_distributions=ran_clf_grid,
                               cv = 5,
                               n_iter=20,
                               verbose=True)

rsc_rf_clf.fit(x_train,y_train)
```

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

Out[36]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

Now, `.best_params_` returns the optimal parameters for the model to achieve the highest accuracy score

In [37]:
```
rsc_rf_clf.best_params_
```

Out[37]:
```
{'n_estimators': 310,
 'min_samples_split': 2,
 'min_samples_leaf': 19,
 'max_depth': 5}
```

In [38]:
```
rsc_rf_clf.score(x_test,y_test)
```

Out[38]:
```
0.8360655737704918
```

In [39]:
```
model_scores
```

Out[39]:
```
{'LogisticRegression': 0.8032786885245902,
 'KNeighborsClassifier': 0.639344262295082,
 'RandomForestClassifier': 0.8360655737704918}
```

Hyperparametric Tuning using GridSearchCV

Since the `RandomForestClassifier()` model provides the best scores so far, we can try and improve the model using GridSearchCV

Basically GridSearchCV improves the model accuracy using cross-validation.

In [40]:
```
ran_clf_grid = {
    'n_estimators': [100, 300, 500, 800],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 4, 8],
    'max_features': ['sqrt'],
    'bootstrap': [True]
}


gs_rf_clf = GridSearchCV(RandomForestClassifier(),
                        param_grid=ran_clf_grid,
                        cv=5,
                        verbose=True)

gs_rf_clf.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
```

Out[40]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [41]:
```
gs_rf_clf.best_params_
```

Out[41]:
```
{'bootstrap': True,
 'max_depth': 10,
 'max_features': 'sqrt',
 'min_samples_leaf': 8,
 'min_samples_split': 5,
 'n_estimators': 500}
```

In [42]:
```
gs_rf_clf.score(x_test,y_test)
```

Out[42]:
```
0.8360655737704918
```

In [43]:
```
model_scores
```

Out[43]:
```
{'LogisticRegression': 0.8032786885245902,
 'KNeighborsClassifier': 0.639344262295082,
 'RandomForestClassifier': 0.8360655737704918}
```

Evaluating the tuned machine learning models beyound accuracy

1. ROC and AUC curve
2. Confusion matrix
3. Classification Report
4. precision
5. Recall
6. F1 score

To make comparision and to evaluate model, we must need to do prediction

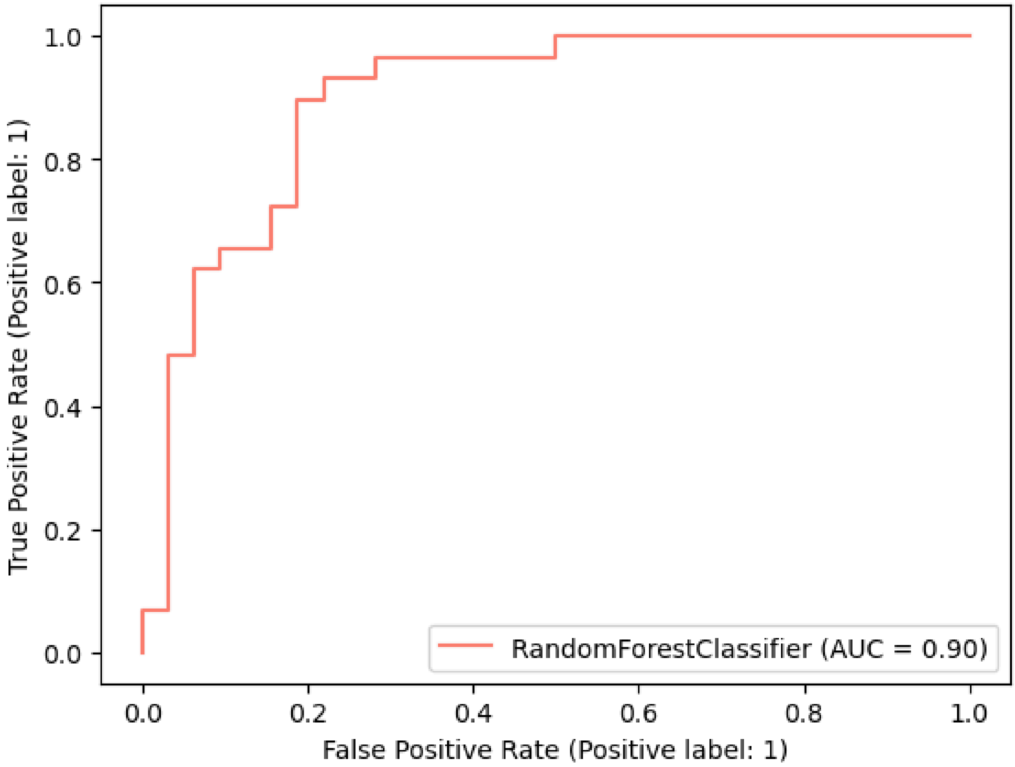
In [44]:
```
y_preds = gs_rf_clf.predict(x_test)
y_preds
```

Out[44]:
```
array([1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1])
```

In [45]:
```
y_test
```

Out[45]:
```
245    1
349    0
135    0
389    1
66     1
      ..
402    1
123    1
739    0
274    1
256    1
Name: target, Length: 61, dtype: int64
```

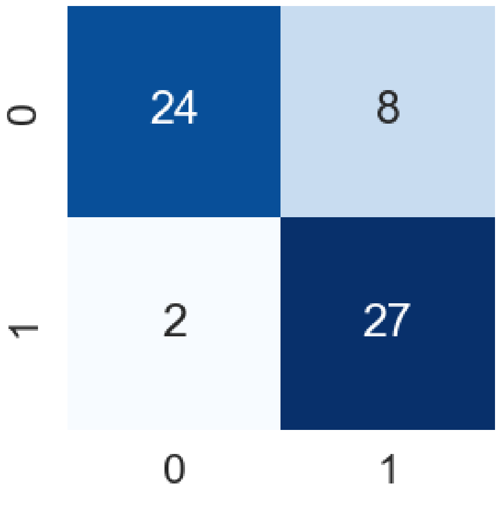
In [46]:
```
#ROC and AUC graph
RocCurveDisplay.from_estimator(gs_rf_clf.best_estimator_, x_test, y_test,colo
plt.show()
```



In [47]:
```
#confusion matrix
confusion_matrix(y_test,y_preds)
```

Out[47]:
```
array([[24,  8],
       [ 2, 27]])
```

In [48]:
```
sns.set(font_scale=1.5)

def plot_conf_mat(y_test,y_preds):
    fig,ax = plt.subplots(figsize=(3,3))
    ax = sns.heatmap(confusion_matrix(y_test,y_preds),
                    annot=True,
                    cmap="Blues",
                    cbar=False)
plot_conf_mat(y_test,y_preds)
plt.show()
```



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In [49]:
```
print(classification_report(y_test,y_preds))
```

```
              precision    recall  f1-score   support

           0       0.92      0.75      0.83        32
           1       0.77      0.93      0.84        29

    accuracy                           0.84        61
   macro avg       0.85      0.84      0.84        61
weighted avg       0.85      0.84      0.84        61
```

In [50]:
```
#calculating Classification report by crossvalidation using `cross_validation
gs_rf_clf.best_params_
```

Out[50]:
```
{'bootstrap': True,
 'max_depth': 10,
 'max_features': 'sqrt',
 'min_samples_leaf': 8,
 'min_samples_split': 5,
 'n_estimators': 500}
```

In [51]:
```
clf = RandomForestClassifier(
    bootstrap=True,
    max_depth=10,
    max_features='sqrt',
    min_samples_leaf=8,
    min_samples_split=5,
    n_estimators=500
)
```

In [52]:
```
# CrossValidation accuracy
crs_acc = cross_val_score(clf, x, y, cv=5, scoring='accuracy')
crs_acc = crs_acc.mean()
crs_acc
```

Out[52]:
```
0.840983606557377
```

Precision (Positive Predictive Value)

In [53]:
```
# CrossValidation pricision
crs_precision = cross_val_score(clf, x, y, cv=5, scoring='precision')
crs_precision = np.mean(crs_precision)
crs_precision
```

Out[53]:
```
0.8285150375939849
```

Recall (Sensitivity or True Positive Rate)

In [54]:
```
# CrossValidation recall
crs_recall = cross_val_score(clf, x, y, cv=5, scoring='recall')
crs_recall = np.mean(crs_recall)
crs_recall
```

Out[54]:
```
0.9028409090909092
```

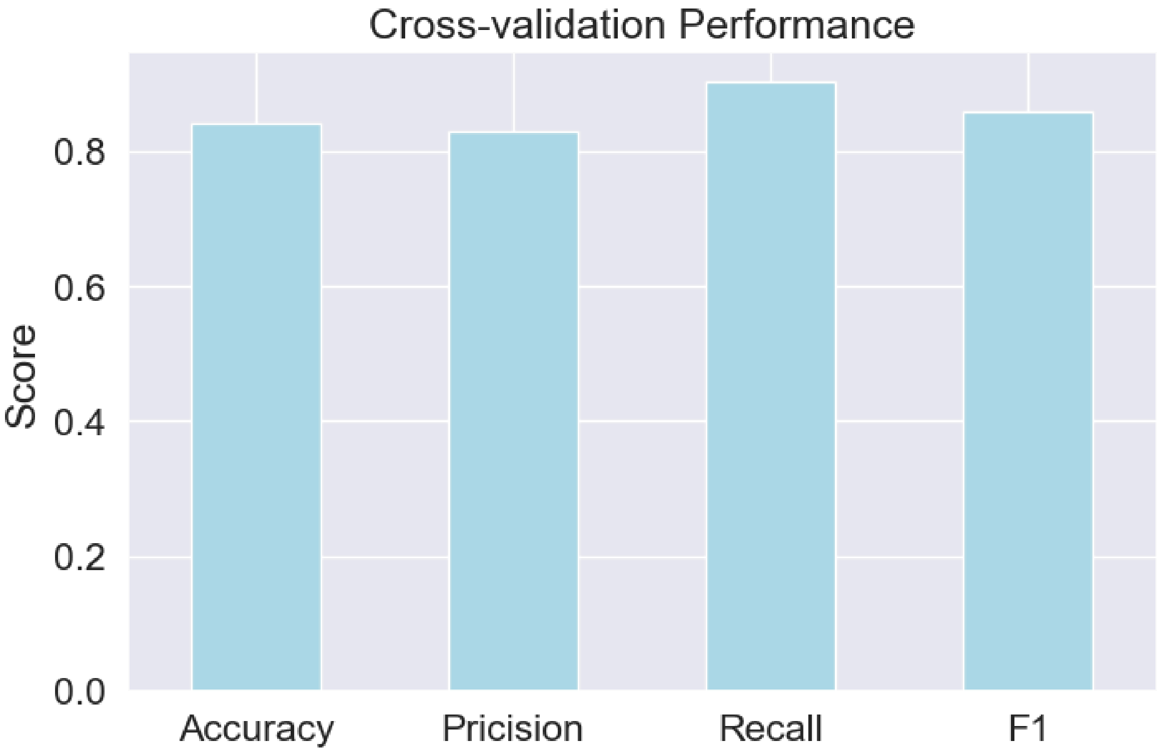
F1 Score (Harmonic Mean of Precision & Recall)

In [55]:
```
# CrossValidation f1_score
crs_f1_score = cross_val_score(clf, x, y, cv=5, scoring='f1')
crs_f1_score = np.mean(crs_f1_score)
crs_f1_score
```

Out[55]: 0.8586529954730378

Cross-validation matrix

In [72]:
```
#lets see the Cross-validation matrix
cv_matrix = pd.DataFrame({'Accuracy':crs_acc,
                          'Pricision':crs_precision,
                          'Recall':crs_recall,
                          'F1':crs_f1_score},
                         index=[0])
cv_matrix.T.plot(kind='bar', figsize=(8, 5),color='lightblue')
plt.title("Cross-validation Performance")
plt.ylabel("Score")
plt.legend().remove()
plt.xticks(rotation=0)
plt.show()
```



Feature Importance

Feature importance shows which data or attribute contributes the most to the model's prediction.

Finding the feature importance for `RandomForestClassifier()`

In [57]:
```
clf.fit(x_train,y_train)
```

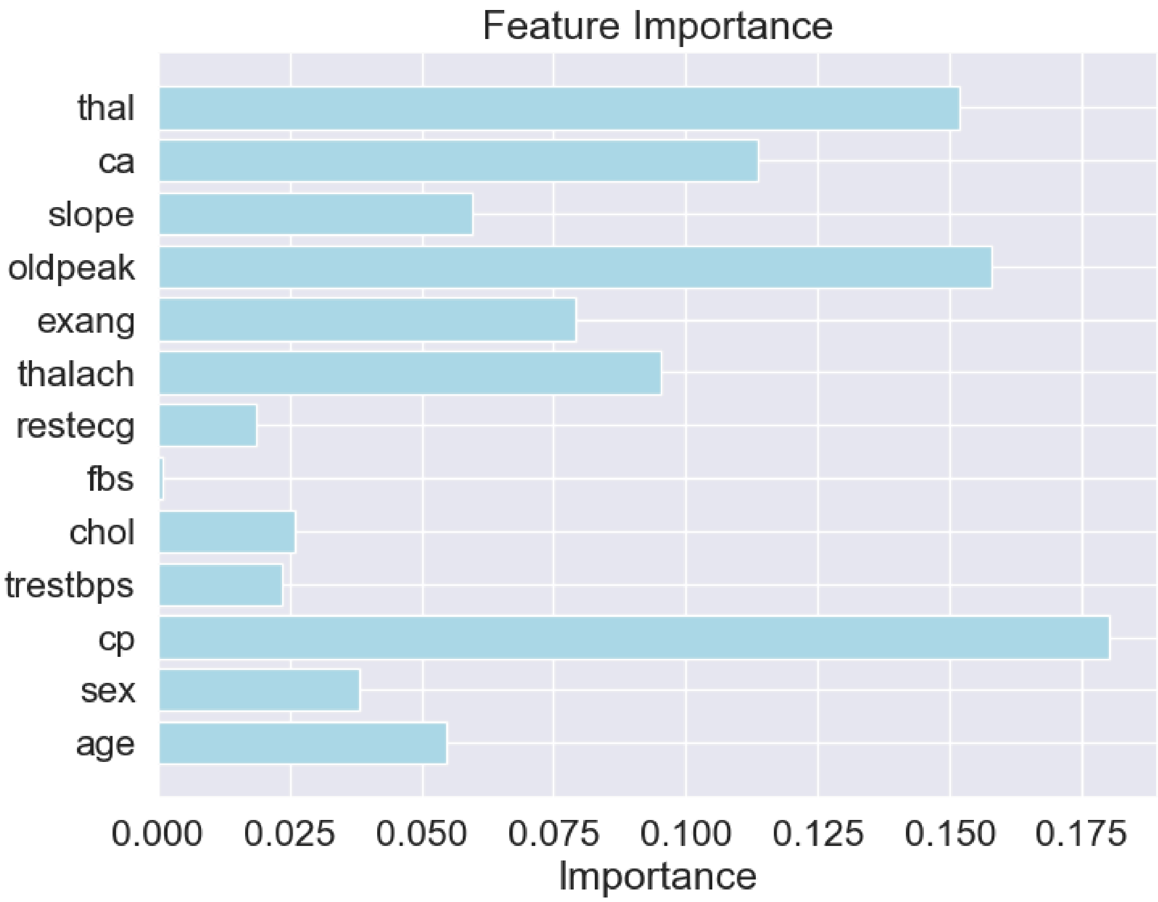
Out[57]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=10, min_samples_leaf=8, min_samples_split=5,
                       n_estimators=500)
```

In [58]:
```
imp = clf.feature_importances_
imp_df = pd.DataFrame({'Feature Names':clf.feature_names_in_,
                      'Feature Importance':imp})
print(imp_df)
```

```
   Feature Names  Feature Importance
0            age            0.054717
1            sex            0.038132
2             cp            0.180200
3       trestbps            0.023690
4           chol            0.026173
5            fbs            0.000965
6        restecg            0.018738
7        thalach            0.095429
8          exang            0.079171
9        oldpeak            0.157725
10         slope            0.059460
11            ca            0.113761
12          thal            0.151837
```

In [59]:
```
plt.figure(figsize=(8, 6))
plt.barh(clf.feature_names_in_,imp, color='lightblue')
plt.xlabel('Importance')
plt.title('Feature Importance')

plt.show()
```



The most important features contributing to the model's prediction are **chest pain (cp), Thalium heart rate (thal), oldpeak, ca, and (Maximum heart rate)thalach**, with chest pain having the highest influence .

In [ ]: