Predicting Heart Disease Using a Machine Learning Classification Model

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1. Problem Definiton

Predicting whether a patient has heart disease or not based on various clinical attributes.

2. Data Source

The imported data that was used to train the model on was taken from the Cleveland data at the UCI Machine Learning Repository.
https://archive.ics.uci.edu/dataset/45/heart+disease
https://www.kaggle.com/datasets/sumaiyatasmeem/heart-disease-classification-dataset/data

3. Hypothesis

The model will be deemed as successful if it produces an accuracy of >95%.

4. Features

Data Dictionary:

1. age: Displays the age of the individual.
2. sex: Displays the gender of the individual using the following format : 1 = male 0 = female
3. cp- Chest-pain type: displays the type of chest-pain experienced by the individual using the following format : 0 = typical angina 1 = atypical angina 2 = non — anginal pain 3 = asymptotic
4. trestbps- Resting Blood Pressure: displays the resting blood pressure value of an individual in mmHg (unit). anything above 130-140 is typically cause for concern.
5. chol- Serum Cholestrol: displays the serum cholesterol in mg/dl (unit)
6. fbs- Fasting Blood Sugar: compares the fasting blood sugar value of an individual with 120mg/dl. If fasting blood sugar > 120mg/dl then : 1 (true) else : 0 (false) '>126' mg/dL signals diabetes
7. restecg- Resting ECG : displays resting electrocardiographic results 0 = normal 1 = having ST-T wave abnormality 2 = left ventricular hyperthrophy
8. thalach- Max heart rate achieved : displays the max heart rate achieved by an individual.
9. exang- Exercise induced angina : 1 = yes 0 = no
10. oldpeak- ST depression induced by exercise relative to rest: displays the value which is an integer or float.
11. slope- Slope of the peak exercise ST segment : 0 = upsloping: better heart rate with excercise (uncommon) 1 = flat: minimal change (typical healthy heart) 2 = downsloping: signs of unhealthy heart
12. ca- Number of major vessels (0–3) colored by flourosopy : displays the value as integer or float.
13. thal : Displays the thalassemia : 1,3 = normal 6 = fixed defect 7 = reversible defect: no proper blood movement when excercising
14. target : Displays whether the individual is suffering from heart disease or not : 1 = yes 0 = no

5. Data Preparation and Analysis

5.1: Importing the Libraries

Tools used: pandas, Matplotlib, and NumPy for data analysis and manipulation.

```
## Importing all the tools

# Regular EDA (Exploratory Data Analysis) and plotting libraries
import numpy as np
import pandas as pd
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 confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import RocCurveDisplay

import warnings
warnings.filterwarnings('ignore')
```

5.2 Importing the Data

```
df=pd.read_csv('drive/MyDrive/AI ML Resources/heart-disease.csv')
df
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

303 rows × 14 columns

Next steps: Generate code with df View recommended plots New interactive sheet

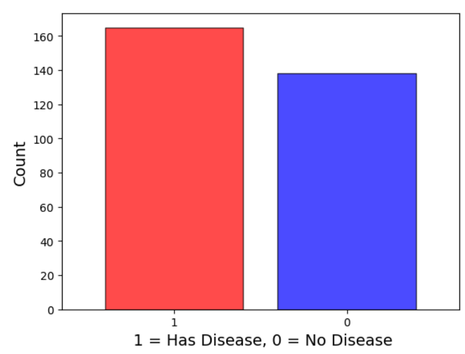
```
df["target"].value_counts()
```

	count
target	
1	165
0	138

dtype: int64

Heart disease Count

```
df["target"].value_counts().plot(
    kind="bar",
    color=["red", "blue"],
    edgecolor='black',
    alpha=0.7,
    width=0.8
)

plt.xlabel(" 1 = Has Disease, 0 = No Disease", fontsize=14)
plt.ylabel("Count", fontsize=14)
plt.xticks(rotation=0)
plt.show()
```



```
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
```

```
# Check null values

df.isna().sum()
```

	0
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

```
df.describe()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	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	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373	2.313531	0.544554
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606	0.612277	0.498835
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	2.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	2.000000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	3.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.000000	1.000000

Heart Disease Frequency According to Sex

```
df.sex.value_counts()
```

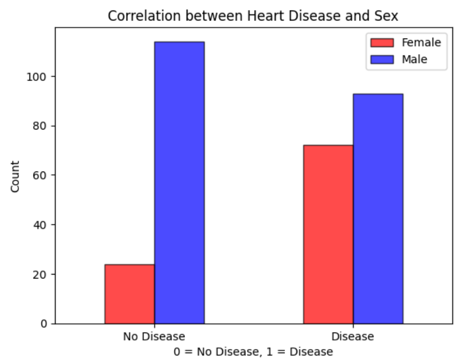
sex	count
1	207
0	96

dtype: int64

```
pd.crosstab(df.target,df.sex)
```

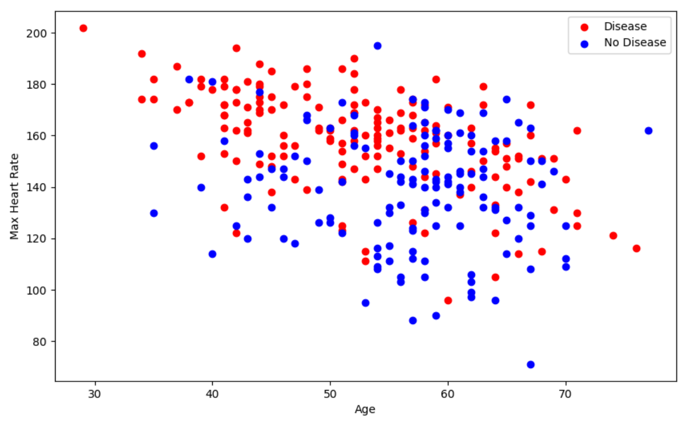
target \ sex	0	1
0	24	114
1	72	93

```
fig, ax = plt.subplots()

pd.crosstab(df.target, df.sex).plot(kind="bar",
                                    color=["red", "blue"],
                                    edgecolor='black',
                                    alpha=0.7,
                                    ax=ax)
ax.set_xlabel("0 = No Disease, 1 = Disease")
ax.set_ylabel("Count")
ax.set_title("Correlation between Heart Disease and Sex")
ax.legend(["Female", "Male"])
ax.set_xticks(ax.get_xticks())
ax.set_xticklabels(["No Disease", "Disease"])
ax.tick_params(axis='x', rotation=0)


plt.show()

```



Correlation Between Age and Thalach (Max Heart Rate) with Heart Disease

```
plt.figure(figsize=(10, 6))
plt.scatter(df.age[df.target==1],df.thalach[df.target==1],c="red")
plt.scatter(df.age[df.target==0],df.thalach[df.target==0],c="blue")
plt.xlabel("Age")
plt.ylabel("Max Heart Rate")
plt.legend(["Disease", "No Disease"]);
```



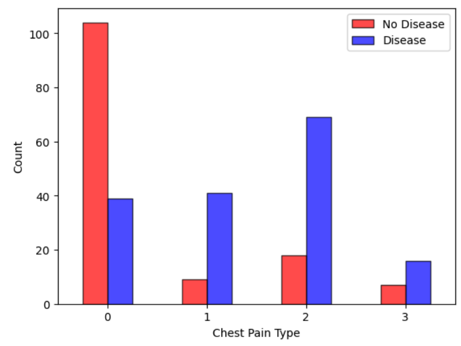
Correlation Between Chest Pain Type and Heart Disease

```
pd.crosstab(df.cp,df.target)
```

target	0	1
cp		
0	104	39
1	9	41
2	18	69
3	7	16

0 = typical angina
1 = atypical angina
2 = non — anginal pain
3 = asymptotic

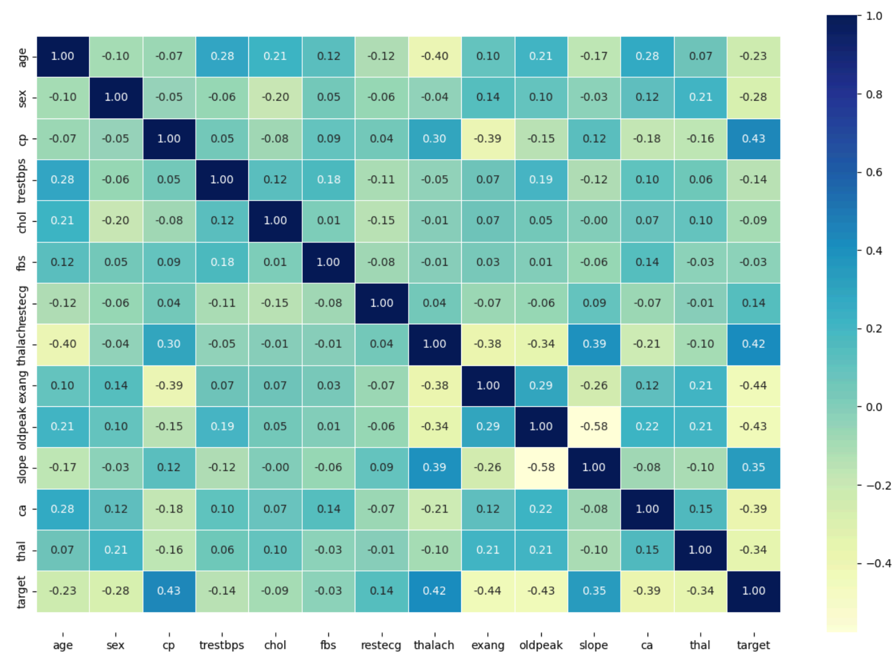
```
pd.crosstab(df.cp,df.target).plot(kind="bar",
                                  color=["red","blue"],
                                  edgecolor="black",
                                  alpha=0.7)
plt.xlabel("Chest Pain Type")
plt.legend(["No Disease", "Disease"])
plt.ylabel("Count")
plt.xticks(rotation=0);
```




```
df.corr()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522	0.096801	0.210013	-0.168814	0.276326	0.068001	-0.225439
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020	0.141664	0.096093	-0.030711	0.118261	0.210041	-0.280937
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762	-0.394280	-0.149230	0.119717	-0.181053	-0.161736	0.433798
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698	0.067616	0.193216	-0.121475	0.101389	0.062210	-0.144931
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940	0.067023	0.053952	-0.004038	0.070511	0.098803	-0.085239
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567	0.025665	0.005747	-0.059894	0.137979	-0.032019	-0.028046
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123	-0.070733	-0.058770	0.093045	-0.072042	-0.011981	0.137230
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000	-0.378812	-0.344187	0.386784	-0.213177	-0.096439	0.421741
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812	1.000000	0.288223	-0.257748	0.115739	0.206754	-0.436757
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187	0.288223	1.000000	-0.577537	0.222682	0.210244	-0.430696
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784	-0.257748	-0.577537	1.000000	-0.080155	-0.104764	0.345877
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177	0.115739	0.222682	-0.080155	1.000000	0.151832	-0.391724
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439	0.206754	0.210244	-0.104764	0.151832	1.000000	-0.344029
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.421741	-0.436757	-0.430696	0.345877	-0.391724	-0.344029	1.000000

```
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");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5);
```



Correlation determines whether the relations are positively or inversely proportional, i.e if it's greater than 0 than whenever the first attribute increases so does the other. For example with thalach and target the value is 0.42, which means that the higher the thalach values the more likely the patient has heart disease. Conversely, for chol and target the lower the chol the higher the chance of heart disease to an extent.

6. Modelling

```
x=df.drop("target",axis=1)
y=df.target
np.random.seed(42)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

This experiment will test on 3 different models:

1. Logistic Regression
2. K-Nearest Neighbors Classifier
3. Random Forest Classifier

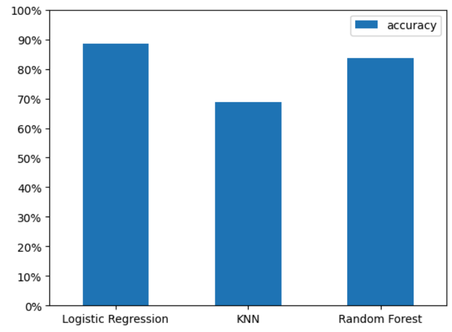
```
models={"Logistic Regression":LogisticRegression(),
        "KNN":KNeighborsClassifier(),
        "Random Forest": RandomForestClassifier()}
def fit_and_score_models(models,x_train,x_test,y_train,y_test):
  np.random.seed(42)
  model_scores={}
  for name,model in models.items():
    model.fit(x_train,y_train)
    model_scores[name]=model.score(x_test,y_test)
  return model_scores

```

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

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

```
model_graphs = pd.DataFrame(model_scores, index=["accuracy"])
ax = model_graphs.T.plot.bar()
ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda y, _: f'{int(y * 100)}%'))
ax.set_yticks([i / 100 for i in range(0, 101, 10)])
ax.set_xticklabels(ax.get_xticklabels(), rotation=0)
print("""Logistic Regression is the most accurate, followed by Random Forest and
then KNN""")
plt.show()
```

```
Logistic Regression is the most accurate, followed by Random Forest and
then KNN
```



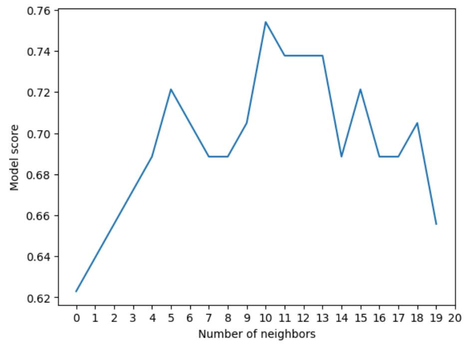
Attempting to Tune KNN

```
test_scores=[]
neighbors=np.arange(1,21)
knn=KNeighborsClassifier()
for i in neighbors:
  knn.set_params(n_neighbors=i)
  knn.fit(x_train,y_train)
  test_scores.append(knn.score(x_test,y_test))
test_scores
```

```
[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]
```

```
plt.plot(test_scores)
plt.xticks(np.arange(0, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")

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

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



K Nearest Neighbors wasn't accurate enough so we will proceed to use the 2 others

Hyperparameter tuning with RandomizedSearchCV

```
# Logistic Regression Hyperparameter Grid
lrGrid={"C": np.logspace(-4, 4, 20),"solver": ["liblinear"]}

# Random Classifier Hyperparameter Grid
rcGrid={"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)}

np.random.seed(42)

# Apply the grid to the cross validations
rsLr=RandomizedSearchCV(LogisticRegression(),
                                param_distributions=lrGrid,
                                cv=5,
                                n_iter=20,
                                verbose=True)

rsRc=RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=rcGrid,
                           cv=5,
                           n_iter=20,
                           verbose=True)

rsLr.fit(x_train,y_train)
rsRc.fit(x_train,y_train)

```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
Fitting 5 folds for each of 20 candidates, totalling 100 fits
▸ RandomizedSearchCV
▾ estimator: RandomForestClassifier
RandomForestClassifier()
▾ RandomForestClassifier
RandomForestClassifier()
```

```
rsLr.best_params_
```

```
{'solver': 'liblinear', 'C': 0.23357214690901212}
```

```
rsRc.best_params_
```

```
{'n_estimators': 360,
 'min_samples_split': 4,
 'min_samples_leaf': 15,
 'max_depth': 5}
```

```
rsLr.score(x_test,y_test)
```

```
0.8852459016393442
```

```
rsRc.score(x_test,y_test)
```

```
0.8688524590163934
```

Not much difference/improvement and we will proceed to use Logistic Regression

Hyperparameter tuning with GridSearchCV

```
lrGrid = {"C": np.logspace(-4, 4, 30),
                "solver": ["liblinear"]}

gsLr = GridSearchCV(LogisticRegression(),
                          param_grid=lrGrid,
                          cv=5,
                          verbose=True)

gsLr.fit(x_train, y_train);
```

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

```
gsLr.best_params_
```

```
{'C': 0.20433597178569418, 'solver': 'liblinear'}
```

```
gsLr.score(x_test, y_test)
```

```
0.8852459016393442
```

```
## Evaluating the Model
```

7. Evaluating the Model

Evaluation Metrics:

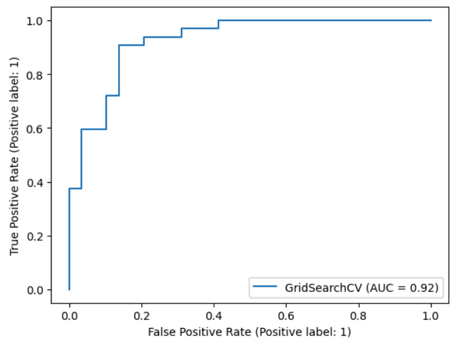
- ROC curve and AUC score
- Confusion matrix
- Classification report

- Precision
- Recall
- F1-Score

```
yPred=gsLr.predict(x_test)
yPred
```

```
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])
```

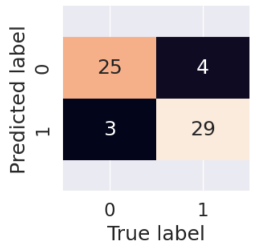
```
RocCurveDisplay.from_estimator(gsLr, x_test, y_test)
plt.show()
# Roc Curve is the plot of the true positive rate against the false positive rate
```




```
print(confusion_matrix(y_test, yPred))
```

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

```
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,
                     cbar=False)
    plt.xlabel("True label")
    plt.ylabel("Predicted label")

    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)

plot_conf_mat(y_test, yPred)
```




```
print(classification_report(y_test, yPred))
```

```
              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
```

```
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")
```

```
cv_acc = cross_val_score(clf,
                         x,
                         y,
                         cv=5,
                         scoring="accuracy")
cv_acc
```

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

```
cv_acc = np.mean(cv_acc)
cv_acc
```

```
0.8446994535519124
```

```
cv_precision = cross_val_score(clf,
                         x,
                         y,
                         cv=5,
                         scoring="precision")
cv_precision=np.mean(cv_precision)
cv_precision
```

```
0.8207936507936507
```

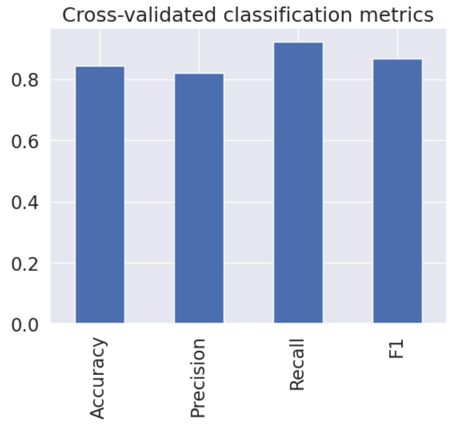
```
cv_recall = cross_val_score(clf,
                         x,
                         y,
                         cv=5,
                         scoring="recall")
cv_recall = np.mean(cv_recall)
cv_recall
```

```
0.9212121212121213
```

```
cv_f1 = cross_val_score(clf,
                         x,
                         y,
                         cv=5,
                         scoring="f1")
cv_f1 = np.mean(cv_f1)
cv_f1
```

```
0.8673007976269721
```

```
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);
```



Feature Importance

```
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")

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

```
clf.coef_
```

```
array([[ 0.00320769, -0.86062049,  0.66001432, -0.01155971, -0.00166496,
         0.04017236,  0.31603405,  0.02458922, -0.60470171, -0.56795456,
         0.45085392, -0.63733328, -0.67555094]])
```

```
feature_dict = dict(zip(df.columns, list(clf.coef_[0])))
feature_df = pd.DataFrame(feature_dict, index=[0])
```

```
feature_df.T.plot.bar(title="Feature Importance", legend=False);
```