Final Project ML Classification: Heart Disease Prediction

IBM Machine Learning Professional Certificate

Course 03: Supervised Machine Learning: Classification

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- Applying various classification models.
- Machine learning analysis and findings.
- Models flaws and advanced steps.

Data Description Section

Introduction

Predicting and diagnosing heart disease is one of the major challenges in the medical industry as it depends on several factors including physical examination and various symptoms and signs present in the patient. Heart disease is considered as one of the deadliest disease in the world for human life due to the heart's inability to push the required amount of blood to other body organs to perform the regular functions in the human body. There are several factors affecting heart disease include but not limited cholesterol levels in the body, smoking habits and obesity, family history of diseases, blood pressure, work environment and others. Today, ML Algorithms play an essential and accurate role in heart disease prediction. Rapid advances in technology allow Machine Language to integrate with Big Data tools to manage the exponentially growing unstructured data that includes medical data for patients around the world. Heart disease can be predicted based on different symptoms like age, gender, heart rate etc. which in turn reduces the death rate for heart patients. In this report we are going to use machine learning algorithms and Python language to do that!

Dataset Description 01

	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

- age: The person's age in years
- sex: The person's sex (1 = male, 0 = female)
- cp: chest pain type:
  - Value 0: asymptomatic
  - Value 1: atypical angina
  - Value 2: non-anginal pain
  - Value 3: typical angina
- trestbps: The person's resting blood pressure (mm Hg on admission to the hospital).
- chol: The person's cholesterol measurement in mg/dl.
- fbs: The person's fasting blood sugar (> 120 mg/dl, 1 = true; 0 = false).

Dataset Description 02

- restecg: resting electrocardiographic results
  Value 0: showing probable or definite left ventricular hypertrophy by Estes' criteria
  Value 1: normal
  Value 2: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV).

- thalach: The person's maximum heart rate achieved.

- exang: Exercise induced angina (1 = yes; 0 = no)

- oldpeak: ST depression induced by exercise relative to rest ('ST' relates to positions on the ECG plot. See more here)

- slope: the slope of the peak exercise ST segment
  0: upsloping; 1: flat; 2: downsloping

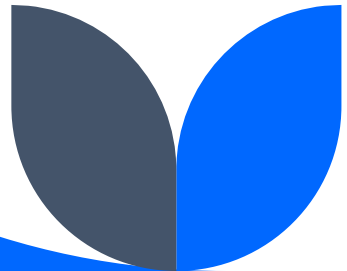
- ca: The number of major vessels (0–3)

- thal: A blood disorder called thalassemia
  Value 0: NULL (dropped from the dataset previously
  Value 1: fixed defect (no blood flow in some part of the heart)
  Value 2: normal blood flow
  Value 3: reversible defect (a blood flow is observed but it is not normal)

- target: Heart disease (0 = no, 1= yes)

Dataset Description 02

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00	303.00
mean	54.37	0.68	0.97	131.62	246.26	0.15	0.53	149.65	0.33	1.04	1.40	0.73	2.31	0.54
std	9.08	0.47	1.03	17.54	51.83	0.36	0.53	22.91	0.47	1.16	0.62	1.02	0.61	0.50
min	29.00	0.00	0.00	94.00	126.00	0.00	0.00	71.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	47.50	0.00	0.00	120.00	211.00	0.00	0.00	133.50	0.00	0.00	1.00	0.00	2.00	0.00
50%	55.00	1.00	1.00	130.00	240.00	0.00	1.00	153.00	0.00	0.80	1.00	0.00	2.00	1.00
75%	61.00	1.00	2.00	140.00	274.50	0.00	1.00	166.00	1.00	1.60	2.00	1.00	3.00	1.00
max	77.00	1.00	3.00	200.00	564.00	1.00	2.00	202.00	1.00	6.20	2.00	4.00	3.00	1.00



Dataset Description 03

Checking for Null values

```
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
```

Great, there is **no missing values** within our features !

Data Analysis Section

Main Objective of the analysis:

In this section I am showing the correlation between the features to find the most influence features on our target which is Target (Heart Disease Existence).

After that I am building different Classification models based on advanced techniques such as GridSearch, ML pipelines, and Hyperparameters tuning to get the best predictive model in terms of accuracy, in addition of what are the flaws of each model.

Data Analysis 01

- **Identifying categorical features and continuous features:**

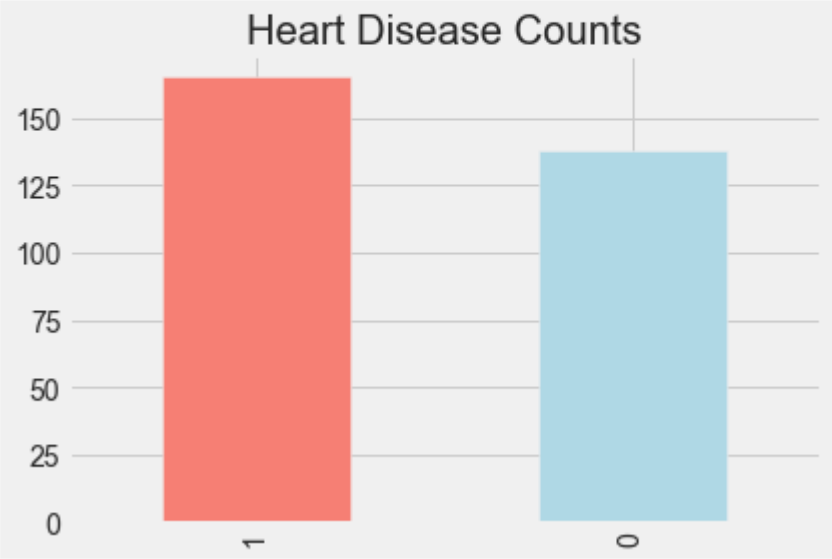
Categorical Features : ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'target']

Continous Features : ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']

Data Analysis 02

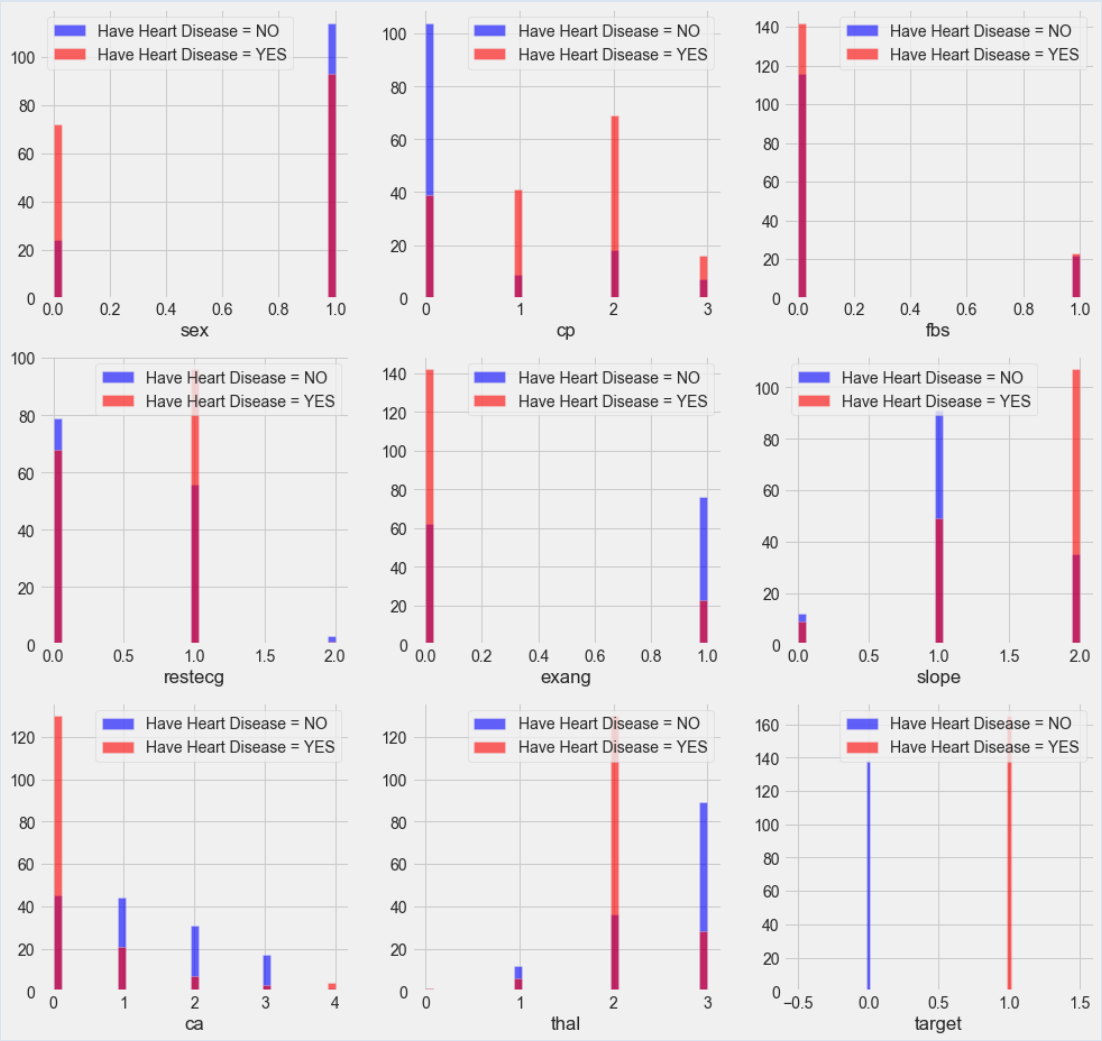
Viewing the status of people in the data set :

```
1    165
0    138
Name: target, dtype: int64

<matplotlib.axes._subplots.AxesSubplot at 0x2d4002c2518>
```



We have 165 people with heart disease and 138 healthy people, so the data for the target variable we want to predict is in balance.

Data Analysis 03



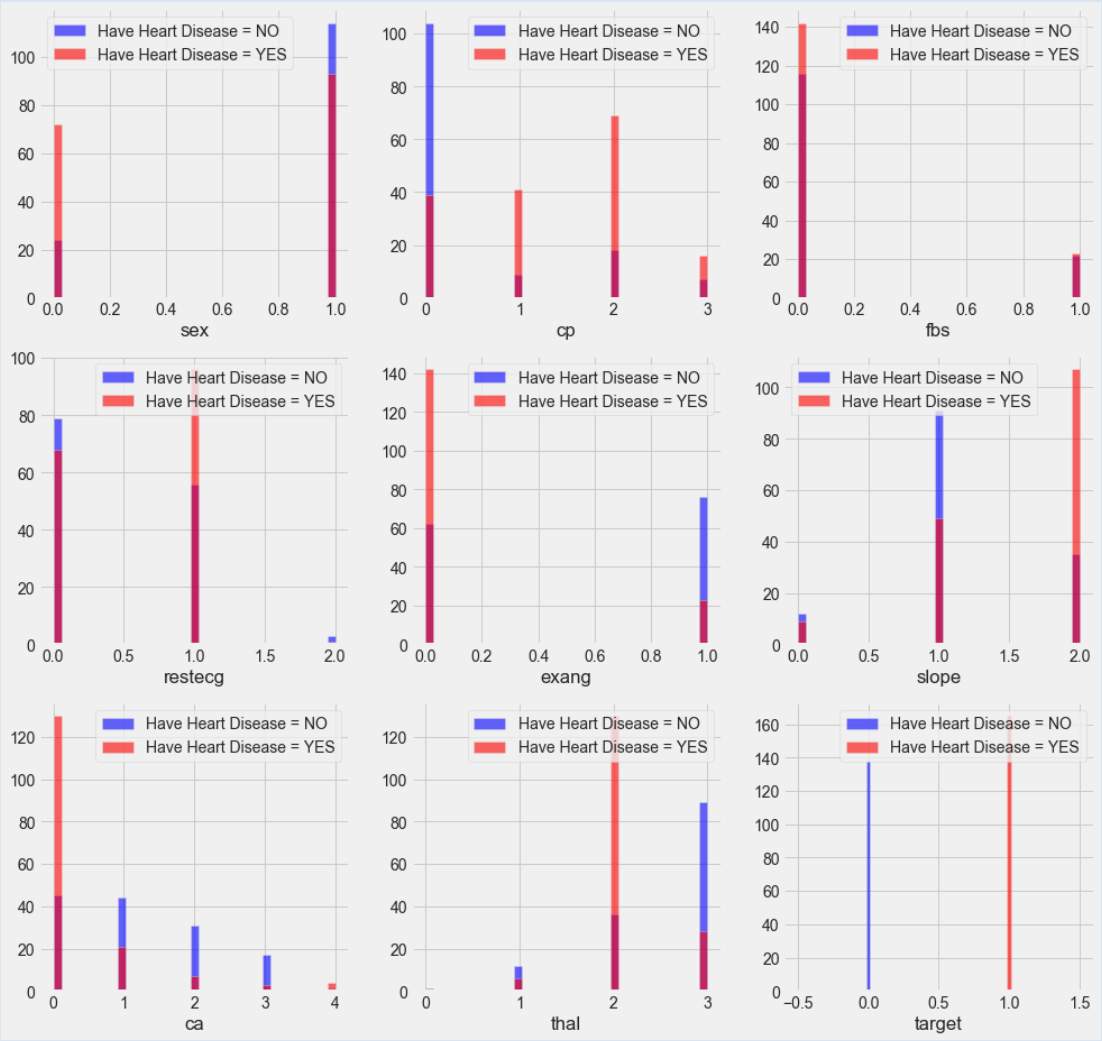
Study of the relationship of categorical features and heart disease:

cp (chest pain): people with chest pain of the type: cp: [1, 2, 3] tend to have more heart disease than people without any chest pain cp: 0

restecg (resting ECG results): People with a value of 1 (having an abnormal heart rhythm, which can range from mild symptoms to severe problems) are more likely to develop heart disease.

exang (exercise-induced angina): People with non-exercise-induced angina who have a value of 0 are more likely to have heart disease than those who have exercise-induced angina with a value of 1.

Data Analysis 04

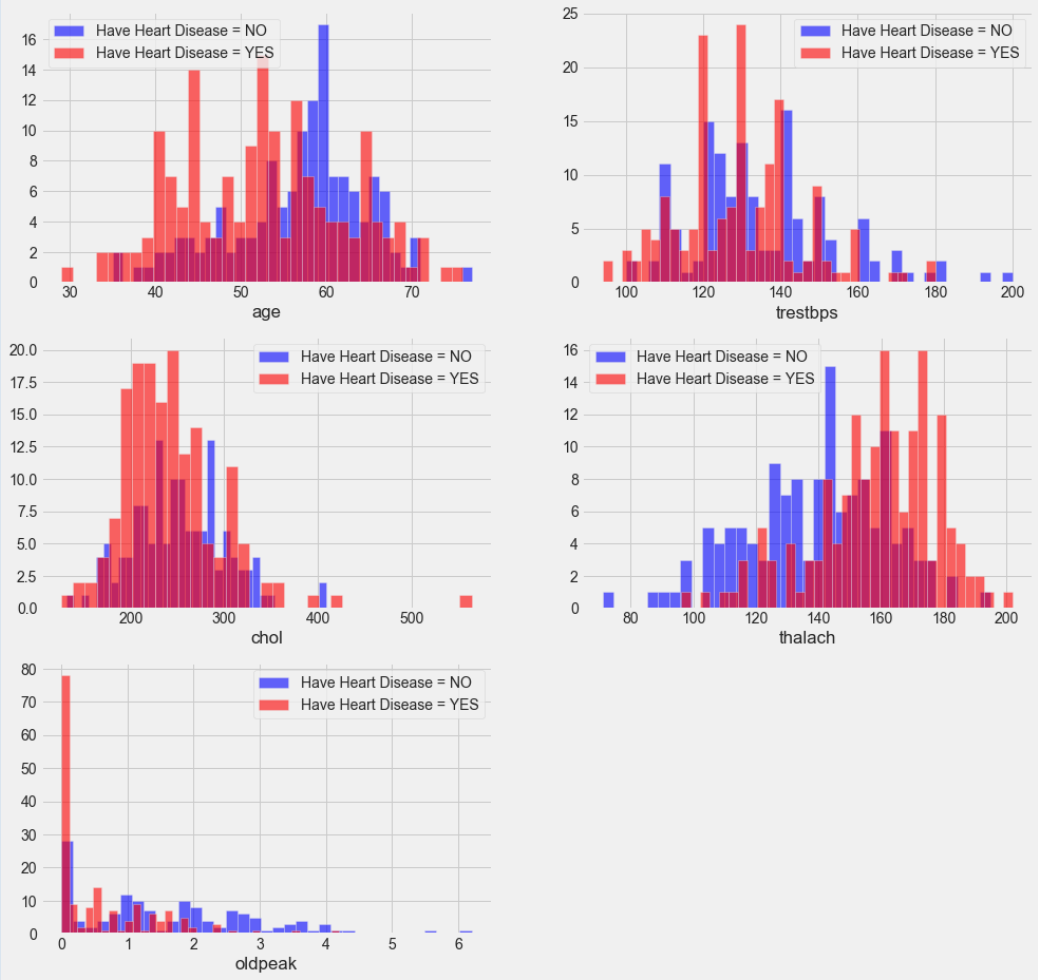


Slope (rectal slope for the ST segment of peak exercise): People with a downsloping slope of 2 have signs of an unhealthy heart therefore they more likely to have heart disease than people with an upsloping of 0 or a flat slope A value of 1: minimal change (typical healthy heart)).

ca (number of blood vessels (0-3)): the more blood flow the better heart, so people with a vessel number ca equal to 0 are more likely to have heart disease.

thal (a blood disorder called thalassemia): People with a thal value = 2 are more likely to have heart disease.

Data Analysis 05



Study of the relationship of continuous features and heart disease:

trestbps: When blood pressure is higher than 130-140 mm Hg, this is a cause for concern.

chol: When cholesterol is higher than 200 mg/dL, it is a very dangerous indicator, as shown in the graphic above.

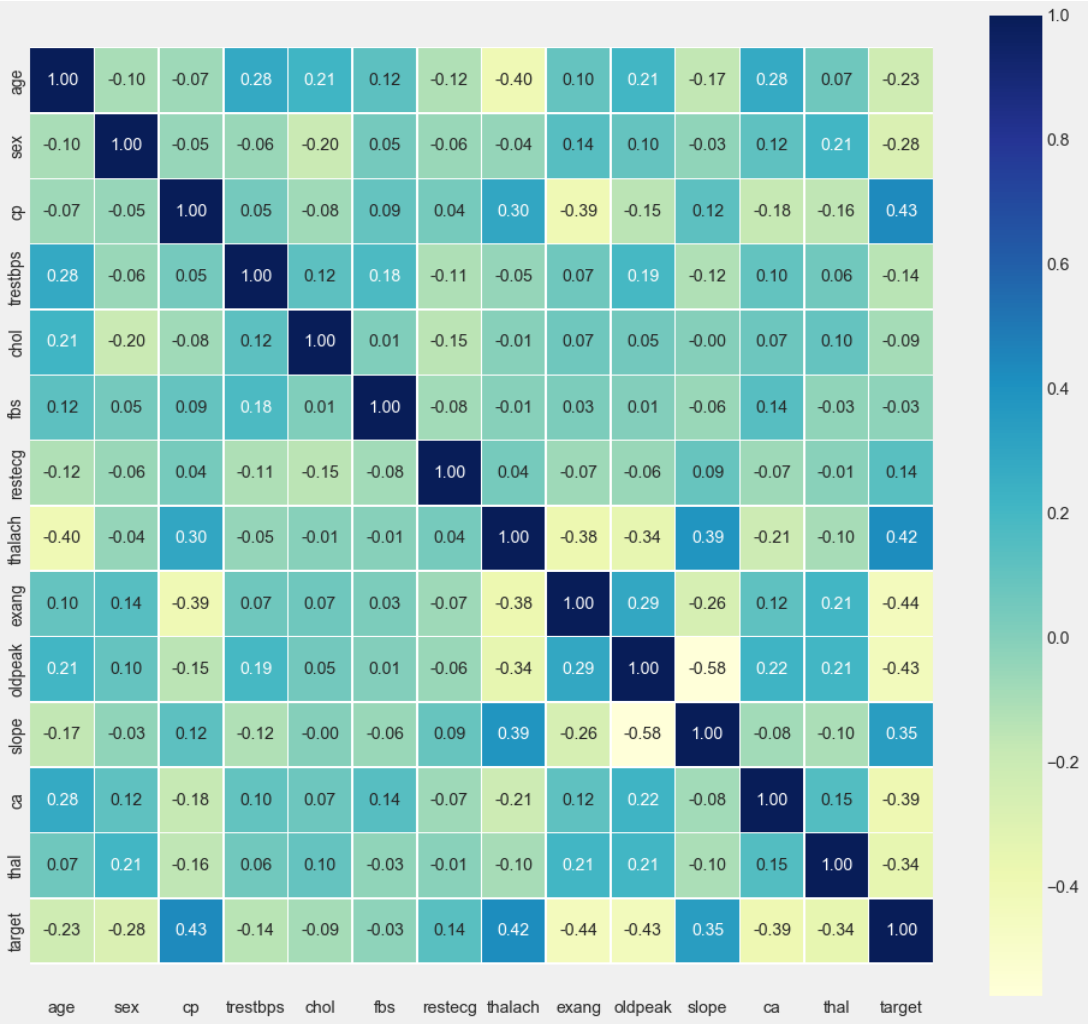
thalach: People with a heart rate above 140 are more likely to have heart disease.

Data Analysis 06

- Studying the correlations between features using Heat Map!

The goal of this matrix is to show the relationship between features, and this is useful for feature engineering techniques, but what matters most to us in this lesson is the relationship between the target variable (knowing whether a person has a heart disease or not) and the rest of the features, meaning that our focus will be on the last row from the matrix.

- ❑ **1.** **fbs** and **chol** are the features least related to the target variable.
- ❑ **2.** All other features have a high correlation with the target variable.



Feature Engineering 01

Converting Categorical features into Numerical features :

	age	trestbps	chol	thalach	oldpeak	target	sex_0	sex_1	cp_0	cp_1	...	slope_2	ca_0	ca_1	ca_2	ca_3	ca_4	thal_0	thal_1	thal_2	thal_3
0	0.95	0.76	-0.26	0.02	1.09	1	0	1	0	0	...	0	1	0	0	0	0	0	1	0	0
1	-1.92	-0.09	0.07	1.63	2.12	1	0	1	0	0	...	0	1	0	0	0	0	0	0	1	0
2	-1.47	-0.09	-0.82	0.98	0.31	1	1	0	0	1	...	1	1	0	0	0	0	0	0	1	0
3	0.18	-0.66	-0.20	1.24	-0.21	1	0	1	0	1	...	1	1	0	0	0	0	0	0	1	0
4	0.29	-0.66	2.08	0.58	-0.38	1	1	0	1	0	...	1	1	0	0	0	0	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	0.29	0.48	-0.10	-1.17	-0.72	0	1	0	1	0	...	0	1	0	0	0	0	0	0	0	1
299	-1.03	-1.23	0.34	-0.77	0.14	0	0	1	0	0	...	0	1	0	0	0	0	0	0	0	1
300	1.50	0.71	-1.03	-0.38	2.04	0	0	1	1	0	...	0	0	0	1	0	0	0	0	0	1
301	0.29	-0.09	-2.23	-1.52	0.14	0	0	1	1	0	...	0	0	1	0	0	0	0	0	0	1
302	0.29	-0.09	-0.20	1.06	-0.90	0	1	0	0	1	...	0	0	1	0	0	0	0	0	1	0

303 rows × 31 columns

Machine Learning Analysis & Findings

Machine Learning Analysis & Findings

In the following analysis will compare between 4 different Classification models Logistic Regression, KNN, SVM and XGBoost in terms of predicting the Heart Disease. Where I am going to use the following techniques to help me in developing robust models:

Standard scaling, cross-validation method, Grid Search, metric measurements such accuracy, precision, F1 Score etc.

Machine Learning Analysis 01

Data Splitting:

```
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
feature_cols = [col_name for col_name in dataset.columns if col_name != 'target']

# Get the split indexes
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.3,
                                          random_state=42)

train_idx, test_idx = next(strat_shuf_split.split(dataset[feature_cols], dataset.target))
# Create the dataframes
X_train = dataset.loc[train_idx, feature_cols]
y_train = dataset.loc[train_idx, 'target']

X_test  = dataset.loc[test_idx, feature_cols]
y_test  = dataset.loc[test_idx, 'target']
```

Machine Learning Analysis 02

Logistic Regression Model:

```
### BEGIN SOLUTION
from sklearn.linear_model import LogisticRegression

# Standard logistic regression
lr = LogisticRegression(solver='liblinear').fit(X_train, y_train)
y_pred_0 = lr.predict(X_test)
clf_report = pd.DataFrame(classification_report(y_test, y_pred_0, output_dict=True))
clf_report
```

	0	1	accuracy	macro avg	weighted avg
precision	0.78	0.80	0.79	0.79	0.79
recall	0.76	0.82	0.79	0.79	0.79
f1-score	0.77	0.81	0.79	0.79	0.79
support	41.00	50.00	0.79	91.00	91.00

Machine Learning Analysis 03

Logistic Regression Model with penalty = L1:

```
from sklearn.linear_model import LogisticRegressionCV

# L1 regularized logistic regression
lr_l1 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear').fit(X_train, y_train)
y_pred_1 = lr_l1.predict(X_test)
clf_report = pd.DataFrame(classification_report(y_test, y_pred_1, output_dict=True))
clf_report
```

	0	1	accuracy	macro avg	weighted avg
precision	0.81	0.78	0.79	0.79	0.79
recall	0.71	0.86	0.79	0.78	0.79
f1-score	0.75	0.82	0.79	0.79	0.79
support	41.00	50.00	0.79	91.00	91.00

Machine Learning Analysis 04

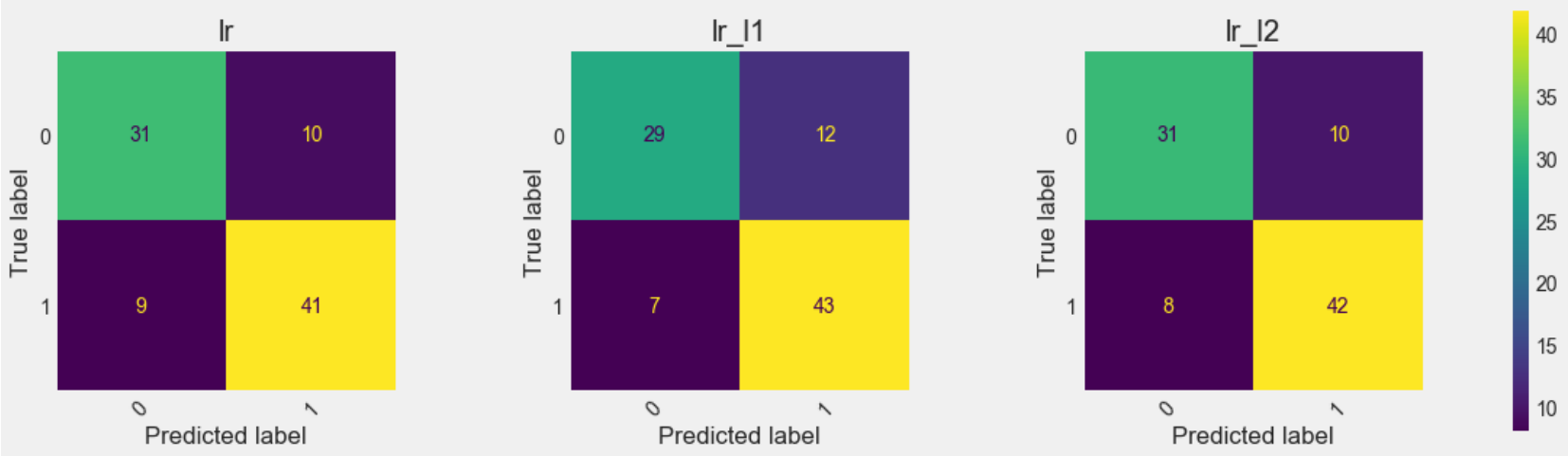
Logistic Regression Model with penalty = L2:

```
# L2 regularized logistic regression
lr_l2 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2', solver='liblinear').fit(X_train, y_train)
y_pred_2 = lr_l2.predict(X_test)
clf_report = pd.DataFrame(classification_report(y_test, y_pred_2, output_dict=True))
clf_report
```

	0	1	accuracy	macro avg	weighted avg
precision	0.79	0.81	0.80	0.80	0.80
recall	0.76	0.84	0.80	0.80	0.80
f1-score	0.77	0.82	0.80	0.80	0.80
support	41.00	50.00	0.80	91.00	91.00

Analysis & Findings

Logistic Regression Models Findings:



The best model in terms of prediction performance is Logistic Regression with penalty = 2

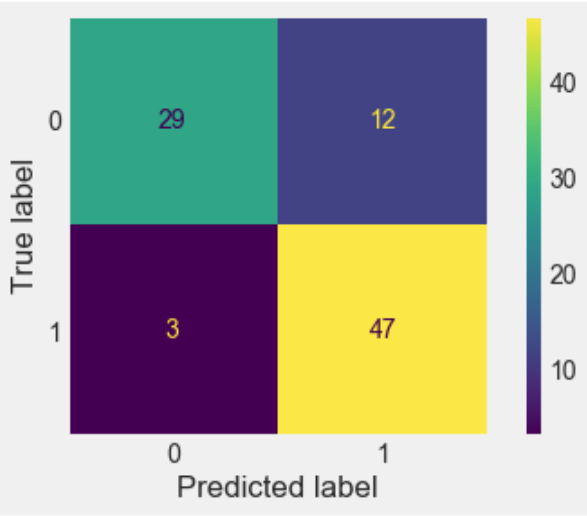
- Accuracy : 80%
- Precision : 80%
- Recall : 80%
- F1-score : 80%
- Support : 91%

Machine Learning Analysis 05

KNN Algorithm

```
knn = KNeighborsClassifier(n_neighbors=25, weights='distance')
knn = knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

KNN_report = pd.DataFrame(classification_report(y_test, y_pred, output_dict=True))
KNN_report
```

	0	1	accuracy	macro avg	weighted avg
precision	0.91	0.80	0.84	0.85	0.85
recall	0.71	0.94	0.84	0.82	0.84
f1-score	0.79	0.86	0.84	0.83	0.83
support	41.00	50.00	0.84	91.00	91.00



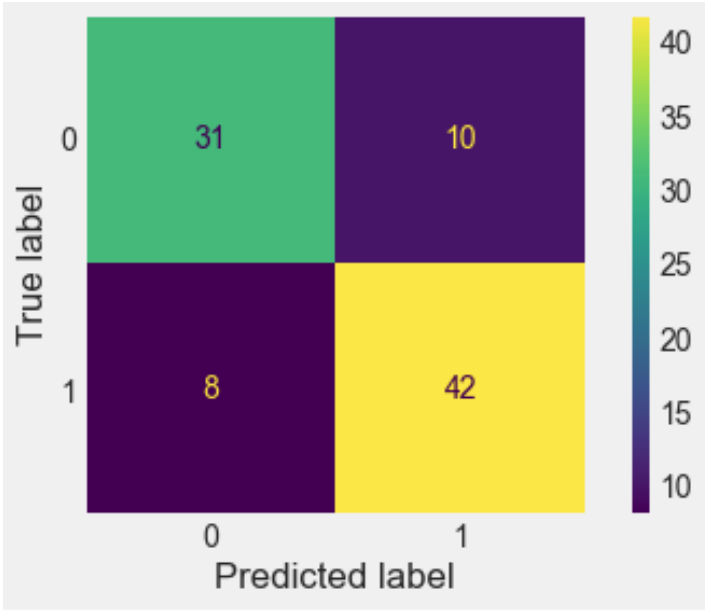
- Accuracy : 84%
- Precision : 85%
- Recall : 84%
- F1-score : 83%
- Support : 91%

Machine Learning Analysis 06

Support Vector Machine Model:

```
from sklearn.svm import SVC

kwargs = {'kernel': 'rbf'}
svc = SVC(**kwargs)

SVC_cl = svc.fit(X_train, y_train)
y_pred = SVC_cl.predict(X_test)
SVC_cl_report = pd.DataFrame(classification_report(y_test, y_pred, output_dict=True))
SVC_cl_report
```

	0	1	accuracy	macro avg	weighted avg
precision	0.79	0.81	0.80	0.80	0.80
recall	0.76	0.84	0.80	0.80	0.80
f1-score	0.77	0.82	0.80	0.80	0.80
support	41.00	50.00	0.80	91.00	91.00



- Accuracy : 80%
- Precision : 80%
- Recall : 80%
- F1-score : 80%
- Support : 91%

Machine Learning Analysis 07

XGBoost Algorithm

```
import xgboost as xgb
from sklearn.model_selection import GridSearchCV

param_grid = {
    "max_depth": [5],
    "learning_rate": [0.05],
    "gamma": [0, 0.25, 1, 10],
    "reg_lambda": [0],
    "scale_pos_weight": [1, 3, 5, 7, 10],
    "subsample": [0.1,0.2, 0.3, 0.4, 0.5, 0.8],
    "colsample_bytree": [0.5,0.7],
}


# Init classifier
xgb_cl = xgb.XGBClassifier(objective="binary:logistic")

# Init Grid Search
grid_cv = GridSearchCV(xgb_cl, param_grid, n_jobs=-1, cv=3, scoring="roc_auc")

# Fit
_ = grid_cv.fit(X_train, y_train)
```

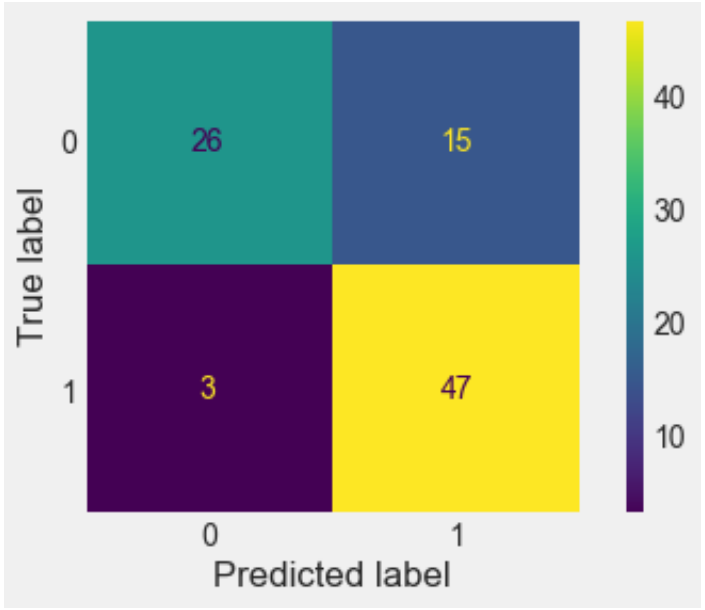
```
final_xgb_cl = xgb.XGBClassifier(
    **grid_cv.best_params_,
    objective="binary:logistic",
)

_ = final_xgb_cl.fit(X_train, y_train)

y_pred = final_xgb_cl.predict(X_test)

xgb_report = pd.DataFrame(classification_report(y_test, y_pred, output_dict=True))
xgb_report
```

Machine Learning Analysis 08

XGBoost Algorithm

	0	1	accuracy	macro avg	weighted avg
precision	0.90	0.76	0.80	0.83	0.82
recall	0.63	0.94	0.80	0.79	0.80
f1-score	0.74	0.84	0.80	0.79	0.80
support	41.00	50.00	0.80	91.00	91.00

- Accuracy : 80%
- Precision : 82%
- Recall : 80%
- F1-score : 80%
- Support : 91%

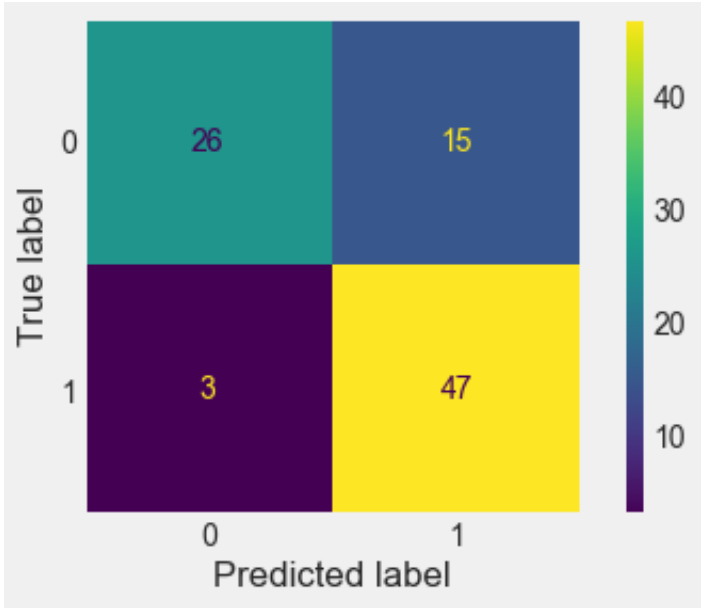


Machine Learning Analysis 09

XGBoost Algorithm

	0	1	accuracy	macro avg	weighted avg
precision	0.90	0.76	0.80	0.83	0.82
recall	0.63	0.94	0.80	0.79	0.80
f1-score	0.74	0.84	0.80	0.79	0.80
support	41.00	50.00	0.80	91.00	91.00

- Accuracy : 80%
- Precision : 82%
- Recall : 80%
- F1-score : 80%
- Support : 91%



Machine Learning Analysis 10

Models Comparison

As shown in the previous analysis all the models provide very good prediction results and these results are so close to each other, But at the end we must choose one model for our dataset and this depends on the highest result.
Below I ordered the models descending:

1- KNN
2- XGBoost
3- Logistic Regression with L2
4- Support Vector Machine

KNN

	0	1	accuracy	macro avg	weighted avg
precision	0.91	0.80	0.84	0.85	0.85
recall	0.71	0.94	0.84	0.82	0.84
f1-score	0.79	0.86	0.84	0.83	0.83
support	41.00	50.00	0.84	91.00	91.00

Models flaws and strengths and advanced steps

Machine Learning Analysis 11

Models Flaws and Strength and further suggestions:

In terms of simplicity, we can say Logistic Regression provided high predictive results and at the same time it is the simplest and fastest Model in terms of parameters and training but if we look to other models like KNN it is providing the best results, but it is slower in terms of prediction process because it requires to calculate the distance between all the points in the dataset to classify every single point.

XGBoost performance was very good as well but in contrast of KNN it takes longer time in the training process since we used grid search technique to search about best fitting parameters, so at the end it is a tradeoff if we have bigger dataset then the performance will be higher with such models, but the training process will take a longer time.

Thank you

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Supervised Machine Learning: Classification

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