ML_Project

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CS-C3240 - Machine Learning D Project

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1 Import Libraries and Data

[1]:
```
# Import libraries
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪StratifiedKFold
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix

%matplotlib inline

# Read the .csv file containing the dataset
data = pd.read_csv('heart_data.csv')
data.head()
```

[1]:

	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			
1	53	1	0	140	203	1	0	155	1	3.1	0			
2	70	1	0	145	174	0	1	125	1	2.6	0			
3	61	1	0	148	203	0	1	161	0	0.0	2			
4	62	0	0	138	294	1	1	106	0	1.9	1			

```
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

2 Clean Data

[2]:
```
data.info() # check basic dataframe's information
```

```
<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
```

[3]:
```
data.duplicated().sum() # look if there are duplicates
```

[3]:
```
723
```

[4]:
```
data.drop_duplicates(inplace=True) # drop druplicates
```

3 EDA

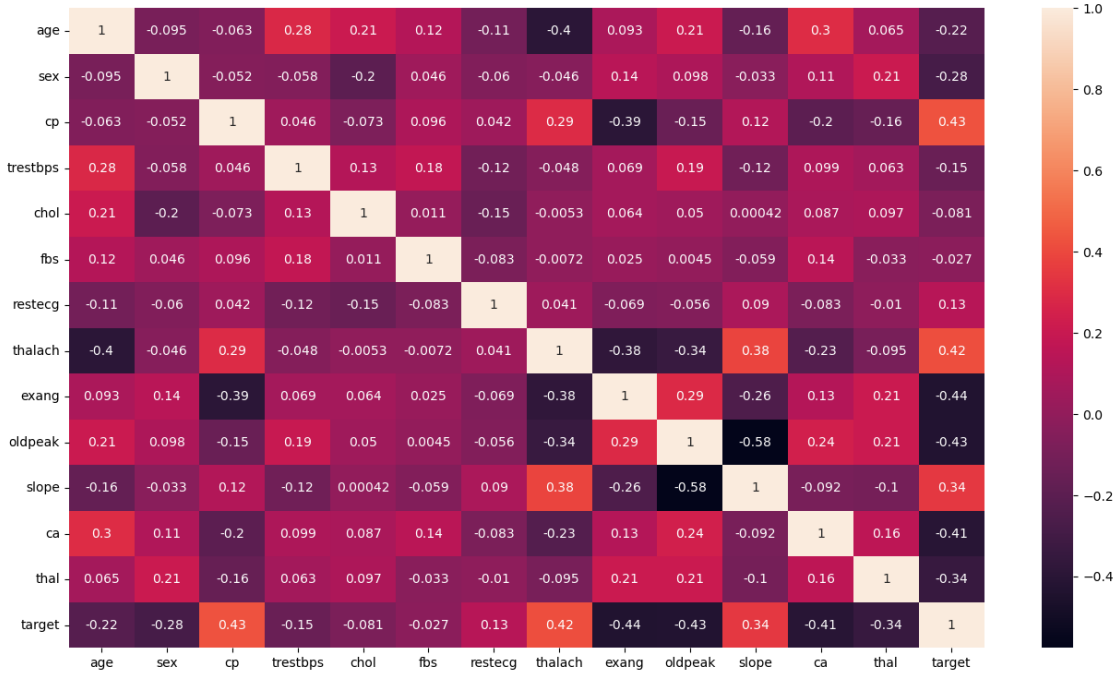
[5]:
```
data.describe() # basic descriptive statistics of the dataframe
```

[5]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  302.00000  302.000000  302.000000  302.000000  302.000000  302.000000
mean    54.42053    0.682119    0.963576  131.602649  246.500000    0.149007
std      9.04797    0.466426    1.032044   17.563394   51.753489    0.356686
min     29.00000    0.000000    0.000000   94.000000  126.000000    0.000000
```

```
25%     48.00000    0.000000    0.000000  120.000000  211.000000    0.000000
50%     55.50000    1.000000    1.000000  130.000000  240.500000    0.000000
75%     61.00000    1.000000    2.000000  140.000000  274.750000    0.000000
max     77.00000    1.000000    3.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  302.000000  302.000000  302.000000  302.000000  302.000000  302.000000
mean     0.526490  149.569536    0.327815    1.043046    1.397351    0.718543
std      0.526027   22.903527    0.470196    1.161452    0.616274    1.006748
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.250000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  152.500000    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  302.000000  302.000000
mean     2.314570    0.543046
std      0.613026    0.498970
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
```

[6]:
```
plt.figure(figsize=(16,9))
sns.heatmap(data.corr(),annot=True) # see correlation between features and␣
 ↪features with response variable
```

[6]:
```
<AxesSubplot:>
```



[7]:
```
plt.figure(figsize=(16,9))
sns.pairplot(data) # see distribution between each pair of features and
 ↪features with response variable
```

[7]: <seaborn.axisgrid.PairGrid at 0x1a50660e790>

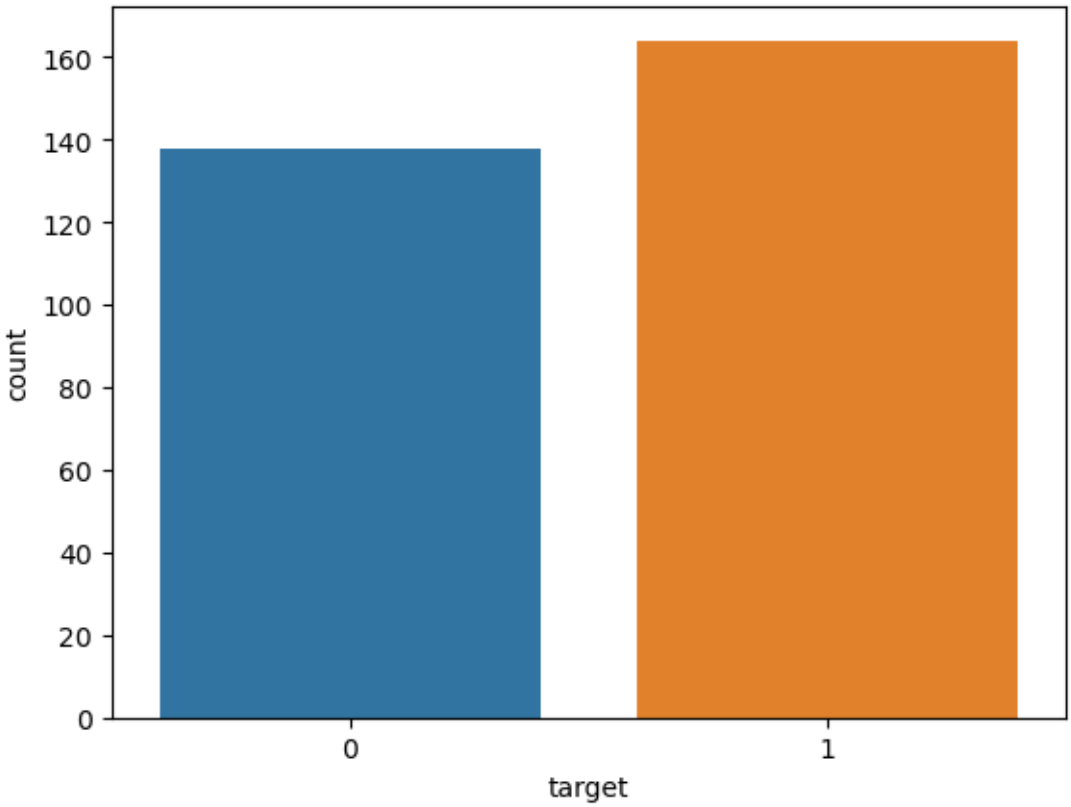
<Figure size 1600x900 with 0 Axes>

[8]:
```
# Look at how the response variable is splitted to avoid fitting the model to just one value
target_counts = data['target'].value_counts() # count response variable values to see if they are not unbalanced
target_ratios = target_counts/len(data)       # get the same information in a ratios format
print(target_counts)
print(50*'_')
print(target_ratios)
sns.countplot(x=data['target'])
```

```
1    164
0    138
```

```
Name: target, dtype: int64
--------------------------------------------------
1    0.543046
0    0.456954
Name: target, dtype: float64
```

[8]: <AxesSubplot:xlabel='target', ylabel='count'>



4 Prepare Data

[9]:
```
# Make categorical data to the corresponding features
categorical_features = ['sex','cp','fbs','restecg','exang','thal','target'] #␣
 ↪columns containing categorical features
data[categorical_features] = data[categorical_features].astype('category')  #␣
 ↪converting dtype to categorical
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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    category
 2   cp        302 non-null    category
 3   trestbps  302 non-null    int64
 4   chol      302 non-null    int64
 5   fbs       302 non-null    category
 6   restecg   302 non-null    category
 7   thalach   302 non-null    int64
 8   exang     302 non-null    category
 9   oldpeak   302 non-null    float64
 10  slope     302 non-null    int64
 11  ca        302 non-null    int64
 12  thal      302 non-null    category
 13  target    302 non-null    category
dtypes: category(7), float64(1), int64(6)
memory usage: 30.1 KB
```

[10]:
```
# Standardize numerical features
numeric_features = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak', 'slope',␣
 ↪'ca'] # columns containing numerical features
scaler = StandardScaler()          # initialize scaler
scaler.fit(data[numeric_features]) # fit the scaler to the selected numeric␣
 ↪columns
data[numeric_features] = scaler.transform(data[numeric_features]) # standardize␣
 ↪the numeric columns
data.describe() # basic descriptive statistics of the dataframe
```

[10]:

	age	trestbps	chol	thalach	oldpeak	\
count	3.020000e+02	3.020000e+02	3.020000e+02	3.020000e+02	3.020000e+02	
mean	-2.721103e-16	-6.690748e-16	-4.411482e-18	-5.418771e-16	8.822964e-17	
std	1.001660e+00	1.001660e+00	1.001660e+00	1.001660e+00	1.001660e+00	
min	-2.814192e+00	-2.144521e+00	-2.332210e+00	-3.436149e+00	-8.995441e-01	
25%	-7.107878e-01	-6.617119e-01	-6.870826e-01	-7.137164e-01	-8.995441e-01	
50%	1.195033e-01	-9.140084e-02	-1.161266e-01	1.281605e-01	-2.096081e-01	
75%	7.283833e-01	4.789102e-01	5.467629e-01	7.185677e-01	4.803280e-01	
max	2.499671e+00	3.900776e+00	6.145034e+00	2.292987e+00	4.447460e+00	

	slope	ca
count	3.020000e+02	3.020000e+02
mean	-1.158014e-16	-1.139633e-17
std	1.001660e+00	1.001660e+00
min	-2.271182e+00	-7.149112e-01
25%	-6.458337e-01	-7.149112e-01
50%	-6.458337e-01	-7.149112e-01
75%	9.795144e-01	2.800344e-01
max	9.795144e-01	3.264871e+00

[11]:
```
X = data.drop('target',axis=1) # split the features from the labels
y = data['target']             # split the labels from the features
print(X.shape,y.shape)
```

```
(302, 13) (302,)
```

5 ML Models

[12]:
```
clfs = ([LogisticRegression(solver='liblinear', penalty='l2'),
         RandomForestClassifier(criterion='entropy',max_depth=5)]) # initialize␣
 ↪proposed classifiers
```

5.1 K-Fold Cross Validation

[13]:
```
kf   = StratifiedKFold(n_splits=5, shuffle=True, random_state=0) # initialize␣
 ↪k-folds
acc_valid = []                                                   # store␣
 ↪validation accuracy
for clf in clfs:
    warnings.filterwarnings('ignore', category=FutureWarning)
    scrs = cross_val_score(clf, X, y, cv=kf, scoring='accuracy') # compute␣
 ↪k-fold cross validation scores
    acc_valid.append(scrs.mean())
    print(70*'_')
    print(clf)
    print(f'Scores: {scrs}')
    print(f'Scores mean: {scrs.mean():.4f}')
```

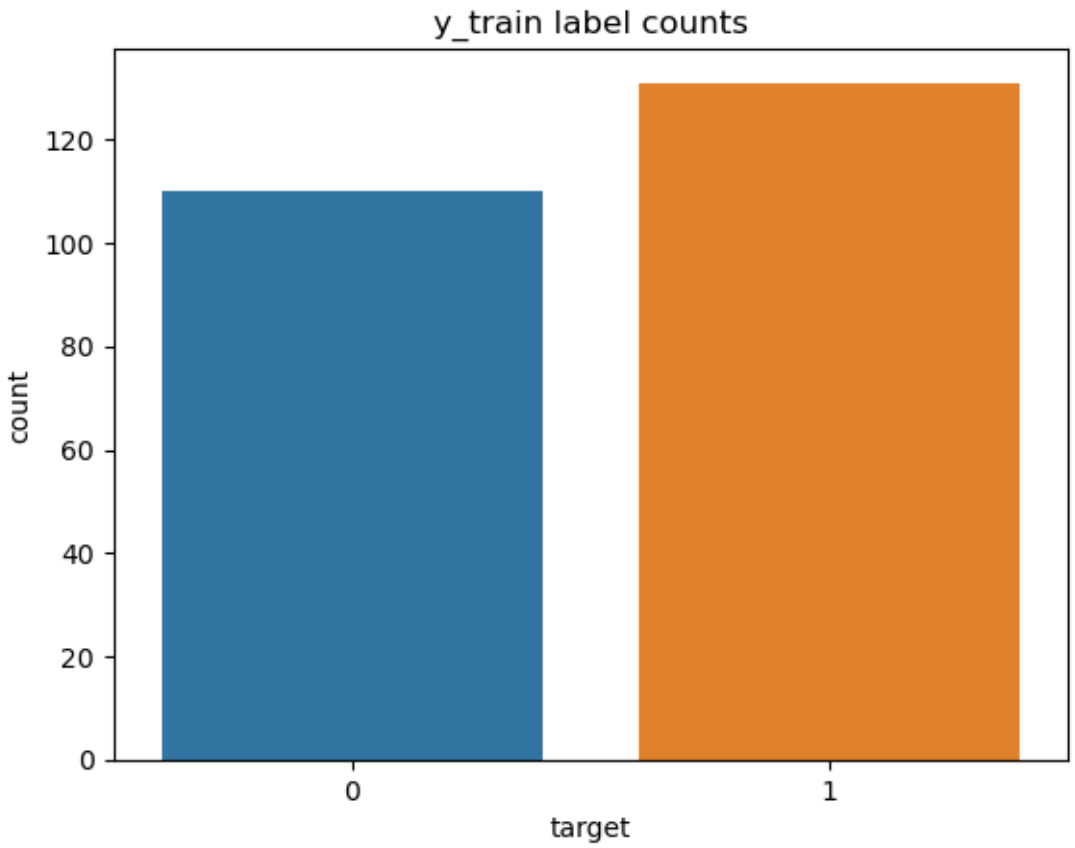
```
----------------------------------------------------------------------
LogisticRegression(solver='liblinear')
Scores: [0.91803279 0.78688525 0.75       0.86666667 0.83333333]
Scores mean: 0.8310
----------------------------------------------------------------------
RandomForestClassifier(criterion='entropy', max_depth=5)
Scores: [0.90163934 0.81967213 0.8        0.78333333 0.8       ]
Scores mean: 0.8209
```

5.2 Split data

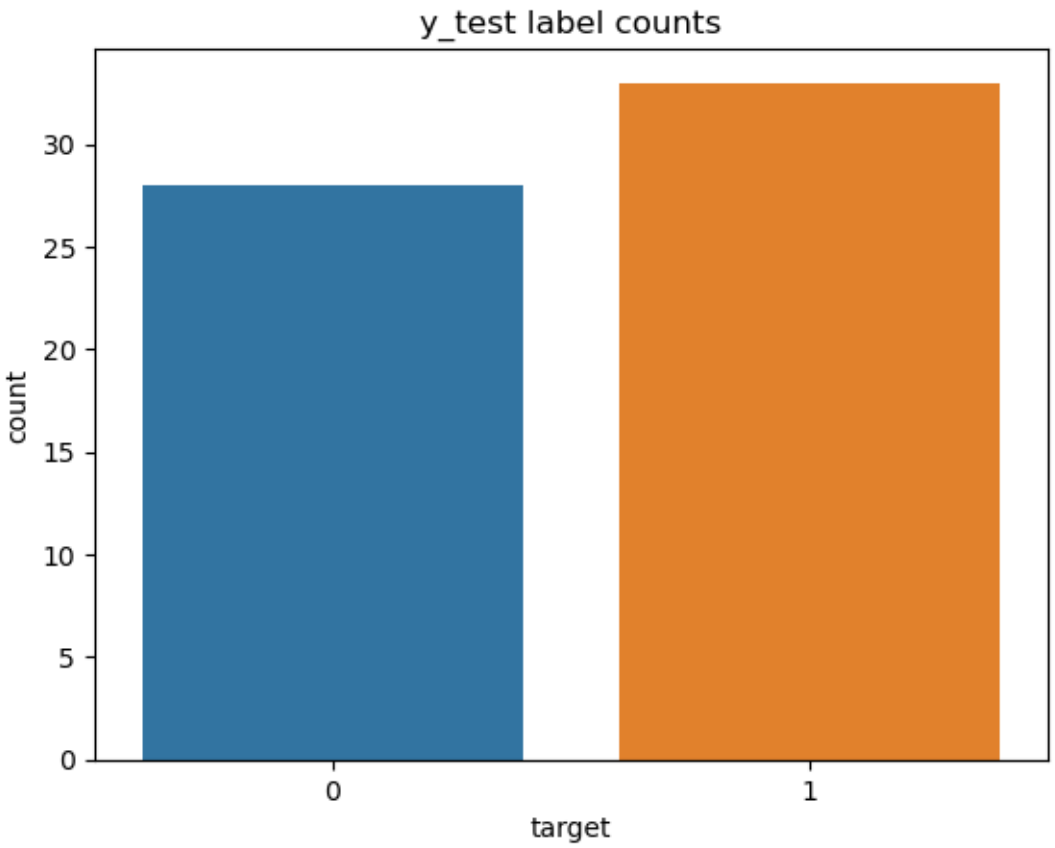
[14]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.2,
                                                    stratify=y, random_state=0)␣
 ↪# split data in training and testing sets
y_sets = {'y_train': y_train, 'y_test': y_test}

for y_name, y_set in y_sets.items():
    y_counts = y_set.value_counts() # count response variable values to see if␣
 ↪they are not unbalanced
```

```
    y_ratios = y_counts/len(y_set)  # get the same information in a ratios␣
↪format
    print(50*'_')
    print(y_name)
    print('Set sizes')
    print(y_set.shape,y_set.shape)
    print('Label counts')
    print(y_counts)
    print('Label ratios')
    print(y_ratios)
    sns.countplot(x=y_set)
    plt.title(str(y_name)+' label counts')
    plt.show()
```

```
--------------------------------------------------
y_train
Set sizes
(241,) (241,)
Label counts
1    131
0    110
Name: target, dtype: int64
Label ratios
1    0.543568
0    0.456432
Name: target, dtype: float64
```




```
--------------------------------------------------
y_test
Set sizes
(61,) (61,)
Label counts
1    33
0    28
Name: target, dtype: int64
Label ratios
1    0.540984
0    0.459016
Name: target, dtype: float64
```



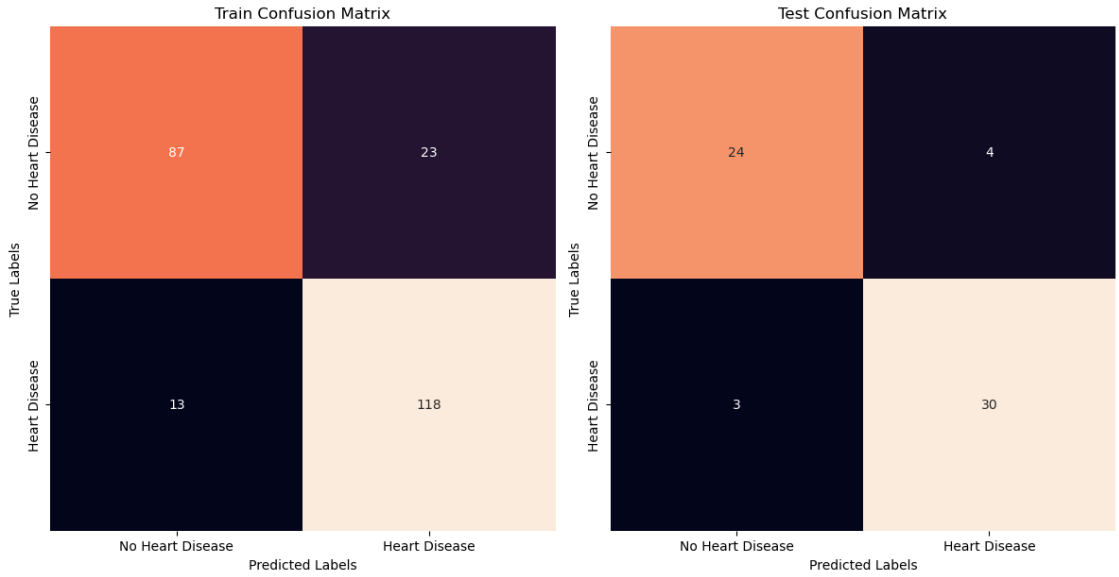
6 Models evaluation

[15]:
```
def plt_confmat(y_true, y_pred, title, ax):
    cm = confusion_matrix(y_true, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', square=True, cbar= False,
                xticklabels=['No Heart Disease', 'Heart Disease'],
                yticklabels=['No Heart Disease', 'Heart Disease'],
                ax=ax)
    ax.set_xlabel('Predicted Labels')
    ax.set_ylabel('True Labels')
    ax.set_title(title)
```

[20]:
```
acc_train = []
acc_test  = []
for clf in clfs:
    clf.fit(X_train, y_train)         # train classifier (fit to training data)␣
 ↪
    y_pred = clf.predict(X_test)      # compute the predictions (use the␣
 ↪trained model on test data)
```

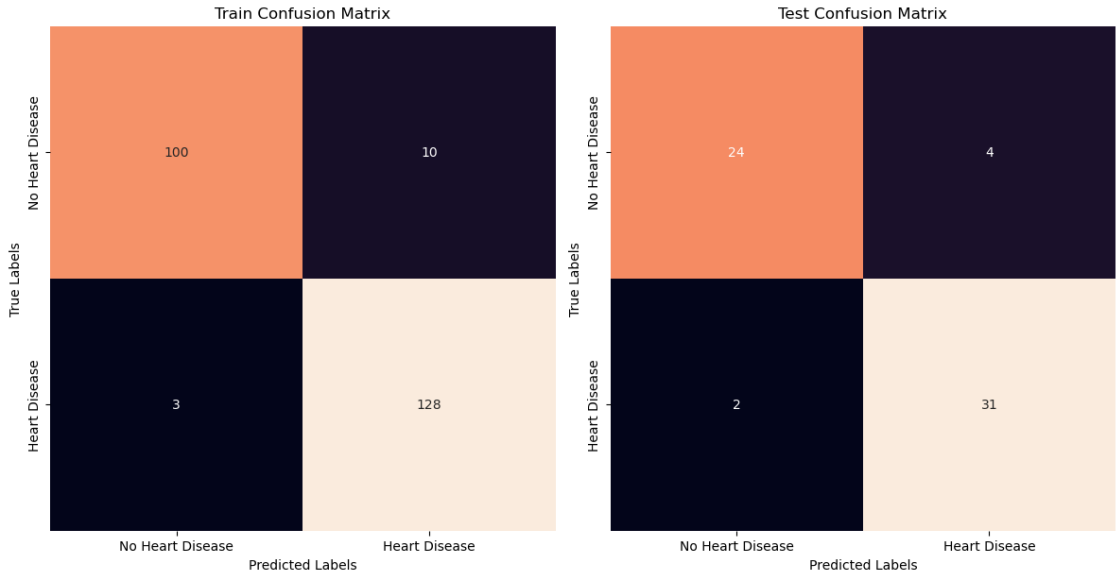
```
    train_pred = clf.predict(X_train) # compute the predictions (use the␣
↪trained model on train data)
    # Train and test scores
    train_score = accuracy_score(y_train, train_pred)
    test_score  = accuracy_score(y_test, y_pred)
    acc_train.append(train_score)
    acc_test.append(test_score)
    # Model evaluation metrics
    print(60*'_')
    print(clf)
    print(f'Train Accuracy: {100*train_score:.2f}','%')
    print(f'Test Accuracy : {100*test_score:.2f}','%')
    print('Report:\n',classification_report(y_test, y_pred))
    # Visualize Confusion Matrices
    fig, axes = plt.subplots(1, 2, figsize=(12,6))
    plt_confmat(y_train, train_pred, 'Train Confusion Matrix', axes[0])
    plt_confmat(y_test, y_pred, 'Test Confusion Matrix', axes[1])
    plt.tight_layout()
    plt.show()
```

```
------------------------------------------------------------
LogisticRegression(solver='liblinear')
Train Accuracy: 85.06 %
Test Accuracy : 88.52 %
Report:
               precision    recall  f1-score   support

           0       0.89      0.86      0.87        28
           1       0.88      0.91      0.90        33

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



RandomForestClassifier(criterion='entropy', max_depth=5)
Train Accuracy: 94.61 %
Test Accuracy : 90.16 %
Report:

	precision	recall	f1-score	support
0	0.92	0.86	0.89	28
1	0.89	0.94	0.91	33
accuracy			0.90	61
macro avg	0.90	0.90	0.90	61
weighted avg	0.90	0.90	0.90	61



6.1 Subset scores

[21]:
```
df = pd.DataFrame(columns=['Logistic Regression', 'Random Forest'])
df.loc[0] = acc_train
df.loc[1] = acc_valid
df.loc[2] = acc_test
df.loc[3] = [1-acc for acc in acc_train]
df.loc[4] = [1-acc for acc in acc_valid]
df.loc[5] = [1-acc for acc in acc_test]
df.loc[6] = df.iloc[0:3].mean()
df.loc[7] = df.iloc[3:6].mean()
rows = {
    0: 'Training Accuracy',
    1: 'Validation Accuracy',
    2: 'Test Accuracy',
    3: 'Training Error',
    4: 'Validation Error',
    5: 'Test Error',
    6: 'Average Accuracy',
    7: 'Average Error'
}
df = df.rename(index=rows)
df = df.round(4)
df
```

[21]:

	Logistic Regression	Random Forest
Training Accuracy	0.8506	0.9461
Validation Accuracy	0.8310	0.8209

```
Test Accuracy                0.8852          0.9016
Training Error               0.1494          0.0539
Validation Error             0.1690          0.1791
Test Error                   0.1148          0.0984
Average Accuracy             0.8556          0.8895
Average Error                0.1444          0.1105
```

[22]:
```
plt.figure(figsize=(8,4.5))
df[0:3].plot(kind='bar',rot=0,alpha=.5)
df[3:6].plot(kind='bar',rot=0,ax=plt.gca(), alpha=1)
plt.legend(title='Classifiers', loc='upper left', bbox_to_anchor=(1, 1),
           labels=['Log Regression Accuracy','Random Forest Accuracy',
                   'Log Regression Error   ','Random Forest Error'])
plt.xlabel('Data subsets')
plt.xticks([0,1,2],['Train','Validation','Test'])
plt.ylabel('Accuracy/Error')
plt.title('Accuracy and Error for data subsets')
plt.show()
```

```
<Figure size 800x450 with 0 Axes>
```