

KNN,SVM & RANDOM FOREST

Final Project Project

Course: CS-634

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Libraries used:

numpy, random and pandas for reading files and display of data in data frame.

- Imported KNeighborsClassifier from sklearn.neighbors
- Imported StandardScaler , MinMaxScaler from sklearn.preprocessing
- Imported train_test_split from sklearn.model_selection
- Imported classification_report , confusion_matrix, accuracy_score, f1_score from sklearn.metrics
- Imported LabelEncoder, StandardScaler from sklearn.preprocessing
- Imported RandomForestClassifier from sklearn.ensemble
- Imported StratifiedKFold, RandomizedSearchCV from sklearn.model_selection

➔ Used all these libraries for classification according to given model

```
# Importing the important libraries

import numpy as np
import random
import pandas as pd

from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler , MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report , confusion_matrix, accuracy_score, f1_score

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import StratifiedKFold, RandomizedSearchCV

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

File (dataset) Input:

Here, I have loaded my data set using pandas library and displayed it.

- ➔ df.shape tells how many rows and columns are there
- ➔ df.isnull().sum() tells if there is any null value in data and if it is then given the sum of the number of items that has null values
- ➔ df.describe() shows the actual data stored in your csv file

▶ # Loading the dataset

```
df = pd.read_csv('heart.csv')
df.head()
```

↳

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
0	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
1	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
2	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
3	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
4	54	M	NAP	150	195	0	Normal	122	N	0.0	Up	0

▶ print(df.shape)
print(df["HeartDisease"].value_counts())

↳ (918, 12)
1 508
0 410
Name: HeartDisease, dtype: int64

[53] df.isnull().sum()

```
Age      0
Sex      0
ChestPainType  0
RestingBP  0
Cholesterol  0
FastingBS  0
RestingECG  0
MaxHR     0
ExerciseAngina  0
Oldpeak   0
ST_Slope  0
HeartDisease  0
dtype: int64
```

[54] df.describe()

↳

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	HeartDisease
count	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000
mean	53.510893	132.396514	198.799564	0.233115	136.809368	0.887364	0.553377
std	9.432617	18.514154	109.384145	0.423046	25.460334	1.066570	0.497414
min	28.000000	0.000000	0.000000	0.000000	60.000000	-2.600000	0.000000
25%	47.000000	120.000000	173.250000	0.000000	120.000000	0.000000	0.000000
50%	54.000000	130.000000	223.000000	0.000000	138.000000	0.600000	1.000000
75%	60.000000	140.000000	267.000000	0.000000	156.000000	1.500000	1.000000
max	77.000000	200.000000	603.000000	1.000000	202.000000	6.200000	1.000000

```
[55] df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Age                    918 non-null    int64
1   Sex                    918 non-null    object
2   ChestPainType          918 non-null    object
3   RestingBP              918 non-null    int64
4   Cholesterol             918 non-null    int64
5   FastingBS              918 non-null    int64
6   RestingECG             918 non-null    object
7   MaxHR                  918 non-null    int64
8   ExerciseAngina         918 non-null    object
9   Oldpeak                918 non-null    float64
10  ST_Slope               918 non-null    object
11  HeartDisease           918 non-null    int64
dtypes: float64(1), int64(6), object(5)
memory usage: 86.2+ KB
```

Separating the dependent and independent columns

Here, X is my training data and Y is my label.

```
[56] # Separating the dependent and the independent columns

X = df.drop("HeartDisease" , axis = 1)
y = df['HeartDisease']
```

Separating the numerical and the categorical columns

Here, cat_cols brings the categorical data like those that don't have any numerical value and num_cols prints those labels that has numerical values to it.

```
✓ [58] print(cat_cols , num_cols)
0s ['Sex', 'ChestPainType', 'RestingECG', 'ExerciseAngina', 'ST_Slope'] ['Age', 'RestingBP', 'Cholesterol', 'FastingBS', 'MaxHR', 'Oldpeak']
```

```

▶ # Separating the numerical and the categorical columns

cat_cols = list(df.select_dtypes(include=['object']).columns)
num_cols = []

for i in list(X.columns):
    if i not in cat_cols:
        num_cols.append(i)

```

Getting mean and percentile of data

```

▶ normal_cols = ["Age", "MaxHR", "RestingBP"]
for col in normal_cols:
    mean = np.mean(df[col])
    std = np.std(df[col])
    lower_range = mean - (3*std)
    upper_range = mean + (3*std)
    df[col] = np.where(((df[col] < lower_range) | (df[col] > upper_range))
                      , random.randint(int(lower_range), int(upper_range)), df[col])

[60] IQR = np.percentile(df["Cholesterol"],75) - np.percentile(df["Cholesterol"],25)
lower_bound = np.percentile(df["Cholesterol"],25) - 1.5 * IQR
upper_bound = np.percentile(df["Cholesterol"],75) + 1.5 * IQR
median_cholesterol = np.median(df["Cholesterol"])

df["Cholesterol"] = np.where(((df["Cholesterol"] > upper_bound) | (df["Cholesterol"] < lower_bound))
                           , random.randint(int(np.percentile(df["Cholesterol"],25)),
                                             int(np.percentile(df["Cholesterol"],75))), df["Cholesterol"])

```

Separating the test and training data set

Here, test_size=0.2 means that 20% is the testing data and rest 80% is the training data.

```

[61] # Separating the train and test dataset
x_train, x_test, y_train, y_test = train_test_split(X, y, stratify = y , random_state=42, test_size=0.2)

```

Standardising the features of training and testing dataset

```

✓ [63] # Standardising the features of training and testing dataset
0s

scaler = StandardScaler()
scaler.fit(X[num_cols])
X[num_cols] = scaler.transform(X[num_cols])

```

```
✓ [64] X = pd.get_dummies(data = X , drop_first=True)
```

Converted categorical data also into numerical data and now again separating the test and training data

```
✓ # Separating the train and test dataset
x_train,x_test,y_train,y_test = train_test_split(X,y,stratify = y , random_state=42,test_size=0.2)
```

```
✓ x_train[:3]
```

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	Sex_M	ChestPainType_ATA	ChestPainType_NAP	ChestPainType_TA	RestingECG
485	1.006537	0.356867	0.166481	1.813758	-0.346192	0.293283	1	1	0	0	
486	0.157954	-1.210356	0.139040	1.813758	1.697314	-0.457194	1	1	0	0	
117	0.582246	-0.129513	1.273277	1.813758	-0.267596	0.574711	0	0	0	0	

KNN Algorithm:

▼ KNN Algorithm

```
[67] knn = KNeighborsClassifier(n_neighbors=7)
      knn.fit(x_train,y_train)
      y_pred_knn = knn.predict(x_test)

      print(knn.score(x_test,y_test))
      print(classification_report(y_test,y_pred_knn))
      print(confusion_matrix(y_test,y_pred_knn))
      #compare with table
```

```
0.8967391304347826
```

	precision	recall	f1-score	support
0	0.90	0.87	0.88	82
1	0.90	0.92	0.91	102
accuracy			0.90	184
macro avg	0.90	0.89	0.90	184
weighted avg	0.90	0.90	0.90	184

```
[[71 11]
 [ 8 94]]
```

We have used the built in functions extracting from library for this algorithm to set up the training data and labels and printing out the report that shows performance metrics. It also prints the accuracy of the algorithm and prints out the confusion matrix.

Refer to this diagram to interpret results for confusion matrix:

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Therefore, 71 is the TP, 11 is FP, 8 is FN and 94 is TN.

SVM Algorithm:

▼ SVM Algorithm

```
✓ [68] from sklearn.svm import SVC  
0s classifier = SVC(kernel='rbf', random_state=27)  
classifier.fit(x_train, y_train)
```

```
SVC(random_state=27)
```

```
✓ [69] y_pred_svm = classifier.predict(x_test)  
0s
```

```
✓ [70] print(classifier.score(x_test,y_test))  
0s print(classification_report(y_test, y_pred_svm))  
print(confusion_matrix(y_test,y_pred_svm))
```

```
0.8858695652173914
```

	precision	recall	f1-score	support
0	0.89	0.85	0.87	82
1	0.89	0.91	0.90	102
accuracy			0.89	184
macro avg	0.89	0.88	0.88	184
weighted avg	0.89	0.89	0.89	184

```
[[70 12]  
 [ 9 93]]
```

We have used the built in functions extracting from library for this algorithm to set up the training data and labels and printing out the report that shows performance metrics. It also prints the accuracy of the algorithm and prints out the confusion matrix.

Refer to this diagram to interpret results for confusion matrix:

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Therefore, 70 is the TP, 12 is FP, 9 is FN and 93 is TN.

Random Forest Algorithm:

Random Forest Algorithm

```

[71] randomforest = RandomForestClassifier()
randomforest.fit(x_train,y_train)
y_pred_rf = randomforest.predict(x_test)

```

```

[72] print('Train Accuracy %s' % round(accuracy_score(y_test, y_pred_rf),2))
print('Train F1-score %s' % f1_score(y_test, y_pred_rf, average=None))
print(classification_report(y_test, y_pred_rf))
print("Confusion Matrix:\n",confusion_matrix(y_test, y_pred_rf))

```

```

Train Accuracy 0.86
Train F1-score [0.84146341 0.87254902]
              precision    recall  f1-score   support

     0       0.84         0.84         0.84         82
     1       0.87         0.87         0.87        102

 accuracy          0.86         0.86         0.86        184
 macro avg         0.86         0.86         0.86        184
 weighted avg      0.86         0.86         0.86        184

Confusion Matrix:
[[69 13]
 [13 89]]

```


We have used the built in functions extracting from library for this algorithm to set up the training data and labels and printing out the report that shows performance metrics. It also prints the accuracy of the algorithm and prints out the confusion matrix.

Refer to this diagram to interpret results for confusion matrix:

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Therefore, 69 is the TP, 13 is FP, 13 is FN and 89 is TN.

10-folds execution Method:

Declaring list for accuracy, tss, precision:

```
▶ knn_acc = []  
knn_tss = []  
knn_prec = []  
knn_tn = []  
knn_tp = []  
knn_fn = []  
knn_fp = []  
  
svm_acc = []  
svm_tss = []  
svm_prec = []  
svm_tn = []  
svm_tp = []  
svm_fn = []  
svm_fp = []  
  
randmf_acc = []  
randmf_tss = []  
randmf_prec = []  
randmf_tn = []  
randmf_tp = []  
randmf_fn = []  
randmf_fp = []
```

```
for i in range(0,11):  
  
    x_train,x_test,y_train,y_test = train_test_split(X,y,stratify = y , random_state=42,test_size=0.3)  
  
    ## Running KNN Algorithm  
    knn.fit(x_train,y_train)  
    y_pred_knn = knn.predict(x_test)  
  
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred_knn).ravel()  
    knn_tn.append(tn)  
    knn_tp.append(fp)  
    knn_fn.append(fn)  
    knn_fp.append(tp)  
  
    acck = (tp + tn) / (tn + fp + fn + tp)  
    tss = (tp / (tp - fn)) - (fp / (fp + tn))  
    precision = tp / (tp + fp)  
  
    knn_acc.append(acck)  
    knn_tss.append(tss)  
    knn_prec.append(precision)
```

```
## Running Random Forest Algorithm
randomforest.fit(x_train,y_train)
y_pred_rf = randomforest.predict(x_test)

tn, fp, fn, tp = confusion_matrix(y_test, y_pred_rf).ravel()
randmf_tn.append(tn)
randmf_tp.append(fp)
randmf_fn.append(fn)
randmf_fp.append(tp)

accrf = (tp + tn) / (tn + fp + fn + tp)
tss = (tp / (tp - fn)) - (fp / (fp + tn))
precision = tp / (tp + fp)

randmf_acc.append(accrf)
randmf_tss.append(tss)
randmf_prec.append(precision)
```

```
## Running SVM Algorithm
classifier.fit(x_train, y_train)
y_pred_svm = classifier.predict(x_test)

tn, fp, fn, tp = confusion_matrix(y_test, y_pred_svm).ravel()
svm_tn.append(tn)
svm_tp.append(fp)
svm_fn.append(fn)
svm_fp.append(tp)

accs = (tp + tn) / (tn + fp + fn + tp)
tss = (tp / (tp - fn)) - (fp / (fp + tn))
precision = tp / (tp + fp)

svm_acc.append(accs)
svm_tss.append(tss)
svm_prec.append(precision)
```

Average:

✓
0s

```
## Average:
avg_knn_acc = sum(knn_acc) / len(knn_acc)
avg_knn_tss = sum(knn_tss) / len(knn_tss)
avg_knn_prec = sum(knn_prec) / len(knn_prec)
avg_knn_tn = sum(knn_tn) / len(knn_tn)
avg_knn_tp = sum(knn_tp) / len(knn_tp)
avg_knn_fn = sum(knn_fn) / len(knn_fn)
avg_knn_fp = sum(knn_fp) / len(knn_fp)
```

✓
1s

```
[75] ## Average:
avg_svm_acc = sum(svm_acc) / len(svm_acc)
avg_svm_tss = sum(svm_tss) / len(svm_tss)
avg_svm_prec = sum(svm_prec) / len(svm_prec)
avg_svm_tn = sum(svm_tn) / len(svm_tn)
avg_svm_tp = sum(svm_tp) / len(svm_tp)
avg_svm_fn = sum(svm_fn) / len(svm_fn)
avg_svm_fp = sum(svm_fp) / len(svm_fp)
```

✓
0s

```
## Average:
avg_randmf_acc = sum(randmf_acc) / len(randmf_acc)
avg_randmf_tss = sum(randmf_tss) / len(randmf_tss)
avg_randmf_prec = sum(randmf_prec) / len(randmf_prec)
avg_randmf_tn = sum(randmf_tn) / len(randmf_tn)
avg_randmf_tp = sum(randmf_tp) / len(randmf_tp)
avg_randmf_fn = sum(randmf_fn) / len(randmf_fn)
avg_randmf_fp = sum(randmf_fp) / len(randmf_fp)
```

✓
0s

```
table_cols = {'Algorithm': ['KNN', 'SVM', 'Random Forest'], 'TP': [avg_knn_tp, avg_svm_tp, avg_randmf_tp], 'FP': [avg_knn_fp, avg_svm_fp, avg_randmf_fp], 'TN': [avg_knn_tn, avg_svm_tn, avg_randmf_tn], 'FN': [avg_knn_fn, avg_svm_fn, avg_randmf_fn], 'ACC': [avg_knn_acc, avg_svm_acc, avg_randmf_acc], 'TSS': [avg_knn_tss, avg_svm_tss, avg_randmf_tss], 'Precision': [avg_knn_prec, avg_svm_prec, avg_randmf_prec]}
```

Table:

This is the final table that shows accuracy of algorithm after running it ten times.

```
[80] table_cols1 = pd.DataFrame.from_dict(table_cols)
```

```
table_cols1
```

	Algorithm	TP	FP	FN	TN	ACC	TSS	Precision
0	KNN	18.000000	137.000000	16.000000	105.000000	0.876812	0.985890	0.883871
1	SVM	14.000000	143.000000	10.000000	109.000000	0.913043	0.961367	0.910828
2	Random Forest	15.818182	139.818182	13.181818	107.181818	0.894928	0.975593	0.898436

Result:

Which algorithm performs better and why? Justify your answer

- ➔ Accuracy for KNN was coming 90 and after 10 folds it is coming as 87
- ➔ Accuracy for SVM was coming 89 and after 10 folds it is coming as 91
- ➔ Accuracy for Random Forest was coming 86 and after 10 folds it is coming as 89

SVM algorithm performs better and you can see that after training the algorithm 10 times the accuracy of it is better. It is also memory efficient. It also performs faster prediction.

