EXERCISE 14

Download heart disease dataset heart.csv in Exercise folder and do following, (credits of dataset: https://www.kaggle.com/fedesoriano/heart-failure-prediction)

1. Load heart disease dataset in pandas dataframe
2. Remove outliers using Z score. Usual guideline is to remove anything that has Z score > 3 formula or Z score < -3
3. Convert text columns to numbers using label encoding and one hot encoding
4. Apply scaling
5. Build a classification model using various methods (SVM, logistic regression, random forest) and check which model gives you the best accuracy
6. Now use PCA to reduce dimensions, retrain your model and see what impact it has on your model in terms of accuracy. Keep in mind that many times doing PCA reduces the accuracy but computation is much lighter and that's the trade off you need to consider while building models in real life

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [6]:
```
df = pd.read_csv('heart.csv')
df.head()
```

Out[6]:

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

In [7]:
```
df.shape
```

Out[7]:
```
(918, 12)
```

In [8]:
```
np.unique(df['HeartDisease'])
```

Out[8]:
```
array([0, 1], dtype=int64)
```

In [12]:
```
df.describe()
```

Out[12]:

	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

Handling Outliers

Now, lets remove some outliers, one way we can do it is by checking or filtering out outliers that significantly differ from the rest of the dataset, to do this u can check by filtering out the rows for each column where the values are greater than 3 standard deviations above the mean.

Mean :

The mean value is the average value

Standard Deviation :

1. Standard deviation is a number that describes how spread out the values are.
2. A low standard deviation means that most of the numbers are close to the mean (average) value.
3. A high standard deviation means that the values are spread out over a wider range.

For example, lets take the Cholesterol column, this column **Mean is 198** and **Standard Deviation is 109** as seen above, now we can filter out the rows that are three times the standard deviation above the mean by doing
`mean + 3 * std`

which is `198 + 3 * 109 = 525`

So any rows above 525 Cholesterol is an outliers since its 3 times above the mean of the column

Below is how you do it

In [20]:
```
df[df.Cholesterol>(df.Cholesterol.mean()+3*df.Cholesterol.std())]
```

Out[20]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	Hea
76	32	M	ASY	118	529	0	Normal	130	N	0.0	Flat	
149	54	M	ASY	130	603	1	Normal	125	Y	1.0	Flat	
616	67	F	NAP	115	564	0	LVH	160	N	1.6	Flat	

As we can see above that there are 3 rows which are 3 times std above the mean, means above 525.

Now, lets check the shape of our entire Dataframe first

In [11]:
```
df.shape
```

Out[11]: (918, 12)

You can see we have 918 rows, now lets only take rows from the Dataframe where the Cholesterol value is below 525 and store it in a new Dataframe called **df1**

In [21]:
```
df1 = df[df.Cholesterol<=(df.Cholesterol.mean()+3*df.Cholesterol.std())]
df1.shape
```

Out[21]: (915, 12)

As seen above now in **df1** Dataframe we have 915 rows since other 3 are outliers as seen previously.

Now, we can do the same thing for the rest of the columns, we will check which other numeric columns have outliers that are 3 times std above the mean and then store the non-outliers in new dataframe

In [27]:
```
df[df.MaxHR>(df.MaxHR.mean()+3*df.MaxHR.std())]
```

Out[27]:

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartD

As seen above, there are no outliers in the MaxHR column, so lets check another column

In [28]:
```
df[df.FastingBS>(df.FastingBS.mean()+3*df.FastingBS.std())]
```

Out[28]:

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartD

Even the FastingBS column has no outliers

In [29]:
```
df[df.Oldpeak>(df.Oldpeak.mean()+3*df.Oldpeak.std())]
```

Out[29]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	Hea
166	50	M	ASY	140	231	0	ST	140	Y	5.0	Flat	
702	59	M	TA	178	270	0	LVH	145	N	4.2	Down	
771	55	M	ASY	140	217	0	Normal	111	Y	5.6	Down	
791	51	M	ASY	140	298	0	Normal	122	Y	4.2	Flat	
850	62	F	ASY	160	164	0	LVH	145	N	6.2	Down	
900	58	M	ASY	114	318	0	ST	140	N	4.4	Down	

We can see that the Oldpeak column has 6 outliers, so lets store the rows which are not outliers in another dataframe

In [30]:
```
df2 = df1[df1.Oldpeak<=(df1.Oldpeak.mean()+3*df1.Oldpeak.std())]
df2.shape
```

Out[30]: (909, 12)

We stored it in **df2** now and u can see we have 909 rows now from 915 since 6 of them were outliers.

Lets do the same with other columns quickly!

In [34]:
```
df[df.RestingBP>(df.RestingBP.mean()+3*df.RestingBP.std())]
```

Out[34]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	Hea
109	39	M	ATA	190	241	0	Normal	106	N	0.0	Up	
241	54	M	ASY	200	198	0	Normal	142	Y	2.0	Flat	
365	64	F	ASY	200	0	0	Normal	140	Y	1.0	Flat	
399	61	M	NAP	200	0	1	ST	70	N	0.0	Flat	
592	61	M	ASY	190	287	1	LVH	150	Y	2.0	Down	
732	56	F	ASY	200	288	1	LVH	133	Y	4.0	Down	
759	54	M	ATA	192	283	0	LVH	195	N	0.0	Up	

In [35]:
```
df3 = df2[df2.RestingBP<=(df2.RestingBP.mean()+3*df2.RestingBP.std())]
df3.shape
```

Out[35]: (902, 12)

Handling Text Columns

Now since we have a new dataframe called **df3** where we removed all the outliers from 3 columns,

Now, we can try to handle the Text columns such as Sex, CHestPainType, RestingECG, ExerciseAngina and ST_Slope.

First we will check unique values from ChestPainType, RestingECG, ExerciseAngina and ST_Slope and then do **Label Encoding**

In [36]:
```
df.ChestPainType.unique()
```

Out[36]: array(['ATA', 'NAP', 'ASY', 'TA'], dtype=object)

We can see ChestPainType column has 4 unique values, and they are **Nominal Variables** where the categories doesn't have any numeric ordering between each other like male,female or apple,banana,kiwi so its not a good idea to use **Label Encoding** here, we will just use **Dummy Variable** on it later

In [37]:
```
df.RestingECG.unique()
```

Out[37]: array(['Normal', 'ST', 'LVH'], dtype=object)

We can see above that the **RestingECG** column has 3 unique values and its an **Ordinal Variables** where the categories have some sort of numerical ordering between them, so we can use **Label Encoding** for this

In [38]:
```
df.ExerciseAngina.unique()
```

Out[38]: array(['N', 'Y'], dtype=object)

ExerciseAngina column has N or Y value which is also an **Ordinal Variables** so we can use **Label Encoding**

In [39]:
```
df.ST_Slope.unique()
```

Out[39]: array(['Up', 'Flat', 'Down'], dtype=object)

The **ST_Slope** is also an **Ordinal Variables** meaning we can do **Label Encoding** here as well.

So we will perform **Label Encoding** on **RestingECG, ExerciseAngina, ST_Slope** columns

Label Encoding

First we will copy all the data in **df3** to a new Dataframe called **df4**

In [40]:
```
df4 = df3.copy()
```

In [41]:
```
df4.head()
```

Out[41]:

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

Now, we will do **Label Encoding** as below where we just replace the value with 0,1,2 or 3 as below

In [42]:
```
df4.ExerciseAngina.replace(
    {
        'N': 0,
        'Y': 1
    },
    inplace=True
)

df4.ST_Slope.replace(
    {
        'Down': 1,
        'Flat': 2,
        'Up': 3
    },
    inplace=True
)

df4.RestingECG.replace(
    {
        'Normal': 1,
        'ST': 2,
        'LVH': 3
    },
    inplace=True
)
```

In [43]:
```
df4.head()
```

Out[43]:

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

Now we can see above that we have done **Label Encoding** on **RestingECG, ExerciseAngina, ST_Slope** columns.

Now, we are left with only two Text columns which are **Sex** and **ChestPainType** which were **Nominal Variables** so doing **Label Encoding** on them were not a good idea, so hence, we will perform **Dummy Variable** here and store it in another Dataframe again called **df5**

In [114…
```
df5 = pd.get_dummies(df4, drop_first=True).astype(int)
df5.head()
```

Out[114]:

	Age	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease	Sex_M	Che
0	40	140	289	0	1	172	0	0	3	0	1	
1	49	160	180	0	1	156	0	1	2	1	0	
2	37	130	283	0	2	98	0	0	3	0	1	
3	48	138	214	0	1	108	1	1	2	1	0	
4	54	150	195	0	1	122	0	0	3	0	1	

X and y splitting

In [48]:
```
X = df5.drop('HeartDisease', axis=1)
y = df5['HeartDisease']
```

Scaling

Standard Scaling

In [50]:
```
scale = StandardScaler()
```

In [55]:
```
X_scaled = scale.fit_transform(X)
X_scaled
```

Out[55]:
```
array([[-1.42896269,  0.46089071,  0.85238015, ...,  2.06757196,
        -0.53547478, -0.22914788],
       [-0.47545956,  1.5925728 , -0.16132855, ..., -0.4836591 ,
         1.86750159, -0.22914788],
       [-1.74679706, -0.10495034,  0.79657967, ...,  2.06757196,
        -0.53547478, -0.22914788],
       ...,
       [ 0.37209878, -0.10495034, -0.61703246, ..., -0.4836591 ,
        -0.53547478, -0.22914788],
       [ 0.37209878, -0.10495034,  0.35947592, ...,  2.06757196,
        -0.53547478, -0.22914788],
       [-1.64085227,  0.3477225 , -0.20782894, ..., -0.4836591 ,
         1.86750159, -0.22914788]])
```

MinMax Scaling

In [57]:
```
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler()
X_minmax = minmax.fit_transform(X)
X_minmax
```

Out[57]:
```
array([[0.24489796, 0.75675676, 0.55791506, ..., 1.        , 0.        ,
        0.        ],
       [0.42857143, 0.86486486, 0.34749035, ..., 0.        , 1.        ,
        0.        ],
       [0.18367347, 0.7027027 , 0.54633205, ..., 1.        , 0.        ,
        0.        ],
       ...,
       [0.59183673, 0.7027027 , 0.25289575, ..., 0.        , 0.        ,
        0.        ],
       [0.59183673, 0.7027027 , 0.45559846, ..., 1.        , 0.        ,
        0.        ],
       [0.20408163, 0.74594595, 0.33783784, ..., 0.        , 1.        ,
        0.        ]])
```

Train Test Splitting

In [203…
```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=30)
```

GridSearchCV

In [204…
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
```

In [205…
```
model_params = {
    'svm': {
```

```
        'model': SVC(gamma='auto'),
        'params' : {
            'C': [1,10,20],
            'kernel': ['rbf','linear']
        }
    },
    'random_forest': {
        'model': RandomForestClassifier(),
        'params' : {
            'n_estimators': [1,5,10]
        }
    },
    'logistic_regression' : {
        'model': LogisticRegression(solver='liblinear',multi_class='auto'),
        'params': {
            'C': [1,5,10]
        }
    },
    'decision_tree' : {
        'model' : DecisionTreeClassifier(),
        'params' : {
            'criterion': ['gini','entropy'],
        }
    },
    'k_neighbors' : {
        'model' : KNeighborsClassifier(),
        'params' : {
            'n_neighbors' : [3, 5, 7, 10]
        }
    }
}
```

In [206…

```
scores = []
for model_name, mp in model_params.items():
    clf =  GridSearchCV(mp['model'], mp['params'], cv=5, return_train_score=False)
    clf.fit(X_train, y_train)
    scores.append({
        'model': model_name,
        'best_score': clf.best_score_,
        'best_params': clf.best_params_
    })
```

In [207…

```
newdf = pd.DataFrame(scores,columns=['model','best_score','best_params'])
newdf
```

Out[207]:

	model	best_score	best_params
0	svm	0.861293	{'C': 1, 'kernel': 'rbf'}
1	random_forest	0.843266	{'n_estimators': 10}
2	logistic_regression	0.851600	{'C': 5}
3	decision_tree	0.805795	{'criterion': 'gini'}
4	k_neighbors	0.865489	{'n_neighbors': 7}

In [208…

```
clf.best_score_
```

Out[208]: 0.8654885057471265

In [209…

```
clf.best_params_
```

Out[209]: {'n_neighbors': 7}

In [210…

```
np.mean(cross_val_score(KNeighborsClassifier(n_neighbors=7), X_scaled, y))
```

Out[210]: 0.8347636586863105

In [211…

```
clf.predict(X_test)
clf.score(X_test, y_test)
```

Out[211]: 0.850828729281768

PCA

In [212…

```
pca = PCA(0.95)
```

In [213…

```
X_pca = pca.fit_transform(X_scaled)
```

In [214…
```
X_pca.shape
```
Out[214]:
```
(902, 12)
```
In [215…
```
pca.explained_variance_ratio_
```
Out[215]:
```
array([0.21920836, 0.11003629, 0.0988713 , 0.09177081, 0.0820894 ,
       0.06946019, 0.06694035, 0.06332667, 0.04874315, 0.04616084,
       0.0383647 , 0.03395929])
```
In [216…
```
pca.n_components_
```
Out[216]:
```
12
```
Train Test split on PCA

In [217…
```
X_trainpca, X_testpca, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_state=30)
```
MODEL

In [218…
```
model = KNeighborsClassifier(n_neighbors=7)
model.fit(X_trainpca, y_train)
model.score(X_testpca, y_test)
```
Out[218]:
```
0.850828729281768
```
In [219…
```
newclf = GridSearchCV(KNeighborsClassifier(), {
    'n_neighbors' : [3, 5, 7, 10]
}, cv=5, return_train_score=False)
newclf.fit(X_trainpca, y_train)
```
Out[219]:
```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
   ▸ KNeighborsClassifier
```
In [220…
```
pd.DataFrame(newclf.cv_results_)
```
Out[220]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	params	split0_test_score	split1_test_
0	0.006456	0.003552	0.009569	0.005712	3	{'n_neighbors': 3}	0.882759	0.8
1	0.000791	0.001147	0.015860	0.001698	5	{'n_neighbors': 5}	0.868966	0.8
2	0.006293	0.007731	0.014113	0.005574	7	{'n_neighbors': 7}	0.848276	0.8
3	0.006313	0.007773	0.020163	0.006699	10	{'n_neighbors': 10}	0.855172	0.8

In [222…
```
predict = newclf.predict(X_testpca)
newclf.score(X_testpca, y_test)
```
Out[222]:
```
0.8453038674033149
```
In [238…
```
X_pca[3]
```
Out[238]:
```
array([ 0.74543134, -0.72939153, -1.10432788, -0.77106847, -0.3270782 ,
        0.64017202,  1.81247202, -0.39242212, -1.31430994, -0.48644066,
        0.14454911,  0.28330645])
```
In [237…
```
y[3]
```
Out[237]:
```
1
```
In [242…
```
predict
```

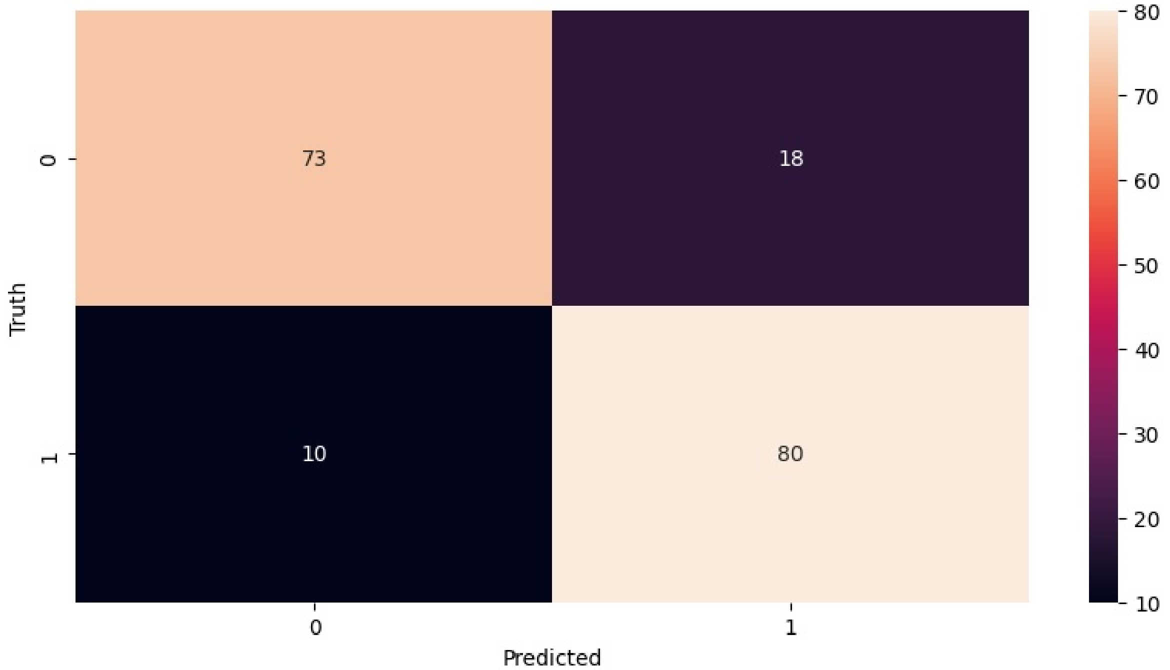
Out[242]:
```
array([1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1,
       1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1,
       1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
       1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       0, 0, 1, 1, 1])
```

In [244…
```
y_test
```

Out[244]:
```
604    0
290    0
255    0
151    0
223    0
      ..
53     0
724    0
506    1
589    1
312    1
Name: HeartDisease, Length: 181, dtype: int32
```

In [246…
```
cm = confusion_matrix(y_test, predict)
plt.figure(figsize=(10, 5))
sn.heatmap(cm, annot=True)
plt.xlabel("Predicted")
plt.ylabel("Truth")
```

Out[246]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



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