inear-logistic-knn-and-naive-bayes

May 9, 2024

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

[5]:
```
df=pd.read_csv('/content/drive/MyDrive/versity/Thesis/data/diabetes.csv')
```

[6]:
```
df.head(10)
```

[6]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1
5            5      116             74              0        0  25.6
6            3       78             50             32       88  31.0
7           10      115              0              0        0  35.3
8            2      197             70             45      543  30.5
9            8      125             96              0        0   0.0

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
5                     0.201   30        0
6                     0.248   26        1
7                     0.134   29        0
8                     0.158   53        1
9                     0.232   54        1
```

[7]:
```
df.isnull().sum()
```

[7]:
```
Pregnancies                 0
Glucose                     0
```

```
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[8]:
```
#display dataset randomly
df.sample(10)
```

[8]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
713            0      134             58             20      291  26.4
207            5      162            104              0        0  37.7
576            6      108             44             20      130  24.0
61             8      133             72              0        0  32.9
326            1      122             64             32      156  35.1
116            5      124             74              0        0  34.0
693            7      129             68             49      125  38.5
80             3      113             44             13        0  22.4
666            4      145             82             18        0  32.5
79             2      112             66             22        0  25.0

     DiabetesPedigreeFunction  Age  Outcome
713                     0.352   21        0
207                     0.151   52        1
576                     0.813   35        0
61                      0.270   39        1
326                     0.692   30        1
116                     0.220   38        1
693                     0.439   43        1
80                      0.140   22        0
666                     0.235   70        1
79                      0.307   24        0
```

[9]:
```
#shape of the dataset
df.shape
```

[9]:
```
(768, 9)
```

[10]:
```
#dataset type info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
```

```
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

[11]:
```
#statistical summery
df.describe()
```

[11]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin
count	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479
std	3.369578	31.972618	19.355807	15.952218	115.244002
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000
75%	6.000000	140.250000	80.000000	32.000000	127.250000
max	17.000000	199.000000	122.000000	99.000000	846.000000

	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000
mean	31.992578	0.471876	33.240885	0.348958
std	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.078000	21.000000	0.000000
25%	27.300000	0.243750	24.000000	0.000000
50%	32.000000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

1 Data cleaning

[12]:
```
#check the shape befor drop the duplicates
df.shape
```

[12]: (768, 9)

[13]:
```
df=df.drop_duplicates()
```

[14]:
```
#check now
df.shape
```

[14]: (768, 9)

[15]:
```
#check null value
df.isnull().sum()
```

[15]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[16]:
```
df.columns
```

[16]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[17]:
```
#check if any column have contain 0 value or not
print("no of zero values in Pregnancies",df[df['Pregnancies']==0].shape[0])
print("no of zero values in Glucose",df[df['Glucose']==0].shape[0])
print("no of zero values in BloodPressure",df[df['BloodPressure']==0].shape[0])
print("no of zero values in SkinThickness",df[df['SkinThickness']==0].shape[0])
print("no of zero values in Insulin",df[df['Insulin']==0].shape[0])
print("no of zero values in BMI",df[df['BMI']==0].shape[0])
print("no of zero values in Age",df[df['Age']==0].shape[0])
```

```
no of zero values in Pregnancies 111
no of zero values in Glucose 5
no of zero values in BloodPressure 35
no of zero values in SkinThickness 227
no of zero values in Insulin 374
no of zero values in BMI 11
no of zero values in Age 0
```

[18]:
```
df['Pregnancies']=df['Pregnancies'].replace(0,df['Pregnancies'].mean())
df['BloodPressure']=df['BloodPressure'].replace(0,df['BloodPressure'].mean())
df['SkinThickness']=df['SkinThickness'].replace(0,df['SkinThickness'].mean())
df['Glucose']=df['Glucose'].replace(0,df['Glucose'].mean())
df['Insulin']=df['Insulin'].replace(0,df['Insulin'].mean())
```

```
df['BMI']=df['BMI'].replace(0,df['BMI'].mean())
df['Age']=df['Age'].replace(0,df['Age'].mean())
```

[19]:
```
#check if any column have contain 0 value or not
print("no of zero values in Pregnancies",df[df['Pregnancies']==0].shape[0])
print("no of zero values in Glucose",df[df['Glucose']==0].shape[0])
print("no of zero values in BloodPressure",df[df['BloodPressure']==0].shape[0])
print("no of zero values in SkinThickness",df[df['SkinThickness']==0].shape[0])
print("no of zero values in Insulin",df[df['Insulin']==0].shape[0])
print("no of zero values in BMI",df[df['BMI']==0].shape[0])
print("no of zero values in Age",df[df['Age']==0].shape[0])
```

```
no of zero values in Pregnancies 0
no of zero values in Glucose 0
no of zero values in BloodPressure 0
no of zero values in SkinThickness 0
no of zero values in Insulin 0
no of zero values in BMI 0
no of zero values in Age 0
```

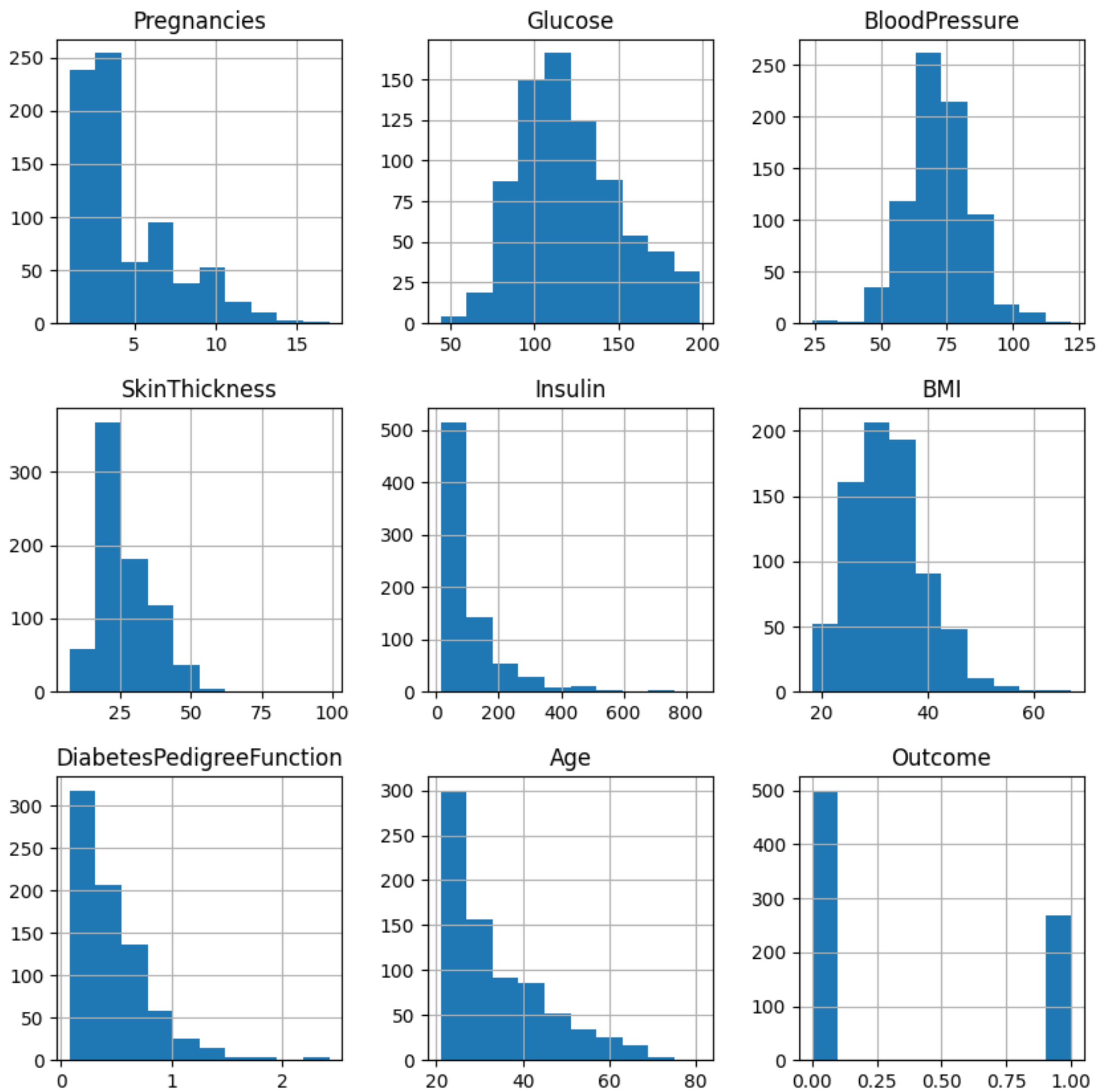
[20]:
```
df.head(10)
```

[20]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
0	6.000000	148.0	72.000000	35.000000	79.799479	33.600000	
1	1.000000	85.0	66.000000	29.000000	79.799479	26.600000	
2	8.000000	183.0	64.000000	20.536458	79.799479	23.300000	
3	1.000000	89.0	66.000000	23.000000	94.000000	28.100000	
4	3.845052	137.0	40.000000	35.000000	168.000000	43.100000	
5	5.000000	116.0	74.000000	20.536458	79.799479	25.600000	
6	3.000000	78.0	50.000000	32.000000	88.000000	31.000000	
7	10.000000	115.0	69.105469	20.536458	79.799479	35.300000	
8	2.000000	197.0	70.000000	45.000000	543.000000	30.500000	
9	8.000000	125.0	96.000000	20.536458	79.799479	31.992578	

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	0
4	2.288	33	1
5	0.201	30	0
6	0.248	26	1
7	0.134	29	0
8	0.158	53	1
9	0.232	54	1

[21]:
```
#histrogram
df.hist(bins=10,figsize=(10,10))
plt.show()
```



2 Split the data frame into X and y

[22]:
```
target_name='Outcome'
y=df['Outcome']
X=df.drop(target_name,axis=1)
```

[23]:
```
y
```

[23]:
```
0      1
1      0
2      1
3      0
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64
```

[24]:
```
X.head()
```

[24]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness     Insulin   BMI  \
0     6.000000    148.0           72.0      35.000000   79.799479  33.6
1     1.000000     85.0           66.0      29.000000   79.799479  26.6
2     8.000000    183.0           64.0      20.536458   79.799479  23.3
3     1.000000     89.0           66.0      23.000000   94.000000  28.1
4     3.845052    137.0           40.0      35.000000  168.000000  43.1

   DiabetesPedigreeFunction  Age
0                     0.627   50
1                     0.351   31
2                     0.672   32
3                     0.167   21
4                     2.288   33
```

3 Feature scaling tecniques

[25]:
```
#standard scaler
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(X)
SSX=scaler.transform(X)
SSX
```

[25]:
```
array([[ 0.5362511 ,  0.86527574, -0.0210444 , …,  0.16725546,
         0.46849198,  1.4259954 ],
       [-1.1403533 , -1.20598931, -0.51658286, …, -0.85153454,
        -0.36506078, -0.19067191],
       [ 1.20689286,  2.01597855, -0.68176235, …, -1.33182125,
         0.60439732, -0.10558415],
       …,
       [ 0.20093022, -0.02240928, -0.0210444 , …, -0.90975111,
```

```
 -0.68519336, -0.27575966],
[-1.1403533 ,  0.14197684, -1.01212132, …, -0.34213954,
 -0.37110101,  1.17073215],
[-1.1403533 , -0.94297153, -0.18622389, …, -0.29847711,
 -0.47378505, -0.87137393]])
```

4 Train Test split

[26]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(SSX,y,test_size=0.
↪25,random_state=42)
X_train.shape,y_train.shape
```

[26]:
```
((576, 8), (576,))
```

[27]:
```
X_test.shape,y_test.shape
```

[27]:
```
((192, 8), (192,))
```

5 Build the classification algorithm

#Linear Regression

[28]:
```
from sklearn.linear_model import LinearRegression
Linearregression=LinearRegression()
Linearregression.fit(X_train,y_train)
```

[28]:
```
LinearRegression()
```

[29]:
```
linear_predict=Linearregression.predict(X_test)
df=pd.DataFrame({'Actual':y_test,'Predicted':linear_predict}).round(0)
df
```

[29]:

	Actual	Predicted
668	0	0.0
324	0	0.0
624	0	0.0
690	0	0.0
473	0	0.0
..	…	…
554	0	0.0
319	1	1.0
594	0	0.0
6	1	0.0
615	0	0.0

[192 rows x 2 columns]

[30]:
```
#check accuracy mean
from sklearn.metrics import mean_absolute_error
mae_for_linear=mean_absolute_error(y_test,linear_predict)
print(f"mean absolute error {mae_for_linear}")
```

```
mean absolute error 0.3465183318718143
```

[31]:
```
# from sklearn.metrics import accuracy_score
# accuracy = accuracy_score(y_test , linear_predict)
```

6 Logistic Regression

[32]:
```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
lr.fit(X_train,y_train)
lr_predict=lr.predict(X_test)
df=pd.DataFrame({'Actual':y_test,'Predicted':lr_predict}).round(0)
df
```

[32]:

	Actual	Predicted
668	0	0
324	0	0
624	0	0
690	0	0
473	0	0
..	…	…
554	0	0
319	1	1
594	0	0
6	1	0
615	0	0

[192 rows x 2 columns]

[33]:
```
from sklearn.metrics import mean_absolute_error
mae_for_log=mean_absolute_error(y_test,lr_predict)
print(f"mean absolute error {mae_for_log}")
```

```
mean absolute error 0.265625
```

7 KNN Classification

[34]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
```

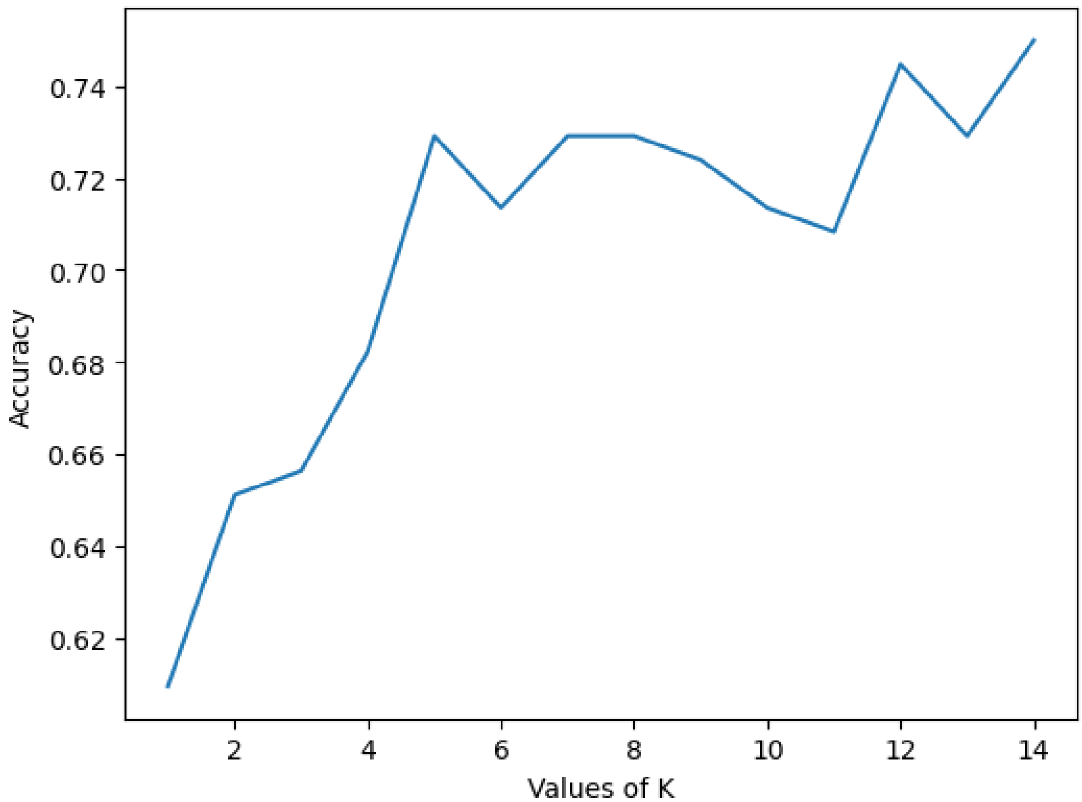
[35]:
```
range_k = range(1,15)
scores = {}
scores_list = []
for k in range_k:
  classifier=KNeighborsClassifier(n_neighbors=k)
  classifier.fit(X_train,y_train)
  knn_predict=classifier.predict(X_test)
  scores[k]=metrics.accuracy_score(y_test,knn_predict)
  scores_list.append(metrics.accuracy_score(y_test,knn_predict))

result=metrics.confusion_matrix(y_test,knn_predict)
print("Confusion Matrix:")
print(result)
result1 = metrics.classification_report(y_test , knn_predict)
print("Classification Report:",)
```

```
Confusion Matrix:
[[106  17]
 [ 31  38]]
Classification Report:
```

Now, we will be plotting the relationship between the values of K and the corresponding testing accuracy. It will be done using matplotlib library.

[36]:
```
plt.plot(range_k,scores_list)
plt.xlabel("Values of K")
plt.ylabel("Accuracy")
```

[36]:
```
Text(0, 0.5, 'Accuracy')
```



[37]:
```
classifier = KNeighborsClassifier(n_neighbors = 2)
classifier.fit(X_train , y_train)
```

[37]: KNeighborsClassifier(n_neighbors=2)

[38]:
```
knn_predict=classifier.predict(X_test)
df=pd.DataFrame({'Actual':y_test,'Predicted':knn_predict}).round(0)
df
```

[38]:

	Actual	Predicted
668	0	0
324	0	0
624	0	0
690	0	0
473	0	1
..	…	…
554	0	0
319	1	0
594	0	0
6	1	0
615	0	0

```
[192 rows x 2 columns]
```

[39]:
```
from sklearn.metrics import mean_absolute_error
knn_predict_mean=mean_absolute_error(y_test,knn_predict)
print(f"mean absolute error{knn_predict_mean}")
```

```
mean absolute error0.3489583333333333
```

8 Naive bayes

Choose Naive Bayes Model: Choose the appropriate Naive Bayes model based on your problem type: For binary or multiclass classification problems, you can use **GaussianNB (for continuous features), MultinomialNB (for discrete features), or BernoulliNB (for binary features).**

For the task of predicting whether a person has diabetes or not based on multiple features, you should use the Gaussian Naive Bayes (GaussianNB) classifier.

Gaussian Naive Bayes is suitable for classification tasks where the features are continuous or real-valued. Since your dataset likely contains numerical features (e.g., blood glucose level, blood pressure, etc.), GaussianNB is a better choice.

Multinomial Naive Bayes (MultinomialNB) is typically used for text classification tasks where features represent the frequency of occurrences of words or tokens. It assumes that features follow a multinomial distribution.

Bernoulli Naive Bayes (BernoulliNB) is suitable for binary feature vectors. It assumes that features are binary-valued, such as presence or absence of certain features. While it can be used for binary data, it may not be the best choice if your dataset contains continuous or real-valued features.

Here's how you can use Gaussian Naive Bayes for your diabetes prediction task:

python

[41]:
```
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB()
nb.fit(X_train,y_train)
```

[41]:
```
GaussianNB()
```

[43]:
```
nb_predict=nb.predict(X_test)
df=pd.DataFrame({'Actual':y_test,'Predicted':nb_predict}).round(0)
df
```

[43]:

	Actual	Predicted
668	0	0
324	0	0
624	0	0
690	0	0

```
473        0          1
..       …        …
554        0          0
319        1          1
594        0          1
6          1          0
615        0          0

[192 rows x 2 columns]
```

[44]:
```python
from sklearn.metrics import mean_absolute_error
nb_predict_mean=mean_absolute_error(y_test,nb_predict)
print(f"mean absolute error{nb_predict_mean}")
```

```
mean absolute error0.265625
```