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# Implement K-Nearest Neighbors algorithm on diabetes.csv dataset. Compute confusion # matrix, accuracy, error rate, precision and recall on the given dataset.
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Dataset link : https://www.kaggle.com/datasets/abdallamahgoub/diabetes

import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split

 $from \ sklearn.preprocessing \ import \ StandardScaler$

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score

data=pd.read_csv("diabetes.csv")

data

→	Pregnanc	ies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
	0	6	148	72	35	0	33.6	0.627	50	1	11.
	1	1	85	66	29	0	26.6	0.351	31	0	+/
	2	8	183	64	0	0	23.3	0.672	32	1	
	3	1	89	66	23	94	28.1	0.167	21	0	
	4	0	137	40	35	168	43.1	2.288	33	1	
			***			***				•••	
7	763	10	101	76	48	180	32.9	0.171	63	0	
7	764	2	122	70	27	0	36.8	0.340	27	0	
7	765	5	121	72	23	112	26.2	0.245	30	0	
7	766	1	126	60	0	0	30.1	0.349	47	1	
7	767	1	93	70	31	0	30.4	0.315	23	0	
76	68 rows × 9 colu	ımns	;								

Next steps:

Generate code with data

View recommended plots

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X = data.drop("Outcome", axis=1) # Features
y = data["Outcome"] # Target variable

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0 6 148 72 35 0 33.6 0.627 50 1 1 85 66 29 0 26.6 0.351 31 2 8 183 64 0 0 23.3 0.672 32 3 1 89 66 23 94 28.1 0.167 21 4 0 137 40 35 168 43.1 2.288 33	<u>-</u>	Pregnancies	egnancies Glucose I	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	8
2 8 183 64 0 0 23.3 0.672 32 3 1 89 66 23 94 28.1 0.167 21 4 0 137 40 35 168 43.1 2.288 33 <td< th=""><th>0</th><th>6</th><th>6 148</th><th>72</th><th>35</th><th>0</th><th>33.6</th><th>0.627</th><th>50</th><th></th></td<>	0	6	6 148	72	35	0	33.6	0.627	50	
3 1 89 66 23 94 28.1 0.167 21 4 0 137 40 35 168 43.1 2.288 33	1	1	1 85	66	29	0	26.6	0.351	31	ŧ
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763 10 101 76 48 180 32.9 0.171 63 764 2 122 70 27 0 36.8 0.340 27	3	1	1 89	66	23	94	28.1	0.167	21	
763 10 101 76 48 180 32.9 0.171 63 764 2 122 70 27 0 36.8 0.340 27	4	0	0 137	40	35	168	43.1	2.288	33	
764 2 122 70 27 0 36.8 0.340 27										
	763	10	10 101	76	48	180	32.9	0.171	63	
765 5 121 72 23 112 26.2 0.245 30	764	2	2 122	70	27	0	36.8	0.340	27	
	765	5	5 121	72	23	112	26.2	0.245	30	
766 1 126 60 0 0 30.1 0.349 47	766	1	1 126	60	0	0	30.1	0.349	47	
767 1 93 70 31 0 30.4 0.315 23	767	1	1 93	70	31	0	30.4	0.315	23	

Next steps:

Generate code with X

View recommended plots

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2. Split the dataset into training and test sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

3. Normalize the data

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

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X_train
```

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⇒ array([[-0.52639686, -1.15139792, -3.75268255, ..., -4.13525578,
             -0.49073479, -1.03594038],
            [ 1.58804586, -0.27664283, 0.68034485, ..., -0.48916881,
            2.41502991, 1.48710085],
[-0.82846011, 0.56687102, -1.2658623 , ..., -0.42452187,
              0.54916055, -0.94893896],
            [\ 1.8901091\ ,\ -0.62029661,\ 0.89659009,\ \ldots,\ 1.76054443,
            1.981245 , 0.44308379],
[-1.13052335, 0.62935353, -3.75268255, ..., 1.34680407,
            -0.78487662, -0.33992901],
[-1.13052335, 0.12949347, 1.43720319, ..., -1.22614383,
             -0.61552223, -1.03594038]])
# 4. Implement K-Nearest Neighbors (KNN)
k = 3 # Choose the number of neighbors (k) based on your needs
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)
\rightarrow
            KNeighborsClassifier
     KNeighborsClassifier(n neighbors=3)
# 5. Predict and Evaluate
y_pred = knn.predict(X_test)
y_pred
0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 0,
            0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 0,\ 1,
            0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
            0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1,
            0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1,
            0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0])
# Compute the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
# Calculate accuracy, error rate, precision, and recall
accuracy = accuracy_score(y_test, y_pred)
error_rate = 1 - accuracy
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
print("Accuracy:", accuracy)
print("Error Rate:", error_rate)
print("Precision:", precision)
print("Recall:", recall)
→ Confusion Matrix:
     [[81 18]
      [27 28]]
     Accuracy: 0.7077922077922078
     Error Rate: 0.29220779220779225
     Precision: 0.6086956521739131
     Recall: 0.509090909090909
# Accuracy: This measures the overall correctness of the classifier's predictions. In this case, the model is about 70.78% accurate.
# Error Rate: The error rate is the complement of accuracy (1 - accuracy), representing the proportion of incorrect predictions. Here, 1
# Precision: Precision measures the ratio of true positive predictions to the total number of positive predictions (true positives + fal
# Recall: Recall measures the ratio of true positive predictions to the total number of actual positive instances (true positives + fals
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