AIM:Program to implement k-NN classification using any standard dataset available in the public domain and find the accuracy of the algorithm.

import numpy as np
import pandas as pd
import matplotlib.pyplot asplt
from sklearn.neghbors import KNeighborsClassifier
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

In [8]:

import pandas as pd
iris=pd.read_csv(Iris.csv')
iris.tail()

Out[8]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	19	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

In [11]:

iris['Species'].value_counts()

Out[11]:

Iris-setosa 50 Iris-versicolor 50 Iris-virginica 50

Name: Species, dtype: int64

In [13]:

iris.columns

Out[13]:

• 'Species'] dtype='object')

In [14]:

```
array([[1, 5.1, 3.5, 1.4, 0.2, 'Iris-setosa'],
    [2, 4.9, 3.0, 1.4, 0.2, 'Iris-setosa'],
    [3, 4.7, 3.2, 1.3, 0.2, 'Iris-setosa'],
    [4, 4.6, 3.1, 1.5, 0.2, 'Iris-setosa'],
    [5, 5.0, 3.6, 1.4, 0.2, 'Iris-setosa'],
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    [7, 4.6, 3.4, 1.4, 0.3, 'Iris-setosa'],
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```

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[136, 7.7, 3.0, 6.1, 2.3, 'Iris-virginica'],
[137, 6.3, 3.4, 5.6, 2.4, 'Iris-virginica'],
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[146, 6.7, 3.0, 5.2, 2.3, 'Iris-virginica'],
[147, 6.3, 2.5, 5.0, 1.9, 'Iris-virginica'],
[148, 6.5, 3.0, 5.2, 2.0, 'Iris-virginica'],
[149, 6.2, 3.4, 5.4, 2.3, 'Iris-virginica'],
[150, 5.9, 3.0, 5.1, 1.8, 'Iris-virginica']], dtype=object)
```

iris.describe(include='all')

Out[15]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
count	150.000000	150.000000	150.000000	150.000000	150.000000	150
unique	NaN	NaN	NaN	NaN	NaN	3
top	NaN	NaN	NaN	NaN	NaN	Iris-setosa
freq	NaN	NaN	NaN	NaN	NaN	50
mean	75.500000	5.843333	3.054000	3.758667	1.198667	NaN
std	43.445368	0.828066	0.433594	1.764420	0.763161	NaN
min	1.000000	4.300000	2.000000	1.000000	0.100000	NaN
25%	38.250000	5.100000	2.800000	1.600000	0.300000	NaN
50%	75.500000	5.800000	3.000000	4.350000	1.300000	NaN
75%	112.750000	6.400000	3.300000	5.100000	1.800000	NaN
max	150.000000	7.900000	4.400000	6.900000	2.500000	NaN

In [17]:

x=iris.iloc[:,:4]
x.head()

0

Out[17]:

	ld	SepalLengthCm	SepalWidthCm	PetalLengthCm
)	1	5.1	3.5	14

	ld	SepalLengthCm	SepalWidthCm	PetalLengthCm	
1	2	4.9	3.0	14	
2	3	4.7	3.2	13	
3	4	4.6	3.1	1.5	
4	5	5.0	3.6	1.4	
y=ir	is.ilo	c[:,-1]			In [18]:
y.he					Out[18]:
1 lr 2 l 3 l 4 l	is-s∈ ris-s∈ ris-s∈ ris-s	etosa tosa etosa etosa etosa pecies, dtype: ob	ject		In [00].
	repro	earn import prepi ocessing.Standard		sform(x)	In [22]:
arra	v/II_^	.72054204, -0.90	068117 1032057 [,]	22 -134127241	O ut[22]:
 	- 1.69 - 1.67	744751, -1.1430169 435299, -1.385352 125846, -1.506520	91, -0.1249576 , -1. 265, 0.33784833,	3412724], , -1.39813811],	
'		1200 10, 1.000020	702, 0.10011000,	2011007 11)	In [26]:
x_tr).3,random_state=1)
(45,					O ut[26]:
(43,	,				In [39]:
knn	mod	earn.neighbors in el=KNeighborsCl el.fit(x_train,y_tra	assifier(n_neighb		Out[39]:
KNe	eighb	orsClassifier(n_n	eighbors=3)		

In [44]:

from sklearn.neighbors import KNeighbors Classifier

KNeighborsClassifier(algorithm='auto',leaf_size=30,metric='minkowski',metric_params=None,n_jobs **=None**,n_neighbors=3,p=2,weights='uniform')

Out[44]:

KNeighborsClassifier(n_neighbors=3)

In [48]:

y_predict1=knnmodel.predict(x_test)

In [49]:

from sklearn.metrics import accuracy_score

In [50]:

acc=accuracy_score(y_test,y_predict1) acc

Out[50]:

1.0

In [52]:

from sklearn.metrics **import** confusion_matrix cm=confusion_matrix(y_test.values,y_predict1) cm

Out[52]:

array([[14, 0, 0], [0, 18, 0],

[0, 0, 13]], dtype=int64)

In [53]:

cm1=pd.DataFrame(data=cm,index=['setosa','versicolor','verginica'],columns=['setosa','versicolor','verginica'] ginica'])

cm1

Out[53]:

	setosa	versicolor	verginica
setosa	14	0	0
versicolor	0	18	0
verginica	0	0	13

In [56]:

prediction_output=pd.DataFrame(data=[y_test.values,y_predict1],index=['y_test','y_predict1])

In [57]:

y_test y_predict1

- 0 Iris-setosa Iris-setosa
- 1 Iris-versicolor Iris-versicolor
- 2 Iris-versicolor Iris-versicolor
- 3 Iris-setosa Iris-setosa
- 4 Iris-virginica Iris-virginica
- 5 Iris-versicolor Iris-versicolor
- 6 Iris-virginica Iris-virginica
- 7 Iris-setosa Iris-setosa
- 8 Iris-setosa Iris-setosa
- 9 Iris-virginica Iris-virginica
- 10 Iris-versicolor Iris-versicolor
- 11 Iris-setosa Iris-setosa
- 12 Iris-virginica Iris-virginica
- 13 Iris-versicolor Iris-versicolor
- 14 Iris-versicolor Iris-versicolor
- 15 Iris-setosa Iris-setosa

y_test y_predict1

- **16** Iris-versicolor Iris-versicolor
- 17 Iris-versicolor Iris-versicolor
- 18 Iris-setosa Iris-setosa
- 19 Iris-setosa Iris-setosa
- 20 Iris-versicolor Iris-versicolor
- 21 Iris-versicolor Iris-versicolor
- 22 Iris-versicolor Iris-versicolor
- 23 Iris-setosa Iris-setosa
- 24 Iris-virginica Iris-virginica
- 25 Iris-versicolor Iris-versicolor
- 26 Iris-setosa Iris-setosa
- 27 Iris-setosa Iris-setosa
- 28 Iris-versicolor Iris-versicolor
- 29 Iris-virginica Iris-virginica
- 30 Iris-versicolor Iris-versicolor
- 31 Iris-virginica Iris-virginica
- 32 Iris-versicolor Iris-versicolor

y_predict1 y_test 33 Iris-virginica Iris-virginica 34 Iris-virginica Iris-virginica 35 Iris-setosa Iris-setosa 36 Iris-versicolor Iris-versicolor 37 Iris-setosa Iris-setosa 38 Iris-versicolor Iris-versicolor 39 Iris-virginica Iris-virginica 40 Iris-virginica Iris-virginica 41 Iris-setosa Iris-setosa 42 Iris-virginica Iris-virginica 43 Iris-virginica Iris-virginica Iris-versicolor Iris-versicolor

prediction_output.iloc[0,:].value_counts()

Iris-versicolor 18 Iris-setosa 14 Iris-virginica 13

Name: y_test, dtype: int64

In [58]:

Out[58]:

In []: