**8. Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem. KNN ALGORITHM**

from sklearn.model\_selection import train\_test\_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import classification\_report, confusion\_matrix

from sklearn import datasets

iris=datasets.load\_iris()

iris\_data=iris.data

iris\_labels=iris.target

print(iris\_data)

print(iris\_labels)

x\_train, x\_test, y\_train, y\_test=train\_test\_split(iris\_data,iris\_labels,test\_size=0.30)

classifier=KNeighborsClassifier(n\_neighbors=5)

classifier.fit(x\_train,y\_train)

y\_pred=classifier.predict(x\_test)

print('confusion matrix is as follows')

print(confusion\_matrix(y\_test,y\_pred))

print('Accuracy metrics')

print(classification\_report(y\_test,y\_pred))

Dataset

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**Output**

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2 2]

confusion matrix is as follows

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[ 0 13 0]

[ 0 2 13]]

Accuracy metrics

precision recall f1-score support

0 1.00 1.00 1.00 17

1 0.87 1.00 0.93 13

2 1.00 0.87 0.93 15

accuracy 0.96 45

macro avg 0.96 0.96 0.95 45

weighted avg 0.96 0.96 0.96 45

In [2]:



1

**from** sklearn.model\_selection **import** train\_test\_split

2

**from** sklearn.n