

Program no. 4

Multipliclass Classification

```
import pandas
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import np_utils
from sklearn.preprocessing import LabelEncoder
```

```
df=pandas.read_csv('Flower.csv',header=None)
print(df)
```

	0	1	2	3	4
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
..
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

[150 rows x 5 columns]

```
X=df.iloc[:,0:4].astype(float)
y=df.iloc[:,4]
```

```
print(X)
```

	0	1	2	3
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
..
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

[150 rows x 4 columns]

```
print(y)
```

0	Iris-setosa
1	Iris-setosa
2	Iris-setosa


```
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[1., 0., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
[0., 1., 0.],
```

```
model= Sequential()
model.add(Dense(8,input_dim=4,activation='relu'))
model.add(Dense(6,activation='relu'))
model.add(Dense(3,activation='softmax'))
```

```
model.compile(loss='categorical_crossentropy',optimizer='adam',metrics='accuracy')
```

```
model.fit(X,encoded_Y,epochs=100,batch_size=10)
```

```
Epoch 72/100
15/15 [=====] - 0s 2ms/step - loss: 0.4370 - accuracy: 0.
Epoch 73/100
15/15 [=====] - 0s 2ms/step - loss: 0.4378 - accuracy: 0.
Epoch 74/100
15/15 [=====] - 0s 2ms/step - loss: 0.4336 - accuracy: 0.
Epoch 75/100
15/15 [=====] - 0s 2ms/step - loss: 0.4324 - accuracy: 0.
Epoch 76/100
15/15 [=====] - 0s 2ms/step - loss: 0.4309 - accuracy: 0.
Epoch 77/100
15/15 [=====] - 0s 2ms/step - loss: 0.4308 - accuracy: 0.
Epoch 78/100
15/15 [=====] - 0s 3ms/step - loss: 0.4278 - accuracy: 0.
Epoch 79/100
15/15 [=====] - 0s 2ms/step - loss: 0.4269 - accuracy: 0.
Epoch 80/100
15/15 [=====] - 0s 2ms/step - loss: 0.4243 - accuracy: 0.
Epoch 81/100
```

```

15/15 [=====] - 0s 2ms/step - loss: 0.4228 - accuracy: 0.
Epoch 82/100
15/15 [=====] - 0s 3ms/step - loss: 0.4210 - accuracy: 0.
Epoch 83/100
15/15 [=====] - 0s 2ms/step - loss: 0.4195 - accuracy: 0.
Epoch 84/100
15/15 [=====] - 0s 2ms/step - loss: 0.4177 - accuracy: 0.
Epoch 85/100
15/15 [=====] - 0s 2ms/step - loss: 0.4156 - accuracy: 0.
Epoch 86/100
15/15 [=====] - 0s 2ms/step - loss: 0.4140 - accuracy: 0.
Epoch 87/100
15/15 [=====] - 0s 2ms/step - loss: 0.4123 - accuracy: 0.
Epoch 88/100
15/15 [=====] - 0s 2ms/step - loss: 0.4108 - accuracy: 0.
Epoch 89/100
15/15 [=====] - 0s 2ms/step - loss: 0.4085 - accuracy: 0.
Epoch 90/100
15/15 [=====] - 0s 2ms/step - loss: 0.4058 - accuracy: 0.
Epoch 91/100
15/15 [=====] - 0s 2ms/step - loss: 0.4035 - accuracy: 0.
Epoch 92/100
15/15 [=====] - 0s 2ms/step - loss: 0.4009 - accuracy: 0.
Epoch 93/100
15/15 [=====] - 0s 2ms/step - loss: 0.3997 - accuracy: 0.
Epoch 94/100
15/15 [=====] - 0s 2ms/step - loss: 0.3965 - accuracy: 0.
Epoch 95/100
15/15 [=====] - 0s 2ms/step - loss: 0.3940 - accuracy: 0.
Epoch 96/100
15/15 [=====] - 0s 2ms/step - loss: 0.3916 - accuracy: 0.
Epoch 97/100
15/15 [=====] - 0s 2ms/step - loss: 0.3886 - accuracy: 0.
Epoch 98/100
15/15 [=====] - 0s 2ms/step - loss: 0.3867 - accuracy: 0.
Epoch 99/100
15/15 [=====] - 0s 2ms/step - loss: 0.3841 - accuracy: 0.
Epoch 100/100

```

```
predictions=model.predict(X)
```

```
for i in range(35,130,3):
```

```
    print(predictions[i],encoded_Y[i])
```

```

[9.9621320e-01 3.1072637e-03 6.7953131e-04] [1. 0. 0.]
[9.947212e-01 4.285797e-03 9.929605e-04] [1. 0. 0.]
[0.9666754 0.02592979 0.0073948 ] [1. 0. 0.]
[9.9751008e-01 2.1157451e-03 3.7422092e-04] [1. 0. 0.]
[9.9624169e-01 3.0868838e-03 6.7143043e-04] [1. 0. 0.]
[0.00116452 0.51556766 0.48326778] [0. 1. 0.]
[0.00139097 0.4846831 0.5139259 ] [0. 1. 0.]
[0.00142675 0.53951555 0.45905763] [0. 1. 0.]
[0.00383383 0.5546972 0.44146895] [0. 1. 0.]
[0.0013135 0.486363 0.51232344] [0. 1. 0.]
[0.0017461 0.52415586 0.474098 ] [0. 1. 0.]
[2.1960029e-04 3.8397127e-01 6.1580908e-01] [0. 1. 0.]
[0.00284184 0.53437746 0.46278074] [0. 1. 0.]

```

```
[0.00189672 0.52601695 0.4720863 ] [0. 1. 0.]
[2.9417503e-04 4.4207478e-01 5.5763108e-01] [0. 1. 0.]
[0.00335193 0.537967 0.45868105] [0. 1. 0.]
[3.4511302e-04 4.4645175e-01 5.5320311e-01] [0. 1. 0.]
[0.00075706 0.49829623 0.5009467 ] [0. 1. 0.]
[0.00211831 0.517938 0.47994366] [0. 1. 0.]
[0.00257358 0.5332306 0.46419576] [0. 1. 0.]
[0.01241769 0.6004778 0.38710442] [0. 1. 0.]
[0.033699 0.58668804 0.379613 ] [0. 1. 0.]
[2.1903153e-04 4.1097513e-01 5.8880579e-01] [0. 0. 1.]
[5.3068743e-05 3.5690138e-01 6.4304560e-01] [0. 0. 1.]
[2.7768167e-05 3.4501082e-01 6.5496141e-01] [0. 0. 1.]
[2.5964502e-04 4.3697530e-01 5.6276500e-01] [0. 0. 1.]
[1.3904169e-04 3.7176162e-01 6.2809938e-01] [0. 0. 1.]
[1.7360432e-04 4.2528740e-01 5.7453901e-01] [0. 0. 1.]
[1.6096994e-04 3.8296032e-01 6.1687875e-01] [0. 0. 1.]
[6.2491135e-06 2.7423811e-01 7.2575563e-01] [0. 0. 1.]
[8.048216e-05 4.051282e-01 5.947913e-01] [0. 0. 1.]
[5.7839919e-05 3.5093457e-01 6.4900756e-01] [0. 0. 1.]
```

✓ 0s completed at 21:28

