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LAB - 6 MULTI-CLASS CLASSIFICATION OF FASHION APPARELS USING DNN

STEPS

1. OPEN

```
In [1]: import tensorflow as tf
import keras
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Flatten
```

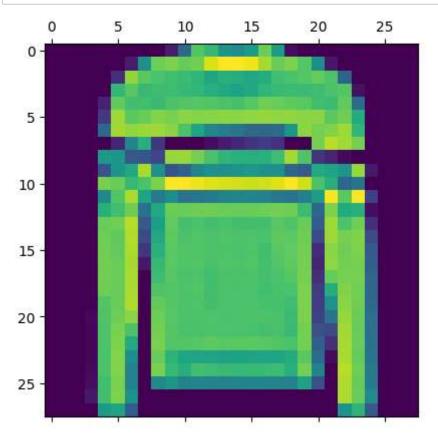
```
In [2]: (x_train, y_train), (x_test, y_test) = tf.keras.datasets.fashion_mnist.load_dat
```

2 . PERFORM BASIC EXPLORATORY DATA ANALYSIS (EDA)

```
In [3]: print('x_train shape: ',x_train.shape,' ''x_train size: ',x_train.size)
    print('y_train shape: ',y_train.shape,' ''y_train size: ',y_train.size)

x_train shape: (60000, 28, 28) x_train size: 47040000
    y_train shape: (60000,) y_train size: 60000
```

In [22]: plt.matshow(x_train[5])
plt.show()



3. NORMALIZE

```
In [5]: X_train = x_train.astype('float32')/255
X_test = x_test.astype('float32')/255
```

```
In [6]: X_train[6]
Out[6]: array([[0.
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```

4 . BUILD A SIMPLE BASELINE MODEL

In [8]: | model.fit(X_train,y_train,epochs=10) Epoch 1/10 curacy: 0.1018 Epoch 2/10 curacy: 0.0991 Epoch 3/10 curacy: 0.0995 Epoch 4/10 curacy: 0.1006 Epoch 5/10 curacy: 0.1006 Epoch 6/10 curacy: 0.1004 Epoch 7/10 curacy: 0.0989 Epoch 8/10 curacy: 0.0996 Epoch 9/10 curacy: 0.1020 Epoch 10/10 curacy: 0.1016 Out[8]: <keras.callbacks.History at 0x1d160fc1270>

In [9]: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 512)	401920
dense_1 (Dense)	(None, 10)	5130

Total params: 407,050 Trainable params: 407,050 Non-trainable params: 0

5. PERFORMANCE ANALYSIS

```
In [10]: model=Sequential()
     model.add(Flatten(input_shape=(28, 28)))
     model.add(Dense(128,activation='relu'))
     model.add(Dense(128,activation='relu'))
     model.add(Dense(10,activation='softmax'))
     model.compile(loss='mean_squared_error',
          optimizer='RMSprop',
          metrics='accuracy')
In [11]: model.fit(X train, y train, epochs=10)
     Epoch 1/10
     curacy: 0.1007
     Epoch 2/10
     curacy: 0.0996
     Epoch 3/10
     curacy: 0.0994
     Epoch 4/10
     curacy: 0.0975
     Epoch 5/10
     curacy: 0.0973
     Epoch 6/10
     curacy: 0.1014
     Epoch 7/10
     curacy: 0.1011
     Epoch 8/10
     curacy: 0.1020
     Epoch 9/10
     curacy: 0.1024
     Epoch 10/10
     curacy: 0.1015
Out[11]: <keras.callbacks.History at 0x1d1619d50f0>
In [12]: model=Sequential()
     model.add(Flatten(input shape=(28, 28)))
     model.add(Dense(256,activation='relu'))
     model.add(Dense(256,activation='relu'))
     model.add(Dense(10,activation='softmax'))
     model.compile(loss='mean_squared_error',
          optimizer='RMSprop',
          metrics='accuracy')
```

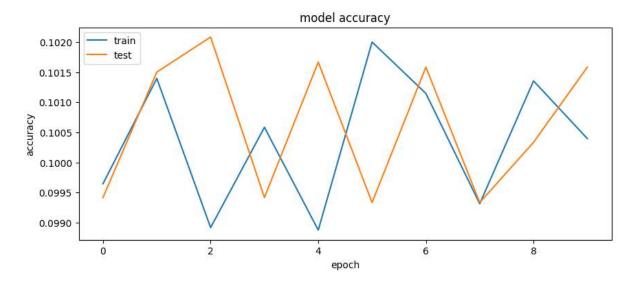
```
In [13]: |model.fit(X_train,y_train,epochs=10)
    Epoch 1/10
    curacy: 0.0998
    Epoch 2/10
    curacy: 0.0996
    Epoch 3/10
    curacy: 0.0990
    Epoch 4/10
    curacy: 0.1012
    Epoch 5/10
    curacy: 0.0983
    Epoch 6/10
    curacy: 0.0997
    Epoch 7/10
    curacy: 0.1012
    Epoch 8/10
    curacy: 0.1009
    Epoch 9/10
    curacy: 0.0989
    Epoch 10/10
    curacy: 0.0993
Out[13]: <keras.callbacks.History at 0x1d1625831c0>
In [14]: model=Sequential()
    model.add(Flatten(input shape=(28, 28)))
    model.add(Dense(512,activation='relu'))
    model.add(Dense(512,activation='relu'))
    model.add(Dense(10,activation='softmax'))
    model.compile(loss='mean_squared_error',
        optimizer='RMSprop',
        metrics='accuracy')
```

```
In [15]: | model.fit(X_train,y_train,epochs=10)
   Epoch 1/10
   ccuracy: 0.1002
   Epoch 2/10
   curacy: 0.0994
   Epoch 3/10
   curacy: 0.1008
   Epoch 4/10
   curacy: 0.0993
   Epoch 5/10
   curacy: 0.1004
   Epoch 6/10
   curacy: 0.0995
   Epoch 7/10
   curacy: 0.1002
   Epoch 8/10
   curacy: 0.0997
   Epoch 9/10
   curacy: 0.0999
   Epoch 10/10
   curacy: 0.1012
Out[15]: <keras.callbacks.History at 0x1d162987490>
In [16]: X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=@
```

```
In [17]: history = model.fit(X train,y train,epochs=10,validation data=(X val, y val))
     Epoch 1/10
     curacy: 0.0996 - val_loss: 27.5198 - val_accuracy: 0.0994
     Epoch 2/10
     curacy: 0.1014 - val_loss: 27.5198 - val_accuracy: 0.1015
     Epoch 3/10
     1500/1500 [============== ] - 8s 5ms/step - loss: 27.6326 - ac
     curacy: 0.0989 - val_loss: 27.5198 - val_accuracy: 0.1021
     curacy: 0.1006 - val_loss: 27.5198 - val_accuracy: 0.0994
     Epoch 5/10
     curacy: 0.0989 - val_loss: 27.5198 - val_accuracy: 0.1017
     Epoch 6/10
     1500/1500 [=============== ] - 8s 5ms/step - loss: 27.6326 - ac
     curacy: 0.1020 - val_loss: 27.5198 - val_accuracy: 0.0993
     Epoch 7/10
     curacy: 0.1011 - val_loss: 27.5198 - val_accuracy: 0.1016
     Epoch 8/10
     curacy: 0.0993 - val_loss: 27.5198 - val_accuracy: 0.0993
     curacy: 0.1014 - val loss: 27.5198 - val accuracy: 0.1003
     Epoch 10/10
     curacy: 0.1004 - val_loss: 27.5198 - val_accuracy: 0.1016
```

```
In [18]: print(history.history.keys())
    figure(figsize=(10, 4))
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```

dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])



```
In [19]: print(history.history.keys())
    figure(figsize=(10, 4))
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('epoch')
    plt.xlabel('accuracy')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```

dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])

