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Roll No.: 225229103

```
H
In [ ]:
                    Lab : 6 : Multi-class Classification of Fashion Apparels using DNN
In [1]:
                                                                                                 M
import pandas as pd
import numpy as np
In [2]:
                                                                                                 M
import tensorflow as tf
import keras
In [3]:
                                                                                                 M
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
In [4]:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Flatten
In [5]:
                                                                                                 M
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
In [6]:
from keras.datasets import fashion_mnist
In [7]:
from tensorflow.keras.optimizers import Adam
In [8]:
                                                                                                 M
from sklearn.model_selection import train_test_split
```

#### **Dataset Split:**

```
In [9]: ▶
```

```
df = tf.keras.datasets.fashion_mnist.load_data()
```

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz (https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz)

29515/29515 [=========== ] - 0s 3us/step

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz (https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz)

26421880/26421880 [============ ] - 66s 3us/step

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t 10k-labels-idx1-ubyte.gz (https://storage.googleapis.com/tensorflow/tf-keras-datase ts/t10k-labels-idx1-ubyte.gz)

5148/5148 [=========== ] - 0s 0s/step

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t 10k-images-idx3-ubyte.gz (https://storage.googleapis.com/tensorflow/tf-keras-datase ts/t10k-images-idx3-ubyte.gz)

4422102/4422102 [=========== ] - 1s Ous/step

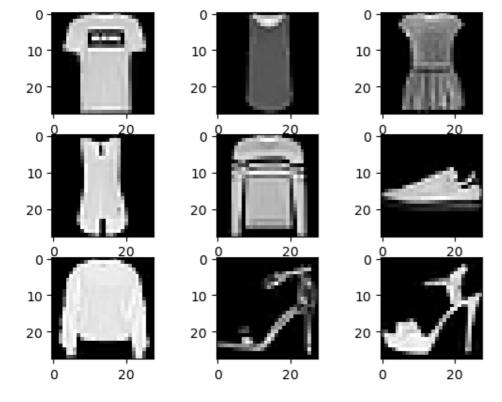
In [10]: ▶

```
(X_train, y_train), (X_test, y_test) = df
```

## Img

In [11]:

```
for i in range(1, 10):
    plt.subplot(3, 3, i)
    plt.imshow(X_train[i], cmap=plt.get_cmap('gray'))
plt.show()
```



#### Shape

In [12]:

```
print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
X train shape: (60000, 28, 28)
y_train shape: (60000,)
X_test shape: (10000, 28, 28)
y_test shape: (10000,)
Size
In [13]:
                                                                                                       M
print("X_train size:", X_train.size)
print("y_train size:", y_train.size)
print("X_test size:", X_test.size)
print("y_test size:", y_test.size)
X train size: 47040000
y_train size: 60000
X_test size: 7840000
y test size: 10000
In [14]:
                                                                                                       M
print(X_train[37])
   89
       89
            88
                97 107 111 97
                                  0
                                       0
                                           0]
                                          94
                                              91
                                                   88
                                                       89
                                                           91
                                                                86
                                                                         95
                                                                             97
    a
        0
             0 111 126 123 111 102 102
                                                                    86
       98 104 102 111 102 111
   91
                                  0
                                       0
                                           0]
    0
        0
             0 108 107 117 146
                                169 111
                                         105
                                              91
                                                   91
                                                       88
                                                           84
                                                                88
                                                                    91
                                                                         92
                                                                             94
  105
       97 136 162 104
                         97 114
                                  0
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                                           0]
             1 118 104 114 169 130
                                      85
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                                          86
                                              82
                                                   85
                                                       85
                                                           85
                                                                86
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                                                                         88
                                                                             92
       94
            95 155 104 104 123
   92
                                   5
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                    97 120
                            92
                                 63 104
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               89 130
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            10 123
                    95 121
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            55
                47 149
                         94 124
                                 37
   81 113
                                       0
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    0
            14 121
                    98 136
                             70
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                                          79
                                              88
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        0
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   79 130
            27
                24 160
                         98 127
                                 43
                                       0
                    91 149
                                                                             92
            20 115
                             46
                                  0 130
                                          88
                                              88 105
                                                       89
                                                           89
    0
        0
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                                                                    94
                                                                         99
   82 123
             8
               15 160 111 121
                                 43
                                       0
                                           0]
            31 118
                    89 140
                             13
                                  0 113 105
                                              97
                                                   91
                                                       94
                                                           88
                                                                94
                                                                    92
                                                                         97
                                                                             95
   89 128
             4
                 0 159 118 121
                                 39
                                       0
                                           0]
                                  0 110 113 101
    0
        0
            42 120
                    86 133
                              4
                                                   92
                                                       89
                                                           91
                                                                89
                                                                    97
                                                                         94
                                                                             97
   89
      131
             0
                 0 155
                       117 126
                                 55
                                       0
                                           0]
            EE 101
    Ω
                    QC 117
                                   A 127 111
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                                                   ۵7
                                                       Ω1
                                                            Q A
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```

M

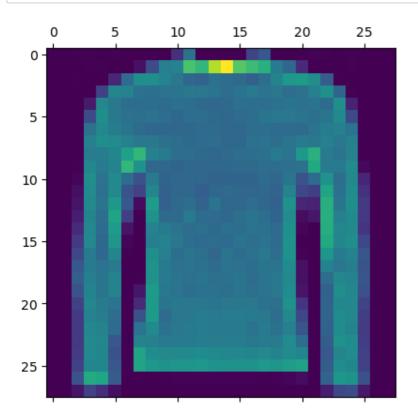
```
In [15]:
y_train[37]
```

# Out[15]:

2

In [16]:

```
plt.matshow(X_train[37])
plt.show()
```



#### **Normalize**

```
In [17]:

X_train = X_train.reshape((X_train.shape[0], 28*28)).astype('float32')
X_test = X_test.reshape((X_test.shape[0], 28*28)).astype('float32')
```

```
In [18]:

X_train = X_train / 255
X_test = X_test / 255
```

# **Baseline model**

```
M
In [19]:
model = Sequential()
model.add(Dense(512, input_dim=28*28, activation='relu'))
model.add(Dense(10, activation='softmax'))
In [20]:
                                              M
model.compile(loss='mean_squared_error', metrics=['accuracy'])
In [21]:
                                              M
model.fit(X_train, y_train, epochs=10)
Epoch 1/10
uracy: 0.1043
Epoch 2/10
uracy: 0.0989
Epoch 3/10
uracy: 0.0975
Epoch 4/10
uracy: 0.0978
Epoch 5/10
uracy: 0.0970
Epoch 6/10
uracy: 0.0969
Epoch 7/10
In [22]:
                                              H
model.evaluate(X_test, y_test)
0.0942
Out[22]:
[27.60999298095703, 0.094200000166893]
```

In [23]:

model.summary()

# Model: "sequential"

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

\_\_\_\_\_

Total params: 407050 (1.55 MB)
Trainable params: 407050 (1.55 MB)
Non-trainable params: 0 (0.00 Byte)

In [24]:

X\_train, X\_val, y\_train, y\_val = train\_test\_split(X\_train, y\_train, test\_size=0.2, random\_state=1

In [25]:

history = model.fit(X\_train,y\_train,epochs=10,validation\_data=(X\_val, y\_val))

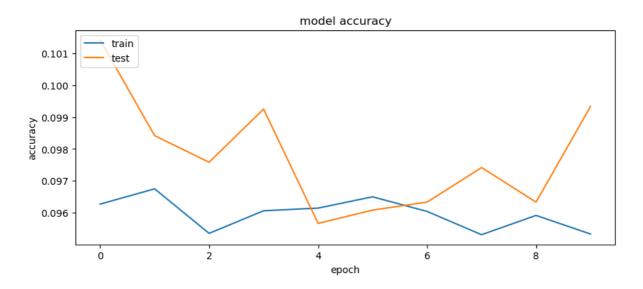
```
Epoch 1/10
uracy: 0.0963 - val_loss: 27.7079 - val_accuracy: 0.1014
uracy: 0.0967 - val_loss: 27.7079 - val_accuracy: 0.0984
Epoch 3/10
uracy: 0.0954 - val_loss: 27.7079 - val_accuracy: 0.0976
Epoch 4/10
uracy: 0.0961 - val_loss: 27.7079 - val_accuracy: 0.0993
Epoch 5/10
uracy: 0.0961 - val_loss: 27.7079 - val_accuracy: 0.0957
Epoch 6/10
uracy: 0.0965 - val_loss: 27.7079 - val_accuracy: 0.0961
Epoch 7/10
```

In [26]: ▶

```
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.ylabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

dict\_keys(['loss', 'accuracy', 'val\_loss', 'val\_accuracy'])



## **Performance Analysis**

# Layer: 2:512

```
In [27]:
model1 = Sequential()
```

```
model1 = Sequential()
model1.add(Dense(512, input_dim=28*28, activation='relu'))
model1.add(Dense(512, input_dim=28*28, activation='relu'))
model1.add(Dense(10,activation='softmax'))
model1.compile(loss='mean_squared_error', metrics=['accuracy'])
```

```
H
In [28]:
model1.fit(X_train,y_train,epochs=10)
Epoch 1/10
uracy: 0.1027
Epoch 2/10
uracy: 0.1010
Epoch 3/10
uracy: 0.0981
Epoch 4/10
uracy: 0.0989
Epoch 5/10
uracy: 0.1003
Epoch 6/10
uracy: 0.1019
Epoch 7/10
In [29]:
model1.evaluate(X_test,y_test)
0.1066
Out[29]:
[27.609987258911133, 0.10660000145435333]
Layer: 2:256
In [30]:
                                                 M
model2 = Sequential()
model2.add(Dense(256, input dim=28*28, activation='relu'))
model2.add(Dense(256, input_dim=28*28, activation='relu'))
model2.add(Dense(10,activation='softmax'))
model2.compile(loss='mean_squared_error', metrics=['accuracy'])
```

```
M
In [31]:
model2.fit(X_train,y_train,epochs=10)
model2.evaluate(X_test,y_test)
Epoch 1/10
racy: 0.1154
Epoch 2/10
uracy: 0.1052
Epoch 3/10
racy: 0.1058
Epoch 4/10
racy: 0.1083
Epoch 5/10
uracy: 0.1079
Epoch 6/10
racy: 0.1110
Epoch 7/10
In [32]:
                                 M
model2.fit(X train,y train,epochs=10)
Epoch 1/10
uracy: 0.1067
Epoch 2/10
racy: 0.1058
Epoch 3/10
racy: 0.1050
Epoch 4/10
racy: 0.1059
Epoch 5/10
racy: 0.1044
Epoch 6/10
racy: 0.1064
Epoch 7/10
                                 M
In [33]:
model2.evaluate(X test,y test)
0.1064
Out[33]:
[27.609987258911133, 0.10639999806880951]
```

Layer: 2:128

```
M
In [34]:
model3 = Sequential()
model3.add(Dense(128, input_dim=28*28, activation='relu'))
model3.add(Dense(128, input_dim=28*28, activation='relu'))
model3.add(Dense(10,activation='softmax'))
model3.compile(loss='mean_squared_error', metrics=['accuracy'])
In [35]:
                                                               H
model3.fit(X_train,y_train,epochs=10)
Epoch 1/10
1500/1500 [============== ] - 10s 6ms/step - loss: 27.5856 - accu
racy: 0.1088
Epoch 2/10
acy: 0.1266
Epoch 3/10
acy: 0.1260
Epoch 4/10
racy: 0.1191
Epoch 5/10
racy: 0.1121
Epoch 6/10
acy: 0.1057
Epoch 7/10
In [36]:
                                                               H
model3.evaluate(X test,y test)
0.0937
Out[36]:
[27.609987258911133, 0.09369999915361404]
Layer: 3:512
In [37]:
                                                               M
model4 = Sequential()
model4.add(Dense(512, input_dim=28*28, activation='relu'))
model4.add(Dense(512, input_dim=28*28, activation='relu'))
model4.add(Dense(512, input_dim=28*28, activation='relu'))
model4.add(Dense(10,activation='softmax'))
model4.compile(loss='mean squared error', metrics=['accuracy'])
```

```
H
In [38]:
model4.fit(X_train,y_train,epochs=10)
Epoch 1/10
uracy: 0.1001
Epoch 2/10
uracy: 0.0927
Epoch 3/10
uracy: 0.0952
Epoch 4/10
uracy: 0.0967
Epoch 5/10
uracy: 0.0979
Epoch 6/10
uracy: 0.0967
Epoch 7/10
In [39]:
model4.evaluate(X_test,y_test)
0.0976
Out[39]:
[27.609987258911133, 0.09759999811649323]
Layer: 3:256
In [40]:
                                                M
model5 = Sequential()
model5.add(Dense(256, input dim=28*28, activation='relu'))
model5.add(Dense(256, input_dim=28*28, activation='relu'))
model5.add(Dense(256, input_dim=28*28, activation='relu'))
model5.add(Dense(10,activation='softmax'))
```

```
localhost:8888/notebooks/225229103_PDL_Lab06.ipynb#
```

model5.compile(loss='mean\_squared\_error', metrics=['accuracy'])

```
H
In [41]:
model5.fit(X_train,y_train,epochs=10)
Epoch 1/10
racy: 0.0962
Epoch 2/10
racy: 0.0938
Epoch 3/10
racy: 0.0959
Epoch 4/10
racy: 0.0967
Epoch 5/10
racy: 0.0951
Epoch 6/10
1500/1500 [============== ] - 13s 9ms/step - loss: 27.5856 - accu
racy: 0.0935
Epoch 7/10
In [42]:
model5.evaluate(X_test,y_test)
0.0948
Out[42]:
[27.609987258911133, 0.09480000287294388]
Layer: 4:512
In [43]:
                                                      M
model7 = Sequential()
model7.add(Dense(512, input dim=28*28, activation='relu'))
model7.add(Dense(512, input_dim=28*28, activation='relu'))
model7.add(Dense(512, input_dim=28*28, activation='relu'))
model7.add(Dense(512, input_dim=28*28, activation='relu'))
```

```
localhost:8888/notebooks/225229103_PDL_Lab06.ipynb#
```

model7.add(Dense(10,activation='softmax'))

model7.compile(loss='mean\_squared\_error', metrics=['accuracy'])

```
M
In [44]:
model7.fit(X_train,y_train,epochs=10)
Epoch 1/10
uracy: 0.0951
Epoch 2/10
uracy: 0.0947
Epoch 3/10
uracy: 0.0979
Epoch 4/10
uracy: 0.1001
Epoch 5/10
uracy: 0.1020
Epoch 6/10
uracy: 0.1025
Epoch 7/10
In [45]:
model7.evaluate(X_test,y_test)
0.1025
Out[45]:
[27.609987258911133, 0.10249999910593033]
Layer: 4: 256
In [46]:
                                    M
```

```
model8 = Sequential()
model8.add(Dense(256, input_dim=28*28, activation='relu'))
model8.add(Dense(256, input_dim=28*28, activation='relu'))
model8.add(Dense(256, input_dim=28*28, activation='relu'))
model8.add(Dense(256, input_dim=28*28, activation='relu'))
model8.add(Dense(10,activation='softmax'))
model8.compile(loss='mean_squared_error', metrics=['accuracy'])
```

```
H
In [47]:
model8.fit(X_train,y_train,epochs=10)
Epoch 1/10
racy: 0.1345
Epoch 2/10
racy: 0.1187
Epoch 3/10
uracy: 0.1129
Epoch 4/10
racy: 0.1113
Epoch 5/10
uracy: 0.1111
Epoch 6/10
1500/1500 [=============== ] - 15s 10ms/step - loss: 27.5856 - acc
uracy: 0.1118
Epoch 7/10
In [48]:
model8.evaluate(X_test,y_test)
0.1144
Out[48]:
[27.609987258911133, 0.1143999993801117]
Layer: 4:128
                                          M
```

```
model9 = Sequential()
model9.add(Dense(128, input_dim=28*28, activation='relu'))
model9.add(Dense(10,activation='softmax'))
model9.compile(loss='mean_squared_error', metrics=['accuracy'])
```

```
M
In [50]:
model9.fit(X_train,y_train,epochs=10)
Epoch 1/10
acy: 0.1103
Epoch 2/10
racy: 0.1074
Epoch 3/10
acy: 0.1024
Epoch 4/10
acy: 0.0956
Epoch 5/10
acy: 0.0921
Epoch 6/10
acy: 0.0918
Epoch 7/10
In [51]:
model9.evaluate(X_test,y_test)
0.0926
Out[51]:
[27.609987258911133, 0.09260000288486481]
Layer: 5:512
In [52]:
                                   M
```

```
model10 = Sequential()
model10.add(Dense(512, input_dim=28*28, activation='relu'))
model10.add(Dense(10,activation='softmax'))
model10.compile(loss='mean_squared_error', metrics=['accuracy'])
```

Epoch 1/10

In [53]: ▶

```
model10.fit(X_train,y_train,epochs=10)
```

```
cy: 0.0960
Epoch 2/10
cy: 0.1028
Epoch 3/10
cy: 0.1066
Epoch 4/10
cy: 0.1088
Epoch 5/10
cy: 0.1084
Epoch 6/10
cy: 0.1074
Epoch 7/10
cy: 0.1080
Epoch 8/10
cy: 0.1066
Epoch 9/10
cy: 0.1059
Epoch 10/10
cy: 0.1036
```

# Out[53]:

<keras.src.callbacks.History at 0x22f85f37510>

```
In [54]: ▶
```

```
model10.evaluate(X_test,y_test)
```

#### Out[54]:

[27.609987258911133, 0.10440000146627426]

# Layer: 5: 256

```
M
In [55]:
model11 = Sequential()
model11.add(Dense(256, input_dim=28*28, activation='relu'))
model11.add(Dense(10,activation='softmax'))
model11.compile(loss='mean_squared_error', metrics=['accuracy'])
In [56]:
model11.fit(X train,y train,epochs=10)
Epoch 1/10
cy: 0.0886
Epoch 2/10
cy: 0.0955
Epoch 3/10
y: 0.0972
Epoch 4/10
cy: 0.0994
Epoch 5/10
y: 0.0983
Epoch 6/10
cy: 0.0981
Epoch 7/10
y: 0.0965
Epoch 8/10
y: 0.0960
Epoch 9/10
cy: 0.0945
Epoch 10/10
cv: 0.0940
Out[56]:
<keras.src.callbacks.History at 0x22f8c1ad690>
In [57]:
                                               M
model11.evaluate(X_test,y_test)
0.0921
Out[57]:
[27.609987258911133, 0.09210000187158585]
```

#### Layer: 5:128

```
model12 = Sequential()
model12.add(Dense(128, input_dim=28*28, activation='relu'))
model12.add(Dense(10,activation='softmax'))
model12.add(Dense(10,activation='softmax'))
model12.compile(loss='mean_squared_error', metrics=['accuracy'])
```

```
In [59]: ▶
```

```
model12.fit(X_train,y_train,epochs=10)
```

```
Epoch 1/10
y: 0.0921
Epoch 2/10
y: 0.1023
Epoch 3/10
y: 0.1038
Epoch 4/10
y: 0.1044
Epoch 5/10
1500/1500 [============== ] - 7s 5ms/step - loss: 27.5856 - accurac
y: 0.1035
Epoch 6/10
y: 0.1015
Epoch 7/10
y: 0.1005
Epoch 8/10
y: 0.0986
Epoch 9/10
y: 0.0982
Epoch 10/10
y: 0.0960
```

#### Out[59]:

<keras.src.callbacks.History at 0x22f95fa6610>

Out[60]:

[27.609987258911133, 0.09139999747276306]