T.E.(Extc) Elective: NNFL Course Code: DJ19ECEL5014

### **EXTC I**

### **NNFL Mini project**

**Title: Clothing Classifier** 

### • Introduction

In the ever-expanding realm of e-commerce and fashion, the ability to automatically classify images of clothing has become paramount. A Clothing Classifier program serves as the technological backbone, enabling businesses to streamline inventory management, enhance user experience, and stay ahead in the competitive landscape.

### Objective:

The primary objective of the Clothing Classifier program is to accurately categorize images of various clothing items into predefined classes such as shirts, pants, dresses, shoes, and more. This automated classification system aids in organizing vast datasets, facilitating efficient search functionality, and improving the overall navigation experience for users.

In conclusion, the Clothing Classifier program represents a pivotal tool in the fusion of technology and fashion, empowering businesses to stay agile and responsive in an ever-evolving market.

### • System Description

Import all the necessary libraries to perform the program

```
# import Tensorflow
import tensorflow as tf

# import the other helper libraries required
import numpy as np
import keras
import cv2
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import KFold
from keras.layers import Conv2D, MaxPooling2D
from keras.models import Sequential
from keras.layers import Dense, Activation, Flatten, BatchNormalization
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```

Dataset to be used using fashion\_mnist

oadin	g the data
Label	Class
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

Labelling the datasets to make it functional. Here we used two columns "class\_names" and "label\_names" which gives them a name and index respectively.

Here, we gave size to the images to be trained. 60000 images were trained with size 28\*28

```
train_images.shape
(60000, 28, 28)
```

Labelled all the 60000 images

```
train_labels.shape
```

Here, we gave size to the images to be tested. 10000 images were trained with size 28\*28

```
test_images.shape
(10000, 28, 28)
```

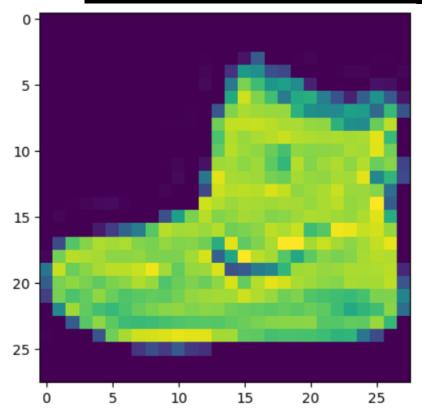
Labelled all the 10000 images

```
test_labels.shape
(10000,)
```

Here we pre-processed the image that is present at "0"

```
plt.imshow(train_images[0])
plt.show()
```

Output:



Now, we need to grayscale all the images trained

```
train_images = train_images / 255.0
test_images = test_images / 255.0
```

To verify that the data is in the correct format and that you are ready to build and train the network, display the first 25 images the training set and display the class name below each image.

```
fig = plt.figure(figsize=(15, 15))
columns = 5
rows = 5
a=0
for i in range(1, columns*rows+1):
    img=train_images[a]
    name=class_df.at[train_labels[a], "Class"]
    fig.add_subplot(rows, columns, i)
    plt.xlabel(name)
    plt.imshow(img, cmap=plt.cm.binary)
    a+=1

plt.show()
```

### Output:



Now we need to create a model having the layers defined

Here Flatten: converts the input to 1- dimensional matrix

Dense: each neuron takes input from previous neurons

Two activations layers

- 1.) Relu (before normalization)
- 2.) Softmax (after normalization)

```
model = Sequential()
model.add(Flatten())
model.add(Dense(128, input_dim=784, activation="relu"))
model.add(BatchNormalization())
model.add(Dense(10, activation="softmax"))
```

Now we compile the model using "model. compile" using "adam" optimiser; "sparsecategorial crossentropy" loss function and metrics.

```
model.compile(optimizer='adam', loss='SparseCategoricalCrossentropy', metrics=['accuracy'])
```

Now, feeding of model is done. To train the model use "model.fit" with 20 epochs.

```
model.fit(train_images, train_labels, epochs=20)
```

```
Epoch 1/20
Epoch 2/20
Epoch 3/20
1875/1875 [=
       Epoch 4/20
         ========= ] - 5s 3ms/step - loss: 0.3488 - accuracy: 0.8740
1875/1875 [=
Epoch 5/20
       1875/1875 [==
Epoch 6/20
         =========] - 5s 3ms/step - loss: 0.3283 - accuracy: 0.8828
1875/1875 [=
Epoch 7/20
         ========= ] - 4s 2ms/step - loss: 0.3161 - accuracy: 0.8867
1875/1875 [=
Epoch 8/20
1875/1875 [=====
       Epoch 9/20
1875/1875 [==
       Epoch 10/20
       1875/1875 [=:
Epoch 11/20
       1875/1875 [==
Epoch 12/20
    1875/1875 [==
Epoch 13/20
1875/1875 [=====
      Epoch 14/20
Epoch 15/20
        1875/1875 [==
Epoch 16/20
Epoch 17/20
Epoch 18/20
        1875/1875 [==
Epoch 19/20
1875/1875 [==
       ============== ] - 4s 2ms/step - loss: 0.2489 - accuracy: 0.9079
Epoch 20/20
       <keras.src.callbacks.History at 0x7e6bc04b5f90>
```

Now after 20 epochs, we have to test the model

```
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print('\nTest accuracy:', test_acc)
```

### Output:

```
313/313 - 1s - loss: 0.3508 - accuracy: 0.8778 - 673ms/epoch - 2ms/step

Test accuracy: 0.8777999877929688
```

Now to add "prediction" feature to the model

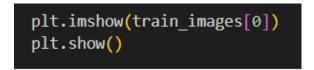
Here, the model has predicted the label for each image in the testing set.

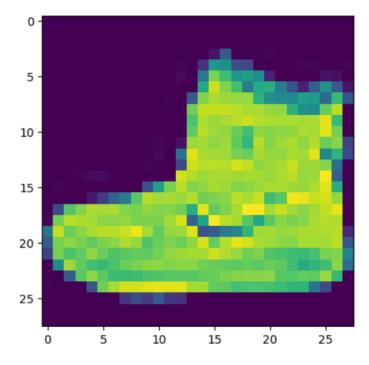
Let's perform 1<sup>st</sup> prediction:

```
arg = np.argmax(predictions, axis=1)
np.argmax(predictions[0])
9
```

```
test_labels[0]
```

The prediction for the value '0' gave is 9 i.e., according the model the clothing that is present at 0<sup>th</sup> place in the dataset is present in the 9<sup>th</sup> place class of clothing we created (ankle boots).



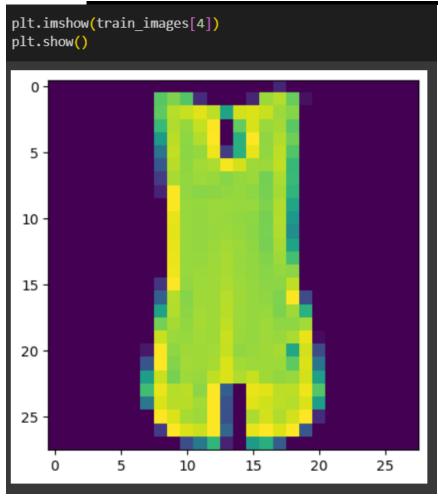


Let's make another prediction for 1234<sup>th</sup> position:

```
arg = np.argmax(predictions, axis=1)
np.argmax(predictions[1234])
4
```

```
test_labels[1234]
4
```

Model gave prediction: 4 i.e.; Coat



### • Results and Discussion

The model we created is working well alongside fashion\_mnist dataset and OpenCV. The working of the model is moderate and could be better. Results it provided were accurate.

### • Conclusion

In conclusion, the Clothing Classifier project redefines the fashion landscape by seamlessly integrating advanced image recognition. Its precision in categorization, user-friendly interface, and scalability empower businesses for efficient inventory management and enhanced customer experiences. Beyond mere classification, it serves as a data-rich tool, providing insights critical for strategic decision-making. This project is a pivotal step towards a more connected, efficient, and data-driven future for the fashion industry.