Importing Libraries

```
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense,Flatten
from tensorflow.keras.callbacks import EarlyStopping
```

Loading Dataset directly into Train & Test parameters

```
(X_train,Y_train),(X_test,Y_test) = keras.datasets.fashion_mnist.load_data()
```

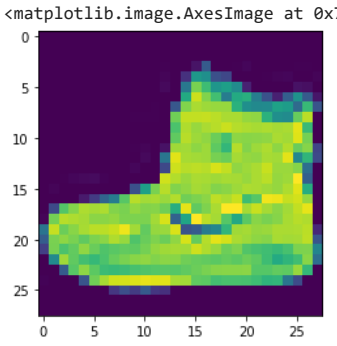
Getting to know the data

```
X_train.shape
```

```
(60000, 28, 28)
```

```
# Plotting the image of the 1st row to see how it looks and what class it is (9 - Ankle Boot)
import matplotlib.pyplot as plt
plt.imshow(X_train[0])
```

```
<matplotlib.image.AxesImage at 0x7f45f45c71c0>
```




```
Y_train[0]
```

```
9
```

The values are divided by 255 to standardize them since colors have a range of 0 to 255.

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

```
len(X_train[0])
```

```
28
```

```
len(set(Y_test))
```

```
10
```

```
# Obj
ann = Sequential()

# Hidden layers
ann.add(Flatten(input_shape=(28,28)))   # Here the image is of (28 x 28) pixels i.e. 28D so using flattening layer to convert it into 1D array
ann.add(Dense(128,activation="relu"))
ann.add(Dense(64,activation="relu"))
ann.add(Dense(32,activation="relu"))


# Output layers
ann.add(Dense(10,activation="softmax"))   # As in total possibilities are [0,1,2...8,9] so total neurons are 10 , Softmax is used for multiclass classifcation

# diagram
ann.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense (Dense)               (None, 128)               100480

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 32)                2080

 dense_3 (Dense)             (None, 10)                330

=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

```
ann.compile(loss="sparse_categorical_crossentropy",optimizer="adam",metrics=["accuracy"])
```

Creating an object of early stopping to save the resources

```
ES = EarlyStopping(mode="min",monitor="val_loss",patience=25,verbose=1)
```

```
ann.fit(X_train,Y_train,validation_split=0.2,epochs=25,batch_size=64,callbacks=ES)
```

```
Epoch 1/25
750/750 [==============================] - 8s 10ms/step - loss: 0.5685 - accuracy: 0.8031 - val_loss: 0.4193 - val_accuracy: 0.8509
Epoch 2/25
750/750 [==============================] - 8s 11ms/step - loss: 0.3899 - accuracy: 0.8586 - val_loss: 0.4013 - val_accuracy: 0.8518
Epoch 3/25
750/750 [==============================] - 7s 9ms/step - loss: 0.3494 - accuracy: 0.8716 - val_loss: 0.3645 - val_accuracy: 0.8681
Epoch 4/25
750/750 [==============================] - 4s 6ms/step - loss: 0.3241 - accuracy: 0.8794 - val_loss: 0.4081 - val_accuracy: 0.8418
Epoch 5/25
750/750 [==============================] - 5s 6ms/step - loss: 0.3049 - accuracy: 0.8867 - val_loss: 0.3598 - val_accuracy: 0.8690
Epoch 6/25
750/750 [==============================] - 4s 6ms/step - loss: 0.2880 - accuracy: 0.8923 - val_loss: 0.3361 - val_accuracy: 0.8780
Epoch 7/25
750/750 [==============================] - 4s 5ms/step - loss: 0.2765 - accuracy: 0.8957 - val_loss: 0.3308 - val_accuracy: 0.8826
Epoch 8/25
750/750 [==============================] - 5s 7ms/step - loss: 0.2663 - accuracy: 0.9017 - val_loss: 0.3282 - val_accuracy: 0.8863
Epoch 9/25
750/750 [==============================] - 4s 5ms/step - loss: 0.2554 - accuracy: 0.9045 - val_loss: 0.3506 - val_accuracy: 0.8734
Epoch 10/25
750/750 [==============================] - 4s 6ms/step - loss: 0.2478 - accuracy: 0.9072 - val_loss: 0.3061 - val_accuracy: 0.8903
Epoch 11/25
750/750 [==============================] - 5s 7ms/step - loss: 0.2389 - accuracy: 0.9109 - val_loss: 0.3285 - val_accuracy: 0.8836
```

```
Epoch 12/25
750/750 [==============================] - 4s 5ms/step - loss: 0.2299 - accuracy: 0.9127 - val_loss: 0.3461 - val_accuracy: 0.8836
Epoch 13/25
750/750 [==============================] - 4s 5ms/step - loss: 0.2222 - accuracy: 0.9159 - val_loss: 0.3224 - val_accuracy: 0.8918
Epoch 14/25
750/750 [==============================] - 5s 7ms/step - loss: 0.2168 - accuracy: 0.9188 - val_loss: 0.3397 - val_accuracy: 0.8891
Epoch 15/25
750/750 [==============================] - 4s 6ms/step - loss: 0.2092 - accuracy: 0.9209 - val_loss: 0.3357 - val_accuracy: 0.8908
Epoch 16/25
750/750 [==============================] - 4s 6ms/step - loss: 0.2057 - accuracy: 0.9227 - val_loss: 0.3264 - val_accuracy: 0.8878
Epoch 17/25
750/750 [==============================] - 5s 7ms/step - loss: 0.1977 - accuracy: 0.9247 - val_loss: 0.3252 - val_accuracy: 0.8930
Epoch 18/25
750/750 [==============================] - 5s 7ms/step - loss: 0.1933 - accuracy: 0.9272 - val_loss: 0.3421 - val_accuracy: 0.8907
Epoch 19/25
750/750 [==============================] - 6s 8ms/step - loss: 0.1863 - accuracy: 0.9288 - val_loss: 0.3605 - val_accuracy: 0.8857
Epoch 20/25
750/750 [==============================] - 4s 6ms/step - loss: 0.1856 - accuracy: 0.9291 - val_loss: 0.3806 - val_accuracy: 0.8857
Epoch 21/25
750/750 [==============================] - 4s 5ms/step - loss: 0.1798 - accuracy: 0.9324 - val_loss: 0.3526 - val_accuracy: 0.8909
Epoch 22/25
750/750 [==============================] - 5s 7ms/step - loss: 0.1744 - accuracy: 0.9347 - val_loss: 0.3647 - val_accuracy: 0.8828
Epoch 23/25
750/750 [==============================] - 4s 6ms/step - loss: 0.1698 - accuracy: 0.9362 - val_loss: 0.3587 - val_accuracy: 0.8896
Epoch 24/25
750/750 [==============================] - 5s 6ms/step - loss: 0.1611 - accuracy: 0.9391 - val_loss: 0.3662 - val_accuracy: 0.8911
Epoch 25/25
750/750 [==============================] - 5s 6ms/step - loss: 0.1623 - accuracy: 0.9383 - val_loss: 0.3770 - val_accuracy: 0.8887
<keras.callbacks.History at 0x7f45f79cf190>
```

```
Y_prob = ann.predict(X_test)
```

```
313/313 [==============================] - 1s 2ms/step
```

Assigning the class based on the highest probability values for the numbers 0 to 9.

```
Y_pred = Y_prob.argmax(axis=1)
```

The probability that the first row belongs to each of the [0-9] classes.

```
Y_prob[0]
```

```
array([1.8610631e-06, 4.0219443e-06, 6.8793802e-06, 3.2166761e-05,
       1.7617293e-07, 1.3151170e-04, 3.4920934e-06, 4.8407752e-04,
       2.2943200e-06, 9.9933356e-01], dtype=float32)
```

```
Y_pred
```

```
array([9, 2, 1, ..., 8, 1, 5])
```

Classification Report

```
from sklearn.metrics import classification_report
print(classification_report(Y_test,Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.81      0.83      1000
           1       0.99      0.98      0.98      1000
           2       0.83      0.78      0.80      1000
           3       0.90      0.90      0.90      1000
           4       0.78      0.82      0.80      1000
           5       0.96      0.97      0.97      1000
           6       0.69      0.72      0.71      1000
           7       0.95      0.95      0.95      1000
           8       0.95      0.98      0.96      1000
           9       0.96      0.96      0.96      1000

    accuracy                           0.89     10000
   macro avg       0.89      0.89      0.89     10000
weighted avg       0.89      0.89      0.89     10000
```