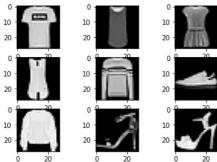
```
In [1]: #Image classification using Deep Learning
import tensorflow as tf
        import numpy as np
        import pandas as pd
import matplotlib.pyplot as plt
        import warnings
        warnings.filterwarnings("ignore")
In [2]: (x_train, y_train), (x_test, y_test) = tf.keras.datasets.fashion_mnist.load_data()
In [4]:
        x_train.shape
Out[4]: (60000, 28, 28)
In [5]:
         x_test.shape
Out[5]: (10000, 28, 28)
In [6]: plt.imshow(x_train[0])
plt.colorbar()
        plt.grid(False)
        plt.show()
          0
                                              250
          5
                                              200
         10
                                             - 150
         15
                                             100
          20
          25
                      10
                           15
                                20
In [7]:
        x_train[0].max()
Out[7]: 255
In [8]:
         x_test[0].max()
Out[8]: 255
In [9]: # normalize values between 0 & 1
        x_train = x_train/255
x_test = x_test/255
        ## another method to normalize
```

x_train = tf.keras.utils.normalize(x_train, axis=1)
x_test = tf.keras.utils.normalize(x_test, axis=1)

```
In [18]: # check if images and class align
for i in range(1, 10):
    # Create a 3x3 grid and place the
    # image in ith position of grid
    plt.subplot(3, 3, i)
    # Insert ith image with the color map 'grap'
    plt.imshow(x_train[i], cmap=plt.get_cmap('gray'))

# Display the entire plot
plt.show()
```



model.fit(x_train, y_train, epochs=30, validation_split=0.2)

```
Epoch 1/30
1500/1500 [
                            - 5s 3ms/step - loss: 0.5191 - accuracy: 0.8187 - val_loss: 0.4226 - val_accuracy: 0.8528
Epoch 2/30
1500/1500 [
                         ====] - 5s 3ms/step - loss: 0.3878 - accuracy: 0.8607 - val_loss: 0.3726 - val_accuracy: 0.8664
Epoch 3/30
1500/1500 [
                            - 4s 2ms/step - loss: 0.3447 - accuracy: 0.8744 - val_loss: 0.3588 - val_accuracy: 0.8708
                        =====]
Epoch 4/30
1500/1500 [
              ==========] - 4s 3ms/step - loss: 0.3207 - accuracy: 0.8834 - val loss: 0.3434 - val accuracy: 0.8763
Epoch 5/30
1500/1500 [
                        ====] - 4s 3ms/step - loss: 0.3020 - accuracy: 0.8888 - val_loss: 0.3268 - val_accuracy: 0.8852
Epoch 6/30
                  ========] - 4s 3ms/step - loss: 0.2848 - accuracy: 0.8947 - val_loss: 0.3448 - val_accuracy: 0.8777
1500/1500 F
Epoch 7/30
Epoch 8/30
1500/1500 [
                  =========] - 4s 3ms/step - loss: 0.2616 - accuracy: 0.9026 - val_loss: 0.3595 - val_accuracy: 0.8769
Epoch 9/30
1500/1500 [
                            - 6s 4ms/step - loss: 0.2514 - accuracy: 0.9055 - val loss: 0.3169 - val accuracy: 0.8895
                       =====]
Epoch 10/30
1500/1500 [=:
                =============== 1 - 6s 4ms/step - loss: 0.2422 - accuracv: 0.9099 - val loss: 0.3079 - val accuracv: 0.8905
Enoch 11/30
                      :======] - 4s 3ms/step - loss: 0.2326 - accuracy: 0.9143 - val_loss: 0.3168 - val_accuracy: 0.8892
1500/1500 [
Epoch 12/30
1500/1500 [=
              =========] - 8s 5ms/step - loss: 0.2252 - accuracy: 0.9153 - val_loss: 0.3279 - val_accuracy: 0.8878
Epoch 13/30
Epoch 14/30
Epoch 15/30
1500/1500 [=
                   :=======] - 4s 3ms/step - loss: 0.2049 - accuracy: 0.9225 - val_loss: 0.3396 - val_accuracy: 0.8875
Epoch 16/30
Epoch 17/30
1500/1500 [=
                      :======] - 6s 4ms/step - loss: 0.1929 - accuracy: 0.9261 - val_loss: 0.3356 - val_accuracy: 0.8903
Epoch 18/30
1500/1500 [=
                            - 5s 4ms/step - loss: 0.1860 - accuracy: 0.9301 - val_loss: 0.3277 - val_accuracy: 0.8936
Epoch 19/30
1500/1500 [:
                          ==] - 7s 5ms/step - loss: 0.1837 - accuracy: 0.9309 - val_loss: 0.3359 - val_accuracy: 0.8911
Epoch 20/30
              1500/1500 [==
Epoch 21/30
1500/1500 [
                        :====] - 8s 5ms/step - loss: 0.1724 - accuracy: 0.9349 - val_loss: 0.3349 - val_accuracy: 0.8929
Epoch 22/30
1500/1500 [=
                    :=======] - 13s 9ms/step - loss: 0.1680 - accuracy: 0.9367 - val_loss: 0.3430 - val_accuracy: 0.8931
Epoch 23/30
Epoch 24/30
1500/1500 [:
                    ========] - 12s 8ms/step - loss: 0.1596 - accuracy: 0.9399 - val_loss: 0.3626 - val_accuracy: 0.8911
Epoch 25/30
1500/1500 [=
                 ==========] - 11s 7ms/step - loss: 0.1548 - accuracy: 0.9418 - val loss: 0.3919 - val accuracy: 0.8849
Epoch 26/30
1500/1500 [=
              Epoch 27/30
Epoch 28/30
               ========= ] - 9s 6ms/step - loss: 0.1437 - accuracy: 0.9460 - val loss: 0.3794 - val accuracy: 0.8877
1500/1500 [=
Fnoch 29/30
Epoch 30/30
```

Out[12]: <keras.callbacks.History at 0x2b19b59d5e0>

```
In [43]: |#overfitting problems
      from tensorflow.keras.optimizers import Adam
      early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=3)
      model = tf.keras.models.Sequential(
        [tf.keras.layers.Flatten(input_shape=(28,28)),
         tf.keras.layers.Dense(128, activation='relu'),
         tf.keras.layers.Dropout(0.25),
         tf.keras.layers.Dense(10, activation='softmax')]
      model.compile(optimizer=Adam(learning rate=1e-3),
               loss='sparse_categorical_crossentropy
               metrics=['sparse categorical accuracy'])
      history = model.fit(x_train, y_train, epochs=20, validation_split=0.25, callbacks=[early_stopping])
      #ReLu function: it's a linear activation function.
      #It is less susceptible to vanishing gradients that prevent deep models from being trained, although it can suffer from other problems
      #like saturated or "dead" units. It is calculated as \max(0.0,x), where if the input value (x) is negative, then a value 0.0 is
      #returned, otherwise, the value is returned.
      Epoch 1/20
      rse_categorical_accuracy: 0.8455
      Epoch 2/20
      1407/1407 [============ 0.8446 - val_loss: 0.3815 - val_spa
      rse_categorical_accuracy: 0.8621
      Epoch 3/20
      1407/1407 [=========== ] - 4s 3ms/step - loss: 0.3855 - sparse_categorical_accuracy: 0.8588 - val_loss: 0.3679 - val_spa
      rse categorical accuracy: 0.8652
      Epoch 4/20
      1407/1407 [===========] - 3s 2ms/step - loss: 0.3670 - sparse_categorical_accuracy: 0.8656 - val_loss: 0.3548 - val_spa
      rse_categorical_accuracy: 0.8692
      1407/1407 [=
              rse_categorical_accuracy: 0.8516
      Epoch 6/20
      1407/1407 [=========== 0.3354 - sparse_categorical_accuracy: 0.8760 - val_loss: 0.3324 - val_spa
      rse_categorical_accuracy: 0.8799
      Epoch 7/20
      1407/1407 [===========] - 4s 3ms/step - loss: 0.3243 - sparse_categorical_accuracy: 0.8808 - val_loss: 0.3424 - val_spa
      rse categorical accuracy: 0.8711
      Epoch 8/20
      1407/1407 [===========] - 3s 2ms/step - loss: 0.3192 - sparse_categorical_accuracy: 0.8820 - val_loss: 0.3272 - val_spa
      rse_categorical_accuracy: 0.8791
      Epoch 9/20
      1407/1407 [============ ] - 4s 3ms/step - loss: 0.3037 - sparse_categorical_accuracy: 0.8874 - val_loss: 0.3353 - val_spa
      rse_categorical_accuracy: 0.8783
      Epoch 10/20
      rse_categorical_accuracy: 0.8823
      Epoch 11/20
      rse_categorical_accuracy: 0.8838
      Epoch 12/20
      1407/1407 [=
                rse_categorical_accuracy: 0.8876
      Epoch 13/20
      1407/1407 [=
               rse_categorical_accuracy: 0.8793
      Epoch 14/20
      1407/1407 [=
              rse categorical accuracy: 0.8845
      Epoch 15/20
                1407/1407 [=
      rse_categorical_accuracy: 0.8879
```

In [44]: model.summary()

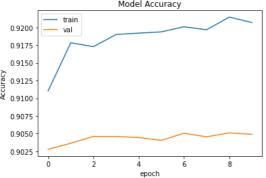
Model: "sequential 5"

Layer (type)	Output Shape	Param #
flatten_5 (Flatten)	(None, 784)	0
dense_10 (Dense)	(None, 128)	100480
dropout_4 (Dropout)	(None, 128)	0
dense_11 (Dense)	(None, 10)	1290

Total params: 101,770
Trainable params: 101,770

Non-trainable params: 0

```
In [45]: test_loss, test_acc = model.evaluate(x_train, y_train)
      print('Test accuracy:', test_acc)
      Test accuracy: 0.9098166823387146
In [46]: predictions = model.predict(x test)
      predictions[0]
      313/313 [=========== ] - 0s 985us/step
Out[46]: array([9.5804626e-07, 5.4533555e-09, 4.0153523e-08, 3.5564550e-08, 6.7747530e-10, 1.1437546e-02, 1.4985049e-07, 2.9816655e-03,
          8.8535188e-07, 9.8557866e-01], dtype=float32)
In [47]: history = model.fit(
        x_train.astype(np.float32), y_train.astype(np.float32),
        epochs=10,
        steps per epoch=100,
        validation_split=0.33
      )
      Epoch 1/10
      100/100 [==
                   :=========] - 2s 13ms/step - loss: 0.2391 - sparse_categorical_accuracy: 0.9110 - val_loss: 0.2731 - val_spar
      se_categorical_accuracy: 0.9028
      Epoch 2/10
      se categorical accuracy: 0.9036
      Epoch 3/10
      100/100 [============] - 1s 12ms/step - loss: 0.2213 - sparse_categorical_accuracy: 0.9173 - val_loss: 0.2716 - val_spar
      se categorical accuracy: 0.9046
      Epoch 4/10
      se_categorical_accuracy: 0.9046
      Epoch 5/10
      100/100 [============] - 1s 14ms/step - loss: 0.2186 - sparse_categorical_accuracy: 0.9192 - val_loss: 0.2702 - val_spar
      se_categorical_accuracy: 0.9044
      Epoch 6/10
      se_categorical_accuracy: 0.9040
      Epoch 7/10
      se_categorical_accuracy: 0.9051
      Epoch 8/10
      100/100 [==
                se_categorical_accuracy: 0.9046
      Epoch 9/10
      100/100 [=============] - 1s 12ms/step - loss: 0.2116 - sparse_categorical_accuracy: 0.9215 - val_loss: 0.2720 - val_spar
      se_categorical_accuracy: 0.9051
      Epoch 10/10
      se_categorical_accuracy: 0.9049
In [50]:
      plt.plot(history.history['sparse_categorical_accuracy'])
      plt.plot(history.history['val_sparse_categorical_accuracy'])
      plt.title('Model Accuracy')
      plt.ylabel('Accuracy')
plt.xlabel('epoch')
      plt.legend(['train', 'val'], loc='upper left')
      plt.show()
                      Model Accuracy
```



```
In [ ]:
```