chit-7-fashion

May 6, 2025

```
[2]: import tensorflow as tf
     #from tensorflow.keras.layers.experimental import preprocessing
     from sklearn.model_selection import train_test_split
     from mlxtend.plotting import plot_confusion_matrix
     from sklearn import metrics
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     %matplotlib inline
     from tqdm.notebook import tqdm
     import random
     import warnings
     warnings.filterwarnings("ignore")
[3]: (trainX, trainY), (testX, testY) = tf.keras.datasets.fashion_mnist.load_data()
     trainX = trainX.reshape((trainX.shape[0], 28, 28, 1))
     testX = testX.reshape((testX.shape[0], 28, 28, 1))
     trainY_cat = tf.keras.utils.to_categorical(trainY)
     testY_cat = tf.keras.utils.to_categorical(testY)
    Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
    datasets/train-labels-idx1-ubyte.gz
    29515/29515
                            Os 9us/step
    Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
    datasets/train-images-idx3-ubyte.gz
    26421880/26421880
                                  9s
    Ous/step
    Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
    datasets/t10k-labels-idx1-ubyte.gz
    5148/5148
                          0s 1us/step
    Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
    datasets/t10k-images-idx3-ubyte.gz
    4422102/4422102
    1us/step
```



```
[7]: model = tf.keras.models.Sequential([

# First convolutional layer

tf.keras.layers.Conv2D(64, kernel_size=(3, 3), input_shape=(28, 28, 1),

activation='relu', name='conv-layer-1'),

# First pooling layer

tf.keras.layers.AvgPool2D(pool_size=(2, 2), name='pooling-layer-1'),

# Second convolutional layer

tf.keras.layers.Conv2D(32, kernel_size=(3, 3), activation='relu',

padding='same', name='conv-layer-2'),
```

```
# Second pooling layer
         tf.keras.layers.AvgPool2D(pool_size=(2, 2), name='pooling-layer-2'),
         # Global average pooling
         tf.keras.layers.GlobalAveragePooling2D(name='pooling-layer-3'),
         # Fully connected layer with softmax activation for multi-class_
      \hookrightarrow classification
         tf.keras.layers.Dense(len(class_names), activation="softmax",_

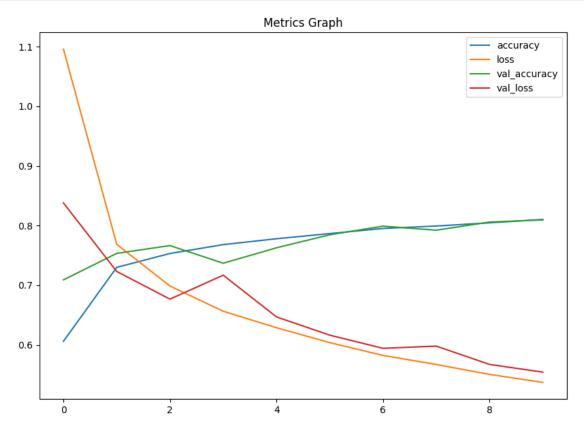
¬name="output-layer")

     ])
[8]: model.compile(loss="categorical_crossentropy",
     optimizer="adam",
     metrics=["accuracy"])
[9]: history = model.fit(train_norm, trainY_cat, epochs=10,__
      ⇔validation_data=(test_norm, testY_cat))
    Epoch 1/10
    1875/1875
                          13s 7ms/step -
    accuracy: 0.4759 - loss: 1.4343 - val_accuracy: 0.7090 - val_loss: 0.8380
    Epoch 2/10
    1875/1875
                          13s 7ms/step -
    accuracy: 0.7230 - loss: 0.7909 - val_accuracy: 0.7534 - val_loss: 0.7231
    Epoch 3/10
    1875/1875
                          13s 7ms/step -
    accuracy: 0.7497 - loss: 0.7128 - val_accuracy: 0.7665 - val_loss: 0.6767
    Epoch 4/10
                          14s 8ms/step -
    1875/1875
    accuracy: 0.7677 - loss: 0.6566 - val_accuracy: 0.7369 - val_loss: 0.7168
    Epoch 5/10
    1875/1875
                          15s 8ms/step -
    accuracy: 0.7777 - loss: 0.6333 - val_accuracy: 0.7628 - val_loss: 0.6469
    Epoch 6/10
    1875/1875
                          16s 9ms/step -
    accuracy: 0.7849 - loss: 0.6138 - val_accuracy: 0.7846 - val_loss: 0.6163
    Epoch 7/10
    1875/1875
                          17s 9ms/step -
    accuracy: 0.7922 - loss: 0.5906 - val_accuracy: 0.7991 - val_loss: 0.5942
    Epoch 8/10
    1875/1875
                          16s 9ms/step -
    accuracy: 0.7973 - loss: 0.5740 - val_accuracy: 0.7923 - val_loss: 0.5979
    Epoch 9/10
    1875/1875
                          16s 9ms/step -
    accuracy: 0.8038 - loss: 0.5531 - val_accuracy: 0.8059 - val_loss: 0.5672
```

Epoch 10/10

```
1875/1875
                           16s 9ms/step -
     accuracy: 0.8126 - loss: 0.5369 - val_accuracy: 0.8096 - val_loss: 0.5543
[10]: tf.keras.utils.plot_model(model, show_shapes=True)
     You must install graphviz (see instructions at
     https://graphviz.gitlab.io/download/) for `plot_model` to work.
[11]: model.summary()
     Model: "sequential"
      Layer (type)
                                              Output Shape
                                                                                   Ш
      →Param #
      conv-layer-1 (Conv2D)
                                              (None, 26, 26, 64)
                                                                                       Ш
      ⇔640
      pooling-layer-1 (AveragePooling2D)
                                              (None, 13, 13, 64)
                                                                                       Ш
       conv-layer-2 (Conv2D)
                                              (None, 13, 13, 32)
                                                                                    Ш
      418,464
      pooling-layer-2 (AveragePooling2D)
                                              (None, 6, 6, 32)
                                                                                       Ш
                                              (None, 32)
      pooling-layer-3
                                                                                       ш
       (GlobalAveragePooling2D)
      output-layer (Dense)
                                              (None, 10)
                                                                                       Ш
      330
      Total params: 58,304 (227.75 KB)
      Trainable params: 19,434 (75.91 KB)
      Non-trainable params: 0 (0.00 B)
      Optimizer params: 38,870 (151.84 KB)
```

```
[12]: pd.DataFrame(history.history).plot(figsize=(10,7))
    plt.title("Metrics Graph")
    plt.show()
```



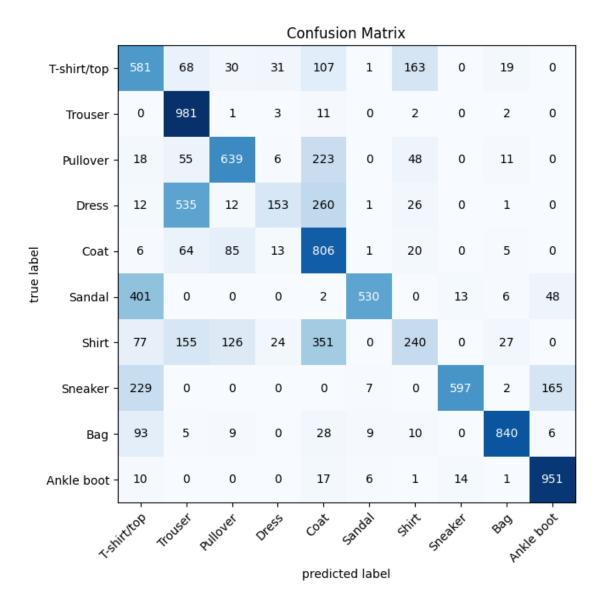
```
[18]: print(metrics.accuracy_score(y_test, predictions))
```

0.6318

[19]: print(metrics.classification_report(y_test, predictions))

```
recall f1-score
              precision
                                                 support
           0
                    0.41
                               0.58
                                         0.48
                                                    1000
                    0.53
                              0.98
                                         0.69
                                                    1000
           1
           2
                    0.71
                              0.64
                                         0.67
                                                    1000
           3
                    0.67
                              0.15
                                         0.25
                                                    1000
           4
                    0.45
                              0.81
                                         0.57
                                                    1000
           5
                    0.95
                              0.53
                                         0.68
                                                    1000
                    0.47
                              0.24
                                         0.32
           6
                                                    1000
           7
                    0.96
                              0.60
                                         0.74
                                                    1000
           8
                    0.92
                              0.84
                                         0.88
                                                    1000
                              0.95
           9
                    0.81
                                         0.88
                                                    1000
                                         0.63
                                                   10000
    accuracy
                                                   10000
   macro avg
                    0.69
                              0.63
                                         0.61
weighted avg
                    0.69
                               0.63
                                         0.61
                                                   10000
```

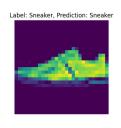
```
[20]: cm = metrics.confusion_matrix(y_test, predictions)
    plot_confusion_matrix(cm, figsize=(10,7), class_names=class_names)
    plt.title("Confusion Matrix")
    plt.show()
```

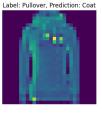


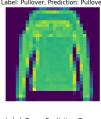
```
[21]: images = []
labels = []
random_indices = random.sample(range(len(testX)), 10)
for idx in random_indices:
    images.append(testX[idx])
    labels.append(testY_cat[idx])
images = np.array(images)
labels = np.array(labels)
fig = plt.figure(figsize=(20, 8))
rows = 2
cols = 5
x = 1
```

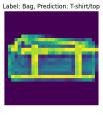
```
for image, label in zip(images, labels):
   fig.add_subplot(rows, cols, x)
   prediction = model.predict(tf.expand_dims(image, axis=0))
   prediction = class_names[tf.argmax(prediction.flatten())]
   label = class_names[tf.argmax(label)]
   plt.title(f"Label: {label}, Prediction: {prediction}")
   plt.imshow(image/255.)
   plt.axis("off")
   x += 1
```

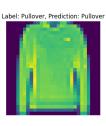
```
1/1
                Os 30ms/step
1/1
                Os 26ms/step
1/1
                Os 23ms/step
1/1
                Os 23ms/step
                Os 20ms/step
1/1
1/1
                Os 19ms/step
                Os 20ms/step
1/1
1/1
                Os 19ms/step
                Os 18ms/step
1/1
1/1
                Os 19ms/step
```

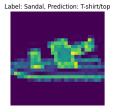


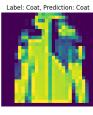


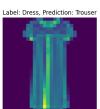


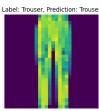


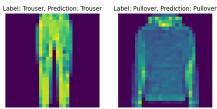












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