

MNIST Handwritten Digits Dataset

```
In [ ]: import tensorflow
        from tensorflow import keras
        from tensorflow.keras import Sequential
        from tensorflow.keras.layers import Dense, Flatten
```

```
In [3]: (X_train,y_train),(X_test,y_test) = keras.datasets.mnist.load_data()
```

```
In [4]: X_test.shape
```

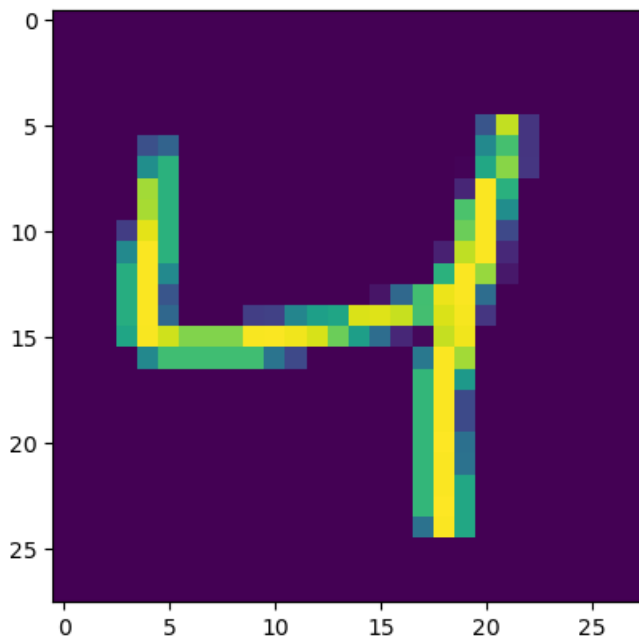
```
Out[4]: (10000, 28, 28)
```

```
In [5]: y_train
```

```
Out[5]: array([5, 0, 4, ..., 5, 6, 8], dtype=uint8)
```

```
In [6]: import matplotlib.pyplot as plt
        plt.imshow(X_train[2])
```

```
Out[6]: <matplotlib.image.AxesImage at 0x180aed5a050>
```



```
In [8]: X_train=X_train/255
        X_test=X_test/255
```

```
In [9]: X_train[0]
```

[illegible]

0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
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0.62745098, 0.42352941, 0.00392157, 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.31764706, 0.94117647,
0.99215686, 0.99215686, 0.46666667, 0.09803922, 0. ,
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0. , 0. , 0.],
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0. , 0. , 0.],
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0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],

```
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 0.      , 0.      , 0.      , 0.      , 0.      ,
 0.      , 0.      , 0.      , 0.      , 0.      ,
 0.      , 0.      , 0.      , 0.      , 0.      ,
 0.      , 0.      , 0.      , ],
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 0.      , 0.      , 0.      , ],
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 0.      , 0.      , 0.      , 0.      , 0.      ,
 0.      , 0.      , 0.      , 0.      , 0.      ,
 0.      , 0.      , 0.      , ]])
```

```
In [15]: model=Sequential()
model.add(Flatten(input_shape=(28,28)))
model.add(Dense(128,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
```

```
In [16]: model.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
flatten_3 (Flatten)	(None, 784)	0
dense_9 (Dense)	(None, 128)	100,480
dense_10 (Dense)	(None, 32)	4,128
dense_11 (Dense)	(None, 10)	330

Total params: 104,938 (409.91 KB)

Trainable params: 104,938 (409.91 KB)

Non-trainable params: 0 (0.00 B)

```
In [17]: model.compile(loss='sparse_categorical_crossentropy',optimizer='Adam',metrics=['accuracy'])
```

```
In [18]: history=model.fit(X_train,y_train,epochs=25,validation_split=0.2)
```

Epoch 1/25
1500/1500 ————— 6s 3ms/step - accuracy: 0.8542 - loss: 0.4945 - val_accuracy: 0.9579 - val_loss: 0.1474

Epoch 2/25
1500/1500 ————— 5s 3ms/step - accuracy: 0.9611 - loss: 0.1300 - val_accuracy: 0.9659 - val_loss: 0.1122

Epoch 3/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9739 - loss: 0.0857 - val_accuracy: 0.9669 - val_loss: 0.1073

Epoch 4/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9819 - loss: 0.0591 - val_accuracy: 0.9702 - val_loss: 0.0991

Epoch 5/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9849 - loss: 0.0476 - val_accuracy: 0.9732 - val_loss: 0.0893

Epoch 6/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9892 - loss: 0.0340 - val_accuracy: 0.9730 - val_loss: 0.0937

Epoch 7/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9907 - loss: 0.0279 - val_accuracy: 0.9738 - val_loss: 0.0957

Epoch 8/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9930 - loss: 0.0224 - val_accuracy: 0.9738 - val_loss: 0.1089

Epoch 9/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9944 - loss: 0.0175 - val_accuracy: 0.9741 - val_loss: 0.1040

Epoch 10/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9953 - loss: 0.0147 - val_accuracy: 0.9715 - val_loss: 0.1225

Epoch 11/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9950 - loss: 0.0150 - val_accuracy: 0.9688 - val_loss: 0.1344

Epoch 12/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9953 - loss: 0.0137 - val_accuracy: 0.9758 - val_loss: 0.1188

Epoch 13/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9961 - loss: 0.0120 - val_accuracy: 0.9727 - val_loss: 0.1322

Epoch 14/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9962 - loss: 0.0109 - val_accuracy: 0.9755 - val_loss: 0.1217

Epoch 15/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9971 - loss: 0.0093 - val_accuracy: 0.9740 - val_loss: 0.1325

Epoch 16/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9966 - loss: 0.0110 - val_accuracy: 0.9747 - val_loss: 0.1355

Epoch 17/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9968 - loss: 0.0096 - val_accuracy: 0.9765 - val_loss: 0.1279

Epoch 18/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9974 - loss: 0.0083 - val_accuracy: 0.9708 - val_loss: 0.1637

Epoch 19/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9964 - loss: 0.0106 - val_accuracy: 0.9747 - val_loss: 0.1408

Epoch 20/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9977 - loss: 0.0079 - val_accuracy: 0.9751 - val_loss: 0.1351

Epoch 21/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9974 - loss: 0.0069 - val_accuracy: 0.9774 - val_loss: 0.1403

Epoch 22/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9982 - loss: 0.0064 - val_accuracy: 0.9746 - val_loss: 0.1545

Epoch 23/25
1500/1500 ————— 4s 3ms/step - accuracy: 0.9975 - loss: 0.0070 - val_accuracy: 0.9775 - val_loss: 0.1436

Epoch 24/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9977 - loss: 0.0064 - val_accuracy: 0.9765 - val_loss: 0.1549

Epoch 25/25
1500/1500 ————— 4s 2ms/step - accuracy: 0.9983 - loss: 0.0049 - val_accuracy: 0.9747 - val_loss: 0.1769

```
In [20]: y_prob=model.predict(X_test)
```

313/313 ————— 1s 2ms/step

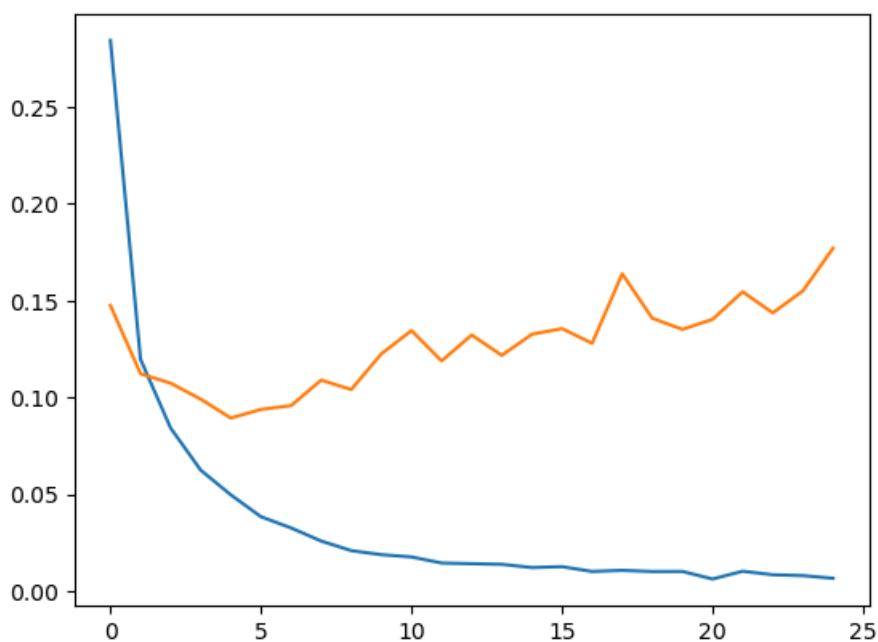
```
In [21]: y_pred=y_prob.argmax(axis=1)
```

```
In [22]: from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

Out[22]: 0.9755

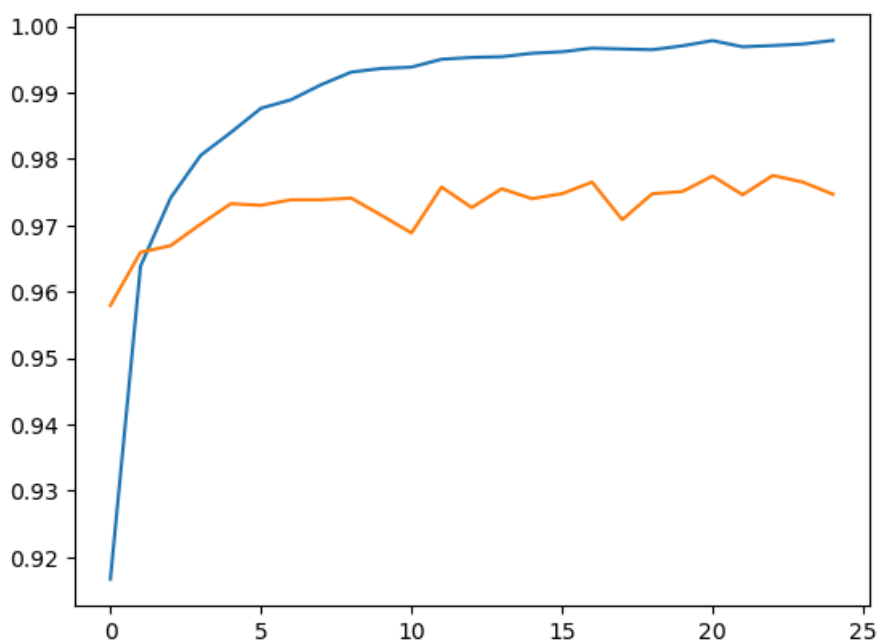
```
In [26]: plt.plot(history.history['loss'])      #blue
plt.plot(history.history['val_loss'])          #orange
```

Out[26]: [



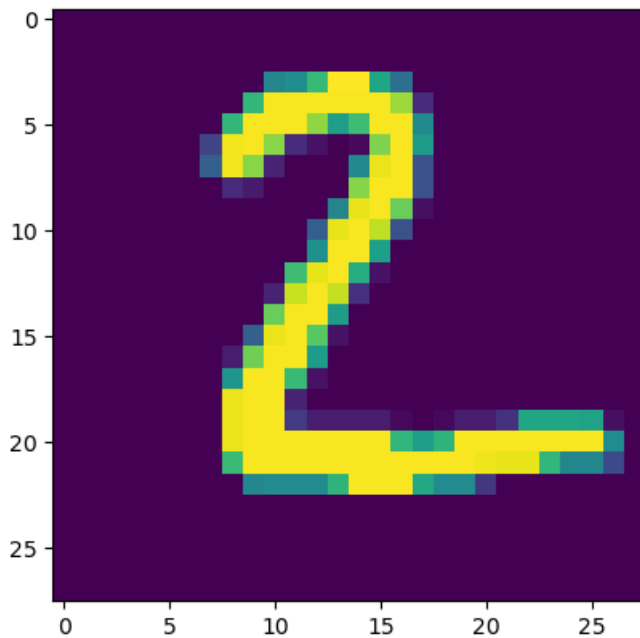
```
In [27]: plt.plot(history.history['accuracy'])  #blue
plt.plot(history.history['val_accuracy'])      #orange
```

Out[27]: [



```
In [28]: plt.imshow(X_test[1])
```

Out[28]: <matplotlib.image.AxesImage at 0x180cb8f7a50>



```
In [29]: model.predict(X_test[1].reshape(1,28,28)).argmax(axis=1)
```

```
1/1 ————— 0s 31ms/step
```

```
Out[29]: array([2], dtype=int64)
```

Fashion MNIST Dataset

```
In [1]: import tensorflow
        from tensorflow import keras
        from tensorflow.keras import Sequential
        from tensorflow.keras.layers import Dense, Flatten
```

```
In [8]: (X_train, y_train), (X_test, y_test) = keras.datasets.fashion_mnist.load_data()
```

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

```
29515/29515 ————— 0s 2us/step
```

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

```
26421880/26421880 ————— 11s 0us/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 ————— 1s 0us/step
```

```
In [9]: X_test.shape
```

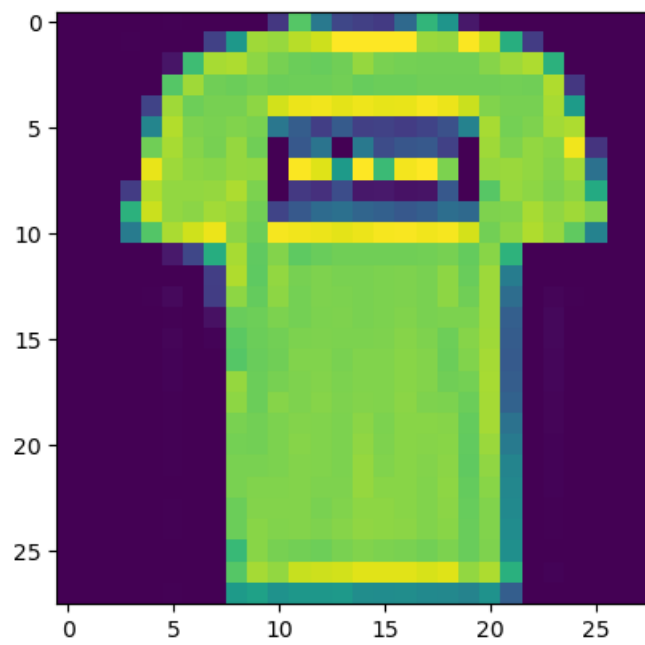
```
Out[9]: (10000, 28, 28)
```

```
In [10]: y_train
```

```
Out[10]: array([9, 0, 0, ..., 3, 0, 5], dtype=uint8)
```

```
In [50]: import matplotlib.pyplot as plt
        plt.imshow(X_train[1])
```

```
Out[50]: <matplotlib.image.AxesImage at 0x20c277a3d90>
```



```
In [18]: X_train=X_train/255  
X_test=X_test/255
```

```
In [19]: X_train[0]
```



```
Out[19]: array([[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
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0.00392157, 0.00392157, 0.      ],
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0.      , 0.      , 0.01176471, 0.      , 0.14117647,
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```

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```
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 0.      , 0.      , 0.      ]])
```

```
In [22]: model=Sequential()
model.add(Flatten(input_shape=(28,28)))
model.add(Dense(128,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
```

```
In [23]: model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
flatten_2 (Flatten)	(None, 784)	0
dense_3 (Dense)	(None, 128)	100,480
dense_4 (Dense)	(None, 32)	4,128
dense_5 (Dense)	(None, 10)	330

Total params: 104,938 (409.91 KB)

Trainable params: 104,938 (409.91 KB)

Non-trainable params: 0 (0.00 B)

```
In [24]: model.compile(loss='sparse_categorical_crossentropy',optimizer='Adam',metrics=['accuracy'])
```

```
In [33]: history=model.fit(X_train,y_train,epochs=20,validation_split=0.2)
```

Epoch 1/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9507 - loss: 0.1505 - val_accuracy: 0.8825 - val_loss: 0.4757
Epoch 2/20
1500/1500 ————— 4s 2ms/step - accuracy: 0.9559 - loss: 0.1313 - val_accuracy: 0.8917 - val_loss: 0.4503
Epoch 3/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9582 - loss: 0.1182 - val_accuracy: 0.8867 - val_loss: 0.4997
Epoch 4/20
1500/1500 ————— 4s 2ms/step - accuracy: 0.9564 - loss: 0.1215 - val_accuracy: 0.8903 - val_loss: 0.4882
Epoch 5/20
1500/1500 ————— 4s 2ms/step - accuracy: 0.9604 - loss: 0.1111 - val_accuracy: 0.8831 - val_loss: 0.4623
Epoch 6/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9617 - loss: 0.1064 - val_accuracy: 0.8905 - val_loss: 0.4774
Epoch 7/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9634 - loss: 0.1023 - val_accuracy: 0.8905 - val_loss: 0.4680
Epoch 8/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9623 - loss: 0.1033 - val_accuracy: 0.8941 - val_loss: 0.4869
Epoch 9/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9653 - loss: 0.0937 - val_accuracy: 0.8882 - val_loss: 0.4798
Epoch 10/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9653 - loss: 0.0973 - val_accuracy: 0.8894 - val_loss: 0.4749
Epoch 11/20
1500/1500 ————— 6s 3ms/step - accuracy: 0.9641 - loss: 0.1010 - val_accuracy: 0.8913 - val_loss: 0.5142
Epoch 12/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9668 - loss: 0.0904 - val_accuracy: 0.8866 - val_loss: 0.5290
Epoch 13/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9663 - loss: 0.0923 - val_accuracy: 0.8878 - val_loss: 0.5081
Epoch 14/20
1500/1500 ————— 5s 3ms/step - accuracy: 0.9681 - loss: 0.0871 - val_accuracy: 0.8915 - val_loss: 0.5422
Epoch 15/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9649 - loss: 0.0952 - val_accuracy: 0.8868 - val_loss: 0.5530
Epoch 16/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9703 - loss: 0.0846 - val_accuracy: 0.8895 - val_loss: 0.5401
Epoch 17/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9688 - loss: 0.0848 - val_accuracy: 0.8893 - val_loss: 0.5489
Epoch 18/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9678 - loss: 0.0863 - val_accuracy: 0.8881 - val_loss: 0.5838
Epoch 19/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9692 - loss: 0.0828 - val_accuracy: 0.8903 - val_loss: 0.5725
Epoch 20/20
1500/1500 ————— 4s 3ms/step - accuracy: 0.9675 - loss: 0.0846 - val_accuracy: 0.8880 - val_loss: 0.5996

In [34]: `y_prob=model.predict(X_test)`

313/313 ————— 0s 2ms/step

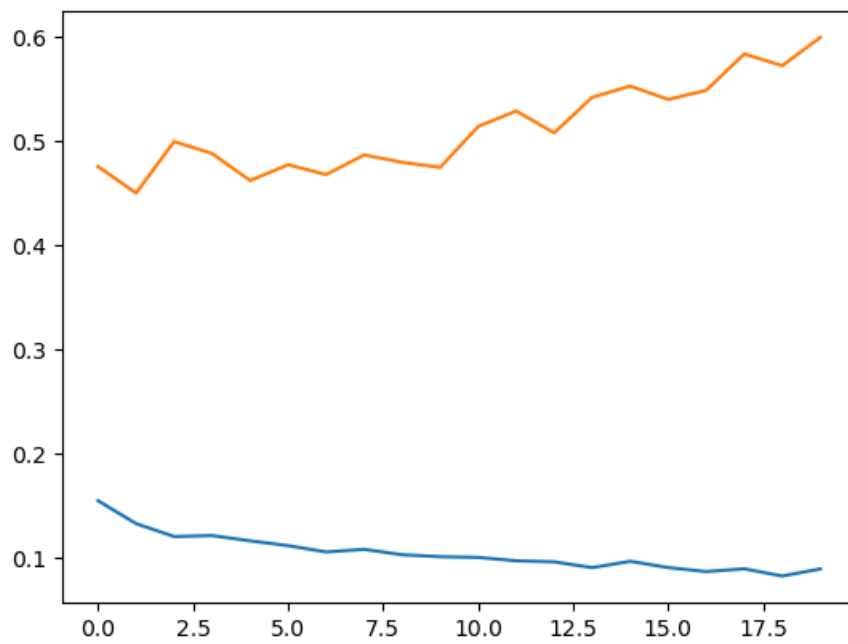
In [35]: `y_pred=y_prob.argmax(axis=1)`

In [36]: `from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)`

Out[36]: 0.8817

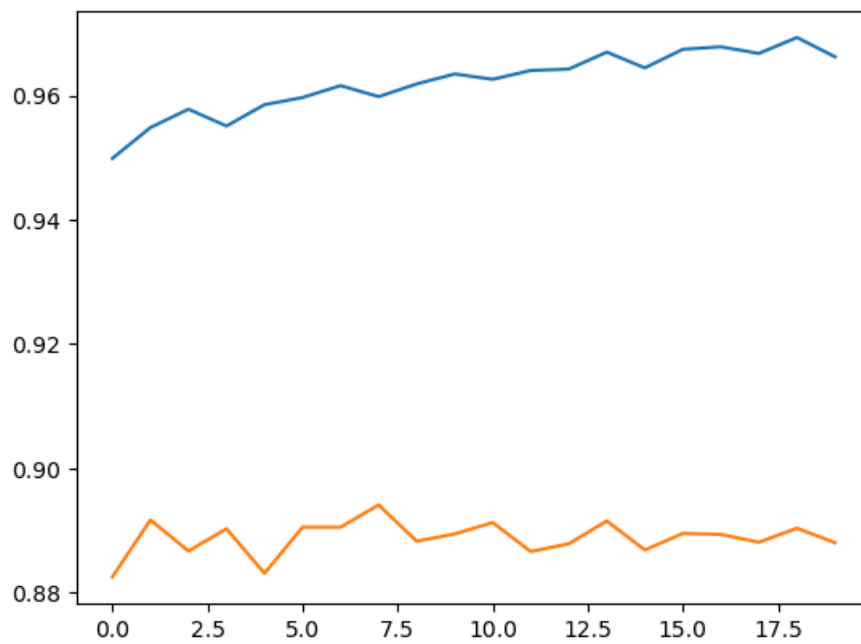
In [37]: `plt.plot(history.history['loss']) #blue
plt.plot(history.history['val_loss']) #orange`

Out[37]: [



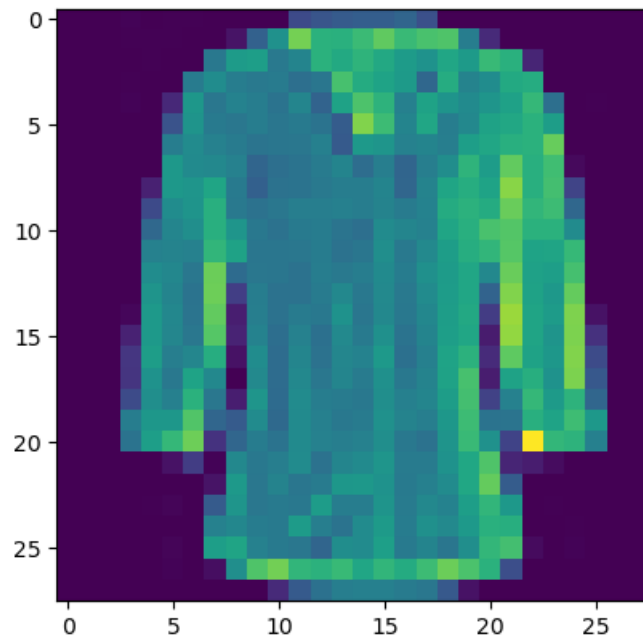
```
In [38]: plt.plot(history.history['accuracy'], #blue  
plt.plot(history.history['val_accuracy'], #orange
```

Out[38]: [



```
In [60]: plt.imshow(X_test[4])
```

Out[60]: <matplotlib.image.AxesImage at 0x20c27b69650>



```
In [61]: model.predict(X_test[4].reshape(1,28,28)).argmax(axis=1)
```

1/1 ————— 0s 31ms/step

```
Out[61]: array([6], dtype=int64)
```