

Hand Written Digit Recognition.

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
mnist=tf.keras.datasets.mnist
(x_train,y_train),(x_test,y_test) = mnist.load_data()
x_train.shape

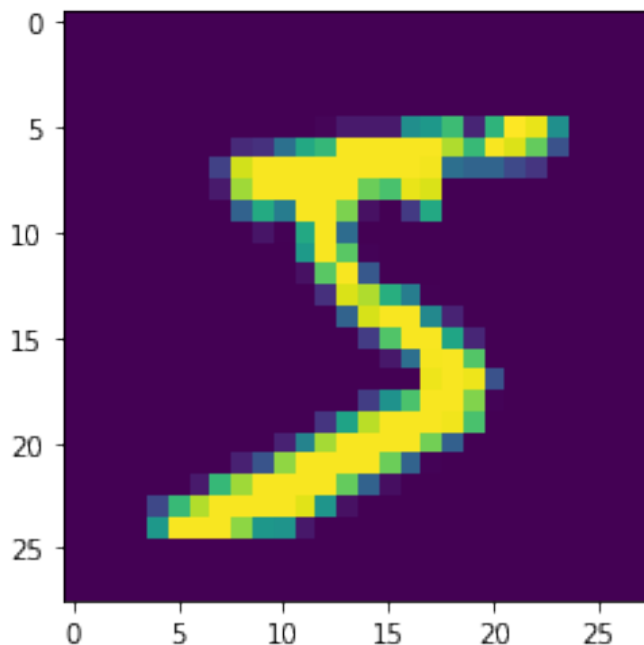
plt.imshow(x_train[0])
plt.show()
plt.imshow(x_train[0], cmap = plt.cm.binary)

print(x_train[0]) # before normalizing

x_train=tf.keras.utils.normalize(x_train, axis = 1)
x_test=tf.keras.utils.normalize(x_test, axis = 1)
plt.imshow(x_train[0], cmap = plt.cm.binary)

print(x_train[0])# after normalizing

print(y_train[0])
```



[illegible]

[illegible]

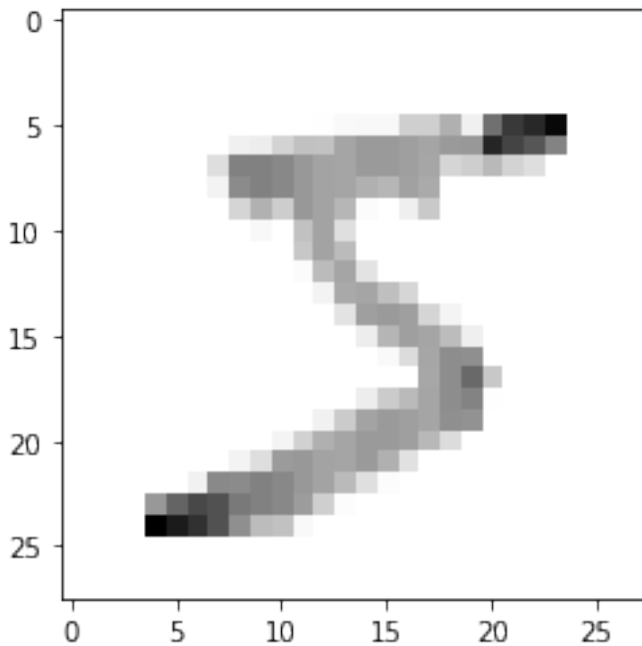
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.00393124	0.02332955	0.02620568	0.02625207	0.17420356	0.17566281
0.28629534	0.05664824	0.51877786	0.71632322	0.77892406	0.89301644
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.05780486	0.06524513	0.16128198	0.22713296
0.22277047	0.32790981	0.36833534	0.3689874	0.34978968	0.32678448
0.368094	0.3747499	0.79066747	0.67980478	0.61494005	0.45002403
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.12250613	0.45858525	0.45852825	0.43408872	0.37314701
0.33153488	0.32790981	0.36833534	0.3689874	0.34978968	0.32420121
0.15214552	0.17865984	0.25626376	0.1573102	0.12298801	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.04500225	0.4219755	0.45852825	0.43408872	0.37314701
0.33153488	0.32790981	0.28826244	0.26543758	0.34149427	0.31128482
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.1541463	0.28272888	0.18358693	0.37314701
0.33153488	0.26569767	0.01601458	0.	0.05945042	0.19891229
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.0253731	0.00171577	0.22713296
0.33153488	0.11664776	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.	0.20500962
0.33153488	0.24625638	0.00291174	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.01622378
0.24897876	0.32790981	0.10191096	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.
0.04586451	0.31235677	0.32757096	0.23335172	0.14931733	0.00129164
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.10498298	0.34940902	0.3689874	0.34978968	0.15370495
0.04089933	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.06551419	0.27127137	0.34978968	0.32678448
0.245396	0.05882702	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.02333517	0.12857881	0.32549285
0.41390126	0.40743158	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.	0.32161793
0.41390126	0.54251585	0.20001074	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.06697006	0.18959827	0.25300993	0.32678448
0.41390126	0.45100715	0.00625034	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.05110617	0.19182076	0.33339444	0.3689874	0.34978968	0.32678448
0.40899334	0.39653769	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.04117838	0.16813739
0.28960162	0.32790981	0.36833534	0.3689874	0.34978968	0.25961929
0.12760592	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.04431706	0.11961607	0.36545809	0.37314701
0.33153488	0.32790981	0.36833534	0.28877275	0.111988	0.00258328
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.	0.
0.05298497	0.42752138	0.4219755	0.45852825	0.43408872	0.37314701
0.33153488	0.25273681	0.11646967	0.01312603	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.]	
[0.	0.	0.	0.	0.37491383	0.56222061

```

0.66525569 0.63253163 0.48748768 0.45852825 0.43408872 0.359873
0.17428513 0.01425695 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. ]
[0. 0. 0. 0. 0.92705966 0.82698729
0.74473314 0.63253163 0.4084877 0.24466922 0.22648107 0.02359823
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. 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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```



```

import numpy as np

IMG_SIZE=28
x_trainr=np.array(x_train).reshape(-1, IMG_SIZE,IMG_SIZE,1)

```

```
x_testr=np.array(x_test).reshape(-1, IMG_SIZE,IMG_SIZE,1)
print("Training Samples dimension",x_trainr.shape)
print("Testing Samples dimension",x_testr.shape)
```

```
Training Samples dimension (60000, 28, 28, 1)
Testing Samples dimension (10000, 28, 28, 1)
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation,
Flatten, Conv2D, MaxPooling2D
```

```
### First Convolution Layer
```

```
model = Sequential()
model.add(Conv2D(64,(3,3),input_shape=x_trainr.shape[1:]))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2,2)))
```

```
### Second Convolution Layer
```

```
model.add(Conv2D(64,(3,3)))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2,2)))
```

```
### 3rd Convolution Layer
```

```
model.add(Conv2D(64,(3,3)))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2,2)))
```

```
### Fully Connected Layer
```

```
model.add(Flatten())
model.add(Dense(64))
model.add(Activation("relu"))
```

```
### Fully Connected Layer #2
```

```
model.add(Dense(32))
model.add(Activation("relu"))
```

```
### Final Fully Connected Layer
```

```
model.add(Dense(10))
model.add(Activation("softmax"))
```

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 64)	640
activation (Activation)	(None, 26, 26, 64)	0
max_pooling2d (MaxPooling2D)	(None, 13, 13, 64)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	36928
activation_1 (Activation)	(None, 11, 11, 64)	0
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 64)	36928
activation_2 (Activation)	(None, 3, 3, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 1, 1, 64)	0
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 64)	4160
activation_3 (Activation)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
activation_4 (Activation)	(None, 32)	0
dense_2 (Dense)	(None, 10)	330
activation_5 (Activation)	(None, 10)	0

Total params: 81,066

Trainable params: 81,066

Non-trainable params: 0

```
print("Total Training Samples =",len(x_trainr))
model.compile(loss ="sparse_categorical_crossentropy", optimizer
```



```
= "adam", metrics=['accuracy'])
h1=model.fit(x_trainr,y_train,epochs=10, validation_split= 0.3)
```

Total Training Samples = 60000

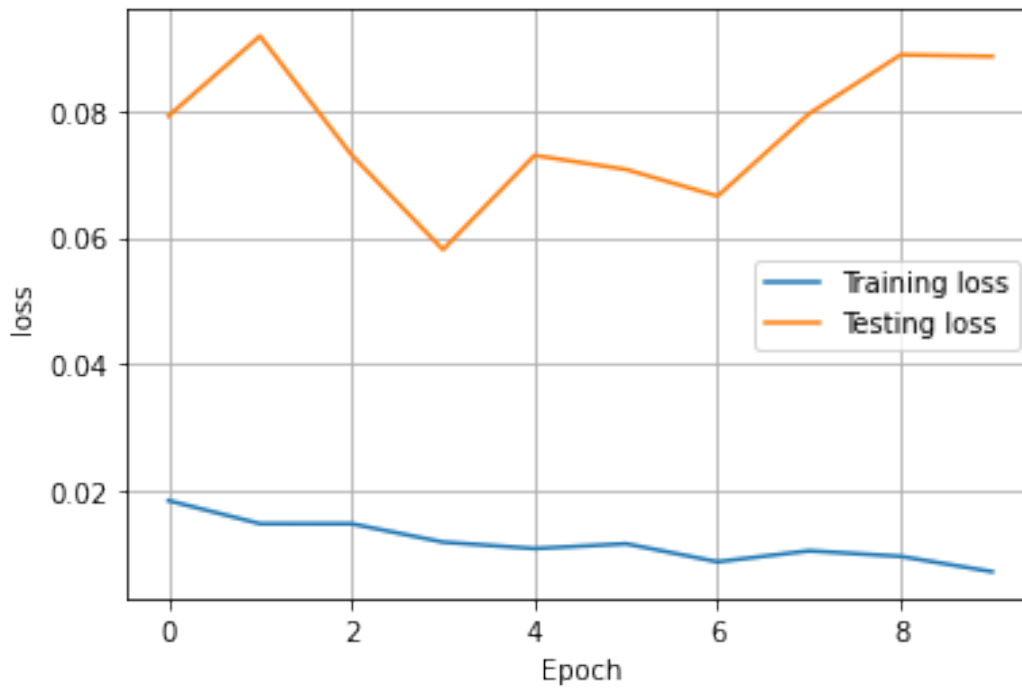
```
Epoch 1/10
1313/1313 [=====] - 69s 52ms/step - loss:
0.0185 - accuracy: 0.9940 - val_loss: 0.0791 - val_accuracy: 0.9812
Epoch 2/10
1313/1313 [=====] - 72s 55ms/step - loss:
0.0149 - accuracy: 0.9950 - val_loss: 0.0918 - val_accuracy: 0.9820
Epoch 3/10
1313/1313 [=====] - 71s 54ms/step - loss:
0.0149 - accuracy: 0.9950 - val_loss: 0.0730 - val_accuracy: 0.9822
Epoch 4/10
1313/1313 [=====] - 68s 52ms/step - loss:
0.0120 - accuracy: 0.9959 - val_loss: 0.0581 - val_accuracy: 0.9858
Epoch 5/10
1313/1313 [=====] - 67s 51ms/step - loss:
0.0109 - accuracy: 0.9964 - val_loss: 0.0729 - val_accuracy: 0.9857
Epoch 6/10
1313/1313 [=====] - 67s 51ms/step - loss:
0.0117 - accuracy: 0.9958 - val_loss: 0.0707 - val_accuracy: 0.9828
Epoch 7/10
1313/1313 [=====] - 67s 51ms/step - loss:
0.0089 - accuracy: 0.9970 - val_loss: 0.0665 - val_accuracy: 0.9851
Epoch 8/10
1313/1313 [=====] - 67s 51ms/step - loss:
0.0106 - accuracy: 0.9968 - val_loss: 0.0795 - val_accuracy: 0.9836
Epoch 9/10
1313/1313 [=====] - 67s 51ms/step - loss:
0.0097 - accuracy: 0.9970 - val_loss: 0.0888 - val_accuracy: 0.9817
Epoch 10/10
1313/1313 [=====] - 68s 51ms/step - loss:
0.0073 - accuracy: 0.9975 - val_loss: 0.0885 - val_accuracy: 0.9837
```

```
r1=pd.DataFrame(h1.history)
r1['Epoch']=h1.epoch
r1.tail
```

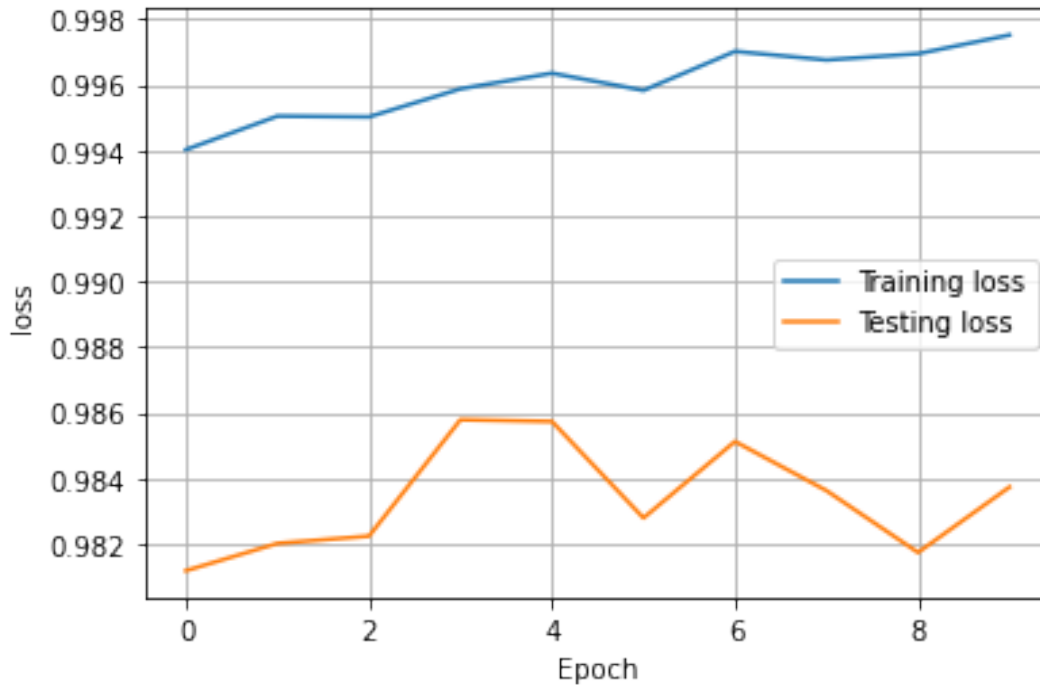
```
<bound method NDFrame.tail of
val_accuracy Epoch      loss  accuracy  val_loss
0  0.018503  0.994024  0.079133  0.981167      0
1  0.014865  0.995048  0.091753  0.982000      1
2  0.014853  0.995024  0.073018  0.982222      2
3  0.011956  0.995881  0.058068  0.985778      3
4  0.010936  0.996357  0.072932  0.985722      4
5  0.011696  0.995833  0.070705  0.982778      5
```

6	0.008851	0.997024	0.066512	0.985111	6
7	0.010582	0.996762	0.079505	0.983611	7
8	0.009707	0.996952	0.088790	0.981722	8
9	0.007292	0.997524	0.088533	0.983722	9>

```
plt.plot(r1['Epoch'],r1['loss'],label='Training loss')
plt.plot(r1['Epoch'],r1['val_loss'],label='Testing loss')
plt.xlabel('Epoch')
plt.ylabel('loss')
plt.legend()
plt.grid()
plt.show()
```



```
plt.plot(r1['Epoch'],r1['accuracy'],label='Training loss')
plt.plot(r1['Epoch'],r1['val_accuracy'],label='Testing loss')
plt.xlabel('Epoch')
plt.ylabel('loss')
plt.legend()
plt.grid()
plt.show()
```



```

test_loss, test_acc= model.evaluate(x_testr,y_test)
print("Test Loss on 10,000 test Samples",test_loss)
print("Validation Accuracy on 10,000 on test Samples",test_acc)

313/313 [=====] - 4s 13ms/step - loss: 0.0742
- accuracy: 0.9854
Test Loss on 10,000 test Samples 0.07422824949026108
Validation Accuracy on 10,000 on test Samples 0.9854000210762024

y_predict = model.predict([x_testr])
y_predict
array([[4.72564765e-10, 1.56244029e-09, 1.34179436e-06, ...,
        9.99998689e-01, 1.09729344e-11, 2.89590329e-09],
       [1.16848263e-12, 3.03815376e-11, 1.00000000e+00, ...,
        2.43454996e-13, 2.36088926e-13, 7.79841265e-16],
       [2.95212232e-13, 1.00000000e+00, 3.16915483e-12, ...,
        2.57694040e-13, 1.70665468e-10, 2.61081152e-12],
       ...,
       [1.50958756e-19, 1.63019541e-13, 2.00130870e-16, ...,
        2.46993103e-11, 1.71084650e-13, 5.23074917e-11],
       [1.23729056e-17, 1.26750246e-24, 1.03572546e-24, ...,
        2.48853405e-22, 4.12881371e-18, 2.45252000e-18],
       [2.31633734e-04, 1.83890048e-09, 6.56145289e-07, ...,
        3.03585579e-09, 2.25770646e-06, 2.17906972e-07]],
      dtype=float32)

print(np.argmax(y_predict[0]))

```

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```
print(np.argmax(y_predict[128]))  
plt.imshow(x_test[128])
```

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<matplotlib.image.AxesImage at 0x7f7a97a070d0>

