Import biblioteki **TensorFlow** (<a href="https://www.tensorflow.org/">https://www.tensorflow.org/</a>) z której będziemy korzystali w uczeniu maszynowym:

```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np

import keras
from keras.models import Sequential
from keras.layers import Dense
```

# Numbers recognition - dataset MNIST

```
Download dataset
```

```
(train data, train labels), (test data, test labels) = tf.keras.datasets.mnist.load data()
(train_data, train_labels), (test_data, test_labels) = tf.keras.datasets.mnist.load_data()
data = np.concatenate([train_data, test_data])
data.shape
    (70000, 28, 28)
label = np.concatenate([train_labels,test_labels])
label.shape
    (70000,)
Informations about dataset
train_data.shape,train_labels.shape
```

```
((60000, 28, 28), (60000,))
test data.shape, test labels.shape
     ((10000, 28, 28), (10000,))
train_data[0]
     array([[ 0,
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      46, 130, 183, 253, 253, 207,
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```

train\_labels[0]

5

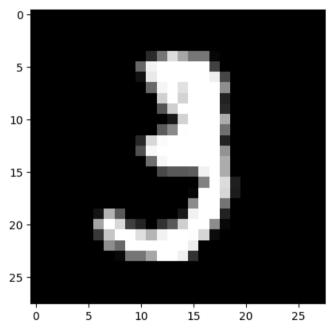
#### One-hot encoding

Visulization

```
def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)
```

[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_6"

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 128)	100480
dense_13 (Dense)	(None, 10)	1290

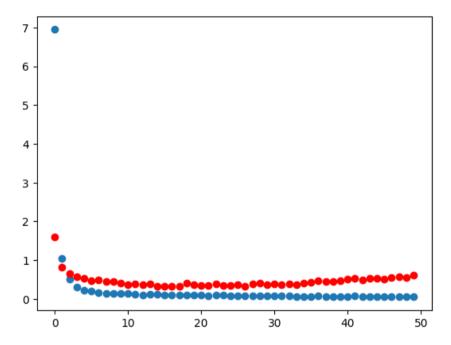
\_\_\_\_\_\_

Total params: 101770 (397.54 KB) Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)

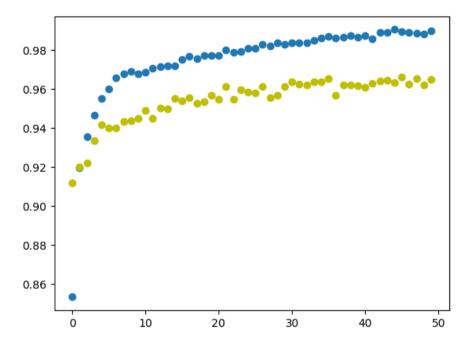
batch\_size = 128
epochs = 50

plt.show()

```
Epoch 38/50
Epoch 39/50
Epoch 40/50
Fnoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val\_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

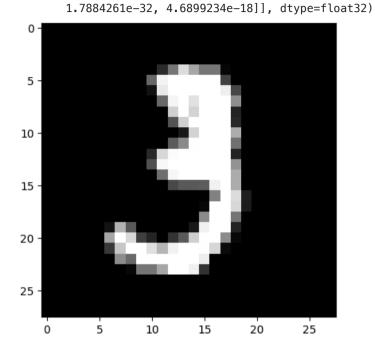
    Test loss: 0.6223078370094299
    Test accuracy: 0.9627000093460083

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

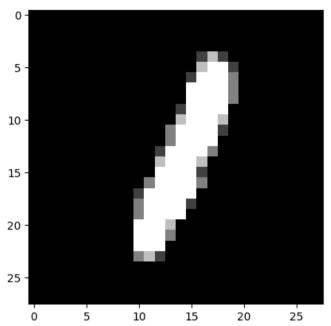
model.predict(picture)
```



## Validation split 0.8

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
    ((14000, 28, 28), (14000, 10))
test_data.shape,test_labels.shape
    ((56000, 28, 28), (56000, 10))
train_labels[0]
    array([0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot image(img index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)
img_index = 10
plot_image(img_index)
```

```
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_7"

Layer (type)	Output Shape	Param #
dense_14 (Dense)	(None, 128)	100480
dense_15 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

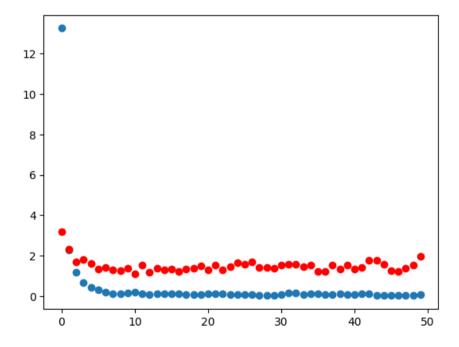
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)

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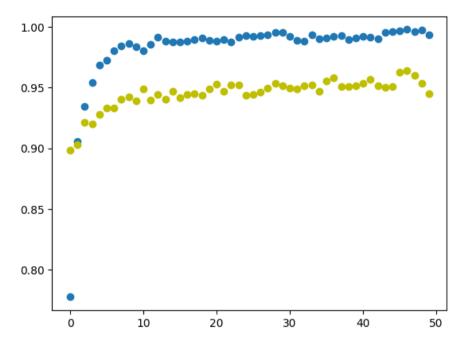
batch\_size = 128
epochs = 50

```
- W5 4HI5/Step - LOSS: W.1WW1 - ACCUIACY: W.9913 - VAL LOSS: 1.4WDW - VAL ACCUIACY: W.9900
   00/00 [=====
   Epoch 43/50
   88/88 [=====
                                - 0s 3ms/step - loss: 0.1233 - accuracy: 0.9902 - val loss: 1.7838 - val accuracy: 0.9518
   Epoch 44/50
   88/88 [=======
                                - 0s 4ms/step - loss: 0.0422 - accuracy: 0.9956 - val loss: 1.7605 - val accuracy: 0.9504
   Epoch 45/50
   88/88 [==============] - 0s 4ms/step - loss: 0.0420 - accuracy: 0.9962 - val loss: 1.5653 - val accuracy: 0.9511
   Epoch 46/50
   88/88 [=========]
                                - 0s 3ms/step - loss: 0.0344 - accuracy: 0.9971 - val loss: 1.2519 - val accuracy: 0.9629
   Epoch 47/50
   88/88 [=============] - 0s 4ms/step - loss: 0.0186 - accuracy: 0.9979 - val loss: 1.2166 - val accuracy: 0.9643
   Epoch 48/50
   88/88 [========
                                - 0s 4ms/step - loss: 0.0347 - accuracy: 0.9965 - val loss: 1.3804 - val accuracy: 0.9604
   Epoch 49/50
   88/88 [========
                     Epoch 50/50
   plt.scatter(np.arange(epochs),h.history['loss'])
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

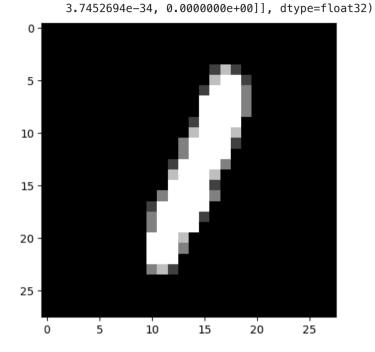
    Test loss: 2.763029098510742
    Test accuracy: 0.9341607093811035

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

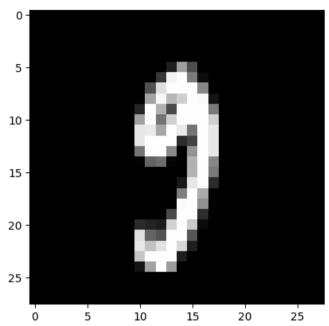
model.predict(picture)
```



## Validation split 0.7

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
    ((21000, 28, 28), (21000, 10))
test_data.shape,test_labels.shape
    ((49000, 28, 28), (49000, 10))
train_labels[0]
    array([0., 0., 0., 0., 1., 0., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot image(img index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)
img_index = 10
plot_image(img_index)
```

```
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
```

Model: "sequential\_8"

model.summary()

Layer (type)	Output Shape	Param #
dense_16 (Dense)	(None, 128)	100480
dense_17 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

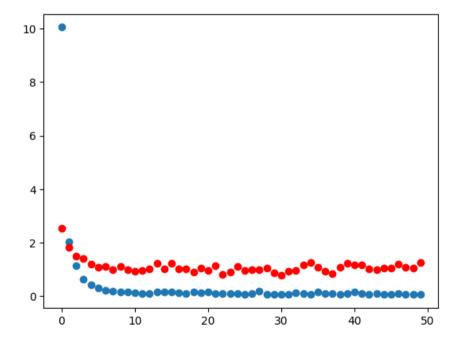
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)

batch\_size = 128 epochs = 50

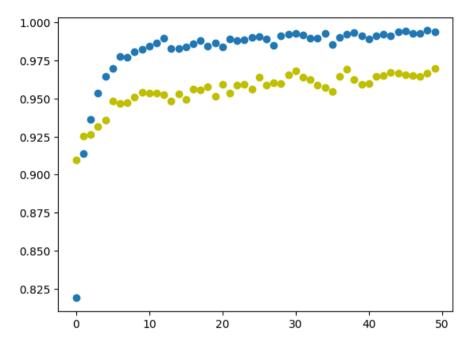
```
Epoch 1/50
Epoch 2/50
Fnoch 3/50
Epoch 4/50
Epoch 5/50
Epoch 6/50
Epoch 7/50
132/132 [=============] - 0s 3ms/step - loss: 0.2164 - accuracy: 0.9777 - val loss: 1.1206 - val accuracy: 0.9469
Epoch 8/50
Epoch 9/50
Epoch 10/50
132/132 [============================== ] - 1s 5ms/step - loss: 0.1486 - accuracy: 0.9825 - val_loss: 0.9944 - val_accuracy: 0.9540
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
132/132 [=============================== ] - 0s 3ms/step - loss: 0.1635 - accuracy: 0.9830 - val loss: 1.2272 - val accuracy: 0.9483
Epoch 15/50
Epoch 16/50
Epoch 17/50
132/132 [============================= ] - 0s 3ms/step - loss: 0.1371 - accuracy: 0.9859 - val_loss: 1.0267 - val_accuracy: 0.9564
Epoch 18/50
Epoch 19/50
132/132 [============================= ] - 0s 3ms/step - loss: 0.1716 - accuracy: 0.9846 - val_loss: 0.9056 - val_accuracy: 0.9576
Epoch 20/50
Epoch 21/50
```

```
Epoch 22/50
Epoch 23/50
132/132 [============================= ] - 0s 3ms/step - loss: 0.1163 - accuracy: 0.9885 - val loss: 0.8128 - val accuracy: 0.9590
Epoch 24/50
Fnoch 25/50
132/132 [=======
           ============] - 0s 3ms/step - loss: 0.0929 - accuracy: 0.9904 - val loss: 1.1108 - val accuracy: 0.9564
Epoch 26/50
132/132 [============================ ] - 0s 3ms/step - loss: 0.0824 - accuracy: 0.9908 - val loss: 0.9721 - val accuracy: 0.9643
Epoch 27/50
132/132 [=============] - 0s 3ms/step - loss: 0.1005 - accuracy: 0.9895 - val loss: 0.9801 - val accuracy: 0.9588
Epoch 28/50
Epoch 29/50
433/433 [
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

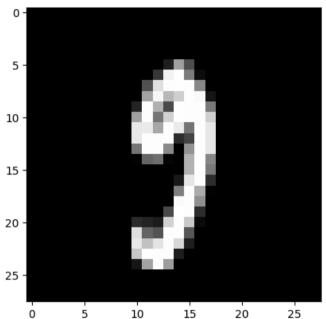
    Test loss: 2.086263656616211
    Test accuracy: 0.9490816593170166

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

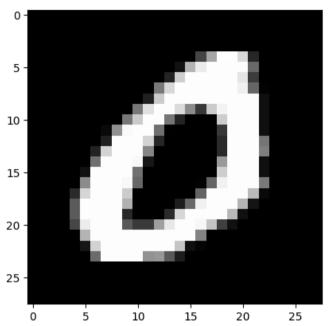
model.predict(picture)
```



# Validation split 0.6

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
    ((28000, 28, 28), (28000, 10))
test_data.shape,test_labels.shape
    ((42000, 28, 28), (42000, 10))
train_labels[0]
    array([0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot image(img index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)
img\_index = 10
plot_image(img_index)
```

[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_9"

Layer (type)	Output Shape	Param #
dense_18 (Dense)	(None, 128)	100480
dense_19 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

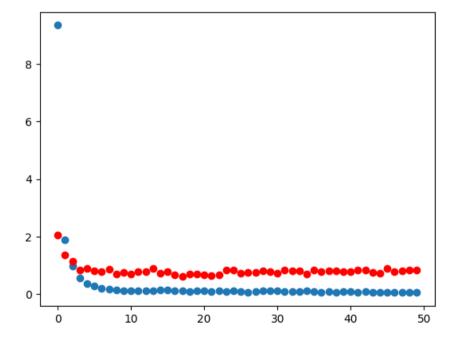
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

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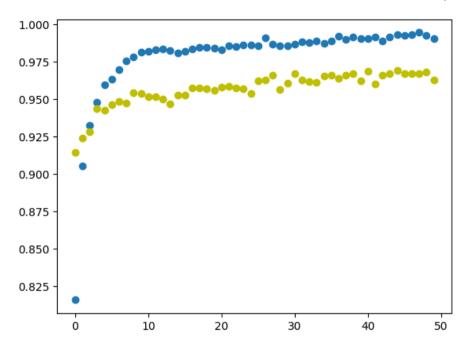
```
batch_size = 128
epochs = 50
```

```
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

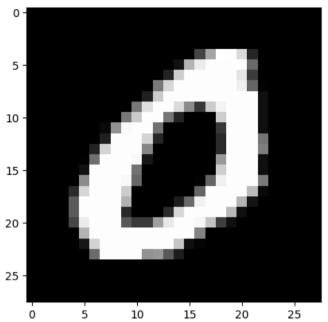
    Test loss: 1.2243731021881104
    Test accuracy: 0.9535238146781921

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

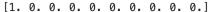
model.predict(picture)
```

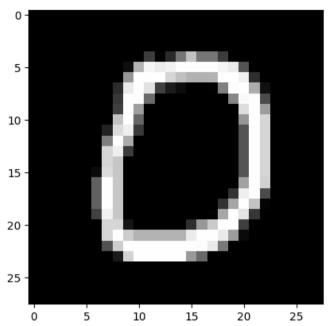


## Model no 1.

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test_data.shape,test_labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot image(img index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)
img_index = 10
plot_image(img_index)
```





```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 64, use_bias=True, activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_10"

Layer (type)	Output Shape	Param #
dense_20 (Dense)	(None, 128)	100480
dense_21 (Dense)	(None, 64)	8256
dense_22 (Dense)	(None, 10)	650

Total params: 109386 (427.29 KB) Trainable params: 109386 (427.29 KB) Non-trainable params: 0 (0.00 Byte)

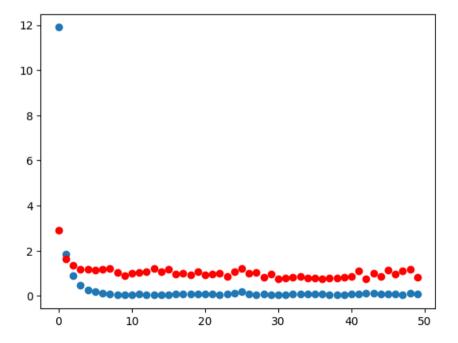
\_\_\_\_\_

batch\_size = 128
epochs = 50

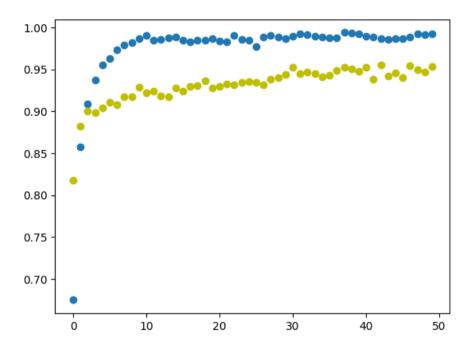
```
Epoch 1/50
Epoch 2/50
63/63 [============================= ] - 0s 4ms/step - loss: 1.8569 - accuracy: 0.8579 - val loss: 1.6379 - val accuracy: 0.8820
Epoch 3/50
63/63 [========================== ] - 0s 4ms/step - loss: 0.9040 - accuracy: 0.9084 - val loss: 1.3717 - val accuracy: 0.9000
Epoch 4/50
63/63 [=============================== ] - 0s 4ms/step - loss: 0.4866 - accuracy: 0.9374 - val loss: 1.1851 - val accuracy: 0.8980
Epoch 5/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.2760 - accuracy: 0.9554 - val loss: 1.1739 - val accuracy: 0.9045
Epoch 6/50
63/63 [============================== ] - 0s 4ms/step - loss: 0.2033 - accuracy: 0.9628 - val loss: 1.1375 - val accuracy: 0.9110
Epoch 7/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.1263 - accuracy: 0.9737 - val loss: 1.1748 - val accuracy: 0.9075
Epoch 8/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.0924 - accuracy: 0.9795 - val loss: 1.2117 - val accuracy: 0.9175
Epoch 9/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.0671 - accuracy: 0.9816 - val loss: 1.0324 - val accuracy: 0.9175
Epoch 10/50
63/63 [=========================== ] - 0s 7ms/step - loss: 0.0548 - accuracy: 0.9865 - val loss: 0.9073 - val accuracy: 0.9290
Epoch 11/50
63/63 [========================== ] - 1s 11ms/step - loss: 0.0353 - accuracy: 0.9906 - val_loss: 1.0076 - val_accuracy: 0.9220
Epoch 12/50
63/63 [========================== ] - 1s 10ms/step - loss: 0.0790 - accuracy: 0.9846 - val_loss: 1.0269 - val_accuracy: 0.9240
Epoch 13/50
63/63 [============================= ] - 0s 7ms/step - loss: 0.0646 - accuracy: 0.9854 - val loss: 1.0565 - val accuracy: 0.9185
Epoch 14/50
63/63 [============================ ] - 0s 5ms/step - loss: 0.0606 - accuracy: 0.9874 - val loss: 1.2062 - val accuracy: 0.9175
Epoch 15/50
Epoch 16/50
63/63 [=========================== ] - 0s 5ms/step - loss: 0.0630 - accuracy: 0.9850 - val loss: 1.1727 - val accuracy: 0.9245
Epoch 17/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0941 - accuracy: 0.9826 - val loss: 0.9767 - val accuracy: 0.9295
Epoch 18/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0817 - accuracy: 0.9852 - val loss: 0.9905 - val accuracy: 0.9305
Epoch 19/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.0803 - accuracy: 0.9847 - val loss: 0.9236 - val accuracy: 0.9365
```

```
Epoch 20/50
63/63 [============================== ] - 0s 4ms/step - loss: 0.0790 - accuracy: 0.9865 - val loss: 1.0741 - val accuracy: 0.9275
Epoch 21/50
Epoch 22/50
Epoch 23/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.0538 - accuracy: 0.9902 - val loss: 0.9885 - val accuracy: 0.9320
Epoch 24/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0742 - accuracy: 0.9856 - val loss: 0.8687 - val accuracy: 0.9345
Epoch 25/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.1153 - accuracy: 0.9846 - val loss: 1.0897 - val accuracy: 0.9350
Epoch 26/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.1814 - accuracy: 0.9774 - val loss: 1.2034 - val accuracy: 0.9345
Epoch 27/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0681 - accuracy: 0.9885 - val loss: 0.9909 - val accuracy: 0.9320
Epoch 28/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.0602 - accuracy: 0.9906 - val loss: 1.0242 - val accuracy: 0.9385
Epoch 29/50
C2/C2 F
                                                                                                  0 0405
```

plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val\_loss'],c='r')
plt.show()



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

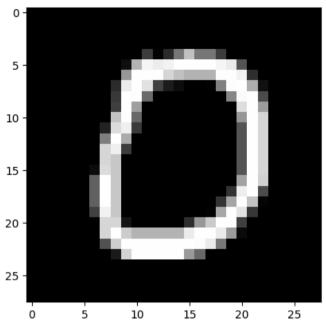
    Test loss: 1.5609794855117798
    Test accuracy: 0.9293166399002075

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

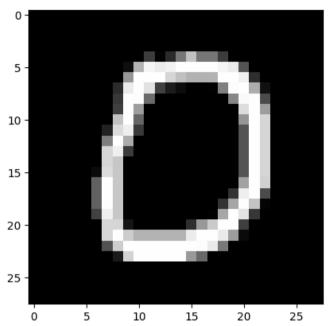


## Model no 2.

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test data.shape,test labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot_image(img_index)
```

```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 256, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 128, use_bias=True, activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_11"

Layer (type)	Output Shape	Param #
dense_23 (Dense)	(None, 256)	200960
dense_24 (Dense)	(None, 128)	32896
dense_25 (Dense)	(None, 10)	1290

\_\_\_\_\_\_

Total params: 235146 (918.54 KB) Trainable params: 235146 (918.54 KB) Non-trainable params: 0 (0.00 Byte)

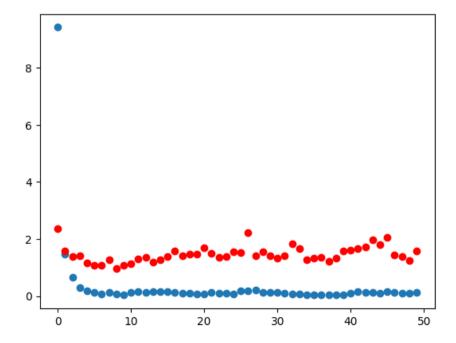
\_\_\_\_\_

batch\_size = 128
epochs = 50

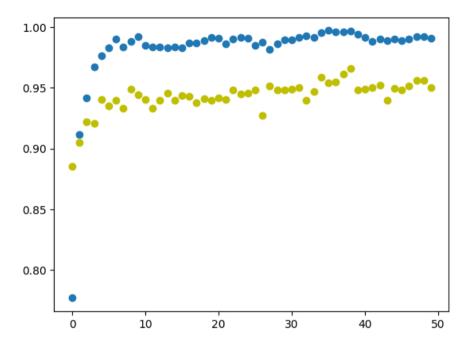
```
Epoch 1/50
63/63 [============================== ] - 1s 7ms/step - loss: 9.4166 - accuracy: 0.7769 - val loss: 2.3691 - val accuracy: 0.8855
Epoch 2/50
63/63 [=========================== ] - 0s 4ms/step - loss: 1.4590 - accuracy: 0.9118 - val loss: 1.5762 - val accuracy: 0.9050
Epoch 3/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.6502 - accuracy: 0.9416 - val loss: 1.3939 - val accuracy: 0.9220
Epoch 4/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.2945 - accuracy: 0.9672 - val loss: 1.4233 - val accuracy: 0.9205
Epoch 5/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.1869 - accuracy: 0.9766 - val loss: 1.1635 - val accuracy: 0.9405
Epoch 6/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.1148 - accuracy: 0.9833 - val loss: 1.0740 - val accuracy: 0.9350
Epoch 7/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.0660 - accuracy: 0.9900 - val loss: 1.0671 - val accuracy: 0.9400
Epoch 8/50
63/63 [============================ ] - 0s 5ms/step - loss: 0.1323 - accuracy: 0.9840 - val loss: 1.2620 - val accuracy: 0.9335
Epoch 9/50
63/63 [=========================== ] - 0s 6ms/step - loss: 0.0774 - accuracy: 0.9880 - val loss: 0.9732 - val accuracy: 0.9490
Epoch 10/50
63/63 [========================== ] - 0s 7ms/step - loss: 0.0499 - accuracy: 0.9925 - val loss: 1.0671 - val accuracy: 0.9445
Epoch 11/50
Epoch 12/50
63/63 [============================= ] - 0s 5ms/step - loss: 0.1580 - accuracy: 0.9836 - val_loss: 1.3119 - val_accuracy: 0.9335
Epoch 13/50
Epoch 14/50
63/63 [========================== - 1s 12ms/step - loss: 0.1523 - accuracy: 0.9831 - val loss: 1.1795 - val accuracy: 0.9455
Epoch 15/50
63/63 [=========================== - 1s 10ms/step - loss: 0.1428 - accuracy: 0.9836 - val loss: 1.2778 - val accuracy: 0.9400
Epoch 16/50
63/63 [============================== ] - 1s 8ms/step - loss: 0.1470 - accuracy: 0.9830 - val loss: 1.3756 - val accuracy: 0.9435
Epoch 17/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.1167 - accuracy: 0.9868 - val loss: 1.5726 - val accuracy: 0.9430
Epoch 18/50
63/63 [============================ ] - 0s 7ms/step - loss: 0.1048 - accuracy: 0.9868 - val loss: 1.4242 - val accuracy: 0.9375
Epoch 19/50
63/63 [============================= ] - 0s 8ms/step - loss: 0.1114 - accuracy: 0.9886 - val loss: 1.4597 - val accuracy: 0.9410
```

```
Epoch 20/50
63/63 [============================= ] - 0s 5ms/step - loss: 0.0605 - accuracy: 0.9916 - val loss: 1.4744 - val accuracy: 0.9400
Epoch 21/50
Epoch 22/50
Epoch 23/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.1072 - accuracy: 0.9900 - val loss: 1.3613 - val accuracy: 0.9485
Epoch 24/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.0954 - accuracy: 0.9912 - val loss: 1.3705 - val accuracy: 0.9450
Epoch 25/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0740 - accuracy: 0.9906 - val loss: 1.5630 - val accuracy: 0.9455
Epoch 26/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.1761 - accuracy: 0.9849 - val loss: 1.5273 - val accuracy: 0.9480
Epoch 27/50
Epoch 28/50
63/63 [============================= ] - 0s 4ms/step - loss: 0.2209 - accuracy: 0.9815 - val loss: 1.4095 - val accuracy: 0.9515
Epoch 29/50
C2/C2 F
                                                                                     0 0405
```

plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val\_loss'],c='r')
plt.show()



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

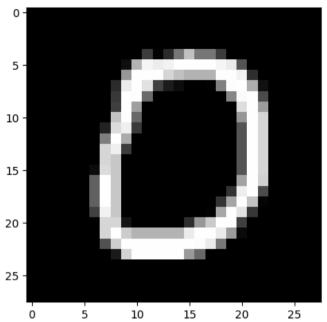
    Test loss: 2.420621871948242
    Test accuracy: 0.9312333464622498

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

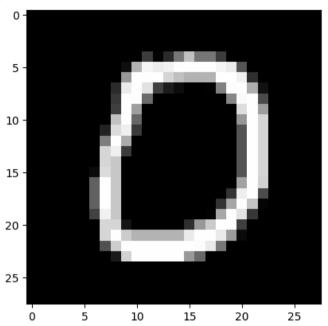


## Model no 3.

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test data.shape,test labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot_image(img_index)
```

[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 64, use_bias=True, activation = "relu"))
model.add(Dense(units = 64, use_bias=True, activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

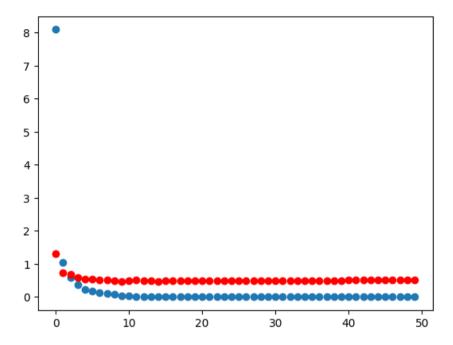
Model: "sequential\_12"

Layer (type)	Output Shape	Param #
dense_26 (Dense)	(None, 128)	100480
dense_27 (Dense)	(None, 64)	8256

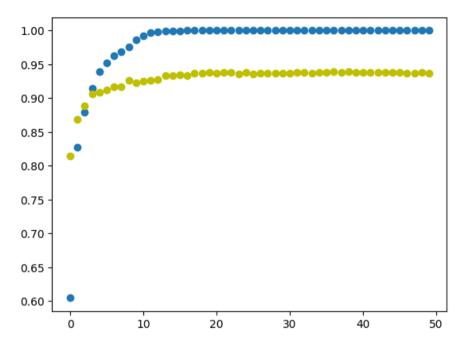
batch\_size = 128 epochs = 50

```
Epoch 1/50
63/63 [=============================== ] - 1s 6ms/step - loss: 8.0931 - accuracy: 0.6046 - val loss: 1.3226 - val accuracy: 0.8145
Epoch 2/50
63/63 [============================= ] - 0s 4ms/step - loss: 1.0409 - accuracy: 0.8278 - val loss: 0.7454 - val accuracy: 0.8690
Epoch 3/50
63/63 [============================ ] - 0s 4ms/step - loss: 0.5915 - accuracy: 0.8789 - val loss: 0.6775 - val accuracy: 0.8890
Epoch 4/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.3824 - accuracy: 0.9153 - val loss: 0.5871 - val accuracy: 0.9065
Epoch 5/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.2347 - accuracy: 0.9394 - val loss: 0.5421 - val accuracy: 0.9085
Epoch 6/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.1717 - accuracy: 0.9529 - val loss: 0.5447 - val accuracy: 0.9120
Epoch 7/50
63/63 [=========================== ] - 0s 5ms/step - loss: 0.1296 - accuracy: 0.9624 - val loss: 0.5195 - val accuracy: 0.9170
Epoch 8/50
63/63 [=========================== ] - 0s 7ms/step - loss: 0.0972 - accuracy: 0.9691 - val loss: 0.5188 - val accuracy: 0.9165
Epoch 9/50
63/63 [============================ ] - 0s 7ms/step - loss: 0.0769 - accuracy: 0.9762 - val loss: 0.4844 - val accuracy: 0.9270
Epoch 10/50
63/63 [============================= ] - 0s 6ms/step - loss: 0.0441 - accuracy: 0.9865 - val_loss: 0.4749 - val_accuracy: 0.9230
Epoch 11/50
63/63 [============================ ] - 0s 5ms/step - loss: 0.0311 - accuracy: 0.9920 - val loss: 0.4920 - val accuracy: 0.9250
Epoch 12/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0171 - accuracy: 0.9969 - val loss: 0.5203 - val accuracy: 0.9260
Epoch 13/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0129 - accuracy: 0.9979 - val loss: 0.4887 - val accuracy: 0.9275
Epoch 14/50
63/63 [============================ ] - 0s 5ms/step - loss: 0.0087 - accuracy: 0.9989 - val loss: 0.4954 - val accuracy: 0.9330
Epoch 15/50
63/63 [=========================== ] - 0s 4ms/step - loss: 0.0049 - accuracy: 0.9998 - val loss: 0.4814 - val accuracy: 0.9335
Epoch 16/50
63/63 [=========================== ] - 0s 5ms/step - loss: 0.0039 - accuracy: 0.9998 - val loss: 0.4900 - val accuracy: 0.9345
Epoch 17/50
63/63 [========================== ] - 0s 4ms/step - loss: 0.0028 - accuracy: 1.0000 - val loss: 0.4940 - val accuracy: 0.9340
```

```
Epoch 18/50
   63/63 [=========================== ] - 0s 5ms/step - loss: 0.0026 - accuracy: 1.0000 - val loss: 0.4885 - val accuracy: 0.9375
   Epoch 19/50
   Epoch 20/50
   Epoch 21/50
   Epoch 22/50
   Epoch 23/50
   63/63 [=========================== ] - 0s 7ms/step - loss: 0.0014 - accuracy: 1.0000 - val loss: 0.4918 - val accuracy: 0.9380
   Epoch 24/50
   63/63 [============================ ] - 0s 6ms/step - loss: 0.0013 - accuracy: 1.0000 - val loss: 0.4940 - val accuracy: 0.9360
   Epoch 25/50
   63/63 [============================ ] - 0s 6ms/step - loss: 0.0012 - accuracy: 1.0000 - val loss: 0.4972 - val accuracy: 0.9380
   Epoch 26/50
   63/63 [=========================== ] - 0s 6ms/step - loss: 0.0011 - accuracy: 1.0000 - val loss: 0.4993 - val accuracy: 0.9360
   Epoch 27/50
   63/63 [================================ ] - 0s 6ms/step - loss: 0.0010 - accuracy: 1.0000 - val loss: 0.5015 - val accuracy: 0.9370
   Epoch 28/50
   63/63 [========================== ] - 0s 5ms/step - loss: 9.8011e-04 - accuracy: 1.0000 - val loss: 0.5007 - val accuracy: 0.9375
   Epoch 29/50
                           plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val\_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

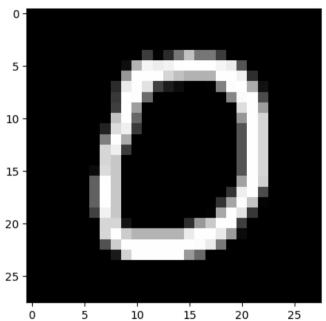
    Test loss: 0.7605254054069519
    Test accuracy: 0.9075000286102295

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



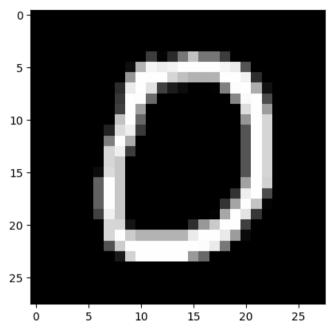
### Model no 4.

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test_data.shape,test_labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label index)
img index = 10
plot_image(img_index)
```

```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

train\_images = train\_data.reshape((-1, 784))



```
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 256, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 128, use_bias=True, activation = "relu"))
model.add(Dense(units = 64, use_bias=True, activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
```

model.compile(loss='categorical\_crossentropy',optimizer=opt,metrics=['accuracy'])

Model: "sequential\_13"

model.summary()

Layer (type)	Output Shape	Param #
dense_30 (Dense)	(None, 256)	200960
dense_31 (Dense)	(None, 128)	32896

dense\_32 (Dense) (None, 64) 8256

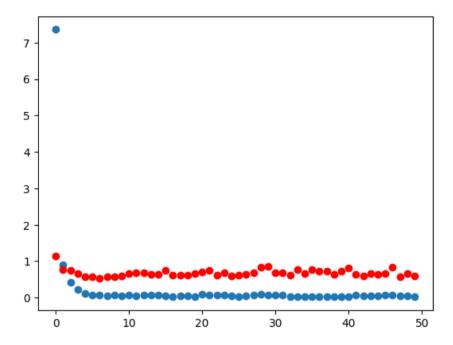
dense\_33 (Dense) (None, 10) 650

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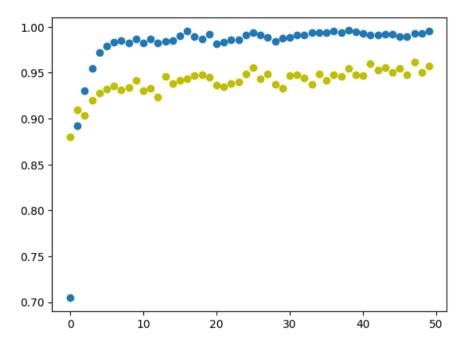
Total params: 242762 (948.29 KB)
Trainable params: 242762 (948.29 KB)
Non-trainable params: 0 (0.00 Byte)

batch\_size = 128
epochs = 50

```
בטטכוו שאון אין
   Epoch 40/50
   63/63 [============================ ] - 0s 4ms/step - loss: 0.0298 - accuracy: 0.9944 - val loss: 0.7367 - val accuracy: 0.9475
   Epoch 41/50
   63/63 [=========================== ] - 0s 4ms/step - loss: 0.0351 - accuracy: 0.9933 - val loss: 0.8223 - val accuracy: 0.9465
   Epoch 42/50
   63/63 [=========================== ] - 0s 4ms/step - loss: 0.0688 - accuracy: 0.9908 - val loss: 0.6381 - val accuracy: 0.9595
   Epoch 43/50
   63/63 [============================ ] - 0s 4ms/step - loss: 0.0510 - accuracy: 0.9915 - val loss: 0.5978 - val accuracy: 0.9530
   Epoch 44/50
   63/63 [=========================== ] - 0s 4ms/step - loss: 0.0580 - accuracy: 0.9916 - val loss: 0.6545 - val accuracy: 0.9555
   Epoch 45/50
   Epoch 46/50
   63/63 [=========================== ] - 0s 4ms/step - loss: 0.0711 - accuracy: 0.9894 - val loss: 0.6655 - val accuracy: 0.9550
   Epoch 47/50
   63/63 [============================ ] - 0s 4ms/step - loss: 0.0724 - accuracy: 0.9898 - val loss: 0.8346 - val accuracy: 0.9475
   Epoch 48/50
   63/63 [=========================== ] - 0s 5ms/step - loss: 0.0393 - accuracy: 0.9933 - val loss: 0.5842 - val accuracy: 0.9620
   Epoch 49/50
   63/63 [=========================== ] - 0s 6ms/step - loss: 0.0422 - accuracy: 0.9927 - val loss: 0.6548 - val accuracy: 0.9505
   Epoch 50/50
   plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val\_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

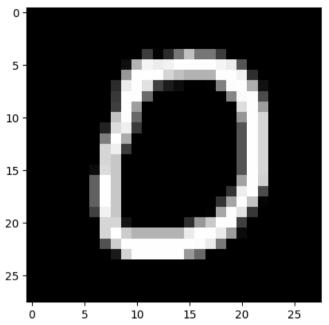
    Test loss: 0.8955525755882263
    Test accuracy: 0.9413833618164062

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

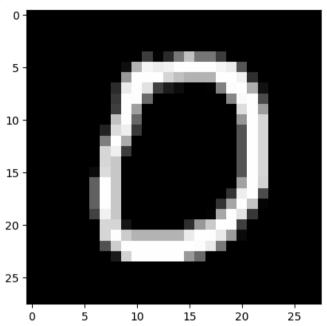


# Epochs 75

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test_data.shape,test_labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot image(img index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)
img_index = 10
plot_image(img_index)
```

[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_14"

Layer (type)	Output Shape	Param #
dense_34 (Dense)	(None, 128)	100480
dense_35 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

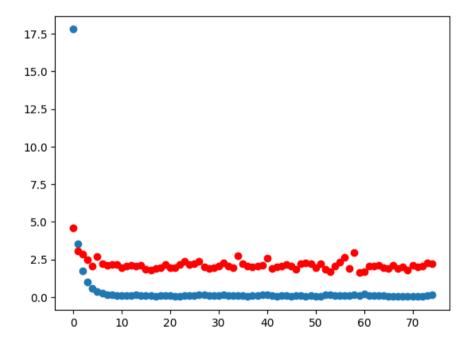
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

\_\_\_\_\_

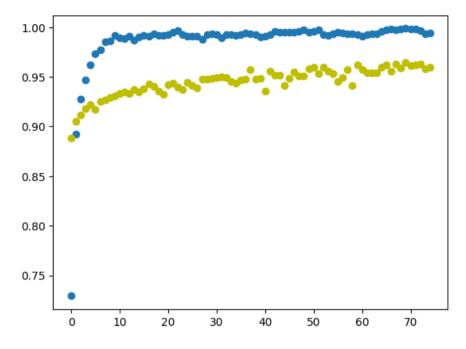
```
batch_size = 128
epochs = 75
```

```
- WS 4HIS/Step - LOSS: W.W14/ - ACCUIACY: W.9901 - VAL LOSS: Z.W91/ - VAL ACCUIACY: W.990W
   03/03 [======
   Epoch 68/75
   63/63 [======
                                    - 0s 4ms/step - loss: 0.0338 - accuracy: 0.9973 - val loss: 1.9060 - val accuracy: 0.9630
   Epoch 69/75
   63/63 [========
                                    - 0s 4ms/step - loss: 0.0228 - accuracy: 0.9985 - val loss: 1.9935 - val accuracy: 0.9590
   Epoch 70/75
   63/63 [============================ ] - 0s 5ms/step - loss: 0.0197 - accuracy: 0.9986 - val loss: 1.8097 - val accuracy: 0.9645
   Epoch 71/75
   - 0s 4ms/step - loss: 0.0206 - accuracy: 0.9983 - val loss: 2.1103 - val accuracy: 0.9615
   Epoch 72/75
   63/63 [============================== ] - 0s 4ms/step - loss: 0.0228 - accuracy: 0.9983 - val loss: 1.9877 - val accuracy: 0.9620
   Epoch 73/75
   63/63 [=========]
                                    - 0s 4ms/step - loss: 0.0493 - accuracy: 0.9969 - val loss: 2.0495 - val accuracy: 0.9630
   Epoch 74/75
   63/63 [=======
                     :===========] - 0s 4ms/step - loss: 0.1163 - accuracy: 0.9934 - val loss: 2.2720 - val accuracy: 0.9585
   Epoch 75/75
   plt.scatter(np.arange(epochs),h.history['loss'])
```

```
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

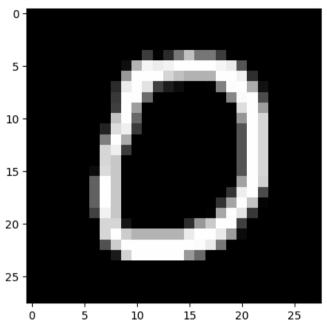
    Test loss: 3.6567094326019287
    Test accuracy: 0.9387500286102295

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

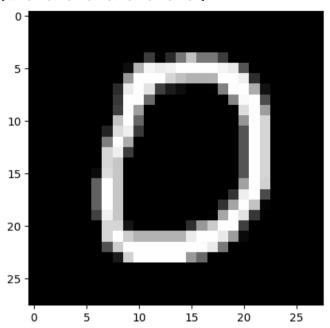


# Epochs 100

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test data.shape,test labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot image(img index)
```

```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_15"

Layer (type)	Output Shape	Param #
dense_36 (Dense)	(None, 128)	100480
dense_37 (Dense)	(None, 10)	1290

\_\_\_\_\_\_

Total params: 101770 (397.54 KB)

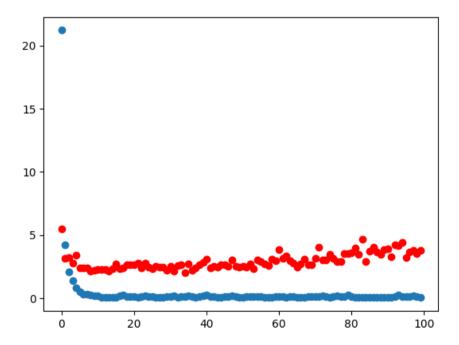
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

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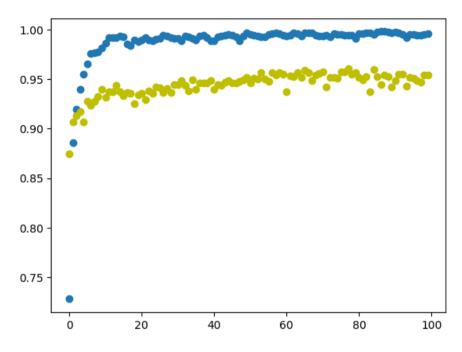
```
batch_size = 128
epochs = 100
```

```
- W5 4HI5/Step - LOSS: W.WOWO - dcculdcy: W.9909 - Val LOSS: 3.24WW - Val dcculdcy: W.990W
03/03 [=====
Epoch 93/100
63/63 [=====
                     - 0s 4ms/step - loss: 0.1044 - accuracy: 0.9956 - val loss: 4.2229 - val accuracy: 0.9550
Epoch 94/100
                     - 0s 5ms/step - loss: 0.2306 - accuracy: 0.9921 - val loss: 4.1469 - val accuracy: 0.9430
63/63 [=====
Epoch 95/100
Epoch 96/100
Epoch 97/100
63/63 [============================== ] - 0s 6ms/step - loss: 0.1339 - accuracy: 0.9946 - val loss: 3.6308 - val accuracy: 0.9485
Epoch 98/100
63/63 [========
                     - 0s 6ms/step - loss: 0.1523 - accuracy: 0.9946 - val loss: 3.7904 - val accuracy: 0.9470
Epoch 99/100
63/63 [=======
           Epoch 100/100
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

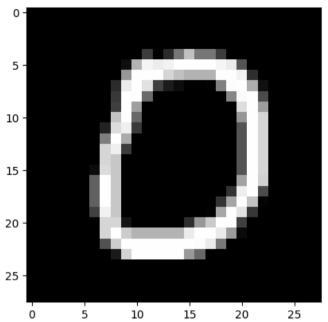
    Test loss: 5.24637508392334
    Test accuracy: 0.941266655921936

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

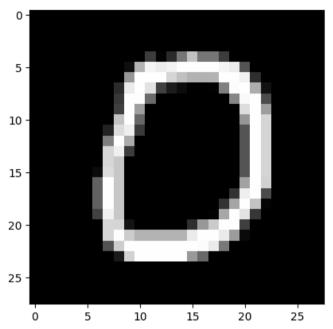


## Batch\_size 256

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test data.shape,test labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot image(img index)
```

```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
```

Model: "sequential\_16"

model.summary()

Layer (type)	Output Shape	Param #
dense_38 (Dense)	(None, 128)	100480
dense_39 (Dense)	(None, 10)	1290

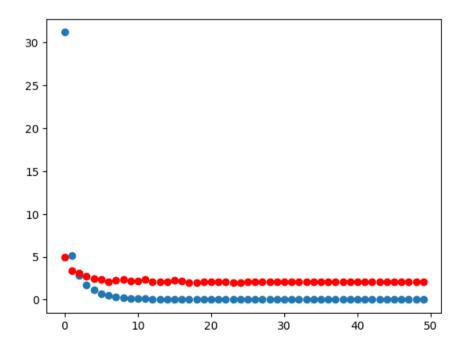
Total params: 101770 (397.54 KB)

```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

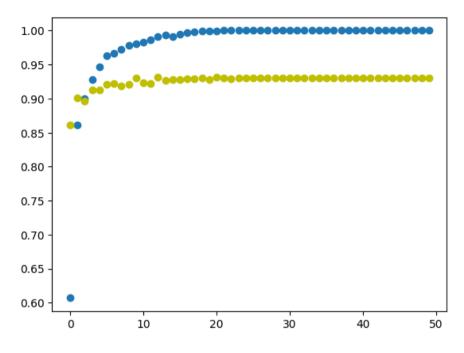
\_\_\_\_\_

```
batch_size = 256
epochs = 50
```

```
- WS 4MB/Step - LOSS: 3.302Ze-WO - dccurdcy: 1.0000 - Vdl LOSS: 2.0461 - Vdl dccurdcy: 0.9500
    Epoch 43/50
    32/32 [======
                                      - 0s 4ms/step - loss: 3.4313e-06 - accuracy: 1.0000 - val loss: 2.0483 - val accuracy: 0.9305
    Epoch 44/50
    32/32 [=======
                                      - 0s 4ms/step - loss: 3.3147e-06 - accuracy: 1.0000 - val loss: 2.0485 - val accuracy: 0.9305
    Epoch 45/50
    32/32 [========================== ] - 0s 5ms/step - loss: 3.2087e-06 - accuracy: 1.0000 - val loss: 2.0486 - val accuracy: 0.9305
    Epoch 46/50
    32/32 [========================== ] - 0s 4ms/step - loss: 3.1195e-06 - accuracy: 1.0000 - val loss: 2.0487 - val accuracy: 0.9305
    Epoch 47/50
    32/32 [========================== ] - 0s 4ms/step - loss: 3.0197e-06 - accuracy: 1.0000 - val loss: 2.0489 - val accuracy: 0.9305
    Epoch 48/50
    32/32 [========
                                      - 0s 5ms/step - loss: 2.9416e-06 - accuracy: 1.0000 - val loss: 2.0491 - val accuracy: 0.9305
    Epoch 49/50
    32/32 [========================== ] - 0s 4ms/step - loss: 2.8533e-06 - accuracy: 1.0000 - val loss: 2.0493 - val accuracy: 0.9305
    Epoch 50/50
    plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

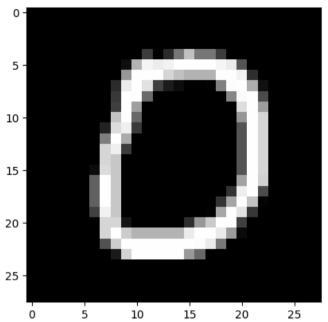
    Test loss: 3.02571439743042
    Test accuracy: 0.909500002861023

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```

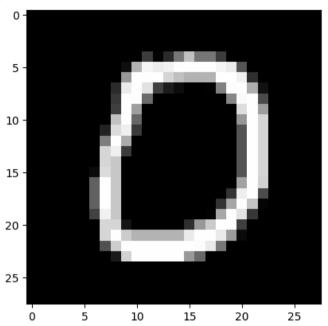


# Number of epochs - 64

Validation split 0.85714285714 (default)

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test data.shape,test labels.shape
    ((60000, 28, 28), (60000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot image(img index)
```

[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_17"

Layer (type)	Output Shape	Param #
dense_40 (Dense)	(None, 128)	100480
dense_41 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

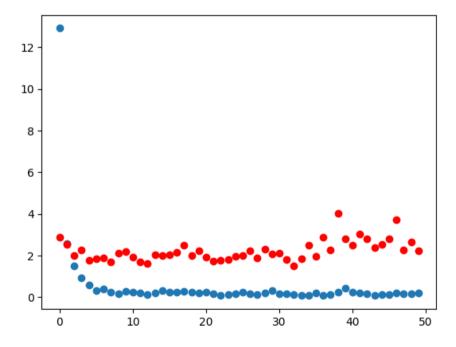
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

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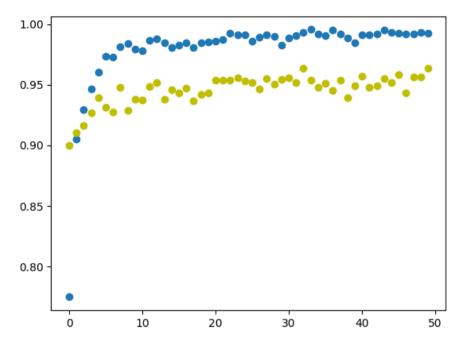
```
batch_size = 64
epochs = 50
```

```
- W5 4HI5/Step - LOSS: W.ZWO1 - dCCUIdCY: W.9911 - Vdt LOSS: 3.WZ/4 - Vdt dCCUIdCY: W.946W
123/123 [=========
Epoch 43/50
125/125 [=======
                  ======== l - 1s 4ms/step - loss: 0.1456 - accuracv: 0.9921 - val loss: 2.8146 - val accuracv: 0.9490
Epoch 44/50
125/125 [=======
                         - 1s 4ms/step - loss: 0.0942 - accuracy: 0.9952 - val loss: 2.3573 - val accuracy: 0.9550
Epoch 45/50
Epoch 46/50
Epoch 47/50
125/125 [============] - 0s 4ms/step - loss: 0.2129 - accuracy: 0.9918 - val loss: 3.6977 - val accuracy: 0.9435
Epoch 48/50
125/125 [===========]
                         - 0s 4ms/step - loss: 0.1684 - accuracy: 0.9921 - val loss: 2.2614 - val accuracy: 0.9565
Epoch 49/50
125/125 [=======
                 ========] - 0s 4ms/step - loss: 0.1477 - accuracy: 0.9933 - val loss: 2.6413 - val accuracy: 0.9565
Epoch 50/50
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

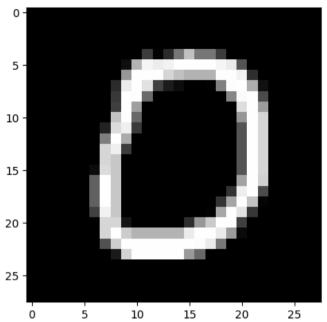
    Test loss: 3.8052914142608643
    Test accuracy: 0.9400500059127808

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



## Learning rate 0.0007

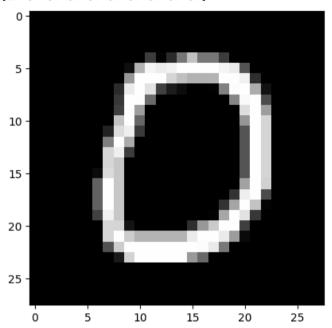
Validation split 0.85714285714 (default)

```
test_data = data[:60000]
train_data = data[60000:]
test_labels = label[:60000]
train_labels = label[60000:]
```

print(test\_data.shape,train\_data.shape,test\_labels.shape,train\_labels.shape)

```
(60000, 28, 28) (10000, 28, 28) (60000,) (10000,)
One-hot coding
train labels = tf.keras.utils.to categorical(train labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((10000, 28, 28), (10000, 10))
test_data.shape,test_labels.shape
    ((60000, 28, 28), (60000, 10))
train labels[0]
    array([0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = train_labels[img_index]
   plt.imshow(train data[img index]/255, cmap = 'gray')
   print(label index)
img index = 10
plot image(img index)
```

```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.007)
#opt = keras.optimizers.SGD(learning_rate=0.001)

model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential\_18"

Layer (type)	Output Shape	Param #
dense_42 (Dense)	(None, 128)	100480
dense_43 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)

\_\_\_\_\_\_

batch\_size = 128
epochs = 50

```
Epoch 1/50
Epoch 2/50
Epoch 3/50
63/63 [========================== ] - 0s 5ms/step - loss: 0.8409 - accuracy: 0.7660 - val loss: 0.8779 - val accuracy: 0.7935
Epoch 4/50
63/63 [============================== ] - 0s 4ms/step - loss: 0.6871 - accuracy: 0.8076 - val loss: 0.9245 - val accuracy: 0.7890
Epoch 5/50
63/63 [============================ ] - 0s 5ms/step - loss: 0.5934 - accuracy: 0.8294 - val loss: 0.8093 - val accuracy: 0.8310
Epoch 6/50
63/63 [=========================== ] - 0s 6ms/step - loss: 0.5231 - accuracy: 0.8506 - val loss: 0.6695 - val accuracy: 0.8595
Epoch 7/50
63/63 [=============== ] - 0s 7ms/step - loss: 0.4556 - accuracy: 0.8636 - val_loss: 0.7397 - val_accuracy: 0.8545
Epoch 8/50
63/63 [=========================== ] - 0s 7ms/step - loss: 0.4378 - accuracy: 0.8763 - val loss: 0.6983 - val accuracy: 0.8790
Epoch 9/50
Epoch 10/50
63/63 [============================ ] - 1s 9ms/step - loss: 0.3583 - accuracy: 0.9021 - val loss: 0.5586 - val accuracy: 0.8725
Epoch 11/50
63/63 [============================ ] - 1s 8ms/step - loss: 0.3321 - accuracy: 0.9005 - val loss: 0.6276 - val accuracy: 0.8710
Epoch 12/50
63/63 [=========================== ] - 0s 7ms/step - loss: 0.3102 - accuracy: 0.9141 - val loss: 0.6188 - val accuracy: 0.9000
Epoch 13/50
63/63 [============================ ] - 0s 6ms/step - loss: 0.2806 - accuracy: 0.9201 - val loss: 0.5288 - val accuracy: 0.9095
Epoch 14/50
63/63 [============================= ] - 0s 6ms/step - loss: 0.2804 - accuracy: 0.9252 - val_loss: 0.5888 - val_accuracy: 0.9120
Epoch 15/50
63/63 [============================ ] - 0s 6ms/step - loss: 0.2757 - accuracy: 0.9281 - val loss: 0.5783 - val accuracy: 0.9100
Epoch 16/50
63/63 [============================ ] - 0s 6ms/step - loss: 0.2922 - accuracy: 0.9273 - val loss: 0.6166 - val accuracy: 0.9035
Epoch 17/50
63/63 [============================ ] - 0s 6ms/step - loss: 0.3362 - accuracy: 0.9144 - val loss: 0.6996 - val accuracy: 0.9175
Epoch 18/50
63/63 [=========================== ] - 0s 6ms/step - loss: 0.2749 - accuracy: 0.9324 - val loss: 0.6785 - val accuracy: 0.9055
Enach 10/50
```