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	225	172	253	242	195	64	0	0	0	0]							
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[93	82	82	56	39	0	0	0	0	0]							
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```
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 35 241 225 160 108 1
 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 81 240 253 253 119
25 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 45 186 253 253
150 27 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 16 93 252
253 187 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 0 249
253 249 64 0 0 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 46 130 183 253
253 207 2 0 0 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 39 148 229 253 253 253
250 182 0 0 0 0 0 0 0 0]
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78 0 0 0 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 23 66 213 253 253 253 253 198 81 2
0 0 0 0 0 0 0 0]
[ 0 0 0 0 0 18 171 219 253 253 253 195 80 9 0 0
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[ 0 0 0 55 172 226 253 253 253 253 244 133 11 0 0 0 0
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[ 0 0 0 0 136 253 253 253 212 135 132 16 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 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]]
```

```
print("X_train shape", x_train.shape)
print("y_train shape", y_train.shape)
print("X_test shape", x_test.shape)
print("y_test shape", y_test.shape)
```

```
X_train shape (60000, 28, 28)
y_train shape (60000,)
X_test shape (10000, 28, 28)
y_test shape (10000,)
```

```
x_train = x_train.reshape(60000, 784)
x_test = x_test.reshape(10000, 784)
x_train = x_train.astype('float32') # use 32-bit precision when training a neural network, so at one point
```

```
x_test = x_test.astype('float32')
x_train /= 255 # Each image has Intensity from 0 to 255
x_test /= 255
```

```
num_classes = 10
y_train = np.eye(num_classes)[y_train]
y_test = np.eye(num_classes)[y_test]
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(784,)))
model.add(Dropout(0.2)) # DROP OUT RATIO 20%
model.add(Dense(512, activation='relu')) #returns a sequence of another vectors of dimension 512
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss='categorical_crossentropy', # for a multi-class classification problem
optimizer=RMSprop(),
metrics=['accuracy'])
```

```
# Train the model
batch_size = 128 # batch_size argument is passed to the layer to define a batch size for the inputs.
epochs = 20
history = model.fit(x_train, y_train,
batch_size=batch_size,
epochs=epochs,
verbose=1, # verbose=1 will show you an animated progress bar eg. [=====]
validation_data=(x_test, y_test))
```

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Epoch 1/20
469/469 [=====] - 19s 37ms/step - loss: 0.2498 - accuracy: 0.9238 - val_loss: 0.1036 - val_accuracy: 0.9665
```

```
Epoch 2/20
469/469 [=====] - 10s 22ms/step - loss: 0.1015 - accuracy: 0.9691 - val_loss: 0.0706 - val_accuracy: 0.9781
Epoch 3/20
469/469 [=====] - 10s 20ms/step - loss: 0.0743 - accuracy: 0.9769 - val_loss: 0.0777 - val_accuracy: 0.9760
Epoch 4/20
469/469 [=====] - 9s 19ms/step - loss: 0.0580 - accuracy: 0.9824 - val_loss: 0.0745 - val_accuracy: 0.9776
Epoch 5/20
469/469 [=====] - 10s 22ms/step - loss: 0.0466 - accuracy: 0.9852 - val_loss: 0.0582 - val_accuracy: 0.9830
Epoch 6/20
469/469 [=====] - 10s 21ms/step - loss: 0.0394 - accuracy: 0.9874 - val_loss: 0.0670 - val_accuracy: 0.9835
Epoch 7/20
469/469 [=====] - 10s 22ms/step - loss: 0.0330 - accuracy: 0.9893 - val_loss: 0.0642 - val_accuracy: 0.9837
Epoch 8/20
469/469 [=====] - 10s 21ms/step - loss: 0.0289 - accuracy: 0.9907 - val_loss: 0.0650 - val_accuracy: 0.9841
Epoch 9/20
469/469 [=====] - 10s 21ms/step - loss: 0.0259 - accuracy: 0.9917 - val_loss: 0.0617 - val_accuracy: 0.9837
Epoch 10/20
469/469 [=====] - 9s 19ms/step - loss: 0.0234 - accuracy: 0.9924 - val_loss: 0.0591 - val_accuracy: 0.9848
Epoch 11/20
469/469 [=====] - 10s 21ms/step - loss: 0.0199 - accuracy: 0.9941 - val_loss: 0.0715 - val_accuracy: 0.9830
Epoch 12/20
469/469 [=====] - 10s 20ms/step - loss: 0.0180 - accuracy: 0.9940 - val_loss: 0.0754 - val_accuracy: 0.9837
Epoch 13/20
469/469 [=====] - 10s 20ms/step - loss: 0.0169 - accuracy: 0.9943 - val_loss: 0.0687 - val_accuracy: 0.9853
Epoch 14/20
469/469 [=====] - 10s 21ms/step - loss: 0.0149 - accuracy: 0.9951 - val_loss: 0.0688 - val_accuracy: 0.9859
Epoch 15/20
469/469 [=====] - 10s 21ms/step - loss: 0.0126 - accuracy: 0.9960 - val_loss: 0.0820 - val_accuracy: 0.9831
Epoch 16/20
469/469 [=====] - 10s 22ms/step - loss: 0.0138 - accuracy: 0.9958 - val_loss: 0.0707 - val_accuracy: 0.9854
Epoch 17/20
469/469 [=====] - 10s 21ms/step - loss: 0.0127 - accuracy: 0.9959 - val_loss: 0.0786 - val_accuracy: 0.9850
Epoch 18/20
469/469 [=====] - 10s 21ms/step - loss: 0.0114 - accuracy: 0.9962 - val_loss: 0.0837 - val_accuracy: 0.9839
Epoch 19/20
469/469 [=====] - 9s 20ms/step - loss: 0.0109 - accuracy: 0.9964 - val_loss: 0.0767 - val_accuracy: 0.9859
Epoch 20/20
469/469 [=====] - 10s 20ms/step - loss: 0.0085 - accuracy: 0.9973 - val_loss: 0.0877 - val_accuracy: 0.9840
Test loss: 0.0877445712685585
Test accuracy: 0.984000027179718
```