


```
1 from sklearn.preprocessing import LabelBinarizer
2 from sklearn.metrics import classification_report
3 from tensorflow.keras.models import Sequential
4 from tensorflow.keras.layers import Dense
5 from tensorflow.keras.optimizers import SGD
6 from tensorflow.keras.datasets import mnist
7 from tensorflow.keras import backend as K
8 import matplotlib.pyplot as plt
9 import numpy as np
10
```

```
1 print("[INFO] accessing MNIST...")
2 ((trainX, trainY), (testX, testY)) = mnist.load_data()
3
4 trainX = trainX.reshape((trainX.shape[0], 28 * 28 * 1))
5 testX = testX.reshape((testX.shape[0], 28 * 28 * 1))
6
7 trainX = trainX.astype("float32") / 255.0
8 testX = testX.astype("float32") / 255.0
```


 [INFO] accessing MNIST...

```
1 Start coding or generate with AI.
```

```
1 lb = LabelBinarizer()
2 trainY = lb.fit_transform(trainY)
3 testY = lb.transform(testY)
```

```
1 model = Sequential()
2 model.add(Dense(256, input_shape=(784,), activation="sigmoid"))
3 model.add(Dense(128, activation="sigmoid"))
4 model.add(Dense(10, activation="softmax"))
```

```
1 print("[INFO] training network...")
2 sgd = SGD(0.01)
3 model.compile(loss="categorical_crossentropy", optimizer=sgd,
4               metrics=["accuracy"])
5 H = model.fit(trainX, trainY, validation_data=(testX, testY),
6               epochs=100, batch_size=128)
```

 [INFO] training network...

```
Epoch 1/100
469/469 [=====] - 6s 11ms/step - loss: 2.2901 - accuracy: 0.1797 - val_loss: 2.2501 - val_accuracy: 0.2269
Epoch 2/100
469/469 [=====] - 5s 10ms/step - loss: 2.2163 - accuracy: 0.3625 - val_loss: 2.1756 - val_accuracy: 0.4378
Epoch 3/100
469/469 [=====] - 5s 10ms/step - loss: 2.1317 - accuracy: 0.4981 - val_loss: 2.0731 - val_accuracy: 0.4991
```

Epoch 4/100
469/469 [=====] - 3s 7ms/step - loss: 2.0105 - accuracy: 0.5653 - val_loss: 1.9254 - val_accuracy: 0.6443
Epoch 5/100
469/469 [=====] - 3s 7ms/step - loss: 1.8410 - accuracy: 0.6192 - val_loss: 1.7304 - val_accuracy: 0.6507
Epoch 6/100
469/469 [=====] - 5s 11ms/step - loss: 1.6364 - accuracy: 0.6621 - val_loss: 1.5181 - val_accuracy: 0.6953
Epoch 7/100
469/469 [=====] - 3s 7ms/step - loss: 1.4324 - accuracy: 0.7030 - val_loss: 1.3235 - val_accuracy: 0.7216
Epoch 8/100
469/469 [=====] - 3s 7ms/step - loss: 1.2529 - accuracy: 0.7373 - val_loss: 1.1577 - val_accuracy: 0.7605
Epoch 9/100
469/469 [=====] - 4s 9ms/step - loss: 1.1027 - accuracy: 0.7652 - val_loss: 1.0217 - val_accuracy: 0.7822
Epoch 10/100
469/469 [=====] - 5s 10ms/step - loss: 0.9799 - accuracy: 0.7862 - val_loss: 0.9121 - val_accuracy: 0.7978
Epoch 11/100
469/469 [=====] - 4s 8ms/step - loss: 0.8808 - accuracy: 0.8016 - val_loss: 0.8233 - val_accuracy: 0.8136
Epoch 12/100
469/469 [=====] - 4s 8ms/step - loss: 0.8014 - accuracy: 0.8148 - val_loss: 0.7523 - val_accuracy: 0.8265
Epoch 13/100
469/469 [=====] - 5s 10ms/step - loss: 0.7374 - accuracy: 0.8251 - val_loss: 0.6947 - val_accuracy: 0.8351
Epoch 14/100
469/469 [=====] - 3s 7ms/step - loss: 0.6856 - accuracy: 0.8345 - val_loss: 0.6488 - val_accuracy: 0.8412
Epoch 15/100
469/469 [=====] - 3s 7ms/step - loss: 0.6431 - accuracy: 0.8416 - val_loss: 0.6097 - val_accuracy: 0.8480
Epoch 16/100
469/469 [=====] - 4s 9ms/step - loss: 0.6079 - accuracy: 0.8469 - val_loss: 0.5771 - val_accuracy: 0.8532
Epoch 17/100
469/469 [=====] - 4s 8ms/step - loss: 0.5782 - accuracy: 0.8531 - val_loss: 0.5501 - val_accuracy: 0.8575
Epoch 18/100
469/469 [=====] - 3s 7ms/step - loss: 0.5533 - accuracy: 0.8572 - val_loss: 0.5260 - val_accuracy: 0.8646
Epoch 19/100
469/469 [=====] - 3s 7ms/step - loss: 0.5317 - accuracy: 0.8611 - val_loss: 0.5062 - val_accuracy: 0.8684
Epoch 20/100
469/469 [=====] - 5s 11ms/step - loss: 0.5130 - accuracy: 0.8643 - val_loss: 0.4886 - val_accuracy: 0.8718
Epoch 21/100
469/469 [=====] - 3s 7ms/step - loss: 0.4965 - accuracy: 0.8677 - val_loss: 0.4737 - val_accuracy: 0.8743
Epoch 22/100
469/469 [=====] - 3s 7ms/step - loss: 0.4820 - accuracy: 0.8708 - val_loss: 0.4599 - val_accuracy: 0.8774
Epoch 23/100
469/469 [=====] - 4s 8ms/step - loss: 0.4691 - accuracy: 0.8741 - val_loss: 0.4472 - val_accuracy: 0.8798
Epoch 24/100
469/469 [=====] - 5s 10ms/step - loss: 0.4575 - accuracy: 0.8764 - val_loss: 0.4367 - val_accuracy: 0.8816
Epoch 25/100
469/469 [=====] - 3s 7ms/step - loss: 0.4471 - accuracy: 0.8787 - val_loss: 0.4264 - val_accuracy: 0.8850
Epoch 26/100
469/469 [=====] - 3s 7ms/step - loss: 0.4375 - accuracy: 0.8807 - val_loss: 0.4176 - val_accuracy: 0.8863
Epoch 27/100
469/469 [=====] - 4s 9ms/step - loss: 0.4288 - accuracy: 0.8828 - val_loss: 0.4098 - val_accuracy: 0.8880
Epoch 28/100
469/469 [=====] - 4s 8ms/step - loss: 0.4210 - accuracy: 0.8846 - val_loss: 0.4019 - val_accuracy: 0.8892
Epoch 29/100

```

1 print("[INFO] evaluating network...")
2 predictions = model.predict(testX, batch_size=128)
3 print(classification_report(testY.argmax(axis=1),
4     predictions.argmax(axis=1),
5     target_names=[str(x) for x in lb.classes_]))

```

```

↗ [INFO] evaluating network...
79/79 [=====] - 0s 4ms/step


```

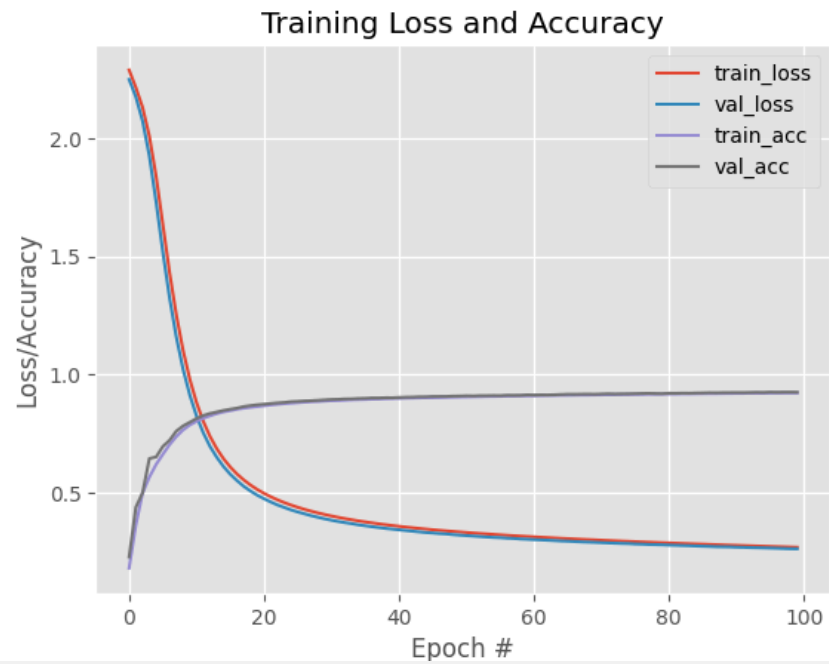
	precision	recall	f1-score	support
0	0.94	0.98	0.96	980
1	0.97	0.98	0.97	1135
2	0.93	0.90	0.92	1032
3	0.90	0.91	0.91	1010
4	0.92	0.94	0.93	982
5	0.90	0.87	0.89	892
6	0.93	0.95	0.94	958
7	0.93	0.92	0.93	1028
8	0.90	0.88	0.89	974
9	0.91	0.91	0.91	1009
accuracy			0.93	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.92	0.93	0.92	10000

```

1 plt.style.use("ggplot")
2 plt.figure()
3 plt.plot(np.arange(0, 100), H.history["loss"], label="train_loss")
4 plt.plot(np.arange(0, 100), H.history["val_loss"], label="val_loss")
5 plt.plot(np.arange(0, 100), H.history["accuracy"], label="train_acc")
6 plt.plot(np.arange(0, 100), H.history["val_accuracy"], label="val_acc")
7 plt.title("Training Loss and Accuracy")
8 plt.xlabel("Epoch #")
9 plt.ylabel("Loss/Accuracy")
10 plt.legend()
11

```

 <matplotlib.legend.Legend at 0x7d677d9e8af0>



1 Start coding or [generate](#) with AI.