

```
In [2]: # import the necessary packages
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import classification_report
```

```
In [3]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.datasets import mnist
from tensorflow.keras import backend as K
```

```
In [4]: import matplotlib.pyplot as plt
import numpy as np
```

```
In [5]: import argparse
```

```
In [7]: # construct the argument parse and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-o", "--output", required=True,
                help="path to the output loss/accuracy plot")
```

```
Out[7]: _StoreAction(option_strings=['-o', '--output'], dest='output', nargs=None, const=None,
default=None, type=None, choices=None, help='path to the output loss/accuracy plot', metavar=None)
```

```
In [8]: args = vars(ap.parse_args())
```

```
usage: ipykernel_launcher.py [-h] -o OUTPUT
ipykernel_launcher.py: error: the following arguments are required: -o/--output
An exception has occurred, use %tb to see the full traceback.
```

```
SystemExit: 2
```

```
In [10]: # grab the MNIST dataset (if this is your first time using this
# dataset then the 11MB download may take a minute)
print("[INFO] accessing MNIST...")
((trainX, trainY), (testX, testY)) = mnist.load_data()

[INFO] accessing MNIST...
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [=====] - 2s 0us/step
```

```
In [11]: # each image in the MNIST dataset is represented as a 28x28x1
# image, but in order to apply a standard neural network we must
# first "flatten" the image to be simple list of 28x28=784 pixels
trainX = trainX.reshape((trainX.shape[0], 28 * 28 * 1))
testX = testX.reshape((testX.shape[0], 28 * 28 * 1))
```

```
In [12]: # scale data to the range of [0, 1]
trainX = trainX.astype("float32") / 255.0
testX = testX.astype("float32") / 255.0
```

```
In [13]: # convert the labels from integers to vectors
lb = LabelBinarizer()
trainY = lb.fit_transform(trainY)
testY = lb.transform(testY)
```

```
In [14]: # define the 784-256-128-10 architecture using Keras
model = Sequential()
model.add(Dense(256, input_shape=(784,), activation="sigmoid"))
model.add(Dense(128, activation="sigmoid"))
model.add(Dense(10, activation="softmax"))
```

```
In [15]: # train the model using SGD
print("[INFO] training network...")
sgd = SGD(0.01)
model.compile(loss="categorical_crossentropy", optimizer=sgd,
              metrics=["accuracy"])
H = model.fit(trainX, trainY, validation_data=(testX, testY),
              epochs=100, batch_size=128)
```

[INFO] training network...

Epoch 1/100

469/469 [=====] - 2s 4ms/step - loss: 2.2793 - accuracy: 0.2024 - val\_loss: 2.2444 - val\_accuracy: 0.4344

Epoch 2/100

469/469 [=====] - 2s 5ms/step - loss: 2.2111 - accuracy: 0.3995 - val\_loss: 2.1703 - val\_accuracy: 0.3639

Epoch 3/100

469/469 [=====] - 3s 5ms/step - loss: 2.1254 - accuracy: 0.5034 - val\_loss: 2.0659 - val\_accuracy: 0.5420

Epoch 4/100

469/469 [=====] - 2s 5ms/step - loss: 2.0006 - accuracy: 0.5695 - val\_loss: 1.9129 - val\_accuracy: 0.5918

Epoch 5/100

469/469 [=====] - 2s 5ms/step - loss: 1.8241 - accuracy: 0.6123 - val\_loss: 1.7100 - val\_accuracy: 0.6264

Epoch 6/100

469/469 [=====] - 2s 5ms/step - loss: 1.6111 - accuracy: 0.6539 - val\_loss: 1.4886 - val\_accuracy: 0.6770

Epoch 7/100

469/469 [=====] - 2s 5ms/step - loss: 1.4007 - accuracy: 0.6913 - val\_loss: 1.2910 - val\_accuracy: 0.7133

Epoch 8/100

469/469 [=====] - 2s 5ms/step - loss: 1.2227 - accuracy: 0.7214 - val\_loss: 1.1318 - val\_accuracy: 0.7435

Epoch 9/100

469/469 [=====] - 2s 5ms/step - loss: 1.0823 - accuracy: 0.7459 - val\_loss: 1.0088 - val\_accuracy: 0.7574

Epoch 10/100

469/469 [=====] - 2s 5ms/step - loss: 0.9728 - accuracy: 0.7640 - val\_loss: 0.9119 - val\_accuracy: 0.7791

Epoch 11/100

469/469 [=====] - 2s 5ms/step - loss: 0.8863 - accuracy: 0.7797 - val\_loss: 0.8346 - val\_accuracy: 0.7932

Epoch 12/100

469/469 [=====] - 2s 5ms/step - loss: 0.8165 - accuracy: 0.7934 - val\_loss: 0.7709 - val\_accuracy: 0.8058

Epoch 13/100

469/469 [=====] - 2s 5ms/step - loss: 0.7592 - accuracy: 0.8057 - val\_loss: 0.7185 - val\_accuracy: 0.8164

Epoch 14/100

469/469 [=====] - 2s 5ms/step - loss: 0.7112 - accuracy: 0.8162 - val\_loss: 0.6741 - val\_accuracy: 0.8258

Epoch 15/100

469/469 [=====] - 2s 5ms/step - loss: 0.6705 - accuracy: 0.8253 - val\_loss: 0.6372 - val\_accuracy: 0.8317

Epoch 16/100

469/469 [=====] - 2s 5ms/step - loss: 0.6355 - accuracy: 0.8335 - val\_loss: 0.6043 - val\_accuracy: 0.8390

Epoch 17/100

469/469 [=====] - 2s 5ms/step - loss: 0.6052 - accuracy: 0.8413 - val\_loss: 0.5754 - val\_accuracy: 0.8479

Epoch 18/100

469/469 [=====] - 2s 5ms/step - loss: 0.5789 - accuracy: 0.8467 - val\_loss: 0.5502 - val\_accuracy: 0.8537

Epoch 19/100

469/469 [=====] - 2s 5ms/step - loss: 0.5556 - accuracy: 0.8531 - val\_loss: 0.5281 - val\_accuracy: 0.8600

Epoch 20/100

469/469 [=====] - 2s 5ms/step - loss: 0.5350 - accuracy: 0.8

584 - val\_loss: 0.5083 - val\_accuracy: 0.8644  
Epoch 21/100  
469/469 [=====] - 2s 5ms/step - loss: 0.5166 - accuracy: 0.8628 - val\_loss: 0.4910 - val\_accuracy: 0.8686  
Epoch 22/100  
469/469 [=====] - 2s 5ms/step - loss: 0.5001 - accuracy: 0.8668 - val\_loss: 0.4755 - val\_accuracy: 0.8726  
Epoch 23/100  
469/469 [=====] - 2s 5ms/step - loss: 0.4852 - accuracy: 0.8704 - val\_loss: 0.4618 - val\_accuracy: 0.8748  
Epoch 24/100  
469/469 [=====] - 3s 5ms/step - loss: 0.4719 - accuracy: 0.8737 - val\_loss: 0.4486 - val\_accuracy: 0.8806  
Epoch 25/100  
469/469 [=====] - 2s 5ms/step - loss: 0.4597 - accuracy: 0.8767 - val\_loss: 0.4368 - val\_accuracy: 0.8828  
Epoch 26/100  
469/469 [=====] - 2s 5ms/step - loss: 0.4486 - accuracy: 0.8792 - val\_loss: 0.4266 - val\_accuracy: 0.8847  
Epoch 27/100  
469/469 [=====] - 2s 5ms/step - loss: 0.4386 - accuracy: 0.8818 - val\_loss: 0.4173 - val\_accuracy: 0.8865  
Epoch 28/100  
469/469 [=====] - 2s 5ms/step - loss: 0.4295 - accuracy: 0.8840 - val\_loss: 0.4089 - val\_accuracy: 0.8879  
Epoch 29/100  
469/469 [=====] - 3s 6ms/step - loss: 0.4210 - accuracy: 0.8857 - val\_loss: 0.4004 - val\_accuracy: 0.8895  
Epoch 30/100  
469/469 [=====] - 3s 6ms/step - loss: 0.4134 - accuracy: 0.8881 - val\_loss: 0.3938 - val\_accuracy: 0.8912  
Epoch 31/100  
469/469 [=====] - 3s 5ms/step - loss: 0.4063 - accuracy: 0.8897 - val\_loss: 0.3863 - val\_accuracy: 0.8941  
Epoch 32/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3998 - accuracy: 0.8906 - val\_loss: 0.3807 - val\_accuracy: 0.8944  
Epoch 33/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3938 - accuracy: 0.8921 - val\_loss: 0.3747 - val\_accuracy: 0.8962  
Epoch 34/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3881 - accuracy: 0.8937 - val\_loss: 0.3698 - val\_accuracy: 0.8973  
Epoch 35/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3829 - accuracy: 0.8946 - val\_loss: 0.3648 - val\_accuracy: 0.8979  
Epoch 36/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3782 - accuracy: 0.8959 - val\_loss: 0.3602 - val\_accuracy: 0.8991  
Epoch 37/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3736 - accuracy: 0.8967 - val\_loss: 0.3563 - val\_accuracy: 0.9005  
Epoch 38/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3694 - accuracy: 0.8976 - val\_loss: 0.3521 - val\_accuracy: 0.9012  
Epoch 39/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3654 - accuracy: 0.8983 - val\_loss: 0.3489 - val\_accuracy: 0.9013  
Epoch 40/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3617 - accuracy: 0.8989

994 - val\_loss: 0.3452 - val\_accuracy: 0.9032  
Epoch 41/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3581 - accuracy: 0.9002 - val\_loss: 0.3416 - val\_accuracy: 0.9036  
Epoch 42/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3547 - accuracy: 0.9008 - val\_loss: 0.3385 - val\_accuracy: 0.9046  
Epoch 43/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3516 - accuracy: 0.9016 - val\_loss: 0.3359 - val\_accuracy: 0.9055  
Epoch 44/100  
469/469 [=====] - 3s 5ms/step - loss: 0.3486 - accuracy: 0.9018 - val\_loss: 0.3326 - val\_accuracy: 0.9064  
Epoch 45/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3457 - accuracy: 0.9031 - val\_loss: 0.3305 - val\_accuracy: 0.9063  
Epoch 46/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3430 - accuracy: 0.9034 - val\_loss: 0.3281 - val\_accuracy: 0.9070  
Epoch 47/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3403 - accuracy: 0.9039 - val\_loss: 0.3251 - val\_accuracy: 0.9081  
Epoch 48/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3378 - accuracy: 0.9047 - val\_loss: 0.3233 - val\_accuracy: 0.9071  
Epoch 49/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3354 - accuracy: 0.9052 - val\_loss: 0.3214 - val\_accuracy: 0.9084  
Epoch 50/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3331 - accuracy: 0.9054 - val\_loss: 0.3192 - val\_accuracy: 0.9092  
Epoch 51/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3309 - accuracy: 0.9063 - val\_loss: 0.3169 - val\_accuracy: 0.9093  
Epoch 52/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3286 - accuracy: 0.9065 - val\_loss: 0.3144 - val\_accuracy: 0.9099  
Epoch 53/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3265 - accuracy: 0.9075 - val\_loss: 0.3131 - val\_accuracy: 0.9098  
Epoch 54/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3246 - accuracy: 0.9075 - val\_loss: 0.3110 - val\_accuracy: 0.9110  
Epoch 55/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3227 - accuracy: 0.9079 - val\_loss: 0.3092 - val\_accuracy: 0.9114  
Epoch 56/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3208 - accuracy: 0.9085 - val\_loss: 0.3075 - val\_accuracy: 0.9121  
Epoch 57/100  
469/469 [=====] - 3s 5ms/step - loss: 0.3190 - accuracy: 0.9085 - val\_loss: 0.3057 - val\_accuracy: 0.9118  
Epoch 58/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3172 - accuracy: 0.9095 - val\_loss: 0.3039 - val\_accuracy: 0.9125  
Epoch 59/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3154 - accuracy: 0.9094 - val\_loss: 0.3028 - val\_accuracy: 0.9124  
Epoch 60/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3138 - accuracy: 0.9

104 - val\_loss: 0.3016 - val\_accuracy: 0.9140  
Epoch 61/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3122 - accuracy: 0.9  
104 - val\_loss: 0.2998 - val\_accuracy: 0.9143  
Epoch 62/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3105 - accuracy: 0.9  
108 - val\_loss: 0.2982 - val\_accuracy: 0.9145  
Epoch 63/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3089 - accuracy: 0.9  
114 - val\_loss: 0.2966 - val\_accuracy: 0.9152  
Epoch 64/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3076 - accuracy: 0.9  
116 - val\_loss: 0.2957 - val\_accuracy: 0.9157  
Epoch 65/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3060 - accuracy: 0.9  
122 - val\_loss: 0.2944 - val\_accuracy: 0.9168  
Epoch 66/100  
469/469 [=====] - 2s 5ms/step - loss: 0.3046 - accuracy: 0.9  
123 - val\_loss: 0.2925 - val\_accuracy: 0.9166  
Epoch 67/100  
469/469 [=====] - 3s 5ms/step - loss: 0.3031 - accuracy: 0.9  
128 - val\_loss: 0.2923 - val\_accuracy: 0.9153  
Epoch 68/100  
469/469 [=====] - 3s 6ms/step - loss: 0.3019 - accuracy: 0.9  
130 - val\_loss: 0.2909 - val\_accuracy: 0.9156  
Epoch 69/100  
469/469 [=====] - 3s 5ms/step - loss: 0.3004 - accuracy: 0.9  
136 - val\_loss: 0.2890 - val\_accuracy: 0.9166  
Epoch 70/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2991 - accuracy: 0.9  
136 - val\_loss: 0.2891 - val\_accuracy: 0.9175  
Epoch 71/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2978 - accuracy: 0.9  
142 - val\_loss: 0.2873 - val\_accuracy: 0.9180  
Epoch 72/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2965 - accuracy: 0.9  
145 - val\_loss: 0.2858 - val\_accuracy: 0.9182  
Epoch 73/100  
469/469 [=====] - 3s 5ms/step - loss: 0.2953 - accuracy: 0.9  
147 - val\_loss: 0.2845 - val\_accuracy: 0.9185  
Epoch 74/100  
469/469 [=====] - 3s 5ms/step - loss: 0.2941 - accuracy: 0.9  
150 - val\_loss: 0.2837 - val\_accuracy: 0.9188  
Epoch 75/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2928 - accuracy: 0.9  
153 - val\_loss: 0.2835 - val\_accuracy: 0.9190  
Epoch 76/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2917 - accuracy: 0.9  
156 - val\_loss: 0.2820 - val\_accuracy: 0.9189  
Epoch 77/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2906 - accuracy: 0.9  
156 - val\_loss: 0.2805 - val\_accuracy: 0.9194  
Epoch 78/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2893 - accuracy: 0.9  
161 - val\_loss: 0.2798 - val\_accuracy: 0.9197  
Epoch 79/100  
469/469 [=====] - 2s 5ms/step - loss: 0.2882 - accuracy: 0.9  
166 - val\_loss: 0.2788 - val\_accuracy: 0.9197  
Epoch 80/100  
469/469 [=====] - 3s 5ms/step - loss: 0.2872 - accuracy: 0.9

```
169 - val_loss: 0.2778 - val_accuracy: 0.9196
Epoch 81/100
469/469 [=====] - 3s 6ms/step - loss: 0.2861 - accuracy: 0.9
168 - val_loss: 0.2765 - val_accuracy: 0.9206
Epoch 82/100
469/469 [=====] - 2s 5ms/step - loss: 0.2850 - accuracy: 0.9
176 - val_loss: 0.2758 - val_accuracy: 0.9206
Epoch 83/100
469/469 [=====] - 2s 5ms/step - loss: 0.2840 - accuracy: 0.9
178 - val_loss: 0.2748 - val_accuracy: 0.9208
Epoch 84/100
469/469 [=====] - 2s 5ms/step - loss: 0.2829 - accuracy: 0.9
180 - val_loss: 0.2741 - val_accuracy: 0.9208
Epoch 85/100
469/469 [=====] - 2s 5ms/step - loss: 0.2818 - accuracy: 0.9
183 - val_loss: 0.2731 - val_accuracy: 0.9213
Epoch 86/100
469/469 [=====] - 2s 5ms/step - loss: 0.2808 - accuracy: 0.9
186 - val_loss: 0.2726 - val_accuracy: 0.9214
Epoch 87/100
469/469 [=====] - 3s 6ms/step - loss: 0.2799 - accuracy: 0.9
188 - val_loss: 0.2712 - val_accuracy: 0.9219
Epoch 88/100
469/469 [=====] - 3s 5ms/step - loss: 0.2789 - accuracy: 0.9
187 - val_loss: 0.2705 - val_accuracy: 0.9220
Epoch 89/100
469/469 [=====] - 2s 5ms/step - loss: 0.2779 - accuracy: 0.9
192 - val_loss: 0.2696 - val_accuracy: 0.9221
Epoch 90/100
469/469 [=====] - 2s 5ms/step - loss: 0.2770 - accuracy: 0.9
192 - val_loss: 0.2686 - val_accuracy: 0.9228
Epoch 91/100
469/469 [=====] - 2s 5ms/step - loss: 0.2759 - accuracy: 0.9
198 - val_loss: 0.2680 - val_accuracy: 0.9223
Epoch 92/100
469/469 [=====] - 2s 5ms/step - loss: 0.2750 - accuracy: 0.9
205 - val_loss: 0.2674 - val_accuracy: 0.9233
Epoch 93/100
469/469 [=====] - 3s 6ms/step - loss: 0.2741 - accuracy: 0.9
202 - val_loss: 0.2668 - val_accuracy: 0.9230
Epoch 94/100
469/469 [=====] - 3s 6ms/step - loss: 0.2732 - accuracy: 0.9
203 - val_loss: 0.2660 - val_accuracy: 0.9238
Epoch 95/100
469/469 [=====] - 3s 6ms/step - loss: 0.2723 - accuracy: 0.9
209 - val_loss: 0.2649 - val_accuracy: 0.9236
Epoch 96/100
469/469 [=====] - 3s 6ms/step - loss: 0.2714 - accuracy: 0.9
210 - val_loss: 0.2643 - val_accuracy: 0.9241
Epoch 97/100
469/469 [=====] - 3s 6ms/step - loss: 0.2705 - accuracy: 0.9
213 - val_loss: 0.2632 - val_accuracy: 0.9241
Epoch 98/100
469/469 [=====] - 3s 6ms/step - loss: 0.2696 - accuracy: 0.9
214 - val_loss: 0.2625 - val_accuracy: 0.9243
Epoch 99/100
469/469 [=====] - 3s 6ms/step - loss: 0.2688 - accuracy: 0.9
218 - val_loss: 0.2614 - val_accuracy: 0.9249
Epoch 100/100
```

469/469 [=====] - 3s 6ms/step - loss: 0.2678 - accuracy: 0.9219 - val\_loss: 0.2610 - val\_accuracy: 0.9252

```
In [16]: # evaluate the network
print("[INFO] evaluating network...")
predictions = model.predict(testX, batch_size=128)
print(classification_report(testY.argmax(axis=1),
    predictions.argmax(axis=1),
    target_names=[str(x) for x in lb.classes_]))
```

[INFO] evaluating network...

79/79 [=====] - 0s 3ms/step

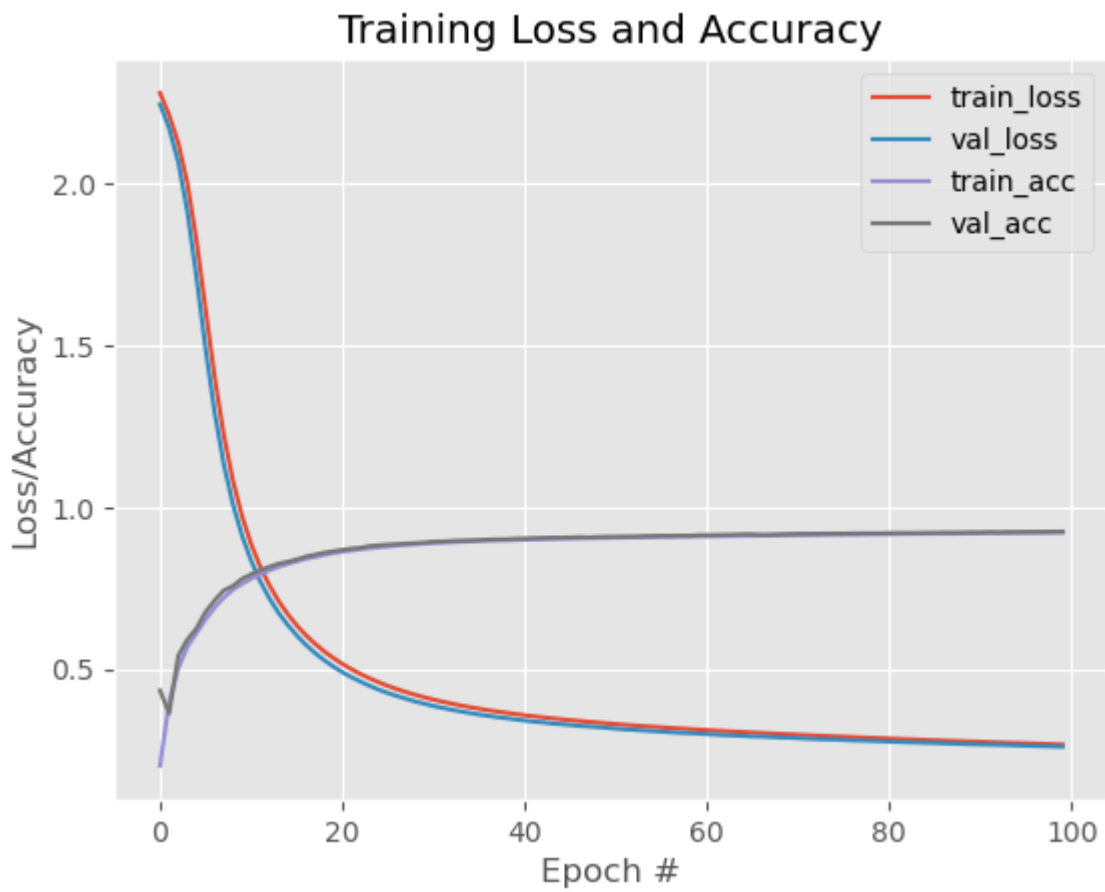
	precision	recall	f1-score	support
0	0.94	0.98	0.96	980
1	0.97	0.97	0.97	1135
2	0.92	0.91	0.91	1032
3	0.90	0.91	0.91	1010
4	0.92	0.93	0.93	982
5	0.91	0.86	0.88	892
6	0.93	0.94	0.94	958
7	0.94	0.92	0.93	1028
8	0.89	0.90	0.89	974
9	0.91	0.91	0.91	1009
accuracy			0.93	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.93	0.93	0.93	10000

```
In [17]: # plot the training loss and accuracy
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, 100), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, 100), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 100), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, 100), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig(args["output"])
```

```
-----
NameError                                Traceback (most recent call last)
Input In [17], in <cell line: 12>()
      10 plt.ylabel("Loss/Accuracy")
      11 plt.legend()
----> 12 plt.savefig(args["output"])

NameError: name 'args' is not defined
```





In [ ]: