

QUESTION 3: Does the model show any indication of overfitting? Why/No?

QUESTION 4: How do the accuracy and loss compare to the previous model? What can you infer from this comparison?

When we look at the graphs generated above the model converges because the loss lines form a horizontal line after the epoch is greater than 300. There is no overfitting in the model because if you look at the validation set it is not different from the behavior of the model with the training data set. It can clearly infer the model does handle generalization very well and above graphs validates that.

Evaluate the model

```
model.evaluate(X_validation, y_validation)
```

Out[102]: [0.01605464507341385, 0.9033999842643738] - 0s 396us/step - loss: 0.0161 - accuracy: 0.9040

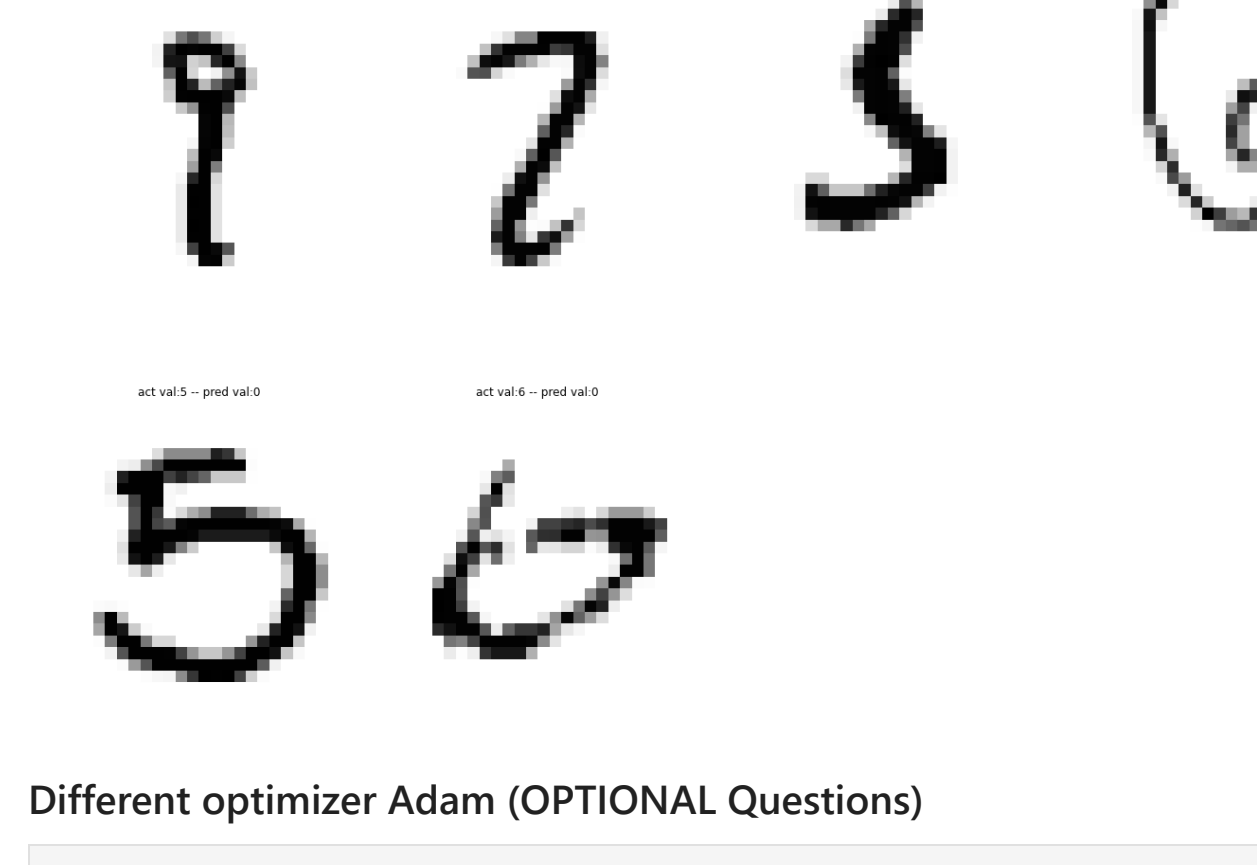
TODO 3

Write code to display the confusion matrix for your classifier and comment on the insights such confusion matrix provides.

See this for an example.



In [103]:



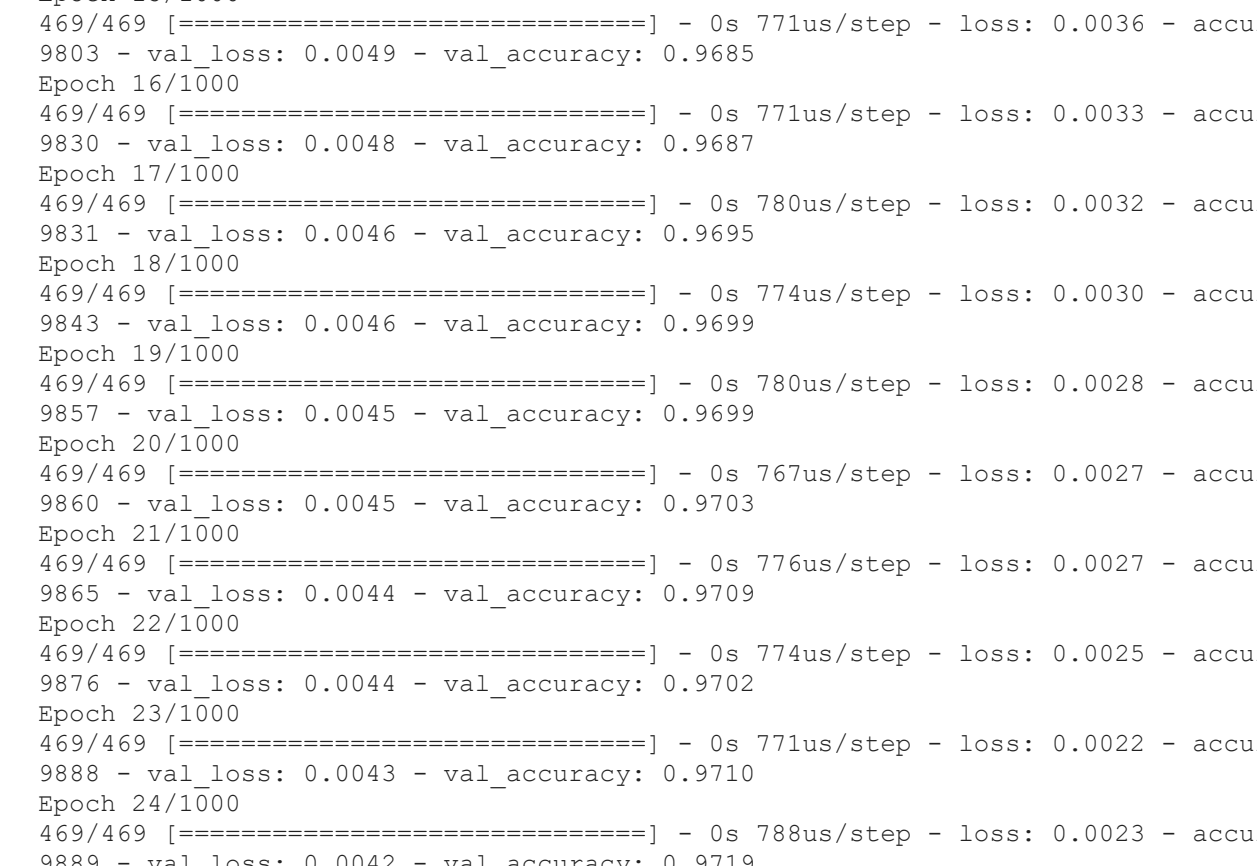
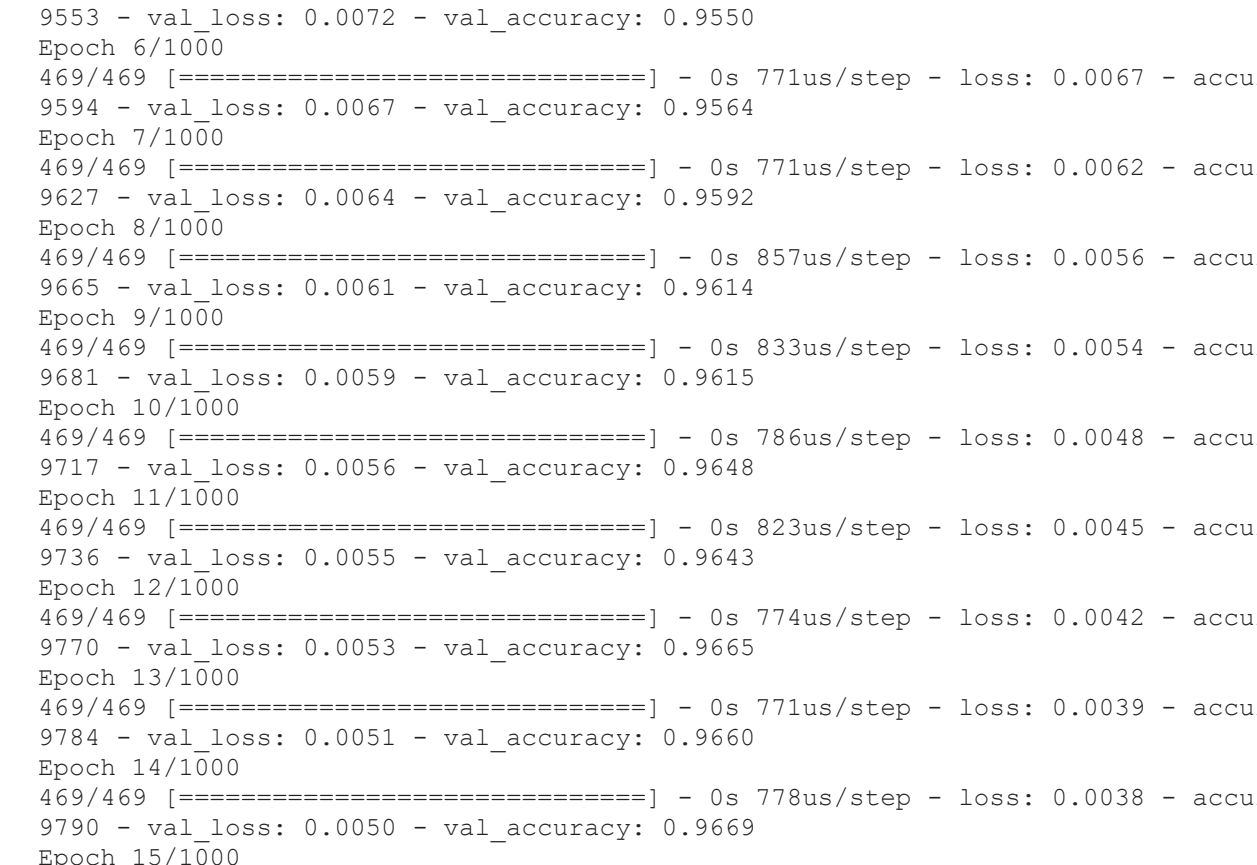
Question 3

The confusion matrix can give us performance metrics of the model some metrics are like accuracy score and overall error. If we look at index 0 on first column you can see the model is doing well. You can see from 980 samples that have 0 label 956 were done classification right. If you look at index 5 you can see support for 892 and 738 classified correctly which is weaker. Index 5 has more issues on correct classification.

(OPTIONAL) TODO 4

Write code to display 10 cases where the classifier makes mistakes. Make sure to display both the true value and as the predicted value.

See this for an example.



Different optimizer Adam (OPTIONAL Questions)

In [107]:

```
batch_size=128
epochs=1000
model.compile(
    loss='mean_squared_error',
    optimizer='adam',
    metrics=['accuracy'])
```

History of model fit:

- X training, # training data
- Y training, # training targets
- Epochs, # number of passes of the entire training dataset
- Batch_size, batch_size, # number of samples processed before the model is updated
- validation_data=(X_validation, y_validation)

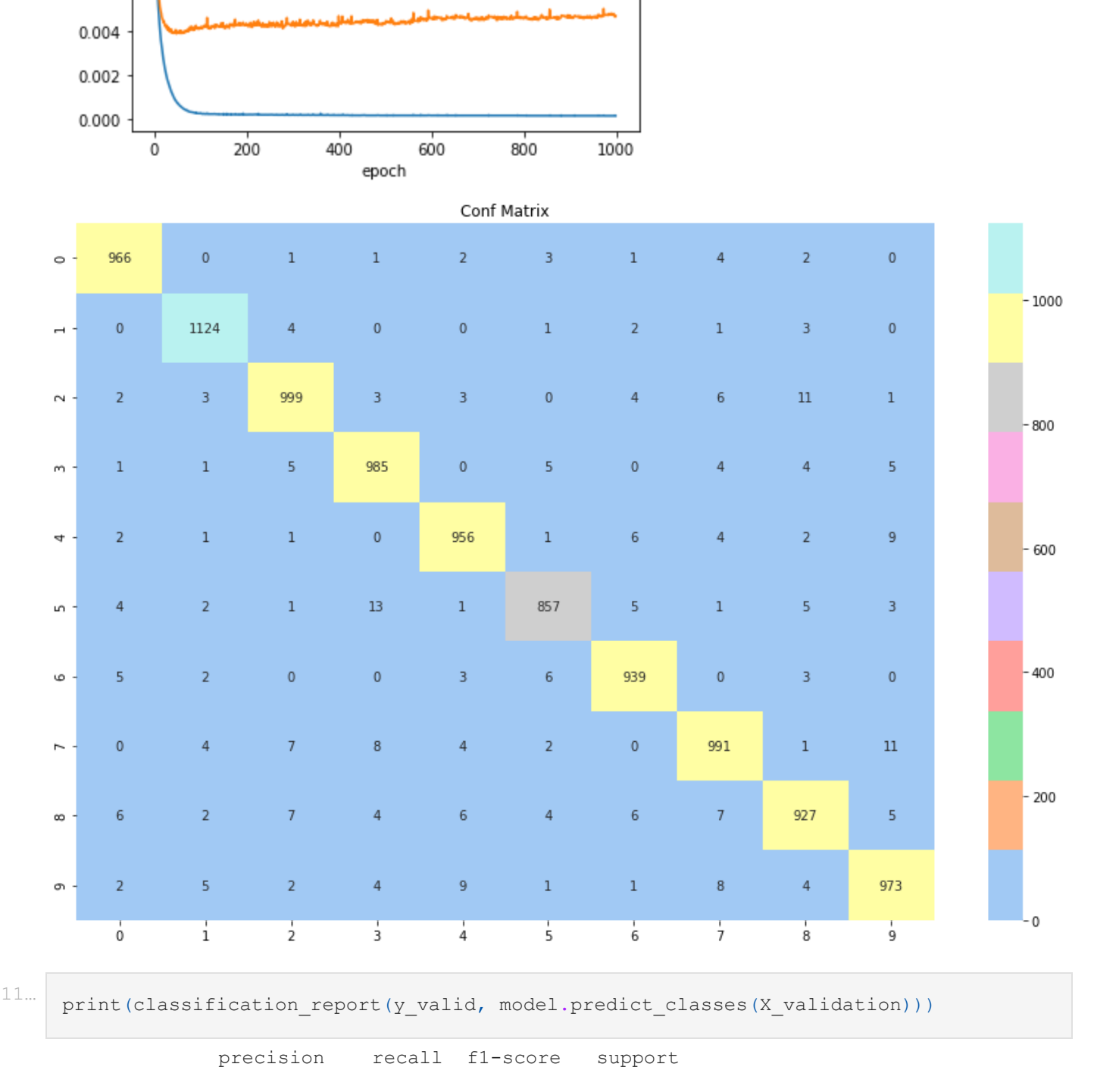
Epoch 1/1000

Epoch	loss	val_loss	val_accuracy
1	0.9079	0.0113	0.9303
2	0.9033	0.0097	0.9386
3	0.9010	0.0085	0.9478
4	0.9008	0.0079	0.9512
5	0.9008	0.0072	0.9550
6	0.9008	0.0067	0.9564
7	0.9008	0.0064	0.9592
8	0.9008	0.0061	0.9614
9	0.9008	0.0059	0.9615
10	0.9008	0.0056	0.9615
11	0.9008	0.0055	0.9643
12	0.9008	0.0053	0.9665
13	0.9008	0.0051	0.9660
14	0.9008	0.0050	0.9669
15	0.9008	0.0049	0.9685
16	0.9008	0.0048	0.9687
17	0.9008	0.0046	0.9695
18	0.9008	0.0045	0.9699
19	0.9008	0.0044	0.9699
20	0.9008	0.0044	0.9703
21	0.9008	0.0044	0.9709
22	0.9008	0.0044	0.9709
23	0.9008	0.0044	0.9702
24	0.9008	0.0044	0.9702
25	0.9008	0.0044	0.9702
26	0.9008	0.0044	0.9702
27	0.9008	0.0044	0.9702
28	0.9008	0.0044	0.9702
29	0.9008	0.0044	0.9702
30	0.9008	0.0044	0.9702
31	0.9008	0.0044	0.9702
32	0.9008	0.0044	0.9702
33	0.9008	0.0044	0.9702
34	0.9008	0.0044	0.9702
35	0.9008	0.0044	0.9702
36	0.9008	0.0044	0.9702
37	0.9008	0.0044	0.9702
38	0.9008	0.0044	0.9702
39	0.9008	0.0044	0.9702
40	0.9008	0.0044	0.9702
41	0.9008	0.0044	0.9702
42	0.9008	0.0044	0.9702
43	0.9008	0.0044	0.9702
44	0.9008	0.0044	0.9702
45	0.9008	0.0044	0.9702
46	0.9008	0.0044	0.9702
47	0.9008	0.0044	0.9702
48	0.9008	0.0044	0.9702
49	0.9008	0.0044	0.9702
50	0.9008	0.0044	0.9702
51	0.9008	0.0044	0.9702
52	0.9008	0.0044	0.9702
53	0.9008	0.0044	0.9702
54	0.9008	0.0044	0.9702
55	0.9008	0.0044	0.9702
56	0.9008	0.0044	0.9702
57	0.9008	0.0044	0.9702
58	0.9008	0.0044	0.9702
59	0.9008	0.0044	0.9702
60	0.9008	0.0044	0.9702
61	0.9008	0.0044	0.9702
62	0.9008	0.0044	0.9702
63	0.9008	0.0044	0.9702
64	0.9008	0.0044	0.9702
65	0.9008	0.0044	0.9702
66	0.9008	0.0044	0.9702
67	0.9008	0.0044	0.9702
68	0.9008	0.0044	0.9702
69	0.9008	0.0044	0.9702
70	0.9008	0.0044	0.9702
71	0.9008	0.0044	0.9702
72	0.9008	0.0044	0.9702
73	0.9008	0.0044	0.9702
74	0.9008	0.0044	0.9702
75	0.9008	0.0044	0.9702
76	0.9008	0.0044	0.9702
77	0.9008	0.0044	0.9702
78	0.9008	0.0044	0.9702
79	0.9008	0.0044	0.9702
80	0.9008	0.0044	0.9702
81	0.9008	0.0044	0.9702
82	0.9008	0.0044	0.9702
83	0.9008	0.0044	0.9702
84	0.9008	0.0044	0.9702
85	0.9008	0.0044	0.9702
86	0.9008	0.0044	0.9702
87	0.9008	0.0044	0.9702
88	0.9008	0.0044	0.9702
89	0.9008	0.0044	0.9702
90	0.9008	0.0044	0.9702
91	0.9008	0.0044	0.9702
92	0.9008	0.0044	0.9702
93	0.9008	0.0044	0.9702
94	0.9008	0.0044	0.9702
95	0.9008	0.0044	0.9702
96	0.9008	0.0044	0.9702
97	0.9008	0.0044	0.9702
98	0.9008	0.0044	0.9702
99	0.9008	0.0044	0.9702
100	0.9008	0.0044	0.9702

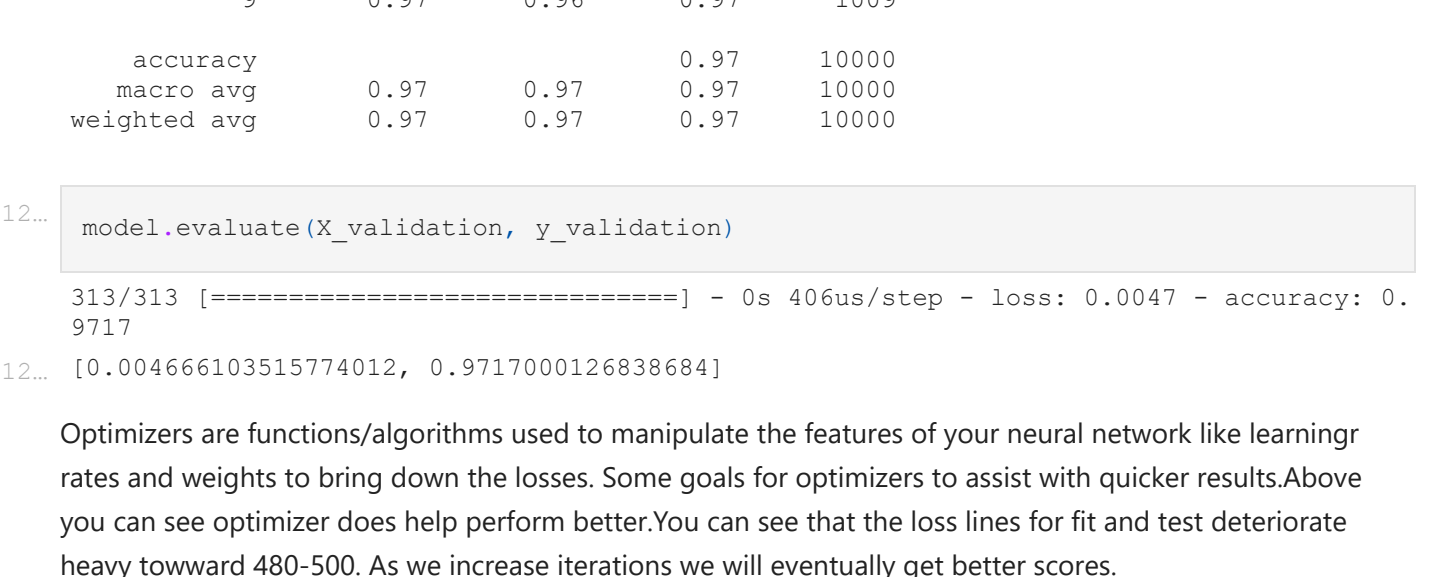
Epoch 239/1000	=====	- 0s	784us/step	loss: 1.8644e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9733					
Epoch 240/1000	=====	- 0s	771us/step	loss: 1.6898e-04	accuar
y1:0.9999 - val_loss: 0.0043 - val_accuracy: 0.9736					
Epoch 241/1000	=====	- 0s	780us/step	loss: 1.4971e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9736					
Epoch 242/1000	=====	- 0s	786us/step	loss: 1.6125e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9736					
Epoch 243/1000	=====	- 0s	776us/step	loss: 1.7575e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9732					
Epoch 244/1000	=====	- 0s	779us/step	loss: 2.1331e-04	accuar
y1:0.9997 - val_loss: 0.0043 - val_accuracy: 0.9745					
Epoch 245/1000	=====	- 0s	774us/step	loss: 1.7288e-04	accuar
y1:0.9989 - val_loss: 0.0042 - val_accuracy: 0.9742					
Epoch 246/1000	=====	- 0s	774us/step	loss: 1.5765e-04	accuar
y1:0.9990 - val_loss: 0.0043 - val_accuracy: 0.9737					
Epoch 247/1000	=====	- 0s	778us/step	loss: 1.6365e-04	accuar
y1:0.9990 - val_loss: 0.0042 - val_accuracy: 0.9740					
Epoch 248/1000	=====	- 0s	784us/step	loss: 2.0238e-04	accuar
y1:0.9988 - val_loss: 0.0042 - val_accuracy: 0.9735					
Epoch 249/1000	=====	- 0s	771us/step	loss: 1.6592e-04	accuar
y1:0.9990 - val_loss: 0.0042 - val_accuracy: 0.9740					
Epoch 250/1000	=====	- 0s	788us/step	loss: 1.5603e-04	accuar
y1:0.9990 - val_loss: 0.0044 - val_accuracy: 0.9727					
Epoch 251/1000	=====	- 0s	780us/step	loss: 1.3319e-04	accuar
y1:0.9992 - val_loss: 0.0043 - val_accuracy: 0.9731					
Epoch 252/1000	=====	- 0s	774us/step	loss: 1.5671e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9737					
Epoch 253/1000	=====	- 0s	782us/step	loss: 1.4189e-04	accuar
y1:0.9999 - val_loss: 0.0043 - val_accuracy: 0.9737					
Epoch 254/1000	=====	- 0s	776us/step	loss: 1.8015e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9732					
Epoch 255/1000	=====	- 0s	778us/step	loss: 1.8328e-04	accuar
y1:0.9998 - val_loss: 0.0042 - val_accuracy: 0.9735					
Epoch 256/1000	=====	- 0s	782us/step	loss: 1.7612e-04	accuar
y1:0.9989 - val_loss: 0.0043 - val_accuracy: 0.9721					
Epoch 257/1000	=====	- 0s	774us/step	loss: 1.8870e-04	accuar
y1:0.9988 - val_loss: 0.0042 - val_accuracy: 0.9730					
Epoch 258/1000	=====	- 0s	784us/step	loss: 1.4960e-04	accuar
y1:0.9991 - val_loss: 0.0042 - val_accuracy: 0.9737					
Epoch 259/1000	=====	- 0s	769us/step	loss: 1.3778e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9734					
Epoch 260/1000	=====	- 0s	778us/step	loss: 1.4080e-04	accuar
y1:0.9991 - val_loss: 0.0043 - val_accuracy: 0.9738					
Epoch 261/1000	=====	- 0s	782us/step	loss: 1.6133e-04	accuar
y1:0.9990 - val_loss: 0.0043 - val_accuracy: 0.9733					
Epoch 262/1000	=====	- 0s	786us/step	loss: 1.6755e-04	accuar
y1:0.9990 - val_loss: 0.0042 - val_accuracy: 0.9745					
Epoch 263/1000	=====	- 0s	780us/step	loss: 1.7434e-04	accuar
y1:0.9999 - val_loss: 0.0043 - val_accuracy: 0.9736					
Epoch 264/1000	=====	- 0s	782us/step	loss: 1.8252e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9738					
Epoch 265/1000	=====	- 0s	776us/step	loss: 1.8314e-04	accuar
y1:0.9999 - val_loss: 0.0042 - val_accuracy: 0.9734					
Epoch 266/1000	=====	- 0s	788us/step	loss: 1.6588e-04	accuar
y1:0.9999 - val_loss: 0.0044 - val_accuracy: 0.9734					
Epoch 267/1000	=====	- 0s	772us/step	loss: 1.5306e-04	accuar
y1:0.9990 - val_loss: 0.0043 - val_accuracy: 0.9727					
Epoch 268/1000	=====	- 0s	778us/step	loss: 1.8707e-04	accuar
y1:0.9989 - val_loss: 0.0043 - val_accuracy: 0.9738					
Epoch 269/1000	=====	- 0s	793us/step	loss: 1.6167e-04	accuar
y1:0.9990 - val_loss: 0.0042 - val_accuracy: 0.9740					
Epoch 270/1000	=====	- 0s	786us/step	loss: 1.9241e-04	accuar
y1:0.9988 - val_loss: 0.0042 - val_accuracy: 0.97					

Epoch 559/1000	=====	-	0s 7930us/step	loss: 1.5696e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9729					
Epoch 560/1000	=====	-	0s 8400us/step	loss: 1.3078e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9736					
Epoch 561/1000	=====	-	0s 825us/step	loss: 1.1674e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9706					
Epoch 562/1000	=====	-	0s 806us/step	loss: 1.1813e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9736					
Epoch 563/1000	=====	-	0s 838us/step	loss: 1.5962e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9736					
Epoch 564/1000	=====	-	0s 791us/step	loss: 1.7338e-04	accuar
y1:0.9988 - val_loss: 0.0044 - val_accuracy: 0.9738					
Epoch 565/1000	=====	-	0s 788us/step	loss: 1.4680e-04	accuar
y1:0.9990 - val_loss: 0.0045 - val_accuracy: 0.9736					
Epoch 566/1000	=====	-	0s 812us/step	loss: 1.2235e-04	accuar
y1:0.9992 - val_loss: 0.0045 - val_accuracy: 0.9735					
Epoch 567/1000	=====	-	0s 803us/step	loss: 1.3913e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9736					
Epoch 568/1000	=====	-	0s 791us/step	loss: 1.3144e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9733					
Epoch 569/1000	=====	-	0s 799us/step	loss: 1.4984e-04	accuar
y1:0.9990 - val_loss: 0.0045 - val_accuracy: 0.9732					
Epoch 570/1000	=====	-	0s 780us/step	loss: 1.3995e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9731					
Epoch 571/1000	=====	-	0s 765us/step	loss: 1.5470e-04	accuar
y1:0.9989 - val_loss: 0.0044 - val_accuracy: 0.9732					
Epoch 572/1000	=====	-	0s 789us/step	loss: 1.2751e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9727					
Epoch 573/1000	=====	-	0s 791us/step	loss: 1.4388e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9727					
Epoch 574/1000	=====	-	0s 780us/step	loss: 1.4645e-04	accuar
y1:0.9991 - val_loss: 0.0044 - val_accuracy: 0.9732					
Epoch 575/1000	=====	-	0s 788us/step	loss: 1.4354e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9730					
Epoch 576/1000	=====	-	0s 799us/step	loss: 1.3081e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9734					
Epoch 577/1000	=====	-	0s 793us/step	loss: 1.3639e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9734					
Epoch 578/1000	=====	-	0s 791us/step	loss: 1.7926e-04	accuar
y1:0.9988 - val_loss: 0.0046 - val_accuracy: 0.9728					
Epoch 579/1000	=====	-	0s 774us/step	loss: 1.4454e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9727					
Epoch 580/1000	=====	-	0s 786us/step	loss: 1.7731e-04	accuar
y1:0.9989 - val_loss: 0.0045 - val_accuracy: 0.9728					
Epoch 581/1000	=====	-	0s 793us/step	loss: 1.2201e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9725					
Epoch 582/1000	=====	-	0s 780us/step	loss: 1.2958e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9725					
Epoch 583/1000	=====	-	0s 785us/step	loss: 1.5348e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9731					
Epoch 584/1000	=====	-	0s 788us/step	loss: 1.0281e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9726					
Epoch 585/1000	=====	-	0s 789us/step	loss: 1.2153e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9728					
Epoch 586/1000	=====	-	0s 788us/step	loss: 1.6731e-04	accuar
y1:0.9991 - val_loss: 0.0045 - val_accuracy: 0.9729					
Epoch 587/1000	=====	-	0s 791us/step	loss: 1.7479e-04	accuar
y1:0.9988 - val_loss: 0.0045 - val_accuracy: 0.9731					
Epoch 588/1000	=====	-	0s 784us/step	loss: 1.3972e-04	accuar
y1:0.9990 - val_loss: 0.0045 - val_accuracy: 0.9732					
Epoch 589/1000	=====	-	0s 780us/step	loss: 1.4810e-04	accuar
y1:0.9990 - val_loss: 0.0045 - val_accuracy: 0.9728					
Epoch 590/1000	=====	-	0s 791us/step	loss: 1.5144e-04	accuar
y1:0.9990 - val_loss: 0.0045 - val_accuracy: 0.					


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Epoch 879/1000
y: 0.9991 - val_loss: 0.0046 - val_accuracy: 0.9727
Epoch 880/1000
y: 0.9992 - val_loss: 0.0046 - val_accuracy: 0.9720
Epoch 881/1000
y: 0.9991 - val_loss: 0.0046 - val_accuracy: 0.9722
Epoch 882/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9719
Epoch 883/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 884/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9719
Epoch 885/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 886/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9719
Epoch 887/1000
y: 0.9991 - val_loss: 0.0046 - val_accuracy: 0.9720
Epoch 888/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 889/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 890/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 891/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 892/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 893/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 894/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 895/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 896/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 897/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 898/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 899/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 900/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 901/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 902/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 903/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 904/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 905/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 906/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 907/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 908/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 909/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 910/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 911/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 912/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 913/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 914/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 915/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 916/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 917/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 918/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 919/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 920/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 921/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 922/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 923/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 924/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 925/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 926/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 927/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 928/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 929/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 930/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 931/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 932/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 933/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 934/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 935/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 936/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 937/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 938/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 939/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 940/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 941/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 942/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 943/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 944/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 945/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 946/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 947/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 948/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 949/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 950/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 951/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 952/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 953/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 954/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 955/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 956/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 957/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 958/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 959/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 960/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 961/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 962/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 963/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 964/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 965/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 966/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 967/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 968/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 969/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 970/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 971/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 972/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 973/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 974/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 975/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 976/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 977/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 978/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 979/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 980/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 981/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 982/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 983/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 984/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 985/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 986/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 987/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 988/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 989/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 990/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 991/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 992/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 993/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 994/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 995/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 996/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 997/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
Epoch 998/1000
y: 0.9992 - val_loss: 0.0047 - val_accuracy: 0.9718
Epoch 999/1000
y: 0.9991 - val_loss: 0.0047 - val_accuracy: 0.9717
```



```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```



```
In [111]: print(classification_report(y_valid, model.predict_classes(X_validation)))
```

	precision	recall	f1-score	support
0	0.98	0.99	0.98	980
1	0.98	0.99	0.99	1135
2	0.97	0.97	0.97	1032
3	0.97	0.98	0.97	1010
4	0.97	0.97	0.97	982
5	0.97	0.96	0.97	892
6	0.97	0.98	0.98	958
7	0.97	0.96	0.96	1028
8	0.96	0.99	0.98	974
9	0.97	0.96	0.97	1009

```
In [112]: model.evaluate(X_validation, y_validation)
```

```
313/313 [=====] - 1s 40ms/step - loss: 0.0047 - accuracy: 0.9717
[0.0046610351574012, 0.971700012683684]
```

Optimizers are functions/algorithms used to manipulate the features of your neural network like learning rates and weights to bring down the losses. Some goals for optimizers to assist with quicker results.Above you can see optimizer does help perform better.You can see that the loss lines for fit and test deteriorate heavily toward 480-500. As we increase iterations we will eventually get better results.

PART 2 - Convolutional neural network (CNN) architecture

```
In [113]: model_cnn=keras.Sequential([
    layers.InputLayer(input_shape),
    layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dense(num_classes, activation="softmax"),
    ])
model_cnn.summary()
```

Layer (type)	Output Shape	Param #
module_wrapper_0 (ModuleWrap (None, 26, 26, 32))		320
module_wrapper_1 (ModuleWrap (None, 13, 13, 32))		0
module_wrapper_2 (ModuleWrap (None, 11, 11, 64))		18496
module_wrapper_3 (ModuleWrap (None, 5, 5, 64))		0
module_wrapper_4 (ModuleWrap (None, 1600))		0
module_wrapper_5 (ModuleWrap (None, 1600))		0
module_wrapper_6 (ModuleWrap (None, 10))		16010
Total params: 34,826		
Trainable params: 34,826		
Non-trainable params: 0		

Configure model

```
In [114]: model_cnn.compile(
    loss="categorical_crossentropy",
    optimizer="adam",
    metrics=["accuracy"])
model_cnn.fit(X_train, y_train, validation_data=(X_valid, y_valid))
```

Prepare the data

The CNN does not expect the images to be flattened.

```
In [116]: # upload
(X_train, y_train), (X_valid, y_valid) = mnist.load_data()

# convert vectors to binary matrices
y_train = keras.utils.np_utils.to_categorical(y_train, num_classes)
y_validation = keras.utils.np_utils.to_categorical(y_valid, num_classes)

# update images to [0, 1] range
X_train_cnn = X_train.astype("float32") / 255
X_valid_cnn = X_valid.astype("float32") / 255

# update dimension of train/test inputs
X_train_cnn = np.expand_dims(X_train_cnn, -1)
X_valid_cnn = np.expand_dims(X_valid_cnn, -1)

# Make sure images have shape (28, 28, 1)
print(X_train_cnn.shape[0], "train samples")
print(X_valid_cnn.shape[0], "test samples")

x_train_shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
```

Train!

```
In [117]: batch_size=128
epochs=15

history = model_cnn.fit(
    X_train_cnn, y_train, validation_data=(X_valid_cnn, y_validation))
```

```
Epoch 1/15 [=====] - 12s 24ms/step - loss: 0.7016 - accuracy: 0.4636
Epoch 2/15 [=====] - 11s 24ms/step - loss: 0.1168 - accuracy: 0.9638
Epoch 3/15 [=====] - 11s 24ms/step - loss: 0.0487 - accuracy: 0.9837
Epoch 4/15 [=====] - 11s 24ms/step - loss: 0.0447 - accuracy: 0.9855
Epoch 5/15 [=====] - 11s 24ms/step - loss: 0.0416 - accuracy: 0.9865
Epoch 6/15 [=====] - 11s 24ms/step - loss: 0.0399 - accuracy: 0.9874
Epoch 7/15 [=====] - 11s 24ms/step - loss: 0.0389 - accuracy: 0.9881
Epoch 8/15 [=====] - 11s 24ms/step - loss: 0.0381 - accuracy: 0.9886
Epoch 9/15 [=====] - 11s 24ms/step - loss: 0.0376 - accuracy: 0.9888
Epoch 10/15 [=====] - 11s 24ms/step - loss: 0.0372 - accuracy: 0.9889
Epoch 11/15 [=====] - 11s 24ms/step - loss: 0.0369 - accuracy: 0.9891
Epoch 12/15 [=====] - 11s 24ms/step - loss: 0.0367 - accuracy: 0.9892
Epoch 13/15 [=====] - 11s 24ms/step - loss: 0.0366 - accuracy: 0.9892
Epoch 14/15 [=====] - 11s 24ms/step - loss: 0.0366 - accuracy: 0.9892
Epoch 15/15 [=====] - 11s 24ms/step - loss: 0.0366 - accuracy: 0.9892
```

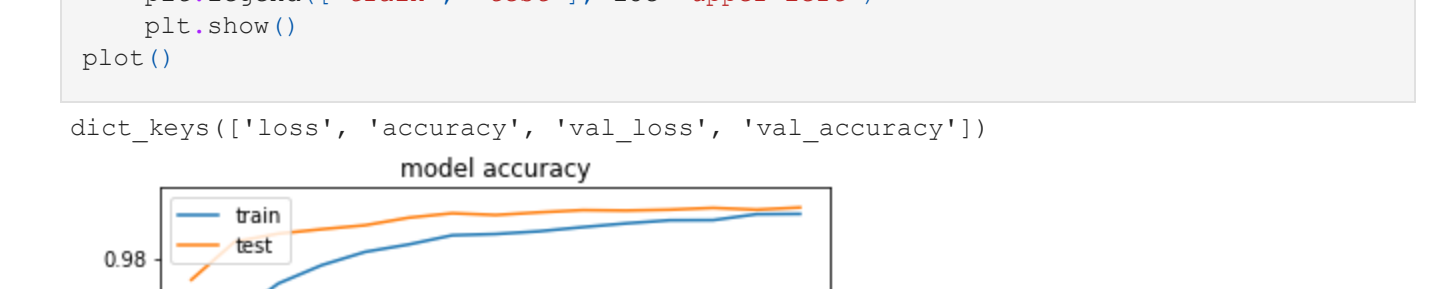
Plot learning curves

```
In [118]: def plot():
    # show all all data in history
    print(history.history.keys())

    # display summary of history for accuracy
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    # breakdown summary history for loss
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    plot()
    dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```



Evaluate the model

```
In [119]: model_cnn.evaluate(X_valid_cnn, y_validation)
```

```
313/313 [=====] - 1s 2ms/step - loss: 0.0254 - accuracy: 0.9914
[0.02536826767027378, 0.991400003432275]
```

Conf Matrix

```
In [124]: def confMatrix():
    plt.figure(figsize=(15,10))
    sns.heatmap(confusion_matrix(y_valid, model_cnn.predict_classes(X_valid_cnn)),
                annot=True, color_palette("pastel", as_cmap=True),
                fmt="d")
    plt.title("Conf Matrix")
    plt.show()
    ConfMatrix()
```



	precision	recall	f1-score	support
0	1.00	1.00	1.00	980
1	0.99	1.00	1.00	1135
2	0.99	0.99	0.99	1032
3	0.99	0.99	0.99	1010
4	0.99	0.99	0.99	982
5	0.99	0.99	0.99	892
6	0.99	0.99	0.99	958
7	0.98	0.99	0.99	1028
8	0.98	0.99	0.99	974
9	0.99	0.98	0.99	1009

```
In [120]: print(model_cnn.predict_classes(X_valid_cnn))
print(y_valid)
print(classification_report(y_valid, model_cnn.predict_classes(X_valid_cnn)))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	980
1	0.99	1.00	1.00	1135
2	0.99	0.99	0.99	1032
3	0.99	0.99	0.99	1010
4	0.99	0.99	0.99	982
5	0.99	0.99	0.99	892
6	0.99	0.99	0.99	958
7	0.98	0.99	0.99	1028
8	0.98	0.99	0.99	974
9	0.99	0.98	0.99	1009

QUESTION 4: How do the accuracy and loss compare to the previous model?What can you infer from this comparison?

You look at the curves and the results from conf matrix above we notice better results from 90% to 99%. Loss value shows how poorly or well a model behaves after each iteration of optimization.The accuracy data used to determine the models performance in an unbiased way. You can also validate with above we reduced iterations which means it helped us reduce the time by 50% which was lot helpful it was taking 4 min and took more time to run our other model. You can validate with example above with deeper models we get more better performance results and also quicker results. This has some things as I was getting better results. I also continued to monitor any over fitting that might happening. So over fitting can be a possible issue with this.