

YANIS TAZI HOMEWORK. 2 DEEP LEARNING SYSTEMS

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Question 1)

Co-adaptation is when neurons depend highly on each other . This is a very important matters because one affected neuron (receiving bad input for example) will affect all the neurons that depend on this one and this is the kind of issue leading to overfitting for example.

Internal covariate shift refers to the change in the distribution of network activations due to change in network parameters during training. To reduce this, we can use normalization at each layer so that we achieve fix distribution of inputs for every layer. One of the most common technique is to use Batch normalization.

Internal covariate shift often leads to slow training and can create non convergence

Question 2)

Train LeNet 5 :

```
In [56]: import tensorflow as tf
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras import models, layers
import tensorflow.keras as keras
from tensorflow.keras.layers import BatchNormalization, LayerNormalizati
on
import tensorflow as tf
from tensorflow.keras.layers import Dropout
import matplotlib.pyplot as plt
if tf.test.gpu_device_name():
    print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
else:
    print("Please install GPU version of TF")
```

Please install GPU version of TF

Model 1: Standard normalization for input layer and batch normalization for hidden layers

a) Data with standard normalization

```
In [2]: # Load dataset as train and test sets
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data
()

# Set numeric type to float32 from uint8
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

# Normalize value to [0, 1]
x_train /= 255
x_test /= 255

# Standard normalization
mean_train = x_train.mean()
std_train = x_train.std()
x_train -= mean_train
x_train /= std_train

x_test -= mean_train
x_test /= std_train

# Transform labels to one-hot encoding
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Reshape the dataset into 4D array
x_train = x_train.reshape(x_train.shape[0], 28,28,1)
x_test = x_test.reshape(x_test.shape[0], 28,28,1)

x_train_std_input = x_train
x_test_std_input = x_test
```

```
In [3]: tf.random.set_seed(17)

#Instantiate an empty model
model = Sequential()
# C1 Convolutional Layer
model.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation='tanh', input_shape=(28,28,1), padding='same'))
model.add(BatchNormalization())
# S2 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(1, 1), padding='valid'))
model.add(BatchNormalization())
# C3 Convolutional Layer
model.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
model.add(BatchNormalization())
# S4 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
model.add(BatchNormalization())
# C5 Fully Connected Convolutional Layer
model.add(layers.Conv2D(120, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
model.add(BatchNormalization())
#Flatten the CNN output so that we can connect it with fully connected layers
model.add(layers.Flatten())
# FC6 Fully Connected Layer
model.add(layers.Dense(84, activation='tanh'))
model.add(BatchNormalization())
#Output Layer with softmax activation
model.add(layers.Dense(10, activation='softmax'))

# Compile the model
model.compile(loss=keras.losses.categorical_crossentropy, optimizer='SGD', metrics=['accuracy'])
```

While the original paper talks about applying batch norm just before the activation function, it has been found in practice that applying batch norm after the activation yields better results.

Therefore, I apply it after activation for the hidden layers

```
In [4]: model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 28, 28, 6)	156
batch_normalization (Batch Normalization)	(None, 28, 28, 6)	24
average_pooling2d (Average Pooling)	(None, 27, 27, 6)	0
batch_normalization_1 (Batch Normalization)	(None, 27, 27, 6)	24
conv2d_1 (Conv2D)	(None, 23, 23, 16)	2416
batch_normalization_2 (Batch Normalization)	(None, 23, 23, 16)	64
average_pooling2d_1 (Average Pooling)	(None, 11, 11, 16)	0
batch_normalization_3 (Batch Normalization)	(None, 11, 11, 16)	64
conv2d_2 (Conv2D)	(None, 7, 7, 120)	48120
batch_normalization_4 (Batch Normalization)	(None, 7, 7, 120)	480
flatten (Flatten)	(None, 5880)	0
dense (Dense)	(None, 84)	494004
batch_normalization_5 (Batch Normalization)	(None, 84)	336
dense_1 (Dense)	(None, 10)	850
=====		
Total params: 546,538		
Trainable params: 546,042		
Non-trainable params: 496		
=====		

```
In [5]: hist = model.fit(x=x_train_std_input,y=y_train, epochs=20, batch_size=128, validation_data=(x_test_std_input, y_test), verbose=1)
```

```
Epoch 1/20
469/469 [=====] - 13s 27ms/step - loss: 0.2075
- accuracy: 0.9425 - val_loss: 0.0996 - val_accuracy: 0.9736
Epoch 2/20
469/469 [=====] - 6s 13ms/step - loss: 0.0860
- accuracy: 0.9778 - val_loss: 0.0716 - val_accuracy: 0.9795
Epoch 3/20
469/469 [=====] - 6s 12ms/step - loss: 0.0634
- accuracy: 0.9839 - val_loss: 0.0545 - val_accuracy: 0.9848
Epoch 4/20
469/469 [=====] - 6s 12ms/step - loss: 0.0514
- accuracy: 0.9867 - val_loss: 0.0542 - val_accuracy: 0.9838
Epoch 5/20
469/469 [=====] - 6s 12ms/step - loss: 0.0436
- accuracy: 0.9889 - val_loss: 0.0437 - val_accuracy: 0.9871
Epoch 6/20
469/469 [=====] - 6s 12ms/step - loss: 0.0375
- accuracy: 0.9908 - val_loss: 0.0445 - val_accuracy: 0.9865
Epoch 7/20
469/469 [=====] - 6s 12ms/step - loss: 0.0333
- accuracy: 0.9919 - val_loss: 0.0407 - val_accuracy: 0.9885
Epoch 8/20
469/469 [=====] - 6s 12ms/step - loss: 0.0297
- accuracy: 0.9929 - val_loss: 0.0359 - val_accuracy: 0.9891
Epoch 9/20
469/469 [=====] - 6s 12ms/step - loss: 0.0265
- accuracy: 0.9938 - val_loss: 0.0359 - val_accuracy: 0.9889
Epoch 10/20
469/469 [=====] - 6s 12ms/step - loss: 0.0238
- accuracy: 0.9945 - val_loss: 0.0329 - val_accuracy: 0.9901
Epoch 11/20
469/469 [=====] - 6s 12ms/step - loss: 0.0223
- accuracy: 0.9952 - val_loss: 0.0340 - val_accuracy: 0.9898
Epoch 12/20
469/469 [=====] - 6s 12ms/step - loss: 0.0203
- accuracy: 0.9959 - val_loss: 0.0306 - val_accuracy: 0.9911
Epoch 13/20
469/469 [=====] - 6s 12ms/step - loss: 0.0184
- accuracy: 0.9962 - val_loss: 0.0303 - val_accuracy: 0.9908
Epoch 14/20
469/469 [=====] - 6s 12ms/step - loss: 0.0171
- accuracy: 0.9966 - val_loss: 0.0314 - val_accuracy: 0.9901
Epoch 15/20
469/469 [=====] - 6s 12ms/step - loss: 0.0160
- accuracy: 0.9968 - val_loss: 0.0288 - val_accuracy: 0.9909
Epoch 16/20
469/469 [=====] - 6s 12ms/step - loss: 0.0149
- accuracy: 0.9973 - val_loss: 0.0317 - val_accuracy: 0.9907
Epoch 17/20
469/469 [=====] - 6s 12ms/step - loss: 0.0139
- accuracy: 0.9976 - val_loss: 0.0294 - val_accuracy: 0.9913
Epoch 18/20
469/469 [=====] - 6s 12ms/step - loss: 0.0131
- accuracy: 0.9978 - val_loss: 0.0300 - val_accuracy: 0.9909
Epoch 19/20
469/469 [=====] - 6s 12ms/step - loss: 0.0123
- accuracy: 0.9979 - val_loss: 0.0275 - val_accuracy: 0.9917
```

Epoch 20/20

469/469 [=====] - 6s 13ms/step - loss: 0.0113
- accuracy: 0.9983 - val_loss: 0.0268 - val_accuracy: 0.9919

```
In [6]: model.save('modell_standnorm_input_batchnorm_hidden.h5')
```

```
In [3]: model = keras.models.load_model('modell_standnorm_input_batchnorm_hidden.h5')
```



```

In [49]: for i in [1,3,5,7,9,12]:
          print(model.layers[i].name)
          print()
          print('Gamma :          '+ str(model.layers[i].get_weights()[0].tolist()))
          print()
          print('Beta :          '+ str(model.layers[i].get_weights()[1].tolist()))
          print()
          print('#####')
          print('#####')
          print('#####')
          print('#####')
          print()

```

batch_normalization

Gamma : [1.0001033544540405, 1.0001364946365356, 1.00005304813385, 1.0000249147415161, 1.0000289678573608, 1.000061273574829]

Beta : [-3.193265651901811e-09, -3.1261129240789387e-09, 1.0744865441836282e-08, -1.8673049773099137e-09, -2.641025842464728e-09, -6.1343565782578935e-09]

#####

batch_normalization_1

Gamma : [1.080140471458435, 1.1022557020187378, 1.0472339391708374, 1.026122808456421, 1.024849772453308, 1.055171012878418]

Beta : [-0.07621415704488754, -0.02155950292944908, 0.22738882899284363, -0.011400452814996243, 0.10398653149604797, -0.0037515745498239994]

#####

batch_normalization_2

Gamma : [1.0000356435775757, 1.0000033378601074, 1.0000083446502686, 1.0000169277191162, 1.0000183582305908, 1.0000218152999878, 1.000011682510376, 1.0000137090682983, 1.0000096559524536, 1.0000061988830566, 1.0000522136688232, 1.0000017881393433, 1.0000300407409668, 1.0000131130218506, 1.0000200271606445, 1.0000075101852417]

Beta : [-2.463348858228187e-09, 2.005402288673963e-09, 1.6207137021329032e-10, 1.5322434432363252e-09, -1.3839591694875253e-09, -3.1252422871830277e-09, -3.3732927562368786e-10, -3.91772919661193e-10, 4.1625791702415427e-10, 1.1608524558281985e-10, 1.0016080187469356e-09, -1.153854012336808e-09, 1.8028366577382826e-09, 2.27690222320132e-09, 3.3491312501077175e-10, -4.598384728549121e-10]

#####

batch_normalization_3

Gamma : [1.0338406562805176, 1.006487250328064, 1.0142003297805786, 1.017224907875061, 1.0104438066482544, 1.0181764364242554, 1.0087862014770508, 1.0160397291183472, 1.005645751953125, 1.0070059299468994, 1.047123670578003, 0.9986793994903564, 1.0332375764846802, 1.0144470930099487, 1.0219016075134277, 1.0124233961105347]

Beta : [-0.002855873666703701, 0.001166807720437646, -0.004663

181956857443, 0.004320188425481319, -0.009904230013489723, -0.011273208
074271679, 0.007533228490501642, -0.013439025729894638, -0.005260499194
264412, 0.008676453493535519, -0.0031983396038413048, 0.003110519843176
0073, 0.012730601243674755, 0.0038798220921307802, -0.00816553272306919
1, 0.002551551442593336]

#####

batch_normalization_4

Gamma : [1.0056623220443726, 1.0002540349960327, 1.00180220603
94287, 1.0066707134246826, 1.0092597007751465, 1.0071388483047485, 1.00
72309970855713, 0.9957995414733887, 1.0101786851882935, 1.0164235830307
007, 1.0066404342651367, 1.0052077770233154, 1.0055514574050903, 1.0036
792755126953, 1.0043503046035767, 1.0096917152404785, 1.00645089149475
1, 1.0025393962860107, 1.0074964761734009, 1.0047550201416016, 1.000993
013381958, 0.9988912343978882, 1.0064479112625122, 0.9974077939987183,
1.0029772520065308, 1.0045174360275269, 1.0033620595932007, 1.007863759
9945068, 1.0041853189468384, 1.002315878868103, 1.0109084844589233, 1.0
090458393096924, 1.0084309577941895, 1.0023661851882935, 1.006669163703
9185, 1.0024234056472778, 1.003269076347351, 1.005169153213501, 1.00593
3165550232, 0.9983053803443909, 1.0032063722610474, 0.9978740215301514,
1.0113455057144165, 1.008239507675171, 1.0073041915893555, 1.0022174119
94934, 1.002747654914856, 0.9994053840637207, 0.9990352392196655, 1.003
086805343628, 0.9998452067375183, 1.0092865228652954, 0.998435318470001
2, 1.0023771524429321, 1.0014634132385254, 1.0023584365844727, 1.008378
7441253662, 1.013611912727356, 0.9999356269836426, 1.0093258619308472,
1.0075217485427856, 1.0061134099960327, 1.0038620233535767, 1.015642166
1376953, 1.0063326358795166, 1.0024514198303223, 1.0096383094787598, 1.
0029706954956055, 1.0026702880859375, 1.0199156999588013, 1.00515305995
94116, 1.0050839185714722, 1.0054091215133667, 1.0023939609527588, 0.99
96649026870728, 1.013514518737793, 1.0103176832199097, 1.01385784149169
92, 0.9989141225814819, 1.0042575597763062, 0.9978541135787964, 1.00949
82385635376, 0.9994216561317444, 1.0033928155899048, 1.001430630683899,
1.0026663541793823, 1.0066559314727783, 1.0063748359680176, 1.002204418
182373, 1.007834792137146, 0.9986542463302612, 1.001767873764038, 1.004
9982070922852, 1.0009055137634277, 1.0031565427780151, 1.00262212753295
9, 1.002833366394043, 1.0056177377700806, 1.0114803314208984, 0.9991413
950920105, 0.9986771941184998, 1.005359172821045, 1.0078128576278687,
1.0053293704986572, 1.001425862312317, 1.0197887420654297, 1.0087956190
109253, 1.0069087743759155, 1.0082004070281982, 1.008539080619812, 1.01
63979530334473, 1.0013022422790527, 0.9979588985443115, 1.0011752843856
812, 1.0037761926651, 1.0104435682296753, 0.9994767904281616, 0.9976818
561553955, 1.0070868730545044, 1.0001554489135742]

Beta : [0.001124291098676622, 0.0005901519907638431, -0.002198
457717895508, 0.00010894873412325978, -0.0019466871162876487, -0.000535
2898151613772, -0.0033958384301513433, -0.0010184940183535218, -0.00345
3400218859315, 0.0015058420831337571, -0.0014921720139682293, 0.0012483
29528607428, -0.0004696552350651473, 2.4880162527551875e-05, 0.00301438
9891177416, -0.0017457314534112811, -0.0007751599187031388, 0.002562392
5030231476, -0.0015817326493561268, 0.002309000352397561, -0.0012567474
04113412, 0.0020975738298147917, 0.0020140092819929123, -0.000500334601
3836563, 0.0015787516022101045, -0.00043038136209361255, -0.00155605922

91876674, 0.0005733513389714062, -0.0025358612183481455, 5.677256194758
229e-05, 0.004662738647311926, -0.00040494761196896434, -0.000196141860
21499336, -0.0009334749775007367, 0.0007417193264700472, 0.001036077970
6388712, -0.0031069170217961073, -0.0001801229373086244, -0.00023045636
771712452, 0.0010385994100943208, 0.0006547464872710407, -0.00150509621
0166812, -0.0013453575083985925, -0.0017636660486459732, -0.00174194399
73309636, 0.002555257175117731, 0.0019506033277139068, -0.0007243838626
891375, -0.0023608196061104536, 0.0013325171312317252, -0.0002909032336
9018734, -5.2844512538285926e-05, -0.001144959358498454, 0.001336176646
873355, 0.0013341348385438323, 0.0018369388999417424, 0.000185029493877
6642, -0.002749239094555378, -0.0012618439504876733, 0.0018150972900912
166, -0.0007615818758495152, 0.00012803601566702127, -0.002366545610129
8332, 0.00011361933866282925, -0.0007389850215986371, 0.000483945943415
16495, -0.0003616343019530177, -0.0005119805573485792, -0.0002927032182
9244494, -0.00016640231478959322, 0.0020666508935391903, 0.000586774316
6163564, -0.0008726856322027743, -0.0005122057627886534, -0.00118294090
4982388, -0.0011479889508336782, -0.0019359468715265393, 0.002917088801
0412455, -0.0020914669148623943, 0.0008942880085669458, -0.001271036569
9604154, -0.0011192521778866649, -9.706370474305004e-05, -0.00089256936
91708148, -0.001172817312180996, -0.0008061046828515828, 0.002108468441
2926435, 0.0013441269984468818, 0.0020949963945895433, 0.00089947861852
12433, -0.0008241339819505811, 0.00014087320596445352, 0.00083104439545
42279, -2.537005093472544e-05, 0.0010218500392511487, 0.001176875084638
5956, -0.0028767904732376337, -0.0002652867406141013, 4.538970097200945
e-05, -0.00208503776229918, -0.0010540963849052787, -0.0013663598801940
68, -0.0014983313158154488, -0.002451713662594557, -0.00058318435912951
83, 0.0027133007533848286, -0.0011870344169437885, 0.002734000794589519
5, 0.0021771600004285574, -0.0011616094270721078, 0.000269299314823001
6, -0.004542726557701826, 0.0011777520412579179, 0.0014645763440057635,
9.493681136518717e-05, -0.002649039961397648, 0.0027524407487362623, -
0.0003103430208284408, -0.0007679365808144212, 0.0005505988374352455]

#####

batch_normalization_5

Gamma : [1.0615262985229492, 1.039718508720398, 1.038655996322
6318, 1.0391103029251099, 1.020777702331543, 1.0288842916488647, 1.0355
119705200195, 1.0326181650161743, 1.0356547832489014, 1.03204476833343
5, 1.0745348930358887, 1.0581867694854736, 1.054201602935791, 1.0620614
290237427, 1.0565823316574097, 1.0438120365142822, 1.0563002824783325,
1.03714919090271, 1.0537210702896118, 1.0315293073654175, 1.03064179420
4712, 1.0392262935638428, 1.037245273590088, 1.0563414096832275, 1.0364
030599594116, 1.050891637802124, 1.062117099761963, 1.0535331964492798,
1.0555459260940552, 1.0582879781723022, 1.0416603088378906, 1.025170207
0236206, 1.0372323989868164, 1.0637003183364868, 1.0374497175216675, 1.
0296249389648438, 1.0574452877044678, 1.0502383708953857, 1.06677579879
76074, 1.0457359552383423, 1.057141900062561, 1.0459693670272827, 1.056
2243461608887, 1.0574266910552979, 1.0156569480895996, 1.05148971080780
03, 1.0520153045654297, 1.0462865829467773, 1.0244661569595337, 1.03965
43741226196, 1.049127459526062, 1.0304591655731201, 1.0449737310409546,
1.034093976020813, 1.0514894723892212, 1.0646445751190186, 1.0314774513
24463, 1.0358623266220093, 1.0460479259490967, 1.0569781064987183, 1.06
28811120986938, 1.0610231161117554, 1.0231566429138184, 1.0534456968307

495, 1.0600019693374634, 1.0535024404525757, 1.043460488319397, 1.02035
 20059585571, 1.0438870191574097, 1.0487699508666992, 1.021136164665222
 2, 1.0495728254318237, 1.0329267978668213, 1.0658795833587646, 1.036788
 7020111084, 1.065355896949768, 1.0290696620941162, 1.028918743133545,
 1.0448110103607178, 1.044732689857483, 1.0588737726211548, 1.0495487451
 553345, 1.041137933731079, 1.0506408214569092]

Beta : [-0.0006841294816695154, 7.09985542926006e-05, -0.00735
 7184309512377, 0.009201510809361935, 0.0005656683933921158, -0.00413913
 931697607, 0.0047630551271140575, 0.007424724753946066, -0.002051409101
 113677, 0.0039805080741643906, -0.0006112591945566237, -0.0052905264310
 53877, -0.0018889709608629346, -0.004128921311348677, -0.00392347527667
 8801, -0.00962114054709673, -8.10254059615545e-05, 0.002112170215696096
 4, 0.003959633409976959, -0.0020060292445123196, 0.010553175583481789,
 0.009844976477324963, -0.007894470356404781, -0.00780536700040102, 0.00
 7520067505538464, 0.01277607399970293, -0.005623600445687771, -0.014072
 90156930685, -0.0021203721407800913, -0.013125053606927395, -0.00855076
 6855478287, -0.006940011400729418, 0.003943008370697498, 0.002421098761
 2605095, -0.0057405284605920315, 0.0026334745343774557, 0.0031888689845
 8004, -0.0005172445089556277, 0.005010656546801329, -0.0028656867798417
 807, 0.004122504033148289, -0.0031393086537718773, 0.000797886052168905
 7, -0.00093594950158149, -0.0023288445081561804, -0.007952450774610043,
 -0.0017311711562797427, 0.0003689189616125077, 0.004880804568529129, 0.
 0024659589398652315, 0.0005395978223532438, -0.0014985940651968122, -0.
 011738463304936886, 0.010742729529738426, -0.0016814022092148662, 0.002
 0558559335768223, 0.006316308863461018, -0.005518085788935423, 0.008858
 502842485905, 0.0036259950138628483, -0.0023634417448192835, 0.00163141
 26551151276, 0.007857171818614006, 0.0055394042283296585, 0.00921817030
 7576656, -0.010433212853968143, 0.004861378576606512, 0.003201061626896
 262, 0.006094268523156643, -0.006958217825740576, -0.00235053035430610
 2, 0.007631663233041763, 0.0004118015931453556, -0.0002614204131532460
 5, -0.0048215556889772415, 0.011411644518375397, 0.00257382751442492, -
 0.00251532974652946, -0.013403575867414474, 0.007119462359696627, 0.005
 5313087068498135, -0.010606273077428341, -0.0036545847542583942, -0.004
 875462036579847]

 #####
 #####
 #####

Question 3:

a) Data without standard normalization

```
In [7]: # Load dataset as train and test sets
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data
()

# Set numeric type to float32 from uint8
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

# Normalize value to [0, 1]
x_train /= 255
x_test /= 255

# Transform labels to one-hot encoding
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Reshape the dataset into 4D array
x_train = x_train.reshape(x_train.shape[0], 28,28,1)
x_test = x_test.reshape(x_test.shape[0], 28,28,1)
```

Model 2: Batch normalization for input and hidden layers

```
In [8]: tf.random.set_seed(17)
#Instantiate an empty model
model_batch = Sequential()
# C1 Convolutional Layer
model_batch.add(BatchNormalization(input_shape=(28,28,1)))
model_batch.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation='tanh', input_shape=(28,28,1), padding='same'))
model_batch.add(BatchNormalization())
# S2 Pooling Layer
model_batch.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(1, 1), padding='valid'))
model_batch.add(BatchNormalization())
# C3 Convolutional Layer
model_batch.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
model_batch.add(BatchNormalization())
# S4 Pooling Layer
model_batch.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
model_batch.add(BatchNormalization())
# C5 Fully Connected Convolutional Layer
model_batch.add(layers.Conv2D(120, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
model_batch.add(BatchNormalization())
#Flatten the CNN output so that we can connect it with fully connected layers
model_batch.add(layers.Flatten())
# FC6 Fully Connected Layer
model_batch.add(layers.Dense(84, activation='tanh'))
model_batch.add(BatchNormalization())
#Output Layer with softmax activation
model_batch.add(layers.Dense(10, activation='softmax'))

# Compile the model
model_batch.compile(loss=keras.losses.categorical_crossentropy, optimizer='SGD', metrics=['accuracy'])
```

```
In [9]: model_batch.summary()
```

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
=====		
batch_normalization_6 (Batch Normalization)	(None, 28, 28, 1)	4
conv2d_3 (Conv2D)	(None, 28, 28, 6)	156
batch_normalization_7 (Batch Normalization)	(None, 28, 28, 6)	24
average_pooling2d_2 (Average Pooling)	(None, 27, 27, 6)	0
batch_normalization_8 (Batch Normalization)	(None, 27, 27, 6)	24
conv2d_4 (Conv2D)	(None, 23, 23, 16)	2416
batch_normalization_9 (Batch Normalization)	(None, 23, 23, 16)	64
average_pooling2d_3 (Average Pooling)	(None, 11, 11, 16)	0
batch_normalization_10 (Batch Normalization)	(None, 11, 11, 16)	64
conv2d_5 (Conv2D)	(None, 7, 7, 120)	48120
batch_normalization_11 (Batch Normalization)	(None, 7, 7, 120)	480
flatten_1 (Flatten)	(None, 5880)	0
dense_2 (Dense)	(None, 84)	494004
batch_normalization_12 (Batch Normalization)	(None, 84)	336
dense_3 (Dense)	(None, 10)	850
=====		
Total params: 546,542		
Trainable params: 546,044		
Non-trainable params: 498		


```
In [10]: hist_batch = model_batch.fit(x=x_train,y=y_train, epochs=20, batch_size=
128, validation_data=(x_test, y_test), verbose=1)
```

```
Epoch 1/20
469/469 [=====] - 7s 15ms/step - loss: 0.2065
- accuracy: 0.9428 - val_loss: 0.0993 - val_accuracy: 0.9731
Epoch 2/20
469/469 [=====] - 6s 13ms/step - loss: 0.0848
- accuracy: 0.9782 - val_loss: 0.0704 - val_accuracy: 0.9804
Epoch 3/20
469/469 [=====] - 6s 13ms/step - loss: 0.0625
- accuracy: 0.9840 - val_loss: 0.0541 - val_accuracy: 0.9849
Epoch 4/20
469/469 [=====] - 6s 13ms/step - loss: 0.0507
- accuracy: 0.9867 - val_loss: 0.0535 - val_accuracy: 0.9850
Epoch 5/20
469/469 [=====] - 6s 13ms/step - loss: 0.0431
- accuracy: 0.9890 - val_loss: 0.0434 - val_accuracy: 0.9871
Epoch 6/20
469/469 [=====] - 6s 13ms/step - loss: 0.0370
- accuracy: 0.9909 - val_loss: 0.0435 - val_accuracy: 0.9868
Epoch 7/20
469/469 [=====] - 6s 13ms/step - loss: 0.0329
- accuracy: 0.9920 - val_loss: 0.0402 - val_accuracy: 0.9886
Epoch 8/20
469/469 [=====] - 6s 13ms/step - loss: 0.0294
- accuracy: 0.9929 - val_loss: 0.0360 - val_accuracy: 0.9887
Epoch 9/20
469/469 [=====] - 6s 13ms/step - loss: 0.0262
- accuracy: 0.9941 - val_loss: 0.0357 - val_accuracy: 0.9888
Epoch 10/20
469/469 [=====] - 6s 13ms/step - loss: 0.0235
- accuracy: 0.9947 - val_loss: 0.0328 - val_accuracy: 0.9901
Epoch 11/20
469/469 [=====] - 6s 13ms/step - loss: 0.0220
- accuracy: 0.9952 - val_loss: 0.0341 - val_accuracy: 0.9895
Epoch 12/20
469/469 [=====] - 6s 13ms/step - loss: 0.0201
- accuracy: 0.9958 - val_loss: 0.0307 - val_accuracy: 0.9912
Epoch 13/20
469/469 [=====] - 6s 13ms/step - loss: 0.0182
- accuracy: 0.9963 - val_loss: 0.0301 - val_accuracy: 0.9910
Epoch 14/20
469/469 [=====] - 6s 13ms/step - loss: 0.0169
- accuracy: 0.9967 - val_loss: 0.0313 - val_accuracy: 0.9901
Epoch 15/20
469/469 [=====] - 6s 13ms/step - loss: 0.0158
- accuracy: 0.9970 - val_loss: 0.0285 - val_accuracy: 0.9915
Epoch 16/20
469/469 [=====] - 6s 13ms/step - loss: 0.0148
- accuracy: 0.9972 - val_loss: 0.0317 - val_accuracy: 0.9901
Epoch 17/20
469/469 [=====] - 6s 13ms/step - loss: 0.0137
- accuracy: 0.9976 - val_loss: 0.0291 - val_accuracy: 0.9913
Epoch 18/20
469/469 [=====] - 6s 13ms/step - loss: 0.0130
- accuracy: 0.9978 - val_loss: 0.0300 - val_accuracy: 0.9911
Epoch 19/20
469/469 [=====] - 6s 13ms/step - loss: 0.0121
- accuracy: 0.9979 - val_loss: 0.0272 - val_accuracy: 0.9916
```

Epoch 20/20

469/469 [=====] - 6s 13ms/step - loss: 0.0112
- accuracy: 0.9983 - val_loss: 0.0266 - val_accuracy: 0.9920

```
In [11]: model_batch.save('model2_batchnorm_all.h5')
```

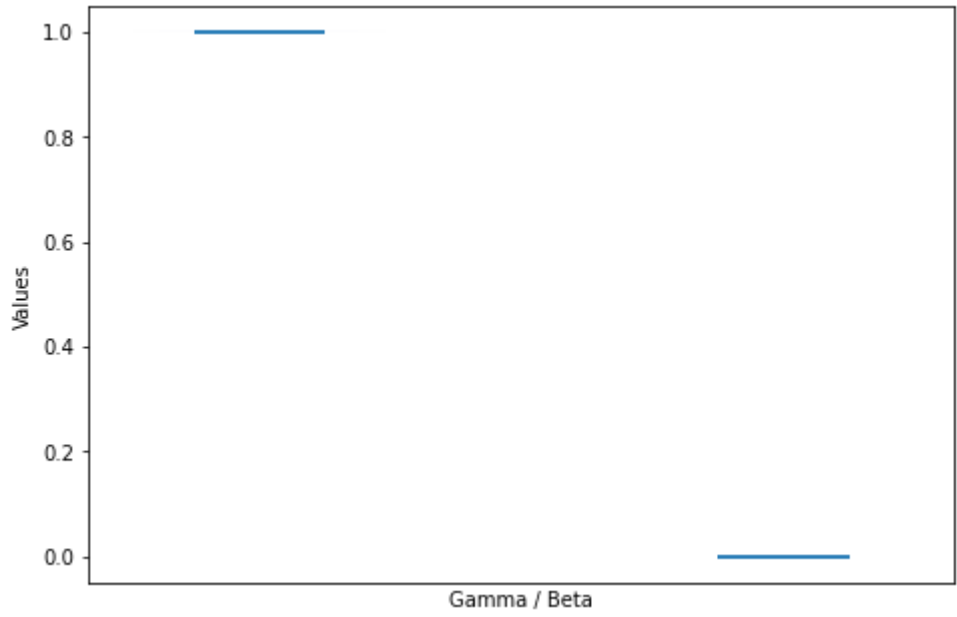
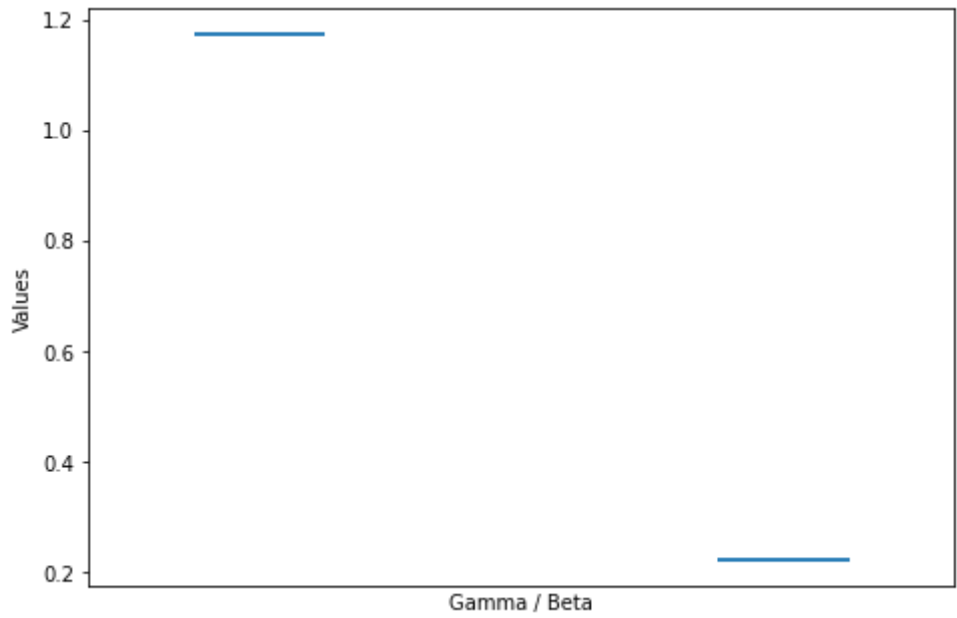
```
In [50]: model_batch = keras.models.load_model('model2_batchnorm_all.h5')
```

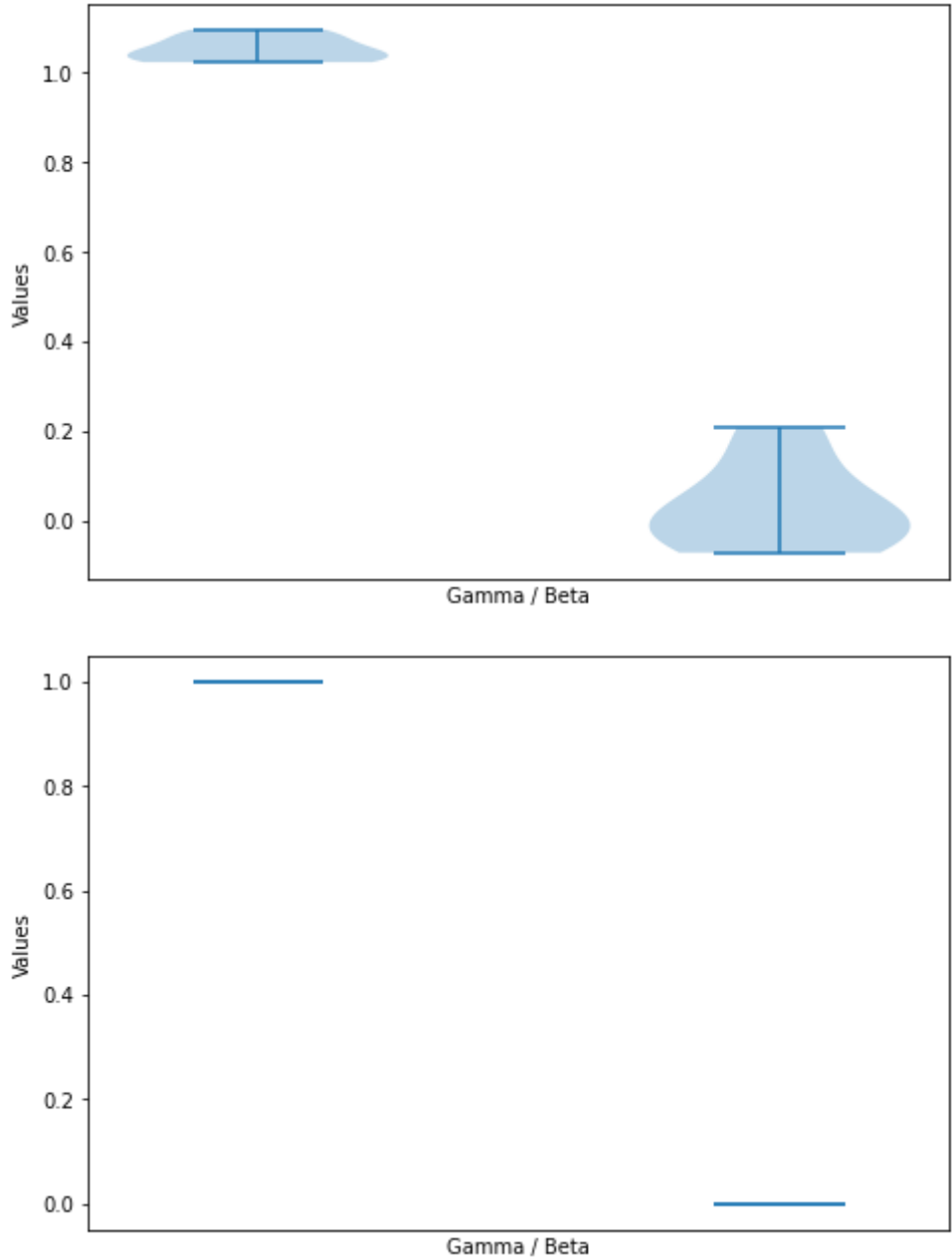
```
In [66]: for i in [0,2,4,6,8,10,13]:
    data_to_plot = [model_batch.layers[i].get_weights()[0].tolist(), model_batch.layers[i].get_weights()[1].tolist()]

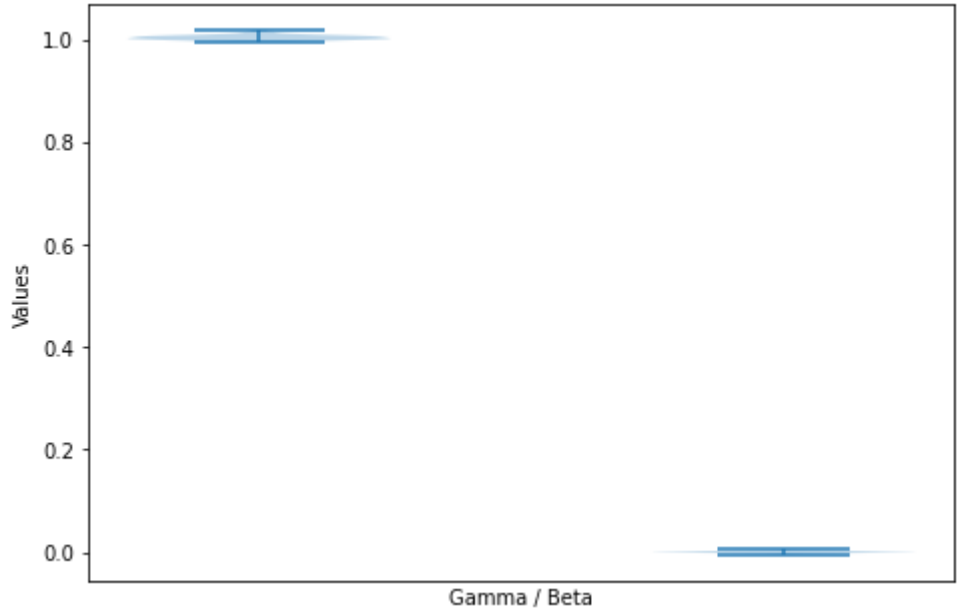
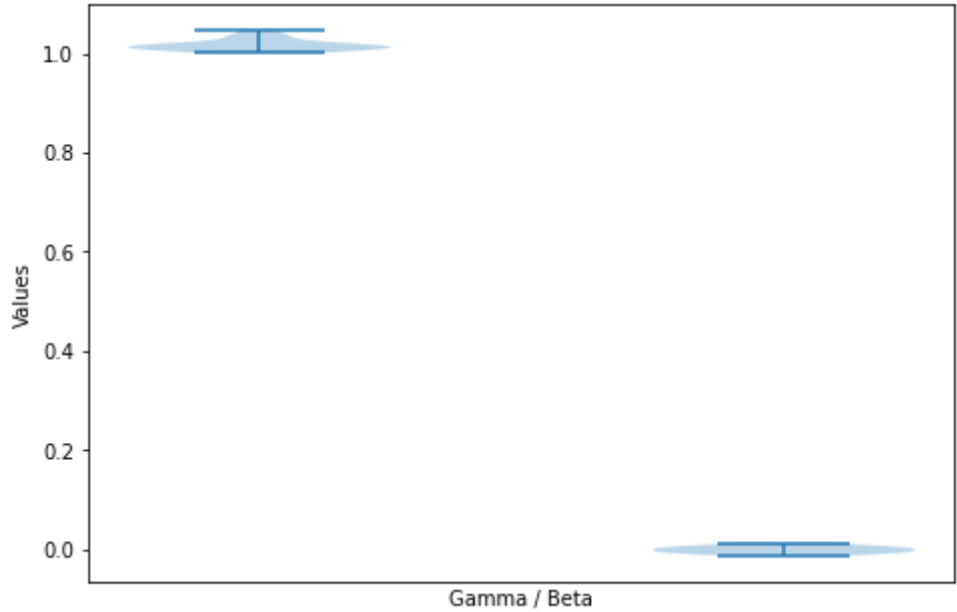
    # Create a figure instance
    fig = plt.figure()

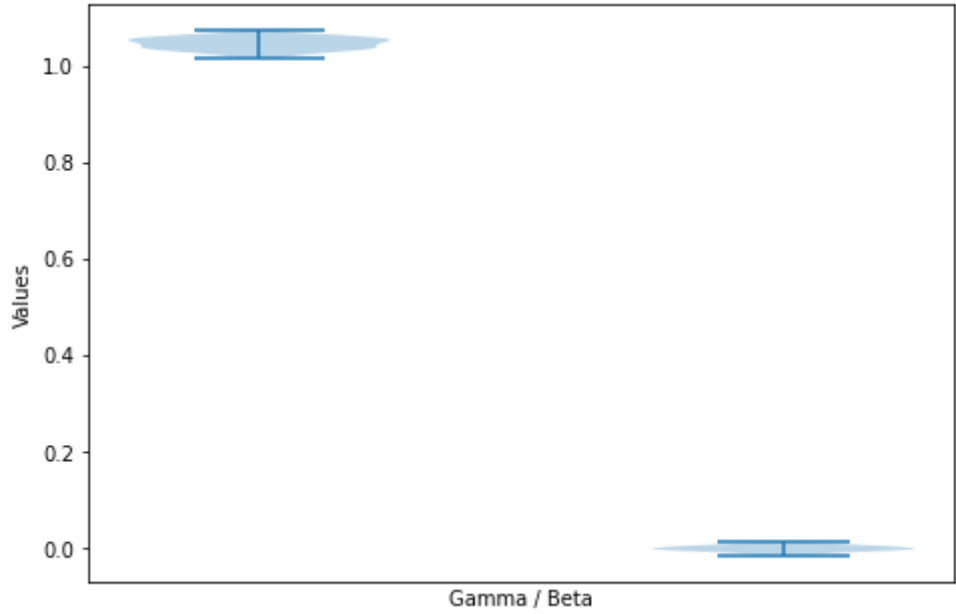
    # Create an axes instance
    ax = fig.add_axes([0,0,1,1])

    # Create the boxplot
    bp = ax.violinplot(data_to_plot)
    ax.axes.get_xaxis().set_ticks([])
    plt.xlabel("Gamma / Beta")
    plt.ylabel("Values")
    plt.show()
```










```
In [61]: for i in [0,2,4,6,8,10,13]:
          print(model_batch.layers[i].name)
          print()
          print('Gamma :          '+ str(model_batch.layers[i].get_weights()[0]
).tolist()))
          print()
          print('Beta :          '+ str(model_batch.layers[i].get_weights()[1]
).tolist()))
          print ()
          print ( '#####' )
#####
#####
#####
#####' )
          print ()
```

batch_normalization_6

Gamma : [1.1744343042373657]

Beta : [0.22457078099250793]

#####

batch_normalization_7

Gamma : [1.0000983476638794, 1.0001249313354492, 1.0000451803207397, 1.000023365020752, 1.0000228881835938, 1.0000643730163574]

Beta : [-7.3766730501745315e-09, -4.5491428402044676e-09, 1.0702621427993719e-10, 4.27229318589184e-09, -4.696779853929911e-09, -1.1279193135038668e-09]

#####

batch_normalization_8

Gamma : [1.0776439905166626, 1.0955561399459839, 1.0428701639175415, 1.0234375, 1.0232908725738525, 1.0513699054718018]

Beta : [-0.07066694647073746, -0.01616567187011242, 0.20733587443828583, -0.008760466240346432, 0.0963069275021553, -0.0007116174092516303]

#####

batch_normalization_9

Gamma : [1.0000356435775757, 1.0000054836273193, 1.0000078678131104, 1.0000122785568237, 1.0000206232070923, 1.0000176429748535, 1.0000079870224, 1.0000152587890625, 1.0000146627426147, 1.000005841255188, 1.000051498413086, 1.000001072883606, 1.0000293254852295, 1.0000181198120117, 1.0000125169754028, 1.0000038146972656]

Beta : [-5.601688002343508e-10, -3.754273281142417e-11, 7.454938333317784e-10, 1.3708636448228617e-09, -3.3621125883342984e-09, -2.1263983907005013e-09, -5.515064793737423e-11, 8.792996886164417e-10, 1.7904006055502464e-09, -2.0890402741002845e-09, -1.368022362058241e-09, 2.1246681497499864e-11, 1.4884056209751861e-09, 7.725603490271737e-10, 3.6389211643950148e-09, 1.5337006109561457e-09]

#####

#####

batch_normalization_10

Gamma : [1.0341215133666992, 1.0039653778076172, 1.0128912925720215, 1.0154327154159546, 1.013261079788208, 1.0165857076644897, 1.0095893144607544, 1.0178035497665405, 1.007718801498413, 1.0067623853683472, 1.047182559967041, 1.0002268552780151, 1.0327712297439575, 1.0152435302734375, 1.020142674446106, 1.010878086090088]

Beta : [-0.0045372662134468555, 0.0005203681066632271, -0.003558523254469037, 0.004170415457338095, -0.009523607790470123, -0.01109848078340292, 0.006995310075581074, -0.01202782429754734, -0.005124170798808336, 0.008881361223757267, -0.0030007953755557537, 0.002937089651823044, 0.012201976031064987, 0.0034679649397730827, -0.006961768958717585, 0.0014267554506659508]

#####

batch_normalization_11

Gamma : [1.0052587985992432, 1.000139832496643, 1.001922845840454, 1.006265640258789, 1.008581280708313, 1.0073052644729614, 1.0076013803482056, 0.9958900213241577, 1.0108489990234375, 1.0162434577941895, 1.0070840120315552, 1.005264163017273, 1.0054093599319458, 1.003129005432129, 1.004520058631897, 1.009005069732666, 1.0070281028747559, 1.0021543502807617, 1.007168173789978, 1.0047032833099365, 1.0007719993591309, 0.9994423389434814, 1.0065604448318481, 0.9974638819694519, 1.0029118061065674, 1.0043927431106567, 1.0034414529800415, 1.0074909925460815, 1.0040936470031738, 1.0027133226394653, 1.0112006664276123, 1.0089330673217773, 1.00880765914917, 1.0024033784866333, 1.0062967538833618, 1.0024409294128418, 1.003140926361084, 1.0053129196166992, 1.0064294338226318, 0.9981534481048584, 1.0038822889328003, 0.9976579546928406, 1.0109071731567383, 1.0082029104232788, 1.0073271989822388, 1.0019510984420776, 1.0029511451721191, 0.9991244673728943, 0.9989830255508423, 1.003076195716858, 1.0000693798065186, 1.0088599920272827, 0.9984415769577026, 1.0024769306182861, 1.0010745525360107, 1.001888632774353, 1.0082155466079712, 1.013014793395996, 0.9997944831848145, 1.0093351602554321, 1.007354736328125, 1.0060356855392456, 1.0035005807876587, 1.0149379968643188, 1.006460428237915, 1.002143383026123, 1.0090845823287964, 1.0028389692306519, 1.0026636123657227, 1.0194510221481323, 1.0047345161437988, 1.0056579113006592, 1.005800485610962, 1.0022318363189697, 0.9996469020843506, 1.0135589838027954, 1.0101220607757568, 1.0128202438354492, 0.9995080232620239, 1.0044492483139038, 0.9978495836257935, 1.0090162754058838, 0.9997790455818176, 1.0031810998916626, 1.0014065504074097, 1.0024688243865967, 1.0062905550003052, 1.0067492723464966, 1.0024688243865967, 1.0076700448989868, 0.9985764026641846, 1.0017824172973633, 1.0050314664840698, 1.000797986984253, 1.0034449100494385, 1.0026159286499023, 1.0024282932281494, 1.0055179595947266, 1.011406660079956, 0.9994918704032898, 0.9990472197532654, 1.0051100254058838, 1.0086188316345215, 1.0054848194122314, 1.0013679265975952, 1.0197211503982544, 1.0090214014053345, 1.0065478086471558, 1.0085139274597168, 1.0084258317947388, 1.0153049230575562, 1.0012198686599731, 0.9983121156692505, 1.0010859966278076, 1.0039886236190796, 1.0109390020370483, 0.9997484087944031, 0.99752

71821022034, 1.007455825805664, 1.0003316402435303]

Beta : [0.0010533033637329936, 0.0007036763709038496, -0.002085362793877721, 9.090618550544605e-05, -0.001968103228136897, -0.0004403733473736793, -0.003414415754377842, -0.0010265377350151539, -0.0035364669747650623, 0.0014711128314957023, -0.0014315377920866013, 0.0013256424572318792, -0.00043726712465286255, 1.2391078030304925e-07, 0.003103038063272834, -0.0017474110936746001, -0.0007057064212858677, 0.0026617127005010843, -0.0015560751780867577, 0.002399908611550927, -0.0011982218129560351, 0.002085247077047825, 0.0018445991445332766, -0.0006213307497091591, 0.0015760164242237806, -0.0005756649188697338, -0.001621804665774107, 0.0006325808935798705, -0.002656911965459585, 0.00015462891315110028, 0.004566132090985775, -0.00044837422319687903, -0.0002062796411337331, -0.0009527691872790456, 0.0006716742063872516, 0.0009920753072947264, -0.003129907650873065, -0.00023055952624417841, -0.0002612094976939261, 0.0010294950334355235, 0.0006142333149909973, -0.0016740458086133003, -0.0014964313013479114, -0.0017876705387607217, -0.0016702774446457624, 0.002510586753487587, 0.0019314270466566086, -0.0007780386949889362, -0.0024118837900459766, 0.0012879582354798913, -0.00036515932879410684, 0.0001681772992014885, -0.0010840485338121653, 0.0012569499667733908, 0.001248324173502624, 0.0018012933433055878, 0.0001351249375147745, -0.0028093259315937757, -0.0012254540342837572, 0.0018925450276583433, -0.0006966259679757059, 0.00011096659727627411, -0.002334713004529476, 6.523869524244219e-05, -0.0006349883042275906, 0.0005626873462460935, -0.0002250545658171177, -0.00048457770026288927, -0.0003365697921253741, -0.00018297780479770154, 0.0019598889630287886, 0.000573505531065166, -0.0007671168423257768, -0.00064840231789276, -0.0011303109349682927, -0.0010996715864166617, -0.0020463543478399515, 0.0028635445050895214, -0.0020908762235194445, 0.0008373147575184703, -0.0012861283030360937, -0.0011515046935528517, -0.0002559356507845223, -0.0008941934211179614, -0.001217835582792759, -0.0006358709651976824, 0.002021131105720997, 0.001275059417821467, 0.002213583793491125, 0.0009163131471723318, -0.0007526439148932695, 2.388357461313717e-05, 0.0007840882171876729, -0.0001455596648156643, 0.001123476424254477, 0.0012963585322722793, -0.0029234394896775484, -0.00032991435728035867, 9.385023440700024e-05, -0.0021514880936592817, -0.001039752154611051, -0.0013921601930633187, -0.001326416851952672, -0.0024970988743007183, -0.0004410594410728663, 0.0027187583036720753, -0.0012052664533257484, 0.0027848673053085804, 0.002017634455114603, -0.0011310462141409516, 0.0004675565578509122, -0.004531759303063154, 0.0012351487530395389, 0.0014310673577710986, -4.221291237627156e-05, -0.0027097766287624836, 0.0027845948934555054, -0.00028952330467291176, -0.0007827087538316846, 0.0005921937408857048]

#####

batch_normalization_12

Gamma : [1.0612136125564575, 1.0398560762405396, 1.0395538806915283, 1.0386760234832764, 1.020702838897705, 1.028437614440918, 1.0354441404342651, 1.0325572490692139, 1.0350160598754883, 1.0318264961242676, 1.0736597776412964, 1.0579160451889038, 1.0536558628082275, 1.0625438690185547, 1.0552042722702026, 1.043561339378357, 1.0550681352615356, 1.0371156930923462, 1.0531249046325684, 1.0316314697265625, 1.0305050611495972, 1.0384547710418701, 1.036906361579895, 1.0566296577453613, 1.0

364665985107422, 1.0501279830932617, 1.061496376991272, 1.0529338121414
185, 1.055050015449524, 1.057979702949524, 1.0413564443588257, 1.025724
8878479004, 1.0366038084030151, 1.063535213470459, 1.0369486808776855,
1.0294815301895142, 1.0567388534545898, 1.0504050254821777, 1.066788673
400879, 1.0452245473861694, 1.0561500787734985, 1.046491265296936, 1.05
67829608917236, 1.0565285682678223, 1.0154483318328857, 1.0512311458587
646, 1.05126953125, 1.0461827516555786, 1.0238131284713745, 1.039643287
6586914, 1.04896879196167, 1.0306458473205566, 1.0446697473526, 1.03395
676612854, 1.0511891841888428, 1.0643560886383057, 1.031791090965271,
1.0357686281204224, 1.0453524589538574, 1.0564340353012085, 1.062582373
6190796, 1.060795545578003, 1.024033784866333, 1.052892804145813, 1.059
4714879989624, 1.0530486106872559, 1.0443867444992065, 1.02026724815368
65, 1.0437109470367432, 1.0490092039108276, 1.0210005044937134, 1.04907
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0407977104187012, 1.0509847402572632]

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0.0022615070920437574, 0.00046671839663758874, -0.0012962330365553498,
-0.011212168261408806, 0.010269800201058388, -0.0014958319952711463, 0.
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1814168691635, 0.003929481841623783, -0.002303466899320483, 0.001259794
8079928756, 0.007495399098843336, 0.0052605909295380116, 0.008851370774
2095, -0.009923121891915798, 0.004494238644838333, 0.00320960395038127
9, 0.005816757213324308, -0.0069657862186431885, -0.002194028347730636
6, 0.007474885787814856, 0.00040936964796856046, -0.000433505076216533
8, -0.004530641250312328, 0.011161871254444122, 0.002604279201477766, -
0.00278839492239058, -0.012905885465443134, 0.007219281978905201, 0.005
192923359572887, -0.010496263392269611, -0.0037754857912659645, -0.0044
82236225157976]

#####

The performances have been similar .

Question4:

a) Data without standard normalization

```
In [12]: # Load dataset as train and test sets
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data
()

# Set numeric type to float32 from uint8
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

# Normalize value to [0, 1]
x_train /= 255
x_test /= 255

# Transform labels to one-hot encoding
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Reshape the dataset into 4D array
x_train = x_train.reshape(x_train.shape[0], 28,28,1)
x_test = x_test.reshape(x_test.shape[0], 28,28,1)
```

Model 3: Dropout and no batch normalization

(dropout not applied on pooling layers)

```
In [14]: #Instantiate an empty model
model_dropout = Sequential()
# C1 Convolutional Layer
model_dropout.add(Dropout(0.2, input_shape=(28,28,1)))
model_dropout.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation='tanh', input_shape=(28,28,1), padding='same'))
# S2 Pooling Layer
model_dropout.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(1, 1), padding='valid'))

# C3 Convolutional Layer
model_dropout.add(Dropout(0.5))
model_dropout.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))

# S4 Pooling Layer
model_dropout.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))

# C5 Fully Connected Convolutional Layer
model_dropout.add(Dropout(0.5))
model_dropout.add(layers.Conv2D(120, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))

#Flatten the CNN output so that we can connect it with fully connected layers
model_dropout.add(layers.Flatten())

# FC6 Fully Connected Layer
model_dropout.add(Dropout(0.5))
model_dropout.add(layers.Dense(84, activation='tanh'))

#Output Layer with softmax activation
model_dropout.add(Dropout(0.5))
model_dropout.add(layers.Dense(10, activation='softmax'))

# Compile the model
model_dropout.compile(loss=keras.losses.categorical_crossentropy, optimizer='SGD', metrics=['accuracy'])
```

```
In [15]: model_dropout.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
dropout_5 (Dropout)	(None, 28, 28, 1)	0
conv2d_9 (Conv2D)	(None, 28, 28, 6)	156
average_pooling2d_6 (Average)	(None, 27, 27, 6)	0
dropout_6 (Dropout)	(None, 27, 27, 6)	0
conv2d_10 (Conv2D)	(None, 23, 23, 16)	2416
average_pooling2d_7 (Average)	(None, 11, 11, 16)	0
dropout_7 (Dropout)	(None, 11, 11, 16)	0
conv2d_11 (Conv2D)	(None, 7, 7, 120)	48120
flatten_3 (Flatten)	(None, 5880)	0
dropout_8 (Dropout)	(None, 5880)	0
dense_6 (Dense)	(None, 84)	494004
dropout_9 (Dropout)	(None, 84)	0
dense_7 (Dense)	(None, 10)	850
=====		
Total params: 545,546		
Trainable params: 545,546		
Non-trainable params: 0		
=====		


```
In [16]: hist_dropout = model_dropout.fit(x=x_train,y=y_train, epochs=20, batch_size=128, validation_data=(x_test, y_test), verbose=1)
```

Epoch 1/20
469/469 [=====] - 5s 12ms/step - loss: 1.0002
- accuracy: 0.6741 - val_loss: 0.3821 - val_accuracy: 0.8858

Epoch 2/20
469/469 [=====] - 5s 11ms/step - loss: 0.5666
- accuracy: 0.8236 - val_loss: 0.3058 - val_accuracy: 0.9061

Epoch 3/20
469/469 [=====] - 5s 11ms/step - loss: 0.5069
- accuracy: 0.8433 - val_loss: 0.2700 - val_accuracy: 0.9205

Epoch 4/20
469/469 [=====] - 5s 11ms/step - loss: 0.4630
- accuracy: 0.8571 - val_loss: 0.2478 - val_accuracy: 0.9299

Epoch 5/20
469/469 [=====] - 5s 11ms/step - loss: 0.4338
- accuracy: 0.8677 - val_loss: 0.2283 - val_accuracy: 0.9333

Epoch 6/20
469/469 [=====] - 5s 12ms/step - loss: 0.4050
- accuracy: 0.8755 - val_loss: 0.2157 - val_accuracy: 0.9369

Epoch 7/20
469/469 [=====] - 6s 12ms/step - loss: 0.3858
- accuracy: 0.8819 - val_loss: 0.2026 - val_accuracy: 0.9407

Epoch 8/20
469/469 [=====] - 5s 11ms/step - loss: 0.3731
- accuracy: 0.8870 - val_loss: 0.1925 - val_accuracy: 0.9429

Epoch 9/20
469/469 [=====] - 5s 11ms/step - loss: 0.3556
- accuracy: 0.8914 - val_loss: 0.1830 - val_accuracy: 0.9453

Epoch 10/20
469/469 [=====] - 5s 11ms/step - loss: 0.3442
- accuracy: 0.8954 - val_loss: 0.1723 - val_accuracy: 0.9483

Epoch 11/20
469/469 [=====] - 5s 11ms/step - loss: 0.3344
- accuracy: 0.8979 - val_loss: 0.1676 - val_accuracy: 0.9492

Epoch 12/20
469/469 [=====] - 5s 11ms/step - loss: 0.3213
- accuracy: 0.9029 - val_loss: 0.1581 - val_accuracy: 0.9507

Epoch 13/20
469/469 [=====] - 5s 11ms/step - loss: 0.3091
- accuracy: 0.9066 - val_loss: 0.1519 - val_accuracy: 0.9543

Epoch 14/20
469/469 [=====] - 5s 11ms/step - loss: 0.3021
- accuracy: 0.9086 - val_loss: 0.1465 - val_accuracy: 0.9555

Epoch 15/20
469/469 [=====] - 5s 11ms/step - loss: 0.2942
- accuracy: 0.9119 - val_loss: 0.1423 - val_accuracy: 0.9554

Epoch 16/20
469/469 [=====] - 5s 11ms/step - loss: 0.2850
- accuracy: 0.9159 - val_loss: 0.1342 - val_accuracy: 0.9581

Epoch 17/20
469/469 [=====] - 5s 11ms/step - loss: 0.2776
- accuracy: 0.9159 - val_loss: 0.1291 - val_accuracy: 0.9603

Epoch 18/20
469/469 [=====] - 5s 11ms/step - loss: 0.2658
- accuracy: 0.9186 - val_loss: 0.1247 - val_accuracy: 0.9611

Epoch 19/20
469/469 [=====] - 5s 11ms/step - loss: 0.2603
- accuracy: 0.9216 - val_loss: 0.1224 - val_accuracy: 0.9617

```
Epoch 20/20  
469/469 [=====] - 5s 11ms/step - loss: 0.2518  
- accuracy: 0.9244 - val_loss: 0.1151 - val_accuracy: 0.9641
```

```
In [17]: model_dropout.save('model3_dropout_all.h5')
```

Test accuracy has significantly dropped ! (0.9641 for dropout only vs 0.9920 for batch norm only)

Question 5 :

a) Data without standard normalization

```
In [18]: # Load dataset as train and test sets  
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()  
  
# Set numeric type to float32 from uint8  
x_train = x_train.astype('float32')  
x_test = x_test.astype('float32')  
  
# Normalize value to [0, 1]  
x_train /= 255  
x_test /= 255  
  
# Transform labels to one-hot encoding  
y_train = tf.keras.utils.to_categorical(y_train, 10)  
y_test = tf.keras.utils.to_categorical(y_test, 10)  
  
# Reshape the dataset into 4D array  
x_train = x_train.reshape(x_train.shape[0], 28,28,1)  
x_test = x_test.reshape(x_test.shape[0], 28,28,1)
```

Model 4: Dropout and batch normalization

```

In [19]: from tensorflow.keras.layers import Dropout
          #Instantiate an empty model
          model_dropout_batch = Sequential()
          # C1 Convolutional Layer
          model_dropout_batch.add(BatchNormalization(input_shape=(28,28,1)))
          model_dropout_batch.add(Dropout(0.2, input_shape=(28,28,1)))
          model_dropout_batch.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1,
          1), activation='tanh', input_shape=(28,28,1), padding='same'))
          model_dropout_batch.add(BatchNormalization())
          # S2 Pooling Layer
          model_dropout_batch.add(layers.AveragePooling2D(pool_size=(2, 2), stride
          s=(1, 1), padding='valid'))
          model_dropout_batch.add(BatchNormalization())
          # C3 Convolutional Layer
          model_dropout_batch.add(Dropout(0.5))
          model_dropout_batch.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1
          , 1), activation='tanh', padding='valid'))
          model_dropout_batch.add(BatchNormalization())
          # S4 Pooling Layer
          model_dropout_batch.add(layers.AveragePooling2D(pool_size=(2, 2), stride
          s=(2, 2), padding='valid'))
          model_dropout_batch.add(BatchNormalization())
          # C5 Fully Connected Convolutional Layer
          model_dropout_batch.add(Dropout(0.5))
          model_dropout_batch.add(layers.Conv2D(120, kernel_size=(5, 5), strides=(
          1, 1), activation='tanh', padding='valid'))
          model_dropout_batch.add(BatchNormalization())
          #Flatten the CNN output so that we can connect it with fully connected l
          ayers
          model_dropout_batch.add(layers.Flatten())
          # FC6 Fully Connected Layer
          model_dropout_batch.add(Dropout(0.5))
          model_dropout_batch.add(layers.Dense(84, activation='tanh'))
          model_dropout_batch.add(BatchNormalization())
          #Output Layer with softmax activation
          model_dropout_batch.add(Dropout(0.5))
          model_dropout_batch.add(layers.Dense(10, activation='softmax'))

          # Compile the model
          model_dropout_batch.compile(loss=keras.losses.categorical_crossentropy,
          optimizer='SGD', metrics=['accuracy'])

```

```
In [20]: model_dropout_batch.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
=====		
batch_normalization_13 (Batch Normalization)	(None, 28, 28, 1)	4
dropout_10 (Dropout)	(None, 28, 28, 1)	0
conv2d_12 (Conv2D)	(None, 28, 28, 6)	156
batch_normalization_14 (Batch Normalization)	(None, 28, 28, 6)	24
average_pooling2d_8 (Average Pooling)	(None, 27, 27, 6)	0
batch_normalization_15 (Batch Normalization)	(None, 27, 27, 6)	24
dropout_11 (Dropout)	(None, 27, 27, 6)	0
conv2d_13 (Conv2D)	(None, 23, 23, 16)	2416
batch_normalization_16 (Batch Normalization)	(None, 23, 23, 16)	64
average_pooling2d_9 (Average Pooling)	(None, 11, 11, 16)	0
batch_normalization_17 (Batch Normalization)	(None, 11, 11, 16)	64
dropout_12 (Dropout)	(None, 11, 11, 16)	0
conv2d_14 (Conv2D)	(None, 7, 7, 120)	48120
batch_normalization_18 (Batch Normalization)	(None, 7, 7, 120)	480
flatten_4 (Flatten)	(None, 5880)	0
dropout_13 (Dropout)	(None, 5880)	0
dense_8 (Dense)	(None, 84)	494004
batch_normalization_19 (Batch Normalization)	(None, 84)	336
dropout_14 (Dropout)	(None, 84)	0
dense_9 (Dense)	(None, 10)	850
=====		
Total params: 546,542		
Trainable params: 546,044		
Non-trainable params: 498		

```
In [22]: hist_dropout_batch = model_dropout_batch.fit(x=x_train,y=y_train, epochs  
=50, batch_size=128, validation_data=(x_test, y_test), verbose=1)
```

Epoch 1/50
469/469 [=====] - 7s 14ms/step - loss: 0.1473
- accuracy: 0.9561 - val_loss: 0.0587 - val_accuracy: 0.9812

Epoch 2/50
469/469 [=====] - 7s 14ms/step - loss: 0.1435
- accuracy: 0.9575 - val_loss: 0.0568 - val_accuracy: 0.9817

Epoch 3/50
469/469 [=====] - 7s 14ms/step - loss: 0.1419
- accuracy: 0.9586 - val_loss: 0.0554 - val_accuracy: 0.9827

Epoch 4/50
469/469 [=====] - 7s 14ms/step - loss: 0.1397
- accuracy: 0.9583 - val_loss: 0.0540 - val_accuracy: 0.9824

Epoch 5/50
469/469 [=====] - 7s 14ms/step - loss: 0.1377
- accuracy: 0.9592 - val_loss: 0.0525 - val_accuracy: 0.9831

Epoch 6/50
469/469 [=====] - 7s 14ms/step - loss: 0.1375
- accuracy: 0.9588 - val_loss: 0.0529 - val_accuracy: 0.9823

Epoch 7/50
469/469 [=====] - 7s 14ms/step - loss: 0.1359
- accuracy: 0.9596 - val_loss: 0.0527 - val_accuracy: 0.9832

Epoch 8/50
469/469 [=====] - 7s 14ms/step - loss: 0.1355
- accuracy: 0.9597 - val_loss: 0.0500 - val_accuracy: 0.9835

Epoch 9/50
469/469 [=====] - 7s 14ms/step - loss: 0.1310
- accuracy: 0.9604 - val_loss: 0.0508 - val_accuracy: 0.9846

Epoch 10/50
469/469 [=====] - 7s 14ms/step - loss: 0.1266
- accuracy: 0.9628 - val_loss: 0.0523 - val_accuracy: 0.9833

Epoch 11/50
469/469 [=====] - 7s 14ms/step - loss: 0.1258
- accuracy: 0.9632 - val_loss: 0.0501 - val_accuracy: 0.9849

Epoch 12/50
469/469 [=====] - 7s 14ms/step - loss: 0.1237
- accuracy: 0.9632 - val_loss: 0.0474 - val_accuracy: 0.9845

Epoch 13/50
469/469 [=====] - 7s 14ms/step - loss: 0.1240
- accuracy: 0.9635 - val_loss: 0.0490 - val_accuracy: 0.9846

Epoch 14/50
469/469 [=====] - 7s 14ms/step - loss: 0.1250
- accuracy: 0.9624 - val_loss: 0.0481 - val_accuracy: 0.9847

Epoch 15/50
469/469 [=====] - 7s 14ms/step - loss: 0.1224
- accuracy: 0.9633 - val_loss: 0.0448 - val_accuracy: 0.9852

Epoch 16/50
469/469 [=====] - 7s 14ms/step - loss: 0.1189
- accuracy: 0.9650 - val_loss: 0.0463 - val_accuracy: 0.9848

Epoch 17/50
469/469 [=====] - 7s 14ms/step - loss: 0.1179
- accuracy: 0.9652 - val_loss: 0.0449 - val_accuracy: 0.9856

Epoch 18/50
469/469 [=====] - 7s 14ms/step - loss: 0.1189
- accuracy: 0.9639 - val_loss: 0.0453 - val_accuracy: 0.9847

Epoch 19/50
469/469 [=====] - 7s 14ms/step - loss: 0.1161
- accuracy: 0.9659 - val_loss: 0.0451 - val_accuracy: 0.9850

```
Epoch 20/50
469/469 [=====] - 7s 14ms/step - loss: 0.1152
- accuracy: 0.9649 - val_loss: 0.0462 - val_accuracy: 0.9853
Epoch 21/50
469/469 [=====] - 7s 14ms/step - loss: 0.1150
- accuracy: 0.9657 - val_loss: 0.0436 - val_accuracy: 0.9853
Epoch 22/50
469/469 [=====] - 7s 14ms/step - loss: 0.1124
- accuracy: 0.9663 - val_loss: 0.0433 - val_accuracy: 0.9858
Epoch 23/50
469/469 [=====] - 7s 14ms/step - loss: 0.1141
- accuracy: 0.9657 - val_loss: 0.0432 - val_accuracy: 0.9855
Epoch 24/50
469/469 [=====] - 7s 14ms/step - loss: 0.1119
- accuracy: 0.9663 - val_loss: 0.0440 - val_accuracy: 0.9861
Epoch 25/50
469/469 [=====] - 7s 14ms/step - loss: 0.1092
- accuracy: 0.9671 - val_loss: 0.0417 - val_accuracy: 0.9860
Epoch 26/50
469/469 [=====] - 7s 14ms/step - loss: 0.1104
- accuracy: 0.9671 - val_loss: 0.0423 - val_accuracy: 0.9862
Epoch 27/50
469/469 [=====] - 7s 14ms/step - loss: 0.1100
- accuracy: 0.9670 - val_loss: 0.0423 - val_accuracy: 0.9863
Epoch 28/50
469/469 [=====] - 7s 14ms/step - loss: 0.1053
- accuracy: 0.9680 - val_loss: 0.0404 - val_accuracy: 0.9871
Epoch 29/50
469/469 [=====] - 7s 14ms/step - loss: 0.1067
- accuracy: 0.9680 - val_loss: 0.0423 - val_accuracy: 0.9863
Epoch 30/50
469/469 [=====] - 7s 14ms/step - loss: 0.1054
- accuracy: 0.9684 - val_loss: 0.0399 - val_accuracy: 0.9868
Epoch 31/50
469/469 [=====] - 7s 14ms/step - loss: 0.1068
- accuracy: 0.9680 - val_loss: 0.0404 - val_accuracy: 0.9868
Epoch 32/50
469/469 [=====] - 7s 14ms/step - loss: 0.1061
- accuracy: 0.9677 - val_loss: 0.0395 - val_accuracy: 0.9868
Epoch 33/50
469/469 [=====] - 7s 14ms/step - loss: 0.1042
- accuracy: 0.9682 - val_loss: 0.0401 - val_accuracy: 0.9864
Epoch 34/50
469/469 [=====] - 7s 14ms/step - loss: 0.1060
- accuracy: 0.9687 - val_loss: 0.0390 - val_accuracy: 0.9869
Epoch 35/50
469/469 [=====] - 7s 14ms/step - loss: 0.1020
- accuracy: 0.9691 - val_loss: 0.0397 - val_accuracy: 0.9870
Epoch 36/50
469/469 [=====] - 7s 14ms/step - loss: 0.1038
- accuracy: 0.9687 - val_loss: 0.0397 - val_accuracy: 0.9873
Epoch 37/50
469/469 [=====] - 7s 14ms/step - loss: 0.1030
- accuracy: 0.9693 - val_loss: 0.0394 - val_accuracy: 0.9865
Epoch 38/50
469/469 [=====] - 7s 14ms/step - loss: 0.1007
- accuracy: 0.9699 - val_loss: 0.0408 - val_accuracy: 0.9870
```



```

Epoch 39/50
469/469 [=====] - 7s 14ms/step - loss: 0.1017
- accuracy: 0.9699 - val_loss: 0.0375 - val_accuracy: 0.9880
Epoch 40/50
469/469 [=====] - 7s 14ms/step - loss: 0.1001
- accuracy: 0.9703 - val_loss: 0.0374 - val_accuracy: 0.9883
Epoch 41/50
469/469 [=====] - 7s 14ms/step - loss: 0.0987
- accuracy: 0.9704 - val_loss: 0.0361 - val_accuracy: 0.9876
Epoch 42/50
469/469 [=====] - 7s 14ms/step - loss: 0.0978
- accuracy: 0.9704 - val_loss: 0.0370 - val_accuracy: 0.9873
Epoch 43/50
469/469 [=====] - 7s 14ms/step - loss: 0.0973
- accuracy: 0.9709 - val_loss: 0.0376 - val_accuracy: 0.9877
Epoch 44/50
469/469 [=====] - 7s 14ms/step - loss: 0.0960
- accuracy: 0.9711 - val_loss: 0.0380 - val_accuracy: 0.9873
Epoch 45/50
469/469 [=====] - 7s 14ms/step - loss: 0.0954
- accuracy: 0.9711 - val_loss: 0.0372 - val_accuracy: 0.9877
Epoch 46/50
469/469 [=====] - 7s 14ms/step - loss: 0.0984
- accuracy: 0.9712 - val_loss: 0.0363 - val_accuracy: 0.9880
Epoch 47/50
469/469 [=====] - 7s 14ms/step - loss: 0.0946
- accuracy: 0.9710 - val_loss: 0.0361 - val_accuracy: 0.9880
Epoch 48/50
469/469 [=====] - 7s 14ms/step - loss: 0.0958
- accuracy: 0.9711 - val_loss: 0.0368 - val_accuracy: 0.9881
Epoch 49/50
469/469 [=====] - 7s 14ms/step - loss: 0.0922
- accuracy: 0.9719 - val_loss: 0.0371 - val_accuracy: 0.9880
Epoch 50/50
469/469 [=====] - 7s 14ms/step - loss: 0.0929
- accuracy: 0.9717 - val_loss: 0.0367 - val_accuracy: 0.9883

```

```
In [ ]: model_dropout_batch.save('model4_dropout_batch_all.h5')
```

The performance compared to dropout only has significantly increased (0.9850 for dropout. + batch. norm vs 0.9641 for dropout only) . (compared on 20 epochs)

The performance compared to batch norm only has been slightly reduced(0.9850 vs 0.9920) . (compared on 20 epochs)

Conclusion :

Dropout seems to increase the training time but also avoid overfitting . Dropout is mostly a technique for regularization. It introduces noise into a neural network to force the neural network to learn to generalize well enough to deal with noise.

Batch normalization is mostly a technique for improving optimization and it happens that it also. introduce some noise and therefore help for regularization. As for large dataset like ours, optimization is more important than regularizationso batch normalization seems to be more important. A combination of both can also be applied.

In []: