

Assignment 13 - CNN - MNIST

May 29, 2019

1 Introduction

MNIST ("Modified National Institute of Standards and Technology") is the de facto "Hello World" dataset of computer vision. Since its release in 1999, this classic dataset of handwritten images has served as the basis for benchmarking classification algorithms. As new machine learning techniques emerge, MNIST remains a reliable resource for researchers and learners alike.

Objective is to correctly identify digits from a dataset of tens of thousands of handwritten images

Importing the libraries

```
In [0]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import tensorflow as tf
import seaborn as sns
```

Now that we have successfully imported the required libraries, let us print out the version of Tensorflow which we will working upon. Also, checking the image format from tensorflow backend.

```
In [2]: print("Version of Tensorflow:", tf.__version__)
print("Image data format: ", tf.keras.backend.image_data_format())
```

```
Version of Tensorflow: 1.13.1
Image data format:  channels_last
```

As we can see, we are using 1.13 tensorflow version. Also, the image data format config is set to channel_last, which means that the 2D shape would be (row, cols, channels)

Loading the dataset

```
In [3]: mnist_data = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist_data.load_data()

print("INPUT : train shape: ", x_train.shape)
print("OUTPUT: train shape: ", y_train.shape)
print("INPUT : test shape: ", x_test.shape)
print("OUTPUT: test shape: ", y_test.shape)
```

```
INPUT : train shape: (60000, 28, 28)
OUTPUT: train shape: (60000,)
INPUT : test shape: (10000, 28, 28)
OUTPUT: test shape: (10000,)
```

As we can see, the shape of the train and test feature are 3D i.e for training set, there are 60k rows of 28 x 28 data.

However, as we are using keras with tensorflow backend, we will have to convert the above shape to be of the form (60k * 28 x 28 X 1) i.e 4D tensor

```
In [4]: x_train_new = x_train.reshape(x_train.shape[0], x_train.shape[1], x_train.shape[2], 1)
        x_test_new = x_test.reshape(x_test.shape[0], x_test.shape[1], x_test.shape[2], 1)

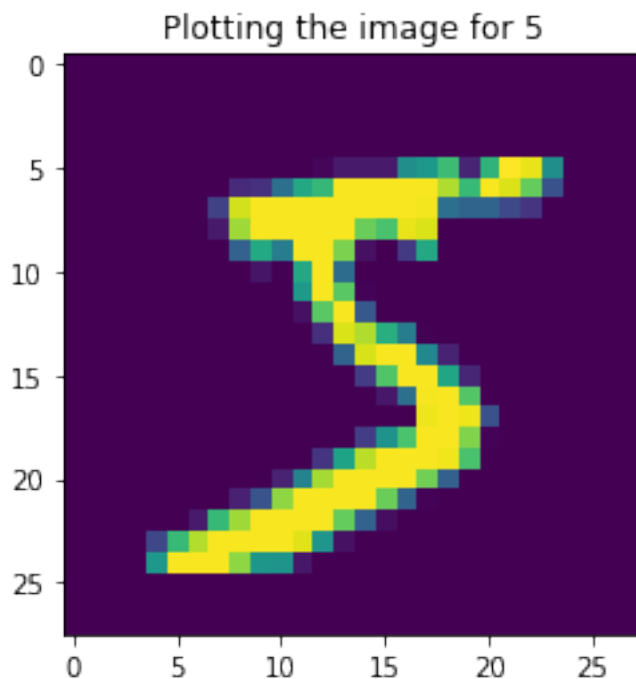
        print("After reshaping -> INPUT : train shape: ", x_train_new.shape)
        print("After reshaping -> INPUT : test shape: ", x_train_new.shape)
```

```
After reshaping -> INPUT : train shape: (60000, 28, 28, 1)
```

```
After reshaping -> INPUT : test shape: (60000, 28, 28, 1)
```

Visualizing the Output

```
In [5]: plt.close()
        plt.title("Plotting the image for " + str(y_train[0]))
        plt.imshow(x_train[0])
        plt.show()
```



Preprocessing the data

Now, we would be normalizing the data before creating our model.

Typically, we employ 2 methods to normalize our data for MNIST

1. Divide each element by 255
2. Just use `keras.utils.normalize`

We would be using the built in function for normalizing

```
In [6]: x_train_new = tf.keras.utils.normalize(x_train_new)
        x_test_new = tf.keras.utils.normalize(x_test_new)

        print("After Normalizing -> INPUT : train shape: ", x_train_new.shape)
        print("After Normalizing -> INPUT : test shape: ", x_test_new.shape)
```

After Normalizing -> INPUT : train shape: (60000, 28, 28, 1)

After Normalizing -> INPUT : test shape: (10000, 28, 28, 1)

So we are done with normalizing. Now we would be one hot encoding the output variable so that we are able to feed it into the output layer for softmax classifier activation function.

```
In [7]: y_train = tf.keras.utils.to_categorical(y_train, num_classes=10)
        y_test = tf.keras.utils.to_categorical(y_test, num_classes=10)

        print("After Encoding -> OUTPUT : train shape: ", y_train.shape)
        print("After Encoding -> OUTPUT : test shape: ", y_test.shape)
```

After Encoding -> OUTPUT : train shape: (60000, 10)

After Encoding -> OUTPUT : test shape: (10000, 10)

2 CNN Model on MNIST dataset

```
In [0]: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization, Conv2D,

        n_epochs = 25
        batchsize = 128

        final_output = pd.DataFrame(columns=["#ConvNets", "#Kernels/Filters", "Padding", "Stride",

In [0]: # https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
        # https://stackoverflow.com/a/14434334
        # this function is used to update the plots for each epoch and error
        def plt_dynamic(x, vy, ty, ax, colors=['b']):
            ax.plot(x, vy, 'b', label="Validation Loss")
```

```
ax.plot(x, ty, 'r', label="Train Loss")
plt.legend()
plt.grid()
fig.canvas.draw()
```

2.1 2 ConvNet Architecture

In this type of architecture, we will be trying out 2 convolution layer along with 2 maxpooling layer for each.

2.1.1 3x3 Filter/Kernel

```
In [10]: m21_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m21_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu, input_shape=(28,28,1)
m21_model.add(MaxPooling2D(pool_size=(2,2)))

# Second Convolutional layer with MaxPooling
m21_model.add(Conv2D(64, kernel_size=(3,3), activation=tf.nn.relu))
m21_model.add(MaxPooling2D(pool_size=(2,2)))

# Three dense layers in MLP
m21_model.add(Flatten())
m21_model.add(Dense(128, activation=tf.nn.relu))
m21_model.add(Dense(64, activation=tf.nn.relu))
m21_model.add(Dense(10, activation=tf.nn.softmax))

m21_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m21_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/resource_variable_ops.py:1432:
Instructions for updating:
Colocations handled automatically by placer.
Train on 60000 samples, validate on 10000 samples
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:306:
Instructions for updating:
Use tf.cast instead.
Epoch 1/25
60000/60000 [=====] - 7s 117us/sample - loss: 0.2405 - acc: 0.9281 - val_loss: 0.2405 - val_acc: 0.9281
Epoch 2/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0697 - acc: 0.9782 - val_loss: 0.0697 - val_acc: 0.9782
Epoch 3/25
60000/60000 [=====] - 6s 98us/sample - loss: 0.0530 - acc: 0.9833 - val_loss: 0.0530 - val_acc: 0.9833
Epoch 4/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0394 - acc: 0.9882 - val_loss: 0.0394 - val_acc: 0.9882
Epoch 5/25
```

```

60000/60000 [=====] - 6s 96us/sample - loss: 0.0331 - acc: 0.9894 - val
Epoch 6/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0270 - acc: 0.9916 - val
Epoch 7/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0213 - acc: 0.9931 - val
Epoch 8/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0173 - acc: 0.9944 - val
Epoch 9/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0140 - acc: 0.9955 - val
Epoch 10/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0127 - acc: 0.9956 - val
Epoch 11/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0109 - acc: 0.9964 - val
Epoch 12/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0087 - acc: 0.9973 - val
Epoch 13/25
60000/60000 [=====] - 6s 98us/sample - loss: 0.0101 - acc: 0.9966 - val
Epoch 14/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0073 - acc: 0.9977 - val
Epoch 15/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0075 - acc: 0.9974 - val
Epoch 16/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0051 - acc: 0.9982 - val
Epoch 17/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0066 - acc: 0.9978 - val
Epoch 18/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0055 - acc: 0.9982 - val
Epoch 19/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0045 - acc: 0.9986 - val
Epoch 20/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0068 - acc: 0.9980 - val
Epoch 21/25
60000/60000 [=====] - 6s 97us/sample - loss: 0.0029 - acc: 0.9991 - val
Epoch 22/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0043 - acc: 0.9986 - val
Epoch 23/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0042 - acc: 0.9987 - val
Epoch 24/25
60000/60000 [=====] - 6s 96us/sample - loss: 0.0069 - acc: 0.9977 - val
Epoch 25/25
60000/60000 [=====] - 6s 95us/sample - loss: 0.0043 - acc: 0.9987 - val

```

```

In [11]: print("*****")
          print("Printing the Model Summary")
          print(m21_model.summary())
          print("*****")

```

```

score = m21_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 2,
                                     "#Kernels/Filters": '3x3',
                                     "Padding": '-',
                                     "Stride": '2x2',
                                     "Dropout": '-',
                                     "BatchNormalization": False,
                                     "Regularization": '-',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

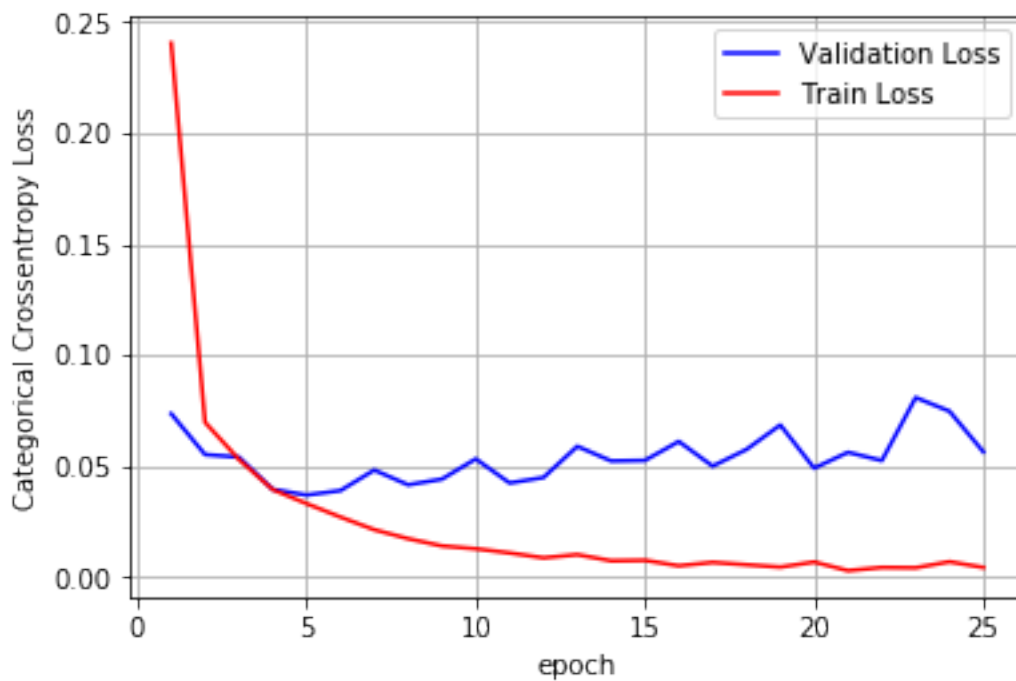
Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense (Dense)	(None, 128)	204928
dense_1 (Dense)	(None, 64)	8256

```

dense_2 (Dense)                (None, 10)                650
=====
Total params: 232,650
Trainable params: 232,650
Non-trainable params: 0
-----
None
*****
10000/10000 [=====] - 1s 82us/sample - loss: 0.0564 - acc: 0.9883
Test score: 0.056394415135847066
Test accuracy: 0.9883

```



```

In [12]: w_after = m21_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

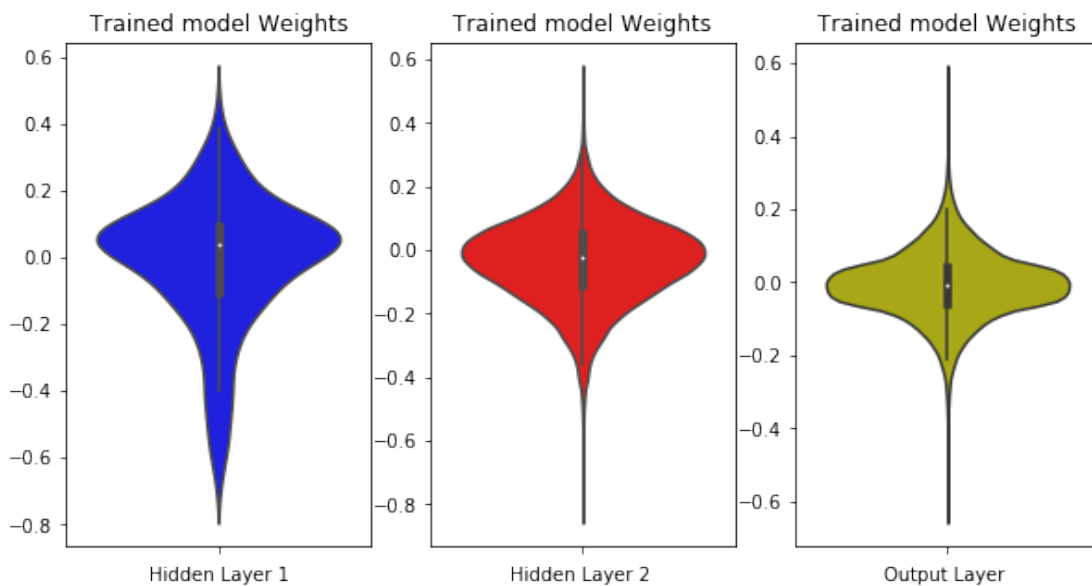
fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')

```

```
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.1.2 5x5 Filter/Kernel

```
In [13]: m22_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m22_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, input_shape=(28,28,1)
m22_model.add(MaxPooling2D(pool_size=(2,2)))

# Second Convolutional layer with MaxPooling
m22_model.add(Conv2D(64, kernel_size=(5,5), activation=tf.nn.relu))
m22_model.add(MaxPooling2D(pool_size=(2,2)))

# Three dense layers in MLP
m22_model.add(Flatten())
m22_model.add(Dense(128, activation=tf.nn.relu))
```



```

m22_model.add(Dense(64, activation=tf.nn.relu))
m22_model.add(Dense(10, activation=tf.nn.softmax))

```

```

m22_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m22_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.2320 - acc: 0.9293 - val_loss: 0.1870
Epoch 2/25
60000/60000 [=====] - 5s 87us/sample - loss: 0.0696 - acc: 0.9778 - val_loss: 0.0540
Epoch 3/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0482 - acc: 0.9848 - val_loss: 0.0380
Epoch 4/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0350 - acc: 0.9888 - val_loss: 0.0300
Epoch 5/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0296 - acc: 0.9901 - val_loss: 0.0250
Epoch 6/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0243 - acc: 0.9923 - val_loss: 0.0200
Epoch 7/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0187 - acc: 0.9940 - val_loss: 0.0150
Epoch 8/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0166 - acc: 0.9947 - val_loss: 0.0130
Epoch 9/25
60000/60000 [=====] - 5s 88us/sample - loss: 0.0150 - acc: 0.9952 - val_loss: 0.0120
Epoch 10/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0119 - acc: 0.9961 - val_loss: 0.0100
Epoch 11/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0095 - acc: 0.9967 - val_loss: 0.0080
Epoch 12/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0115 - acc: 0.9962 - val_loss: 0.0090
Epoch 13/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0089 - acc: 0.9969 - val_loss: 0.0070
Epoch 14/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0088 - acc: 0.9971 - val_loss: 0.0060
Epoch 15/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0070 - acc: 0.9978 - val_loss: 0.0050
Epoch 16/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0082 - acc: 0.9975 - val_loss: 0.0040
Epoch 17/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0060 - acc: 0.9981 - val_loss: 0.0030
Epoch 18/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0064 - acc: 0.9977 - val_loss: 0.0020
Epoch 19/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0046 - acc: 0.9985 - val_loss: 0.0010
Epoch 20/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0053 - acc: 0.9982 - val_loss: 0.0000

```

```

Epoch 21/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0070 - acc: 0.9976 - val
Epoch 22/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0046 - acc: 0.9985 - val
Epoch 23/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0058 - acc: 0.9979 - val
Epoch 24/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0043 - acc: 0.9986 - val
Epoch 25/25
60000/60000 [=====] - 5s 89us/sample - loss: 0.0034 - acc: 0.9990 - val

```

```

In [14]: print("*****")
         print("Printing the Model Summary")
         print(m22_model.summary())
         print("*****")

         score = m22_model.evaluate(x_test_new, y_test)

         print('Test score:', score[0])
         print('Test accuracy:', score[1])

         final_output = final_output.append({"#ConvNets": 2,
                                             "Kernels/Filters": '5x5',
                                             "Padding": '-',
                                             "Stride": '2x2',
                                             "Dropout": '-',
                                             "BatchNormalization": False,
                                             "Regularization": '-',
                                             "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                             "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                             "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                             "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

         fig,ax = plt.subplots(1,1)
         ax.set_xlabel('epoch')
         ax.set_ylabel('Categorical Crossentropy Loss')

         # list of epoch numbers
         x = list(range(1,n_epochs+1))

         vy = model.history['val_loss']
         ty = model.history['loss']
         plt_dynamic(x, vy, ty, ax)

*****
Printing the Model Summary

```

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 24, 24, 32)	832
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 32)	0
conv2d_3 (Conv2D)	(None, 8, 8, 64)	51264
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 64)	0
flatten_1 (Flatten)	(None, 1024)	0
dense_3 (Dense)	(None, 128)	131200
dense_4 (Dense)	(None, 64)	8256
dense_5 (Dense)	(None, 10)	650

Total params: 192,202

Trainable params: 192,202

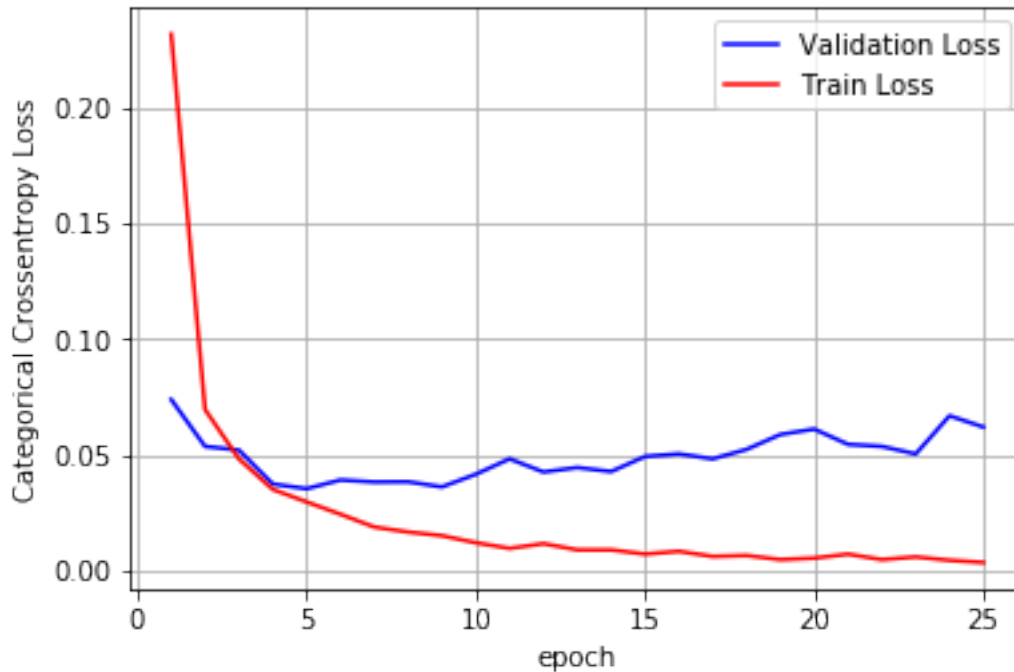
Non-trainable params: 0

None

10000/10000 [=====] - 1s 84us/sample - loss: 0.0620 - acc: 0.9887

Test score: 0.061998865842755914

Test accuracy: 0.9887



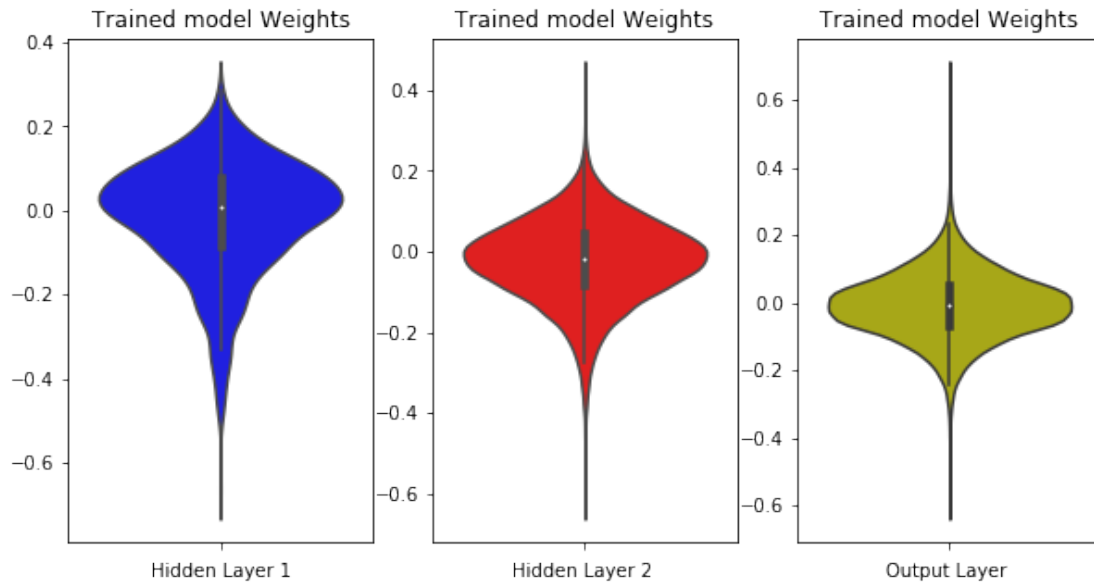
```
In [15]: w_after = m22_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.1.3 3x3 Filter/Kernel with Dropout and Weight Regularization & Initialization and Batch Normalization

In [16]: m23_model = Sequential()

```
# First Convolutional layer with MaxPooling
m23_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m23_model.add(MaxPooling2D(pool_size=(2,2)))

m23_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m23_model.add(Conv2D(64, kernel_size=(3,3), activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m23_model.add(MaxPooling2D(pool_size=(2,2)))

m23_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m23_model.add(Flatten())
m23_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m23_model.add(BatchNormalization())
m23_model.add(Dropout(rate=0.5))
m23_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m23_model.add(BatchNormalization())
m23_model.add(Dropout(rate=0.5))
```

```
m23_model.add(Dense(10, activation=tf.nn.softmax))
```

```
m23_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])  
model = m23_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/layers/core.py:107: *tf.nn.conv2d* is deprecated and will be removed in a future version. Instructions for updating:

Please use ``rate`` instead of ``keep_prob``. Rate should be set to ``rate = 1 - keep_prob``.

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 9s 143us/sample - loss: 1.1191 - acc: 0.6388 - val_loss: 0.7000 - val_acc: 0.7000

Epoch 2/25

60000/60000 [=====] - 8s 130us/sample - loss: 0.4228 - acc: 0.8740 - val_loss: 0.3500 - val_acc: 0.8500

Epoch 3/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.2772 - acc: 0.9200 - val_loss: 0.2500 - val_acc: 0.9000

Epoch 4/25

60000/60000 [=====] - 8s 130us/sample - loss: 0.2323 - acc: 0.9350 - val_loss: 0.2000 - val_acc: 0.9200

Epoch 5/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.2026 - acc: 0.9440 - val_loss: 0.1800 - val_acc: 0.9300

Epoch 6/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1786 - acc: 0.9511 - val_loss: 0.1600 - val_acc: 0.9400

Epoch 7/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1705 - acc: 0.9537 - val_loss: 0.1500 - val_acc: 0.9400

Epoch 8/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1592 - acc: 0.9571 - val_loss: 0.1400 - val_acc: 0.9400

Epoch 9/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1523 - acc: 0.9592 - val_loss: 0.1300 - val_acc: 0.9400

Epoch 10/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1448 - acc: 0.9619 - val_loss: 0.1200 - val_acc: 0.9400

Epoch 11/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1397 - acc: 0.9628 - val_loss: 0.1100 - val_acc: 0.9400

Epoch 12/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1367 - acc: 0.9636 - val_loss: 0.1000 - val_acc: 0.9400

Epoch 13/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1283 - acc: 0.9661 - val_loss: 0.0900 - val_acc: 0.9400

Epoch 14/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1255 - acc: 0.9678 - val_loss: 0.0800 - val_acc: 0.9400

Epoch 15/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1248 - acc: 0.9686 - val_loss: 0.0700 - val_acc: 0.9400

Epoch 16/25

60000/60000 [=====] - 8s 129us/sample - loss: 0.1256 - acc: 0.9675 - val_loss: 0.0600 - val_acc: 0.9400

Epoch 17/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1187 - acc: 0.9704 - val_loss: 0.0500 - val_acc: 0.9400

Epoch 18/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1193 - acc: 0.9706 - val_loss: 0.0400 - val_acc: 0.9400

Epoch 19/25

60000/60000 [=====] - 8s 128us/sample - loss: 0.1193 - acc: 0.9701 - val_loss: 0.0300 - val_acc: 0.9400

```

Epoch 20/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.1173 - acc: 0.9718 - va
Epoch 21/25
60000/60000 [=====] - 8s 128us/sample - loss: 0.1166 - acc: 0.9709 - va
Epoch 22/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.1131 - acc: 0.9729 - va
Epoch 23/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.1125 - acc: 0.9729 - va
Epoch 24/25
60000/60000 [=====] - 8s 128us/sample - loss: 0.1102 - acc: 0.9738 - va
Epoch 25/25
60000/60000 [=====] - 8s 128us/sample - loss: 0.1119 - acc: 0.9736 - va

```

```

In [17]: print("*****")
         print("Printing the Model Summary")
         print(m23_model.summary())
         print("*****")

         score = m23_model.evaluate(x_test_new, y_test)

         print('Test score:', score[0])
         print('Test accuracy:', score[1])

         final_output = final_output.append({"#ConvNets": 2,
                                             "#Kernels/Filters": '3x3',
                                             "Padding": '-',
                                             "Stride": '2x2',
                                             "Dropout": True,
                                             "BatchNormalization": True,
                                             "Regularization": 'L2 (0.00001)',
                                             "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                             "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                             "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                             "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])

         fig,ax = plt.subplots(1,1)
         ax.set_xlabel('epoch')
         ax.set_ylabel('Categorical Crossentropy Loss')

         # list of epoch numbers
         x = list(range(1,n_epochs+1))

         vy = model.history['val_loss']
         ty = model.history['loss']
         plt_dynamic(x, vy, ty, ax)

```

```

*****
Printing the Model Summary

```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 13, 13, 32)	0
dropout (Dropout)	(None, 13, 13, 32)	0
conv2d_5 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_5 (MaxPooling2D)	(None, 5, 5, 64)	0
dropout_1 (Dropout)	(None, 5, 5, 64)	0
flatten_2 (Flatten)	(None, 1600)	0
dense_6 (Dense)	(None, 128)	204928
batch_normalization_v1 (Batch Normalization)	(None, 128)	512
dropout_2 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 64)	8256
batch_normalization_v1_1 (Batch Normalization)	(None, 64)	256
dropout_3 (Dropout)	(None, 64)	0
dense_8 (Dense)	(None, 10)	650

Total params: 233,418

Trainable params: 233,034

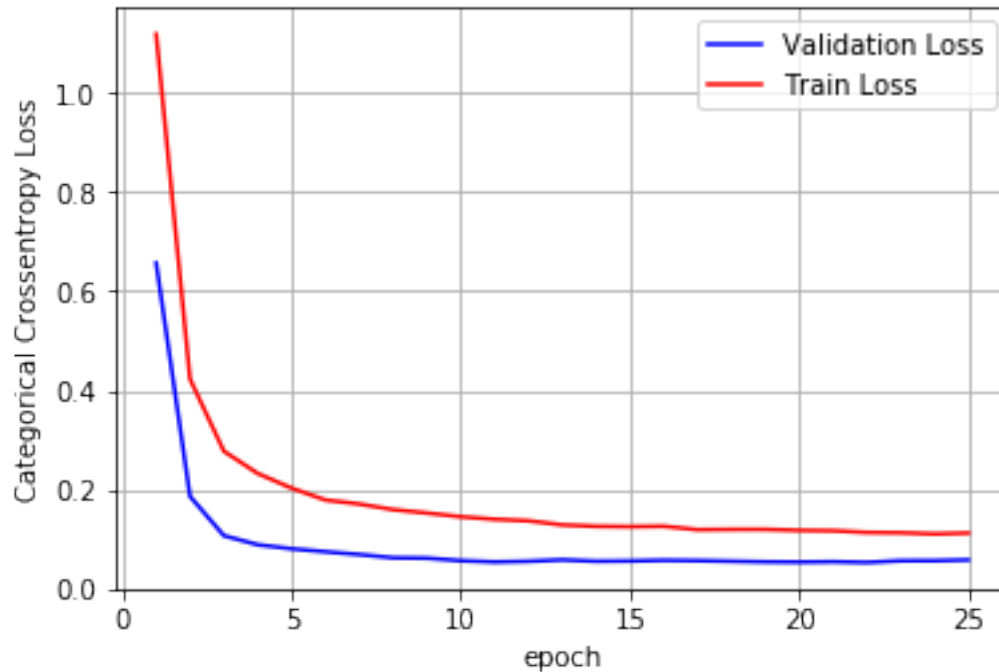
Non-trainable params: 384

None

10000/10000 [=====] - 1s 103us/sample - loss: 0.0577 - acc: 0.9881

Test score: 0.05770807054638863

Test accuracy: 0.9881



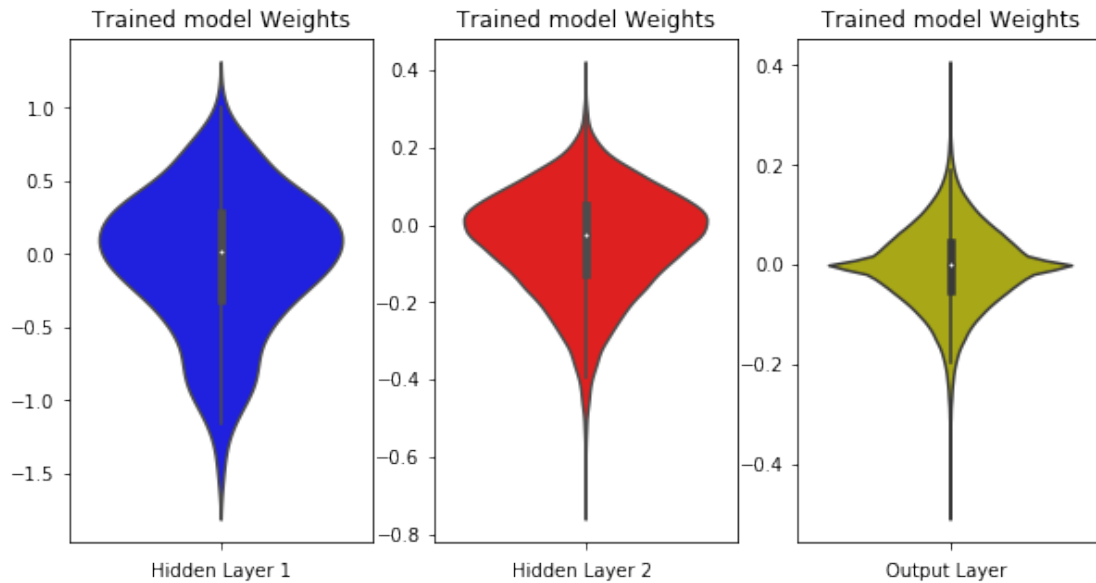
```
In [18]: w_after = m23_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.1.4 5x5 Kernel/Filter with Dropout, Weight Regularization/ initialization and Batch Normalization

```
In [19]: m24_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m24_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m24_model.add(MaxPooling2D(pool_size=(2,2)))

m24_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m24_model.add(Conv2D(64, kernel_size=(5,5), activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m24_model.add(MaxPooling2D(pool_size=(2,2)))

m24_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m24_model.add(Flatten())
m24_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m24_model.add(BatchNormalization())
m24_model.add(Dropout(rate=0.5))
m24_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m24_model.add(BatchNormalization())
m24_model.add(Dropout(rate=0.5))
```

```
m24_model.add(Dense(10, activation=tf.nn.softmax))
```

```
m24_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])  
model = m24_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)
```

Train on 60000 samples, validate on 10000 samples

```
Epoch 1/25  
60000/60000 [=====] - 8s 134us/sample - loss: 1.0503 - acc: 0.6756 - va  
Epoch 2/25  
60000/60000 [=====] - 7s 121us/sample - loss: 0.3364 - acc: 0.9034 - va  
Epoch 3/25  
60000/60000 [=====] - 7s 121us/sample - loss: 0.2353 - acc: 0.9347 - va  
Epoch 4/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.1901 - acc: 0.9484 - va  
Epoch 5/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.1669 - acc: 0.9546 - va  
Epoch 6/25  
60000/60000 [=====] - 7s 121us/sample - loss: 0.1498 - acc: 0.9595 - va  
Epoch 7/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.1355 - acc: 0.9646 - va  
Epoch 8/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.1291 - acc: 0.9658 - va  
Epoch 9/25  
60000/60000 [=====] - 7s 115us/sample - loss: 0.1223 - acc: 0.9679 - va  
Epoch 10/25  
60000/60000 [=====] - 7s 116us/sample - loss: 0.1185 - acc: 0.9699 - va  
Epoch 11/25  
60000/60000 [=====] - 7s 118us/sample - loss: 0.1096 - acc: 0.9718 - va  
Epoch 12/25  
60000/60000 [=====] - 7s 118us/sample - loss: 0.1050 - acc: 0.9727 - va  
Epoch 13/25  
60000/60000 [=====] - 7s 117us/sample - loss: 0.1038 - acc: 0.9742 - va  
Epoch 14/25  
60000/60000 [=====] - 7s 118us/sample - loss: 0.1009 - acc: 0.9743 - va  
Epoch 15/25  
60000/60000 [=====] - 7s 118us/sample - loss: 0.0999 - acc: 0.9751 - va  
Epoch 16/25  
60000/60000 [=====] - 7s 117us/sample - loss: 0.0973 - acc: 0.9761 - va  
Epoch 17/25  
60000/60000 [=====] - 7s 117us/sample - loss: 0.0974 - acc: 0.9764 - va  
Epoch 18/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.0923 - acc: 0.9783 - va  
Epoch 19/25  
60000/60000 [=====] - 7s 121us/sample - loss: 0.0940 - acc: 0.9777 - va  
Epoch 20/25  
60000/60000 [=====] - 7s 120us/sample - loss: 0.0950 - acc: 0.9776 - va  
Epoch 21/25
```

```

60000/60000 [=====] - 7s 121us/sample - loss: 0.0926 - acc: 0.9780 - va
Epoch 22/25
60000/60000 [=====] - 7s 121us/sample - loss: 0.0896 - acc: 0.9793 - va
Epoch 23/25
60000/60000 [=====] - 7s 122us/sample - loss: 0.0885 - acc: 0.9792 - va
Epoch 24/25
60000/60000 [=====] - 7s 122us/sample - loss: 0.0907 - acc: 0.9795 - va
Epoch 25/25
60000/60000 [=====] - 7s 122us/sample - loss: 0.0853 - acc: 0.9804 - va

```

```

In [20]: print("*****")
         print("Printing the Model Summary")
         print(m24_model.summary())
         print("*****")

         score = m24_model.evaluate(x_test_new, y_test)

         print('Test score:', score[0])
         print('Test accuracy:', score[1])

         final_output = final_output.append({"#ConvNets": 2,
                                             "Kernels/Filters": '5x5',
                                             "Padding": '-',
                                             "Stride": '2x2',
                                             "Dropout": True,
                                             "BatchNormalization": True,
                                             "Regularization": 'L2 (0.00001)',
                                             "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                             "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                             "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                             "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])

         fig, ax = plt.subplots(1,1)
         ax.set_xlabel('epoch')
         ax.set_ylabel('Categorical Crossentropy Loss')

         # list of epoch numbers
         x = list(range(1,n_epochs+1))

         vy = model.history['val_loss']
         ty = model.history['loss']
         plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

```

-----
Layer (type)                Output Shape                Param #

```

```

=====
conv2d_6 (Conv2D)          (None, 24, 24, 32)      832
-----
max_pooling2d_6 (MaxPooling2 (None, 12, 12, 32)      0
-----
dropout_4 (Dropout)        (None, 12, 12, 32)      0
-----
conv2d_7 (Conv2D)          (None, 8, 8, 64)       51264
-----
max_pooling2d_7 (MaxPooling2 (None, 4, 4, 64)        0
-----
dropout_5 (Dropout)        (None, 4, 4, 64)        0
-----
flatten_3 (Flatten)        (None, 1024)            0
-----
dense_9 (Dense)            (None, 128)            131200
-----
batch_normalization_v1_2 (Ba (None, 128)            512
-----
dropout_6 (Dropout)        (None, 128)            0
-----
dense_10 (Dense)           (None, 64)             8256
-----
batch_normalization_v1_3 (Ba (None, 64)            256
-----
dropout_7 (Dropout)        (None, 64)             0
-----
dense_11 (Dense)           (None, 10)             650
=====

```

```

Total params: 192,970
Trainable params: 192,586
Non-trainable params: 384

```

```

-----
None

```

```

*****

```

```

10000/10000 [=====] - 1s 107us/sample - loss: 0.0497 - acc: 0.9899

```

```

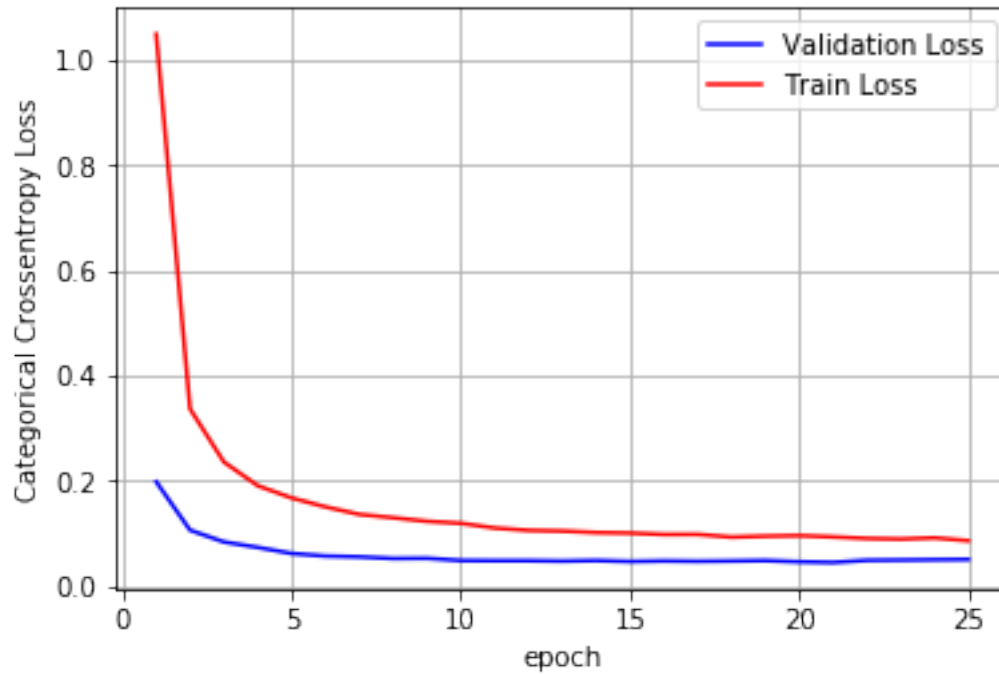
Test score: 0.04970202516615391

```

```

Test accuracy: 0.9899

```



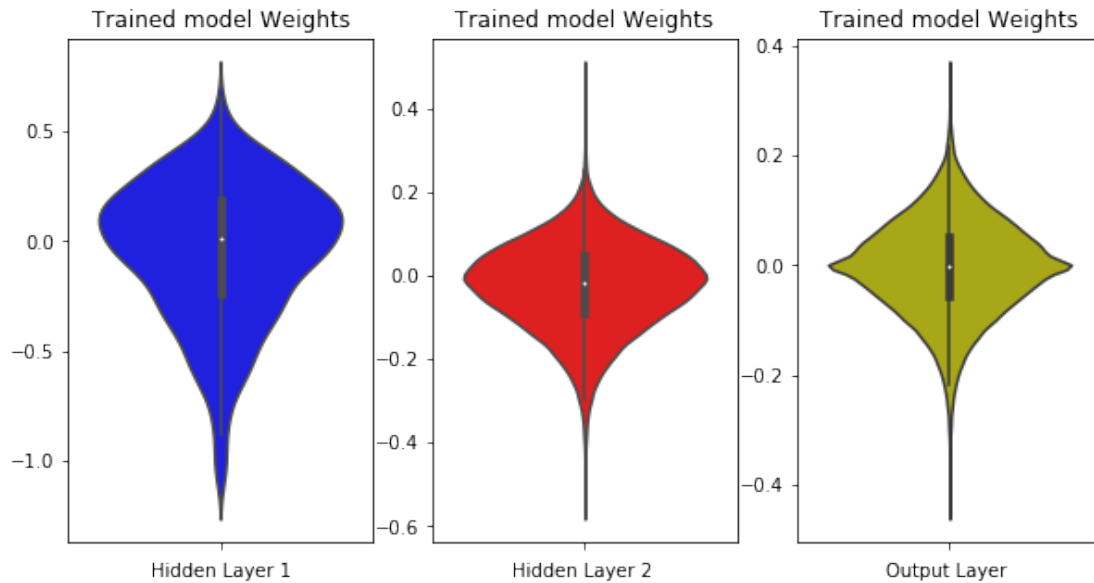
```
In [21]: w_after = m24_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.2 3 ConvNet Architecture

In this type of architecture, we will be trying out 3 convolution layer along with 3 maxpooling layer for each.

2.2.1 3x3 Filter/Kernel

```
In [22]: m31_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m31_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu, input_shape=(28,28,1)
m31_model.add(MaxPooling2D(pool_size=(2,2)))

# Second Convolutional layer with MaxPooling
m31_model.add(Conv2D(64, kernel_size=(3,3), activation=tf.nn.relu))
m31_model.add(MaxPooling2D(pool_size=(2,2)))

# Third Convolutional layer with MaxPooling
m31_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu))
m31_model.add(MaxPooling2D(pool_size=(2,2)))

# Three dense layers in MLP
m31_model.add(Flatten())
m31_model.add(Dense(128, activation=tf.nn.relu))
m31_model.add(Dense(64, activation=tf.nn.relu))
m31_model.add(Dense(10, activation=tf.nn.softmax))
```

```

m31_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m31_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 7s 110us/sample - loss: 0.4676 - acc: 0.8478 - val_loss: 0.4676 - val_acc: 0.8478
Epoch 2/25
60000/60000 [=====] - 6s 104us/sample - loss: 0.1543 - acc: 0.9522 - val_loss: 0.1543 - val_acc: 0.9522
Epoch 3/25
60000/60000 [=====] - 6s 104us/sample - loss: 0.1131 - acc: 0.9648 - val_loss: 0.1131 - val_acc: 0.9648
Epoch 4/25
60000/60000 [=====] - 6s 102us/sample - loss: 0.0940 - acc: 0.9704 - val_loss: 0.0940 - val_acc: 0.9704
Epoch 5/25
60000/60000 [=====] - 6s 102us/sample - loss: 0.0804 - acc: 0.9750 - val_loss: 0.0804 - val_acc: 0.9750
Epoch 6/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.0691 - acc: 0.9785 - val_loss: 0.0691 - val_acc: 0.9785
Epoch 7/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.0607 - acc: 0.9808 - val_loss: 0.0607 - val_acc: 0.9808
Epoch 8/25
60000/60000 [=====] - 6s 102us/sample - loss: 0.0535 - acc: 0.9830 - val_loss: 0.0535 - val_acc: 0.9830
Epoch 9/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.0492 - acc: 0.9846 - val_loss: 0.0492 - val_acc: 0.9846
Epoch 10/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.0444 - acc: 0.9861 - val_loss: 0.0444 - val_acc: 0.9861
Epoch 11/25
60000/60000 [=====] - 6s 101us/sample - loss: 0.0408 - acc: 0.9863 - val_loss: 0.0408 - val_acc: 0.9863
Epoch 12/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0355 - acc: 0.9886 - val_loss: 0.0355 - val_acc: 0.9886
Epoch 13/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0324 - acc: 0.9895 - val_loss: 0.0324 - val_acc: 0.9895
Epoch 14/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0294 - acc: 0.9904 - val_loss: 0.0294 - val_acc: 0.9904
Epoch 15/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0262 - acc: 0.9912 - val_loss: 0.0262 - val_acc: 0.9912
Epoch 16/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0251 - acc: 0.9921 - val_loss: 0.0251 - val_acc: 0.9921
Epoch 17/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0214 - acc: 0.9930 - val_loss: 0.0214 - val_acc: 0.9930
Epoch 18/25
60000/60000 [=====] - 6s 100us/sample - loss: 0.0200 - acc: 0.9932 - val_loss: 0.0200 - val_acc: 0.9932
Epoch 19/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0190 - acc: 0.9934 - val_loss: 0.0190 - val_acc: 0.9934
Epoch 20/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0186 - acc: 0.9937 - val_loss: 0.0186 - val_acc: 0.9937
Epoch 21/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0148 - acc: 0.9952 - val_loss: 0.0148 - val_acc: 0.9952
Epoch 22/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0153 - acc: 0.9946 - val_loss: 0.0153 - val_acc: 0.9946

```



```
Epoch 23/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0121 - acc: 0.9961 - val
Epoch 24/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0146 - acc: 0.9947 - val
Epoch 25/25
60000/60000 [=====] - 6s 99us/sample - loss: 0.0114 - acc: 0.9961 - val
```

```
In [23]: print("*****")
print("Printing the Model Summary")
print(m31_model.summary())
print("*****")

score = m31_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 3,
                                     "#Kernels/Filters": '3x3',
                                     "Padding": '-',
                                     "Stride": '2x2',
                                     "Dropout": '-',
                                     "BatchNormalization": False,
                                     "Regularization": '-',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
*****
```

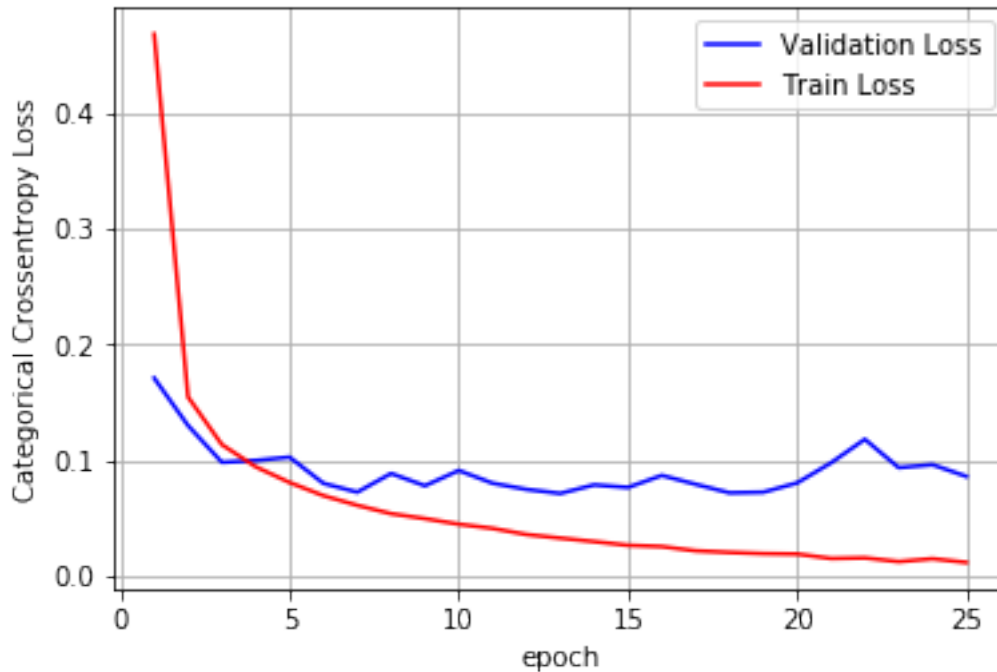
```
Printing the Model Summary
```

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 26, 26, 32)	320

```

-----
max_pooling2d_8 (MaxPooling2 (None, 13, 13, 32)      0
-----
conv2d_9 (Conv2D)          (None, 11, 11, 64)      18496
-----
max_pooling2d_9 (MaxPooling2 (None, 5, 5, 64)      0
-----
conv2d_10 (Conv2D)         (None, 3, 3, 32)      18464
-----
max_pooling2d_10 (MaxPooling (None, 1, 1, 32)      0
-----
flatten_4 (Flatten)        (None, 32)          0
-----
dense_12 (Dense)           (None, 128)         4224
-----
dense_13 (Dense)           (None, 64)          8256
-----
dense_14 (Dense)           (None, 10)          650
=====
Total params: 50,410
Trainable params: 50,410
Non-trainable params: 0
-----
None
*****
10000/10000 [=====] - 1s 85us/sample - loss: 0.0857 - acc: 0.9812
Test score: 0.08567447326574075
Test accuracy: 0.9812

```



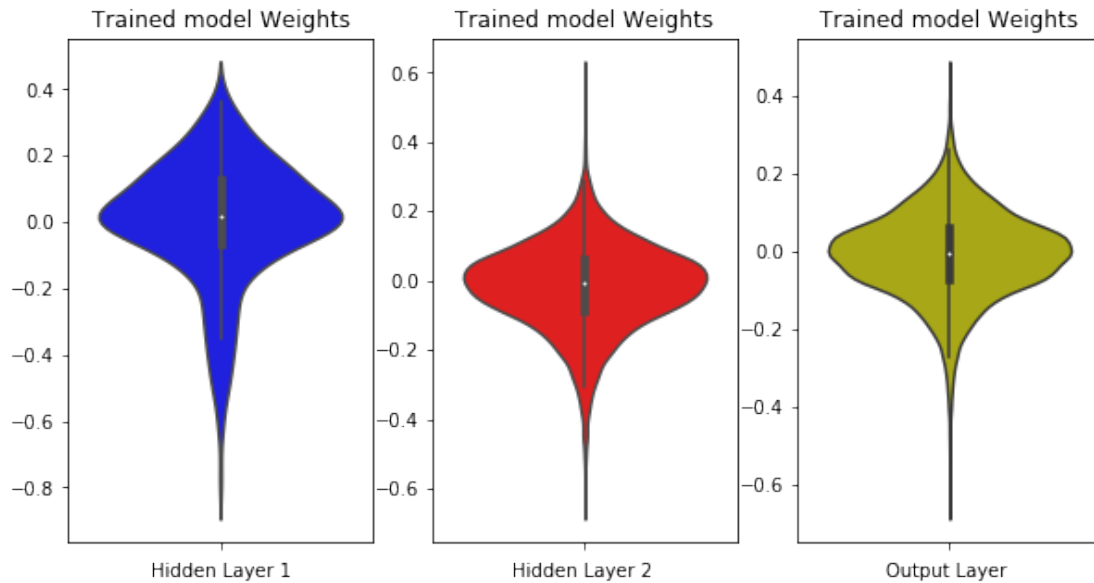
```
In [24]: w_after = m31_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.2.2 5x5 Kernel/Filter

In [25]: m32_model = Sequential()

```
# First Convolutional layer with MaxPooling
m32_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu, inp
m32_model.add(MaxPooling2D(pool_size=(2,2)))

# Second Convolutional layer with MaxPooling
m32_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m32_model.add(MaxPooling2D(pool_size=(2,2)))

# Third Convolutional layer with MaxPooling
m32_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m32_model.add(MaxPooling2D(pool_size=(2,2)))

# Three dense layers in MLP
m32_model.add(Flatten())
m32_model.add(Dense(128, activation=tf.nn.relu))
m32_model.add(Dense(64, activation=tf.nn.relu))
m32_model.add(Dense(10, activation=tf.nn.softmax))

m32_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy
model = m32_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verb
```

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 8s 138us/sample - loss: 0.2470 - acc: 0.9249 - va
Epoch 2/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.0691 - acc: 0.9786 - va
Epoch 3/25
60000/60000 [=====] - 8s 129us/sample - loss: 0.0485 - acc: 0.9851 - va
Epoch 4/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0383 - acc: 0.9875 - va
Epoch 5/25
60000/60000 [=====] - 8s 129us/sample - loss: 0.0329 - acc: 0.9895 - va
Epoch 6/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0250 - acc: 0.9916 - va
Epoch 7/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.0224 - acc: 0.9926 - va
Epoch 8/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0175 - acc: 0.9944 - va
Epoch 9/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0160 - acc: 0.9944 - va
Epoch 10/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0141 - acc: 0.9952 - va
Epoch 11/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0114 - acc: 0.9962 - va
Epoch 12/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0125 - acc: 0.9960 - va
Epoch 13/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0111 - acc: 0.9961 - va
Epoch 14/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0098 - acc: 0.9969 - va
Epoch 15/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0095 - acc: 0.9967 - va
Epoch 16/25
60000/60000 [=====] - 8s 127us/sample - loss: 0.0082 - acc: 0.9972 - va
Epoch 17/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0072 - acc: 0.9976 - va
Epoch 18/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0064 - acc: 0.9979 - va
Epoch 19/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0081 - acc: 0.9974 - va
Epoch 20/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0056 - acc: 0.9982 - va
Epoch 21/25
60000/60000 [=====] - 8s 125us/sample - loss: 0.0055 - acc: 0.9982 - va
Epoch 22/25
60000/60000 [=====] - 8s 125us/sample - loss: 0.0078 - acc: 0.9976 - va
Epoch 23/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0059 - acc: 0.9981 - va
Epoch 24/25
60000/60000 [=====] - 8s 126us/sample - loss: 0.0064 - acc: 0.9980 - va
Epoch 25/25

60000/60000 [=====] - 8s 126us/sample - loss: 0.0026 - acc: 0.9994 - va

```
In [26]: print("*****")
print("Printing the Model Summary")
print(m32_model.summary())
print("*****")

score = m32_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 3,
                                     "#Kernels/Filters": '5x5',
                                     "Padding": 'same',
                                     "Stride": '2x2',
                                     "Dropout": False,
                                     "BatchNormalization": False,
                                     "Regularization": '-',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)
```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_11 (Conv2D)	(None, 28, 28, 32)	832
max_pooling2d_11 (MaxPooling)	(None, 14, 14, 32)	0
conv2d_12 (Conv2D)	(None, 14, 14, 64)	51264

max_pooling2d_12 (MaxPooling (None, 7, 7, 64))	0

conv2d_13 (Conv2D) (None, 7, 7, 32)	51232

max_pooling2d_13 (MaxPooling (None, 3, 3, 32))	0

flatten_5 (Flatten) (None, 288)	0

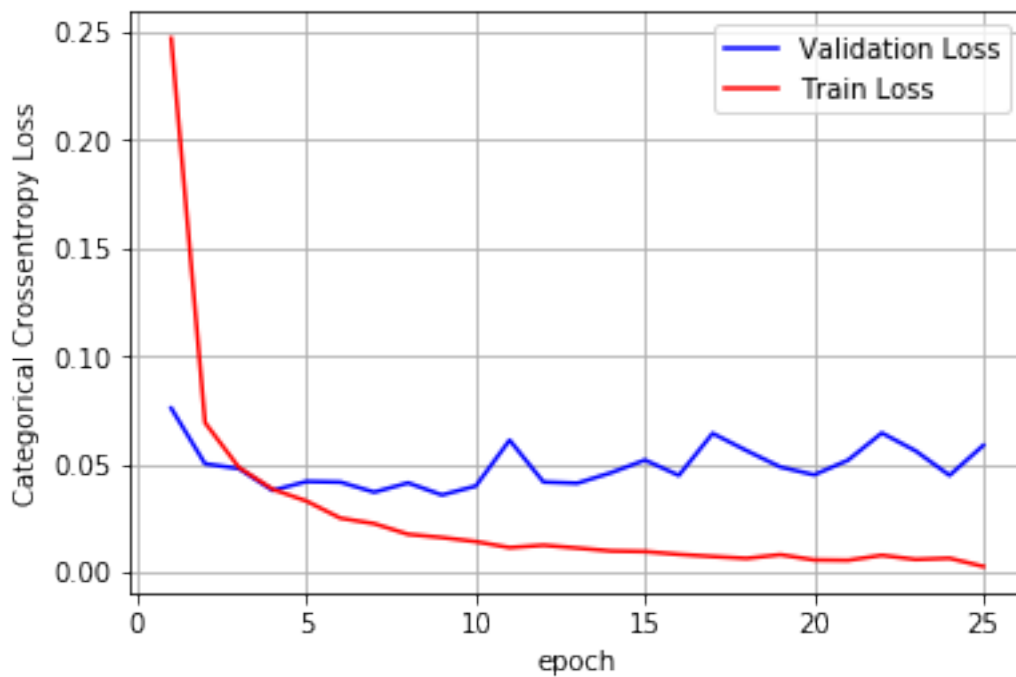
dense_15 (Dense) (None, 128)	36992

dense_16 (Dense) (None, 64)	8256

dense_17 (Dense) (None, 10)	650
=====	
Total params: 149,226	
Trainable params: 149,226	
Non-trainable params: 0	

None	

10000/10000 [=====] - 1s 106us/sample - loss: 0.0587 - acc: 0.9890	
Test score: 0.05866653555549251	
Test accuracy: 0.989	



```

In [27]: w_after = m32_model.get_weights()

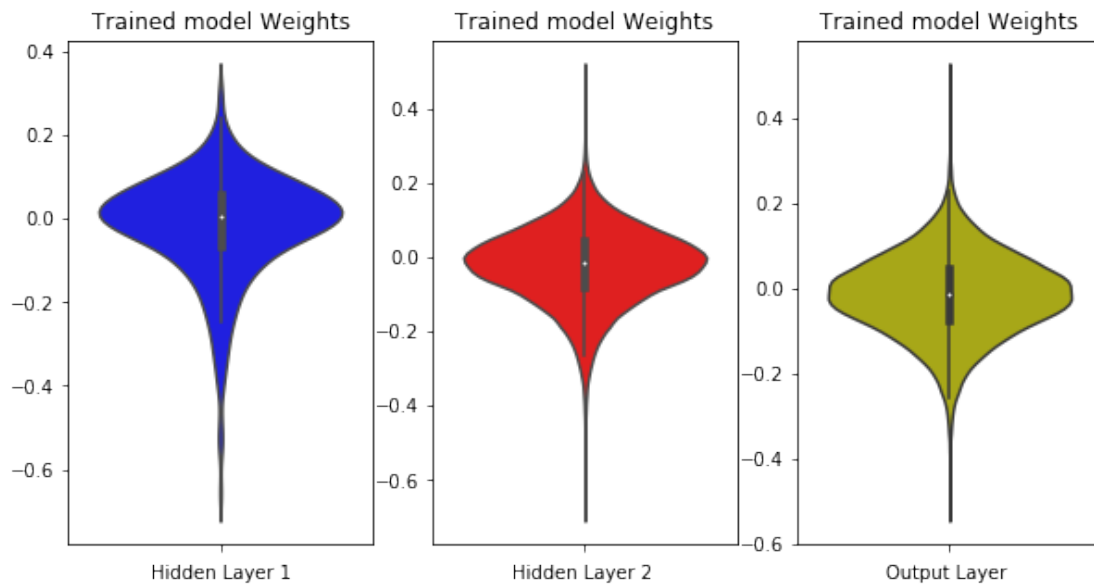
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()

```



2.2.3 3x3 Kernel/Filter with Dropout and Weights Regularization & Initialization and Batch Normalization

```
In [28]: m33_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m33_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m33_model.add(MaxPooling2D(pool_size=(2,2)))

m33_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m33_model.add(Conv2D(64, kernel_size=(3,3), activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m33_model.add(MaxPooling2D(pool_size=(2,2)))

m33_model.add(Dropout(rate=0.5))

# Third Convolutional layer with MaxPooling
m33_model.add(Conv2D(32, kernel_size=(3,3), activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m33_model.add(MaxPooling2D(pool_size=(2,2)))

m33_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m33_model.add(Flatten())
m33_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m33_model.add(BatchNormalization())
m33_model.add(Dropout(rate=0.5))
m33_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m33_model.add(BatchNormalization())
m33_model.add(Dropout(rate=0.5))
m33_model.add(Dense(10, activation=tf.nn.softmax))
```

```
m33_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m33_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)
```

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 10s 161us/sample - loss: 2.4852 - acc: 0.1963 - val_loss: 2.4852 - val_acc: 0.1963

Epoch 2/25

60000/60000 [=====] - 8s 140us/sample - loss: 1.5537 - acc: 0.4574 - val_loss: 1.5537 - val_acc: 0.4574

Epoch 3/25

60000/60000 [=====] - 8s 140us/sample - loss: 1.1184 - acc: 0.6223 - val_loss: 1.1184 - val_acc: 0.6223

Epoch 4/25

60000/60000 [=====] - 8s 139us/sample - loss: 0.9041 - acc: 0.7059 - val_loss: 0.9041 - val_acc: 0.7059

```

Epoch 5/25
60000/60000 [=====] - 8s 138us/sample - loss: 0.7661 - acc: 0.7604 - va
Epoch 6/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.6918 - acc: 0.7858 - va
Epoch 7/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.6360 - acc: 0.8064 - va
Epoch 8/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.5914 - acc: 0.8265 - va
Epoch 9/25
60000/60000 [=====] - 8s 137us/sample - loss: 0.5582 - acc: 0.8349 - va
Epoch 10/25
60000/60000 [=====] - 8s 136us/sample - loss: 0.5350 - acc: 0.8443 - va
Epoch 11/25
60000/60000 [=====] - 8s 136us/sample - loss: 0.5124 - acc: 0.8513 - va
Epoch 12/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4988 - acc: 0.8566 - va
Epoch 13/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4872 - acc: 0.8616 - va
Epoch 14/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4703 - acc: 0.8667 - va
Epoch 15/25
60000/60000 [=====] - 8s 138us/sample - loss: 0.4619 - acc: 0.8695 - va
Epoch 16/25
60000/60000 [=====] - 8s 137us/sample - loss: 0.4499 - acc: 0.8731 - va
Epoch 17/25
60000/60000 [=====] - 8s 140us/sample - loss: 0.4434 - acc: 0.8752 - va
Epoch 18/25
60000/60000 [=====] - 8s 140us/sample - loss: 0.4376 - acc: 0.8776 - va
Epoch 19/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4296 - acc: 0.8812 - va
Epoch 20/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4274 - acc: 0.8802 - va
Epoch 21/25
60000/60000 [=====] - 9s 142us/sample - loss: 0.4229 - acc: 0.8820 - va
Epoch 22/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4182 - acc: 0.8842 - va
Epoch 23/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4122 - acc: 0.8852 - va
Epoch 24/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4126 - acc: 0.8870 - va
Epoch 25/25
60000/60000 [=====] - 8s 139us/sample - loss: 0.4088 - acc: 0.8870 - va

```

```

In [29]: print("*****")
         print("Printing the Model Summary")
         print(m33_model.summary())
         print("*****")

```

```

score = m33_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 3,
                                     "#Kernels/Filters": '3x3',
                                     "Padding": '-',
                                     "Stride": '2x2',
                                     "Dropout": True,
                                     "BatchNormalization": True,
                                     "Regularization": 'L2 (0.00001)',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"][-1]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"][-1]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"][-1]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"][-1])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_14 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_14 (MaxPooling)	(None, 13, 13, 32)	0
dropout_8 (Dropout)	(None, 13, 13, 32)	0
conv2d_15 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_15 (MaxPooling)	(None, 5, 5, 64)	0
dropout_9 (Dropout)	(None, 5, 5, 64)	0
conv2d_16 (Conv2D)	(None, 3, 3, 32)	18464

max_pooling2d_16 (MaxPooling)	(None, 1, 1, 32)	0

dropout_10 (Dropout)	(None, 1, 1, 32)	0

flatten_6 (Flatten)	(None, 32)	0

dense_18 (Dense)	(None, 128)	4224

batch_normalization_v1_4 (Batch Normalization)	(None, 128)	512

dropout_11 (Dropout)	(None, 128)	0

dense_19 (Dense)	(None, 64)	8256

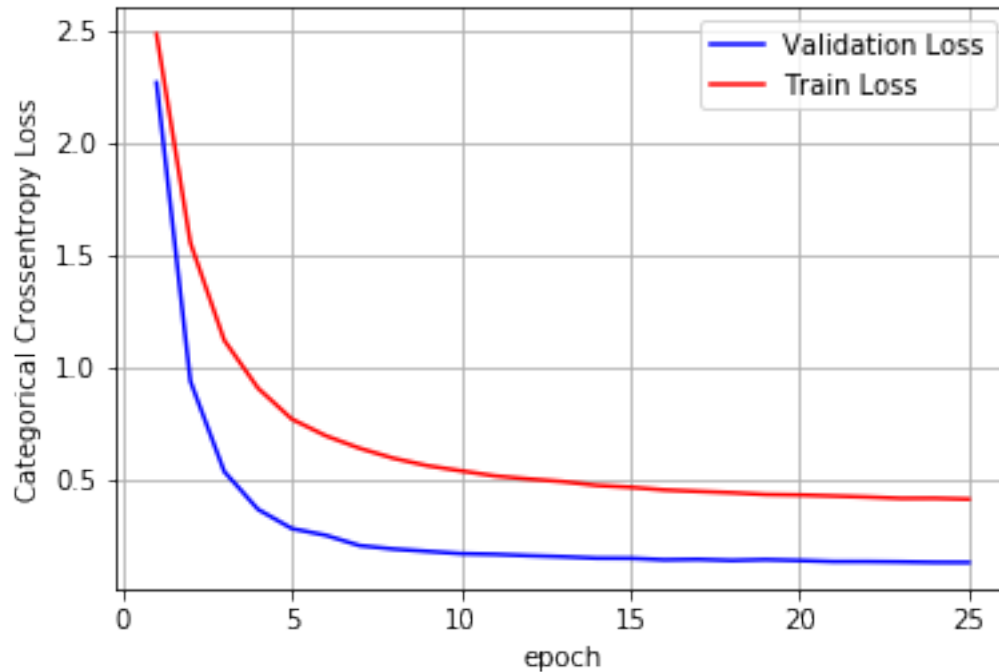
batch_normalization_v1_5 (Batch Normalization)	(None, 64)	256

dropout_12 (Dropout)	(None, 64)	0

dense_20 (Dense)	(None, 10)	650
=====		
Total params: 51,178		
Trainable params: 50,794		
Non-trainable params: 384		

None		

10000/10000 [=====] - 1s 112us/sample - loss: 0.1261 - acc: 0.9679		
Test score: 0.1261051001906395		
Test accuracy: 0.9679		



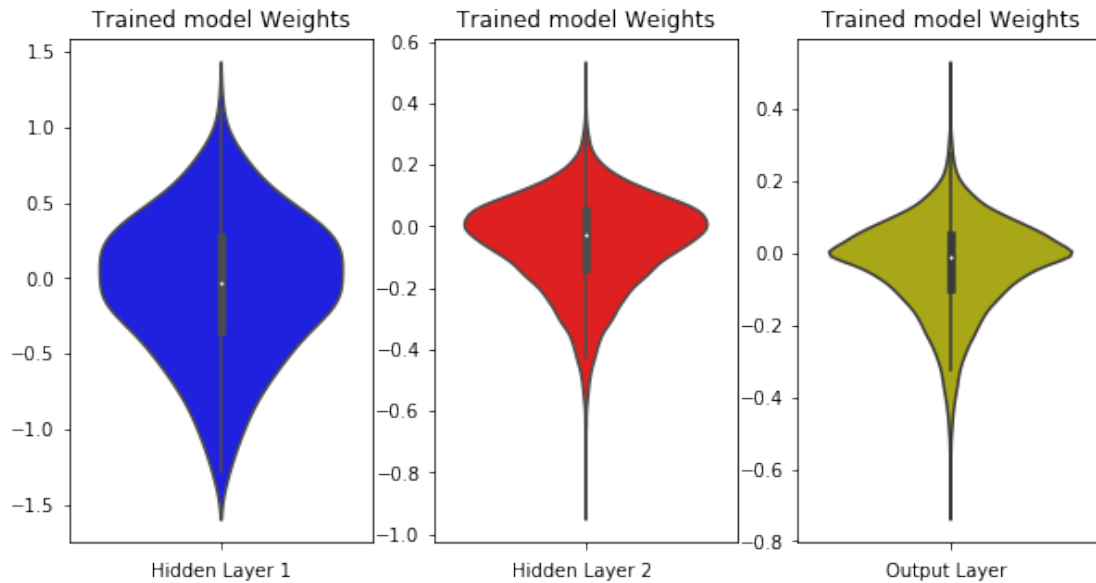
```
In [30]: w_after = m33_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.2.4 5x5 Kernel/Filter with Dropout, Weight Regularization/ initialization and Batch Normalization

In [31]: `m34_model = Sequential()`

```
# First Convolutional layer with MaxPooling
m34_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, padding="same", input_shape=(28, 28, 1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m34_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m34_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m34_model.add(Conv2D(64, kernel_size=(5,5), activation=tf.nn.relu, padding="same",
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m34_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m34_model.add(Dropout(rate=0.5))

# Third Convolutional layer with MaxPooling
m34_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, padding="same",
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m34_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m34_model.add(Dropout(rate=0.5))

# Fourth Convolutional layer with MaxPooling
```

```

m34_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, padding="same",
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(1e-4)))
m34_model.add(MaxPooling2D(pool_size=(2,2)))

m34_model.add(Dropout(rate=0.5))

# Fifth Convolutional layer with MaxPooling
m34_model.add(Conv2D(32, kernel_size=(5,5), activation=tf.nn.relu, padding="same",
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(1e-4)))
m34_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m34_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m34_model.add(Flatten())
m34_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(1e-4)))
m34_model.add(BatchNormalization())
m34_model.add(Dropout(rate=0.5))
m34_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(1e-4)))
m34_model.add(BatchNormalization())
m34_model.add(Dropout(rate=0.5))
m34_model.add(Dense(10, activation=tf.nn.softmax))

m34_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m34_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 12s 199us/sample - loss: 2.4554 - acc: 0.1821 - val_loss: 2.4554 - val_acc: 0.1821
Epoch 2/25
60000/60000 [=====] - 11s 178us/sample - loss: 1.6683 - acc: 0.3192 - val_loss: 1.6683 - val_acc: 0.3192
Epoch 3/25
60000/60000 [=====] - 11s 178us/sample - loss: 1.4748 - acc: 0.3810 - val_loss: 1.4748 - val_acc: 0.3810
Epoch 4/25
60000/60000 [=====] - 11s 178us/sample - loss: 1.3223 - acc: 0.4378 - val_loss: 1.3223 - val_acc: 0.4378
Epoch 5/25
60000/60000 [=====] - 11s 178us/sample - loss: 1.1281 - acc: 0.5334 - val_loss: 1.1281 - val_acc: 0.5334
Epoch 6/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.9818 - acc: 0.6104 - val_loss: 0.9818 - val_acc: 0.6104
Epoch 7/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.8646 - acc: 0.6875 - val_loss: 0.8646 - val_acc: 0.6875
Epoch 8/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.6982 - acc: 0.7766 - val_loss: 0.6982 - val_acc: 0.7766
Epoch 9/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.5794 - acc: 0.8276 - val_loss: 0.5794 - val_acc: 0.8276
Epoch 10/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.4943 - acc: 0.8582 - val_loss: 0.4943 - val_acc: 0.8582

```

```

Epoch 11/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.4528 - acc: 0.8742 - v
Epoch 12/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.4146 - acc: 0.8893 - v
Epoch 13/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.3819 - acc: 0.8985 - v
Epoch 14/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.3710 - acc: 0.9036 - v
Epoch 15/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.3453 - acc: 0.9120 - v
Epoch 16/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.3310 - acc: 0.9179 - v
Epoch 17/25
60000/60000 [=====] - 11s 178us/sample - loss: 0.3109 - acc: 0.9244 - v
Epoch 18/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.3003 - acc: 0.9275 - v
Epoch 19/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2858 - acc: 0.9311 - v
Epoch 20/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2788 - acc: 0.9354 - v
Epoch 21/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2730 - acc: 0.9369 - v
Epoch 22/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2666 - acc: 0.9392 - v
Epoch 23/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2602 - acc: 0.9403 - v
Epoch 24/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.2580 - acc: 0.9419 - v
Epoch 25/25
60000/60000 [=====] - 11s 179us/sample - loss: 0.2488 - acc: 0.9449 - v

```

```

In [32]: print("*****")
          print("Printing the Model Summary")
          print(m34_model.summary())
          print("*****")

          score = m34_model.evaluate(x_test_new, y_test)

          print('Test score:', score[0])
          print('Test accuracy:', score[1])

          final_output = final_output.append({"#ConvNets": 3,
                                              "#Kernels/Filters": '5x5',
                                              "Padding": 'same',
                                              "Stride": '2x2',
                                              "Dropout": True,
                                              "BatchNormalization": True,

```



```

"Regularization": 'L2 (0.00001)',
"TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
"TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
"TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
"TEST_ACC": '{:.5f}'.format(model.history["val_acc"])

```

```

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

```

```

# list of epoch numbers
x = list(range(1,n_epochs+1))

```

```

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_17 (Conv2D)	(None, 28, 28, 32)	832
max_pooling2d_17 (MaxPooling)	(None, 14, 14, 32)	0
dropout_13 (Dropout)	(None, 14, 14, 32)	0
conv2d_18 (Conv2D)	(None, 14, 14, 64)	51264
max_pooling2d_18 (MaxPooling)	(None, 7, 7, 64)	0
dropout_14 (Dropout)	(None, 7, 7, 64)	0
conv2d_19 (Conv2D)	(None, 7, 7, 32)	51232
max_pooling2d_19 (MaxPooling)	(None, 4, 4, 32)	0
dropout_15 (Dropout)	(None, 4, 4, 32)	0
conv2d_20 (Conv2D)	(None, 4, 4, 32)	25632
max_pooling2d_20 (MaxPooling)	(None, 2, 2, 32)	0
dropout_16 (Dropout)	(None, 2, 2, 32)	0
conv2d_21 (Conv2D)	(None, 2, 2, 32)	25632

max_pooling2d_21 (MaxPooling)	(None, 1, 1, 32)	0

dropout_17 (Dropout)	(None, 1, 1, 32)	0

flatten_7 (Flatten)	(None, 32)	0

dense_21 (Dense)	(None, 128)	4224

batch_normalization_v1_6 (Batch Normalization)	(None, 128)	512

dropout_18 (Dropout)	(None, 128)	0

dense_22 (Dense)	(None, 64)	8256

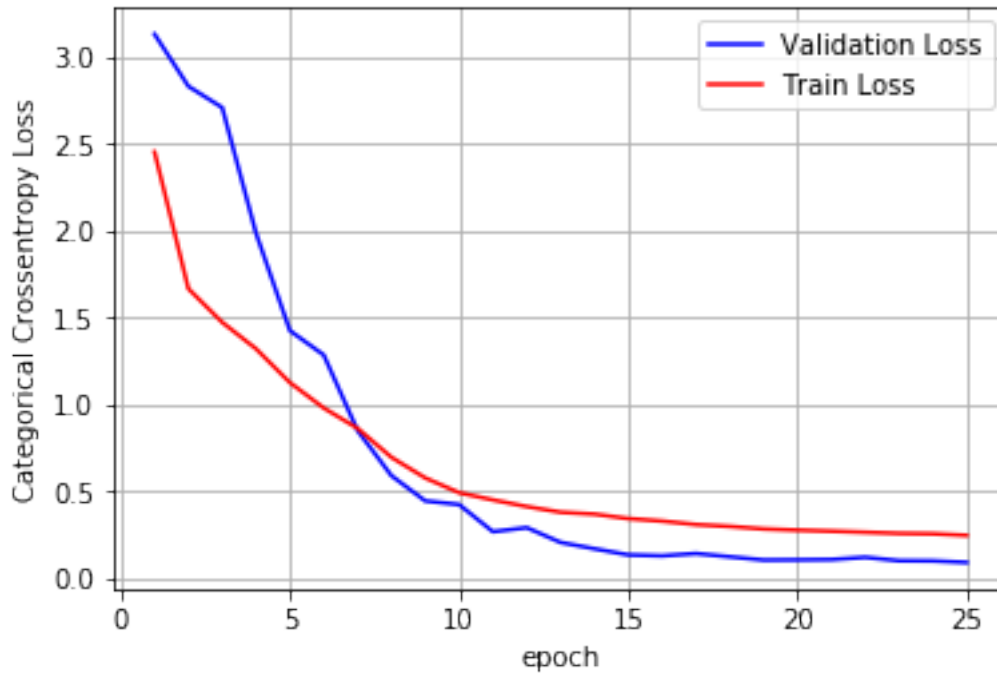
batch_normalization_v1_7 (Batch Normalization)	(None, 64)	256

dropout_19 (Dropout)	(None, 64)	0

dense_23 (Dense)	(None, 10)	650
=====		
Total params: 168,490		
Trainable params: 168,106		
Non-trainable params: 384		

None		

10000/10000 [=====] - 1s 143us/sample - loss: 0.0930 - acc: 0.9821		
Test score: 0.0929575339615345		
Test accuracy: 0.9821		



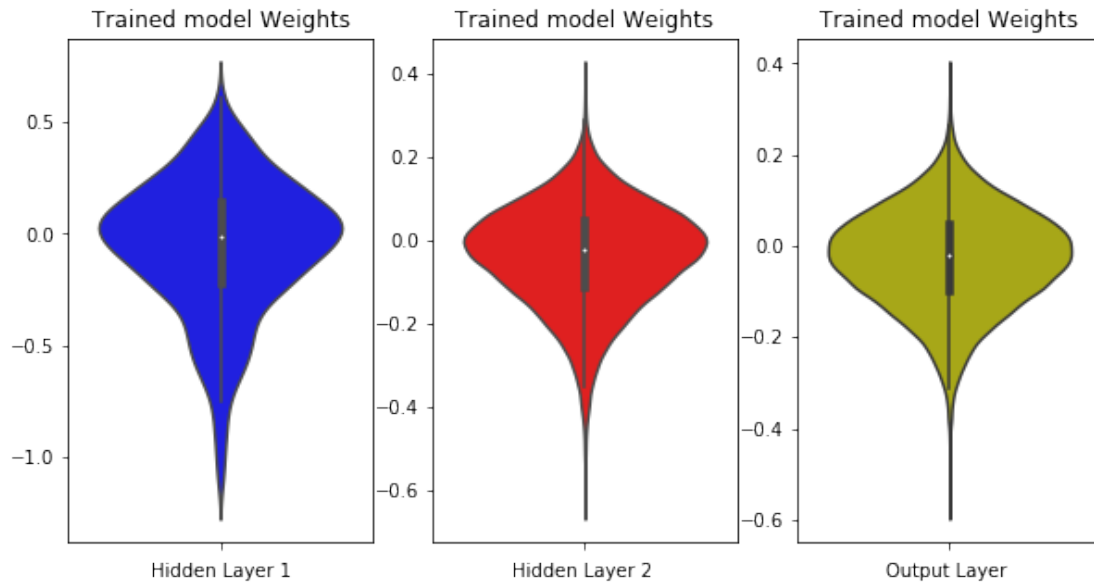
```
In [33]: w_after = m34_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.3 5 ConvNet Architecture

In this type of architecture, we will be trying out 5 convolution layers along with 5 maxpooling layer for each.

2.3.1 3x3 Kernel/Filter

```
In [34]: m51_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m51_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu, input_shape=(28,28,1)))
m51_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Second Convolutional layer with MaxPooling
m51_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu))
m51_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Third Convolutional layer with MaxPooling
m51_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu))
m51_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Fourth Convolutional layer with MaxPooling
m51_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu))
m51_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Fifth Convolutional layer with MaxPooling
m51_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu))
m51_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))
```

```

# Three dense layers in MLP
m51_model.add(Flatten())
m51_model.add(Dense(128, activation=tf.nn.relu))
m51_model.add(BatchNormalization())
m51_model.add(Dropout(rate=0.5))
m51_model.add(Dense(64, activation=tf.nn.relu))
m51_model.add(BatchNormalization())
m51_model.add(Dropout(rate=0.5))
m51_model.add(Dense(10, activation=tf.nn.softmax))

m51_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m51_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 11s 191us/sample - loss: 0.4281 - acc: 0.8713 - val_loss: 0.3801 - val_acc: 0.8850
Epoch 2/25
60000/60000 [=====] - 10s 169us/sample - loss: 0.1139 - acc: 0.9693 - val_loss: 0.0808 - val_acc: 0.9776
Epoch 3/25
60000/60000 [=====] - 10s 169us/sample - loss: 0.0808 - acc: 0.9776 - val_loss: 0.0646 - val_acc: 0.9819
Epoch 4/25
60000/60000 [=====] - 10s 169us/sample - loss: 0.0646 - acc: 0.9819 - val_loss: 0.0543 - val_acc: 0.9851
Epoch 5/25
60000/60000 [=====] - 10s 169us/sample - loss: 0.0543 - acc: 0.9851 - val_loss: 0.0415 - val_acc: 0.9882
Epoch 6/25
60000/60000 [=====] - 10s 168us/sample - loss: 0.0415 - acc: 0.9882 - val_loss: 0.0403 - val_acc: 0.9884
Epoch 7/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0403 - acc: 0.9884 - val_loss: 0.0339 - val_acc: 0.9904
Epoch 8/25
60000/60000 [=====] - 10s 165us/sample - loss: 0.0339 - acc: 0.9904 - val_loss: 0.0296 - val_acc: 0.9913
Epoch 9/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0296 - acc: 0.9913 - val_loss: 0.0272 - val_acc: 0.9923
Epoch 10/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0272 - acc: 0.9923 - val_loss: 0.0222 - val_acc: 0.9931
Epoch 11/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0222 - acc: 0.9931 - val_loss: 0.0237 - val_acc: 0.9932
Epoch 12/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0237 - acc: 0.9932 - val_loss: 0.0205 - val_acc: 0.9935
Epoch 13/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0205 - acc: 0.9935 - val_loss: 0.0193 - val_acc: 0.9945
Epoch 14/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0193 - acc: 0.9945 - val_loss: 0.0151 - val_acc: 0.9956
Epoch 15/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0151 - acc: 0.9956 - val_loss: 0.0151 - val_acc: 0.9955
Epoch 16/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0151 - acc: 0.9955 - val_loss: 0.0151 - val_acc: 0.9955

```

```

Epoch 17/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0147 - acc: 0.9954 - v
Epoch 18/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0144 - acc: 0.9954 - v
Epoch 19/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0145 - acc: 0.9956 - v
Epoch 20/25
60000/60000 [=====] - 10s 166us/sample - loss: 0.0123 - acc: 0.9965 - v
Epoch 21/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0103 - acc: 0.9969 - v
Epoch 22/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0109 - acc: 0.9967 - v
Epoch 23/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0107 - acc: 0.9966 - v
Epoch 24/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0117 - acc: 0.9967 - v
Epoch 25/25
60000/60000 [=====] - 10s 167us/sample - loss: 0.0082 - acc: 0.9976 - v

```

```

In [35]: print("*****")
         print("Printing the Model Summary")
         print(m51_model.summary())
         print("*****")

         score = m51_model.evaluate(x_test_new, y_test)

         print('Test score:', score[0])
         print('Test accuracy:', score[1])

         final_output = final_output.append({"#ConvNets": 5,
                                             "#Kernels/Filters": '3x3',
                                             "Padding": 'same',
                                             "Stride": '2x2',
                                             "Dropout": False,
                                             "BatchNormalization": False,
                                             "Regularization": '-',
                                             "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                             "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                             "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                             "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

         fig,ax = plt.subplots(1,1)
         ax.set_xlabel('epoch')
         ax.set_ylabel('Categorical Crossentropy Loss')

         # list of epoch numbers
         x = list(range(1,n_epochs+1))

```

```

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_22 (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d_22 (MaxPooling)	(None, 14, 14, 32)	0
conv2d_23 (Conv2D)	(None, 14, 14, 64)	18496
max_pooling2d_23 (MaxPooling)	(None, 7, 7, 64)	0
conv2d_24 (Conv2D)	(None, 7, 7, 64)	36928
max_pooling2d_24 (MaxPooling)	(None, 4, 4, 64)	0
conv2d_25 (Conv2D)	(None, 4, 4, 64)	36928
max_pooling2d_25 (MaxPooling)	(None, 2, 2, 64)	0
conv2d_26 (Conv2D)	(None, 2, 2, 32)	18464
max_pooling2d_26 (MaxPooling)	(None, 1, 1, 32)	0
flatten_8 (Flatten)	(None, 32)	0
dense_24 (Dense)	(None, 128)	4224
batch_normalization_v1_8 (Batch Normalization)	(None, 128)	512
dropout_20 (Dropout)	(None, 128)	0
dense_25 (Dense)	(None, 64)	8256
batch_normalization_v1_9 (Batch Normalization)	(None, 64)	256
dropout_21 (Dropout)	(None, 64)	0
dense_26 (Dense)	(None, 10)	650

Total params: 125,034

Trainable params: 124,650

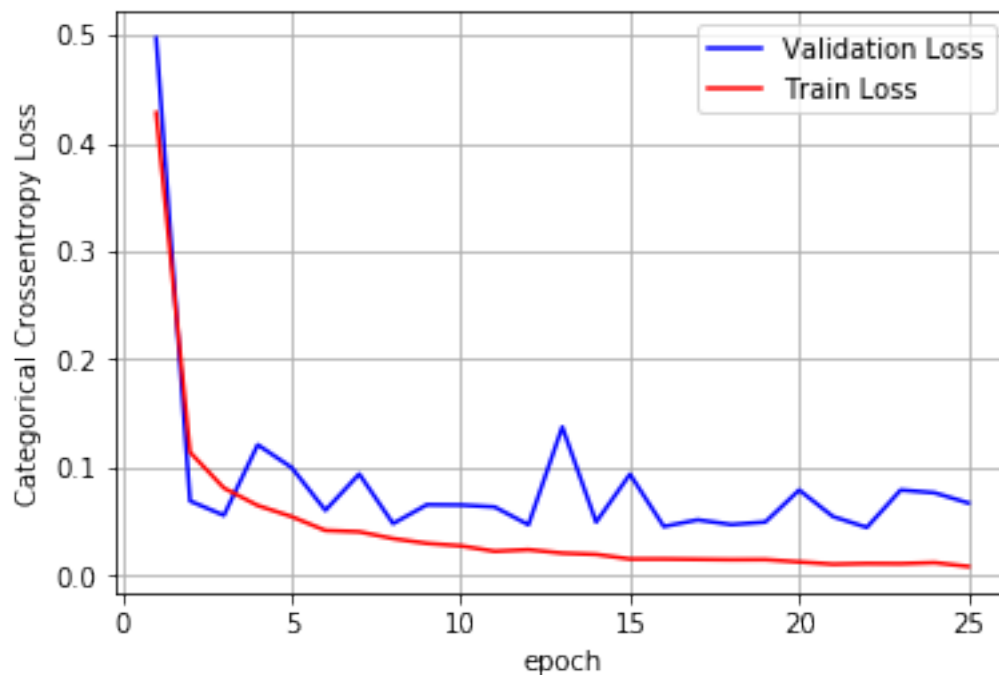
Non-trainable params: 384

None

10000/10000 [=====] - 1s 123us/sample - loss: 0.0669 - acc: 0.9879

Test score: 0.06689615963574229

Test accuracy: 0.9879



```
In [36]: w_after = m51_model.get_weights()
```

```
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)
```

```
fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
```

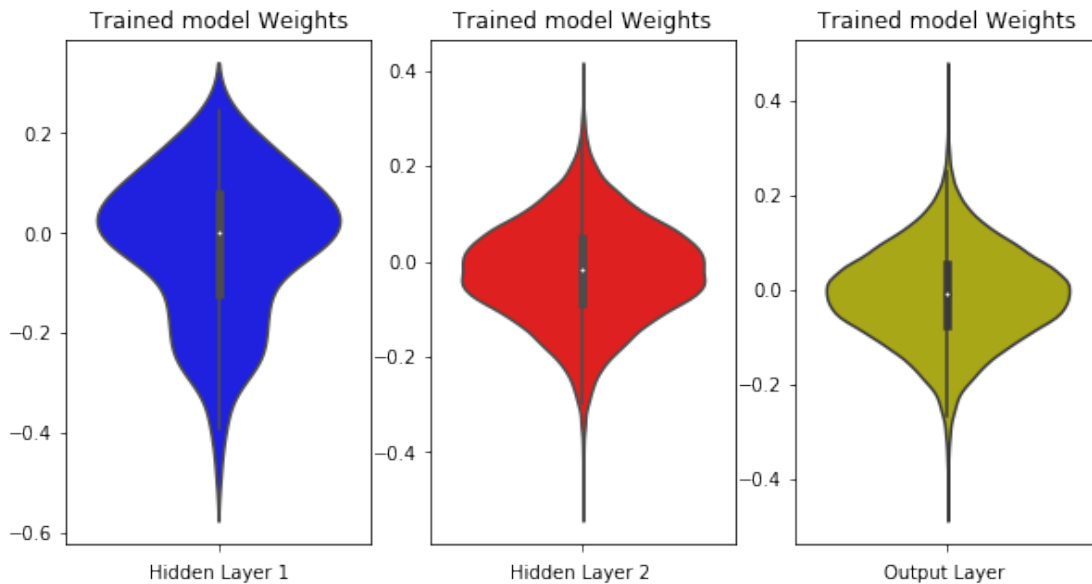


```

ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()

```



2.3.2 5x5 Kernel/Filter

```
In [37]: m52_model = Sequential()
```

```

# First Convolutional layer with MaxPooling
m52_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu, input_shape=(28,28,1)))
m52_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Second Convolutional layer with MaxPooling
m52_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m52_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Third Convolutional layer with MaxPooling
m52_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m52_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Fourth Convolutional layer with MaxPooling
m52_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m52_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

```

```

# Fifth Convolutional layer with MaxPooling
m52_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu))
m52_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Three dense layers in MLP
m52_model.add(Flatten())
m52_model.add(Dense(128, activation=tf.nn.relu))
m52_model.add(BatchNormalization())
m52_model.add(Dropout(rate=0.5))
m52_model.add(Dense(64, activation=tf.nn.relu))
m52_model.add(BatchNormalization())
m52_model.add(Dropout(rate=0.5))
m52_model.add(Dense(10, activation=tf.nn.softmax))

m52_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m52_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 12s 203us/sample - loss: 0.4521 - acc: 0.8658 - v
Epoch 2/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.1033 - acc: 0.9724 - v
Epoch 3/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0690 - acc: 0.9812 - v
Epoch 4/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.0572 - acc: 0.9846 - v
Epoch 5/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0458 - acc: 0.9878 - v
Epoch 6/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.0402 - acc: 0.9888 - v
Epoch 7/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0326 - acc: 0.9909 - v
Epoch 8/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0287 - acc: 0.9921 - v
Epoch 9/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.0272 - acc: 0.9922 - v
Epoch 10/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0218 - acc: 0.9939 - v
Epoch 11/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0188 - acc: 0.9945 - v
Epoch 12/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0171 - acc: 0.9950 - v
Epoch 13/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0152 - acc: 0.9959 - v
Epoch 14/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.0146 - acc: 0.9958 - v

```

```

Epoch 15/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0138 - acc: 0.9958 - v
Epoch 16/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0132 - acc: 0.9961 - v
Epoch 17/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.0134 - acc: 0.9964 - v
Epoch 18/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0113 - acc: 0.9969 - v
Epoch 19/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0089 - acc: 0.9974 - v
Epoch 20/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0098 - acc: 0.9972 - v
Epoch 21/25
60000/60000 [=====] - 11s 180us/sample - loss: 0.0106 - acc: 0.9972 - v
Epoch 22/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0088 - acc: 0.9975 - v
Epoch 23/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0072 - acc: 0.9979 - v
Epoch 24/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0081 - acc: 0.9976 - v
Epoch 25/25
60000/60000 [=====] - 11s 181us/sample - loss: 0.0081 - acc: 0.9976 - v

```

```

In [38]: print("*****")
          print("Printing the Model Summary")
          print(m52_model.summary())
          print("*****")

          score = m52_model.evaluate(x_test_new, y_test)

          print('Test score:', score[0])
          print('Test accuracy:', score[1])

          final_output = final_output.append({"#ConvNets": 5,
                                              "#Kernels/Filters": '5x5',
                                              "Padding": 'same',
                                              "Stride": '2x2',
                                              "Dropout": False,
                                              "BatchNormalization": False,
                                              "Regularization": '-',
                                              "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                              "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                              "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                              "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])

          fig, ax = plt.subplots(1, 1)
          ax.set_xlabel('epoch')

```

```
ax.set_ylabel('Categorical Crossentropy Loss')
```

```
# list of epoch numbers
```

```
x = list(range(1,n_epochs+1))
```

```
vy = model.history['val_loss']
```

```
ty = model.history['loss']
```

```
plt_dynamic(x, vy, ty, ax)
```

```
*****
```

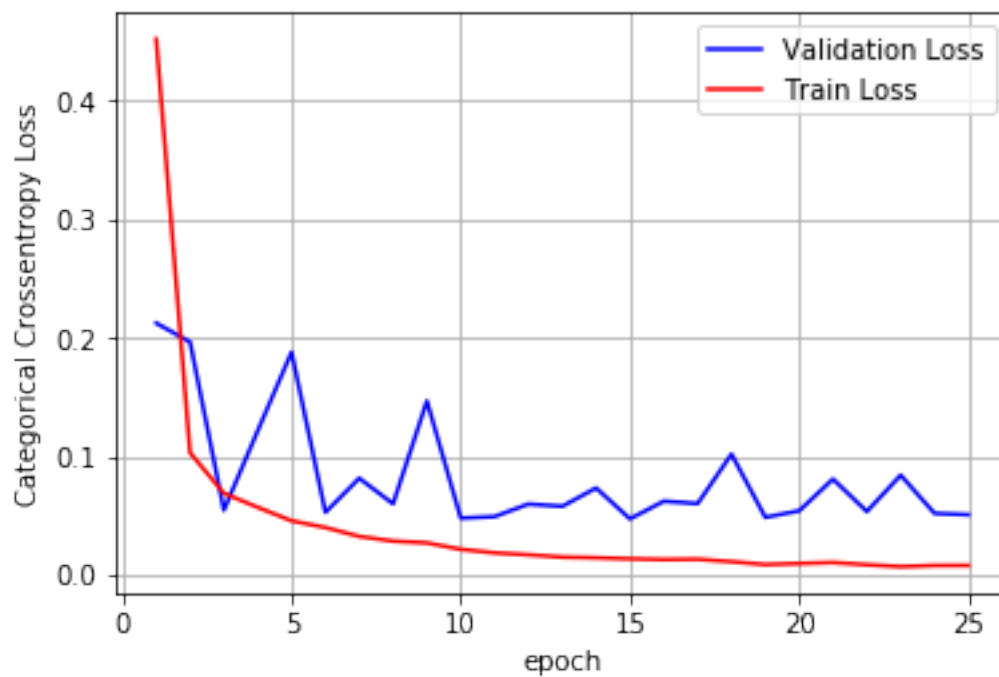
```
Printing the Model Summary
```

Layer (type)	Output Shape	Param #
conv2d_27 (Conv2D)	(None, 28, 28, 32)	832
max_pooling2d_27 (MaxPooling)	(None, 14, 14, 32)	0
conv2d_28 (Conv2D)	(None, 14, 14, 64)	51264
max_pooling2d_28 (MaxPooling)	(None, 7, 7, 64)	0
conv2d_29 (Conv2D)	(None, 7, 7, 64)	102464
max_pooling2d_29 (MaxPooling)	(None, 4, 4, 64)	0
conv2d_30 (Conv2D)	(None, 4, 4, 64)	102464
max_pooling2d_30 (MaxPooling)	(None, 2, 2, 64)	0
conv2d_31 (Conv2D)	(None, 2, 2, 32)	51232
max_pooling2d_31 (MaxPooling)	(None, 1, 1, 32)	0
flatten_9 (Flatten)	(None, 32)	0
dense_27 (Dense)	(None, 128)	4224
batch_normalization_v1_10 (B	(None, 128)	512
dropout_22 (Dropout)	(None, 128)	0
dense_28 (Dense)	(None, 64)	8256
batch_normalization_v1_11 (B	(None, 64)	256
dropout_23 (Dropout)	(None, 64)	0

```

dense_29 (Dense)                (None, 10)                650
=====
Total params: 322,154
Trainable params: 321,770
Non-trainable params: 384
-----
None
*****
10000/10000 [=====] - 1s 145us/sample - loss: 0.0510 - acc: 0.9899
Test score: 0.0509517434184585
Test accuracy: 0.9899

```



```

In [39]: w_after = m52_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

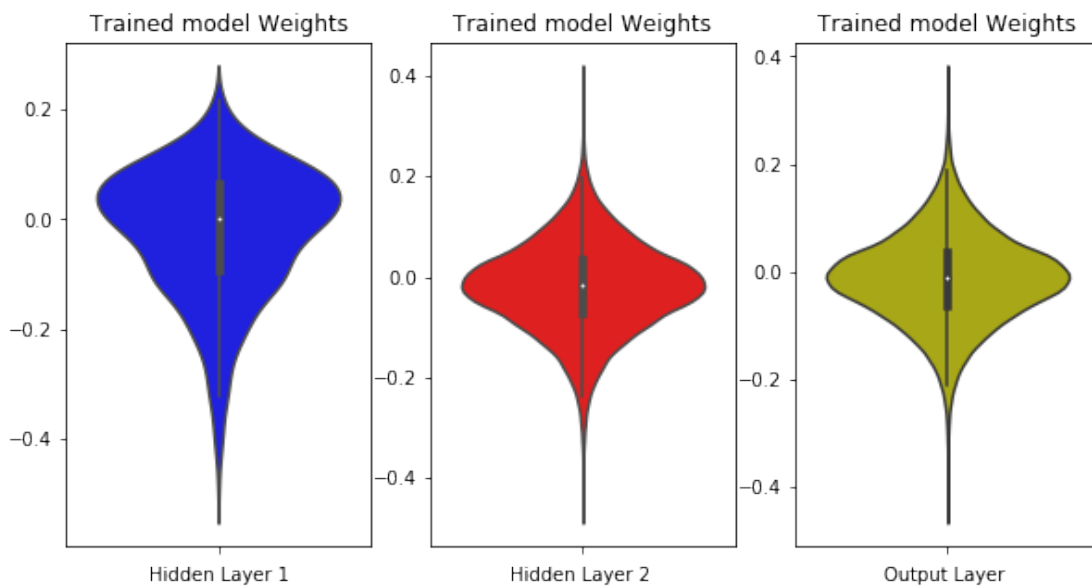
fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')

```

```
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.3.3 3x3 Filter/Kernel with Dropout and Weight Regularization & Initialization and Batch Normalization

```
In [40]: m53_model = Sequential()
```

```
# First Convolutional layer with MaxPooling
m53_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(0.01)))
m53_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m53_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m53_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(0.01)))
```

```

m53_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m53_model.add(Dropout(rate=0.5))

# Third Convolutional layer with MaxPooling
m53_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m53_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m53_model.add(Dropout(rate=0.5))

# Fourth Convolutional layer with MaxPooling
m53_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m53_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m53_model.add(Dropout(rate=0.5))

# Fifth Convolutional layer with MaxPooling
m53_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m53_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m53_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m53_model.add(Flatten())
m53_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m53_model.add(BatchNormalization())
m53_model.add(Dropout(rate=0.5))
m53_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m53_model.add(BatchNormalization())
m53_model.add(Dropout(rate=0.5))
m53_model.add(Dense(10, activation=tf.nn.softmax))

m53_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m53_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=0)

```

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 13s 212us/sample - loss: 2.5089 - acc: 0.1661 - val_loss: 2.5089 - val_acc: 0.1661

Epoch 2/25

60000/60000 [=====] - 11s 186us/sample - loss: 1.8547 - acc: 0.2749 - val_loss: 1.8547 - val_acc: 0.2749

Epoch 3/25

60000/60000 [=====] - 11s 186us/sample - loss: 1.5292 - acc: 0.3967 - val_loss: 1.5292 - val_acc: 0.3967

Epoch 4/25

60000/60000 [=====] - 11s 186us/sample - loss: 1.2578 - acc: 0.5101 - val_loss: 1.2578 - val_acc: 0.5101

```

Epoch 5/25
60000/60000 [=====] - 11s 186us/sample - loss: 1.0671 - acc: 0.6069 - v
Epoch 6/25
60000/60000 [=====] - 11s 186us/sample - loss: 0.8918 - acc: 0.6987 - v
Epoch 7/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.7286 - acc: 0.7781 - v
Epoch 8/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.6200 - acc: 0.8219 - v
Epoch 9/25
60000/60000 [=====] - 11s 182us/sample - loss: 0.5430 - acc: 0.8506 - v
Epoch 10/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.4870 - acc: 0.8700 - v
Epoch 11/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.4545 - acc: 0.8814 - v
Epoch 12/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.4160 - acc: 0.8951 - v
Epoch 13/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.3847 - acc: 0.9025 - v
Epoch 14/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.3691 - acc: 0.9079 - v
Epoch 15/25
60000/60000 [=====] - 11s 182us/sample - loss: 0.3567 - acc: 0.9126 - v
Epoch 16/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.3454 - acc: 0.9169 - v
Epoch 17/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.3358 - acc: 0.9183 - v
Epoch 18/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.3239 - acc: 0.9235 - v
Epoch 19/25
60000/60000 [=====] - 11s 182us/sample - loss: 0.3151 - acc: 0.9244 - v
Epoch 20/25
60000/60000 [=====] - 11s 182us/sample - loss: 0.3090 - acc: 0.9269 - v
Epoch 21/25
60000/60000 [=====] - 11s 183us/sample - loss: 0.3054 - acc: 0.9293 - v
Epoch 22/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.2996 - acc: 0.9308 - v
Epoch 23/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.2945 - acc: 0.9324 - v
Epoch 24/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.2903 - acc: 0.9322 - v
Epoch 25/25
60000/60000 [=====] - 11s 184us/sample - loss: 0.2826 - acc: 0.9348 - v

```

```

In [41]: print("*****")
          print("Printing the Model Summary")
          print(m53_model.summary())
          print("*****")

```



```

score = m53_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 5,
                                     "#Kernels/Filters": '3x3',
                                     "Padding": 'same',
                                     "Stride": '2x2',
                                     "Dropout": True,
                                     "BatchNormalization": True,
                                     "Regularization": 'L2 (0.00001)',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
=====		
conv2d_32 (Conv2D)	(None, 28, 28, 32)	320

max_pooling2d_32 (MaxPooling)	(None, 14, 14, 32)	0

dropout_24 (Dropout)	(None, 14, 14, 32)	0

conv2d_33 (Conv2D)	(None, 14, 14, 64)	18496

max_pooling2d_33 (MaxPooling)	(None, 7, 7, 64)	0

dropout_25 (Dropout)	(None, 7, 7, 64)	0

conv2d_34 (Conv2D)	(None, 7, 7, 64)	36928

max_pooling2d_34 (MaxPooling)	(None, 4, 4, 64)	0

dropout_26 (Dropout)	(None, 4, 4, 64)	0

conv2d_35 (Conv2D)	(None, 4, 4, 64)	36928

max_pooling2d_35 (MaxPooling)	(None, 2, 2, 64)	0

dropout_27 (Dropout)	(None, 2, 2, 64)	0

conv2d_36 (Conv2D)	(None, 2, 2, 32)	18464

max_pooling2d_36 (MaxPooling)	(None, 1, 1, 32)	0

dropout_28 (Dropout)	(None, 1, 1, 32)	0

flatten_10 (Flatten)	(None, 32)	0

dense_30 (Dense)	(None, 128)	4224

batch_normalization_v1_12 (B	(None, 128)	512

dropout_29 (Dropout)	(None, 128)	0

dense_31 (Dense)	(None, 64)	8256

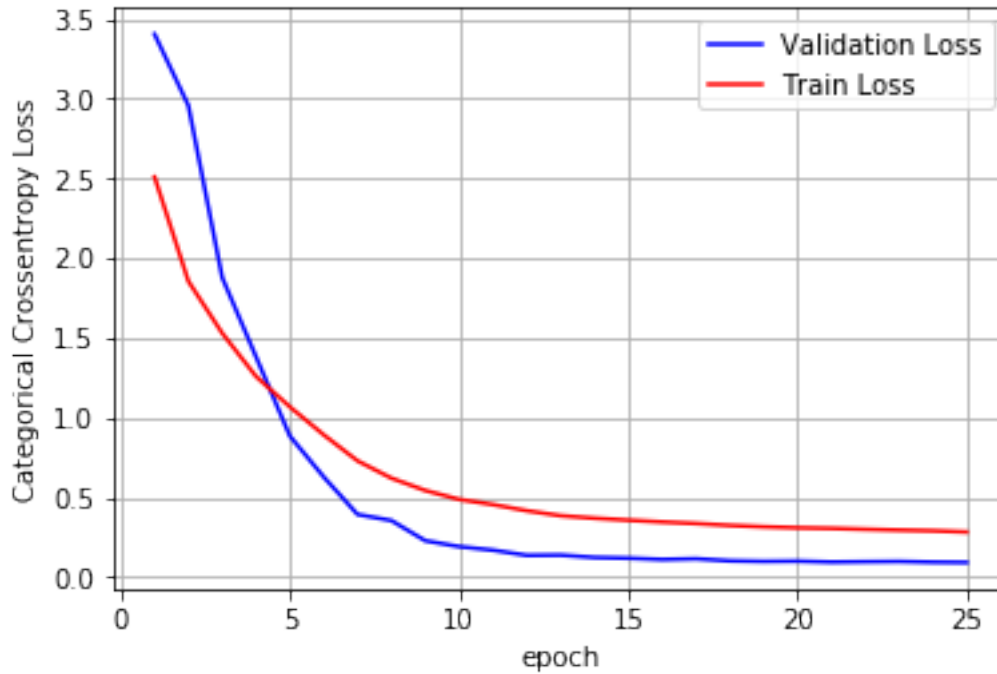
batch_normalization_v1_13 (B	(None, 64)	256

dropout_30 (Dropout)	(None, 64)	0

dense_32 (Dense)	(None, 10)	650
=====		
Total params: 125,034		
Trainable params: 124,650		
Non-trainable params: 384		

None		

10000/10000 [=====] - 1s 136us/sample - loss: 0.0917 - acc: 0.9828		
Test score: 0.09166334240734578		
Test accuracy: 0.9828		



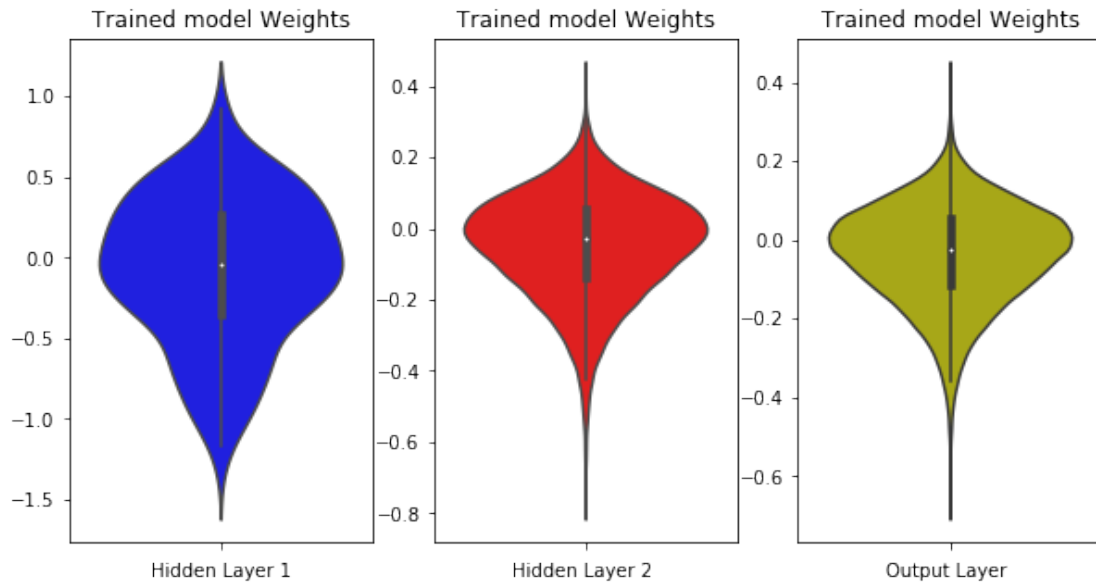
```
In [42]: w_after = m53_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.3.4 5x5 Kernel/Filter with Dropout, Weight Regularization/ initialization and Batch Normalization

In [43]: `m54_model = Sequential()`

```
# First Convolutional layer with MaxPooling
m54_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m54_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m54_model.add(Dropout(rate=0.5))

# Second Convolutional layer with MaxPooling
m54_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m54_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m54_model.add(Dropout(rate=0.5))

# Third Convolutional layer with MaxPooling
m54_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
m54_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m54_model.add(Dropout(rate=0.5))

# Fourth Convolutional layer with MaxPooling
```

```

m54_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(1e-4)))
m54_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m54_model.add(Dropout(rate=0.5))

# Fifth Convolutional layer with MaxPooling
m54_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(1e-4)))
m54_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

m54_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m54_model.add(Flatten())
m54_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(1e-4)))
m54_model.add(BatchNormalization())
m54_model.add(Dropout(rate=0.5))
m54_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(1e-4)))
m54_model.add(BatchNormalization())
m54_model.add(Dropout(rate=0.5))
m54_model.add(Dense(10, activation=tf.nn.softmax))

m54_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m54_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)

```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/25
60000/60000 [=====] - 13s 225us/sample - loss: 2.4886 - acc: 0.1789 - val_loss: 2.4886 - val_acc: 0.1789
Epoch 2/25
60000/60000 [=====] - 12s 198us/sample - loss: 1.7058 - acc: 0.3115 - val_loss: 1.7058 - val_acc: 0.3115
Epoch 3/25
60000/60000 [=====] - 12s 198us/sample - loss: 1.4386 - acc: 0.4155 - val_loss: 1.4386 - val_acc: 0.4155
Epoch 4/25
60000/60000 [=====] - 12s 198us/sample - loss: 1.1361 - acc: 0.5479 - val_loss: 1.1361 - val_acc: 0.5479
Epoch 5/25
60000/60000 [=====] - 12s 199us/sample - loss: 0.8199 - acc: 0.7095 - val_loss: 0.8199 - val_acc: 0.7095
Epoch 6/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.6351 - acc: 0.7962 - val_loss: 0.6351 - val_acc: 0.7962
Epoch 7/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.5185 - acc: 0.8469 - val_loss: 0.5185 - val_acc: 0.8469
Epoch 8/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.4583 - acc: 0.8717 - val_loss: 0.4583 - val_acc: 0.8717
Epoch 9/25
60000/60000 [=====] - 12s 196us/sample - loss: 0.4002 - acc: 0.8941 - val_loss: 0.4002 - val_acc: 0.8941
Epoch 10/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.3514 - acc: 0.9144 - val_loss: 0.3514 - val_acc: 0.9144

```

```

Epoch 11/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.3157 - acc: 0.9266 - v
Epoch 12/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2918 - acc: 0.9331 - v
Epoch 13/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2768 - acc: 0.9384 - v
Epoch 14/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2599 - acc: 0.9420 - v
Epoch 15/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2473 - acc: 0.9459 - v
Epoch 16/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2449 - acc: 0.9464 - v
Epoch 17/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2383 - acc: 0.9498 - v
Epoch 18/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2336 - acc: 0.9503 - v
Epoch 19/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2237 - acc: 0.9534 - v
Epoch 20/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2286 - acc: 0.9526 - v
Epoch 21/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2173 - acc: 0.9558 - v
Epoch 22/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2166 - acc: 0.9561 - v
Epoch 23/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2131 - acc: 0.9567 - v
Epoch 24/25
60000/60000 [=====] - 12s 198us/sample - loss: 0.2074 - acc: 0.9584 - v
Epoch 25/25
60000/60000 [=====] - 12s 197us/sample - loss: 0.2086 - acc: 0.9590 - v

```

```

In [44]: print("*****")
          print("Printing the Model Summary")
          print(m54_model.summary())
          print("*****")

          score = m54_model.evaluate(x_test_new, y_test)

          print('Test score:', score[0])
          print('Test accuracy:', score[1])

          final_output = final_output.append({"#ConvNets": 5,
                                              "#Kernels/Filters": '5x5',
                                              "Padding": 'same',
                                              "Stride": '2x2',
                                              "Dropout": True,
                                              "BatchNormalization": True,

```

```

"Regularization": 'L2 (0.00001)',
"TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
"TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
"TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
"TEST_ACC": '{:.5f}'.format(model.history["val_acc"])

```

```

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

```

```

# list of epoch numbers
x = list(range(1,n_epochs+1))

```

```

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_37 (Conv2D)	(None, 28, 28, 32)	832
max_pooling2d_37 (MaxPooling)	(None, 14, 14, 32)	0
dropout_31 (Dropout)	(None, 14, 14, 32)	0
conv2d_38 (Conv2D)	(None, 14, 14, 64)	51264
max_pooling2d_38 (MaxPooling)	(None, 7, 7, 64)	0
dropout_32 (Dropout)	(None, 7, 7, 64)	0
conv2d_39 (Conv2D)	(None, 7, 7, 64)	102464
max_pooling2d_39 (MaxPooling)	(None, 4, 4, 64)	0
dropout_33 (Dropout)	(None, 4, 4, 64)	0
conv2d_40 (Conv2D)	(None, 4, 4, 64)	102464
max_pooling2d_40 (MaxPooling)	(None, 2, 2, 64)	0
dropout_34 (Dropout)	(None, 2, 2, 64)	0
conv2d_41 (Conv2D)	(None, 2, 2, 32)	51232

max_pooling2d_41 (MaxPooling)	(None, 1, 1, 32)	0

dropout_35 (Dropout)	(None, 1, 1, 32)	0

flatten_11 (Flatten)	(None, 32)	0

dense_33 (Dense)	(None, 128)	4224

batch_normalization_v1_14 (B	(None, 128)	512

dropout_36 (Dropout)	(None, 128)	0

dense_34 (Dense)	(None, 64)	8256

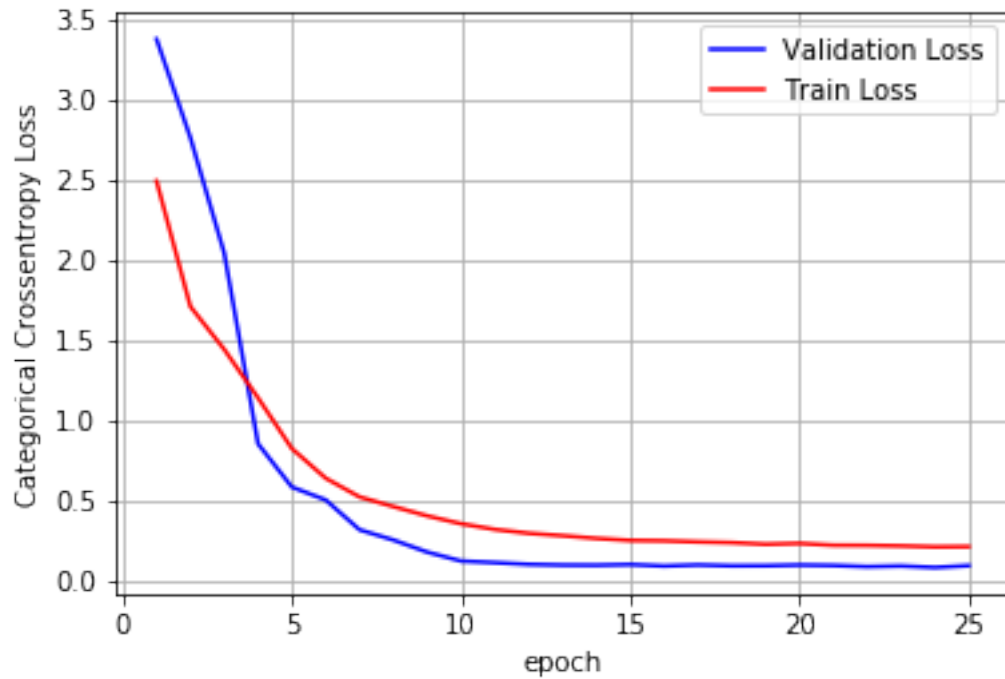
batch_normalization_v1_15 (B	(None, 64)	256

dropout_37 (Dropout)	(None, 64)	0

dense_35 (Dense)	(None, 10)	650
=====		
Total params: 322,154		
Trainable params: 321,770		
Non-trainable params: 384		

None		

10000/10000 [=====] - 2s 162us/sample - loss: 0.0901 - acc: 0.9868		
Test score: 0.0901069624900818		
Test accuracy: 0.9868		



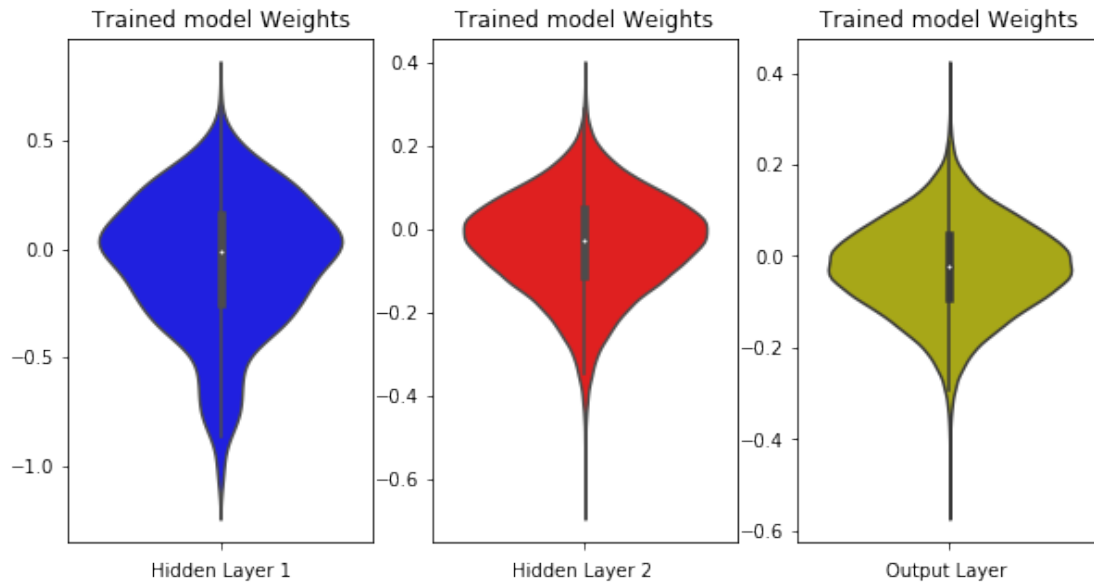
```
In [45]: w_after = m54_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.4 7 Convnet

In this type of architecture, we will be trying out 7 convolution layer along with 2 maxpooling layer after 3 convolution layers.

2.4.1 3x3 Filter/Kernel with Dropout and Weight Regularization & Initialization and Batch Normalization

```
In [46]: m71_model = Sequential()
```

```
# First Convolutional layer
```

```
m71_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
```

```
m71_model.add(Dropout(rate=0.5))
```

```
# Second Convolutional layer
```

```
m71_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
```

```
m71_model.add(Dropout(rate=0.5))
```

```
# Third Convolutional layer with MaxPooling
```

```
m71_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.l2(0.01)))
```

```
m71_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))
```

```

m71_model.add(Dropout(rate=0.5))

# Fourth Convolutional layer
m71_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))

m71_model.add(Dropout(rate=0.5))

# Fifth Convolutional layer
m71_model.add(Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))

m71_model.add(Dropout(rate=0.5))

# Sixth Convolutional layer with MaxPooling
m71_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))

m71_model.add(Dropout(rate=0.5))

m71_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Seventh Convolutional layer
m71_model.add(Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))

m71_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m71_model.add(Flatten())
m71_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))
m71_model.add(BatchNormalization())
m71_model.add(Dropout(rate=0.5))
m71_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizer.L2(1e-4)))
m71_model.add(BatchNormalization())
m71_model.add(Dropout(rate=0.5))
m71_model.add(Dense(10, activation=tf.nn.softmax))

m71_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model = m71_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verbose=1)

```

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 30s 501us/sample - loss: 1.4084 - acc: 0.5541 - val_loss: 1.4084 - val_acc: 0.5541

Epoch 2/25

60000/60000 [=====] - 28s 464us/sample - loss: 0.5161 - acc: 0.8457 - val_loss: 0.5161 - val_acc: 0.8457

Epoch 3/25

```

60000/60000 [=====] - 28s 462us/sample - loss: 0.3433 - acc: 0.9033 - v
Epoch 4/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.2640 - acc: 0.9283 - v
Epoch 5/25
60000/60000 [=====] - 28s 463us/sample - loss: 0.2180 - acc: 0.9416 - v
Epoch 6/25
60000/60000 [=====] - 28s 464us/sample - loss: 0.1915 - acc: 0.9501 - v
Epoch 7/25
60000/60000 [=====] - 28s 461us/sample - loss: 0.1694 - acc: 0.9563 - v
Epoch 8/25
60000/60000 [=====] - 28s 463us/sample - loss: 0.1603 - acc: 0.9595 - v
Epoch 9/25
60000/60000 [=====] - 28s 460us/sample - loss: 0.1495 - acc: 0.9631 - v
Epoch 10/25
60000/60000 [=====] - 28s 464us/sample - loss: 0.1387 - acc: 0.9662 - v
Epoch 11/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1329 - acc: 0.9676 - v
Epoch 12/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1314 - acc: 0.9697 - v
Epoch 13/25
60000/60000 [=====] - 28s 463us/sample - loss: 0.1255 - acc: 0.9706 - v
Epoch 14/25
60000/60000 [=====] - 28s 464us/sample - loss: 0.1228 - acc: 0.9716 - v
Epoch 15/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1180 - acc: 0.9728 - v
Epoch 16/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1159 - acc: 0.9739 - v
Epoch 17/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1161 - acc: 0.9737 - v
Epoch 18/25
60000/60000 [=====] - 28s 463us/sample - loss: 0.1127 - acc: 0.9750 - v
Epoch 19/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1108 - acc: 0.9763 - v
Epoch 20/25
60000/60000 [=====] - 28s 461us/sample - loss: 0.1133 - acc: 0.9757 - v
Epoch 21/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1084 - acc: 0.9777 - v
Epoch 22/25
60000/60000 [=====] - 28s 461us/sample - loss: 0.1056 - acc: 0.9779 - v
Epoch 23/25
60000/60000 [=====] - 28s 461us/sample - loss: 0.1087 - acc: 0.9772 - v
Epoch 24/25
60000/60000 [=====] - 28s 462us/sample - loss: 0.1081 - acc: 0.9783 - v
Epoch 25/25
60000/60000 [=====] - 28s 460us/sample - loss: 0.1029 - acc: 0.9798 - v

```

```
In [47]: print("*****")
```

```

print("Printing the Model Summary")
print(m71_model.summary())
print("*****")

score = m71_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 7,
                                     "#Kernels/Filters": '3x3',
                                     "Padding": 'same',
                                     "Stride": '2x2',
                                     "Dropout": True,
                                     "BatchNormalization": True,
                                     "Regularization": 'L2 (0.00001)',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_42 (Conv2D)	(None, 28, 28, 32)	320
dropout_38 (Dropout)	(None, 28, 28, 32)	0
conv2d_43 (Conv2D)	(None, 28, 28, 64)	18496
dropout_39 (Dropout)	(None, 28, 28, 64)	0
conv2d_44 (Conv2D)	(None, 28, 28, 64)	36928
max_pooling2d_42 (MaxPooling)	(None, 14, 14, 64)	0

dropout_40 (Dropout)	(None, 14, 14, 64)	0
conv2d_45 (Conv2D)	(None, 14, 14, 64)	36928
dropout_41 (Dropout)	(None, 14, 14, 64)	0
conv2d_46 (Conv2D)	(None, 14, 14, 64)	36928
dropout_42 (Dropout)	(None, 14, 14, 64)	0
conv2d_47 (Conv2D)	(None, 14, 14, 32)	18464
dropout_43 (Dropout)	(None, 14, 14, 32)	0
max_pooling2d_43 (MaxPooling)	(None, 7, 7, 32)	0
conv2d_48 (Conv2D)	(None, 7, 7, 32)	9248
dropout_44 (Dropout)	(None, 7, 7, 32)	0
flatten_12 (Flatten)	(None, 1568)	0
dense_36 (Dense)	(None, 128)	200832
batch_normalization_v1_16 (Batch Normalization)	(None, 128)	512
dropout_45 (Dropout)	(None, 128)	0
dense_37 (Dense)	(None, 64)	8256
batch_normalization_v1_17 (Batch Normalization)	(None, 64)	256
dropout_46 (Dropout)	(None, 64)	0
dense_38 (Dense)	(None, 10)	650

Total params: 367,818

Trainable params: 367,434

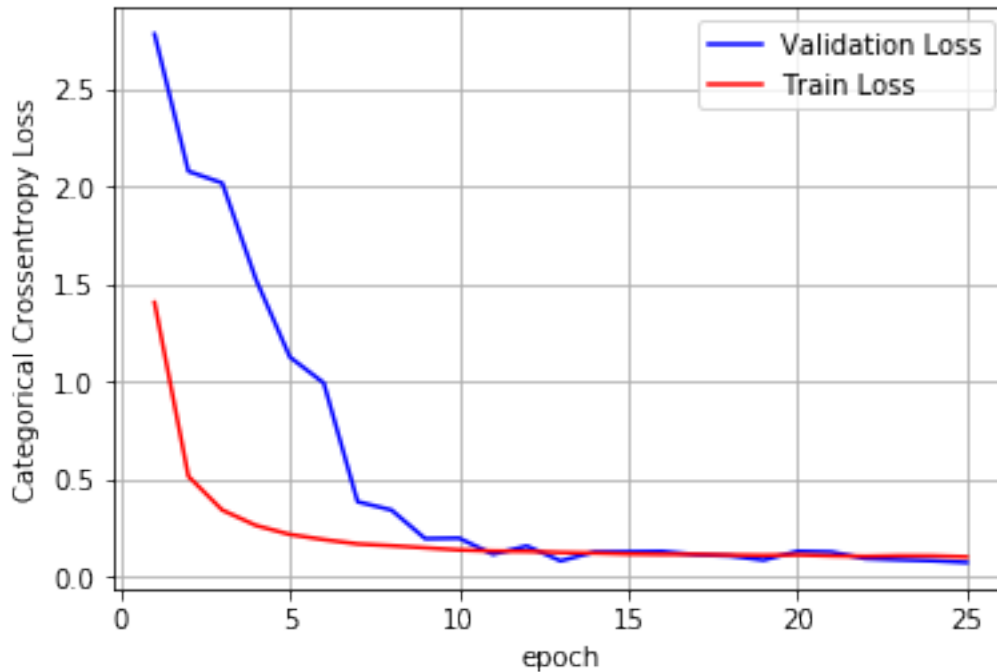
Non-trainable params: 384

None

10000/10000 [=====] - 2s 218us/sample - loss: 0.0743 - acc: 0.9879

Test score: 0.07434590795636177

Test accuracy: 0.9879



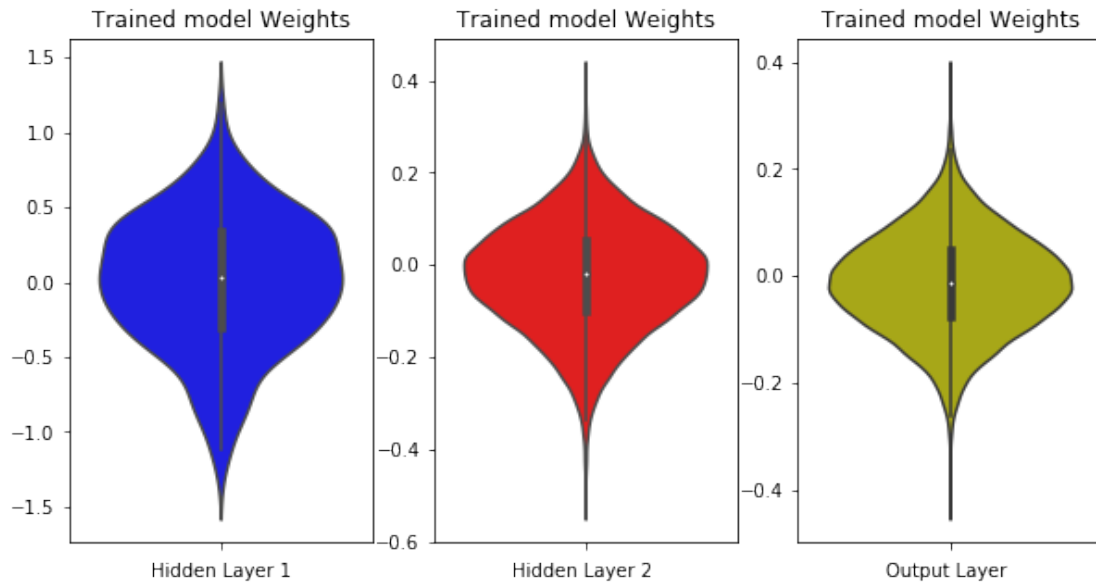
```
In [48]: w_after = m71_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



2.4.2 5x5 Filter/Kernel with Dropout and Weight Regularization & Initialization and Batch Normalization

In [49]: `m72_model = Sequential()`

First Convolutional layer

```
m72_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu, input_shape=(28,28,1),
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(0.01)))
```

```
m72_model.add(Dropout(rate=0.5))
```

Second Convolutional layer

```
m72_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(0.01)))
```

```
m72_model.add(Dropout(rate=0.5))
```

Third Convolutional layer with MaxPooling

```
m72_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regularizers.L2(0.01)))
```

```
m72_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))
```

```
m72_model.add(Dropout(rate=0.5))
```

Fourth Convolutional layer


```

m72_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regular

m72_model.add(Dropout(rate=0.5))

# Fifth Convolutional layer
m72_model.add(Conv2D(64, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regular

m72_model.add(Dropout(rate=0.5))

# Sixth Convolutional layer with MaxPooling
m72_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regular

m72_model.add(Dropout(rate=0.5))

m72_model.add(MaxPooling2D(pool_size=(2,2), padding="same"))

# Seventh Convolutional layer
m72_model.add(Conv2D(32, kernel_size=(5,5), padding="same", activation=tf.nn.relu,
                    kernel_initializer='he_normal', kernel_regularizer=tf.keras.regular

m72_model.add(Dropout(rate=0.5))

# Three dense layers in MLP
m72_model.add(Flatten())
m72_model.add(Dense(128, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_r
m72_model.add(BatchNormalization())
m72_model.add(Dropout(rate=0.5))
m72_model.add(Dense(64, activation=tf.nn.relu, kernel_initializer='he_normal', kernel_r
m72_model.add(BatchNormalization())
m72_model.add(Dropout(rate=0.5))
m72_model.add(Dense(10, activation=tf.nn.softmax))

m72_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy
model = m72_model.fit(x_train_new, y_train, epochs=n_epochs, batch_size=batchsize, verb

```

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

60000/60000 [=====] - 35s 582us/sample - loss: 1.7129 - acc: 0.4547 - v

Epoch 2/25

60000/60000 [=====] - 32s 536us/sample - loss: 0.4255 - acc: 0.8813 - v

Epoch 3/25

60000/60000 [=====] - 32s 536us/sample - loss: 0.2254 - acc: 0.9433 - v

Epoch 4/25

60000/60000 [=====] - 32s 536us/sample - loss: 0.1759 - acc: 0.9552 - v

```

Epoch 5/25
60000/60000 [=====] - 32s 534us/sample - loss: 0.1442 - acc: 0.9658 - v
Epoch 6/25
60000/60000 [=====] - 32s 535us/sample - loss: 0.1293 - acc: 0.9703 - v
Epoch 7/25
60000/60000 [=====] - 32s 535us/sample - loss: 0.1197 - acc: 0.9730 - v
Epoch 8/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.1161 - acc: 0.9736 - v
Epoch 9/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.1110 - acc: 0.9765 - v
Epoch 10/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.1062 - acc: 0.9778 - v
Epoch 11/25
60000/60000 [=====] - 32s 535us/sample - loss: 0.1000 - acc: 0.9793 - v
Epoch 12/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.0998 - acc: 0.9799 - v
Epoch 13/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.0968 - acc: 0.9808 - v
Epoch 14/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.0976 - acc: 0.9808 - v
Epoch 15/25
60000/60000 [=====] - 32s 535us/sample - loss: 0.0924 - acc: 0.9830 - v
Epoch 16/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.0904 - acc: 0.9834 - v
Epoch 17/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.0919 - acc: 0.9831 - v
Epoch 18/25
60000/60000 [=====] - 32s 538us/sample - loss: 0.0914 - acc: 0.9841 - v
Epoch 19/25
60000/60000 [=====] - 32s 536us/sample - loss: 0.0925 - acc: 0.9835 - v
Epoch 20/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.0902 - acc: 0.9845 - v
Epoch 21/25
60000/60000 [=====] - 32s 538us/sample - loss: 0.0904 - acc: 0.9857 - v
Epoch 22/25
60000/60000 [=====] - 32s 540us/sample - loss: 0.0884 - acc: 0.9856 - v
Epoch 23/25
60000/60000 [=====] - 32s 538us/sample - loss: 0.0942 - acc: 0.9851 - v
Epoch 24/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.0881 - acc: 0.9866 - v
Epoch 25/25
60000/60000 [=====] - 32s 537us/sample - loss: 0.0895 - acc: 0.9860 - v

```

```

In [50]: print("*****")
          print("Printing the Model Summary")
          print(m72_model.summary())
          print("*****")

```

```

score = m72_model.evaluate(x_test_new, y_test)

print('Test score:', score[0])
print('Test accuracy:', score[1])

final_output = final_output.append({"#ConvNets": 7,
                                     "#Kernels/Filters": '5x5',
                                     "Padding": 'same',
                                     "Stride": '2x2',
                                     "Dropout": True,
                                     "BatchNormalization": True,
                                     "Regularization": 'L2 (0.00001)',
                                     "TRAIN_LOSS": '{:.5f}'.format(model.history["loss"]),
                                     "TEST_LOSS": '{:.5f}'.format(model.history["val_loss"]),
                                     "TRAIN_ACC": '{:.5f}'.format(model.history["acc"]),
                                     "TEST_ACC": '{:.5f}'.format(model.history["val_acc"])})

fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch')
ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1, n_epochs+1))

vy = model.history['val_loss']
ty = model.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Printing the Model Summary

Layer (type)	Output Shape	Param #
conv2d_49 (Conv2D)	(None, 28, 28, 32)	832
dropout_47 (Dropout)	(None, 28, 28, 32)	0
conv2d_50 (Conv2D)	(None, 28, 28, 64)	51264
dropout_48 (Dropout)	(None, 28, 28, 64)	0
conv2d_51 (Conv2D)	(None, 28, 28, 64)	102464
max_pooling2d_44 (MaxPooling)	(None, 14, 14, 64)	0
dropout_49 (Dropout)	(None, 14, 14, 64)	0

conv2d_52 (Conv2D)	(None, 14, 14, 64)	102464

dropout_50 (Dropout)	(None, 14, 14, 64)	0

conv2d_53 (Conv2D)	(None, 14, 14, 64)	102464

dropout_51 (Dropout)	(None, 14, 14, 64)	0

conv2d_54 (Conv2D)	(None, 14, 14, 32)	51232

dropout_52 (Dropout)	(None, 14, 14, 32)	0

max_pooling2d_45 (MaxPooling)	(None, 7, 7, 32)	0

conv2d_55 (Conv2D)	(None, 7, 7, 32)	25632

dropout_53 (Dropout)	(None, 7, 7, 32)	0

flatten_13 (Flatten)	(None, 1568)	0

dense_39 (Dense)	(None, 128)	200832

batch_normalization_v1_18 (B	(None, 128)	512

dropout_54 (Dropout)	(None, 128)	0

dense_40 (Dense)	(None, 64)	8256

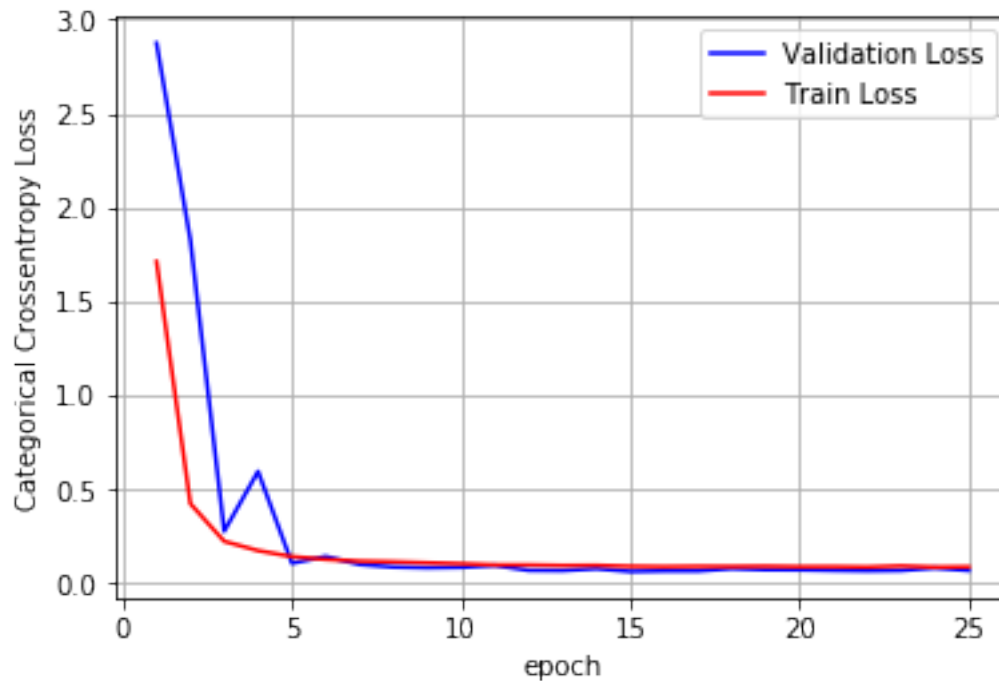
batch_normalization_v1_19 (B	(None, 64)	256

dropout_55 (Dropout)	(None, 64)	0

dense_41 (Dense)	(None, 10)	650
=====		
Total params: 646,858		
Trainable params: 646,474		
Non-trainable params: 384		

None		

10000/10000 [=====] - 3s 278us/sample - loss: 0.0706 - acc: 0.9911		
Test score: 0.07064299584031106		
Test accuracy: 0.9911		



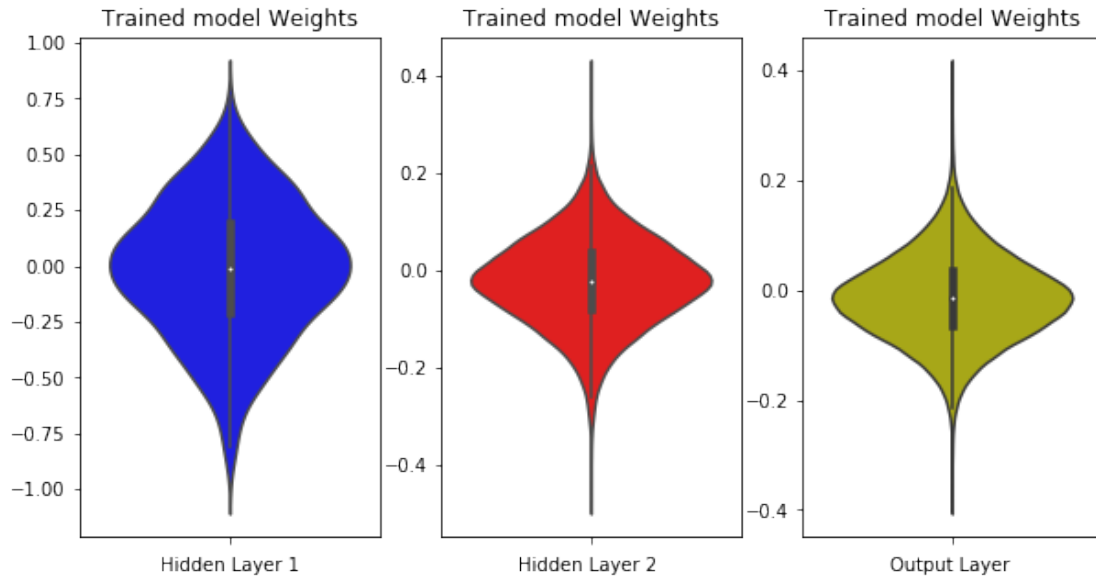
```
In [51]: w_after = m72_model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



3 Conclusion

In [52]: final_output

```
Out[52]:
```

	#ConvNets	#Kernels/Filters	Padding	...	TEST_LOSS	TRAIN_ACC	TEST_ACC
0	2	3x3	-	...	0.05639	0.99870	0.98830
1	2	5x5	-	...	0.06200	0.99898	0.98870
2	2	3x3	-	...	0.05771	0.97355	0.98810
3	2	5x5	-	...	0.04970	0.98045	0.98990
4	3	3x3	-	...	0.08567	0.99605	0.98120
5	3	5x5	same	...	0.05867	0.99938	0.98900
6	3	3x3	-	...	0.12611	0.88702	0.96790
7	3	5x5	same	...	0.09296	0.94485	0.98210
8	5	3x3	same	...	0.06690	0.99763	0.98790
9	5	5x5	same	...	0.05095	0.99762	0.98990
10	5	3x3	same	...	0.09166	0.93482	0.98280
11	5	5x5	same	...	0.09011	0.95897	0.98680
12	7	3x3	same	...	0.07435	0.97978	0.98790
13	7	5x5	same	...	0.07064	0.98602	0.99110

[14 rows x 11 columns]

In this task, We tried Convolution Neural Networks on MNIST Dataset with Keras.

There are a couple different CNN-architecture that we tried - 2 *ConvNets*, 3 *ConvNets*, 5 *ConvNets*, and 7 *ConvNets*.

For each *ConvNet*, 3x3 and 5x5 kernels/filters were used. Also, dropouts, batch normalization, weight regularization were also used to differentiate the effect of these methods.

Note -

Dropout was set to rate = 0.5 which meant onyl 50% of the neurons will remain active at a partico

Weight regularization was set to L2 (Ridge) = 0.00001.

Weight intialization was set to he-normal

Number of epochs was set to 25

Batch size was set to 128

- 3.0.1 The main conclusion that we can draw from the above table and train-test-loss plots is that without dropout and regularization, the architecture tends to overfit after 10-15 epochs. However, with dropout(0.5) and L2-regularization we can see that the overall loss i.e train loss and test loss is somewhat converging to be equal. Though we tried only 25 epochs in this task, that is only reason the train and validation accuracy is less for the models with regularization than that of the model without regularization.**
- 3.0.2 Thus we can guarantee that with the use of regularization in CNN where the ConvNets are more, we are sure that the model is generalizing better.**