Applying different Convolutional Neural Networks on MNIST data

ConvNets are designed specifically for image datasets. It is inspired from Biological visual cortex.

Steps followed in this assignment:-

1. Load libraries and MNIST data
2. Defing parameters
3. Normalizing the data
4. Convert class label values to one-hot encoded values
5. Implementing CNN with 3 Convolution layers with Kernel size of 2X2 , 5 Convolution layers with Kernel size of 5X5 and 7 Convolution layers with Kernel size of 3X3.
6. Implementing max-pooling, Padding, Strides, Dropouts and Batch Normalization in each model.
7. Compiling the model
8. Plotting Categorical Crossentropy Loss vs Epochs plot
9. Plotting Violin plots to check weights distribution.

1. Loading Libraries

In [0]:

```
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
Using TensorFlow backend.
```

1.1 Loading MNIST data

In [0]:
```
# Defing some parameters
batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

# Loading MNIST data
# the data, split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 1s 0us/step
```

1.2 Normalizing the data

In [0]:
```
if K.image_data_format() == 'channels_first':
    X_train = X_train.reshape(X_train.shape[0], 1, img_rows, img_cols)
    X_test = X_test.reshape(X_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    X_train = X_train.reshape(X_train.shape[0], img_rows, img_cols, 1)
    X_test = X_test.reshape(X_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)

X_train = X_train.astype('float32')
X_test = X_test.astype('float32')

# Normalizing the data
X_train /= 255
X_test /= 255

print('X_train shape:', X_train.shape)

# Printing to see how many data points are there for train and test and to see
each image size

print("Number of Train data points :", X_train.shape[0], "and each image is of
shape (%d, %d)"%(X_train.shape[1], X_train.shape[2]))
print("Number of Test data points :", X_test.shape[0], "and each image is of s
hape (%d, %d)"%(X_test.shape[1], X_test.shape[2]))
```

```
X_train shape: (60000, 28, 28, 1)
Number of Train data points : 60000 and each image is of shape (28, 28)
Number of Test data points : 10000 and each image is of shape (28, 28)
```

1.3 Converting to One-Hot encoding

In [0]:
```
# Here in this dataset, class labels for each image are numbers (0,1,2,3,...),
so I want to convert them into one-hot encoded vectors

print("Class label of first image :", y_train[0])

# lets convert this into a 10 dimensional vector
# ex: consider an image with class label of 5 and convert it into one-hot enco
ded vector of 0's and 1's - 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion is needed for MLPs

# convert class vectors to binary class matrices
Y_train = keras.utils.to_categorical(y_train, num_classes)
Y_test = keras.utils.to_categorical(y_test, num_classes)

print("After converting the output into a vector : ",Y_train[0])
```

```
Class label of first image : 5
After converting the output into a vector :  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

In [0]:
```
# this function is used draw Categorical Crossentropy Loss vs No. of epochs pl
ot

import numpy as np
import time

def plt_dynamic(x, vy, ty):
    plt.figure(figsize=(10,6))
    plt.plot(x, ty, 'b', label="Train Loss")
    plt.plot(x, vy, 'r', label="Validation/Test Loss")
    plt.title('\nCategorical Crossentropy Loss VS Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Categorical Crossentropy Loss-Train and Test loss')
    plt.legend()
    plt.grid()
    plt.show()
```

2. CNN with 3 Convolution layers with Kernel size of 2X2

2.1 Building the model

In [0]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [0]:
```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# start building a model
# Initializing the sequential model as the layers are in sequential

model_1 = Sequential()

# Adding first Convolution layer
model_1.add(Conv2D(32, kernel_size=(2, 2), activation='relu', input_shape=inpu
t_shape))
# Adding Maxpooling layer
model_1.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_1.add(Dropout(0.25))

# Adding second Convolution layer
model_1.add(Conv2D(64, (2, 2), activation='relu'))
# Adding Batch Normalization
model_1.add(BatchNormalization())
# Adding Maxpooling layer
model_1.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_1.add(Dropout(0.25))

# Adding third Convolution layer
model_1.add(Conv2D(128, (2, 2), activation='relu'))
# Adding Maxpooling layer
model_1.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_1.add(Dropout(0.25))

# Adding flatten layer
model_1.add(Flatten())
# Adding a dense layer
model_1.add(Dense(256, activation='relu', kernel_initializer=he_normal(seed=No
ne)))
# Adding Batch Normalization
model_1.add(BatchNormalization())
# Adding Dropout
model_1.add(Dropout(0.5))

# Output softmax layer
model_1.add(Dense(num_classes, activation='softmax'))

# Printing model summary
model_1.summary()
```

```
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_356 (Conv2D)          (None, 27, 27, 32)        160       
_________________________________________________________________
max_pooling2d_325 (MaxPoolin (None, 13, 13, 32)        0         
_________________________________________________________________
dropout_337 (Dropout)        (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_357 (Conv2D)          (None, 12, 12, 64)        8256      
_________________________________________________________________
batch_normalization_179 (Bat (None, 12, 12, 64)        256       
_________________________________________________________________
max_pooling2d_326 (MaxPoolin (None, 6, 6, 64)          0         
_________________________________________________________________
dropout_338 (Dropout)        (None, 6, 6, 64)          0         
_________________________________________________________________
conv2d_358 (Conv2D)          (None, 5, 5, 128)         32896     
_________________________________________________________________
max_pooling2d_327 (MaxPoolin (None, 2, 2, 128)         0         
_________________________________________________________________
dropout_339 (Dropout)        (None, 2, 2, 128)         0         
_________________________________________________________________
flatten_31 (Flatten)         (None, 512)               0         
_________________________________________________________________
dense_67 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_180 (Bat (None, 256)               1024      
_________________________________________________________________
dropout_340 (Dropout)        (None, 256)               0         
_________________________________________________________________
dense_68 (Dense)             (None, 10)                2570      
=================================================================
Total params: 176,490
Trainable params: 175,850
Non-trainable params: 640
_________________________________________________________________
```

2.2 Compiling the model

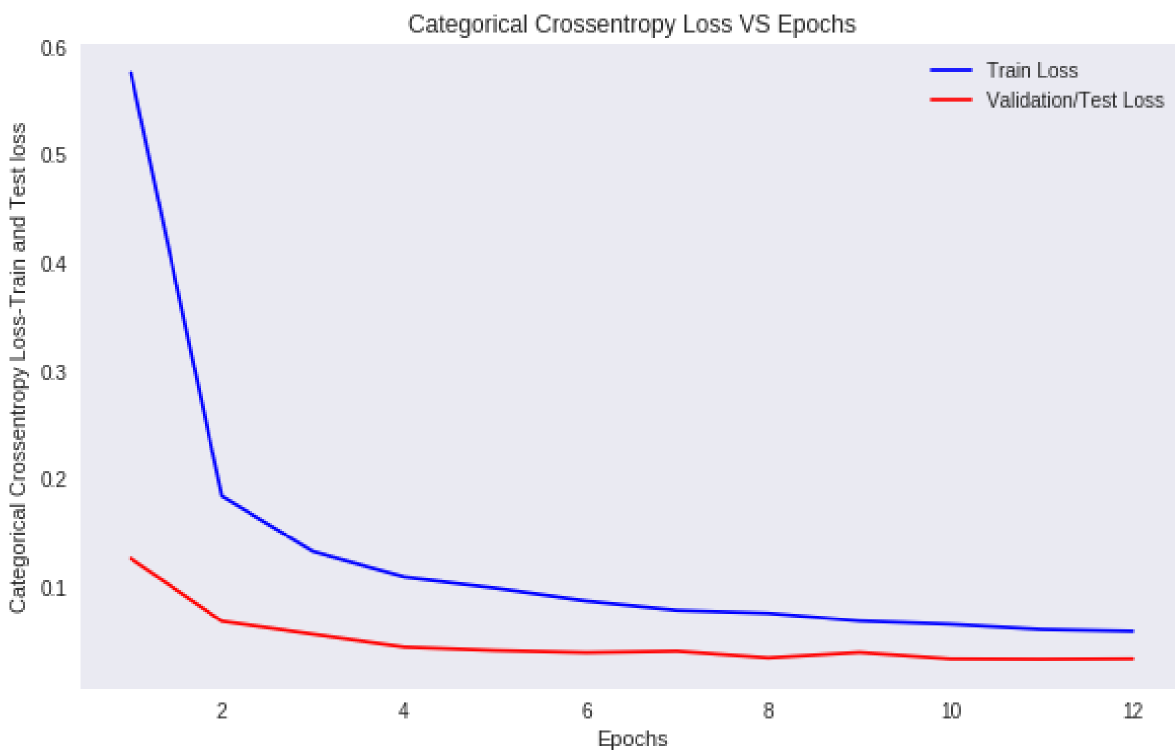
In [0]:
```
# Compiling the model
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a
ccuracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data
history = model_1.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs,
verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 20s 327us/step - loss: 0.5757
- acc: 0.8230 - val_loss: 0.1265 - val_acc: 0.9602
Epoch 2/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.1843
- acc: 0.9416 - val_loss: 0.0685 - val_acc: 0.9784
Epoch 3/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.1330 -
acc: 0.9582 - val_loss: 0.0565 - val_acc: 0.9813
Epoch 4/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.1096
- acc: 0.9665 - val_loss: 0.0447 - val_acc: 0.9855
Epoch 5/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.0992 -
acc: 0.9689 - val_loss: 0.0416 - val_acc: 0.9870
Epoch 6/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.0874 -
acc: 0.9729 - val_loss: 0.0396 - val_acc: 0.9873
Epoch 7/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.0788
- acc: 0.9752 - val_loss: 0.0410 - val_acc: 0.9874
Epoch 8/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.0760 -
acc: 0.9765 - val_loss: 0.0348 - val_acc: 0.9889
Epoch 9/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.0688
- acc: 0.9784 - val_loss: 0.0398 - val_acc: 0.9872
Epoch 10/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.0657
- acc: 0.9792 - val_loss: 0.0338 - val_acc: 0.9892
Epoch 11/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.0609 -
acc: 0.9804 - val_loss: 0.0335 - val_acc: 0.9897
Epoch 12/12
60000/60000 [==============================] - 9s 158us/step - loss: 0.0592 -
acc: 0.9808 - val_loss: 0.0338 - val_acc: 0.9886
```

2.3 Plotting the Loss vs Epoch Plot

In [0]:
```
# Evaluating the model on test data
score_1 = model_1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

# Plotting the results
# list of epoch numbers
x = list(range(1, epochs+1))

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.03383973254601297
Test accuracy: 0.9886
```

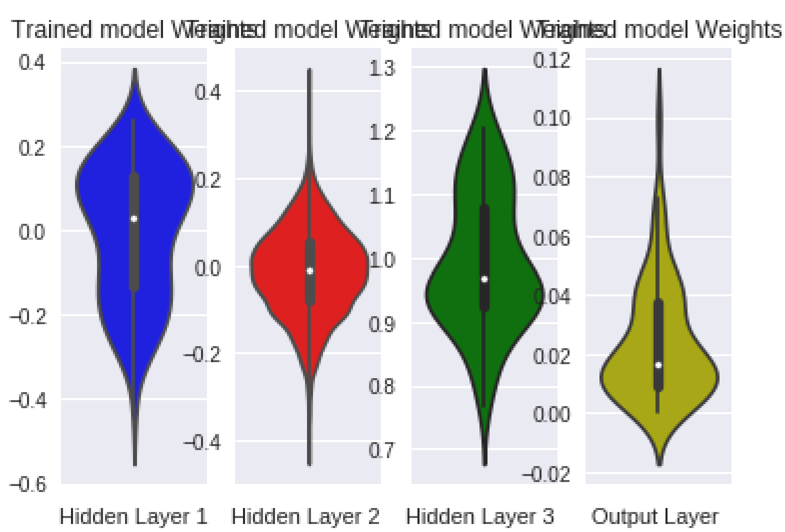


Observation:-

1. In this plot both Train and Test loss are significantly reducing/converging and there is no divergence / increasing between them .
2. This means model is not overfitting and it is working well.

2.4 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
import seaborn as sns

w_after = model_1.get_weights()

# weights of convolution layer 1
c1_w = w_after[0].flatten().reshape(-1,1)
# weights of convolution layer 2
c2_w = w_after[2].flatten().reshape(-1,1)
# weights of convolution layer 3
c3_w = w_after[4].flatten().reshape(-1,1)
# weights of output layer
out_w = w_after[6].flatten().reshape(-1,1)

fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# Hidden layer 1
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c1_w,color='b')
plt.xlabel('Hidden Layer 1')

# Hidden layer 2
plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

# Hidden layer 3
plt.subplot(1, 4, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

# Output layer
plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



Observation:-

For all the layers, I got good gaussian structures and weights are nicely distributed . For some layers it is like combination of 2 gaussian structures.

3. CNN with 5 Convolution layers with Kernel size of 5X5

In [0]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# start building a model
# Initializing the sequential model as the layers are in sequential

model_2 = Sequential()

# Adding first Convolution layer
model_2.add(Conv2D(16, kernel_size=(5, 5), activation='relu', padding='same', 
input_shape=input_shape))
# Adding Maxpooling layer
model_2.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_2.add(Dropout(0.25))

# Adding second Convolution layer
model_2.add(Conv2D(32, (5, 5), activation='relu', padding='same'))
# Adding Batch Normalization
model_2.add(BatchNormalization())
# Adding Maxpooling layer
model_2.add(MaxPooling2D(pool_size=(2, 2), strides=(1, 1)))
# Adding Dropout
model_2.add(Dropout(0.25))

# Adding third Convolution layer
model_2.add(Conv2D(32, (5, 5), activation='relu', padding='same'))
# Adding Maxpooling layer
model_2.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_2.add(Dropout(0.25))

# Adding fourth Convolution layer
model_2.add(Conv2D(64, (5, 5), activation='relu', padding='same'))
# Adding Batch Normalization
model_2.add(BatchNormalization())
# Adding Maxpooling layer
model_2.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_2.add(Dropout(0.25))

# Adding fifth Convolution layer
model_2.add(Conv2D(64, (5, 5), activation='relu', padding='same'))
# Adding Maxpooling layer
model_2.add(MaxPooling2D(pool_size=(2, 2), strides=(1, 1)))
# Adding Dropout
model_2.add(Dropout(0.25))

# Adding flatten layer
model_2.add(Flatten())
# Adding a dense layer
model_2.add(Dense(128, activation='relu', kernel_initializer=he_normal(seed=No
ne)))
# Adding Batch Normalization
model_2.add(BatchNormalization())
```

```
# Adding Dropout
model_2.add(Dropout(0.5))

# Output softmax layer
model_2.add(Dense(num_classes, activation='softmax'))

# Printing model summary
model_2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_359 (Conv2D)          (None, 28, 28, 16)        416       
_________________________________________________________________
max_pooling2d_328 (MaxPoolin (None, 14, 14, 16)        0         
_________________________________________________________________
dropout_341 (Dropout)        (None, 14, 14, 16)        0         
_________________________________________________________________
conv2d_360 (Conv2D)          (None, 14, 14, 32)        12832     
_________________________________________________________________
batch_normalization_181 (Bat (None, 14, 14, 32)        128       
_________________________________________________________________
max_pooling2d_329 (MaxPoolin (None, 13, 13, 32)        0         
_________________________________________________________________
dropout_342 (Dropout)        (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_361 (Conv2D)          (None, 13, 13, 32)        25632     
_________________________________________________________________
max_pooling2d_330 (MaxPoolin (None, 6, 6, 32)          0         
_________________________________________________________________
dropout_343 (Dropout)        (None, 6, 6, 32)          0         
_________________________________________________________________
conv2d_362 (Conv2D)          (None, 6, 6, 64)          51264     
_________________________________________________________________
batch_normalization_182 (Bat (None, 6, 6, 64)          256       
_________________________________________________________________
max_pooling2d_331 (MaxPoolin (None, 3, 3, 64)          0         
_________________________________________________________________
dropout_344 (Dropout)        (None, 3, 3, 64)          0         
_________________________________________________________________
conv2d_363 (Conv2D)          (None, 3, 3, 64)          102464    
_________________________________________________________________
max_pooling2d_332 (MaxPoolin (None, 2, 2, 64)          0         
_________________________________________________________________
dropout_345 (Dropout)        (None, 2, 2, 64)          0         
_________________________________________________________________
flatten_32 (Flatten)         (None, 256)               0         
_________________________________________________________________
dense_69 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_183 (Bat (None, 128)               512       
_________________________________________________________________
dropout_346 (Dropout)        (None, 128)               0         
_________________________________________________________________
dense_70 (Dense)             (None, 10)                1290      
=================================================================
Total params: 227,690
Trainable params: 227,242
Non-trainable params: 448
_________________________________________________________________
```

3.1 Compiling the model

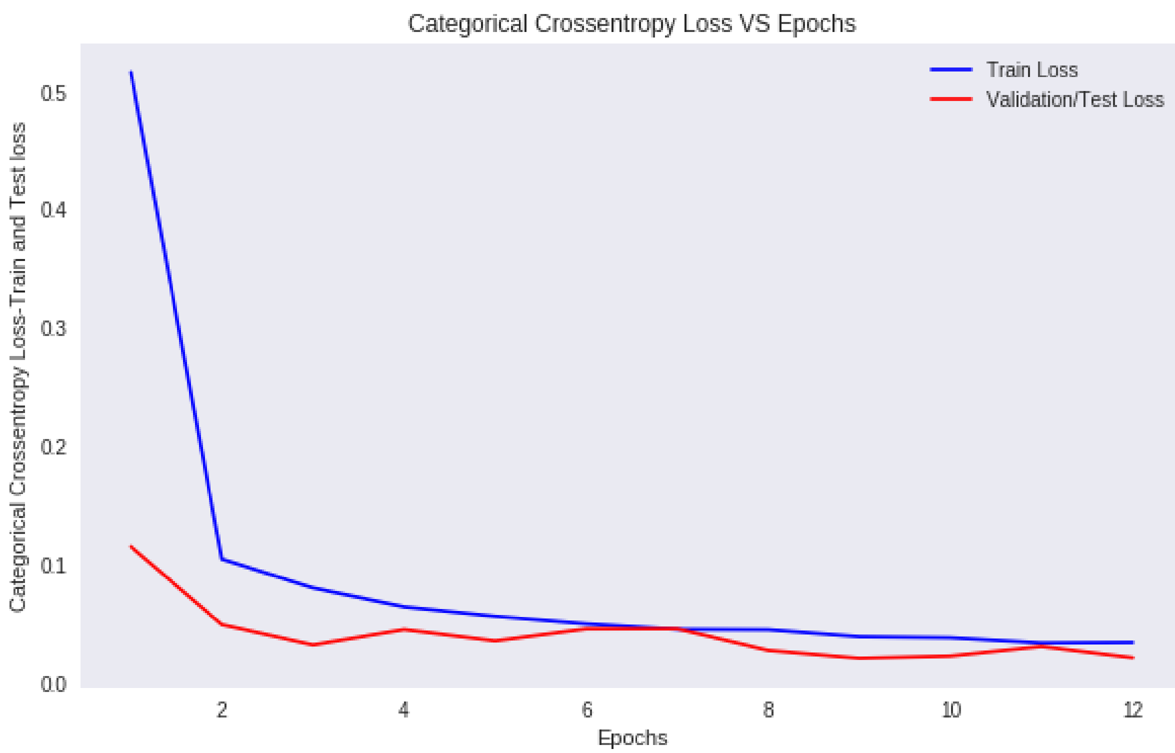
In [0]:
```
# Compiling the model
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a
ccuracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data
history = model_2.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs,
verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 23s 386us/step - loss: 0.5162
- acc: 0.8433 - val_loss: 0.1152 - val_acc: 0.9660
Epoch 2/12
60000/60000 [==============================] - 12s 206us/step - loss: 0.1046
- acc: 0.9700 - val_loss: 0.0493 - val_acc: 0.9841
Epoch 3/12
60000/60000 [==============================] - 12s 207us/step - loss: 0.0804
- acc: 0.9763 - val_loss: 0.0322 - val_acc: 0.9906
Epoch 4/12
60000/60000 [==============================] - 12s 205us/step - loss: 0.0644
- acc: 0.9819 - val_loss: 0.0451 - val_acc: 0.9868
Epoch 5/12
60000/60000 [==============================] - 12s 205us/step - loss: 0.0563
- acc: 0.9838 - val_loss: 0.0356 - val_acc: 0.9899
Epoch 6/12
60000/60000 [==============================] - 12s 204us/step - loss: 0.0499
- acc: 0.9860 - val_loss: 0.0457 - val_acc: 0.9876
Epoch 7/12
60000/60000 [==============================] - 12s 204us/step - loss: 0.0453
- acc: 0.9868 - val_loss: 0.0458 - val_acc: 0.9872
Epoch 8/12
60000/60000 [==============================] - 12s 206us/step - loss: 0.0450
- acc: 0.9869 - val_loss: 0.0276 - val_acc: 0.9920
Epoch 9/12
60000/60000 [==============================] - 12s 207us/step - loss: 0.0392
- acc: 0.9891 - val_loss: 0.0210 - val_acc: 0.9941
Epoch 10/12
60000/60000 [==============================] - 12s 205us/step - loss: 0.0383
- acc: 0.9887 - val_loss: 0.0229 - val_acc: 0.9923
Epoch 11/12
60000/60000 [==============================] - 12s 205us/step - loss: 0.0339
- acc: 0.9899 - val_loss: 0.0309 - val_acc: 0.9913
Epoch 12/12
60000/60000 [==============================] - 12s 206us/step - loss: 0.0343
- acc: 0.9903 - val_loss: 0.0214 - val_acc: 0.9940
```

3.2 Plotting the Loss vs Epochs plot

In [0]:
```
# Evaluating the model on test data
score_2 = model_2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_2[0])
print('Test accuracy:', score_2[1])

# Plotting the results
# list of epoch numbers
x = list(range(1, epochs+1))

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.021437889415866681
Test accuracy: 0.994
```



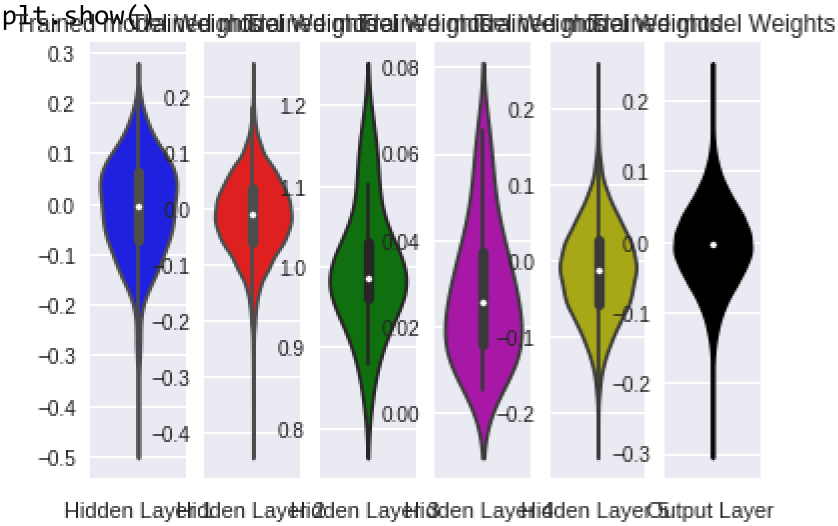
Observation:-

In this plot both Train and Test loss are significantly reducing/converging and there is no divergence / increasing between them . This means model is working well without overfitting .

3.3 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
import seaborn as sns

w_after = model_2.get_weights()

# weights of convolution layer 1
c1_w = w_after[0].flatten().reshape(-1,1)
# weights of convolution layer 2
c2_w = w_after[2].flatten().reshape(-1,1)
# weights of convolution layer 3
c3_w = w_after[4].flatten().reshape(-1,1)
# weights of convolution layer 4
c4_w = w_after[6].flatten().reshape(-1,1)
# weights of convolution layer 5
c5_w = w_after[8].flatten().reshape(-1,1)

# weights of output layer
out_w = w_after[10].flatten().reshape(-1,1)

fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# Hidden layer 1
plt.subplot(1, 6, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c1_w,color='b')
plt.xlabel('Hidden Layer 1')

# Hidden layer 2
plt.subplot(1, 6, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

# Hidden layer 3
plt.subplot(1, 6, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

# Hidden layer 4
plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c4_w, color='m')
plt.xlabel('Hidden Layer 4 ')

# Hidden layer 5
plt.subplot(1, 6, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c5_w, color='y')
plt.xlabel('Hidden Layer 5 ')

# Output layer
plt.subplot(1, 6, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='k')
```

```
plt.xlabel('Output Layer ')
plt.show()
```



4. CNN with 7 Convolution layers with Kernel size of 3X3

In [0]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# start building a model
# Initializing the sequential model as the layers are in sequential

model_3 = Sequential()

# Adding first Convolution layer
model_3.add(Conv2D(16, kernel_size=(3, 3), activation='relu', padding='same',
input_shape=input_shape))

# Adding second Convolution layer
model_3.add(Conv2D(16, (3, 3), activation='relu', padding='same'))
# Adding Batch Normalization
model_3.add(BatchNormalization())
# Adding Maxpooling layer
model_3.add(MaxPooling2D(pool_size=(2, 2), strides=(1,1)))
# Adding Dropout
model_3.add(Dropout(0.25))

# Adding third Convolution layer
model_3.add(Conv2D(32, (3, 3), activation='relu', padding='same'))

# Adding fourth Convolution layer
model_3.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
# Adding Batch Normalization
model_3.add(BatchNormalization())
# Adding Maxpooling layer
model_3.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_3.add(Dropout(0.25))


# Adding fifth Convolution layer
model_3.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
# Adding Maxpooling layer
model_3.add(MaxPooling2D(pool_size=(2, 2)))
# Adding Dropout
model_3.add(Dropout(0.25))

# Adding sixth Convolution layer
model_3.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
# Adding Batch Normalization
model_3.add(BatchNormalization())
# Adding Maxpooling layer
model_3.add(MaxPooling2D(pool_size=(2, 2), strides=(1,1)))
# Adding Dropout
model_3.add(Dropout(0.25))

# Adding seventh Convolution layer
model_3.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
# Adding Maxpooling layer
model_3.add(MaxPooling2D(pool_size=(2, 2), strides=(1,1)))
# Adding Dropout
```

```
model_3.add(Dropout(0.25))

# Adding flatten layer
model_3.add(Flatten())
# Adding a dense layer
model_3.add(Dense(128, activation='relu', kernel_initializer=he_normal(seed=No
ne)))
# Adding Batch Normalization
model_3.add(BatchNormalization())
# Adding Dropout
model_3.add(Dropout(0.5))

# Adding a dense layer
model_3.add(Dense(128, activation='relu', kernel_initializer=he_normal(seed=No
ne)))

# Adding Dropout
model_3.add(Dropout(0.5))


# Output softmax layer
model_3.add(Dense(num_classes, activation='softmax'))

# Printing model summary
model_3.summary()
```

Layer (type)	Output Shape	Param #
conv2d_385 (Conv2D)	(None, 28, 28, 16)	160
conv2d_386 (Conv2D)	(None, 28, 28, 16)	2320
batch_normalization_190 (Bat	(None, 28, 28, 16)	64
max_pooling2d_345 (MaxPoolin	(None, 27, 27, 16)	0
dropout_364 (Dropout)	(None, 27, 27, 16)	0
conv2d_387 (Conv2D)	(None, 27, 27, 32)	4640
conv2d_388 (Conv2D)	(None, 27, 27, 32)	9248
batch_normalization_191 (Bat	(None, 27, 27, 32)	128
max_pooling2d_346 (MaxPoolin	(None, 13, 13, 32)	0
dropout_365 (Dropout)	(None, 13, 13, 32)	0
conv2d_389 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_347 (MaxPoolin	(None, 6, 6, 64)	0
dropout_366 (Dropout)	(None, 6, 6, 64)	0
conv2d_390 (Conv2D)	(None, 6, 6, 64)	36928
batch_normalization_192 (Bat	(None, 6, 6, 64)	256
max_pooling2d_348 (MaxPoolin	(None, 5, 5, 64)	0
dropout_367 (Dropout)	(None, 5, 5, 64)	0
conv2d_391 (Conv2D)	(None, 5, 5, 64)	36928
max_pooling2d_349 (MaxPoolin	(None, 4, 4, 64)	0
dropout_368 (Dropout)	(None, 4, 4, 64)	0
flatten_36 (Flatten)	(None, 1024)	0
dense_80 (Dense)	(None, 128)	131200
batch_normalization_193 (Bat	(None, 128)	512
dropout_369 (Dropout)	(None, 128)	0
dense_81 (Dense)	(None, 128)	16512
dropout_370 (Dropout)	(None, 128)	0
dense_82 (Dense)	(None, 10)	1290

```
Total params: 258,682
Trainable params: 258,202
Non-trainable params: 480
_________________________________________________________________
```

4.1 Compiling the model

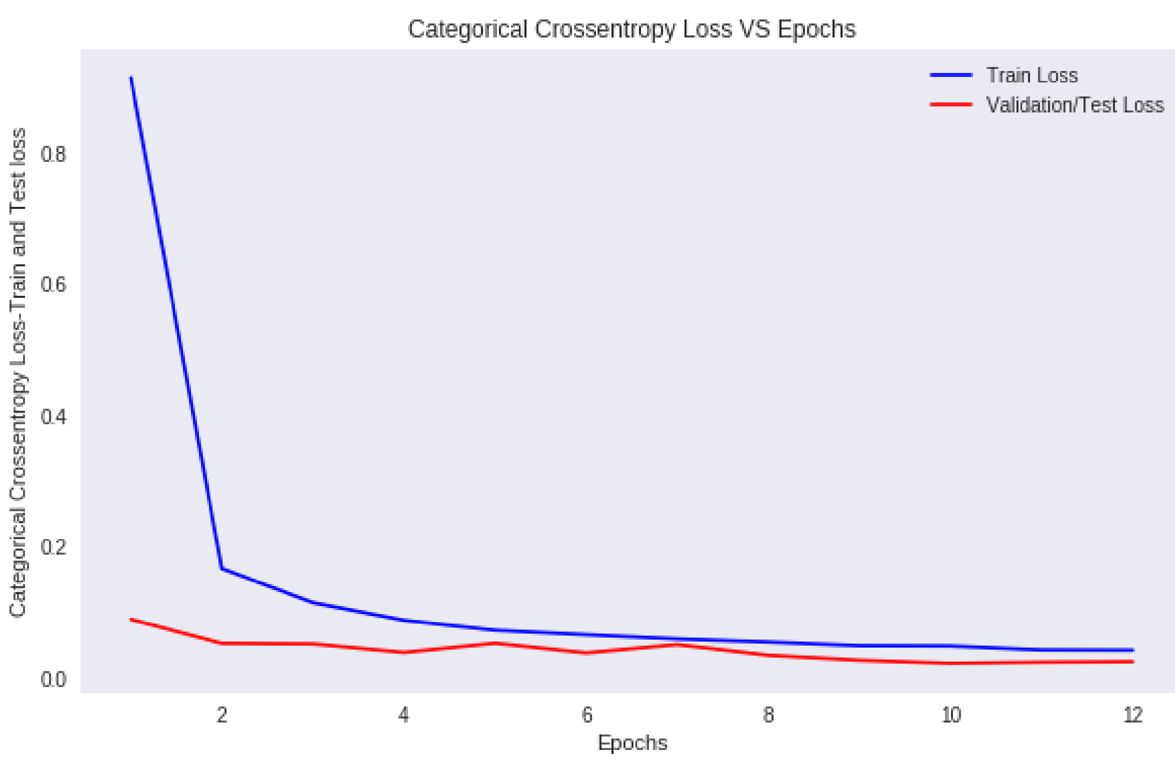
In [0]:
```
# Compiling the model
model_3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a
ccuracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data
history = model_3.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs,
verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 34s 560us/step - loss: 0.9147
- acc: 0.7261 - val_loss: 0.0885 - val_acc: 0.9715
Epoch 2/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.1660
- acc: 0.9536 - val_loss: 0.0521 - val_acc: 0.9836
Epoch 3/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.1141
- acc: 0.9685 - val_loss: 0.0511 - val_acc: 0.9863
Epoch 4/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0871
- acc: 0.9765 - val_loss: 0.0383 - val_acc: 0.9881
Epoch 5/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0720
- acc: 0.9806 - val_loss: 0.0522 - val_acc: 0.9830
Epoch 6/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0652
- acc: 0.9829 - val_loss: 0.0376 - val_acc: 0.9880
Epoch 7/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0588
- acc: 0.9844 - val_loss: 0.0501 - val_acc: 0.9839
Epoch 8/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0540
- acc: 0.9854 - val_loss: 0.0340 - val_acc: 0.9899
Epoch 9/12
60000/60000 [==============================] - 20s 340us/step - loss: 0.0485
- acc: 0.9868 - val_loss: 0.0265 - val_acc: 0.9934
Epoch 10/12
60000/60000 [==============================] - 20s 338us/step - loss: 0.0480
- acc: 0.9871 - val_loss: 0.0216 - val_acc: 0.9939
Epoch 11/12
60000/60000 [==============================] - 20s 339us/step - loss: 0.0420
- acc: 0.9889 - val_loss: 0.0234 - val_acc: 0.9937
Epoch 12/12
60000/60000 [==============================] - 20s 339us/step - loss: 0.0417
- acc: 0.9886 - val_loss: 0.0243 - val_acc: 0.9932
```

4.2 Plotting the Loss vs Epoch values

In [0]:
```
# Evaluating the model on test data
score_3 = model_3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_3[0])
print('Test accuracy:', score_3[1])

# Plotting the results
# list of epoch numbers
x = list(range(1, epochs+1))

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.02432433779832136
Test accuracy: 0.9932
```



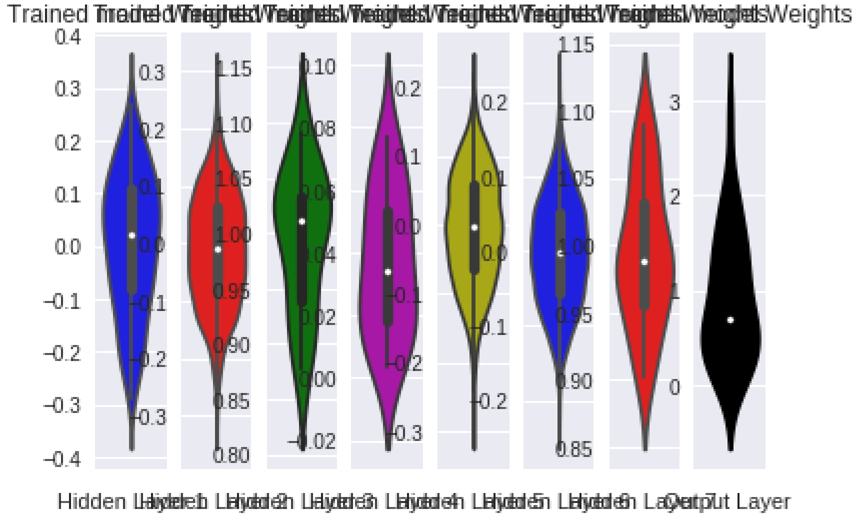
Observation:-

In this plot both Train and Test loss are significantly reducing/converging and there is no divergence / increasing between them . This means model is working well without overfitting .

4.3 Plotting Violin plots of hidden and output layers to see weights distribution

In [130]:
```
import seaborn as sns

w_after = model_3.get_weights()

# weights of convolution layer 1
c1_w = w_after[0].flatten().reshape(-1,1)
# weights of convolution layer 2
c2_w = w_after[2].flatten().reshape(-1,1)
# weights of convolution layer 3
c3_w = w_after[4].flatten().reshape(-1,1)
# weights of convolution layer 4
c4_w = w_after[6].flatten().reshape(-1,1)
# weights of convolution layer 5
c5_w = w_after[8].flatten().reshape(-1,1)
# weights of convolution layer 6
c6_w = w_after[10].flatten().reshape(-1,1)
# weights of convolution layer 7
c7_w = w_after[12].flatten().reshape(-1,1)

# weights of output layer
out_w = w_after[14].flatten().reshape(-1,1)

fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# Hidden layer 1
plt.subplot(1, 8, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c1_w,color='b')
plt.xlabel('Hidden Layer 1')

# Hidden layer 2
plt.subplot(1, 8, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

# Hidden layer 3
plt.subplot(1, 8, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

# Hidden layer 4
plt.subplot(1, 8, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c4_w, color='m')
plt.xlabel('Hidden Layer 4 ')

# Hidden layer 5
plt.subplot(1, 8, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c5_w, color='y')
plt.xlabel('Hidden Layer 5 ')

# Hidden layer 6
```

```
plt.subplot(1, 8, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c6_w, color='b')
plt.xlabel('Hidden Layer 6 ')

# Hidden layer 7
plt.subplot(1, 8, 7)
plt.title("Trained model Weights")
ax = sns.violinplot(y=c7_w, color='r')
plt.xlabel('Hidden Layer 7 ')


# Output layer
plt.subplot(1, 8, 8)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='k')
plt.xlabel('Output Layer ')
plt.show()
```



5. Models Summarization

In [0]:

```
from pandas import DataFrame
CNN = {'CNN Model':['3-Conv layers','5-Conv layers','7-Conv layers'], 'Kernel
 size':['2X2','5X5','3X3'],
             'Activation':['ReLU','ReLU','ReLU'],'Optimizer':['Adam','Adam','A
dam'],
             'Kernel_initializer':['he_normal','he_normal','he_normal'], 'outp
ut layer':['softmax','softmax','softmax'],
             'Training accuracy':['0.980','0.990','0.98'], 'Train loss':['0.0
5','0.03','0.04'],
             'Test accuracy':['0.988','0.994','0.99'], 'Test loss':['0.03','0.
02','0.02']}
```

In [132]:
```
Final_conclusions = DataFrame(CNN)
Final_conclusions
```

Out[132]:

	Activation	CNN Model	Kernel size	Kernel_initializer	Optimizer	Test accuracy	Test loss	Train loss	Training accurac
0	ReLU	3-Conv layers	2X2	he_normal	Adam	0.988	0.03	0.05	0.980
1	ReLU	5-Conv layers	5X5	he_normal	Adam	0.994	0.02	0.03	0.990
2	ReLU	7-Conv layers	3X3	he_normal	Adam	0.99	0.02	0.04	0.98

6. Conclusions:-

From the above observations we can observe,

1. As I had used ReLU activation and Adam optimizer, all the accuracies are good.
2. Output layer is softmax layer.
3. As I added dropout, Batch normalization, max-pooling, padding, all the accuracies are good.
4. Test accuracy is little more than Train accuracy in all models, so the model is working well.
5. Test loss is less than train loss for every model.
6. In the Categorical Crossentropy Loss VS Epochs plot, train and test loss also converged or decreased gradually , there is no overfitting.
7. I have used he_normal as kernel initializer as it have inbuilt mean and std values, without need of defing them explicitly.