Apply 3 different CNN's on the MNIST dataset

In [2]:

```
# Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py
#Refer this link for making better CNN networks
#https://towardsdatascience.com/a-guide-to-an-efficient-way-to-build-neural-network-arc
hitecturespart-ii-hyper-parameter-42efca01e5d7
import warnings
warnings.filterwarnings("ignore")
#from __future__ import print_function
exec('from __future__ import absolute_import, division, 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
batch_size = 128
num_classes = 10
epochs = 12
# Preparing trainining and testing data
# input image dimensions
img_rows, img_cols = 28, 28
# the data, split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()
#print(x_train.shape)
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')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
# 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)
```

```
Using TensorFlow backend.

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

In [3]:

```
%matplotlib notebook
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time
# 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()
```

Model 1-> 2 conv + 2 maxpoll+ 3 dense layers

In [4]:

```
import warnings
warnings.filterwarnings("ignore")
# In this (First Model) lets follow the general structure of the lenet we will make a s
imple model
# Network Architecture
# input -> conv -> polling -> conv -> polling -> FC -> FC -> output
# 8 16 120 84 10
model = Sequential()
model.add(Conv2D(8, kernel_size=(3, 3),activation='relu',padding='same',input_shape=inp
ut_shape))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(16, (5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Flatten())
model.add(Dense(120, activation='relu'))
model.add(Dense(84, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.adam(),
              metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
WARNING: Logging before flag parsing goes to stderr.
W0822 19:34:18.362667  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:74: The name tf.get_d
efault_graph is deprecated. Please use tf.compat.v1.get_default_graph inst
ead.

W0822 19:34:18.420886  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:517: The name tf.plac
eholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0822 19:34:18.426529  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:4138: The name tf.ran
dom_uniform is deprecated. Please use tf.random.uniform instead.

W0822 19:34:18.504054  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:3976: The name tf.nn.
max_pool is deprecated. Please use tf.nn.max_pool2d instead.

W0822 19:34:19.321984  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\optimizers.py:790: The name tf.train.Optimizer is d
eprecated. Please use tf.compat.v1.train.Optimizer instead.

W0822 19:34:19.341834  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:3295: The name tf.log
is deprecated. Please use tf.math.log instead.
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 28, 28, 8)         80        
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 8)         0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 10, 10, 16)        3216      
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 16)          0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 400)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 120)               48120     
_________________________________________________________________
dense_2 (Dense)              (None, 84)                10164     
_________________________________________________________________
dense_3 (Dense)              (None, 10)                850       
=================================================================
Total params: 62,430
Trainable params: 62,430
Non-trainable params: 0
_________________________________________________________________
```

In [5]:

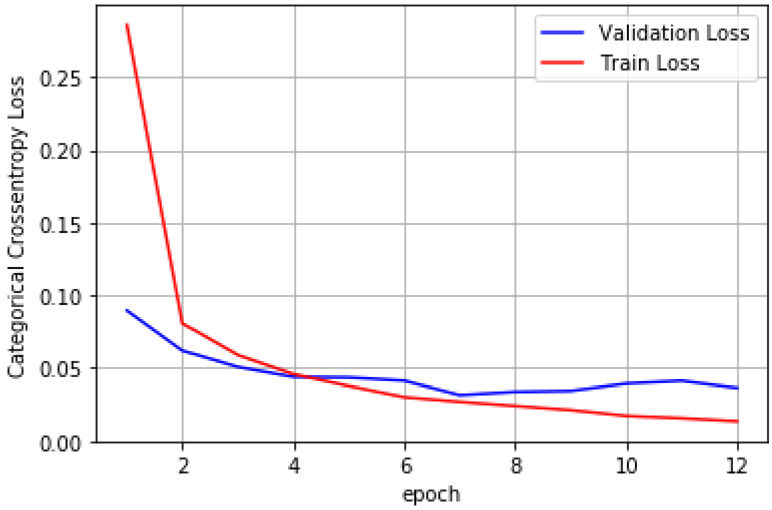
```
import warnings
warnings.filterwarnings("ignore")
history=model.fit(x_train, y_train,
                  batch_size=batch_size,
                  epochs=epochs,
                  verbose=1,
                  validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
W0822 19:34:20.446787  1320 deprecation.py:323] From C:\anaconda\lib\site-
packages\tensorflow\python\ops\math_grad.py:1250: add_dispatch_support.<lo
cals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and wil
l be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0822 19:34:21.303331  1320 deprecation_wrapper.py:119] From C:\anaconda\l
ib\site-packages\keras\backend\tensorflow_backend.py:986: The name tf.assi
gn_add is deprecated. Please use tf.compat.v1.assign_add instead.


Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 53s 891us/step - loss: 0.28
57 - acc: 0.9150 - val_loss: 0.0895 - val_acc: 0.9711
Epoch 2/12
60000/60000 [==============================] - 53s 882us/step - loss: 0.05
88 - acc: 0.9818 - val_loss: 0.0507 - val_acc: 0.9826
Epoch 4/12
60000/60000 [==============================] - 51s 849us/step - loss: 0.04
58 - acc: 0.9854 - val_loss: 0.0439 - val_acc: 0.9856
Epoch 5/12
60000/60000 [==============================] - 29s 484us/step - loss: 0.03
77 - acc: 0.9884 - val_loss: 0.0436 - val_acc: 0.9850
Epoch 6/12
60000/60000 [==============================] - 28s 463us/step - loss: 0.03
01 - acc: 0.9903 - val_loss: 0.0414 - val_acc: 0.9854
Epoch 7/12
60000/60000 [==============================] - 30s 495us/step - loss: 0.02
69 - acc: 0.9914 - val_loss: 0.0315 - val_acc: 0.9902
Epoch 8/12
60000/60000 [==============================] - 28s 467us/step - loss: 0.02
41 - acc: 0.9922 - val_loss: 0.0337 - val_acc: 0.9891
Epoch 9/12
60000/60000 [==============================] - 27s 447us/step - loss: 0.02
13 - acc: 0.9926 - val_loss: 0.0343 - val_acc: 0.9889
Epoch 10/12
60000/60000 [==============================] - 27s 445us/step - loss: 0.01
73 - acc: 0.9942 - val_loss: 0.0394 - val_acc: 0.9885
Epoch 11/12
60000/60000 [==============================] - 28s 470us/step - loss: 0.01
57 - acc: 0.9948 - val_loss: 0.0413 - val_acc: 0.9884
Epoch 12/12
60000/60000 [==============================] - 28s 469us/step - loss: 0.01
36 - acc: 0.9954 - val_loss: 0.0364 - val_acc: 0.9894
Test loss: 0.03637638606526252
Test accuracy: 0.9894
```

In [6]:

```
score = model.evaluate(x_train, y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n*********************** ********************\n')
#test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
# plot
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch');
ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,12+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.010844710362486997
Train accuracy: 99.645

*********************** ********************

Test score: 0.03637638606526252
Test accuracy: 98.94
```



Model 2-> 3 conv + 3 maxpoll+ 2 dense layers

In [7]:

```
import warnings
warnings.filterwarnings("ignore")
# go basic model to deep layer model
# Network Architecture
# input -> conv -> polling -> conv -> polling -> conv -> polling -> FC -> output
# 8 32 128 64
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.adam(),
metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_3 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 11, 11, 64)        18496     
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 3, 3, 128)         73856     
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 1, 1, 128)         0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 128)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 64)                8256      
_________________________________________________________________
dense_5 (Dense)              (None, 10)                650       
=================================================================
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0
_________________________________________________________________
```

In [8]:

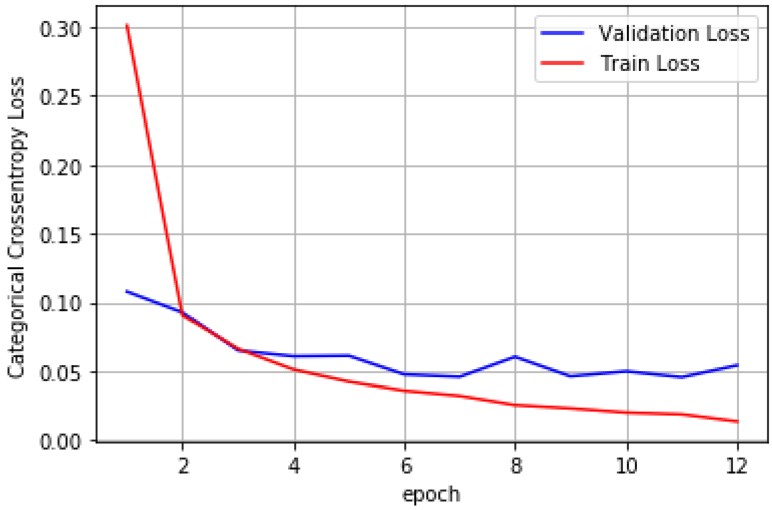
```
import warnings
warnings.filterwarnings("ignore")
history=model.fit(x_train, y_train,
                  batch_size=batch_size,
                  epochs=epochs,
                  verbose=1,
                  validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.3010
- acc: 0.9099 - val_loss: 0.1078 - val_acc: 0.9688
Epoch 2/12
60000/60000 [==============================] - 62s 1ms/step - loss: 0.0905
- acc: 0.9723 - val_loss: 0.0926 - val_acc: 0.9704
Epoch 3/12
60000/60000 [==============================] - 62s 1ms/step - loss: 0.0661
- acc: 0.9792 - val_loss: 0.0649 - val_acc: 0.9808
Epoch 4/12
60000/60000 [==============================] - 62s 1ms/step - loss: 0.0511
- acc: 0.9837 - val_loss: 0.0608 - val_acc: 0.9807
Epoch 5/12
60000/60000 [==============================] - 67s 1ms/step - loss: 0.0424
- acc: 0.9868 - val_loss: 0.0611 - val_acc: 0.9816
Epoch 6/12
60000/60000 [==============================] - 65s 1ms/step - loss: 0.0358
- acc: 0.9887 - val_loss: 0.0476 - val_acc: 0.9858
Epoch 7/12
60000/60000 [==============================] - 66s 1ms/step - loss: 0.0321
- acc: 0.9899 - val_loss: 0.0458 - val_acc: 0.9871
Epoch 8/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.0255
- acc: 0.9923 - val_loss: 0.0604 - val_acc: 0.9837
Epoch 9/12
60000/60000 [==============================] - 66s 1ms/step - loss: 0.0231
- acc: 0.9922 - val_loss: 0.0462 - val_acc: 0.9872
Epoch 10/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.0200
- acc: 0.9935 - val_loss: 0.0498 - val_acc: 0.9868
Epoch 11/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.0188
- acc: 0.9935 - val_loss: 0.0455 - val_acc: 0.9880
Epoch 12/12
60000/60000 [==============================] - 62s 1ms/step - loss: 0.0136
- acc: 0.9952 - val_loss: 0.0541 - val_acc: 0.9875
Test loss: 0.05412146498494658
Test accuracy: 0.9875
```

In [9]:

```
score = model.evaluate(x_train, y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n*********************** ********************\n')
#test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
# plot
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch');
ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,12+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.012100143584344308
Train accuracy: 99.59166666666667

*********************** ********************

Test score: 0.05412146498494658
Test accuracy: 98.75
```



Finally we train a model with the trend Conv-Conv-Pool-Conv-Conv-Pool

Model 3 -> 4 conv+ 2 maxpoll + 2 dence

In [10]:

```
# go basic model to deep layer model
# Network Architecture
# input -> conv -> conv -> polling -> conv -> conv -> polling -> FC -> output
# 16 16 32 32 512
model = Sequential()
model.add(Conv2D(16, kernel_size=(3, 3),activation='relu',padding='same',input_shape=in
put_shape))
model.add(Conv2D(16,(3, 3),activation='relu',padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.adam(),
metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_6 (Conv2D)            (None, 28, 28, 16)        160       
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 28, 28, 16)        2320      
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 14, 14, 16)        0         
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 12, 12, 32)        4640      
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 10, 10, 32)        9248      
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 5, 5, 32)          0         
_________________________________________________________________
flatten_3 (Flatten)          (None, 800)               0         
_________________________________________________________________
dense_6 (Dense)              (None, 512)               410112    
_________________________________________________________________
dense_7 (Dense)              (None, 10)                5130      
=================================================================
Total params: 431,610
Trainable params: 431,610
Non-trainable params: 0
_________________________________________________________________
```

In [11]:

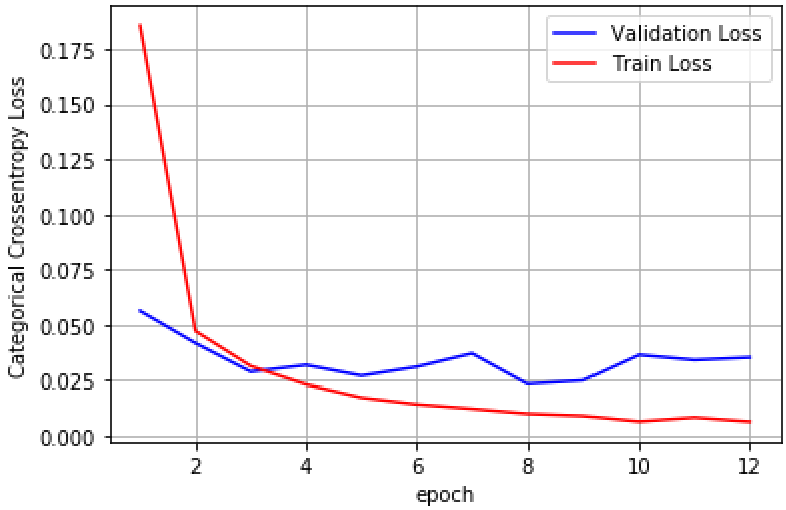
```
import warnings
warnings.filterwarnings("ignore")
history=model.fit(x_train, y_train,
                  batch_size=batch_size,
                  epochs=epochs,
                  verbose=1,
                  validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 102s 2ms/step - loss: 0.185
7 - acc: 0.9447 - val_loss: 0.0564 - val_acc: 0.9812
Epoch 2/12
60000/60000 [==============================] - 105s 2ms/step - loss: 0.047
2 - acc: 0.9855 - val_loss: 0.0418 - val_acc: 0.9864
Epoch 3/12
60000/60000 [==============================] - 95s 2ms/step - loss: 0.0314
- acc: 0.9903 - val_loss: 0.0289 - val_acc: 0.9905
Epoch 4/12
60000/60000 [==============================] - 96s 2ms/step - loss: 0.0231
- acc: 0.9926 - val_loss: 0.0319 - val_acc: 0.9890
Epoch 5/12
60000/60000 [==============================] - 94s 2ms/step - loss: 0.0172
- acc: 0.9943 - val_loss: 0.0271 - val_acc: 0.9909
Epoch 6/12
60000/60000 [==============================] - 618s 10ms/step - loss: 0.01
42 - acc: 0.9956 - val_loss: 0.0311 - val_acc: 0.9909
Epoch 7/12
60000/60000 [==============================] - 100s 2ms/step - loss: 0.012
2 - acc: 0.9960 - val_loss: 0.0371 - val_acc: 0.9899
Epoch 8/12
60000/60000 [==============================] - 95s 2ms/step - loss: 0.0100
- acc: 0.9966 - val_loss: 0.0234 - val_acc: 0.9926
Epoch 9/12
60000/60000 [==============================] - 97s 2ms/step - loss: 0.0090
- acc: 0.9973 - val_loss: 0.0250 - val_acc: 0.9920
Epoch 10/12
60000/60000 [==============================] - 96s 2ms/step - loss: 0.0065
- acc: 0.9976 - val_loss: 0.0364 - val_acc: 0.9914
Epoch 11/12
60000/60000 [==============================] - 98s 2ms/step - loss: 0.0083
- acc: 0.9972 - val_loss: 0.0341 - val_acc: 0.9897
Epoch 12/12
60000/60000 [==============================] - 101s 2ms/step - loss: 0.006
4 - acc: 0.9978 - val_loss: 0.0353 - val_acc: 0.9909
Test loss: 0.035289469616033374
Test accuracy: 0.9909
```

In [12]:

```
score = model.evaluate(x_train, y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n************************ *********************\n')
#test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
# plot
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch');
ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,12+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.008017680925130662
Train accuracy: 99.74333333333333

************************ *********************

Test score: 0.035289469616033374
Test accuracy: 99.09
```



Model 1-> 2 conv + 2 maxpoll+ 3 dense layer +Dropout (0.5)

In [13]:

```
#Same models with Dropouts
import warnings
warnings.filterwarnings("ignore")
# In this (First Model) lets follow the general structure of the lenet we will make a s
imple model
# Network Architecture
# input -> conv -> polling -> conv -> polling ->droupout-> FC -> FC -> output
# 8 16 120 84 10
model = Sequential()
model.add(Conv2D(8, kernel_size=(3, 3),activation='relu',padding='same',input_shape=inp
ut_shape))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(16, (5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(120, activation='relu'))
model.add(Dense(84, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.adam(),
metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
W0822 20:24:07.094106  1320 deprecation.py:506] From C:\anaconda\lib\site-
packages\keras\backend\tensorflow_backend.py:3445: calling dropout (from t
ensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be remo
ved in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep_prob`.

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_10 (Conv2D)           (None, 28, 28, 8)         80
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 14, 14, 8)         0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 10, 10, 16)        3216
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 5, 5, 16)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 5, 5, 16)          0
_________________________________________________________________
flatten_4 (Flatten)          (None, 400)               0
_________________________________________________________________
dense_8 (Dense)              (None, 120)               48120
_________________________________________________________________
dense_9 (Dense)              (None, 84)                10164
_________________________________________________________________
dense_10 (Dense)             (None, 10)                850
=================================================================
Total params: 62,430
Trainable params: 62,430
Non-trainable params: 0
_________________________________________________________________
```

In [14]:

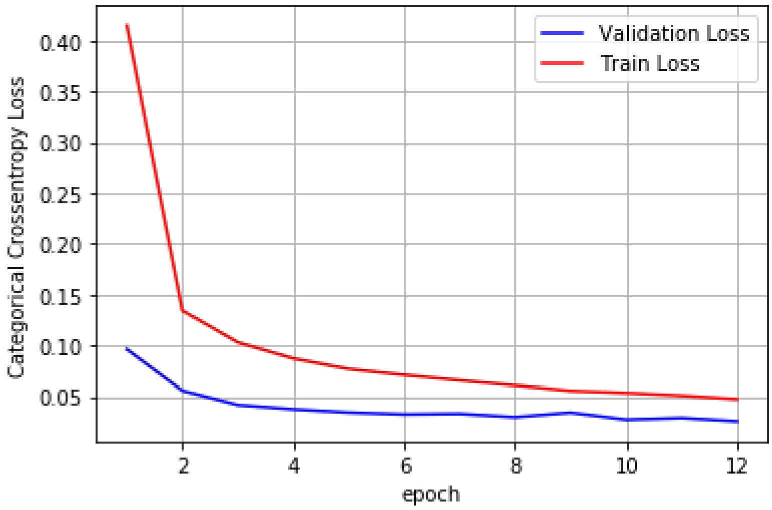
```
history=model.fit(x_train, y_train,
                  batch_size=batch_size,
                  epochs=epochs,
                  verbose=1,
                  validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 31s 521us/step - loss: 0.41
48 - acc: 0.8659 - val_loss: 0.0964 - val_acc: 0.9711
Epoch 2/12
60000/60000 [==============================] - 31s 516us/step - loss: 0.13
44 - acc: 0.9582 - val_loss: 0.0558 - val_acc: 0.9816
Epoch 3/12
60000/60000 [==============================] - 30s 507us/step - loss: 0.10
31 - acc: 0.9676 - val_loss: 0.0418 - val_acc: 0.9862
Epoch 4/12
60000/60000 [==============================] - 30s 508us/step - loss: 0.08
73 - acc: 0.9731 - val_loss: 0.0376 - val_acc: 0.9866
Epoch 5/12
60000/60000 [==============================] - 30s 499us/step - loss: 0.07
71 - acc: 0.9753 - val_loss: 0.0345 - val_acc: 0.9875
Epoch 6/12
60000/60000 [==============================] - 31s 509us/step - loss: 0.07
13 - acc: 0.9780 - val_loss: 0.0326 - val_acc: 0.9886
Epoch 7/12
60000/60000 [==============================] - 30s 502us/step - loss: 0.06
60 - acc: 0.9793 - val_loss: 0.0331 - val_acc: 0.9889
Epoch 8/12
60000/60000 [==============================] - 30s 504us/step - loss: 0.06
11 - acc: 0.9798 - val_loss: 0.0299 - val_acc: 0.9904
Epoch 9/12
60000/60000 [==============================] - 31s 518us/step - loss: 0.05
56 - acc: 0.9820 - val_loss: 0.0343 - val_acc: 0.9888
Epoch 10/12
60000/60000 [==============================] - 31s 509us/step - loss: 0.05
36 - acc: 0.9824 - val_loss: 0.0274 - val_acc: 0.9910
Epoch 11/12
60000/60000 [==============================] - 30s 506us/step - loss: 0.05
10 - acc: 0.9836 - val_loss: 0.0291 - val_acc: 0.9907
Epoch 12/12
60000/60000 [==============================] - 31s 518us/step - loss: 0.04
75 - acc: 0.9847 - val_loss: 0.0258 - val_acc: 0.9922
Test loss: 0.025816060557204763
Test accuracy: 0.9922
```

In [15]:

```
score = model.evaluate(x_train, y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n************************ *********************\n')
#test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
# plot
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch');
ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,12+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.015612688764524258
Train accuracy: 99.53

************************ *********************

Test score: 0.025816060557204763
Test accuracy: 99.22
```



Model 2-> 3 conv + 3 maxpoll+ 2 dense layers + Dropout (0.9)

In [16]:

```
import warnings
warnings.filterwarnings("ignore")
# go basic model to deep layer model
# Network Architecture
# input -> conv -> polling -> conv -> polling -> conv -> polling ->dropout-> FC -> outp
ut
# 8 32 128 64
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Dropout(0.9))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.adam(),
metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
W0822 20:30:38.725002  1320 nn_ops.py:4224] Large dropout rate: 0.9 (>0.
5). In TensorFlow 2.x, dropout() uses dropout rate instead of keep_prob. P
lease ensure that this is intended.

_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_12 (Conv2D)           (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 11, 11, 64)        18496     
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 3, 3, 128)         73856     
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 1, 1, 128)         0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 1, 1, 128)         0         
_________________________________________________________________
flatten_5 (Flatten)          (None, 128)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_12 (Dense)             (None, 10)                650       
=================================================================
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0
_________________________________________________________________
```

In [17]:

```
history=model.fit(x_train, y_train,
batch_size=batch_size,
epochs=epochs,
verbose=1,
validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 64s 1ms/step - loss: 1.2593
- acc: 0.5415 - val_loss: 0.2457 - val_acc: 0.9450
Epoch 2/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.7342
- acc: 0.7326 - val_loss: 0.1495 - val_acc: 0.9600
Epoch 3/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.6122
- acc: 0.7760 - val_loss: 0.1151 - val_acc: 0.9683
Epoch 4/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.5505
- acc: 0.8000 - val_loss: 0.0934 - val_acc: 0.9736
Epoch 5/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.5010
- acc: 0.8188 - val_loss: 0.0850 - val_acc: 0.9754
Epoch 6/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.4635
- acc: 0.8331 - val_loss: 0.0811 - val_acc: 0.9762
Epoch 7/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.4433
- acc: 0.8416 - val_loss: 0.0809 - val_acc: 0.9760
Epoch 8/12
60000/60000 [==============================] - 63s 1ms/step - loss: 0.4183
- acc: 0.8507 - val_loss: 0.0802 - val_acc: 0.9774
Epoch 9/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.4049
- acc: 0.8554 - val_loss: 0.0757 - val_acc: 0.9776
Epoch 10/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.3944
- acc: 0.8621 - val_loss: 0.0768 - val_acc: 0.9764
Epoch 11/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.3740
- acc: 0.8681 - val_loss: 0.0769 - val_acc: 0.9781
Epoch 12/12
60000/60000 [==============================] - 64s 1ms/step - loss: 0.3656
- acc: 0.8723 - val_loss: 0.0715 - val_acc: 0.9796
Test loss: 0.07153915164452046
Test accuracy: 0.9796
```

In [18]:

```
keras.layers.BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001, center=True, scale=True, beta_initializer='zeros', gamma_initializer='ones', moving_mean_initializer='zeros', moving_variance_initializer='ones', beta_regularizer=None, gamma_regularizer=None, beta_constraint=None, gamma_constraint=None)
```

Out[18]:

```
<keras.layers.normalization.BatchNormalization at 0x1dca2053cf8>
```

Model 3-> 4 conv + 2 maxpoll+ 2 dense layers + Dropout (0.3)

In [19]:

```
# go basic model to deep layer model
# Network Architecture
# input -> conv -> conv -> polling -> conv -> conv -> polling ->dropout-> FC -> output
# 16 16 32 32 512
model = Sequential()
model.add(Conv2D(16, kernel_size=(3, 3),activation='relu',padding='same',input_shape=in
put_shape))
model.add(Conv2D(16,(3, 3),activation='relu',padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))# for the location invariants
model.add(Dropout(0.3))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.adam(),
metrics=['accuracy'])
# this will train the model and validate the model in this fit function
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_15 (Conv2D)           (None, 28, 28, 16)        160       
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 28, 28, 16)        2320      
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 14, 14, 16)        0         
_________________________________________________________________
conv2d_17 (Conv2D)           (None, 12, 12, 32)        4640      
_________________________________________________________________
conv2d_18 (Conv2D)           (None, 10, 10, 32)        9248      
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 5, 5, 32)          0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 5, 5, 32)          0         
_________________________________________________________________
flatten_6 (Flatten)          (None, 800)               0         
_________________________________________________________________
dense_13 (Dense)             (None, 512)               410112    
_________________________________________________________________
dense_14 (Dense)             (None, 10)                5130      
=================================================================
Total params: 431,610
Trainable params: 431,610
Non-trainable params: 0
_________________________________________________________________
```

In [20]:

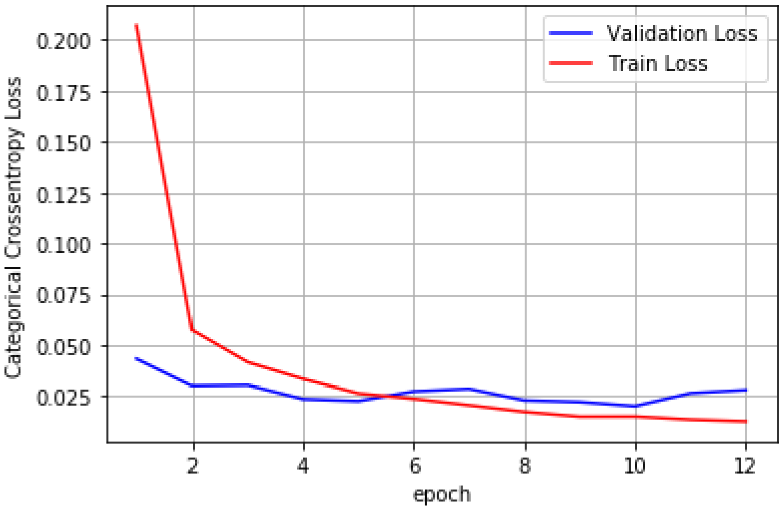
```
history=model.fit(x_train, y_train,
batch_size=batch_size,
epochs=epochs,
verbose=1,
validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 105s 2ms/step - loss: 0.207
1 - acc: 0.9358 - val_loss: 0.0434 - val_acc: 0.9860
Epoch 2/12
60000/60000 [==============================] - 104s 2ms/step - loss: 0.057
4 - acc: 0.9824 - val_loss: 0.0301 - val_acc: 0.9898
Epoch 3/12
60000/60000 [==============================] - 103s 2ms/step - loss: 0.041
7 - acc: 0.9864 - val_loss: 0.0305 - val_acc: 0.9902
Epoch 4/12
60000/60000 [==============================] - 105s 2ms/step - loss: 0.033
5 - acc: 0.9890 - val_loss: 0.0236 - val_acc: 0.9920
Epoch 5/12
60000/60000 [==============================] - 108s 2ms/step - loss: 0.026
4 - acc: 0.9913 - val_loss: 0.0227 - val_acc: 0.9921
Epoch 6/12
60000/60000 [==============================] - 105s 2ms/step - loss: 0.023
8 - acc: 0.9921 - val_loss: 0.0274 - val_acc: 0.9917
Epoch 7/12
60000/60000 [==============================] - 102s 2ms/step - loss: 0.020
6 - acc: 0.9934 - val_loss: 0.0287 - val_acc: 0.9909
Epoch 8/12
60000/60000 [==============================] - 104s 2ms/step - loss: 0.017
4 - acc: 0.9944 - val_loss: 0.0230 - val_acc: 0.9929
Epoch 9/12
60000/60000 [==============================] - 104s 2ms/step - loss: 0.015
1 - acc: 0.9951 - val_loss: 0.0222 - val_acc: 0.9928
Epoch 10/12
60000/60000 [==============================] - 103s 2ms/step - loss: 0.015
1 - acc: 0.9951 - val_loss: 0.0202 - val_acc: 0.9942
Epoch 11/12
60000/60000 [==============================] - 103s 2ms/step - loss: 0.013
6 - acc: 0.9952 - val_loss: 0.0265 - val_acc: 0.9923
Epoch 12/12
60000/60000 [==============================] - 104s 2ms/step - loss: 0.012
7 - acc: 0.9958 - val_loss: 0.0281 - val_acc: 0.9921
Test loss: 0.02808658135307 56
Test accuracy: 0.9921
```

In [21]:

```
score = model.evaluate(x_train, y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n*********************** ********************\n')
#test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
# plot
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch');
ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,12+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.006600003199334939
Train accuracy: 99.77666666666667

*********************** ********************

Test score: 0.0280865813530756
Test accuracy: 99.21
```



MLP + ReLU +SGD

In [35]:

```
from keras.initializers import RandomNormal
from keras.layers import Activation, Dense
from keras.initializers import RandomNormal
#from keras.utils.visualize_util import to_graph
from keras.models import Sequential
```

In [39]:

```
import warnings
warnings.filterwarnings("ignore")
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use th
is command
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
#from keras.utils.visualize_util import to_graph
from keras.models import Sequential
#to_graph(Sequential())
```

In [29]:

```
%matplotlib notebook
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time
# 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()
```

In [30]:

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

In [31]:

```
print("Number of training examples :", X_train.shape[0], "and each image is of shape (%
d, %d)"%(X_train.shape[1], X_train.shape[2]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d
,%d)"%(X_test.shape[1], X_test.shape[2]))
```

```
Number of training examples : 60000 and each image is of shape (28, 28)
Number of training examples : 10000 and each image is of shape (28,28)
```

In [32]:

```
# if you observe the input shape its 2 dimensional vector
# for each image we have a (28*28) vector
# we will convert the (28*28) vector into single dimensional vector of 1 * 784
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
# after converting the input images from 3d to 2d vectors
print("Number of training examples :", X_train.shape[0], "and each image is of shape(%d
)"%(X_train.shape[1]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d
)"%(X_test.shape[1]))
```

```
Number of training examples : 60000 and each image is of shape(784)
Number of training examples : 10000 and each image is of shape (784)
```

In [33]:

```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets try to normalize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255
X_train = X_train/255
X_test = X_test/255
```

In [40]:

```
# here we are having a class number for each image
print("Class label of first image :", y_train[0])
# lets convert this into a 10 dimensional vector
# ex: consider an image is 5 convert it into 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion needed for MLPs
Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)

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 [41]:

```
# some model parameters
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 112
nb_epoch = 20
print(input_dim)
```

```
784
```

In [43]:

```
# Multilayer perceptron

# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.062  => N(0,σ) = N(0,0.062)
# h2 =>  σ=√(2/(fan_in) = 0.125  => N(0,σ) = N(0,0.125)
# out =>  σ=√(2/(fan_in+1) = 0.120  => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_19 (Dense)             (None, 512)               401920    
_________________________________________________________________
dense_20 (Dense)             (None, 128)               65664     
_________________________________________________________________
dense_21 (Dense)             (None, 10)                1290      
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
```

In [46]:

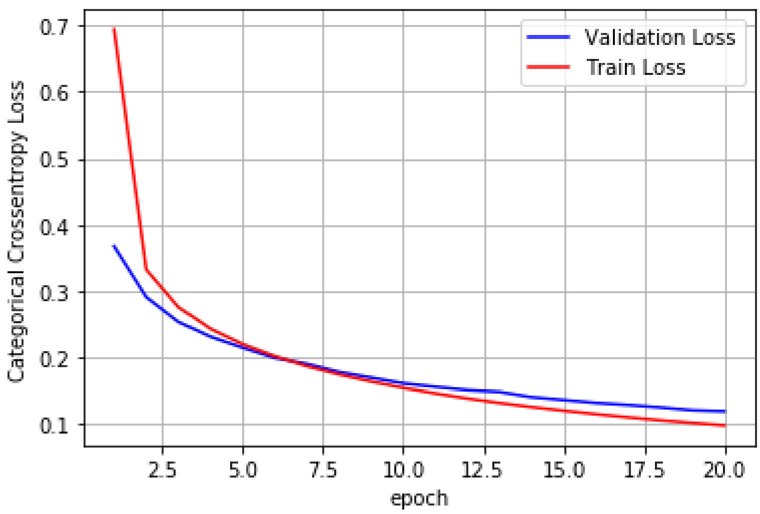
```
model_relu.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accurac
y'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.694
1 - acc: 0.8031 - val_loss: 0.3673 - val_acc: 0.8982
Epoch 2/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.332
2 - acc: 0.9054 - val_loss: 0.2906 - val_acc: 0.9160
Epoch 3/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.275
4 - acc: 0.9218 - val_loss: 0.2532 - val_acc: 0.9261
Epoch 4/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.242
6 - acc: 0.9308 - val_loss: 0.2306 - val_acc: 0.9325
Epoch 5/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.219
3 - acc: 0.9381 - val_loss: 0.2141 - val_acc: 0.9378
Epoch 6/20
60000/60000 [==============================] - 7s 125us/step - loss: 0.201
3 - acc: 0.9430 - val_loss: 0.1987 - val_acc: 0.9421
Epoch 7/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.186
4 - acc: 0.9470 - val_loss: 0.1898 - val_acc: 0.9453
Epoch 8/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.174
0 - acc: 0.9511 - val_loss: 0.1775 - val_acc: 0.9472
Epoch 9/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.163
4 - acc: 0.9538 - val_loss: 0.1692 - val_acc: 0.9486
Epoch 10/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.153
8 - acc: 0.9571 - val_loss: 0.1606 - val_acc: 0.9518
Epoch 11/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.145
5 - acc: 0.9596 - val_loss: 0.1554 - val_acc: 0.9529
Epoch 12/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.137
9 - acc: 0.9616 - val_loss: 0.1505 - val_acc: 0.9541
Epoch 13/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.131
2 - acc: 0.9635 - val_loss: 0.1478 - val_acc: 0.9553
Epoch 14/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.125
1 - acc: 0.9652 - val_loss: 0.1399 - val_acc: 0.9584
Epoch 15/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.119
6 - acc: 0.9667 - val_loss: 0.1357 - val_acc: 0.9591
Epoch 16/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.114
3 - acc: 0.9681 - val_loss: 0.1313 - val_acc: 0.9604
Epoch 17/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.109
6 - acc: 0.9699 - val_loss: 0.1282 - val_acc: 0.9605
Epoch 18/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.105
2 - acc: 0.9710 - val_loss: 0.1246 - val_acc: 0.9616
Epoch 19/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.101
3 - acc: 0.9723 - val_loss: 0.1203 - val_acc: 0.9629
Epoch 20/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.097
5 - acc: 0.9732 - val_loss: 0.1187 - val_acc: 0.9634
```

In [48]:

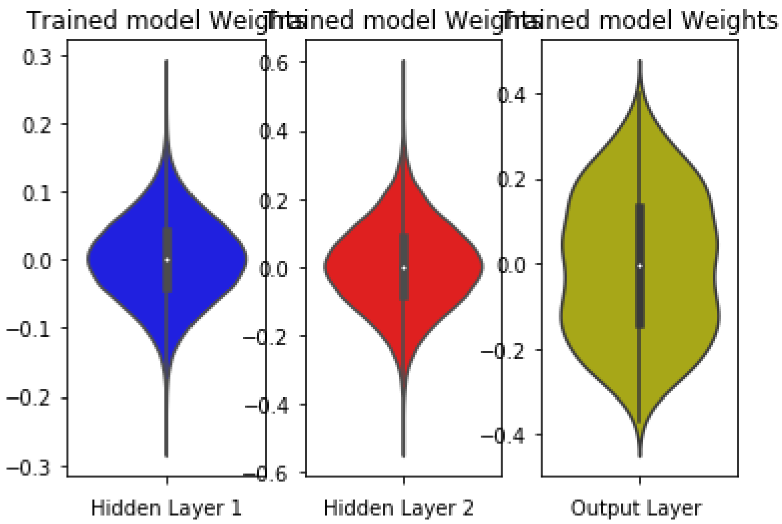
```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_los
s)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, ve
rbose=1, validation_data=(X_test, Y_test))
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of ep
ochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.09366472623236477
Train accuracy: 97.47666666666667

*********************** ********************

Test score: 0.11871300079077482
Test accuracy: 96.34
```



In [49]:

```
w_after = model_relu.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()
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()
```



MLP + ReLU + adam

In [59]:

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializ
er=RandomNormal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0,
stddev=0.125, seed=None)) )
model_relu.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0,
stddev=0.125, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_22 (Dense)             (None, 610)               478850    
_________________________________________________________________
dense_23 (Dense)             (None, 420)               256620    
_________________________________________________________________
dense_24 (Dense)             (None, 210)               88410     
_________________________________________________________________
dense_25 (Dense)             (None, 10)                2110      
=================================================================
Total params: 825,990
Trainable params: 825,990
Non-trainable params: 0
_________________________________________________________________
```

In [60]:

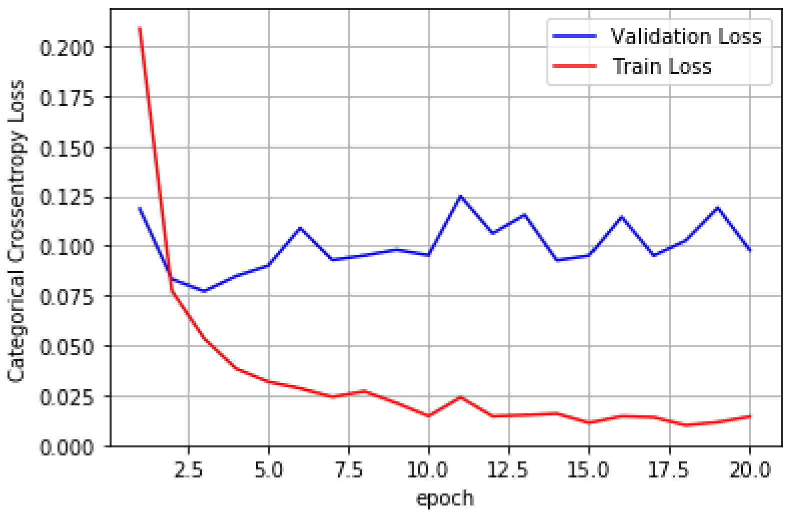
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accurac
y'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 20s 332us/step - loss: 0.20
89 - acc: 0.9367 - val_loss: 0.1186 - val_acc: 0.9628
Epoch 2/20
60000/60000 [==============================] - 18s 296us/step - loss: 0.07
74 - acc: 0.9760 - val_loss: 0.0833 - val_acc: 0.9712
Epoch 3/20
60000/60000 [==============================] - 17s 288us/step - loss: 0.05
34 - acc: 0.9828 - val_loss: 0.0771 - val_acc: 0.9761
Epoch 4/20
60000/60000 [==============================] - 17s 285us/step - loss: 0.03
82 - acc: 0.9875 - val_loss: 0.0848 - val_acc: 0.9758
Epoch 5/20
60000/60000 [==============================] - 17s 286us/step - loss: 0.03
17 - acc: 0.9894 - val_loss: 0.0901 - val_acc: 0.9757: 0.0313
Epoch 6/20
60000/60000 [==============================] - 17s 291us/step - loss: 0.02
84 - acc: 0.9910 - val_loss: 0.1089 - val_acc: 0.9724
Epoch 7/20
60000/60000 [==============================] - 17s 287us/step - loss: 0.02
42 - acc: 0.9918 - val_loss: 0.0929 - val_acc: 0.9756
Epoch 8/20
60000/60000 [==============================] - 17s 286us/step - loss: 0.02
69 - acc: 0.9910 - val_loss: 0.0952 - val_acc: 0.9736
Epoch 9/20
60000/60000 [==============================] - 17s 285us/step - loss: 0.02
11 - acc: 0.9929 - val_loss: 0.0980 - val_acc: 0.9781
Epoch 10/20
60000/60000 [==============================] - 17s 287us/step - loss: 0.01
46 - acc: 0.9953 - val_loss: 0.0953 - val_acc: 0.9767
Epoch 11/20
60000/60000 [==============================] - 17s 282us/step - loss: 0.02
40 - acc: 0.9921 - val_loss: 0.1249 - val_acc: 0.9711
Epoch 12/20
60000/60000 [==============================] - 17s 286us/step - loss: 0.01
45 - acc: 0.9956 - val_loss: 0.1062 - val_acc: 0.9778
Epoch 13/20
60000/60000 [==============================] - 17s 287us/step - loss: 0.01
50 - acc: 0.9950 - val_loss: 0.1155 - val_acc: 0.9741
Epoch 14/20
60000/60000 [==============================] - 17s 284us/step - loss: 0.01
58 - acc: 0.9951 - val_loss: 0.0927 - val_acc: 0.9777
Epoch 15/20
60000/60000 [==============================] - 17s 280us/step - loss: 0.01
12 - acc: 0.9965 - val_loss: 0.0951 - val_acc: 0.9791
Epoch 16/20
60000/60000 [==============================] - 17s 280us/step - loss: 0.01
45 - acc: 0.9955 - val_loss: 0.1145 - val_acc: 0.9785
Epoch 17/20
60000/60000 [==============================] - 17s 284us/step - loss: 0.01
40 - acc: 0.9955 - val_loss: 0.0951 - val_acc: 0.9800
Epoch 18/20
60000/60000 [==============================] - 17s 284us/step - loss: 0.00
99 - acc: 0.9972 - val_loss: 0.1026 - val_acc: 0.9800
Epoch 19/20
60000/60000 [==============================] - 17s 282us/step - loss: 0.01
15 - acc: 0.9967 - val_loss: 0.1191 - val_acc: 0.9747
Epoch 20/20
60000/60000 [==============================] - 18s 292us/step - loss: 0.01
43 - acc: 0.9960 - val_loss: 0.0978 - val_acc: 0.9808
```

In [61]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_los
s)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, ve
rbose=1, validation_data=(X_test, Y_test))
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of ep
ochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.008483383478405585
Train accuracy: 99.72666666666666

*********************** ********************

Test score: 0.09776807529597008
Test accuracy: 98.08
```



Compare all the model results

In [58]:

```
from prettytable import PrettyTable
tb = PrettyTable()
tb.field_names= ("conv_layers", "MAxPoll_layers", "Dense_layers","Dropout","Accuracy")
tb.add_row(["2", "2","3","NO",98.94])
tb.add_row(["3", "3","2","NO",98.75])
tb.add_row(["4", "2","2","NO",99.09])
tb.add_row(["2", "2","3","0.5",99.22])
tb.add_row(["3", "3","2","0.9",97.92])
tb.add_row(["4", "2","2","0.3",99.21])

print(tb.get_string(titles = "CNN Models - Observations"))
```

```
+-------------+----------------+--------------+---------+----------+
| conv_layers | MAxPoll_layers | Dense_layers | Dropout | Accuracy |
+-------------+----------------+--------------+---------+----------+
|      2      |       2        |      3       |    NO   |  98.94   |
|      3      |       3        |      2       |    NO   |  98.75   |
|      4      |       2        |      2       |    NO   |  99.09   |
|      2      |       2        |      3       |   0.5   |  99.22   |
|      3      |       3        |      2       |   0.9   |  97.92   |
|      4      |       2        |      2       |   0.3   |  99.21   |
+-------------+----------------+--------------+---------+----------+
```

CONCLUSION:

Train accuracy is low for higher number of layers.

Test accuracy is almost same for all case.

Overall conclusion: We can conclude that all the 3 different architectures i.e 3, 5 and 9 performed very well with close accuracy of 98.7%. Also, We can conclude that regularizers like drop out resulted in close accuracy of 99.4%

CONCLUSION FOR OPTIMIZERS: Accuracy for Adam optimizer is little higher when compared with SGD optimizer