Apply 3 different CNN's on the MNIST dataset

In [8]:

```
# 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-architecturespart-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 [10]:

```
%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 [12]:

```
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()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_3 (Conv2D)            (None, 28, 28, 8)         80        
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 8)         0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 10, 10, 16)        3216      
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 5, 5, 16)          0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 400)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 120)               48120     
_________________________________________________________________
dense_5 (Dense)              (None, 84)                10164     
_________________________________________________________________
dense_6 (Dense)              (None, 10)                850       
=================================================================
Total params: 62,430
Trainable params: 62,430
Non-trainable params: 0
_________________________________________________________________
```

In [14]:

```
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 [==============================] - 17s 288us/step - loss: 0.06
89 - acc: 0.9789 - val_loss: 0.0538 - val_acc: 0.9838
Epoch 2/12
60000/60000 [==============================] - 15s 243us/step - loss: 0.05
10 - acc: 0.9845 - val_loss: 0.0496 - val_acc: 0.9834
Epoch 3/12
60000/60000 [==============================] - 15s 246us/step - loss: 0.03
95 - acc: 0.9879 - val_loss: 0.0364 - val_acc: 0.9880
Epoch 4/12
60000/60000 [==============================] - 15s 254us/step - loss: 0.03
18 - acc: 0.9898 - val_loss: 0.0342 - val_acc: 0.9877
Epoch 5/12
60000/60000 [==============================] - 15s 258us/step - loss: 0.02
90 - acc: 0.9908 - val_loss: 0.0356 - val_acc: 0.9884
Epoch 6/12
60000/60000 [==============================] - 15s 249us/step - loss: 0.02
39 - acc: 0.9921 - val_loss: 0.0292 - val_acc: 0.9912
Epoch 7/12
60000/60000 [==============================] - 15s 255us/step - loss: 0.02
15 - acc: 0.9932 - val_loss: 0.0334 - val_acc: 0.9884
Epoch 8/12
60000/60000 [==============================] - 15s 252us/step - loss: 0.01
81 - acc: 0.9940 - val_loss: 0.0331 - val_acc: 0.9895
Epoch 9/12
60000/60000 [==============================] - 15s 247us/step - loss: 0.01
56 - acc: 0.9948 - val_loss: 0.0322 - val_acc: 0.9898
Epoch 10/12
60000/60000 [==============================] - 15s 249us/step - loss: 0.01
33 - acc: 0.9956 - val_loss: 0.0348 - val_acc: 0.9894
Epoch 11/12
60000/60000 [==============================] - 15s 252us/step - loss: 0.01
25 - acc: 0.9957 - val_loss: 0.0407 - val_acc: 0.9869
Epoch 12/12
60000/60000 [==============================] - 15s 251us/step - loss: 0.01
11 - acc: 0.9965 - val_loss: 0.0391 - val_acc: 0.9881
Test loss: 0.039050305695623684
Test accuracy: 0.9881
```

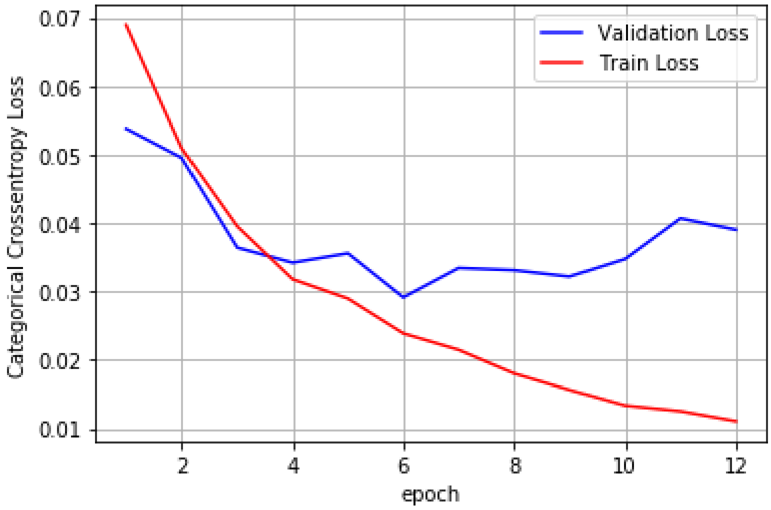
In [15]:

```
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: 0.010427321565627062
Train accuracy: 99.67333333333333

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

Test score: 0.039050305695623684
Test accuracy: 98.81
```



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

In [16]:

```
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_5 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 11, 11, 64)        18496     
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 3, 3, 128)         73856     
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 1, 1, 128)         0         
_________________________________________________________________
flatten_3 (Flatten)          (None, 128)               0         
_________________________________________________________________
dense_7 (Dense)              (None, 64)                8256      
_________________________________________________________________
dense_8 (Dense)              (None, 10)                650       
=================================================================
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0
_________________________________________________________________
```

In [17]:

```
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 [==============================] - 40s 670us/step - loss: 0.32
16 - acc: 0.9046 - val_loss: 0.1012 - val_acc: 0.9684
Epoch 2/12
60000/60000 [==============================] - 38s 627us/step - loss: 0.09
35 - acc: 0.9714 - val_loss: 0.0711 - val_acc: 0.9772
Epoch 3/12
60000/60000 [==============================] - 37s 620us/step - loss: 0.06
65 - acc: 0.9797 - val_loss: 0.0708 - val_acc: 0.9789
Epoch 4/12
60000/60000 [==============================] - 37s 620us/step - loss: 0.05
37 - acc: 0.9834 - val_loss: 0.0510 - val_acc: 0.9845
Epoch 5/12
60000/60000 [==============================] - 38s 627us/step - loss: 0.04
58 - acc: 0.9854 - val_loss: 0.0579 - val_acc: 0.9832
Epoch 6/12
60000/60000 [==============================] - 37s 620us/step - loss: 0.03
80 - acc: 0.9881 - val_loss: 0.0448 - val_acc: 0.9861
Epoch 7/12
60000/60000 [==============================] - 37s 624us/step - loss: 0.03
23 - acc: 0.9901 - val_loss: 0.0474 - val_acc: 0.9864
Epoch 8/12
60000/60000 [==============================] - 38s 626us/step - loss: 0.02
71 - acc: 0.9917 - val_loss: 0.0484 - val_acc: 0.9867
Epoch 9/12
60000/60000 [==============================] - 38s 634us/step - loss: 0.02
31 - acc: 0.9926 - val_loss: 0.0564 - val_acc: 0.9846
Epoch 10/12
60000/60000 [==============================] - 37s 622us/step - loss: 0.02
13 - acc: 0.9931 - val_loss: 0.0584 - val_acc: 0.9823
Epoch 11/12
60000/60000 [==============================] - 38s 627us/step - loss: 0.01
74 - acc: 0.9946 - val_loss: 0.0461 - val_acc: 0.9872
Epoch 12/12
60000/60000 [==============================] - 38s 629us/step - loss: 0.01
62 - acc: 0.9948 - val_loss: 0.0454 - val_acc: 0.9881
Test loss: 0.04539995787585067
Test accuracy: 0.9881
```

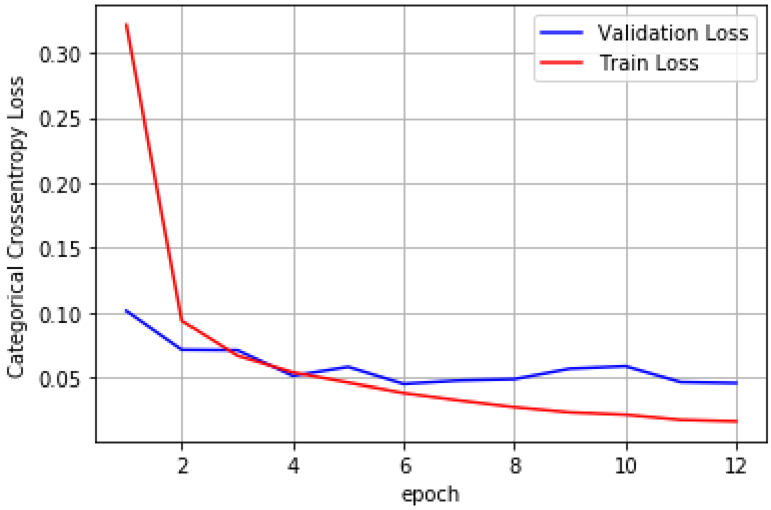
In [18]:

```
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: 0.009743525346997921
Train accuracy: 99.69833333333334

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

Test score: 0.04539995787585067
Test accuracy: 98.81
```



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

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

In [19]:

```
# 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_8 (Conv2D)            (None, 28, 28, 16)        160       
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 16)        2320      
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 14, 14, 16)        0         
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 12, 12, 32)        4640      
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 10, 10, 32)        9248      
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 5, 5, 32)          0         
_________________________________________________________________
flatten_4 (Flatten)          (None, 800)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 512)               410112    
_________________________________________________________________
dense_10 (Dense)             (None, 10)                5130      
=================================================================
Total params: 431,610
Trainable params: 431,610
Non-trainable params: 0
_________________________________________________________________
```

In [20]:

```
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 [==============================] - 64s 1ms/step - loss: 0.1727
- acc: 0.9479 - val_loss: 0.0515 - val_acc: 0.9826
Epoch 2/12
60000/60000 [==============================] - 59s 987us/step - loss: 0.04
42 - acc: 0.9862 - val_loss: 0.0300 - val_acc: 0.9905
Epoch 3/12
60000/60000 [==============================] - 59s 983us/step - loss: 0.03
06 - acc: 0.9906 - val_loss: 0.0258 - val_acc: 0.9912
Epoch 4/12
60000/60000 [==============================] - 61s 1ms/step - loss: 0.0221
- acc: 0.9931 - val_loss: 0.0296 - val_acc: 0.9905
Epoch 5/12
60000/60000 [==============================] - 67s 1ms/step - loss: 0.0173
- acc: 0.9940 - val_loss: 0.0294 - val_acc: 0.9912
Epoch 6/12
60000/60000 [==============================] - 57s 957us/step - loss: 0.01
47 - acc: 0.9952 - val_loss: 0.0319 - val_acc: 0.9904
Epoch 7/12
60000/60000 [==============================] - 61s 1ms/step - loss: 0.0112
- acc: 0.9963 - val_loss: 0.0282 - val_acc: 0.9922
Epoch 8/12
60000/60000 [==============================] - 58s 963us/step - loss: 0.00
95 - acc: 0.9970 - val_loss: 0.0339 - val_acc: 0.9897
Epoch 9/12
60000/60000 [==============================] - 58s 973us/step - loss: 0.00
99 - acc: 0.9967 - val_loss: 0.0374 - val_acc: 0.9897
Epoch 10/12
60000/60000 [==============================] - 59s 976us/step - loss: 0.00
70 - acc: 0.9975 - val_loss: 0.0287 - val_acc: 0.9914
Epoch 11/12
60000/60000 [==============================] - 59s 980us/step - loss: 0.00
67 - acc: 0.9978 - val_loss: 0.0307 - val_acc: 0.9912
Epoch 12/12
60000/60000 [==============================] - 59s 987us/step - loss: 0.00
51 - acc: 0.9986 - val_loss: 0.0242 - val_acc: 0.9935
Test loss: 0.024233603691490725
Test accuracy: 0.9935
```

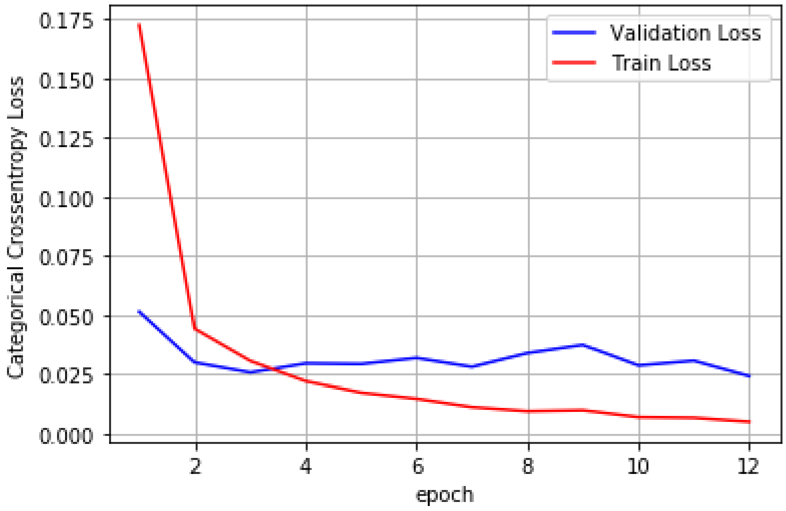
In [21]:

```
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: 0.0032476350627371935
Train accuracy: 99.90833333333333

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

Test score: 0.024233603691490725
Test accuracy: 99.35000000000001
```



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

In [23]:

```
#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 simple 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=input_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()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_14 (Conv2D)           (None, 28, 28, 8)         80        
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 14, 14, 8)         0         
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 10, 10, 16)        3216      
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 5, 5, 16)          0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 5, 5, 16)          0         
_________________________________________________________________
flatten_6 (Flatten)          (None, 400)               0         
_________________________________________________________________
dense_14 (Dense)             (None, 120)               48120     
_________________________________________________________________
dense_15 (Dense)             (None, 84)                10164     
_________________________________________________________________
dense_16 (Dense)             (None, 10)                850       
=================================================================
Total params: 62,430
Trainable params: 62,430
Non-trainable params: 0
_________________________________________________________________
```

In [24]:

```
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 [==============================] - 17s 284us/step - loss: 0.42
44 - acc: 0.8639 - val_loss: 0.0859 - val_acc: 0.9748
Epoch 2/12
60000/60000 [==============================] - 16s 268us/step - loss: 0.13
36 - acc: 0.9576 - val_loss: 0.0558 - val_acc: 0.9824
Epoch 3/12
60000/60000 [==============================] - 17s 278us/step - loss: 0.10
68 - acc: 0.9662 - val_loss: 0.0446 - val_acc: 0.9849
Epoch 4/12
60000/60000 [==============================] - 17s 276us/step - loss: 0.08
97 - acc: 0.9710 - val_loss: 0.0395 - val_acc: 0.9867
Epoch 5/12
60000/60000 [==============================] - 17s 286us/step - loss: 0.07
77 - acc: 0.9746 - val_loss: 0.0351 - val_acc: 0.9891
Epoch 6/12
60000/60000 [==============================] - 17s 278us/step - loss: 0.07
33 - acc: 0.9768 - val_loss: 0.0346 - val_acc: 0.9881
Epoch 7/12
60000/60000 [==============================] - 17s 277us/step - loss: 0.06
53 - acc: 0.9791 - val_loss: 0.0342 - val_acc: 0.9888
Epoch 8/12
60000/60000 [==============================] - 17s 277us/step - loss: 0.06
15 - acc: 0.9804 - val_loss: 0.0302 - val_acc: 0.9898
Epoch 9/12
60000/60000 [==============================] - 17s 287us/step - loss: 0.05
72 - acc: 0.9813 - val_loss: 0.0303 - val_acc: 0.9894
Epoch 10/12
60000/60000 [==============================] - 17s 282us/step - loss: 0.05
53 - acc: 0.9819 - val_loss: 0.0302 - val_acc: 0.9897
Epoch 11/12
60000/60000 [==============================] - 17s 286us/step - loss: 0.05
24 - acc: 0.9833 - val_loss: 0.0260 - val_acc: 0.9910
Epoch 12/12
60000/60000 [==============================] - 17s 286us/step - loss: 0.05
00 - acc: 0.9837 - val_loss: 0.0273 - val_acc: 0.9910
Test loss: 0.027327572450373556
Test accuracy: 0.991
```

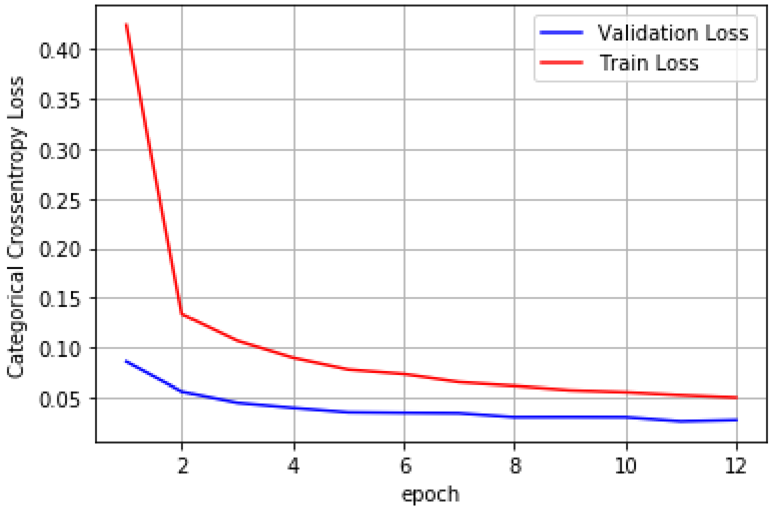
In [25]:

```
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: 0.018932762710633686
Train accuracy: 99.43666666666667

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

Test score: 0.027327572450373556
Test accuracy: 99.1
```



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

In [27]:

```
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()
```

```
W0629 22:43:29.693563   692 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_19 (Conv2D)           (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_20 (Conv2D)           (None, 11, 11, 64)        18496     
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 3, 3, 128)         73856     
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 1, 1, 128)         0         
_________________________________________________________________
dropout_4 (Dropout)          (None, 1, 1, 128)         0         
_________________________________________________________________
flatten_8 (Flatten)          (None, 128)               0         
_________________________________________________________________
dense_19 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_20 (Dense)             (None, 10)                650       
=================================================================
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0
_________________________________________________________________
```

In [28]:

```
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 [==============================] - 39s 654us/step - loss: 1.30
13 - acc: 0.5210 - val_loss: 0.2997 - val_acc: 0.9407
Epoch 2/12
60000/60000 [==============================] - 37s 615us/step - loss: 0.80
30 - acc: 0.7029 - val_loss: 0.1820 - val_acc: 0.9527
Epoch 3/12
60000/60000 [==============================] - 37s 616us/step - loss: 0.67
01 - acc: 0.7518 - val_loss: 0.1444 - val_acc: 0.9614
Epoch 4/12
60000/60000 [==============================] - 36s 605us/step - loss: 0.60
75 - acc: 0.7772 - val_loss: 0.1168 - val_acc: 0.9679
Epoch 5/12
60000/60000 [==============================] - 37s 620us/step - loss: 0.55
34 - acc: 0.8004 - val_loss: 0.1155 - val_acc: 0.9679
Epoch 6/12
60000/60000 [==============================] - 37s 610us/step - loss: 0.51
37 - acc: 0.8165 - val_loss: 0.1043 - val_acc: 0.9701
Epoch 7/12
60000/60000 [==============================] - 37s 617us/step - loss: 0.48
18 - acc: 0.8267 - val_loss: 0.0927 - val_acc: 0.9736
Epoch 8/12
60000/60000 [==============================] - 37s 613us/step - loss: 0.45
95 - acc: 0.8352 - val_loss: 0.1023 - val_acc: 0.9700
Epoch 9/12
60000/60000 [==============================] - 36s 596us/step - loss: 0.43
43 - acc: 0.8478 - val_loss: 0.0919 - val_acc: 0.9736
Epoch 10/12
60000/60000 [==============================] - 36s 604us/step - loss: 0.41
74 - acc: 0.8532 - val_loss: 0.0951 - val_acc: 0.9716
Epoch 11/12
60000/60000 [==============================] - 36s 599us/step - loss: 0.39
85 - acc: 0.8642 - val_loss: 0.0918 - val_acc: 0.9724
Epoch 12/12
60000/60000 [==============================] - 36s 594us/step - loss: 0.38
30 - acc: 0.8711 - val_loss: 0.0968 - val_acc: 0.9701
Test loss: 0.09679163726270198
Test accuracy: 0.9701
```

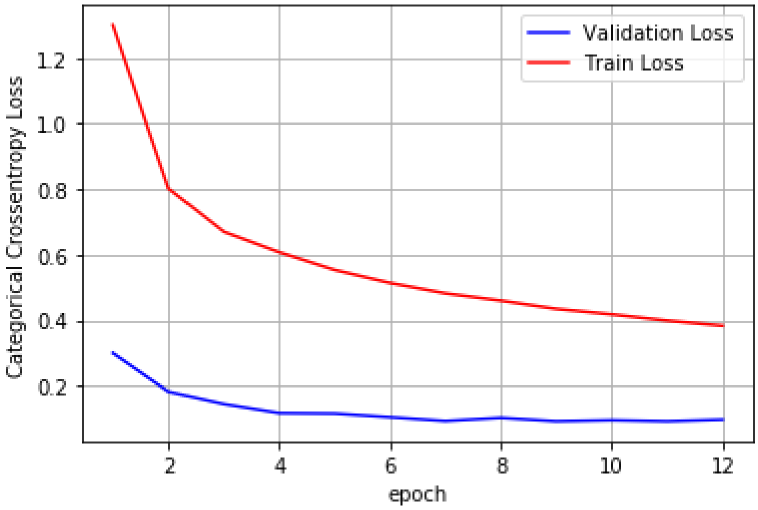
In [29]:

```
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: 0.08697761877303323
Train accuracy: 97.515

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


Test score: 0.09679163726270198
Test accuracy: 97.00999999999999
```



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

In [30]:

```
# 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_22 (Conv2D)           (None, 28, 28, 16)        160       
_________________________________________________________________
conv2d_23 (Conv2D)           (None, 28, 28, 16)        2320      
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 14, 14, 16)        0         
_________________________________________________________________
conv2d_24 (Conv2D)           (None, 12, 12, 32)        4640      
_________________________________________________________________
conv2d_25 (Conv2D)           (None, 10, 10, 32)        9248      
_________________________________________________________________
max_pooling2d_21 (MaxPooling (None, 5, 5, 32)          0         
_________________________________________________________________
dropout_5 (Dropout)          (None, 5, 5, 32)          0         
_________________________________________________________________
flatten_9 (Flatten)          (None, 800)               0         
_________________________________________________________________
dense_21 (Dense)             (None, 512)               410112    
_________________________________________________________________
dense_22 (Dense)             (None, 10)                5130      
=================================================================
Total params: 431,610
Trainable params: 431,610
Non-trainable params: 0
_________________________________________________________________
```

In [31]:

```
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 [==============================] - 59s 975us/step - loss: 0.20
71 - acc: 0.9347 - val_loss: 0.0499 - val_acc: 0.9845
Epoch 2/12
60000/60000 [==============================] - 57s 957us/step - loss: 0.06
00 - acc: 0.9814 - val_loss: 0.0342 - val_acc: 0.9890
Epoch 3/12
60000/60000 [==============================] - 58s 963us/step - loss: 0.04
14 - acc: 0.9868 - val_loss: 0.0331 - val_acc: 0.9896
Epoch 4/12
60000/60000 [==============================] - 57s 957us/step - loss: 0.03
30 - acc: 0.9895 - val_loss: 0.0222 - val_acc: 0.9932
Epoch 5/12
60000/60000 [==============================] - 58s 967us/step - loss: 0.02
86 - acc: 0.9907 - val_loss: 0.0241 - val_acc: 0.9920
Epoch 6/12
60000/60000 [==============================] - 59s 979us/step - loss: 0.02
42 - acc: 0.9922 - val_loss: 0.0213 - val_acc: 0.9929
Epoch 7/12
60000/60000 [==============================] - 59s 976us/step - loss: 0.01
98 - acc: 0.9939 - val_loss: 0.0239 - val_acc: 0.9923
Epoch 8/12
60000/60000 [==============================] - 58s 968us/step - loss: 0.01
82 - acc: 0.9936 - val_loss: 0.0235 - val_acc: 0.9927
Epoch 9/12
60000/60000 [==============================] - 58s 965us/step - loss: 0.01
72 - acc: 0.9942 - val_loss: 0.0228 - val_acc: 0.9917
Epoch 10/12
60000/60000 [==============================] - 57s 958us/step - loss: 0.01
45 - acc: 0.9953 - val_loss: 0.0279 - val_acc: 0.9915
Epoch 11/12
60000/60000 [==============================] - 58s 964us/step - loss: 0.01
39 - acc: 0.9954 - val_loss: 0.0217 - val_acc: 0.9925
Epoch 12/12
60000/60000 [==============================] - 58s 959us/step - loss: 0.01
15 - acc: 0.9962 - val_loss: 0.0234 - val_acc: 0.9936
Test loss: 0.023363230100554574
Test accuracy: 0.9936
```

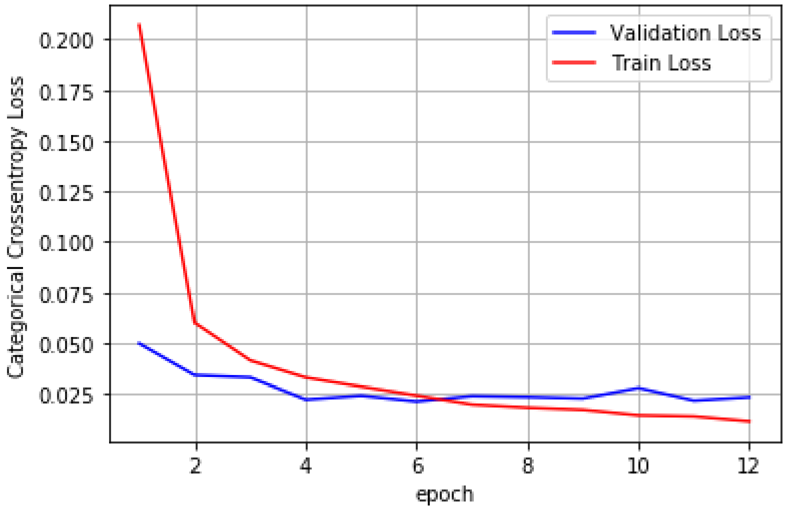
In [32]:

```
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: 0.00590441487302293
Train accuracy: 99.80166666666666

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

Test score: 0.023363230100554574
Test accuracy: 99.36
```



Compare all the model results

In [33]:

```
from prettytable import PrettyTable
tb = PrettyTable()
tb.field_names= ("conv_layers", "MAxPoll_layers", "Dense_layers","Dropout","Accuracy")
tb.add_row(["2", "2","3","NO",98.81])
tb.add_row(["3", "3","2","NO",98.81])
tb.add_row(["4", "2","2","NO",99.35])
tb.add_row(["2", "2","3","0.5",99.1])
tb.add_row(["3", "3","2","0.9",97.0])
tb.add_row(["4", "2","2","0.3",99.36])
print(tb.get_string(titles = "CNN Models - Observations"))
```

```
+-------------+----------------+--------------+---------+----------+
| conv_layers | MAxPoll_layers | Dense_layers | Dropout | Accuracy |
+-------------+----------------+--------------+---------+----------+
|      2      |       2        |      3       |    NO   |  98.81   |
|      3      |       3        |      2       |    NO   |  98.81   |
|      4      |       2        |      2       |    NO   |  99.35   |
|      2      |       2        |      3       |   0.5   |   99.1   |
|      3      |       3        |      2       |   0.9   |   97.0   |
|      4      |       2        |      2       |   0.3   |  99.36   |
+-------------+----------------+--------------+---------+----------+
```