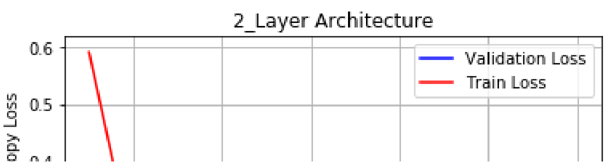
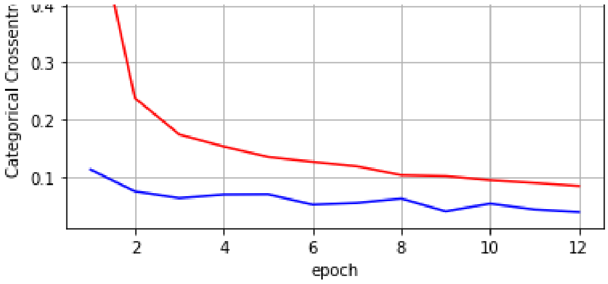
In [3]:

```
# Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py

from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
from keras.layers.normalization import BatchNormalization

%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time

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()



batch_size = 128
num_classes = 10
nb_epoch = 12

# 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()

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)

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',input_shape=input_shape)) #here we taking
32 kernels  matrix shape 3*3
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Conv2D(64, (3, 3), activation='relu')) # here we taking 64 kernals matrix shape 2*2
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2))) # here we max_pooling with 2*2 means we taking highest
value in each 2*2 matrix and depends upon its strides value
model.add(Dropout(0.5))# here we adding dropout layer
model.add(Flatten()) #we flatten our matrix to 1 dimensional vector
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5)) # again we applying dropout on flatten vector
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
```

```
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history1 = model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          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])

#plotting train loss vs test loss

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))

vy = history1.history['val_loss']
ty = history1.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 13s 214us/step - loss: 0.5901 - acc: 0.8212 - val_l
oss: 0.1137 - val_acc: 0.9642
Epoch 2/12
60000/60000 [==============================] - 12s 197us/step - loss: 0.2381 - acc: 0.9297 - val_l
oss: 0.0756 - val_acc: 0.9787
Epoch 3/12
60000/60000 [==============================] - 12s 197us/step - loss: 0.1748 - acc: 0.9483 - val_l
oss: 0.0642 - val_acc: 0.9826
Epoch 4/12
60000/60000 [==============================] - 12s 199us/step - loss: 0.1539 - acc: 0.9544 - val_l
oss: 0.0704 - val_acc: 0.9832
Epoch 5/12
60000/60000 [==============================] - 12s 197us/step - loss: 0.1357 - acc: 0.9588 - val_l
oss: 0.0708 - val_acc: 0.9838
Epoch 6/12
60000/60000 [==============================] - 12s 197us/step - loss: 0.1271 - acc: 0.9623 - val_l
oss: 0.0528 - val_acc: 0.9854
Epoch 7/12
60000/60000 [==============================] - 12s 200us/step - loss: 0.1194 - acc: 0.9643 - val_l
oss: 0.0558 - val_acc: 0.9854
Epoch 8/12
60000/60000 [==============================] - 12s 200us/step - loss: 0.1041 - acc: 0.9692 - val_l
oss: 0.0634 - val_acc: 0.9847
Epoch 9/12
60000/60000 [==============================] - 12s 195us/step - loss: 0.1024 - acc: 0.9694 - val_l
oss: 0.0410 - val_acc: 0.9882
Epoch 10/12
60000/60000 [==============================] - 12s 197us/step - loss: 0.0953 - acc: 0.9712 - val_l
oss: 0.0547 - val_acc: 0.9867
Epoch 11/12
60000/60000 [==============================] - 12s 196us/step - loss: 0.0906 - acc: 0.9736 - val_l
oss: 0.0443 - val_acc: 0.9887
Epoch 12/12
60000/60000 [==============================] - 12s 199us/step - loss: 0.0850 - acc: 0.9753 - val_l
oss: 0.0398 - val_acc: 0.9887
Test loss: 0.03982257423208571
Test accuracy: 0.9887
```





If we see the above model it gives 98% accuracy intitial we got 98% accuracy with test loss 0.03

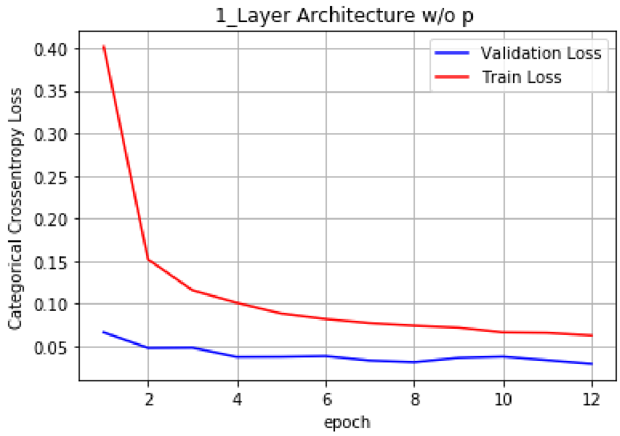
With Single CNN Layer with valid (No) padding

In [4]:

```
model2 = Sequential()
model2.add(Conv2D(30, kernel_size=(5, 5), padding='valid', activation='relu',input_shape=input_shap
e))
model2.add(BatchNormalization())
model2.add(MaxPooling2D(pool_size=(3, 3)))
model2.add(Dropout(0.5))
#model2.add(Conv2D(48, (2, 2), activation='relu'))
#model2.add(MaxPooling2D(pool_size=(2, 2)))
#model2.add(Dropout(0.25))
model2.add(Flatten())
model2.add(Dense(128, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(num_classes, activation='softmax'))

model2.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history2 = model2.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score2 = model2.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score2[0])
print('Test accuracy:', score2[1])

#plotting train loss vs test loss

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))

vy = history2.history['val_loss']
ty = history2.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('1_Layer Architecture w/o p ')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 5s 90us/step - loss: 0.4016 - acc: 0.8776 -
val_loss: 0.0664 - val_acc: 0.9776
Epoch 2/12
60000/60000 [==============================] - 5s 77us/step - loss: 0.1520 - acc: 0.9544 -
val_loss: 0.0482 - val_acc: 0.9838
Epoch 3/12
60000/60000 [==============================] - 5s 77us/step - loss: 0.1159 - acc: 0.9647 -
val_loss: 0.0485 - val_acc: 0.9843
Epoch 4/12
60000/60000 [==============================] - 5s 77us/step - loss: 0.1011 - acc: 0.9692 -
val_loss: 0.0376 - val_acc: 0.9875
Epoch 5/12
60000/60000 [==============================] - 5s 79us/step - loss: 0.0886 - acc: 0.9734 -
```

```
val_loss: 0.0378 - val_acc: 0.9869
Epoch 6/12
60000/60000 [==============================] - 5s 80us/step - loss: 0.0822 - acc: 0.9747 -
val_loss: 0.0386 - val_acc: 0.9873
Epoch 7/12
60000/60000 [==============================] - 5s 80us/step - loss: 0.0773 - acc: 0.9760 -
val_loss: 0.0334 - val_acc: 0.9890
Epoch 8/12
60000/60000 [==============================] - 5s 81us/step - loss: 0.0743 - acc: 0.9778 -
val_loss: 0.0315 - val_acc: 0.9894
Epoch 9/12
60000/60000 [==============================] - 5s 80us/step - loss: 0.0719 - acc: 0.9775 -
val_loss: 0.0366 - val_acc: 0.9874
Epoch 10/12
60000/60000 [==============================] - 5s 81us/step - loss: 0.0665 - acc: 0.9797 -
val_loss: 0.0380 - val_acc: 0.9878
Epoch 11/12
60000/60000 [==============================] - 5s 85us/step - loss: 0.0659 - acc: 0.9797 -
val_loss: 0.0338 - val_acc: 0.9885
Epoch 12/12
60000/60000 [==============================] - 5s 88us/step - loss: 0.0629 - acc: 0.9804 -
val_loss: 0.0295 - val_acc: 0.9901
Test loss: 0.02952045173299921
Test accuracy: 0.9901
```



We also tried with single CNN layer with no padding it gives accuracy of nearly 99% with loss 0.02

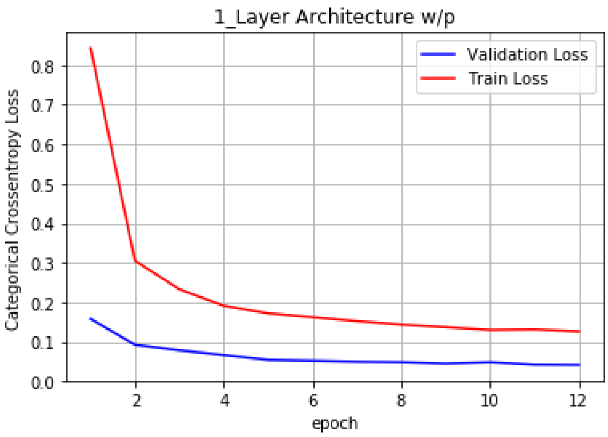
With Single CNN Layer with same padding

In [5]:

```
model3 = Sequential()
model3.add(Conv2D(30, kernel_size=(5, 5),strides=(2,2), padding='same',
activation='relu',input_shape=input_shape))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(3, 3)))
model3.add(Dropout(0.5))
#model3.add(Conv2D(48, (2, 2), activation='relu'))
#model3.add(MaxPooling2D(pool_size=(2, 2)))
#model3.add(Dropout(0.25))
model3.add(Flatten())
model3.add(Dense(128, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(num_classes, activation='softmax'))

model3.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history3 = model3.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score3 = model3.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score3[0])
print('Test accuracy:', score3[1])
```

```
#plotting train loss vs test loss

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))

vy = history3.history['val_loss']
ty = history3.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('1_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 5s 80us/step - loss: 0.8429 - acc: 0.7309 -
val_loss: 0.1582 - val_acc: 0.9526
Epoch 2/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.3049 - acc: 0.9053 -
val_loss: 0.0924 - val_acc: 0.9693
Epoch 3/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.2332 - acc: 0.9284 -
val_loss: 0.0787 - val_acc: 0.9745
Epoch 4/12
60000/60000 [==============================] - 4s 67us/step - loss: 0.1912 - acc: 0.9409 -
val_loss: 0.0667 - val_acc: 0.9780
Epoch 5/12
60000/60000 [==============================] - 4s 66us/step - loss: 0.1722 - acc: 0.9467 -
val_loss: 0.0545 - val_acc: 0.9825
Epoch 6/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.1624 - acc: 0.9513 -
val_loss: 0.0524 - val_acc: 0.9823
Epoch 7/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.1525 - acc: 0.9537 -
val_loss: 0.0498 - val_acc: 0.9834
Epoch 8/12
60000/60000 [==============================] - 4s 66us/step - loss: 0.1437 - acc: 0.9563 -
val_loss: 0.0487 - val_acc: 0.9853
Epoch 9/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.1372 - acc: 0.9583 -
val_loss: 0.0452 - val_acc: 0.9850
Epoch 10/12
60000/60000 [==============================] - 4s 66us/step - loss: 0.1301 - acc: 0.9595 -
val_loss: 0.0486 - val_acc: 0.9857
Epoch 11/12
60000/60000 [==============================] - 4s 65us/step - loss: 0.1313 - acc: 0.9603 -
val_loss: 0.0423 - val_acc: 0.9865
Epoch 12/12
60000/60000 [==============================] - 4s 64us/step - loss: 0.1264 - acc: 0.9612 -
val_loss: 0.0416 - val_acc: 0.9869
Test loss: 0.0416140385431936
Test accuracy: 0.9869
```



we also tried with padding in single CNN layer compare to With out padding model it gives 1% less accuracy and in test loss also it gives 0.04 with out padding model gives 0.02

gives 0.04 with out padding model gives 0.02

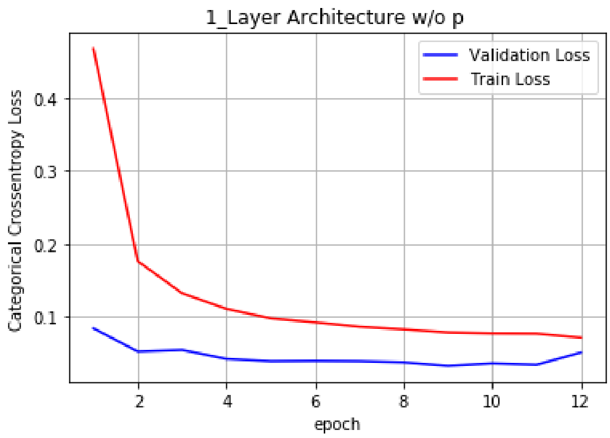
Single CNN with-out padding with adadelta optimizere </h3

In [6]:

```
model2 = Sequential()
model2.add(Conv2D(30, kernel_size=(5, 5), padding='valid', activation='relu',input_shape=input_shap
e))
model2.add(BatchNormalization())
model2.add(MaxPooling2D(pool_size=(3, 3)))
model2.add(Dropout(0.5))
#model2.add(Conv2D(48, (2, 2), activation='relu'))
#model2.add(MaxPooling2D(pool_size=(2, 2)))
#model2.add(Dropout(0.25))
model2.add(Flatten())
model2.add(Dense(128, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(num_classes, activation='softmax'))

model2.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history2 = model2.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score2 = model2.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score2[0])
print('Test accuracy:', score2[1])

#plotting train loss vs test loss

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))

vy = history2.history['val_loss']
ty = history2.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('1_Layer Architecture w/o p ')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 6s 103us/step - loss: 0.4678 - acc: 0.8581 -
val_loss: 0.0834 - val_acc: 0.9729
Epoch 2/12
60000/60000 [==============================] - 5s 89us/step - loss: 0.1757 - acc: 0.9473 -
val_loss: 0.0517 - val_acc: 0.9830
Epoch 3/12
60000/60000 [==============================] - 5s 88us/step - loss: 0.1317 - acc: 0.9612 -
val_loss: 0.0538 - val_acc: 0.9824
Epoch 4/12
60000/60000 [==============================] - 5s 87us/step - loss: 0.1103 - acc: 0.9673 -
val_loss: 0.0416 - val_acc: 0.9869
Epoch 5/12
60000/60000 [==============================] - 5s 88us/step - loss: 0.0972 - acc: 0.9718 -
val_loss: 0.0384 - val_acc: 0.9880
Epoch 6/12
60000/60000 [==============================] - 5s 88us/step - loss: 0.0917 - acc: 0.9731 -
val_loss: 0.0388 - val_acc: 0.9880
Epoch 7/12
60000/60000 [==============================] - 5s 87us/step - loss: 0.0857 - acc: 0.9751 -
val_loss: 0.0383 - val_acc: 0.9877
Epoch 8/12
60000/60000 [==============================] - 5s 87us/step - loss: 0.0821 - acc: 0.9765 -
val_loss: 0.0367 - val_acc: 0.9883
Epoch 9/12
60000/60000 [==============================] - 5s 86us/step - loss: 0.0778 - acc: 0.9783 -
```

```
val_loss: 0.0319 - val_acc: 0.9908
Epoch 10/12
60000/60000 [==============================] - 5s 87us/step - loss: 0.0765 - acc: 0.9783 -
val_loss: 0.0354 - val_acc: 0.9889
Epoch 11/12
60000/60000 [==============================] - 5s 83us/step - loss: 0.0762 - acc: 0.9776 -
val_loss: 0.0335 - val_acc: 0.9901
Epoch 12/12
60000/60000 [==============================] - 5s 86us/step - loss: 0.0707 - acc: 0.9804 -
val_loss: 0.0503 - val_acc: 0.9874
Test loss: 0.05028205864073407
Test accuracy: 0.9874
```



Here we try with adadelta optimizer with out padding it gives 0.05 test loss and accuracy 0.98

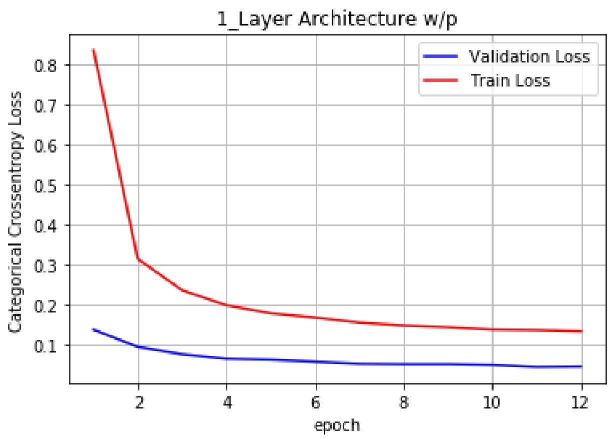
Single CNN with padding with Adadelta optimizer

In [7]:

```
model3 = Sequential()
model3.add(Conv2D(30, kernel_size=(5, 5),strides=(2,2), padding='same',
activation='relu',input_shape=input_shape))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(3, 3)))
model3.add(Dropout(0.5))
#model3.add(Conv2D(48, (2, 2), activation='relu'))
#model3.add(MaxPooling2D(pool_size=(2, 2)))
#model3.add(Dropout(0.25))
model3.add(Flatten())
model3.add(Dense(128, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(num_classes, activation='softmax'))

model3.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history3 = model3.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score3 = model3.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score3[0])
print('Test accuracy:', score3[1])

#plotting train loss vs test loss

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))

vy = history3.history['val_loss']
ty = history3.history['loss']
```

```
plt_dynamic(x, vy, ty, ax)
plt.title('1_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 5s 84us/step - loss: 0.8368 - acc: 0.7378 -
val_loss: 0.1387 - val_acc: 0.9599
Epoch 2/12
60000/60000 [==============================] - 4s 67us/step - loss: 0.3154 - acc: 0.9025 -
val_loss: 0.0958 - val_acc: 0.9690
Epoch 3/12
60000/60000 [==============================] - 4s 69us/step - loss: 0.2373 - acc: 0.9281 -
val_loss: 0.0774 - val_acc: 0.9754
Epoch 4/12
60000/60000 [==============================] - 4s 67us/step - loss: 0.1999 - acc: 0.9403 -
val_loss: 0.0662 - val_acc: 0.9792
Epoch 5/12
60000/60000 [==============================] - 4s 69us/step - loss: 0.1797 - acc: 0.9453 -
val_loss: 0.0639 - val_acc: 0.9795
Epoch 6/12
60000/60000 [==============================] - 4s 67us/step - loss: 0.1692 - acc: 0.9489 -
val_loss: 0.0589 - val_acc: 0.9814
Epoch 7/12
60000/60000 [==============================] - 4s 68us/step - loss: 0.1565 - acc: 0.9522 -
val_loss: 0.0537 - val_acc: 0.9825
Epoch 8/12
60000/60000 [==============================] - 4s 68us/step - loss: 0.1492 - acc: 0.9552 -
val_loss: 0.0528 - val_acc: 0.9833
Epoch 9/12
60000/60000 [==============================] - 4s 68us/step - loss: 0.1450 - acc: 0.9571 -
val_loss: 0.0528 - val_acc: 0.9830
Epoch 10/12
60000/60000 [==============================] - 4s 69us/step - loss: 0.1389 - acc: 0.9584 -
val_loss: 0.0509 - val_acc: 0.9834
Epoch 11/12
60000/60000 [==============================] - 4s 67us/step - loss: 0.1376 - acc: 0.9588 -
val_loss: 0.0456 - val_acc: 0.9857
Epoch 12/12
60000/60000 [==============================] - 4s 68us/step - loss: 0.1347 - acc: 0.9595 -
val_loss: 0.0466 - val_acc: 0.9842
Test loss: 0.04658047350185952
Test accuracy: 0.9842
```



Here we see with padding using adadelta optimizer we got 0.04 test loss and 0.98 accuracy

3 Layer CNN with out padding

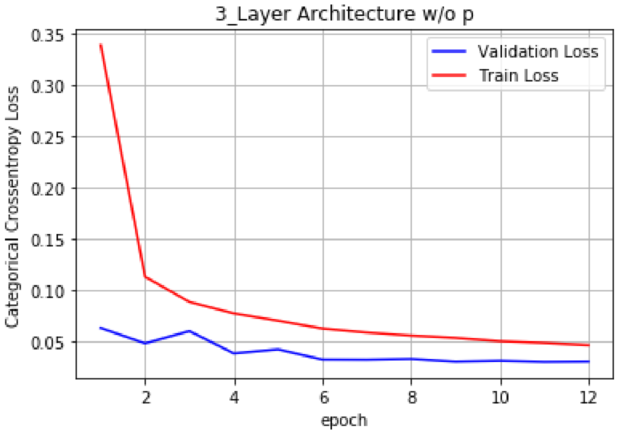
In [8]:

```
model4 = Sequential()
model4.add(Conv2D(20, kernel_size=(2, 2),activation='relu',input_shape=input_shape))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(3, 3)))
model4.add(Dropout(0.2))
#layer-2
```

```
model4.add(Conv2D(40, (4, 4), activation='relu'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2, 2)))
model4.add(Dropout(0.2))
#layer-3
model4.add(Conv2D(60, (3, 3), activation='relu'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(1, 1)))
model4.add(Dropout(0.2))
#flatten to 1-d
model4.add(Flatten())
model4.add(Dense(128, activation='relu'))
model4.add(Dropout(0.2))
model4.add(Dense(num_classes, activation='softmax'))

model4.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history4 = model4.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score4 = model4.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score4[0])
print('Test accuracy:', score4[1])

#plotting train loss vs test loss

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))

vy = history4.history['val_loss']
ty = history4.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 9s 150us/step - loss: 0.3388 - acc: 0.8956 -
val_loss: 0.0626 - val_acc: 0.9797
Epoch 2/12
60000/60000 [==============================] - 7s 119us/step - loss: 0.1126 - acc: 0.9653 -
val_loss: 0.0476 - val_acc: 0.9845
Epoch 3/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.0881 - acc: 0.9726 -
val_loss: 0.0596 - val_acc: 0.9816
Epoch 4/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.0769 - acc: 0.9765 -
val_loss: 0.0379 - val_acc: 0.9869
Epoch 5/12
60000/60000 [==============================] - 7s 119us/step - loss: 0.0697 - acc: 0.9787 -
val_loss: 0.0417 - val_acc: 0.9862
Epoch 6/12
60000/60000 [==============================] - 7s 119us/step - loss: 0.0621 - acc: 0.9809 -
val_loss: 0.0318 - val_acc: 0.9894
Epoch 7/12
60000/60000 [==============================] - 7s 119us/step - loss: 0.0582 - acc: 0.9818 -
val_loss: 0.0316 - val_acc: 0.9905
Epoch 8/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.0551 - acc: 0.9831 -
val_loss: 0.0324 - val_acc: 0.9892
Epoch 9/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.0529 - acc: 0.9834 -
val_loss: 0.0297 - val_acc: 0.9909
Epoch 10/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.0497 - acc: 0.9835 -
val_loss: 0.0306 - val_acc: 0.9909
Epoch 11/12
60000/60000 [==============================] - 7s 118us/step - loss: 0.0480 - acc: 0.9852 -
```

```
val_loss: 0.0295 - val_acc: 0.9905
Epoch 12/12
60000/60000 [==============================] - 7s 119us/step - loss: 0.0458 - acc: 0.9860 -
val_loss: 0.0298 - val_acc: 0.9906
Test loss: 0.029789605866084458
Test accuracy: 0.9906
```



Here we try with 3 layer CNN with out padding we got 99% accuracy with test loss 0.02 which is good we also compare with with padding model below

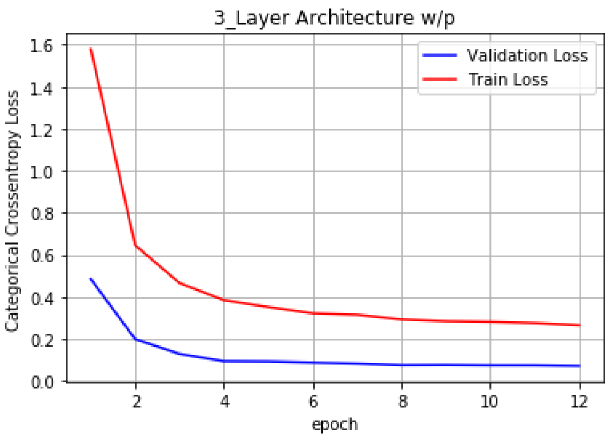
3 Layer CNN with same padding at every layer

In [9]:

```
model5 = Sequential()
model5.add(Conv2D(20, kernel_size=(2, 2),strides=(1,1),
padding='same',activation='relu',input_shape=input_shape))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(3, 3)))
model5.add(Dropout(0.5))
#layer-2
model5.add(Conv2D(40, (4, 4),strides=(2,2), padding='same', activation='relu'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(2, 2)))
model5.add(Dropout(0.5))
#layer-3
model5.add(Conv2D(60, (3, 3),strides=(2,2), padding='same', activation='relu'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(1, 1)))
model5.add(Dropout(0.5))
#flatten to 1-d
model5.add(Flatten())
model5.add(Dense(128, activation='relu'))
model5.add(Dropout(0.5))
model5.add(Dense(num_classes, activation='softmax'))

model5.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history5 = model5.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score5 = model5.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score5[0])
print('Test accuracy:', score5[1])

#plotting train loss vs test loss

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))
```

```
vy = history5.history['val_loss']
ty = history5.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 9s 149us/step - loss: 1.5788 - acc: 0.4623 -
val_loss: 0.4845 - val_acc: 0.8743
Epoch 2/12
60000/60000 [==============================] - 7s 115us/step - loss: 0.6457 - acc: 0.7908 -
val_loss: 0.1986 - val_acc: 0.9448
Epoch 3/12
60000/60000 [==============================] - 7s 115us/step - loss: 0.4655 - acc: 0.8583 -
val_loss: 0.1285 - val_acc: 0.9604
Epoch 4/12
60000/60000 [==============================] - 7s 115us/step - loss: 0.3843 - acc: 0.8846 -
val_loss: 0.0940 - val_acc: 0.9697
Epoch 5/12
60000/60000 [==============================] - 7s 113us/step - loss: 0.3515 - acc: 0.8952 -
val_loss: 0.0926 - val_acc: 0.9713
Epoch 6/12
60000/60000 [==============================] - 7s 115us/step - loss: 0.3218 - acc: 0.9046 -
val_loss: 0.0871 - val_acc: 0.9740
Epoch 7/12
60000/60000 [==============================] - 7s 117us/step - loss: 0.3148 - acc: 0.9073 -
val_loss: 0.0824 - val_acc: 0.9761
Epoch 8/12
60000/60000 [==============================] - 7s 114us/step - loss: 0.2927 - acc: 0.9142 -
val_loss: 0.0752 - val_acc: 0.9768
Epoch 9/12
60000/60000 [==============================] - 7s 114us/step - loss: 0.2841 - acc: 0.9158 -
val_loss: 0.0759 - val_acc: 0.9767
Epoch 10/12
60000/60000 [==============================] - 7s 113us/step - loss: 0.2810 - acc: 0.9182 -
val_loss: 0.0743 - val_acc: 0.9765
Epoch 11/12
60000/60000 [==============================] - 7s 115us/step - loss: 0.2751 - acc: 0.9205 -
val_loss: 0.0741 - val_acc: 0.9771
Epoch 12/12
60000/60000 [==============================] - 7s 114us/step - loss: 0.2651 - acc: 0.9229 -
val_loss: 0.0712 - val_acc: 0.9775
Test loss: 0.07115179373547435
Test accuracy: 0.9775
```



We add same padding at every layer compare to valid padding model in previous model we get here 97% accuracy and 0.07 test loss compare to padding model valid padding gives better results than padding model

3 CNN with padding with Adadelta optimizer

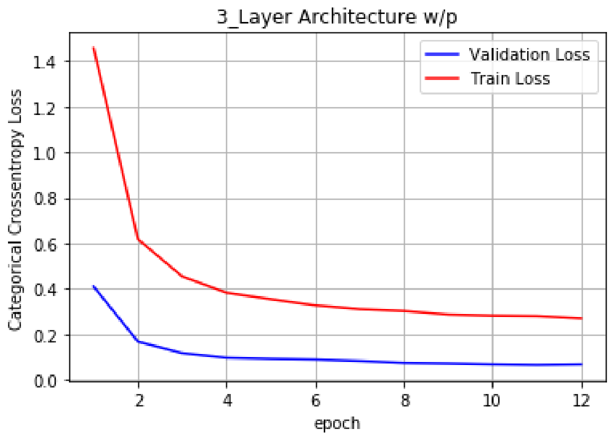
In [10]:

```
model5 = Sequential()
model5.add(Conv2D(20, kernel_size=(2, 2),strides=(1,1),
```

```
padding='same',activation='relu',input_shape=input_shape))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(3, 3)))
model5.add(Dropout(0.5))
#layer-2
model5.add(Conv2D(40, (4, 4),strides=(2,2), padding='same', activation='relu'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(2, 2)))
model5.add(Dropout(0.5))
#layer-3
model5.add(Conv2D(60, (3, 3),strides=(2,2), padding='same', activation='relu'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(1, 1)))
model5.add(Dropout(0.5))
#flatten to 1-d
model5.add(Flatten())
model5.add(Dense(128, activation='relu'))
model5.add(Dropout(0.5))
model5.add(Dense(num_classes, activation='softmax'))

model5.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history5 = model5.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score5 = model5.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score5[0])
print('Test accuracy:', score5[1])

#plotting train loss vs test loss

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))

vy = history5.history['val_loss']
ty = history5.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 9s 156us/step - loss: 1.4570 - acc: 0.5033 -
val_loss: 0.4102 - val_acc: 0.8810
Epoch 2/12
60000/60000 [==============================] - 7s 124us/step - loss: 0.6177 - acc: 0.8032 -
val_loss: 0.1679 - val_acc: 0.9518
Epoch 3/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.4541 - acc: 0.8651 -
val_loss: 0.1176 - val_acc: 0.9663
Epoch 4/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.3829 - acc: 0.8861 -
val_loss: 0.0974 - val_acc: 0.9700
Epoch 5/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.3543 - acc: 0.8960 -
val_loss: 0.0927 - val_acc: 0.9708
Epoch 6/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.3276 - acc: 0.9032 -
val_loss: 0.0897 - val_acc: 0.9726
Epoch 7/12
60000/60000 [==============================] - 7s 121us/step - loss: 0.3110 - acc: 0.9100 -
val_loss: 0.0831 - val_acc: 0.9754
Epoch 8/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.3031 - acc: 0.9124 -
val_loss: 0.0746 - val_acc: 0.9767
Epoch 9/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.2869 - acc: 0.9175 -
val_loss: 0.0720 - val_acc: 0.9765
Epoch 10/12
```

```
60000/60000 [==============================] - 7s 122us/step - loss: 0.2820 - acc: 0.9184 -
val_loss: 0.0682 - val_acc: 0.9797
Epoch 11/12
60000/60000 [==============================] - 7s 122us/step - loss: 0.2801 - acc: 0.9195 -
val_loss: 0.0657 - val_acc: 0.9799
Epoch 12/12
60000/60000 [==============================] - 7s 120us/step - loss: 0.2701 - acc: 0.9221 -
val_loss: 0.0681 - val_acc: 0.9797
Test loss: 0.06812153178970329
Test accuracy: 0.9797
```



Here we see with adadelta optimizer with padding we got test loss 0.06 with accuracy 0.97

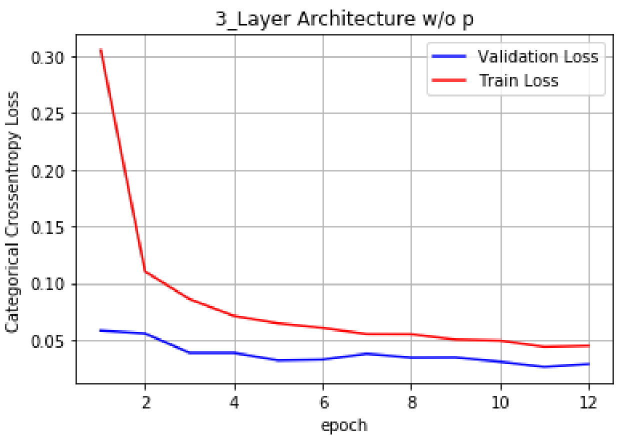
3 CNN with out padding with Adadelta optimizer

In [11]:

```
model4 = Sequential()
model4.add(Conv2D(20, kernel_size=(2, 2),activation='relu',input_shape=input_shape))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(3, 3)))
model4.add(Dropout(0.2))
#layer-2
model4.add(Conv2D(40, (4, 4), activation='relu'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2, 2)))
model4.add(Dropout(0.2))
#layer-3
model4.add(Conv2D(60, (3, 3), activation='relu'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(1, 1)))
model4.add(Dropout(0.2))
#flatten to 1-d
model4.add(Flatten())
model4.add(Dense(128, activation='relu'))
model4.add(Dropout(0.2))
model4.add(Dense(num_classes, activation='softmax'))

model4.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history4 = model4.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score4 = model4.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score4[0])
print('Test accuracy:', score4[1])

#plotting train loss vs test loss

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))

vy = history4.history['val_loss']
ty = history4.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.3054 - acc: 0.9062 - val_l
oss: 0.0580 - val_acc: 0.9805
Epoch 2/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.1101 - acc: 0.9670 -
val_loss: 0.0554 - val_acc: 0.9816
Epoch 3/12
60000/60000 [==============================] - 8s 133us/step - loss: 0.0858 - acc: 0.9739 -
val_loss: 0.0384 - val_acc: 0.9865
Epoch 4/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0710 - acc: 0.9785 -
val_loss: 0.0384 - val_acc: 0.9881
Epoch 5/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0644 - acc: 0.9806 -
val_loss: 0.0317 - val_acc: 0.9902
Epoch 6/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0604 - acc: 0.9818 -
val_loss: 0.0324 - val_acc: 0.9899
Epoch 7/12
60000/60000 [==============================] - 8s 133us/step - loss: 0.0549 - acc: 0.9834 -
val_loss: 0.0376 - val_acc: 0.9898
Epoch 8/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0548 - acc: 0.9835 -
val_loss: 0.0342 - val_acc: 0.9900
Epoch 9/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0501 - acc: 0.9844 -
val_loss: 0.0343 - val_acc: 0.9901
Epoch 10/12
60000/60000 [==============================] - 8s 132us/step - loss: 0.0492 - acc: 0.9852 -
val_loss: 0.0306 - val_acc: 0.9910
Epoch 11/12
60000/60000 [==============================] - 8s 131us/step - loss: 0.0437 - acc: 0.9867 -
val_loss: 0.0259 - val_acc: 0.9915
Epoch 12/12
60000/60000 [==============================] - 8s 130us/step - loss: 0.0446 - acc: 0.9863 -
val_loss: 0.0286 - val_acc: 0.9916
Test loss: 0.028550590935177752
Test accuracy: 0.9916
```



Here we see with out padding model using adadelta optimizer we got test loss 0.02 and accuracy 0.99

5 Layer Simple CNN architecture with out padding

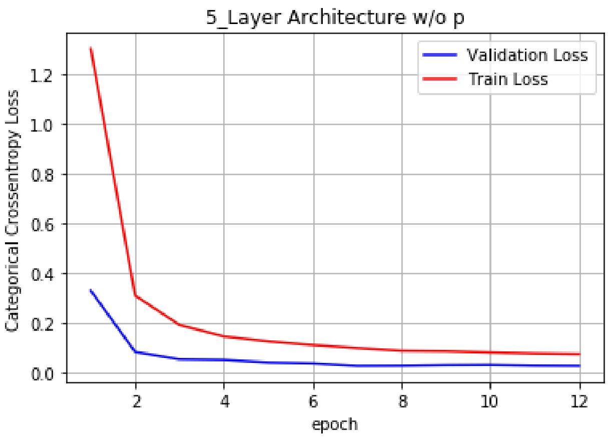
In [12]:

```
model6 = Sequential()
```

```
model6.add(Conv2D(20, kernel_size=(2, 2),activation='relu',input_shape=input_shape))
model6.add(BatchNormalization())
#model6.add(MaxPooling2D(pool_size=(3, 3)))
model6.add(Dropout(0.5))
#layer-2
model6.add(Conv2D(40, (7, 7), activation='relu'))
model6.add(BatchNormalization())
#model6.add(MaxPooling2D(pool_size=(2, 2)))
model6.add(Dropout(0.5))
#layer-3
model6.add(Conv2D(60, (5, 5), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(3, 3)))
model6.add(Dropout(0.5))
#layer-4
model6.add(Conv2D(80, (3, 3), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(1, 1)))
model6.add(Dropout(0.5))
#layer-5
model6.add(Conv2D(100, (2, 2), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(2, 2)))
model6.add(Dropout(0.5))
#flatten to 1-d
model6.add(Flatten())
model6.add(Dense(128, activation='relu'))
model6.add(Dropout(0.5))
model6.add(Dense(num_classes, activation='softmax'))

model6.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history6 = model6.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score6 = model6.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score6[0])
print('Test accuracy:', score6[1])

#plotting train loss vs test loss

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))

vy = history6.history['val_loss']
ty = history6.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 21s 347us/step - loss: 1.2994 - acc: 0.5843 - val_l
oss: 0.3280 - val_acc: 0.8882
Epoch 2/12
60000/60000 [==============================] - 18s 292us/step - loss: 0.3082 - acc: 0.9073 - val_l
oss: 0.0820 - val_acc: 0.9737
Epoch 3/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.1903 - acc: 0.9443 - val_l
oss: 0.0526 - val_acc: 0.9844
Epoch 4/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.1441 - acc: 0.9586 - val_l
oss: 0.0504 - val_acc: 0.9841
Epoch 5/12
60000/60000 [==============================] - 18s 292us/step - loss: 0.1243 - acc: 0.9650 - val_l
oss: 0.0394 - val_acc: 0.9894
Epoch 6/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.1097 - acc: 0.9688 - val_l
oss: 0.0360 - val_acc: 0.9882
```

```
Epoch 7/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.0974 - acc: 0.9729 - val_l
oss: 0.0260 - val_acc: 0.9927
Epoch 8/12
60000/60000 [==============================] - 17s 290us/step - loss: 0.0866 - acc: 0.9759 - val_l
oss: 0.0266 - val_acc: 0.9932
Epoch 9/12
60000/60000 [==============================] - 17s 292us/step - loss: 0.0850 - acc: 0.9764 - val_l
oss: 0.0293 - val_acc: 0.9914
Epoch 10/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.0801 - acc: 0.9781 - val_l
oss: 0.0301 - val_acc: 0.9919
Epoch 11/12
60000/60000 [==============================] - 17s 292us/step - loss: 0.0759 - acc: 0.9795 - val_l
oss: 0.0270 - val_acc: 0.9922
Epoch 12/12
60000/60000 [==============================] - 17s 291us/step - loss: 0.0735 - acc: 0.9794 - val_l
oss: 0.0261 - val_acc: 0.9932
Test loss: 0.02613280111870845
Test accuracy: 0.9932
```



We also try with 5 layer CNN with out padding and padding here we see without padding results we got 99% accuracy with test loss 0.02 like an 3 CNN model valid model we got slightly simmilar results here

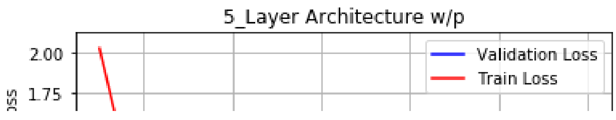
5 Layer CNN with same padding at every layer

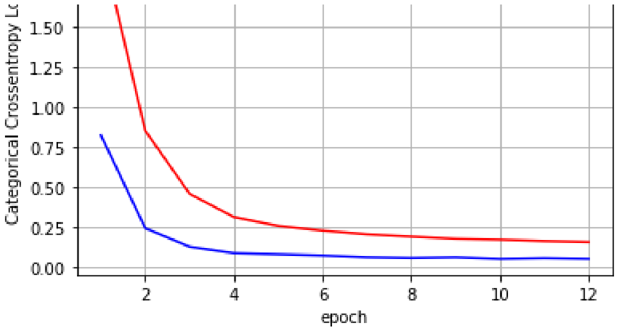
In [13]:

```
model7 = Sequential()
model7.add(Conv2D(20, kernel_size=(9, 9),strides=(2,2),
padding='same',activation='relu',input_shape=input_shape))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(3, 3)))
model7.add(Dropout(0.5))
#layer-2
model7.add(Conv2D(40, (7, 7), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(2, 2)))
model7.add(Dropout(0.5))
#layer-3
model7.add(Conv2D(60, (5, 5), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
model7.add(MaxPooling2D(pool_size=(3, 3)))
model7.add(Dropout(0.5))
#layer-4
model7.add(Conv2D(80, (3, 3), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(1, 1)))
model7.add(Dropout(0.5))
#layer-5
model7.add(Conv2D(100, (2, 2), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
model7.add(MaxPooling2D(pool_size=(1, 1)))
model7.add(Dropout(0.5))
#flatten to 1-d
model7.add(Flatten())
```

```
model7.add(Dense(128, activation='relu'))
model7.add(Dropout(0.5))
model7.add(Dense(num_classes, activation='softmax'))

model7.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history7 = model7.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score7 = model7.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score7[0])
print('Test accuracy:', score7[1])

#plotting train loss vs test loss

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))

vy = history7.history['val_loss']
ty = history7.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 13s 219us/step - loss: 2.0294 - acc: 0.3055 - val_l
oss: 0.8246 - val_acc: 0.7053
Epoch 2/12
60000/60000 [==============================] - 10s 161us/step - loss: 0.8533 - acc: 0.7004 - val_l
oss: 0.2444 - val_acc: 0.9413
Epoch 3/12
60000/60000 [==============================] - 10s 160us/step - loss: 0.4590 - acc: 0.8638 - val_l
oss: 0.1286 - val_acc: 0.9635
Epoch 4/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.3137 - acc: 0.9156 - val_l
oss: 0.0889 - val_acc: 0.9764
Epoch 5/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.2585 - acc: 0.9320 - val_l
oss: 0.0817 - val_acc: 0.9777
Epoch 6/12
60000/60000 [==============================] - 10s 159us/step - loss: 0.2289 - acc: 0.9408 - val_l
oss: 0.0739 - val_acc: 0.9786
Epoch 7/12
60000/60000 [==============================] - 10s 160us/step - loss: 0.2061 - acc: 0.9477 - val_l
oss: 0.0629 - val_acc: 0.9822
Epoch 8/12
60000/60000 [==============================] - 10s 160us/step - loss: 0.1920 - acc: 0.9526 - val_l
oss: 0.0584 - val_acc: 0.9844
Epoch 9/12
60000/60000 [==============================] - 10s 160us/step - loss: 0.1781 - acc: 0.9560 - val_l
oss: 0.0627 - val_acc: 0.9834
Epoch 10/12
60000/60000 [==============================] - 10s 161us/step - loss: 0.1724 - acc: 0.9568 - val_l
oss: 0.0525 - val_acc: 0.9857
Epoch 11/12
60000/60000 [==============================] - 10s 161us/step - loss: 0.1637 - acc: 0.9581 - val_l
oss: 0.0574 - val_acc: 0.9845
Epoch 12/12
60000/60000 [==============================] - 10s 161us/step - loss: 0.1577 - acc: 0.9602 - val_l
oss: 0.0528 - val_acc: 0.9856
Test loss: 0.05276366615106817
Test accuracy: 0.9856
```





Here above we see 5 layer CNN with padding we got 98% accuracy with test loss 0.05 which is slightly similar to 5 layer CNN valid model so using 5 layer CNN we got nearly similar results by using padding and without padding and valid padding gives better results then padding model

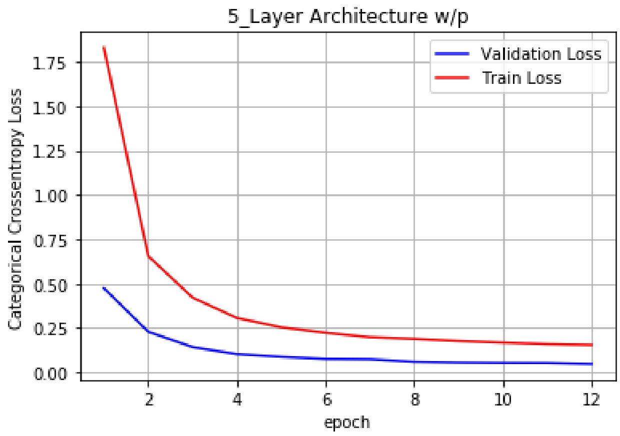
5 CNN layer with padding using Adadelta optimizer

In [14]:

```
model7 = Sequential()
model7.add(Conv2D(20, kernel_size=(9, 9),strides=(2,2),
padding='same',activation='relu',input_shape=input_shape))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(3, 3)))
model7.add(Dropout(0.5))
#layer-2
model7.add(Conv2D(40, (7, 7), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(2, 2)))
model7.add(Dropout(0.5))
#layer-3
model7.add(Conv2D(60, (5, 5), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
model7.add(MaxPooling2D(pool_size=(3, 3)))
model7.add(Dropout(0.5))
#layer-4
model7.add(Conv2D(80, (3, 3), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
#model7.add(MaxPooling2D(pool_size=(1, 1)))
model7.add(Dropout(0.5))
#layer-5
model7.add(Conv2D(100, (2, 2), activation='relu',strides=(2,2), padding='same'))
model7.add(BatchNormalization())
model7.add(MaxPooling2D(pool_size=(1, 1)))
model7.add(Dropout(0.5))
#flatten to 1-d
model7.add(Flatten())
model7.add(Dense(128, activation='relu'))
model7.add(Dropout(0.5))
model7.add(Dense(num_classes, activation='softmax'))

model7.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history7 = model7.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score7 = model7.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score7[0])
print('Test accuracy:', score7[1])

#plotting train loss vs test loss

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))
```

```
vy = history7.history['val_loss']
ty = history7.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 14s 231us/step - loss: 1.8318 - acc: 0.3739 - val_l
oss: 0.4745 - val_acc: 0.8685
Epoch 2/12
60000/60000 [==============================] - 10s 172us/step - loss: 0.6553 - acc: 0.7842 - val_l
oss: 0.2283 - val_acc: 0.9397
Epoch 3/12
60000/60000 [==============================] - 10s 171us/step - loss: 0.4211 - acc: 0.8768 - val_l
oss: 0.1419 - val_acc: 0.9603
Epoch 4/12
60000/60000 [==============================] - 10s 172us/step - loss: 0.3063 - acc: 0.9173 - val_l
oss: 0.1024 - val_acc: 0.9733
Epoch 5/12
60000/60000 [==============================] - 10s 172us/step - loss: 0.2534 - acc: 0.9356 - val_l
oss: 0.0871 - val_acc: 0.9771
Epoch 6/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.2226 - acc: 0.9434 - val_l
oss: 0.0752 - val_acc: 0.9800
Epoch 7/12
60000/60000 [==============================] - 10s 168us/step - loss: 0.1976 - acc: 0.9489 - val_l
oss: 0.0735 - val_acc: 0.9802
Epoch 8/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.1879 - acc: 0.9538 - val_l
oss: 0.0587 - val_acc: 0.9827
Epoch 9/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.1761 - acc: 0.9557 - val_l
oss: 0.0545 - val_acc: 0.9844
Epoch 10/12
60000/60000 [==============================] - 10s 168us/step - loss: 0.1671 - acc: 0.9591 - val_l
oss: 0.0527 - val_acc: 0.9859
Epoch 11/12
60000/60000 [==============================] - 10s 168us/step - loss: 0.1585 - acc: 0.9607 - val_l
oss: 0.0521 - val_acc: 0.9852
Epoch 12/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.1538 - acc: 0.9618 - val_l
oss: 0.0463 - val_acc: 0.9872
Test loss: 0.04632472553304979
Test accuracy: 0.9872
```



Here we see with padding using adadelta optimizer we got test loss 0.04 with accuracy 0.98

5 CNN layer with out padding with Adadelta optimizer

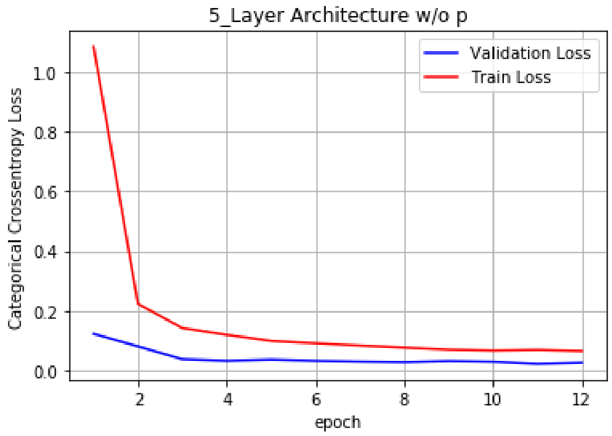
In [15]:

```
model6 = Sequential()
model6.add(Conv2D(20, kernel_size=(2, 2),activation='relu',input_shape=input_shape))
model6.add(BatchNormalization())
#model6.add(MaxPooling2D(pool_size=(3, 3)))
```

```
model6.add(Dropout(0.5))
#layer-2
model6.add(Conv2D(40, (7, 7), activation='relu'))
model6.add(BatchNormalization())
#model6.add(MaxPooling2D(pool_size=(2, 2)))
model6.add(Dropout(0.5))
#layer-3
model6.add(Conv2D(60, (5, 5), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(3, 3)))
model6.add(Dropout(0.5))
#layer-4
model6.add(Conv2D(80, (3, 3), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(1, 1)))
model6.add(Dropout(0.5))
#layer-5
model6.add(Conv2D(100, (2, 2), activation='relu'))
model6.add(BatchNormalization())
model6.add(MaxPooling2D(pool_size=(2, 2)))
model6.add(Dropout(0.5))
#flatten to 1-d
model6.add(Flatten())
model6.add(Dense(128, activation='relu'))
model6.add(Dropout(0.5))
model6.add(Dense(num_classes, activation='softmax'))

model6.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history6 = model6.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score6 = model6.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score6[0])
print('Test accuracy:', score6[1])

#plotting train loss vs test loss

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))

vy = history6.history['val_loss']
ty = history6.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 22s 363us/step - loss: 1.0834 - acc: 0.6574 - val_l
oss: 0.1227 - val_acc: 0.9640
Epoch 2/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.2228 - acc: 0.9347 - val_l
oss: 0.0806 - val_acc: 0.9742
Epoch 3/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.1419 - acc: 0.9602 - val_l
oss: 0.0380 - val_acc: 0.9896
Epoch 4/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.1193 - acc: 0.9672 - val_l
oss: 0.0325 - val_acc: 0.9898
Epoch 5/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.0988 - acc: 0.9731 - val_l
oss: 0.0366 - val_acc: 0.9898
Epoch 6/12
60000/60000 [==============================] - 18s 301us/step - loss: 0.0910 - acc: 0.9747 - val_l
oss: 0.0324 - val_acc: 0.9909
Epoch 7/12
60000/60000 [==============================] - 18s 301us/step - loss: 0.0834 - acc: 0.9765 - val_l
```

```
oss: 0.0298 - val_acc: 0.9928
Epoch 8/12
60000/60000 [==============================] - 18s 301us/step - loss: 0.0766 - acc: 0.9791 - val_l
oss: 0.0279 - val_acc: 0.9926
Epoch 9/12
60000/60000 [==============================] - 18s 301us/step - loss: 0.0699 - acc: 0.9804 - val_l
oss: 0.0318 - val_acc: 0.9919
Epoch 10/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.0669 - acc: 0.9814 - val_l
oss: 0.0294 - val_acc: 0.9920
Epoch 11/12
60000/60000 [==============================] - 18s 301us/step - loss: 0.0690 - acc: 0.9809 - val_l
oss: 0.0222 - val_acc: 0.9936
Epoch 12/12
60000/60000 [==============================] - 18s 300us/step - loss: 0.0652 - acc: 0.9826 - val_l
oss: 0.0262 - val_acc: 0.9920
Test loss: 0.026176282831970456
Test accuracy: 0.992
```



Here we see with out paddng model using adadelta optimizer we got test loss 0.02 with accuracy 0.99

7 layer Simple CNN architecture same padding at every layer

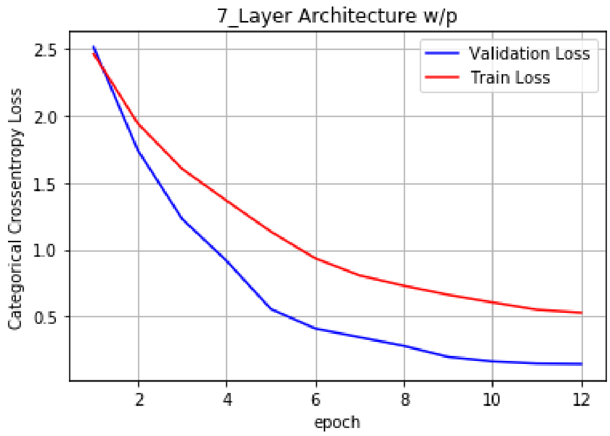
In [16]:

```
model8 = Sequential()
model8.add(Conv2D(12, kernel_size=(4, 4),strides=(2,2),
padding='same',activation='relu',input_shape=input_shape))
#model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(3, 3)))
model8.add(Dropout(0.5))
#layer-2
model8.add(Conv2D(24, (3, 3), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-3
model8.add(Conv2D(34, (5, 5), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-4
model8.add(Conv2D(44, (3, 3), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(1, 1)))
model8.add(Dropout(0.5))
#layer-5
model8.add(Conv2D(54, (4, 4), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-6
model8.add(Conv2D(64, (2, 2), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-7
```

```python
model8.add(Conv2D(74, (2, 2), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
model8.add(MaxPooling2D(pool_size=(1, 1)))
model8.add(Dropout(0.5))
#flatten to 1-d
model8.add(Flatten())
model8.add(Dense(128, activation='relu'))
model8.add(Dropout(0.5))
model8.add(Dense(num_classes, activation='softmax'))

model8.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history8 = model8.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score8 = model8.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score8[0])
print('Test accuracy:', score8[1])

#plotting train loss vs test loss

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))

vy = history8.history['val_loss']
ty = history8.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('7_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 15s 249us/step - loss: 2.4588 - acc: 0.1338 - val_l
oss: 2.5094 - val_acc: 0.1219
Epoch 2/12
60000/60000 [==============================] - 10s 169us/step - loss: 1.9397 - acc: 0.2385 - val_l
oss: 1.7395 - val_acc: 0.3297
Epoch 3/12
60000/60000 [==============================] - 10s 167us/step - loss: 1.6019 - acc: 0.3563 - val_l
oss: 1.2280 - val_acc: 0.4941
Epoch 4/12
60000/60000 [==============================] - 10s 168us/step - loss: 1.3652 - acc: 0.4609 - val_l
oss: 0.9166 - val_acc: 0.6908
Epoch 5/12
60000/60000 [==============================] - 10s 168us/step - loss: 1.1344 - acc: 0.5787 - val_l
oss: 0.5570 - val_acc: 0.8010
Epoch 6/12
60000/60000 [==============================] - 10s 169us/step - loss: 0.9356 - acc: 0.6752 - val_l
oss: 0.4121 - val_acc: 0.8573
Epoch 7/12
60000/60000 [==============================] - 10s 167us/step - loss: 0.8078 - acc: 0.7247 - val_l
oss: 0.3478 - val_acc: 0.8759
Epoch 8/12
60000/60000 [==============================] - 10s 168us/step - loss: 0.7310 - acc: 0.7621 - val_l
oss: 0.2834 - val_acc: 0.9445
Epoch 9/12
60000/60000 [==============================] - 10s 171us/step - loss: 0.6632 - acc: 0.8015 - val_l
oss: 0.2007 - val_acc: 0.9571
Epoch 10/12
60000/60000 [==============================] - 10s 170us/step - loss: 0.6065 - acc: 0.8277 - val_l
oss: 0.1674 - val_acc: 0.9608
Epoch 11/12
60000/60000 [==============================] - 10s 170us/step - loss: 0.5526 - acc: 0.8500 - val_l
oss: 0.1515 - val_acc: 0.9641
Epoch 12/12
60000/60000 [==============================] - 10s 171us/step - loss: 0.5299 - acc: 0.8575 - val_l
oss: 0.1481 - val_acc: 0.9635
Test loss: 0.14812748791873456
Test accuracy: 0.9635
```

Test accuracy: 0.9655



Here we see 7 layer CNN model with padding model we got 96% accuracy with test loss 0.14 compare to 3CNN and 5CNN this 7CNN model gives less results

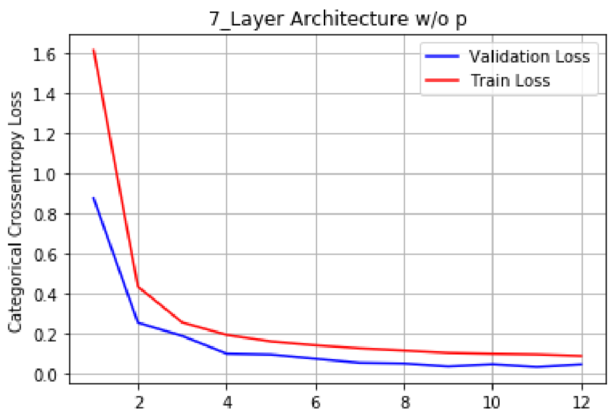
7 Layer CNN with out Padding

In [17]:

```
model9 = Sequential()
model9.add(Conv2D(12, kernel_size=(4, 4),activation='relu',input_shape=input_shape))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(3, 3)))
model9.add(Dropout(0.5))
#layer-2
model9.add(Conv2D(24, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-3
model9.add(Conv2D(34, (5, 5), activation='relu'))
model9.add(BatchNormalization())
model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-4
model9.add(Conv2D(44, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(1, 1)))
model9.add(Dropout(0.5))
#layer-5
model9.add(Conv2D(54, (4, 4), activation='relu' ))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-6
model9.add(Conv2D(64, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-7
model9.add(Conv2D(74, (2, 2), activation='relu'))
model9.add(BatchNormalization())
model9.add(MaxPooling2D(pool_size=(1, 1)))
model9.add(Dropout(0.5))
#flatten to 1-d
model9.add(Flatten())
model9.add(Dense(128, activation='relu'))
model9.add(Dropout(0.5))
model9.add(Dense(num_classes, activation='softmax'))

model9.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])

history9 = model9.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
```

```
          verbose=1,
          validation_data=(x_test, y_test))
score9 = model9.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score9[0])
print('Test accuracy:', score9[1])

#plotting train loss vs test loss

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))

vy = history9.history['val_loss']
ty = history9.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('7_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 20s 342us/step - loss: 1.6117 - acc: 0.4638 - val_l
oss: 0.8743 - val_acc: 0.7388
Epoch 2/12
60000/60000 [==============================] - 15s 250us/step - loss: 0.4349 - acc: 0.8718 - val_l
oss: 0.2556 - val_acc: 0.9275
Epoch 3/12
60000/60000 [==============================] - 15s 248us/step - loss: 0.2569 - acc: 0.9278 - val_l
oss: 0.1900 - val_acc: 0.9472
Epoch 4/12
60000/60000 [==============================] - 15s 248us/step - loss: 0.1952 - acc: 0.9464 - val_l
oss: 0.1016 - val_acc: 0.9718
Epoch 5/12
60000/60000 [==============================] - 15s 249us/step - loss: 0.1623 - acc: 0.9570 - val_l
oss: 0.0973 - val_acc: 0.9724
Epoch 6/12
60000/60000 [==============================] - 15s 249us/step - loss: 0.1437 - acc: 0.9620 - val_l
oss: 0.0769 - val_acc: 0.9793
Epoch 7/12
60000/60000 [==============================] - 15s 251us/step - loss: 0.1280 - acc: 0.9662 - val_l
oss: 0.0563 - val_acc: 0.9843
Epoch 8/12
60000/60000 [==============================] - 15s 248us/step - loss: 0.1173 - acc: 0.9693 - val_l
oss: 0.0529 - val_acc: 0.9854
Epoch 9/12
60000/60000 [==============================] - 15s 249us/step - loss: 0.1057 - acc: 0.9720 - val_l
oss: 0.0384 - val_acc: 0.9894
Epoch 10/12
60000/60000 [==============================] - 15s 250us/step - loss: 0.1012 - acc: 0.9733 - val_l
oss: 0.0492 - val_acc: 0.9863
Epoch 11/12
60000/60000 [==============================] - 15s 248us/step - loss: 0.0980 - acc: 0.9746 - val_l
oss: 0.0357 - val_acc: 0.9894
Epoch 12/12
60000/60000 [==============================] - 15s 250us/step - loss: 0.0906 - acc: 0.9758 - val_l
oss: 0.0486 - val_acc: 0.9871
Test loss: 0.04856768414489925
Test accuracy: 0.9871
```



epoch

Here we see above CNN with 7 layer compare to 7 layer CNN with padding this valid model gives better results it gives 98% accuracy with test loss 0.04

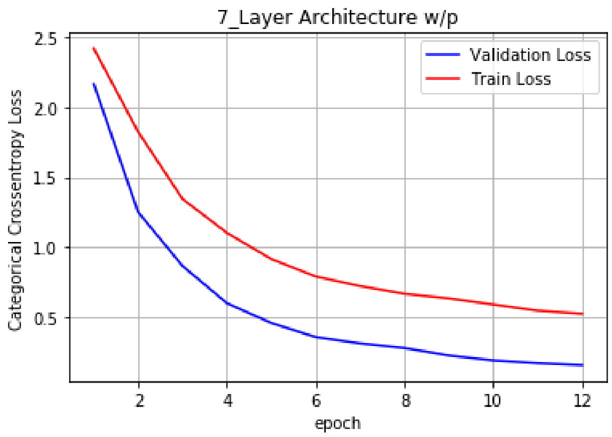
CNN 7 layer with padding using Adadelt optimizer

In [18]:

```
model8 = Sequential()
model8.add(Conv2D(12, kernel_size=(4, 4),strides=(2,2),
padding='same',activation='relu',input_shape=input_shape))
#model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(3, 3)))
model8.add(Dropout(0.5))
#layer-2
model8.add(Conv2D(24, (3, 3), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-3
model8.add(Conv2D(34, (5, 5), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-4
model8.add(Conv2D(44, (3, 3), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(1, 1)))
model8.add(Dropout(0.5))
#layer-5
model8.add(Conv2D(54, (4, 4), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-6
model8.add(Conv2D(64, (2, 2), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
#model8.add(MaxPooling2D(pool_size=(2, 2)))
model8.add(Dropout(0.5))
#layer-7
model8.add(Conv2D(74, (2, 2), activation='relu', padding='same',strides=(2,2)))
model8.add(BatchNormalization())
model8.add(MaxPooling2D(pool_size=(1, 1)))
model8.add(Dropout(0.5))
#flatten to 1-d
model8.add(Flatten())
model8.add(Dense(128, activation='relu'))
model8.add(Dropout(0.5))
model8.add(Dense(num_classes, activation='softmax'))

model8.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history8 = model8.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score8 = model8.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score8[0])
print('Test accuracy:', score8[1])

#plotting train loss vs test loss

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))

vy = history8.history['val_loss']
ty = history8.history['loss']
```

```
ty = history8.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('7_Layer Architecture w/p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 16s 273us/step - loss: 2.4212 - acc: 0.1410 - val_l
oss: 2.1676 - val_acc: 0.2135
Epoch 2/12
60000/60000 [==============================] - 11s 182us/step - loss: 1.8249 - acc: 0.2833 - val_l
oss: 1.2498 - val_acc: 0.5414
Epoch 3/12
60000/60000 [==============================] - 11s 182us/step - loss: 1.3443 - acc: 0.4648 - val_l
oss: 0.8643 - val_acc: 0.5883
Epoch 4/12
60000/60000 [==============================] - 11s 181us/step - loss: 1.1016 - acc: 0.5701 - val_l
oss: 0.5978 - val_acc: 0.7803
Epoch 5/12
60000/60000 [==============================] - 11s 180us/step - loss: 0.9140 - acc: 0.6781 - val_l
oss: 0.4562 - val_acc: 0.8725
Epoch 6/12
60000/60000 [==============================] - 11s 180us/step - loss: 0.7894 - acc: 0.7335 - val_l
oss: 0.3559 - val_acc: 0.8902
Epoch 7/12
60000/60000 [==============================] - 11s 182us/step - loss: 0.7210 - acc: 0.7664 - val_l
oss: 0.3107 - val_acc: 0.9003
Epoch 8/12
60000/60000 [==============================] - 11s 181us/step - loss: 0.6655 - acc: 0.7912 - val_l
oss: 0.2777 - val_acc: 0.9197
Epoch 9/12
60000/60000 [==============================] - 11s 181us/step - loss: 0.6323 - acc: 0.8111 - val_l
oss: 0.2244 - val_acc: 0.9478
Epoch 10/12
60000/60000 [==============================] - 11s 180us/step - loss: 0.5885 - acc: 0.8322 - val_l
oss: 0.1888 - val_acc: 0.9568
Epoch 11/12
60000/60000 [==============================] - 11s 183us/step - loss: 0.5449 - acc: 0.8496 - val_l
oss: 0.1693 - val_acc: 0.9592
Epoch 12/12
60000/60000 [==============================] - 11s 181us/step - loss: 0.5226 - acc: 0.8606 - val_l
oss: 0.1556 - val_acc: 0.9623
Test loss: 0.15555355408489704
Test accuracy: 0.9623
```



Here we see with adadelta opimizer with padding model we got test loss 0.15 with accuracy 0.96

CNN 7 Layer with out padding using Adadelta optimizer

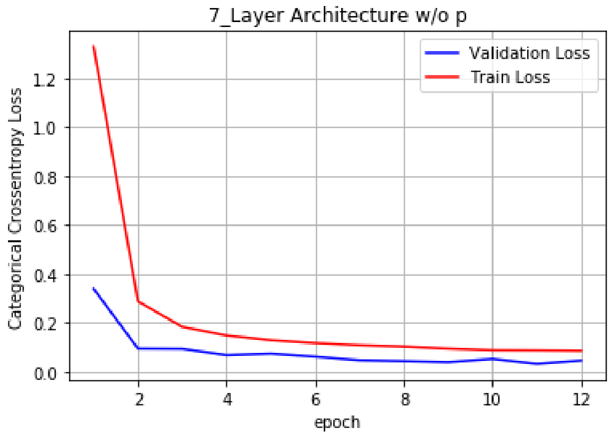
In [19]:

```
model9 = Sequential()
model9.add(Conv2D(12, kernel_size=(4, 4),activation='relu',input_shape=input_shape))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(3, 3)))
model9.add(Dropout(0.5))
#layer-2
```

```
model9.add(Conv2D(24, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-3
model9.add(Conv2D(34, (5, 5), activation='relu'))
model9.add(BatchNormalization())
model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-4
model9.add(Conv2D(44, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(1, 1)))
model9.add(Dropout(0.5))
#layer-5
model9.add(Conv2D(54, (4, 4), activation='relu' ))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-6
model9.add(Conv2D(64, (3, 3), activation='relu'))
model9.add(BatchNormalization())
#model9.add(MaxPooling2D(pool_size=(2, 2)))
model9.add(Dropout(0.5))
#layer-7
model9.add(Conv2D(74, (2, 2), activation='relu'))
model9.add(BatchNormalization())
model9.add(MaxPooling2D(pool_size=(1, 1)))
model9.add(Dropout(0.5))
#flatten to 1-d
model9.add(Flatten())
model9.add(Dense(128, activation='relu'))
model9.add(Dropout(0.5))
model9.add(Dense(num_classes, activation='softmax'))

model9.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history9 = model9.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=nb_epoch,
          verbose=1,
          validation_data=(x_test, y_test))
score9 = model9.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score9[0])
print('Test accuracy:', score9[1])

#plotting train loss vs test loss

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))

vy = history9.history['val_loss']
ty = history9.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('7_Layer Architecture w/o p')
plt.show()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 22s 363us/step - loss: 1.3290 - acc: 0.5624 - val_l
oss: 0.3395 - val_acc: 0.9029
Epoch 2/12
60000/60000 [==============================] - 16s 262us/step - loss: 0.2881 - acc: 0.9168 - val_l
oss: 0.0947 - val_acc: 0.9742
Epoch 3/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.1836 - acc: 0.9499 - val_l
oss: 0.0937 - val_acc: 0.9744
Epoch 4/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.1483 - acc: 0.9604 - val_l
oss: 0.0682 - val_acc: 0.9815
```

```
Epoch 5/12
60000/60000 [==============================] - 16s 262us/step - loss: 0.1289 - acc: 0.9664 - val_l
oss: 0.0743 - val_acc: 0.9809
Epoch 6/12
60000/60000 [==============================] - 16s 261us/step - loss: 0.1171 - acc: 0.9693 - val_l
oss: 0.0619 - val_acc: 0.9850
Epoch 7/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.1083 - acc: 0.9717 - val_l
oss: 0.0471 - val_acc: 0.9875
Epoch 8/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.1028 - acc: 0.9742 - val_l
oss: 0.0435 - val_acc: 0.9901
Epoch 9/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.0946 - acc: 0.9760 - val_l
oss: 0.0393 - val_acc: 0.9900
Epoch 10/12
60000/60000 [==============================] - 16s 261us/step - loss: 0.0882 - acc: 0.9773 - val_l
oss: 0.0525 - val_acc: 0.9883
Epoch 11/12
60000/60000 [==============================] - 16s 263us/step - loss: 0.0875 - acc: 0.9780 - val_l
oss: 0.0324 - val_acc: 0.9921
Epoch 12/12
60000/60000 [==============================] - 16s 261us/step - loss: 0.0861 - acc: 0.9788 - val_l
oss: 0.0458 - val_acc: 0.9889
Test loss: 0.045807891574608586
Test accuracy: 0.9889
```



Here we see 7 layer CNN using adadelta optimizer with out padding model we got test loss 0.04 with accuracy 0.98

In [22]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["No_of_layers","Padding","optimizer","Accuracy","Vald_loss"]

x.add_row([2,"with-out","Adam",0.98,0.03])

x.add_row([1,"with-out","Adam",0.99,0.02])
x.add_row([1,"with"    ,"Adam",0.98,0.04])



x.add_row([3,"with-out","Adam",0.99,0.02])
x.add_row([3,"with"    ,"Adam",0.97,0.07])



x.add_row([5,"with-out","Adam",0.99,0.02])
x.add_row([5,"with"    ,"Adam",0.98,0.05])



x.add_row([7,"with-out","Adam",0.98,0.04])
x.add_row([7,"with"    ,"Adam",0.96,0.14])
```

```
print(x)

x2 = PrettyTable()

x2.field_names = ["No_of_layers","Padding","optimizer","Accuracy","Vald_loss"]

x2.add_row([1,"with-out","Adadelta",0.98,0.05])
x2.add_row([1,"with"    ,"Adadelta",0.98,0.04])

x2.add_row([3,"with-out","Adadelta",0.99,0.02])
x2.add_row([3,"with"    ,"Adadelta",0.97,0.06])

x2.add_row([5,"with-out","Adadelta",0.99,0.02])
x2.add_row([5,"with"    ,"Adadelta",0.98,0.04])

x2.add_row([7,"with-out","Adadelta",0.98,0.04])
x2.add_row([7,"with"    ,"Adadelta",0.96,0.15])

print(x2)
```

```
+--------------+----------+-----------+----------+-----------+
| No_of_layers | Padding  | optimizer | Accuracy | Vald_loss |
+--------------+----------+-----------+----------+-----------+
|      2       | with-out |    Adam   |   0.98   |    0.03   |
|      1       | with-out |    Adam   |   0.99   |    0.02   |
|      1       |   with   |    Adam   |   0.98   |    0.04   |
|      3       | with-out |    Adam   |   0.99   |    0.02   |
|      3       |   with   |    Adam   |   0.97   |    0.07   |
|      5       | with-out |    Adam   |   0.99   |    0.02   |
|      5       |   with   |    Adam   |   0.98   |    0.05   |
|      7       | with-out |    Adam   |   0.98   |    0.04   |
|      7       |   with   |    Adam   |   0.96   |    0.14   |
+--------------+----------+-----------+----------+-----------+
+--------------+----------+-----------+----------+-----------+
| No_of_layers | Padding  | optimizer | Accuracy | Vald_loss |
+--------------+----------+-----------+----------+-----------+
|      1       | with-out |  Adadelta |   0.98   |    0.05   |
|      1       |   with   |  Adadelta |   0.98   |    0.04   |
|      3       | with-out |  Adadelta |   0.99   |    0.02   |
|      3       |   with   |  Adadelta |   0.97   |    0.06   |
|      5       | with-out |  Adadelta |   0.99   |    0.02   |
|      5       |   with   |  Adadelta |   0.98   |    0.04   |
|      7       | with-out |  Adadelta |   0.98   |    0.04   |
|      7       |   with   |  Adadelta |   0.96   |    0.15   |
+--------------+----------+-----------+----------+-----------+
```

Observations

1. We applied Multiple CNN layers in MNIST hand digit Recoignition data to detect the images
2. We tried with 2,3,5,7 layer's CNN with same padding and No padding models with differnt kernels
3. Results observed in Non_padding models gives better than Padding models
4. Intitally Keras done with Adadelta optimizer and got 99% accuracy with 2 layer CNN , we used adam optimizer
5. Some errors occured whie taking random Filter sizes for layers it is better to take odd number layers for small kernerls better to use 3*3 for large kernels better to use 5*5 for getting good results
6. If wee used Even number filter sizes we may encounter problems like interpolation of central pixel so always recommedn to use 3*3 filter size for small kernels 5*5 is used for large kernels for more information visit here : Here
7. So finally models like 1,3,5 CNN almost gives similar results like 99% accuracy with test loss 0.03 with-out padding models
8. We also implemented with Adadelta optimimzer we got similar results like Adam optimizer with 3 CNN model and 5 CNN model gives 99% accuracy and test loss 0.02 there is no much difference in Adadm and Adadelta in 3 and 5 CNN with out padding models
9. We can observe results in above preety table