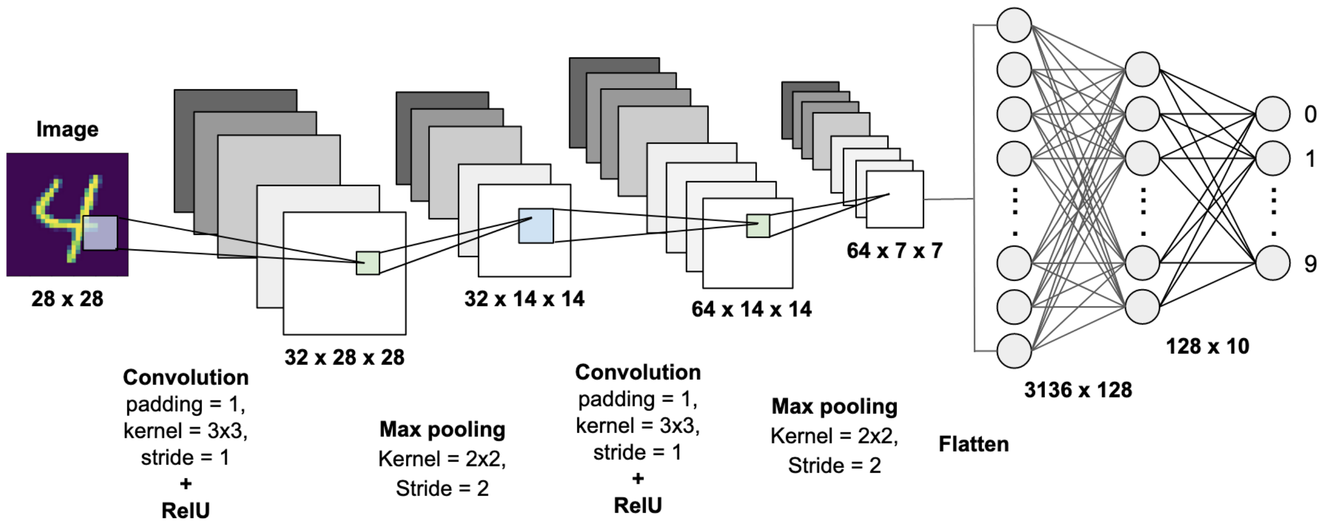
Document Created Date:06-02-2020

Image Source:https://cdn-images-1.medium.com/fit/t/1600/480/1*cPAmSB9nziZPI73VC5HAHg.png (https://cdn-images-1.medium.com/fit/t/1600/480/1*cPAmSB9nziZPI73VC5HAHg.png)



Understanding the MNIST Dataset

- The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.
- The database is also widely used for training and testing in the field of machine learning & deeplearning
- The MNIST database contains 60,000 training images and 10,000 testing images.
- Half of the training set and half of the test set were taken from NIST's training dataset, while the other half of the training set and the other half of the test set were taken from NIST's testing dataset.

source:https://en.wikipedia.org/wiki/MNIST_database (https://en.wikipedia.org/wiki/MNIST_database)

Step by Step Procedure

- Tried various models with diffrent hidden layer architecture and diffrent Approches (Kernel size,maxpooling, activation, optimizer, regularizer, padding and dropout)
- ploting loss with each epoch of model
- Overall Summary (Conclusion) .

Applying Various CNN Networks on MNIST Dataset

Model 1 : 2 Layer Architecture + kernel (3, 3) + relu + Adadelta + MaxPooling(2, 2) + Dropout(0.25)

In [7]:

```
# Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py
import warnings
warnings.filterwarnings("ignore")

import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import tensorflow as tf
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Activation
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
import seaborn as sns
from keras import regularizers

batch_size = 128
num_classes = 10
epochs = 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)
```

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

In [8]:

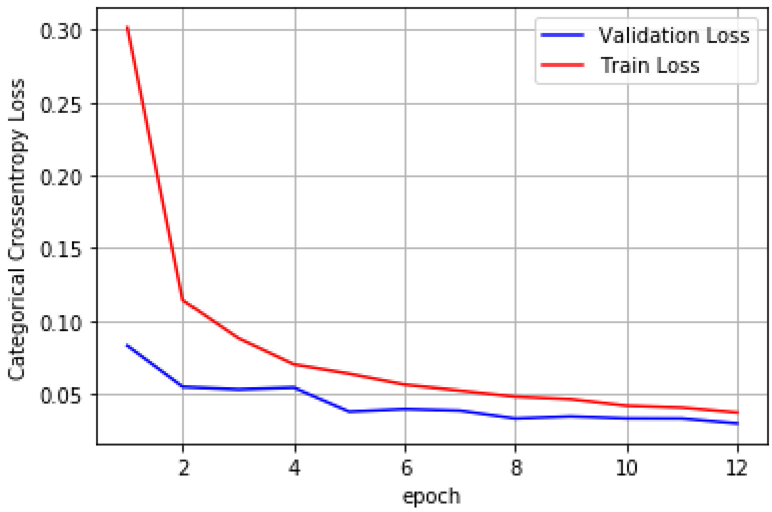
```
# Model 1 : 2 Layer Architecture + kernel (3, 3) + relu + Adadelta + MaxPooling(2, 2) +
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),kernel_regularizer=regularizers.l2(0.01),activa
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.optimizers.Ada
history = model.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verbose=1,vali
score = model.evaluate(x_test, y_test, verbose=1)
score_train = model.evaluate(x_train, y_train, verbose=1)
print('train loss', score_train[0])
print('train accuracy:', score_train[1])
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backe
nd/tensorflow_backend.py:148: The name tf.placeholder_with_default is depr
ecated. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backe
nd/tensorflow_backend.py:3733: calling dropout (from tensorflow.python.op
s.nn_ops) with keep_prob is deprecated and will be removed in a future ver
sion.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep_prob`.
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 165s 3ms/step - loss: 0.301
7 - acc: 0.9140 - val_loss: 0.0830 - val_acc: 0.9809
Epoch 2/12
60000/60000 [==============================] - 162s 3ms/step - loss: 0.114
2 - acc: 0.9714 - val_loss: 0.0547 - val_acc: 0.9865
Epoch 3/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.088
1 - acc: 0.9772 - val_loss: 0.0530 - val_acc: 0.9862
Epoch 4/12
60000/60000 [==============================] - 162s 3ms/step - loss: 0.070
1 - acc: 0.9824 - val_loss: 0.0543 - val_acc: 0.9853
Epoch 5/12
60000/60000 [==============================] - 162s 3ms/step - loss: 0.063
6 - acc: 0.9833 - val_loss: 0.0378 - val_acc: 0.9902
Epoch 6/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.056
2 - acc: 0.9852 - val_loss: 0.0396 - val_acc: 0.9887
Epoch 7/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.052
2 - acc: 0.9864 - val_loss: 0.0385 - val_acc: 0.9885
Epoch 8/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.048
1 - acc: 0.9874 - val_loss: 0.0331 - val_acc: 0.9912
Epoch 9/12
```

```
60000/60000 [==============================] - 163s 3ms/step - loss: 0.046
4 - acc: 0.9879 - val_loss: 0.0345 - val_acc: 0.9901
Epoch 10/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.041
9 - acc: 0.9889 - val_loss: 0.0332 - val_acc: 0.9910
Epoch 11/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.040
6 - acc: 0.9889 - val_loss: 0.0331 - val_acc: 0.9908
Epoch 12/12
60000/60000 [==============================] - 163s 3ms/step - loss: 0.037
2 - acc: 0.9905 - val_loss: 0.0297 - val_acc: 0.9916
10000/10000 [==============================] - 8s 785us/step
60000/60000 [==============================] - 47s 791us/step
train loss 0.0170726533845067
train accuracy: 0.9965333333333334
Test loss: 0.02973237971663475
Test accuracy: 0.9916
```

In [9]:

```python
%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()

# ploting loss with epoch of model
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,epochs+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



Model_2 : 3Layer Architecture + kernel (5, 5) + relu + Adadelta + MaxPooling(2, 2) + Dropout(0.25)

In [10]:

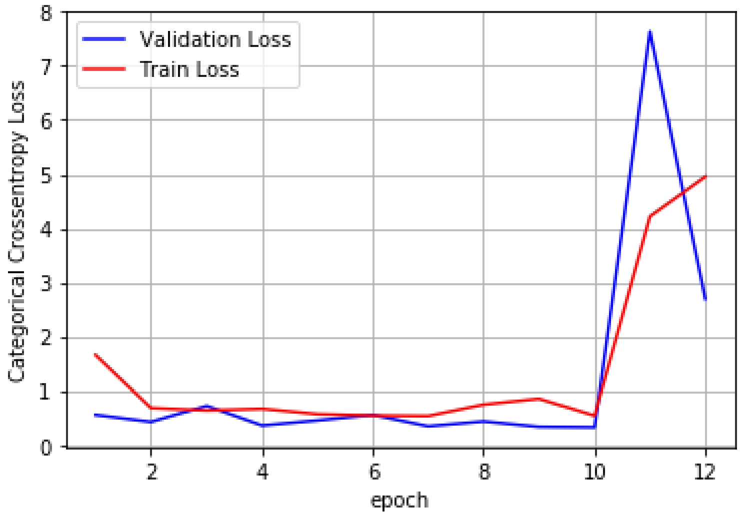
```
# Model_2 : 3Layer Architecture + kernel (5, 5) + relu + Adadelta + MaxPooling(2, 2) + 
%%time
model_2 = Sequential()
model_2.add(Conv2D(32, kernel_size=(5, 5),kernel_regularizer=regularizers.l2(0.01),acti
model_2.add(Conv2D(64, (5, 5), activation='relu', kernel_regularizer=regularizers.l2(0.
model_2.add(MaxPooling2D(pool_size=(2, 2)))
model_2.add(Dropout(0.25))
model_2.add(Conv2D(128, (5, 5), activation='relu', kernel_regularizer=regularizers.l2(0
model_2.add(MaxPooling2D(pool_size=(2, 2)))
model_2.add(Dropout(0.25))
model_2.add(Flatten())
model_2.add(Dense(254, activation='relu'))
model_2.add(Dropout(0.5))
model_2.add(Dense(num_classes, activation='softmax'))

model_2.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.optimizers.A
history_2 = model_2.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verbose=1,
score_2 = model_2.evaluate(x_test, y_test, verbose=1)
print('Test loss:', score_2[0])
print('Test accuracy:', score_2[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 324s 5ms/step - loss: 1.6
607 - acc: 0.6241 - val_loss: 0.5549 - val_acc: 0.8968
Epoch 2/12
60000/60000 [==============================] - 323s 5ms/step - loss: 0.6
823 - acc: 0.8545 - val_loss: 0.4263 - val_acc: 0.9265
Epoch 3/12
60000/60000 [==============================] - 323s 5ms/step - loss: 0.6
378 - acc: 0.8780 - val_loss: 0.7211 - val_acc: 0.9124
Epoch 4/12
60000/60000 [==============================] - 323s 5ms/step - loss: 0.6
676 - acc: 0.8871 - val_loss: 0.3600 - val_acc: 0.9513
Epoch 5/12
60000/60000 [==============================] - 321s 5ms/step - loss: 0.5
693 - acc: 0.8985 - val_loss: 0.4533 - val_acc: 0.9537
Epoch 6/12
60000/60000 [==============================] - 313s 5ms/step - loss: 0.5
435 - acc: 0.9043 - val_loss: 0.5548 - val_acc: 0.9184
Epoch 7/12
60000/60000 [==============================] - 313s 5ms/step - loss: 0.5
354 - acc: 0.9065 - val_loss: 0.3462 - val_acc: 0.9546
Epoch 8/12
60000/60000 [==============================] - 313s 5ms/step - loss: 0.7
455 - acc: 0.9009 - val_loss: 0.4350 - val_acc: 0.9399
Epoch 9/12
60000/60000 [==============================] - 313s 5ms/step - loss: 0.8
524 - acc: 0.8984 - val_loss: 0.3356 - val_acc: 0.9594
Epoch 10/12
60000/60000 [==============================] - 313s 5ms/step - loss: 0.5
402 - acc: 0.9119 - val_loss: 0.3263 - val_acc: 0.9645
Epoch 11/12
60000/60000 [==============================] - 312s 5ms/step - loss: 4.2
258 - acc: 0.8007 - val_loss: 7.6364 - val_acc: 0.7656
Epoch 12/12
60000/60000 [==============================] - 312s 5ms/step - loss: 4.9
607 - acc: 0.8499 - val_loss: 2.6980 - val_acc: 0.9390
```

```
10000/10000 [==============================] - 12s 1ms/step
Test loss: 2.6980424322128296
Test accuracy: 0.939
CPU times: user 2h 52s, sys: 2min 1s, total: 2h 2min 54s
Wall time: 1h 3min 34s
```

In [11]:

```python
# ploting loss with each epoch of model2
fig, ax=plt.subplots(1,1)
ax.set_xlabel('epoch'); ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,epochs+1)) # List of epoch Numbers
vy = history_2.history['val_loss']
ty = history_2.history['loss']
plt_dynamic(x, vy, ty, ax)
```



Model_3: 3Layer Architecture + kernel (7, 7) + relu + Adam + MaxPooling(2, 2) + padding(same) + with out Dropout

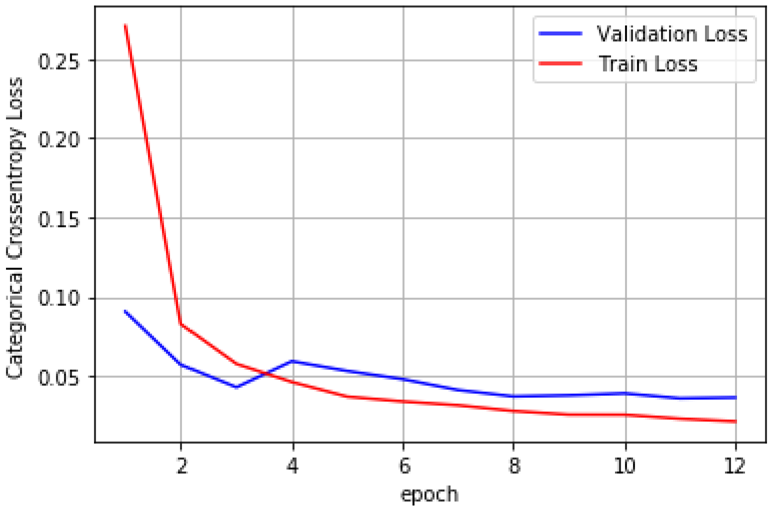
In [6]:

```
# Model_3: 3Layer Architecture + kernel (7, 7) + relu + Adam + MaxPooling(2, 2) + paddi
%%time
model_3 = Sequential()
model_3.add(Conv2D(32,kernel_size=(7, 7),padding='same', kernel_regularizer=regularizer
model_3.add(MaxPooling2D(pool_size=(2, 2)))
model_3.add(Conv2D(64, kernel_size=(7,7),activation='relu'))
model_3.add(Conv2D(128, kernel_size=(7, 7), activation='relu'))
model_3.add(MaxPooling2D(pool_size=(2,2)))
model_3.add(Flatten())
model_3.add(Dense(254, activation='relu'))
model_3.add(Dense(num_classes, activation='softmax'))

model_3.compile(optimizer='adam', loss='categorical_crossentropy',metrics=['accuracy'])
history_3= model_3.fit(x_train, y_train, batch_size=batch_size,epochs=epochs,verbose=1,
score_3 = model_3.evaluate(x_test,y_test, verbose=1)
print('Test loss:', score_3[0])
print('Test accuracy:', score_3[1])
```

```
CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 7.15 µs
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 198s 3ms/step - loss: 0.270
9 - acc: 0.9214 - val_loss: 0.0907 - val_acc: 0.9779
Epoch 2/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.082
8 - acc: 0.9783 - val_loss: 0.0571 - val_acc: 0.9855
Epoch 3/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.057
7 - acc: 0.9852 - val_loss: 0.0429 - val_acc: 0.9910
Epoch 4/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.046
2 - acc: 0.9881 - val_loss: 0.0593 - val_acc: 0.9847
Epoch 5/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.037
0 - acc: 0.9911 - val_loss: 0.0532 - val_acc: 0.9873
Epoch 6/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.033
9 - acc: 0.9921 - val_loss: 0.0480 - val_acc: 0.9870
Epoch 7/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.031
5 - acc: 0.9919 - val_loss: 0.0412 - val_acc: 0.9901
Epoch 8/12
60000/60000 [==============================] - 193s 3ms/step - loss: 0.027
9 - acc: 0.9935 - val_loss: 0.0371 - val_acc: 0.9905
Epoch 9/12
60000/60000 [==============================] - 192s 3ms/step - loss: 0.025
6 - acc: 0.9939 - val_loss: 0.0378 - val_acc: 0.9903
Epoch 10/12
60000/60000 [==============================] - 192s 3ms/step - loss: 0.025
5 - acc: 0.9938 - val_loss: 0.0390 - val_acc: 0.9900
Epoch 11/12
60000/60000 [==============================] - 192s 3ms/step - loss: 0.023
0 - acc: 0.9945 - val_loss: 0.0359 - val_acc: 0.9915
Epoch 12/12
60000/60000 [==============================] - 191s 3ms/step - loss: 0.021
3 - acc: 0.9954 - val_loss: 0.0364 - val_acc: 0.9925
10000/10000 [==============================] - 6s 567us/step
```

In [7]:

```
# ploting loss with each epoch of mode3

fig, ax=plt.subplots(1,1)
ax.set_xlabel('epoch'); ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,epochs+1)) # List of epoch Numbers
vy = history_3.history['val_loss']
ty = history_3.history['loss']
plt_dynamic(x, vy, ty, ax)
```



Model E1(Experiment1) = 3Layer Architecture + kernel (9, 9) + relu + adam + L2 reg + MaxPooling + padding(same) + Dropout(0.3)

In [10]:

```
# Model E1(Experiment1) = 3Layer Architecture + kernel (9, 9) + relu + adam + L2 reg + 
%%time
batch_size_E = 150
num_classes_E = 10
epochs_E = 15
model_E1 = Sequential()
model_E1.add(Conv2D(32,kernel_size=(9, 9),padding='same', kernel_regularizer=regularize
model_E1.add(MaxPooling2D(pool_size=(2, 2)))
model_E1.add(Dropout(0.3))
model_E1.add(Conv2D(64, kernel_size=(9,9),padding='same',activation='relu'))
model_E1.add(MaxPooling2D(pool_size=(2, 2)))
model_E1.add(Dropout(0.3))
model_E1.add(Conv2D(128, kernel_size=(9, 9),padding='same', activation='relu'))
model_E1.add(MaxPooling2D(pool_size=(2,2)))
model_E1.add(Flatten())
model_E1.add(Dense(254, activation='relu'))
model_E1.add(Dense(num_classes_E, activation='softmax'))

model_E1.compile(optimizer='adam', loss='categorical_crossentropy',metrics=['accuracy']
history= model_E1.fit(x_train, y_train, batch_size=batch_size_E,epochs=epochs_E,verbose
score_E1 = model_E1.evaluate(x_test,y_test, verbose=1)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 622s 10ms/step - loss: 0.32
96 - acc: 0.8995 - val_loss: 0.0811 - val_acc: 0.9788
Epoch 2/15
60000/60000 [==============================] - 622s 10ms/step - loss: 0.08
92 - acc: 0.9768 - val_loss: 0.0548 - val_acc: 0.9865
Epoch 3/15
60000/60000 [==============================] - 621s 10ms/step - loss: 0.06
76 - acc: 0.9830 - val_loss: 0.0463 - val_acc: 0.9874
Epoch 4/15
60000/60000 [==============================] - 621s 10ms/step - loss: 0.05
58 - acc: 0.9855 - val_loss: 0.0541 - val_acc: 0.9873
Epoch 5/15
60000/60000 [==============================] - 619s 10ms/step - loss: 0.04
85 - acc: 0.9876 - val_loss: 0.0398 - val_acc: 0.9906
Epoch 6/15
60000/60000 [==============================] - 618s 10ms/step - loss: 0.04
47 - acc: 0.9884 - val_loss: 0.0419 - val_acc: 0.9905
Epoch 7/15
60000/60000 [==============================] - 618s 10ms/step - loss: 0.04
06 - acc: 0.9900 - val_loss: 0.0353 - val_acc: 0.9916
Epoch 8/15
60000/60000 [==============================] - 618s 10ms/step - loss: 0.03
87 - acc: 0.9906 - val_loss: 0.0432 - val_acc: 0.9891
Epoch 9/15
60000/60000 [==============================] - 618s 10ms/step - loss: 0.03
53 - acc: 0.9915 - val_loss: 0.0372 - val_acc: 0.9911
Epoch 10/15
60000/60000 [==============================] - 619s 10ms/step - loss: 0.03
52 - acc: 0.9914 - val_loss: 0.0362 - val_acc: 0.9911
Epoch 11/15
60000/60000 [==============================] - 619s 10ms/step - loss: 0.03
31 - acc: 0.9918 - val_loss: 0.0323 - val_acc: 0.9926
Epoch 12/15
60000/60000 [==============================] - 619s 10ms/step - loss: 0.03
```

```
09 - acc: 0.9929 - val_loss: 0.0394 - val_acc: 0.9909
Epoch 13/15
60000/60000 [==============================] - 619s 10ms/step - loss: 0.03
10 - acc: 0.9930 - val_loss: 0.0567 - val_acc: 0.9870
Epoch 14/15
60000/60000 [==============================] - 622s 10ms/step - loss: 0.02
97 - acc: 0.9928 - val_loss: 0.0458 - val_acc: 0.9886
Epoch 15/15
60000/60000 [==============================] - 622s 10ms/step - loss: 0.02
93 - acc: 0.9935 - val_loss: 0.0403 - val_acc: 0.9906
10000/10000 [==============================] - 21s 2ms/step
CPU times: user 4h 57min 17s, sys: 4min 14s, total: 5h 1min 32s
Wall time: 2h 35min 16s
```

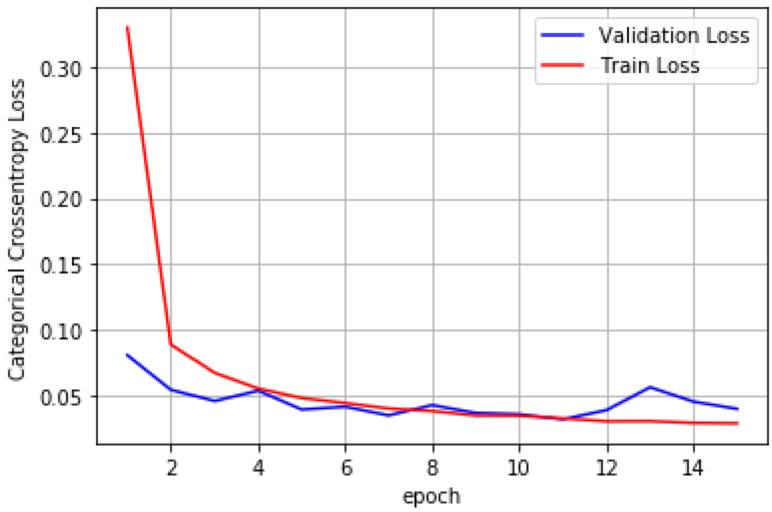
In [11]:

```python
print('Test loss:', score_E1[0])
print('Test accuracy:', score_E1[1])
```

```
Test loss: 0.04032821790426969
Test accuracy: 0.9906
```

In [12]:

```python
# ploting loss with each epoch of model_E1

fig, ax=plt.subplots(1,1)
ax.set_xlabel('epoch'); ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,epochs_E+1)) # List of epoch Numbers
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



Model_E2(Experiment2) = Single Layer Architecture + kernel (7, 7) + relu + Adadelta + MaxPooling(2,2) + padding + Dropout(0.3)

In [13]:

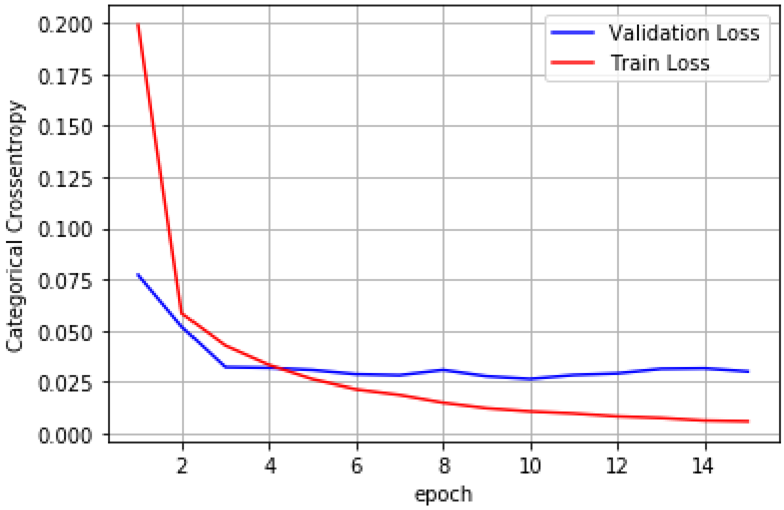
```
# Model E2(Experiment2) = Single Layer Architecture + kernel (7, 7) + relu + Adadelta +
%%time
from keras.layers import Activation
model_E2 = Sequential()
model_E2.add(Conv2D(64,kernel_size=(7, 7), activation='relu',input_shape=input_shape))
model_E2.add(MaxPooling2D(pool_size=(2, 2)))
model_E2.add(Dropout(0.3))
model_E2.add(Flatten())
model_E2.add(Dense(254, activation='relu'))
model_E2.add(Dense(num_classes_E, activation='softmax'))

model_E2.compile(optimizer=keras.optimizers.Adadelta(), loss='categorical_crossentropy'
history= model_E2.fit(x_train, y_train, batch_size=batch_size_E,epochs=epochs_E,verbose
score_E2 = model_3_conv_5L.evaluate(x_test,y_test, verbose=1)
print('Test loss:', score_E2[0])
print('Test accuracy:', score_E2[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 63s 1ms/step - loss: 0.19
91 - acc: 0.9400 - val_loss: 0.0772 - val_acc: 0.9749
Epoch 2/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.05
84 - acc: 0.9824 - val_loss: 0.0518 - val_acc: 0.9832
Epoch 3/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.04
26 - acc: 0.9864 - val_loss: 0.0321 - val_acc: 0.9892
Epoch 4/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.03
32 - acc: 0.9896 - val_loss: 0.0318 - val_acc: 0.9895
Epoch 5/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.02
62 - acc: 0.9916 - val_loss: 0.0307 - val_acc: 0.9898
Epoch 6/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.02
14 - acc: 0.9932 - val_loss: 0.0286 - val_acc: 0.9902
Epoch 7/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.01
87 - acc: 0.9945 - val_loss: 0.0281 - val_acc: 0.9913
Epoch 8/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.01
49 - acc: 0.9952 - val_loss: 0.0307 - val_acc: 0.9907
Epoch 9/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.01
22 - acc: 0.9959 - val_loss: 0.0276 - val_acc: 0.9907
Epoch 10/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.01
07 - acc: 0.9967 - val_loss: 0.0263 - val_acc: 0.9922
Epoch 11/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.00
97 - acc: 0.9970 - val_loss: 0.0282 - val_acc: 0.9916
Epoch 12/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.00
82 - acc: 0.9976 - val_loss: 0.0290 - val_acc: 0.9915
Epoch 13/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.00
75 - acc: 0.9975 - val_loss: 0.0313 - val_acc: 0.9906
```

```
Epoch 14/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.00
62 - acc: 0.9981 - val_loss: 0.0315 - val_acc: 0.9909
Epoch 15/15
60000/60000 [==============================] - 62s 1ms/step - loss: 0.00
58 - acc: 0.9981 - val_loss: 0.0300 - val_acc: 0.9913
10000/10000 [==============================] - 6s 563us/step
Test loss: 0.036390860442072154
Test accuracy: 0.9925
CPU times: user 28min 38s, sys: 40.7 s, total: 29min 19s
Wall time: 15min 38s
```

In [15]:

```python
# ploting loss with each epoch of model_E2
fig, ax = plt.subplots(1,1)
ax.set_xlabel('epoch'); ax.set_ylabel('Categorical Crossentropy')
x = list(range(1,epochs_E+1)) # List of epoch Numbers
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



Model_E3(Experiment3) = 4Layer Architecture + kernel (11, 11) + relu + L2 Reg + Adam + MaxPooling(2, 2) + padding + Dropout(0.5)

In [13]:

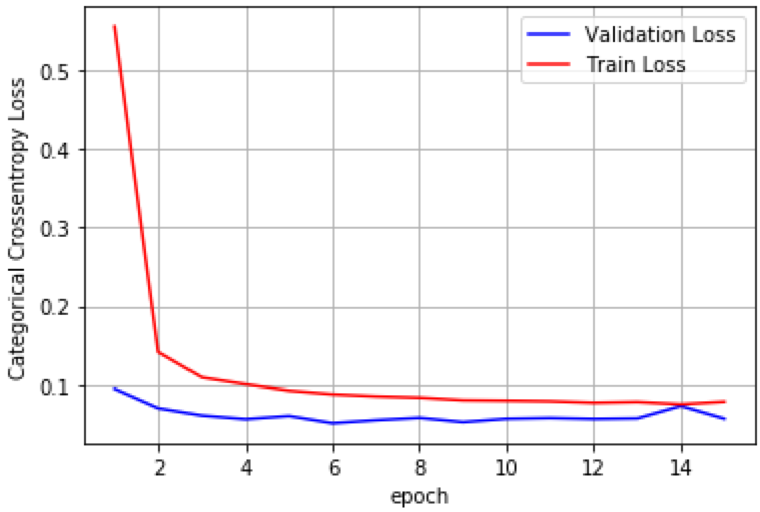
```
# Model E3(Experiment3) = 4Layer Architecture + kernel (11, 11) + relu + L2 Reg + Adam
%%time
model_E3 = Sequential()
model_E3.add(Conv2D(16,kernel_size=(11, 11),padding='same', kernel_regularizer=regulari
model_E3.add(MaxPooling2D(pool_size=(2, 2)))
model_E3.add(Dropout(0.5))
model_E3.add(Conv2D(32, kernel_size=(11, 11), padding='same', kernel_regularizer=regula
model_E3.add(Conv2D(64, kernel_size=(11,11),padding='same',activation='relu'))
model_E3.add(MaxPooling2D(pool_size=(2, 2)))
model_E3.add(Dropout(0.5))
model_E3.add(Conv2D(128, kernel_size=(11, 11),padding='same', activation='relu'))
model_E3.add(MaxPooling2D(pool_size=(2,2)))
model_E3.add(Dropout(0.5))
model_E3.add(Flatten())
model_E3.add(Dense(254,activation='relu'))
model_E3.add(Dense(num_classes, activation='softmax'))

model_E3.compile(optimizer='adam', loss='categorical_crossentropy',metrics=['accuracy']
history= model_E3.fit(x_train, y_train, batch_size=batch_size_E,epochs=epochs_E,verbose
score_E3 = model_E3.evaluate(x_test,y_test, verbose=1)

print('test loss :', score_E3[0])
print('test accuracy :', score_E3[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 1282s 21ms/step - loss: 0.5
560 - acc: 0.8143 - val_loss: 0.0947 - val_acc: 0.9786
Epoch 2/15
60000/60000 [==============================] - 1291s 22ms/step - loss: 0.1
416 - acc: 0.9643 - val_loss: 0.0701 - val_acc: 0.9847
Epoch 3/15
60000/60000 [==============================] - 1300s 22ms/step - loss: 0.1
093 - acc: 0.9742 - val_loss: 0.0609 - val_acc: 0.9879
Epoch 4/15
60000/60000 [==============================] - 1285s 21ms/step - loss: 0.1
006 - acc: 0.9770 - val_loss: 0.0563 - val_acc: 0.9899
Epoch 5/15
60000/60000 [==============================] - 1285s 21ms/step - loss: 0.0
924 - acc: 0.9797 - val_loss: 0.0603 - val_acc: 0.9888
Epoch 6/15
60000/60000 [==============================] - 1303s 22ms/step - loss: 0.0
878 - acc: 0.9818 - val_loss: 0.0512 - val_acc: 0.9923
Epoch 7/15
60000/60000 [==============================] - 1268s 21ms/step - loss: 0.0
852 - acc: 0.9817 - val_loss: 0.0550 - val_acc: 0.9928
Epoch 8/15
60000/60000 [==============================] - 1266s 21ms/step - loss: 0.0
836 - acc: 0.9838 - val_loss: 0.0580 - val_acc: 0.9907
Epoch 9/15
60000/60000 [==============================] - 1273s 21ms/step - loss: 0.0
803 - acc: 0.9841 - val_loss: 0.0526 - val_acc: 0.9917
Epoch 10/15
60000/60000 [==============================] - 1299s 22ms/step - loss: 0.0
798 - acc: 0.9839 - val_loss: 0.0568 - val_acc: 0.9917
Epoch 11/15
60000/60000 [==============================] - 1256s 21ms/step - loss: 0.0
```

```
791 - acc: 0.9845 - val_loss: 0.0578 - val_acc: 0.9906
Epoch 12/15
60000/60000 [==============================] - 1260s 21ms/step - loss: 0.0
772 - acc: 0.9855 - val_loss: 0.0566 - val_acc: 0.9916
Epoch 13/15
60000/60000 [==============================] - 1264s 21ms/step - loss: 0.0
781 - acc: 0.9850 - val_loss: 0.0573 - val_acc: 0.9913
Epoch 14/15
60000/60000 [==============================] - 1300s 22ms/step - loss: 0.0
752 - acc: 0.9862 - val_loss: 0.0731 - val_acc: 0.9863
Epoch 15/15
60000/60000 [==============================] - 1243s 21ms/step - loss: 0.0
785 - acc: 0.9854 - val_loss: 0.0569 - val_acc: 0.9914
10000/10000 [==============================] - 45s 5ms/step
test loss : 0.05688948290348053
test accuracy : 0.9914
CPU times: user 10h 15min 28s, sys: 10min 28s, total: 10h 25min 57s
Wall time: 5h 20min 20s
```

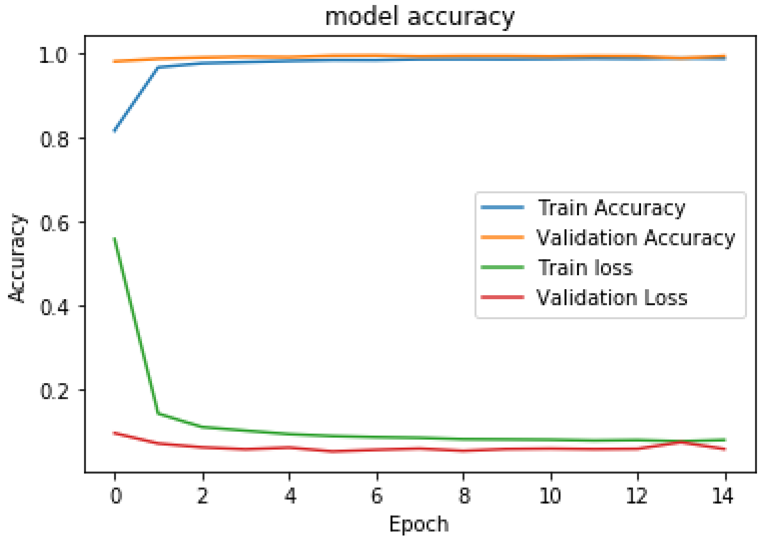
In [17]:

```
# ploting loss with epoch of model_E3
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,epochs_E+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [19]:

```
# ploting Train Accuracy , validation Accuracy , train loss , validation loss
import matplotlib.pyplot as plt
plt.plot(history.history["acc"])
plt.plot(history.history['val_acc'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.grid()
plt.title("model accuracy")
plt.ylabel("Accuracy")
plt.xlabel("Epoch")
plt.legend(["Train Accuracy","Validation Accuracy","Train loss","Validation Loss"])
plt.show()
```



Model_4(Experiment4) : 2Layer Architecture + Kernel(3, 3) with relu followed by maxpooling (2, 2), padding, L2 reg, Adam, and with out Dropout

In [6]:

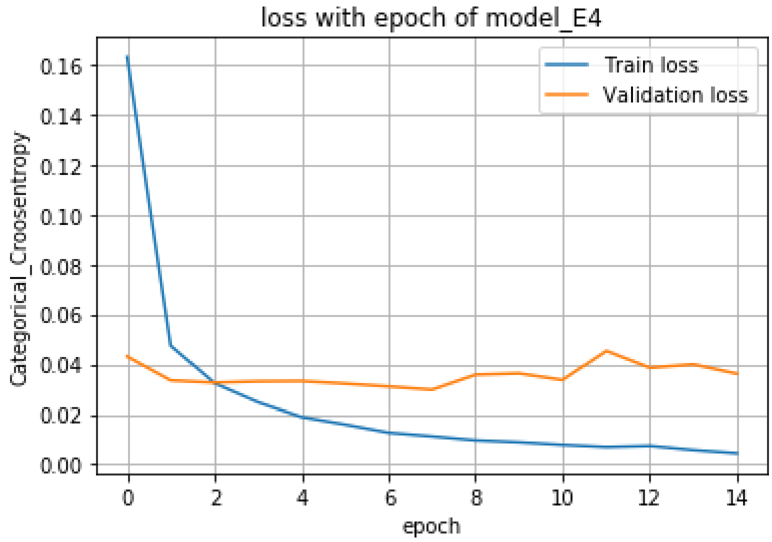
```
# Model_4(Experiment4) : 2Layer Architecture + Kernel(3, 3) with relu followed by maxpo
%%time
model_E4 = Sequential()
model_E4.add(Conv2D(64,kernel_size=(3, 3),padding='same', kernel_regularizer=regularize
model_E4.add(MaxPooling2D(pool_size=(2, 2)))
model_E4.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model_E4.add(MaxPooling2D(pool_size=(2, 2)))
model_E4.add(Flatten())
model_E4.add(Dense(254,activation='relu'))
model_E4.add(Dense(num_classes, activation='softmax'))

model_E4.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'
history_E4 = model_E4.fit(x_train, y_train, verbose=1, batch_size=batch_size_E, epochs=
score_E4 = model_E4.evaluate(x_test, y_test, verbose=1,)
print('Test Loss:', score_E4[0])
print('Test Accuracy:', score_E4[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 141s 2ms/step - loss: 0.166
5 - acc: 0.9510 - val_loss: 0.0467 - val_acc: 0.9866
Epoch 2/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.048
7 - acc: 0.9855 - val_loss: 0.0348 - val_acc: 0.9901
Epoch 3/15
60000/60000 [==============================] - 139s 2ms/step - loss: 0.033
4 - acc: 0.9899 - val_loss: 0.0329 - val_acc: 0.9899
Epoch 4/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.024
0 - acc: 0.9935 - val_loss: 0.0332 - val_acc: 0.9902
Epoch 5/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.019
1 - acc: 0.9953 - val_loss: 0.0309 - val_acc: 0.9911
Epoch 6/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.015
5 - acc: 0.9959 - val_loss: 0.0279 - val_acc: 0.9914
Epoch 7/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.012
9 - acc: 0.9968 - val_loss: 0.0323 - val_acc: 0.9902
Epoch 8/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.011
0 - acc: 0.9975 - val_loss: 0.0322 - val_acc: 0.9911
Epoch 9/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.009
8 - acc: 0.9976 - val_loss: 0.0347 - val_acc: 0.9900
Epoch 10/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.008
1 - acc: 0.9982 - val_loss: 0.0302 - val_acc: 0.9922
Epoch 11/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.007
7 - acc: 0.9984 - val_loss: 0.0411 - val_acc: 0.9901
Epoch 12/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.007
2 - acc: 0.9983 - val_loss: 0.0344 - val_acc: 0.9905
Epoch 13/15
60000/60000 [==============================] - 139s 2ms/step - loss: 0.006
```

```
9 - acc: 0.9985 - val_loss: 0.0353 - val_acc: 0.9904
Epoch 14/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.007
1 - acc: 0.9984 - val_loss: 0.0429 - val_acc: 0.9892
Epoch 15/15
60000/60000 [==============================] - 140s 2ms/step - loss: 0.006
6 - acc: 0.9984 - val_loss: 0.0356 - val_acc: 0.9909
10000/10000 [==============================] - 6s 632us/step
Test Loss: 0.03564334284737706
Test Accuracy: 0.9909
CPU times: user 1h 5min 48s, sys: 1min 6s, total: 1h 6min 55s
Wall time: 35min 6s
```

In [5]:

```python
# ploting loss with epoch of model_E4
import matplotlib.pyplot as plt
plt.plot(history_E4.history['loss'])
plt.plot(history_E4.history['val_loss'])
plt.grid()
plt.title('loss with epoch of model_E4')
plt.xlabel('epoch')
plt.ylabel('Categorical_Croosentropy')
plt.legend(['Train loss', 'Validation loss'])
plt.show()
```



In [12]:

```
from prettytable import PrettyTable
p = PrettyTable()

p.field_names = ['Model', 'Architec',"batch",'epochs','kernel','MaxPool','Activation',
                'Dropout','Val_loss', 'Val_Acc' ]
p.add_row(["Model_1","2 Layer", 128, 12, "3, 3", "2, 2",  "relu", "Adadelta", "L2 (0.01
p.add_row(["Model_2","3 Layer", 128, 12, "5, 5", "2, 2",  "relu", "Adadelta", "L2 (0.01
p.add_row(["Model_3","3 Layer", 128, 12, "7, 7", "2, 2",  "relu", "Adam",     "L2 (0.01

p.add_row(["Model_E1","3 Layer",150, 15, "9, 9", "2, 2",  "relu", "Adam",     "L2 (0.01
p.add_row(["Model_E2","1 Layer",150, 15, "7, 7", "2, 2",  "relu", "Adadelta", "--",
p.add_row(["Model_E3","4 Layer",150, 15, "11, 11","2, 2", "relu", "Adam",     "L2 (0.00
p.add_row(["Model_E4","2 Layer",150, 15, "3, 3",  "2, 2", "relu", "Adam",     "L2 (0.00


print(p)
```

```
+----------+----------+-------+--------+--------+---------+------------+--
---------+-----------+---------+----------+---------+
|  Model   | Architec | batch | epochs | kernel | MaxPool | Activation | O
ptimizer | Regulrize  | Dropout | Val_loss | Val_Acc |
+----------+----------+-------+--------+--------+---------+------------+--
---------+-----------+---------+----------+---------+
| Model_1  | 2 Layer  |  128  |   12   |  3, 3  |   2, 2  |    relu    |
Adadelta | L2 (0.01)  |   0.25  |  0.029   |  0.9916 |
| Model_2  | 3 Layer  |  128  |   12   |  5, 5  |   2, 2  |    relu    |
Adadelta | L2 (0.01)  |   0.25  |  2.698   |  0.939  |
| Model_3  | 3 Layer  |  128  |   12   |  7, 7  |   2, 2  |    relu    |
Adam     | L2 (0.01)  |    --   |  0.0364  |  0.9925 |
| Model_E1 | 3 Layer  |  150  |   15   |  9, 9  |   2, 2  |    relu    |
Adam     | L2 (0.01)  |   0.3   |  0.0403  |  0.9906 |
| Model_E2 | 1 Layer  |  150  |   15   |  7, 7  |   2, 2  |    relu    |
Adadelta |     --    |   0.3   |   0.03   |  0.9913 |
| Model_E3 | 4 Layer  |  150  |   15   | 11, 11 |   2, 2  |    relu    |
Adam     | L2 (0.001) |   0.5   |  0.0569  |  0.9914 |
| Model_E4 | 2 Layer  |  150  |   15   |  3, 3  |   2, 2  |    relu    |
Adam     | L2 (0.001) |    --   |  0.0356  |  0.9909 |
+----------+----------+-------+--------+--------+---------+------------+--
---------+-----------+---------+----------+---------+
```

Conclusion : Overall Summary with Experiment

- **Tried various models with diffrent hidden layer architecture and diffrent Approches (Kernel size,maxpooling, activation, optimizer, regularizer, padding and dropout)**
- **L2 Regularization was helps to the model performence and it avoid's the model overfit.**
- **All models took larger amount of computional power(worked with CPU).**
- **For better model performence, the hidden layer size , batchsize, and epochs should be choose reasonably and it shouldn't be too hegh numbers and it shouldn't be low numbers based on the dataset size we have .**
- **By experimenting with all diffrent apprroches to the model, loss and accutracy changes within reasonable limits.**
- **CNN models works very well with large amount of layers and large kernel sizes also.**
- **Overall CNN models works very well with heigh accuracy and low eroor loss on MNIST Dataset.**

Thank You.

Sign Off RAMESH BATTU (https://www.linkedin.com/in/rameshbattuai/)