```
In [1]:
from tensorflow.python.client import device lib
print(device lib.list local devices())
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
incarnation: 14453497738175562891
]
In [2]:
import keras
import tensorflow as tf
config = tf.ConfigProto( device count = {'GPU': 1 , 'CPU': 56} )
sess = tf.Session(config=config)
keras.backend.set_session(sess)
Using TensorFlow backend.
In [1]:
from keras.utils import np_utils
from keras.layers import Flatten, Dropout, Conv2D, MaxPooling2D, BatchNormalization, Dense, Activation
from keras import backend as k
from keras.models import Sequential
from keras.datasets import mnist
Using TensorFlow backend.
In [2]:
batch size = 128
out dim = 10
nb = pochs = 12
img rows, img cols = 28,28
In [3]:
(X train, y train), (X test, y test) = mnist.load data()
In [4]:
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)
In [5]:
X_train = X_train/255
X \text{ test} = X \text{ test}/255
y train = np utils.to categorical(y train, 10)
y_test = np_utils.to_categorical(y_test,10)
```

# Model with 3 by 3 kernels or filters.

# Model 1 with 3 CNN layers

```
In [7]:
```

```
model 1 = Sequential()
model 1.add(Conv2D(96,kernel size=(3,3),padding='same',input shape=input shape))
model_1.add(BatchNormalization())
model 1.add(Activation('relu'))
model 1.add(MaxPooling2D(pool size=(2,2)))
model_1.add(Dropout(0.5))
model 1.add(Conv2D(64, kernel size = (3,3), padding='same'))
model 1.add(BatchNormalization())
model 1.add(Activation('relu'))
model 1.add(MaxPooling2D(pool size =(2,2)))
model 1.add(Dropout(0.5))
model 1.add(Conv2D(32,kernel size=(3,3),padding='same'))
model 1.add(BatchNormalization())
model_1.add(Activation('relu'))
model 1.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_1.add(Dropout(0.5))
model_1.add(Flatten())
model_1.add(Dense(64))
model 1.add(BatchNormalization())
model 1.add(Activation('relu'))
model 1.add(Dropout(0.5))
model_1.add(Dense(out_dim,activation = 'softmax'))
model 1.summary()
WARNING: Logging before flag parsing goes to stderr.
W0825 09:29:22.765383 7884 deprecation_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow backend.py:74: The name tf.get default graph is deprecated. Please
use tf.compat.v1.get default graph instead.
W0825 09:29:23.070569 7884 deprecation wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow backend.py:517: The name tf.placeholder is deprecated. Please use t
f.compat.v1.placeholder instead.
\verb|W0825 09:29:23.076552| 7884 deprecation_wrapper.py:119| From C:\Users\patha\Anaconda3\lib\site-pace | Property | Control of the control o
kages\keras\backend\tensorflow backend.py:4138: The name tf.random uniform is deprecated. Please u
se tf.random.uniform instead.
W0825 09:29:23.111462 7884 deprecation wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow_backend.py:174: The name tf.get_default_session is deprecated. Plea
se use tf.compat.v1.get_default_session instead.
W0825 09:29:23.115463 7884 deprecation_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow_backend.py:181: The name tf.ConfigProto is deprecated. Please use t
f.compat.v1.ConfigProto instead.
W0825 09:29:23.273027 7884 deprecation_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow backend.py:1834: The name tf.nn.fused batch norm is deprecated. Ple
ase use tf.compat.vl.nn.fused batch norm instead.
W0825 09:29:23.346829 7884 deprecation wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\backend\tensorflow backend.py:3976: The name tf.nn.max pool is deprecated. Please use
tf.nn.max pool2d instead.
W0825 09:29:23.353812 7884 deprecation.py:506] From C:\Users\patha\Anaconda3\lib\site-
packages\keras\backend\tensorflow backend.py:3445: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future
version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

Layer (type)	Output	Shaj	ре		Param #
				=======	========
conv2d_1 (Conv2D)	(None,	28,	28,	96)	960
batch normalization 1 (Batch	(None,	28,	28,	96)	384
activation 1 (Activation)	(None,	28.	28.	96)	0

-					
max_pooling2d_1 (MaxPooling2	(None,	14,	14,	96)	0
dropout_1 (Dropout)	(None,	14,	14,	96)	0
conv2d_2 (Conv2D)	(None,	14,	14,	64)	55360

activation\_2 (Activation) (None, 14, 14, 64) 0
max\_pooling2d\_2 (MaxPooling2 (None, 7, 7, 64) 0

batch normalization 2 (Batch (None, 14, 14, 64)

dropout\_2 (Dropout) (None, 7, 7, 64) 0

conv2d\_3 (Conv2D) (None, 7, 7, 32) 18464

batch\_normalization\_3 (Batch (None, 7, 7, 32) 128

activation\_3 (Activation) (None, 7, 7, 32) 0

max\_pooling2d\_3 (MaxPooling2 (None, 4, 4, 32) 0

dropout\_3 (Dropout) (None, 4, 4, 32) 0

flatten\_1 (Flatten) (None, 512) 0

dense 1 (Dense) (None, 64) 32832

dense\_1 (Dense) (None, 64) 32832
batch normalization 4 (Batch (None, 64) 256

activation\_4 (Activation) (None, 64) 0

dropout\_4 (Dropout) (None, 64) 0

dense\_2 (Dense) (None, 10) 650

Total params: 109,290 Trainable params: 108,778 Non-trainable params: 512

### In [8]:

model\_1.compile(loss = 'categorical\_crossentropy',optimizer = 'adam',metrics = ['accuracy'])
model\_1.fit(X\_train,y\_train,batch\_size=batch\_size,epochs=nb\_epochs,validation\_data=(X\_test,y\_test))

256

score = model\_1.evaluate(X\_test, y\_test, verbose=0)

print('Test loss:', score[0])

print('Test accuracy:', score[1])

W0825 09:29:33.614658 7884 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0825 09:29:33.735855 7884 deprecation.py:323] From C:\Users\patha\Anaconda3\lib\site-packages\tensorflow\python\ops\math\_grad.py:1250: add\_dispatch\_support.<locals>.wrapper (from tensorflow.python.ops.array\_ops) is deprecated and will be removed in a future version. Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

Train on 60000 samples, validate on 10000 samples
Epoch 1/12

Epoch 2/12

C0000 / C0000

60000/60000 [=============== ] - 194s 3ms/step - loss: 0.3607 - acc: 0.8943 - val\_lo

ss: 0.0904 - val\_acc: 0.9747

Epoch 3/12

60000/60000 [==============] - 194s 3ms/step - loss: 0.2461 - acc: 0.9276 - val\_lo

ss: 0.0845 - val acc: 0.9749

Epoch 4/12

60000/60000 [============== ] - 194s 3ms/step - loss: 0.1996 - acc: 0.9405 - val\_lo

ss: 0.0482 - val\_acc: 0.9837

Fnoch 5/19

```
בויסורוו מויסולוו
60000/60000 [=============] - 193s 3ms/step - loss: 0.1708 - acc: 0.9495 - val lo
ss: 0.0409 - val_acc: 0.9873
Epoch 6/12
60000/60000 [============= ] - 193s 3ms/step - loss: 0.1627 - acc: 0.9523 - val lo
ss: 0.0414 - val_acc: 0.9865
Epoch 7/12
60000/60000 [============== ] - 193s 3ms/step - loss: 0.1478 - acc: 0.9576 - val lo
ss: 0.0363 - val acc: 0.9890
Epoch 8/12
60000/60000 [============= ] - 193s 3ms/step - loss: 0.1380 - acc: 0.9597 - val lo
ss: 0.0351 - val acc: 0.9878
Epoch 9/12
60000/60000 [============== ] - 192s 3ms/step - loss: 0.1306 - acc: 0.9621 - val lo
ss: 0.0303 - val acc: 0.9898
Epoch 10/12
60000/60000 [============== ] - 193s 3ms/step - loss: 0.1303 - acc: 0.9632 - val lo
ss: 0.0296 - val acc: 0.9904
Epoch 11/12
60000/60000 [============ ] - 193s 3ms/step - loss: 0.1202 - acc: 0.9652 - val lo
ss: 0.0354 - val acc: 0.9885
Epoch 12/12
60000/60000 [============= ] - 193s 3ms/step - loss: 0.1161 - acc: 0.9663 - val lo
ss: 0.0280 - val acc: 0.9912
Test loss: 0.027954894275800325
Test accuracy: 0.9912
```

# **Weights Distribution in Each CNN Layers**

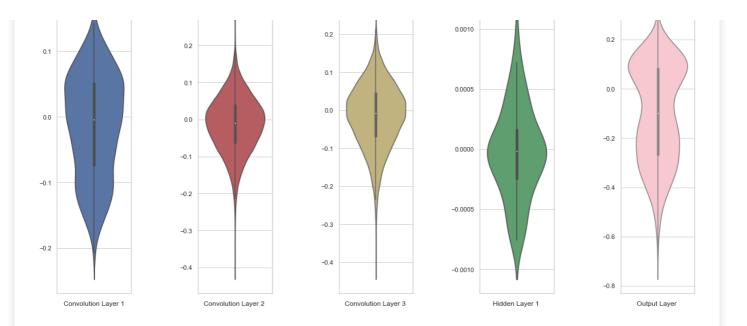
In [139]:

```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_1.get_weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
h1 w = w after[19].flatten().reshape(-1,1)
out_2 = w_after[24].flatten().reshape(-1,1)
sns.set(style='whitegrid',palette='RdBu')
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(1, 5, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(1, 5, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(1, 5, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='g')
plt.xlabel('Hidden Layer 1 ')
plt.subplot(1, 5, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='pink')
plt.xlabel('Output Layer ')
plt.show()
```

.

0.3

0.4



# Model 1 with sigmoid activation layer

```
In [6]:
```

```
model 1 = Sequential()
model 1.add(Conv2D(96,kernel size=(3,3),padding='same',input shape=input shape,kernel initializer =
'glorot uniform'))
model 1.add(BatchNormalization())
model_1.add(Activation('sigmoid'))
model_1.add(MaxPooling2D(pool_size=(2,2)))
model 1.add(Dropout(0.2))
model_1.add(Conv2D(64,kernel_size = (3,3),padding='same',kernel_initializer = 'glorot_uniform'))
model 1.add(BatchNormalization())
model 1.add(Activation('sigmoid'))
model_1.add(MaxPooling2D(pool_size =(2,2)))
model 1.add(Dropout(0.2))
model 1.add(Conv2D(32,kernel size=(3,3),padding='same',kernel initializer = 'glorot uniform'))
model 1.add(BatchNormalization())
model 1.add(Activation('sigmoid'))
model_1.add(MaxPooling2D(pool_size=(2,2),padding='same'))
model 1.add(Dropout(0.2))
model 1.add(Flatten())
model 1.add(Dense(64,kernel initializer = 'glorot uniform'))
model 1.add(BatchNormalization())
model_1.add(Activation('sigmoid'))
model_1.add(Dropout(0.2))
model 1.add(Dense(out dim,activation = 'softmax'))
model 1.summary()
```

WARNING: Logging before flag parsing goes to stderr.

W0826 10:56:00.857348 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:74: The name tf.get\_default\_graph is deprecated. Please use tf.compat.v1.get\_default\_graph instead.

W0826 10:56:00.933397 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:517: The name tf.placeholder is deprecated. Please use t f.compat.v1.placeholder instead.

W0826 10:56:00.938510 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:4138: The name tf.random\_uniform is deprecated. Please u se tf.random.uniform instead.

W0826 10:56:00.963576 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:174: The name tf.get\_default\_session is deprecated. Plea se use tf.compat.v1.get\_default\_session instead.

W0826 10:56:00.964574 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:181: The name tf.ConfigProto is deprecated. Please use t f.compat.v1.ConfigProto instead.

W0826 10:56:01.022996 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow backend.pv:1834: The name tf.nn.fused batch norm is deprecated. Ple

ase use tf.compat.v1.nn.fused\_batch\_norm instead.

W0826 10:56:01.073306 23336 deprecation\_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac kages\keras\backend\tensorflow\_backend.py:3976: The name tf.nn.max\_pool is deprecated. Please use tf.nn.max\_pool2d instead.

W0826 10:56:01.082176 23336 deprecation.py:506] From C:\Users\patha\Anaconda3\lib\site-packages\keras\backend\tensorflow\_backend.py:3445: calling dropout (from tensorflow.python.ops.nn\_ops) with keep\_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`.

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)	(None,	28, 28, 96)	960
batch_normalization_1 (Batch	(None,	28, 28, 96)	384
activation_1 (Activation)	(None,	28, 28, 96)	0
max_pooling2d_1 (MaxPooling2	(None,	14, 14, 96)	0
dropout_1 (Dropout)	(None,	14, 14, 96)	0
conv2d_2 (Conv2D)	(None,	14, 14, 64)	55360
batch_normalization_2 (Batch	(None,	14, 14, 64)	256
activation_2 (Activation)	(None,	14, 14, 64)	0
max_pooling2d_2 (MaxPooling2	(None,	7, 7, 64)	0
dropout_2 (Dropout)	(None,	7, 7, 64)	0
conv2d_3 (Conv2D)	(None,	7, 7, 32)	18464
<pre>batch_normalization_3 (Batch</pre>	(None,	7, 7, 32)	128
activation_3 (Activation)	(None,	7, 7, 32)	0
max_pooling2d_3 (MaxPooling2	(None,	4, 4, 32)	0
dropout_3 (Dropout)	(None,	4, 4, 32)	0
flatten_1 (Flatten)	(None,	512)	0
dense_1 (Dense)	(None,	64)	32832
batch_normalization_4 (Batch	(None,	64)	256
activation_4 (Activation)	(None,	64)	0
dropout_4 (Dropout)	(None,	64)	0
dense_2 (Dense)	(None,	10)	650
Total params: 109,290 Trainable params: 108,778			

# In [10]:

Non-trainable params: 512

TT000C 11 10 07 C004C0 0000C 1

```
from keras.optimizers import SGD
sgd = SGD(lr = 0.01, decay=1e-4, momentum=0.90, nesterov = True)
model_1.compile(loss = 'categorical_crossentropy', optimizer = sgd, metrics = ['accuracy'])
model_1.fit(X_train,y_train,batch_size=batch_size,epochs=nb_epochs,validation_data=(X_test,y_test))
score = model_1.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
WU826 11:12:27.698462 23336 deprecation_wrapper.py:119] From C:\Users\patha\Anaconda3\lib\site-pac
kages\keras\optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use
tf.compat.v1.train.Optimizer instead.

W0826 11:12:27.843074 23336 deprecation.py:323] From C:\Users\patha\Anaconda3\lib\site-
packages\tensorflow\python\ops\math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=============== ] - 198s 3ms/step - loss: 1.9369 - acc: 0.3211 - val lo
ss: 1.0569 - val_acc: 0.6987
Epoch 2/12
60000/60000 [=============== ] - 201s 3ms/step - loss: 1.0784 - acc: 0.6615 - val lo
ss: 0.5644 - val_acc: 0.8662
Epoch 3/12
60000/60000 [==============] - 199s 3ms/step - loss: 0.7056 - acc: 0.7842 - val lo
ss: 0.3160 - val acc: 0.9232
Epoch 4/12
ss: 0.2223 - val acc: 0.9425
Epoch 5/12
60000/60000 [============== ] - 190s 3ms/step - loss: 0.4094 - acc: 0.8761 - val lo
ss: 0.1802 - val acc: 0.9486
Epoch 6/12
60000/60000 [============== ] - 190s 3ms/step - loss: 0.3518 - acc: 0.8939 - val lo
ss: 0.1564 - val acc: 0.9541
Epoch 7/12
60000/60000 [============= ] - 190s 3ms/step - loss: 0.3144 - acc: 0.9030 - val lo
ss: 0.1376 - val_acc: 0.9573
Epoch 8/12
60000/60000 [==============] - 184s 3ms/step - loss: 0.2876 - acc: 0.9119 - val lo
ss: 0.1248 - val acc: 0.9601
Epoch 9/12
60000/60000 [============== ] - 184s 3ms/step - loss: 0.2658 - acc: 0.9168 - val lo
ss: 0.1098 - val acc: 0.9653
Epoch 10/12
60000/60000 [============== ] - 183s 3ms/step - loss: 0.2490 - acc: 0.9238 - val lo
ss: 0.1022 - val acc: 0.9679
Epoch 11/12
60000/60000 [============= ] - 183s 3ms/step - loss: 0.2311 - acc: 0.9284 - val lo
ss: 0.1022 - val_acc: 0.9669
Epoch 12/12
60000/60000 [============= ] - 183s 3ms/step - loss: 0.2223 - acc: 0.9312 - val lo
ss: 0.0988 - val acc: 0.9687
Test loss: 0.09881273467317224
Test accuracy: 0.9687
```

### In [14]:

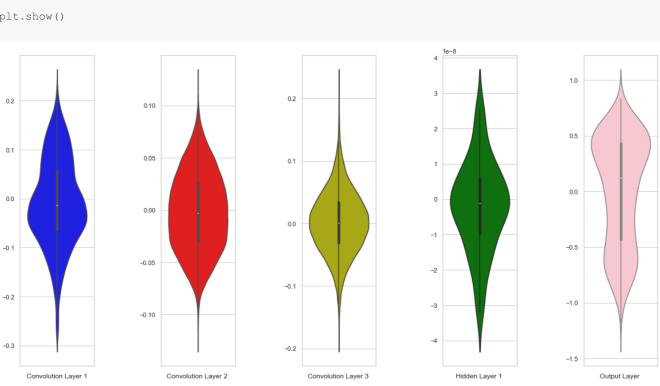
```
import matplotlib.pyplot as plt
import seaborn as sns
w after = model 1.get weights()
C1_w = w_after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
h1_w = w_after[19].flatten().reshape(-1,1)
out w = w after[24].flatten().reshape(-1,1)
sns.set(style='whitegrid',palette='RdBu')
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(1, 5, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2_w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(1, 5, 3)
#nlt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)

plt.subplot(1, 5, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='g')
plt.xlabel('Hidden Layer 1 ')

plt.subplot(1, 5, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='pink')
plt.xlabel('Output Layer ')

plt.show()
```



# Model 2 with 5 CNN layers

### In [88]:

```
model 2 = Sequential()
model 2.add(Conv2D(16, kernel size=(3,3), padding='same', input shape=input shape, kernel initializer='
he normal'))
model 2.add(BatchNormalization())
model 2.add(Activation('relu'))
model_2.add(MaxPooling2D(pool_size=(2,2)))
model_2.add(Dropout(0.5))
model 2.add(Conv2D(32,kernel size = (3,3),padding='valid',kernel initializer='he normal'))
model 2.add(BatchNormalization())
model 2.add(Activation('relu'))
#model_2.add(MaxPooling2D(pool_size =(2,2)))
model_2.add(Dropout(0.5))
model_2.add(Conv2D(32,kernel_size=(3,3),padding='same',kernel initializer='he normal'))
model 2.add(BatchNormalization())
model 2.add(Activation('relu'))
model 2.add(MaxPooling2D(pool size=(2,2)))
model 2.add(Dropout(0.5))
model_2.add(Conv2D(64,kernel_size = (3,3),padding = 'valid',kernel initializer='he normal'))
model 2.add(BatchNormalization())
model 2.add(Activation('relu'))
#model 2.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_2.add(Dropout(0.5))
model_2.add(Conv2D(96,kernel_size = (3,3),padding = 'same',kernel_initializer='he_normal'))
model 2.add(BatchNormalization())
model 2.add(Activation('relu'))
model 2.add(MaxPooling2D(pool_size=(2,2)))
model 2.add(Dropout(0.5))
model 2.add(Flatten())
```

```
model_2.add(Dense(64,kernel_initializer='he_normal'))
model_2.add(BatchNormalization())
model_2.add(Activation('relu'))
model_2.add(Dropout(0.5))
model_2.add(Dense(out_dim,activation = 'softmax'))
model_2.summary()
```

Layer (type) ====================================	Output	Shape	Param #
conv2d_14 (Conv2D)	(None,	28, 28, 16)	160
batch_normalization_17 (Batc	(None,	28, 28, 16)	64
activation_17 (Activation)	(None,	28, 28, 16)	0
max_pooling2d_10 (MaxPooling	(None,	14, 14, 16)	0
dropout_17 (Dropout)	(None,	14, 14, 16)	0
conv2d_15 (Conv2D)	(None,	12, 12, 32)	4640
batch_normalization_18 (Batc	(None,	12, 12, 32)	128
activation_18 (Activation)	(None,	12, 12, 32)	0
dropout_18 (Dropout)	(None,	12, 12, 32)	0
conv2d_16 (Conv2D)	(None,	12, 12, 32)	9248
batch_normalization_19 (Batc	(None,	12, 12, 32)	128
activation_19 (Activation)	(None,	12, 12, 32)	0
max_pooling2d_11 (MaxPooling	(None,	6, 6, 32)	0
dropout_19 (Dropout)	(None,	6, 6, 32)	0
conv2d_17 (Conv2D)	(None,	4, 4, 64)	18496
batch_normalization_20 (Batc	(None,	4, 4, 64)	256
activation_20 (Activation)	(None,	4, 4, 64)	0
dropout_20 (Dropout)	(None,	4, 4, 64)	0
conv2d_18 (Conv2D)	(None,	4, 4, 96)	55392
batch_normalization_21 (Batc	(None,	4, 4, 96)	384
activation_21 (Activation)	(None,	4, 4, 96)	0
max_pooling2d_12 (MaxPooling	(None,	2, 2, 96)	0
dropout_21 (Dropout)	(None,	2, 2, 96)	0
flatten_4 (Flatten)	(None,	384)	0
dense_7 (Dense)	(None,	64)	24640
batch_normalization_22 (Batc	(None,	64)	256
activation_22 (Activation)	(None,	64)	0
dropout_22 (Dropout)	(None,	64)	0
dense_8 (Dense)	(None,	10)	650

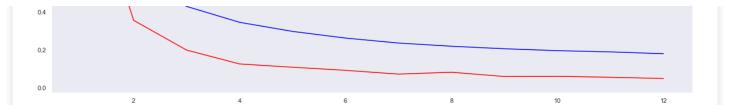
Total params: 114,442 Trainable params: 113,834 Non-trainable params: 608

```
model 2.compile(loss = 'categorical crossentropy',optimizer = 'adadelta',metrics = ['accuracy'])
result = model_2.fit(X_train,y_train,batch_size=batch_size,epochs=12,validation data=(X test,y test
))
score = model_2.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
60000/60000 [============== ] - 75s 1ms/step - loss: 1.5499 - acc: 0.4738 - val los
s: 1.2353 - val acc: 0.5987
Epoch 2/12
s: 0.3567 - val acc: 0.8862
Epoch 3/12
s: 0.1993 - val acc: 0.9344
Epoch 4/12
60000/60000 [============ ] - 61s 1ms/step - loss: 0.3463 - acc: 0.8972 - val los
s: 0.1258 - val acc: 0.9598
Epoch 5/12
60000/60000 [============= ] - 62s 1ms/step - loss: 0.2982 - acc: 0.9125 - val los
s: 0.1085 - val acc: 0.9668
Epoch 6/12
60000/60000 [============== ] - 64s 1ms/step - loss: 0.2629 - acc: 0.9234 - val los
s: 0.0921 - val acc: 0.9711
Epoch 7/12
60000/60000 [============= ] - 65s 1ms/step - loss: 0.2366 - acc: 0.9315 - val los
s: 0.0720 - val acc: 0.9775
Epoch 8/12
60000/60000 [============= ] - 65s 1ms/step - loss: 0.2197 - acc: 0.9369 - val los
s: 0.0820 - val_acc: 0.9744
Epoch 9/12
60000/60000 [============= ] - 63s 1ms/step - loss: 0.2064 - acc: 0.9400 - val los
s: 0.0594 - val_acc: 0.9817
Epoch 10/12
s: 0.0602 - val_acc: 0.9818
Epoch 11/12
60000/60000 [============== ] - 63s 1ms/step - loss: 0.1897 - acc: 0.9455 - val los
s: 0.0554 - val acc: 0.9832
Epoch 12/12
60000/60000 [============== ] - 63s 1ms/step - loss: 0.1800 - acc: 0.9494 - val los
s: 0.0488 - val acc: 0.9843
Test loss: 0.04878361739309039
Test accuracy: 0.9843
```

# In [98]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red')
sns.lineplot(x = epochs,y = val_loss,color = 'blue')
plt.grid()
```

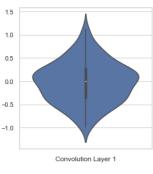


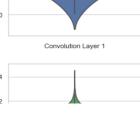


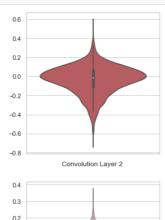
# Weights Distribution in Each CNN Layers

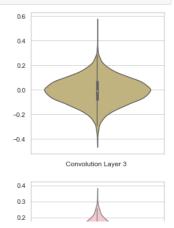
```
In [140]:
```

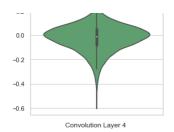
```
import matplotlib.pyplot as plt
import seaborn as sns
w after = model 2.get weights()
C1 w = w \text{ after}[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3_w = w_after[12].flatten().reshape(-1,1)
C4 w = w after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
h1_w = w_after[30].flatten().reshape(-1,1)
out w = w after[36].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 3, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 3, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(2, 3, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 3, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5 w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 3, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='pink')
plt.xlabel('Hidden Layer ')
plt.show()
```

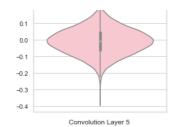


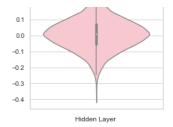












### In [16]:

```
model 2 = Sequential()
model 2.add(Conv2D(16,kernel size=(3,3),padding='same',input shape=input shape,kernel initializer='
glorot uniform'))
model 2.add(BatchNormalization())
model 2.add(Activation('sigmoid'))
model_2.add(MaxPooling2D(pool_size=(2,2)))
model_2.add(Dropout(0.5))
model_2.add(Conv2D(32,kernel_size = (3,3),padding='valid',kernel_initializer='glorot_uniform'))
model 2.add(BatchNormalization())
model_2.add(Activation('sigmoid'))
#model_2.add(MaxPooling2D(pool_size =(2,2)))
model 2.add(Dropout(0.5))
model_2.add(Conv2D(32,kernel_size=(3,3),padding='same',kernel_initializer='glorot uniform'))
model 2.add(BatchNormalization())
model 2.add(Activation('sigmoid'))
model_2.add(MaxPooling2D(pool_size=(2,2)))
model_2.add(Dropout(0.5))
model 2.add(Conv2D(64,kernel size = (3,3),padding = 'valid',kernel initializer='glorot uniform'))
model 2.add(BatchNormalization())
model 2.add(Activation('sigmoid'))
#model 2.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_2.add(Dropout(0.5))
model 2.add(Conv2D(64,kernel size = (3,3),padding = 'same',kernel initializer='glorot uniform'))
model 2.add(BatchNormalization())
model 2.add(Activation('sigmoid'))
model 2.add(MaxPooling2D(pool size=(2,2)))
model_2.add(Dropout(0.5))
model_2.add(Flatten())
model 2.add(Dense(24,kernel initializer='glorot uniform'))
model 2.add(BatchNormalization())
model 2.add(Activation('sigmoid'))
model 2.add(Dropout(0.5))
model_2.add(Dense(out_dim,activation = 'softmax'))
model 2.summary()
```

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 28, 28, 16)	160
batch_normalization_11 (Batc	(None, 28, 28, 16)	64
activation_11 (Activation)	(None, 28, 28, 16)	0
max_pooling2d_7 (MaxPooling2	(None, 14, 14, 16)	0
dropout_11 (Dropout)	(None, 14, 14, 16)	0
conv2d_10 (Conv2D)	(None, 12, 12, 32)	4640
batch_normalization_12 (Batc	(None, 12, 12, 32)	128
activation_12 (Activation)	(None, 12, 12, 32)	0
dropout_12 (Dropout)	(None, 12, 12, 32)	0
conv2d_11 (Conv2D)	(None, 12, 12, 32)	9248
batch_normalization_13 (Batc	(None, 12, 12, 32)	128
activation_13 (Activation)	(None, 12, 12, 32)	0
max_pooling2d_8 (MaxPooling2	(None, 6, 6, 32)	0

dropout_13 (Dropout)	(None,	6, 6,	32)	0
conv2d_12 (Conv2D)	(None,	4, 4,	64)	18496
batch_normalization_14 (Batc	(None,	4, 4,	64)	256
activation_14 (Activation)	(None,	4, 4,	64)	0
dropout_14 (Dropout)	(None,	4, 4,	64)	0
conv2d_13 (Conv2D)	(None,	4, 4,	64)	36928
batch_normalization_15 (Batc	(None,	4, 4,	64)	256
activation_15 (Activation)	(None,	4, 4,	64)	0
max_pooling2d_9 (MaxPooling2	(None,	2, 2,	64)	0
dropout_15 (Dropout)	(None,	2, 2,	64)	0
flatten_3 (Flatten)	(None,	256)		0
dense_5 (Dense)	(None,	24)		6168
batch_normalization_16 (Batc	(None,	24)		96
activation_16 (Activation)	(None,	24)		0
dropout_16 (Dropout)	(None,	24)		0
dense 6 (Dense)	(None,	10)		250

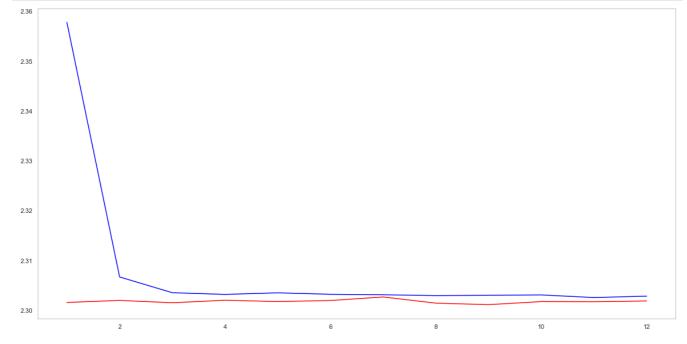
Total params: 76,818 Trainable params: 76,354 Non-trainable params: 464

### In [17]:

```
from keras.optimizers import SGD
sgd = SGD(lr = 0.01,decay=1e-4,momentum=0.90,nesterov = True)
model 2.compile(loss = 'categorical crossentropy',optimizer = sgd,metrics = ['accuracy'])
result = model 2.fit(X train,y train,batch size=batch size,epochs=nb epochs,validation data=(X test
,y_test))
score = model 2.evaluate(X test, y test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
s: 2.3015 - val acc: 0.1135
Epoch 2/12
60000/60000 [=============] - 56s 927us/step - loss: 2.3067 - acc: 0.1050 - val 1
oss: 2.3020 - val acc: 0.1135
Epoch 3/12
60000/60000 [============== ] - 60s 999us/step - loss: 2.3035 - acc: 0.1071 - val 1
oss: 2.3015 - val acc: 0.1135
Epoch 4/12
60000/60000 [============== ] - 59s 986us/step - loss: 2.3032 - acc: 0.1090 - val 1
oss: 2.3020 - val_acc: 0.1135
Epoch 5/12
60000/60000 [============== ] - 58s 974us/step - loss: 2.3035 - acc: 0.1073 - val 1
oss: 2.3017 - val_acc: 0.1135
Epoch 6/12
s: 2.3019 - val_acc: 0.1135
Epoch 7/12
60000/60000 [============= ] - 64s lms/step - loss: 2.3031 - acc: 0.1098 - val_los
s: 2.3027 - val acc: 0.1135
Epoch 8/12
60000/60000 [============== ] - 62s 1ms/step - loss: 2.3029 - acc: 0.1083 - val_los
s: 2.3014 - val_acc: 0.1135
Epoch 9/12
60000/60000 [==============] - 58s 966us/step - loss: 2.3030 - acc: 0.1100 - val 1
```

### In [18]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red')
sns.lineplot(x = epochs,y = val_loss,color = 'blue')
plt.grid()
```

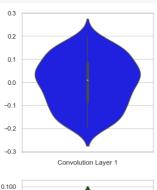


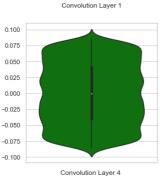
# **Weights Distribution in Each CNN Layers**

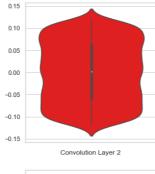
### In [19]:

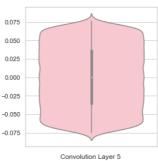
```
import matplotlib.pyplot as plt
import seaborn as sns
w after = model 2.get weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
C4 w = w after[18].flatten().reshape(-1,1)
C5 w = w after[24].flatten().reshape(-1,1)
h1_w = w_after[30].flatten().reshape(-1,1)
out w = w after[36].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 3, 2)
```

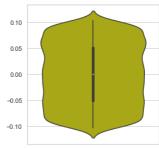
```
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 3, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust(wspace=0.9)
plt.subplot(2, 3, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4_w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 3, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5_w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 3, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='pink')
plt.xlabel('Hidden Layer ')
plt.show()
 0.3
```

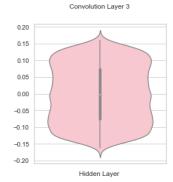












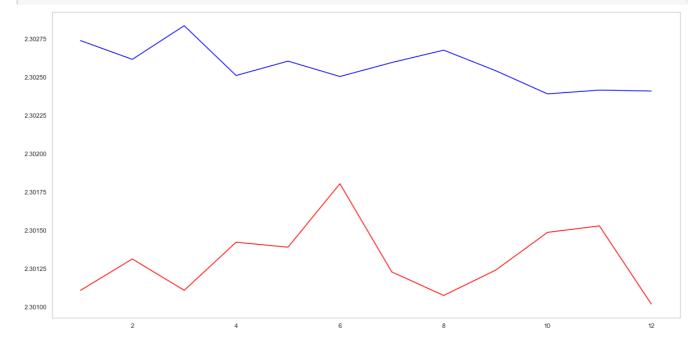
In [21]:

```
#from keras.optimizers import SGD
#sgd = SGD(lr = 0.01,decay=1e-4,momentum=0.90,nesterov = True)
model_2.compile(loss = 'categorical_crossentropy',optimizer = 'adadelta',metrics = ['accuracy'])
result = model_2.fit(X_train,y_train,batch_size=batch_size,epochs=nb_epochs,validation_data=(X_test,y_test))
score = model_2.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
oss: 2.3014 - val acc: 0.1135
Epoch 5/12
60000/60000 [============== ] - 59s 985us/step - loss: 2.3026 - acc: 0.1087 - val 1
oss: 2.3014 - val acc: 0.1135
Epoch 6/12
60000/60000 [=============] - 59s 991us/step - loss: 2.3025 - acc: 0.1087 - val 1
oss: 2.3018 - val acc: 0.1135
Epoch 7/12
60000/60000 [============== ] - 60s 996us/step - loss: 2.3026 - acc: 0.1104 - val 1
oss: 2.3012 - val_acc: 0.1135
Epoch 8/12
60000/60000 [============== ] - 59s 990us/step - loss: 2.3027 - acc: 0.1086 - val 1
oss: 2.3011 - val_acc: 0.1135
Epoch 9/12
oss: 2.3012 - val acc: 0.1135
Epoch 10/12
60000/60000 [=============] - 59s 991us/step - loss: 2.3024 - acc: 0.1094 - val 1
oss: 2.3015 - val acc: 0.1135
Epoch 11/12
s: 2.3015 - val_acc: 0.1028
Epoch 12/12
60000/60000 [=============] - 81s 1ms/step - loss: 2.3024 - acc: 0.1091 - val los
s: 2.3010 - val acc: 0.1135
Test loss: 2.3010182960510255
Test accuracy: 0.1135
```

### In [22]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red')
sns.lineplot(x = epochs,y = val_loss,color = 'blue')
plt.grid()
```



# **Weights Distribution In Each CNN Layers**

```
In [25]:
```

```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_2.get_weights()

C1_w = w_after[0].flatten().reshape(-1,1)
C2_w = w_after[6] flatten().reshape(-1,1)
```

```
w - w arcer[o].rraccen().resmape( r,r)
C3w = w_after[12].flatten().reshape(-1,1)
C4 w = w after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
h1_w = w_after[30].flatten().reshape(-1,1)
out w = w after[36].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 3, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 3, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust (wspace=0.9)
plt.subplot(2, 3, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 3, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5_w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 3, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='g')
plt.xlabel('Hidden Layer ')
plt.show()
 0.3
                                                                                     0.10
                                           0.10
                                                                                     0.05
 0.1
                                           0.05
 0.0
                                           0.00
                                                                                     0.00
 -0.1
                                                                                     -0.05
                                          -0.10
 -0.2
                                          -0.15
          Convolution Layer 1
                                                    Convolution Layer 2
                                                                                              Convolution Layer 3
                                          0.100
 0.10
                                                                                     0.2
                                          0.075
                                                                                     0.1
 0.00
                                          0.000
                                          -0.025
                                                                                     -0.1
-0.05
                                          -0.050
                                          -0.075
                                                                                     -0.2
-0.10
```

# Model 3 with 7 CNN layers

Convolution Laver 4

```
In [122]:
```

```
model_3 = Sequential()
model_3.add(Conv2D(16,kernel_size=(3,3),padding='valid',input_shape=input_shape,kernel_initializer=
'he_normal'))
model_3.add(BatchNormalization())
model_3.add(BatchNormalization())
```

Convolution Laver 5

Hidden Laver

```
model 3.add(Activation('relu'))
#model_3.add(MaxPooling2D(pool_size=(2,2),padding = 'same'))
model 3.add(Dropout(0.5))
model_3.add(Conv2D(16,kernel_size = (3,3),padding='valid',kernel_initializer='he_normal'))
model 3.add(BatchNormalization())
model_3.add(Activation('relu'))
model_3.add(MaxPooling2D(pool_size =(2,2)))
model_3.add(Dropout(0.5))
model 3.add(Conv2D(32,kernel size=(3,3),padding='same',kernel initializer='he normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('relu'))
#model 3.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_3.add(Dropout(0.5))
model_3.add(Conv2D(32,kernel_size = (3,3),padding = 'valid',kernel_initializer='he_normal'))
model_3.add(BatchNormalization())
model 3.add(Activation('relu'))
#model 3.add(MaxPooling2D(pool size=(2,2)))
model_3.add(Dropout(0.5))
model_3.add(Conv2D(32,kernel_size = (3,3),padding = 'valid',kernel_initializer='he normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('relu'))
model 3.add(MaxPooling2D(pool size=(2,2)))
model_3.add(Dropout(0.5))
model_3.add(Conv2D(64,kernel_size = (3,3),padding = 'same',kernel_initializer='he normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('relu'))
#model 3.add(MaxPooling2D(pool size=(2,2),padding='same'))
model 3.add(Dropout(0.5))
model_3.add(Conv2D(64,kernel_size = (3,3),padding = 'same',kernel_initializer='he_normal'))
{\tt model\_3.add(BatchNormalization())}
model 3.add(Activation('relu'))
model 3.add(MaxPooling2D(pool size=(2,2)))
model 3.add(Dropout(0.5))
model_3.add(Flatten())
model_3.add(Dense(128,kernel_initializer='he_normal'))
model_3.add(BatchNormalization())
model 3.add(Activation('relu'))
model 3.add(Dropout(0.5))
model_3.add(Dense(out_dim,activation = 'softmax'))
model 3.summary()
```

Layer (type)	Output	Shar	pe		Param #
conv2d_26 (Conv2D)	(None,	26 <b>,</b>	26 <b>,</b>	16)	160
batch_normalization_31 (Batc	(None,	26,	26,	16)	64
activation_31 (Activation)	(None,	26,	26,	16)	0
dropout_31 (Dropout)	(None,	26,	26,	16)	0
conv2d_27 (Conv2D)	(None,	24,	24,	16)	2320
batch_normalization_32 (Batc	(None,	24,	24,	16)	64
activation_32 (Activation)	(None,	24,	24,	16)	0
max_pooling2d_16 (MaxPooling	(None,	12,	12,	16)	0
dropout_32 (Dropout)	(None,	12,	12,	16)	0
conv2d_28 (Conv2D)	(None,	12,	12,	32)	4640
batch_normalization_33 (Batc	(None,	12,	12,	32)	128
activation_33 (Activation)	(None,	12,	12,	32)	0
dropout_33 (Dropout)	(None,	12,	12,	32)	0
conv2d_29 (Conv2D)	(None,	10,	10,	32)	9248
batch_normalization_34 (Batc	(None,	10,	10,	32)	128
activation_34 (Activation)	(None,	10,	10,	32)	0
dropout 34 (Dropout)	(None.	10.	10.	32)	0

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conv2d_30 (Conv2D)	(None,	8, 8, 32)	9248
batch_normalization_35 (Batc	(None,	8, 8, 32)	128
activation_35 (Activation)	(None,	8, 8, 32)	0
<pre>max_pooling2d_17 (MaxPooling</pre>	(None,	4, 4, 32)	0
dropout_35 (Dropout)	(None,	4, 4, 32)	0
conv2d_31 (Conv2D)	(None,	4, 4, 64)	18496
<pre>batch_normalization_36 (Batc</pre>	(None,	4, 4, 64)	256
activation_36 (Activation)	(None,	4, 4, 64)	0
dropout_36 (Dropout)	(None,	4, 4, 64)	0
conv2d_32 (Conv2D)	(None,	4, 4, 64)	36928
batch_normalization_37 (Batc	(None,	4, 4, 64)	256
activation_37 (Activation)	(None,	4, 4, 64)	0
max_pooling2d_18 (MaxPooling	(None,	2, 2, 64)	0
dropout_37 (Dropout)	(None,	2, 2, 64)	0
flatten_6 (Flatten)	(None,	256)	0
dense_11 (Dense)	(None,	128)	32896
batch_normalization_38 (Batc	(None,	128)	512
activation_38 (Activation)	(None,	128)	0
dropout_38 (Dropout)	(None,	128)	0
dense_12 (Dense)	(None,	10)	1290
Total params: 116,762			

Total params: 116,762 Trainable params: 115,994 Non-trainable params: 768

### In [123]:

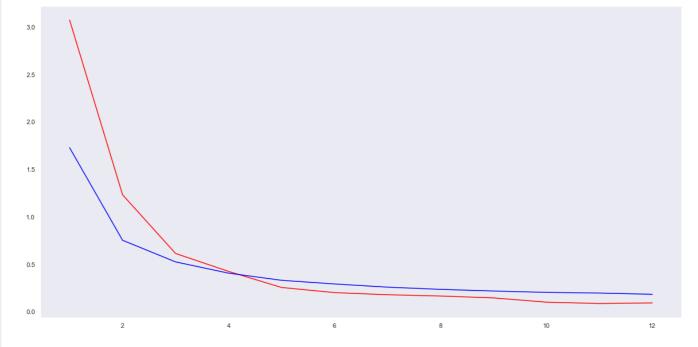
```
result = model_3.fit(X_train,y_train,batch_size=batch_size,epochs=12,validation_data=(X_test,y_test
score = model_3.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=============] - 90s 1ms/step - loss: 1.7270 - acc: 0.4045 - val los
s: 3.0717 - val acc: 0.2675
Epoch 2/12
60000/60000 [============== ] - 81s 1ms/step - loss: 0.7519 - acc: 0.7491 - val los
s: 1.2310 - val acc: 0.6194
Epoch 3/12
60000/60000 [============== ] - 81s 1ms/step - loss: 0.5242 - acc: 0.8339 - val los
s: 0.6130 - val acc: 0.8036
Epoch 4/12
60000/60000 [============== ] - 81s 1ms/step - loss: 0.4056 - acc: 0.8760 - val los
s: 0.4241 - val_acc: 0.8703
Epoch 5/12
60000/60000 [============] - 80s 1ms/step - loss: 0.3303 - acc: 0.8994 - val los
s: 0.2549 - val acc: 0.9212
Epoch 6/12
60000/60000 [============== ] - 81s 1ms/step - loss: 0.2918 - acc: 0.9119 - val los
s: 0.2007 - val_acc: 0.9392
Epoch 7/12
```

model 3.compile(loss = 'categorical crossentropy',optimizer = 'adadelta',metrics = ['accuracy'])

```
60000/60000 [=============] - 80s 1ms/step - loss: 0.2582 - acc: 0.9233 - val los
s: 0.1782 - val acc: 0.9476
Epoch 8/12
60000/60000 [=============] - 80s 1ms/step - loss: 0.2349 - acc: 0.9304 - val los
s: 0.1647 - val acc: 0.9507
Epoch 9/12
60000/60000 [=============] - 80s 1ms/step - loss: 0.2174 - acc: 0.9357 - val los
s: 0.1450 - val_acc: 0.9578
Epoch 10/12
60000/60000 [============= ] - 80s 1ms/step - loss: 0.2029 - acc: 0.9396 - val_los
s: 0.1000 - val_acc: 0.9701
Epoch 11/12
60000/60000 [============= ] - 81s 1ms/step - loss: 0.1961 - acc: 0.9430 - val los
s: 0.0859 - val_acc: 0.9736
Epoch 12/12
60000/60000 [============== ] - 80s 1ms/step - loss: 0.1828 - acc: 0.9464 - val los
s: 0.0920 - val acc: 0.9734
Test loss: 0.0920174268199131
Test accuracy: 0.9734
```

#### In [130]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red')
sns.lineplot(x = epochs,y = val_loss,color = 'blue')
plt.grid()
```



# Weights Distribution in Each CNN Layers

# In [141]:

```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_3.get_weights()

C1_w = w_after[0].flatten().reshape(-1,1)
C2_w = w_after[6].flatten().reshape(-1,1)
C3_w = w_after[12].flatten().reshape(-1,1)
C4_w = w_after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
C6_w = w_after[30].flatten().reshape(-1,1)
C7_w = w_after[36].flatten().reshape(-1,1)
h1_w = w_after[42].flatten().reshape(-1,1)
```

```
out w = w after[48].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 4, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1_w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 4, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 4, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust(wspace=0.9)
plt.subplot(2, 4, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 4, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5 w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 4, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C6_w, color='b')
plt.xlabel('Convolution Layer 6 ')
plt.subplot(2, 4, 7)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C7 w, color='g')
plt.xlabel('Convolution Layer 7 ')
plt.subplot(2, 4, 8)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='y')
plt.xlabel('Hidden Layer ')
plt.show()
                                                                                            0.4
 1.5
                                                              0.4
 1.0
                                                                                            0.2
                               0.4
                                                              0.2
 0.5
                               0.2
                                                                                            0.0
                                                              0.0
 0.0
                               0.0
                                                                                            -0.2
                               -0.2
                                                              -0.4
 -1.0
                               -0.4
                                                                                            -0.4
                                                              -0.6
 -1.5
      Convolution Layer 1
                                                                   Convolution Layer 3
                                                                                                 Convolution Layer 4
                                                                                            0.4
                                                              0.3
                                                              0.2
                               0.2
                                                                                            0.2
 0.2
                                                              0.1
                                                                                            0.0
 0.0
                                                              0.0
                               -0.2
                                                             -0.1
                                                                                            -0.2
                                                             -0.2
                                                              -0.3
```

Model 3 with 7 CNN layers and with sigmoid as an activation function.

Convolution Layer 6

Hidden Layer

Convolution Layer 7

Convolution Layer 5

```
model 3 = Sequential()
model 3.add(Conv2D(16,kernel size=(3,3),padding='valid',input shape=input shape,kernel initializer=
'glorot normal'))
model 3.add(BatchNormalization())
model_3.add(Activation('sigmoid'))
#model 3.add(MaxPooling2D(pool size=(2,2),padding = 'same'))
model 3.add(Dropout(0.5))
model 3.add(Conv2D(16,kernel size = (3,3),padding='valid',kernel initializer='glorot normal'))
model 3.add(BatchNormalization())
model_3.add(Activation('sigmoid'))
model_3.add(MaxPooling2D(pool_size =(2,2)))
model 3.add(Dropout(0.5))
model_3.add(Conv2D(32,kernel_size=(3,3),padding='same',kernel_initializer='glorot_normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
#model 3.add(MaxPooling2D(pool size=(2,2),padding='same'))
model 3.add(Dropout(0.5))
model 3.add(Conv2D(32,kernel size = (3,3),padding = 'valid',kernel initializer='glorot normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
#model 3.add(MaxPooling2D(pool size=(2,2)))
model_3.add(Dropout(0.5))
     _3.add(Conv2D(32,kernel_size = (3,3),padding = 'valid',kernel_initializer='glorot_normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
model_3.add(MaxPooling2D(pool_size=(2,2)))
model_3.add(Dropout(0.5))
model 3.add(Conv2D(64,kernel size = (3,3),padding = 'same',kernel initializer='glorot normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
#model 3.add(MaxPooling2D(pool size=(2,2),padding='same'))
model 3.add(Dropout(0.5))
model_3.add(Conv2D(64,kernel_size = (3,3),padding = 'same',kernel initializer='glorot normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
model 3.add(MaxPooling2D(pool size=(2,2)))
model 3.add(Dropout(0.5))
model_3.add(Flatten())
model 3.add(Dense(128,kernel initializer='glorot normal'))
model 3.add(BatchNormalization())
model 3.add(Activation('sigmoid'))
model 3.add(Dropout(0.5))
model_3.add(Dense(out_dim,activation = 'softmax'))
model 3.summary()
```

Layer (type)	Output	Shaj	pe		Param #
conv2d_21 (Conv2D)	(None,	26 <b>,</b>	26 <b>,</b>	16)	160
batch_normalization_25 (Batc	(None,	26,	26,	16)	64
activation_25 (Activation)	(None,	26,	26,	16)	0
dropout_25 (Dropout)	(None,	26,	26,	16)	0
conv2d_22 (Conv2D)	(None,	24,	24,	16)	2320
batch_normalization_26 (Batc	(None,	24,	24,	16)	64
activation_26 (Activation)	(None,	24,	24,	16)	0
max_pooling2d_13 (MaxPooling	(None,	12,	12,	16)	0
dropout_26 (Dropout)	(None,	12,	12,	16)	0
conv2d_23 (Conv2D)	(None,	12,	12,	32)	4640
batch_normalization_27 (Batc	(None,	12,	12,	32)	128
activation_27 (Activation)	(None,	12,	12,	32)	0
dropout_27 (Dropout)	(None,	12,	12,	32)	0
conv2d_24 (Conv2D)	(None,	10,	10,	32)	9248
1 · 1 · 1 · · · · · · · · · · · · · · ·	/37	1 ^	1 ^	201	100

<pre>batcn_normalization_28 (Batc</pre>	(None, 10, 10, 32)	128
activation_28 (Activation)	(None, 10, 10, 32)	0
dropout_28 (Dropout)	(None, 10, 10, 32)	0
conv2d_25 (Conv2D)	(None, 8, 8, 32)	9248
batch_normalization_29 (Batc	(None, 8, 8, 32)	128
activation_29 (Activation)	(None, 8, 8, 32)	0
max_pooling2d_14 (MaxPooling	(None, 4, 4, 32)	0
dropout_29 (Dropout)	(None, 4, 4, 32)	0
conv2d_26 (Conv2D)	(None, 4, 4, 64)	18496
batch_normalization_30 (Batc	(None, 4, 4, 64)	256
activation_30 (Activation)	(None, 4, 4, 64)	0
dropout_30 (Dropout)	(None, 4, 4, 64)	0
conv2d_27 (Conv2D)	(None, 4, 4, 64)	36928
<pre>batch_normalization_31 (Batc</pre>	(None, 4, 4, 64)	256
activation_31 (Activation)	(None, 4, 4, 64)	0
max_pooling2d_15 (MaxPooling	(None, 2, 2, 64)	0
dropout_31 (Dropout)	(None, 2, 2, 64)	0
flatten_5 (Flatten)	(None, 256)	0
dense_9 (Dense)	(None, 128)	32896
batch_normalization_32 (Batc	(None, 128)	512
activation_32 (Activation)	(None, 128)	0
dropout_32 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 10)	1290
Total params: 116,762 Trainable params: 115,994		

Total params: 116,762 Trainable params: 115,994 Non-trainable params: 768

# In [27]:

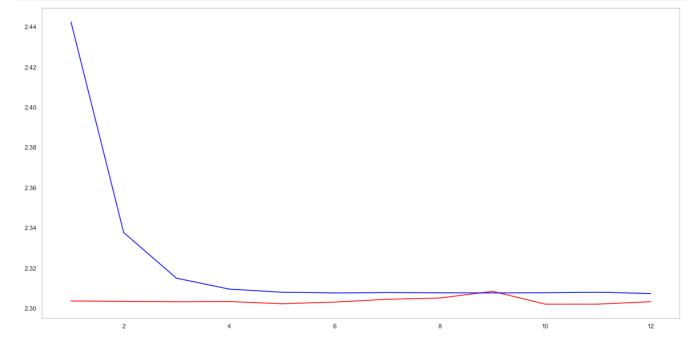
```
result = model_3.fit(X_train,y_train,batch_size=batch_size,epochs=12,validation_data=(X_test,y_test
score = model 3.evaluate(X test, y test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [============= ] - 138s 2ms/step - loss: 2.4424 - acc: 0.0999 - val lo
ss: 2.3036 - val acc: 0.1009
Epoch 2/12
ss: 2.3034 - val acc: 0.1135
Epoch 3/12
ss: 2.3031 - val acc: 0.1135
Epoch 4/12
60000/60000 [============== ] - 121s 2ms/step - loss: 2.3095 - acc: 0.1040 - val_lo
ss: 2.3033 - val_acc: 0.1028
Epoch 5/12
60000/60000 [=============] - 123s 2ms/step - loss: 2.3079 - acc: 0.1035 - val lo
ss: 2.3022 - val acc: 0.1135
```

model 3.compile(loss = 'categorical crossentropy',optimizer = 'adadelta',metrics = ['accuracy'])

```
var acc. v.rrc
Epoch 6/12
60000/60000 [=============] - 125s 2ms/step - loss: 2.3075 - acc: 0.1033 - val lo
ss: 2.3030 - val acc: 0.1135
Epoch 7/12
60000/60000 [==============] - 128s 2ms/step - loss: 2.3077 - acc: 0.1049 - val lo
ss: 2.3044 - val acc: 0.1009
Epoch 8/12
ss: 2.3050 - val_acc: 0.1009
Epoch 9/12
60000/60000 [==============] - 128s 2ms/step - loss: 2.3076 - acc: 0.1042 - val lo
ss: 2.3083 - val acc: 0.0974
Epoch 10/12
60000/60000 [=============] - 128s 2ms/step - loss: 2.3076 - acc: 0.1033 - val_lo
ss: 2.3020 - val acc: 0.1135
Epoch 11/12
60000/60000 [=============] - 133s 2ms/step - loss: 2.3079 - acc: 0.1033 - val lo
ss: 2.3020 - val_acc: 0.1135
Epoch 12/12
60000/60000 [============== ] - 134s 2ms/step - loss: 2.3073 - acc: 0.1047 - val_lo
ss: 2.3032 - val acc: 0.1135
Test loss: 2.3031921058654787
Test accuracy: 0.1135
```

### In [28]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red')
sns.lineplot(x = epochs,y = val_loss,color = 'blue')
plt.grid()
```



### In [29]:

```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_3.get_weights()

C1_w = w_after[0].flatten().reshape(-1,1)
C2_w = w_after[6].flatten().reshape(-1,1)
C3_w = w_after[12].flatten().reshape(-1,1)
C4_w = w_after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
C6_w = w_after[30].flatten().reshape(-1,1)
C7_w = w_after[36].flatten().reshape(-1,1)
h1 w = w_after[42].flatten().reshape(-1,1)
```

```
out_w = w_after[48].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 4, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 4, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2_w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 4, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust (wspace=0.9)
plt.subplot(2, 4, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 4, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5_w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 4, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C6 w, color='b')
plt.xlabel('Convolution Layer 6 ')
plt.subplot(2, 4, 7)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C7_w, color='g')
plt.xlabel('Convolution Layer 7 ')
plt.subplot(2, 4, 8)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='y')
plt.xlabel('Hidden Layer')
plt.show()
                                0.2
 0.3
                                                                                             0.10
 0.2
                                                              0.10
                                0.1
                                                                                             0.05
 0.1
                                                              0.05
                                                                                             0.00
                                                              0.00
 0.0
                                0.0
                                                              -0.05
 -0.1
                                                                                            -0.05
                                -0.1
                                                              -0.10
 -0.2
                                -0.2
                                                                                            -0.15
       Convolution Layer 1
                                     Convolution Layer 2
                                                                    Convolution Layer 3
                                                                                                   Convolution Layer 4
                                                                                             0.3
                               0.15
                                                                                             0.2
 0.10
                               0.10
 0.05
                                                                                             0.1
                                0.05
                                                              0.05
 0.00
                                                              0.00
                               0.00
                                                                                             0.0
                                                              -0.05
                               -0.05
                                                                                             -0.1
-0.10
```

-0.10

-0.15

Convolution Layer 7

-0.15

Convolution Layer 6

-0.2

Hidden Laver

In [ ]:

Convolution Layer 5

-0.15

# Models with 5 by 5 kernels or filters

# **Model with 3 CNN Layers**

```
In [145]:
```

```
model_1_5 = Sequential()
model 1 5.add(Conv2D(16,kernel size=(5,5),padding='same',input shape=input shape,kernel initializer
='he uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('relu'))
model_1_5.add(MaxPooling2D(pool_size=(2,2)))
model_1_5.add(Dropout(0.5))
model 1 5.add(Conv2D(32,kernel size = (5,5),padding='same',kernel initializer='he uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('relu'))
model 1 5.add(MaxPooling2D(pool size = (2,2)))
model_1_5.add(Dropout(0.5))
model_1_5.add(Conv2D(64,kernel_size=(5,5),padding='valid',kernel_initializer='he_uniform'))
model_1_5.add(BatchNormalization())
model 1 5.add(Activation('relu'))
model 1 5.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_1_5.add(Dropout(0.5))
model_1_5.add(Flatten())
model_1_5.add(Dense(128,kernel_initializer='he_uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('relu'))
model_1_5.add(Dropout(0.5))
model_1_5.add(Dense(out_dim,activation = 'softmax'))
model 1 5.summary()
```

Layer (type)	Output Sha	ape	Param #
conv2d_39 (Conv2D)	(None, 28		416
batch_normalization_46 (Batc	(None, 28	, 28, 16)	64
activation_46 (Activation)	(None, 28	, 28, 16)	0
max_pooling2d_24 (MaxPooling	(None, 14	, 14, 16)	0
dropout_45 (Dropout)	(None, 14	, 14, 16)	0
conv2d_40 (Conv2D)	(None, 14	, 14, 32)	12832
batch_normalization_47 (Batc	(None, 14	, 14, 32)	128
activation_47 (Activation)	(None, 14	, 14, 32)	0
max_pooling2d_25 (MaxPooling	(None, 7,	7, 32)	0
dropout_46 (Dropout)	(None, 7,	7, 32)	0
conv2d_41 (Conv2D)	(None, 3,	3, 64)	51264
batch_normalization_48 (Batc	(None, 3,	3, 64)	256
activation_48 (Activation)	(None, 3,	3, 64)	0
max_pooling2d_26 (MaxPooling	(None, 2,	2, 64)	0
dropout_47 (Dropout)	(None, 2,	2, 64)	0
flatten_8 (Flatten)	(None, 25	6)	0
dense_15 (Dense)	(None, 12	8)	32896
batch_normalization_49 (Batc	(None, 12	8)	512
activation_49 (Activation)	(None, 12	8)	0
	/NT 1 O		^

```
dense 16 (Dense)
                   (None, 10)
                                    1290
______
Total params: 99,658
Trainable params: 99,178
Non-trainable params: 480
```

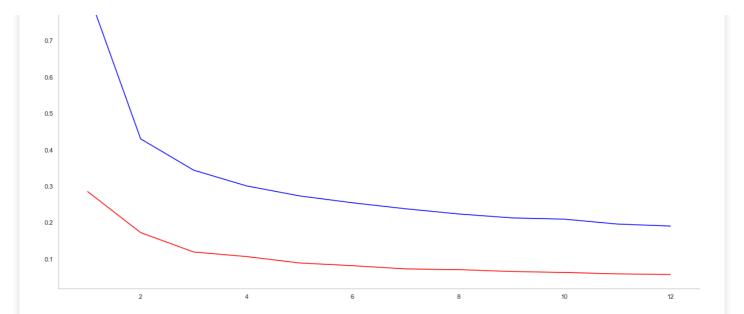
#### In [146]:

```
result = model 1 5.fit(X train,y train,batch size=batch size,epochs=12,validation data=(X test,y te
score = model 1 5.evaluate(X test, y test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=============] - 70s 1ms/step - loss: 0.8357 - acc: 0.7237 - val los
s: 0.2850 - val acc: 0.9171
Epoch 2/12
60000/60000 [============= ] - 61s 1ms/step - loss: 0.4298 - acc: 0.8667 - val los
s: 0.1724 - val acc: 0.9491
Epoch 3/12
60000/60000 [============== ] - 56s 928us/step - loss: 0.3438 - acc: 0.8944 - val 1
oss: 0.1191 - val acc: 0.9649
Epoch 4/12
60000/60000 [============== ] - 58s 970us/step - loss: 0.3005 - acc: 0.9075 - val 1
oss: 0.1065 - val acc: 0.9681
Epoch 5/12
60000/60000 [============== ] - 56s 941us/step - loss: 0.2731 - acc: 0.9168 - val 1
oss: 0.0889 - val acc: 0.9723
Epoch 6/12
60000/60000 [============== ] - 56s 930us/step - loss: 0.2542 - acc: 0.9231 - val 1
oss: 0.0815 - val_acc: 0.9746
Epoch 7/12
60000/60000 [============= ] - 55s 924us/step - loss: 0.2378 - acc: 0.9281 - val 1
oss: 0.0726 - val acc: 0.9764
Epoch 8/12
oss: 0.0707 - val_acc: 0.9781
Epoch 9/12
60000/60000 [============== ] - 56s 938us/step - loss: 0.2128 - acc: 0.9362 - val 1
oss: 0.0655 - val acc: 0.9796
Epoch 10/12
60000/60000 [============= ] - 57s 945us/step - loss: 0.2092 - acc: 0.9369 - val 1
oss: 0.0629 - val acc: 0.9809
Epoch 11/12
60000/60000 [============== ] - 55s 908us/step - loss: 0.1958 - acc: 0.9415 - val 1
oss: 0.0590 - val acc: 0.9816
Epoch 12/12
60000/60000 [============== ] - 58s 961us/step - loss: 0.1902 - acc: 0.9423 - val 1
oss: 0.0572 - val acc: 0.9827
Test loss: 0.057249614653922615
Test accuracy: 0.9827
```

model 1 5.compile(loss = 'categorical crossentropy',optimizer = 'adagrad',metrics = ['accuracy'])

### In [150]:

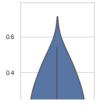
```
import numpy as np
train loss = result.history['val loss']
val loss = result.history['loss']
epochs = list(np.arange(1,nb epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
```

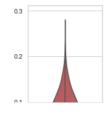


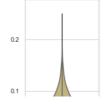
# Weights Distribution in Each CNN Layers

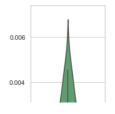
```
In [151]:
```

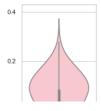
```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_1_5.get_weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2_w = w_after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
h1 w = w after[19].flatten().reshape(-1,1)
out_2 = w_after[24].flatten().reshape(-1,1)
sns.set(style='whitegrid',palette='RdBu')
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(1, 5, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2_w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(1, 5, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(1, 5, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='g')
plt.xlabel('Hidden Layer 1 ')
plt.subplot(1, 5, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='pink')
plt.xlabel('Output Layer ')
plt.show()
```

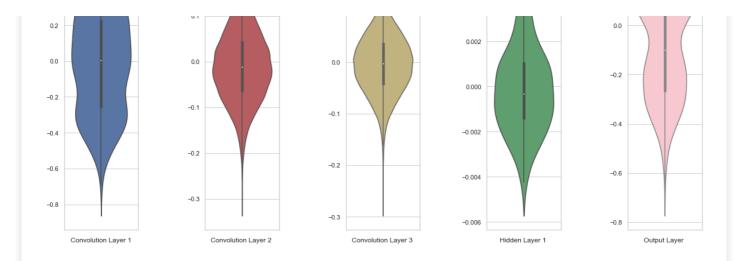












# Model 1 with 3 CNN layers and sigmoid as an activation.

### In [30]:

```
model 1 5 = Sequential()
model 1 5.add(Conv2D(16, kernel size=(5,5), padding='same', input shape=input shape, kernel initializer
='glorot uniform'))
model 1 5.add(BatchNormalization())
model_1_5.add(Activation('sigmoid'))
model_1_5.add(MaxPooling2D(pool_size=(2,2)))
model 1 5.add(Dropout(0.5))
model_1_5.add(Conv2D(32,kernel_size = (5,5),padding='same',kernel_initializer='glorot_uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('sigmoid'))
model_1_5.add(MaxPooling2D(pool_size =(2,2)))
model_1_5.add(Dropout(0.5))
     1 5.add(Conv2D(32,kernel size=(5,5),padding='valid',kernel initializer='glorot uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('sigmoid'))
model 1 5.add(MaxPooling2D(pool size=(2,2),padding='same'))
model_1_5.add(Dropout(0.5))
model 1 5.add(Flatten())
model 1_5.add(Dense(64,kernel_initializer='glorot_uniform'))
model 1 5.add(BatchNormalization())
model 1 5.add(Activation('sigmoid'))
model_1_5.add(Dropout(0.5))
model_1_5.add(Dense(out_dim,activation = 'softmax'))
model_1_5.summary()
```

Layer (type)	Output Shape	Param #
conv2d_28 (Conv2D)	(None, 28, 28, 16)	416
batch_normalization_33 (Batc	(None, 28, 28, 16)	64
activation_33 (Activation)	(None, 28, 28, 16)	0
max_pooling2d_16 (MaxPooling	(None, 14, 14, 16)	0
dropout_33 (Dropout)	(None, 14, 14, 16)	0
conv2d_29 (Conv2D)	(None, 14, 14, 32)	12832
batch_normalization_34 (Batc	(None, 14, 14, 32)	128
activation_34 (Activation)	(None, 14, 14, 32)	0
max_pooling2d_17 (MaxPooling	(None, 7, 7, 32)	0
dropout_34 (Dropout)	(None, 7, 7, 32)	0
conv2d_30 (Conv2D)	(None, 3, 3, 32)	25632
batch normalization 35 (Batc	(None, 3, 3, 32)	128

activation_35 (Activation)	(None,	3, 3, 32)	0
max_pooling2d_18 (MaxPooling	(None,	2, 2, 32)	0
dropout_35 (Dropout)	(None,	2, 2, 32)	0
flatten_6 (Flatten)	(None,	128)	0
dense_11 (Dense)	(None,	64)	8256
batch_normalization_36 (Batc	(None,	64)	256
activation_36 (Activation)	(None,	64)	0
dropout_36 (Dropout)	(None,	64)	0
dense_12 (Dense)	(None,	10)	650
Total params: 48,362			

Total params: 48,362 Trainable params: 48,074 Non-trainable params: 288

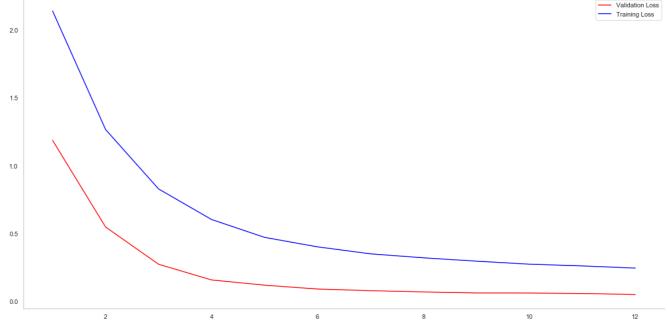
\_\_\_\_\_

### In [31]:

```
result = model 1 5.fit(X train,y train,batch size=batch size,epochs=12,validation data=(X test,y te
score = model 1 5.evaluate(X test, y test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
s: 1.1863 - val_acc: 0.7140
Epoch 2/12
60000/60000 [=============] - 84s 1ms/step - loss: 1.2663 - acc: 0.5702 - val los
s: 0.5486 - val acc: 0.9032
Epoch 3/12
60000/60000 [============= ] - 75s 1ms/step - loss: 0.8289 - acc: 0.7325 - val los
s: 0.2746 - val acc: 0.9472
Epoch 4/12
60000/60000 [=============] - 78s 1ms/step - loss: 0.6040 - acc: 0.8125 - val los
s: 0.1592 - val acc: 0.9614
Epoch 5/12
60000/60000 [==============] - 79s 1ms/step - loss: 0.4726 - acc: 0.8572 - val los
s: 0.1207 - val_acc: 0.9656
Epoch 6/12
60000/60000 [==============] - 78s 1ms/step - loss: 0.4027 - acc: 0.8809 - val los
s: 0.0923 - val_acc: 0.9724
Epoch 7/12
60000/60000 [============= ] - 75s 1ms/step - loss: 0.3512 - acc: 0.8970 - val los
s: 0.0802 - val acc: 0.9750
Epoch 8/12
60000/60000 [=============] - 75s 1ms/step - loss: 0.3219 - acc: 0.9046 - val los
s: 0.0707 - val acc: 0.9772
Epoch 9/12
60000/60000 [============= ] - 74s 1ms/step - loss: 0.2973 - acc: 0.9136 - val los
s: 0.0633 - val acc: 0.9805
Epoch 10/12
60000/60000 [============= ] - 76s lms/step - loss: 0.2751 - acc: 0.9207 - val los
s: 0.0629 - val acc: 0.9796
Epoch 11/12
60000/60000 [============== ] - 78s 1ms/step - loss: 0.2622 - acc: 0.9246 - val los
s: 0.0594 - val acc: 0.9796
Epoch 12/12
60000/60000 [============= ] - 73s 1ms/step - loss: 0.2463 - acc: 0.9276 - val los
s: 0.0519 - val_acc: 0.9835
Test loss: 0.051908576199412346
Test accuracy: 0.9835
```

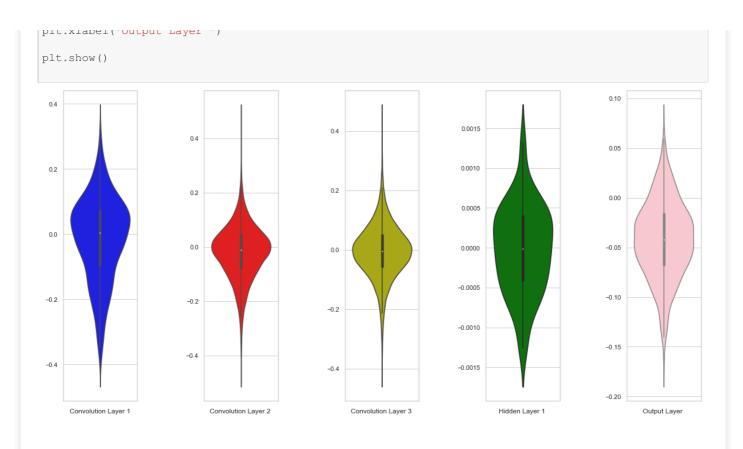
model 1 5.compile(loss = 'categorical crossentropy',optimizer = 'adam',metrics = ['accuracy'])

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
```



## In [33]:

```
import matplotlib.pyplot as plt
import seaborn as sns
w after = model 1 5.get weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2_w = w_after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
h1_w = w_after[19].flatten().reshape(-1,1)
out_2 = w_after[24].flatten().reshape(-1,1)
sns.set(style='whitegrid',palette='RdBu')
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(1, 5, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(1, 5, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3_w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(1, 5, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='g')
plt.xlabel('Hidden Layer 1 ')
plt.subplot(1, 5, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='pink')
mit viahal/loutnut Tavan
```



# Model with 5 CNN layers

```
In [154]:
```

In [ ]:

```
model 2 5 = Sequential()
model_2_5.add(Conv2D(32,kernel_size=(5,5),padding='same',input_shape=input_shape,kernel_initializer
='he uniform'))
model 2 5.add(BatchNormalization())
model 2 5.add(Activation('relu'))
#model 2 5.add(MaxPooling2D(pool_size=(2,2)))
model 2 5.add(Dropout(0.5))
model 2 5.add(Conv2D(32,kernel size = (5,5),padding='valid',kernel initializer='he uniform'))
model 2 5.add(BatchNormalization())
model 2 5.add(Activation('relu'))
model_2_5.add(MaxPooling2D(pool_size =(2,2)))
model 2 5.add(Dropout(0.5))
model_2_5.add(Conv2D(64,kernel_size=(5,5),padding='same',kernel_initializer='he_uniform'))
model_2_5.add(BatchNormalization())
model_2_5.add(Activation('relu'))
#model 2 5.add(MaxPooling2D(pool size=(2,2)))
model 2 5.add(Dropout(0.5))
model 2 5.add(Conv2D(64,kernel size = (5,5),padding = 'valid',kernel initializer='he uniform'))
model 2 5.add(BatchNormalization())
model 2 5.add(Activation('relu'))
model 2 5.add(MaxPooling2D(pool size=(2,2),padding='same'))
model 2 5.add(Dropout(0.5))
model 2 5.add(Conv2D(128,kernel size = (5,5),padding = 'same',kernel initializer='he uniform'))
model 2 5.add(BatchNormalization())
model_2_5.add(Activation('relu'))
model_2_5.add(MaxPooling2D(pool_size=(2,2)))
model 2 5.add(Dropout(0.5))
model 2 5.add(Flatten())
model 2 5.add(Dense(32, kernel initializer='he uniform'))
model_2_5.add(BatchNormalization())
model_2_5.add(Activation('relu'))
model_2_5.add(Dropout(0.5))
model_2_5.add(Dense(out_dim,activation = 'softmax'))
model 2 5.summary()
```

Layer (type)	Output Shape	Param #
conv2d_52 (Conv2D)	(None, 28, 28, 32)	832
batch_normalization_60 (Batc	(None, 28, 28, 32)	128
activation_60 (Activation)	(None, 28, 28, 32)	0
dropout_57 (Dropout)	(None, 28, 28, 32)	0
conv2d_53 (Conv2D)	(None, 24, 24, 32)	25632
batch_normalization_61 (Batc	(None, 24, 24, 32)	128
activation_61 (Activation)	(None, 24, 24, 32)	0
max_pooling2d_33 (MaxPooling	(None, 12, 12, 32)	0
dropout_58 (Dropout)	(None, 12, 12, 32)	0
conv2d_54 (Conv2D)	(None, 12, 12, 64)	51264
batch_normalization_62 (Batc	(None, 12, 12, 64)	256
activation_62 (Activation)	(None, 12, 12, 64)	0
dropout_59 (Dropout)	(None, 12, 12, 64)	0
conv2d_55 (Conv2D)	(None, 8, 8, 64)	102464
batch_normalization_63 (Batc	(None, 8, 8, 64)	256
activation_63 (Activation)	(None, 8, 8, 64)	0
max_pooling2d_34 (MaxPooling	(None, 4, 4, 64)	0
dropout_60 (Dropout)	(None, 4, 4, 64)	0
conv2d_56 (Conv2D)	(None, 4, 4, 128)	204928
batch_normalization_64 (Batc	(None, 4, 4, 128)	512
activation_64 (Activation)	(None, 4, 4, 128)	0
max_pooling2d_35 (MaxPooling	(None, 2, 2, 128)	0
dropout_61 (Dropout)	(None, 2, 2, 128)	0
flatten_9 (Flatten)	(None, 512)	0
dense_17 (Dense)	(None, 32)	16416
batch_normalization_65 (Batc	(None, 32)	128
activation_65 (Activation)	(None, 32)	0
dropout_62 (Dropout)	(None, 32)	0
dense_18 (Dense)	(None, 10)	330

Non-trainable params: 704

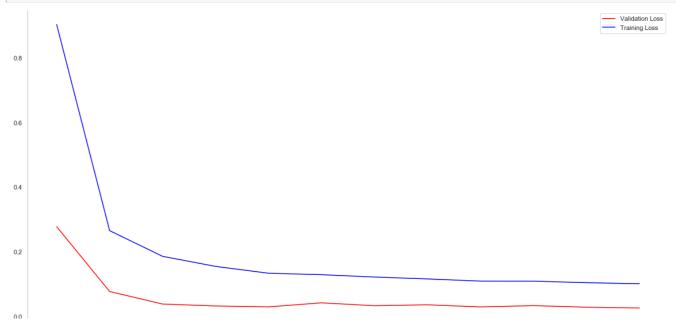
### In [155]:

```
model_2_5.compile(loss = 'categorical_crossentropy',optimizer = 'RMSprop',metrics = ['accuracy'])
result = model_2_5.fit(X_train,y_train,batch_size=batch_size,epochs=12,validation_data=(X_test,y_te
score = model_2_5.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
TEATH OH OUTOU SAMPLES, VALIDACE OH TOOUS SAMPLES
Epoch 1/12
ss: 0.2779 - val acc: 0.9191
Epoch 2/12
60000/60000 [============== ] - 244s 4ms/step - loss: 0.2654 - acc: 0.9251 - val lo
ss: 0.0771 - val acc: 0.9771
Epoch 3/12
ss: 0.0383 - val acc: 0.9891
Epoch 4/12
60000/60000 [============== ] - 241s 4ms/step - loss: 0.1547 - acc: 0.9568 - val lo
ss: 0.0323 - val acc: 0.9913
Epoch 5/12
60000/60000 [============= ] - 238s 4ms/step - loss: 0.1336 - acc: 0.9623 - val lo
ss: 0.0295 - val acc: 0.9922
Epoch 6/12
ss: 0.0421 - val_acc: 0.9902
Epoch 7/12
ss: 0.0330 - val acc: 0.9927
Epoch 8/12
60000/60000 [============== ] - 254s 4ms/step - loss: 0.1160 - acc: 0.9685 - val_lo
ss: 0.0360 - val acc: 0.9912
Epoch 9/12
60000/60000 [============== ] - 239s 4ms/step - loss: 0.1093 - acc: 0.9700 - val lo
ss: 0.0294 - val acc: 0.9935
Epoch 10/12
ss: 0.0334 - val acc: 0.9924
Epoch 11/12
ss: 0.0285 - val_acc: 0.9931
Epoch 12/12
60000/60000 [============= ] - 249s 4ms/step - loss: 0.1011 - acc: 0.9734 - val lo
ss: 0.0260 - val acc: 0.9940
Test loss: 0.02603177259878953
Test accuracy: 0.994
```

### In [156]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
```

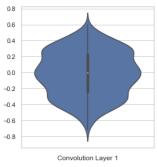


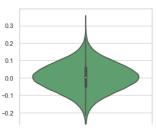
2 4 6 8 10 12

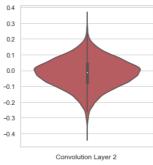
# Weights Distribution in Each CNN Layers

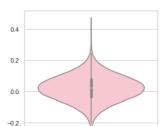
In [157]:

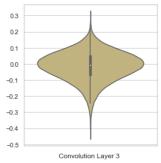
```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_2_5.get_weights()
C1_w = w_after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
C4_w = w_after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
h1 w = w after[30].flatten().reshape(-1,1)
out w = w after[36].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1_w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 3, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 3, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust(wspace=0.9)
plt.subplot(2, 3, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4_w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 3, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5_w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 3, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='pink')
plt.xlabel('Hidden Layer')
plt.show()
```

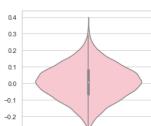














# Model 3 with 7 CNN layers

```
In [159]:
```

```
model 3 5 = Sequential()
model_3_5.add(Conv2D(10,kernel_size=(5,5),padding='same',input_shape=input_shape,kernel_initializer
='he uniform'))
model 3 5.add(BatchNormalization())
model 3 5.add(Activation('relu'))
model 3 5.add(MaxPooling2D(pool size=(2,2),padding = 'valid'))
model 3 5.add(Dropout(0.5))
model_3_5.add(Conv2D(32,kernel_size = (5,5),padding='same',kernel_initializer='he uniform'))
     _3_5.add(BatchNormalization())
model_3_5.add(Activation('relu'))
#model 3 5.add(MaxPooling2D(pool size =(2,2)))
model_3_5.add(Dropout(0.5))
model_3_5.add(Conv2D(32,kernel_size=(5,5),padding='same',kernel_initializer='he uniform'))
model 3 5.add(BatchNormalization())
model 3 5.add(Activation('relu'))
#model 3 5.add(MaxPooling2D(pool_size=(2,2),padding='same'))
model 3 5.add(Dropout(0.5))
model 3 5.add(Conv2D(32,kernel size = (5,5),padding = 'same',kernel initializer='he uniform'))
model_3_5.add(BatchNormalization())
model 3 5.add(Activation('relu'))
model_3_5.add(MaxPooling2D(pool_size=(2,2)))
model 3 5.add(Dropout(0.5))
model_3_5.add(Conv2D(64,kernel_size = (5,5),padding = 'same',kernel initializer='he uniform'))
model_3_5.add(BatchNormalization())
model_3_5.add(Activation('relu'))
#model 3 5.add (MaxPooling2D (pool size=(2,2)))
model 3 5.add(Dropout(0.5))
model 3 5.add(Conv2D(64,kernel size = (5,5),padding = 'same',kernel initializer='he uniform'))
model_3_5.add(BatchNormalization())
model_3_5.add(Activation('relu'))
       3 5.add(MaxPooling2D(pool size=(2,2),padding='same'))
model 3 5.add(Dropout(0.5))
model 3 5.add(Conv2D(64,kernel size = (5,5),padding = 'valid',kernel initializer='he uniform'))
model 3 5.add(BatchNormalization())
model_3_5.add(Activation('relu'))
model_3_5.add(MaxPooling2D(pool_size=(2,2),padding = 'same'))
model 3 5.add(Dropout(0.5))
model 3 5.add(Flatten())
model 3 5.add(Dense(128,kernel initializer='he uniform'))
model_3_5.add(BatchNormalization())
model_3_5.add(Activation('relu'))
model_3_5.add(Dropout(0.5))
model 3_5.add(Dense(out_dim,activation = 'softmax'))
model 3 5.summary()
```

Layer (type)	Output	Sha	ре 		Param #
conv2d_64 (Conv2D)	(None,	28,	28,	10)	260
batch_normalization_73 (Batc	(None,	28,	28,	10)	40
activation_73 (Activation)	(None,	28,	28,	10)	0
max_pooling2d_39 (MaxPooling	(None,	14,	14,	10)	0
dropout_69 (Dropout)	(None,	14,	14,	10)	0
conv2d_65 (Conv2D)	(None,	14,	14,	32)	8032
batch_normalization_74 (Batc	(None,	14,	14,	32)	128
activation_74 (Activation)	(None,	14,	14,	32)	0
dropout_70 (Dropout)	(None,	14,	14,	32)	0

conv2d_66 (Conv2D)	(None, 14, 14, 32	) 25632
batch_normalization_75 (Batc	(None, 14, 14, 32	) 128
activation_75 (Activation)	(None, 14, 14, 32	) 0
dropout_71 (Dropout)	(None, 14, 14, 32	) 0
conv2d_67 (Conv2D)	(None, 14, 14, 32	) 25632
batch_normalization_76 (Batc	(None, 14, 14, 32	) 128
activation_76 (Activation)	(None, 14, 14, 32	) 0
max_pooling2d_40 (MaxPooling	(None, 7, 7, 32)	0
dropout_72 (Dropout)	(None, 7, 7, 32)	0
conv2d_68 (Conv2D)	(None, 7, 7, 64)	51264
batch_normalization_77 (Batc	(None, 7, 7, 64)	256
activation_77 (Activation)	(None, 7, 7, 64)	0
dropout_73 (Dropout)	(None, 7, 7, 64)	0
conv2d_69 (Conv2D)	(None, 7, 7, 64)	102464
batch_normalization_78 (Batc	(None, 7, 7, 64)	256
activation_78 (Activation)	(None, 7, 7, 64)	0
dropout_74 (Dropout)	(None, 7, 7, 64)	0
conv2d_70 (Conv2D)	(None, 3, 3, 64)	102464
batch_normalization_79 (Batc	(None, 3, 3, 64)	256
activation_79 (Activation)	(None, 3, 3, 64)	0
max_pooling2d_41 (MaxPooling	(None, 2, 2, 64)	0
dropout_75 (Dropout)	(None, 2, 2, 64)	0
flatten_10 (Flatten)	(None, 256)	0
dense_19 (Dense)	(None, 128)	32896
batch_normalization_80 (Batc	(None, 128)	512
activation_80 (Activation)	(None, 128)	0
dropout_76 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 10)	1290
Total params: 351,638 Trainable params: 350,786 Non-trainable params: 852		

## In [160]:

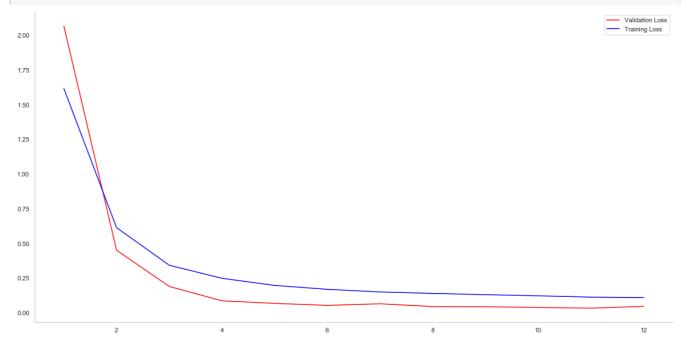
```
model_3_5.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics = ['accuracy'])
result = model_3_5.fit(X_train,y_train,batch_size=batch_size,epochs=12,validation_data=(X_test,y_te
st))
score = model_3_5.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [============= ] - 195s 3ms/step - loss: 1.6159 - acc: 0.4320 - val lo
ss: 2.0662 - val_acc: 0.4915
Epoch 2/12
```

```
60000/60000 [============== ] - 169s 3ms/step - loss: 0.6132 - acc: 0.7983 - val_lo
ss: 0.4509 - val acc: 0.8596
Epoch 3/12
60000/60000 [=============== ] - 167s 3ms/step - loss: 0.3424 - acc: 0.8968 - val lo
ss: 0.1894 - val acc: 0.9425
Epoch 4/12
ss: 0.0860 - val acc: 0.9738
Epoch 5/12
60000/60000 [=============] - 166s 3ms/step - loss: 0.1969 - acc: 0.9419 - val lo
ss: 0.0675 - val acc: 0.9801
Epoch 6/12
60000/60000 [==============] - 165s 3ms/step - loss: 0.1688 - acc: 0.9508 - val lo
ss: 0.0531 - val_acc: 0.9823
Epoch 7/12
60000/60000 [=============== ] - 164s 3ms/step - loss: 0.1497 - acc: 0.9572 - val lo
ss: 0.0646 - val_acc: 0.9811
Epoch 8/12
60000/60000 [=============] - 167s 3ms/step - loss: 0.1395 - acc: 0.9602 - val lo
ss: 0.0445 - val_acc: 0.9853
Epoch 9/12
60000/60000 [=============] - 165s 3ms/step - loss: 0.1302 - acc: 0.9633 - val lo
ss: 0.0432 - val acc: 0.9867
Epoch 10/12
60000/60000 [=============] - 165s 3ms/step - loss: 0.1221 - acc: 0.9657 - val_lo
ss: 0.0381 - val_acc: 0.9873
Epoch 11/12
60000/60000 [=============== ] - 168s 3ms/step - loss: 0.1124 - acc: 0.9679 - val lo
ss: 0.0332 - val acc: 0.9897
Epoch 12/12
60000/60000 [==============] - 166s 3ms/step - loss: 0.1093 - acc: 0.9689 - val lo
ss: 0.0459 - val acc: 0.9855
Test loss: 0.045862794393161314
Test accuracy: 0.9855
```

#### In [161]:

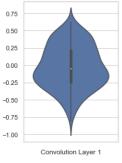
```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
```



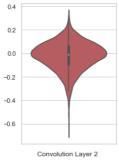
## Weights Distribution in Each CNN Layers

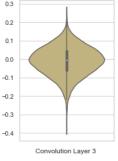
In [162]:

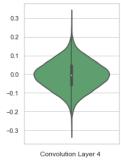
```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_3_5.get_weights()
C1_w = w_after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
C4_w = w_after[18].flatten().reshape(-1,1)
C5 w = w after[24].flatten().reshape(-1,1)
C6\ w = w_after[30].flatten().reshape(-1,1)
C7 w = w after[36].flatten().reshape(-1,1)
h1 w = w after[42].flatten().reshape(-1,1)
out w = w after[48].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 4, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 4, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 4, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust (wspace=0.9)
plt.subplot(2, 4, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 4, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5 w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 4, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C6 w, color='b')
plt.xlabel('Convolution Layer 6 ')
plt.subplot(2, 4, 7)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C7_w, color='g')
plt.xlabel('Convolution Layer 7 ')
plt.subplot(2, 4, 8)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='y')
plt.xlabel('Hidden Layer ')
plt.show()
                             0.4
                                                         0.3
                                                                                     0.3
                                                         0.2
                             0.2
0.50
                                                                                     0.2
```



0.3

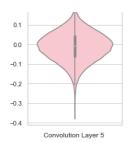


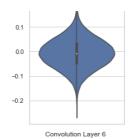


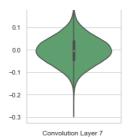


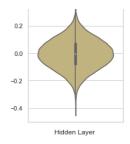
02

0.4









## Models with 7 by 7 kernels or filters

#### Model 1 with 3 CNN layers

#### In [165]:

```
model_1_7 = Sequential()
model_1_7.add(Conv2D(10,kernel_size=(7,7),padding='valid',input_shape=input_shape,kernel_initialize
r='he uniform'))
model 1 7.add(BatchNormalization())
model_1_7.add(Activation('relu'))
model_1_7.add(MaxPooling2D(pool_size=(2,2),padding = 'same',strides=(1,1)))
model_1_7.add(Dropout(0.5))
model_1_7.add(Conv2D(32,kernel_size = (7,7),padding='valid',kernel_initializer='he_uniform'))
model_1_7.add(BatchNormalization())
model_1_7.add(Activation('relu'))
#model_1_7.add (MaxPooling2D (pool_size = (2,2)))
model_1_7.add(Dropout(0.5))
model_1_7.add(Conv2D(32,kernel_size=(7,7),padding='valid',kernel_initializer='he_uniform'))
model_1_7.add(BatchNormalization())
model_1_7.add(Activation('relu'))
model_1_7.add(MaxPooling2D(pool_size=(2,2),padding='valid'))
model_1_7.add(Dropout(0.5))
model_1_7.add(Flatten())
model_1_7.add(Dense(64,kernel_initializer='he_uniform'))
model_1_7.add(BatchNormalization())
model_1_7.add(Activation('relu'))
model_1_7.add(Dropout(0.5))
model_1_7.add(Dense(out_dim,activation = 'softmax'))
```

Layer (type)	Output Shape	Param #
conv2d_77 (Conv2D)	(None, 22, 22, 10)	500
batch_normalization_85 (Batc	(None, 22, 22, 10)	40
activation_85 (Activation)	(None, 22, 22, 10)	0
max_pooling2d_44 (MaxPooling	(None, 22, 22, 10)	0
dropout_81 (Dropout)	(None, 22, 22, 10)	0
conv2d_78 (Conv2D)	(None, 16, 16, 32)	15712
batch_normalization_86 (Batc	(None, 16, 16, 32)	128
activation_86 (Activation)	(None, 16, 16, 32)	0
dropout_82 (Dropout)	(None, 16, 16, 32)	0
conv2d_79 (Conv2D)	(None, 10, 10, 32)	50208
batch_normalization_87 (Batc	(None, 10, 10, 32)	128
activation_87 (Activation)	(None, 10, 10, 32)	0
max_pooling2d_45 (MaxPooling	(None, 5, 5, 32)	0
dropout 83 (Dropout)	(None, 5, 5, 32)	0

flatten_11 (Flatten)	(None,	800)	0
dense_21 (Dense)	(None,	64)	51264
batch_normalization_88 (Batc	(None,	64)	256
activation_88 (Activation)	(None,	64)	0
dropout_84 (Dropout)	(None,	64)	0
dense_22 (Dense)	(None,	10)	650
Total params: 118,886 Trainable params: 118,610			

Trainable params: 118,610 Non-trainable params: 276

#### In [166]:

```
model 1 7.compile(loss = 'categorical crossentropy',optimizer = 'adadelta',metrics = ['accuracy'])
result = model 1 7.fit(X train,y train,batch size=batch size,epochs=12,validation data=(X test,y te
st))
score = model 1 7.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=============] - 181s 3ms/step - loss: 0.6765 - acc: 0.7924 - val lo
ss: 0.1134 - val acc: 0.9664
Epoch 2/12
60000/60000 [=============] - 158s 3ms/step - loss: 0.2062 - acc: 0.9414 - val lo
ss: 0.0524 - val_acc: 0.9840
Epoch 3/12
60000/60000 [==============] - 154s 3ms/step - loss: 0.1445 - acc: 0.9592 - val lo
ss: 0.0470 - val_acc: 0.9851
Epoch 4/12
60000/60000 [============== ] - 142s 2ms/step - loss: 0.1199 - acc: 0.9660 - val lo
ss: 0.0367 - val acc: 0.9887
Epoch 5/12
60000/60000 [============== ] - 132s 2ms/step - loss: 0.1041 - acc: 0.9709 - val lo
ss: 0.0327 - val acc: 0.9901
Epoch 6/12
60000/60000 [============= ] - 134s 2ms/step - loss: 0.0946 - acc: 0.9732 - val lo
ss: 0.0292 - val acc: 0.9903
Epoch 7/12
60000/60000 [==============] - 131s 2ms/step - loss: 0.0868 - acc: 0.9764 - val lo
ss: 0.0259 - val acc: 0.9918
Epoch 8/12
60000/60000 [============== ] - 132s 2ms/step - loss: 0.0783 - acc: 0.9781 - val lo
ss: 0.0289 - val acc: 0.9908
Epoch 9/12
60000/60000 [=============] - 132s 2ms/step - loss: 0.0757 - acc: 0.9784 - val lo
ss: 0.0252 - val acc: 0.9925
Epoch 10/12
60000/60000 [==============] - 132s 2ms/step - loss: 0.0728 - acc: 0.9803 - val lo
ss: 0.0264 - val acc: 0.9924
Epoch 11/12
ss: 0.0235 - val acc: 0.9938
Epoch 12/12
60000/60000 [=============] - 134s 2ms/step - loss: 0.0693 - acc: 0.9807 - val lo
ss: 0.0254 - val acc: 0.9927
Test loss: 0.025438149282336234
Test accuracy: 0.9927
```

#### In [167]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
```

```
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()

Validation Loss

Training Loss

Validation Loss

Training Loss

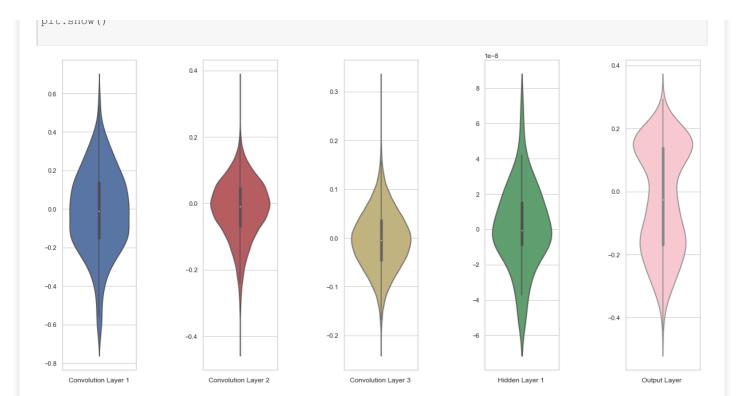
10

12
```

# **Weights Distribution in Each CNN Layers**

In [168]:

```
import matplotlib.pyplot as plt
import seaborn as sns
w after = model_1_7.get_weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
h1_w = w_after[19].flatten().reshape(-1,1)
out 2 = w after [24].flatten().reshape (-1,1)
sns.set(style='whitegrid',palette='RdBu')
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(1, 5, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(1, 5, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(1, 5, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w, color='g')
plt.xlabel('Hidden Layer 1 ')
plt.subplot(1, 5, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=out w, color='pink')
plt.xlabel('Output Layer ')
n1+ chorr/)
```



## Model 2 with 5 CNN Layers

#### In [169]:

```
model 2 7 = Sequential()
model 2 7.add(Conv2D(10,kernel size=(7,7),padding='same',input shape=input shape,kernel initializer
='he uniform'))
model_2_7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
model_2_7.add(MaxPooling2D(pool_size=(2,2)))
model 2 7.add(Dropout(0.5))
model 2 7.add(Conv2D(24,kernel size = (7,7),padding='valid',kernel initializer='he uniform'))
model_2_7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
#model_2_7.add(MaxPooling2D(pool_size =(2,2)))
model 2 7.add(Dropout(0.5))
model_2_7.add(Conv2D(24,kernel_size=(7,7),padding='same',kernel_initializer='he_uniform'))
model_2_7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
model_2_7.add(MaxPooling2D(pool_size=(2,2)))
model_2_7.add(Dropout(0.5))
model 2 7.add(Conv2D(48,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model 2 7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
#model_2_7.add(MaxPooling2D(pool_size=(2,2),padding='same'))
model_2_7.add(Dropout(0.5))
model 2 7.add(Conv2D(48,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model 2 7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
model_2_7.add(MaxPooling2D(pool_size=(2,2)))
model_2_7.add(Dropout(0.5))
model 2 7.add(Flatten())
model 2 7.add(Dense(32, kernel initializer='he uniform'))
model_2_7.add(BatchNormalization())
model_2_7.add(Activation('relu'))
model_2_7.add(Dropout(0.5))
model 2 7.add(Dense(out dim,activation = 'softmax'))
model 2 7.summary()
```

Layer (type)	Output Shape	Param #
conv2d 80 (Conv2D)	 (None, 28, 28, 10)	500
batch_normalization_89 (Batc	(None, 28, 28, 10)	40

activation_89 (Activation)	(None,	28, 28, 10)	0
max_pooling2d_46 (MaxPooling	(None,	14, 14, 10)	0
dropout_85 (Dropout)	(None,	14, 14, 10)	0
conv2d_81 (Conv2D)	(None,	8, 8, 24)	11784
batch_normalization_90 (Batc	(None,	8, 8, 24)	96
activation_90 (Activation)	(None,	8, 8, 24)	0
dropout_86 (Dropout)	(None,	8, 8, 24)	0
conv2d_82 (Conv2D)	(None,	8, 8, 24)	28248
batch_normalization_91 (Batc	(None,	8, 8, 24)	96
activation_91 (Activation)	(None,	8, 8, 24)	0
max_pooling2d_47 (MaxPooling	(None,	4, 4, 24)	0
dropout_87 (Dropout)	(None,	4, 4, 24)	0
conv2d_83 (Conv2D)	(None,	4, 4, 48)	56496
batch_normalization_92 (Batc	(None,	4, 4, 48)	192
activation_92 (Activation)	(None,	4, 4, 48)	0
dropout_88 (Dropout)	(None,	4, 4, 48)	0
conv2d_84 (Conv2D)	(None,	4, 4, 48)	112944
batch_normalization_93 (Batc	(None,	4, 4, 48)	192
activation_93 (Activation)	(None,	4, 4, 48)	0
max_pooling2d_48 (MaxPooling	(None,	2, 2, 48)	0
dropout_89 (Dropout)	(None,	2, 2, 48)	0
flatten_12 (Flatten)	(None,	192)	0
dense_23 (Dense)	(None,	32)	6176
batch_normalization_94 (Batc	(None,	32)	128
activation_94 (Activation)	(None,	32)	0
dropout_90 (Dropout)	(None,	32)	0
dense_24 (Dense)	(None,	10)	330
Total params: 217,222 Trainable params: 216,850			

Total params: 217,222 Trainable params: 216,850 Non-trainable params: 372

In [170]:

```
Epoch 3/12
ss: 0.0826 - val_acc: 0.9774
Epoch 4/12
60000/60000 [============== ] - 93s 2ms/step - loss: 0.2930 - acc: 0.9236 - val los
s: 0.0791 - val acc: 0.9797
Epoch 5/12
60000/60000 [============== ] - 92s 2ms/step - loss: 0.2555 - acc: 0.9338 - val los
s: 0.0610 - val acc: 0.9845
Epoch 6/12
60000/60000 [=============] - 95s 2ms/step - loss: 0.2304 - acc: 0.9404 - val los
s: 0.0663 - val acc: 0.9843
Epoch 7/12
60000/60000 [==============] - 97s 2ms/step - loss: 0.2162 - acc: 0.9440 - val los
s: 0.0534 - val acc: 0.9865
Epoch 8/12
60000/60000 [==============] - 94s 2ms/step - loss: 0.2057 - acc: 0.9477 - val los
s: 0.0549 - val acc: 0.9871
Epoch 9/12
60000/60000 [=============== ] - 93s 2ms/step - loss: 0.1970 - acc: 0.9500 - val los
s: 0.0448 - val acc: 0.9883
Epoch 10/12
s: 0.0478 - val_acc: 0.9886
Epoch 11/12
s: 0.0479 - val acc: 0.9892
Epoch 12/12
60000/60000 [============= ] - 99s 2ms/step - loss: 0.1790 - acc: 0.9560 - val los
s: 0.0451 - val acc: 0.9891
Test loss: 0.0451300366629599
Test accuracy: 0.9891
In [171]:
import numpy as np
train loss = result.history['val loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
                                                                      Training Loss
1.4
1.0
0.8
0.6
0.4
0.2
```

# Weights Distribution in Each CNN Layers

```
import matplotlib.pyplot as plt
import seaborn as sns
w_after = model_2_7.get_weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3 w = w after[12].flatten().reshape(-1,1)
C4 w = w after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
h1_w = w_after[30].flatten().reshape(-1,1)
out w = w after[36].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 3, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 3, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots adjust(wspace=0.9)
plt.subplot(2, 3, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4_w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 3, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5 w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 3, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='pink')
plt.xlabel('Hidden Layer ')
plt.show()
                                                                                    0.3
0.6
                                          0.4
0.4
                                                                                    0.2
                                          0.2
                                                                                    0.1
0.0
                                          0.0
-0.2
                                          -0.2
                                                                                   -0.1
                                                                                    -0.2
                                          -0.4
-0.6
-0.8
                                                                                   -0.3
                                          -0.6
                                                  Convolution Laver 2
         Convolution Laver 1
                                                                                            Convolution Laver 3
                                          0.3
0.2
                                                                                    0.2
0.1
                                          0.1
0.0
                                                                                    0.0
                                          0.0
-0.1
                                                                                   -0.2
```

-0.1

-0.2

Convolution Layer 5

Hidden Layer

Convolution Layer 4

-0.3

### Model 3 with 7 CNN Layers

```
In [174]:
```

```
model_3_7 = Sequential()
model 3 7.add(Conv2D(16,kernel size=(7,7),padding='valid',input shape=input shape,kernel initialize
r='he uniform'))
model 3 7.add(BatchNormalization())
model 3 7.add(Activation('relu'))
model 3 7.add(MaxPooling2D(pool size=(2,2),padding = 'valid'))
model_3_7.add(Dropout(0.5))
model_3_7.add(Conv2D(32,kernel_size = (7,7),padding='same',kernel_initializer='he_uniform'))
model_3_7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
#model_3_7.add(MaxPooling2D(pool_size =(2,2)))
model 3 7.add(Dropout(0.5))
\verb|model_3_7.add(Conv2D(32,kernel_size=(7,7),padding='same',kernel_initialize='he\_uniform')||
model_3_7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
#model_3_7.add(MaxPooling2D(pool_size=(2,2),padding='same'))
model 3 7.add(Dropout(0.5))
model 3 7.add(Conv2D(32,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model_3_7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
      3 7.add(MaxPooling2D(pool_size=(2,2)))
model
model 3 7.add(Dropout(0.5))
model 3 7.add(Conv2D(64,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model_3_7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
#model 3 7.add(MaxPooling2D(pool size=(2,2)))
model 3 7.add(Dropout(0.5))
model 3 7.add(Conv2D(64,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model 3 7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
#model_3_7.add(MaxPooling2D(pool_size=(2,2),padding='same'))
model_3_7.add(Dropout(0.5))
model 3 7.add(Conv2D(64,kernel size = (7,7),padding = 'same',kernel initializer='he uniform'))
model 3 7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
model_3_7.add(MaxPooling2D(pool_size=(2,2),padding = 'valid'))
model 3 7.add(Dropout(0.5))
model_3_7.add(Flatten())
model 3 7.add(Dense(32, kernel initializer='he uniform'))
model_3_7.add(BatchNormalization())
model_3_7.add(Activation('relu'))
model_3_7.add(Dropout(0.5))
model 3_7.add(Dense(out_dim,activation = 'softmax'))
model_3_7.summary()
```

Layer (type)	Output	Shaj	pe		Param #
conv2d_92 (Conv2D)	(None,	22,	22,	16)	800
batch_normalization_103 (Bat	(None,	22,	22,	16)	64
activation_103 (Activation)	(None,	22,	22,	16)	0
max_pooling2d_52 (MaxPooling	(None,	11,	11,	16)	0
dropout_99 (Dropout)	(None,	11,	11,	16)	0
conv2d_93 (Conv2D)	(None,	11,	11,	32)	25120
batch_normalization_104 (Bat	(None,	11,	11,	32)	128
activation_104 (Activation)	(None,	11,	11,	32)	0
dropout_100 (Dropout)	(None,	11,	11,	32)	0
conv2d_94 (Conv2D)	(None,	11,	11,	32)	50208
batch_normalization_105 (Bat	(None,	11,	11,	32)	128
activation_105 (Activation)	(None,	11,	11,	32)	0

dropout_101 (Dropout)	(None, 11, 11, 32)	0
conv2d_95 (Conv2D)	(None, 11, 11, 32)	50208
batch_normalization_106 (Bat	(None, 11, 11, 32)	128
activation_106 (Activation)	(None, 11, 11, 32)	0
max_pooling2d_53 (MaxPooling	(None, 5, 5, 32)	0
dropout_102 (Dropout)	(None, 5, 5, 32)	0
conv2d_96 (Conv2D)	(None, 5, 5, 64)	100416
batch_normalization_107 (Bat	(None, 5, 5, 64)	256
activation_107 (Activation)	(None, 5, 5, 64)	0
dropout_103 (Dropout)	(None, 5, 5, 64)	0
conv2d_97 (Conv2D)	(None, 5, 5, 64)	200768
batch_normalization_108 (Bat	(None, 5, 5, 64)	256
activation_108 (Activation)	(None, 5, 5, 64)	0
dropout_104 (Dropout)	(None, 5, 5, 64)	0
conv2d_98 (Conv2D)	(None, 5, 5, 64)	200768
batch_normalization_109 (Bat	(None, 5, 5, 64)	256
activation_109 (Activation)	(None, 5, 5, 64)	0
max_pooling2d_54 (MaxPooling	(None, 2, 2, 64)	0
dropout_105 (Dropout)	(None, 2, 2, 64)	0
flatten_14 (Flatten)	(None, 256)	0
dense_27 (Dense)	(None, 32)	8224
batch_normalization_110 (Bat	(None, 32)	128
activation_110 (Activation)	(None, 32)	0
dropout_106 (Dropout)	(None, 32)	0
dense_28 (Dense)	(None, 10)	330
Total params: 638,186 Trainable params: 637,514 Non-trainable params: 672		

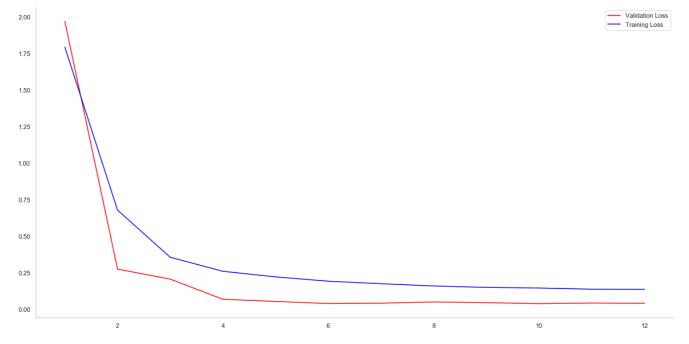
#### In [175]:

```
model_3_7.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics = ['accuracy'])
result = model 3 7.fit(X train, y_train, batch_size=batch_size, epochs=12, validation_data=(X_test, y_te
st))
score = model_3_7.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============] - 226s 4ms/step - loss: 1.7923 - acc: 0.3654 - val lo
ss: 1.9683 - val_acc: 0.3683
Epoch 2/12
ss: 0.2738 - val acc: 0.9307
Epoch 3/12
60000/60000 [============= ] - 179s 3ms/step - loss: 0.3548 - acc: 0.9094 - val lo
ss: 0.2052 - val acc: 0.9500
Epoch 4/12
60000/60000 [-----
                        ______1 1720 2mg/ston 1000. 0 2500 000. 0 0271 wol 10
```

```
__________
                           =========| - 1/38 3M8/8tep - 1088; U.2300 - acc; U.33/1 - val 10
ss: 0.0673 - val acc: 0.9846
Epoch 5/12
60000/60000 [============== ] - 170s 3ms/step - loss: 0.2204 - acc: 0.9454 - val lo
ss: 0.0528 - val acc: 0.9866
Epoch 6/12
60000/60000 [============= ] - 169s 3ms/step - loss: 0.1910 - acc: 0.9528 - val lo
ss: 0.0382 - val acc: 0.9906
Epoch 7/12
60000/60000 [==============] - 170s 3ms/step - loss: 0.1739 - acc: 0.9578 - val lo
ss: 0.0408 - val acc: 0.9906
Epoch 8/12
60000/60000 [==============] - 171s 3ms/step - loss: 0.1584 - acc: 0.9614 - val lo
ss: 0.0491 - val acc: 0.9896
Epoch 9/12
60000/60000 [============= ] - 171s 3ms/step - loss: 0.1487 - acc: 0.9640 - val lo
ss: 0.0443 - val acc: 0.9891
Epoch 10/12
60000/60000 [=============] - 170s 3ms/step - loss: 0.1443 - acc: 0.9659 - val lo
ss: 0.0376 - val_acc: 0.9919
Epoch 11/12
60000/60000 [============== ] - 172s 3ms/step - loss: 0.1362 - acc: 0.9661 - val lo
ss: 0.0418 - val_acc: 0.9901
Epoch 12/12
60000/60000 [==============] - 172s 3ms/step - loss: 0.1356 - acc: 0.9682 - val lo
ss: 0.0397 - val acc: 0.9914
Test loss: 0.039670931791243126
Test accuracy: 0.9914
```

#### In [176]:

```
import numpy as np
train_loss = result.history['val_loss']
val_loss = result.history['loss']
epochs = list(np.arange(1,nb_epochs+1))
plt.figure(figsize = (20,10))
sns.lineplot(x = epochs,y = train_loss,color = 'red',label = "Validation Loss")
sns.lineplot(x = epochs,y = val_loss,color = 'blue',label = "Training Loss")
plt.grid()
plt.legend()
sns.despine()
```



## Weights Distribution in Each CNN Layers

#### In [177]:

```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
w after = model 3 /.get weights()
C1 w = w after[0].flatten().reshape(-1,1)
C2 w = w after[6].flatten().reshape(-1,1)
C3_w = w_after[12].flatten().reshape(-1,1)
C4 w = w after[18].flatten().reshape(-1,1)
C5_w = w_after[24].flatten().reshape(-1,1)
C6_w = w_after[30].flatten().reshape(-1,1)
  w = w \text{ after}[36].flatten().reshape(-1,1)
h1_w = w_after[42].flatten().reshape(-1,1)
out w = w after[48].flatten().reshape(-1,1)
fig = plt.figure(figsize=(20,10))
#plt.title("Weight matrices after model trained")
plt.subplot(2, 4, 1)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C1 w,color='b')
plt.xlabel('Convolution Layer 1')
plt.subplot(2, 4, 2)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C2 w, color='r')
plt.xlabel('Convolution Layer 2 ')
plt.subplot(2, 4, 3)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C3 w,color='y')
plt.xlabel('Convolution Layer 3 ')
plt.subplots_adjust(wspace=0.9)
plt.subplot(2, 4, 4)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C4 w, color='g')
plt.xlabel('Convolution Layer 4 ')
plt.subplot(2, 4, 5)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C5 w, color='pink')
plt.xlabel('Convolution Layer 5 ')
plt.subplot(2, 4, 6)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C6_w, color='b')
plt.xlabel('Convolution Layer 6 ')
plt.subplot(2, 4, 7)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=C7 w, color='g')
plt.xlabel('Convolution Layer 7 ')
plt.subplot(2, 4, 8)
#plt.title("Trained model Weights")
ax = sns.violinplot(y=h1 w, color='y')
plt.xlabel('Hidden Layer ')
plt.show()
                                                                                          0.3
                                                            0.3
0.6
                               0.3
                               0.2
                                                             0.2
                                                                                           0.2
0.4
0.2
                                                            0.1
                                                                                          0.1
                               0.0
0.0
                                                             0.0
                                                                                           0.0
-0.2
                                                            -0.1
                                                                                          -0.1
                              -0.2
-0.4
                              -0.3
                                                                                          -0.2
                              -0.4
                                                                                          -0.3
-0.8
                              -0.5
      Convolution Layer 1
                                    Convolution Laver 2
                                                                 Convolution Layer 3
                                                                                               Convolution Layer 4
0.3
                                                                                           0.4
0.2
                                                             0.2
                               0.2
0.1
                                                                                          0.2
                                                             0.1
```

0.0

-0.1

0.0

-0.2

0.0

-0.2

0.0

-0.2

```
-0.3 Convolution Layer 5 Convolution Layer 6 Convolution Layer 7 Hidden Layer
```

#### # Conclusion

```
In [34]:
```

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x = PrettyTable()
x.field names = ["Model", "Kernels size", "Initialization", "Val Acc Score"]
x.add_row(["3 CNN Layer ","3*3","he_normal",0.9912])
x.add row(["3 CNN Layer ","3*3","glorot uniform",0.9687])
x.add row(["3 CNN Layer ","5*5","he normal",0.9843])
x.add_row(["3 CNN Layer ","5*5","glorot_normal",0.1135])
x.add row(["3 CNN Layer ","7*7","he normal",0.9734])
x.add row(["3 CNN Layer ","7*7","glorot_uniform",0.1135])
x.add_row(["5 CNN Layer ","3*3","he_normal",0.9835])
x.add row(["5 CNN Layer ","3*3","glorot normal",0.9827])
x.add_row(["5 CNN Layer ","5*5","glorot_uniform",0.9941])
x.add row(["5 CNN Layer","7*7","he uniform",0.9855])
x.add_row(["7 CNN Layer","3*3","he_normal",0.9927])
x.add_row(["7 CNN Layer","5*5","he_normal",0.9891])
x.add row(["7 CNN Layer","7*7","he normal",0.9914])
print(x)
```

+	+		++
Model	'   Kernels size +	   Initialization	   Val_Acc_Score
3 CNN Layer	'   3*3	he normal	0.9836
3 CNN Layer	3*3	glorot uniform	0.9807
3 CNN Layer	5*5	he normal	0.8776
3 CNN Layer	5*5	glorot normal	0.9812
3 CNN Layer	7*7	he normal	0.982
3 CNN Layer	7*7	glorot uniform	0.982
5 CNN Layer	3*3	he_normal	0.9836
5 CNN Layer	3*3	glorot normal	0.9813
5 CNN Layer	5*5	glorot uniform	0.4981
5 CNN Layer	7*7	he uniform	0.9845
7 CNN Layer	3*3	he normal	0.9846
7 CNN Layer	5*5	he normal	0.9846
7 CNN Layer	7*7	he_normal	0.9846
+	+	+	++

# After doing experiment with CNN with different Layers and kernels ,I interpreted that :-

- 1. CNN layers with sigmoid as an activation layer doesn't give a good accuracy at all or it gives worst accuracy of all of 11.35%.
- 2. Sigmoid activation gives worst result if CNN layers is 5,7 and more but with 3 CNN layers it giving good result as other models.
- 3. The reason can be that as layers increases and with sigmoid activation layer there might be vanishing gradient problem.