In [1]:
```
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dropout
from keras.layers import BatchNormalization
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
from keras.initializers import he_normal

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

```
Using TensorFlow backend.
```

In [2]:
```
#getting the size of input image
img_rows,img_cols = 28,28

#splitting the dataset
(X_train,Y_train),(X_test,Y_test) = mnist.load_data()
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz (https://s3.amazonaws.com/img-datasets/mnist.npz)
11493376/11490434 [==============================] - 11s 1us/step
```

In [3]:
```
print('Number of images in training set are:',X_train.shape[0],'And shape of each image is {} x {}'.format(X
print('Number of images in test set are:',X_test.shape[0],'And shape of each image is {} x {}'.format(X_test
```

```
Number of images in training set are: 60000 And shape of each image is 28 x 28
Number of images in test set are: 10000 And shape of each image is 28 x 28
```

In [0]:
```
#as keras backend perceives incoming input to be of 4 dimensional tensor that's why we need to reshape the s

if K.image_data_format() == 'channels_first':
  X_train = X_train.reshape(X_train.shape[0],1,img_row,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.shape
X_test.shape
#backend percieves other than channels first
```

Out[5]: (10000, 28, 28, 1)

In [6]:
```
#display a plot number
plt.figure(figsize=(10,10))
rows = 3
cols= 3
for i in range(rows*cols):
    plt.subplot(rows,cols,i+1)
    plt.imshow(X_train[i].reshape(28,28),cmap="afmhot",interpolation="none")
    print(Y_train[i])
    #reshaping from 1D to 2D array
    plt.xticks([])
    plt.yticks([])
```

```
5
0
4
1
9
2
1
3
1
```

In [7]:
```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
X_test /= 255
print('Shape of training data is',X_train.shape)
print(X_train.shape[0],'train_samples')
print(X_test.shape[0],'test_samples')
```

```
Shape of training data is (60000, 28, 28, 1)
60000 train_samples
10000 test_samples
```

In [8]:
```
#converting the labels into vectos using one hot encoding

from keras.utils import to_categorical

num_classes = 10
Y_train = to_categorical(Y_train,num_classes)
Y_test = to_categorical(Y_test,num_classes)
Y_train.shape
```

Out[8]: (60000, 10)

In [0]:
```
def classifier_1(n_kernel):
  model = Sequential()
  model.add(Conv2D(64,kernel_size = (n_kernel,n_kernel),activation = 'relu',kernel_initializer = he_normal(s
  model.add(Conv2D(32,(n_kernel,n_kernel),activation = 'relu',kernel_initializer = he_normal(seed = None)))
  model.add(MaxPooling2D(pool_size=(2, 2)))
  model.add(BatchNormalization())
  model.add(Dropout(0.3))

  #adding a flattening layer
  model.add(Flatten())
  model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))
  model.add(BatchNormalization())
  model.add(Dropout(0.5))

  #addding the output layer
  model.add(Dense(10,activation = 'softmax'))

  model.compile(loss = 'categorical_crossentropy',optimizer ='adam', metrics = ['accuracy'])

  return model
```

In [0]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [0]:

```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
import time

start_time = time.time()

batch_size = 100
epochs = 20
#writing the fucntion to perform parameter tuning and pass the argument of different kernel sizes as a list
n_kernel = [2,3,5,7,11]


model_gs = KerasClassifier(build_fn = classifier_1,batch_size = batch_size,epochs = epochs,verbose = 0)
param_grid = dict(n_kernel = n_kernel)
grid = GridSearchCV(estimator = model_gs,param_grid = param_grid,cv = 5,verbose = 1)
grid_result = grid.fit(X_train,Y_train)

end_time = time.time()
print('Time taken for execution of the hypereparamter searching is:',(end_time - start_time))


print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:66: The n
ame tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:541: The
name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4479: The
name tf.truncated_normal is deprecated. Please use tf.random.truncated_normal instead.


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4267: The
name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:190: The
name tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session instead.
```

In [11]:

```
#after getting the best kernel_size
# we need to evaluate it on the test data

#best_kernel_size is 7
batch_size = 100
epochs = 20
model = Sequential()
model.add(Conv2D(64,kernel_size = (7,7),activation = 'relu',kernel_initializer = he_normal(seed  = None),inp
model.add(Conv2D(32,(7,7),activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())
model.add(Dropout(0.3))

  #adding a flattening layer
model.add(Flatten())
model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(BatchNormalization())
model.add(Dropout(0.5))

  #addding the output layer
model.add(Dense(10,activation = 'softmax'))
print(model.summary())


model.compile(loss = 'categorical_crossentropy',optimizer ='adam', metrics = ['accuracy'])
history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = (X_test,Y_test
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:66: The name
tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:541: The nam
e tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4479: The na
me tf.truncated_normal is deprecated. Please use tf.random.truncated_normal instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4267: The na
me tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:190: The nam
e tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session instead.
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:197: The nam
e tf.ConfigProto is deprecated. Please use tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:2041: The na
me tf.nn.fused_batch_norm is deprecated. Please use tf.compat.v1.nn.fused_batch_norm instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3733: callin
g dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future vers
ion.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 22, 22, 64)        3200
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 32)        100384
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
batch_normalization_1 (Batch (None, 8, 8, 32)          128
_________________________________________________________________
dropout_1 (Dropout)          (None, 8, 8, 32)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               262272
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1290
=================================================================
Total params: 367,786
Trainable params: 367,466
Non-trainable params: 320
_________________________________________________________________
None
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name tf.train.Optim
izer is deprecated. Please use tf.compat.v1.train.Optimizer instead.
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_grad.py:1250: add_dis
patch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a fu
ture 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 1/20
60000/60000 [==============================] - 10s 164us/step - loss: 0.1793 - acc: 0.9458 - val_loss: 0.0477 -
val_acc: 0.9845
Epoch 2/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0652 - acc: 0.9811 - val_loss: 0.0315 - v
al_acc: 0.9908
Epoch 3/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0490 - acc: 0.9851 - val_loss: 0.0253 - v
al_acc: 0.9921
Epoch 4/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0387 - acc: 0.9881 - val_loss: 0.0268 - v
al_acc: 0.9923
Epoch 5/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0326 - acc: 0.9899 - val_loss: 0.0230 - v
al_acc: 0.9921
Epoch 6/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0264 - acc: 0.9917 - val_loss: 0.0231 - v
al_acc: 0.9927
Epoch 7/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0255 - acc: 0.9918 - val_loss: 0.0227 - v
al_acc: 0.9917
Epoch 8/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0248 - acc: 0.9922 - val_loss: 0.0207 - v
al_acc: 0.9931
Epoch 9/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0218 - acc: 0.9929 - val_loss: 0.0214 - v
al_acc: 0.9930
Epoch 10/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0176 - acc: 0.9944 - val_loss: 0.0195 - v
al_acc: 0.9938
Epoch 11/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0170 - acc: 0.9944 - val_loss: 0.0211 - v
al_acc: 0.9931
Epoch 12/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0165 - acc: 0.9943 - val_loss: 0.0217 - v
al_acc: 0.9928
```

```
Epoch 13/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0154 - acc: 0.9949 - val_loss: 0.0281 - v
al_acc: 0.9911
Epoch 14/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0149 - acc: 0.9950 - val_loss: 0.0181 - v
al_acc: 0.9947
Epoch 15/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.0133 - acc: 0.9960 - val_loss: 0.0197 - v
al_acc: 0.9934
Epoch 16/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0113 - acc: 0.9964 - val_loss: 0.0192 - v
al_acc: 0.9940
Epoch 17/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0109 - acc: 0.9966 - val_loss: 0.0208 - v
al_acc: 0.9940
Epoch 18/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0102 - acc: 0.9967 - val_loss: 0.0205 - v
al_acc: 0.9941
Epoch 19/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0104 - acc: 0.9967 - val_loss: 0.0242 - v
al_acc: 0.9928
Epoch 20/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0100 - acc: 0.9967 - val_loss: 0.0196 - v
al_acc: 0.9951
```

In [0]:
```
1
```

Though we got an absolutely amazing accuracy of 99.31 % on test data,in the next model that we will build,data augmentation would be used on the data for better understanding the data

In [0]:
```
import pickle

import pickle
def savetofile(obj,filename):
  pickle.dump(obj,open(filename+".p",'wb'))

def openfromfile(filename):
  temp = pickle.load(open(filename+".p",'rb'))
  return temp

```

In [0]:
```
history1 = savetofile(history,'history_1')
model1 = savetofile(model,'model1')
```

In [14]:
```
model1 = openfromfile('model1')
score_model1 = model1.evaluate(X_test,Y_test)
print('Loss on test data is',score_model1[0])
print('Accuracy on test data is',score_model1[1])
```

```
10000/10000 [==============================] - 1s 89us/step
Loss on test data is 0.01964392685413427
Accuracy on test data is 0.9951
```

In [15]:
```
X_train.shape
```

Out[15]:
```
(60000, 28, 28, 1)
```

In [16]:

```
#CNN with 5 layers

model = Sequential()

#1st and 2nd layer with maxpooling layer
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None),input_sh
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))

#3rd and 4th layer with maxpooling layer
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))


#5th layer
model.add(Conv2D(128,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(BatchNormalization())
model.add(Dropout(0.4))

#flattening adn adding another 2 dense layers with relu activation
model.add(Flatten())
model.add(Dense(256,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Dropout(0.4))


model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Dropout(0.4))


#output layer
model.add(Dense(10,activation = 'softmax'))

print(model.summary())
```

```
Model: "sequential_2"
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 24, 24, 32)        9248
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 12, 12, 32)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 12, 12, 32)        128
_________________________________________________________________
dropout_3 (Dropout)          (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 11, 11, 64)        8256
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 10, 10, 64)        16448
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
batch_normalization_4 (Batch (None, 5, 5, 64)          256
_________________________________________________________________
dropout_4 (Dropout)          (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 1, 1, 128)         204928
_________________________________________________________________
batch_normalization_5 (Batch (None, 1, 1, 128)         512
_________________________________________________________________
dropout_5 (Dropout)          (None, 1, 1, 128)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 256)               33024
_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                1290
=================================================================
Total params: 307,306
Trainable params: 306,858
Non-trainable params: 448
```

```
_________________________________________________________________
```

None

In [17]:
```
#optimization for compilation

model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics = ['accuracy'])
history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = (X_test,Y_test
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.7325 - acc: 0.7727 - val_loss: 0.1535
- val_acc: 0.9553
Epoch 2/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.1859 - acc: 0.9471 - val_loss: 0.1055
- val_acc: 0.9669
Epoch 3/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.1418 - acc: 0.9615 - val_loss: 0.0475
- val_acc: 0.9845
Epoch 4/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.1171 - acc: 0.9675 - val_loss: 0.0447
- val_acc: 0.9873
Epoch 5/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.1005 - acc: 0.9726 - val_loss: 0.0389
- val_acc: 0.9886
Epoch 6/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0924 - acc: 0.9747 - val_loss: 0.0388
- val_acc: 0.9886
Epoch 7/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0879 - acc: 0.9760 - val_loss: 0.0454
- val_acc: 0.9877
Epoch 8/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0760 - acc: 0.9791 - val_loss: 0.0380
- val_acc: 0.9880
Epoch 9/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0752 - acc: 0.9788 - val_loss: 0.0360
- val_acc: 0.9899
Epoch 10/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0696 - acc: 0.9808 - val_loss: 0.0314
- val_acc: 0.9915
Epoch 11/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0678 - acc: 0.9821 - val_loss: 0.0278
- val_acc: 0.9922
Epoch 12/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0632 - acc: 0.9829 - val_loss: 0.0326
- val_acc: 0.9917
```

```
Epoch 13/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0591 - acc: 0.9837 - val_loss: 0.0283
- val_acc: 0.9931
Epoch 14/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0564 - acc: 0.9841 - val_loss: 0.0291
- val_acc: 0.9916
Epoch 15/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0541 - acc: 0.9846 - val_loss: 0.0304
- val_acc: 0.9922
Epoch 16/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0562 - acc: 0.9846 - val_loss: 0.0263
- val_acc: 0.9929
Epoch 17/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0488 - acc: 0.9862 - val_loss: 0.0262
- val_acc: 0.9917
Epoch 18/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0497 - acc: 0.9863 - val_loss: 0.0242
- val_acc: 0.9936
Epoch 19/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0504 - acc: 0.9861 - val_loss: 0.0225
- val_acc: 0.9932
Epoch 20/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0490 - acc: 0.9867 - val_loss: 0.0232
- val_acc: 0.9937
```

In [0]:

```
history2 = savetofile(history,'history2')
model2 = savetofile(model,'model2')
```

In [19]:

```
model2 = openfromfile('model2')
score_model2 = model2.evaluate(X_test,Y_test)
print('Loss on test data is',score_model2[0])
print('Accuracy on test data is',score_model2[1])
```

```
10000/10000 [==============================] - 1s 112us/step
Loss on test data is 0.023159436680417637
Accuracy on test data is 0.9937
```

In [20]:

```
#arch 3
#building a 7 layer of Conv2d ,7 layers of maxpooling and 2 dense layers

model = Sequential()

model.add(Conv2D(16,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None),input_sh
model.add(MaxPooling2D(1,1))
model.add(BatchNormalization())
model.add(Dropout(0.5))


model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(1,1))
model.add(BatchNormalization())
model.add(Dropout(0.5))


model.add(Conv2D(64,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(1,1))
model.add(BatchNormalization())
model.add(Dropout(0.5))


model.add(Conv2D(96,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(1,1))
model.add(BatchNormalization())
model.add(Dropout(0.3))




model.add(Conv2D(128,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.3))


model.add(Conv2D(160,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.3))

```

```
43
44
45 #flattening adn adding another 2 dense layers with relu activation
46 model.add(Flatten())
47 model.add(Dense(256,activation = 'relu',kernel_initializer = he_normal(seed = None)))
48 model.add(BatchNormalization())
49 model.add(Dropout(0.3))
50
51
52 model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))
53 model.add(Dropout(0.3))
54
55
56 #output layer
57 model.add(Dense(10,activation = 'softmax'))
58
59 print(model.summary())
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 26, 26, 16)        160
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 26, 26, 16)        0
_________________________________________________________________
batch_normalization_6 (Batch (None, 26, 26, 16)        64
_________________________________________________________________
dropout_8 (Dropout)          (None, 26, 26, 16)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 24, 24, 32)        4640
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 24, 24, 32)        0
_________________________________________________________________
batch_normalization_7 (Batch (None, 24, 24, 32)        128
_________________________________________________________________
dropout_9 (Dropout)          (None, 24, 24, 32)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 22, 22, 64)        18496
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
```

```
batch_normalization_8 (Batch (None, 22, 22, 64)        256
_________________________________________________________________
dropout_10 (Dropout)         (None, 22, 22, 64)        0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 18, 18, 96)        153696
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 18, 18, 96)        0
_________________________________________________________________
batch_normalization_9 (Batch (None, 18, 18, 96)        384
_________________________________________________________________
dropout_11 (Dropout)         (None, 18, 18, 96)        0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 14, 14, 128)       307328
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 7, 7, 128)         0
_________________________________________________________________
batch_normalization_10 (Batc (None, 7, 7, 128)         512
_________________________________________________________________
dropout_12 (Dropout)         (None, 7, 7, 128)         0
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 3, 3, 160)         512160
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 1, 1, 160)         0
_________________________________________________________________
batch_normalization_11 (Batc (None, 1, 1, 160)         640
_________________________________________________________________
dropout_13 (Dropout)         (None, 1, 1, 160)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 160)               0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               41216
_________________________________________________________________
batch_normalization_12 (Batc (None, 256)               1024
_________________________________________________________________
dropout_14 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_7 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_15 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_8 (Dense)              (None, 10)                1290
=================================================================
Total params: 1,074,890
```

```
Trainable params: 1,073,386
Non-trainable params: 1,504
_________________________________________________________________
None
```

In [21]:
```
#optimization for compilation

model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics = ['accuracy'])
history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = (X_test,Y_test
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 22s 369us/step - loss: 0.5196 - acc: 0.8393 - val_loss: 0.097
4 - val_acc: 0.9700
Epoch 2/20
60000/60000 [==============================] - 20s 329us/step - loss: 0.1517 - acc: 0.9543 - val_loss: 0.060
7 - val_acc: 0.9809
Epoch 3/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.1020 - acc: 0.9699 - val_loss: 0.046
4 - val_acc: 0.9860
Epoch 4/20
60000/60000 [==============================] - 19s 321us/step - loss: 0.0813 - acc: 0.9758 - val_loss: 0.037
7 - val_acc: 0.9884
Epoch 5/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0729 - acc: 0.9784 - val_loss: 0.031
7 - val_acc: 0.9902
Epoch 6/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.0626 - acc: 0.9813 - val_loss: 0.036
6 - val_acc: 0.9888
Epoch 7/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.0561 - acc: 0.9832 - val_loss: 0.022
2 - val_acc: 0.9933
Epoch 8/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0527 - acc: 0.9846 - val_loss: 0.036
6 - val_acc: 0.9906
Epoch 9/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0464 - acc: 0.9862 - val_loss: 0.021
4 - val_acc: 0.9942
Epoch 10/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0458 - acc: 0.9866 - val_loss: 0.025
4 - val_acc: 0.9932
Epoch 11/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0414 - acc: 0.9881 - val_loss: 0.024
3 - val_acc: 0.9928
Epoch 12/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0386 - acc: 0.9885 - val_loss: 0.029
2 - val_acc: 0.9919
```

```
Epoch 13/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0354 - acc: 0.9894 - val_loss: 0.021
6 - val_acc: 0.9934
Epoch 14/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0350 - acc: 0.9893 - val_loss: 0.023
5 - val_acc: 0.9933
Epoch 15/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0325 - acc: 0.9905 - val_loss: 0.026
3 - val_acc: 0.9929
Epoch 16/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0290 - acc: 0.9911 - val_loss: 0.021
6 - val_acc: 0.9937
Epoch 17/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0290 - acc: 0.9910 - val_loss: 0.021
1 - val_acc: 0.9940
Epoch 18/20
60000/60000 [==============================] - 19s 321us/step - loss: 0.0277 - acc: 0.9914 - val_loss: 0.023
9 - val_acc: 0.9931
Epoch 19/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0245 - acc: 0.9923 - val_loss: 0.019
0 - val_acc: 0.9940
Epoch 20/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0268 - acc: 0.9919 - val_loss: 0.022
7 - val_acc: 0.9938
```

In [0]:

```
history3 = savetofile(history,'history3')
model3 = savetofile(model,'model3')
```

In [23]:

```
model3 = openfromfile('model3')

score_model3 = model1.evaluate(X_test,Y_test)
print('Loss on test data is',score_model3[0])
print('Accuracy on test data is',score_model3[1])
```

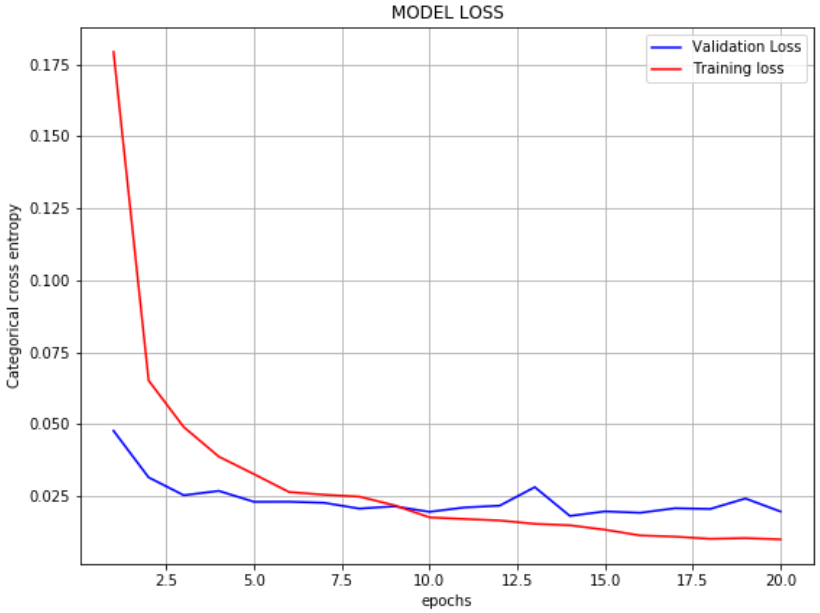
```
10000/10000 [==============================] - 1s 92us/step
Loss on test data is 0.01964392685413427
Accuracy on test data is 0.9951
```

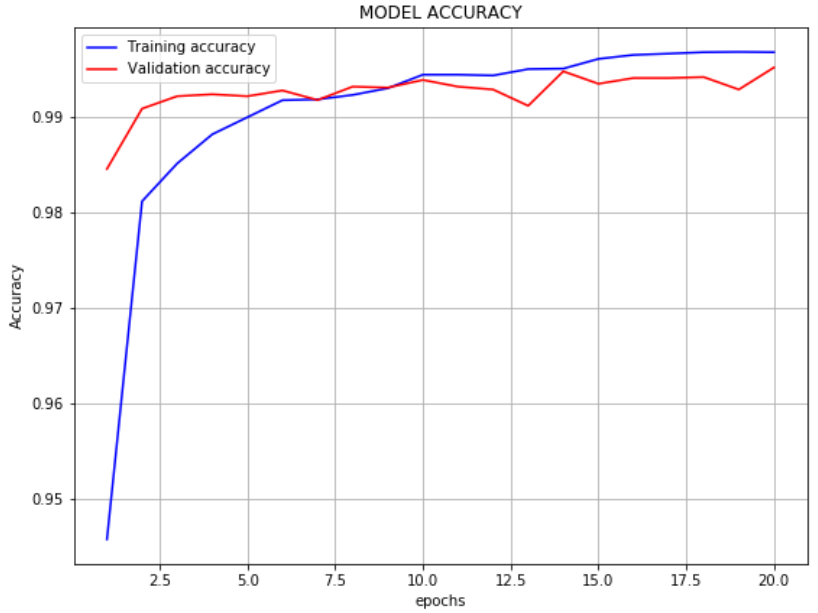
In [0]:

```
#plotting all the results
def plots(model_h):


  plt.figure(figsize = (20,15))
  #plt.grid()
  x = list(range(1,epochs+1))

  #model loss
  plt.subplot(2,2,1)
  plt.title('MODEL LOSS')
  plt.grid()
  plt.plot(x,model_h.history['val_loss'],color = 'b',label = 'Validation Loss')
  plt.plot(x,model_h.history['loss'],color = 'r',label = 'Training loss')
  plt.xlabel('epochs')
  plt.ylabel('Categorical cross entropy')
  plt.legend()

  #model accuracy
  plt.subplot(2,2,2)
  plt.title('MODEL ACCURACY')
  plt.grid()
  plt.plot(x,model_h.history['acc'],color = 'b',label = 'Training accuracy')
  plt.plot(x,model_h.history['val_acc'],color = 'r',label = 'Validation accuracy')
  plt.xlabel('epochs')
  plt.ylabel('Accuracy')
  plt.legend()
  plt.show()
```

In [25]:
```
print('MODEL 1')
history1 = openfromfile('history_1')
plots(history1)
```

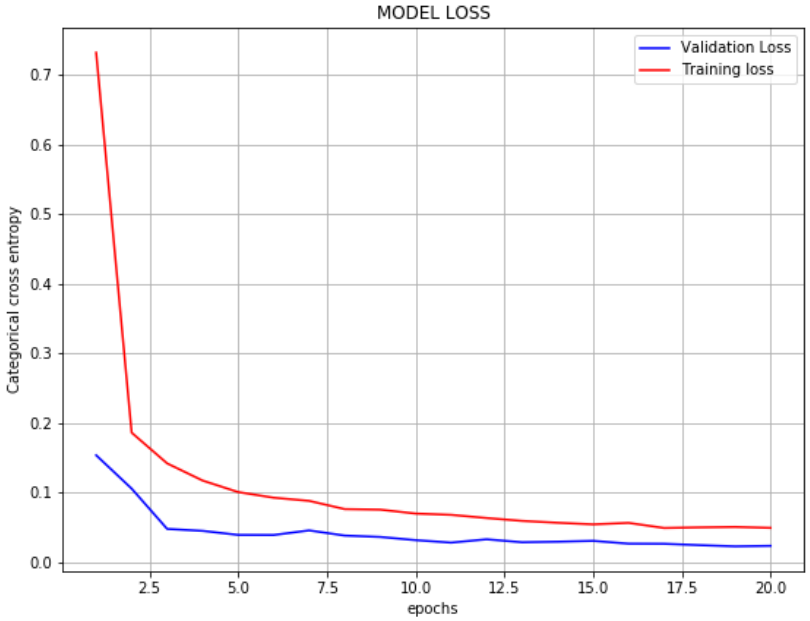
MODEL 1

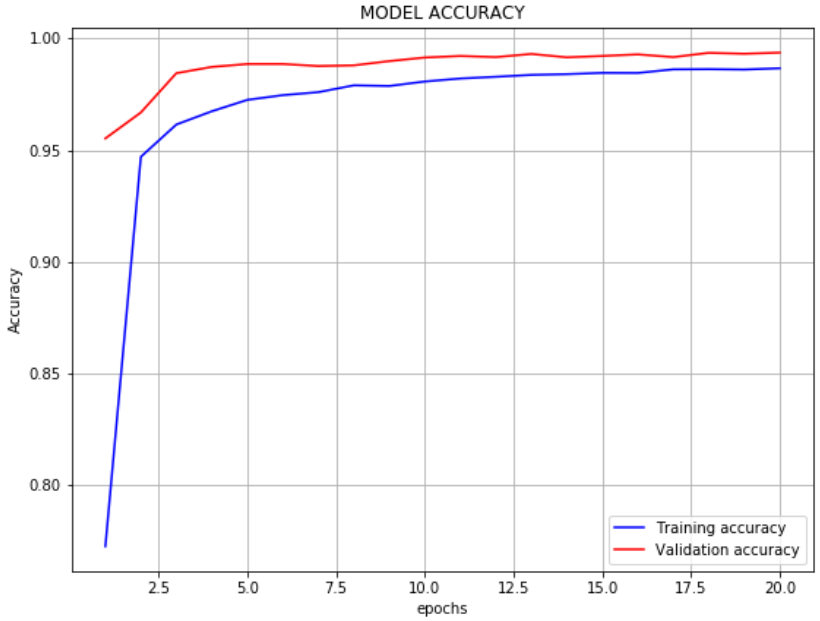




In [26]:
```
history2 = openfromfile('history2')
print('MODEL 2')
plots(history2)
```

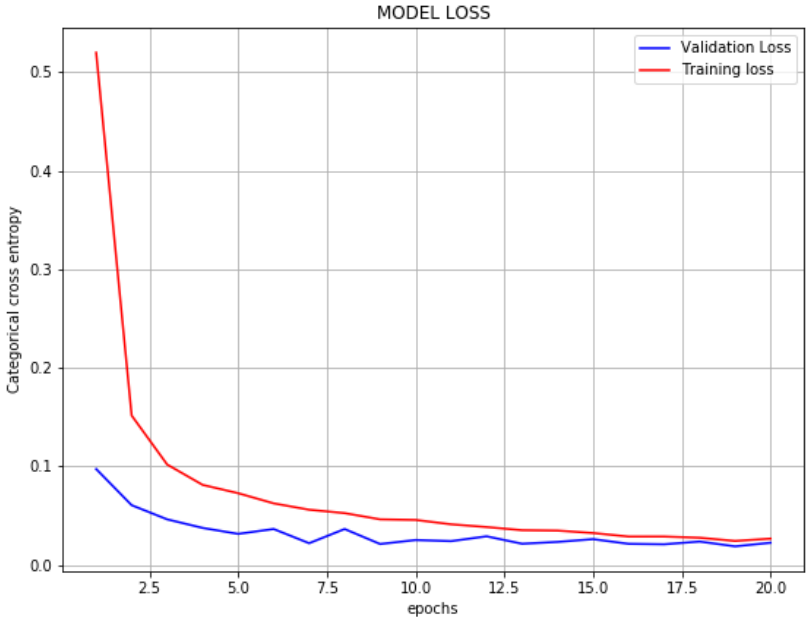
```
MODEL 2
```

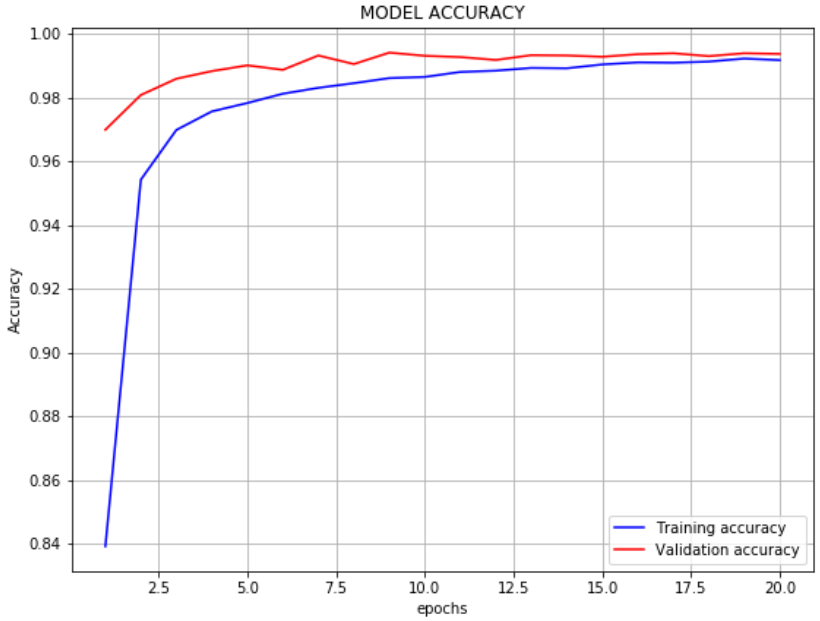




In [27]:
```
history3 = openfromfile('history3')
print('MODEL 3')
plots(history3)
```

```
MODEL 3
```





Best Model with Different parameters

- In this section we will use 3 different models each one following the same architecture but with different tuned parameters

MODEL 1: Removing dropout and batchNormalization layers

In [28]:

```
model = Sequential()

#1st and 2nd layer with maxpooling layer
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None),input_sh
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))


#3rd and 4th layer with maxpooling layer
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))



#5th layer
model.add(Conv2D(128,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))


#flattening adn adding another 2 dense layers with relu activation
model.add(Flatten())
model.add(Dense(256,activation = 'relu',kernel_initializer = he_normal(seed = None)))


model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))


#output layer
model.add(Dense(10,activation = 'softmax'))

print(model.summary())

batch_size = 100
epochs = 20

model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics  = ['accuracy'])

history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = [X_test,Y_test

```

```
Model: "sequential_4"
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_14 (Conv2D)           (None, 26, 26, 32)        320       
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 24, 24, 32)        9248      
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 12, 12, 32)        0         
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 11, 11, 64)        8256      
_________________________________________________________________
conv2d_17 (Conv2D)           (None, 10, 10, 64)        16448     
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_18 (Conv2D)           (None, 1, 1, 128)         204928    
_________________________________________________________________
flatten_4 (Flatten)          (None, 128)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 256)               33024     
_________________________________________________________________
dense_10 (Dense)             (None, 128)               32896     
_________________________________________________________________
dense_11 (Dense)             (None, 10)                1290      
=================================================================
Total params: 306,410
Trainable params: 306,410
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 134us/step - loss: 0.1402 - acc: 0.9563 - val_loss: 0.0402
- val_acc: 0.9872
Epoch 2/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0429 - acc: 0.9866 - val_loss: 0.0407
- val_acc: 0.9864
Epoch 3/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0314 - acc: 0.9903 - val_loss: 0.0309
- val_acc: 0.9906
Epoch 4/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0252 - acc: 0.9918 - val_loss: 0.0289
- val_acc: 0.9910
```

```
Epoch 5/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0193 - acc: 0.9943 - val_loss: 0.0281
- val_acc: 0.9916
Epoch 6/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0162 - acc: 0.9948 - val_loss: 0.0375
- val_acc: 0.9890
Epoch 7/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0141 - acc: 0.9957 - val_loss: 0.0271
- val_acc: 0.9914
Epoch 8/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0135 - acc: 0.9955 - val_loss: 0.0368
- val_acc: 0.9908
Epoch 9/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0108 - acc: 0.9963 - val_loss: 0.0273
- val_acc: 0.9919
Epoch 10/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0106 - acc: 0.9966 - val_loss: 0.0298
- val_acc: 0.9919
Epoch 11/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0092 - acc: 0.9972 - val_loss: 0.0363
- val_acc: 0.9895
Epoch 12/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0101 - acc: 0.9968 - val_loss: 0.0360
- val_acc: 0.9910
Epoch 13/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0080 - acc: 0.9975 - val_loss: 0.0318
- val_acc: 0.9914
Epoch 14/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0067 - acc: 0.9981 - val_loss: 0.0353
- val_acc: 0.9911
Epoch 15/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0066 - acc: 0.9980 - val_loss: 0.0276
- val_acc: 0.9927
Epoch 16/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0091 - acc: 0.9974 - val_loss: 0.0300
- val_acc: 0.9930
Epoch 17/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0053 - acc: 0.9984 - val_loss: 0.0463
- val_acc: 0.9887
Epoch 18/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0060 - acc: 0.9982 - val_loss: 0.0455
- val_acc: 0.9909
Epoch 19/20
```

```
60000/60000 [==============================] - 5s 85us/step - loss: 0.0071 - acc: 0.9980 - val_loss: 0.0380
- val_acc: 0.9922
Epoch 20/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0045 - acc: 0.9987 - val_loss: 0.0346
- val_acc: 0.9927
```

In [0]:
```
history_11 = savetofile(history,'history11')
model_11 = savetofile(model,'model_11')
```

MODEL2: Using Tanh activation function along with glorot normal weight initilization

In [30]:

```
#CNN with 5 layers
from keras.initializers import glorot_normal

model = Sequential()

#1st and 2nd layer with maxpooling layer
model.add(Conv2D(32,kernel_size = 3,activation = 'tanh',kernel_initializer = glorot_normal(seed = None),inpu
model.add(Conv2D(32,kernel_size = 3,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))

#3rd and 4th layer with maxpooling layer
model.add(Conv2D(64,kernel_size = 2,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(Conv2D(64,kernel_size = 2,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))


#5th layer
model.add(Conv2D(128,kernel_size = 5,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(BatchNormalization())
model.add(Dropout(0.4))

#flattening adn adding another 2 dense layers with relu activation
model.add(Flatten())
model.add(Dense(256,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(Dropout(0.4))


model.add(Dense(128,activation = 'tanh',kernel_initializer = glorot_normal(seed = None)))
model.add(Dropout(0.4))


#output layer
model.add(Dense(10,activation = 'softmax'))

print(model.summary())


model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics  = ['accuracy'])
```

```
43
44 history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = [X_test,Y_test
45
46
47
48
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_19 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_20 (Conv2D)           (None, 24, 24, 32)        9248
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 12, 12, 32)        0
_________________________________________________________________
batch_normalization_13 (Batc (None, 12, 12, 32)        128
_________________________________________________________________
dropout_16 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 11, 11, 64)        8256
_________________________________________________________________
conv2d_22 (Conv2D)           (None, 10, 10, 64)        16448
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 5, 5, 64)          0
_________________________________________________________________
batch_normalization_14 (Batc (None, 5, 5, 64)          256
_________________________________________________________________
dropout_17 (Dropout)         (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_23 (Conv2D)           (None, 1, 1, 128)         204928
_________________________________________________________________
batch_normalization_15 (Batc (None, 1, 1, 128)         512
_________________________________________________________________
dropout_18 (Dropout)         (None, 1, 1, 128)         0
_________________________________________________________________
flatten_5 (Flatten)          (None, 128)               0
_________________________________________________________________
dense_12 (Dense)             (None, 256)               33024
_________________________________________________________________
dropout_19 (Dropout)         (None, 256)               0
```

```
_________________________________________________________________
dense_13 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_20 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_14 (Dense)             (None, 10)                1290      
=================================================================
Total params: 307,306
Trainable params: 306,858
Non-trainable params: 448
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.3995 - acc: 0.8748 - val_loss: 0.2793 -
val_acc: 0.9227
Epoch 2/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1660 - acc: 0.9508 - val_loss: 0.1027 -
val_acc: 0.9703
Epoch 3/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.1301 - acc: 0.9621 - val_loss: 0.0946 -
val_acc: 0.9727
Epoch 4/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1192 - acc: 0.9655 - val_loss: 0.4779 -
val_acc: 0.8763
Epoch 5/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1069 - acc: 0.9686 - val_loss: 0.1466 -
val_acc: 0.9570
Epoch 6/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0999 - acc: 0.9712 - val_loss: 0.0786 -
val_acc: 0.9771
Epoch 7/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0942 - acc: 0.9728 - val_loss: 0.0824 -
val_acc: 0.9756
Epoch 8/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0954 - acc: 0.9719 - val_loss: 0.1230 -
val_acc: 0.9637
Epoch 9/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0918 - acc: 0.9738 - val_loss: 0.1418 -
val_acc: 0.9592
Epoch 10/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0879 - acc: 0.9741 - val_loss: 0.0620 -
val_acc: 0.9812
```

```
Epoch 11/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0888 - acc: 0.9744 - val_loss: 0.0724 -
val_acc: 0.9781
Epoch 12/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0839 - acc: 0.9761 - val_loss: 0.0610 -
val_acc: 0.9833
Epoch 13/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0841 - acc: 0.9759 - val_loss: 0.0572 -
val_acc: 0.9850
Epoch 14/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0838 - acc: 0.9760 - val_loss: 0.1263 -
val_acc: 0.9610
Epoch 15/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0807 - acc: 0.9770 - val_loss: 0.0864 -
val_acc: 0.9741
Epoch 16/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0776 - acc: 0.9777 - val_loss: 0.0649 -
val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0778 - acc: 0.9771 - val_loss: 0.0335 -
val_acc: 0.9890
Epoch 18/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0774 - acc: 0.9781 - val_loss: 0.0395 -
val_acc: 0.9875
Epoch 19/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0783 - acc: 0.9780 - val_loss: 0.0443 -
val_acc: 0.9879
Epoch 20/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0761 - acc: 0.9783 - val_loss: 0.0354 -
val_acc: 0.9903
```

In [31]:

```
score = model.evaluate(X_test,Y_test)
print('Loss on test data is',score[0])
print('Accuracy on test data is',score[1])
```

```
10000/10000 [==============================] - 1s 77us/step
Loss on test data is 0.03541449715318158
Accuracy on test data is 0.9903
```

In [0]:

```
history_22 = savetofile(history,'history_22')
model_22 = savetofile(model,'model_22')
```

MODEL 3: Using RMSPROP as optimizer

In [33]:

```
from keras.optimizers import RMSprop

#CNN with 5 layers

model = Sequential()

#1st and 2nd layer with maxpooling layer
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None),input_sh
model.add(Conv2D(32,kernel_size = 3,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))

#3rd and 4th layer with maxpooling layer
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Conv2D(64,kernel_size = 2,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(MaxPooling2D(2,2))
model.add(BatchNormalization())
model.add(Dropout(0.5))


#5th layer
model.add(Conv2D(128,kernel_size = 5,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(BatchNormalization())
model.add(Dropout(0.4))

#flattening adn adding another 2 dense layers with relu activation
model.add(Flatten())
model.add(Dense(256,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Dropout(0.4))


model.add(Dense(128,activation = 'relu',kernel_initializer = he_normal(seed = None)))
model.add(Dropout(0.4))


#output layer
model.add(Dense(10,activation = 'softmax'))

print(model.summary())

model.compile(loss = 'categorical_crossentropy',optimizer = 'RMSProp',metrics  = ['accuracy'])
```

```
43
44 history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,validation_data = [X_test,Y_test
45
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_24 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_25 (Conv2D)           (None, 24, 24, 32)        9248
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 12, 12, 32)        0
_________________________________________________________________
batch_normalization_16 (Batc (None, 12, 12, 32)        128
_________________________________________________________________
dropout_21 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_26 (Conv2D)           (None, 11, 11, 64)        8256
_________________________________________________________________
conv2d_27 (Conv2D)           (None, 10, 10, 64)        16448
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 5, 5, 64)          0
_________________________________________________________________
batch_normalization_17 (Batc (None, 5, 5, 64)          256
_________________________________________________________________
dropout_22 (Dropout)         (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_28 (Conv2D)           (None, 1, 1, 128)         204928
_________________________________________________________________
batch_normalization_18 (Batc (None, 1, 1, 128)         512
_________________________________________________________________
dropout_23 (Dropout)         (None, 1, 1, 128)         0
_________________________________________________________________
flatten_6 (Flatten)          (None, 128)               0
_________________________________________________________________
dense_15 (Dense)             (None, 256)               33024
_________________________________________________________________
dropout_24 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_16 (Dense)             (None, 128)               32896
_________________________________________________________________
```

```
dropout_25 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_17 (Dense)             (None, 10)                1290
=================================================================
Total params: 307,306
Trainable params: 306,858
Non-trainable params: 448
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.5762 - acc: 0.8275 - val_loss: 0.1235 -
val_acc: 0.9669
Epoch 2/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1622 - acc: 0.9568 - val_loss: 0.0620 -
val_acc: 0.9814
Epoch 3/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1273 - acc: 0.9667 - val_loss: 0.0445 -
val_acc: 0.9880
Epoch 4/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1194 - acc: 0.9708 - val_loss: 0.0449 -
val_acc: 0.9869
Epoch 5/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1043 - acc: 0.9740 - val_loss: 0.0541 -
val_acc: 0.9881
Epoch 6/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.1003 - acc: 0.9760 - val_loss: 0.0368 -
val_acc: 0.9913
Epoch 7/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1030 - acc: 0.9761 - val_loss: 0.0338 -
val_acc: 0.9910
Epoch 8/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0971 - acc: 0.9776 - val_loss: 0.0399 -
val_acc: 0.9903
Epoch 9/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0977 - acc: 0.9786 - val_loss: 0.0408 -
val_acc: 0.9903
Epoch 10/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0964 - acc: 0.9787 - val_loss: 0.0398 - v
al_acc: 0.9912
Epoch 11/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0967 - acc: 0.9796 - val_loss: 0.0368 - v
al_acc: 0.9927
```

```
Epoch 12/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0964 - acc: 0.9797 - val_loss: 0.0406 -
val_acc: 0.9915
Epoch 13/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0951 - acc: 0.9804 - val_loss: 0.0447 -
val_acc: 0.9907
Epoch 14/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0940 - acc: 0.9805 - val_loss: 0.0401 -
val_acc: 0.9911
Epoch 15/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0939 - acc: 0.9803 - val_loss: 0.0366 -
val_acc: 0.9921
Epoch 16/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0875 - acc: 0.9820 - val_loss: 0.0363 - v
al_acc: 0.9923
Epoch 17/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0978 - acc: 0.9809 - val_loss: 0.0464 -
val_acc: 0.9903
Epoch 18/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0975 - acc: 0.9815 - val_loss: 0.0497 -
val_acc: 0.9909
Epoch 19/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0921 - acc: 0.9816 - val_loss: 0.0516 -
val_acc: 0.9894
Epoch 20/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0919 - acc: 0.9821 - val_loss: 0.0466 -
val_acc: 0.9907
```

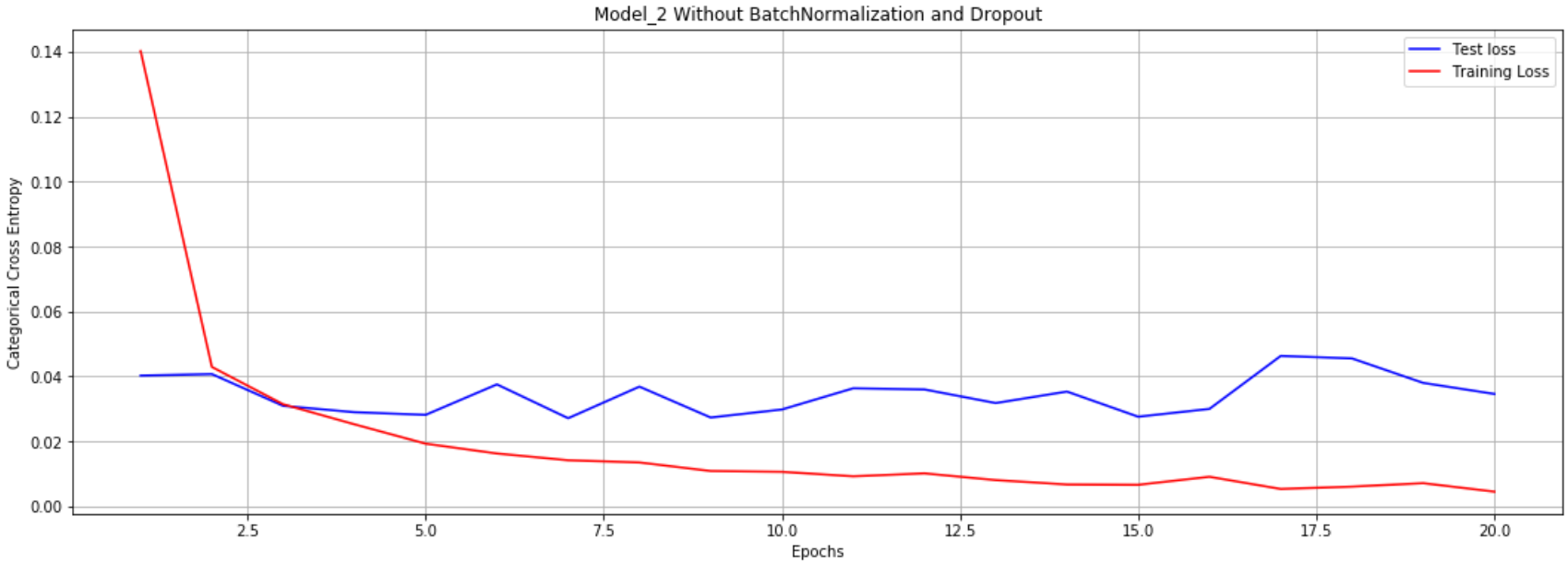
In [34]:

```
score = model.evaluate(X_test,Y_test)
print('loss on test data is: ',score[0])
print('Accuracy on test data is:',score[1])

history_33 = savetofile(history,'history_33')
model_33 = savetofile(model,'model33')
```

```
10000/10000 [==============================] - 1s 78us/step
loss on test data is:  0.046560718773310396
Accuracy on test data is: 0.9907
```

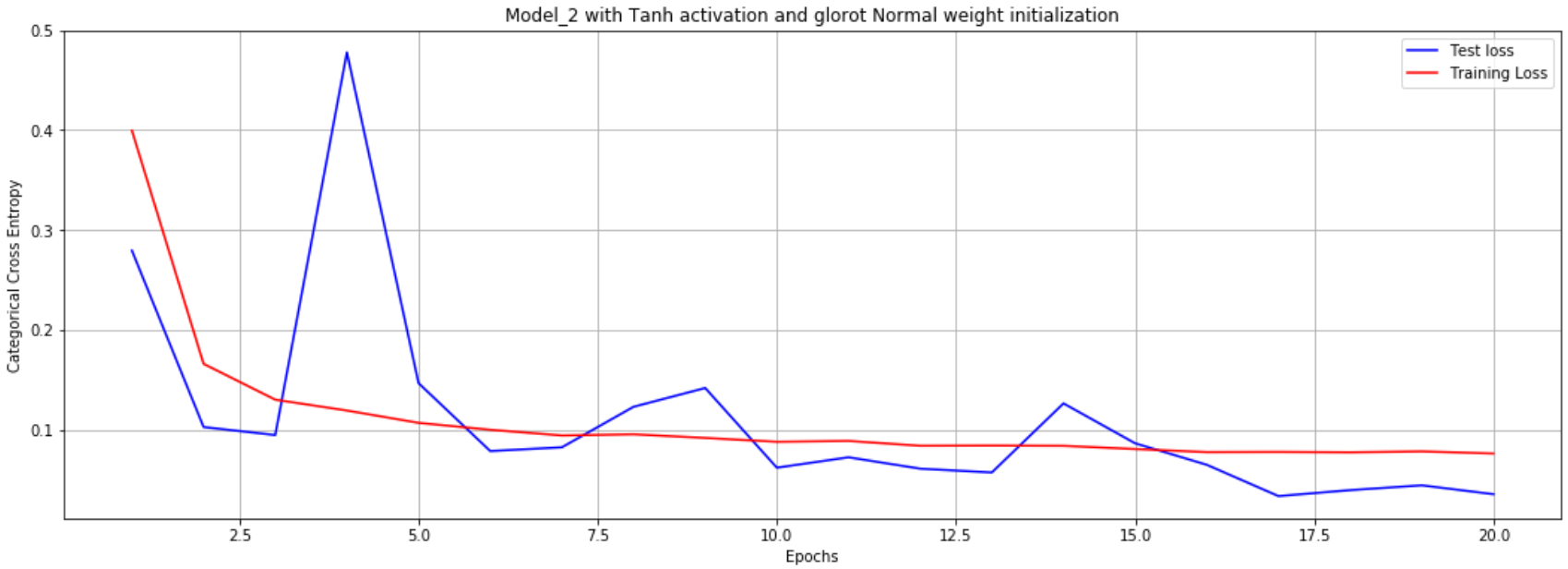
In [0]:
```
def diff_ops(model_h,text):

  x = list(range(1,(epochs)+1))#definig the bin size on the x axis as we want to plot for each of the epochs
  plt.figure(figsize = (18,6))
  plt.grid()
  plt.plot(x,model_h.history['val_loss'],'b',label = 'Test loss')
  plt.plot(x,model_h.history['loss'],'r',label = 'Training Loss')
  plt.xlabel('Epochs')
  plt.ylabel('Categorical Cross Entropy')
  plt.title(text)
  plt.legend(loc = 'best')
  plt.show()
```

In [36]:
```
text = 'Model_2 Without BatchNormalization and Dropout'
diff_ops(openfromfile('history11'),text)

```



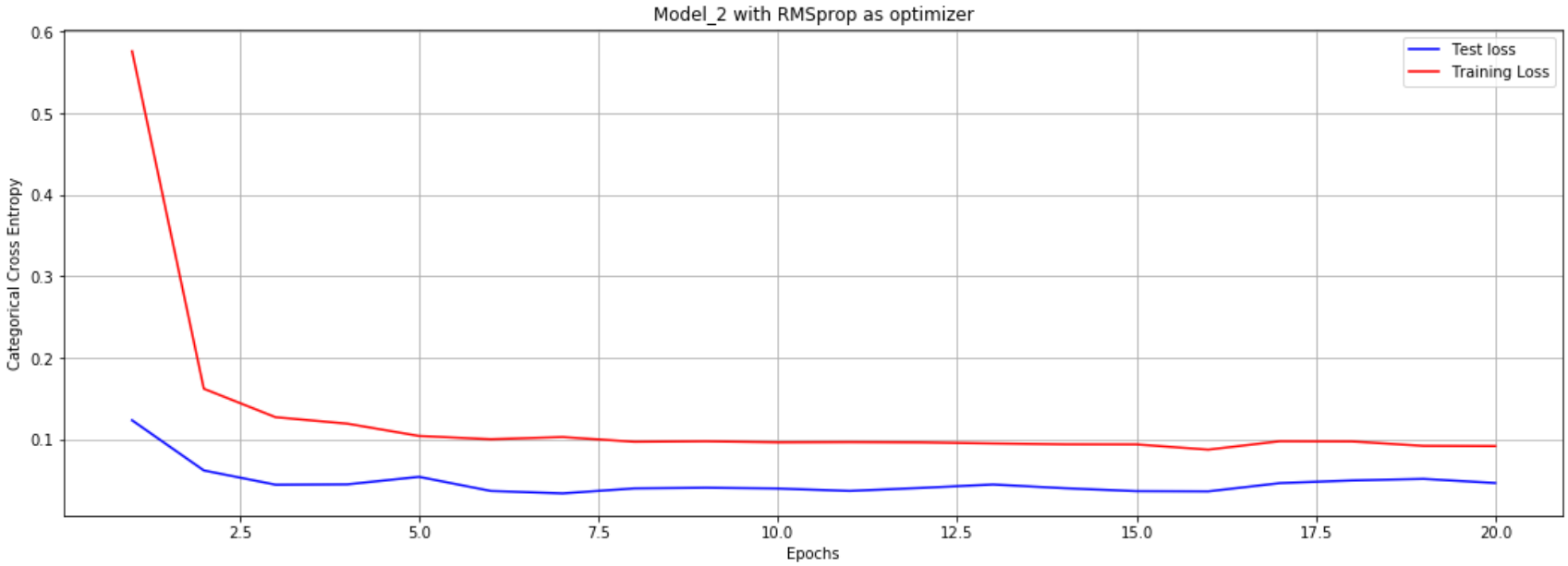
We removed the BatchNormalization layer and the Dropout layers for the best performing model,so as to experiment with overfitting of the model.As it can be clearly seen that model leraned well on the training data ,but performing generalization by this model was not as easy task.Though it gives an accuracy of 99.13 % on test data becuase of low complexity and unsophisticated MNIST data,but it can be clearly observed that the loss is fluctuating with each epoch like an unsmoothed sinusoidal wave.

In [37]:
```
#plot_2
text = 'Model_2 with Tanh activation and glorot Normal weight initialization'
diff_ops(openfromfile('history_22'),text)
```



from the above graph we can clearly observe that using a different activation function 'Tanh' and initializing the weights using glorot deacreased the accuracy by 1%,though surprisingly the model performed better on test data than the train data after few initial epochs i.e generalization accuracy comes to be higher and loss lower in this case. Sudden increase in the loss around 3rd epoch can be undertood from the concept of vanishing gradients.

In [38]:
```
1 text = 'Model_2 with RMSprop as optimizer'
2 diff_ops(openfromfile('history_33'),text)
```



Here we see that using RMSProp as the optimizer instead of Adam has no significant impact,the accuracy on test is more or less same,also the execution time on test data is also same.As the data we are using is trivial ,that's why RMSProp also converges fastly.

Conclusion

In [41]:

```
from prettytable import PrettyTable

table_arch1 = PrettyTable()
models = ['2 Convolution layers + 1 pooling layer  + 1 Dense layer + Adam ','5 Convolution layers + 2 poolin
          '6 Convolution layers + 1 6 pooling layers + 2 Dense Layers + Adam']
tr_loss = [history1.history['loss'][19],history2.history['loss'][19],history3.history['loss'][19]]
tr_acc = [history1.history['acc'][19],history2.history['acc'][19],history3.history['acc'][19]]
te_loss = [score_model1[0],score_model2[0],score_model3[0]]
te_acc = [score_model1[1],score_model2[1],score_model3[1]]

table_arch1.add_column('Model',models)
table_arch1.add_column('trainig loss',tr_loss)
table_arch1.add_column('Training Accuracy(%)',tr_acc)
table_arch1.add_column('Test loss',te_loss)
table_arch1.add_column('Test_Accuracy(%)',te_acc)
print('\t\t\t\t\t\t\t\t 3 Different CNN architectures')
print(table_arch1)
print('\n\n\n')


#table after tuning the best performing model

score_model11 = openfromfile('model_11').evaluate(X_test,Y_test,verbose = 0)
score_model22 = openfromfile('model_22').evaluate(X_test,Y_test,verbose = 0)
score_model33 = openfromfile('model33').evaluate(X_test,Y_test,verbose = 0)

table_arch2 = PrettyTable()
models = ['Model_2 without BatchNormalization and Dropout','Model_2 with using Tanh activation and glorot no
          'Model_2 with RMSProp optimizer']
tr_loss = [openfromfile('history11').history['loss'][19],openfromfile('history_22').history['loss'][19],open
tr_acc = [openfromfile('history11').history['acc'][19],openfromfile('history_22').history['acc'][19],openfro
te_loss = [score_model11[0],score_model22[0],score_model33[0]]
te_acc = [score_model11[1],score_model22[1],score_model33[1]]

table_arch2.add_column('Model',models)
table_arch2.add_column('trainig loss',tr_loss)
table_arch2.add_column('Training Accuracy(%)',tr_acc)
table_arch2.add_column('Test loss',te_loss)
table_arch2.add_column('Test_Accuracy(%)',te_acc)
print('\t\t\t\t\t\t\t\t Different output of best performing model')
print(table_arch2)
```

```
43 print('\n\n\n')
44
45
46
47
```

```
                                                                3 Different CNN architectures
+-------------------------------------------------------------------------+----------------------+----------------
------+----------------------+------------------+
|                                Model                                    |     trainig loss     | Training Accura
cy(%) |      Test loss       | Test_Accuracy(%) |
+-------------------------------------------------------------------------+----------------------+----------------
------+----------------------+------------------+
|  2 Convolution layers + 1 pooling layer  + 1 Dense layer + Adam   | 0.009973527063508906 |  0.996700003147
1253  | 0.01964392685413427  |      0.9951      |
|   5 Convolution layers + 2 pooling layer + 2 Dense Layers +Adam   | 0.04901980113451524  |  0.986700010200
3416  | 0.023159436680417637 |      0.9937      |
| 6 Convolution layers + 1 6 pooling layers + 2 Dense Layers + Adam |  0.0268287254908743  |  0.991850007375
0813  | 0.01964392685413427  |      0.9951      |
+-------------------------------------------------------------------------+----------------------+----------------
------+----------------------+------------------+



                                                                Different output of best performing model
+-------------------------------------------------------------------------+----------------------+---------
------------+----------------------+------------------+
|                                Model                                    |     trainig loss     | Training
Accuracy(%) |      Test loss       | Test_Accuracy(%) |
+-------------------------------------------------------------------------+----------------------+---------
------------+----------------------+------------------+
|              Model_2 without BatchNormalization and Dropout             | 0.004473916407167261 |  0.99871
66678905487  | 0.03456393923192763  |      0.9927      |
| Model_2 with using Tanh activation and glorot normal weight initializer  |  0.0761473451834172  |  0.97828
33438118299  | 0.03541449715318158  |      0.9903      |
|                      Model_2 with RMSProp optimizer                     | 0.09186855908615446  |  0.98205
00112573306  | 0.046560718773310396 |      0.9907      |
+-------------------------------------------------------------------------+----------------------+---------
------------+----------------------+------------------+
```

#observation A 10 layer CNN which consists of 5 Convolutional layers and 2 maxpooling layers and Dense layers with relu activation and a final softmax output layer gives us the best accuracy of 99.5% on test data and a test loss of 0.018 .BatchNormalization and Dropout rate helps us in avoiding overfitting in such a complex architecture.This also gives us insight of how we can further tune the dropout rates kernel sizes and model with 7 Convolutional layers which is our 3rd model with.We also tried the GridSearch Cross validation on our first model with different kernel sizes,though it increases the training time by huge margin.A subsequent tuning may result in less time complexity

We also observe that removing BatchNormalization and dropout layers from the best performing model leads to overffitting and slow convergence by the model.using Tanh activation and glorot normal weight initialization decreases the accuracy by 1% to 98% where on an average we were getting the accuracy of 99%,which shos that how significant activation function is while initializing the model.RMSprop instead of AdamOptimizer does not have any major impact,and everything remains same more or less.