#MLP ASSIGNMENT OVER MNIST DATASET

###MLP WHICH IS APPLYING THE MULTI LAYER PERCEPTRONS WE USE THIS DEEP LEARNING TECHNIQUES WITH THE HIDDEN LAYERS WITH THE CELLS OF ACTIVATION FUNCTIONA THAT ARE INTERNALLY CONNECTED AND PEFORM THE BACKPRPOGATION INORDER TO REDUCE THE LOSS BETWEEN PREDICTED VALUE AND THE ACTUAL VALUE. WE USE THE OPTIMIASTION FUNCTIONS TO MINIMISE THE LOSS OF STOCHASTIC GRADIENT DESCENT WE WILL CONVERGE TO MINIMISE OUT LOSS. WE WILL TRAIN MODELS AND VALIDATE THE MODELS USING THE TEST DATA.

```
In [0]:
       from keras.utils import np utils
       from keras.datasets import mnist
       import seaborn as sns
       from keras.initializers import RandomNormal
       Using TensorFlow backend.
In [0]:
       import matplotlib.pyplot as plt
       import numpy as np
       import time
In [0]: def dynamicplot(x,validationy,testy,ax):
         ax.plot(x,validationy,label='validatiomn loss')
         ax.plot(x,testy,label='testloss')
         plt.xlabel('epoch')
         plt.ylabel('categroicalcrossentropy')
         plt.legend()
         plt.show()
In [0]: (xtrain,ytrain),(xtest,ytest)=mnist.load data()
       Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz (https://
       s3.amazonaws.com/img-datasets/mnist.npz)
       In [0]: | print(xtrain[0][27])
       In [0]: #the imput is of shape 3dimensional vector
       print(xtrain.shape)
       (60000, 28, 28)
```

```
#we want it as 60000data points and reshape data as 784 which data is 784 pixels
In [0]:
         xtrain=xtrain.reshape(xtrain.shape[0],xtrain.shape[1]*xtrain.shape[2])
         xtest=xtest.reshape(xtest.shape[0],xtest.shape[1]*xtest.shape[2])
         print(xtrain.shape)
         print(xtest.shape)
         (60000, 784)
         (10000, 784)
In [0]:
        print(ytrain.shape)
         (60000,)
In [0]:
        #the values are between 0 and 255
         #normalixzing the data
         xtrain=xtrain/255
         xtest=xtest/255
In [0]: print(xtrain[0])
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In [0]: print(xtrain[0].shape)
         (784,)
In [0]:
         #onehot encode the ytrain just comnverting the features into ccategorical
         ytrain=np_utils.to_categorical(ytrain,10)
         ytest=np_utils.to_categorical(ytest,10)
```

```
In [0]: from keras.models import Sequential
    from keras.layers import Dense,Activation,Dropout
    from keras.layers.normalization import BatchNormalization

outputdimensions=10
    inputdimensions=xtrain.shape[1]
    print(inputdimensions)
```

784

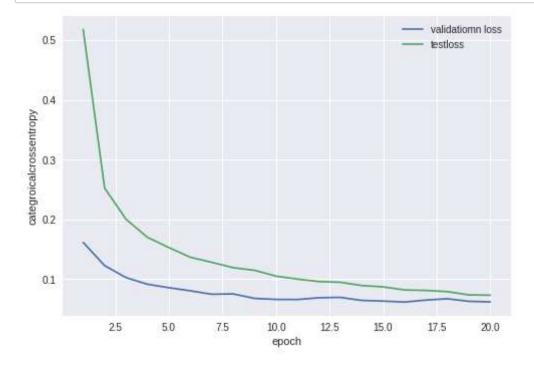
```
In [0]:
    model=Sequential()
     model.add(Dense(364,input_dim=inputdimensions,activation='relu'))
     model.add(BatchNormalization())
     model.add(Dropout(0.5))
     model.add(Dense(52,activation='relu'))
     model.add(BatchNormalization())
     model.add(Dropout(0.5))
     model.add(Dense(10,activation='softmax'))
     model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accurac'
     history=model.fit(xtrain,ytrain,batch_size=128,epochs=20,validation_data=(xtest,
    Train on 60000 samples, validate on 10000 samples
    Epoch 1/20
    acc: 0.8458 - val_loss: 0.1616 - val_acc: 0.9501
    Epoch 2/20
    acc: 0.9274 - val_loss: 0.1228 - val_acc: 0.9627
    Epoch 3/20
    acc: 0.9425 - val_loss: 0.1027 - val_acc: 0.9691
    Epoch 4/20
    acc: 0.9508 - val_loss: 0.0916 - val_acc: 0.9721
    acc: 0.9551 - val loss: 0.0858 - val acc: 0.9741
    Epoch 6/20
    acc: 0.9608 - val_loss: 0.0807 - val_acc: 0.9745
    Epoch 7/20
    acc: 0.9625 - val_loss: 0.0749 - val_acc: 0.9781
    Epoch 8/20
    acc: 0.9653 - val_loss: 0.0755 - val_acc: 0.9778
    Epoch 9/20
    60000/60000 [============ ] - 12s 200us/step - loss: 0.1149 -
    acc: 0.9665 - val loss: 0.0679 - val acc: 0.9802
    Epoch 10/20
    60000/60000 [============ ] - 12s 200us/step - loss: 0.1052 -
    acc: 0.9693 - val loss: 0.0663 - val acc: 0.9803
    Epoch 11/20
    acc: 0.9699 - val_loss: 0.0660 - val_acc: 0.9804
    Epoch 12/20
    acc: 0.9715 - val loss: 0.0690 - val acc: 0.9799
    Epoch 13/20
    acc: 0.9720 - val loss: 0.0697 - val acc: 0.9786
    Epoch 14/20
    acc: 0.9735 - val loss: 0.0646 - val acc: 0.9798
    Epoch 15/20
```

```
acc: 0.9739 - val loss: 0.0634 - val acc: 0.9817
Epoch 16/20
acc: 0.9757 - val_loss: 0.0618 - val_acc: 0.9818
Epoch 17/20
60000/60000 [============ ] - 12s 196us/step - loss: 0.0813 -
acc: 0.9757 - val_loss: 0.0651 - val_acc: 0.9809
Epoch 18/20
acc: 0.9763 - val loss: 0.0674 - val acc: 0.9809
Epoch 19/20
acc: 0.9778 - val_loss: 0.0631 - val_acc: 0.9813
Epoch 20/20
60000/60000 [============= ] - 12s 207us/step - loss: 0.0733 -
acc: 0.9784 - val_loss: 0.0621 - val_acc: 0.9816
```

```
In [0]: score=model.evaluate(xtest,ytest,verbose=0)
    print('test score',score[0])
    print('test accuracy',score[1])
```

test score 0.0621104669367196 test accuracy 0.9816

```
In [0]: fig,ax=plt.subplots()
    x=list(range(1,21))
    validationy=history.history['val_loss']
    testy=history.history['loss']
    dynamicplot(x,validationy,testy,ax)
```



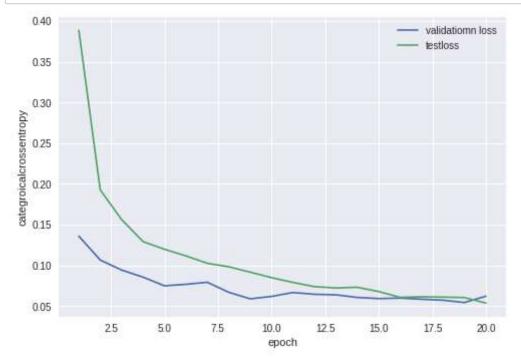
```
In [0]:
     model1=Sequential()
     model1.add(Dense(364,input dim=inputdimensions,activation='relu'))
     model1.add(BatchNormalization())
     model1.add(Dropout(0.5))
     model1.add(Dense(512,input dim=inputdimensions,activation='relu'))
     model1.add(BatchNormalization())
     model1.add(Dropout(0.2))
     model1.add(Dense(52,activation='relu'))
     model1.add(BatchNormalization())
     model1.add(Dropout(0.3))
     model1.add(Dense(10,activation='softmax'))
     model1.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accura
     history=model1.fit(xtrain,ytrain,batch_size=128,epochs=20,validation_data=(xtest
     Train on 60000 samples, validate on 10000 samples
     Epoch 1/20
     acc: 0.8828 - val_loss: 0.1358 - val_acc: 0.9583
     Epoch 2/20
     acc: 0.9423 - val_loss: 0.1065 - val_acc: 0.9677
     Epoch 3/20
     acc: 0.9535 - val_loss: 0.0942 - val_acc: 0.9706
     60000/60000 [============ ] - 19s 318us/step - loss: 0.1291 -
     acc: 0.9618 - val loss: 0.0854 - val acc: 0.9735
     Epoch 5/20
     acc: 0.9640 - val_loss: 0.0748 - val_acc: 0.9772
     Epoch 6/20
     acc: 0.9664 - val_loss: 0.0766 - val_acc: 0.9776
     Epoch 7/20
     acc: 0.9685 - val_loss: 0.0791 - val_acc: 0.9762
     Epoch 8/20
     acc: 0.9698 - val loss: 0.0668 - val acc: 0.9806
     60000/60000 [============ ] - 20s 329us/step - loss: 0.0916 -
     acc: 0.9720 - val loss: 0.0588 - val acc: 0.9805
     Epoch 10/20
     acc: 0.9746 - val_loss: 0.0618 - val_acc: 0.9815
     Epoch 11/20
     acc: 0.9759 - val loss: 0.0666 - val acc: 0.9809
     Epoch 12/20
     acc: 0.9764 - val loss: 0.0644 - val acc: 0.9815
     Epoch 13/20
     60000/60000 [============ ] - 19s 315us/step - loss: 0.0721 -
     acc: 0.9772 - val loss: 0.0637 - val acc: 0.9812
     Epoch 14/20
```

```
acc: 0.9772 - val loss: 0.0605 - val acc: 0.9826
Epoch 15/20
acc: 0.9791 - val_loss: 0.0591 - val_acc: 0.9826
Epoch 16/20
60000/60000 [============ ] - 20s 330us/step - loss: 0.0606 -
acc: 0.9809 - val_loss: 0.0597 - val_acc: 0.9833
Epoch 17/20
acc: 0.9797 - val loss: 0.0583 - val acc: 0.9832
acc: 0.9799 - val_loss: 0.0571 - val_acc: 0.9836
Epoch 19/20
acc: 0.9806 - val_loss: 0.0542 - val_acc: 0.9846
Epoch 20/20
acc: 0.9830 - val_loss: 0.0620 - val_acc: 0.9827
```

In [0]: score=model.evaluate(xtest,ytest,verbose=0)
 print('test score',score[0])
 print('test accuracy',score[1])

test score 0.0621104669367196 test accuracy 0.9816

In [0]: fig,ax=plt.subplots()
 x=list(range(1,21))
 validationy=history.history['val_loss']
 testy=history.history['loss']
 dynamicplot(x,validationy,testy,ax)

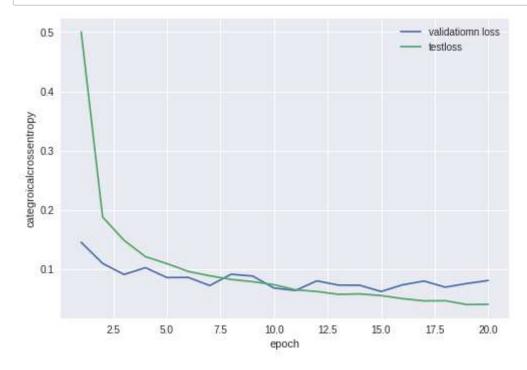


```
In [0]:
     model2=Sequential()
      model2.add(Dense(364,input dim=inputdimensions,activation='relu'))
      model2.add(BatchNormalization())
      model2.add(Dropout(0.2))
      model2.add(Dense(512,input dim=inputdimensions,activation='relu'))
      model2.add(BatchNormalization())
      model2.add(Dropout(0.3))
      model2.add(Dense(784,input dim=inputdimensions,activation='relu'))
      model2.add(BatchNormalization())
      model2.add(Dropout(0.4))
      model2.add(Dense(512,input dim=inputdimensions,activation='relu'))
      model2.add(BatchNormalization())
      model2.add(Dropout(0.5))
      model2.add(Dense(200,activation='relu'))
      model2.add(BatchNormalization())
      model2.add(Dropout(0.6))
      model2.add(Dense(10,activation='softmax'))
      model2.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accura
      history=model2.fit(xtrain,ytrain,batch_size=128,epochs=20,validation_data=(xtest
     Train on 60000 samples, validate on 10000 samples
     Epoch 1/20
     acc: 0.8530 - val_loss: 0.1449 - val_acc: 0.9583
     acc: 0.9456 - val loss: 0.1093 - val acc: 0.9699
     Epoch 3/20
     acc: 0.9575 - val_loss: 0.0906 - val_acc: 0.9734
     Epoch 4/20
     acc: 0.9648 - val_loss: 0.1021 - val_acc: 0.9707
     Epoch 5/20
     acc: 0.9682 - val_loss: 0.0855 - val_acc: 0.9740
     Epoch 6/20
     acc: 0.9720 - val loss: 0.0856 - val acc: 0.9747
     60000/60000 [============ ] - 26s 433us/step - loss: 0.0884 -
     acc: 0.9749 - val loss: 0.0719 - val acc: 0.9796
     Epoch 8/20
     acc: 0.9765 - val_loss: 0.0910 - val_acc: 0.9759
     Epoch 9/20
     acc: 0.9772 - val loss: 0.0880 - val acc: 0.9745
     Epoch 10/20
     acc: 0.9786 - val loss: 0.0678 - val acc: 0.9803
     Epoch 11/20
     60000/60000 [============ ] - 26s 442us/step - loss: 0.0647 -
     acc: 0.9814 - val loss: 0.0635 - val acc: 0.9811
     Epoch 12/20
     60000/60000 [============ ] - 26s 434us/step - loss: 0.0619 -
```

```
acc: 0.9824 - val loss: 0.0798 - val acc: 0.9798
    Epoch 13/20
    acc: 0.9834 - val_loss: 0.0727 - val_acc: 0.9807
    Epoch 14/20
    60000/60000 [============ ] - 26s 437us/step - loss: 0.0578 -
    acc: 0.9837 - val_loss: 0.0723 - val_acc: 0.9798
    Epoch 15/20
    acc: 0.9838 - val loss: 0.0619 - val acc: 0.9832
    acc: 0.9852 - val_loss: 0.0731 - val_acc: 0.9808
    Epoch 17/20
    acc: 0.9867 - val_loss: 0.0795 - val_acc: 0.9798
    Epoch 18/20
    acc: 0.9863 - val_loss: 0.0692 - val_acc: 0.9814
    Epoch 19/20
    acc: 0.9882 - val_loss: 0.0753 - val_acc: 0.9803
    Epoch 20/20
    acc: 0.9879 - val_loss: 0.0804 - val_acc: 0.9825
In [0]: | score=model.evaluate(xtest,ytest,verbose=0)
    print('test score',score[0])
    print('test accuracy',score[1])
```

test score 0.07184817352769897 test accuracy 0.9785

In [0]: fig,ax=plt.subplots()
 x=list(range(1,21))
 validationy=history.history['val_loss']
 testy=history.history['loss']
 dynamicplot(x,validationy,testy,ax)



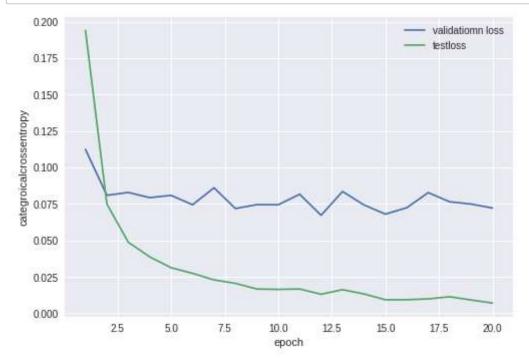
```
In [0]:
     model3=Sequential()
     model3.add(Dense(364,input dim=inputdimensions,activation='relu'))
     model3.add(BatchNormalization())
     model3.add(Dense(512,input dim=inputdimensions,activation='relu'))
     model3.add(BatchNormalization())
     model3.add(Dense(52,activation='relu'))
     model3.add(BatchNormalization())
     model3.add(Dense(10,activation='softmax'))
     model3.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accura
     history=model3.fit(xtrain,ytrain,batch_size=128,epochs=20,validation_data=(xtest
     Train on 60000 samples, validate on 10000 samples
     Epoch 1/20
     acc: 0.9429 - val_loss: 0.1124 - val_acc: 0.9655
     Epoch 2/20
     acc: 0.9768 - val_loss: 0.0809 - val_acc: 0.9734
     Epoch 3/20
     acc: 0.9845 - val_loss: 0.0829 - val_acc: 0.9732
     Epoch 4/20
     acc: 0.9879 - val_loss: 0.0793 - val_acc: 0.9748
     acc: 0.9897 - val loss: 0.0809 - val acc: 0.9766
     Epoch 6/20
     60000/60000 [============= ] - 10s 166us/step - loss: 0.0275 -
     acc: 0.9910 - val_loss: 0.0745 - val_acc: 0.9777
     Epoch 7/20
     acc: 0.9925 - val_loss: 0.0861 - val_acc: 0.9740
     Epoch 8/20
     acc: 0.9929 - val_loss: 0.0719 - val_acc: 0.9787
     Epoch 9/20
     60000/60000 [============ ] - 10s 168us/step - loss: 0.0167 -
     acc: 0.9945 - val loss: 0.0745 - val acc: 0.9789
     Epoch 10/20
     60000/60000 [============ ] - 10s 166us/step - loss: 0.0164 -
     acc: 0.9944 - val loss: 0.0745 - val acc: 0.9802
     Epoch 11/20
     acc: 0.9946 - val_loss: 0.0817 - val_acc: 0.9775
     Epoch 12/20
     acc: 0.9957 - val loss: 0.0673 - val acc: 0.9819
     Epoch 13/20
     acc: 0.9942 - val loss: 0.0836 - val acc: 0.9785
     Epoch 14/20
     60000/60000 [============ ] - 10s 167us/step - loss: 0.0133 -
     acc: 0.9955 - val loss: 0.0744 - val acc: 0.9806
     Epoch 15/20
```

```
acc: 0.9970 - val loss: 0.0680 - val acc: 0.9813
Epoch 16/20
acc: 0.9969 - val_loss: 0.0724 - val_acc: 0.9807
Epoch 17/20
60000/60000 [============ ] - 10s 167us/step - loss: 0.0099 -
acc: 0.9966 - val_loss: 0.0828 - val_acc: 0.9790
Epoch 18/20
acc: 0.9962 - val loss: 0.0765 - val acc: 0.9816
Epoch 19/20
acc: 0.9971 - val_loss: 0.0749 - val_acc: 0.9812
Epoch 20/20
60000/60000 [============= ] - 12s 197us/step - loss: 0.0071 -
acc: 0.9976 - val_loss: 0.0722 - val_acc: 0.9818
```

```
In [0]: score=model.evaluate(xtest,ytest,verbose=0)
    print('test score',score[0])
    print('test accuracy',score[1])
```

test score 0.12161973871234805 test accuracy 0.9695

```
In [0]: fig,ax=plt.subplots()
    x=list(range(1,21))
    validationy=history.history['val_loss']
    testy=history.history['loss']
    dynamicplot(x,validationy,testy,ax)
```



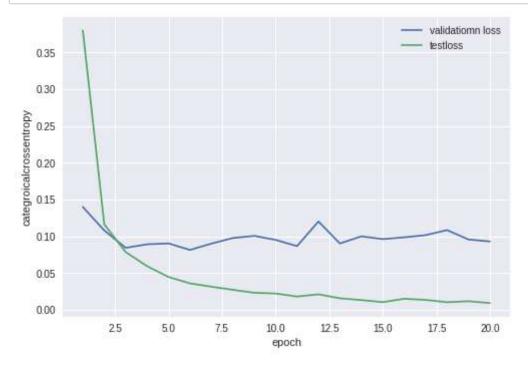
```
In [0]:
     model4=Sequential()
     model4.add(Dense(364,input_dim=inputdimensions,activation='relu'))
     model4.add(Dense(512,input dim=inputdimensions,activation='relu'))
     model4.add(Dense(20,input dim=inputdimensions,activation='relu'))
     model4.add(Dense(10,input_dim=inputdimensions,activation='relu'))
     model4.add(Dense(60,input_dim=inputdimensions,activation='relu'))
     model4.add(Dense(52,activation='relu'))
     model4.add(Dense(10,activation='softmax'))
     model4.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accura
     history1=model4.fit(xtrain,ytrain,batch_size=128,epochs=20,validation_data=(xtes
     Train on 60000 samples, validate on 10000 samples
     Epoch 1/20
     acc: 0.8813 - val_loss: 0.1399 - val_acc: 0.9600
     Epoch 2/20
     acc: 0.9656 - val_loss: 0.1081 - val_acc: 0.9672
     Epoch 3/20
     acc: 0.9764 - val_loss: 0.0844 - val_acc: 0.9759
     Epoch 4/20
     acc: 0.9820 - val_loss: 0.0892 - val_acc: 0.9752
     acc: 0.9858 - val loss: 0.0905 - val acc: 0.9742
     Epoch 6/20
     acc: 0.9886 - val_loss: 0.0816 - val_acc: 0.9773
     Epoch 7/20
     acc: 0.9901 - val_loss: 0.0901 - val_acc: 0.9769
     Epoch 8/20
     60000/60000 [============ ] - 15s 252us/step - loss: 0.0274 -
     acc: 0.9913 - val_loss: 0.0977 - val_acc: 0.9756
     Epoch 9/20
     60000/60000 [============ ] - 15s 252us/step - loss: 0.0234 -
     acc: 0.9925 - val loss: 0.1007 - val acc: 0.9772
     Epoch 10/20
     60000/60000 [============ ] - 15s 249us/step - loss: 0.0224 -
     acc: 0.9928 - val loss: 0.0952 - val acc: 0.9773
     Epoch 11/20
     acc: 0.9939 - val_loss: 0.0868 - val_acc: 0.9801
     Epoch 12/20
     acc: 0.9935 - val_loss: 0.1202 - val_acc: 0.9717
     Epoch 13/20
     acc: 0.9949 - val loss: 0.0904 - val acc: 0.9805
     Epoch 14/20
     acc: 0.9958 - val loss: 0.1000 - val acc: 0.9789
     Epoch 15/20
```

```
acc: 0.9968 - val loss: 0.0963 - val acc: 0.9806
Epoch 16/20
acc: 0.9952 - val_loss: 0.0987 - val_acc: 0.9793
Epoch 17/20
acc: 0.9960 - val_loss: 0.1016 - val_acc: 0.9789
Epoch 18/20
acc: 0.9968 - val loss: 0.1085 - val acc: 0.9799
Epoch 19/20
acc: 0.9966 - val_loss: 0.0958 - val_acc: 0.9810
Epoch 20/20
acc: 0.9972 - val_loss: 0.0930 - val_acc: 0.9823
```

```
In [0]: score=model.evaluate(xtest,ytest,verbose=0)
    print('test score',score[0])
    print('test accuracy',score[1])
```

test score 0.12161973871234805 test accuracy 0.9695

```
In [0]: fig,ax=plt.subplots()
    x=list(range(1,21))
    validationy=history1.history['val_loss']
    testy=history1.history['loss']
    dynamicplot(x,validationy,testy,ax)
```



with out dropouts and batchnormalisation the test accuracy is decreasing

#DOCUMENTATION CONCLUSION AND KEYTAKEAWAYS.

Out[48]:

| | number of layers | layers | testscore | testsccuracy | using_dropouts | using_batch_normalisation |
|---|---------------------|----------------------------------|-----------|--------------|----------------|---------------------------|
| 1 | 3 | [364, 562, 10] | 0.060 | 0.9820 | yes | yes |
| 2 | 4 | [364, 512, 52, 10] | 0.071 | 0.9785 | yes | yes |
| 3 | 6 | [364, 512, 784, 512, 200, 10] | 0.060 | 0.9785 | yes | yes |
| 4 | 6 | [364, 512, 784, 512, 200, 10] | 0.060 | 0.9785 | no | yes |
| 5 | 6 | [364, 512, 784, 512, 200, 10] | 0.060 | 0.9785 | no | no |

AS THE PART OF ASSIGNEMENT TASKWE USE THE MULTIPLE HIDDEN LAYERS WITH THE DIFFERENT DROPOUT RATES AND BATCH NORMALISATION LAYER. WE USE THE DROPUTS TO PREVENT THE MODEL FORM OVERFITTING WE WILL SWITH OF THE SOME OF THE CELLS IN THE HIDDEN LAYER BASED ON THE PERCENTAGE OF DROPOUT.WE ALSO USE THE BATCH NORMALISATION LAYER TO PERFORM THE BATCHNORMALISATION BECAUSE AFTER WE SEND THE DATA THROUGH THE ACTIVATION FUNCTIONS AND SUMMING WIL HAPPEN OVER THE DATA WHICH LEADS THE DATA TO LOOSE OTS ORIGINAL BEHAVIOR SO WE USE THE BATCH NORMALISATION TO NORMALIE THE DATA.

WE HAVE LOADED THE DATA AND NORMALISED THE OBTAINED DATA.WE CAN USE DIFFERENT ACTIVATION FUNCTIONS LIKE SIGMOID, RELU, TANH AND PERFORM THE ACTIVATION. WE FIT THE DATA. WE VARIED THE NUMBER OF DENSE LAYERS AND THE NUMBER OF CELLS IN THE EACH LAYER AND OBSERVED HOE THE MODEL IS CONVERGING REDUCING THE LOSS OF CATEGORICAL CROSS ENTROPY.WE USING THE GRAPH WE VISUALISED THE MODEL IS CONVERGING AND DEVIATING AND AGAIN CONVERGING O REDUCE ERROR. THE MAIN THING IS WE GONNA CONSIDER THE OUTPUT LAYER AS THE SOFTMAX LAYER IN WHICH THE OUTPUT IS TAKEN IN THE FORM OF PROBABILITIES THAT IT BELONGS TO EACH CLASS LABEL AND WE TAKE MAXIMUM OUT OF THAT PROBABILITY.

###IF WE OBSERVE WE HAVE OBTAINED THE MORE ACCURACY WITH THE SIMPLE MODEL ITESELF USING THE BATCH NORMALISATION AND DROPOUT LAYER. IF WE OBSERVE THE MODELS PERFORMNCE IS REDUCING WHEN THE DROPOUTS AND BATCH NORMALISATION ARE NOT USED.

WITH SIMPLE DEEPLEARNING MODEL OF MLP WITHOUT ANY FEATUERS WE ARE ABLE TOACHIEVE ACCURACY OF 98 PERCENT.

| In [0]: | |
|---------|--|
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