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Rectifying the Problem of Vanishing Gradient Problem using Relu Activation Function Based on Blstm Neural Network

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Abstract: Character reorganization is a big task to apply on Hand written documents, using keyword spotting is best solution in now a days. Here keyword spotting is playing major role to extract the character or manuscripts from unconstrained written text and recognize based on probability of the character or letter and manuscripts. It performs template free spotting with the help of CTC Token passing algorithm. the main problem here while performing back propagation for the neural network to find out the vanishing gradient problem .Reorganization rate will get down because error rate will be more, to keep on to increase the no of hidden layers that will be effect the output time of the neural network .Huge amount of data will be lose during carrying the output value from one layer to another layer through activation function. To simulate the problem with the help of the activation function like sigmoid activation function but accuracy of the character reorganization is very low. Instead of sigmoid to use rectified linear unit (ReLU) will update the neuron never reach to zero the output of the hidden layer.

Keywords: keyword-spotting, BLST, ReLU, CTC

1. INTRODUCTION

Handwritten character reorganization from hand written historical documents is very difficult and challenging task in image processing. With the help of neural network to recognize the characters or numbers. Character reorganization using OCR Technology will be more easy than hand written character, The main task of an OCR is to successfully identify printed text and recognize it because especially in this case to read character from printed document or printed image by input scanners like scanning device so easily identify the input and recognize it because the size of the character or segmentation will be perfect[1] ,to translate the printed character into text character with help of Neural network. where as to read character from handwritten images not accurate because different authors may have different style of hand writing so difficult to segment the character ,probability of character reorganization will very low . to improve reorganization rate of the character to implement efficient Neural network like BLSTM[2] .

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BLSTM means Bidirectional long short term memory it reads the character from both directions of each line of the input. The main issue will be occurring while recognizing the hand written will not produce accurate output of the neural network .here to face the problem is vanishing gradient problem while training the network. Training will be get down from carrying the output of one layer to another layer. The total performance will be get down .the solution of this problem to use efficient activation function.

II. RESEARCH METHODOLOGY

The architectural diagram of proposed system has been discussed. Here various typical steps have been involved to get the accurate result. Initially to implement pre processing

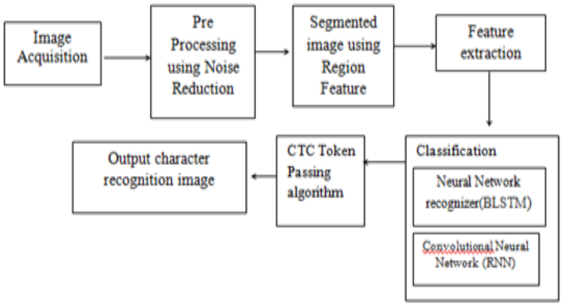

Figure 1. Proposed handwritten character recognition system

followed by segmentation techniques then feature extraction. The output put of feature extraction will be given to input of neural network here use BLSTM Neural network and finally apply CTC Token parsing algorithm [3] .the proposed recognition system is shown in the Fig.1

III. RNN: RECURRENT NEURAL NETWORK

Repeatedly the information of the neural network will be process on a loop will generate the different weights of the network model. Due to the error in the network greatly introduce gradients problem that means the every iteration need to update the weight of the model it is not be stable and exponential growth by the multiple of gradients values, the value of gradient will be range in between more than 1 or less than 1

In recurrent each time steps generate the output Network becomes the input to the next time step would be carried like that and generate gradient value for each iteration due to the value training of the network will be slow down layer by layer [10]

IV.LSTM (LONG SHORT TERM MEMORY)

To overcome this problem in RNN to allow memory in the network to develop long-term Prediction with the help of classification. In this use activation function like sigmoid or tanh functions to avoid vanishing the gradient problem. The input X(t) and h(t-1) here the old output will be replaced with the new output that gate is called forget gate f(t) finally the output of the gate is f(t)*c(t-1)

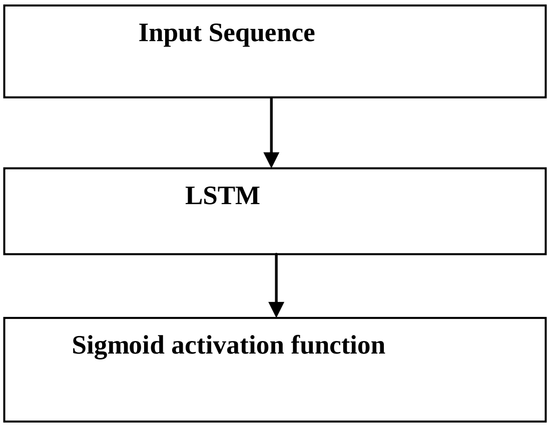

Figure 2: Sigmoid Function To train the network use 784 neurons of layers and the no of hidden layers between the input layers will be 512 and corresponding output layer are 10

train for 5 epochs Train on 80000 sample, validate on 20,000 sample
Epoch 1/5
80000/80000[***********************]3s-loss:0.3612 -acc:0.8802
-val loss:0.2876 -val_acc:0.9091
Epoch 2/5
80000/80000[***********************]-3s -loss:0.3200 -acc:0.8923
-val_loss: 0.2833 -val_acc:0.9193
Epoch 1/5
80000/80000[***********************]-3s-loss:0.3012 -acc:0.9102
-val loss:0.2876 -val_acc:0.9191
Epoch 2/5
80000/80000[***********************]-3s -loss:0.2873 -acc:0.9223
-val_loss: 0.2833 -val_acc:0.9193
Epoch 1/5
80000/80000[***********************]-3s-loss:0.2835 -acc:0.9279
-val loss:0.2976 -val_acc:0.9291
Test accuracy : 0.919

5. BLSTM (Bi Directional Long Short Term Memory)

When comparing with LSTM to achieve more accurate result in the form of accuracy and very low error rate. During the training the neural network calculate the probabilities of sequence letters and it's position at each and every line of the document. This sequence will be moved from one state to another state that can be efficiently used next state, always the new state probability will depend on previous probability of the state. The CTC token passing algorithm use non linear

V. RELU ACTIVATION FUNCTIONS

train for 5 epochs Train on 80000 sample, validate on 20,000 sample
Epoch 1/5
80000/80000[***********************]3s-loss:0.3612 -acc:0.8802
-val loss:0.2876 -val_acc:0.9091
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In sigmoid the range in between -1 and 1 one particular point the gradient will become very strong, automatically to increase the no of hidden layers due to learning speed will be decrees. To consider Relu activation function, the range of the function greater than 1 or less than 1 so the activation value will be 0 for negative values that means some of the neurons not activated [6]. Fewer neurons will be involved in the weight of the network learning speed will be increased for outer layer of the network. For negative values the gradient value reaches 0 because the weights will not change

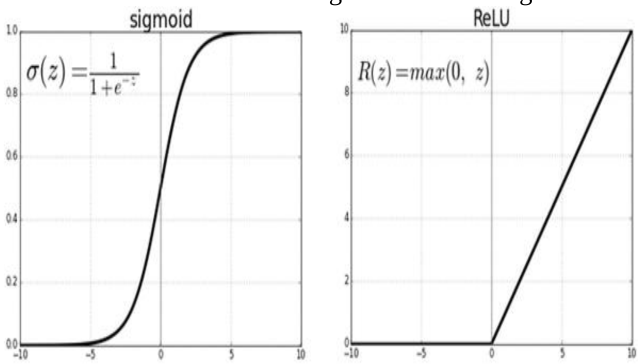

Figure 3: ReLU Vs Sigmoid function

CTC: while training the NN, the CTC is given the RNN output matrix and the ground truth text and it computes the **loss value**. The CTC token parsing gives the matrix and finally changes in to text.

Begin
CTC Parser()
Lower Case Elements (# [a]-[z] #) //identify the lower case letters
Upper Cases Elements (#[A]-[Z]#) or Digits (#[0]-[9]#) // identify the upper case letters
operators using * or+ (Spotting between 0 and ∞ times a character, or spotting between1and ∞ times a character)
#[0]-[9]+#

Lower cases Elements ((#[a]-[z]*)#)
Beginning line(#[a]-[z]*#)
Identify the pixel (#[a]* [z]*#))
Equalize to pixel format(Le[a]-[z]*)
((#le[a]-[z]*#)), or both (# [A]-[Z]o[a]-[z]#)

Convert->text format
S->store
Process->Continue
(# [0-9]*#) or word beginning by one upper case element
(#[A-Z][a-z]*#) word beginning by one lower case element
Relocate Data from Pm to Database
Convert -> number format
S->store
Process->Continue
Relocate number from (#[0-9]*)
Relocate word from (# [A-Z] *[a-z])
End

Performance analysis

The performance analysis of the proposed system is calculated by using some parameters such as recognition rate, accuracy, error rate. The keyword spotting is done using a with the help of CTC Token Passing Algorithm in BLSTM[9].

Recognition Rate:

The recognition rate is the number of words can be recognition in given time

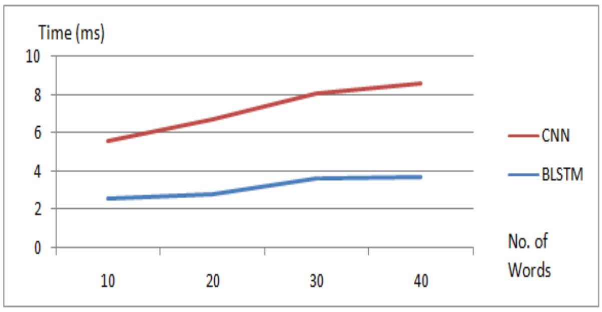

Figure 5: Recognition rate graph

Accuracy:

The accuracy level is calculated by using number of words can be correctly recognized by number of words given.

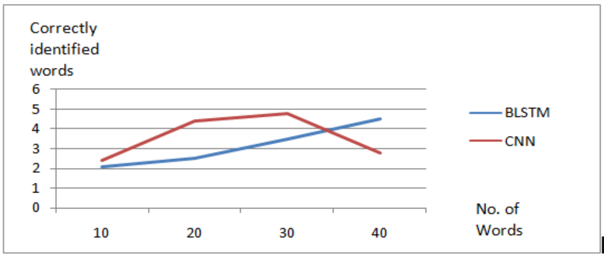

Figure 6: Accuracy level graph

Error rate:

The error rate is calculated by number of words can be incorrectly identified on a given time.

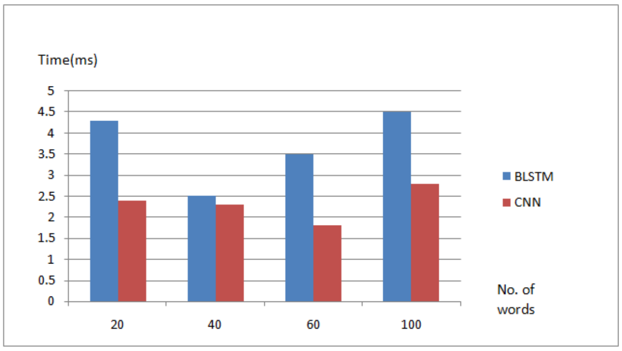

Figure 7: Error rate graph

Parameters	BLSTM	LSTM
	(In Percentage)	
Recognition rate	0.982	0.918
Accuracy	0.982	0.918
Test Loss	0.0645	15

Table 1: Comparison table

VI.CONCLUSION

It is more important to develop efficient character recognition system to produce more accuracy for that to solve the problem of vanishing gradient problem while during training of the neural network[8]. we must use efficient activation function to speed up the process of network training and reduce the loss function , so we can achieve the targeted accuracy of the output. the main aim of the this reorganization system to provide lot of valuable hidden data from historical documents to facilitate to public in the form search engines. Hand written character reorganization system very important even security issues. When compared to CNN, the BLSTM is best to recognize the character in word file.

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