

ONLINE ENGLISH HANDWRITING RECOGNITION USING CNN

Priyanka U Lamani¹, Dr. Lakshman Naika R².

¹P G Scholar, Department of Electronic and communication, UNIVERSITY B.D.T. COLLEGE OF ENGINEERING, DAVANGERE-577004, Karnataka, India.

²Associate Professor, Department of Electronic and communication, UNIVERSITY B.D.T. COLLEGE OF ENGINEERING, DAVANGERE-577004, Karnataka, India.

Abstract - Online Handwriting Recognition is the flow of the handwriting which is recorded on touch sensed screen. The inputs are collected and carried for pre-processing and segmentation then the recognition is done by our trained model. Online Handwriting Recognition is one of the trending, most challenging task to perform with high precise. It is used in real time systems like digitizer, form filling, digital content creation, notes taking etc. For the present report we outline the detail study of demonstration and mechanization used in Online Handwriting Recognition.

KEYWORDS: Online handwriting recognition, Deep Learning, Convolution neural network, Datasets, convolutional layer, pooling layer, fully connected layer.

1. INTRODUCTION

Deep learning has put forward a substantial loop in the field of Machine learning. It uses the concepts of NEURAL NETWORK (NN), CONVOLUTION NEURAL NETWORK (CNN), RECURRENT NEURAL NETWORK (RNN), DEEP REINFORCEMENT LEARNING (DRL) etc. Also, Deep learning pre-owned in health, surveillance, Robotics, Medicine etc. CNN has exist predominantly in Pattern, Speech & Face recognition, Documental analysis. With times the number of sectors are expanding in which Deep learning could be applied. The accuracies over handwritten recognition using CNN now have reached human level perfection. Technological advancements is leading in discovering new methods of human and computer interaction. In present-days Smartphones

and laptops, a touch sensor screen is at hand which makes the handwriting recognition even more easier. we are collecting our own handwriting dataset and training them using neural network for fast prediction with good accuracy.

2. OBJECTIVES: Online handwriting recognition system recognizes the user writings in real-time. The transfer of user inputs to the Characters which can be known by the computer system is carried out dynamically. By this, the rate of speed where the characters written by user are recognized with good precise. The characters recognized having high confidence value is taken. Experimental analysis and results with code implementation and evaluation is concluded.

3. PROBLEM STATEMENT: Online handwriting recognition has set a subject of interest between researchers. It is quite demanding to obtain a good performance as large number of parameters are needed for the wide-range neural networks. Most of the researchers often trying to improve the accuracy level with less considerable loss in CNN. An additional research came up with results that deep networks perform better after training. Meanwhile, our architecture results having high confidence values on proposed dataset.

4.METHODOLOGY: Supervised learning is the used as a key tool in our methodology , where the labeled dataset is used for training the algorithms so that it can classify and predict the outcomes with good accuracy. The technology involves real time input as images following pre-processing step in which the image size is normalized to standard, later segmentation process (i.e , line, word and character segmentation). Prior which each image is fed to the convolution neural network with automated learning it generates the results detailed explanation is seen in further chapters.

5.LITERATURE REVIEW:

[1].English alphabets through the previous decade have been analyzed in this survey paper. Various preprocessing, segmentation methods, feature extraction process. Classification techniques are discussed in detail.

[2].In this, Numerous methods for Handwriting recognition . In general, most of them are both to on-line and off-line recognition approaches. The main differentiation connecting the two is the coordinate of that is being recognized.

[3].Special focus on On-line handwriting recognition with comparison in the middle of continuous & discrete density HMM, its task for both continuous and discrete HMM with samples of data and different feature extraction sets.

[4].In this researcher introduce context dependent hidden markov models for cursive and unconstrained handwriting recognition with vocabularies.

[5].In this method online handwriting recognition using HMM, 4 separate feature experiments were

performed with 4 sets of global-information features, the systems obtained word error rate with 9.1% from the performance of base line system - 13.8%.

[6].It describes that the system is capable of directly transcribing online handwritten data. The system consisting an RNN with output layer outline for Sequence labeling, combined with a probabilistic model.

[7].This paper uses , SVM methodology for recognition rates which are significantly better due to risk minimization, implemented using maximizing margin of separation in Decision function.

[8].Image feature extraction has several constraints such as differences in image capture position and different lightning conditions when the image is taken .there are seven methods dicussed and which have the highest accuracy is the method of CNN.

[9].The objective is to recognize on-line handwritten documents which involves characters, words, lines & paragraphs etc. This approach, recognizes the handwriting by making use of templates, additionally it maintains special user accounts, which allows particular user to create their training sets.

[10].It proposes a on-line handwritten characters recognition algorithm, which is suitable for personal use computer. A handwritten character on digitizer tablet is indicated as a directional Angle sequence, Recognition is carried out using dynamic programming built using pattern matching technique.

6. DESIGN:

CNN is widely used in handwriting recognition. It consists of 3 main layers ;

- Convolutional Layer.

- Pooling Layer.
- Fully Connected Layer.
- Softmax Layer(Additional Layer).

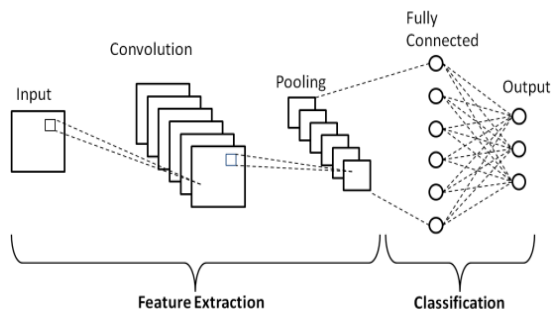


Figure 1:Architecture of Convolution Neural Network

Convolutional layer: The image size is $(S \times S \times 3)$ (height, width, depth) where, $S=80$. Since the image has three channels it is a color image in RGB format.

Convolutional layer makes use of learnable filters which detects the features present in input image. Filter size is 3×3 , Number of filters is 32, Stride=1. This filter is convolved with input layer and fed to activation layer.

Activation function: It is the node put in between neural networks and it is Non-Linear Transformation that is done on the input image and output is forwarded to the next as input. There are different types of activation layers but the key focus in our paper is on the Rectified Linear Unit (ReLU). It converts all negative inputs to zero.

Formula for Activation maps: $(S+2P-F) / s+1$

Where; S = Dimensions of input image; P = Paddings ;
 F = Dimensioning of Filter; s = Stride.

Pooling Layer: This layer is found after convolutional

layer. The function of this layer is reducing the spatial size of the image also reduces number of parameters to learn and the amount of computations performed in the neural network. In particular we use **Max-pooling** (2×2) which helps in extracting low-level features like edges, points etc.

- Formula for Max-pooling: $(S-F) / s+1$.

Fully Connected Layer: The output of final pooling or convolution layer is fed into the fully connected layer which is flattened, assembles the data extracted by preceding layers to shape the output.

Softmax Layer: This layer is also known as logistic layer. It resides at the end of fully connected layer. Logistic is used for binary classification and softmax is for multiple classification.

7. BLOCK DIAGRAM:

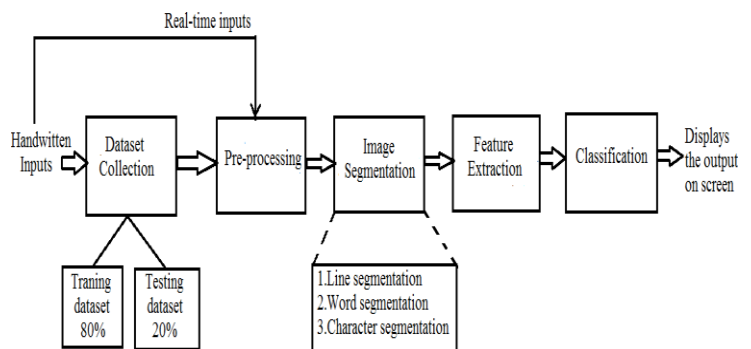


Figure 2:Block Diagram of our proposed Handwriting Recognition using CNN.

The block diagram of our proposed methodology includes:

- Dataset collection
- Pre-processing
- Image segmentation
- Feature extraction
- Classification

The input to the touch sensitive screen i.e, laptop is taken as real time input image. Dataset collection was

easy because it was taken virtually. After the collection of dataset, it is divided into two: Training Dataset-80% and Testing Dataset-20%.

Pre-processing has a sequence of operations to be performed for enhancing and making it fit for image segmentation. In our process, resizing is done to convert the input image to standard.

Image Segmentation is the process of partitioning of an image into multiple segments which makes easier to analyze and understand.

There are 3 types of Segmentations namely,

- Line Segmentation.
- Word Segmentation.
- Character Segmentation.

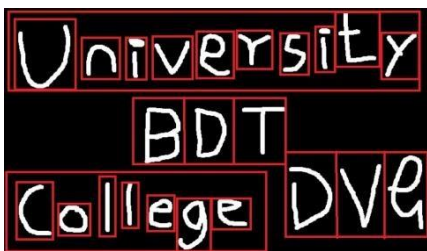


Figure 3: Example of line, word and character segmentation.

Feature extraction is the procedure of collecting sensible information in an image. Followed by Classification, here the classifiers compare the input feature with labeled data, matches with the best fit. This stage is the decision making of the handwriting recognition. The recognized output will be printed in structured text form.

8. ALGORITHM:

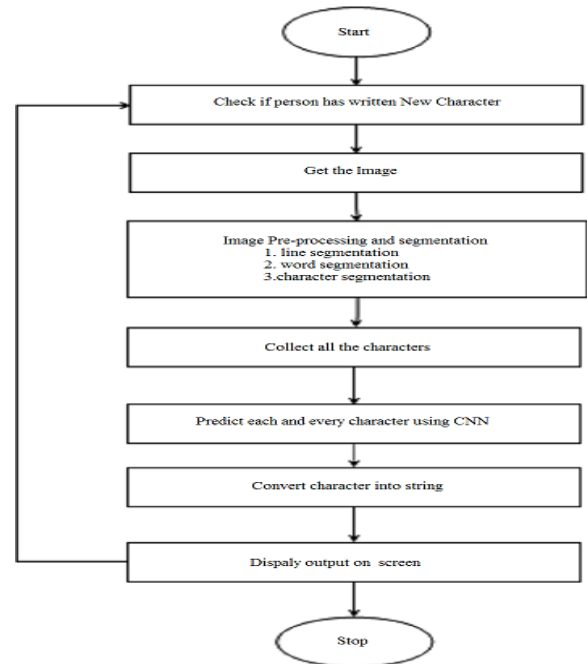


Figure 4: Algorithm for our proposed methodology

1. When a person starts writing on a touch sensor screen collects the user input as image.
2. Upon complete writing waits for 2 secs, then that image is segmented into line, word and characters.
3. All the individual character will be fed as input to the CNN.
4. CNN model is trained and developed such that the character should be predicted having highest confidence value.
5. After prediction, characters are converted into strings and the output displays on the screen.
6. Process repeats until the person is writing.
7. Stops upon complete prediction.

9. Implementation :

9.1 Representation of an image:

An image will be classified into grid of pixel values. i.e, Image size is $80 \times 80 = 6400$ pixels, here image consist of three channels(RGB) with each pixel values varies from 0 to 255. In python, image representation

by default is in BGR format. Hence conversion from BGR to RGB is done. After converting the image is resized to standard size.

Image Normalization commonly used for dataset preparation where the numerous images are placed at statistical distribution in the form of size and pixel values.

9.2 Collection of Dataset:

The data set contains 3100 images of handwritten through virtual mode . For this we used the screen touch laptop where the program has written to collect the data, this reduced the time in collection of data set. Background is set as Black and Foreground is set with White color.

Characters: A-Z, a-z.

Numbers: 0-9.

Image size: 80×80×3.

Number of images for each character/number=50.



Figure 5: Handwritten images along with its label.

9.3 Divide the dataset into training dataset and testing dataset:

Out of total 3100 images, it is divided into two:

Training dataset=2500

Testing dataset=600

Each image size is 80×80×3; where- 3 denotes the number of channels present in image.

9.4 Architecture of the CNN:

CNN consists of Convolutional Layer, Pooling Layer, Fully Connected Layer and Softmax layer. The shape of each layers is set as shown in the below table;

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 78, 78, 32)	896
max_pooling2d_4 (MaxPooling2)	(None, 39, 39, 32)	0
conv2d_5 (Conv2D)	(None, 37, 37, 64)	18496
max_pooling2d_5 (MaxPooling2)	(None, 18, 18, 64)	0
conv2d_6 (Conv2D)	(None, 16, 16, 128)	73856
max_pooling2d_6 (MaxPooling2)	(None, 15, 15, 128)	0
dropout_3 (Dropout)	(None, 15, 15, 128)	0
flatten_2 (Flatten)	(None, 28800)	0
dense_3 (Dense)	(None, 64)	1843264
dropout_4 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 62)	4030
Total params: 1,940,542		
Trainable params: 1,940,542		
Non-trainable params: 0		

Figure 6: CNN model shape and parameters

EPOCHES is the term which implies the number of passes undertakes in training datasets. Datasets are formed into batches . If the batch size is entire training datasets then Number of Epochs will be Number of Iterations.

As shown in the table , In the beginning of epoch the loss was high with less accuracy . Later as the number of iteration increased we got the result at epoch=30 as,

Training: loss=0.063 and accuracy=98%

Testing: loss=0.6757 and accuracy=87.69%

```

epochs = 30
history = model.fit(trainX, trainY, epochs=epochs, batch_size=40, verbose=1)

Epoch 1/30
2502/2502 [=====] - 1s 440us/step - loss: 3.0786 - accuracy: 0.2446
Epoch 2/30
2502/2502 [=====] - 1s 346us/step - loss: 1.3987 - accuracy: 0.6251
Epoch 3/30
2502/2502 [=====] - 1s 346us/step - loss: 0.8274 - accuracy: 0.7566
Epoch 4/30
2502/2502 [=====] - 1s 347us/step - loss: 0.5386 - accuracy: 0.8349
Epoch 5/30
2502/2502 [=====] - 1s 347us/step - loss: 0.3753 - accuracy: 0.8801
    
```

```

Epoch 25/30
2502/2502 [=====] - 1s 350us/step - loss: 0.0475 - accuracy: 0.9840
Epoch 26/30
2502/2502 [=====] - 1s 356us/step - loss: 0.0916 - accuracy: 0.9704
Epoch 27/30
2502/2502 [=====] - 1s 357us/step - loss: 0.0678 - accuracy: 0.9776
Epoch 28/30
2502/2502 [=====] - 1s 354us/step - loss: 0.0571 - accuracy: 0.9820
Epoch 29/30
2502/2502 [=====] - 1s 346us/step - loss: 0.0544 - accuracy: 0.9792
Epoch 30/30
2502/2502 [=====] - 1s 353us/step - loss: 0.0639 - accuracy: 0.9804
    
```

Figure 7: Results of the trained CNN with validation loss and accuracy

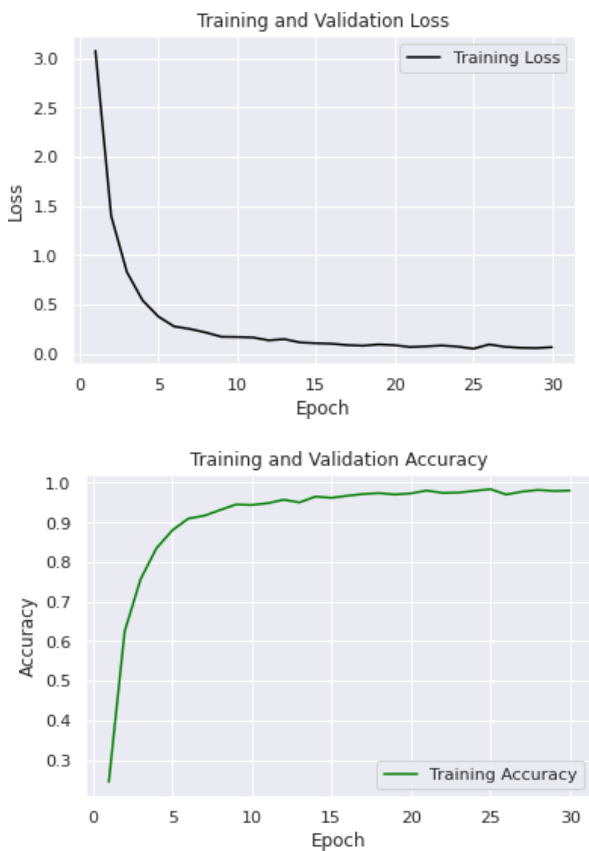


Figure 8: Graphical representation of trained CNN with validation loss and accuracy.

As shown above, the results of above trained CNN can be improved with increasing number of iterations and epochs. The additional benefit of getting high accuracy also depends on the number of hidden layers as this increases the CNN prediction will be more accurate but as the number of layer increases training take more time to be trained.

10. RESULTS AND DISCUSSION:

Online handwriting recognition system recognizes the writing, which is written on touch sensitive screen in real time. This paper discusses about the human and computer interaction context. For taking real time input and displaying the output Tkinter is used. Tkinter is a GUI library used for Python. In order to design GUI applications, Tkinter is integrated with Python.

Real-time user input image is fed to the pre-processing stage, then processed image goes through segmentation process. The segmented images are predicted using CNN model and classifies the output image, where the characters is converted back to string and displays the output in standard text format as shown in the below figure,

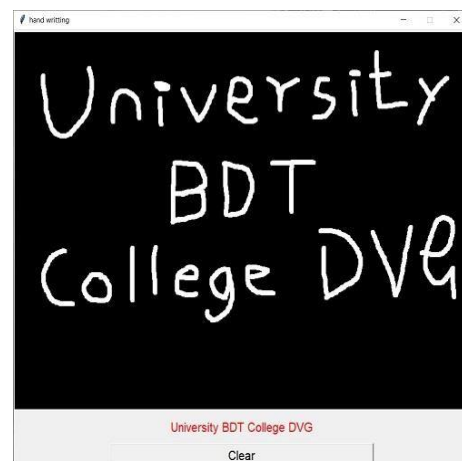


Figure 9: Result of Online Handwriting Recognition.

CONCLUSIONS:

In our paper we introduced online handwriting recognition, where we collected dataset virtually and trained using CNN for classification and hence we accomplished the results having highest confidence

value. This comprehensive discussion will provide a brief idea about the concepts involved in online English handwriting recognition with latest technologies.

FUTURE ENHANCEMENTS:

In the future enhancement the handwriting should be tested for cursive writing, other languages and also for large data sets with other optimized network parameters in order to improve the accuracy level.

REFERENCES:

1. Manoj sonkusare and Narendra sahu" A survey on handwritten character recognition(HCR)techniques for English alphabets" In(AVC) vol.3, No.1, March 2016.
2. Pratishrutisaxena "A review: English online handwriting recognition" national conference on cloud computing and big data.
3. R. Plamondon and S.N.Srihari,"online and offline handwritten character recognition: A Comprehensive Survey", IEEE transaction on pattern analysis and machine intelligence, Vol22, No1,pp-63-84,2000.
4. J.Pradeep, E.Srinivasan, S.Himawathi,"performance analysis of hybrid feature extraction technique for recognizing English handwritten character", 978-1-4763-4805-8/12/2012IEEE.
5. Aanshul Gupta, Manish srivastva, chotraks mahanta,"Off-line Handwritten Character Recognition using Neural Networks" 2011-International Conference on Computer Applications and Industrial Electronics.
6. Aiquanyuan, Gang bai, Lijing jiao, yajieliu,"Offline Handwritten English Character Recognition based on Convolution Neural Network", 2012, 10th IAPR International workshops on document analysis systems.
7. Abdul Rahim Ahmad, Christian Viard-gaudin, Marzuki Khalid, Rubiyah yusuf, "On-line handwriting recognition using SVM", proceeding of the 2nd International Conference on AIET, Aug 3-5 2004, Malaysia.
8. Salma Shofia Roysda and Tito waluyo purboyo , "A review of various handwriting recognition methods", International journal of applied engineering research ISSN 0973-4562 volume13, number2(2018) pp.1155-1164.
9. Farha mehdi, "Online handwritten character recognition:, IOSR journal of computer engineering(IOSR-JCE) e-ISSN:, Issue 5(may-june 2013), pp 30-36
10. Zafar, M.F. Informatics complex, Islamabad mohamad D.anwar, M.M Multitopic conference2006 INMIC 06 IEEE.