

Handwritten Character Recognition: A Comparative Study

Aishani Sengupta, Anubrata Mukherjee, Tanaya Pal, Sourav Das

Department of Information Technology

Narula Institute of Technology, Kolkata, India

aishanisengupta4@gmail.com, anubratamukherjee89@gmail.com,

tanayapalstar@gmail.com, dassourav845@gmail.com

Abstract: *Handwriting recognition is a technique used to interpret intelligible handwritten input and convert it into digital text using Machine Learning tools. This research paper provides a comparison of the application of CRNN and CNN for handwriting recognition, using a dataset containing about 370,000 handwritten names. Our experiments demonstrate that the CRNN hybrid model produces the highest accuracy compared to the CNN model. This paper summarises contributions reported on the A-Z Handwritten Alphabets in .csv format dataset for handwritten character recognition. This dataset has been extensively used to validate novel techniques in computer vision. This paper makes a distinction between those works using some kind of data augmentation and works using the original dataset.*

Keywords: Handwriting recognition, CRNN, CNN

I. INTRODUCTION

Handwritten character recognition (HCR) is a mechanism that enables the translation of different types of documents into analyzable, editable, and searchable data. An ultimate aim of HCR is to emulate human reading capabilities in such a way that the machine can read, edit, and interact with text as a human in a short time. Identification of HCR has drawn great attention from numerous researchers over half a century, and many great achievements have been made in this field.

A computer performing handwriting recognition is defined as a system capable of acquiring and detecting characters or words in a paper document, images, and others converting them into machine-encoded form. To perform these tasks, machine learning algorithms have to be implemented for more advanced intelligent Handwriting recognition. It has contributed immensely to the advancement of automation processes in many fields and made improvements to the interface between man and machine in numerous applications. During the past years, the main focus was on the implementation of new techniques and methods to reduce the processing time while ensuring higher recognition accuracy.

II. OBJECTIVE

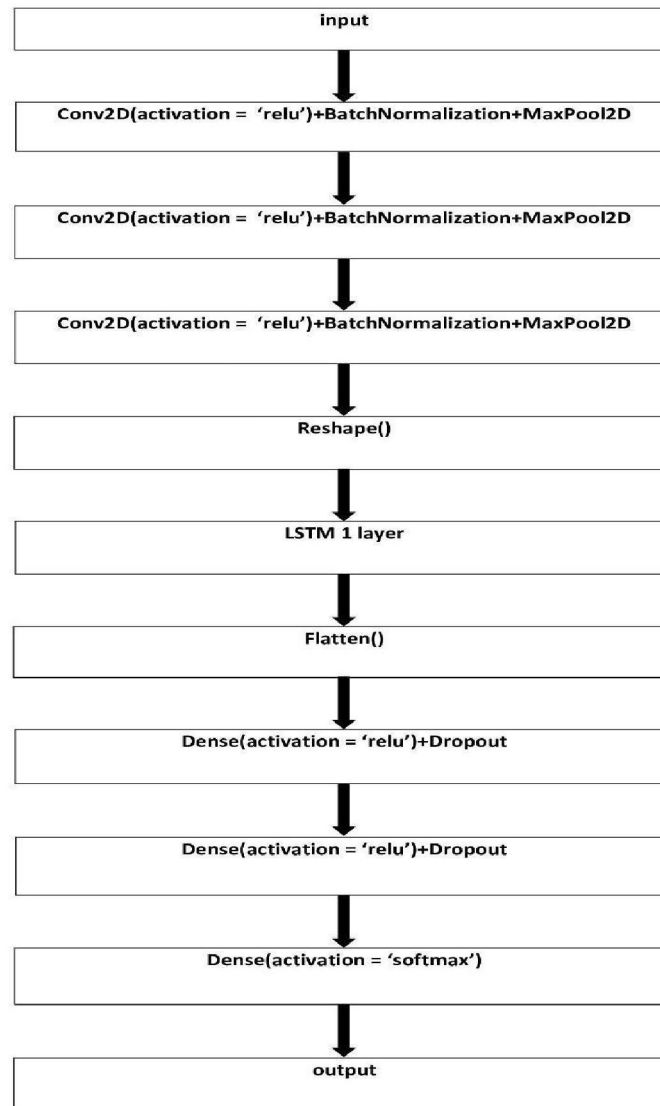
In an attempt to find an accurate machine learning model for Handwriting Recognition, the main objective of this research work is to compare the accuracy of a hybrid Convolutional Recurrent Neural Network (CRNN) model against the Convolutional Neural Network (CNN) model.

III. METHODOLOGY

Model A: CRNN model

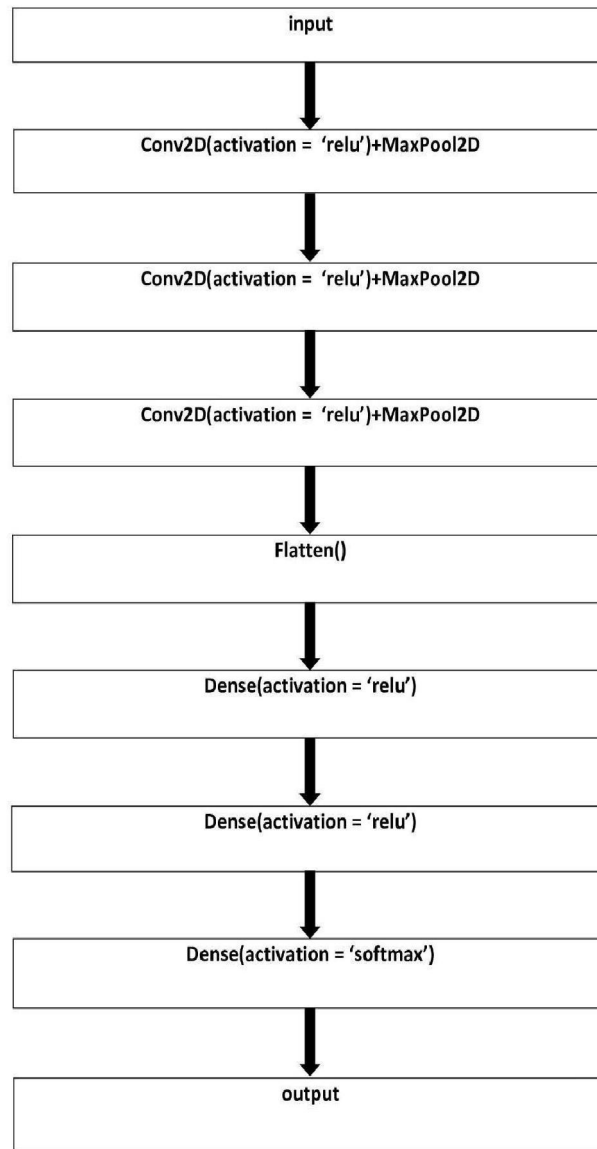
The CRNN model which is a hybrid model is created using the tensor flow and Keras library of Python. The model consists of different layers. Layer 1 where the input is fed and is reshaped into (28,28,1). Layers 2,3 and 4 are Convolutional Layers. Layer 2 creates 32 feature maps as output using 32 different filters. Layer 3 is another Convolutional layer having 64 feature maps while Layer 4 uses 128 feature maps. For the 3 layers of CNN, MaxPooling is used to reduce the spatial size of the image i.e. (2,2), (2,2) and (2,2) respectively, uses a filter of size (3,3) and uses ReLU as the activation function and to stabilize the learning process we added Batch Normalization.

Layer 5 is the RESHAPE Layer it reshapes the convolution layer output for the LSTM layer and Layer 6 is the LSTM layer. In layer 7 we flattened the output of the LSTM layer and in layer 8 and layer 9 we added two dense layers with Relu activation functions with dropout with 0.5 drop rate. Layer 10 is another dense layer where the neurons are activated using SOFTMAX as the activation function. Layer 11 is the last layer that outputs the results.



Model B: CNN model

The CNN model is created using the tensor flow and the Keras library of Python. The model consists of different layers. Layer 1 where the input is fed and is reshaped into (28,28,1). Layers 2,3 and 4 are Convolutional Layers. Layer 2 creates 256 feature maps as output using 256 different filters. Layer 3 is another Convolutional layer having 256 feature maps while Layer 4 uses 128 feature maps. For the 3 layers of CNN, MaxPooling is used to reduce the spatial size of the image i.e. (2,2), (2,2) and (2,2) respectively, uses a filter of size (3,3), and uses ReLU as the activation function. In the 5th layer, we flatten the convolution layer output. In layers 6 and 7 we added two dense layers with activation function relu. Layer 8 is another dense layer where the neurons are activated using SOFTMAX as the activation function. Layer 9 is the last layer that outputs the results.



IV. PROPOSED RECOGNITION SYSTEM

In this section, the proposed recognition system is described. A typical handwriting recognition system consists of pre-processing, segmentation, feature extraction, classification and recognition, and post-processing stages. The schematic diagram of the proposed recognition system is shown in Fig.1

4.1. Image Acquisition

In Image acquisition, the recognition system acquires a scanned image as an input image. The image should have a specific format such as JPEG, BMT, etc. This image is acquired through a scanner, digital camera, or any other suitable digital input device.

4.2. Pre-processing

The pre-processing is a series of operations performed on the scanned input image. It essentially enhances the image rendering it suitable for segmentation. The various tasks performed on the image in the pre-processing stage are shown in Fig.2. The Binarization process converts a grayscale image into a binary image using a global thresholding technique. Detection of edges in the binarized image using the Sobel technique, dilation of the image, and filling the holes present in it are the operations performed in the last two stages to produce the pre-processed image suitable for segmentation.

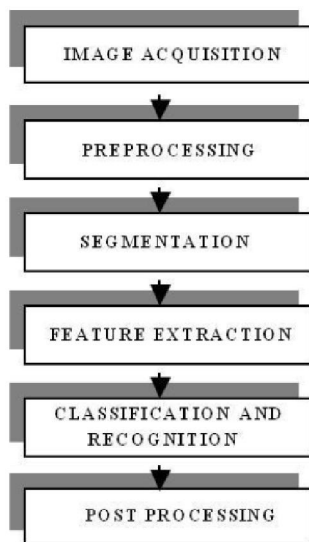


Figure 1. Schematic diagram of the proposed recognition system

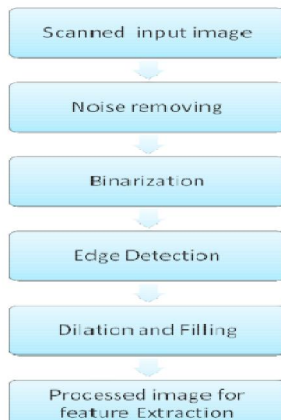


Figure 2. Pre-processing of handwritten character

4.3. Segmentation

In the segmentation stage, an image of a sequence of characters is decomposed into sub-images of individual characters. In the proposed system, the pre-processed input image is segmented into isolated characters by assigning a number to each character using a labeling process. This labelling provides information about several characters in the image. Each character is uniformly resized into pixels for the classification and recognition stage.

V. RESULTS AND DISCUSSION

All the accuracy of the models (Deep CNN, CNN, CMAM, TPP-PHOCNet, and AFDM) found in previous research papers was taken into consideration. The two models that we have created, tested, and validated are included in the

table with their accuracy. For models A and B, the accuracy was calculated by having an array of alphabets. The Machine learning model identifies the handwritten text in the image and predicts each character using the array. The percentage of the number of correct characters predicted is also calculated. The characters are concatenated and it is compared with the identity of the image. An algorithm is applied that is number of correct words * 100 and it is divisible by the total number of the validation size. Hence the total accuracy is achieved. The accuracy for all models ranges from 32.89 % to 98.9 %. Model A: CRNN has an accuracy of 99.32 % and Model B: CNN has an accuracy of 96.89%. We have trained the 2 models using the same dataset.

	Accuracy Obtained
Deep CNN	80.0
CNN	87.1
CM AM	74.45
TPP-PHOCNet	94.31
AFDM	92.94
Model A: CRNN	99.32
Model B: CNN	96.89

VI. CONCLUSION AND LIMITATIONS

This research paper provided a comparison of the application of CRNN and CNN for handwriting recognition. Based on the results obtained, it can be concluded that CRNN has the highest accuracy of 99.32 % compared to other models. The difference in accuracy for all the models varied because it depends on the number of datasets trained, tested, and on different PCs with different specifications. Hence it can be concluded that the CRNN model is the best compared to the other models.

Handwriting can vary significantly across individuals, making it challenging to develop a universal recognition system that performs well for all writing styles. Cross-lingual and multilingual recognition requires robust models capable of generalizing across diverse linguistic contexts while maintaining high accuracy. Moving forward, there is still room for improvement in the system, such as improving the accuracy on more complex datasets, reducing computational costs, and optimizing the model for deployment on low-resource devices. Nevertheless, the project provides a strong foundation for building more advanced image recognition systems that can have a significant impact on various industries.

REFERENCES

- [1]. Nisha Sharma et al, "Recognition for handwritten English letters: A Review" International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 7, January 2013.
- [2]. Shubham Sanjay Mor, Shivam Solanki, Saransh Gupta and al, HANDWRITTEN TEXT RECOGNITION: with Deep Learning and Android, International Journal of Engineering andAdvanced Technology (IJEAT), 2019
- [3]. TensorFlow, Recurrent Neural Networks (RNN) with Keras, <https://www.tensorflow.org/guide/keras/rnn>
- [4]. D. K. Patel, T. Som, and M. K Singh," Improving the Recognition of Handwritten Characters using Neural Network through Multiresolution Technique and Euclidean Distance Metric", International Journal of Computer Applications (0975 – 8887) Volume 45– No.6 May 2012.
- [5]. Harald Scheidl, build a Handwritten Text Recognition System using TensorFlow, <https://towardsdatascience.com/build-a-handwritten-text-recognition-systemusing-tensorflow-2326a3487cd5>
- [6]. Pal, A., & Singh, D. (2010). Handwritten English character recognition using neural network. International Journal of Computer Science & Communication
- [7]. Srihari, S. N., Cha, S. H., Arora, H., & Lee, S. (2002). The individuality ofhandwriting. Journalof Forensic Science.
- [8]. Bouchain, D., Character recognition using convolutional neural networks. Institute for Neural Information Processing, 2006. 2007

- [9]. Kaensar, C. A Comparative Study on Handwriting Digit Recognition Classifier Using Neural Network, Support Vector Machine, and KNearest Neighbour. In The 9th International Conference on Computing and Information Technology (IC2IT2013). 2013. Springer.
- [10]. J. Pradeep, E. Srinivasan, and S. Himavathi, "Neural network based handwritten character recognition system without feature extraction," in 2011 International Conference on Computer, Communication and Electrical Technology (ICCCET), Tirunelveli, Tamil Nadu, India, 2011
- [11]. The dataset was collected from: <https://www.kaggle.com/datasets/sachinpatel21/az-handwritten-alphabets-in-csv-format>