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Handwriting Text Recognition using Neural Networks

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Abstract*: Handwritten text recognition is a laborious task because humans can write a similar message in numerous ways or due to huge diversity in individual's style of writing. The performance of text recognition systems implemented as neural networks has better results and accuracy than normal traditional classifiers. In this paper we explore the methods used to recognize and detect handwritten text or words in different languages. The major method used to recognize text is the Convolutional neural network (CNN) as a deep learning classifier. The other techniques used are Recurrent Neural Network (RNN) and a custom developed model called deep-writer, which is a variant of CNN architecture.

***Keywords*: Handwritten Text Recognition, Deep Learning, Convolutional Neural Networks.**

I. INTRODUCTION

Due to drastic increase in communication and information technologies, the necessity of digitization is rapidly increasing where digitized content of the printed material is preferred. One of the technique for digitization is OCR, or optical character recognition, whose prior task is to recognize the printed text in an image. Once we recognize the printed text with the help of OCR, we can use that information in various ways. Various Phases of OCR are initial Pre-Processing which includes Segmentation and Feature extraction, secondly Classification and finally the post-processing techniques. There are different set of solutions for text recognition in an image where classical computer vision techniques can be applied which is filters to make the characters stand out from the background or segmentation can be performed which may be line, word or character segmentation. The other types of segmentation techniques applied on different languages are Kalman filter, Projection based, Smearing method and Grouping method.

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Another major technique for handwriting recognition is deep learning where neural networks are able to learn features from analyzing a dataset, and then classify an unseen image. The introduction of specific type of neural network called convolutional neural networks (CNNs) solved the issue of feature extraction in OCR methods. Features are extracted in the convolutional layers, where a kernel is passed over the image to extract a certain feature. In the end result, multiple kernels learn all the features within a dataset, in order to make classifications.

II. LITERATURE REVIEW

In this paper the author depicts the project that classifies individual handwritten word so that handwritten text can be translated to a digital form. They have used Convolutional Neural Network (CNN) with various architectures and Long Short Term Memory networks (LSTM) to classify the words directly and for the construction of bounding boxes for each character. Classification is done by passing each segmented character to CNN, and based on the results of classification reconstruction of each word is carried out to increase the efficiency of the CNN [1]. In this paper the author presents an effective method for detecting handwritten characters using deep neural networks. Image processing is done using OpenCV library and for implementing neural networks Tensorflow framework is used. The steps followed by them are initial pre-processing, converting colored image to gray-scale, segmentation and thresholding. In pre-processing they used median filtering to remove noise in images, Gray-Scale conversion is used to reduce the complexity of the process, and thresholding is used to abstract the text from its background [2]. In this paper, Arabic text recognition is carried out using CNN as a deep learning classifier. Five orientations are made for a single character for training. The process of text recognition has been divided into three different stages. These stages include text localization, extraction of text and final phase of prediction of text. Convolutional neural network is used as a technique for feature extraction for the EAST dataset which contains Arabic text images [3].
DropSegment approach which is a part of DeepWriterID is implemented to improve general applicability and data augmentation of CNN, train when the data is inadequate and it aims to avoid over-fitting of the data. The problem of text-independent writer problem is overcome by this approach of path signature method [4]. To overcome the challenges in Text-independent writer identification, DeepWriter method is used in this paper.

It focuses mainly on design and optimization, data augmentation learning and scanning strategy in the paper. The experiments are performed on English and Chinese languages. Analysis on how the identification accuracy is affected due to network structure and also the method applied to increase the training data using data augmentation for writer identification [5].

In this paper, a new Kannada language dataset is generated which is a handwritten-digits dataset, which can replace the original MNIST dataset which consists of numerical handwritten digits. The whole pre-processing technique involved four major phases: Data-gathering, slicing, Sanity-check and Train-test split. The classification results obtained by training a CNN using Adadelta optimizer. For the main dataset, an accuracy of 97.13% is achieved [6]. In this paper dual stream architecture is introduced where a three staged CNN is trained for the datasets IAM, NIST and RIMES which recognizes handwritten characters. A mechanism is also introduced in the paper as attention based mechanism where variations in handwriting is targeted such as slant, stroke width, or noise. CER (Character Error Rate) is computed in the training process and vocabulary matching is also performed on the detected text [7].

In this paper a framework is proposed which is a combination of both Recurrent and Convolutional neural network architectures, known as fully convolutional recurrent network (FCRN) for recognition of handwritten Chinese text. LSTM layer is used with FCRN for making the prediction. The training of the proposed model is made on two sets of Chinese datasets CASIA-OLHWDB and ICDAR-2013.A method called beam search method is introduced which significantly improve the recognition results [8]. This paper gives the different segmentation methods used in the OCR process of recognizing Guajarati handwritten text. The different types of segmentation described on Guajarati text is line, word and character segmentations. Comparative summary of different segmentation methods has also been made which includes techniques like Kalman filter, Projection based, Smearing method and Grouping method, applied on languages of English, Bangla, Arabic, Gujarati and Hindi [9].

Segmentation on structure based approach for handwritten Hindi text has been illustrated in this paper where the proposed model is evaluated on handwritten data written by 15 different writers which consists of 1380 words of 200 lines. The algorithm for line segmentation is designed where an assumption that the minimum character consonant height is eight pixel in a line and 30 pixels is the mean line height, is made on the data. Accuracy of Text line segmentation is 91.5% and 98.1% is achieved on word segmentation [10].The enhancement of handwritten text image is done in this paper using techniques: Gaussian Mixture Model (GMM), learning-based windowing and k-means algorithm is used as a clustering technique. When the image if of low contrast, Contrast enhancement method is used and to create a final document image GMM is applied. The proposed method has been tested for the datasets which is Swedish historical documents and the experimental result of image enhancement achieved is 3.17 bpp (bits per pixel) [11].

This paper proposes a unique method for enhancing and cleaning of handwritten data. The method used is the threshold technical, which removes noise from the images. The noise free images are fed to Multilayer perceptron's (MLPs) and the activation functions used at the hidden layer and the output layers is the sigmoid and identity functions. Results shows that this method by using threshold technical in combination with MLP, has yielded a better performance than by using filter for cleaning Image [12]. In this paper two variations of Convolutional Neural Network (CNN) are proposed for handwriting recognition. The two proposed methods include alternately trained relaxation convolutional neural network (ATR-CNN) and Relaxation convolutional neural network (R-CNN). The total type of layers used in R-CNN and ATRCNN are six in number. The proposed R-CNN enhances the learning effectiveness of the neural network and ATR-CNN performs the function of regularizing the neural network during training. The model is trained and tested on ICDAR 2013 and CASIA-HWDB 1.1 datasets, where error rate of 3.87% is obtained as a result [13].

Convolutional Neural Network has been used for handwriting recognition for the language Kannada. Many layers are used in this model. The image is first converted to the gray scale then to remove noise, contrast of the image is improved by the method of normalization and finally converting them back to binary images. This model for Chars74k dataset achieved an accuracy of 99% and for their own dataset which consisted of handwritten characters achieved an accuracy of 96% [14].They have used Neural Network model on MNIST dataset and have achieved an optimal result of 99.55% on the dataset. The process include BP neural network which has back propagation is used along with the convolutional neural network. Multiple layers are used for down sampling and to calculate the value of small regions. Two networks are used to find the combined results [15].

Prediction of handwritten characters using Recurrent Neural Networks (RNN) with Long Short-Term memory cells has the better result when dropout technique is applied in the layers of the RNN. Dropout is a new regularization method applied for best results where certain neurons in the network is made non-functional while training the network. The proposed model is trained on Rimes, IAM and OpenHaRT datasets. Reduction of CER and WER rates by 10-20% is obtained [16]. In this paper CNN is used to predict handwritten characters where attributes vector is obtained from text word conversion and given as a input to the neural network. The proposed model consists of convolutional layers which are nine in number and fully connected layers which are three in total. Data augmentation has been applied to increase the training data by applying suitable rotations and transformations. The datasets they have used for training are IAM which consists of English handwritten text and RIMES which consists of French handwritten text.96.88% accuracy is obtained after applying the proposed model on the test dataset [17].

A deeper CNN architecture is introduced which involves a streamlined version of GoogLeNet to recognize handwritten characters. A GoogLeNet is a pre-trained CNN which has 22 layers. The proposed CNN model along with GoogLeNet involved 19 layers. To enhance the performance of the model techniques like Gabor feature, HoG feature and gradient feature has been applied. CASIA-HWDB 1.0 and CASIA-HWDB 1.1 datasets which have been used for training are handwritten Chinese datasets. Error rate of 3.26% is achieved [18].

In this paper they have demonstrated a modified version of long short-term memory recurrent neural networks. And in feed-forward neural networks they have used mini-batching and applied it to RNN to keep the variability within a small batch. And they have evaluated this using Hybrid Hidden Markov model on the datasets IAM and RIMES containing English and French handwriting. They have obtained WER (12.9%) and CER (4.3%) at the end for the RIMES dataset and WER (12.2%) and CER (4.7%) for the IAM dataset [19]. In this paper they have proposed an algorithm which is built using deep learning neural networks for handwritten Arabic numerals recognition. The proposed method consists of Convolutional Neural Network and Multi-layer perceptron (MLP) in which they have used Dropout method to choose neurons randomly so it will not get gradient update by which they have overcome the over-fitting problem. At the end they have obtained an accuracy of 97.4% on the Arabic dataset [20].

III. COMPARISON OF DIFFERENT HANDWRITING RECOGNITION TECHNIQUES

The Table I, gives us a picturesque idea about the methodologies used by various authors in the field of handwriting recognition using deep learning.

Table I. Comparison of different Handwriting recognition techniques

SL No	Author	Year	Methods	Dataset	Language	Accuracy
1	Batuhan Balci, et al.	2017	1) Convolutional Neural Network - classifying words 2) Long ShortTerm Memory networks - character segmentation	IAM Handwriting Dataset	English	Training accuracy of 35% and validation accuracy of 27%.
2	R. Vaidya, et al.	2018	1) Deep neural networks 2)OpenCV for performing Image processing 3)Neural Network is trained using Tensorflow	NIST Dataset	English	Accuracy of 94% is obtained
3	S. B. Ahmed, et al.	2017	For feature extraction ConvNets is used and also as a learning classifier	EAST dataset (English Arabic Scene Text)	Arabic	Error rate of 14.57% is obtained by using learning rate value as 0.005
4	W. Yang, et al.	2016	1) DeepWriterID 2) DropSegment	NLPR handwriting dataset	Chinese and English	Chinese-95.72% English-98.51%
5	Xing, et al.	2016	DeepWriter	1) IAM dataset 2) HWDB dataset	English and Chinese	English on 301 writers-99.01% and on 657 writers-97.03% Chinese on 300 writers -93.85%
6	Vinay, et al.	2019	Convolutional neural network	1)Kannada-MNIST dataset 2)Dig-MNIST dataset	Kannada	Accuracy of 97% on kannada-MNIST and 77% on Dig-MNIST dataset is obtained
7	Such, et al.	2019	Three staged Convolutional neural network	1)IAM 2)RIMES and 3)NIST datasets	French	CER of 2.22% on RIMES dataset and 92.4% accuracy on NIST dataset
8	Xie, et al.	2016	1)Recurrent neural network 2)Convolutional neural network	1)CASIA-OLHWDB 2)ICDAR 2013	Chinese	Accuracy of 95.34% is obtained.

9	Rakesh, et al.	2017	Line, word and character segmentations are used	-	Gujarati	-
10	Garg, et al.	2010	Text line segmentation and word segmentation	Dataset comprises of handwritten characters in Hindi which includes 1380 words of 200 lines	Hindi	Achieved 91.5% on Text line segmentation and 98.1% on Word segmentation
11	H. Kusetogullari, et al.	2016	For Image Representation Gaussian Mixture Model (GMM) and k-means as a clustering technique is used.	DIBCO2010, DIBCO2012, DIBCO2013 and Swedish historical documents	Swedish	Enhancement of 3.17 bpp(bit per pixel) is achieved
12	B. Z. Varghahan, et al.	2011	Multilayer perceptron's (MLPs) and threshold method for cleaning image	IAM Handwriting Dataset	English	-
13	C. Wu, et al.	2014	Methods used are alternately trained relaxation convolutional neural network (ATR-CNN) and Relaxation convolutional neural network (R-CNN)	ICDAR 2013, CASIA-HWDB 1.1	Chinese	Error rate of 3.87% is obtained
14	A. K and K. H K, et al.	2018	Convolutional Neural Network	Chars74k	Kannada	99% accuracy on Char74k dataset
15	Y. Hou, et al.	2017	Convolutional Neural Network and Back Propagation Neural network	MNIST dataset	-	99.55% accuracy is obtained on using depth network
16	Pham, et al.	2013	Recurrent neural networks (RNN) and dropout technique	Rimes, IAM and OpenHaRT datasets	French, English and Arabic	Reduction of CER and WER rates by 10-20%
17	A. Poznanski, et al.	2016	Convolutional Neural Network	IAM, RIMES dataset	English and French	96.88% accuracy
18	Z. Zhong, et al.	2015	Convolutional Neural Network and streamlines GoogLeNet	CASIA-HWDB 1.0 and CASIA- HWDB 1.1	Chinese	96.35% accuracy
19	P. Doetsch, et al.	2014	Hybrid Hidden Markov model and Recurrent neural networks	IAM, RIMES	English and French	WER-12.9% CER-4.3%
20	Ashiquzzaman, et al.	2017	Multi-layer perceptron and ConvNet	CMATERDB 3.3.1	Arabic	97.4% accuracy

IV. CONCLUSION

Handwriting recognition is a difficult task since there are variations in the writing styles and also depends on the complexity of the handwritten language which needs to be recognized. In this paper we explore the different methods used to recognize text from handwritten images. This paper illustrate the overview of using CNN as a classifier, various techniques of segmentation phase and pre-processing techniques which may be image enhancement or cleaning the dataset before the training process. The review also includes the languages on which the proposed model is applied for the detection and recognition of text.

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