International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 SJIF 2023: 8.176 ISSN: 2582-3930

A Survey on Handwritten Text Recognition.

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ABSTRACT

Handwritten Text Recognition (HTR) is the detection of characters from images. HTR is a complex task due to the variability and diversity of handwritten characters in the script. CNNs are a type of deep learning algorithm that can automatically learn features from images and are widely used in image recognition tasks. This paper presents a CNN-based approach for HTR that achieves state-of-theatre performance on a benchmark dataset. The proposed approach involves a pre-processing step to normalize and segment the input images, followed by a CNN architecture that consists of several convolutional layers and fully connected layers. The network is trained using a massive character labelled dataset. The outcomes demonstrate that the suggested method achieves excellent accuracy in recognizing characters and can be applied to real-world applications such as document digitization and text-to-speech conversion.

INTRODUCTION

Handwritten text recognition is a challenging problem in the field of computer vision and machine learning. Document and other source and change them in machine learning shape further processing. The accurate recognition of shaped compound handwritten text is still great challenge. The increasing use of digital technology, the need for automatic HTR systems has become more important for applications such as document digitization, text-to- speech conversion, and language translation. Convolutional Neural Networks (CNN) have been shown to be effective for image recognition tasks, and recent studies have demonstrated their potential for HTR. In this paper, we propose a CNN-based approach for HTR that achieves state-of the-art performance on a benchmark dataset. The proposed approach involves a pre-processing step to normalize and segment the input images, followed by aCNN architecture that consists of several convolutional layers and fully connected layers.The network is trained using a large dataset of labelled English characters. We demonstrate the effectiveness of the proposed approach by comparing it with other state-of-the-art methods. The results show that the proposed approach achieves high accuracy in recognizing characters and can be applied to real-world applications such as document digitization and text to-speech conversion.

LITERATURE REVIEW

CNN-based handwriting image recognition is learning. This scheme normalizes the display of collected characters images and then uses CNN to classify individual images. It does not usea feature extraction like other functions. In this study, 20,000 different image and transformation authors were used. The proposed method has proven to be more reliable and more efficient than other available methods. The difficulty of handwritten characters varies from word to language, due to the different shapes, strokes, and character counts.[1]

This project aims at distributing the written word to the individual to translate the written textinto digital form. We use two main methods for this task: direct message classification and character classification. For the first, we use multi-model convolutional neural networks (CNNs) to represent patterns that can classify messages correctly. For the latter, we create bounding boxes for each character using a linked short-term memory network (LSTM). We then forward the segments to CNN for classification and then reconstruct each word based on the classification and segmentation results.Despite the abundance of writing tools, many people still choose to write traditionally: pen and paper. However, handwriting also has disadvantages. It is difficult to store and access physical information efficiently, to search it effectively and to share it with others. As a result, a lot of important information is lost or not analysed because the data is not converted to digital format.[2]

Recently, Transformers, a new iteration of neural network architecture, has successfully improved the performance of many natural language processing (NLP) applications. Because transformers represent a regular string-to-string (S2S), they can be used for many functions such as read-to-write (HTR). We propose a bidirectional Transformer architecture for line- based HTR with a convolutional neural network (CNN) for feature extraction. The voter combines the two predictions to produce a result. Our network performs worse than the physical link (CTC) method on the IAM dataset, but about 25% less than the state-of-the-art Transformers-based method, no additional information used. On larger datasets, the proposed Transformer outperforms our benchmark by about 26%. In error analysis, we found that Transformer can learn strong language patterns, we explain why larger training datasets are needed to outperform traditional methods, and we discuss why Transformer should be used with caution for HTR due to repetitions in the text.[3]

Deep convolutional neural networks (CNNs) have been one of the most competitive neural network architectures and are state-of-the-art in many areas of computer vision. In this article,we introduce OCR-Nets, which is the difference between (Alex Net and Google Net) for character recognition through adaptive learning. Our proposed network has been tested with a single dataset. Additional data of symbols with different letters and sizes were generated manually to compare the recognition rate with the behavioural model and confirm the accuracy of the test. Test results show that OCR-Alex Net and OCR-Google Net have a success rate of 96%. The average success rate is 3% and 94.7%, respectively. CR-Alex Net: Winner of the 2012 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), CNN's first successful application for large-scale data with a top 5 test error of 15.3%. The network has 8 deep layers and a simple layout (compared to modern architectures) that looks good on
a 1000 class ImageNet dataset.[4]

Handwriting has been one of the most active and complex studies in image processing and pattern recognition. It has many applications such as reading aids for the blind, bank checks and converting written information to text. In this article, letters of the English alphabet are tried to be recognized without subtraction using a multilayer feedforward neural network. There are 26 letters in each character dataset. Fifty different character datasets are used to train the neural network. It is used for network training, classification and recognition. In the proposed method, each character is converted to 30×20 pixels and trained directly. That is, each resized character has 600 pixels for training the neural network. The results show that the proposed method is more efficient than the written character information based on featureextraction.[5]

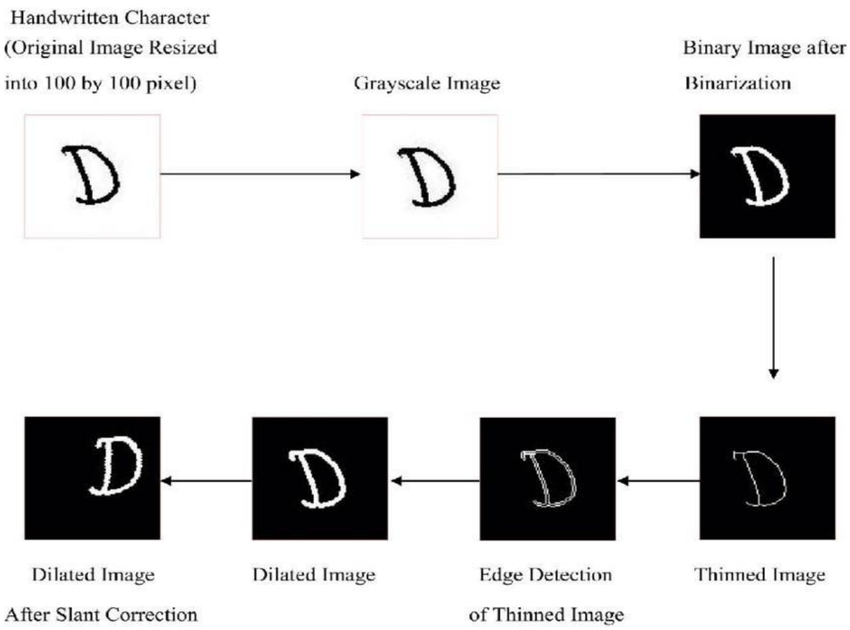
Transfer of historical data is a big problem in making this data public. Currently, many historical documents are available on online portals around the world. It is impractical to manually record this information, so the automated process should be used. Tran Scriptorium is a project that explores modern text recognition (HTR) techniques for documenting historical documents. The HTR system used in Tran Scriptorium is based on a model learned from examples. This HTR system was used in 15th century Dutch manuscripts selected for the Tran Scriptorium project. Considering the limited resources used to create the printers, this article presents the first HTR results of this Dutch book, which is very encouraging.[6]

Literacy is a necessary innovation today. Until this innovation is successfully implemented, we rely on our own writing, which may make some mistakes. Securing and storing good information is not easy. It takes a lot of work to keep the data consistent. A recurrent neural network is used to detect changes in signals. Today we have OCR that understands English well. We can also see the OCR of the English text, but the OCR of the written content is not so much. Also, the ones used are not correct. We hope to create an OCR that will allow us to guarantee the authenticity of the text written using different phone numbers. The proposed model is implemented using Conda used with the TensorFlow Framework. The purpose of retraining the neural network is to improve accuracy. English is the most spoken language in the world and the language of 53 countries. The number of research papers written in English began to exceed the number of articles written as an analyst language. In the Netherlands, for example, the odds are surprisingly 40 to 1.[7]

Document Writing, signature verification, bank verification etc. It is a useful technique that can be used in different applications. However, offline handwritten text recognition is still a very difficult task, not limited by the complexity of text and background images. This article presents a new method for segmented handwritten text recognition integrating a recurrent neural network (RNN) classifier. First, two RNN models were studied, the commonly used geometric features and the Histogram of Directed Gradients (HOG) features. Given a handwritten image, the best results are obtained by combining two RNN models trained witha dictionary. Testing on public records demonstrates the superior performance of our proposed method.[8]

Handwriting recognition (HWR) is the process of recognizing and interpreting written information in machine-readable form. Recent advances in deep learning, such as the emergence of transformer architectures, have increased our progress in writing text. Text recognition is known as Intelligent Character Recognition (ICR) because the algorithms required to decode ICR require more intelligence than OCR. In this article, we will understand the task of writing text, its complexity and how we can solve it using deep learning techniques. The optical character recognition (OCR) market size is estimated to be13 USD. It will reach 38 billion by 2025, an annual increase of 13.7%. Although OCR is considered a solution to the problem, one of its key features is OCR or Handwritten Text Recognition (HTR), which is still considered a problem. Handwritten notes differ from person to person, and handwritten notes are weak compared to printed notes, making them difficult to transcribe. However, for many sectors such as health, insurance, banking, this isan important issue that needs to be addressed.[9]

Character recognition is one in all the emerging fields within the computer vision. The most abilities of humans are they will recognize any object or thing. The hand transcription can easily identify by humans. Different languages have different patterns to spot. Humans can identify the text accurately. The hand transcription cannot be identified by the machine. It's difficult to spot the text by the system. During this text recognition, we process the input image, extraction of features, and classification schema takes place, training of system to acknowledge the text. During this approach, the system is trained to seek out the similarities, and the differences among various handwritten samples. This application takes the image of ahand transcription and converts it into a digital text. Image processing could be a manipulation of images within the computer vision. With the event of technology, there are many techniques for the manipulation of the photographs. The text recognition includes a huge role in many areas. But it's difficult to try and do such a task by a machine. For recognition, we've to coach the system to acknowledge the text.[10]



The Above Figure is showing an example of image pre-processing.

Reference	Method	Accuracy	Purpose
Gurav Kumar et al. [1] e-ISSN: 2231-034	Hand printed symbol recognition	97 %	Extract the geometrical, topological and local measurements required to identify the character.
Salvador Espan˜a-Boquera et al .[3] 0162-8828	OCR for cursive handwriting.	88%	To implement segmentation and recognition algorithms for cursive handwriting

Sushree Sangita et al .[3] BIM-506352	Recognition of handwritten numerals based upon fuzzy model	95% for Hindi and 98.4% for English numerals overall	The aim is to utilize the fuzzy technique to recognize handwritten numerals for Hindi and English numerals
K.V.K.SASIKANTH et al .[4] (ISSN-2349-5162)	Combining decision of multiple connectionist classifiers for Devanagari numeral recognition	89.6%	To use a reliable and an efficient technique for classifying numerals
U. Pal et al [3] 9870052	Handwritten numeral recognition for six popular Indian scripts.	99.56% for Devanagari, 98.99% for Bangla, 99.37% for Telugu, 98.40% for Oriya, 98.71% for Kannada and 98.51% for Tamil overall.	To find out the recognition rate for the six popular Indian scripts.
Ayush Purohit et al [1] ISSN:0975-9646	Hill climbing algorithm for handwritten character recognition.	93% for uppercase letters	To implement hill climbing algorithm for selecting feature subset.

Conclusion

In conclusion, the proposed CNN-based approach for Handwritten Text Recognition (HTR) has several advantages over other HTR methods, including high accuracy, automation, scalability, flexibility, and state-of-the-art performance. However, there are also some limitations to consider, such as dataset dependency, pre-processing errors, computational intensity, limited interpretability, and contextual constraints. Despite these limitations, the proposed approach has the potential to be a valuable tool for applications such as document digitization, text-to-speech conversion, and language translation. Further research is neededto address the limitations and improve the effectiveness and efficiency of the approach.

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