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HANDWRITTEN TEXT RECOGNITION USING ML

[1]K.RISHITHA, [2]S.MADHESH, [3]CH.MANISRI, [4]V.SEETHARAMA RAO

[1]Student, [2]Student, [3]Student, [4] Assistant Professor
[1,2,3,4] Department of Electronics and Communication Engineering
Sreenidhi Institute of Science and Technology, Hyderabad, India

ABSTRACT: As everything becomes increasingly digitised in this rapidly evolving world, exchanging information plays a crucial role in any work. However, sometimes we may not have access to a computer or other electronic device to create a document, and instead use pen and paper. Unfortunately, people may not be able to understand everything that is expressed on paper due to factors such as poor penmanship. To address this issue, we are developing a platform that can convert handwritten text into editable text. Our primary goal is to classify words directly and segment characters using a convolutional neural network (CNN). Long-term memory networks (LSTM) are also used to create bounding boxes for each character, which are divided and classified.Resulting neural networks can then be used for handwriting character recognition, allowing the platform to reconstruct each word in the handwritten text. This technology can be particularly useful in situations where people need to quickly share information, but don't have access to a computer or other electronic device. By converting handwritten notes into editable text, this platform makes it easier to read, edit, and share information, regardless of the format in which it was originally written.

KEYWORDS —- Machine leaning, LSTM, Convolutional Neural Networks

I. INTRODUCTION

Although advanced technological writing tools are readily available, a considerable number of individuals still favor taking notes using pen and paper. This conventional approach has several drawbacks, including difficulties in efficiently storing and accessing physical documents, searching through them, and sharing them with others. Consequently, valuable information may be lost or not reviewed due to a lack of digital conversion.

Therefore, We believe that digital text offers significantly easier management than handwritten text We have made the decision to facilitate individuals in accessing, searching, sharing, and analyzing their records more efficiently, all while still utilizing their preferred method of writing.Goal of project to further investigate process is to classify handwritten text and convert it into digital format. To focus our project, we have defined the term "handwritten text" to suit our purposes.

Although there are many tools available, peple still prefer taking notesin traditional way, which makes it difficult to access ,store physicaldocuments efficiently. Thus, important information often volatile or is notbeen considered. The project's objective is to look into the method forclassifying handwritten text and converting it to a digital representation.,making it easier for people to access, search, share, and analyze their records.

This project focuses on classifying handwritten words, whether they are written in cursive or block writing formats. To create a fully functional model,within images, and segment line images within whole handwritten pages. Theend product will be a deliverable that prompts users to take pictures of their handwritten notes, and converts them into digital format.

In summary, this project addresses the challenge of converting handwritten documents into digital format, which makes it easier for peopleto store, access, search, share, and analyze their records.

II. LITERATURE SURVEY

[1] Andrew Smith has presented The technique of removing text from a picture and converting it into a digital image is known as offline handwritten text recognition. The previous methods relied on lexical segmentation, intricate feature extractions, and some linguistic knowledge. To recognise offline handwritten writings, the suggested method combines a convolutional recurrent neural network with connectionist temporal classification, a type of neural network output that will be associated with a scoring function. Since the approaches used are character neutral, the model can be trained globally and used for a variety of languages. The technique of turning printed texts—whether printed or handwritten—into digital, computer-readable language is known as optical character recognition.A convolutional recurrent neural network was used to recognise texts. This network had three neural network blocks: a convolutional block for extracting image features, a recurrent block for learning sequences, and a final block for labelling with connectionist temporal classification connected to the scoring function..

[2] The handwritten text Recognition (HTR) technology, created by [2]Thomas Deselaers, is used with the Optical Character Recognition (OCR) paradigm. The HTR system, the OCR model, and a Dual head technique—which combines HTR and OCR—were combined to construct a scalable handwritten text recognition system. The dual head model was able to classify both printed and handwritten text, delivering the highest accuracy when compared to optical character recognition models and handwritten text recognition systems.First, a sufficient quantity of high-quality training data is required, followed by a neural network-based line recognition model devoid of any recurrent connections.

[3] Anshul Gupta has developed a technique for offline handwritten English word identification in which individual letters are identified first, then the entire word. The two main methods for recognising handwritten text are segmentation and holistic techniques. A holistic technique is utilised to recognise words with a little vocabulary, where the retrieved global properties from the full word image are taken into account. The complexity of this comprehensive technique increases along with the vocabulary size, which lowers the rate of character recognition. The alternative technique is segmentation-based, which starts at the character level and builds up to producing a coherent word.The issue of recognising a whole word will be reduced to recognising a single character after segmentation is complete, expanding the vocabulary. Using neural networks, the individual characters' identities will be determined.

[4] Peng Ren has created a programme for handwritten text recognition using deep learning techniques. The suggested approach is founded on an object detection algorithm. Here, character recognition for offline handwritten texts happens in two steps: first through preprocessing, then through character recognition. The character is first identified using a faster R-CNN for preprocessing, and then it is recognised using a convolutional neural network. Character segmentation is no longer a concern, thanks to improvements in object detection. Preliminary processing will involve breaking down sentences into words, followed by thorough processing, which involves breaking down words into characters before recognising the characters.

[5] A new method for eliminating slants from handwritten writing has been created, and artificial neural networks have been used to balance the size of the text pictures, according to Francisco Zamora-Martinez. Line detection, page skew correction, and image cleaning are all included in the normalisation of the handwritten text from the scanned image. Pages for skew correction and line detection have been skipped because the skew-corrected lines database has been used. To lessen the variances in handwriting, there are many preprocessing processes. Before preprocessing, the line from the image that has been scanned is first cleaned. The elimination of the slope and tilt are the following steps.The size of the text line is normalised once the complete image is free of slopes and slants in order to reduce variations in size and location. The offline handwritten text lines were recognised using the ANN method.

[6] In order to convert each handwritten word into a digital format, Batuhan Balsi created a classification system. In this procedure, two approaches have been used: the segmentation of the characters comes after the direct classification of the words. A convolutional neural network with multiple topologies was used to train a word categorization model. Long short term memory networks with convolution are utilised to create the bounding boxes for a single character. Each word is then reassembled using the results of character classification and segmentation. The segmented characters are then sent to a convolutional neural network for classification. By segmenting the characters first, the word is reconstructed by classifying each character separately, which improves the results of direct classification for a word.

[7] Deep neural networks were used by Rohan Vaidya to introduce the technique for detecting offline handwritten characters. This method's suggested design for the handwritten character recognition system is based on picture segmentation, and it was created using the Python computer language. The offline handwritten character recognition system was created using a variety of tools, including Android OpenCV and TensorFlow. Using the Android phone's camera, the user must be able to take a photo of handwritten text that must be recognised. Pretrained neural network model is used to serve the predictions, and after that, image processing is carried out. Tensor flow is used to train the neural network model. Preprocessing is a step in image processing that involves taking out the image's noise. After preprocessing, the image will be converted to grayscale. The image will be converted to grayscale, and the darker and lighter areas will be distinguished using thresholding.

[8] Vu Pham introduces a recurrent neural network to identify handwritten texts. The image is taken as an image, divided into blocks, and sent to the long short term memory layers. These layers scan the input, and the output of these layers is sent to a convolutional layer. The output of the convolutional layer will be added vertically, given for softmaxing, and the output of the softmax layer will then be subjected to connectionist temporal classification processing. In this case, dropout entails randomly removing some concealed units from the training and using them for testing.Drop connect is a similar technique to dropout, except that rather than dropping the values of the hidden units, the connection is lost. Recurrent and convolutional layers can both work with the dropout. For the top layer of the long short term memory, the dropout will be used first. The dropout is useful if the model is large and there is evidence of overfitting.

[9] The method for recognising handwritten text in the Comenia font was developed by Martin Rajnoha. The suggested approach includes preprocessing In summary, this project addresses the challenge of converting handwritten documents into digital format, which makes it easier for people to store, access, search, share, and analyze their records.handwritten notes, and converts them into digital format.In summary, this project, normalisation, and optical character recognition based on the Support Vector Machine.The comenia script is straightforward and contemporary, similar to block letters. In comparison to the single model approach, the proposed model's utilisation of multiple categorization models for character recognition demonstrated an improvement in accuracy. The support vector machine is used for classification during the entire process of recognising handwritten texts, which also comprises feature extraction.

III EXISTING SYSTEM

OCR (Optical Character Recognition) software is a technology that enables therecognition of printed or handwritten text characters. The first OCR softwarewas invented in 1974 and was capable of recognizing any font. The software used feature extraction techniques to recognize text characters, but this method had some drawbacks. In order to get over these restrictions, researchers created a brand-new method that used letters as a state to take the context of the character into account when figuring out the next hidden variable. In comparison to feature extraction methods and the Naive Bayes approach, this method produced text character recognition accuracy that wasgreater. The fundamental disadvantage of this system was the manual featureextraction that was still necessary, which necessitated prior language proficiency and was not very resistant to the variety and complexity of handwriting. Despite this limitation, OCR technology has come a long way since its inception and is widely used today in various applications, includingdocument digitization and text recognition.

IV.PROPOSED SYSTEM

In this research, our goal is to create neural networks that are capable of locating and identifying text in images. This is accomplished by combiningdeep convolutional neural networks (CNN), recurrent neural networks (RNN), and connectionist temporal classification (CTC) neural networks. To improvethe precision of our recognition models, we incorporate attention mechanisms into our deep convolutional neural networks. Also, we chose to use word images for our models since CNNs frequently perform better when working with raw input pixels rather than learning image attributes or sections.

To handle sequential data in our recognition models, we use RNNs, which are able to store information from previous time steps and incorporateit into the current decision-making process. We use connectionist temporal classification to train our RNN models, which is a method used to solve sequence labeling problems.

Our findings have shown that LSTM-based OCR produces low error rates, which we implement into our project. Our goal is to develop a system that is capable of precisely identifying and localising text within an image using these neural networks.

A.DATASET

IAM is a vast collection of vision datasets that are used for training and testing.

figure 1. Example image from IAM dataset

It is possible to train and test text recognizers, as well as conduct writer identification and verification studies, using the handwritten English text that is available in the IAM Handwriting Database in a number of formats. The IAM Handwriting English Sentence Database was made public in 2002. Unrestricted handwritten text forms were scanned at 300 dpi and saved as PNG images with 256 grey levels in the database.

B.SYSTEM ARCITECTURE

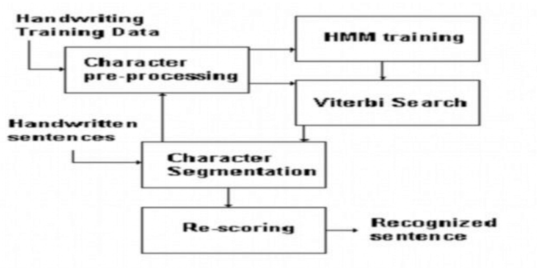

figure 2 architecture of proposed system

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C.RESULTS

The outcome of the system's processing of the text file after it was entered.

INPUT

OUTPUT

figure 3 recognition of text

INPUT

OUTPUT

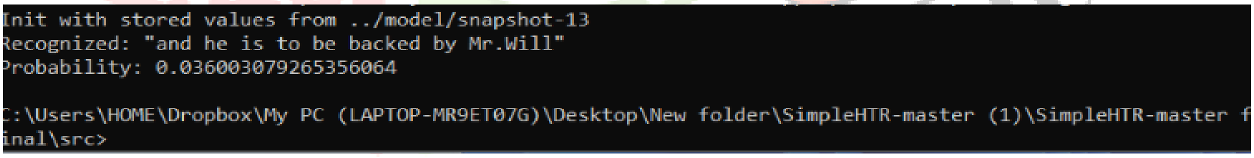

figure 4 recognition of text

V CONCLUSION

We discussed a neural network (NN) that can identify text in photos in our earlier discussion. Two recurrent neural network (RNN) layers and five convolutional neural network (CNN) layers make up the NN. Its output is a character-probability matrix that may be applied to both decoding and computing the Connectionist Temporal Classification (CTC) loss.

We also discussed an implementation of this NN using TensorFlow, a popularopen-source machine learning framework. During our discussion, we highlighted some important parts of the code, including the CNN and RNN layers and the CTC loss calculation. We also provided some suggestions on how to improve the recognition accuracy of the NN, such as adding more training data, fine-tuning the hyperparameters, and using a larger network architecture.

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