A Synopsis on

Handwriting Recognition

Submitted in partial fulfillment of the requirements
of the degree of

Bachelor of Engineering

in

Information Technology

by

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CERTIFICATE

This is to certify that the project Synopsis entitled ***"Handwriting Recognition"*** Submitted by ***"Aditya Saini (18104046), Kunal Sant (18104011), Sumeet Swain (18104008)"*** for the partial fulfillment of the requirement for award of a degree ***Bachelor of Engineering*** in **.**to the University of Mumbai,is a bonafide work carried out during academic year 2021-2022

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Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

In the current world of automation everything is getting atomized as reducing manual labor is the key to efficiency. This paper focuses on Off-line Handwriting Recognition. Handwriting Recognition is the process of extracting text from handwritten scripts, this is also known as Offline Handwriting Recognition. The purpose of this paper is to attempt to improve the accuracy and efficiency of the system using Neural Networks and data-sets used for training the model, as well as detecting and identifying the characters and exporting them in a text format. The proposed system can be used to recognize handwritten characters and convert them into text from the scanned image of a page.

Introduction

Handwriting Recognition is a subject which exists for a long period of time but the accuracy of the process can be improved by the usage of more refined technology and better techniques which reduce the error rates and the difference between the actual text and the detected text of the system. Handwriting Recognition is the process of extracting text from handwritten scripts, this is also known as Offline Handwriting Recognition.In Offline Handwriting Recognition the image of a script is captured using a scanner and sent forward for further processing. This is a step into the world of automation and can help us improve efficiency in this field. Handwriting Recognition works on similar techniques of text detection and recognition. Text detection includes various techniques to extract text from an image such as Texture Detection method and Connected Component method. In texture detection the text is extracted which is detected by texture difference from the background and text is registered by further processing of the information. In the Connected Component method text is extracted using the relation between pixel connectivity and pixel intensity to detect text patterns and checks are made to clear non character elements. The next step in extracting text from an image is Text Recognition which is done by OCR(Optical Character Recognition) which depends on identifying the character from the detected text which can be done by training the model using data-set which gives the model the basic characteristics of characters like the height, width, shape and size and font style. This includes all the alphanumeric characters 10 digits(0-9) and 26 alphabets with uppercase and lowercase for a total of 62 characters. Handwritten characters are more challenging to recognize as compared to printed characters as they carry more parameters like the standard and cursive style of writing. These challenges can be overcome by using new technologies like LSTMs, RNNs, CNNs and different training methods with various data-sets.Through this set of processes the handwriting can be extracted from an image.

Objectives

- To recognize and convert the handwritten characters and numbers into digitized text characters.
- To convert text to handwritten characters using GANs and LSTM.

Literature Review

Literature Review		
Author	Research Paper	Findings
Md. Rabiul Islam , Chayan Mondal, Md. Kawsar Azam, and Abu Syed Md. Jannatul Islam	Text Detection and Recognition Using Enhanced MSER Detection and a Novel OCR Technique	The work of different text detection methods on how they extract text from an image such as MSER and canny edge integration, stroke width variation and OCR for text recognition
Dan Claudiu Cireşan and Ueli Meier and Luca Maria Gambardella and Jurgen Schmidhuber	Convolutional Neural Network Committees For Handwritten Character Classification	How using CNNs and their training with GPUs to train models can reduce character recognition error rates in offline handwriting
J.Pradeep , E.Srinivasan , S.Himavathi	Diagonal Based Feature Extraction For Handwritten Character Recognition System Using Neural Network	Use of techniques such as preprocessing, segmentation, and feature extraction that are used to improve the accuracy of text recognition and identification.
Patrick Doetsch, Michal Kozielski and Hermann Ney Lehrstuhl für Informatik	Fast and robust training of recurrent neural networks for offline handwriting recognition	LSTM-RNN with Backpropagation Through Time training can be used to speed up the process while increasing the accuracy of recognition process
Dewi Suryani, Patrick Doetsch and Hermann Ney	On the Benefits of Convolutional Neural Network Combinations in Offline Handwriting Recognition	Combination of CNN and LSTM showing a better performance for Offline Handwriting Recognition

Problem Definition

- To convert text to handwriting.
- Creating a lightweight model so it can be implemented in applications.
- To convert handwriting to text.

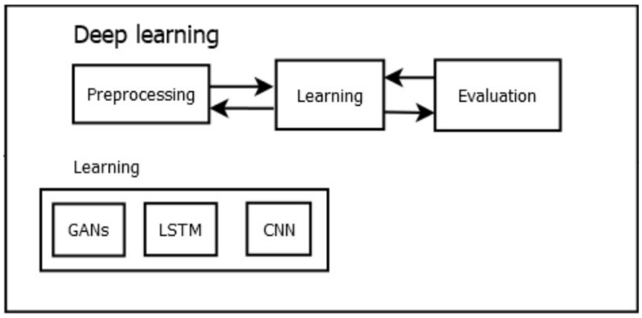


Figure 1: Model

Proposed System Architecture/Working

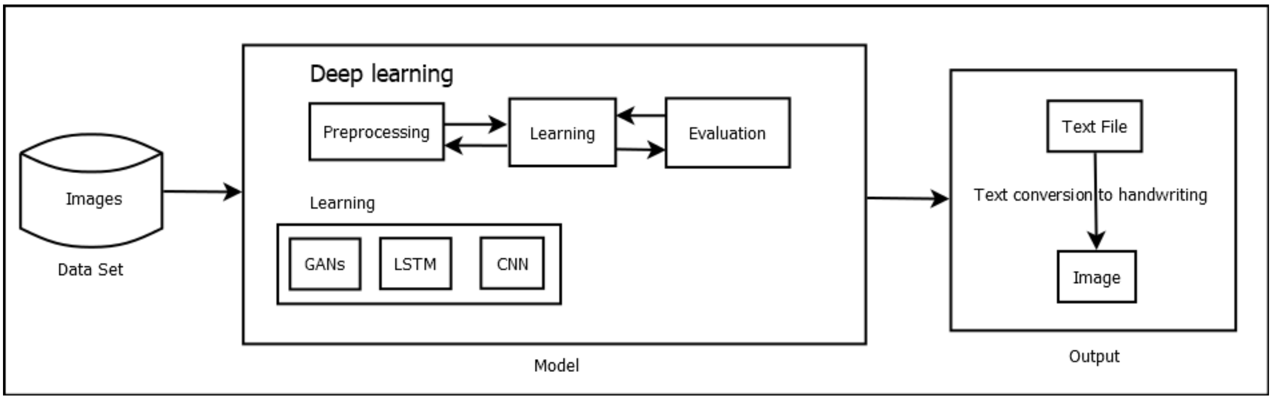


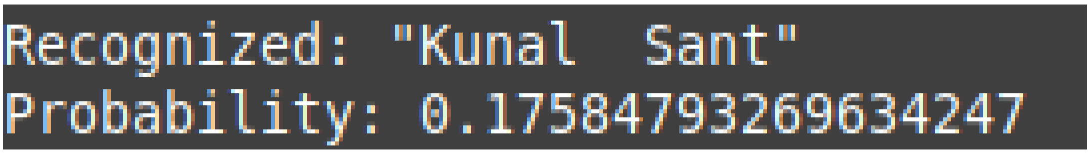
Figure 2: Proposed System Architecture

Design and Implementation

CNN: the input image is fed into the CNN layers. These layers are trained to extract relevant features from the image. Each layer consists of three operations. First, the convolution operation, which applies a filter kernel of size 5×5 in the first two layers and 3×3 in the last three layers to the input. Then, the non-linear RELU function is applied. Finally, a pooling layer summarizes image regions and outputs a downsized version of the input. While the image height is downsized by 2 in each layer, feature maps (channels) are added, so that the output feature map (or sequence) has a size of 32×256.
RNN: the feature sequence contains 256 features per time-step, the RNN propagates relevant information through this sequence. The popular Long Short-Term Memory (LSTM) implementation of RNNs is used, as it is able to propagate information through longer distances and provides more robust training-characteristics than vanilla RNN. The RNN output sequence is mapped to a matrix of size 32×80. The IAM dataset consists of 79 different characters, further one additional character is needed for the CTC operation (CTC blank label), therefore there are 80 entries for each of the 32 time-steps.
CTC: while training the NN, the CTC is given the RNN output matrix and the ground truth text and it computes the loss value. While inferring, the CTC is only given the matrix and it decodes it into the final text. Both the ground truth text and the recognized text can be at most 32 characters long.
Data Input:
it is a gray-value image of size 128×32. Usually, the images from the dataset do not have exactly this size, therefore we resize it (without distortion) until it either has a width of 128 or a height of 32. Then, we copy the image into a (white) target image of size 128×32. This process is shown in Fig. 3. Finally, we normalize the gray-values of the image which simplifies the task for the NN. Data augmentation can easily be integrated by copying the image to random positions instead of aligning it to the left or by randomly resizing the image.
CNN Output: Each entry contains 256 features. Of course, these features are further processed by the RNN layers, however, some features already show a high correlation with certain high-level properties of the input image: there are features which have a high correlation with characters (e.g. “e”), or with duplicate characters (e.g. “tt”), or with character-properties such as loops (as contained in handwritten “l”s or “e”s).
Implementation using TF:
The implementation consists of 4 modules:
SamplePreprocessor.py: prepares the images from the IAM dataset for the NN
DataLoader.py: reads samples, puts them into batches and provides an iterator-interface to go through the data
Model.py: creates the model as described above, loads and saves models, manages the TF sessions and provides an interface for training and inference
main.py: puts all previously mentioned modules together We only look at Model.py, as the other source files are concerned with basic file IO (DataLoader.py) and image processing (SamplePreprocessor.py).

Output

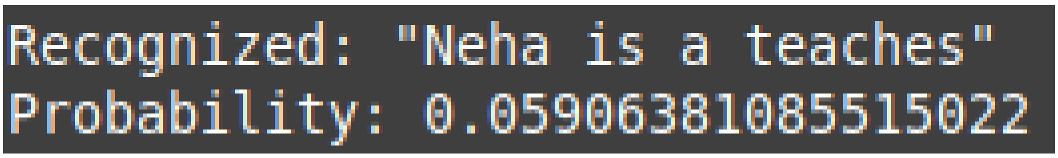
Figure 3: Input 1



```
Recognized: "Kunal  Sant"
Probability: 0.17584793269634247
```

Figure 4: Result 1

Figure 5: Input 2



```
Recognized: "Neha is a teaches"
Probability: 0.05906381085515022
```

Figure 6: Result 2

Summary

Our project aims to create a more efficient handwriting recognition model. We discussed a NN which is able to recognize text in images. The NN consists of 5 CNN and 2 RNN layers and outputs a character-probability matrix. This matrix is either used for CTC loss calculation or for CTC decoding. An implementation using TF is provided.

References

[1] Text Detection and Recognition Using Enhanced MSER Detection and a Novel OCR Technique Md. Rabiul Islam, Chayan Mondal, Md. Kawsar Azam, and Abu Syed Md. Jannatul Islam Department of Electrical and Electronic Engineering (Khulna University of Engineering & Technology, Bangladesh),2016

[2] Convolutional Neural Network Committees For Handwritten Character Classification Dan Claudiu Cires¸an and Ueli Meier and Luca Maria Gambardella and Jurgen Schmidhuber IDSIA USI, SUPSI 6928 Manno-Lugano, Switzerland,2011

[3] Diagonal Based Feature Extraction For Handwritten Character Recognition System Using Neural Network J.Pradeep , E.Srinivasan , S.Himavathi Department of ECE, Pondicherry Engineering College, Pondicherry, India,2011

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[6] HMM Based On-Line Handwriting Recognition Jianying Hu, Member, IEEE, Michael K. Brown, Senior Member, I€€€, and William Turin, Senior Member, IEEE,1996