

HANDWRITING DETECTION

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Abstract- Machine learning aims to extract hidden information that is present in the data using knowledge of current data on a certain subject. We can achieve machine learning and predict results for unknown data by using specific mathematical functions and concepts to uncover hidden information. One of the key uses for ML is pattern recognition. Large image data sets are typically used to recognise patterns. An example of pattern recognition through an image is handwriting recognition. We may teach computers to interpret letters and numbers from any language that are contained in an image by employing such notions. Handwritten characters can be recognised using a variety of techniques. Some of the techniques used in this work will be discussed.

KEYWORDS: CNN Zoning, Incremental, Handwriting recognition

I. INTRODUCTION

The most sought-after skill in machine learning is now object recognition. Face recognition, handwriting recognition, disease diagnosis, and other examples of object recognition are a few. All of these things are possible thanks to a sizable image data set. Both positive and negative information pertaining to that domain will be included in this image data set. This makes it easier for the algorithm to classify the unknown data. The 21st century will benefit from the new technology of handwriting.

The capacity of a computer or mobile device to recognise handwriting as actual text is known as handwriting recognition. In today's mobile era, handwriting recognition as a direct input to a touchscreen with a pen or finger is the most frequent use case. This is advantageous since it enables the user to quickly write down contact information, such as phone numbers and names, as opposed to entering the same information using the onscreen keyboard. This is so that most individuals can write more rapidly and with more comfort. Although most smartphones and tablets don't come with this feature by default, there are several handwriting recognition apps available.

Offline handwritten text recognition (HTR) systems convert text found in scanned images into digital text. A neural network (NN) that has been trained using word-images from the IAM dataset will be constructed. NN-training is possible on the CPU (a GPU would obviously be preferable), as the input layer (and thus all the other layers) can be kept minimal for word-images. The absolute bare minimum for HTR with TF is this implementation.

A method for contrasting competing offline handwritten text recognition (HTR) systems is called Handprint (Handwritten Page Recognition Test). Although it was created to be used with records from the Caltech Archives, it is totally independent and can be used with any pictures of text records.

To display the results, handprints can produce photos with recognised text layered on them. A sample is seen in the picture to the right. The software may also compare full-text results to expected/ground-truth findings, display bounding boxes, threshold results by confidence values, and output the raw results from an HTR service as JSON

and text files, among other capabilities. It is compatible with single images, image directories, and URLs leading to images on distant servers.

II. LITERATURE SURVEY

"Handwritten word recognition based on lexical support and structural characteristics"[5]. In this study, a handwritten recognition formula that is based on fundamental features has been proposed. To treat the 32x32 letter matrix as a 280-evaluation

Combining the recently discovered spiral, out-in outspread, and in-out outspread histograms with well-known, even, vertical vectors. The recognition process has been maintained by a language component that depends on FSAs (non-cyclic). Disconnected character images are given at the pre-processing step and used as a contribution to the character recognition module. At that time, each character is handled as a 280-measurement vector. A 32x32 framework is used to standardise each character. the in-out spiral profile, the out-in profile, the spread histogram, the vertical histogram, and the even histogram.

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Measurement vector of 280. A 32x32 framework is used to standardise each character. At that stage, the even histogram, vertical histogram, outspread histogram, out-in profile, and in-out spiral profile are established. The lexical component, which is dependent on particular non-cyclic FSAs (Finite-State-Automata), has supported the acknowledgment interaction. A day and a half's worth of letters make up the 230,000 Greek words in the developed dictionary used in the present framework. The average word length is 9.5 characters.

Natives are broken up in a word's graphic depiction. Using dynamic coding, the ideal mix of indigenous group affiliations and a vocabulary series has been identified. Information is distributed through neural organisations. Characters and pieces must correspond in terms of scores. Neural Organisations assign various groups of pieces a level of certainty that is appropriate for circumstances requiring character clarity, and this certainty is incorporated into the special programming.

At first, the division interaction identifies related segments. Simple gathering and commotion evacuation are carried out. The underlying components are hinted to as being the results.

The accompanying interaction is hinted at by the character certainty task: With a picture s and a character class c as inputs, assign s a value that indicates how much s addresses c : This is in contrast to the character acknowledgment approach, which works like this: given an image, a group of character classes determine which class the picture belongs to. A match network approach is used to perform the calculation. We first illustrate it using the scenario of single-character neural organisations. An exhibit is created for every vocabulary string. When compared to the characters, the exhibit's columns.

III. USED TECHNOLOGY

A. Python

It is a computer language with multiple paradigms. Many of its features support both object-oriented and structured programming in addition to functional and aspect-oriented programming, including metaprogramming and metaobjects. Dynamic typing is combined with reference counting, a cycle-detecting garbage collector, and memory management in Python. Dynamic resolution is another feature that binds variable and method names as programmes are executed.

B. CNN output

A sequence of length 32 is displayed in Fig. 4 as the output of the CNN layers. There are 256 features per entry. There are features that have a high correlation with characters (like "e"), duplicate characters (like "tt"), or character-properties like loops (like those found in handwritten "l"s or "e"s), but some of these features already show a high correlation with certain high-level properties of the input image.

C. RNN layers

Recurrent neural network layers then take control and pull input from RNN.

RNN was chosen because it relies on sequences and operates in temporal order. We use an RNN implementation called the Bidirectional Long Short-Term Memory (LSTM) LSTM. Input from CNN is extracted by RNN before it passes through the fully connected (FC) layer.

Unlike RNN, which produces output of the type (100X80), this is of the type (512X100). An artificial neural network that forms connections between nodes into a directed or undirected graph along a temporal sequence is called a recurrent neural network (RNN). It can display temporal dynamic behaviour as a result of this.

D. CTC

For training recurrent neural networks (RNNs), such as LSTM networks, to handle sequence issues where the time is uncertain, connectionist temporal classification (CTC) is a form of neural network output and related scoring function. The connectionist classification of time layer receives the output from the RNN at the time of training. Ground Truth Text (GTC) is made available to CTC in order to determine deprivation. By demystifying the matrix it is given at the time of inference, CTC provides the result.

A sort of neural network output called Connectionist Temporal Classification (CTC) is useful for solving sequence problems like speech and handwriting recognition where the time fluctuates. Using CTC guarantees that an aligned dataset is not required, which simplifies the training procedure.

IV. WORKING OF THE MODEL

For our work, a NN is used. It consists of a final Connectionist Temporal Classification (CTC) layer as well as recurrent NN (RNN) and convolutional NN (CNN) layers. An overview of our HTR system is shown in figure.

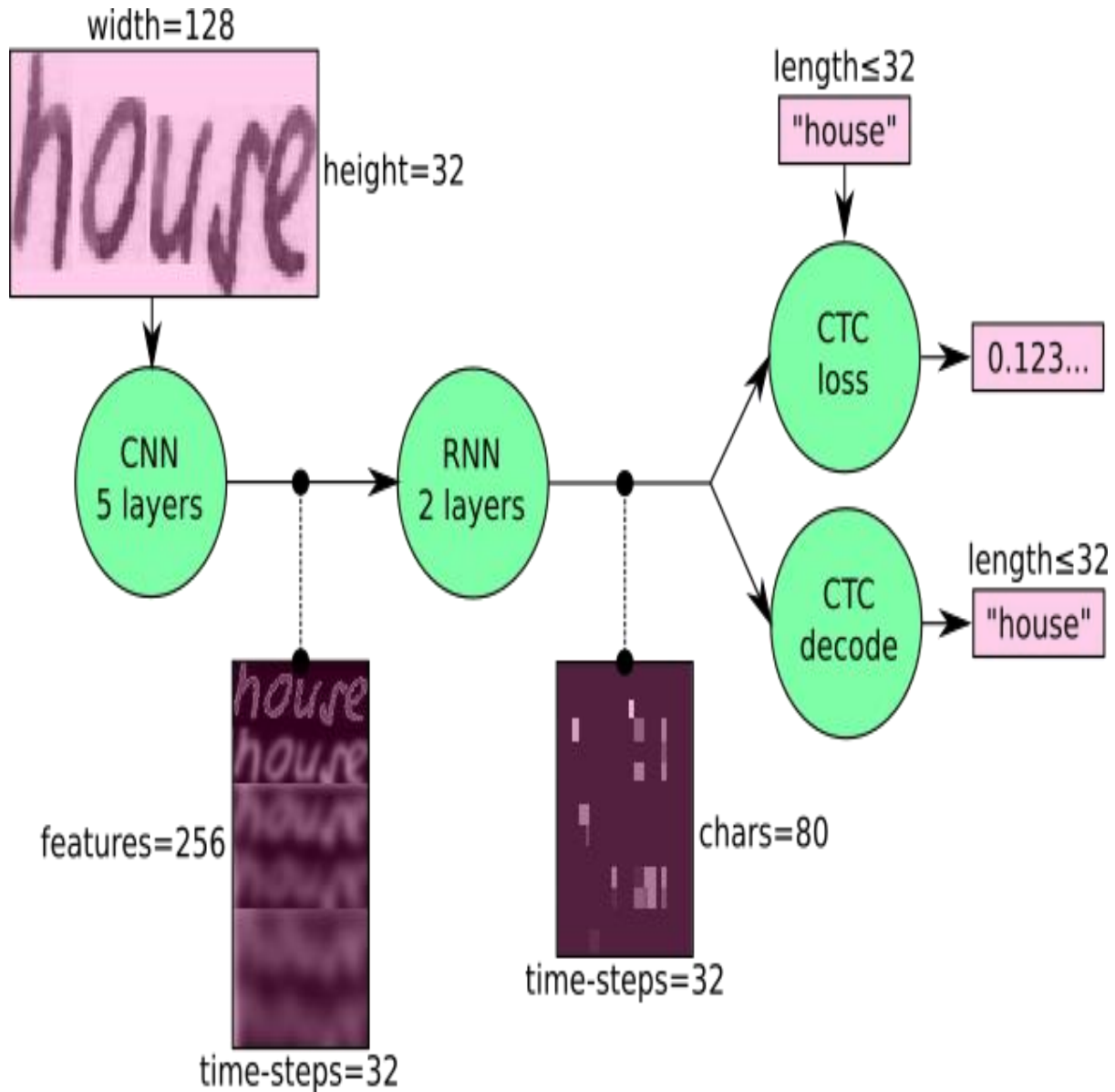
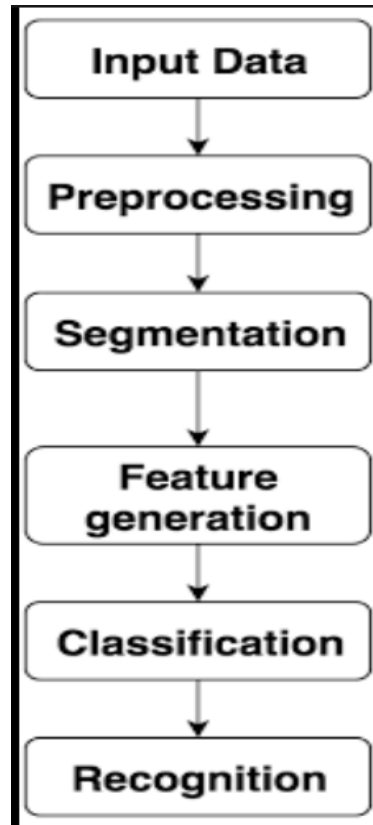


Fig: Data flow via the NN (pink) and an overview of NN activities (green).

The NN may also be viewed more formally as a function that converts a character sequence (c_1, c_2, \dots) having a length between 0 and L into an image (or matrix) M of size WH . As you can see, since text is recognised at the character level, it is possible to recognise words or sentences that are not part of the training data as long as the individual characters are correctly identified.

V. FLOWCHART



VI. CONCLUSION

We talked about a NN that can spot text in pictures. The NN generates a character-probability matrix and comprises 5 CNN and 2 RNN layers. Either CTC decoding or CTC loss computation are done using this matrix. A TF implementation is offered, and key sections of the code are highlighted. Finally, suggestions for increasing recognition accuracy were provided.

There are numerous methods for recognising handwriting. Some of these are semi-incremental segmentation, incremental segmentation, Zoning, Convolutional Neural Network (CNN), slope and slant correction. Convolutional neural networks (CNN) have the highest accuracy of these methods, whereas the Slope and Slant Correction method has the lowest accuracy. This is one of the successful methods for handwriting identification, and when the photos are trained with CNN, we will obtain good accuracy. The main drawback with this method is that the model's training time is too long due to the large number of image samples used. Zoning accuracy will drop using this method if the number of zones created after dividing the input image is lower.

VII. FUTURE SCOPE

The task of handwritten text recognition using a classifier is very important and has many applications, including online handwriting recognition on computer tablets, reading zip codes from mail to sort postal mail, processing bank check amounts, processing numeric entries in forms filled out by hand, and more. While attempting to address this problem, many difficulties are encountered. The size, thickness, orientation, and placement of the handwritten texts in relation to the margins are not always uniform. Our objective is to create a pattern classification approach to identify the user-provided handwritten texts.

REFERENCES

- [1]. Surya Nath RS, and S. Afseena. "Handwritten Character Recognition—A Review." International Journal of Scientific and Research Publications (2015).
- [2]. Salma Shofia Rosyda, and Tito Waluyo Purboyo. "A Review of Various Handwriting Recognition Methods." International Journal of Applied Engineering Research 13.2 (2018): 1155-1164.
- [3]. Younus, S. B. S., S. Shajun Nisha, and M. Mohamed Sathik. "Comparative Analysis of Activation Functions in Neural Network for Handwritten Digits." Studies in Indian Place Names 40.71 (2020): 793-799.
- [4]. Jagan Mohan Reddy D, A Vishnuvardhan Reddy "Recognition of Handwritten Characters using Deep Convolutional Neural Network".
- [5]. Hruday M. "Implementation of Handwritten Character Recognition using Neural Network".
- [6]. Meenu Mohan, and R. L. Jyothi. "Handwritten Character Recognition: A Comprehensive Review on Geometrical Analysis."
- [7]. Yuval Netzer, Tao Wang Adam Coates Alessandro Bissacco Bo Wu Andrew Y. Ng. "Reading digits in natural images with unsupervised feature learning." (2011).
- [8]. Polaiah Bojja., Naga Sai Satya Teja Velpuri, Gautham Kumar Pandala, S D Lalitha Rao Sharma Polavarapu "Handwritten Text Recognition using Machine Learning Techniques in Application of NLP".
- [9]. Ahmed Mahdi Obaid, IHHazem M. El Bakry, IIIM.A. Eldosuky, IVA.I. Shehab "Handwritten text recognition system based on neural network." Int. J. Adv. Res. Computer Sci. Technol.(IJARCST) 4.1 (2016): 72-77.
- [10]. S. M. Shamim, Mohammad Badrul Alam Miah, Angona Sarker, Masud Rana, Abdullah Al Jobair "Handwritten digit recognition using machine learning algorithms." Global Journal Of Computer Science And Technology (2018).
- [11]. P. Shankar Rao, J. Aditya. "Handwriting Recognition – “Offline” Approach".