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Paper Authors

MANJULA.K, ARPITHA K. RAO

SKIT, Bangalore.

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RECOGNITION OF LEFTWARD SLANT HANDWRITTEN ALPHABETS USING CNN

[1]MANJULA.K, [2]ARPITHA K. RAO
[2]UG Scholar, Department of ISE, SKIT, Bangalore.
[1]Assistant professor, Department of ISE-SKIT, Bangalore.

ABSTRACT

Recognizing the handwritten characters is a major challenge for many aspects like bank slips and cheque processing, identification of postal address. A subdomain of handwritten character recognition is a tilt or slant handwritten alphabets that are to be recognized. In this paper, we would like to propose a deep learning algorithm for the recognition of leftward slant handwritten alphabets in the English script as well as digits, a Feed forward Back propagation Convolutional Neural Networks is used in achieving this task. To avoid losing the aspect ratio and size of the input image, we use dynamic resizing technique.

KEYWORDS

Handwritten Character Recognition; Neural Networks; Dynamic Resizing; Leftward Slant Handwriting; Convolutional Neural Network; Deep Learning.

1. INTRODUCTION

This paper describes a Handwritten Character Recognition (HCR) System. It can be defined as the ability of a computer system to identify and display the handwritten inputs like digits, characters etc. from a various sources like emails, notes, images, letters etc. Some of the applications of this system include signature verification, bank slips and cheque processing, identification of postal address from envelopes etc. In the field of digital processing and pattern recognition, HCR is one of the most intricate research areas. To build an accurate system for handwritten character recognition, it is important to improve and automate the systems for a better interface between the humans and the technologies that are used in various applications. The main challenge is posed by handwriting variations that are observed frequently in individuals writing style. This paper proposes an English Handwriting Recognition system that deals with recognition of handwriting styles of leftward slant handwriting. The angle, in which the writing is tilted, will show in which direction and in which side the handwriting is tilted. The slant of writing could be classified as left, to the right or vertical. This concept intends to recognize the other handwriting styles along with the leftward slant writing style.Deep learning has amassed more favorable results in a variety of application domains which include image processing, lip reading, action recognition etc. This field of machine learning is new and it has been growing rapidly, and its applications are seen in traditional implementations. Deep Convolutional Neural Network (CNN) is a successful deep learning neural network algorithm for image processing and understanding the contents of the image. A pecking order of features of the images is learnt by building distinguished characteristics from the other characteristics. In CNN, sifts are implemented in the form of convolutional operations and are trained by supervised or unsupervised approaches. The trained filters are then applied one after the other in an alternative pattern on the raw input images. The results are computed from the distinguished characteristics that are obtained after training.

2. RELATED WORK

Deep Learning

A minimal subgroup of Artificial Intelligence (AI), which is called Machine Learning (ML), has transfigured sternly in different fields over the most recent couple of years. Deep learning is a sub area of AI in man-made reasoning (AI) that has systems that are equipped for taking in unsupervised from information that is unstructured or unlabeled. It is otherwise called profound neural learning or profound neural system. Neural Networks (NN) are a subfield of ML, and it was this subfield that generated Deep Learning (DL). DL is grounded on delination learning and requires a stepping stool of properties, where one component or the property can be interpretted by other component of the picture.

Artificial Neural Network

Artificial neural networks are one of the important tools that are employed in machine learning. As the "neural" portion of their label suggests, they are brain-inspired systems which are predetermined to recreate the way that we humans assimilate. Artificial neurons are the fundamental for building ANNs. The chief computational element called a node receives inputs and produce outputs. This is called a perceptron. The rudimentary block diagram of a perceptron for NNs is shown in the Fig. 1.

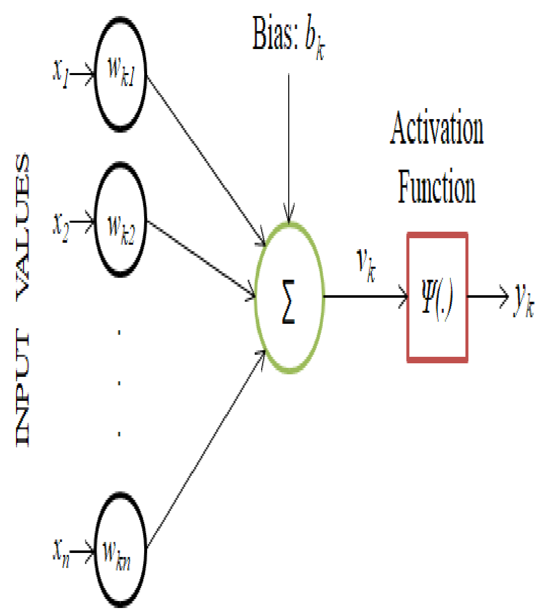

Fig. 1. Basic Architecture of Perceptron

Convolutional Neural Networks (CNN)

A convolutional neural network (CNN) is categorized under diverse kinds of artificial neural network implemented in image validation and undertaking certain activities that is distinctly depicted to operate pixel data. CNN has considerable outgrowth in different applications that are identified with designing issues like picture handling and understanding appointed work. CNN comprise of neurons that are of various loads and inclinations. Every neuron

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secures some info, plays out a lot of activities and afterward delivers the outcome. The portrayal of the Convolutional Neural Network is as appeared in Fig. 2.

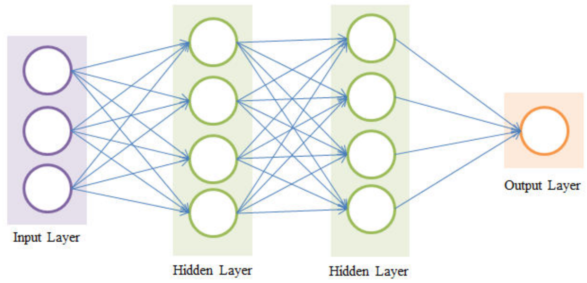

Fig. 2. Basic Layout of Convolutional Neural Network

Handwritten Character Recognition

Different researches have proposed various calculations for HCR in the earlier decade. In any case, HCR is a zone that has been looked into additional. This is done in the field of AI and example acknowledgment. The hearty and effective calculations are required improving the precision of the framework at lower cost of calculation. A CNN consists number of layers, when used in a repeated fashion leads to a formation of a Deep Neural Network which are used for image processing. Three main layers are used to build a CNN are:

1. **Input**: This layer holds the raw pixel values taken in RGB format of the given input image.

2. **Convolutional Layer**: This layer gets the results of the input layer that is connected to the input regions of the perceptron. The number of filters to be used in this layer for the computation of the result is defined here. Each filter takes the input data and produces the pixel with the maximum intensity as the output depending on the features that are to be evaluated.

3. **Rectified Linear Unit [ReLU] Layer**: This layer applies an activation function for the output of the convolutional layer. A CNN uses back propagation. ReLU function is applied to retain the same values of the pixels, here the negative values are eliminated and are not being changed by the back propagation.

4. **Pooling Layer**: This layer perform a down-sampling operation and eliminate the amount of characteristics used by which over fitting of data is avoided.

5. **Fully Connected Layer**: This layer is used to compute the score classes i.e. which class has the maximum score corresponding to the input and are flattened and sent to output transformation.

3. PROPOSED METHOD

This paper proposes a CNN algorithm to identify the leftward slant in the handwriting. This system consists of two stages, character segmentation and character recognition. After this, the system will be able to recognize the characters of the given input image as shown in Fig 3.

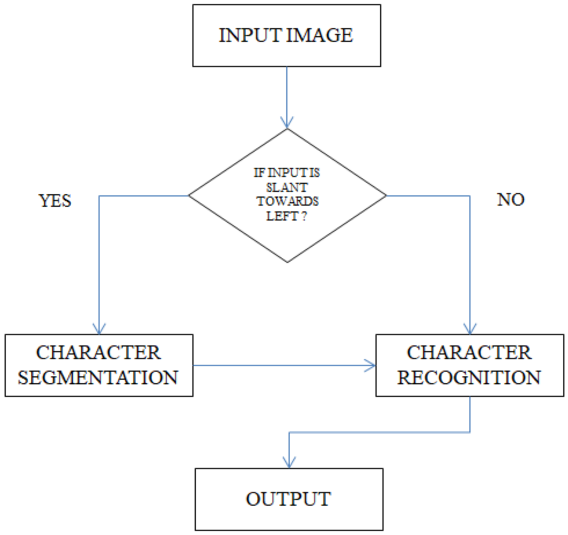

Fig. 3. Flow diagram of the Proposed System

Character Segmentation

The first step in Character Segmentation is to know the angle at which there is a slant in the given input. As shown in the Fig. 4(b), if the angle between the Line 1 (base line) and the Line 2 (line of the Slant Handwriting) is θ, then the angle of inclination is found by using trigonometric functions. The following equation is used:

$$\theta = \cos^{-1}\left(\frac{line\ 1}{line\ 2}\right) \tag{1}$$

Here, the Fig. 4(c) shows the rotated image of the given input image. After that, labeling is performed and then we inspect all of candidate blobs. The red rectangles show the segmented characters in Fig. 4(d)

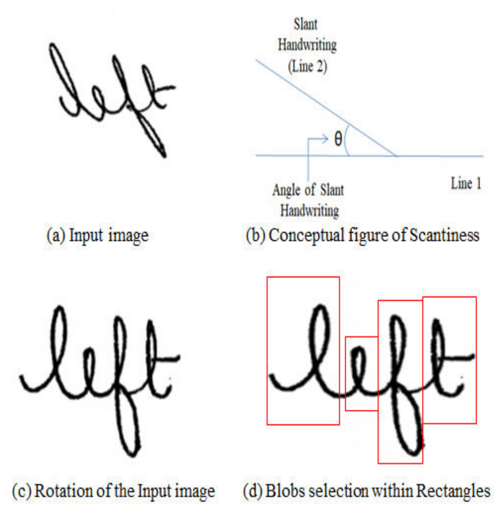

Fig. 4. Sequence of Character Segmentation

Character Recognition

The CNN for Handwritten Character Recognition works in three main phases.

1. **Phase1 - Input Data:** The initial step is to enter the information. For perceiving manually written structures, the absolute initial step was to assemble information in a significant sum for preparing. The Kaggle dataset contains 26 envelopes (A-Z) containing manually written pictures in size 28*28 pixels, every letter set in the picture is focus fitted to 20*20 pixel box. Each picture is put away as Gray-level

2. **Phase2 – Building Network Architecture:** In the second step, the bunch of ANN perceptron that will be utilized to construct a neural system is characterized. In this system, we have three layers "CONV =>ReLU=> POOL".

a) First Convolution Layer: Each convolution channel of a specific emphasis speaks to an element of enthusiasm of the picture. Here element implies the pictures that are to be contemplated for the further investigation. This element is moved to every one of the situations in the picture and checks how the component coordinates that zone from the dataset. The yield of the information that will experience the convolution channel isn't subject to the situation of the highlights that are situated in the info picture, however it checks whether the highlights are available in the dataset. The convolution is a strategy that utilizes Back Propagation for assurance of the yield.

b) ReLU Function: ReLU is an initiation work possibly enacts a hub if the information is over a specific amount or the normal benchmark and, while the info is underneath zero, the yield is zero, however when the info transcends a specific edge esteem or the edge esteem, a direct association with the needy variable. The primary point is to expel all the negative qualities from the convolution.

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c) Pooling Layer: In this layer, we decrease the picture stack into a littler size for example we diminish the extent of the picture. Pooling is done in the wake of going through the actuation layer or the ReLU work. The pooling layer gets information from the ReLU work registers them. In short it consolidates every one of the pixels acquired from past layers and intermittently shapes another picture lattice whose measure is littler than the first picture estimate.

These images are again given as a input into the second set of layers i.e. "CONV => ReLU=> POOL" and this process is repeated till we get to a smallest set of pixels from which we compute the result.

3. Phase 3 –Fully Connected Layer: The fully connected layer is utilized to interface the past layers to the following layers. Neurons of going before layers are associated with each neuron in resulting layers. This is like abnormal state thinking where every single imaginable pathway from the contribution to yield are considered. This is the last layer where the characterization really occurs. Here we take the separated and littler size pictures and places them into one single rundown.A Softmax Classifier is connected and it restores a rundown of probabilities of event of a specific name for every one of the 10 class names. The yield will be the class name whose likelihood is the most elevated and this is picked as the last characterization from the system. This yield acquired from this is utilized to frame the disarray framework for the model. The outcomes demonstrate the quantity of occasions that are right for example the each incentive at a specific position in the disarray grid tells the quantity of examples of the class which are arranged.

Here, we can add more number of layers. Adding more layers might affect the accuracy of the system. Since, it uses multiple layers, so it's called a Deep Learning system. As shown in Fig. 5, steps involved in character recognition are represented.

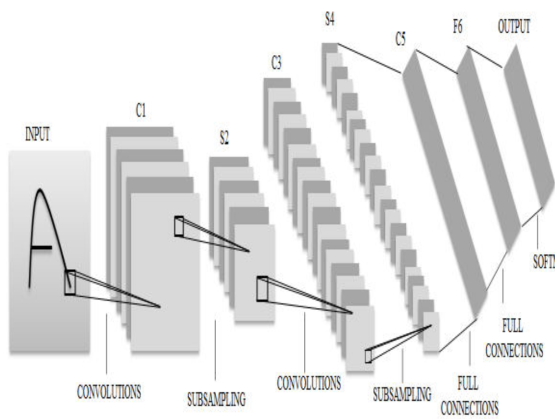

Fig. 5. Convolutional Neural Network in Character Recognition

4. CONCLUSION

An implementation of Handwritten Character Recognition of leftward slant handwriting using Deep Learning has been implemented in this paper. The paper proposes parallel computation architecture to check if the handwriting has a leftward slant, in the way it is written and presented as input, then the character Recognition takes place. If the handwriting is not slant, then the system skips the character segmentation and carries out the process of recognition to get the output. The nature of a HCR framework is principally subject to the measure of the preparation set and its quality. Convolutional neural system uses the information that the sources of info are not autonomous components, yet these emerge from a specific structure.

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