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Text Recognition with Artificial Neural Networks and OpenCV

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Abstract: Recognizing text in images has received attention recently. Traditional systems during this space have relied on elaborating models incorporating rigorously hand-designed options or giant amounts of previous information. This paper proposed by taking a different route and combines the representational power of large, multilayer neural networks together with recent developments in unsupervised feature learning, which allows us to use a standard framework to coach highly accurate character recognizer and text detector modules. The recognition pipeline of scanning, segmenting, and recognition is examined and delineated completely

Keywords: Artificial Neural Network, Handwriting Recognition, Segmentation. .

I. INTRODUCTION

In many practical applications, extracting textual information from natural images is a challenging problem. Unlike recognizing text in unconstrained images and character recognition for scanned documents, it is complicated by a wide range of variations in backgrounds, textures, fonts, and lighting conditions. As a result, To represent the underlying data, many text detection, and recognition systems rely on cleverly hand-engineered features [13, 12, 15]. Sophisticated models such as conditional random fields [14, 17] or pictorial structures [16] are also often required to combine the raw detection/recognition outputs into a complete system

A. Proposed Work

Segmenting text features is an important step provided the text is of same level and the scan is of acceptable quality. Character recognition involves extracting character's attributes which are inputs to be recognized in a synthetic Neural Network. Provided that the ANN is trained well, this method of recognition would allow a broad set of varying characters to be recognized. The ANN can be trained on typewritten characters or on any printed text, therefore, the application itself isn't essentially restricted to handwriting or

II. OFFLINE RECOGNITION

Online and offline are the two fundamental types of handwriting recognition. Online recognition deals with text that has been input to a machine through an analog-to-digital converter. Offline deals with writing that's on a physical sheet of paper and scanned into a pc for analysis. Here it is dealt with the latter. There are many distinct and ordered steps that enter recognizing offline handwriting: scanning, segmentation, and recognition. These steps are visibly laid out in figure 1 with the substeps of the segmentation process outlined as well.

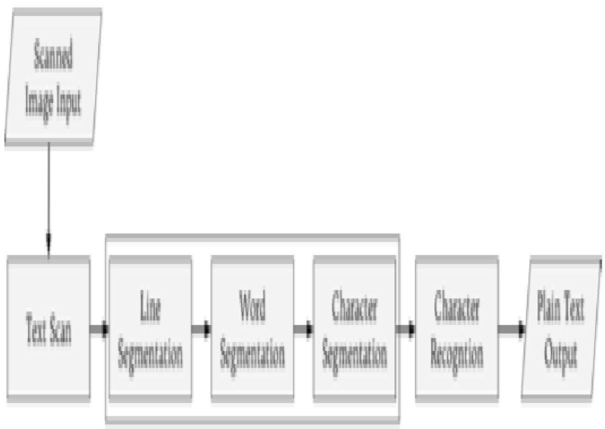

Fig.1.The recognition pipeline, segmentation steps have been grouped together. Slanted boxes signify some input or output

A. Text Scanning

There are 3 major steps that are involved to prepare the image for the process, first finding the text on the page, and if necessary, normalizing it. It's best for the software system to acknowledge higher distinction areas, an image operation that makes this easier by turning the whole image into simple black and white pixels. The most basic operation by OpenCV scans through associate degree image's pixels and applies the operation:

$$dst(x, y) = \begin{cases} maxvalue & \text{if } src(x, y) > \text{threshold value} \\ 0 & \text{otherwise} \end{cases}$$

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Where max value [1] is usually 255 for white. The threshold values are set up adaptively. By taking a mean of the area around the pixel as a threshold value and then comparing the pixel's value (src(x, y)), a more optimal threshold value can be determined.

if the area gets the lowest threshold value h, the image as a result of an adaptive threshold can be loaded with features we don't want to be brought out rendering it useless for feature extraction. [1] Unlike printed text, the handwritten notes can be aligned on different angles due to the writer's handwriting style. In case the text area might not be at the required level, without using the linear rotation transformation [10] the whole text areas and the text lines can be normalized or made straight.

III. FEATURE SEGMENTATION

A. Line Segmentation

For segmenting handwritten lines imaginary baselines are considered. clustering technique based baselines can find a leftmost point where the lines can start and also find the straight direction where they continue in. [9] One of the simple approaches is to scan the text from Top to bottom and segment on lines if there is no ink or features.

B. Word Segmentation

Components of the line are then extracted word by word. This approach is very similar to line segmentation however instead of scanning for gaps from top to bottom; it is scanned side to side. Larger gaps are easily distinguished as spaces. At this point, the application can go down in two ways once a word has been segmented. A word can be recognized by the integrated approach without looking at the characters closely. To match the image of the word, to the actual word, uses the approach which exploits a lexicon of possible words and also uses another approach which is template based or shape recognition approach. The use of the lexicon recognition system can be limited because not every word may be entered. The analytic approach identifies and extracts the characters from the word and tries to get the output that matches the exact word letter by letter. [4] Higher accuracy in recognizing words can be accomplished by combining the holistic and analytical approaches. [9] In this paper the analytical approach is only considered due to its dynamic nature.

C. Character Segmentation

For each word image extracted, to identify which textual characters contain in the word image extractions, variety of ways are available. Some drawbacks are there while using the mixed text of upper and lowercase letters. [9] By applying this algorithm in word segmentation, by weighing space between components, can be applied here assuming letters are reasonably spaced in a word. [9] If components or letters in a word are connected, it will lead to an Issues. It's connected letters that make character segmentation less trivial than a line or word segmentation. Cursive characters can also be searched for a letter's landmarks, ascending or descending strokes. Characteristics of certain letters are known by comparing those landmarks to a pool of stroke templates, so the separation of characters can be identified by looking at which landmarks occur on the left or right side of the character.

IV. CHARACTER RECOGNITION

A. Artificial Neural Network

ANN has become prevalent in computing primarily for its learning capability. There are a few different types of ANNs, and here the most used and basic type: a feed-forward ANN is used. A single layer feed-forward ANN consists of input neurons, hidden neurons, and output neurons each in their own layer. Each hidden layer neuron has an activation function and returns some function that takes parameters from input neurons. On the connections between neurons there are weights that alter the input in some way. Suppose the function for y in 2 is w1x1 + w2x2 and the activation function for y is a piecewise function

$$f(s) = \begin{cases} 1 & \text{if } s \text{ is even} \\ -1 & \text{otherwise} \end{cases}$$

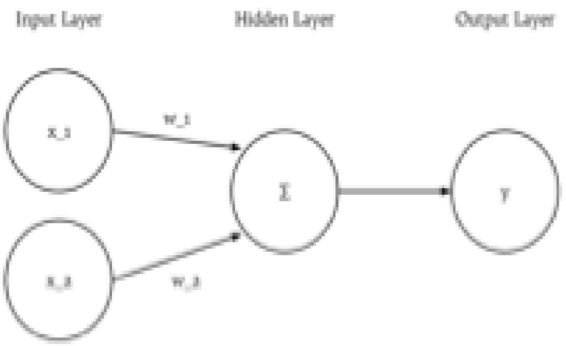

Fig. 2. A single layer artificial neural network with a single neuron in the hidden layer.

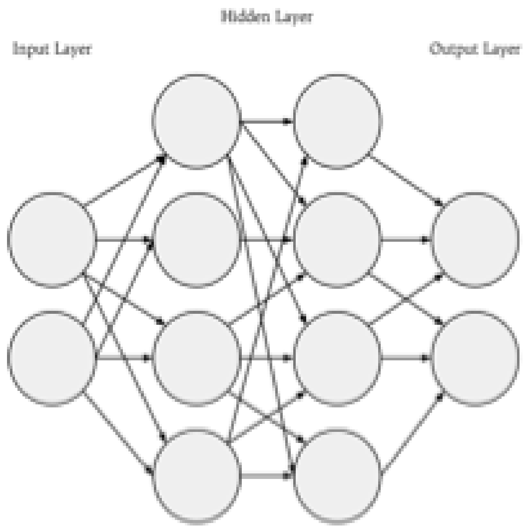

Fig.3. A multilayer Artificial Neural Network with two hidden layers, four neurons each.

The network output will be either be a 1 or -1. However, depending on the weights between the input and output (w1 and w2), the NN can output a wrong answer. We can train to rectify this.The most basic way to train a NN is with the perceptron learning rule. [6]

1. Suppose that the weights are at first random. Input and output nodes are as in (figure 1)
2. Given some training value y.
3. If y =6 f(y), modify the weights by $\Delta wi = f(y)xi$.

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4. Go to 2.

After some amount of training the NN's weights will be adjusted such that the output of the NN is almost always correct and provide the correct solution.

B. Multi- Layer Artificial Neural Networks and Back Propagation

By adding another layer of neurons to the hidden layer, many complex calculations can be solved, such as analyzing the shape of a letter and determining what letter it is. Then the Artificial Neural Network will become multi-layer Artificial Neural Network (figure 3). Due to a new topology, perceptron learning rule to update weights cannot be used, instead a method called backpropagation which works similarly to it is introduced. Connections between two neurons j and k in the hidden layer have weights too and are annotated as work.

1. Initialize all weights randomly.
2. Given some training values z for output nodes y.
3. If y =6 z, update each of the weights for the output and hidden layers in the network so that $\Delta wij = \gamma\delta kyj$.

[6]This is called the generalized delta rule, δ is an error rate from the training value and γ a learning rate. The error rate depends on the weights, whenever the weights are being changed, the error rate will also change. Due to the weight change, the whole network gets affected.so if the weights are in a perceptron learning model it should not be changed drastically; because the error has there is some gradient descent value [8].

C. Deficiency of Artificial Neural Network

By using Artificial Neural Network will get a fine balance. If there is too much training of the network, the NN will only give accurate output for values similar to the training values; this is suitably called overtraining or over fitting. In a handwriting recognition context, if the NN is to be trained on single-user handwriting alone, it would only be able to accurately recognize the handwriting. Here overtraining is prevented by finding out an optimal training set size by incrementing as many training sets that are available and then running a validation set on the NN, the lower the error on the validation set the more precise we can find n. [8] If input or output values are too large, network paralysis can occur due to the weights being too large for backpropagation, to have a proper effect. [6] A careful design of the network's input neurons and output neurons can aid against it.

D. Using Artificial Neural Networks to Recognize Characters

Recognizing a character is dependent on the quality of the scanning and segmentation steps. If character segmentation infirmly slites a character in half, and if the network is trained with that value, it will not be able to recognize the full versions of that character or it might incorrectly categorize other characters. Even with good segmentation, the input for an ANN must be something that can quantify a character. Likewise, its output must be something that can get a character from. There is a wide variety of data that can be used to analyze an individual character from as simple as a ratio of pixels on the top half to the bottom half, to analyzing the contour analysis of the binary image and histograms of the image. [11] The more information it can get about a character the better, and more input neurons will exist. Having too many input values across a wide range can lead to network paralysis. The above same value goes for the output values, an intended large output value from a cluster of small inputs can easily lead to a case of paralysis because the input values will not change as relative to the output.

V. CONCLUSION

Classifier	Recognition Rate (%)	Misclassified Image (%)	Error Rate (%)	Time(s)
ANN	95.10	0.73	4.17	0.658

Table 1.1. Rate of ANN on UCI Data Set

The result of ANN the classifier used for handwritten text is shown in the form of Table 1.1. That is, the individual recognition rate (Rec. Rate), misclassified image (Misc Image), error rates and recognition times (Rec. Time) of the ANNs is represented. An ANNs provide a low misclassification rate and take significantly very less time for training. Hence, by opting the ANN classifier it is easy to recognize the natural image in a high standard in spite of complex images and textures with less time and high rate of recognition.

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