OPTICAL CHARACTER RECOGNITION USING ARTIFICIAL NEURAL NETWORK

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Abstract

Optical character recognition is the mechanical or electronic translation of images of handwritten, typewritten or printed text into machine-editable text. In this paper, a simple neural approach to recognition of optical or visual characters is portrayed and discussed.

Keywords- Optical character recognition, Artificial Neural Network, supervised learning, the back propagation algorithm.

1. Introduction: OCR is the acronym for Optical Character Recognition. This technology allows a machine to automatically recognize characters through an optical mechanism. Optical Character Recognition that would use an Artificial Neural Network as the backend to solve the classification problem. Optical character recognition is the mechanical or electronic translation of images of handwritten, typewritten or printed text (usually captured by a scanner) into machine-editable text. One of the most classical applications of the Artificial Neural Network is the Character Recognition System. This system is the base for many different types of applications in various fields, many of which we use in our daily lives. Cost effective and less time consuming, businesses, post offices, banks, security systems, and even the field of robotics employ this system as the base of their operations. We are processing a check, performing an eye/face scan at the airport entrance, or teaching a robot to pick up and object, employing the system of Character Recognition.

2. OCR Working: A typical OCR system consists of several components. The first step in the process is to digitize the analog document using an optical scanner. When the regions containing text are located, each symbol is extracted through a segmentation process. The extracted symbols may then be preprocessed, eliminating noise, to facilitate the extraction of features in the next step.

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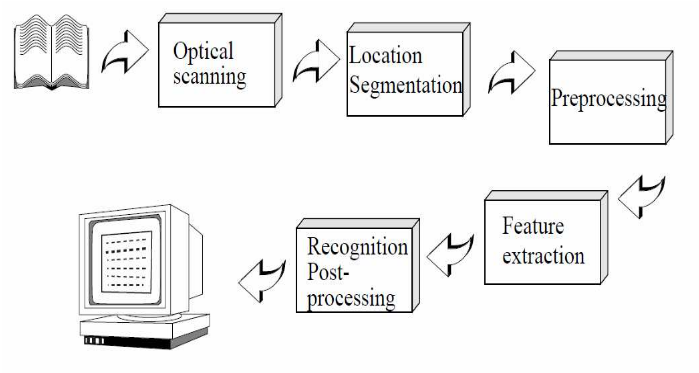


Figure: Components of an OCR system

The identity of each symbol is found by comparing t he extracted features with descriptions of the symbol classes obtained through a previous learning phase. Finally contextual information is used to reconstruct the w ords and numbers of the original text. In the next sections these steps and some of the m e thods involved are described in more detail.

3. **OCR Methods** There are five types of OCR methods-

1. Optical Character Recognition (OCR)- OCR engines turn images of machine-printed characters into machine-readable characters. Images of machine-printed characters are extracted from a bitmap. Forms can b e scanned through an imaging scanner, faxed, or computer generated to produce the bitmap. OCR is less accurate than optical mark recognition but more accurate than int elligent character recognition.

2. Intelligent Character Recognition (ICR)- ICR reads images of hand-printed characters (not cursive) and converts them into mac hine-readable characters. Images of hand-printed characters are extracted from a bitmap of the scanned image. ICR recognition of numeric characters is much more accu rate than the recognition of letters. ICR is less accurate than OMR and requires some edi ting and verification. However, proven form design methods can be used to help a percentage minimize ICR errors.

3. Optical Mark Recognition (OMR)- OMR technology detects the existence of a mark, not its shape. OMR forms usually contain small ovals, referred to as 'bubbles,' or check boxes that the respondent fills in. OMR cannot recognize alphabetic or numeric characters. OMR is the fastest and most accurate of the data collection technologies. It is also relatively user-friendly. The accuracy of OMR is a result of precise measurement of the darkness of a mark, and the sophisticated mark discrimination algorithms for determining whether what is detected is an erasure or a mark.

4. Magnetic Ink Character Recognition:- MICR is a specialized character recognition technology adopted by the U.S. banking industry to facilitate check processing. Almost

al US and UK checks include MICR characters at the bottom of the paper in a font known as E-13B. Many modern recognition engines can recognize E-13B fonts that are not printed with magnetic ink. However, since background designs can interfere with optical recognition, the banking industry uses magnetic ink on checks to ensure accuracy.

Figure: Magnetic Ink Character Recognition

5. Barcode Recognition:- A barcode is a machine-readable representation of information. Barcodes can be read by optical scanners called barcode readers or scanned from an image using software. A 2D barcode is similar to a linear, one-dimensional barcode, but has more data representation capability.

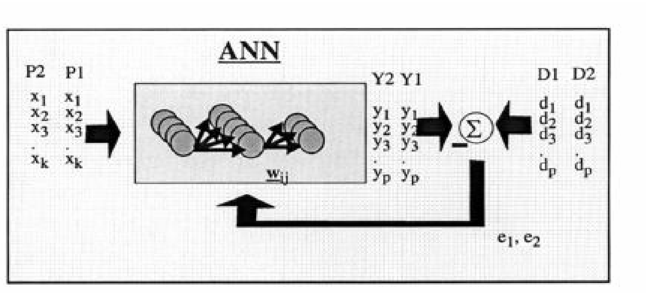
0 12345 67890 5

1D barcode
Universal Product Code (UPC)

2D barcode
The Gettysburg Address

Figure: Barcode Recognition

4. Artificial Neural Network: An **artificial neural network (ANN)**, usually called "neural network" (NN), is a mathematical model or computational model that tries to simulate the structure consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.



The style of neural computation.

Figure: Artificial neural network

In neural network design, the engineer or designer chooses the network topology, the trigger function or performance function, learning rule and the criteria for stopping the

training phase. Simplicity of the future term in ing the size and parameters of the network achieve in order to formulate. The best w e can do of having success w ithout design is playing with. The problem with this m ethod w hen the system does not w ork properly is hard to refine the solution. Despite this issue, neural networks based solution is very efficient in terms of development, time and resources. A ll neural networks provide a solution that useful form at with other technologies.

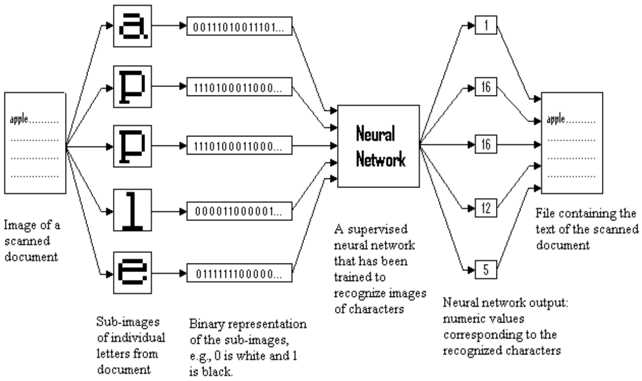


Figure A typical artificial neural network

5. **Backpropagation Algorithm :** The algorithm behind backpropagation networks was discovered independently by several research groups at about the same time in 1985-86. A backpropagation network usually consists of three layers of neurons: the input layer, the hidden layer, and the output layer.

The algorithm works like this-

1. First apply the inputs to the network and work out the output – remember the initial output could be anything, as the initial weights were random numbers.

2. Next work out the error for neuron B. The error is what you want – What we actually *get*, in other words:

ErrorB = OutputB (1-OutputB)(TargetB – OutputB)
The "Output(1-Output)" term is necessary in the equation because of the Sigmoid Function – if we were only using a threshold neuron it would just be (Target – Output).

3. Change the weight. Let W+AB be the new (trained) weight and WAB be the initial weight

W+AB = WAB + (ErrorB x OutputA)

Notice that it is the output of the connecting neuron (neuron A) we use (not B). We update all the weights in the output layer in this way.

4. Calculate the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly (because we don't have a Target), so we *Back Propagate* them from the output layer (hence the name of the algorithm). This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example if neuron A is connected as shown to B and C then we take the errors from B and C to generate an error for A.

$$\text{Error}_A = \text{Output}_A (1 - \text{Output}_A)(\text{Error}_B W_{AB} + \text{Error}_C W_{AC})$$

Again, the factor "*Output (1 - Output)*" is present because of the sigmoid squashing function.

5. Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

6. Conclusion: At the current stage of development, the software does perform well either in terms of speed or accuracy but not better. It is unlikely to replace existing OCR methods, especially for English text. Artificial neural networks are commonly used to perform character recognition due to their high noise tolerance. The systems have the ability to yield excellent results. The feature extraction step of optical character recognition is the most important. A poorly chosen set of features will yield poor classification rates by any neural network. Features must be chosen such that they are lossless or accurately represent the character. A simple approach for recognition of Optical characters using artificial neural networks has been described. Despite the computational complexity involved, artificial neural networks offer several advantages in back-propagation network and classification in the sense of emulating adaptive human intelligence to a small extent.

This requires some effort, but clearly more training data would lead to a more robust and accurate ANNs. Some other helpful features are worth using. For example, characters like the apostrophe (') and comma (,) look very similar and can be distinguished only by vertical location.

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