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ARTIFICIAL NEURAL NETWORKS FOR HANDWRITING AND DIGITS RECOGNITION

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ABSTRACT

Artificial intelligenceand neural networks represent powerful and exciting machine learning techniques which are used to solve many real-world problems. Artificial neural networks (ANNs) or connectionist systems are computing systems that are inspired by the biological neural networks that constitute animal brains. Such systems learn to do tasks by considering examples, generally without task-specific programming.

An ANN is based on a collection of interconnected units called artificial neurons. Each connection between neurons can transmit a signal to another neuron. The receiving neuron can process the signal(s) and then signal downstream neurons connected to it. In common the implementation of ANN is the synapse signal is simply a real number, and the output of each neuron is calculated by a non-linear function of the sum of all its input.

Handwriting recognition is the ability of a computer to receive and interpret intelligible handwritten input from the sources such as paperdocuments, photographs, and other devices. The image of the written text may be sensed either "offline" from optical scanning or "online".

This paper demonstrates the use of neural networks for developing a system that can recognize hand-written English alphabets and digits by the corner detection method.

Keywords: Artificial Neural network, digit recognition, handwritten character.

I. INTRODUCTION

Artificial neural networks (ANNs) are paradigms used for information processing in computing systems inspired by the biological neural networks that constitute of animal brains. Such systems will have a highly composed of artificial neurons working together which uses signals to transmit of the data for and the receiving signal will process the data by sending the signal downstream for solving a specific problem. By using the rule-based programming they have found that the difficult computer algorithms can be expressed. ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

Researchers demonstrated (2010) that when deep neural networks interfaced with hidden Markov model with context-dependent, states that define the neural network output layer that can drastically reduce the errors in large-vocabulary speech recognition tasks such as voice search.

Handwriting recognition can be divided into two categories depending on the input methods: off-line handwriting recognition and on-line handwriting recognition. For off-line recognition, the optically scanned image is used. For on-line recognition, a digitizer samples the handwriting to time-sequenced pixels as it is being written. Hence, the on-line handwriting signal contains additional time information which is not present in the off-line signal. The method implemented in this paper is implied for both online as well as off-line recognition of handwriting and digits. The task of recognizing the handwriting (i.e.. digits, and alphabets) varies from person to person. Since each person possess a unite handwriting style. This is one of the major reason as to why handwriting is considered as one of the major challenging study.

Natural hand-writing recognition has been studied for nearly forty years and there have been many proposed and existing approaches. The problem is quite complex, and till now there is no approach that solves it both completely and efficiently in allcontexts. In written language recognition processes, an image containing

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text must be appropriately supplied and preprocessed. Then the text must undergo noise removal and or feature extraction. The processed handwriting of the text will be the result, and these must undergo recognition by the system. Finally, contextual information should be applied to the recognized symbols to verify the result. Artificial neural networks, applied in handwriting recognition, allow for high ability to generalize easily and do not require deep background knowledge.

ANN **capabilities** are broadly categorized into:

- Function approximation, or regression analysis, including time series prediction, fitness approximation, and modeling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Data processing, including filtering, blind source separation, clustering, and compression.
- Robotics, including directing manipulators and prostheses.
- Control, including computer numerical control.

ANN **applications** are as follows:

- Application areas include system identification and control (vehicle control, trajectory prediction, process control, natural resources management), quantum chemistry,game-playing and decision making (backgammon, chess, poker), pattern recognition (radar systems, face identification, signal classification,object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, finance, data mining, visualization, machine translation, social network filtering and e-mail spam filtering.
- ANNs have been used to diagnose cancers, including lung cancer, prostate cancer, colorectal cancer and to distinguish highly invasive cancer cell lines from less invasive lines using only cell shape information.
- ANNs have been used for building black-box models in geoscience: hydrology, ocean modeling and coastal engineering, and geomorphology are just a few examples of this kind.

II. DESIGN

Neurons are organized in different layers which perform different kinds of transformations based on their inputs. Signals travel from the first (input) to the last (output) layer, after traversing the layers multiple times in multiple ways.The goal of the neural network approach is to solve problems in the same way that a human brain would solve. Over time, attention was focused on matching specific mental abilities, leading to deviations from biology such as backpropagation, or passing information in the reverse direction and adjusting the network to reflect that information.Neural networks have been used on a variety of tasks such as speech recognition, machine translation, computer vision, social network filtering, playing board and video games, medical diagnosis and in many other domains. Christo Ananth et al. proposed a method in which the minimization is per-formed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Hence, the segmentation methods are validated by calculating statistical measures. The false positive (FP) is reduced and sensitivity and specificity improved by multiple MTANN.

NEURAL NETWORK ARCHITECTURE:

The neural network is stimulatedto obtain a better understanding of the human brain and to develop computers that can deal with abstract and poorly defined problems. For example, conventional computers have trouble understanding speech and recognizing people's faces. In comparison, humans do extremely well at these tasks.

Many different neural network structures have been proposed, some based on a more mathematical analysis of the problem, some based on imitating what a biologist sees under the microscope. The fig below illustrates a typical neural network architecture. A neural network is formed in three layers, **input layer, hidden layer,** andan**output layer**. Each layer consists of one or more nodes, represented in the diagram by the small circles. The lines between the nodes indicate the flow of information from one node to the next. Other types of neural networks have more intricate connections, such as feedback paths.

The nodes of the input layer are passive, i.e. the data will not be modified. They receive only a single value on their input and duplicate the value to their multiple outputs. Each value from the input layer is duplicated and then sent to all of the hidden nodes. This is called a fully interconnected structure. And finally, the value gets transmitted to the output layer, where the result is produced.

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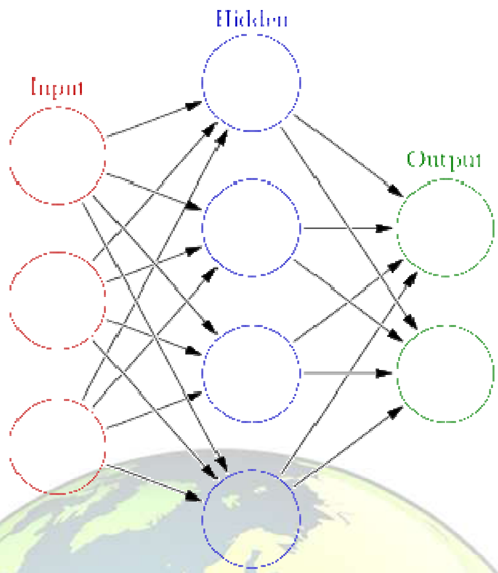


Fig1:Neural network architecture

2.1 IMAGE PROCESSING

When the input document is put to visual recognition, it is expected to be consisting of printed (or handwritten) characters pertaining to one or more scripts or fonts. The document might contain information besides optical characters alone. For example, it may contain pictures and colors that do not provide any useful information in the instant sense of character recognition. In addition, characters which need to be singly analyzed may exist as word clusters or may be located at various points in the document. Such an image is usually processed for noise-reduction and separation of individual characters from the document. This process is called the image processing.

2.1.1 NOICE REMOVAL

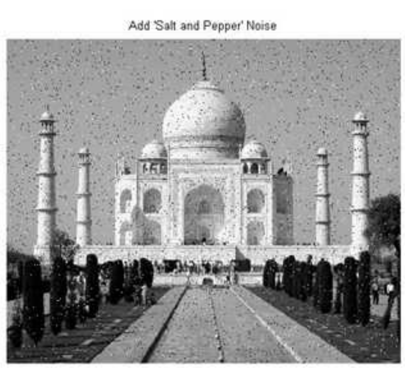
Image noise is the variation of color or the brightness information in the images. Noise can be produced by the sensorand circuitry of a scanner or a digital camera. Image noise is an undesirable by-product of an image capture that obscures the desired information. It is convenient that the submitted image is freed from noise.

Types of noises present and noise removal techniques:

1. SALT AND PEPPER NOISE

Impulsive or fat-tail distributed noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc.It can be eliminated by using dark frame subtraction, median filtering and interpolating around dark/bright pixels.

BEFORE **AFTER**



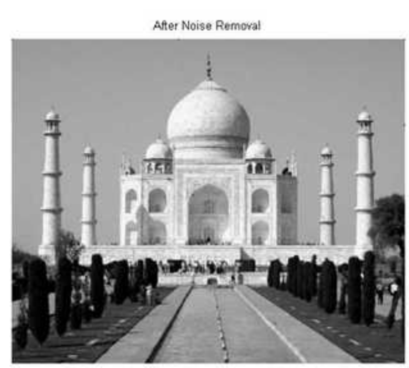


Fig2: Removal of salt and pepper noise

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2. GAUSSIAN NOISE

Principal sources of Gaussian noise in digital images arise during acquisition. The sensor has inherent noise due to the level of illumination and its own temperature, and the electronic circuits connected to the sensor inject their own share of electronic circuit noise.

DE-BLURRING

When the image is taken in motion then the image would be blurred which also includes the noise. It has to be eliminated in order to get the proper view of the characters or digits. A neural network model combining an adaptive auto-associative network with a random Gaussian process is proposed to restore the blurred image and blur function simultaneously. The noisy and blurred images are modeled as continuous associative networks, whereas auto-associative part determines the image model coefficients and the hetero-associative part determines the blur function of the system. The self-organization like structure provides the potential solution to the blind image restoration problem. The estimation and restoration are implemented by using an iterative gradient-based algorithm to minimize the error function. De-blurring can be done by the median filter technique.

BEFORE **AFTER**

Fig3: De-blurring the image

A typical model of image noise is Gaussian, additive, independent at each pixel, and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise), including that which comes from the reset noise of capacitors ("kTC noise"). Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image.In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel.

BEFORE AFTER

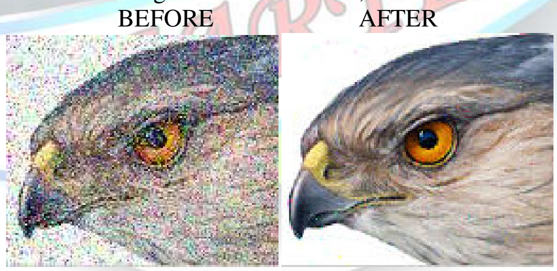

Fig4:Removal of Gaussian noise

III. FEATURE EXTRACTION WITH RESULTS:

The acquirement procedure for the feature extraction phase is the procedure under which data is taken out of the images for categorization. Under this procedure, sub-features of the segmented characters are recognized on the basis of their starting points, end points, lines, curves, sizes, shapes, and widths, etc. For the feature extraction, the important parameters such as features of handwriting capital letters were extracted and were studied in detail.

The process of feature extraction is important for the neural network used in the system. In this process, the input image is sampled into a window which forwards the input to the recognition system. The feature input of the characters is executed and subsequently the solitude. Following this, they are processed with the data acquired from the databank, therefore it facilitates evaluation for any identical structures. For example, an image consisting of text is divided into various lower levels of symbols and characters. Subsequently, these characters are recognized by the corner detection format, which can be easily facilitated by the computer. The

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categorization procedure recognizes the information sourced from the extracted features. The phases of this process are provided below:

- **Input:** Reading the image document from a file or the text typed online.
- **Noise removal:** Using different noise removal techniques for the generation of clear images.
- **Corner detection:** Detect the corners by using the algorithm and perform the traversal operation until the character is recognized.
- **Output:** Handwritten characters and digits recognized and stored in a file.

CORNER-DETECTION METHOD:

Corner detection is amethod usedin the computer vision systems to extract only certain kinds of features and infer the contents of the image. Corner detection method is frequently used in 3D-modeling, image-recognition, video-tracking, motion-detection, and object recognition.

FORMALIZATION:

A corner can be determined by the intersection of 2 edges. It can also be defined as a point for which there is two dominant and different edge directions in a local neighborhood of the point.

An interest-point is a point in an image which has a defined position and can be easily detected. This means, that a corner is an interesting point. In practice, most of the corner detection methods, detect interest points. In fact, the terms “corner” and “interest-point” are used more or less interchangeably.

Corner detector algorithms require large redundancies that are introduced to prevent the effect of individual errors and are very robust in nature.One quality of a corner detector is the ability to detect the same corner in multiple similar images, under conditions of differenttranslations, lighting, rotations and other transforms.

Fig: Illustration of Corner-detection.

Moravec corner detection algorithm:

Denote the image intensity of a pixel at (x, y) by I(x, y).

Input: grayscale image, window size, threshold T

Output: map indicating position of each detected corner

1. For each pixel (x, y) in the image calculate the intensity variation from ashift (u, v) as: where the shifts (u,v) considered are:
(1,0),(1,1),(0,1),(-1,1),(-1,0),(-1,-1),(0,-1),(1,-1)
2. By calculating the cornerness measure C(x, y) for each pixel (x, y) construct the cornerness map:
3. Threshold the interest map by setting all C(x, y) below a threshold T to zero.
4. Perform non-maximal suppression to find local maxima.

All the non-zero points remaining in the cornerness map are corners.

In the below figure1 the alphabet C and the digit 1 can be traversed through cells, each having a single color, either black or white. It becomes important for us to encode this information in a form meaningful to a computer. For this, we extract a single character/digit one at a time. Now, we find the corners of each black pixel and mark the corners using the corner detection method as shown in figure2. So much of conversion is enough for neural networking to carry out the traversal. Traversalof the image starts as soon as the corners get detected. The traversal of the black pixel proceeds until the entire character/digit is recognized as shown in figure3. By the end of the traversal, the neural system recognizes the character/ digit and outputs the content. Hence an image of whatever size gets transformed into a pre-determined font as shown in the figure4. This establishes uniformity in the input and stored patterns as they move through the recognition system.

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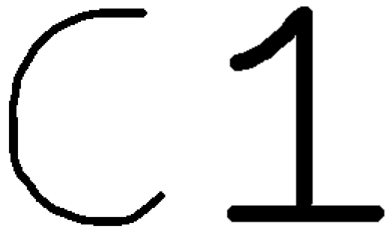

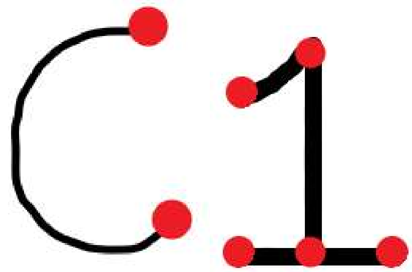

Fig1:Input image **Fig2: Corner detection**

C1

Fig3: Traversal of the character **Fig4: Pre-defined font**

IV. CONCLUSION

A simplistic approach to recognition of handwritten characters and digits using artificial neural networks has been described. Despite the computational complexity involved, artificial neural networks offer several advantages in pattern recognition and classification in the sense of emulating adaptive human intelligence to a small extent. The span of this research involved functions, i.e. acquisition of images, selection of characters, pre-processing, and creation of outcomes.

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