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# A Study of Associative Memories with Hopfield neural network Model for handwritten character recognition

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**ABSTRACT**

Neural network is the most important model which has been studied in past decades by several researchers. Hopfield model is one of the network model proposed by J.J. Hopfield that describes the organization of neurons in such a way that they function as associative memory or also called content addressable memory. This is a recurrent network similar to recurrent layer of the hamming network but which can effectively perform the operation of both layer hamming network. The design of recurrent network has always been interesting problems to research and a lot of work is going on present application. In present paper we will discuss about the design of Hopfield Neural Network (HNNs), bidirectional associative memory (BAMs) and multidirectional associative memory (MAMs) for handwritten characters recognition. Recognized characters are Hindi alphabets.

## 1. INTRODUCTION

This paper deals with the basics of artificial neural networks (ANN) and their applications in handwritten characters recognition. ANN can be viewed as computing models inspired by the structure and function of the biological neural network. These models are expected to deal with problem solving in a manner different from conventional computing. A distinction is made between pattern and data to emphasize the need for developing pattern processing systems to address handwritten characters recognition tasks. After introducing the basic principles of ANN, some fundamental networks are examined in detail for their ability to solve Hindi handwritten characters recognition. These fundamental networks together with the principles of ANN will lead to the development of architectures for complex handwritten characters recognition tasks. A few popular architectures are described to illustrate the need to develop an architecture specific to a given handwritten characters recognition problem. Finally several issues that still need to be addressed to solve practical problems using ANN approach are discussed [1].

One of the most common applications of NNs is in image processing. Some examples would be: identifying hand-written characters; matching a photograph of a person's face with a different photo in a database; performing data compression on an image with minimal loss of content. Other applications could be voice recognition; RADAR signature analysis; stock market prediction. All of these problems involve large amounts of data, and complex relationships between the different parameters [2]. Functionally also humans and machines differ in the sense that humans ***understand*** patterns, whereas machines can be said to ***recognize*** patterns in data. In other words, humans can get the whole object in the data even though there may be no clear identification of sub patterns in the data. For example, consider the name of a person written in a handwritten cursive script [3]. Even though individual patterns for each letter may not be evident, the name is understood due to the visual hints provided in the written script. Likewise, speech is understood even though the patterns corresponding to individual sounds may be distorted sometimes to unrecognizable extents. Another major characteristic of a human being is the ability to continuously learn from examples, which is not well understood at all in order to implement it in an algorithmic fashion in a machine. Human beings are capable of making mental patterns in their biological neural network from input data given in the form of numbers, text, pictures, sounds etc., using their sensory mechanisms of vision, sound, touch, smell and taste. These mental patterns are formed even when the data are noisy, or deformed due to variations such as translation, rotation and scaling. The patterns are also formed from a temporal sequence of data as in the case of speech and motion pictures. Humans have the ability to recall the stored patterns even when the input information is noisy or partial (incomplete) or mixed with information pertaining to other patterns [4].An association is an input-output pair. Associative memory, also known as *content-addressable memory*, is a memory organization that accesses memory by its content instead of its address. It picks up a desirable match from all stored prototypes. An associative memory can be auto-associative or hetero-associative. The architecture of an associative memory network may be feed forward, bidirectional, or recurrent. The Hopfield model and the Boltzmann machine are popular auto-associative memories [4].Associative memories are useful for pattern recognition and pattern association. When an incomplete or corrupted sample is presented to the neural network, the network is required to recall the stored correct pattern [5].

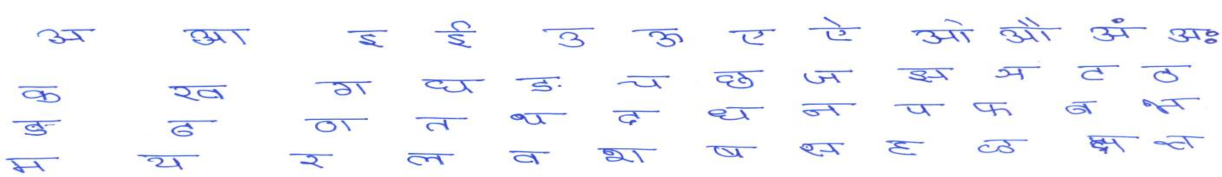
Neural network has many applications. The most likely applications for the neural networks

are (1) Classification (2) Association and (3) Reasoning. One of the applications of neural networks is in the field of pattern recognition. Pattern recognition is a branch of artificial intelligence concerned with the classification or description of observations. Its aim is to classify patterns based on either a priori knowledge or on the features extracted from the patterns. Pattern recognition is the recognition or separation of one particular sequence of bits or pattern from other such patterns. Pattern recognition [PR] applications have been varied, and so also the associated data structures and processing paradigms. In the course of time, four significant approaches to PR have evolved. In this paper, we have described a method used in our research work for the recognition of handwritten character. In the proposed work, we have used Neural–Network technique in the first phase and then the Euclidean distance metric is used to improve the recognition performance [6-10].

## 2. DATA COLLECTION AND PREPROCESSING

Data collection for the experiment has been done from the different individuals. Currently we are developing datasets for Hindi. We have collected 2000 Hindi numeral samples from 200 different writers. Writers were provided with the plain A4 sheet and each writer has asked to write Hindi numerals from 0 to 12 for one time. The database is totally unconstrained and has been created for validating the recognition system .

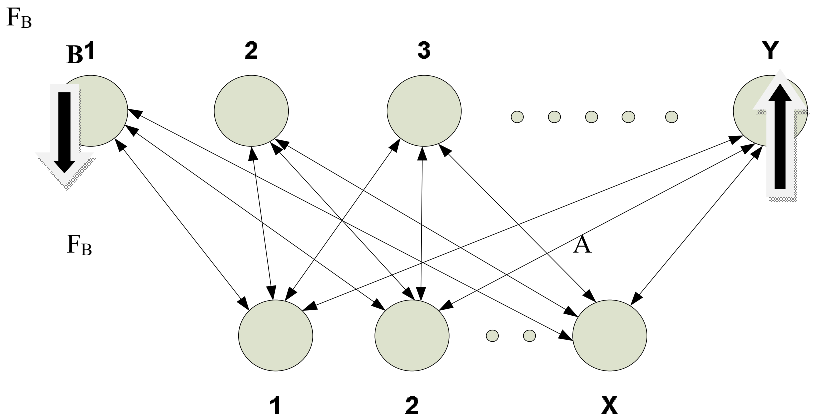
The collected documents are scanned using HP-scan jet 5400c at 300dpi which is usually a low noise and good quality image. The digitized images are stored as binary images in BMP format. A sample of Hindi handwritten numerals from the data set are shown in figure (a) respectively.



Sample handwritten Figure (a)

## 3. BIDIRECTIONAL ASSOCIATIVE MEMORY (BAM) NETWORK:

The bidirectional associative memory (BAM) is the minimal two-layer nonlinear feedback network. Bidirectional, forward and backward information flow, is introduced in neural networks to produce two way associative searches for stored stimulus-response associations ($A_i$, $B_i$). Two fields of neurons, $F_A$ and $F_B$, are connected by an n X p synaptic matrix M. Passing information through M gives one direction, passing information through its transpose $M^T$ gives the other. Every matrix is bidirectional stable for bivalent and for continuous neurons. Paired data ($A_i$, $B_i$) are encoded in M by summing bipolar correlation matrices. The bidirectional associative memory (BAM) behaves as a two-layer hierarchy of symmetrically connected neurons. When the neurons in $F_A$ and $F_B$ are activated, the network quickly evolves to a stable state of two pattern reverberation, or pseudo adaptive resonance, for every connection topology M. The stable reverberation corresponds to a system energy local minimum [7-20]. An adaptive BAM allows M to rapidly learn associations without supervision. Stable short-term memory reverberations across $F_A$ and $F_B$ gradually seep pattern information into the long-term memory connections M, allowing input associations ($A_i$, $B_i$) to dig their own energy wells in the network state space. The BAM correlation encoding scheme is extended to a general Hebbian learning law. Then every BAM adaptively resonates in the sense that all nodes and edges quickly equilibrate in a system energy local minimum [8-12]. A sampling adaptive BAM results when many more training samples are presented than there are neurons in $F_A$ and $F_B$, but presented for brief pulses of learning, not allowing learning to fully or nearly converge. Learning tends to improve with sample size. Sampling adaptive BAMs can learn some simple continuous mappings and can rapidly abstract bivalent associations [9-15].




BAM two-layer hierarchy of symmetrically connected neurons Figure (b)

## 4. MULTIDIRECTIONAL ASSOCIATIVE MEMORY (MAM):

Multidirectional Associative Memory (MAM) is an associative memory model that can deal with multiple associations. It can be considered as a generalized Bidirectional Associative Memory (BAM). Multidirectional Associative Memory with a Hidden Layer (MAMH) improves the storage capacity of MAM [10]. MAM (Multidirectional Associative Memory) is an extended BAM (Bidirectional Associative Memory), and an associative memory model which can deal with multiple associations. If the training set has common terms, the conventional MAM often recalls the convolution MAM (Multidirectional Associative Memory) is an extended BAM (Bidirectional Associative Memory), and an associative memory model which can deal with multiple associations. If the training set has common terms, the conventional MAM often recalls the convolution patterns. IMAM (Improved Multidirectional Associative Memory) can store them, but the structure is complex and the storage capacity is extremely small because it must use correlation matrix all patterns. IMAM (Improved Multidirectional Associative Memory) can store them, but the structure is complex and the storage capacity is extremely small because it must use correlation matrix [11].

## 5. HOPFIELD NEURAL NETWORK (HNN) :

The Hopfield neural network was introduced by Hopfield in 1982, which introduced the climax of the research on the neural networks. This network was extended to bidirectional associative memory (BAM) neural network by Kosko in 1987 and to multidirectional associative memory (MAM) neural network by Hagiwara in 1990. They all can realize associative memory. But by using the MAM neural networks, one can achieve the many-to-many association which is a very advanced function of human brain. The many-to-many association has found wide applications in image de-noising, speech recognition, pattern recognition, and intelligent information processing . For example, it was shown that today most Indians are derived from the two-ancestor group gene by DNA analyzing [22]. If we need to distinguish which category an Indian belongs to, then this is a many-to-many associative problem [12-25]. Hopfield neural network look like figure (c)

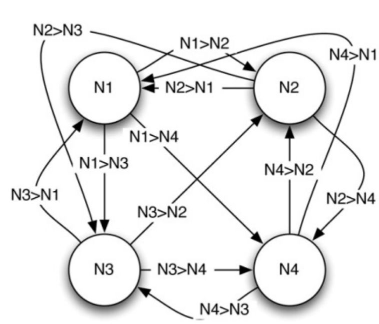
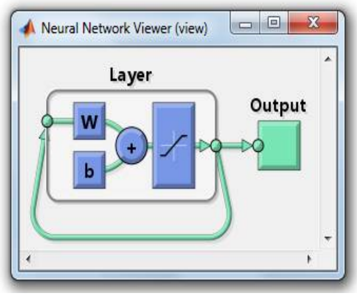


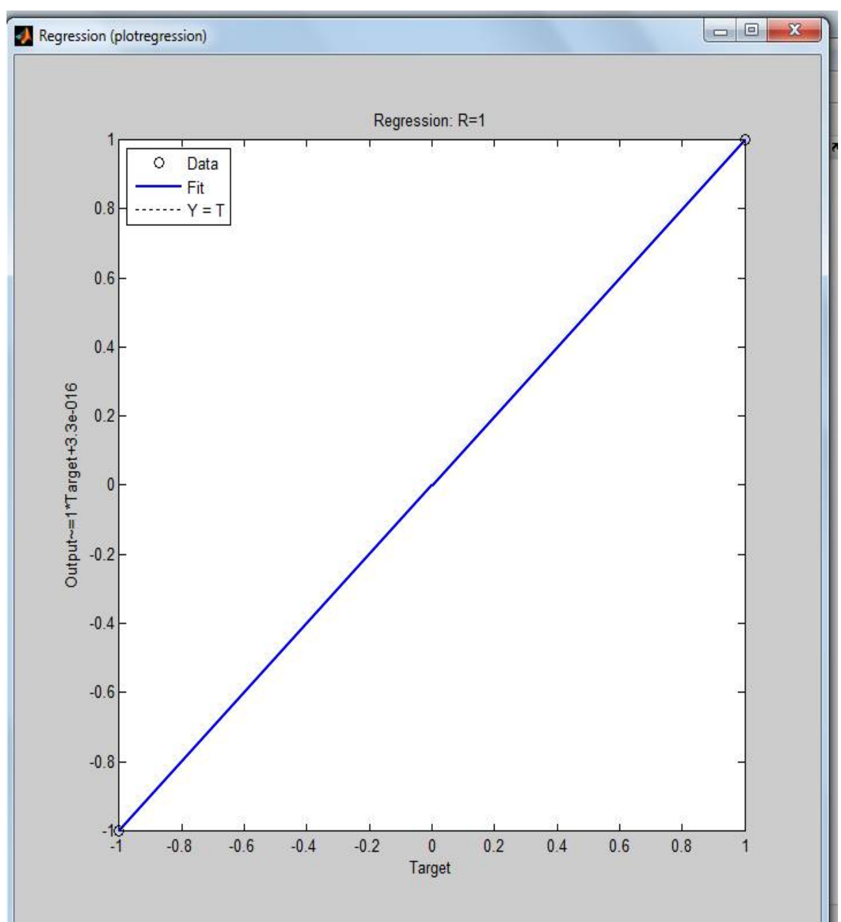

Figure (c)

## 6. RESULTS DISCUSSION

Recognition system has been implemented using Mat lab 7.10 The scanned image and the image drawn using paint application is given as an input to the Hopfield neural net architecture where it is first converted from .png to .bmp file and then it is resized to a standard format of 30*30 pixels image followed by the thresholding / binarization operation. The structure of neural network includes an input layer with 52 inputs including row wise and column wise features, two hidden layers each with 100 neurons and an output layer with 52 neurons. The gradient descent back propagation method with momentum and adaptive learning rate and log-sigmoid transfer functions is used for neural network training .




Hopfield Neural Network Figure (C)




Regression result Figure (d)

## 7. CONCLUSION:

In this paper we have presented a hybrid type Zone based feature extraction algorithm for the recognition of popular Indian Hindi scripts. Nearest neighbor and Hopfield neural network classifiers are used for classification and recognition. We have obtained 99% recognition rate for Hindi numerals. Using zone based feature extraction, we have achieved good results even when certain preprocessing steps like filtering, Smoothing and slant removing are not considered. Our future work aims to improve classifier to achieve still better recognition rate and also to develop new zone based feature extractions algorithms, which provides efficient results. Also we plan to extend our work to other Indian numeral scripts. Also effective implementation of multiple classifier system is one of our future research directions.

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