

Handwritten Digit Recognition Using Neural Network with Scale Conjugate Gradient Method

A

DISSERTATION-II

Submitted in partial fulfillment of the requirements for the

Award of degree of

Master of Technology

In

Electronics & Communication Engineering

Submitted by

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May 2017

CERTIFICATE

This is to certify that the dissertation report entitled '**Handwritten digit classification using Neural network with scale conjugate gradient method**' submitted by me to **Lovely Professional University** for the partial fulfillment of the requirement for the award of the degree of Master of Technology in **ELECTRONICS & COMMUNICATION DEPARTMENT** is a record of bonfide dissertation work carried out by me under the guidance of Mr. Anil Kumar Rawat.

To the best of my knowledge, the matter embodied in the report has not been submitted to any other University/institute for the award of any degree.

Date: 29 April, 2017

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DECLARATION

I hereby declared that the dissertation report entitled '**Handwritten digit classification using Neural network with scale conjugate gradient method**' submitted by me to Lovely Professional University for the partial fulfillment of the requirement for the award of the degree of Master of Technology in **ELECTRONICS & COMMUNICATION DEPARTMENT** is a record of bonfide dissertation work carried out by me under the guidance of Mr. Anil Kumar Rawat. I further declare that the work reported in this dissertation has not submitted and will not be submitted, either in part or full, for the award of any other degree in this University or any other University.

Date: 29 April, 2017

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Abbreviations

K-nn	K mean nearest neighbor classifier
CNN	Convolution Neural Network
MLP	Multilayer Perceptron
BPNN	Back Propagation Neural Network
ANN	Artificial Neural Network
CNN	Convolution Neural Network
DBN	Deep Belief Network
ROC	Receiver Operating Characteristics
NN	Neural Network
PCA	Principal Component Analysis
CE	Cross-Entropy
SVM	Support Vector Machine
ELM	Extreme Learning Machine
SCG	Scale Conjugate Gradient

Acknowledgement

First of all I would like to thank my God who giving me strength to achieve the best result in this research. This Dissertation-II work would have not been possible without the guidance and the help of my guide who in one way or another, contributed and extended his valuable assistance in this work.

My utmost gratitude to my dissertation guide Assistant Prof. Anil Kumar Rawat (ECE Dept. Lovely Professional University) whose sincerity and encouragement I will never forget. He has been my inspiration as I hurdles all the obstacles in the completion of this literature work and supported me throughout my work with patience and knowledge. Next I would like to thank all the M.Tech students and the faculty present in the Digital Signal Processing Domain for their support and timely help. Above all, I again would like to thank God whose indirect support helped me to complete my proposed work in time. The Dissertation work would have been impossible without their perpetual moral support.

Date: 29 April, 2017

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Abstract

This dissertation introduces a new system for handwritten digit Classification based on deep belief neural network design. Most of the existing neural networks architecture treats mean square error function as the standard cost function. Our proposed system in this dissertation use cross-entropy as a cost function. This can be applied using softmax transfer function; an activation function which defines the relation between input and output..

For training we use scale conjugate gradient algorithm. To check the performance of a proposed system, there are three essential factors that are to be considered, and they are from high to low importance priority: Receiver operating characteristics of proposed system which actually gives the classification stability result, gradient value and percentage accuracy of proposed system. It is observed that bounded training methods accelerate the training process. In our proposed work we had applied various techniques on image dataset which are used to pre-process the data; these techniques refer to morphological image processing technique. These preprocessing techniques are used to remove redundant information present in the dataset. Then we passed our preprocess results to the classifier which itself calculates the features of the image, those features are required to the classifier for classification handwritten digit. Conventional proposed method used 10,000 maximum testing data images and achieved an accuracy rate of about 97.94%. Our proposed methodology used 28,000 testing images and achieved an accuracy rate in the range of 98.8 - 99.2%.

Chapter 1

Introduction

1.1 Handwritten Digit Classification

Handwritten digit recognition is the ability of a computer or a machine to interpret and receive intelligible handwritten input from various sources such as cameras, tablets, photographs and other devices. Today handwritten digits are used in bank checks, exam form filled by hand, smart calculators etc. A complete handwriting recognition system handles formatting problem, reduce classification error and recognize the broken digits.

Today is a huge demand of information processing units because its plays important role in fast moving and highly automated Technology. We know humans have a tendency to do their work faster and in the most efficient way. Hence there is a need of automated technology which makes our work easier and faster. Next trend in today's fast changing Technology is digitalization. Since this is the age of computers we want information available in whatever form be digitized and stored in the computer because they have faster computing capabilities and also computers make task efficient. But the main problem in digitizing information into digital domain is that there is a need to teach the computer or machine especially about our concerned real world data then only it is possible to make an efficient machine for certain task. But this requires lot of efforts. It is easy to teach human brain. In order to make a learning machine a set of instructions or rules are needed to be performed on a machine.

The above discussion is aimed to developing the system which will be helpful to make learning machine model for recognizing the handwritten digits of English language. The development of idea behind handwriting recognition systems began since 1950s. At that time there were human operators, who are responsible to convert data from various documents into electronic readable format, this making the process quite long, complex and often affected by errors. In the early 1980's, commercial applications incorporating handwriting recognition system as a replacement of keyboard inputs. As the use of personal computer is increasing day by day, commercial products were introduce to replace the traditional way of using mouse or keyboard for enter inputs. These systems are replaced by single pointing handwriting systems. Advancement in electronics provides the sufficient computing power for recognition systems to fit into smaller systems like tablets. Handwritten recognition systems are also used to provide inputs for handheld PDA's. Apple Newton was the first

PDA to provide written inputs. The major problem by using these devices is the accuracy. They are not accurate system. People finds on screen keyboards more efficient than these systems. In the 1990's researchers start working on this area of pattern recognition. Automatic digit recognition aims to reduce these errors by using some image preprocessing techniques that helps to increased computational efficiency and precision to the entire classification process. There is a tradeoff between accuracy and computational time. Techniques which give better result in term of accuracy may not suitable for computational time or vice versa. That's why researchers tried to make a system which balances these tradeoff points. Continuously study is going on in this area in order to develop a kind of a system which is capable of giving 100% accurate result with desired time specification. In general, handwriting recognition is classified into two major types as off-line and on-line.

On-line Recognition: This is a digital representation of handwriting. On-line handwriting consist two dimensional coordinates. One is expressed as function of time and other is the order of strokes made by writer. The sample image of on-line digit is shown in figure 1.1.

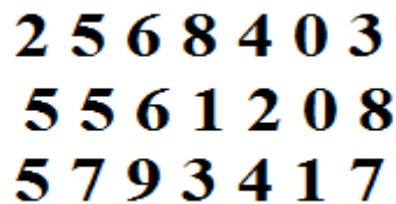


Figure 1.1 On-Line Digits

These coordinates tells the location of the pens and the force applied by the writer during writing. The element of on-line digit acquisition includes:

- A pen or stylus on a tablet.
- Touch screen or display.

Off-line Recognition: Digit scanned by scanner or any optical devices refer to as off-line digit. The task of off-line digit recognition is comparatively difficult than on-line digit recognition as different person have different writing styles. It is easy to recognize an on-line handwritten digit that's why the area of research includes off-line handwritten digit for recognition purpose. The sample images of off-line handwritten digits are shown in figure 1.2. From this figure we can analyze that why this task is difficult than on-line digit

recognition. This figure contains broken images also. So this is a major challenge for researchers to make a machine which recognize broken digits as well.

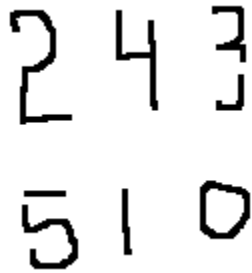


Figure 1.2 Off-Line Handwritten Digits

Digit recognition is one of the primary applications of pattern recognition. The knowledge of computer vision is necessary for pattern recognition task. Various fields are come under computer vision they are described in following sections.

1.2 Related Fields of Computer Vision

Several fields are associated with computer vision, two of which are particularly related, they are *Image Preprocessing and Machine Vision*; in fact, those two fields are very important in pattern recognition application or we can say that these two fields are the major building block of recognition system. Here is an attempt to outline their explanation, although no agreed definitions and distinctions are available:

- Image Preprocessing is the method or operations applied on an image to represent the image at low level of abstraction. This stage is quite useful in a variety of situations. Preprocessing stage helps to suppress the information content present in an image which is not relevant for image processing task.
- Machine vision is a process of integrate existing technology in such a ways so that the implemented new technology is used to solve some real world problem. Image processing and pattern recognition are typically associated with machine vision.

There are other fields that are related with computer vision:

- Pattern Recognition (Machine Learning) is the branch of computer vision that focus on patterns and regularity of data. It sometimes called machine learning; is the branch of soft computing that makes efficient model of learning through which machine can learn how to perform task according to given set of instructions.

Classification is necessary to be performed on a given Image data for pattern recognition. Some refer classification is an identification or detection process but they are different as described in following section.

1.3 Recognition-An Overview

Recognition task is divided into three major principles, namely

- Classification is a general term of categorization that link with one or several learned objects or their classes that can be recognized. The term class can be better explained with the help of suitable example. Like in handwritten digit there are total of ten classes from 0 to 9. These refer to output classes. Classification is needed to be performed on these classes.
- Identification is a process of recognized instance of an object, e.g. Identification of Handwritten off-line digits.
- Detection is the process of extracting relevant information from a larger stream of information processing unit, e.g. Detection of kidney disease.

Till now we discussed basic concept of pattern recognition including off-line pattern and on-line pattern. Then we studied overview of recognition process. Here the question arises how this task is possible. Which methodology is useful for making machine learn to recognize handwritten digit. For this we move toward Neural Networks architecture that is highly inspired by human brain.

1.4 Artificial Neural Networks

Neural networks are particularly useful for solving that kind of problems which cannot be expressed as a series of steps, such as pattern recognizing, classify them into groups, data mining and series prediction.

Pattern recognition is perhaps the most common application of artificial neural networks. The artificial neural network model is derived from biological nervous system where neurons act as an information processing unit. The learning task in human brain is possible through these neurons. Like in a human brain neurons are interconnected with each other and passing information from one neuron to another. Figure 1.3 shows schematic diagram of biological neuron. Axon are responsible for carries the impulse of neurons. Cell nucleus is located in cell body. Through dendrites nerves are connected to the cell body. Artificial neural network

is highly inspired by biological nervous system. Although the terminologies are different as described in table I but functionality is same throughout.

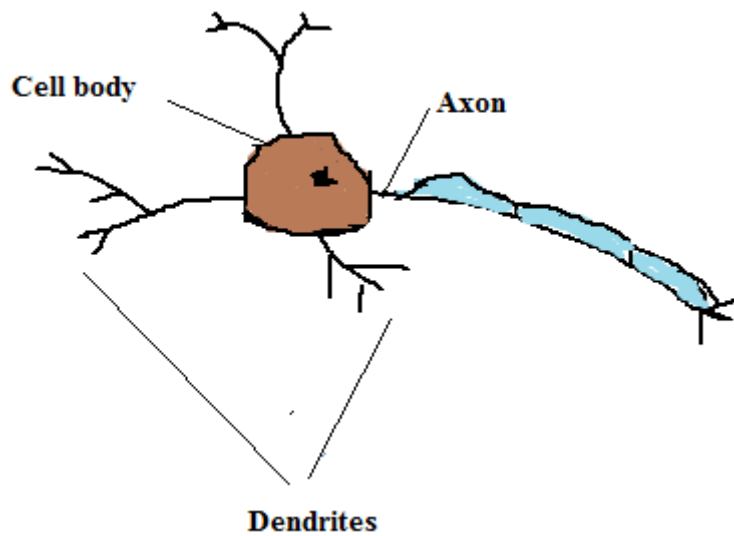


Figure 1.3 Schematic Diagram of Biological Neuron.

Neural network is a processing device or a computational model, whose interconnection units are inspired by the design and functioning of animal brains and components. The computing world has a lot of advantages gain from artificial neural networks. The neural networks have the ability to learn by example as biological nervous system is capable of learn by experience, which make them flexible and powerful. These networks are well suited for real time systems because of their fast response and computational efficiency. The key element of the ANN is the novel structure of its information processing systems. Figure 1.4 depicts the typical mathematical model of artificial neuron.

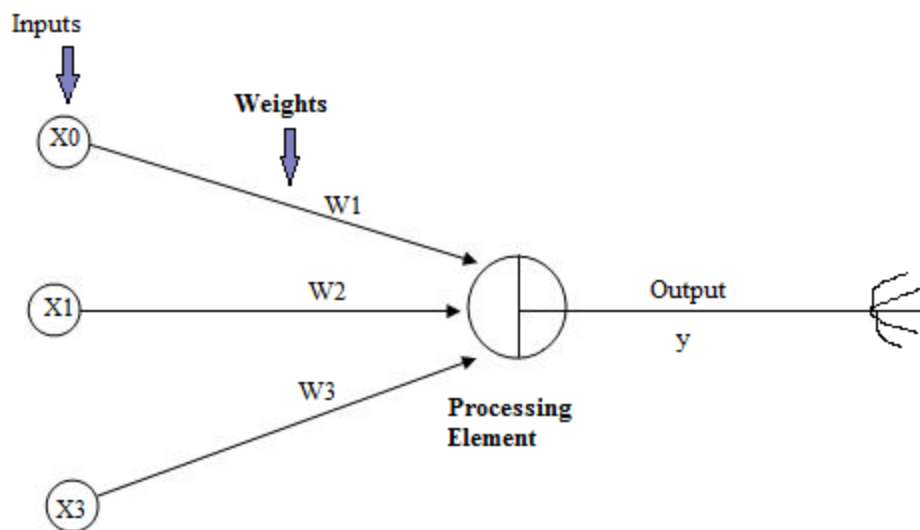


Figure 1.4 Mathematical Model of Artificial Neuron

In this model, the output y is formed by using following expression:

$$Y = x_1w_1 + x_2w_2 + x_3w_3 + \dots + x_rw_r = \sum_{i=1}^r x_iw_i \quad (i)$$

Where i represents the processing element. The output is calculated by applying activation function at the output unit.

Table .I Terminology difference between biological Neuron and Artificial neuron

Biological neuron	Artificial neuron
Axon	Output
Dendrites	Weights or Interconnection
Cell	Neuron

Handwritten digit classification task is related with pattern recognition which deals with machine learning. Before going ahead it is necessary to know the idea behind machine learning models, these are described in next section.

1.5 Neural Networks Learning Model

Machine learning is the ability of computers or machine to learn. It is a very important task in network computation architecture. A neural network learns through its weights and biasing unit connected with its input unit. Different person had different view regarding learning process. We define learning in the context of artificial neural network as:

“Learning is a sequence of steps applied on the neural network by which the network parameter modifies through a process of stimulation by the environment in which the neurons weights are embedded”.

In artificial neural network, learning is divided into two types as described in figure 1.5 unsupervised and supervised learning.

- Supervised learning is possible with the help of teacher. In artificial neural network, supervised learning means target values are known prior to the information processing unit.
- Unsupervised learning is performed in the absence of teacher means target values are not known prior to the information processing unit.

The general block diagram of ANN learning model is shown in figure 1.5. This figure also described the techniques which fall under this category.

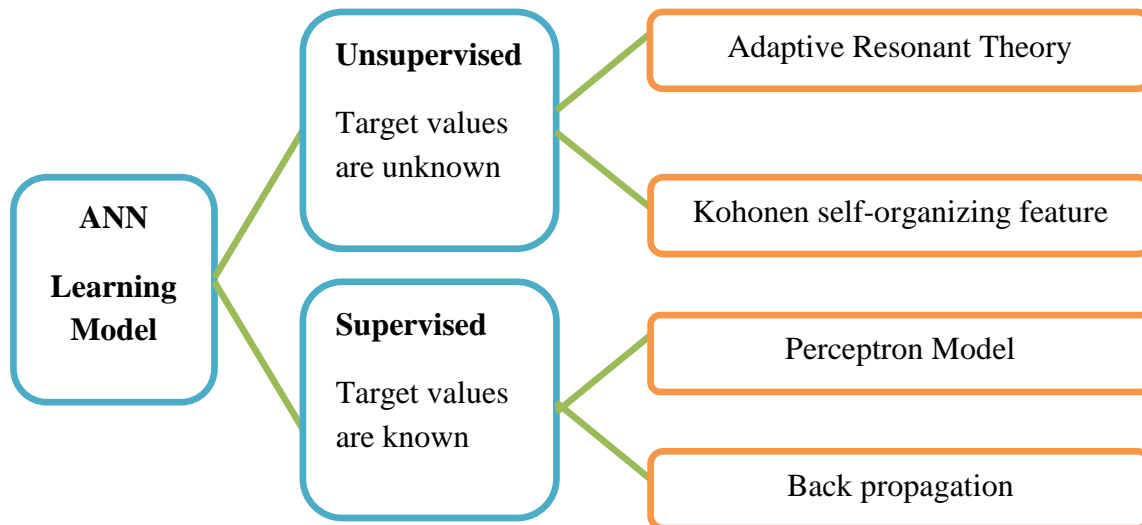


Figure 1.5 Block Diagram of ANN Learning Model

1.6 Why use Neural Networks?

Neural networks, with their remarkable ability to derive its computing power through its parallel distributed structure and its ability to learn from associated weights, can be used to extract pattern and detect regularity that are too complex to be noticed by either humans or any computer techniques. A trained neural network can be thought of as an “expert system”. Which performed given task based on the set of instructions define prior to the information processing unit. Neural network architecture exhibit following advantages:

- Adaptive learning is the capability of neural network to modify its weight according to the surrounding environment.
- Self-Organization An ANN can create its own organization that helps to represent the information it receive during learning time.
- Real Time Operation ANN computational may be carried out in parallel, and special hardware devices are being designed and manufactured which take the advantage of this capability.
- Fault Tolerance; neural networks have a potential to be inherently fault tolerance; means networks are capable to perform robust computation. Network capabilities may be retained even with major network damage.

Chapter 2

Literature Review

2.1 Literature Survey

In 1997, Zheru Chi and Zhongkang Lu [1] proposed multichannel handwritten digit recognition using neural networks technique. They used intensity based, rotation invariant and noise deducted based feature for recognize handwritten digit dataset. By using multilayer perceptron model they achieved classification accuracy in the range of 82-89.5%. The average classification result on the dataset of 1900 images is reasonable good.

In 1998, Daniel Cruces Alvarez [2], proposed a neural network method for classify printed handwritten digits. The task is performed using a multilayer feed forward and clustered back propagation technique. For extracting the unique features, Kirsch masks are adopted and for classifying the numerals, they used neural network algorithm. The main goal of using multilayer neural network is to minimize the cost function i.e. mean square error between the obtained output and the desired output. Thus with this method, the rejection rate is 9% and error rate is reduced to 1%.

In 2010, Dewi Nasian [3], proposed a method for recognizing handwritten Latin characters using freeman chain coding and feed forward neural network classifier. It generally undergoes three stages as pre-processing, feature extraction and classification. During the preprocessing stage, they used thinning method for obtaining the skeleton of a character, this operation removes any redundant information as well as it, maintains the feature of the image. For feature extraction, they proposed a randomized algorithm and finally they used neural network as a classifier for classification of handwritten character.

Vishnu and Jasper Lin [6], developed several supervised learning algorithms such as K nearest neighbors, support vector machine, stochastic gradient descent to classify images. With KNN they achieved train accuracy on a different dataset of 5000 images is 93.07% and test accuracy of 93.28%. Likewise for the Chars74K dataset, they were able to achieve an accuracy rate of about 35.84%.

In 2012, P.Pandi Selvi [7] proposed a method for recognizing handwritten numerals using multilayer feed forward back propagation neural network. The new method that they had used consists of three phases' namely preprocessing, training and classification. Preprocessing stage performs noise removal, labeling, rescaling and segmentation operations to remove redundant information present in given dataset. Training stage adopts back-

propagation with feed forward technique. The proposed method is implemented in matlab. The proposed method achieves an overall accuracy of 95%.

In 2014, Ishani Patel [9] presents survey on handwritten digit Recognition systems with recent techniques called MLP, SVM, k-NN used for classification. Major steps that they have performed include data acquisition, preprocessing, segmentation, feature extraction and classification. They used various feature extraction method like Diagonal based feature extraction method, in this the whole image is divided into equal zones and then features are extracted from each diagonal zone. Hotspot feature extraction, in this the distance between black pixel and hotspot is calculated by using technique. Four view projection profile method, in this type of feature extraction, first convert the gray scale image into binary image of numerals. Divide the image into equal zones. For each zone divide the horizontally, vertically and right diagonal projection profile in each direction. Store the average largest values means a peak value of each zone. These values are nothing but a feature vector. The study shows that four view projection profile feature extraction method with MLP gives highest recognition rate.

In 2015, Yasin Zamani and Yaser Soury [10] presented well known random forest (RF) and convolution neural network (CNN) algorithm for Persian Handwritten digit recognition on the Honda dataset. Two different kinds of features they have been used for classification one is block feature and other is HOG feature. For classification they used RF and CNN .it is then show that RFs and CNN performance gives precise result on this dataset.

In 2016, Emmanuel and Sherry [11] introduce linear support vector machine, naïve bays and multilayer perceptron model to classify handwritten digits. Performance of each algorithm is analyzed in term of accuracy. Study shows that naïve bays classifier gives 40% accurate result on the other hand neural networks gives 90% accurate result. It is prove that deep learning model gives more accurate result than other existing techniques.

A few techniques that use handwritten character/Digits recognition for classify handwritten digit have been summarized here:

- **Diagonal Based Feature Extraction method for Handwritten Character Recognition using Neural Network.**

J.Pradeep, E.Shrinivasan and S.Himavathi, 2010

An offline handwritten character recognition using multilayer feed forward neural network is described in this paper. Diagonal based feature extraction method is

introduced for extracting the feature of handwritten alphabet character. Fifty data sets, each containing 26 alphabets written by various people, are used for training the neural network and twenty different handwritten alphabets character are used for testing. In diagonal based feature extraction scheme each character image of size 90x60 pixels is divided into equal zone with size of 10x10 pixels. A feed forward back propagation neural network is used for classification. The proposed recognition system performs quite well yielding higher level of recognition accuracy as compared to feature extraction method [5]. The proposed system uses diagonal based feature extraction with gradient descent neural network yields good recognition accuracy of 98% with 54 features.

- **Character Recognition Using Neural Network.**

Rokus Arnold and PothMiklos, 2010

Neural networks are commonly used for pattern recognition application. This paper describes the steepest descent or gradient descent method as a learning model for character recognition task. The important parameters used in this method are learning rate (LR) and momentum. There is no general method or formula for selection of the LR. It is required to start training with high LR values, and decrease them during the learning process until we find the best suitable result [4]. During weight modification heuristic method is employed. It also provide momentum factor. Without momentum factor the learning process would take too much time to passing through each interconnected layers. They choose learning rate and momentum factor randomly or choose them in a way which minimizes the cost function. In this paper they performed following preprocessing techniques converting to binary, morphological methods and segmentation. Segmentation is the most important part of the preprocessing method because after segmentation we have to decide which details are important for us. Feature extraction step uses following method-momentum based details, Hough and Chain code Transformation and Fourier transformations. With this methodology they achieved 60% precise result

- **An Efficient Three Stage Classifier for Handwritten Digit Recognition.**

Dejan Gorgevik and Dusan Cakmakov, 2004

This paper proposes an efficient three stage classifier for handwritten digit recognition based on neural network (NNs) and support vector machine (SVM). The classification is performed by 2 NNs and one SVM. The first NN is designed in such

a way so that it provides low misclassification error. Rejected pattern are forwarded to the second NN that uses additional features, and utilizes a misclassification error. Finally misclassify pattern from the second NN are forwarded to SVM. In this way the classification accuracy is much [13] better than the single SVM applied on feature set.

- **Recognition of Handwritten Digits using Deformable Templates.**

Anil K.Jain and Douglas zongker, 1997

They introduce the concept of deformable templates for recognition of hand printed digits. Two characters are matched by deforming the template matching through contour one to fit the edge strengths of other, and dissimilarity results misclassification, the goodness of fit of the edges, and the interior overlap between the deformed shapes. Classification result using [16] the minimum dissimilarity criteria rate up to 99% on 2,000 character subset of NIST special database.

- **Handwritten Character Recognition Using HOG Features in Deep Learning of Artificial Neural Network.**

SuthasineeIamsa-at and Punyaphol Horata, 2013

Feature extraction methods generally make task easy to recognize handwritten character or digits. This paper comparing the recognition ability of two classifiers: Deep Learning Feed forward-Back propagation Neural Network (DFBNN) and extreme learning machine (ELM) [18]. Data set is divided into two categories non extracted means unidentified feature and extracted feature by histograms of oriented gradient (HOG) method. The experimental result shows that using HOG (Histogram of oriented Gradient) method, the extracted features can improve recognition rates by using both of DFBNN and ELM techniques. Furthermore feed forward-back propagation neural network provides slightly higher recognition rates than those of ELM.

- **Handwritten Character Recognition Using Neural Network and Euclidian Distance metric.**

Sumit Saha and Tanmoy Som, 2010

In this paper handwritten characters are recognized by using neural network and Euclidean distance metric. At first the training set is passed through learning phase and then the network is used to recognize [19] the unknown handwritten characters.

For the mismatched handwritten character, Euclidean distance metric is used that helps to reduce the misclassify error and improves recognition ability of classifier.

- **A Neural Network Based Distance Function for the K-Nearest Neighbor Classifier.**

Szilard Vajda and Barna Szocs, 2014

The K-nearest neighbor method is one of the most commonly used techniques to address different classification problems. However to apply such a classification technique, a distance metric is to be considered to define a certain distance in the feature space. The main aim of this research is to learn the distance function by exploiting the specificity of the data [20]. Training helps to estimate the distance between two patterns by adapting the weight of the network accordingly.

- **Offline Handwritten Character Recognition Using Neural Network.**

Anshul Gupta, Manisha Srivastava and Chiteralekha Mahanta, 2011

In this paper the main approaches for offline handwritten word recognition can be divided into two classes, holistic and segmentation based. The holistic approach is used in recognition of limited size vocabulary where global features extracted from the entire word image are considered. As the size of the vocabulary increases, the complexity of holistic based algorithms also increases and correspondingly the recognition rate also decreases rapidly. The segmentation based strategies, on the other hand employ bottom up approaches, starting from the stroke or the character level and going towards producing the meaningful word. In this paper we adopt segmentation based handwritten word recognition where neural networks are used to identify individual character. For both training and testing phase, a heuristic algorithm is used.

- **Intelligent Handwritten Digit Recognition using Artificial Neural Network.**

Saeed AL-Mansoori, 2015

The aim of this paper is to implement a multilayer perceptron (MLP) neural network to recognize and predict handwritten digits from 0 to 9. A dataset of 5000 samples were obtained from MNIST [15]. The dataset was trained using gradient descent back-propagation algorithm and further tested using the feed forward neural network

algorithm. The system performance is characterized by varying the number of interconnected units and the number of iterations. The methodology used in this paper gives precise and reliable result.

- **Multilayer Perceptron Neural Network based Handwritten Character Recognition using combined feature extraction**

Gauri Katiyar, Shabana Mehruz

They had proposed combined feature extraction based methodology to classify handwritten characters. For training they used steepest descent gradient back propagation, it is a very good optimization techniques. Feed forward neural network architecture is presented in this paper. CEDAR benchmark dataset they have used to evaluate proposed methodology. The overall accuracy of proposed method is 93.23.

Chapter 3

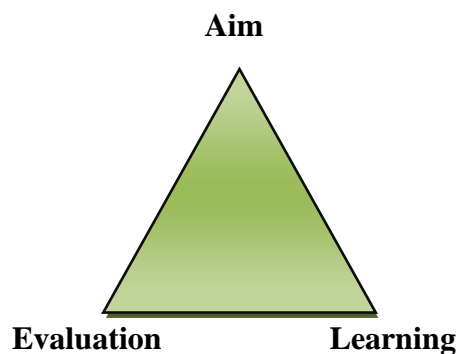
Research Methodology

3.1 Research Problem

This dissertation establishes a complete system that recognizes scan images of handwritten digits. The system consists of series of operations that includes image acquisition, preprocessing, Morphological image processing and classification. The task of preprocessing relates to the removal of noise, labeling and reshape the data. Preprocessing techniques helps to remove redundant information present in given dataset. This make the task of subsequent recognition simplified [6]. In this dissertation, the important issue of increasing diversity of training sets is added in preprocessing phase. One of the primary mean by which computers bestow with human like abilities is through the use of neural network. This research concerns detecting free handwritten digits.

3.2 Objective

The main objectives of this research are to evaluate the performance and learning capability of purposed system.



Objectives in term of performance are demonstrated as:

(a) To build a system that helps to find a new solution for handwritten digit recognition of different fonts and styles by improving the design structure of the traditional Artificial Neural Network (ANN). ANNs have been successfully applied to pattern recognition, data mining, pattern matching and classification.

(b) The purpose of this research is to take handwritten digit as input, preprocess the digits, trained with scale conjugate gradient method, and then classify handwritten digits by using neural network to recognize the pattern and modify the digits to a beautiful version of the input.

(c) Check the system stability in term of visualizing the receiver operating characteristics; minimize the cost function rather than minimize mean square error.

3.3 Motivation

Automated mail sorting, processing bank checks, smart calculators and other variety of modern applications of pattern recognition is becoming increasingly important to build a system which can adjust the difficulty of the learning problem at hand. The system design specification should be adaptive which means the system automatically adjust their behavior to achieve performance as per the given problem. My work has concerned not only classification accuracy but also the learning capability of the proposed system.

Theoretically, the human brain has a very low rate of operations per second when we compared with the art of computer. The most important characteristics of human brain is: its learning capability. The human brain is able to learn how to perform certain tasks based on past experience and prior knowledge.

How to teach computers to learn? To clarify the term “Learning” in respect to computers, we assume a set of training data $T = \{(X_n, T_n): 1 \leq n \leq N\}$ for some $N \in \mathbb{N}$ and an arbitrary target function of which we know the target values $T_n = s(X_n)$. Our goal is to teach the computer through learning parameter find out by applying certain transformation techniques. Classification and regression problem can be formulated in this way only. The target function may even be unknown or known depending upon learning model as describe in chapter 1.

3.4 Proposed Methodology

A lot of research has been lately focused on deep neural network based architecture. The advantage of these networks is the automated feature extraction of pattern from data [9]. This type of architecture has been applied successfully in many tasks, including handwritten digit recognition. In this paper we use benchmark Kaggle handwritten digit dataset. The sample images of dataset are shown in figure 3.1. We took mainly 42,000 images and use 28,000 images for testing. These gray scale images do not require any image representation techniques like bounding box, image crop etc. This is one of the advantages that we got by using handwritten digit dataset. Dataset contains separate images of digit for both training and testing. This is a good database for those who want to try research on learning techniques and pattern recognition algorithm as there is no need to format the handwritten digit. So this

is a time saving process while there is no need to perform formatting and resize operation on handwritten digit dataset.

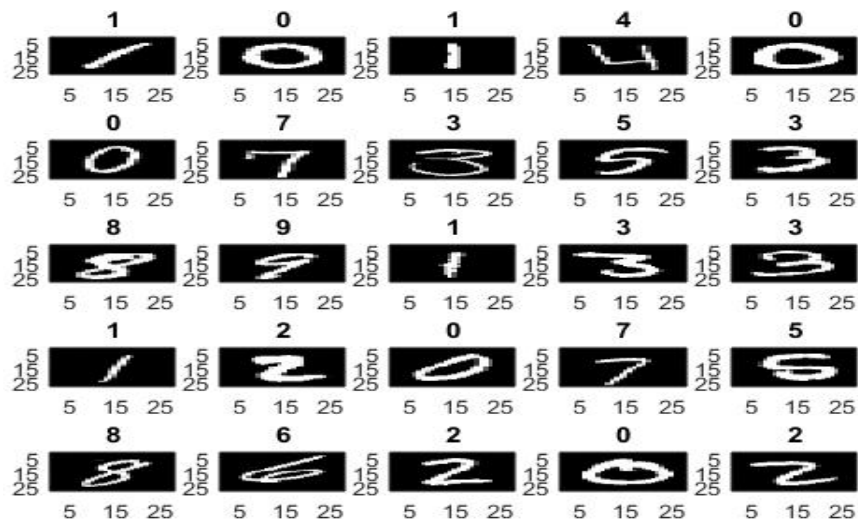


Figure 3.1 Sample Images of Handwritten Digits

Before applying classifier, various stages are used to make data more useful for representation. The proposed method comprises of mainly four phases. Block diagram shown in figure 3.2 is showing step by step procedure require to classify handwritten digit dataset.

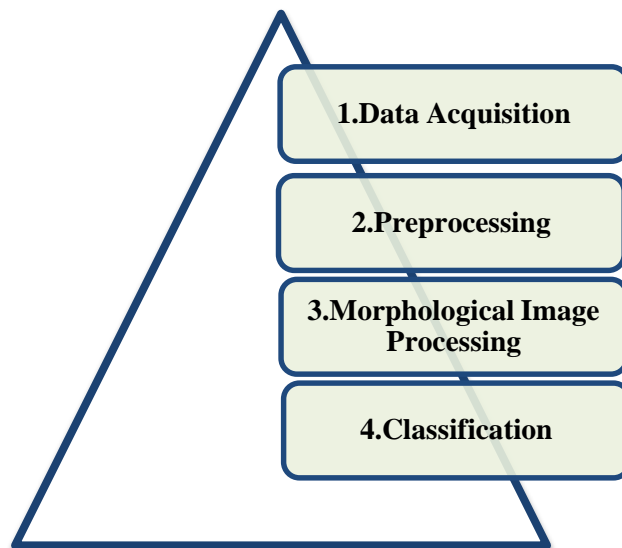


Figure 3.2 Processing Blocks

These four phase represent the basic building block element of handwritten digit recognition system. The flow diagram of proposed system in figure defines these phases step by step. The step by step process includes image acquisition, preprocessing stage, morphological image processing; which represent the desired qualities of an image. Before apply classification

these techniques are necessary to be used for desired result. It is easy to extract feature in term of boundaries, corner point and edges if we apply preprocessing techniques on given dataset.

3.5 Flow Chart

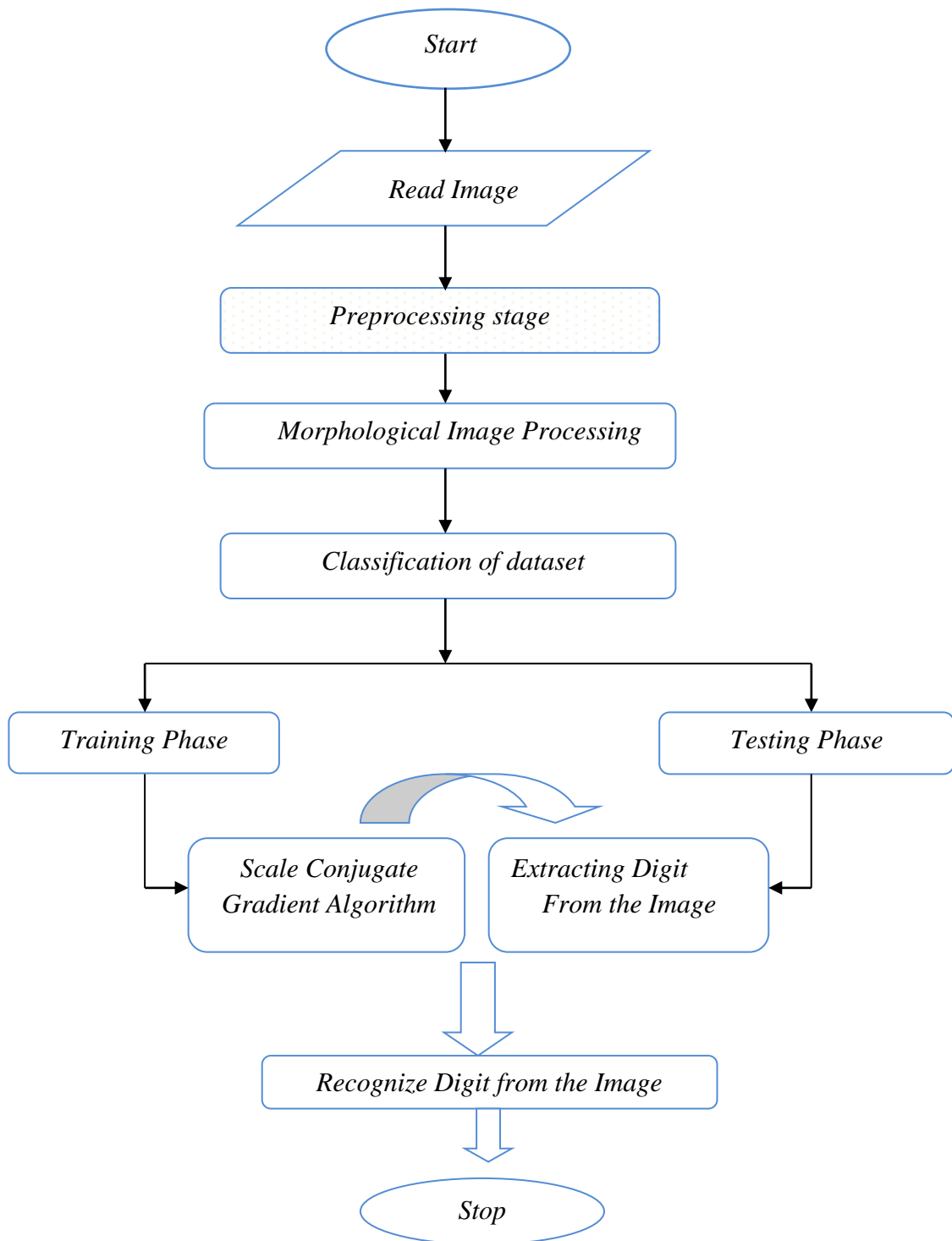


Figure 3.3 Flow Chart of Proposed Method

The flow chart of proposed methodology as shown in figure 3.3 gives brief explanation of sequence of steps or actions that need to be performed for classify handwritten digits. The step by step description of whole process is defined in next session.

3.6 Image Acquisition

Image acquisition or data acquisition is the first step in image processing. It is the process of retrieving an image from some source like scanner or other hardware devices. Acquired image contain some kind of artifacts. It means the image that is acquired is completely unprocessed. To make data useful for correct classification, we had used preprocessing techniques.

3.7 Preprocessing Stage

Preprocessing is an essential stage prior to classification as it controls the suitability of the result for next stage. Preprocessing is the method or operations applied on an image to represent the image at low level of abstraction. This stage is quite useful in a variety of situations. Preprocessing stage helps to suppress the information content present in an image which is not relevant for image processing task. In this phase we used reshape algorithm to reshape the dataset into 28x28 matrices using zero padding. As each image in the dataset is converted into 28x28 matrices, it is useful to apply operations in reshaped dataset. The reshape function returns the new array with i rows and j column (The product of i and j must equal to the size of original array). The main objective of preprocessing stage is to normalize the digits and remove extra information which is responsible for affecting classification rate.

3.8 Morphological Image Processing

Morphological image processing is the series of nonlinear operation that has to be applied on an image to extract shape and morphological features in an image or it is a mathematical tool of extracting important component in an image that is useful in the representation and description of region and shapes such as boundaries, Thinning, skeletons etc. we are also interested in morphological filtering. As we know binary images contains some kind of imperfections. In order to remove these all, we had used morphological operation in context to binary image. This technique can be used for gray scale images but these shows better result for binary scale images only. The need of morphological operation is arises due to the presence of blob and holes in image dataset. These holes create problem in classification

stage as they reduce the capability of classifier to identify the digit correctly. The sample image of broken handwritten digits is shown in figure 3.4. Because of these unconnected regions following morphological operation described in coming section are used to fill those connected part.



Figure 3.4 Samples of Broken Handwritten Digits

3.8.1 Morphological Thinning

It is a morphological operation that is used to find skeletons of an object. The basic two techniques used to find a skeleton of an object is medial axis transform and thinning. Out of these two thinning operation gives better result. I have used thinning operation to find skeletons of an object.

The behavior of the thinning operation is determined by a structuring element; a predefined shape used to examine another binary image as shown in figure 3.5. This figure also showing the mapping of structuring element with binary image.

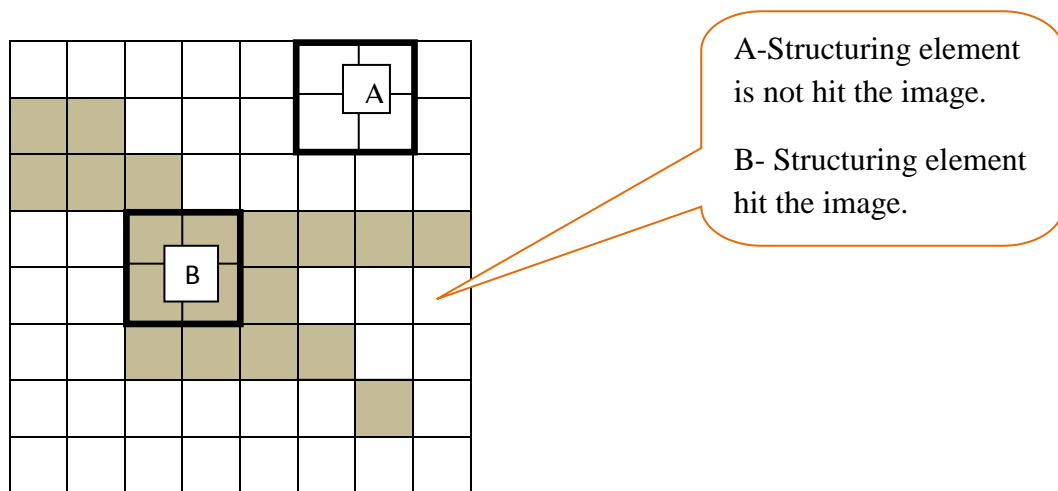


Figure 3.5 Mapping of Image with Structuring Element

These all operations like thinning, dilation, erosion are related to set theory. Let E and F be two structuring elements satisfying $E \cap F = \phi$. The pair (E, F) sometimes called a composite structuring element.

The hit-or-miss transform of a given image A by $B = (E, F)$ is given by:

$$A \odot B = (A \ominus E) \cap (\bar{A} \ominus F) \quad (ii)$$

Where \bar{A} is the set complement of A .

Structuring element can have varying sizes; Structuring element can be represented as a dilation of two structuring element B_1 and B_2 :

$$B = B_1 \oplus B_2 \quad (iii)$$

Structuring elements are available with a variety of shape and size as shown below:

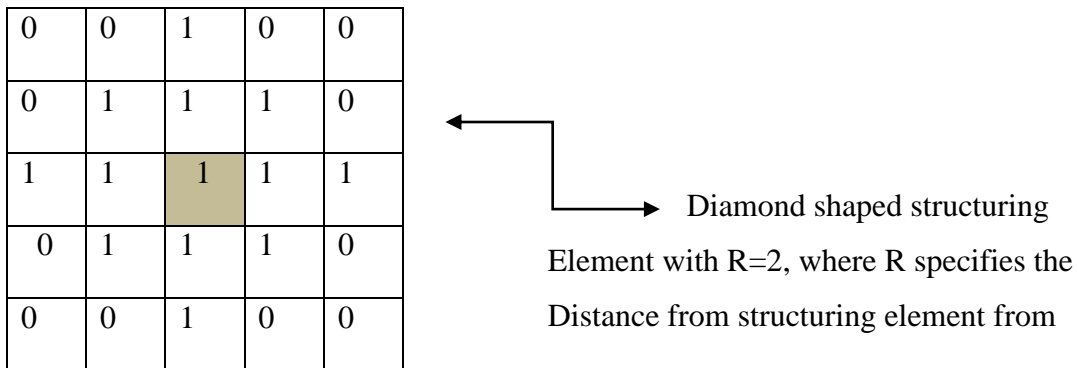


Figure 3.6 Diamonds Shaped Structuring Element

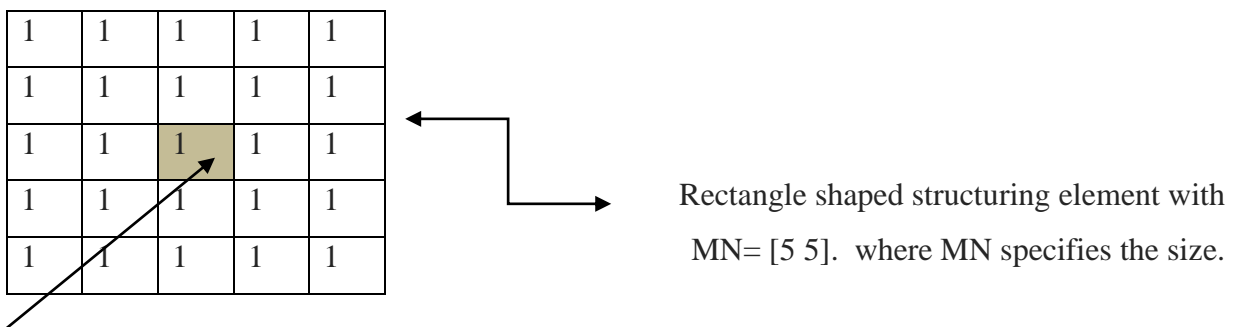


Figure 3.7 Rectangular Shaped Structuring Element

From equation (iv) $A \ominus B$ represent Erosion operation, the erosion of A by B , denoted $A \ominus B$, and is defined as:

$$A \ominus B = \{z | (B)z \subseteq A\} \quad (iv)$$

Where, as usual, the notation $E \subseteq F$ means that E is a subset of F . this equation (ii) says that the erosion of A by B is the set of all points z such that B , translated by Z is contained in A . The thinning operation is related to the hit-and-miss transformation. And so it is helpful to have an understanding of that operator before going further.

3.8.2 Hit-or-Miss Transformation

The morphological hit-and-miss transformation is basic tool for shape detection. It is useful to find unbroken region in an image. The resulted thinning operation is shown in figure 3.8.

The hit-or-miss transformation of A by B is denoted as $A \otimes B$, where B is a structuring element pair, $B = (B_1, B_2)$ rather than a single element as before. The hit-and-miss transformation is defined in term of two structuring element as:

$$A \otimes B = (A \ominus B_1) \cap (\bar{A} \ominus B_2) \quad (v)$$

Thinning of a set A by a structuring element B, denoted by $A \otimes B$, can be defined in terms of hit-or-miss transformation:

$$A \otimes B = A - (A \otimes B) \quad (vi)$$

The thinning of an image A by a structuring element B can be represented as:

$$Thin(A, B) = A - hit - and - miss(A, B)$$

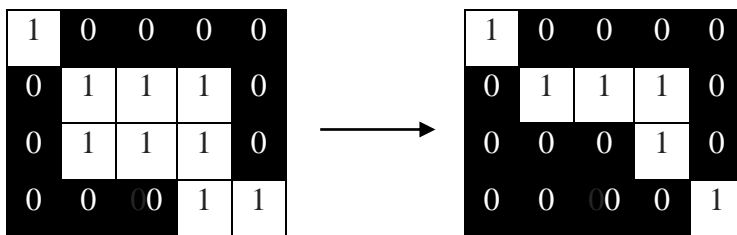


Figure 3.8 Thinning Operation

3.8.3 Dilation

The dilation of A by B is denoted as $A \oplus B$ is defined as,

$$A \oplus B = \{Z | (\hat{B})_z \cap A \neq \emptyset\} \quad (vii)$$

Where \hat{B} is the reflection of the structuring element B. in other words, it is the set of pixel locations Z, where the reflected structuring element overlaps with foreground pixels in a when translated to z.

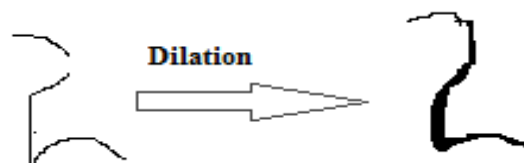


Figure 3.9 Dilated Image

Dilation operation generally increase the pixel intensity that leads to removal of unconnected

region as shown in figure 3.9. It is easy for a classifier to recognize connected pattern. These morphological operations make the classification task easy as they tend to remove unconnected component.

3.8.4 Skeletons

The skeleton of A can be expressed in terms of erosion and opening. It can be described as:

$$S(A) = \bigcup_{k=0}^K Sk(A) \quad (viii)$$

With

$$Sk(A) = (A \ominus kB) - (A \ominus kB) \circ B \quad (ix)$$

Where B is a structuring element, and $(A \ominus kB)$ indicates k successive erosions of A:

$$(A \ominus kB) = ((\dots((A \ominus B) \ominus B) \ominus B) \ominus \dots) \ominus B \quad (x)$$

K is the last iterative step before A erodes to any empty set .in other words,

$$K = \max \{k | (A \ominus kB) \neq \Phi\} \quad (xi)$$

The formulation given in equations (vii) and (viii) states that $S(A)$ can be obtained from the union of the skeleton subsets

3.9 Classification

Classification or categorization task generally depends upon labeled dataset, which means humans must transfer their knowledge to the dataset to make artificial neuron able to learn the correlation between dataset and labels so that learned neurons gives desired output as shown in figure 3.10.

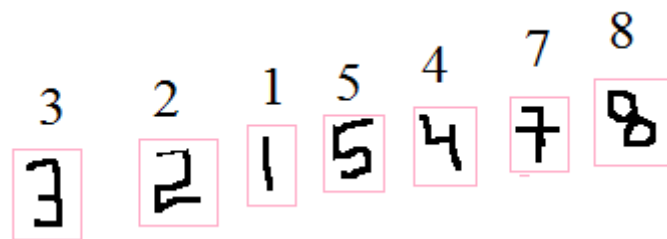


Figure 3.10 Samples of Correctly Classified Digits

In our proposed methodology, I have used deep learning networks; networks containing several layer as shown in figure 3.11. Typically deep learning network consists of a set of input layer, hidden layer and output layer. The key advantage of using this model is that this network automatically extracts relevant features in a dataset. So there is no need to apply separately feature extraction techniques as applied by [5]. Deep learning network come under the category of multilayer feed forward network. It means the input signal propagates in

forward direction throughout the network. This type of network architecture is used to solve difficult problem like handwritten digit classification [5]. They are trained with supervised manner with a highly popular optimization technique known as back propagation algorithm.

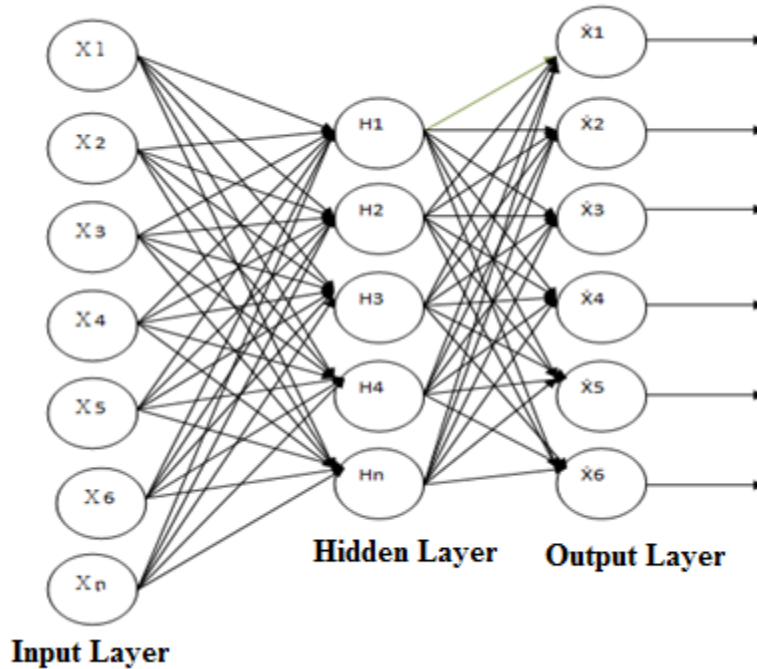


Figure 3.11 Deep Belief Network Architecture

Mathematical model of back propagation algorithm is evolved in this section. The operation of back propagation neural network is divided into two passes, one is forward pass and other is backward pass. In the forward pass, input pattern is propagates through each layer with fixed synaptic weights and in the backward pass the error generated at the output layer propagate back through hidden layer that leads to modify the weights. Weight updating task is done in this phase. First we present the summary of notation used to derive back propagation algorithm.

Notation

- The list of indices i, j , and k represent different neurons.
- Iteration is denoted by n which represent the n th training pattern of the network.
- Error energy or cost function at iteration n is denoted by $E_j(n)$.
- The symbol $e_j(n)$ refer error signal at iteration n for the neuron j .
- Desired response for the neuron j at the output layer is denoted by $t_j(n)$.
- The symbol $w_{ji}(n)$ denote synaptic weights connecting output of neuron i to the neuron j .

- The learning rate parameter is denoted by η .
- The activation function is denoted by $\delta(n)$.

3.9.1 Back propagation Algorithm

1.) First the training data is fed to the input layer, and then the weighted sum of input at the j th node of hidden layer is calculated as:

$$N_j = \sum w_{ji}X_j + \omega_j \quad (xii)$$

Equation () calculates the aggregate input pattern associated with each neuron. ω_j represent bias node. It acts as a pseudo node that helps to overcome the problem created when any value at the input pattern is zero. Default value of bias factor is one.

2.) To calculate the output pattern at output layer, appropriate transfer function or activation function is used. We used softmax transfer function that produces an output in response to input pattern.

$$O_j = \frac{e^{N_j}}{\sum e^{N_j}} \quad (xiii)$$

3.) The next very important step is the error calculation. Error is computed by taking the difference of desired output and actual output. Error at node j is calculated as:

$$\mathbb{E}_j = t_j - O_j \quad (xiv)$$

Error signal at node j is calculated by:

$$\delta_j = \mathbb{E}_j O_j(1 - O_j)$$

$$\delta_j = (t_j - O_j)O_j(1 - O_j)$$

Where $O_j(1 - O_j)$ is the derivative of softmax function.

4.) Apply chain result to calculate gradient vector.

$$\frac{\partial N_j(n)}{\partial w_{ji}(n)} = \frac{\partial N_j}{\partial \mathbb{E}_j} \frac{\partial \mathbb{E}_j}{\partial \delta_j} \quad (xv)$$

5.) Updating weights are calculated by scale conjugate gradient method. This method is defined in next section.

3.9.2 Scale conjugate gradient algorithm

Conjugate gradient algorithm is often implemented as iterative manner. We use this algorithm to train our handwritten digit dataset.

Suppose $AX = b$ this represent linear system of equation. Where A is a symmetric matrix of size $m \times m$, real and b is known as well. We denote the unique solution of the system by $s(n)$.

Initialization

Choose the initial value $\mathbf{w}(0) = 0$.

Computation

1. For $\mathbf{w}(0)$, use back propagation algorithm to compute gradient vector $\mathbf{g}(0)$.

2. Set $s(0) = r(0) = -\mathbf{g}(0)$. (xvi)

3. Use linear search to determine $\eta(n)$.

4. Update the weight vector:

$$\mathbf{W}(n+1) = \mathbf{w}(n) + \eta(n)s(n) \quad (xvii)$$

5. For $\mathbf{w}(n+1)$, use back propagation to compute $\mathbf{g}(n+1)$.

6. Set $r(n+1) = -\mathbf{g}(n+1)$ (xviii)

7. Calculate $B(n+1)$

$$B(n+1) = \frac{r_v r_v}{r_i r_i} \quad (xix)$$

Where $v = n+1$

8. Update the direction vector.

$$S(n+1) = r(n+1) + B(n+1)s(n) \quad (xx)$$

9. Set $n = n+1$ and go back to step 3.

Stopping Criteria

If r_v is very small then exit loop.

$$\|r(n)\| \leq \lambda \|r(0)\|$$

Chapter 4

Result and Analysis

4.1 Introduction

In this chapter, we present the detailed experimental results to illustrate the suitability of handwritten digit recognition system. All the experiments are implemented in MATLAB 2015 under a windows 8.1 environment on an Intel Core i3 processor and performed on gray-scale digit images.

The first section deals with parameter study. In parameter study we have studied different parameters that create the blue print of our proposed work. The results are presented in the form of graph and table. The second section deals with comparison analysis. Here we compare our proposed methodology with existing techniques and finally we conclude the proposed work.

4.2 Performance Parameter

The performance parameter shows the accuracy of the system in terms of parameter like receiver operation characteristics, gradient, validation and accuracy percentage. They are defined as follow:

4.2.1 Receiver operating Characteristics (ROC)

In statistics, a receiver operating characteristics (ROC) or ROC curve is a graphical plot that depicts the performance of a classifier whether it classifies all classes correctly or not. The curve is created by the true positive rate against the false rate. The true rate is also known as exact classification or probability of detection in machine learning. The false rate is also known as the fall out or probability of false classification. ROC curve can be generated by plotting the detection probability in y-axis versus the fall out probability in x-axis as shown in figure 4.1. The closer of a result to the upper left corner, the better it predicts, but the distance from random guess line in either direction is the best indicator of how much predictive power a method has. If a result is below a line, the method is worse than a random guess. ROC curve also depicts the stability of our proposed system. ROC curve demonstrates the following things:

- It shows the tradeoff between false positive rate and true positive rate.
- Closer the curve to the top and left hand corner, more accurate the result we get.
- Closer the curve to the bottom and right hand corner, less accurate result we get.

- Area under the ROC curve is a measure of test accuracy.

The graph shown in figure 15 consist ten ROC curves. Area under the curve gives accuracy. Area 1 represents excellent testing. Out proposed method achieve 98.8% testing accuracy. ROC curve shows graphical model of testing accuracy. It is shown that all the ten classes lies in the range of 0.98 – 1. This is a clear evident of achieving this much accuracy in this dissertation work.

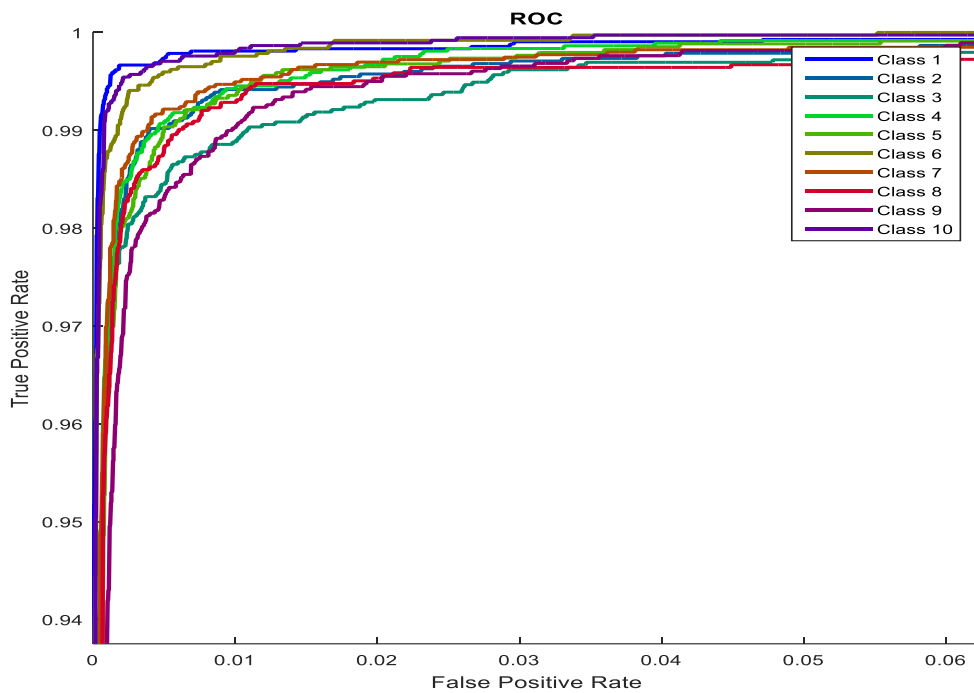


Figure 4.1 Receiver Operating Characteristics

In order getting a better result, the curve must be lying at top left corner. We clearly analyze that our classifier perform very good prediction result as all the curves are lying on left side of the curve.

4.2.2 Cross Entropy versus number of epochs

When using a neural network to perform classification and prediction, it is usually better to use cross-entropy error than mean square error to evaluate the quality of the neural network. We have used softmax activation function so that we get output values that can be interpreted as probabilities. We define the cross-entropy cost function as:

$$C = \frac{-1}{n} \sum_x [y \ln a + (1 - y) \ln(1 - a)] \quad (xxi)$$

Where n is the total number of items of training data, the sum is overall all training input. x and y is the corresponding desired output. Test line is represented by red color as shown in

figure 4.2. This test line is below the validation line, this indicate that the pattern are matched properly. There is no mismatch in our proposed system.

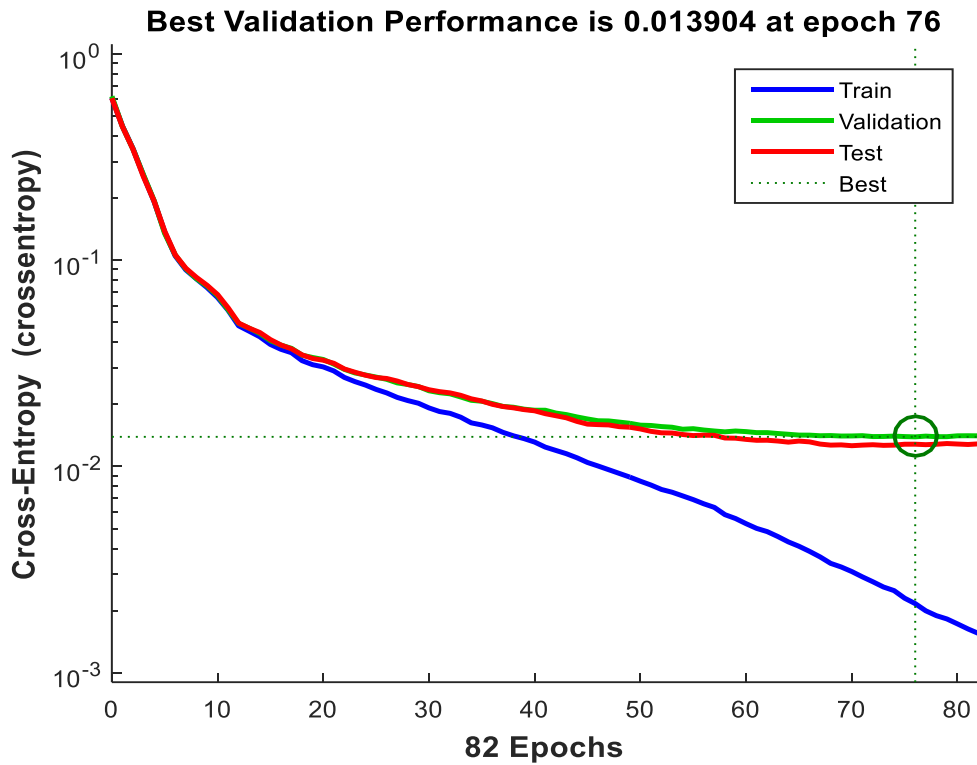


Figure 4.2 Cross-Entropy versus Number of Epochs

In training network we have used 85 iterations. From figure 4.3 it is shown that our network gives best validation performance at epochs 85.

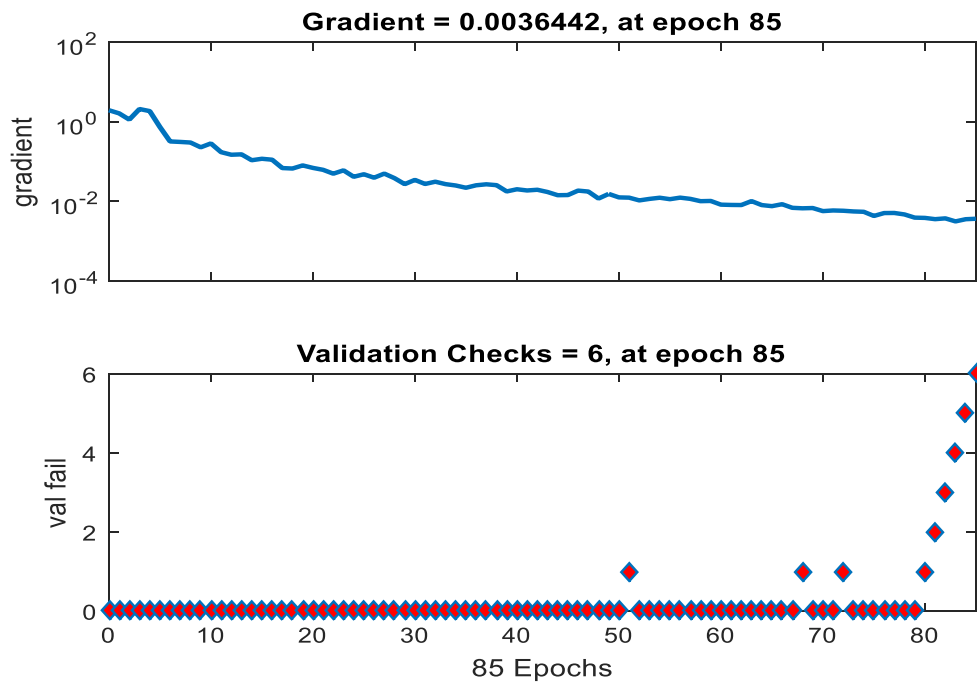


Figure 4.3 Gradient versus Epochs

Gradient means change of error energy with respect to synaptic weight. The scale conjugate gradient algorithm is used to train the training dataset. Training in neural network involves finding the minimum of error function or cost function. Cross entropy used as a cost function in our proposed work.

4.2.4 Confusion matrix

With the help of confusion matrix we can analyze proposed system accuracy. In figure 4.4, the diagonal elements in confusion matrix represent the correct classify digits. Like in first row there are total 3030 digits of digit '0'. Our system classify 3003 digit as digit '0', 1 as digit '1', 1 as digit '2', 3 as digit '3', 4 as digit '4', 2 as digit '5', 2 as digit '6', 9 as digit '7', 0 as digit '8' and 2 as digit '9'. From this we can understand the complete confusion matrix.

Confusion Matrix

		1	2	3	4	5	6	7	8	9	10	
Output Class	1	3006 10.7%	1 0.0%	1 0.0%	3 0.0%	4 0.0%	2 0.0%	2 0.0%	9 0.0%	0 0.0%	2 0.0%	99.2% 0.8%
	2	4 0.0%	2736 9.8%	9 0.0%	0 0.0%	1 0.0%	5 0.0%	10 0.0%	1 0.0%	3 0.0%	2 0.0%	98.7% 1.3%
	3	4 0.0%	3 0.0%	2839 10.1%	2 0.0%	9 0.0%	0 0.0%	0 0.0%	5 0.0%	6 0.0%	0 0.0%	99.0% 1.0%
	4	3 0.0%	4 0.0%	0 0.0%	2736 9.8%	2 0.0%	6 0.0%	4 0.0%	2 0.0%	20 0.1%	0 0.0%	98.5% 1.5%
	5	2 0.0%	1 0.0%	10 0.0%	0 0.0%	2507 9.0%	6 0.0%	1 0.0%	7 0.0%	2 0.0%	2 0.0%	98.8% 1.2%
	6	0 0.0%	1 0.0%	1 0.0%	0 0.0%	3 0.0%	2726 9.7%	0 0.0%	3 0.0%	0 0.0%	4 0.0%	99.6% 0.4%
	7	1 0.0%	8 0.0%	4 0.0%	10 0.0%	1 0.0%	1 0.0%	2904 10.4%	1 0.0%	21 0.1%	2 0.0%	98.3% 1.7%
	8	4 0.0%	8 0.0%	4 0.0%	4 0.0%	7 0.0%	0 0.0%	2 0.0%	2693 9.6%	3 0.0%	5 0.0%	98.6% 1.4%
	9	1 0.0%	2 0.0%	7 0.0%	25 0.1%	7 0.0%	0 0.0%	18 0.1%	3 0.0%	2756 9.8%	1 0.0%	97.7% 2.3%
	10	0 0.0%	5 0.0%	1 0.0%	1 0.0%	2 0.0%	2 0.0%	1 0.0%	1 0.0%	2 0.0%	2760 9.9%	99.5% 0.5%
		99.4% 0.6%	98.8% 1.2%	98.7% 1.3%	98.4% 1.6%	98.6% 1.4%	99.2% 0.8%	98.7% 1.3%	98.8% 1.2%	98.0% 2.0%	99.4% 0.6%	98.8% 1.2%
		1	2	3	4	5	6	7	8	9	10	
		Target Class										

Figure 4.4 Confusion Matrix

4.3 Comparison Analysis

In comparison analysis we compared our proposed system accuracy with existing handwritten classification techniques. In figure 19, we are comparing our proposed methodology with existing techniques. It is shown that our method works better than other in term of classification accuracy.

Table II shows the feature extraction methods and classifier used by other researcher in the field of handwritten digit recognition. Some authors used benchmark MNIST dataset and many other uses their own dataset. In our research work we Kaggle handwritten dataset. By

extracting gradient features my overall accuracy is in the range of about 98.8%. When we compared this accuracy with other recognition system, it is shown that our system gives more accurate result than all other conventional system.

Sr.No	Feature extraction method	Classifier	Accuracy (%)	Dataset
1	Proposed method	SCGBPNN	98.8	Kaggle data
3	Hog Feature[9]	CNN	97	Own
4	Water Reservoir method[14]	K-nn	96.94	Own
5	Hough Transform[9]	MLP	72.7	Own
6	Bat Algorithm[23]	SVM	95.6	MNIST
7	BPNN[13]	MLP	80	Own

Table II Feature Extraction Method with Recognition Rate and Classifier

Figure 4.5 shows the recognition accuracy with respect to existing method from this figure it is clear that our proposed system gives more accurate result than previous method.

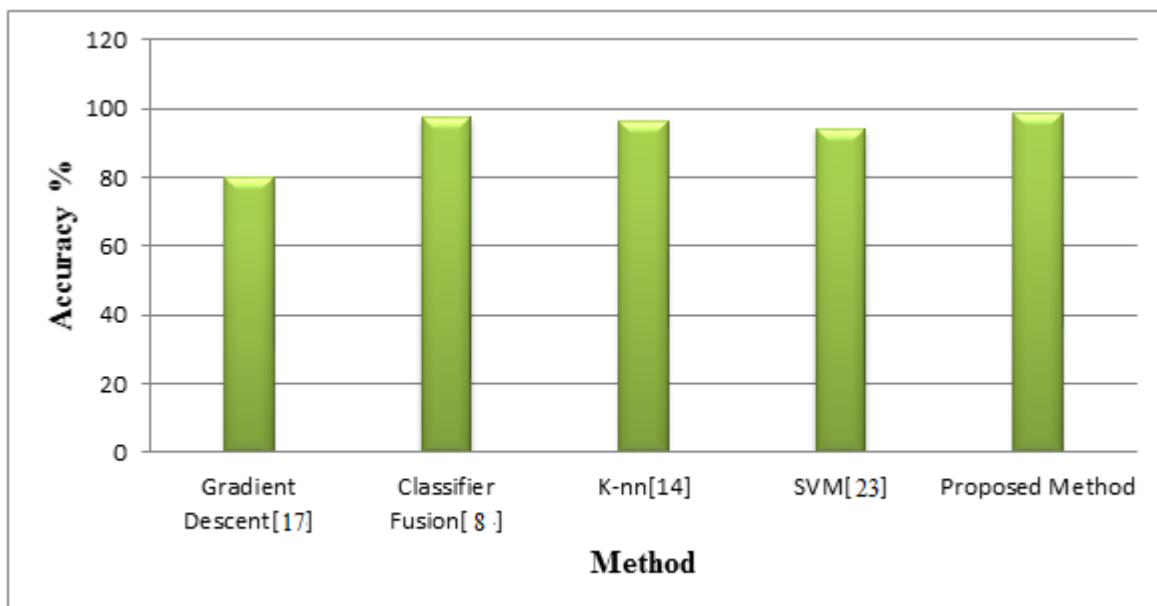


Figure 4.5 Recognition Accuracy wrt Existing Method

All these classifier mentioned in table III are used for pattern recognition i.e. Handwritten digit recognition. From this we got an idea about classifier in term of accuracy. Accuracy wise classifier fusion method gives desired result but if our application demand less complexity, then Naïve Bayes classifier majorly used although it give less accurate result but

for simpler application user use this classifier . Although classifier fusion method achieve high accuracy because of its high computational cost this algorithm they are used for certain application which requires high accuracy. If we move toward ANN, it provides efficient and suitable result. With the help of feature extraction techniques this classifier gives more accurate result than other. That is the only reason of using neural network to classify handwritten digits. This classifier gives more accurate result in term of accuracy.

Classifier	Techniques	Accuracy	Pros & Cons
Naive Bayes [11]	L2-Norm	40%	<ul style="list-style-type: none"> • Easy to compute • Less Accurate
ANN [11]	MLP,CNN	90%	<ul style="list-style-type: none"> • Efficient & Reliable • Architecture wise complex
SVM [10]	Structural Feature	94.2%	<ul style="list-style-type: none"> • Avoid over-fitting problem • Difficult to determine exact parameter
k-NN[14]	Water Reservoir principle based feature	96.94%	<ul style="list-style-type: none"> • Suitable for large training data • Computation cost is high
Classifier Fusion [8]	Decision Template Approach, PCA	97.28%	<ul style="list-style-type: none"> • High accuracy • Require more computational ability

Table III. Distribution of Classification techniques corresponding to accuracy

Parameter study and comparison study shows that our proposed system provides greater accuracy than previous system. From this study we analyze that with less feature how can we perform better recognition result. Less features help to reduce complexity of the system as well. The various parameters like error histogram, validation, ROC tells the stability of our

proposed system. The parameters that we have studied are the blue print of our proposed work. We have also compared our training algorithm with another algorithm as shown in figure 4.7 from this we conclude that our proposed system gives more accurate result than conventional system. Table II shows comparison with different training method. From this we conclude that our proposed system or scale conjugate gradient method gives more accurate result than all other training method.

Conclusion

This dissertation presented a new system for handwritten digit classification based on an improved artificial neural network. The neural network is compared to another two popular techniques. In general, it has the best recognition result and efficiency.

The bounded training method significantly accelerates the training process and gives better or at least equal results. This method work well together and improve both the efficiency and accuracy of the artificial neural network. Morphological operation that we have performed on handwritten digit helps to recognize digit shape and characteristics. In this way stacked auto-encoder easily extracts the features from the given handwritten digits.

As we trained our system with scale conjugate gradient back-propagation method, we also compared our method with all other method, from that we conclude our system gives accurate result.

We have studied various research papers; the only drawback that we have found is a neural network training. Since the system has to go through much iteration (approximately 5000) during the training phase, this may cause training to take a long time, especially when run on computers using older hardware. But we analyze that our system achieves performance at 76 epochs. This relatively decreases the time complexity in our system.

The only limitation that we faced is the processing delay during initial preprocessing stage. In order to process the huge data set CPU takes a lot of time to process these all steps. In future we will try to reduce this time that is used to process all these data set images. The major focus is on the feature extraction method to improve classification accuracy. We try to work on handwritten text document also. The recognizable text will also be extended from lines to paragraphs and pages. The system will understand punctuations, numbers and symbols in the text.

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