Digit Recognition Using Neural Network

Frank Ekene Ozioko[1], Chioma Uchechukwu Ugwa[2] & Izuchukwu Louis Akwudi[3]

Computer Science Department, Enugu State University of Science and Technology[1], Project Development Institute (PRODA) Enugu[2], & ICTC, ESUT[3]

DOI: https://doi.org/10.51244/IJRSI.2025.1213CS004

Received: 18 September 2025; Accepted: 24 September 2025; Published: 25 October 2025

ABSTRACT

The application of neural networks to digital recognition through a relatively easy-to-understand by the general public cannot be over emphasize. This paper investigated the several techniques used for preprocessing the handwritten digits, as well as several ways in which neural networks are used for the digital recognition task. Whereas the main goal was a purely educational one, a moderate recognition rate of 98% was reached on a test set.

Keywords: Neural-Network, Artificial-neural, Segmentation, Dgital Recognition, Feed-Forward and Back-Propagation.

INTRODUCTION

Handwritten digit recognition has been a major area of research in the field of Optical Character Recognition (OCR). Based on the input to the system, handwritten digit recognition can be categorized into online and offline recognition. In the online mode, the movements of a pen on a pen-based software screen surface were used to provide input into the system designed to predict the handwritten digits. Meanwhile, the offline mode uses an interface such as a scanner or camera as an input to the system [1]. The conversion of an image based on the digit contained to letter codes for further use in a computer or text processing application is the prior step in an offline handwriting recognition system. This form of data provides a static representation of any handwriting contained. The task of recognizing the handwriting of one individual from another is difficult as each person possesses a unique handwriting style. This is one reason why handwriting is considered one of the main challenging studies. The need for handwritten digit recognition came about at a time when combinations of digits were included in the records of an individual.

The current scenario calls for the need for handwritten digit recognition in banks to identify the digits on a bank cheque and also to collect other users' account-related information. Moreover, it can be used in post offices to identify pin code box numbers, as well as in pharmacies to identify doctors' prescriptions. Although there are several image processing techniques designed, the fact that the handwritten digits do not follow any fixed image recognition pattern in each of its digits makes it a challenging task to design an optimal recognition system. This study concentrates on the offline recognition of digits

using an MLP neural network. Many methods have been proposed to date to recognize and predict handwritten digits. Some of the most interesting are those briefly described below. A wide range of research has been performed on the MNIST database to explore the potential and drawbacks of the best-recommended approach. The best methodology to date offers a training accuracy of 99.81% using the Convolution Neural Network for feature extraction and an RBF network model for the prediction of the handwritten digits [2]. According to [3] extended research conducted for identifying and predicting the handwritten digits attained from the Concordia University database, the Mexican hat wavelet transformation technique was used for preprocessing the input data. With the help of the backpropagation algorithm, this input was used to train a multilayered feed-forward neural network and thereby attained a training accuracy of 99.17%. Although higher than the accuracies obtained for the same architecture without data preprocessing, the testing for isolated digits was estimated to be just 90.20%. A novel approach based on radon transform for handwritten digit recognition is reported in [4].

The radon transform is applied on a range of theta from -45 to 45 degrees. This transformation represents an image as a collection of projections in various directions resulting in a feature vector. The feature vector is then fed as an input to the classification phase. In this paper, the authors used the nearest neighbor classifier for digit recognition. An overall accuracy of 96.6% was achieved for English handwritten digits, whereas 91.2% was obtained for Kannada digits. A comparative study in [5] was conducted by training the neural network using a back-propagation algorithm and using PCA for feature extraction. Digit recognition was finally carried out using the thirteen algorithms, neural network algorithm, and FDA algorithm. The FDA algorithm proved less efficient with an overall accuracy of 77.67%, whereas the back-propagation algorithm with PCA for its feature extraction gave an accuracy of 91.2%. In 2014 [6], a novel approach using SVM binary classifiers and unbalanced decision trees was presented. Two classifiers were proposed in this study, where one uses the digit characteristics as input, and the other uses the whole image as such. It was observed that a handwritten digit recognition accuracy of 100% was achieved. In [7] authors presented the rotation variant feature vector algorithm to train a probabilistic neural network. The proposed system has been trained on samples of 720 images and tested on samples of 480 images written by 120 persons. The recognition rate was achieved at 99.7%. The use of multiple classifiers reveals multiple aspects of handwriting samples that help to better identify hand-written characters. A DWT classifier and a Fourier transform classifier aid in a better decision-making ability of the entire classification system [8].

Data pre-processing plays a very significant role in the precision of handwritten character identification. It has been proved that the practice of using different data processing techniques coupled together has led to a better-trained neural network and also improved the computational efficiency of the training mechanism. The choice of data preprocessing technique and the training algorithm is extremely important for better training but can only be determined on a trial-and-error basis [9].

The objective of the seminar

The following are the seminar objectives:

To help understand the current trends in Neural networks.

To help understand the importance of digit recognition in our everyday life.

To help individuals and institutions develop a good digit recognition system using neural networks.

Problem statement

The purpose of this project was to introduce neural networks through a relatively easy-to-understand application to the general public. This paper describes several techniques used for preprocessing the handwritten digits, as well as several ways in which neural networks were used for the recognition task.

Research methodology

The following methods listed below were used in this seminar's development

Image acquisition: We will acquire an image for our system as input. This image should have a specific format, for example, BMP format, and with a determined size such as 30´20 pixels. This image can be acquired through the scanner, digital camera, or other digital input devices [9].

Preprocessing: After acquiring the image, it will be processed through a sequence of preprocessing steps to be ready for the next step.

Noise removal: reducing noise in an image. For online, there is no noise to eliminate, so there is no need for noise removal. In offline mode, the noise may come from the writing style or the optical device capturing the image [21].

Normalization-scaling: standardize the font size within the image. This problem appears clearly in handwritten text because the font size is not restricted when using handwriting.

Thinning and skeletonization: Representing the shape of the object in a relatively smaller number of pixels [20]. Thinning algorithms can be parallel or sequential. The parallel is applied on all pixels simultaneously. Sequential examine pixels and transform them depending on the preceding processed results.

Segmentation: Since the data are isolated, no need for segmentation. With regards to the isolated digits, applying vertical segmentation on the image containing more than one digit will isolate each digit alone.

Normalization scaling and translation: Handwriting

produces variability in the size of written digits. This leads to the need to scale the size of the digits within the image to a standard size, which may lead to better recognition accuracy. We tried to normalize the size of the digit within the image and also translate it to a specific position by the following.

Feature extraction: Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. Classification and recognition: Neural Network is a network of a non-linear system that may be characterized according to a particular network topology

Scope of the seminar

This seminar will be focused on the methodologies we can adopt to study Digit recognition systems using neural networks.

LITERATURE REVIEW

An early notable attempt in the area of character recognition research is by Grimsdale in 1959. The origin of a great deal of research work in the early sixties was based on an approach known as the analysis-by-synthesis method suggested by Eden in 1968. The great importance of Eden's work was that he formally proved that all handwritten characters are formed by a finite number of schematic features, a point that was implicitly included in previous works. This notion was later used in all methods in syntactic (structural) approaches to character recognition. K. Gaurav,

Bhatia P. K. [10] Et al, this paper deals with the various pre-processing techniques involved in character recognition with different kinds of images ranging from simple handwritten form-based documents and documents containing colored and complex backgrounds and varying intensities. In this, different preprocessing techniques like skew detection and correction, image enhancement techniques of contrast stretching, binarization, noise removal techniques, normalization and segmentation, and morphological processing techniques are discussed. It was concluded that using a single technique for preprocessing, we can’t completely process the image. However, even after applying all the said techniques might not be possible to achieve full accuracy in a preprocessing system.

Salvador España-Boqueria et al [11], in this paper hybrid Hidden Markov Model (HMM) model is proposed for recognizing unconstrained offline handwritten texts. In this, the structural part of the optical model has been modeled with Markov chains, and a Multilayer Perceptron is used to estimate the emission probabilities. In this paper, different techniques are applied to remove slope and slant from handwritten text and to normalize the size of text images with supervised learning methods. The key features of this recognition system were to develop a system having high accuracy in preprocessing and recognition, which are both based on ANNs.

In [12], a modified quadratic classifier-based scheme to recognize the offline handwritten numerals of six popular Indian scripts is proposed. Multilayer perceptron has been used for recognizing Handwritten English characters [13]. The features are extracted from Boundary tracing and their Fourier Descriptors. The character is identified by analyzing its shape and comparing the features that distinguish each character. Also, an analysis has been carried out to determine the number of hidden layer nodes to achieve high performance of the backpropagation network. A recognition accuracy of 94% has been reported for Handwritten English characters with less training time.

In [14], diagonal feature extraction has been proposed for offline character recognition. It is based on the ANN model. Two approaches using 54 features and 69 features are chosen to build this Neural Network recognition system. To compare the recognition efficiency of the proposed diagonal method of feature extraction, the neural network recognition system is trained using the horizontal and vertical feature extraction methods. It is found that the diagonal method of feature extraction yields a recognition accuracy of 97.8 % for 54 features and 98.5% for 69 features.

A. Brakensiek, J. Rottland, A. Kosmala, J. Rigoll [15] et al, in this paper a system for off-line cursive handwriting recognition described which is based on Hidden Markov Models (HMM) using discrete and hybrid modeling techniques. Handwriting recognition experiments using discrete and two different hybrid approaches, which consist of discrete and semi-continuous structures, are compared. A segmentation-free approach is considered to develop the system. It is found that the recognition rate performance can be improved by a hybrid modeling technique for HMMs, which depends on a neural vector quantizer (hybrid MMI), compared to discrete and hybrid HMMs, based on tired mixture structure (hybrid - TP), which may be caused by a relatively small data set.

R. Bajaj, L. Dey, S. Chaudhari, et al [16], employed three different kinds of features, namely, the density features, moment features, and descriptive component features for the classification of Devanagari Numerals. They proposed multi-classifier connectionist architecture for increasing the recognition reliability and they obtained 89.6% accuracy for handwritten Devanagari numerals. Sandhya Arora in [17], used four feature extraction techniques namely, intersection, shadow feature, chain code histogram, and straight-line fitting features. Shadow features are computed globally for character images while intersection features, chain code histogram features, and line fitting features are computed by dividing the character image into different segments. On experimentation with a dataset of 4900 samples, the overall recognition rate observed was 92.80% for Devanagari characters.

Mohammed Z. Khedher, Gheith A. Abandah, and Ahmed M. Al Khawaldeh [18] et al, this paper describe that Recognition of characters greatly depends upon the features used. Several features of the handwritten Arabic characters are selected and discussed. An offline recognition system based on the selected features was built. The system was trained and tested with realistic samples of handwritten Arabic characters. Evaluation of the importance and accuracy of the selected features is made. The recognition based on the selected features gives average accuracies of 88% and 70% for the numbers and letters, respectively. Further improvements are achieved by using feature weights based on insights gained from the accuracies of individual features.

Sushree Sangita Patnaik and Anup Kumar Panda May 2011 [19] et al, this paper proposes the implementation of particle swarm optimization (PSO) and bacterial foraging optimization (BFO) algorithms which are intended for optimal harmonic compensation by minimizing the undesirable losses occurring inside the APF itself. The efficiency and effectiveness of the implementation of the two approaches are compared for two different conditions of supply. The total harmonic distortion (THD) in the source current which is a measure of APF performance is reduced drastically to nearly 1% by employing BFO. The results demonstrate that BFO outperforms the conventional and PSO-based approaches by ensuring excellent functionality of APF and quick prevail over harmonics in the source current even under unbalanced supply.

METHODOLOGY

Digit Recognition Using Neural Networks

Handwritten digit recognition is already widely used in the automatic processing of bank cheques, postal addresses, etc. Some of the existing systems include computational intelligence techniques such as artificial neural networks or fuzzy logic, whereas others may just be large lookup tables that contain possible realizations of handwritten digits.

Artificial neural networks have been developed since the 1940s, but only in the past fifteen years have they been widely applied in a large variety of disciplines. Originating from the artificial neuron, which is a simple mathematical model of a biological neuron, many varieties of neural networks exist nowadays. Although some are implemented in hardware, the majority are simulated in software. Artificial neural nets have successfully been applied to handwritten digit recognition numerous times, with very small error margins, see e.g. [2] and [4].

Neural Networks

Artificial neural networks, usually called neural networks (NNs), are systems composed of many simple processing elements (neurons) operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes [1] (other definitions can also be found). NNs exist in many varieties, though they can be categorized into two main groups, where the distinction lies in the learning method:

– supervised learning: the network is trained with examples of input and desired output;

– unsupervised learning: the network tries to organize the input data in a useful way without using external feedback.

In its simplest form, an artificial neural network (ANN) is an imitation of the human brain. A natural brain can learn new things and adapt to a new and changing environment. The brain has the most amazing capability to analyze incomplete and unclear, fuzzy information, and make its judgment out of it. For example, we can read others' handwriting though the way they write may be completely different from the way we write. A child can identify that the shape of a ball and an orange are both a circle. Even after a few days, the old baby can recognize its mother from touch, voice, and smell. We can identify a known person even from a blurry photograph. The brain is a highly complex organ that controls the entire body. The brain of even the most primitive animal has more capability than the most advanced computer. Its function is not just controlling the physical parts of the body, but also more complex activities like thinking, visualizing, dreaming, imagining, learning, etc, activities that cannot be described in physical terms. An artificial thinking machine is still beyond the capacity of the most advanced supercomputers.

Brain Neuron

The brain is made of cells called neurons. The interconnection of such cells (neurons) makes up the neural network or the brain neuron (fig3.1). There are about 1011 neurons in the human brain and about 10000 connections with each other. ANN is an imitation of the natural neural network where the artificial neurons are connected similarly as the brain network. A biological neuron is made up of a cell body, axon, and dendrite. Dendrite receives electrochemical signals from other neurons in the cell body. The cell body, called Soma contains the nucleus and other chemical structures required to support the cell. Axon carries the signal from the neuron to other neurons. The connection between the dendrites of two neurons, or neurons to muscle cells is called synapse [1].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XIII September 2025
Special Issue on Emerging Paradigms in Computer Science and Technology

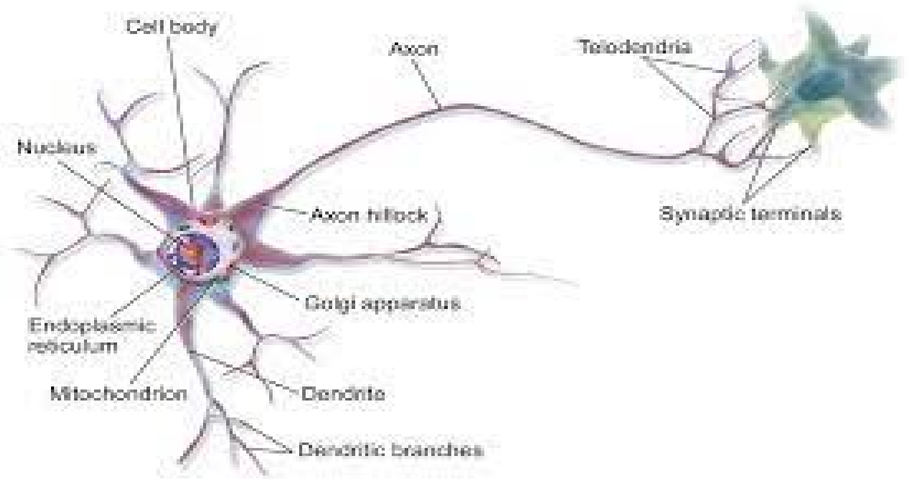

Fig 3.1 Brain Neurons

The neuron receives signals from other neurons through dendrites. When the strength of the signal exceeds a certain threshold, this neuron triggers its own signal to be passed on to the next neuron via the axon using synapses. The signal sent to other neurons through synapses triggers them, and this process continues [2]. A huge number of such neurons work simultaneously. The brain has the capacity to store large amounts of data.

Artificial Neuron

An artificial neural network consists of processing units called neurons. An artificial neuron network (Fig 3.2) tries to replicate the structure and behavior of the natural neuron. A neuron consists of one input (dendrites), and one output (synapse via axon). The neuron has a function that determines the activation of the neuron.

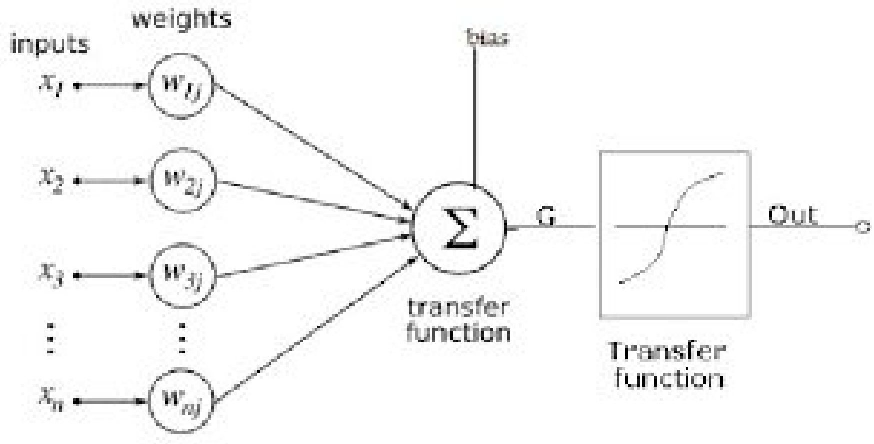

Fig 3.2 Model of an artificial neural network

x1...xn are the inputs to the neuron. A bias is also added to the neuron along with inputs. Usually, the bias value is initialized to 1. W0...Wn is the weights. Weight is the connection to the signal. The product of weight and input gives the strength of the signal. A neuron receives multiple inputs from different sources and has a single output. There are various functions used for activation. One of the most commonly used activation functions is the sigmoid function (Fig 1.3), given by

$$S(x) = \frac{1}{1+e^{-x}} \qquad \text{----------Eqn 3.1}$$

Where sum = $\sum_{i=0}^{n}$ xiw2 ----------Eqn 3.2

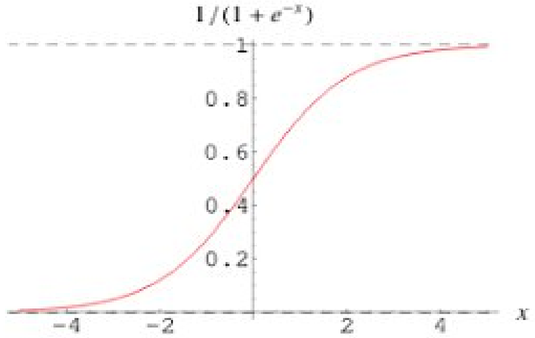

Fig 3.3 Sigmoid Function

The other functions used are the Step function, Linear function, Ramp function, Hyperbolic tangent function. The hyperbolic tangent (tanh) function is similar in shape to a sigmoid, but its limits are from -1 to +1, unlike a sigmoid which is from 0 to 1. The sum is the weighted sum of the inputs multiplied by the weights between one layer and the next. The activation function used is a sigmoid function, which is a continuous and differentiable approximation of a step function [2]. An interconnection of such individual neurons forms the neural network.

The ANN architecture (Fig3.4) comprises of:

input layer: Receives the input values

hidden layer(s): A set of neurons between input and output layers. There can be single or multiple layers

output layer: Usually, it has one neuron, and its output ranges between 0 and 1, that is, greater than 0 and less than 1. But multiple outputs can also be present [4].

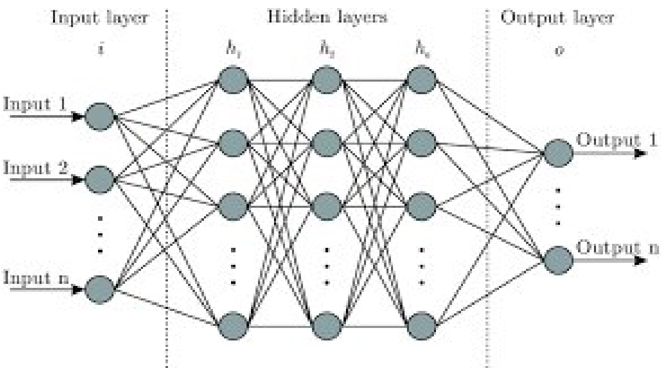

Fig 3.4 Neural Network Architecture

The processing ability is stored in inter-unit connection strengths, called weights [3]. Input strength depends on the weight value. Weight value can be positive, negative or zero. A negative weight means that the signal is reduced or inhibited. Zero weight means that there is no connection between the two neurons. The weights are adjusted to obtain the required output. There are algorithms to adjust the weights of ANN to get the required output. This process of adjusting weights is called learning or training [2].

Materials and methods

There are four steps to building the isolated digits recognition system. These steps are presented in Fig. 1 and below are the descriptions of them:

Image acquisition: We will acquire an image for our system as input .this image should have a specific format, for example, BMP format, and with a determined size such as 30´20 pixels. This image can be acquired through the scanner, digital camera, or other digital input devices[9].

Preprocessing: After acquiring the image, it will be processed through a sequence of preprocessing steps to be ready for the next step.

Noise removal: reducing noise in an image. For online, there is no noise to eliminate so no need for noise removal. In offline mode, the noise may come from the writing style or from the optical device capturing the image [21].

Normalization-scaling: standardize the font size within the image. This problem appears clearly in handwritten text because the font size is not restricted when using handwriting.

Thinning and skeletonization: Representing the shape of the object in a relatively smaller number of pixels [20]. Thinning algorithms can be parallel or sequential. The parallel is applied on all pixels simultaneously. Sequential examine pixels and transform them depending on the preceding processed results.

Segmentation: Since the data are isolated, no need for segmentation. With regards to the isolated digits, applying vertical segmentation on the image containing more than one digit will isolate each digit alone.

Normalization scaling and translation: Handwriting

produces variability in the size of written digits. This leads to the need to scale the size of the digits within the image to a standard size, which may lead to better recognition accuracy. We tried to normalize the size of the digit within the image and also translate it to a specific position by the following.

Feature extraction: Feature extraction is not part of this project. Feature types are categorized as follows:

Structural features: These describe the geometrical and topological characteristics of a pattern by representing its global and local properties

Statistical features: Statistical features are derived from the statistical distribution of pixels and describe the characteristic measurements of the pattern

Global transformation: Global transformation technique transforms the pixel representation to a more compact form. This reduces the dimensionality of the feature vector and provides feature invariants to global deformation like translation, dilation, and rotation

Classification and recognition: Neural Network is a network of non-linear systems that may be characterized according to a particular network topology. Where this topology is determined by the characteristics of the neurons and the learning methodology. The most popular architecture Of Neural Networks used in Arabic digits recognition takes a network with three layers. These are the Input layer, hidden layer, and output layer. The number of nodes in the input layer differs according to the feature vector's dimensionality of the segment image size.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XIII September 2025
Special Issue on Emerging Paradigms in Computer Science and Technology

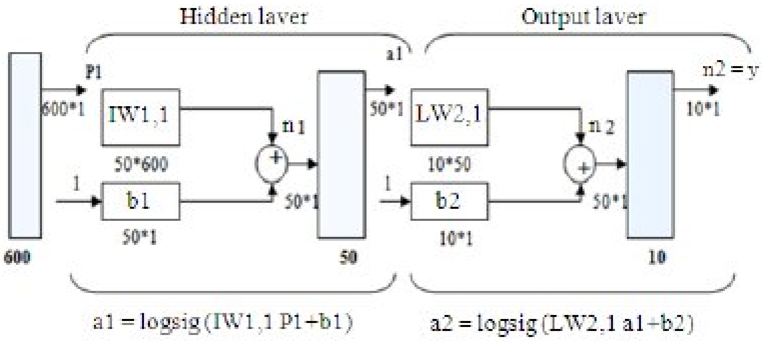

Figure 3.5: Two layers network, one hidden and one output, with 50, and 10 neurons respectively

In the hidden layer, the number of nodes governs the variance of samples which can be accurately and correctly recognized by this Network. In our system project, the data will be divided using neural networks. In addition, we use the algorithm of backpropagation [22]. The backpropagation algorithm consists of three stages. The first is the forward phase, which spread inputs from the input layer to the output layer through

the hidden layer to provide outputs. The second is the backward stage, calculating and propagating back the associated error from the output layer to the input layer through the hidden layer. And the third stage is the adjustment of the weights[23].

The backward stage is similar to the forward stage except that error values are propagated back through the network to determine how the weights are to be changed during training. During training, each input pattern will have an associated target pattern. After training, the application of the net involves only the computations of the feed-forward stage. Thereafter, we will describe the algorithm used to train the network in detail [24].

Training algorithm:

Initialize weights by zero

2. While E >= 0.000001 iterates steps 3-9

{Feed forward stage}

For the input layer, assign as net input to each unit (Xi, i = 1,…,n) its corresponding element in the input vector. The output for each unit is its net input. We have (a 600×10) input vector

For the first hidden layer, units calculate the net input and output:

$$net_j = b_j + \sum_{i=1}^{n} x_i w_{ij}, \ \ o_j = f(net_j)$$

----- Eqn 3.3

And repeat step 4 for all subsequent hidden layers

For the output, layer units calculate the net input and output:

$$net_j = b_j + \sum_{i=1}^{n} x_i w_{ij}, \ \ o_j = f(net_j)$$

----- Eqn 3.4

{Back propagation stage}

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XIII September 2025
Special Issue on Emerging Paradigms in Computer Science and Technology

For each output unit calculate its error:

$$\delta_j = (t_j - o_j).f'(net_j)$$

----- Eqn 3.5

For the last hidden layer calculate the error for each unit:

$$\delta_k = f'(net_j).\sum_k \delta_k w_{kj}$$

----- Eqn 3.6

And repeat step 7 for all subsequent hidden layers:

{Update weights and biases}

For all layers update weight for each unit:

$$\Delta w_{ij}(n+1) = \alpha \delta_j o_i + \Delta w_{ij}(n)$$
$$\Delta b_j(n+1) = \alpha \delta_j + \Delta b_j(n)$$

----- Eqn 3.7

Test stopping condition in step 2

As shown in Fig. 3 applying the three stages, feed-forward, backpropagation of error, and adjustment of weights and biases represent one epoch. In our research, the first network used needed 36 epochs to reach the goal and the other network needed 33 epochs to reach the goal. The goal in the first network was until E <= 0.00001, while in the second network was until E

<= 0.000001.

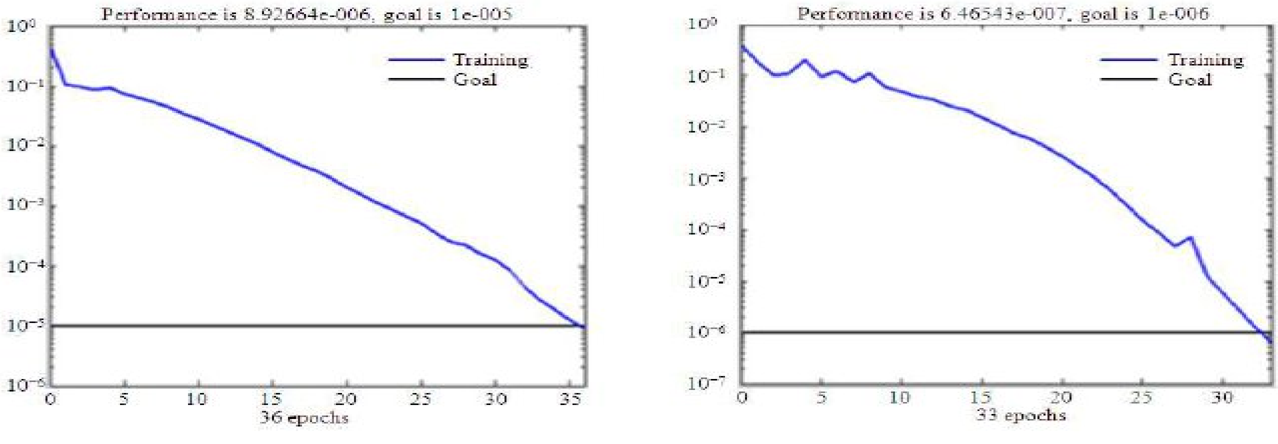

Figure 3.7: Training performance function for both networks.

CONCLUSION

We can conclude that we reached the computer to the human brain through the important use of isolated digit recognition for different applications. This recognition starts with acquiring the image to be preprocessed throw a number of steps involved in neural network. As an important point, feature classification and recognition must be done to gain a numeral text. In a final conclusion, the neural network seems to be better than other techniques used for recognition.

REFERENCES

1. R. Plamondon and S. N. Srihari, On-line and off-line handwritten character recognition: A comprehensive survey, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, no. 1, 2000, 63-84.
2. Xiao-Xiao Niu and Ching Y. Suen, A novel hybrid CNN–SVM classifier for recognizing handwritten digits, ELSEVIER, The Journal of the Pattern Recognition Society, Vol. 45, 2012, 1318– 1325.
3. Diego J. Romero, Leticia M. Seijas, Ana M. Ruedin, Directional Continuous Wavelet Transform Applied to Handwritten Numerals Recognition Using Neural Networks, JCS&T, Vol. 7 No. 1, 2007.
4. V.N. Manjunath Aradhya, G. Hemantha Kumar and S. Noushath, Robust Unconstrained Handwritten Digit Recognition using Radon Transform, IEEE-ICSCN, 2007, 626-629.
5. Zhu Dan and Chen Xu, The Recognition of Handwritten Digits Based on BP Neural Network and the Implementation on Android, Fourth International Conference on Intelligent Systems Design and Engineering Applications (ISDEA), 2013, 1498-1501.
6. Adriano Mendes Gil, Cícero Ferreira Fernandes Costa Filho, Marly Guimarães Fernandes Costa, Handwritten Digit Recognition Using SVM Binary Classifiers and Unbalanced Decision Trees, Image Analysis and Recognition, Springer, 2014, 246-255.
7. Al-Omari F., Al-Jarrah O, Handwritten Indian numerals recognition system using probabilistic neural networks, Adv. Eng. Inform, 2004, 9–16.
8. Junchuan Yanga, ,Xiao Yanb and Bo Yaoc, Character Feature Extraction Method Based on Integrated Neural Network, AASRI Conference on Modelling, Identification and Control, ELSEVIER, AASRI Pro.
9. Nazri Mohd Nawi, Walid Hasen Atomi, and M. Z. Rehman, The Effect of Data Pre-Processing on Optimized Training of Artificial Neural Networks, Procedia Technology, ELSEVIER, 11, 2013, 32 – 39.
10. K. Gaurav and Bhatia P. K., “Analytical Review of Preprocessing Techniques for Offline Handwritten Character Recognition”, 2nd International Conference on Emerging Trends in Engineering & Management, ICETEM, 2013.
11. Salvador España-Boquera, Maria J. C. B., Jorge G. M., and Francisco Z. M., “Improving Offline Handwritten Text Recognition with Hybrid HMM/ANN Models”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 33, No. 4, April 2011.
12. U. Pal, T. Wakabayashi, and F. Kimura, “Handwritten numeral recognition of six popular scripts,” Ninth International conference on Document Analysis and Recognition ICDAR 07, Vol.2, pp.749-753, 2007.
13. Anita Pal & Dayashankar Singh, “Handwritten English Character Recognition Using Neural,” Network International Journal of Computer Science & Communication. Vol. 1, No. 2, July-December 2010, pp. 141-144.
14. J. Pradeep, E. Srinivasan and S. Himavathi, “Diagonal Based Feature Extraction For Handwritten Alphabets Recognition System Using Neural Network”, International Journal of Computer Science & Information Technology (IJCSIT), Vol 3, No 1, Feb 2011.
15. Brakensiek, J. Rottland, A. Kosmala and J. Rigoll, “Offline Handwriting Recognition using various Hybrid Modeling Techniques & Character N-Grams”, Available at http://irs.ub.rug.nl/dbi/4357a84695495.
16. Reena Bajaj, Lipika Dey, and S. Chaudhury, “Devnagari numeral recognition by combining decision of multiple connectionist classifiers”, Sadhana, Vol.27, part. 1, pp.-59-72, 2002.
17. Sandhya Arora, “Combining Multiple Feature Extraction Techniques for Handwritten Devnagari Character Recognition”, IEEE Region 10 Colloquium and the Third ICIIS, Kharagpur, INDIA, December 2008.
18. Mohammed Z. Khedher, Gheith A. Abandah, and Ahmed M. AlKhawaldeh, “Optimizing Feature Selection for Recognizing Handwritten Arabic Characters”, Proceedings of World Academy of Science Engineering and Technology, vol. 4, February 2005 ISSN 1307-6884.
19. Sushree Sangita Patnaik and Anup Kumar Panda, “Particle Swarm Optimization and Bacterial Foraging Optimization Techniques for Optimal Current Harmonic Mitigation by Employing Active Power Filter Applied Computational Intelligence and Soft Computing”, Volume 2012, Article ID 897127.
20. Rafael Gonzalez, C., E. Richard Woods and L. Steven Eddins, 2003. Digital Image Processing using MATLAB. 2nd Edn., Prentice Hall, USA., ISBN: 10: 0130085197, pp: 624.
21. Rafael C. Gonzalez and Richard E. Woods, 2002. Digital Image Processing. 2nd Edn., Prentice-Hall, Inc., USA., ISBN: 10: 0201180758, pp: 28-29.

22. Grother, P.J. and G.T. Candela, 1993. Comparison of handprinted digit classifiers. Technical Report NISTIR 5209, NIST. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.45.8934
23. Pfister, M., 1996. Learning algorithms for feedforward neural networks design, combination, and analysis. Number 435 in Fortschrittberichte Reihe 10. VDI-Verlag, Diisseldorf. http://en.scientificcommons.org/6488386
24. Lee, S.W. and Y.J. Kim, 1995. Direct extraction of topographic features for grayscale character recognition. IEEE. Trans. Patt. Anal. Mach. Intell., 17: 724-729. DOI: 10.1109/34.391416