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Research paper

Adaptive learning based improved performance of activation functions in hidden layer using artificial neural network

Tahir Khan [1] *, Dr. J. S. Yadav [1]

[1] *Maulana Azad National Institute of Technology, Bhopal MP India*
**Corresponding author E-mail: prof.tahirkhan@gmail.com*

Abstract

Advancement in Artificial Neural Network always playing vital role in complex pattern recognition system. In this research work improved performance of the activation functions for the hidden layer in artificial neural network supervised by backpropagation algorithm with adaptive learning feature has been recorded for pattern recognition. Complexity of large data of pattern such as face recognition, cancer detection, object recognition, number plate surveillance etc is increasing day by day. To resolve complexity, performance of hidden layer is registered using Log-sigmoid, Tan-sigmoid and purelin activation functions respectively due to their inherent properties. An excellent neural network training model of 1460 Alpha-Numeric data set with 3000 Epoch (iterations) have been trained in neural net-work through activation functions for number plate recognition. Hence the performance efficiency of hidden layer activation functions is recorded for pruning the overall back propagation neural network architecture with improved learning rate along with better time com-plexity for pattern matching.

Keywords: *Activation Function; Adaptive Learning; Back Propagation Neural Network; Hidden Layer; Learning Rate; Pattern Recognition; Time Complexity.*

1. Introduction

Artificial Neural Network is a rising field which is extremely valuable for many applications like, medical diagnosis, pattern matching, robot control, remote sensing and E-trading. This Artificial neural network comprised of three layers viz. Input layer, Hidden layer and Output layer. Input layer is in charge of accepting signals from external environment which is sent to Hidden layer for further processing. Hidden layer is middle layer which comprises of various activation functions. Activation Function is a numerical recipe which rapidly process input signal along with weight values among the input and hidden layer and then forward the resultant to the next layer called output layer. The Output layer is associated with the Display system where the resultant signal values are presented in readable form.

2. Artificial neural network

An Artificial Neural Network (ANN) is an information processing model that is motivated by the way in which human biological cerebrum systems process information. The key component of this neural network model is its structure in which huge number of interconnected information processing elements called as Neuron working together to solve specific task. An ANN is designed to solve challenges such as pattern recognition, data classification and many more through a deep learning process [1] such like brain learn by examples. First, the Network gathers Knowledge from its environment through a learning process. Second, Interneuron connection strength is used to store learning and process information in desired manner.

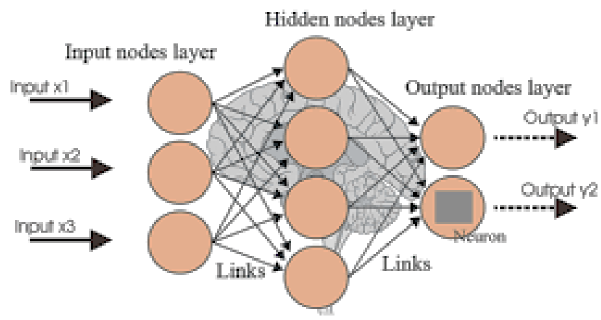


Fig.1: Structure of Artificial Neural Network.

3. Literature survey

In this paper author R. Panahi and I. Gholampour [2], presents an online highly accurate framework for automatic number plate recognition (ANPR) that can be utilized as a basis for many real-worlds ITS applications. The system is developed to manage with lighting conditions, unclear vehicle plates, variations in weather and different traffic situations, and high-speed vehicles. This paper addresses many issues by presenting proper hardware platforms along with robust, real-time, and innovative algorithms. To achieve reliable evaluations, two new data sets were created one for violation detection called “Crossroad Data set” and the other for vehicle counting in highways called “Highway Data set.” Through this data sets an industrial, robust and reliable ANPR system for high speed applications is proposed. The main advantage of this system is its high detection and recognition accuracies on dirty plates.They have tried framework on accessible English plates informational collection and accomplished 97% by and large precision.

Yo-Ping Huang, Shi-Yong Lai and Wei-Po Chuang [3] have composed a framework which is required to have high recognition accuracy and reliability with the end goal that the objective of programme can be accomplished. They exhibited a framework to perceive the license number plate in the acquired image captured from a video camera. The acknowledgment procedure of framework contains four noteworthy steps. Initially, the framework to locate the probable position of the license plate within the acquired image by using gradient analysis and image processing. Second, model estimates the image parameters needed to normalize the license plate and uses the cross-correlation to detect the skew of the license plate and rectify the tilt. Third, they used a template technique to recognize the characters in the license plate. Finally, they use the information gained from the previous step to analyze the probable license numbers. In view of the test results, the proposed framework can adequately recognize the license number. The time needed to recognize a license plate takes only 1.5 seconds.

All over the world breast cancer is the most common form of cancer which causes death in 12.6% of women all around the world. K. A. Mohamed Junaid [4] presents a practical way to deal with normal, malignant and benign tumor using two layer neural network back propagation algorithm. Back propagation Neural network BPNN algorithm is used to train the neural network. Parallelization strategies accelerate the calculation procedure and accordingly two layer neural network beat the past work regarding precision. Breast cancer tumor database utilized for the testing design is from the CIA machine learning vault. The highest accuracy of 97.12% is accomplished utilizing the two layer neural network back propagation algorithm. Excessively numerous hidden neurons lead to over fit. As the quantity of neurons increments there is a need to retain the preparation set, hence making the network useless on new data sets. Clearly if there are insufficient hidden neurons then the system can't learn legitimately.

N. Wang, X. Zhu and J. Zhang, [5] put forward a set of Artificial Network algorithms about license plate segmentation and recognition. The complete algorithms are bifurcated into four segment firstly image pre-processing, secondly license plate location, thirdly license plate segmentation and fourthly character recognition respectively. The aim of image pre-processing is rapidly and effectively location the license plate, because the algorithm directly affects the authenticity of character segmentation and its recognition. Hence the image pre-processing algorithm is vital parameter that affects whole system performance.

JosephTarigan Nadia Ryanda Diedan and YayaSuryana [6] in their research have implemented Genetic Algorithm in optimising the number of hidden neuron with top-hat transformation and otsu threshold for effective learning rate and momentum rate on BPNN that is applied for NPR. They have tested 220 images of license plate with various plate conditions and lightening conditions for recognition. In in whole characters recognition they found 85.97 per cent success rate and 97.18 per cent in single character recognition accuracy by using GA in BPNN.

4. Implementation details

Performance comparison of activation function in artificial Neural Network has been recorded by excellent training model of data set of 1460 Alpha-Numeric characters with 3000 Epoch (iterations) have been trained in neural network for pattern recognition with 110 Numbers Plates through Adaptive Learning–BPNN Network. With the weight initialization of 150 neurons as input and 136 neuron constituted to hidden layer which forward results to output layer with 36 neuron through which 26 Alphabets and 10 numeric data is recognized at output.

4.1. Back propagation neural network

In due process of Learning and training of Neuron there are limitation due to which neuron miss to achieve the desired result. To conquer this restriction, in 1974 back propagation algorithm was made by Paul Werbous and later rediscovered energetically by Rumelhart, Hinton and Williams. BPNN is a supervised algorithm in which error difference between the desired output and calculated output is back propagated. The methodology is repeated during learning to minimize the output error by adjusting the weights thought the back propagation of error. As a result of these weight adjustments, hidden layers set their weights to represent important features of the desired task. Learning of BPNN consists of two steps [7], first Forward Propagation, secondly Back Propagation of error.

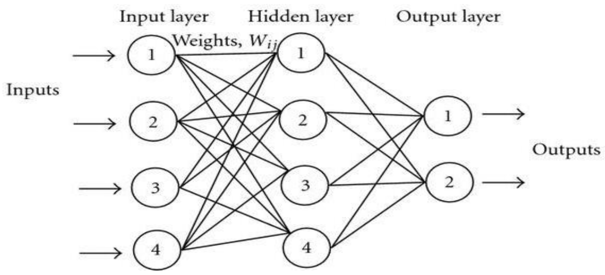


Fig. 2: Back-Propagation Neural Network Approach.

In back propagation error is calculated by the difference between the targeted output that is desired output and actual output of each output unit. This error difference is back propagated to the previous layer that is hidden layer.

4.2. Activation function

A function which is developed to transform the activation level of neuron (weighted sum of inputs) to an desired output signal is known as Activation Function. There are numerous Activation Functions [8] which are being utilized according to the necessity of use for which the neural system is utilized. There are many activation function available in Neural system like Sigmoid, Log-Sigmoid, Identity, Tan-Sigmoid, Purelin, Binary step, Inverse square root unit and so forth. Each activation function is unique in itself and must be utilized according to the necessity of implemented application. For training and testing purpose,

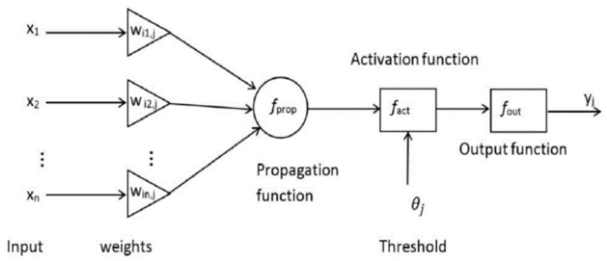
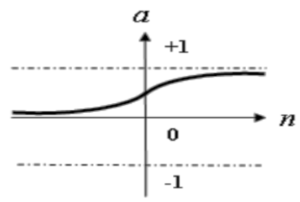


Fig.3: Artificial Neural Network with Activation Function.

we have applied log-sigmoid, tan-sigmoid and purelin activation function in hidden layer for pattern recognition through number plate recognition on data set of 1460 Alpha-Numeric characters with 3000 Epoch (iterations) in order to get better performance in terms of accuracy as well as minimum time required in training the data.

4.3. Log-sigmoid function



$$a = \text{Logsig}\,(n) = \frac{1}{1+e^{-n}}$$

Fig 4: Log-Sigmoid Function.

A log-sigmoid function, also known as a logistic function, which is represented by the below relationship:

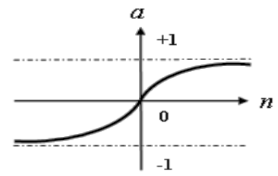
logsig(n) = 1 / (1 + exp(-n))

Where n is a slope parameter. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. This is known as log-sigmoid because a sigmoid can also be developed using the hyperbolic tangent function.

4.4. Tan-sigmoid function

A Tan-Sigmoid function is a neural transfer function which is also known as hyperbolic tangent sigmoid transfer function. It calculates a layer's output from its net input.

It is represented by: tansig(n) = 2/(1+exp(-2*n))-1

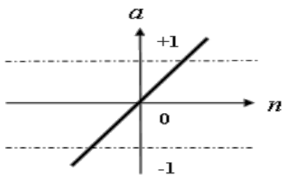


$$a = \text{Tansig}\ (n) = \frac{2}{1+e^{-2n}} - 1$$

Fig. 5: Log-Sigmoid Function.

As tan-sigmoid varies from -1 to +1 it gives better response out of other functions.

4.5. Purlin function



$$a = \text{Purelin}\ (n)$$

Fig. 6: Purelin Function.

A Purelin function is a neural transfer function which is also known as Linear transfer function. It evaluates a layer's output from its net input. It is represented by :

Purelin(n) = n

4.6. Network propagation function

It is exceptionally hard to know which training algorithm (Network Propagation algorithm) calculation will be the quickest for a given issue. It relies upon numerous components [9], including the problem complexity, nature of the issue, data points in the training set, the number of weights and biases in the network, and most important whether the neural network is being used for function approximation or pattern recognition.
In this research work our aim is to develop robust neural network-back propagation architecture with activation function which can be further utilized for patter recognition or data classification problems like cancer detection, number plate recogniton and many more. We have used traingdx (Variable Learning Rate Back propagation) propagation function for getting the best results in performance comparison of activation functions in hidden layer in neural network [10] [11].

net.trainFcn = 'traingdx'

[net,tr] = train (net,)

traingdx is a network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate.

net.trainFcn = 'traingdx' instructs the neural network architecture trainFcn inherent property.

[net,tr] = train (net) provides training to the neural network architecture with traingdx.

The neural network function traingdx consolidates adaptive learning rate with momentum training with the exception that it has the momentum coefficient **mc** as an additional training parameter [12] [13].

4.7. Neural network training

For evaluation of activation functions in Artificial Neural Network in Hidden Layer we have used MATLAB Neural Network training tool V-R2016a for our research work. Neural network tool gives a structure to outlining and actualizing neural systems with calculations, pretrained models, and applications. When command nntool is passed in matlab command window than data manager tool allows you to implement the desired research.
>>
>> nntool

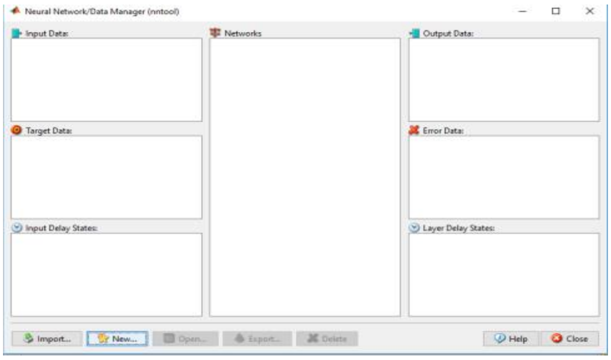


Fig. 7: GUI Model of Data Manager of Neural Network in MATLAB.

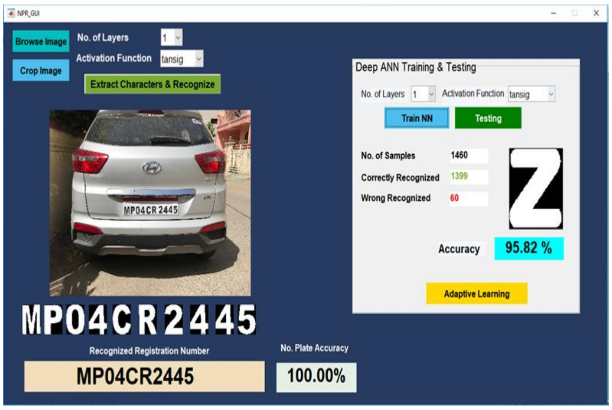


Fig. 8: GUI Interface in Matlab for Number Plate Recognition.

5. Results analysis

In backpropagation neural network architecture, activation functions in hidden layers plays a vital role in the performance especially when a database is big and much faster results are required for calculations.
Best results for performance comparison of activation function in ANN-BPNN architecture with adaptive learning has been recorded by excellent training a data set of 1460 Alpha-Numeric characters with 3000 Epoch (iterations) in MATLAB. We have also developed GUI (Fig.8) Interface for pattern recognition with 110 Numbers

Plates with different font size data base through Adaptive Learning–BPNN Network.
Performance output for backpropogation neural network training is shown in (Fig.9(a)(b)(c)) with the weight initialization of 150 neurons as input and 136 neuron constituted to constituted to hidden layer which forward results to output layer with 36 neuron through which 26 Alphabets and 10 numeric data is recognized at output.

Table 1: Comparison of ANN-BPNN Activation Functions

Activation Function	Hidden Layer	Epoch (Iterations)	Gradient	Performance	Training Time
Log-Sigmoid	1	3000	6.88	368	0.00.31 Sec
Tan-Sigmoid	1	3000	23.5	591	0.00.29 sec
Purelin	1	3000	74.8	824	0.03.26 sec

The proposed tan-sigmoid activation function out of log-sigmoid and purelin function for single hidden layer for pattern recognition in ANN-BPNN architecture showed the remarkable fastest results in the neural network training on complex 1460 AlphaNumeric datasets.

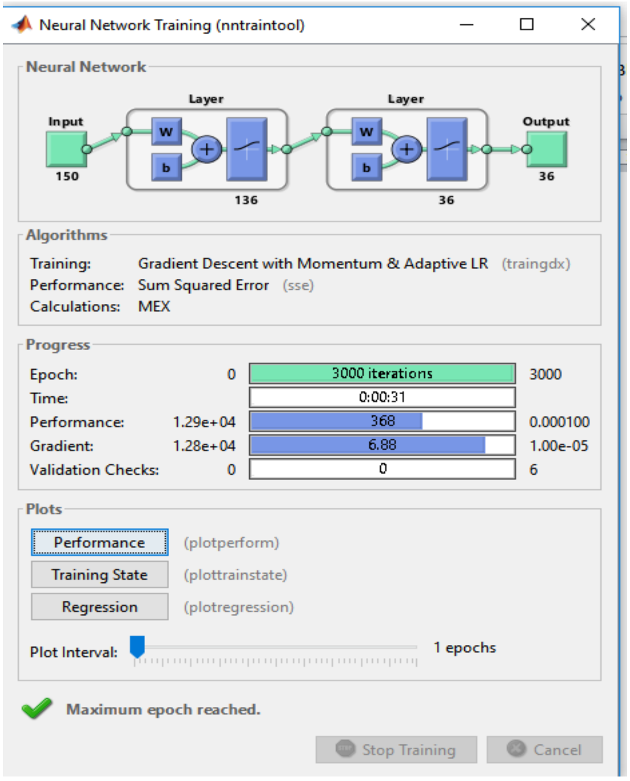


Fig. 9: a): Performance Output a) Log-Sigmoid in ANN-BPNN.

In training and testing period of activation functions for single hidden layer in neural network for pattern recognition, tan-sigmoid function gave best performance in complex training of 1460 alphanumeric dataset for number plate recognition in 29seconds only.

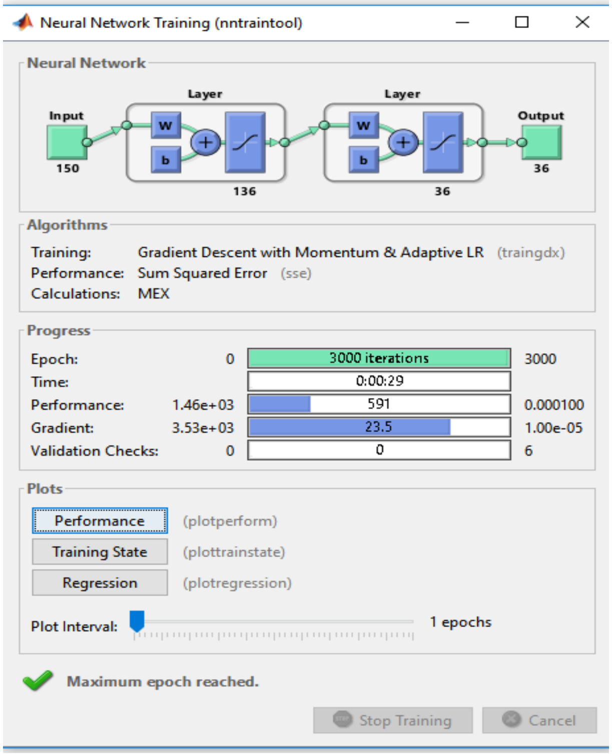


Fig. 9: B): Performance Output B) Tan-Sigmoid in ANN-BPNN.

which is the minimum time taken by tan-sigmoid (Table1) to train a huge data of 1460 data sets for pattern recognition is recorded with 95.82% neural network training accuracy and 100% recognition (Fig.8) (Table2) of number plates.

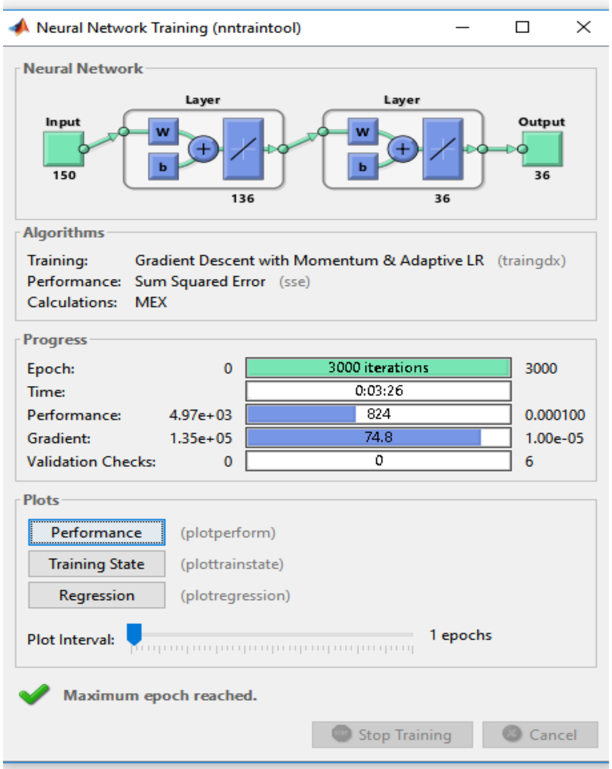


Fig. 9: C): Performance Output C) Purlin in ANN-BPNN.

If the authenticity of number plate in complex datasets is prime concern then multilayer perceptron model of multiple hidden layers should be chosen but if training time is major factor then the neural network of single hidden layer with BPNN and tan-sigmoid activation function (Table1) should be used for research purpose.

Table 2: Neural Network Training Accuracy Comparison of Activation functions

Activation Function	Hidden Layer	Epoch (Iterations)	Training Time	NN Training Accuracy (%)	No Plate Accuracy (%)
Log-Sigmoid	1	3000	0.00.31 Sec	88.84	100
Tan-Sigmoid	1	3000	0.00.29 sec	95.82	100
Purelin	1	3000	0.03.26 sec	89.25	100

During research, fact to keep into consideration is the quantity of hidden layers is also proportional to the number of epochs in ANN training. This implies as the number of hidden layers is expanded, the training process of the neural network slows down because of extra branching of weight modification. However, the training of the neural network is more precise for large data, if more than one hidden layers are used. This precision is accomplished at the cost of neural network training time.

6. Conclusion

In this research work improved performance of the activation functions for the hidden layer in artificial neural network supervised by backpropagation algorithm with adaptive learning feature has been recorded for number plate recognition. An excellent training model of data set of 1460 Alpha-Numeric characters with 3000 Epoch (iterations) have been trained in neural network through activation functions for pattern recognition.

Out of three, hyperbolic tangent sigmoid activation function performance in hidden layer registered with faster training time of 29 Seconds for 1460 Alphanumeric data set in neural network with training efficiency of 95.83 percent along with 100 percent number plate recognition under natural conditions. Hence all the research work which is discussed in this paper will support the systematic performance evaluation of activation function to scientific community worldwide and enable researchers to know which function in neural network are most appropriate for pattern recognition.

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