ISSN (Online) 2456-1290
International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)
Vol 2, Issue 4, April 2017

Data Classification via Intelligent Machine Learning

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***Abstract*: Classification is one of the technique of machine learning. This paper focuses on data classification using Modular neural network. Modular neural networkdivides the task into sub modules.Paper considers five bench mark problem -Iris dataset, E. Coli dataset, Glass datasetWine dataset andSPECT heart dataset on cardiac Single Proton Emission Computational Tomography(SPECT) images.The problem consider classification of each dataset, on the basis of physical attributes.Experimental results on five popular data set demonstrate that proposed classification model enhance the classification accuracy of over conventional neural network model.By using this modular neural network model to implement classification problem, in future upcoming yearsthe unknown data can be predicted more precisely.**

***Keywords* –Machine learning, Classification, Modular neural network, Back -propagation algorithm.**

I. INTRODUCTION

Machine learning is a theory that computer can learn without being explicitly programmed to perform specific task. One of the most important areas that make use of machine learning technique is the data classification.In Machine learning [1], there are various method for classification such as Artificial neural network, Principal component analysis, Support vector machine, K-Neighbor. In this work, we consider Artificial neural network due to its accuracy for classification than the other method of machine learning.Modular neural network[2]consists of several modules of each task using different or same neural network specialized for specific task. In this paperwe proposed a methodology of data classification via intelligent machine learning, we implement neural network back-propagation learning algorithm of various bench mark problem taken from different domains.Classification [3] is supervised learning, its concept is to predict group membership for data instances. Classification aim is to implement function that classify input pattern into their specific class. Before applying classification algorithm, important step is to be done on dataset i.e. normalization to improve accuracy of classification algorithm. We use linear normalization technique on dataset problem, as dataset we have taken have continues values. Classification concept is successfully introduced by back-propagation algorithm [4].Firstly, back propagation neural network is implement by artificial neural network and then we combine different modules to solve complex classification problem.However, Feed-forward neural network is fully coupled neural networks in which each input sample activates all hidden nodes. This characteristic of Feed-forward neural network not only leads to a large calculation cost but also makes knowledge accumulation extremely difficult, since the Feed-forward neural network tend to forget previously learned mappings rather quickly when exposed to new mappings.This paper focus on introducing traditional Back-propagation algorithm by modular neural network, typically follows a greedy strategywhere in each new neuron added to the network is trained to minimize the residual error as much as possible. This paper also contains an analysis of the performance results of modularneural networks with various numbers of hidden layer neurons, and differing number of cycles(epochs).

II. PROBLEM STATEMENT

A. Iris Dataset

Iris data set is popular data set for classification. Itcontains 3 classes with 150 number of instances and 4 attributes. Classes of iris plant species -Iris Setosa, Iris Versicolour, Iris Virginica.

B. E.Coli Dataset

Escherichia coli is a bacterium, have powerful toxic for human and animal health. E. coli dataset is Protein Localization Sites. It contains 8 classes with 336 number of instances and 8 attributes (1 name +7 predictive)

C. Glass Dataset

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Glass Identification dataset collect form crime scene, help in investigation. It contains214 instances, 10 Attributes(including an Id#) and 7 class. All attributes are continuously valued.

D. Wine dataset

Wine dataset contain information of a chemical analysis ofwines grown in Italy, with three cultivators.There are 3 class with 178 instances and 13 attribute.

E. SPECT dataset

The dataset contains report of diagnosing of cardiac Single Proton Emission Computed Tomography (SPECT) images. On the basis of report patients is classified into two categories: normal and abnormal.SPECT dataset contain 267 instances and 45 attribute (44 continuous + 1 binary class).

III. NORMALIZATION

Normalization [6] is a method used to standardize the range of independent variables or features of data. It is generally performed during the data pre-processing step.

We used this method for normalizing each attribute of data set:-

$$Ia = (I - min)\frac{newMax - newMin}{Max - Min} + newMin$$

Where newMax=0.9,newMin=0.1;

IV. PROPOSED METHODOLOGY

A. Back-Propagation Neural Network Algorithm

Here we focus on the use of modular neural networkarchitecture using back-propagation algorithm for identification of classes of dataset on the basis of attributes of dataset.Back-Propagation neural network algorithm use local gradient descent (delta rule) method to minimize error. Minimum error is a result of BPN algorithm for dataset classification. Figure 1show the architecture of multilayer feed-forward neural network. Number of input neuron depend upon number of attribute and output neuron depend upon class of each dataset respectively.Hidden layer neuron range from 1 to [(input neuron+ output neuron)/2].

The training of the Back-Propagation algorithm is done in three stages-

- the feed-forward of the input training pattern
- compare output with target, calculation back-propagation of the error
- updating of weight and bias.
- Repeat at different epochs till stopping condition occur.

The testing of the BPN involves the computation of feed-forward phase only.

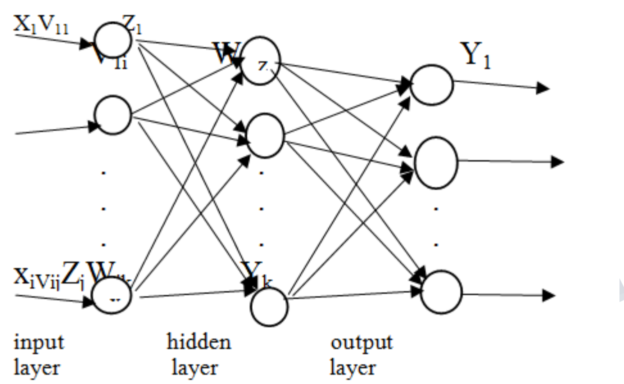

Fig 1. Architecture of Back Propagation Neural Network

Training algorithm

The algorithm for training network is as follows: -

Step 1 feed forward phase

For each training pair.

- each input unit receive signal x_i and transfer to hidden layer (i=1to n)
- each hidden unit z_j (j=1to p) sum its weighted input signal to calculate net input (Z_{inj})

$z_{inj=}v_{oj+}\sum x_i v_{ij}$… (1.1)

where vij is a weight associated with input-hidden unit, voj output-hidden weight,

- calculate the output of hidden unit(Z_j) by applying its activation function over z_{inj}

$z_j=f(z_{inj})$ … (1.2)

and send the output signal from the hidden unit to the input of output layer unit

- for each input (y_k) calculate the net input (y_{ink})

$y_{ink}=w_{ok}+\sum zj w_{jk}$ …(1.3)

ISSN (Online) 2456-1290
International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)
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and apply the activation function to compute output signal (y_k)

$y_k=f(y_{ink})$ …(1.4)

Step 2 back-propagation of error

- each output unit y_k(k=1 to m) receives a target pattern corresponding to input training pattern ad computes the error correction terms(δ_k)

$\delta_k=(t_k-y_k)f'(y_{ink})$ ... (2.1)

Step 3 weight updating

On the basis of error correction term,update the change in weight(Δw_{jk}) and bias(Δw_{ok})

$\Delta w_{jk}=\alpha\delta_k z_j$ … (3.1)

$\Delta w_{ok}= \alpha\delta_k$ … (3.2)

Also send δ_k to hidden layer back

- Each hidden unit z_j (j=1to p) sum its delta input (δ_{in_J})from the output unit

$\delta_{in_J}=\sum\delta_k w_{jk}$ …(3.3)

The term δ_{in_J} gets multiplied with the derivative of $f(z_{inj})$ to calculate the error term(δ_J)

$\delta_J=\delta_{in_J} f'(z_{inj})$ ... (3.4)

On the basis of calculated δ_J, update change in weight (Δvij) and bias(Δv_{ok})

$\Delta vij=\alpha\delta_J x_i$ … (3.5)

$\Delta v_{ok}=\alpha\delta_J$ … (3.6)

Step 4 weight and bias updating

Each output unit y_k(k=1to m) update the weight and bias

$W_{jk}(new)=w_{jk}(old)+\Delta w_{jk}$ …(4.1)

$W_{ok}(new)=w_{ok}(old)+\Delta w_{ok}$… (4.2)

Each hidden unit z_j (j=1 to p) its weight and bias

$V_{ij}(new)=v_{oj}(old)+\Delta v_{ij}$...(4.3)

$V_{oj}(new)=v_{oj}(old)+\Delta v_{oj}$ …(4.4)

Testing algorithm

Testing procedure of Back-P algorithm is as follows: -

- Initialize the weights. Weights are taken from training algorithm.
- Set the activation of input unit x_i (i=1to n).
- Calculate the net input(Z_{inj}) for hidden unit x and its output(Z_j). For j (1 to p),

$Z_{inj}=v_{oj}+\sum x_i v_{ij}$ …(5.1)

$Z_j=f(z_{inj})$ …(5.2)

- Compute output(Y_k) for output layer unit. For k (1 to m),

$Y_{ink}=wok+\sum z_j w_{jk}$ ... (5.3)

$Y_k=f(y_{ink})$ ... (5.4)

Use sigmoidal function for calculating the output

A. Modular neural network algorithm

Artificial neural network is model inspired by the working of human brain to performs a task, however they lack modularity. In contrast, our brain has distinct specialized areas that are responsible for specific tasks, such as: vision, audition, and speech. Modular neural networks (MNNs) aim to construct specialized neural networks using the divide-to-conquer approach [7].In modular neural network we combine different model and transform each single network in a module that can freely link with other module. Herein this paper, we combine different module of neural network design to solve classification of each class on the basis of attribute. So we used modular neural network here to solve complex problem efficiently. Figure 2 show the hierarchy of modules in modular neural network. A five benchmark database is used here to prove the efficiency and effectiveness of the proposed method.

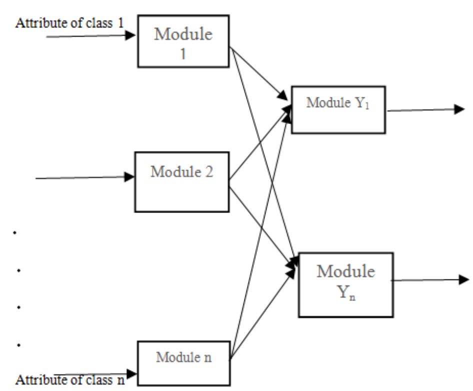

Fig 2. Architecture of modular neural network

V. EXPERIMENT AND RESULT

We have taken five benchmark problem from UCI Data Repository and perform classification using Back-propagation algorithm. All these datasetshave different instances,attribute and class. Table1 describe about dataset. Some expert work on these Dataset and found there is no missing value. We have train algorithm by changing Hidden Layerat different Epoch. By increasing hidden layer, we observe on each dataset that error reduce.

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ISSN (Online) 2456-1290
International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)
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Table 1: Dataset For Classification Problem

Dataset	Instances (Training + Testing)	Attribute	Class
IRIS	150(75+75)	4	3
E. coli	336(168+168)	7	8
Glass	214(107+107)	10	7
SPECT	267(80+187)	23	2
Wine	178(89+89)	13	3

Training mechanically stops once generalization stops rising,asindicated by a rise within the Mean sq. Error(M.S.E) of the validationsamples.TheMeanSquared Error is that the average square distinction between outputs andtargets.Lowervalues squaremeasure higher where as zero means that no error.

IRIS Dataset–

Classification training result on iris data set
In classification of iris dataset neural network architecture is 4-h-3 i.e. 4 input neuron, one hidden layer with h(10,15,20) neuron that vary to observe change in M.S.E and 3 neuron in output layer.

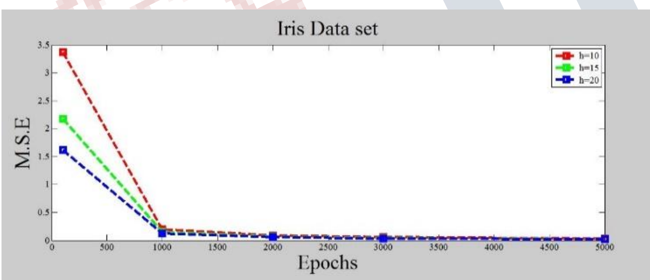

Fig 3.For 5000 Epochs vs. M.S.E

E.coli Dataset-

Classification training result on E. coli dataset
In classification of E. coli data set we create neural network architecture of 7-h-8 i.e. 7 input neuron, one hidden layer with h(10,11,14,15,20,21) neuron that vary to observe change in M.S.E and 8 neuron in output layer.

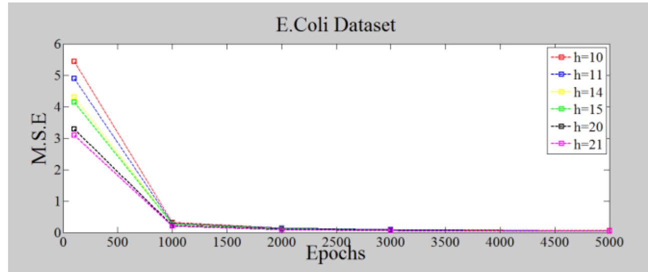

Fig 4.For 5000 Epochs vs. M.S.E

GLASS Dataset-

Classification training result on Glass dataset
In classification of glass data set we create neural network architecture of 10-h-7 i.e. 10 input neuron, one hidden layer with h(10,15,20,25) neuron that vary to observe change in M.S.E and 7 neuron in output layer.

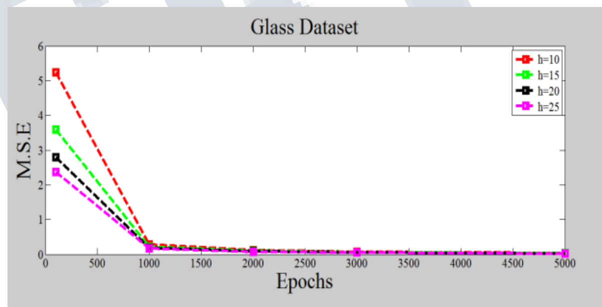

Fig 5. For 5000 Epochs vs. M.S.E

SPECT Dataset-

Classification training result on SPECTdataset
In classification of SPECT data set we create neural network architecture of 23-h-2 i.e. 23 input neuron, one hidden layer with h(10,15,20) neuron that vary to observe change in M.S.E and 2 neuron in output layer.

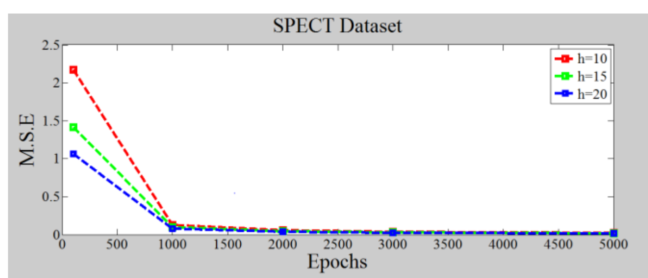

Fig 6. For 5000 Epochs vs. M.S.E.

ISSN (Online) 2456-1290
International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)
Vol 2, Issue 4, April 2017

WINE Dataset-

Classification training result on WINE dataset

In classification of wine data set we create neural network architecture of 13-h-3 i.e. 13 input neuron, one hidden layer with h(10,15,20,25) neuron that vary to observe change in M.S.E and 3 neuron in output layer.

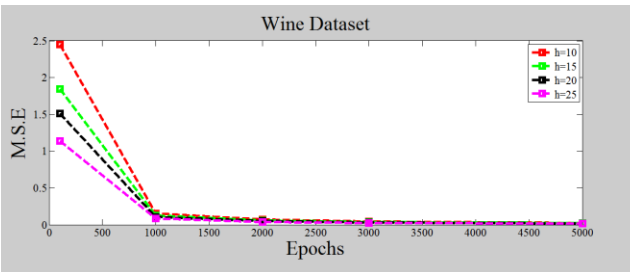

Fig 7. For 5000 Epochs VS M.S.E

TABLE2: TESTING PERFORMANCE

IRIS	E.COLI	GLASS	SPECT	WINE
100%	89.88%	86.91%	100%	91.01%

Testing accuracy of each dataset observe at theta 0.1 on different hidden layer. Classification performance depend upon characteristic of dataset to be classified. So we observe different testing accuracy of each dataset.

VI. CONCLUSION

Machine learning is a computational learning using algorithm to learn from and make prediction on data. That's why this paper aimed to evaluate the artificial modular neural network in predicting classes of different dataset. The feedforward backpropagation neural network with supervised learning is proposed to classification. The reliability of the proposed neural network method depends on data collected that's why we have chosen different domain of dataset. Backpropagation learning algorithm is used to train the feedforward neural network to perform a given task of classification using intelligent machine learning. We achieved relatively better accuracy as compared to conventional neural network.It is shown that for different real world data sets the training is much easier and faster with a modular architecture. Due to the independence of the modules in the input layer parallel training is readily feasible.

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