CONSTRUCTING AN APPROPRIATE NEURAL NETWORK FOR MAXIMISING SUGARCANE YIELD IN A PARTICULAR REGION

Rajesh S Budihal
Department of MCA , School of Computer Science and IT
Jain University, Knowledge Campus
Jayanagar 9th Block , Bangalore
Email: rajeshbudihal@gmail.com

S Krishna Anand
[2]Faculty of Computer Science and Engineering, Sreenidhi Institute of Science and Technology,
Yamnampet, Hyderabad
Email: skanand86@gmail.com

Abstract
With vast degree of industrialization there is a severe amount of depletion in the Levels of soil fertility which in turn could impact the growth of crops. Care needs to be taken to identify the right soil conducive for growing various kinds of crops. This work focuses on the ideal variety of sugar cane crop that could be grown in a particular type of soil in India which in turn could maximize the overall yield of sugarcane. An additional parameter dealing with the amount of sugar content has also been taken into consideration. The choice of an appropriate decision would go a long way in reducing avoidable losses in terms of both capital and effort. With this view in perspective, a wide range of artificial neural networks have been constructed and the results have been compiled. Besides, choices of appropriate training function and learning rates have been made.

Keywords: Backpropagation Neural Network, Training function, Sugarcane yield, Bayesian regularization, Regression Coefficient.

I. INTRODUCTION

In India, Cane sugar is being grown while in European Countries Beet Sugar is being cultivated. Sugarcane is being grown in Tropical Countries where the climate is conducive for cultivation. Sugar cane is a seasonal (annual) crop. The height of the cane stalks before harvesting is around ten to twelve feet. Studies have shown that harvesting period for a wide range of sugarcane crops lie in the range of ten to twelve months. Besides, in case of over harvested /premature harvesting, the quality of cane in terms of sugar recovery would be low. However, other parameters like leaf size, stem size girth, spine and joint are likely to make a significant impact on the yield of sugar cane (computed in tonnes per hectare). A series of artificial neural networks have been constructed and analyzed. The networks learn by experience and are able to handle a wide variety of nonlinear data with a good degree of accuracy. Besides, a detailed analysis has been performed where the sensitive parameters have been identified. It has been observed that cane yield is more sensitive to leaf size. The additional novelty in this work lies in identifying the appropriate type of sugarcane crop that could be cultivated in the particular region to yield the maximum benefits.

II. LITERATURE REVIEW

Neural Network made its first presence in the globe as early as the early 1940's. In 1943, Mc Culloh and Pits developed a computational model. However, its popularity had a rapid decline during the second half of the 20th century .Soft computing techniques made a revival of sorts during the late 1990's. M. Dimitrova, M. Hubert and D. Boyadjiev again brought the usage of neural network into focus by using it in classification problems. They recognized data pattern using a neural network way back in 1997. Z L Liu and J P Castagana designed an artificial neural network in 1998 for approximations of function in the field of seismic study and obtained reasonable results . However, the system they had designed was completely data driven. In 2004, C. Chen & H. Mcnairn extended the scope of neural network by introducing its usage in agriculture. They developed a rice crop monitoring system which was able to segregate production areas for wet and dry seasons. In the year 2006, Yidan Bao and Haiyan CenYong explored the nuances of a back propagation neural network by identifying the methodology to reduce the training time and use its results in an agriculture application. In the year 2007, Yusuf E designed a neural network for predicting soil behavior by focusing specifically on suction and swell pressure and identified the level of performance generated by the network. In the year 2011, Murat Ozturk, Ozlem Salman and Murat Koc improved the earlier studies by concentrating on design of a cost effective network. Their results bore fruit when they successfully designed a feed forward neural network for estimating soil temperature using geographical and metallurgical data. They considered data from various regions of turkey to validate their model.

Raju Prasad Paswan and Shahin Ara Begum provided further impetus in the field of agriculture. In the year 2013, they carried out extensive research to explore the intricacies of neural network by exploring its usage in the prediction of crop yields. Two years later in the year 2015, Snehal S, Dahikar and Sandeep complimented the effort of their research carried out by Raju and his team by considering additional parameters like PH, nitrogen and potassium for giving accurate prediction of the yield. However, their prediction has been limited to a very small set of crops. During the same year, SnehaMurmu and SujataBiswas combined the concept of fuzzy logic with neural network for classification of crops. The novelty in their work lies in the design of hybrid model which deals with the combination of both supervised and unsupervised learning. In the year 2016, AnandkumarPatil and Lalitha Y S utilized the services of a neural network tool for training and identifying the crop species. Later, Swaroopa Shastri and Arati focused on the ideal crop that could be cultivated based on weather condition existing in that particular region later during the same year. Sushama Kiran, Bindhu Lal and S. S. Tripathy considered a wide range of soil parameters like plasticity index, gravel and clay to design a neural network that predicts the shear strength of the soil. The Bayesian method of estimation has been used to predict a value of cohesion and internal friction angle. In early 2017, Ismail El Massi and Youssef Es-saady combined the techniques of image processing with the neural network. They carried out segmentation using K-means clustering and extracted features like colour, texture and shape and used the same for training and classification using an appropriate neural network. It has been observed that the usage of neural network has been extensive during the recent years. However, the performance could be improved further through the appropriate choice of learning rate and activation function and in turn the choice of the neural network.

III. ARTIFICIAL NEURAL NETWORK

A neural network is a complex structure which consist a group of interconnected neurons which provides very exciting alternatives for complex problem solving and also in real world applications. An Artificial Neural Network (ANN) can also be defined as a system or mathematical model consisting of many nonlinear artificial neurons running in parallel. It can have one or more layers. ANN has been designed after the learning functions of human brain in order to recognize patterns and make predictions. ANN are formed from simulated neurons that are analogous to function of the human brain. There are different types of neural networks that fit various kinds of problems. Neural networks have been successfully applied to problems in the field of pattern recognition, image processing, data comparison, forecasting and optimization. Neural networks are good at fitting function as well as to recognize patterns.Researches have shown a neural network fitting any practical function. For instance, data from different sugarcane varieties are taken into consideration. The present study aim is to design a network that can predict the sugarcane variety by relating the output values, with the given seven inputs of sugarcane different variety.

3.1 Feed Forward Neural Network and Backpropagation

A Feed-Forward Neural Network consists of at least three layers of neurons: an input layer, at least one intermediate hidden layer, and an output layer. Neurons are connected in a feed-forward fashion with input units fully connected to neurons in the hidden layer and hidden neurons fully connected to neurons in the output layer. Although a large number of neural networks exist, some of them are found to be more efficient for real world applications. Backpropagation is one such common network where the neurons adapt their weights to acquire new knowledge. Each input pattern from the training set is applied to the input layer and then propagated forward. The pattern of activation arriving at the output layer is then compared with the correct (associated) output pattern to calculate an error signal. The error signal for each such target output pattern is then backpropagated from the output layer to the input neurons in order to adjust the weights in each layer of the network. After the training phase during which the network learns the correct classification for a set of inputs, it can be tested on another set of samples to test its learning capability.

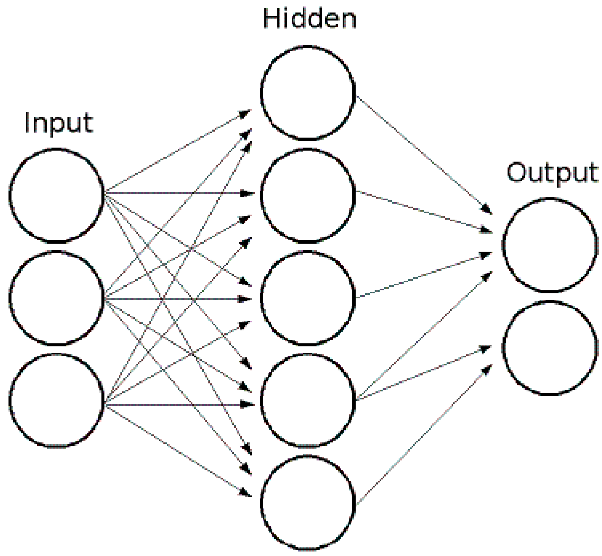

Fig1. A sample Neural Network

3.2 Choice of Training Function

In order for the successful implementation of neural network, the choice of an ideal training function is necessary. Studies have shown that the Levenberg-Marquardt backpropagation function (trainlm) is suitable for approximation problems. However, there is a tendency for overfitting to occur. Besides, the convergence rate is very slow. The details of the same have been highlighted in Fig.2. In order to overcome this drawback, Bayesian regularization (trainbr) or Scaled conjugate gradient (trainscg) backpropagation function is worth investigating. Apart from the situated described, cases may arise when early stopping of training may be needed. For all the mentioned cases, trainbr acts as a more appropriate choice. The implementation of the same is in full concordance with the characteristics as can be seen in Fig.3.

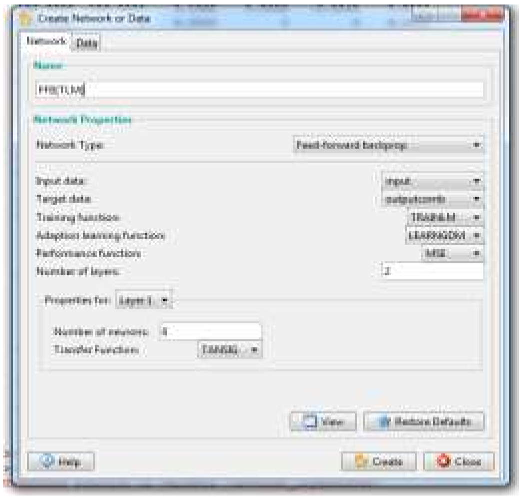

Fig 2a. Network Creation on Trainlm

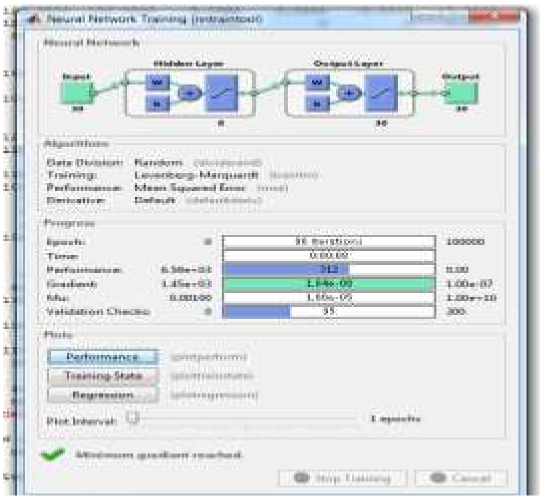

Fig 2b. Training on Trainlm

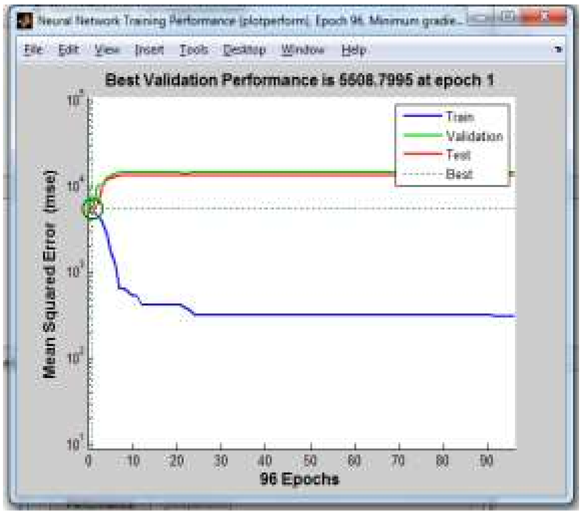

Fig 2c. Performance Validation on Trainlm

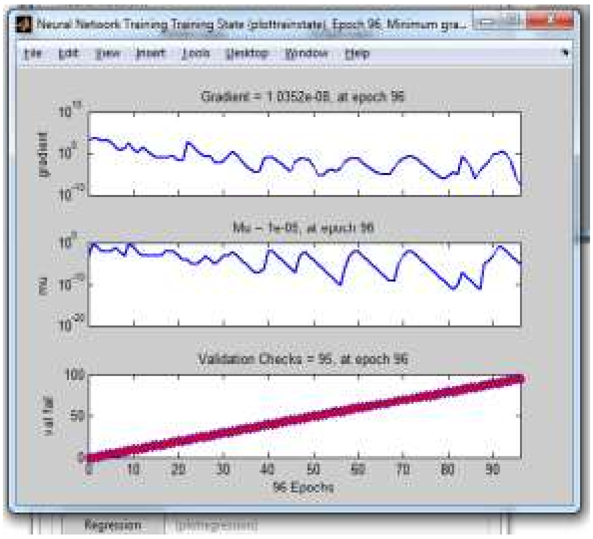

Fig 2d. Training state plots on Trainlm

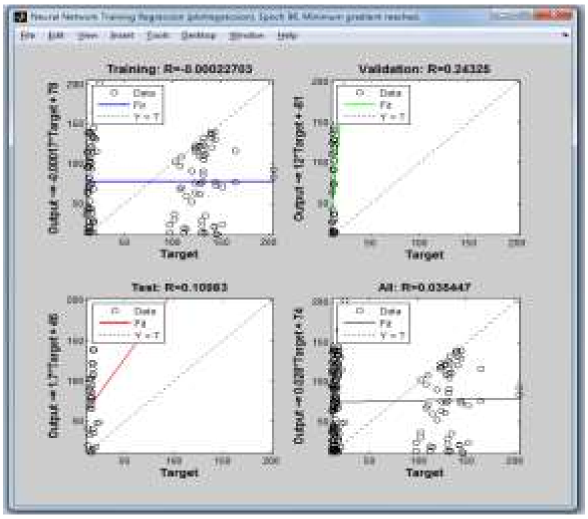

Fig 2e. Regression Coefficient on Trainlm

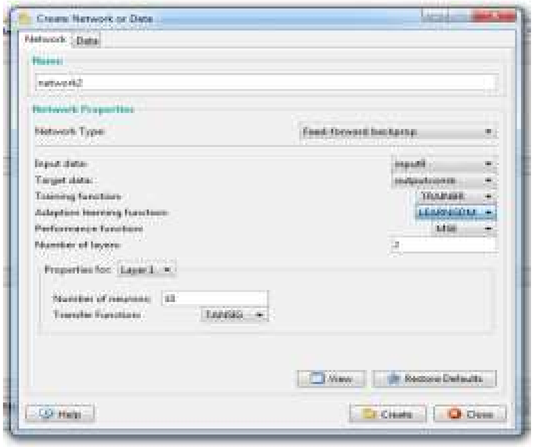

Fig3a. Network Creation on Trainbr

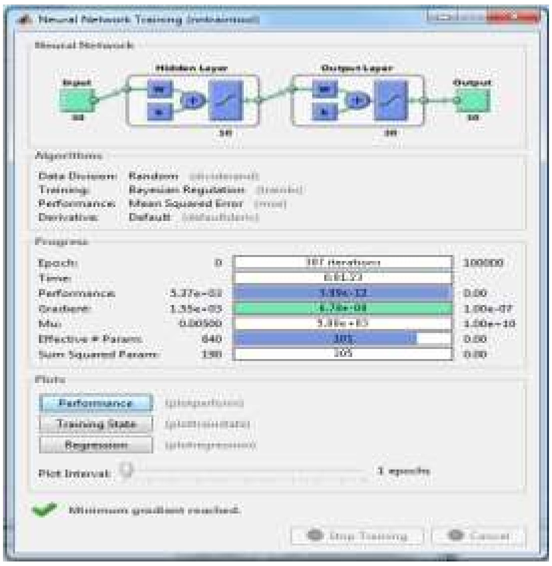

Fig3b.Training on Trainbr

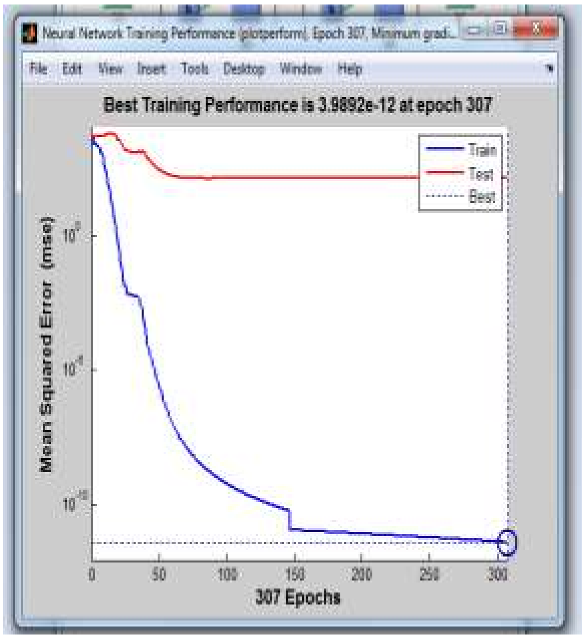

Fig3c. Performance Validation on Trainbr

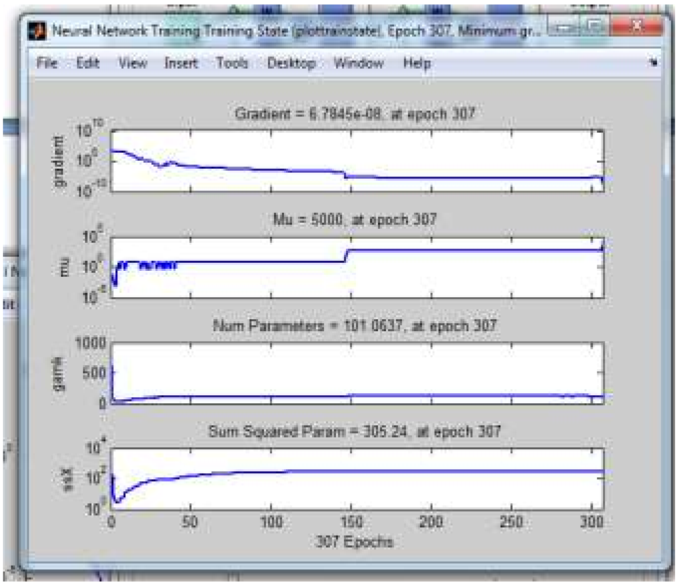

Fig3d. Training State Plots on Trainbr

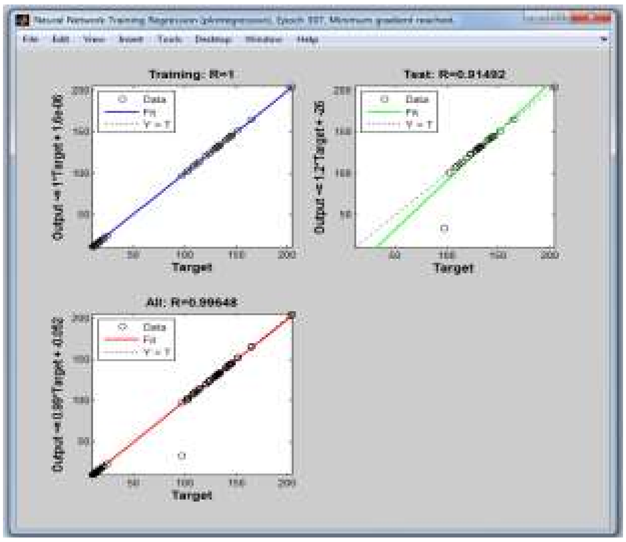

Fig3e. Regression Coeffiecient on Trainbr

It can be observed that when the training function trainlm is used, it is found to get a good result achieving a minimum error co-efficient of less than 10-7. However, performance is not satisfactory. Besides, a poor regression co-efficient value is generated indicating possible high levels of overfitting. On the contrary, when the training function trainbr is used, apart from generating a minimum value of error coefficient, performance values are also high as exhibited in the generated output graph (Fig.3c-3e). Besides, the high value of regression coefficient (close to 1) indicates a perfect file.

A similar experiment has been tried with Polak-Ribiere conjugate gradient backpropagation (traincgp) function. Interesting results have been observed. A cascaded forward backpropagation network has been taken into consideration as shown in Fig 4. Results have shown that there is reasonable match between inputs and outputs as indicated. High values of regression coefficient have been obtained during the training phase. However, the low R value obtained during testing phase indicates high levels of overfitting.

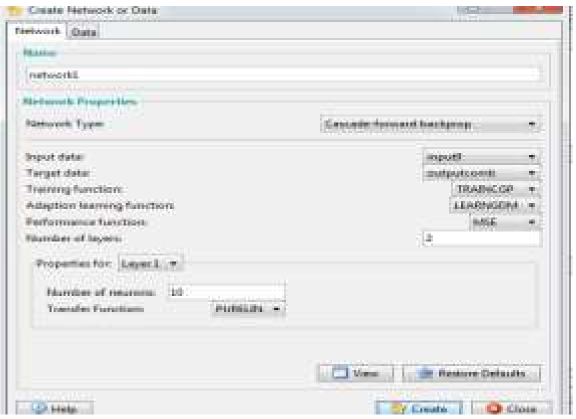

Fig4a. Network Creation of Traincgp

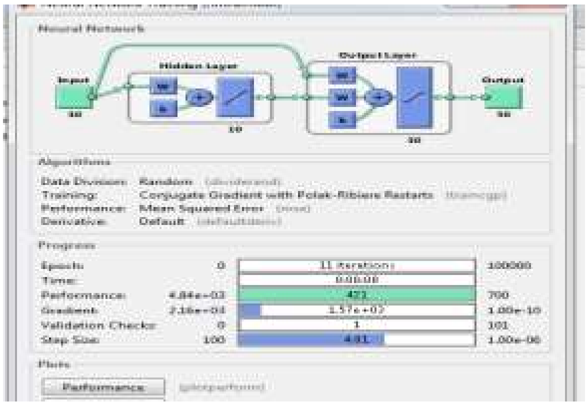

Fig4b.Training on Traincgp

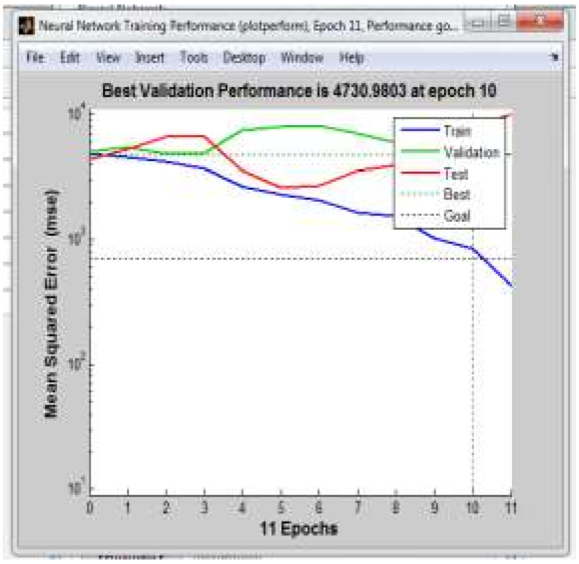

Fig4c. Performance validation of Traincgp

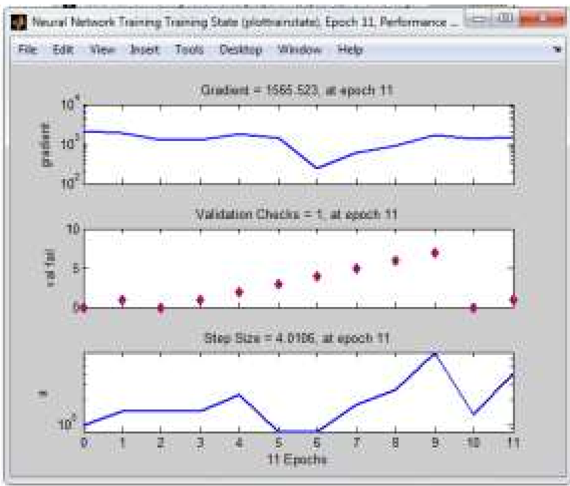

Fig4d. Training state plots on Traincgp

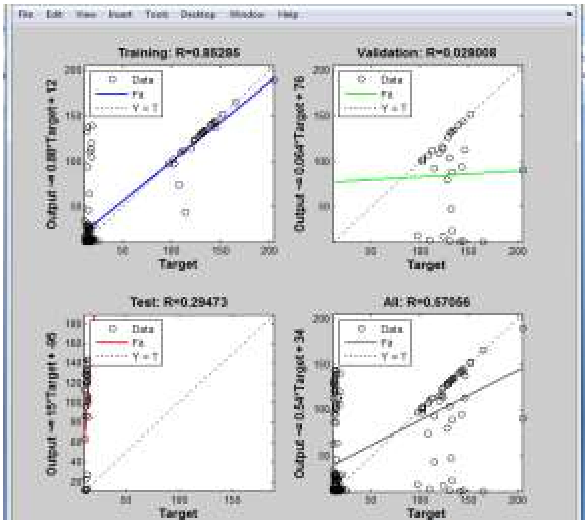

Fig4e. Regression coefficient on Traincgp

The next choice in dealing with efficient working of a network is to select an appropriate activation function. A wide range of activation functions are available. However, the researchers have shown that hyperbolic tangent (tanh), logarithmic sigmoidal (logsig) and the purelinear (pureln) functions are found to generate efficient results for backpropagation neural network designed for a wide variety of applications. On trying to implement the same for the agricultural application taken into consideration, it has been found that the pure linear function did not converge to the minimum error rates. The choice of implementation now rested between tanh and logsig functions. Although all three functions gave good performance, a good regression coefficient was generated only for linear and hyperbolic tangent function as shown in Fig 5.

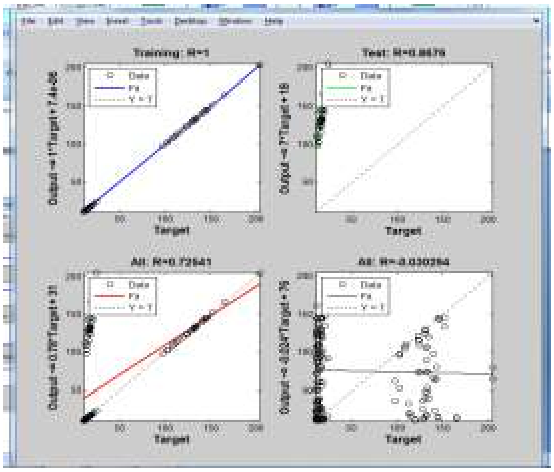

Fig5a. Regression coefficient for sigmoidal function

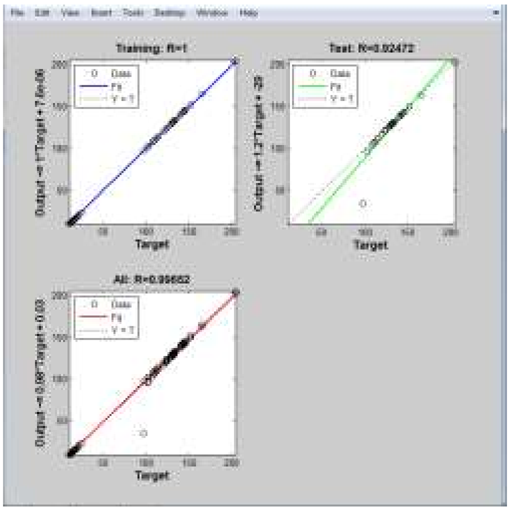

Fig5b. Regression coefficient for Tangent function

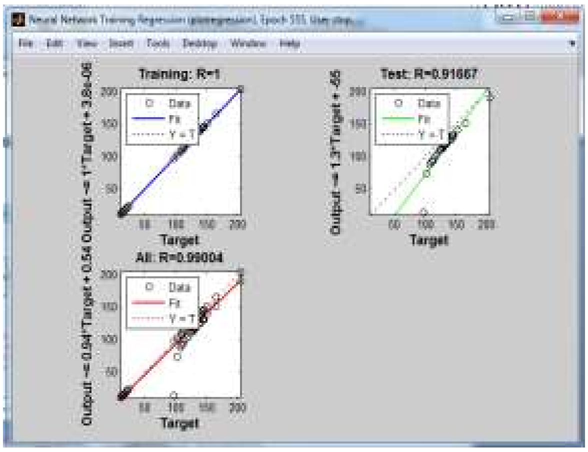

Fig5c. Regression Coefficient for Purelinear Function

3.3 Identification of Sugarcane crops:

A wide variety of canesugar is available across the globe. Each variety differs in its structure the size and colour of the leaf, girth and many other parameters. There is a significant variation in the amount of caneyield and the percentage of sugar content. A backpropagation neural network has been designed taking into consideration a set of seven inputs namely leaf size, leaf colour, spines, girth, Joint, bud grooves and size as shown in Fig 6.

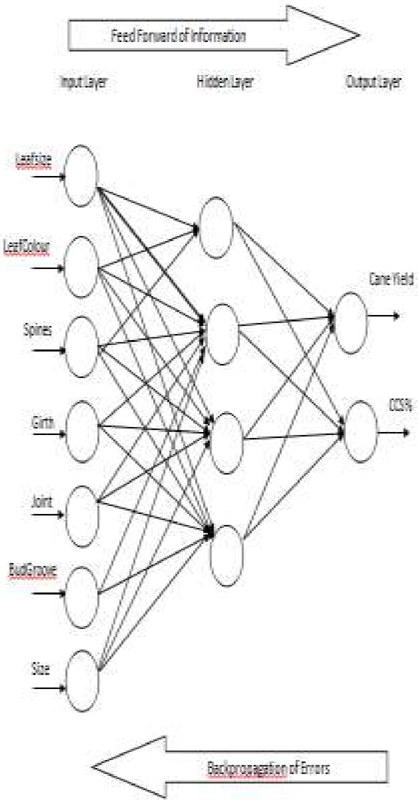

Fig 6.Structure of designed Backpropagation Network

The usage of a hyperbolic target function is able to find the relationship between the various inputs and two outputs namely cane sugar yield and percentage of sugar content(ccs%). A sample set of crops with their parameters have been shown in Table -1. After successful training, the network has been tested to identify the outputs for a particular type sugarcane. The results match with the actual yield.

Variety	Leaf Size	Leaf Colour	Spines	Girth	Joint	Bud groove	Size	Cane Yield (per/ha)	CCS %	CCS (t/ha)
COC671	Broad	Green	Present	Thick	Staggered	Absent	Medium	123.5	14.2	17.5
COC771	Broad	Green	Present	Medium	Straight	Present	Medium	140	13.1	18.3
COC419	Broad	Green	Present	Thick	Staggered	Present	Medium	112.5	10.5	11.8

Table-1. Set of crops and their parameters

The trained neural neural network is now ready for prediction. On providing a sample value of leaf size as 8, leaf colour as green, spines as 1, girth as 5, joint as 4, budgroove as 0 and size as 10, output has been generated as shown in Table. 2.

Output	Caneyield(tone/ha)	Content of Cane Sugar(ccs)%	Content of Cane Sugar(tone/ha)
Values	45.939	26.2681	48.9853

Table-2. Sample results for specific inputs

An additional novelty in this work lies with prediction of the variety which had been planted before harvesting after observing the cane sugar yield and percentage of sugar content. For instance, when the crop yield has been observed to be 132.7tonnes/hectare and the cane sugar % is found to be 12.76%, the system has predicted the crop to be COC9206. Similarly, when the figures are 115 and 13.5, the predicted crop is CO6304. This has been demonstrated in Fig. 8.

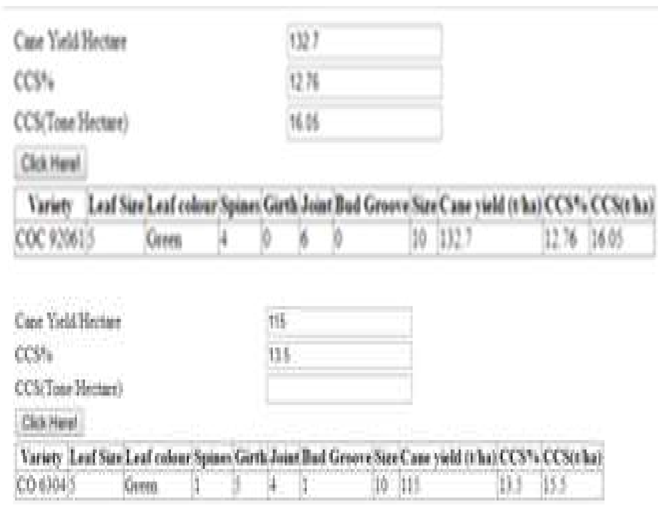

Fig 8. Identification of appropriate sugarcane variety

3.4 Sensitivity Analysis

Although the designed network has been able to make accurate predictions, chances may arise in an unacceptable error rate owing to variation in the input measurements. Hence, it is decided to perform sensitivity analysis in order to find those critical parameters whose variation in values would result in unfavourable solution. On experimentation, it has not been found that cane yield is more sensitive to leaf size. Besides, girth and joint are found to be more sensitive to ccs%(content of canesugar percentage). Variation in stem size plays a minor role in variation of content of canesugar percentage (ccs%) while they play no role in the variation of yield. Besides, the inputs leaf colour and spines are found to play a negligible role in the values of outputs.

IV. Conclusions and Recommendations

An efficient Backpropagation neural network with feed forward characteristics has been designed. It has been observed through experiment that hyperbolic tangent function is the ideal activation function producing high regression coefficient. This network is able to predict the cane yield and the amount of sugar content based on a wide range of parameters. Besides, the system helps in predicting the type of sugarcane crop that could be grown in particular region in order to maximize the cane yield. Besides, the parameters which are sensitive as well as the parameters which play no significant role have also been identified.

Although the network is highly efficient, there could arise some unpredictability owing to climate condition and other man made causes. Usages of organic and manmade fertilizers at inappropriate times and in abundant quantities cause also play a detrimental role in estimation.

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