International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 24 (2015) pp 44570-44578

Effect of different statistical measures in error reduction in Feed Forward Back Propagation Neural Network (FFBPNN) to predict rice production

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Abstract
Accurate prediction of rice production is one of the most important issues in managing the food security of Tamilnadu. The early warnings of shortage of rice production or increased production is used by the decision makers to import or export rice for the benefit of the consumers of the state. Feed Forward Back Propagation Neural Network (FFBPNN) was designed and implemented with an application software to predict rice production. The input layer has six independent variables from Kuruvai, Samba and Kodai seasons. Sigmoid activation function was adopted to convert input data into values between 0 to 1. The hidden layer computes the summation of six sigmoid values with six sets of weightings. The final output was converted into sigmoid values using a sigmoid transfer function. FFBPNN outputs are the predicted results. The error between targeted (original) data and FFBPNN predicted values were computed. A threshold value of 10^{-9} was used to test whether the error is greater than the threshold level. Statistical error analyses have been used to assess the performance of the error reduction pattern of the FFBPNN model. Some of such error analyses methods used are Coefficient of Determination (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Absolute Relative Error (ARE). It was found that R^2 is a poor statistical measure in the reduction of error for the prediction of rice production. It was also found that RMSE is a much better statistical measure compared to MSE because more data sets get zero error compared to MSE. It was established that t ARE is zero for all the data items for the three seasons at the 9th iteration itself. Hence, ARE is the best statistical measure used in FFBPNN system to predict rice production. The predicted results were printed and it was found to be matching with the expected values.

Keywords: FFBPNN; Sigmoid activation function; prediction; rice production; Tamilnadu.

Introduction
In recent years, Amr El-Shafie [1] have begun to investigate the potential of Artificial Neural Networks (ANN) as a tool for simulation of behaviour of systems that are governed by nonlinear multivariate, generally unknown, interconnections within a noisy, less-controllable physical environment. A significant growth in the interest of this computational mechanism has occurred since Rumelhart et al. [2] developed a mathematically rigorous theoretical framework for neural networks. According to ASCE Task Committee and Maria [3-5], stated that ANNs have found increasing use in diverse disciplines ranging over perhaps all branches of engineering and science. Artificial neural networks (ANNs) are computational modelling tools which can be used to classify and predict data. ANNs have been applied to agricultural and meteorological research in the past with great success by Jain, A., and Smith, B. A; [6-9].
Artificial neural networks (ANNs) have been applied to model complex relations, and it was found that ANNs have the capability to handle a large number of inputs and generalize correlations by Bose, N. K; and Haykin, S; [10-11]. Artificial neural networks are used for the prediction of air temperatures by Jain, A., [6-7] to predict the possibility of frost by testing various combinations of input. Improved prediction of air temperature was developed by [10-11] with the multiple ANN models and selected the most accurate ANN model. ANNs were used to predict dew point temperatures by Shank, D. B., [12-13]. In their approach, they developed a number of separate ANNs to predict the dew point temperatures for different time periods ranging from one to twelve hours in advance.
One of the objectives of the research presented in this paper is the development of Multi Layer Perceptron (MLP) Feed Forward Back Propagation Neural Network (FFBPNN) with selected inputs for the prediction of rice production in the Tamilnadu state of India. This research is based on rice production data collected [14] from 31 districts of Tamilnadu for the year 2009-10 as training set and five years average rice production data from 2005-2010 as testing set. The overall objective of the research presented in this paper is to find out the effect of various statistical measures in the Feed Forward Back Propagation Neural Network towards the prediction of rice production in different districts of Tamilnadu, India. The specific objectives are given below:

1. To study the effect of sigmoid activation function in converting the raw data of area of rice cultivation and rice production
2. To study the effect of coefficient of determination (R^2) in the error reduction pattern of FFBPNN system of the prediction of rice production
3. To study the effect of Mean Squared Error (MSE) in the error reduction pattern of FFBPNN system of the prediction of rice production

4. To study the effect of Root Mean Squared Error (RMSE) in the error reduction pattern of FFBPNN system of the prediction of rice production
5. To study the effect of Absolute Relative Error (ARE) in the error reduction pattern of FFBPNN system of the prediction of rice production.

Related Work

Prediction of crop production was carried out using mathematical and statistical models. As time changes and new technologies are developed to predict complex and non linear data. Today, ANNs have emerged as a powerful tool in modelling complex systems and also solving pattern recognition problems such as estimating and predicting crop production. Several technical papers and researches have been carried out to address many problems in the agriculture sector; most specifically are researches done using artificial neural network, which has a most expert feature of analysing and recognizing patterns.

A neural network can be defined as a model of reasoning based on the human brain. The brain consists of a densely interconnected set of nerve cells, or basic information-processing units, called neurons. Shepherd et al [15] stated that the human brain incorporates nearly 10 billion neurons and 60 trillion connections, synapses, between them. By using multiple neurons simultaneously, the brain can perform its functions much faster than the fastest computers in existence today.

Although each neuron has a very simple structure, an army of such elements constitutes a tremendous processing power. A neuron consists of a cell body, soma, a number of fibres called dendrites, and a single long fibre called the axon. While dendrites branch into a network around the soma, the axon stretches out to the dendrites and somas of other neurons. Fig. 1 is a schematic drawing of a biological neural network.

Owing to the plasticity, connections between neurons leading to the 'right answer' are strengthened while those leading to the 'wrong answer' weakened. As a result, neural networks have the ability to learn through experience. Learning is a fundamental and essential characteristic of biological neural networks. The ease and naturalness with which they can learn led to attempts to emulate a biological neural network in a computer.

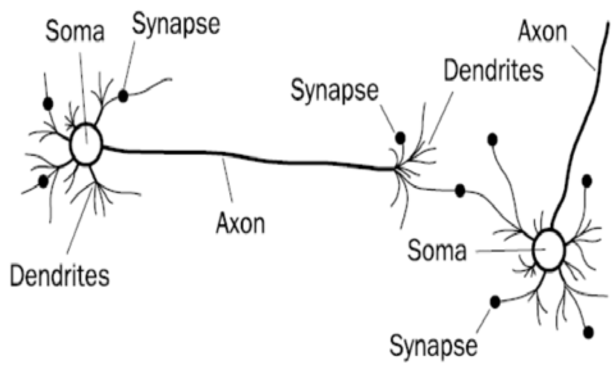

Fig. 1. Biological Neural Network (Source: Shepherd [2] Oxford University Press)

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron based on certain threshold. ANNs combine artificial neurons in order to process information.

The term, "Feed-Forward" describes how this neural network processes and recalls patterns. In a feed forward neural network, neurons are only connected forward. Each layer of the neural network contains connections to the next layer (for example, from the input to the hidden layer), but there are no connections back. This differs from the Hopfield neural network which is also popularly known. The Hopfield neural network is fully connected, and its connections are both forward and backward.

The term "Back-Propagation" describes how this type of neural network is trained. Back-Propagation is a form of supervised training. When using a supervised training method, the network must be provided with both sample inputs and anticipated outputs. The anticipated outputs are compared against the actual outputs for given input. Using the anticipated outputs, the back propagation training algorithm then takes a calculated error and adjusts the weights of the various layers backwards from the output layer to the input layer.

The Back-Propagation and Feed-Forward algorithms are often used together; however, this is not always happens. It would be quite permissible to create a neural network that uses the Feed-Forward algorithm only to determine its output and does not use the Back-Propagation training algorithm. Similarly, if there is a need to create a neural network that uses Back-Propagation training methods, it is essential to combine both a Feed-Forward algorithm to determine the output of the neural network and a Back Propagation algorithm to update the weights which is based on error value between ANN output and desired output. In this study, we will examine only the case in which the Feed-Forward and Back-Propagation algorithms are used together.

Mohaghegh et al [16] described that ANN is a biologically inspired computing scheme which is an analog, adaptive, distributive and highly parallel system that has been used in many disciplines and has proven to have potential in solving problems that require pattern recognition. They resemble the human brain in acquiring knowledge through learning process and in storing knowledge in inter neuron connection strength [17-20].

The advantages of ANN over the conventional correlations are: neural networks have large degrees of freedom for fitting parameters, and thus, capture the systems' non-linearity better than regression methods and they are superior to the regression models in that they could be further trained and refined when additional data become available and hence improve their prediction accuracy while it is impossible to make any further change in a linear or non linear regression model as soon as a model development is over [19-21].

Arun Balaji et. al [28] described the Feed-Forward Back-Propagation Neural Network (FFBPNN) model to predict the rice production for three seasons in a year for Tamilnadu state of India. The FFBPNN is a multi-layered architecture where information flows from the input to the output through one hidden layer. Each layer contains neurons that are connected to all neurons in the neighbouring layers. The connections have numerical values (weights) associated with them which will be adjusted during the training phase [22, 30-31].

Machine learning approach is used for artificial intelligence because it is based on the principle of learning from training and experience. ANNs are connectionist models. It is very well suited for machine learning because connection weights are updated to improve the performance of a network. An ANN is a network of nodes connected with directed arcs each with a numerical weight, specifying the strength of the connection. These weights indicate the influence of previous node and the next node. The positive weights represent improvement towards prediction and the negative weights represent inhibition as stated by Gallant SI [23].

Generally the initial connection weights are randomly selected from 0 to 1. Feed-forward networks were first studied by Rosenblatt [24]. Input layer is composed of a set of inputs that feed input patterns to the network. Following the input layer there will be at least one or more intermediate layers, often called hidden layers. Hidden layers will then be followed by an output layer, where the results can be achieved. In feed forward networks all connections are unidirectional.

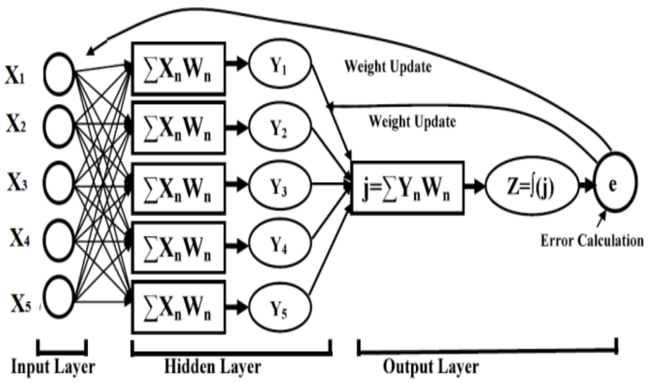

Fig. 2. ANN with FFBBNN (Source: Zabir Haider et al [25])

Multi Layer Perceptron (MLP) networks are layered feed-forward networks typically trained with static back propagation as shown in fig. 2. These networks, also known as back propagation networks, are mainly used for applications requiring static pattern classification. The back propagation algorithm selects a training example, makes a forward and a backward pass, and then repeats until algorithm converges satisfying a pre-specified mean squared error value. The main advantage of MLP networks is their ease of use and approximation of any input/output map. The main disadvantage is that they train slowly and require lots of training data.

Generalized feed-forward (GFF) networks are a generalization of the MLP networks where connections can jump over one or more layers, but these networks often solve problems much more efficiently [22].

Transfer or Activation Function

According to Iebeling Kaastra et al [26], transfer functions are mathematical formulas that determine the output of a processing neuron. The purpose of the transfer function is to prevent output from reaching very large values which can make paralyze the NN and inhibit the training process. The types of transfer functions used in ANN are:

- Linear transfer function
- Sigmoid transfer function
- Step transfer function
- Hyperbolic tangent transfer function
- Arc tangent transfer function and
- Gaussian function

It was stated by Klimasuaskas [27] that if the NN is used to learn the average behaviour then sigmoid transfer function should be used. If the NN is used to learn deviations from the average then hyperbolic transfer function is the best one. Ramping and step transfer functions are used for binary variables since sigmoid transfer functions approaches 0 and 1 asymptotically. In a standard BP network, the input layer neuron uses linear transfer functions while output neuron uses sigmoid transfer function.

Linear Transfer Function

In linear transfer function, the input raw data is scaled between 0 and 1. In linear scaling, all observations are linearly scaled between the minimum (0) and the maximum values (1) according to the following formula:

$$SV = \frac{(D - Dmin)}{(Dmax - Dmin)} \qquad (1)$$

Where SV is the scaled up value of raw data. D is the value of observation. Dmin and Dmax are minimum and maximum value of the observations respectively.

Sigmoid Transfer Function

Sigmoid functions are very similar to the input-output relationships of biological neurons, although not exactly the same. Sigmoid function exhibits smoothness and has the desired asymptotic properties. The sigmoid curve is shown in Fig. 3. As x goes to minus infinity, S(x) goes to 0. As x goes to infinity, S(x) goes to 1. As x =0, S(x) =0. 5.

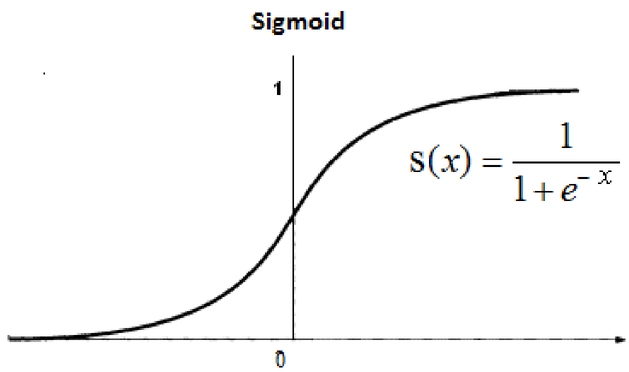

Fig. 3. Sigmoid function varies from 0 to 1

Methodology

3. 1 Using Turbo C++ Programming to create a FFBPNN

The primary objective of this study is to develop a user friendly software to predict rice production based on training data, test data and initially assumed weights stored in a sequential file. The technique used is Feed-Forward Neural Networks coupled with a Back-Propagation training to predict annual rice production in Tamilnadu. There are generally four steps in the modelling process: Assembling the training data, testing data and initially assumed weights in a sequential file, writing a software in C++ for FFBPNN, training the software to get 100% perfect prediction, and testing the trained software to simulate the response to new test data.

3. 2 Selection of Variable

Rice is produced in all the 31 districts of Tamilnadu during the three cropping seasons namely Kuruvai, Samba and Kodai seasons. The area of cultivation in Hectares and rice production in tonnes are selected as variables for prediction.

3. 3 Data Collection

The published data by the Government of Tamil Nadu was used. Training data was collected in the form of area and rice production of 31 districts for the year 2009-10. The test data was collected from the 5 years average of the area and rice production of 31 districts for the years 2005-06 to 2009-10.

3. 4 Data Pre-processing

The training and test data collected had some missing data marked with 0 values. If the study uses these 0 values in computation, this 0 may divide any real number leading to infinity condition. Computer cannot compute such infinity conditions. There are many data cleaning techniques available for data pre-processing. The present study adopted the use of a global constant 0. 01 in place of 0 in training and test data. This replacement avoids the computational problem of avoiding infinity during computations.

3. 5 Assembling the training and testing data along with initial weights

The training data consist of the area (ha) and rice production (tonnes) for three seasons of Kuruvai, Samba and Kodai for the year 2009-10 pertaining to 31 districts. The test data comprises of the 5 years average of the area (ha) and rice production (tonnes) for three seasons of Kuruvai, Samba and Kodai from 2005-06 to 2009-10. The initial weights of 42 data within the range of 0 to 1 were assumed. The training and testing data along with initial weights were assembled (stored) in a input file. The training data sets were used to train the FFBPNN model and the testing data sets were used to test the FFBPNN model to evaluate their accuracy through statistical analysis.

3. 6 Normalization of Input Data

The training data were normalized using sigmoid activation equation before being presented to the network for training. This step was taken to ensure that input data with different ranges were transformed into one similar range of 0 to 1 and allows for easier and faster model training.

3. 7 Creating the Network Object

The FFBPNN architecture in this study begins with an input layer. The input layer is connected to a hidden layer; the hidden layer is then connected to output layer. In this study, the architecture used for the neural network consist of one input layer, one hidden layer and lastly, the output layer which is used to predict the area of rice cultivation and rice production in the three seasons for 31 districts.

3. 8 Development of FFBPNN software and data processing

A computer program is written in turbo C++ language. It reads the test data from a file. It also reads the initial weights for the six neurons. The initial feed forward network is carried out. The summations in the hidden layer forms the input to the output layer after passing through the sigmoid activation function. The predicted output was computed. ARE was computed and the checking of ARE with threshold was also carried out. According to the conditions laid out, back propagation of network continued until the predicted data has desired accuracy and it was printed in a output file. The program was executed for the test data of 2005-06 and the training set of data for the years 2006-07 to 2009-10. The FFBPNN architecture used in the present study is shown in Fig. 4.

3. 8. 1 The Input Layer

The input layer is the beginning through which the external environment presents a pattern to the neural network. Once a pattern is presented to the input layer, the output layer will produce another pattern. In essence, this is all the neural network does. The input layer should represent the condition for which we are training the neural network. Every input neuron should represent some independent variable (targeted data) like area, production for Kuruvai, Samba and Kodai seasons that has an influence over the output of the neural network. The input layer is made with six (6) neurons which are area for Kuruvai, Production for Kuruvai, area for Samba, Production for Samba, area for Kodai and Production for Kodai seasons. The input layer takes the targeted data pertaining to the area of cultivation and the rice production for the three seasons. These targeted data are converted into sigmoid data between 0 to 1 using a sigmoid activation function and the corresponding converted data between 0 to 1 are represented as x1(i), x2(i)……. x6(i). The general format of the sigmoid action functional equation is given below:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

Where

S(x) is the sigmoid value. It varies from 0 to 1.

x is the independent input values like area in hectare and rice production in tonnes.

Arun Balaji et. al [28] [30-31] developed the FFBPNN network with necessary application software for predicting rice production. The FFBPNN architecture used in the present study is shown in Fig. 4 below:

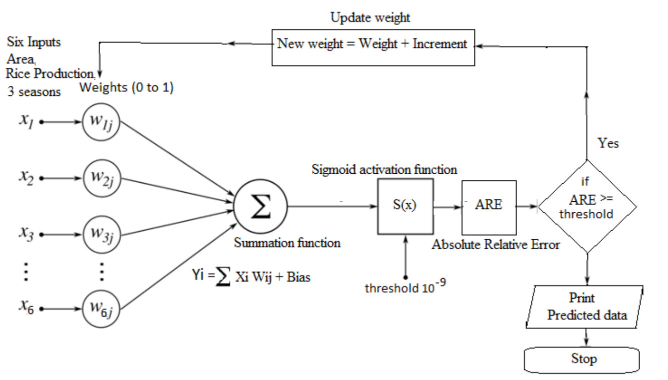

Fig. 4. Feed Forward Back Propagation Neural Network used in this research

3. 8. 2 Hidden layer

The function of the hidden layer is to compute the summation of the sigmoid values and the weights coming from each nodes of the input layer and produces something that the output layer can use. An assumed bias is also added to the summation to prevent negative values. The equation for summation is given below:

$$Yi = \sum Xi\, Wij + Bias\,(+1) \tag{3}$$

Where Y_i is the summation of each node X_{ij} with corresponding initially assumed weights W_i plus bias. Bias used is +1. Bias is added to the summation to make the summation a number other than 0. It is essential to avoid 0 so that subsequent computations may not face division by zero (infinity).

3. 8. 3 Output layer

The hidden layer computes the summation by multiplying each input with its corresponding weights and adds them together with the bias and applies the sigmoid action function. The output layer gets its input from the hidden layer. It also computes coefficient of determination (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Absolute Relative error (ARE) and test it with the prescribed threshold value to improve the accuracy of prediction. If ARE ≥ threshold value then the updating of weights and the back propagation starts from the beginning else the desired accuracy of prediction is achieved and it can be printed.

3. 9 Statistical Analysis as performance measure of error reduction pattern in FFBPNN

The coefficient of determination (R^2) is used to understand the type of fitting between the predicted value and the known value. The value of R^2 varies from 0 to 1. If R^2=1 then the regression line fits very correctly with the data. If R^2=0 then the regression line does not fits well with the data. It provides a measure of how well predicted data fit with the known data. In order to measure the performance of FFBPNN model on a data set, four measures of error were adopted. According to Sanjay R. Bhatikar et al [29] the formula adopted for computing R^2 and RMSE are given below. Also the Absolute Relative (ARE) can be computed as per Zabir Haider Khan et al [25].

$$R^2 = 1-\frac{\sum_{i=1}^{N}(t_i-y_i)^2}{\sum_{i=1}^{N}(t_i-t_m)^2} \tag{4}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i-y_i)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i-y_i)^2} \tag{6}$$

$$ARE = \frac{1}{N}\sum_{i=1}^{N}\frac{|t_i-y_i|}{t_i}\, x\, 100 \tag{7}$$

Where N is the total number of data points. ti is the target output. tm is the mean of the target output values, and yi is the FFBPNN model's predicted output.

Results and Discussions

A total of 476 data items were used in this work. Training data set contains 217 data items and the testing data set also contains 217 data items for area of cultivation and rice production for 31 districts with 3 seasons. The initially assumed weights are 42. The total of the above three break ups gives rise to 476 data items. Of the 476 data items, 217 were used to train the FFBPNN models and another 217 data sets were used to cross-validate and test the relationships established during training process and the remaining 42 data items were initially assumed weights used to evaluate the accuracy of error through statistical analysis. The neural network converged after 18 iterations with 6 neurons in the hidden layer. The initial weights were assumed from 0 to 1 with increments of 0. 1 added with initial weights for every back propagation.

4. 1 Sigmoid action function transferred values of raw data into values from 0 to 1

The pre-processed training data was converted into sigmoid data using the sigmoid activation function and the input sigmoid values for 3 seasonal area and productions are given below:

TABLE. 1. Frequency of sigmoid values of training data

. No	Sigmoid value (0 to 1)	Kuruvai Season		Samba Season		Kodai Season	
		Area	Production	Area	Production	Area	Production
1	1	27	28	30	30	28	28
2	0. 5025	4	3	1	1	3	3
	Total	31	31	31	31	31	31

Table 1 show that the sigmoid value of 1 and 0. 5025 were present after transformation of independent data like area and rice production using sigmoid activation function. It was found that there is a range of occurrence of 0. 5025 is from 1 to 4 and the majority values are 1s. The total number of 0. 5025 is 15 and the remaining 171 items are 1s.

4. 2 Statistical error analysis

Statistical error analyses have been used to assess the performance of the error reduction pattern of the FFBPNN model developed in this work. Some of such error analyses methods used are: coefficient of determination (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) or also called Absolute Relative Error (ARE).

4. 2. 1 Coefficient of determination

The coefficient of determination is a simple statistical parameter that tells how the model fits the data, and there by represents a measure of the utility of the model. The error between the observed data and the predicted data varies according to the R^2 computed. If R^2 is 1, then the error between the observed data and the predicted data is lesser and the prediction model is better fits the data. In the present research, the computation of R^2 is done for every iteration and it was found that $R^2 = 1$ in the first iteration itself but there is variations between the observed data and the predicted data and hence the iterations were continued to have the so as to have the predicted values equal to observed values. Table A1 in annexure gives observed data and predicted data during the first iteration where $R^2 =1$.

It was found that the observed data is equal to the predicted data only in the 18th iteration and all other iterations there is difference between the observed data and predicted data. But it was noted that the difference between the observed and predicted data (error in prediction) is narrowing down as the iteration is in progress from 1 to 18. In the present research, R^2 is 1 from iteration 1 to 18. R^2 does not give any proper idea of the decreasing trend of error. Hence, computation of R^2 was not found to be a good statistical measure to study the effect of error reduction between observed data and predicted data in the present research.

TABLE. 2. MSE variations between observed and FFBPNN predicted data in different iterations

	Kuruvai season		Samba season		Kodai season	
Iteration	Area	Production	Area	Production	Area	Production
1	0.2754	3.2690	16.6523	71.1825	0.0634	0.7337
2	0.0966	1.1558	6.4428	26.5877	0.0220	0.2558
3	0.0331	0.3981	2.4488	9.7326	0.0075	0.0866
4	0.0110	0.1332	0.9123	3.5057	0.0025	0.0285
5	0.0036	0.0436	0.3335	1.2397	0.0008	0.0091
6	0.0011	0.0139	0.1189	0.4329	0.0002	0.0028
7	0.0003	0.0042	0.0413	0.1463	0.0001	0.0008
8	0.0001	0.0013	0.0147	0.0502	0.0000	0.0003
9	0.0000	0.0004	0.0049	0.0161	0.0000	0.0001
10	0.0000	0.0001	0.0016	0.0053	0.0000	0.0000
11	0.0000	0.0000	0.0006	0.0018	0.0000	0.0000
12	0.0000	0.0000	0.0002	0.0006	0.0000	0.0000
13	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000
14	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
16	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
17	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
18	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4. 2. 2 Mean Squared Error

This is a measure of the mean sum of square of deviation of targeted training data and the predicted values (FFBPNN output). For all the 31 districts, MSE is calculated for the area of cultivation and rice production for the three seasons. Then the mean of all districts together were also computed for the 18 iterations. It is given in Table 2.

Table 2 shows that the MSE is 0 at 16th iteration for area of rice cultivation and MSE is zero at the 17th iteration for the rice production data for the Kuruvai season. Similarly for the Samba season, MSE is zero during the 18th iteration for both area and rice production data. It is found for the Kodai season that MSE is zero at 15th iteration for both area and rice production data. MSE is decreasing from higher error value in the first iteration and reduces as the iteration increases. Hence, it is understood that the error reduction pattern is very clear with reference to the computation of MSE. The relationship observed is MSE is inversely proportional to the number of iterations. As the iterations increases, there is decrease in MSE. Hence, MSE is a good statistical measure for the error reduction pattern in the FFBPNN for predicting the rice production in Tamilnadu.

TABLE. 3. RMSE variations between observed and FFBPNN predicted data in different iterations

Iteration	Kuruvai season		Samba season		Kodai season	
	Area	Production	Area	Production	Area	Production
1	0.5247	1.8080	4.0807	8.4370	0.2518	0.8565
2	0.3108	1.0751	2.5383	5.1563	0.1484	0.5058
3	0.1818	0.6309	1.5649	3.1197	0.0863	0.2942
4	0.1047	0.3650	0.9551	1.8724	0.0495	0.1688
5	0.0598	0.2088	0.5775	1.1134	0.0280	0.0952
6	0.0333	0.1178	0.3448	0.6580	0.0156	0.0527
7	0.0182	0.0648	0.2031	0.3824	0.0084	0.0285
8	0.0105	0.0367	0.1211	0.2240	0.0048	0.0170
9	0.0052	0.0190	0.0699	0.1270	0.0024	0.0082
10	0.0029	0.0111	0.0397	0.0725	0.0012	0.0042
11	0.0017	0.0062	0.0237	0.0419	0.0009	0.0023
12	0.0013	0.0044	0.0137	0.0247	0.0005	0.0020
13	0.0002	0.0007	0.0076	0.0113	0.0000	0.0001
14	0.0002	0.0007	0.0040	0.0057	0.0000	0.0001
15	0.0002	0.0007	0.0014	0.0029	0.0000	0.0000
16	0.0000	0.0000	0.0014	0.0028	0.0000	0.0000
17	0.0000	0.0000	0.0014	0.0028	0.0000	0.0000
18	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4. 2. 3 Root Mean Squared Error

RMSE is a measure of the root of the mean sum of square of deviation between the targeted training data and the predicted values (FFBPNN output). For all the 31 districts, RMSE is calculated for the area of cultivation and rice production for the three seasons. Then the mean of all districts together were also computed for the 18 iterations and it is given in Table 3.

Table 3 shows that the RMSE is zero at 18th iteration for area of rice cultivation and rice production for the Kuruvai season and Samba seasons. It is also found the RMSE is zero at 15th iteration for area of rice cultivation and rice production for the Kodai season. The interesting feature noted is that the RMSE is decreasing from higher error value in the first iteration and reduces gradually as the iteration increases. Hence, it is understood that the error reduction pattern is very clear with reference to the computation of RMSE. The relationship observed is RMSE is inversely proportional to the number of iterations. As the iterations increases, there is decrease in RMSE. Hence, RMSE is also a good statistical measure for the error reduction pattern in the FFBPNN for predicting the rice production in Tamilnadu. In fact, RMSE is a much better statistical measure compared to MSE because among the three seasons taken up, two seasons (Kuruvai and Samba) are finishing with zero RMSE simultaneously on 18th iteration where as MSE is zero in different iterations for the three seasons.

TABLE. 4. ARE variations between observed and FFBPNN predicted data in different iterations

IT	Kuruvai season		Samba season		Kodai season	
	Area	Production	Area	Production	Area	Production
1	0.0000021	0.0000191	0.0000240	0.0000405	0	0.0000056
2	0	0.0000055	0.0000123	0.0000199	0	0.0000018
3	0	0.0000015	0.0000049	0.0000091	0	0.0000004
4	0	0	0.0000026	0.0000036	0	0
5	0	0	0.0000011	0.0000015	0	0
6	0	0	0.0000004	0.0000005	0	0
7	0	0	0	0.0000002	0	0
8	0	0	0	0.0000002	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0
16	0	0	0	0	0	0
17	0	0	0	0	0	0
18	0	0	0	0	0	0

4. 2. 4 Absolute Relative Error

The effect of updating the weights with increments in different iterations shows the reduction of absolute relative error(ARE) when sigmoid activation function was used. ARE is a measure of the mean of the sum of the deviation of observed and FFBPNN predicted values with reference to the observed values. It may be expressed as decimal or some time with percent also. ARE variations between observed and FFBPNN predicted data in different iterations are given in Table 4.

Table 4 shows that ARE is zero for all the data items of area of cultivation and rice productions for the three seasons at the 9th iteration only. Table A2 in the annexure gives the clear picture of observed data and the FFBPNN predicted data to understand the effect of ARE. From Table A2, it is found that the minimum difference between the observed and predicted data is zero error and the maximum error is 0. 61 tonnes found for the rice production data during Samba season for the Sivaganga district. The observed rice production for Samba in Sivaganga district is 138095. 00 tonnes and the predicted rice production is 138094. 39 tonnes. The error is as small as 0. 61 tonnes only. The error is negligible compared to the observed rice production during the 9th iteration. Table A3 in the annexure gives the 100% matching of observed data and FFBPNN predicted data at the 18th iteration at which ARE = RMSE = MSE = 0 and R^2 =1.

Hence, ARE is also a good statistical measure for the error reduction pattern in the FFBPNN for predicting the rice production in Tamilnadu. In fact, ARE is a much better statistical measure compared to MSE and RMSE because ARE is zero at 9th iteration itself with negligible difference between observed and predicted data in the present research. The iterations are continued beyond 9th to 18th iteration to make the observed and predicted data with 100% matching.

TABLE. 5. Different statistical measures and their rate of reduction of errors

No	Statistical techniques	Explanations
1	Coefficient of determination, R^2	R^2 = 1 for all iterations. R^2 does not properly convey at which iteration error between observed and predicted data is 0. Hence R^2 is a poor statistical measure for FFBPNN rice production prediction system
2	Mean Squared Error, MSE	MSE = 0 from 15th iteration onwards to 18th iteration for the different data sets considered. As the iterations increases, there is decrease in MSE. Hence, MSE is a good statistical measure for the error reduction pattern in the FFBPNN for predicting the rice production in Tamilnadu.
3	Root Mean Squared Error, RMSE	RMSE = 0 from 15th iteration onwards to 18th iteration for the different data sets considered. RMSE is a much better statistical measure compared to MSE because more data sets get 0 error compared to MSE.
4	Absolute Relative Error, ARE	ARE =0 for all the data items of area of cultivation and rice productions for the three seasons at the 9th iteration only. Hence, ARE is the best statistical measure used in FFBPNN system to predict rice production.

4. 2. 5 Effect of statistical measures on the rate of reduction of errors between observed and predicted data

The effect of different statistical measures on the rate of reduction of errors between observed and predicted data in the FFBPNN system is summarized in Table 5.

From table 5, it is clear that the rank of statistical measures in the rate of reduction of errors between the observed data and FFBPNN predicted data are in the order of 1) Absolute Relative Error (ARE) 2) Root Mean Squared Error (RMSE) and 3) Mean Squared Error (MSE). It is found that the coefficient of determination, R^2 is the poor statistical measure in the rate of reduction of errors between the observed data and FFBPNN predicted data.

Conclusion

During this research, FFBPNN architecture was designed and developed. A program in C++ was developed to implement the FFBPNN system developed. The training data and the testing data were used as input and the output data was recorded in a sequential file. Initial weights were assumed from 0 to 1. Weights were updated with the increment of 0. 01 when the observed data was not equal to the predicted data by feed forward back propagation system. Each iteration predicted the data and it was compared with the observed data. The different statistical measures like coefficient of determination (R^2), Mean Squared Error (MSE, Root Mean Squared Error (RMSE) and Absolute Relative Error (ARE) and predicted data is zero. The effect of different statistical measures was studied with reference to the error between the observed and predicted data during different iterations. The following is the conclusion drawn from the research:

1. It was found that the sigmoid value of 1 and 0. 5025 were present after transformation of independent data like area and rice production using sigmoid activation function. It was found that the value of 0. 5025 occurred with the range of 1 to 4 and the majority values are 1s. The total number of 0. 5025 is 15 and the remaining 171 items are 1s.
2. It was found that the value of R^2 is 1 for all iterations from 1 to 18. Hence, R^2 does not properly convey at which iteration error between observed and predicted data is zero. Hence R^2 is a poor statistical measure for FFBPNN system of prediction of rice production.
3. It was found that MSE is zero from 15th iteration onwards to 18th iteration for the different data sets considered in this research. As the iterations increases, there is decrease in MSE. Hence, MSE is a good statistical measure for the error reduction pattern in the FFBPNN for predicting the rice production in Tamilnadu.
4. It was found that RMSE is zero from 15th iteration onwards to 18th iteration for the different data sets considered. RMSE is a much better statistical measure compared to MSE because more data sets get zero error compared to MSE.
5. It was found that ARE is zero for all the data items of area of cultivation and rice productions for the three seasons at the 9th iteration itself while other statistical measures takes 15 to 18 iterations. Hence, ARE is the best statistical measure used in FFBPNN system to predict rice production.
6. It was found that the targeted data is exactly matching with predicted data at 18th iteration when sigmoid activation function is used It means the training of FFBPNN software is perfectly done. The software understood the complexities, non linearity and structure of training data with 100% accuracy. Similarly, the test data also was exactly matched with its predicted data.
7. It was found that the software developed in the present research works with 100% accuracy; it can be used for Tamilnadu Government's rice prediction studies.

Acknowledgements

The PhD scholar first and foremost thank the almighty God for his abundant blessings and protection during my studies and research work. I am highly indebted to Dr. P. Manimegalai**,** my research guide and Professor, Dept. of Electronics and Communication Engineering, Karpagam University, Coimbatore for her involvement, encouragement, suggestions and constructive criticism to make the research a grand success. I also thank the members of my research committee Dr. M. Hemalatha, Head of the Department of Software systems, Karpagam University Coimbatore for the suggestions and guidance to make my work more applied to the society. I also thank all the teaching staff and the administration of Karpagam University for guidance and encouragement. Finally, I thank Dr. K. Baskaran, Professor of Computer Science and Engineering, Government College of Technology, Coimbatore for his advises and suggestions to carry out the task more efficiently.

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