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# Advances in rice yield estimation using Neural Networks

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## ABSTRACT

*Timely and reliable estimation of rice yield is an important dimension in effective and timely policy decisions in the present context of ban on rice exports, EL Nino disturbances, inflation, rising rice price. The present study has been taken up to identify the effect of weather parameters as they affect crop yields and rice crop is no exception. In order to suggest suitable neural network model for rice yield estimation, Ranga Reddy District of Telangana state was chosen and weekly averages of weather variables namely bright sunshine hours, maximum temperature, minimum temperature, morning relative humidity, evening relative humidity and weekly total rainfall from 30th to 47th meteorological standard weeks (MSWs) of 31 years and rice yield data from 1988-89 to 2018-19 were considered in the study. Back propagation neural network and two activation functions namely logistic sigmoid and linear were employed in the neural network model. The proposed neural network model "F" (Input Neurons =11, Hidden Neurons=12, Output Neuron=1, Train Data Size = 80 % and Test data Size=20%) exhibited better results with the low MAE and AEER% while estimating rice yields as compared with others. All the estimated yields of respective years were close to the actual yields as the multiple correlation coefficients (R) values for train and test data were also close to 1.The errors of simulated estimation of rice yield ranged between -8.1 to -3.8 % for the proposed neural networks model. Thus, better rice yield was estimated by using proposed neural network model "F".*

***Keywords:*** *Forecast, Activation function, Rice Yield, Neural network, Weather parameters, Min- max normalization, AEER, MAE, Simulated rice yield*

## INTRODUCTION

The present challenging situation of ban on rice exports, EL Nino disturbances, inflation, rising price of rice show cases that, timely and reliable yield estimate of rice, need not be overstated for the most populous country like India where, the economy is principally agrarian based. Yield estimation of rice is significant in economic programming in the global scenario as it aids in effective policy decision.

Weather is a major factor affecting crop yield in agriculture domain. There are many weather parameters contributing to the growth and development of rice crop. India, the largest rice producing country, plants rice in an area of about 43 million hectares and produces about 125 million tons of rice during 2018 [1]. Ranga Reddy being the major rice growing district of Telangana was selected for the present study. This study was undertaken with a view to develop appropriate neural network model for estimating of rice yield. Neural network model is a composition of artificial neurons that are interconnected; and depending on the network topology, they exchange the actuation signals in the form of an activation transition function [14]. Neural network models are simple mathematical models defining a function f: X→Y. Every type of a model created by the artificial neural network corresponds to a class of such functions [8][15][6]. As described by [10] machine learning is a field of study that uses the statistics and computer science principles, to create statistical models, used to perform major tasks like estimations and inference. ANNs have been widely used in studies of complex time series forecasting, such as weather, energy consumption and financial series [4].

Artificial neural networks (ANN) and multiple linear regressions (MLR) are widely used on crop yield estimation [13]. They designed and developed Customized-ANN (C-ANN) by changing number of hidden layers, number of neurons in the hidden layer and learning rate. [12] used neural networks, multi-layer-perception, regression tree, support vector regression to estimate wheat yield from fertilizer and additional sensor input. They found that support vector regression can serve as a better reference model for yield estimation. [3] demonstrated effects of climate factors on wheat yield using ANN model. They found that the ANN model is a suitable way of estimating wheat yield. studied a complete review of literature comparing feed-forward neural networks and regression analysis with respect to estimation of crop yield. The majority of the research works have used linear regression models for estimation of crop yield. But the yield of a crop has a non-linear relationship with independent weather variables. Thus ANN is better suited for estimating crop yield. The specific objective of present study was to explore the possibility of suggesting suitable back propagation neural network for estimating of rice yield in Ranga Reddy district of Telangana.

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The Matlab R2018a software was used to explore the possibility of estimating the yield of rice due to combined effects of weekly weather parameters. Rice yield data for Ranga Reddy District of Telangana for the years 1988-89 to 2018-19 were extracted from Directorate of Economics and Statistics, Government of Telangana, 2018-19 [2]. The meteorological data set for the same periods of Ranga Reddy station was collected from Telangana State Development and Planning Society, Government of Telangana, Hyderabad for the present study. Weekly averaged data of weather variables *viz*., Bright Sunshine Hours, Maximum Temperature, Minimum Temperature, Morning Relative Humidity, Evening Relative Humidity and weekly total Rainfall were collected for the period of the growing season of rice in Ranga Reddy district for the years under consideration. The details of weekly weather variables included in the study upto 18 weeks of crop period are given in Table 1.

In assessing joint influence of week-wise weather variables, Back Propagation Neural Networks approach was considered. Here 108 factors were considered as the input variables and rice crop yield was taken as the target variable. As few input variables may be superfluous, affecting estimation of yield. So, from 108 input variables; only 11 input variables (Table 3) have positive and strong correlation with target variable were selected using Pearson's correlation coefficients. It is the test statistics that measures the degree of association between input and target variables. It gives information about the magnitude of the association and the direction of the relationship. Normalization is scaling procedure, where, we can find new range between 0 and 1 from an existing range of values of different variables and is used to reduce the large variation of estimation. Min-Max Normalization (Eq.1) technique was used to normalize the experimental dataset to minimize the Average Estimating Error Rate (Eq.2).

***Min-Max normalization:*** It is one of the most familiar ways to normalize data. It transforms the data from measured units to a new interval from New_MinX to New_MaxX for feature X.

$$\mathbf{V'} = \frac{\mathbf{V-MinX}}{\mathbf{MaxX-MinX}}(\text{New\_MaxX} - \text{New\_MinX}) + \text{New\_MinX} \qquad (1)$$

Where, V' is Min-Max Normalized data one
V is the respective value of the attribute
MinX is the respective Minimum value of the attribute
MaxX is the respective Maximum value of the attribute

***Average Estimating Error Rate (AERR %)***: The per cent deviations of estimated yields and actual yields were worked out to evaluate the suitability of fitted neural networks. [7][14].

$$\textbf{AEER}\ (\%) = \left(\sum_{i=1}^{n}\left(\frac{\textbf{abs(Estimated Value i}-\textbf{Actual Value i)}}{\textbf{Actual Value i}}\right)\right)/n * 100 \qquad (2)$$

Where, n is number of instances

***Back Propagation Neural Network***: Back Propagation is a learning algorithm used by neural network with supervised learning. Back Propagation works by resembling the nonlinear relationship between the input and the output (target) by correcting the weight values within. It can further be generalized for the input that is not included in the training patterns (estimation capacities). The Fig.1demonstrates the simple architecture of node in neural network and Fig.2 demonstrates the architecture of neural network for the estimation of rice crop yield. There are n number of inputs coming from nodes (1,2, 3,...n) with related inputs and weights values as $In_1, In_2,...In_n$ and $W_1,W_2...W_n$ respectively. The rice yield estimation was shown by the output. Two activation functions (Logistic Sigmoid and Linear) were applied to the input values flow in the network.

***Number of Neurons (Hidden Layer)***: Neural Network has one hidden layer. It was examined with 10 and 12 numbers of hidden neurons to achieve the best output value (Table 4).

***Activation Functions:*** Activation functions are mathematical equations that resolve the output of a neural network. Logistic Sigmoid and Linear activation functions were employed in hidden layer and output layer respectively (Table 2).

***Weight:*** It is the learnable parameter within a neural network that transforms input data within the neural network's hidden layers. It is initialized randomly with ranges [0, 1], which are further updated using the gradient descent rule (Eq.3).

$$Weight(New) = Weight(Old) - \beta * \frac{dC}{dw} \qquad (3)$$

Where, $\beta$ is learning rate and $\frac{dC}{dw}$

$$C(n) = 1/2\left(\sum_{i=1}^{n}(Yi - Y')^2\right) \qquad (4)$$

is first order derivative of the cost function C(*n*).

Where, Y is estimated yield, Y' is actual yield and *n* is number of instances

***Learning Rate:*** It calculates speed of convergence of the system. Its value ranges as 0, 1. The learning rate was set to 0.0001 and increases as long as the error does not increase in order to avoid trapping in local optima.

***Momentum Factor:*** It is a method that frequently improves both training speed and accuracy. The momentum factor was set to 0.9.

***Stopping Condition:*** Generally fixed number of epochs (Iterations) were considered as the stooping criteria. The stopping condition was set to minimum of 1000 epochs (Iterations) or error $1\times e^{-10}$, whichever occurs earlier.

## RESULTS AND DISCUSSION

The Table 4 shows the comparison of Average Estimating Error Rate for train data set. Out of 6 formations of neural networks in this research work (given notation as "A" to "F"), Neural Network "A" has achieved highest AEER with 6.95 % and "F" has achieved lowest AEER (2.60 %) followed by Neural Network "E" (3.70 %) as compared with other neural networks.

The Fig.3 and Fig. 4 explains Mean Absolute Error of Neural Network "F" for training and testing data set, respectively. The measure of estimation accuracy is also called as Mean Absolute Error (MAE) and a low MAE suggests the neural network is good at estimation, while a sizable MAE suggests that neural network may have problem in certain areas. Multiple Correlation Coefficient (R) is a measure of how well a target variable can be estimated using a linear function of a set of input variables. Usually the R values range between 0.0 and 1.0, a higher R value indicates a better estimation of the target variable from the selected input variables. In case of train data set, MAE (63.32) and R (0.95) values were low and high respectively and thus indicated good job by neural network. On the other hand, MAE (188.17) and R (0.99) values were moderate and high respectively, for test data set,

Estimated Rice Yield Error Rate of Neural Network “F” for train and test data set respectively as shown in the Fig.5 and Fig. 6 depicts that, the estimated yields were over and underestimated for different years. In case of train data set, the estimated yield was underestimated by 0.3 % ,3.8 %, 0.9 %, 0.8 %, 1.1 %, 3.3 %, 0.3 %, 1.3 %, 8.7 %, 0.2 %, 0.6 %, 1.0 % ,0.3 % ,3.2 % and 10.3 % for the years 1990-91, 1993-94 , 1996-97 , 1997-98 , 1998-99, 2000-01, 2001-02 , 2003-04 , 2005-06 , 2006-07 , 2007-08 , 2008-09 , 2009-10, 20011-12 and 2012-13, respectively But, rice yield were overestimated by 2.4 % , 8.3 %, 4.0 % , 2.3 %, 5.6 %, 2.8 %, and 2.2 % accordingly for the years 1989-90, 1991-92, 1992-93, 1994-95, 1995-96, 1999-2000 and 2002-03, respectively. In case of test data set only underestimation happened and it was by 7.5 %, 8.1 %, 5.9 %, 8.0 %, 3.8 % and 6.1 % for the years 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19, respectively. The estimated yield error rates ranged from –10.3 % to 8.3 % for train data set and while it ranged from – 8.1 % to -3.8 % in case of test data set.

The estimated rice yields based on the train data set were presented in Table 5. The actual rice yields were also given for a comparison. The same is demonstrated in Fig.7. It is noticed that except for erring years like 1991-92, 1995-96, 2005-06 and 2012-13, the actual yields and the estimated yields were very close to each other. The estimated rice yields showed deviations from actual yields ranging between –10.3 to 8.3 %.

The simulated estimation of rice yield based on test data set is shown in Table 6 and Fig.8. The actual rice yields were also given for comparison. It is observed that the actual yield and the simulated estimation of rice yield were close to each other. The simulated estimation of rice yields showed deviations from observed yields ranging between -8.1 to -3.8 %. Crop yield forecasting using neural networks was studied [7] and similar results by fuzzy logic for crop yield forecasting was also corroborated [5] [9].

The Table 7 shows the comparison of Average Estimating Error Rate of proposed Neural Network “F” with other researchers. The proposed neural network “F” has achieved lowest AEER (2.60 %) as compared with other methods.

## CONCLUSION

Rice crop yield estimation was carried out by considering different weekly weather variables viz., bright sunshine hours, maximum temperature, minimum temperature, morning relative humidity, evening relative humidity, rainfall and supplied in back propagation neural network models. The proposed neural network architecture and various computational parameters like number of neurons in hidden layer, weight, learning rate, momentum factor and stopping condition were selected by trail-and-error approach. The proposed neural network model “F” (Input Neurons =11, Hidden Neurons=12, Output Neuron=1, Train Data Size = 80 % and Test data Size=20%, AEER=2.60 %) has obtained better results with the low MAE and AEER (%). All the estimated yields of respective years were close to the actual yields as the multiple correlation coefficients (R) values for train and test data were close to 1.

**Future scope of work:** The proposed neural network model may be further enhanced by including more factors like economic, physical and technological aspects for better estimation of rice yields.

**Conflict of Interest:** The authors declare that they have no conflict of interest.

**Acknowledgement:** The authors are thankful to Directorate of Economics and Statistics, Government of Telangana, for sparing rice yield data and Telangana State Development and Planning Society, Government of Telangana, Hyderabad for providing weather data.

***Table 1: Details of weekly weather variables***

| Sr. No. | BSS | Rainfall | Temperature | | Relative Humidity | |
|---|---|---|---|---|---|---|
| | | | Max. | Min. | Morning (RH1) | Evening (RH2) |
| 1 | $X_{130}$ | $X_{230}$ | $X_{330}$ | $X_{430}$ | $X_{530}$ | $X_{630}$ |
| 2 | $X_{131}$ | $X_{231}$ | $X_{331}$ | $X_{431}$ | $X_{531}$ | $X_{631}$ |
| 3 | $X_{132}$ | $X_{232}$ | $X_{332}$ | $X_{432}$ | $X_{532}$ | $X_{632}$ |
| 4 | $X_{133}$ | $X_{233}$ | $X_{333}$ | $X_{433}$ | $X_{533}$ | $X_{633}$ |
| 5 | $X_{134}$ | $X_{234}$ | $X_{334}$ | $X_{434}$ | $X_{534}$ | $X_{634}$ |
| 6 | $X_{135}$ | $X_{235}$ | $X_{335}$ | $X_{435}$ | $X_{535}$ | $X_{635}$ |
| 7 | $X_{136}$ | $X_{236}$ | $X_{336}$ | $X_{436}$ | $X_{536}$ | $X_{636}$ |
| 8 | $X_{137}$ | $X_{237}$ | $X_{337}$ | $X_{437}$ | $X_{537}$ | $X_{637}$ |
| 9 | $X_{138}$ | $X_{238}$ | $X_{338}$ | $X_{438}$ | $X_{538}$ | $X_{638}$ |
| 10 | $X_{139}$ | $X_{239}$ | $X_{339}$ | $X_{439}$ | $X_{539}$ | $X_{639}$ |
| 11 | $X_{140}$ | $X_{240}$ | $X_{340}$ | $X_{440}$ | $X_{540}$ | $X_{640}$ |
| 12 | $X_{141}$ | $X_{241}$ | $X_{341}$ | $X_{441}$ | $X_{541}$ | $X_{641}$ |
| 13 | $X_{142}$ | $X_{242}$ | $X_{342}$ | $X_{442}$ | $X_{542}$ | $X_{642}$ |
| 14 | $X_{143}$ | $X_{243}$ | $X_{343}$ | $X_{443}$ | $X_{543}$ | $X_{643}$ |
| 15 | $X_{144}$ | $X_{244}$ | $X_{344}$ | $X_{444}$ | $X_{544}$ | $X_{644}$ |
| 16 | $X_{145}$ | $X_{245}$ | $X_{345}$ | $X_{445}$ | $X_{545}$ | $X_{645}$ |
| 17 | $X_{146}$ | $X_{246}$ | $X_{346}$ | $X_{446}$ | $X_{546}$ | $X_{646}$ |
| 18 | $X_{147}$ | $X_{247}$ | $X_{347}$ | $X_{447}$ | $X_{547}$ | $X_{647}$ |

Where,
$X_{1i}$= Weekly Average of BSS for $i^{th}$ week, $X_{2i}$= Weekly Total Rainfall for $i^{th}$ week
$X_{3i}$= Weekly Average of Max.T. for $i^{th}$ week, $X_{4i}$= Weekly Average of Min.T. for $i^{th}$ week
$X_{5i}$= Weekly Average of RH1 for $i^{th}$ week, $X_{6i}$= Weekly Average of RH2 for $i^{th}$ week
(i=30, 31, 32, 33, 34... 46, 47 MSW), (e.g.$X_{132}$ =Weekly Average of BSS for $32^{nd}$ MSW)

***Table 2: Details of activation functions***

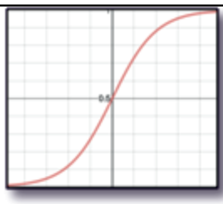
| Sr. No. | Name | Plot | Equation | First Order Derivative |
|---|---|---|---|---|
| 1 | Logistic Sigmoid |  | $f(x) = \frac{1}{1+e^{-x}}$ | $f'(x) = f(x)(1-f(x))$ |
| 2 | Linear |  | $f(x) = x$ | $f'(x) = 1$ |

***Table 3: Detail of selected input variables***

| Input | | Descriptions |
|---|---|---|
| Neurons | Variables | |
| $In_1$ | $X_{132}$ | Weekly Average of BSS for $32^{nd}$ MSW |
| $In_2$ | $X_{142}$ | Weekly Average of BSS for $42^{nd}$ MSW |
| $In_3$ | $X_{147}$ | Weekly Average of BSS for $47^{th}$ MSW |
| $In_4$ | $X_{245}$ | Weekly Total Rainfall for $45^{th}$ MSW |
| $In_5$ | $X_{247}$ | Weekly Total Rainfall for $47^{th}$ MSW |
| $In_6$ | $X_{439}$ | Weekly Average of Minimum Temperature for $39^{th}$ MSW |
| $In_7$ | $X_{440}$ | Weekly Average of Minimum Temperature for $40^{th}$ MSW |
| $In_8$ | $X_{536}$ | Weekly Average of Relative Humidity (Morning) for $36^{th}$ MSW |
| $In_9$ | $X_{537}$ | Weekly Average of Relative Humidity (Morning) for $37^{h}$ MSW |
| $In_{10}$ | $X_{538}$ | Weekly Average of Relative Humidity (Morning) for $38^{th}$ MSW |
| $In_{11}$ | $X_{646}$ | Weekly Average of Relative Humidity (After Noon) for $46^{th}$ MSW |

***Table 4: Comparison of average estimating error rate for the training data sets***

| Formation of Neural Networks | No of Inputs Neurons | No of Neurons | | Data (%) | | AEER (%) |
|---|---|---|---|---|---|---|
| | | Hidden Layer | Output Layer | Training | Testing | |
| A | 11 | 10 | 01 | 60 | 40 | 06.95 |
| B | 11 | 10 | 01 | 70 | 30 | 05.46 |
| C | 11 | 10 | 01 | 80 | 20 | 04.01 |
| D | 11 | 12 | 01 | 60 | 40 | 04.30 |
| E | 11 | 12 | 01 | 70 | 30 | 03.70 |
| **F** | **11** | **12** | **01** | **80** | **20** | **02.60** |

***Table 5: Estimated rice yield based on the training data set using neural network "F"***

| Year | Actual yield (kg/ha) | Estimated Yield (kg/ha) | Deviation from Actual Yield (%) | Year | Actual yield (kg/ha) | Estimated Yield (kg/ha) | Deviation from Actual Yield (%) |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1988-89 | 2133 | 2132 | 0.0 | 2001-02 | 2656 | 2649 | -0.3 |
| 1989-90 | 2259 | 2313 | 2.4 | 2002-03 | 1972 | 2015 | 2.2 |
| 1990-91 | 2421 | 2413 | -0.3 | 2003-04 | 2357 | 2327 | -1.3 |
| 1991-92 | 2217 | 2401 | 8.3 | 2004-05 | 2621 | 2620 | 0.0 |
| 1992-93 | 2101 | 2184 | 4.0 | 2005-06 | 2786 | 2544 | -8.7 |
| 1993-94 | 2251 | 2165 | -3.8 | 2006-07 | 2667 | 2662 | -0.2 |
| 1994-95 | 2350 | 2404 | 2.3 | 2007-08 | 2867 | 2851 | -0.6 |
| 1995-96 | 1972 | 2083 | 5.6 | 2008-09 | 2534 | 2508 | -1.0 |
| 1996-97 | 2322 | 2300 | -0.9 | 2009-10 | 2599 | 2590 | -0.3 |
| 1997-98 | 2309 | 2290 | -0.8 | 2010-11 | 2361 | 2361 | 0.0 |
| 1998-99 | 2207 | 2182 | -1.1 | 2011-12 | 2307 | 2233 | -3.2 |
| 1999-00 | 2183 | 2244 | 2.8 | 2012-13 | 3277 | 2940 | -10.3 |
| 2000-01 | 2551 | 2466 | -3.3 | - | | | |

*Table 6: Simulated estimation of rice yield based on testing data set using neural network "F"*

| Year | Actual yield (kg/ha) | Simulated Estimation Yield (kg/ha) | Deviation from Actual Yield (%) |
|---|---|---|---|
| 2013-14 | 3297 | 3050 | -7.5 |
| 2014-15 | 2615 | 2402 | -8.1 |
| 2015-16 | 2529 | 2381 | -5.9 |
| 2016-17 | 2826 | 2601 | -8.0 |
| 2017-18 | 2787 | 2681 | -3.8 |
| 2018-19 | 3091 | 2901 | -6.1 |

*Table 7: Comparison of average estimating error rate*

| Method | AEER (%) |
|---|---|
| (Kumar & Kumar, 2012) | 21.87 % |
| (Narendra et al., 2010) | 11.40 % |
| (Meena & Singh, 2013) | 3.82 % |
| **Proposed Neural Network "F"** | **2.60 %** |

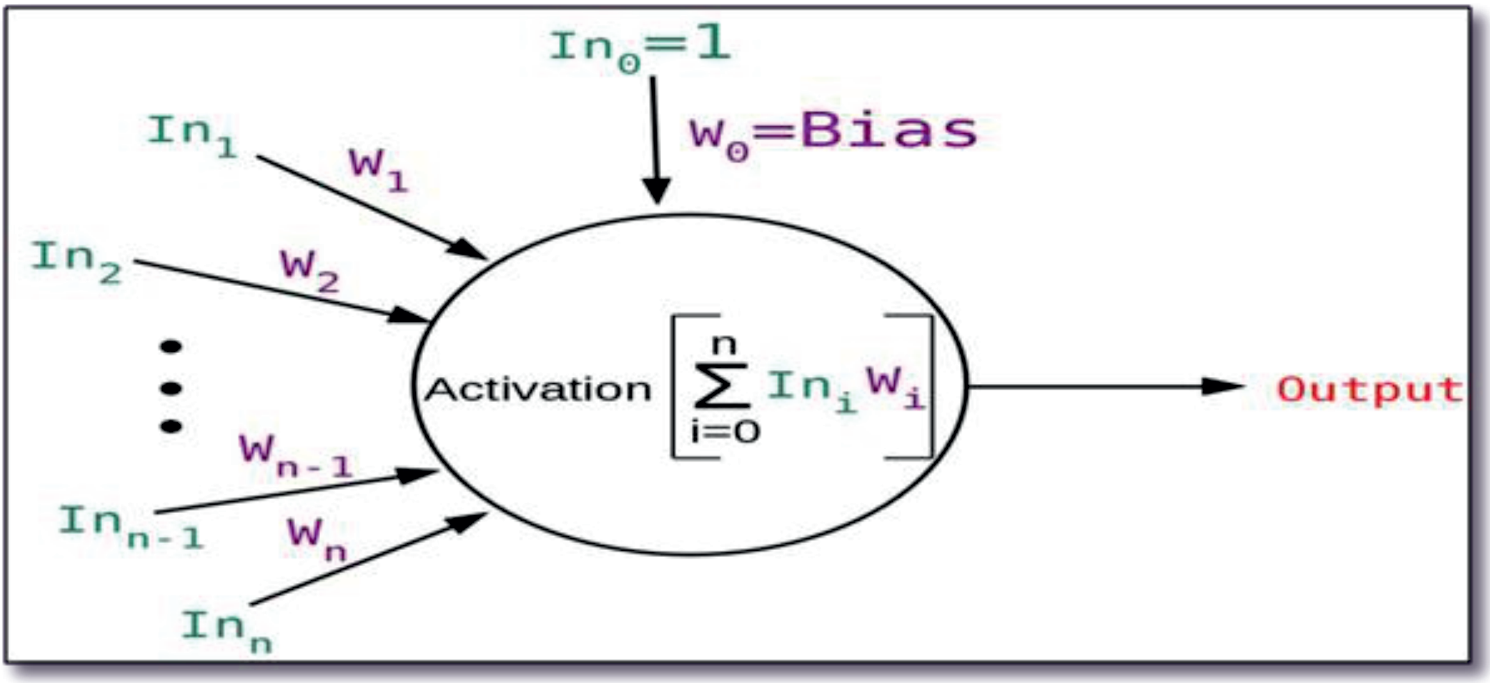



*Fig. 1: Architecture of node in neural network*

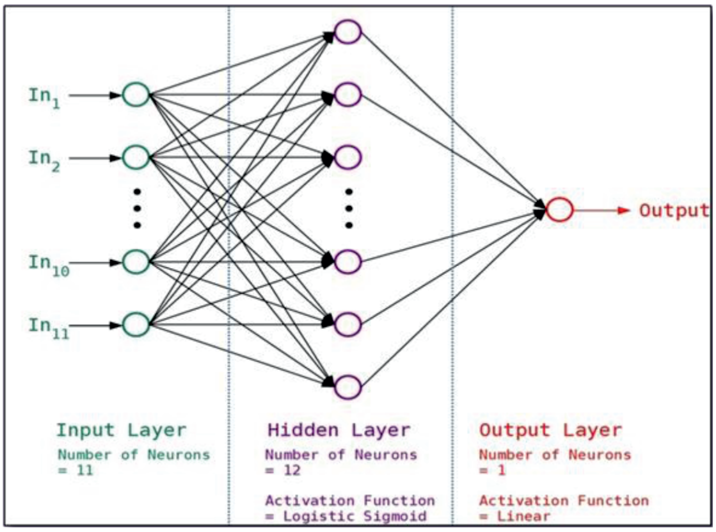



***Fig. 2: Architecture of neural network for estimation of rice yield***

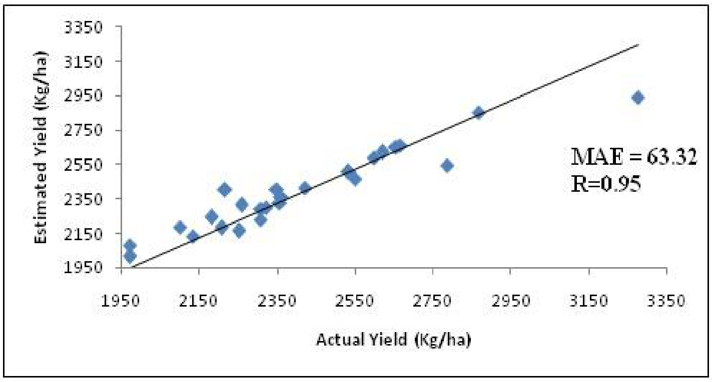



***Fig.3: Mean Absolute Error of neural network "F" (Training data set)***

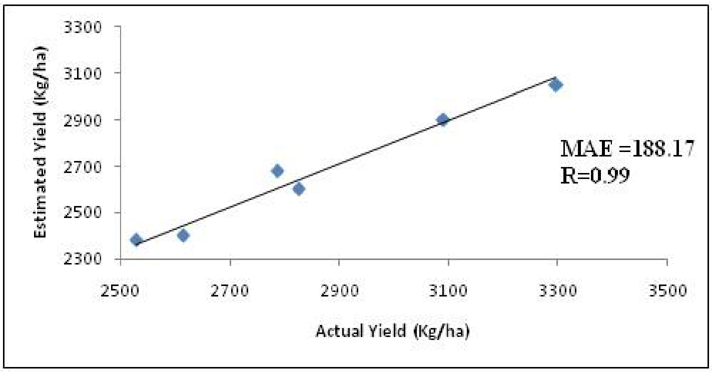



***Fig .4: Mean Absolute Error of neural network "F" (Test data set)***

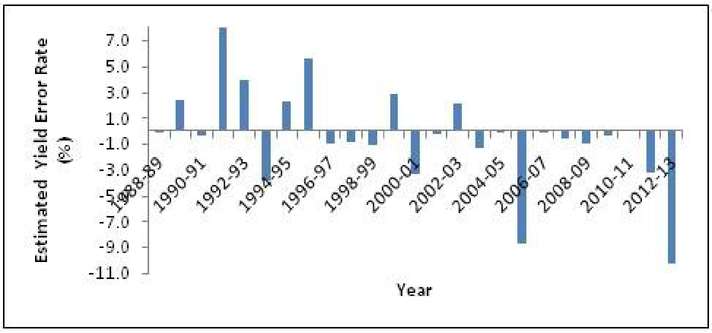



***Fig .5: Estimated rice yield error rate of neural network "F" (Train data set)***

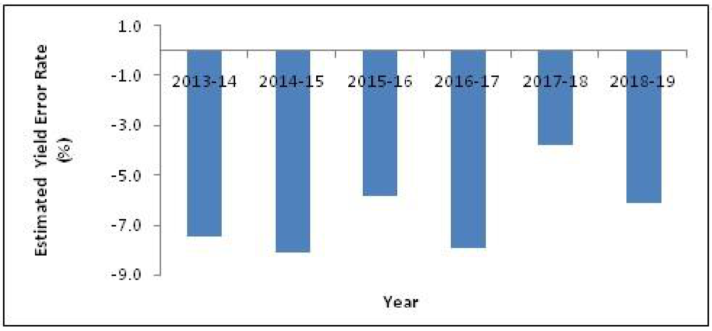



***Fig .6: Estimated rice yield error rate of neural network "F" (Test Data Set)***

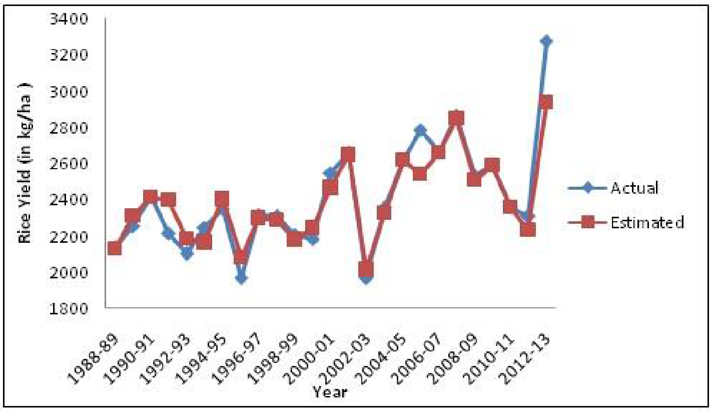



***Fig .7: Comparisons between actual and estimated rice yield based on the training data set using neural network "F"***

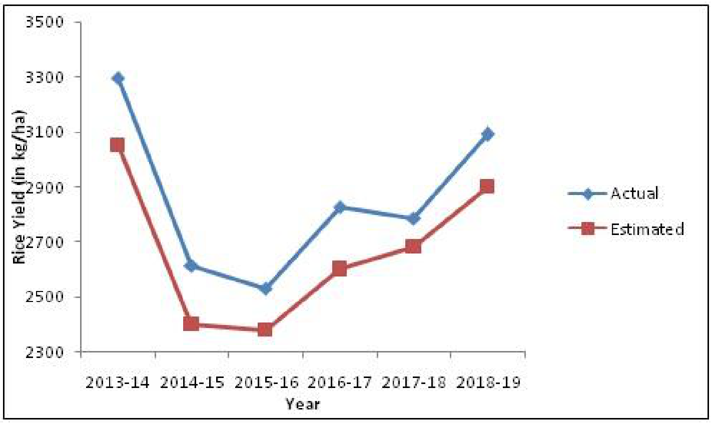



***Fig .8: Comparisons between actual and simulated estimation of rice yield based on testing data set using neural network "F"***

## REFERENCES


1. Food and Agriculture Organization Of the united states.2018. FAOSTAT Statistical Database. (http://www.fao.org/).

2. Agricultural Statistics at a glance. 2018-2019. Government of Telangana, Directorate of Economics and statistics. Directorate of Economics and Statistics, Government of Telangana (https://ecostat.telangana.gov.in).

3. Ghodsi, R., mirabdollah yani, R., Jalali, R., & Ruzbahman, M. (2012). Predicting Wheat Production in Iran Using an Artificial Neural Networks Approach. Int.J.Acad.Res.Bus.Soc.Sci., 02, 34- 47.

4. Gomes, G., Ludermir, T., & Lima, L. (2011). Comparison of new activation functions in neural network for forecasting financial time series. Neural Computing and Appli, 20, 417–439. https://doi.org/10.1007/s00521-010-0407-3

5. Kumar, S., & Kumar, N. (2012). Fuzzy Time Series based Method for Wheat production Forecasting. Int. J. Comput.Appl., 44, 5–10. https://doi.org/10.5120/6313-8651

6. Lim, T.-S., Loh, W.-Y., & Shih, Y.-S. (2000). A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-Three Old and New Classification Algorithms. Mach. Learn., 40(3), 203–228. https://doi.org/10. 1023/A:1007608224229

7. Meena, M., & Singh, P. (2013). "Crop Yield Forecasting Using Neural Networks". 8298, 319–331. https://doi.org/ 10.1007/978-3-319-03756-1_29

8. Michie, D., Spiegelhalter, D. J., & Taylor, C. C. (1994). Machine Learning, Neural and Statistical Classification. Inst. Public Health, Cambridge.

9. Narendra, K., Ahuja, S., Shashank, B., & Vipin, K. (2010). Fuzzy time series forecasting of wheat production. Int.J. Comput. Sci. Engg., 2, 635-640.

10. Nwankpa, C., Ijomah, W., Gachagan, A., & Marshall, S. (2018). "Activation Functions: Comparison of trends in Practice and Research for Deep Learning".

11. Paswan, R. P., & Begum, S. A. (2013). Regression and Neural Networks Models for Prediction of Crop Production. Int. J. Sci. Engg.Res., 04(9), 98-108.

12. Ruß, G. (2009). Data Mining of Agricultural Yield Data: A Comparison of Regression Models. Adv. in Data Mining. 5633, 24–37. https://doi.org/10.1007/978-3-642-03067-3_3

13. Shastry, K. A., Sanjay, H., & Deshmukh, A. (2016). A Parameter Based Customized Artificial Neural Network Model for Crop Yield Prediction. J. Artf. Int., 9, 23–32. https://doi.org/10.3923/jai.2016.23.32

14. Stastny, J., Konecny, V., & Trenz, O. (2011). Agricultural data prediction by means of neural network. Agric.econ., 57. https://doi.org/10.17221/108/2011-AGRICECON

15. Zheng, T., & Ishizuka, O. (1995). Design and implementations of a learning T-model neural network. Electricals and Electrical Engg., 4, 259–263.