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A Comparative Analysis of Neural Network Architectures for Predicting Indian Rice Production

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

Rice (*Oryza sativa*) is one of the most important cereal crops in World and feeds more than a third of the world's population. In Asian region, rice is a main source of nutrition and provides 30% to 70% of the daily calories for half of the world's population. Here, in this study two different neural network models were used in prediction of rice production of India. It was observed that the accuracy score of Multi-layer perceptron neural network is better than Radial basis function in prediction of rice production. The loss/error value for Multi-layer perceptron (MLP) model is lower than Radial basis function (RBF) model. The relative error is found to be high for MLP.

Keywords: Multi-layer perceptron; artificial neural network; yield prediction; radial basis function.

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1. INTRODUCTION

The world's most significant cereal crop, rice (*Oryza sativa*), provides food for almost one-third of the global population. About half of the world's population gets between 30% and 70% of their daily calories from rice, making it a staple food in the Asian region. It is a staple food in India that contributes significantly to food security and accounts for more than 40% of crop production. On a harvested area of 47.0 million hectares (mha), India is expected to produce 2.84 tonnes of rice per hectare, according to USDA projections, a decrease of around 3% from 2022. It is true that over 40% of the world's rice exports come from India. India imposed export restrictions on rice in 2022 as a result of below-average monsoon rainfall, which caused rice production to decline by 5.6% annually. However, given that oil prices have a significant role in international trade, the ongoing conflict between Russia and Ukraine may increase food costs as a result of commodities shipments. Despite conflicts, fluctuations in the global economy, the existence of other variables, and unseasonal rainfall during the Kharif crop harvesting season (October and November), India's rice production has been growing linearly since 2017. The USDA projects that India's rice production for the 2023–24 fiscal year will drop to 132.0 million tonnes, although it will still be the second-highest on record. As per agriculture ministry, India's rice-growing area is expected to grow during the following five years. Numerous scholars have endeavoured to forecast worldwide rice productivity and output in diverse Indian states through a range of time series methodologies, including Multiple Linear Regression, Box-Jenkins ARIMA model, and machine learning techniques like Artificial Neural Network and Support Vector Regression. Agro meteorologists have always found the study of crop yield prediction, particularly for strategic plants like rice, wheat, and maize, to be fascinating because it plays a significant role in both domestic and global economic planning. Aside from the relationship to the cultivator's genetics, adaphic terms, the impact of pests, diseases, and weeds, the management and control quality during the growing season, and other factors, the production of crops in dry farming is heavily dependent on meteorological occurrences. As a result, the most accurate prediction systems are those that make use of meteorological data. There are several yield prediction models available today, and the majority of them can be broadly divided into two categories: statistical models and crop simulation models. Lately, the use of artificial intelligence (AI) has increased. In this study, artificial neural network (ANN) was used to forecast India's yearly rice production. A network that accurately learns the relationships between the effective climatic parameters and crop yield can be utilized to estimate crop production over a long-or short-time horizon. Machine learning techniques are being used to estimate paddy yields in the state of Tamil Nadu, in eastern India. Support Vector Regression (SVR), General Regression Neural Networks (GRNNs), Radial Basis Functional Neural Networks (RBFNNs), and Back-Propagation Neural Networks (BPNNs) have all been demonstrated to be capable of accurately estimating the paddy yield for the Cauvery Delta Zone (CDZ) [1]. A method based on convolutional neural networks (CNNs) may be utilised to assist in achieving specific prediction study related to rice nitrogen shortage. To boost classification accuracy, the CNN architecture is changed by replacing the final output layer with a better classifier, like the support vector machine (SVM) [2]. GEP, or gene expression programming, with rainfall and temperature data collected between 1979 and 2011. GEP has the ability to statistically downscale local climate variables and produce reliable rice YIELDCAST tools. In order to prepare for adaptation, the model can encourage the deployment of enhanced drought-resistant and short-duration cultivars that are matched to a particular weather pattern and a shift to appropriate planting periods [3]. The ARIMA Model was used to forecast the yearly rice output, consumption, imports, exports, and self-sufficiency of the Benin Republic [4]. Based on past rice cultivation data, the ARIMA model and long short-term memory neural network (LSTM-NN) models might be employed for prediction [5]. Artificial neural networks (ANN) and boosted tree regression could be used to forecast the upland rice yield under the climate change approach [6]. Using long-term meteorological data, rice yield is predicted using stepwise multiple linear regression (SMLR), artificial neural networks (ANN), principle components analysis (PCA), and penalised regression models [7]. In order to forecast rice production yield and look into the variables influencing rice crop output, the WEKA tool and an MLP neural network are also utilised [8]. To predict the best crop, crop prediction methodologies could take into account a number of soil parameters (like depth, PH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulphur, manganese, copper, and iron) and atmospheric parameters (like temperature, rainfall, and humidity) [9]. ARIMA, the auto correlation function (ACF), and the partial auto correlation function (PACF) can be used to anticipate rice production as well as area [10]. Another significant time series model for rice production forecasting is the Box-Jenkins ARIMA model [11]. Paddy prediction also makes use of the ARIMA model, the autocorrelation function (ACF), and the partial auto correlation function (PACF) [12]. ARIMA models provide the best match for short-term projections [13]. Artificial neural networks (ANN) are used to predict rice production in mountainous areas. The daily daylight hours, daily solar radiation, daily temperature total, daily wind speed, and rainfall specific to a field are among the weather variables included by these models [14]. Based on modifications applied to neural network categorization, a rice crop monitoring system was created. The system was able to extract data on rice cultivation as a function of different planting dates and designate areas for one wet and one dry season. It also defined rice production [15]. This analysis solely considers how climate affects rice yield. The present study has used two different neural networks model approach to predict and find the best predicted neural network model between them. Additionally, using India's latitude and longitude, the study employed meteorological data from the NASA Power data access window [16].

2. MATERIALS AND METHODS

The data for this study is secondary in nature. The annual rice production data was collected from Indian government database for the period of1981 to 2015. The weather variables such as rainfall, surface pressure, temperature at 2 meters, precipitation, specific humidity and surface soil wetness were considered for the study. The data regarding these factors were collected from NASA Power data access window from 1981 to 2015.

Artificial neural networks are computational models that are inspired by human central nervous systems, particularly the brain, and are used in computer science and related fields. These models are capable of pattern recognition and machine learning. They are typically depicted as networks of linked "neurons" that can process incoming data and compute values by passing information across the network. Neural networks, like other machine learning techniques, have been used to address a wide range of problems, such as speech recognition and computer vision, that are challenging to handle using standard rule-based programming. The analysis of the study is performed through neural network models integrated in IBM SPSS Statistics 22 software. multi-layer perceptron (MLP) and radial basis function (RBF) neural network models were considered for the study. The MLP is build with hyperbolic tangent as activation function for the hidden layer and identity function for the output layer. On the other hand RBF neural network model is constructed with softmax as activation function for the hidden layers and identity function in the output layer. A brief discussion of the neural network models are given below

2.1 Multi-layer Perceptron

It is one of the important neural network models of present time. The word percepton in MLP neural network model is an algorithm which uses human like perception of seeing and recognizing images. It is used for both classification and prediction purpose and consists of multiple hidden layers. The neural network model doesn't have any restrictions on number of nodes/neurons for hidden layers. The nodes of input and output layer of the model depend on the number of inputs and outputs respectively. The non-linear and linear relationship among input and output variable is entertained in this neural network model. The mathematical form of a multilayer perceptron neural network can be described as follows:

Let's denote

- X as the input vector
- $W^{(i)}$ as the weight matrix of layer i
- $b^{(i)}$ as the bias vector of layer i
- $a^{(i)}$as the output layer i before applying the activation function.
- $z^{(i)}$ as the output layer i after applying the activation function.
- $f^{(i)}$ as activation function of layer i.

For a network with L layers (excluding the input layer), the mathematical form of the forward pass through the MLP can be represented as

- For the input layer
  $a^{(0)} = X$

- For the layers i= 1,2,……L-1
  $Z^{(i)} = W^{(i)}a^{(i-1)} + b^{(i)}$

$a^{(i)} = f^{(i)}(z^{(i)})$

- For output layer i=L
  $z^{(L)} = W^{(L)}a^{(L-1)} + b^{(L)}$
  $\hat{y} = a^{(L)} = f^{(L)}(z^{(L)})$

Where,

$\hat{y}$is the output (prediction) of MLP.

2.2 Radial Basis Function

The structural form of radial basis function (RBF) neural network model is different from other neural networks. It consists of a single hidden layer with respective number of nodes. This neural network (NN) falls under feed forward neural network models. RBF network uses single hidden layer for computational work and it is considered to be most powerful and different from other neural networks. The network is used for both classification and prediction purpose. The most common radial basis function is Gaussian function. The architecture of an RBFNN typically consists of three layers:

- **Input Layer**: This layer consists of neurons representing the input features.
- **Hidden Layer**: This layer contains radial basis neurons. Each neuron in this layer computes its output based on the radial distance between the input data and a center point, and applies a radial basis function to this distance. Common radial basis functions include gaussian, multiquadric, inverse multiquadric, etc. These functions take the form:

$$\phi_i(x) = \exp\left(-\frac{||x-c_i||^2}{2\sigma_i^2}\right)$$

Where $\phi_i(x)$ is the output of the i-th neuron, x is the input vector, c_i is the center of the i-th neuron, and σ_i is the width parameter (spread) of the gaussian function.

- **Output Layer**: This layer typically consists of a single neuron (for regression tasks) or multiple neurons (for classification tasks). The output of the hidden layer is combined linearly to produce the final output of the network.

3. RESULTS

In order to evaluate the performance of the two selected neural network models, the data were split into two parts- one for training of the models and the other for testing as well as evaluation of the models performance. The training part and testing part of the data consists of 70 percent and 30 percent respectively. The decision regarding number of nodes, hidden layers and activation function were predefined in the IBM statistical software (SPSS, version 22) itself. Here in this study, rice production is considered as dependent variable and rainfall, surface pressure, temperature at 2 meters, precipitation, specific humidity and surface soil wetness were independent variables.

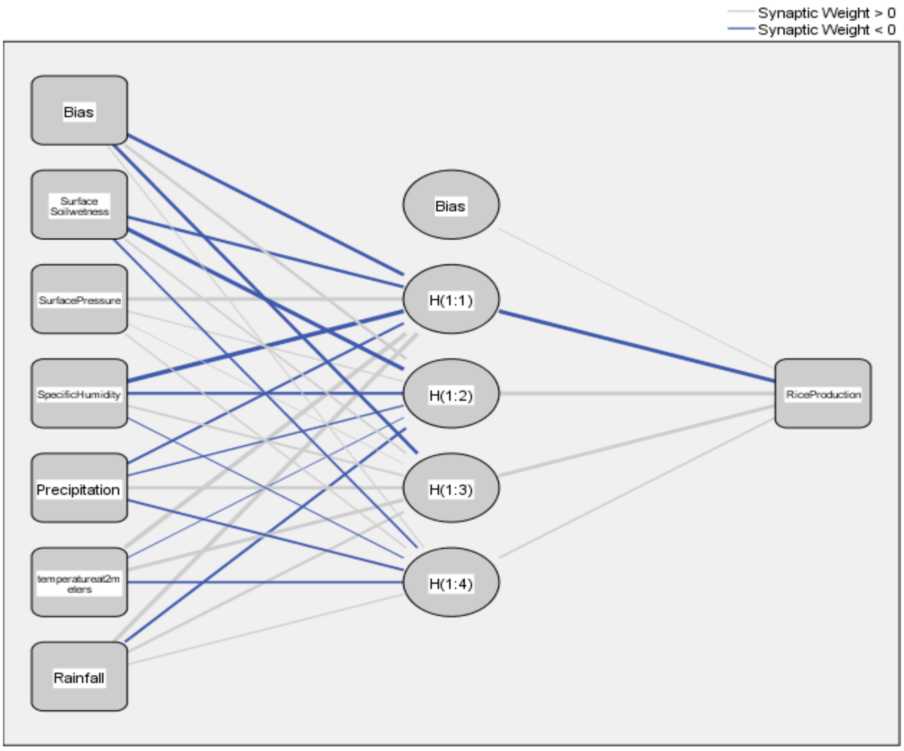
The evaluations of the neural network models are based on the loss function i.e. sums of squares. The following results of the study are discussed in Table 1.

From Table 1, it is observed that both the neural network models for prediction of rice production has considered same number of units in input layer and hidden layers. The number of hidden layers is also similar in both the models. Multi Layer Perceptron neural network model has considered hyperbolic tangent as activation function whereas radial basis function has considered Softmax. The loss function or error function i.e. sums of square is considered by both the models.

Table 1. Information of neural network models

Neural network models	Number of units in input layer	Number of hidden layers	Number of Units in hidden layer	Activation function (hidden layer)	Activation function (output layer)	Loss/Error function
Multi-layer Perceptron	6	1	4	Hyperbolic tangent	Identity	Sums of Squares
Radial Basis Function	6	1	4	Softmax	Identity	Sums of Squares

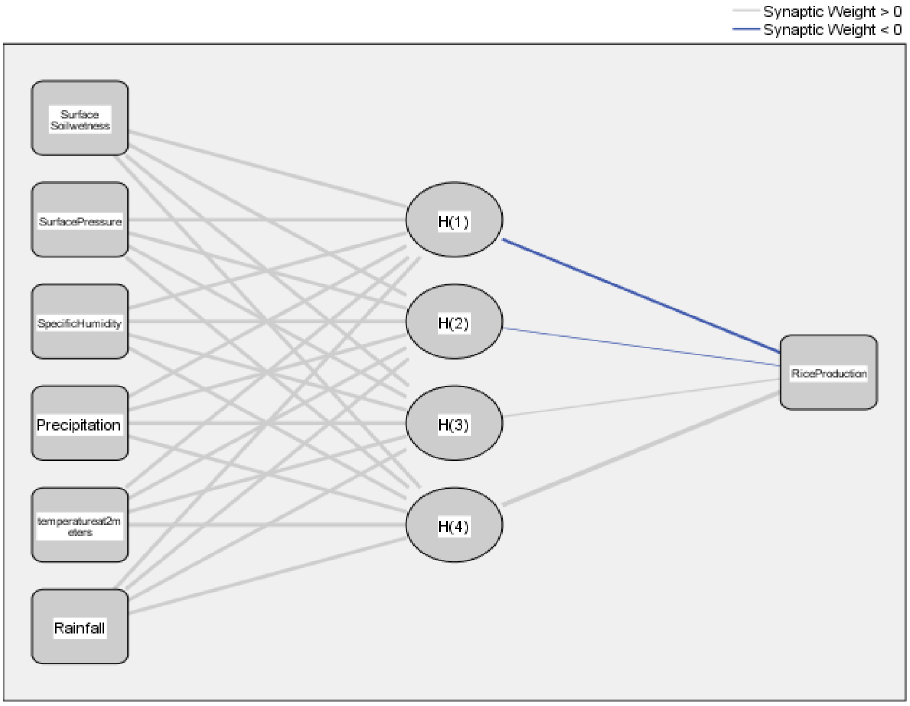
The following diagrammatic representation of the neural network models is given below:



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Fig. 1. Multilayer perceptron neural network



Hidden layer activation function: Softmax

Output layer activation function: Identity

Fig. 2. Radial basis function neural network

Table 2. Evaluation metrics for neural network models

Neural Network Model	Accuracy Score	Loss/Error	Relative error
Multi-layer Perceptron	98.04	1.96	0.48
Radial Basis Function	90.27	9.73	1.15

These neural network model summary metrics are based on testing data. From the above Table 2, it is observed that the accuracy score of Multi-layer perceptron neural network is better than Radial basis function in prediction of rice production. The loss/error value for Multi-layer perceptron (MLP) model is low than Radial basis function (RBF) model. The relative error is found to be high for MLP.

4. CONCLUSION

The study employed two distinct neural network model approaches to predict India's rice yield. It was observed that the accuracy score of multi layer perceptron (MLP) neural network is better than radial basis function in prediction of rice production. The loss/error value for multi-layer perceptron (MLP) model is low than radial basis function (RBF) model. The relative error is found to be high for MLP. The decision regarding number of nodes, hidden layer and activation function for neural network models are in researcher hand. The present study has tried to overcome such decisions with the help of automated software decisions regarding respective neural network models. In terms of future prospects, the study could be further generalized to considerations of other neural network models for better comparison among them. The efficiency of the neural network models could be improved if compared with conventional statistical methods.

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COMPETING INTERESTS

Author has declared that no competing interests exist.

REFERENCES

1. Joshua V, Priyadharson SM, Kannadasan R. Exploration of machine learning approaches for paddy yield prediction in eastern part of Tamil Nadu, Agronomy. 2021;11(10):2068. DOI: 10.3390/agronomy11102068.
2. Sethy PK, Barpanda NK, Rath AK. Nitrogen deficiency prediction of rice crop based on convolutional neural network, J. Ambient Intell. Hum. Comput. 2020;11: 5703–5711.
3. Traore S, Zhang L, Guven A, Fipps G. Rice yield response forecasting tool (YIELDCAST) for supporting climate change adaptation decision in Sahel, Agric. Water Manag. 2020;239:106242. DOI: 10.1016/j.agwat.2020.106242
4. Akouegnonhou O, Demirbaş N. Forecasting of rice self-sufficiency in the Benin Republic using Arima model. Selcuk, J. Agric. Food Sci. 2019;33(3):204–214.
5. Paidipati K, Banik A. Forecasting of rice cultivation in India–a comparative analysis with Arima and LSTM-NN models, ICST Transactions on Scalable Information Systems. 2019;7(24). DOI: 10.4108/eai.13-7-2018.161409
6. Zhang L, et al. Using boosted tree regression and artificial neural networks to forecast upland rice yield under climate change in Sahel, Comput. Electron. Agric. 2019;166:105031. DOI: 10.1016/j.compag.2019.105031
7. Das B, Nair B, Reddy VK, Venkatesh P. Evaluation of multiple linear, neural network and penalised regression models for prediction of rice yield based on weather parameters for west coast of India, Int. J. Biometeorol. 2018;62(10): 1809–1822. DOI: 10.1007/s00484-018-1583-6
8. Gandhi N, Petkar O, Armstrong LJ. Rice crop yield prediction using artificial neural networks, Technological Innovations in ICT for Agriculture and Rural Development. 2016;105–110. DOI: 10.1109/TIAR.2016.7801222
9. Dahikar SS, Rode SV. Agricultural crop yield prediction using artificial neural network approach, Int. J. Innov. Res. Electr. Electron. Instrum. Control Eng. 2014;2(1):683–686.
10. Prabakaran K, Sivapragasam C. Forecasting areas and production of rice in India using Arima model, Int. J. Farm Sci. 2014;4(1):99–106.

11. Suleman N, Sarpong S. Forecasting milled rice production in Ghana using Box-Jenkins approach, Int. J. Agric. Manag. Dev. 2012;2(2):79–84.
12. Raghavender M. Forecasting paddy production in Andhra Pradesh with Arima model, Int. J. Agric. Stat. Sci. 2010; 6(1):251–258.
13. Rahman NMF. Forecasting of boro rice production in Bangladesh: An Arima approach, J. Bangladesh Agric. Univ. 2010; 8(1):103–112.
DOI: 10.3329/jbau.v8i1.6406
14. Ji B, Sun Y, Yang S, Wan J. Artificial neural networks for rice yield prediction in mountainous regions, J. Agric. Sci. 2007; 145(3):249–261.
DOI: 10.1017/S0021859606006691
15. Chen C, Mcnairn H. A neural network integrated approach for rice crop monitoring, Int. J. Remote Sens. 2006; 27(7):1367–1393.
DOI: 10.1080/01431160500421507
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