Original Research Article

A Comparative Approach of Neural Network Models in Prediction of India's Rice Production

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.

Key-words

Multi-layer Perceptron; Artificial Neural network; Yield Prediction, Radial Basis Function

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 the previous year. 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

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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. According to a 2023 study, 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 simulationmodels. 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. This analysis solely considers how climate affects rice yield. The 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 MERRA-2 satellite.

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2. Review of Literature

Following are the researchers who have studied, developed models andforecasted rice productivity using the above techniques in India and other nations:

Joshua et. al. (2021) experimented exploration of Machine Learning Approaches for paddy yield prediction in Eastern Part of Tamil Nadu state in India. In their paper, Support Vector Regression (SVR), General Regression Neural Networks (GRNNs), Radial Basis Functional Neural Networks (RBFNNs) and Back-Propagation Neural Networks (BPNNs) are demonstrated to predict the paddy yield accurately for the Cauvery Delta Zone (CDZ). The performance of each developed model is examined using assessment metrics such as Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Coefficient of Variance (CV), and Normalized Mean Squared Error (NMSE). Performance of the GRNN model is compared with other available models from several studies in the literature. Sethy et. al. (2020) proposes a convolutional neural network (CNN) based approach for prediction of rice nitrogen deficiency in in their paper. In their paper pre-trained CNN architecture is modified to improve the classification accuracy with the inclusion of pre-eminent classifier like support vector machine (SVM) by replacing the last output layer of CNN. They used 6 leading deep learning architectures with SVM are used for prediction of nitrogen deficiency with 5790 image samples. The performance of each classifier is measured and compared in terms of accuracy, sensitivity, specificity, false positive rate (FPR) and F 1score. Traore et. al. (2020) constructs upland rice yield responses forecasting algebraic formulation code referred as YIELDCAST by using gene-expression programming (GEP) based on observed rainfall and temperatures data (1979–2011), and forcing with global climate model (GCM) downscaled outputs under CO_2 emission scenarios SR-A1B, A 2 and B 1 (2012–2100) over Bobo-Dioulasso, a Sahelian region located at the Houet province within the Haut-Bassin region in the Western Burkina Faso. Statistically, GEP is a capable tool to downscale climate variables in the region and constructs reliable rice YIELDCAST tools. The model can help anticipate adaptation decision support on-farm water management, shift to suitable planting periods, and use of improved drought resistant and short duration varieties adapted to a local weather pattern. Akouegnonhou et. al. (2019) forecasted year wise rice production, consumption, importation, exportation and self-sufficiency in the Benin Republic Using ARIMA Model. Their study will help policy makers to make decision regarding year wise requirements of rice production and consumption behaviour. Their study will also help the Govt. to boost rice sector and thereby reduce rice importation. Paidipati et. al. (2019) studied forecasting of rice cultivation in India by using ARIMA and Long Short-Term Memory Neural Network (LSTM-NN) models on the basis of the historical data of rice cultivation from the year 1950-51 to 2017-18. They have fitted models for Area under Cultivation, Production and Yielding from the significant spikes of their respective Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plots. But, their models fitted in LSTM-NN are found much better than the ARIMA models. The performances of these models validated with the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values. Zhang et. al. (2019) forecasted upland rice yield under climate change in Burkina Faso, a Sahelian region using boosted tree regression and artificial neural networks (ANN). Then the modeled rice yield function was calibrated and tested against the observed yield data and climate variables of three states of Burkina Faso, West Africa. They have forecasts yield trends over 2052 by taking the global climate model (GCM) outputs AR4-SR-A1B, A2, and B1 mean ensemble CO2 emissions scenarios. The weather parameters in this study are rain, maximum and minimum temperatures. They have used statistical parameters as MSE, NMSE, MAE, R and Multiple Linear Regression in their analysis. From application of ANNPNN, it is anticipated that site-specific rice yield may substantially decline with climate change, as rainfall is projected to decrease while temperatures increase. Das et. al. (2018) evaluates multiple linear, neural network and penalised regression models for prediction of rice yield of west coast of India based on weather data. They examined Stepwise Multiple Linear Regression (SMLR), Artificial Neural Network (ANN) and in combination with Principal Components Analysis (PCA) and penalised regression models for prediction of rice yield by using long-term weather data. They have used statistical parameters like R 2 , Root Mean Square Error (RMSE), normalised Root Mean Square Error (nRMSE). Moreover, Non-Parametric Friedman test was applied to check the significant difference among the models. Then, they performed pairwise multiple comparison test which indicated Least Absolute Shrinkage and Selection Operator (LASSO) as the best model which was found similar to SMLR and elastic net (ENET). Gandhi et. al. (2016) used Neural Networks to predict rice production yield and investigate the factors affecting the rice crop yield for various districts of Maharashtra state in India for the years 1998 to 2002. The data for 27 districts of Maharashtra state were taken from publicly available Government's record. The parameters in the study are precipitation, minimum temperature, average temperature, maximum temperature and reference crop evapotranspiration, area, production and yield for the Kharif season (June to November). The dataset was processed using WEKA tool and a Multilayer Perceptron Neural Network was developed. The statistical parameters Mean Absolute Error, Root Mean Squared Error (RMSE), Relative Absolute Error and Root Relative Squared Error were calculated for this study and the performance of the classifier is visually summarized using ROC curve. Dahikar et. al. (2014) predicts agriculture crop yield using Artificial Neural Network (ANN). They have taken both crop varieties Kharif crops (Corn, Cotton, Bajara, Groundnut, Jawar, Rice, Soyabean and Sugarcane) and Rabi crop (Wheat). They have used Crop prediction methodology to predict the suitable crop by sensing various parameter of soil (Depth, PH, Nitrogen, Phosphate, Potassium, Organic Carbon, Calcium, Magnesium, Sulphur, Manganese, Copper and Iron) and parameters related to atmosphere (Temperature, Rainfall and Humidity). Prabakaran et. al. (2014) in their paper emphasized on forecasting areas and production of rice for the period 1950–51 to 2011–12 using time series method, i.e. ARIMA. Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) were also calculated for the dataset. Suleman et. al. (2012) forecasted milled Rice production in Ghana using time series data from 1960 to 2010 and they used Box-Jenkins ARIMA model. Their have found that ARIMA (2, 1, 0) was the best model for forecasting milled rice production in Ghana. They examined 10 year forecast with their ARIMA model for the year 2015 (283.16 thousand metric tons) but that was not good enough to compare with West Africa's largest rice producer i.e. Nigeria (2700 thousand metric tons in 2011).m Raghavender (2010) forecasted year wise paddy production in Andhra Pradesh withARIMA model for the period of 1955-56 to 2007-08. Autocorrelation (ACF) and partialautocorrelation functions (PACF) were evaluated for their study. Validity of the ARIMAmodel was tested using standard statistical techniques and forecasting done for riceproduction for three leading years. Rahman (2010) examined the best fitted ARIMA model that could be used to make efficient forecast Boro rice production in Bangladesh from 2008-09 to 2012-13. It was revealed thatlocal, modern and total boro time series are 1 st order homogenous stationary. It has also beenobserved from the study that short term forecasts are best fitted in ARIMA models. If specialmeasures can be taken against losses and production can forecasts well then, the productionuncertainty of boro rice can be minimized. Ji et. al. (2007) used Artificial Neural Network for rice yield prediction in mountainousregion of the Fujian state of China where weather disturbances like typhoons, floods anddroughts threaten rice production. They predict Fujian rice yield for typical climaticconditions of the mountainous region using ANN models, evaluates ANN model performancerelative to variations of developmental parameters and evaluates a comparison ofeffectiveness of multiple linear regression models with ANN models. The weather variablessuch as daily sunshine hours, daily solar radiation, daily temperature sum and daily windspeed along with field-specific rainfall data were used for each location of the state.Chen et. al. (2006) in their paper developed the rice crop monitoring system based onvariations as applied to a neural network classification. The system delineated rice production, areas for one wet and one dry season, and was able to extract information on rice cultivationas a function of different planting dates. A minimum mapping accuracy of 96% was achievedfor both seasons. To predict rice yield on a regional basis for the wet season this informationwas then used in a neural network-based yield model.

3. Material and Methods

The data for this study is secondary in nature. The annual rice production data was collected from a useful website **data.gov.in** 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 MERRA-2 satellite 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

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Commented [g5]: ???/ quote in the review the correct source 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 modelswereconsidered 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 withsoftmax 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

- **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
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$$Z^{(i)} = W^{(i)}a^{(i-1)} + b^{(i)}$$

$$a^{(i)} = f^{(i)}\left(z^{(i)}\right)$$

- 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.

- **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.

4. Results and Discussion

Research on crop production prediction, particularly for rice, corn, and wheat, has always been fascinating areas of research. Artificial Neural Networks (ANNs), Fuzzy Systems, and Genetic Algorithms are examples of Artificial Intelligence (AI) applications that have demonstrated increased problem-solving efficiency recently. By using them, models of complicated natural systems with numerous inputs can be simplified and made more accurate.One of the objectives of agricultural production is to maximize crop yield at the lowest possible cost. Large-scale meteorological events have the potential to significantly affect agricultural productivity through altering regional weather patterns. Crop managers could use predictions to reduce losses in the event of unfavorable conditions. When there is a chance for favorable growing circumstances, these forecasts may also be utilized to optimize crop prediction.

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 andrainfall, surface pressure, temperature at 2 meters, precipitation, specific humidity and surface soil wetnesswere 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 below:

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

Table 1- Information of Neural Network Models

From above 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 squareis considered by both the models.

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

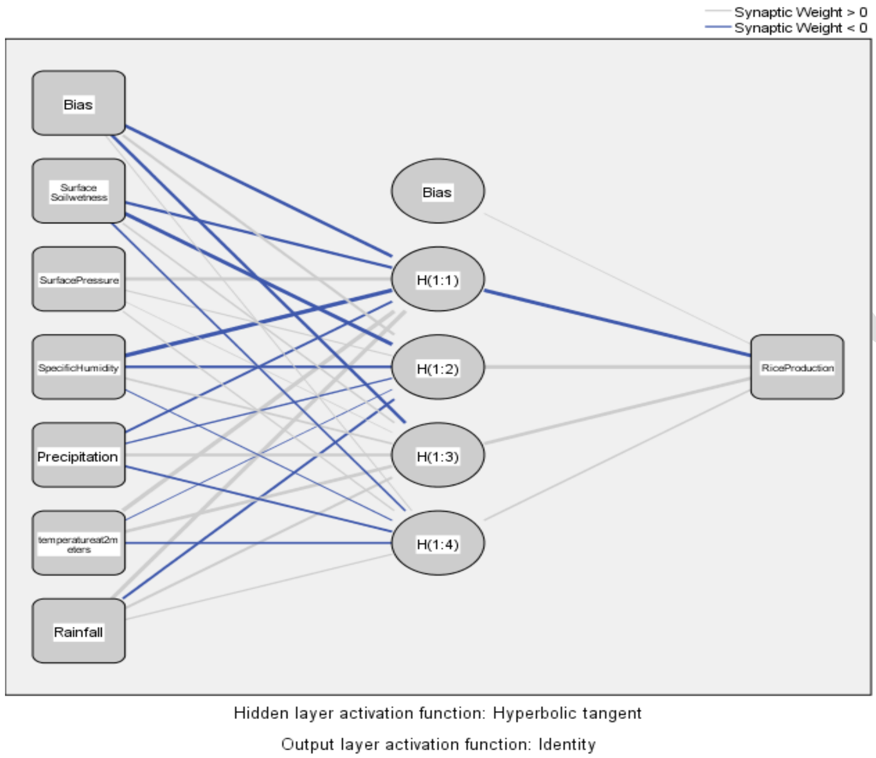

Figure 1- Multilayer Perceptron Neural Network

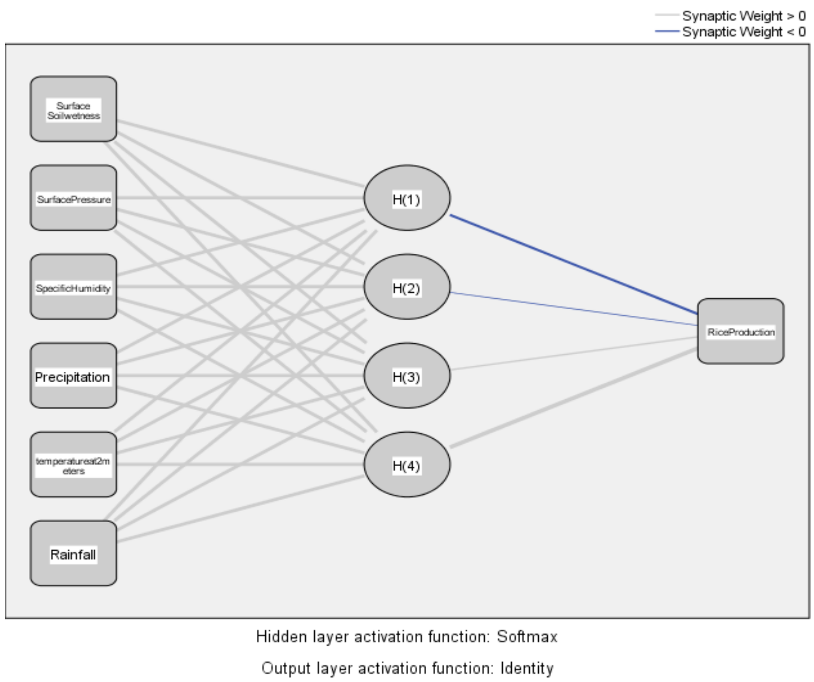

Figure 2- Radial Basis Function Neural Network

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

Table 2.Evaluation metrics for neural network models

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.

5.Conclusion

This analysis only evaluates how climate influences rice yield. The study employed two distinct neural network model approaches to predict and select the best predicted neural network.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 low than Radial basis function (RBF) model. The relative error is found to be high for MLP.

6. Future Prospects

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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