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Original Article

Teaching and Learning based Optimization with Deep Learning Model for Rice Crop Yield Prediction

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Abstract - *Rice crop yield prediction suggests the procedure of estimating the rice quantity which is harvested in a provided land region dependent upon several features like farming practices, weather conditions, and soil quality. The main aim of rice crop yield prediction is to offer farmers and agricultural planners correct crop yield calculations in progress, creating informed decisions assuming harvesting, marketing, and planting their crops. It supports farmers in optimizing their production and enhancing their profitability, but also improving food security by ensuring an even supply of rice for consumers. Deep learning (DL) approaches are utilized for predicting crop yield by leveraging the influence of neural networks for learning complex patterns and connections in data. This study presents a Teaching and Learning Based Optimization with Deep Learning for Rice Crop Yield Prediction (TLBODL-RCYP) technique. The proposed TLBODL-RCYP approach emphasizes the accurate forecasting of the rice yield using DL and hyperparameter optimizers. To accomplish this, the TLBODL-RCYP technique performs different preprocessing stages to improve the data quality. Besides, the TLBODL-RCYP technique employs a hybrid Convolution Recurrent HopField Neural Network (HCRHNN) model for yield prediction. At last, the TLBO algorithm was utilized to adjust the hyperparameter values of the HCRHNN technique and thereby enhance the predictive results. The experimental outcome investigation of the TLBODL-RCYP approach is tested with the Kaggle dataset, and the outcomes assured the improvized predictive results of the TLBODL-RCYP method over other recent DL techniques.*

Keywords - *Agriculture, Rice crop yield, Prediction models, Deep learning, Metaheuristics.*

1. Introduction

Accurate crop yield predictions enhance decisions regarding exports, and imports of agricultural goods, planning effective crop management, preparing aid distributions, and allotting government resources [1]. However, due to complicated communications between yield-influencing natural factors and crop growth like disease, weather, and soil conditions, and anthropogenic factors like rotation, irrigation, tillage, seed varieties, and fertilizers, yield predictions have become a challenge [2]. Continuously breeding new rice varieties with high nutrient utilization rate, high yield, raising yield per unit area, and good stress resistance, and evolving the genetic potential of rice yield are significant objectives in the cultivation and rice breeding field in recent times [3]. Learning the features of rice yield was extremely important to increase farmers' income, support land scale management, and ensure countrywide food safety, which is of utmost value to mitigate the food shortage problem efficiently [5].

The conventional technique of measuring yield in the domain found to be destructive that is, as per the principle of average sampling or equivalent area in groups [6], choose certain small domains, clean, thresh, weigh, and dry the rice after harvesting, subsequent measures the content of water with a moisture meter, and compute the final yield as per the quantity of japonica rice and indica rice of 14.5 and 13.5 percentages [7]. This technique is burdensome and consumes several material resources and a workforce. Hence, learning a novel method for precise rice yield anticipation in the domain is vital [8].

Various governments worldwide are more concerned about food shortage and food security [9]. Accurate crop yield prediction becomes a foundation for agriculture departments to perform scientific production regulation and cultivation management that can be a significant reference for nations to develop appropriate crop management [10, 11]. Different parameters influence crop yield, and it is tough to construct a reliable prediction method with conventional approaches [12]. However, the training and advancement of a new technique for crop yield prediction are possible with progressions in computational technology [13, 14]. Deep learning (DL) is an effective method widely utilized in

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agriculture since its numerous high-performance computing and data technologies [15]. DL is a class of machine learning that includes many layers of neural networks that can learn from unlabelled and unstructured data, whereby the learning can be unsupervised, supervised, or semi-supervised [16].

This study presents a Teaching and Learning Based Optimization with Deep Learning for Rice Crop Yield Prediction (TLBODL-RCYP) model. The TLBODL-RCYP technique performs different stages of preprocessing to improve the data quality. Besides, the TLBODL-RCYP technique employs a hybrid Convolution Recurrent HopField Neural Network (HCRHNN) model for yield prediction. At last, the TLBO algorithm is utilized to adjust the hyperparameter values of the HCRHNN approach and thereby enhance the predictive results. The experimental outcome investigation of the TLBODL-RCYP approach is tested through the Kaggle dataset.

2. Related Works

Cao et al. [17] present 11 combinations of climate dataset, geography, and phenology tested to predict the site-related rice yield with the traditional regression-oriented method (multiple linear regression, MLR) and three ML approaches: BP, SVM, and RF. Bondre and Mahagaonkar [18] present a system to forecast agricultural yields from earlier datasets. This can be accomplished using ML techniques such as SVM and RF on crop data and suggesting fertilizers appropriate for all crop yields. This study focuses on forming predictive models that might be used for the future prediction of crop yields. Nosratabadi et al. [19] developed two ML algorithms for forecasting food manufacturing. The MLP and Adaptive Network Oriented Fuzzy Inference System methods were utilized to advance the predictive techniques. In this article, two parameters, cattle and farming manufacturing, are the sources of food production. The parameters have been used for assessing livestock production, such as live animals, livestock yield, and animals slaughtered. Two parameters have been utilized for evaluating agricultural production losses and yields.

In [21], the authors presented a new approach to sugarcane yield prediction using Normalized Vegetation Index (NDVI), Long Term Time Series (LTTS), Supervised ML (SML), and Weather-and-soil qualities. The technique splits yield prediction into 3 phases, 1) weather-and-soil characteristics were forecasted for the period of SCLC, 2) sugarcane crop was forecasted through SVR by taking NDVI as input into account 3) NDVI is forecasted by considering the weather -and-soil characteristics as input through Support Vector Machine Regression (SVR) method. Paudel et al. [22] devised a crop yield prediction technique for many spatial levels depending on region-wise crop yield prediction from ML. With its data-driven method, ML can capture nonlinear relations between yield and predictors at the regional level using extensive data.

In [23], the authors compared and proposed four methods to forecast rice blast diseases, two operational process-related methods Water Accounting Rice Model and Yoshino, and two techniques depending on ML techniques (RNN and M5Rules), building a NN and the latter inducing rule-related approach. Lamba et al. [25] developed a hybrid predictive method for estimating other cruelty of blast ailment levels depending on affected plant imaging. With the CNN technique, features are first extracted. After the classification and identification of the severity level of blast diseases were carried out utilizing an SVM.

3. The Proposed Model

In this study, we introduced a new TLBODL-RCYP technique for accurately anticipating crop yield. The goal of the presented TLBODL-RCYP technique focuses lies on the precise forecasting of the rice yield using DL and hyperparameter optimizers. To accomplish this, the TLBODL-RCYP technique involves three crucial processes: data preprocessing, HCRHNN-based forecasting, and TLBO-based tuning process. Figure 1 represents the comprehensive flow of the TLBODL-RCYP algorithm.

3.1. Data Preprocessing

The TLBODL-RCYP technique performs different stages of preprocessing to improve the data quality. Primarily, the categorical values are transformed into numerical values. Then, the null values in the dataset are removed. Thirdly, the input data gets normalized by the use of min-max normalizing.

3.2. Yield Forecasting by Implementing HCRHNN Approach

In this study, the HCRHNN approach is enforced for forecasting crop yield. The HCRHNN architecture comprises the LSTM layer, input layer, CSV matrix, Hopfeld network, an output layer, recurrent neural network, and summation function [26]. A CSV matrix was generated by applying the Python libraries when preprocessing of input data was accomplished and fed into the LSTM layer. One type of RNN, the LSTM, learns order dependency in prediction based on applications. The network architecture of LSTM was similar to RNN. The process inside various LSTM cells differs. The LSTM exploits the process of forgetting or remembering knowledge. The hidden layer amount in the dropout rate was fixed to 0.25, and LSTM was fixed to 100. The 5-fold cross-validation was mainly based on the training set for every sample, and the key hyperparameter was finetuned to obtain the optimal efficiency. The computation part of LSTM has been formulated in the following:

$$a(x) = s\big(W(i)z(x) + U(a)h(x-1)\big) \tag{1}$$

A summation function is applied for input gate $an\ (x)$ in Eq. (1).

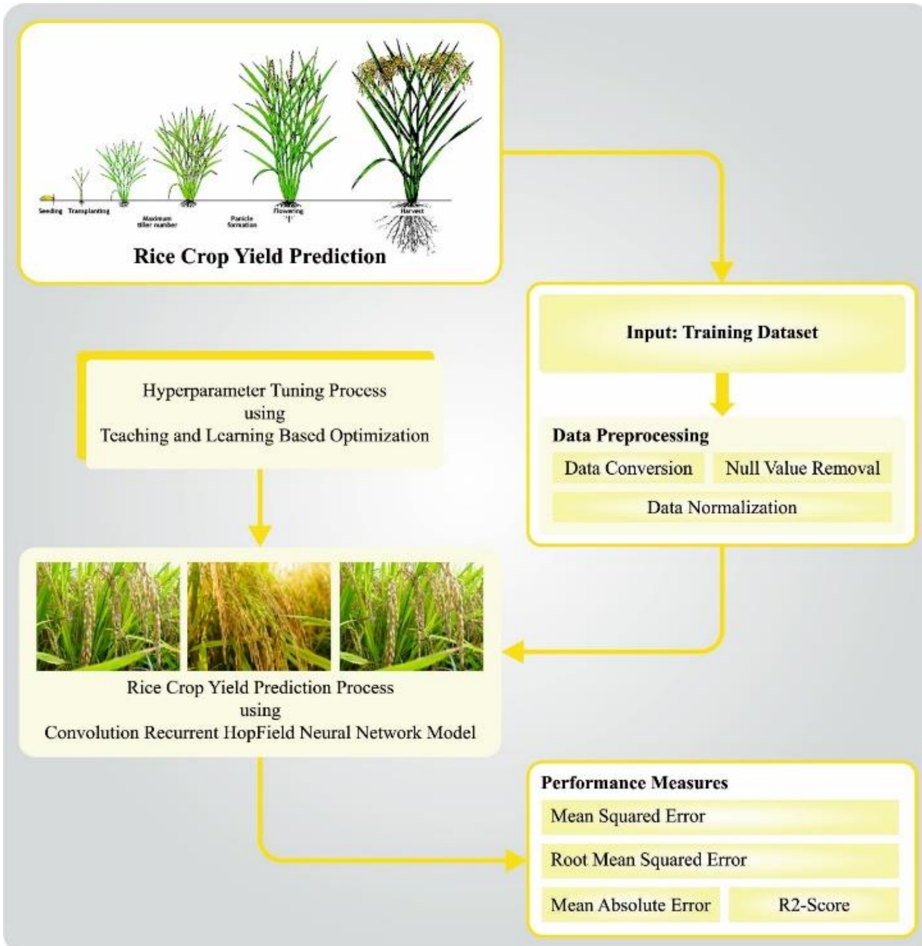

Fig. 1 Overall flow of TLBODL-RCYP algorithm

$$b(x) = s\big(W(i)z(x) + U(b)h(x-1)\big) \qquad (2)$$

A summation function was applied for forgot gate $b(x)$ in Eq. (2).

$$c(x) = s\big(W(0)z(x) + U(c)h(x-1)\big) \; (3)$$

A summation function applied for output gate $c(x)$ in Eq. (3)

$$d(x) = \tanh\big(W(c)z(x) + U(c)h(x-1)\big) \quad (4)$$

A tangent function for novel memory cell creation denotes eq. (4).

$$e(x) = c(x) * d(x-1) + a(x) * d(x) \qquad (5)$$

Eq. (5) signifies the last memory cell creation.

$$n(x) = c(x) * \tanh\big(e(x)\big) \qquad (6)$$

Eq. (6) illustrates the LSTM output.

Now $n(x)$ denotes the new hidden state, s indicates the sigmoid function, $an\,(x)$ represents the input gate, $b(x)$ represents forget gate, $c(x)$ denotes the output gate, $d(x)$ shows the presented cell value, and $e(x)$ indicates the true cell value.

In the beginning, the LSTM eradicates the problems of exploding gradient. Since the LSTM was activated through the hyperbolic tangent activation function and 0.25% dropout was set, the method was not overfitting. Eq. (7) shows the investigation metrics required to compute hidden state $n(x)$.

$$n(x) = \tanh\big(W.n(x-1) + V.z(x-1)\big) \qquad (7)$$

Where $n(x)$ represents the past data repeated by the hidden layer, the weight parameter is characterized as $O, V, and\ W$. Eq. (8) evaluates $p(z(x+1)|n(x))$, which represents the possibility of predicting diseases.

$$p\big(z(x+1)\big|n(x)\big) \propto \exp\big(O.n(x)\big) \qquad (8)$$

The overall probability for the sequence of input vectors $y = \{y_1, y_2, y_3 \dots y_t\}$ is shown.

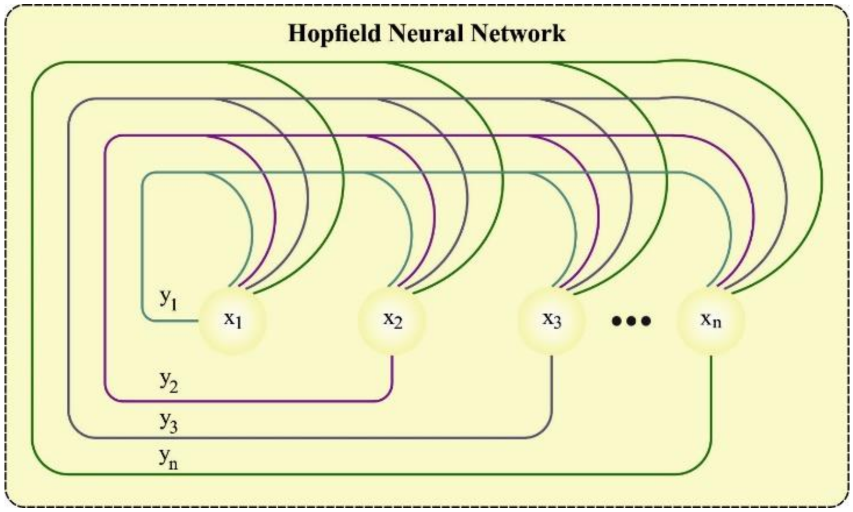

Fig. 2 Structure of HNN

$$p(y) = \sum_{t=1}^{T} p\left(z(x)\middle|n(x-1)\right) \quad (9)$$

Eq. (6) shows the joint probability that assists in training and testing the model.

The outcomes of LSTM can be fed as input to Hopfield Networking, having neurons of four layers. Every neuron was connected. The outputs of neurons were supplied as input in each neuron. The weight connections among two interlinked neurons are symmetric, viz., when there exist two $n1$ neurons and an n2 neuron, the weight connection of both neurons is similar to the weight connection of n2 with $n1$. It was a distinct Hopfeld networking as the weight connection of neurons with itself is often:

$$wij = \sum_{p=1}^{P}[\,2si(p) - 1][2sj(p) - 1]\; for\; i \neq j \quad (10)$$

In Eq. (10), s indicates the sequence of binary patterning taken from CSV datasets, i and j denote the two diverse neurons, and wij shows the weighted matrices of two neurons. The summation function employed through these patterns ranges from one to P.

The result of the Hopfeld networking was supplied to the two-way RNN. Bi-directional RNN (Bi-RNN) seems to be just two individual RNNs linked together. For single networking, the input series can be given in time series, while for others, it is specified in inverse time series. At every sample break, the outcome of 2 networking is commonly integrated.

This architecture enables the system to have both ahead and prior information about the event. The output value is provided in the summation function for getting better knowledge from the presented architecture through the transfer learning method. Figure 2 illustrates the structure of HNN.

3.3. Hyperparameter Tuning using TLBO Algorithm

At last, the TLBO model is implemented to adjust the hyperparameter values of the HCRHNN method. The TLBO model is a compelling human population-based technique [27]. This model resembled the teach-learn method of the teacher and learner in the lecturer's classroom. In the presented model, a group of learners in the class is regarded as a populace. As well, the learner's knowledge was the objective function.

The number of subjects provided to the learner can be variable, and the learner's outcome is the fitness value. This variable regarded in the objective function is the variable for the presented issue, and the better fitness values of the primary process are considered the better solution. The proposed technique is separated into the tutor and learner phases. Initially, the learner is learning from the teacher, and then, the learner is learning by discussing with others. The stages of TLBO are defined in the following.

3.3.1. Teaching Phase

Here, the tutor constantly attempts to enhance the mean results of the classroom for the topic. The better resolution determined by the objective function can be regarded as a tutor in that populace. This stage begins to identify the better solution. Firstly, produce an arbitrary population having N rows and S columns where N indicates the populace magnitude (amount of learners present in classroom $i = 1,2,\ldots,N$) and S shows the designing parameters number (amount of topics $j = 1,2,\ldots,S$). The jth parameter of the ith learner can be randomly initialized by Eq. (11),

$$X_{i,j}^{1} = X_j^{\min} + rand\, * \left(X_j^{\max} - X_j^{\min}\right) \quad (11)$$

Where $rand$ represents a uniform distribution random integer within [0,1] and $X_j^{\min}$ and $x_j^{\max}$ characterize the minimal and maximal values for $the\ jth$ variable.

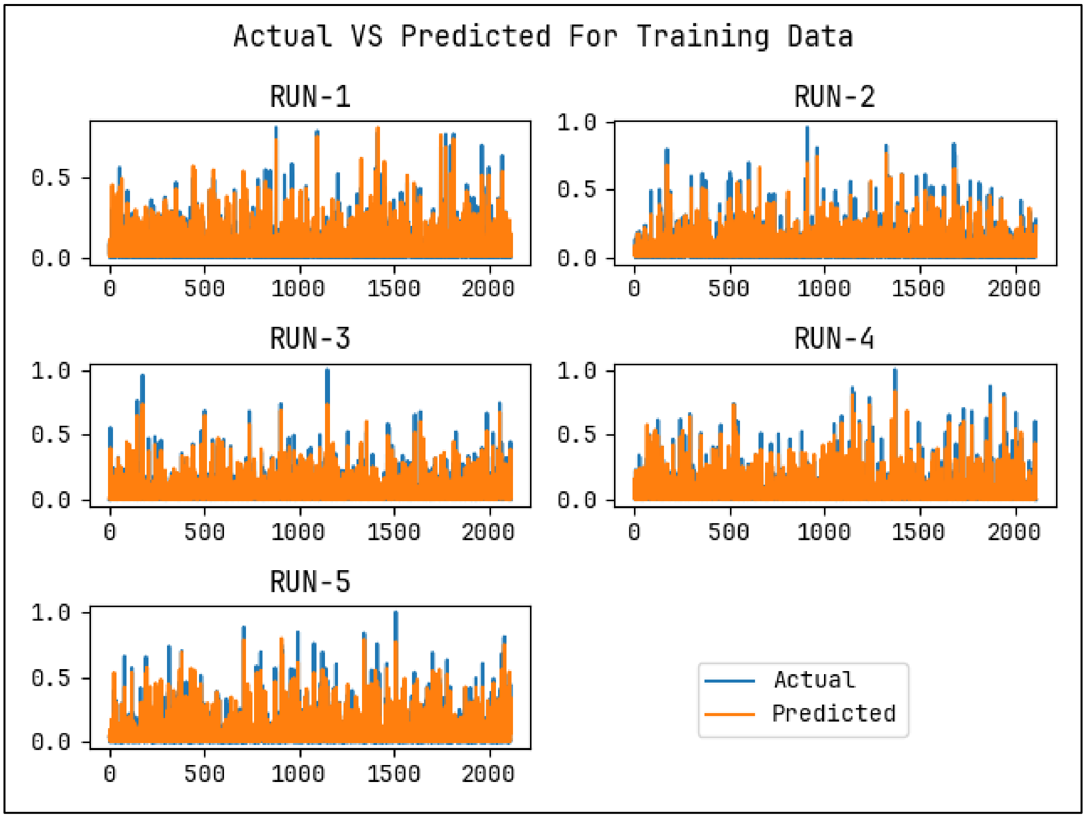

Fig. 3 Results of training dataset on different runs

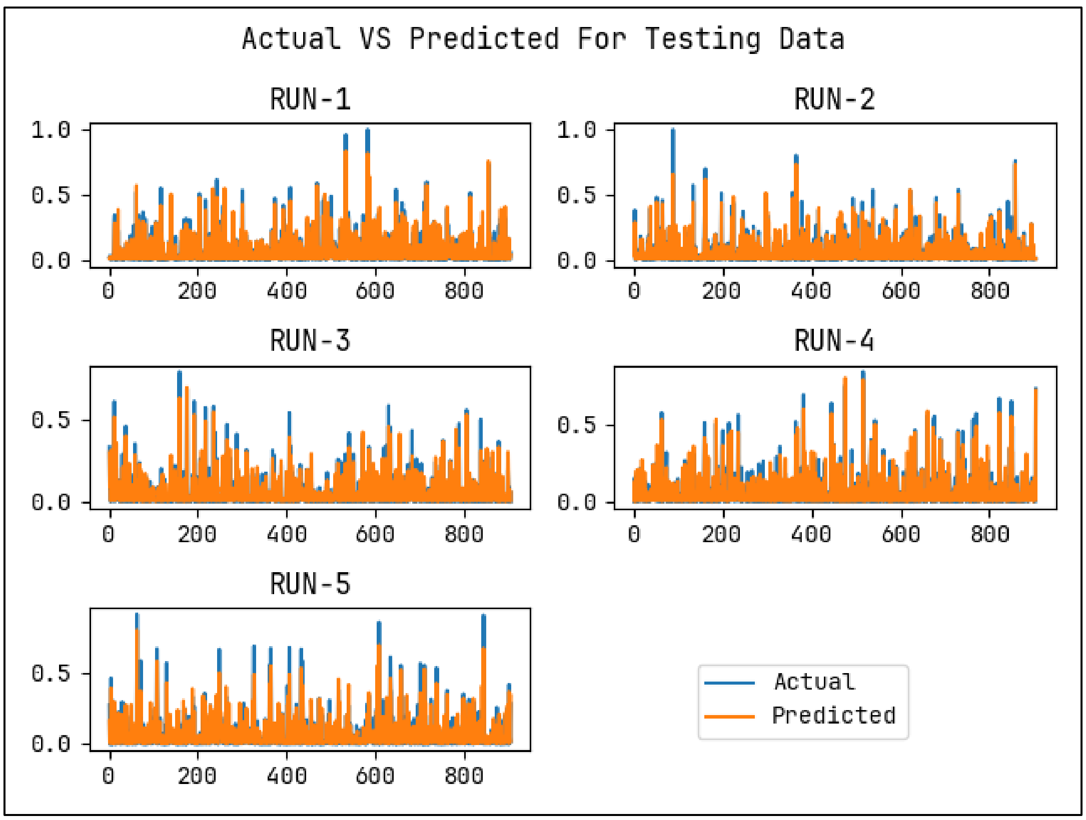

Fig. 4 Results of testing dataset on different runs

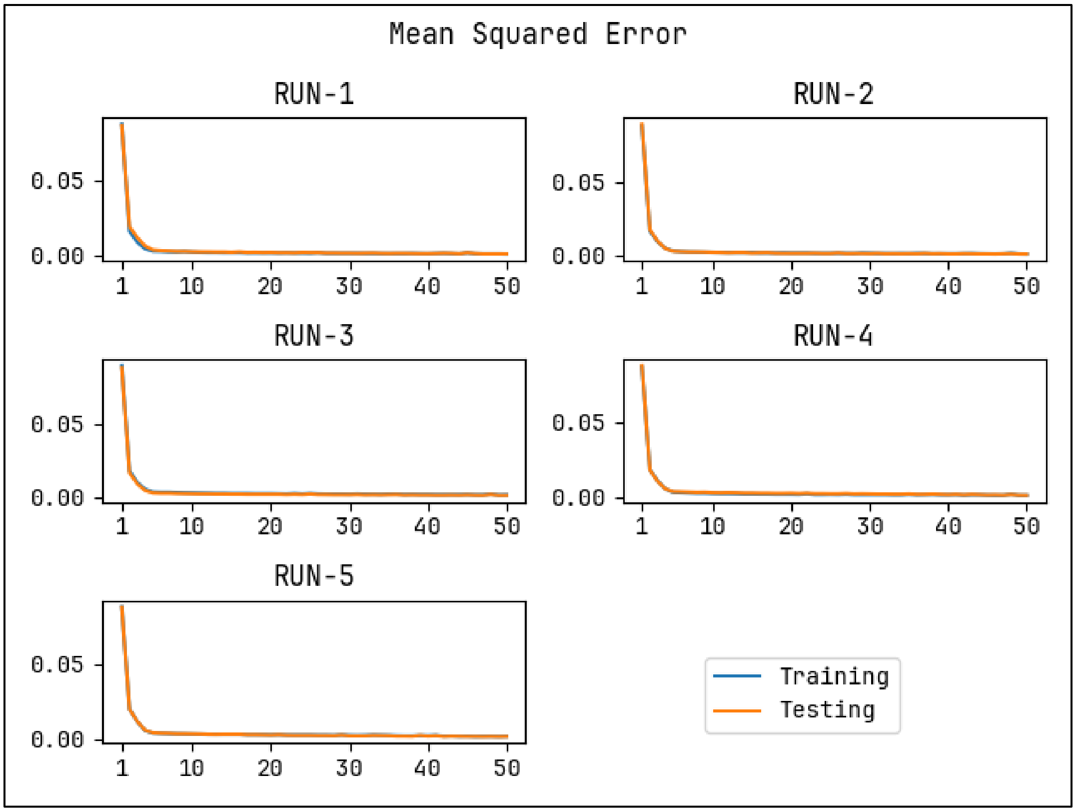

Fig. 5 MSE on training and investigating dataset by means of various epochs

Table 1. Classifier outcome of TLBODL-RCYP approach under five runs

No. of Runs	MSE	RMSE	MAE	R2-Score
RUN-1	0.0013	0.1391	0.0194	0.8994
RUN-2	0.0013	0.1379	0.0190	0.8721
RUN-3	0.0010	0.1312	0.0172	0.8829
RUN-4	0.0014	0.1388	0.0193	0.8781
RUN-5	0.0016	0.1496	0.0224	0.8624
AVERAGE	**0.0013**	**0.1393**	**0.0195**	**0.8790**

The difference $is\ D^k_{diff_j}$. Amongst better resolution and mean results of classroom or the jth subject in the kth iterating was represented.

$$D^k_{diffj} = rand\left(X^k_{T,j} - T_F M^k_j\right) \tag{12}$$

In Eq. (12), M^k_j denotes the mean results of the learner for $the\ jth$ subject and $X^k_{T,and\ j}$ signifies the better solution for the jth subject at the kth iterating. The tutor features TF, as shown in (15), which is suggestive of the tutor's capability of the tutor, where the mean results of the topic will be changed. The value can be chosen between zero and one.

$$T_F = round\ [1 + rand\ (0,1) \tag{13}$$

The solution for the problems is upgraded at all the iterations using

$$X^k_{new,i,j} = X^k_{old,i,j} + D^k_{diff_j} \tag{14}$$

In Eq. (14), $X^k_{oldi\ and\ j}$ represent the older solution for the jth subject in the prior iteration and $X^k_{newi\ and\ j}$ shows the newest solution for the jth subject. When the upgraded solution exceeds the prior one, it becomes a suitable solution and inputs to the following stage.

3.3.2. Learner Phase

In this phase, the learner improves the knowledge via mutual interaction. In the presented algorithm, every random learner interacts with others to assist in knowledge sharing based on their knowledge level. Based on knowledge sharing, the solution to the problem is upgraded. To mathematically characterize it, two learners are randomly regarded as $X^k_{(i)}$ and $X^k_{(r)}$. The upgraded solution is given as follows.

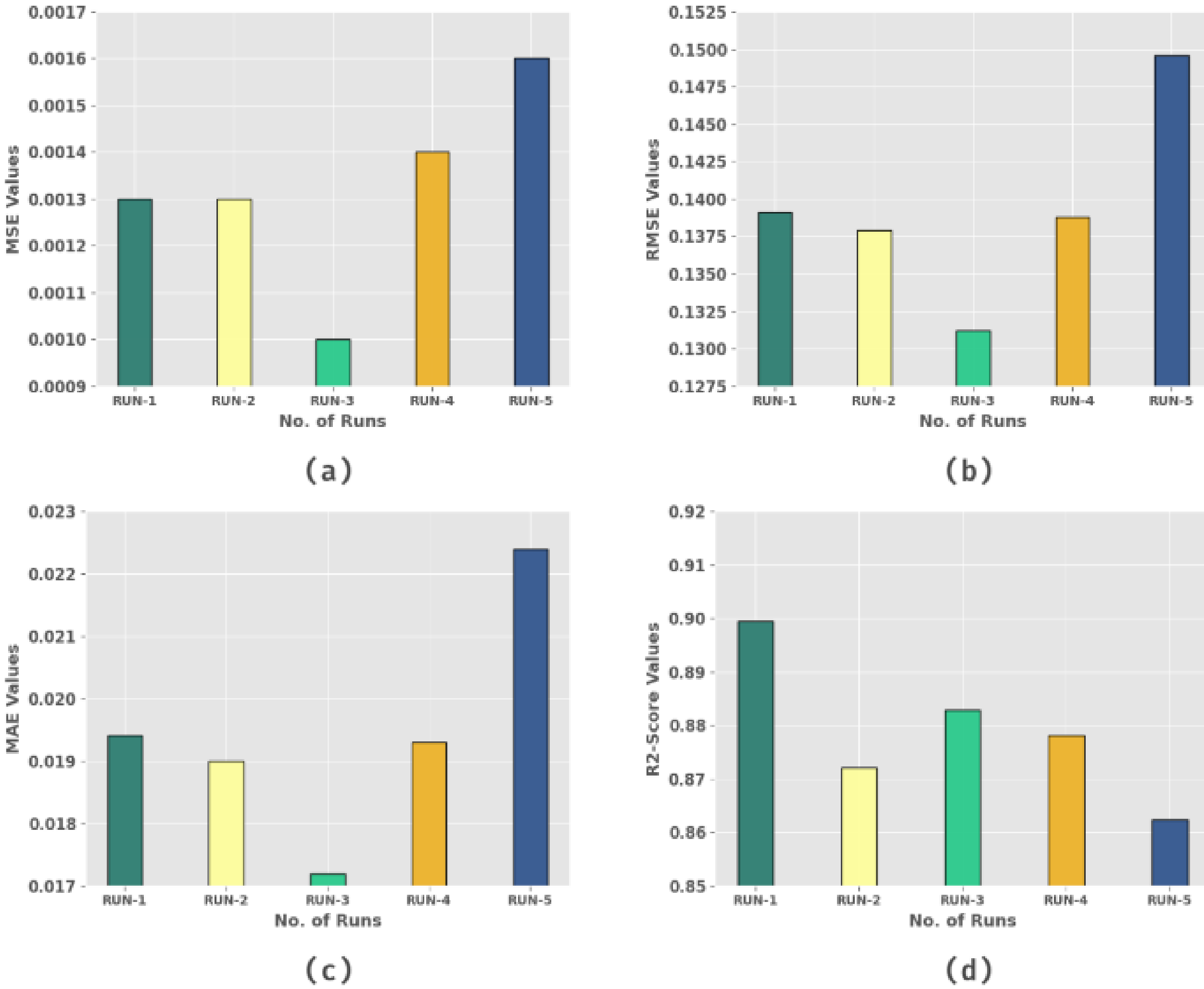

Fig. 6 Classifier outcome of TLBODL-RCYP system (a) MSE, (b) RMSE, (c) MAE, and (d) R2-score

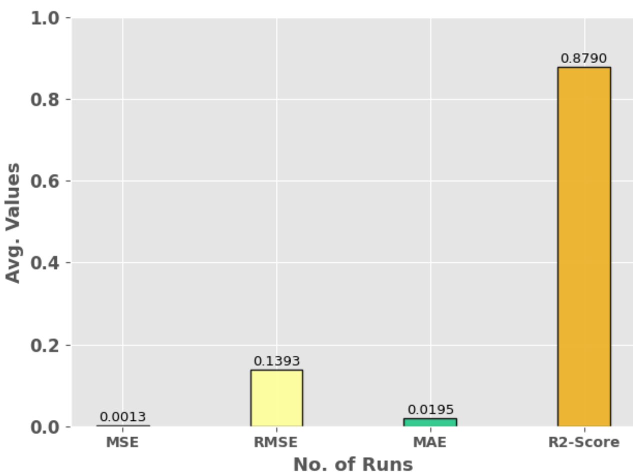

Fig. 7 Average outcome of TLBODL-RCYP system with various measures

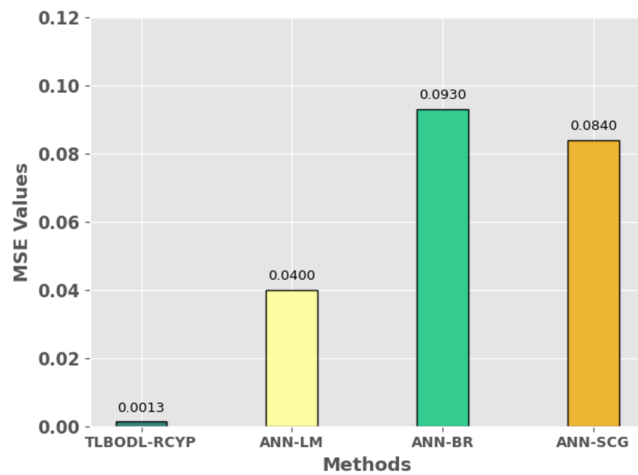

Fig. 8 MSE analysis of TLBODL-RCYP approach with recent systems

$$X_{new,i}^k = \begin{cases} X_i^k + rand \times \left(X_i^k - X_r^k\right) & if\left(X_i^k < X_r^k\right) \\ X_i^k + rand \times \left(X_r^k - X_i^k\right) & otherwise \end{cases} \quad (15)$$

The better solution for the various subjects is accepted, and this solution is input for the tutor stage. The tutor and learner stages are reiterated till the ending condition is satisfied.

During this case, the TLBO algorithm was utilized to ascertain the hyperparameter contained in the DL technique. The MSE can be assumed that the primary function is determined as:

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \quad (16)$$

In which M and L imply the outcome of layer and info value, y_j^i and d_j^i indicate the accomplished and suitable magnitudes for $the\ j^{th}$ unit in the outcome networking layer in time $t$uy'.

4. Results and Discussion

In this segment, the yield prediction outputs of the TLBODL-RCYP technique are studied under varying runs. Figure 3 demonstrates the actual vs predicted outcomes of the TLBODL-RCYP technique on the training data presented. The results show that the variance between the predicted and actual values is considered low.

Figure 4 demonstrates the actual vs predicted outcomes of the TLBODL-RCYP method on the testing data. The results reveal that the variance among the predicted and actual values is considered low.

Figure 5 shows the predicted results of the TLBODL-RCYP technique under training and testing data. The result indicates that the TLBODL-RCYP technique reaches closer results under training and testing data.

Table 1 and Figure 6 exhibits brief predictive results of the TLBODL-RCYP approach under five runs. The figure indicates that the TLBODL-RCYP method improved results under all runs. For example, with run-1, the TLBODL-RCYP methodology offers MSE, RMSE, MAE, and R2-score of 0.0013, 0.1391, 0.0194, and 0.8994, correspondingly. Meanwhile, with run-2, the TLBODL-RCYP technique offers MSE, RMSE, MAE, and R2-score of 0.0013, 0.1379, 0.0190, and 0.8721, respectively. Eventually, with run-4, the TLBODL-RCYP approach offers MSE, RMSE, MAE, and R2-score of 0.0014, 0.1388, 0.0193, and 0.8781 correspondingly. Finally, with run-5, the TLBODL-RCYP technique offers MSE, RMSE, MAE, and R2-score of 0.0016, 0.1496, 0.0224, and 0.8624, respectively.

Figure 7 reveals the average prediction outcomes of the TLBODL-RCYP approach. The results exhibit that the TLBODL-RCYP technique reaches effectual MSE values. In addition, it is noticeable that the TLBODL-RCYP technique gains an average MSE of 0.0013, RMSE of 0.1393, MAE of 0.0195, and R2-score of 0.8790.

Finally, a comparative MSE analysis of the TLBODL-RCYP technique with current methods is given in Table 2 and Figure 8 [28].

Table 2. MSE analysis of TLBODL-RCYP approach with recent algorithms

Methods	MSE
TLBODL-RCYP	0.0013
ANN-LM	0.0400
ANN-BR	0.0930
ANN-SCG	0.0840

The figure demonstrates that the ANN-BR and ANN-SCG models obtain lower MSE values of 0.0930 and 0.0840. Simultaneously, the ANN-LM method has resulted in a moderate MSE of 0.0400. However, the TLBODL-RCYP technique performs better with a minimal MSE of 0.0013. These results confirmed the enhanced performance of the TLBODL-RCYP technique over other methods.

5. Conclusion

In this research, we have suggested a new TLBODL-RCYP method for accurate crop yield forecasting. The proposed TLBODL-RCYP approach's end goal focuses on the precise forecasting of the rice yield using DL and hyperparameter optimizers. To accomplish this, the TLBODL-RCYP technique involves three crucial processes: data preprocessing, HCRHNN based on prediction, and TLBO based on parameter tuning. Finally, the TLBO algorithm is utilized to adjust the hyperparameter values of the HCRHNN technique and thereby enhance the predictive results. The experimental outcome investigation of the TLBODL-RCYP approach is tested using the Kaggle dataset, and the outcomes assured the improvized predictive outcomes of the TLBODL-RCYP approach over other recent DL methods.

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