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Research paper

LSTM Modeling and Optimization of Rice (*Oryza sativa* L.) Seedling Growth using Intelligent Chamber

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Abstract

An intelligent growth chamber was designed in 2021 to model and optimize rice seedlings' growth. According to this, an experiment was implemented at Sari University of Agricultural Sciences and Natural Resources, Iran, in March, April, and May 2021. The model inputs included radiation, temperature, carbon dioxide, and soil acidity. These growth factors were studied at ambient and incremental levels. The model outputs were seedlings' height, root length, chlorophyll content, CGR, RGR, the leaves number, and the shoot's dry weight. Rice seedlings' growth was modeled using LSTM neural networks and optimized by the Bayesian method. It concluded that the best parameter setting was at epoch = 100, learning rate = 0.001, and iteration number = 500. The best performance during training was obtained when the validation RMSE = 0.2884.

1. Introduction

Rice (*Oryza sativa* L.) is one of the most important cereals, and is popular in Asia. Therefore, identifying the essential parameters for rice seedling growth and the best scheduling for rice planting is crucial [15]. The rice growth prediction is an essential research front of modern agriculture [9, 14].

Statistical and crop growth models are effective methods in agriculture to evaluate the effects of environmental parameters on agricultural production [6, 11]. Environmental monitoring in agriculture is significantly progressing through the development of artificial intelligence and the Internet of Things (IoT) technology. Monitoring technology of crop growth provides technical help for timely and accurate planting management [6, 13, 26]. Technologies like the IoT and machine learning improve production and increase profitability for farmers [16].

Machine learning is the science that allows computers to learn about a specific subject without the need for an explicit program. As a subset of artificial intelligence, machine learning algorithms create a mathematical model based on sample or training data to make predictions or decisions without overt programming [12]. An artificial neural network is a mathematical model inspired by biological neural networks. It models different aspects relevant to the behavior of the human brain such as smart processing of data, learning, generalization, adaptation, and high tolerance to inaccurate (or wrong) information [26]. The Recurrent Neural Network (RNN) is a well-constructed neural network for sequential data. The RNN algorithm is the first algorithm that uses internal memory to store its inputs. While traditional deep neural networks assume that inputs and outputs are independent, RNNs can remember significant received inputs, which helps them predict what will happen in the future due to their internal memory [24]. Thus the RNN performs well for sequential data such as time series, speech, text, financial data, audio, and video. The RNN can obtain a deeper understanding of the sequence and background knowledge of the inputs than other algorithms [2, 18]. Long Short-Term Memory

(LSTM) is an extension of the RNN that extends memory. As a result, this model is helpful for cases where learning occurs from experiences that have passed a long time ago [7, 8, 19].

Alhnaity *et al*. [1] studied machine learning and deep learning techniques to predict yield and plant growth variation in controlled greenhouse environments. They developed an LSTM model for tomato yield prediction and achieved high prediction accuracy. Their results represented that the deep learning technique using an LSTM model outperformed other traditional machine learning techniques, such as support vector machine (SVR) and Random Forest (RF), in terms of the Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) criteria. They suggested extending the deep learning method to perform multi-step growth and yield prediction in greenhouses. Castro Filho *et al*. [4] studied rice crop detection using LSTM, Bidirectional Long Short-Term Memory (Bi-LSTM), and machine learning models from time series. They illustrated that the RNN model is an advanced approach to recognize time-sequenced data. Also they showed that the Bi-LSTM and LSTM models achieve a better performance compared to the traditional machine learning methods. They proposed an RNN using the LSTM neuron architecture to model the targeted growth parameters. Jiao *et al*. [11] studied the prediction model of rice seedling growth and rhizosphere fertility and detected the relation between the circumstance element and growth. They designed a model of rice growth prediction based on the Elman neural network. The Elman neural network falls into the local extreme value, which leads to a significant deviation of individual points. They used a genetic algorithm to optimize the weight and threshold of their model. Moon *et al*. [17] predicted CO_2 concentration via LSTM using environmental factors in greenhouses. In a greenhouse with mango trees (Mangifera indica L. cv. Irwin), temperature, humidity, radiation, atmospheric pressure, soil temperature, soil humidity, and CO_2 concentration were measured using sensors. In this experiment, the LSTM neural network was designed to predict changes in CO_2 concentration from the present to 2 h later using historical data. They concluded that the LSTM model can be used to predict the future CO_2 concentration in greenhouses. Rizkiana *et al*. [20] studied plant growth using the artificial neural network with environmental parameter input and compared different network architectures. They showed that adding the number of nodes in the hidden layers increased the convergence effect and reduced errors. However, the over-addition of nodes decelerated the convergence and increased the network training time. Sakurai *et al*. [21] investigated plant growth prediction using convolutional LSTM to learn the long-term dependencies in plant growth based on images. They predicted the shape of leaves at the pixel level from the past pictures rather than only predicting the size of leaves. An encoder-decoder architecture of convolutional LSTM for learning video representation was proposed to predict future images from the past. Samiei *et al*. [22] studied deep learning-based detection of seedling development. They investigated various strategies of neural networks and concluded that the best results belonged to a deep neural network followed by the LSTM, which achieved more than 90% accuracy of correct detection. Tan *et al*. [23] investigated machine learning to detect the rice seedling growth stages. They demonstrated that deep learning methods could be an effective tool and help to identify the seedling growth stages. They described that rice seedling growth stages and performing operations such as temperature control, irrigation, and cultivation are significant in crop management. They stated that it is insufficient to manually investigate growth stages and environmental factors due to effects on growth stage variation. Machine learning algorithms could be used to estimate the growth stages of rice seedlings. They concluded that experiments should employ more cultivars, different crops, and more growth stages recognition and investigate other factors. Zhu *et al*. [27] suggested a prediction method of seedling transplanting time with the Densely-Connected LSTM (DCNN-LSTM) neural network based on the attention mechanism. They studied a prediction method with broad applicability to judge the time of cabbage transplanting based on the textual information of cabbage growth indicators and environmental factors. Based on their findings, the DCNN-LSTM model could extract high-level features of multi-dimensional data and have a better fitting for time series prediction.

This experiment investigated combinations of some main growth factors of rice seedlings using a designed growth chamber. Also this study aimed to propose an optimized growth model for automated rice nurseries with usability in similar climates of northern Iran. According to this, the LSTM models based on collected data were designed to achieve a shortened growth period and prevent damage due to adverse environmental conditions.

The rest of the paper is organized as follows. Section 2 contains the material and methods.

Section 3 contains the results and discussion. Section 4 contains the conclusions.

2. Material and Methods

To model the growth of rice (*Oryza sativa* L.) seedlings, a prototype of an intelligent growth chamber was made at the Sari Agricultural Sciences and Natural Resources University (SANRU), Iran, in 2021. The designed growth chamber was equipped with soil moisture, light, temperature, and CO_2 sensors. Also environmental control systems consist of heaters, fans, irrigation, and lighting systems embedded in the chamber. For the experiment, four environmental factors were considered including ambient and increased levels of carbon dioxide, radiation, temperature, and acidity. Sixteen different combinations of the factors were provided inside the growth chamber. During the implementation of the experiment, the environmental data were recorded by the embedded sensors and stored on the memory card connected to an electronic board (Arduino) for three 25-day periods of rice seedlings' growth in March, April, and May (Figure 1).

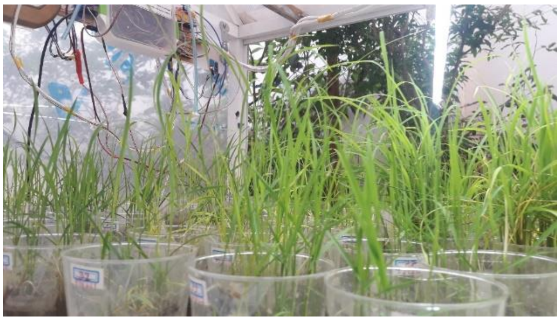

Figure 1. Intelligent growth chamber.

2.1. Data pre-processing

Data pre-processing and scaling are essential steps in neural network models. The main aim of data scaling is that many different features are considered in the same numerical scale or range [5].

Before the design and application of the LSTM model on a dataset, data were investigated for the presence of any non-numeric or missing values and specified that there were no non-numeric entries. The dataset was normalized to set all the values in a consistent range.

The normalization of the data was carried out by using a min-max scalar. Equation 1 shows the formula used for the normalization of data.

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

where z is a normalized value, x is a data value, min(x) is the lowest value in the dataset, and max(x) is the highest value in the dataset [3].

The processed data (inputs and outputs) were divided into train, test, and validation data. Each partition was used as input and output to train, test, and validate the model. Training samples were 640 rows of data for each of the nine input features.

2.2. Model parameters

The model inputs (16 groups) were arranged in a completely randomized factorial design with four replications (pots) (Table 1). The groups consisted of a combination of acidity in the two levels (6 and 7.5), temperature, radiation, and carbon dioxide at two levels (the ambient and elevated levels). All of the 64 pots contained Tarom Hashemi rice seedlings. The sensors measured the minimum, maximum, and average brightness and temperature every five days after extracting from the memory card. The gas sensor measured the concentration of carbon dioxide after injection in the controlled environment. The average values were considered for both incremental and ambient groups. Soil acidity was controlled by a digital pH-meter (with values equal to 6 and 7.5).

Measurements were done for three other five-day periods. The model outputs were morphological and physiological characteristics of rice seedlings containing Crop Growth Rate (CGR), Relative Growth Rate (RGR), root length, shoot height levels (minimum, average, and maximum), shoot's dry weight (oven-dried at 70 ^{o}C for 24 hr.), chlorophyll content, and number of leaves. The chlorophyll content was measured by a Spad502 Chlorophyll-meter.

CGR indicates the change in dry matter accumulation over a period of time. CGR will be measured by the following formula:

$$CGR = \frac{1}{A} \times \frac{w_2 - w_1}{t_2 - t_1} gm^{-2} day^{-1} \quad (2)$$

where w_1 = dry weight at t_1 of the period, w_2 = dry weight at t_2 of the Period, t_1 = time in date at the start of the period, t_2 = time in the date at the end of the period, and A = Area.

RGR is a measure used to quantify the speed of plant growth. It is measured as the mass increase per above-ground biomass per day and is considered to be used for plant growth estimation.

RGR will be measured by the following formula:

$$RGR = \frac{\ln w_2 - \ln w_1}{t_2 - t_1} mg \ g^{-1} day^{-1} \quad (3)$$

where t_1 = time one (in days), t_2 = time two (in days), w_1 = dry weight of plant at time one (in grams), w_2 = dry weight of plant at time two (in grams).

Table 1. Treatments groups.

Input factors	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16
CO_2									*	*	*	*	*	*	*	*
Temperature					*	*	*	*					*	*	*	*
Light			*	*			*	*			*	*			*	*
pH		*		*		*		*		*		*		*		*

* It means a 25% increase compared to the controlled environmental conditions.
G = Treatments group number

2.3. Model design

The proposed artificial neural network had three main layers (input, hidden, and output) (Figure 2). The model was obtained by detecting relationships between the input and output data in the neural network. The input layer received the raw data, which was processed and transferred to the hidden layer along with weights and biases that could solve complex functions. Information was passed from the hidden to the output layer (Figure 2).

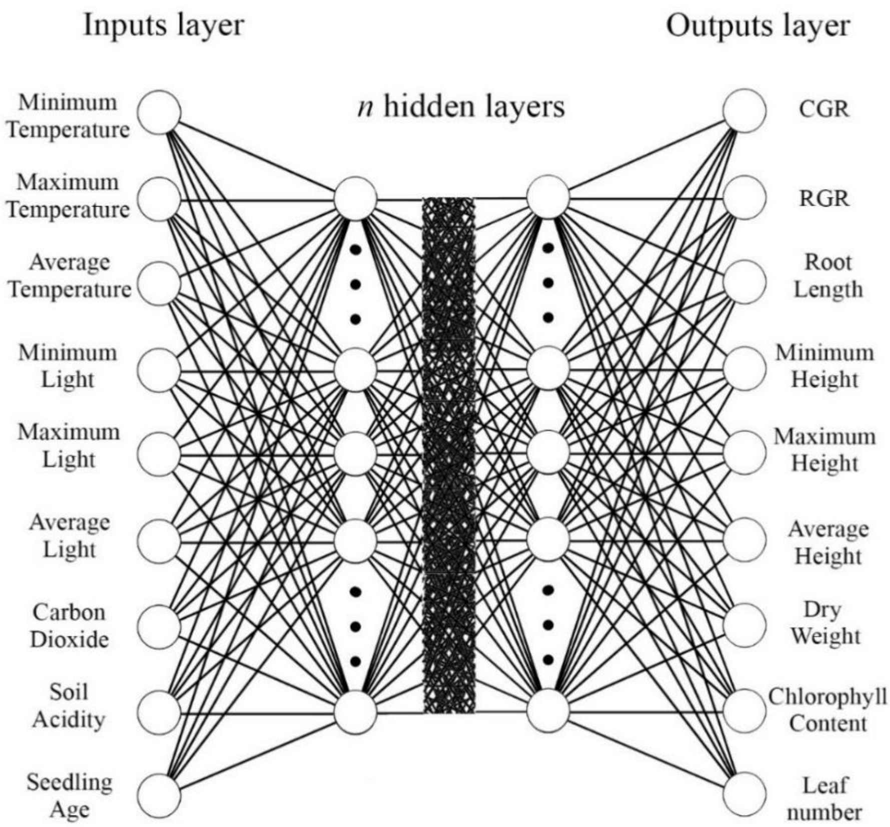

Figure 2. Structure of proposed neural network.

MATLAB numerical computing environment (version R2021a) was used to design and create an artificial neural network. Since the outputs of each period (5 days) could affect the next period, the reversible LSTM architecture was used in the modeling neural network.

The proposed model included a feature input layer, an LSTM layer with 128 hidden units, a layer for fully connecting neurons, and a regression output layer displayed as blocks in the MATLAB software (Figure 3).

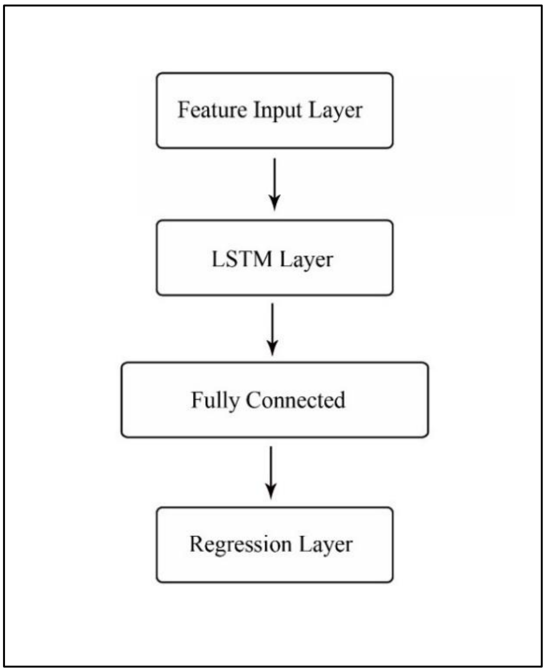

Figure 3. Model diagram.

Time-dependent data for each input and output parameter were divided into three sets: training (70%), validation (15%), and testing (15%) of all data. This study performed the training, validation, and test steps according to the designed algorithm. The algorithm performance was evaluated based on the RMSE and loss function. The mathematical expression for RMSE is in Equation 4:

$$RMSE = \sqrt{\frac{\sum_{1}^{n}\left(p_i - p_j\right)^2}{n}} \quad (4)$$

where p_i is a predicted value, a_i is an actual value, and N is the total number of values [10]. Lowering the RMSE values gives better results compared to the observed parameters.

Figure 4 shows the flowchart of the experiment execution process that indicates the experiment execution process initiated by designing and constructing the intelligent growth chamber and completed by the optimized model achievement.

The plan consisted of three independent periods of twenty-five days from seed sowing to seedling transplanting (the twenty-fifth day).

It takes about five days for the germination and emergence of the coleoptile seedling, and the first step starts on the fifth day after planting the seeds. There were four time steps (twenty days in total), and the duration of every time step was five days.

The plant's reaction to environmental conditions as the model output was measured on the tenth, fifteenth, twenty, and twenty-fifth days after planting. On the mentioned days, the average of the environmental growth factors in the previous five days was included as input to the model.

The first step started on the fifth day after sowing the seeds, and the measurements were done on the tenth day. Similarly, the second time step started on the 11th day, and the measurements were done on the 15th day.

The third time step started on the 16th day, and measurements were done on the 20th day. The fourth time step started on the 21st day, and measurements were done on the 25th day.

After collecting the data in three months, the LSTM modeling process was performed on five data cross-folds, and the best model was selected and optimized by the Bayesian method.

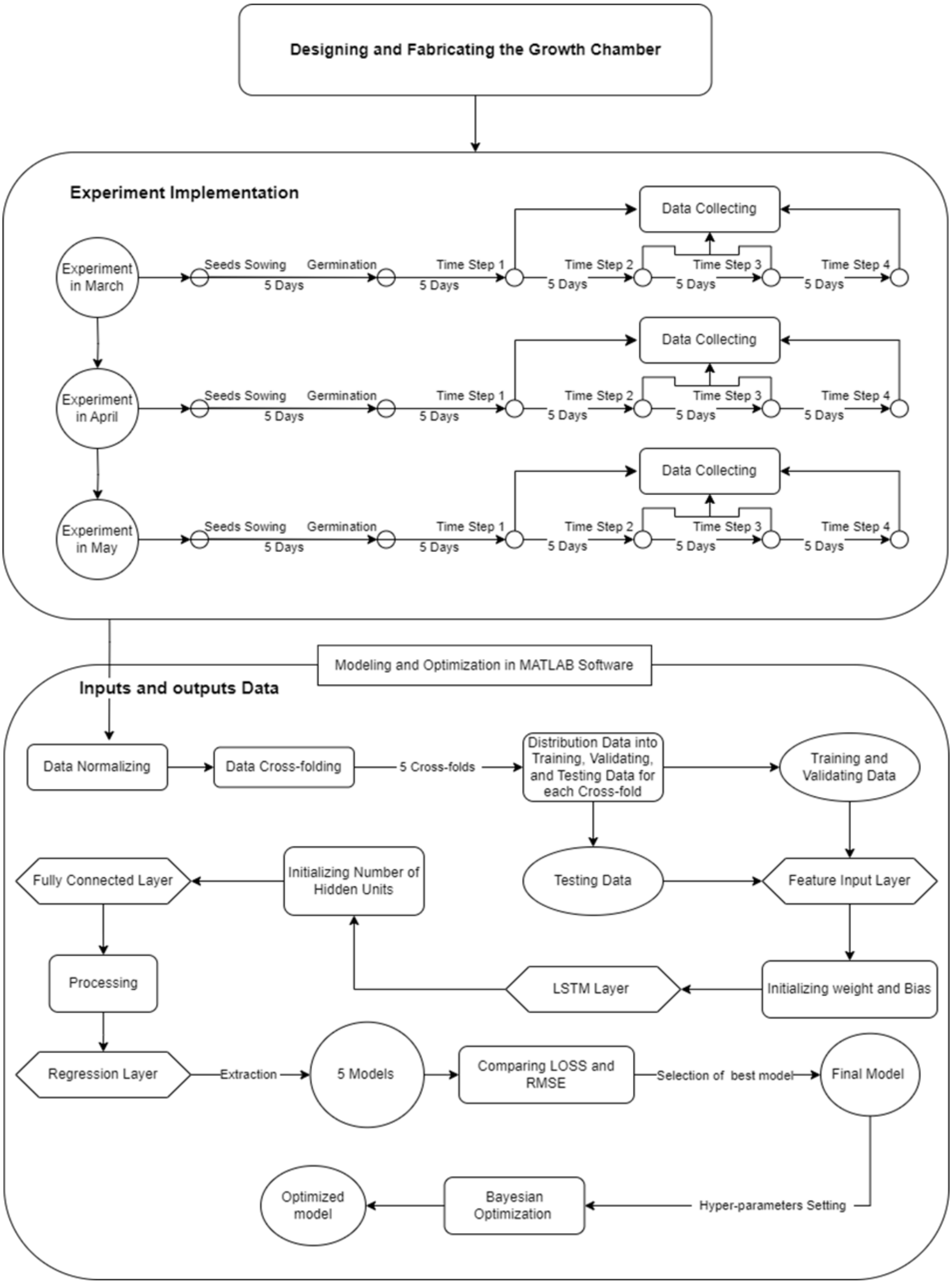

Figure 4. Flowchart of the experiment process (from designing to optimization).

3. Results and Discussion

After performing the experiment stages and input and output data collecting, the responses of rice seedlings against environmental factors were evaluated. Figures 5 and 6 show the sample of rice seedlings' reaction in terms of height average against fluctuations in radiation and temperature in four measurement periods in 16 experimental treatment groups (Table 1). Each of the growth factors was effective in the seedlings' growth, but their mutual effects and the environmental conditions determined the growth rate of the seedlings.

Due to cloudy conditions during some periods, the reduction of illumination and radiation entering the environment was partially effective in the growth rate of seedlings. However, the effect of temperature on the growth of seedlings and the difference in treatments is quite evident.

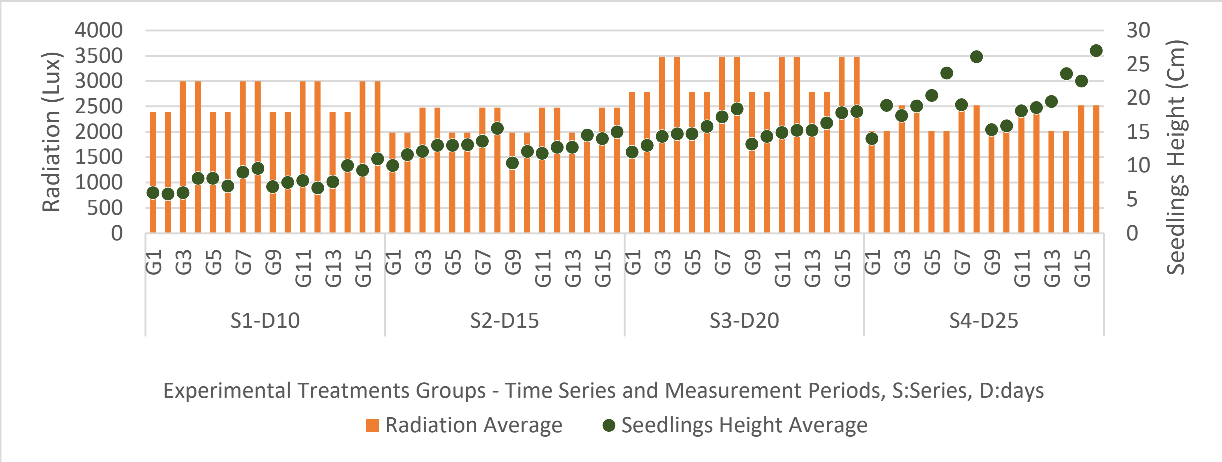

Figure 5. Seedlings height growth due to the influence of radiation fluctuations.

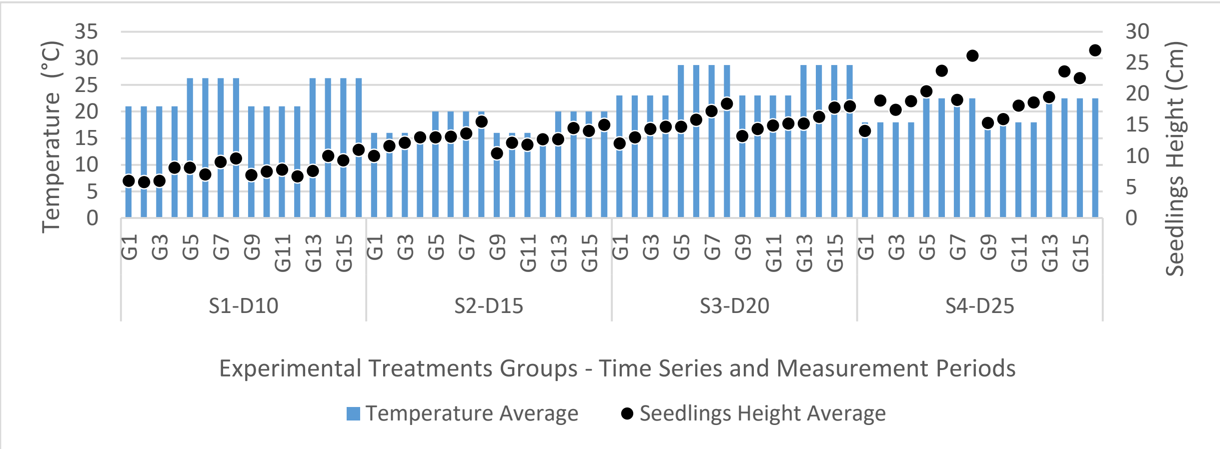

Figure 6. Seedling's height growth according to the influence of temperature fluctuations.

The learning parameters were determined consisting of input weight, bias, recurrent weight, and activation functions (Table 2). The dataset was randomly divided into five partitions (folds). Then each cross-fold was used to train, validate, and test phase. The modeling was repeated five times by each of the cross-folded data to check the stability of the built neural network models. The diagrams of RMSE and loss for five models were displayed (Figures 7 and 8).

Table 2. Deep learning network analyzer.

Name	Type description	Activations	Learnable	Total learnable
Feature input	Feature Input layer	9	-	0
LSTM	LSTM layer	128	Input weights 512 × 9 recurrent weights (512 × 128) Bias (512 × 1)	70656
fc	Fully connected layer	9	Weights (9 × 128) Bias (9 × 1)	1161
Regression output Mean squared error	Regression output layer	9	-	0

Based on the results, the best performance in these experiments could be seen in cross-fold 2 with Epoch = 100, learning rate = 0.001, RMSE = 0.2884, and MSE = 0.0832 (Table 3).

Table 3. Observed RMSE and MSE in the five models training.

Cross-fold	RMSE	MSE
Cross-fold 1	0.3291	0.1083
Cross-fold 2	0.2884	0.0832
Cross-fold 3	0.3307	0.1093
Cross-fold 4	0.4291	0.1841
Cross-fold 5	0.3530	0.1246

Epoch = 100, learning rate = 0.001

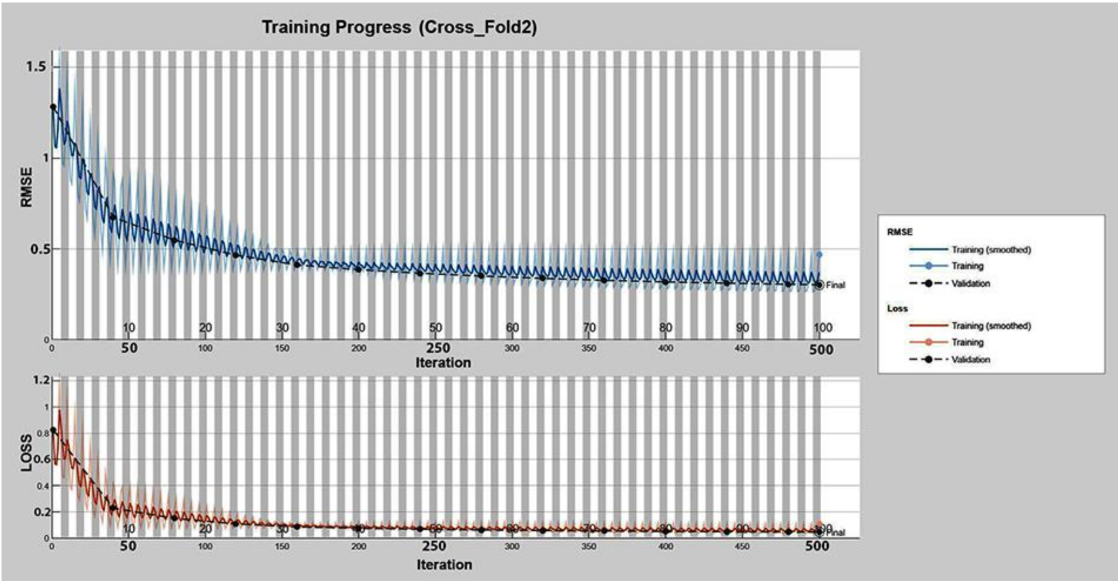

Figure 7. Training progress for cross-fold 2.

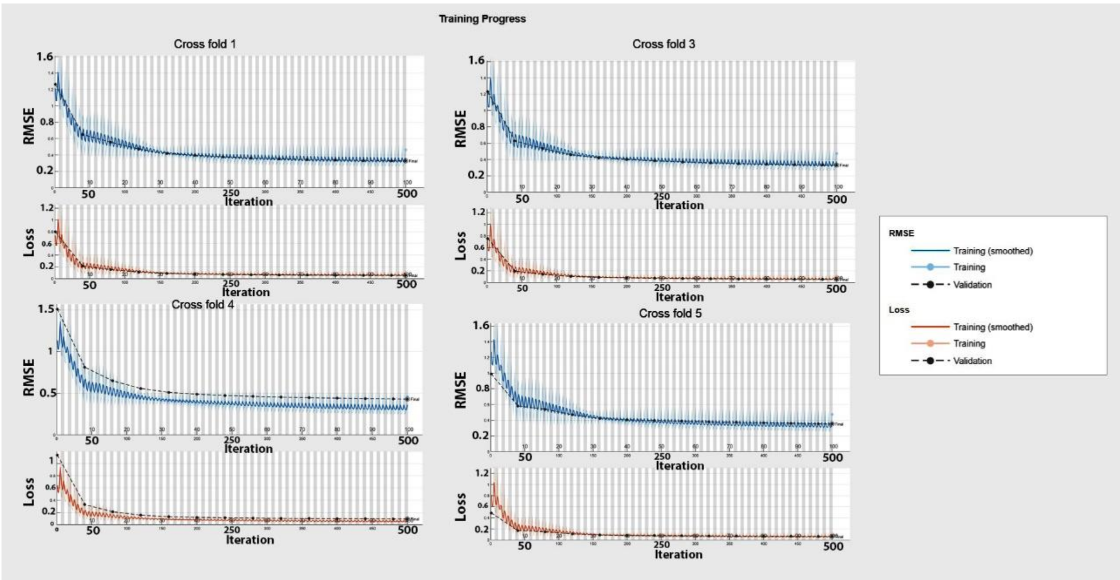

Figure 8. Training progress plots.

It concluded that the best parameter setting was at epoch = 100, learning rate = 0.001, and the number of iterations = 500. The parameter settings results were shown on the graphs of the RMSE and loss models (Figures 7 and 8). The diagram showed that the training loss and RMSE decreased, indicating that the model was well-trained. The smaller the RMSE values, the better the system efficiency.

Among the designed models, cross-fold 2 showed the best performance during training when the validation RMSE was equal to 0.2884. The five graphs comparison (Loss and RMSE) concluded that there was relative stability between these models, which validated the modeling. The proposed model has the learning ability of time-dependence data.

3.1. Optimization of designed models

The performance of the LSTM neural network depends on hyperparameter settings. Therefore, correct adjustment of the hyperparameters causes good performance of the LSTM neural network. Hyperparameters such as learning rates and the number of units per layer affect the accuracy of the LSTM neural network. Finding the optimal settings of the hyperparameter by a manual approach can be difficult and time-consuming. Bayesian optimization is the suitable approach to optimize hyperparameters in various machine learning algorithms [25].

This study used Bayesian optimization and determined hyperparameters consisting of Threshold, LSTM depth, the number of hidden layers of neural network (NumHiddenUnits), and initial learning rate to optimize the designed model. With 300 trials for each cross-fold, the best trials were selected (Table 4). The best performance was obtained in cross-fold 2 when the validation RMSE = 0.2626 and loss = 0.0345.

Bayesian optimization in the Experiment Manager MATLAB environment is shown in Figure 9. The graphs were drawn and displayed after 300 executions. Based on the results, the proposed model in this study showed a good learning ability in analyzing seedlings' growth data.

Table 4. Optimization results.

Model	Best trial	Threshold	LSTM Depth	Initial learn rate	Training RMSE	Training loss	Validation RMSE	Validation loss
Cross-fold 2	186	200	1	0.0197	0.4086	0.0835	0.2626	0.0345

Figure 9. Bayesian optimization result for cross-fold 2.

The results of MAE, RMSE, and Mean Absolute Percentage Error (MAPE) on the testing dataset under different models are shown in Table 5. The values of MAE, RMSE, and MAPE according to the LSTM were lower than the other models, and the Bi-LSTM was higher than others. When using the Bi-LSTM model, MAE is 0.0690, RMSE is 0.2913, and MAPE is 0.7512 higher than the LSTM. When using the Gated Recurrent Unit (GRU) model, MAE is 0.0683, RMSE is 0.2902, and MAPE is 0.7500 higher than the LSTM. GRU is an improved variant of LSTM. However, the LSTM model performance was better than GRU in this experiment and showed a strong correlation between actual and predicted values.

Table 5. MAE, RMSE, and MAPE on the cross-fold 2 dataset.

Model	RMSE	MAE	MAPE
LSTM	0.2884	0.0670	0.7409
Bi-LSTM	0.2913	0.0690	0.7512
GRU	0.2902	0.0683	0.7500

4. Conclusion

According to this study, LSTM neural networks based on regression were proposed to model rice (*Oryza Sativa* L.) seedlings' growth. The models were designed to shorten the growth period and prevent damage due to adverse environmental conditions. The methods of this research work include real-time analysis of rice seedlings using IoT, selecting effective parameters, LSTM neural network modeling, optimizing, and making decisions intelligently. Two approaches were considered in the modeling process regarding the factors affecting the growth of rice seedlings: first, investigating the reaction of seedlings to environmental conditions according to their age, and secondly, the effect of phenology and situations of seedlings on their growth in the following stages. These approaches highlighted the need to use time-dependent RNN modeling. The LSTM model helped increase the accuracy considering the environmental conditions that can be different in each period during the rice seedling growth period. For future studies, it is suggested to investigate the model in different climatic conditions by considering other factors and the response of other rice varieties to environmental conditions.

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مدل‌سازی LSTM و بهینه‌سازی مدل رشد گیاهچه برنج (*Oryza sativa* L.) در محیط کنترل هوشمند

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چکیده:

به منظور مدل‌سازی و بهینه‌سازی الگوی رشد گیاهچه برنج، یک اتاقک رشد هوشمند در سال ۱۳۹۹ طراحی و آزمایشی در دانشگاه علوم کشاورزی و منابع طبیعی ساری در ماه‌های اسفند، فروردین و اردیبهشت سال ۱۴۰۰-۱۳۹۹ انجام شد. ورودی‌های مدل شامل تشعشع، دما، دی اکسید کربن و اسیدیته خاک بودند. این عوامل رشد در دو سطح محیطی و افزایشی مورد مطالعه قرار گرفتند. خروجی‌های مدل شامل ارتفاع گیاهچه، طول ریشه، محتوای کلروفیل، CGR، RGR، تعداد برگ و وزن خشک اندام هوایی بودند. رشد گیاهچه برنج با استفاده از شبکه‌های عصبی LSTM مدل‌سازی و با روش بیزین بهینه‌سازی شد. بر اساس نتایج حاصل از اجرای آزمایش بهترین تنظیم پارامتر در دوره ۱۰۰ با نرخ یادگیری ۰,۰۰۱ و تعداد ۵۰۰ تکرار به دست آمد. همچنین برای بهترین عملکرد بدست آمده در طی آموزش مدل، RMSE برابر ۰,۲۸۸۴ بود.

کلمات کلیدی: دما، شبکه‌های عصبی بازگشتی، نرم افزار متلب، نور، هوش مصنوعی.