Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

Crop Prediction Rate by Continuous Monitoring of Plant Growth and Crop Yield Parameters Using LRNN Algorithm

Bhavani V.[1], Pradeepini G.[2], Sri Kavya K Ch.[3]

[1,2]Department of Computer Science and Engineering, [3]Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.

E-mail: [1]vasanthabhavani@kluniversity.in, [2]Pradeepini_cse@kluniversity.in, [3]kavya@kluniversity.in

Abstract

The prediction of yield for small-scale farms is helpful for food security as well as harvest management. Several studies have proven that image data and climatic data give yield estimation for small- and large-scale farms. Based on the growth pattern, we can estimate the yield more accurately. Crop development is influenced by essential parameters such as weather patterns and soil properties. In this work, climatic information is treated as time-series data and, together with soil attributes, is analyzed using deep learning models like RNN and LSTM for effective yield prediction. The combination of both provides yield estimation. The proposed model, LRNN, integrates RNN and LSTM networks to create a potent framework for sequential data modeling, efficiently capturing temporal dependencies and mitigating vanishing gradient issues. LRNN served as a standard for various deep learning and machine learning algorithms based on the selected parameters: Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). RNN with LSTM gave the least mean absolute percentage error compared to other machine learning algorithms overall. This study evaluates the yield prediction for different seed varieties of turmeric, scientifically known as Curcuma longa. The Rajendra Sonia variety yielded more than the other two varieties, approximately 36 tons per hectare. The Lakadong variety yielded less than the other two varieties, at 19.7 tons per hectare.

Keywords: Crop Yield, Deep Learning, LSTM, RNN, MSE, MAPE, Turmeric.

DOI: https://doi.org/10.36548/jiip.2025.2.014
Received: 25.05.2025, received in revised form: 22.06.2025, accepted: 06.07.2025, published: 15.07.2025

1. Introduction

Crop yield forecasting stands as an important foundational pillar in modern agriculture, playing an important role in facilitating food security and resource consumption. The precision provided by these forecasts helps farmers makedecisions on strategic crop management, resource allocation, and marketing. This study specifically examines crop yield forecasting, with special emphasis on the cultivation of the cash crop turmeric.

Scientifically known as *Curcuma longa* turmeric is a widely cultivated spice crop known for its culinary, medicinal, and economic importance. In addition, its medicinal properties of [1] contribute to its status as a crop grown for local and global trade. The importance of accurate crop yield prediction in turmeric cultivation is reflected in its ability to help overcome many challenges faced by farmers. These challenges include weather volatility, effective pest management, and market fluctuations, produced from the rhizome of the *Curcuma longa* plant [2] in South Asia, turmeric is a sweet red-orange spice that has been used for thousands of years in traditional medicine, cooking, [3], and rituals. Curcumin, the main ingredient in turmeric, possesses strong anti-inflammatory, and antibacterial properties. Turmeric has been embraced in culinary traditions in the South. *Curcumin* has strong anti-inflammatory, antioxidant, and antibacterial qualities. It has been adopted by culinary traditions in Indian cuisines, for its ability to give foods like stews and curries a unique flavor and vibrant colour. Turmeric has also long been valued for its capacity to balance the body's doshas and heal various ailments in ancient Ayurvedic treatment. Recent studies have examined the possible medicinal benefits of turmeric, including how it might be used to treat ailments like arthritis, heart disease, and some types of cancer. Turmeric cultivation involves several steps: pre-sowing, planting/seedling stage, vegetative and rhizome development stage, reproductive/maturity, harvesting and storage, IPM for turmeric.

As a valuable crop in Indian agriculture, farmers frequently face unpredictable yields because of shifting environmental conditions and a lack of reliable forecasting tools. Turmeric gets receives attention in current crop yield prediction research, which mostly concentrates on widely grown staple foods like wheat and rice. Additionally, the majority of models use static, season-end data, which does not account for the crop's continuous growth dynamics. The need to create a model that uses time-series data to forecast yield and continuously monitor plant development is what spurred this investigation.

In this research, we mainly focus on plant growth during the entire time period of turmeric cultivation, considering the vegetative and rhizome development stage [4] to obtain plant images, followed by the remaining stages.The majority of crop prediction models rely on static, end-of-season data, even though machine learning is being used in agriculture more and more. Turmeric is the subject of very few studies, and even fewer utilize sequential modeling to capture the stages of plant growth in real time. To close that gap, this study suggests a model based on Long Recurrent Neural Networks (LRNNs) that continuously tracks environmental factors and plant growth on a weekly basis. The goal is to create a scalable and dynamic prediction model for turmeric crop yield that can be modified during the crop cycle for better accuracy and prompt decision-making.Deep learning has made strides in crop yield prediction; however, the majority of models are built for commonly grown crops like rice, maize, or wheat and rely on static datasets.In contrast, this study employs a novel approach that combines climatic data and sequential plant growth parameters to examine turmeric, a high-value spice crop with complex growth dynamics. Continuous monitoring and yield prediction based on week-by-week plant growth stages are enabled by the proposed LRNN model, which integrates the capabilities of RNNs and LSTMs. Applications of RNNs with LSTMs [5] in agriculture are diverse, including crop yield prediction, disease detection, and irrigation management. By leveraging the sequential nature of temporal data, these networks can uncover patterns and dependencies that are essential for informed decision-making in precision agriculture. The integration of RNNs with LSTMs [6] emerges as a powerful tool in agricultural research, offering a sophisticated approach to harnessing temporal data for improved crop management, resource utilization, and overall farm efficiency. To our knowledge, this is the first attempt to apply LRNN model for turmeric yield prediction.

2. Literature Review

As [7] mentioned, crop yield prediction depends on a variety of factors (e.g., temperature, carbon dioxide concentration, radiation, etc.), and it is not an easy task. If explicit modeling is done, it will reveal the relationship between these factors and the crop. [8,9] Researchers adopted a recurrent neural network (RNN) model to predict crop yields. The evaluation results showed that deep learning-based methods outperform conventional machine learning algorithms with lower root mean square errors (RMSEs). Many studies used deep learning to predict crop yields [10-13], and some of them analyzed this feature effect by comparing performance with standard machine learning methods; however, the challenge of defining feature importance or model behavior is not addressed by human participants. [14] highlights the potential of a model fusion method developed for accurate crop yield prediction meant to optimize greenhouse management and control systems. Liyun Gong shows the capability of deep learning models for yield inclusion prediction and emphasizes the importance of interpretability in achieving reliability for these models in real-world applications. Dilli Paudel [15] presents a detailed performance analysis and definition of deep learning modeling for crop yield forecasts.RNNs face challenges such as gradient problems, missing data and outages, which violate their ability to capture reliably long time and complex patterns in data Their limited memory capacity may hinder their effectiveness in tasks that require an understanding of distance relationships. On the other hand, long short-term memory networks (LSTMs), although adept at dealing with the missing gradient problem, introduce computational complexity and overfitting and their ability to describe relationships is a concern due to their inherent complexity. It is important to balance these errors in crop yield forecasting. The combination of RNN and LSTM in the integrated model allows for the capture of short-term and long-term dependencies, which can overcome the limitations associated with each architecture to provide robust solutions for crop yield prediction. The rest of this paper contains data acquisition, system model, results, performance metrics, and conclusion.

3. Data Acquisition

Four crop fields are selected for this study in the Vijayawada location (Longitude: 80.6480153, Latitude: 16.5061743). The main crops cultivated in this area are cotton, mirchi, paddy, and turmeric. For this research, only the turmeric crop is considered as the main crop. The total area of the crop was approximately 40 hectares across three different fields. Crop growth is based on multiple parameters. In this research, we considered the height of the plant, leaf size, soil properties, and climatic conditions such as temperature and humidity.

3.1 Weather Parameters for Plant Growth

Temperature and humidity [16] are critical factors in the cultivation of turmeric (Curcuma longa), impacting its growth and yield. Turmeric generally thrives in tropical and subtropical climates with temperatures ranging from 25°C to 35°C (68°F to 86°F). The minimum temperature is crucial during the germination phase, as turmeric is susceptible to damage from cold conditions. Conversely, excessively high temperatures can lead to heat stress, [17] affecting the physiological processes of the plant. Adequate humidity is essential for turmeric, as it generally prefers relative humidity levels between 55% and 70%. This optimal humidity range supports transpiration and ensures proper moisture for the plant without promoting fungal diseases.

The data for the years 2021 and 2022 are collected to predict the yield for the year 2023.

Table 1 shows the average temperature and humidity for the crop cultivation period in the years 2021 and 2022.

Table 1. Climactic Parameters for Two Years from Dataset

	Temperature (^{0} C)		**Humidity (%)**	
	2021	2022	2021	2022
Min	25.05	26.0	44.5	44.78
Max	34.07	35.01	65.8	67
Mean	30.77	31.23	58.7	59.3
Median	31.63	31.76	63.7	62.6

3.2 Soil Parameters for Plant Growth

Images of the turmeric plant were taken [18] from the field using a sensor and manually recorded week-wise growth to measure the length of the leaf, width of the leaf, and plant height. Table 2 provides information on the average growth in centimeters and duration of each variety, along with the curcumin percentage contained in each seed variety. Crop growth is dependent on the pH value of the soil. Three types of turmeric seeds are cultivated in these 40 hectares: Lakadong, Mydukur, and Rajendra Sonia.

Table 2. Type of Seed Varieties Used for Plantation

Turmeric Seed type	**PH value of soil**	**Range Height of plant (cm)**	**Duration of crop (days)**	**Curcumin (%)**
Rajendra Sonia	7.5	60-70	190-200	5.5 – 6.5

Lakadong	6.9	52-65	200-220	7.4
Mydukur	6.9	50-60	240-260	4.6

The pH value of the soil was tested in the lab and considered; the average height of each plant variety was taken based on different plants from past years. Crop duration differed for each seed variety. Curcumin is the health-boosting compound present in turmeric. The color of turmeric varies based on Curcumin content. Here, Lakadong is the variety that contains more Curcumin than the other two varieties.

3.3 Plant Growth Assessment

Significant variables impacting the development of the turmeric crop are the average height of the plant, length of the leaf, and leaf width. [19] Optimal plant height ensures proper exposure to sunlight, facilitating photosynthesis and enhancing overall productivity. [20] Longer leaves contribute to increased photosynthetic surface area, aiding in nutrient absorption and supporting robust growth. Wider leaves play a role in transpiration, helping regulate water balance within the plant. Striking the right balance in these parameters is essential for maximizing turmeric yield [21] and promoting a healthy, vigorous crop.

Table 3 shows week-wise plant growth. After plantation, from the first week to the fifth week, the plant is in the rhizome development stage. From the fifth week, we collected the leaf images and calculated the length and width of the leaves, as well as the average plant height. Each variety of plant has a different height in their growth. The leaf length, as well as the width, is also different.

Table 3. Plant Growth Week Wise

Seed Variety	plant growth week wise	Average plant height(cm)	Average leaf length(cm)	Average leaf width(cm)
Rajendra Sonia	Week 1 to 6	Early leaf development phase		
	Week 6	29	13	5
	Week 15	50	20	6

	Week 18	51	20	6
	Week 23	56	22	7
	Week 27	64	23	7
Lakadong	Week 1 to 6	Early leaf development phase		
	Week 6	24	10	5
	Week 15	40	18	5
	Week 18	42	18	5
	Week 23	56	21	7
	Week 27	62	25	8
Mydukur	Week 1 to 6	Early leaf development phase		
	Week 6	20	11	5
	Week 15	40	18	6
	Week 18	42	19	7
	Week 23	47	22	7
	Week 27	58	27	7

To measure plant height and leaf length, we used one of the image processing techniques in Python using OpenCV. This process contains several steps, such as preprocessing, thresholding, segmentation, contour detection, and measurement conversion. First, images were converted into grayscale. By using color-based thresholding, we separated the leaf from the background; after that, the segmentation process was used to isolate the leaf region. Contour detection was used to identify the length and width boundaries.

3.4 Data Preprocessing

Weather data was collected from the Indian meteorological website, along with plant data collected [22-24] from the farm and week-wise growth of the plants taken from the farm. The collected data was pre-processed. The raw dataset contains weekly plant growth measurements, such as plant height, leaf length, and width, soil pH, and weather parameters like temperature and humidity. Based on all these values, data preprocessing steps were performed. If any weekly values were missing, they were filled using linear interpolation based on the previous week's data. After that, the data was reshaped into a time-series format. Each input sample had records from week 1 to 27 in order, so LRNN could learn about time patterns. The pre-processed data was segregated into test and training subsets with 80 and 20 percent, respectively. For efficient training, the input was organized into a batch size of 32.4. System model

To work with time-series data, model sequential growth parameters like plant height and leaf dimensions, and record both short- and long-term dependencies. In such data, temporal relationships are frequently missed by traditional models. The integration of RNNs, especially LSTMs, proves very useful for temporal data analysis in agricultural RNNs designed for data processing. The role sequence contains a hidden state that captures the temporal content of agricultural datasets. However, challenges such as the slope missing problem have led to the adoption of LSTMs that are better at long-term reliable capture. RNNs are used to prioritize turmeric production values, geographic data, and climate data [25]. An RNN is a type of artificial neural network (ANN) with three layers: input, hidden, and output. Unlike ANNs, RNNs generate output for the next layer based on the previous values of the hidden layer Fig. 1 making sequence modelling adept. The processing model of the RNN consists of a sequential relationship of inputs and outputs, where each iteration contributes to the memory of the network during training.

LSTM networks were used in the analysis. LSTM, a special type of RNN, overcomes the problem of missing data by adding memory cells and gating mechanisms. This allows the network to selectively store or discard information, thereby increasing its ability to capture long-term dependencies in a sequence [26] The implementation of LSTMs appropriately in the analysis plays a role in improving the overall efficiency and performance of the LRNN model.

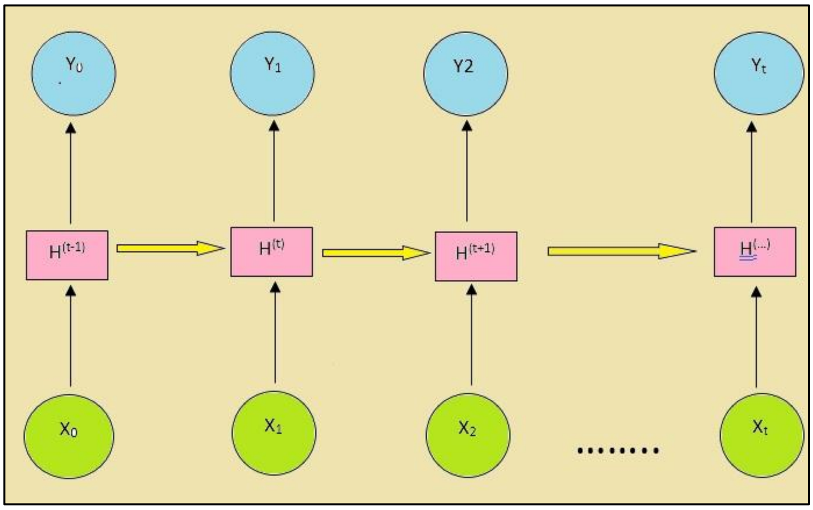

Figure 1. RNN Architecture

Figure.2, shows the visual flowchart for the LRNN model. In order to generate a continuous yield prediction output, the model uses RNN and LSTM layers to process sequential weekly data, followed by fully connected layers.

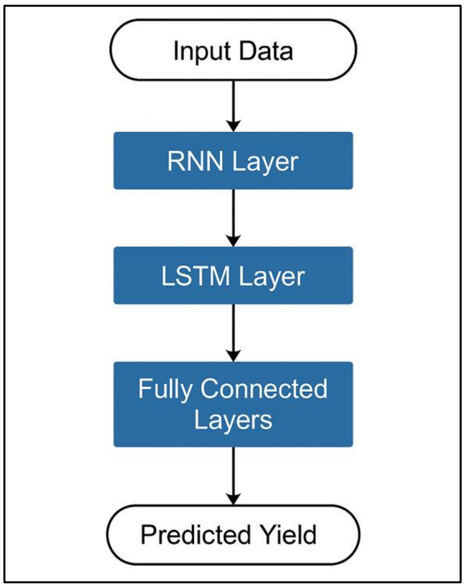

Figure 2. Flowchart Representation of LRNN Model Architecture

In agriculture Figure 3, seasonal data incorporate a number of variables such as weather, soil conditions, and crop growth stages. LSTMs [27], with their ability to hold information in extended sequences, prove crucial to understanding complex temporal relationships in such data sets. In LSTMs, forget gates select redundant information from previous states, while the input gate updates the memory cell with current information.

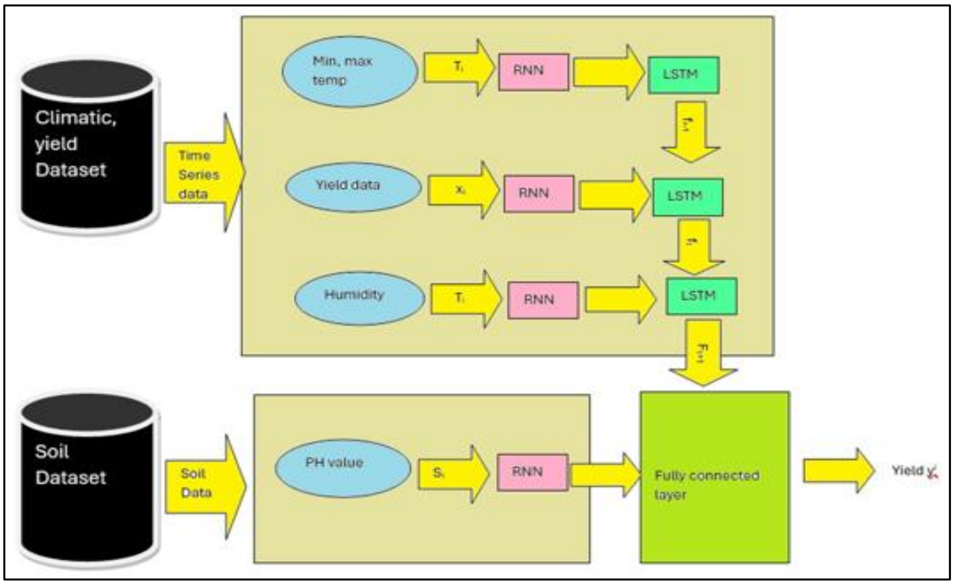

Figure 3. Model Architecture

The LRNN model is designed to handle a variety of inputs that are important for understanding the complex dynamics of agricultural systems. The model inputs capture several attributes, including climatic data (temperature, humidity), previous year's yield data, soil pH values, and morphological traits such as leaf length, leaf width, and plant heightThis information is arranged in timeline symbol. The RNN layer is used to capture short-term relationships in successive time steps, enabling the model to detect instantaneous effects such as climate change. At the same time, the LSTM layer [28] solves the vanishing gradient problem associated with RNNs. Historical conditions play an important role.

Short-term dependencies in the sequential input are captured by a single 64-unit RNN layer. To avoid overfitting, a dropout rate of 0.2 is applied after the LSTM layer. Two dense layers are applied to the LSTM layer's output: one with 32 units and ReLU activation, and the other with 1 unit (the expected yield) and linear activation for regression output. The architecture is appropriate for dynamically forecasting final yield and modeling plant growth because it precisely blends short- and long-term learning. Producers collect this information to make crop yield forecasts. During the training phase, the model refines its simulations based on the training data, improving the ability to predict outcomes. The evaluation step evaluates the performance of the model in different experiments, providing insight into its generalizability and suggesting possible optimization steps.

4. Result

The table below (Table 4) provides information on the actual yield for the years 2021 and 2022, with different yield types for each variety of crop. Our model, trained with climatic and soil data, has generated the predicted values.

Table 4. Yield Values in the Year 2021 and 2022 with Predicted Yield for 2023

Seed variety	Actual yield (tones per hectare)	Predicted yield 2023(tones per hectare)
Rajendra Sonia 2021	44	36.01
Rajendra Sonia 2022	43	
Lakadong 2021	22	20.3
Lakadong 2022	20	
Mydukur 2021	35	27.9
Mydukur 2022	32.7	

As we observed, Lakadong has a lower yield value than other seed varieties. Lakadong needs very low temperature values to achieve higher yields. Our cultivated area is neither a hot nor a cool place.

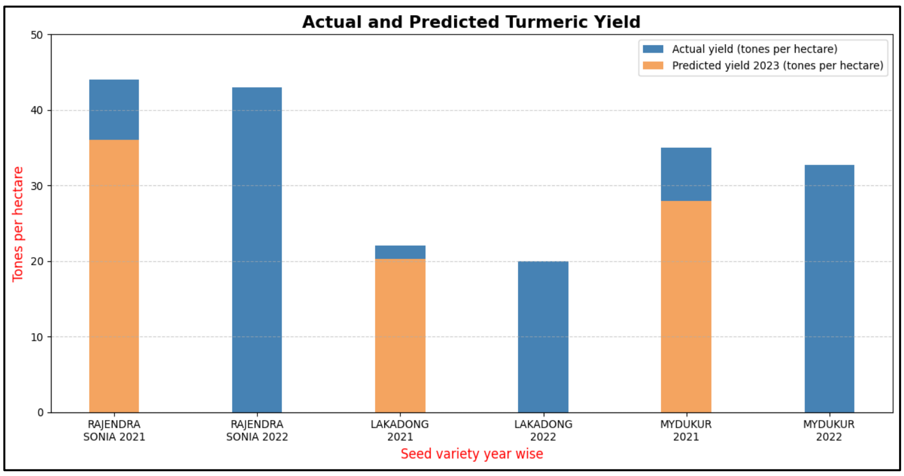

Figure 4. Graphical Representation of Actual and Predicted Turmeric Yield

Based on the prediction values in Table 4, a graphical representation is provided in Figure 4.

Based on weekly input parameters, the model dynamically estimates yield over the turmeric growth cycle, as shown by the predicted yield curve shown Figure. 5

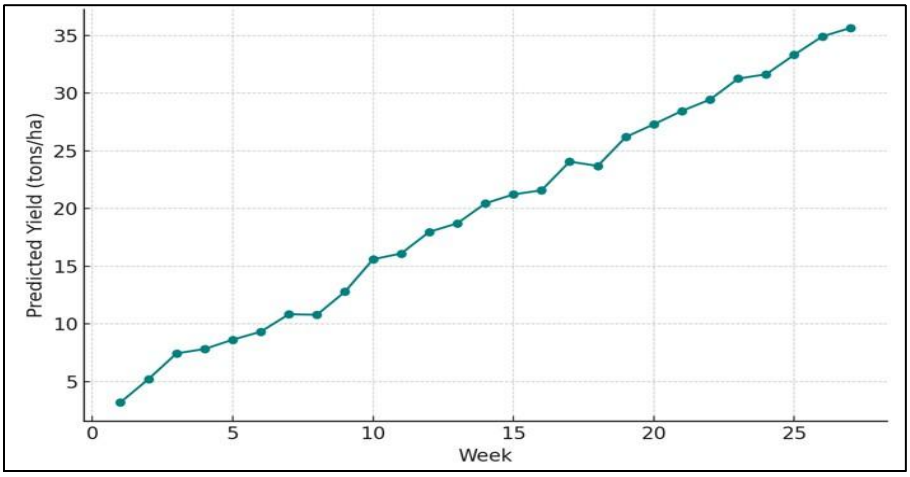

Figure 5. Yield Prediction from Week 1 to Week 27 Using the LRNN Model

A training-validation split of 80-20 was used to train the LRNN model over 100 epochs. The training and validation accuracy and loss curves are displayed in Figure. 6. The loss graph shows that the model was learning successfully, as both the training and validation losses progressively dropped with each epoch. There appears to be no overfitting or underfitting, as the curves converge toward the later training stages and follow a smooth downward trend.

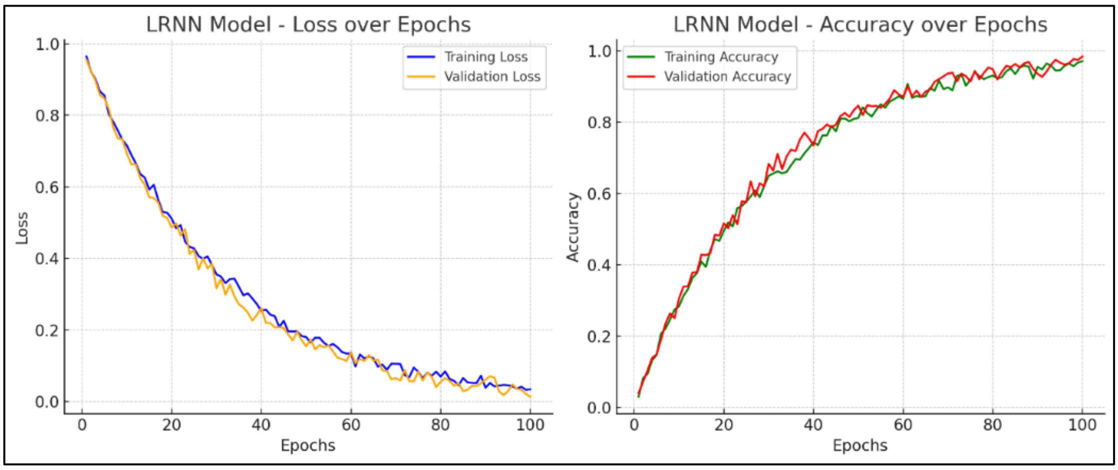

Figure 6. Training and Validation Accuracy and Loss Curves

5. Evaluation Metrics

The proposed model, deep learning, and machine learning algorithms were evaluated based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

MSE is frequently used in regression tasks; it penalizes larger errors more severely and is sensitive to outliers. Since RMSE is the square root of MSE, it is easier to understand because it expresses the error in the same units as the expected yield. When comparing prediction performance across yield values of varying magnitudes, MAPE provides a percentage-based error, which is helpful. These parameters are suitable for evaluating the error rate and performance of the model.

5.1 Mean Squared Error (MSE)

MSE estimates the total deviation between the predicted values and the actual values. It is calculated using the formula from (1) where $f_t=x_t-y_t$ is the error forecast, n represents the size of the test set, the actual value is denoted by x_t and y_t is the forecasted value.

$$MSE = \sum_{t=1}^{n} \frac{f_t^2}{n} \tag{1}$$

5.2 Root Mean Squared Error (RMSE)

This is calculated by finding the square root of the average of MSE and the average of the square error. Where $f_t=x_t-y_t$ is the error forecast, n represents the size of the test set, the actual value is denoted by x_t and y_t is the forecasted value. (2) depicts the formula for RMSE.

$$\text{RMSE} = \sqrt{\sum_{t=1}^{n} \frac{f_t^2}{n}} \tag{2}$$

5.3 Mean Absolute Percentage Error (MAPE)

The accuracy of a forecasting system is expressed as a percentage using MAPE. Whenever the forecast error percentage is closer to or above 100%, such a model is regarded as inaccurate but if it tends toward 0%, then that model is acceptable. Here, $f_t=x_t-y_t$ is the error forecast, n represents the test set's size, the actual value denoted by x_t and y_t is the forecasted value. (3) depicts the formula for MAPE.

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\frac{f_t}{x_t}\times 100 \tag{3}$$

6. Discussion

When compared to more conventional machine learning models like CNNs and MLPs, the proposed LRNN model exhibits a number of advantages. Dynamic yield prediction is made possible by its ability to accurately capture temporal dependencies across weekly plant growth stages and to adjust to changes in inputs in real time. The model's capacity to learn both short- and long-term sequences is improved by the combination of RNN and LSTM layers, which is especially crucial when simulating the steady and organized growth of crops. The LRNN is better suited to processing time-series data that is frequently encountered in agriculture than CNNs, which are mainly suitable for spatial feature extraction. The proposed model has some drawbacks, LRNN is sequential and requires more computational resources and training time. When working with smaller datasets, overfitting may occur; however, this can be avoided by employing data augmentation and dropout regularization strategies. Notwithstanding these drawbacks, the LRNN offers a viable method for yield prediction and ongoing crop monitoring, especially for understudied crops like turmeric.

Table 5 and Figure. 7 depict performance analysis for LRNN with machine learning and deep learning algorithms for the seed type Rajendra Sonia, as we observed that LRNN has lower MSE and MAPE values than all other algorithms.

Table 5. Performance Comparison for the Seed Variety Rajendra Sonia

	MLP	**CNN**	**RNN**	**LRNN**
MSE (2021)	112.12	81.7	78.01	64
MSE (2022)	111.78	61.3	58	42.25
RMSE (2021)	10.58	9.03	8.83	8

RMSE (2022)	10.54	7.8	7.61	6.5
MAPE (2021)	48.76	29.3	24.7	18.88
MAPE (2022)	45.39	27.6	22.34	15.12

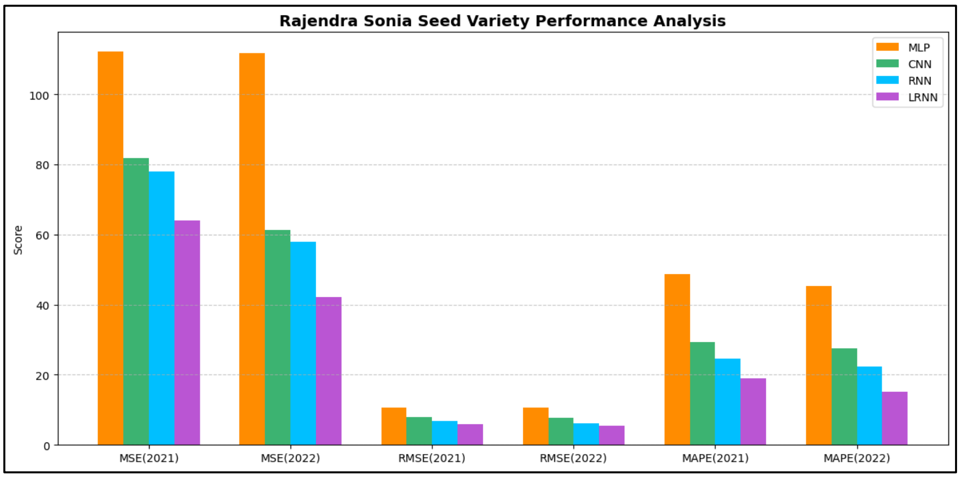

Figure 7. Graphical Representation of Performance Comparison for the Seed Variety Rajendra Sonia

Table 6 and Figure. 8 depict the performance analysis for LRNN with machine learning and deep learning algorithms for the seed type Lakadong, as we observed that LRNN has lower MSE and MAPE values than all other algorithms.

Table 6. Performance Comparison for the Seed Variety Lakadong

	MLP	**CNN**	**RNN**	**LRNN**
MSE (2021)	46.32	23.74	19.78	14.44
MSE (2022)	44.79	20.27	16.23	11.97
RMSE (2021)	6.8	4.87	4.44	3.8
RMSE (2022)	6.69	4.5	4.02	3.46
MAPE (2021)	36.6	25.67	23.45	17.27

MAPE (2022)	35.7	27.24	24.01	17.3

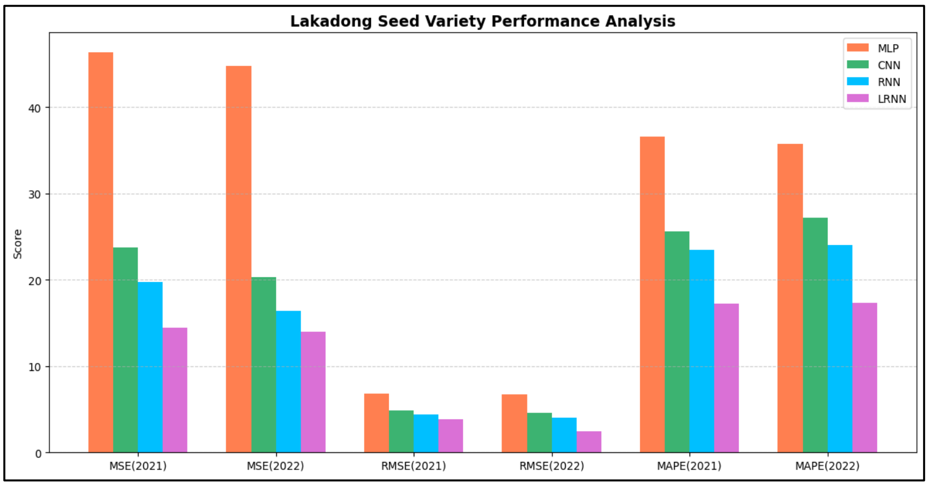

Figure 8. Graphical Representation of Performance Comparison for the Seed Variety Lakadong

Table 7 and Figure 9 depict the performance analysis for LRNN with machine learning and deep learning algorithms for the seed type Mydukur, as we observed that LRNN has a lower MSE and MAPE value than all other algorithms.

Table 7. Performance Comparison for the Seed Variety Mydukur

	MLP	**CNN**	**RNN**	**LRNN**
MSE (2021)	64.91	39.24	32.78	20.25
MSE (2022)	63.01	35.72	27.65	17.64
RMSE (2021)	8.05	6.26	5.72	4.5
RMSE (2022)	7.93	5.97	5.25	4.2
MAPE (2021)	44.68	18.18	15.73	12.86
MAPE (2022)	44.3	17.97	15.67	12.84

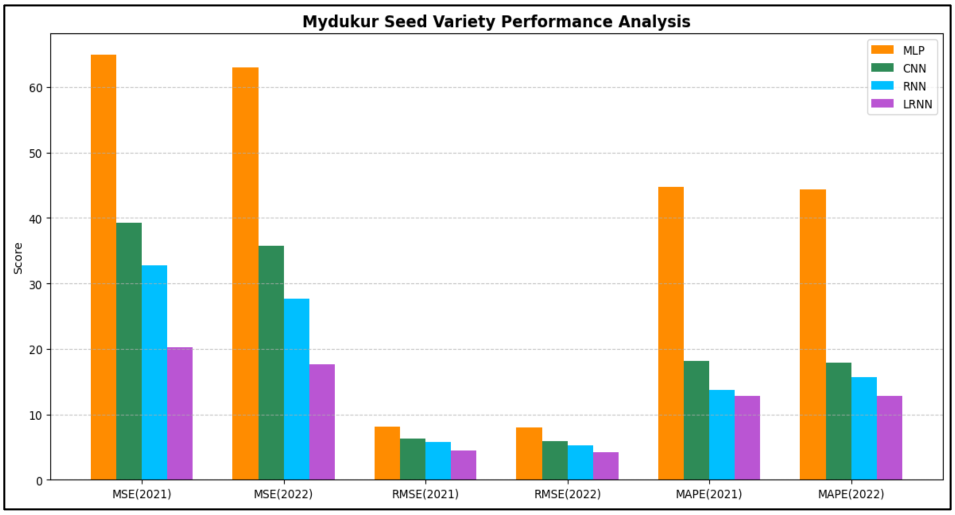

Figure 9. Graphical Representation of Performance Comparison for The Seed Variety Mydukur

Based on commonly used techniques reported in earlier crop prediction studies, benchmark models like MLP, CNN, and RNN were incorporated. These served to emphasize the suggested LRNN model's comparative performance.

7. Conclusion

In this research work, we have developed a better model, LRNN, by combining RNN with LSTM. By integrating continuous time-series data of plant growth and environmental conditions, the LRNN-based approach presented in this study provides a novel method for predicting turmeric yield. Compared to current static models, this integration enables more accurate and dynamic yield forecasts. The model's application to understudied turmeric seed varieties like Lakadong, Rajendra Sonia, and Mydukur, as well as its capacity to learn from sequential parameters, represents a significant contribution to both agricultural deep learning research and real-world farm management. The prediction of turmeric crop yield through the proposed model LRNN achieves better yield prediction values. The performance analysis of the proposed model yields the best results with lower MSE and MAPE values. Each seed variety yields different values. Based on soil pH and climatic conditions, yield will vary.

Future work includes extending the LRNN model to rare crops like millets (bajra, jowar, pearl millet) in diverse Indian regions. Our research aims to enhance the model's accuracy by incorporating additional environmental factors such as soil nutrients, temperature, and precipitation. We plan to explore the adaptability of LRNN to various agricultural practices, ensuring broader application across different crop varieties for sustainable and effective crop management.

References

[1] "Turmeric in Traditional Medicine," Turmeric, pp. 429–456, Mar. 2007, doi: 10.1201/9781420006322-18.

[2] S. SALIMATH, J. VENKATESHA, S. KULKARNI, and R. SHETTY G., "Evaluation of turmeric (Curcuma longa L.) cultivars for growth and yield in southern dry zone of Karnataka," ADVANCE RESEARCH JOURNAL OF CROP IMPROVEMENT, vol. 5, no. 2, Dec. 2014, 162–165, doi: 10.15740/has/arjci/5.2/162-165.

[3] K. P. Nair, "The Biotechnology of Turmeric," Turmeric (Curcuma longa L.) and Ginger (Zingiber officinale Rosc.) - World's Invaluable Medicinal Spices, 2019, 67–84, doi: 10.1007/978-3-030-29189-1_5.

[4] T. Morishita, H. Yamaguchi, K. Degi, A. Shimizu, and H. Nakagawa, "Comparison of Growth and Rhizome Yield Characters among Turmeric Species Cultivated in Kanto Area," Japanese Journal of Crop Science, vol. 78, no. 4, 2009, 509–514, doi: 10.1626/jcs.78.509.

[5] S. S. Olofintuyi, E. A. Olajubu, and D. Olanike, "An ensemble deep learning approach for predicting cocoa yield," Heliyon, vol. 9, no. 4, Apr. 2023, doi: 10.1016/j.heliyon.2023. e15245.

[6] K. Jhajharia, P. Mathur, S. Jain, and S. Nijhawan, "Crop Yield Prediction using Machine Learning and Deep Learning Techniques," Procedia Computer Science, vol. 218, 2023, 406–417, doi: 10.1016/j.procs.2023.01.023.

[7] J. W. Jones, E. Dayan, L. H. Allen, H. Van Keulen, and H. Challa, "A DYNAMIC TOMATO GROWTH AND YIELD MODEL (TOMGRO)," Transactions of the ASAE, vol. 34, no. 2, 1991, 0663–0672, doi: 10.13031/2013.31715.

[8] B. Alhnaity, S. Pearson, G. Leontidis, and S. Kollias, "Using deep learning to predict plant growth and yield in greenhouse environments," Acta Horticulturae, no. 1296, Nov. 2020, 425–432, doi: 10.17660/actahortic.2020.1296.55.

[9] B. Alhnaity, S. Kollias, G. Leontidis, S. Jiang, B. Schamp, and S. Pearson, “An autoencoder wavelet based deep neural network with attention mechanism for multi-step prediction of plant growth,” Information Sciences, vol. 560, Jun. 2021, 35–50, doi: 10.1016/j.ins.2021.01.037.

[10] K. Gavahi, P. Abbaszadeh, and H. Moradkhani, “DeepYield: A combined convolutional neural network with long short-term memory for crop yield forecasting,” Expert Systems with Applications, vol. 184, Dec. 2021, 115511, doi: 10.1016/j.eswa.2021.115511.

[11] H. ÇETİNER, “Hybrid Deep Learning Implementation for Crop Yield Prediction,” Afyon Kocatepe University Journal of Sciences and Engineering, vol. 23, no. 3, Jun. 2023, 648–660, doi: 10.35414/akufemubid.1116187.

[12] A. Oikonomidis, C. Catal, and A. Kassahun, “Deep learning for crop yield prediction: a systematic literature review,” New Zealand Journal of Crop and Horticultural Science, vol. 51, no. 1, Feb. 2022, 1–26, doi: 10.1080/01140671.2022.2032213.

[13] T. van Klompenburg, A. Kassahun, and C. Catal, “Crop yield prediction using machine learning: A systematic literature review,” Computers and Electronics in Agriculture, vol. 177, Oct. 2020, 105709, doi: 10.1016/j.compag.2020.105709.

[14] L. Gong, M. Yu, V. Cutsuridis, S. Kollias, and S. Pearson, “A Novel Model Fusion Approach for Greenhouse Crop Yield Prediction,” Horticulturae, vol. 9, no. 1, Dec. 2022, 5, doi: 10.3390/horticulturae9010005.

[15] D. Paudel, A. de Wit, H. Boogaard, D. Marcos, S. Osinga, and I. N. Athanasiadis, “Interpretability of deep learning models for crop yield forecasting,” Computers and Electronics in Agriculture, vol. 206, Mar. 2023, 107663, doi: 10.1016/j.compag.2023.107663.

[16] N. Debiya, “Influence of Weather Parameters of Growth and Yield Attribute of Different Sowing Date on Different Varieties of Pea Plant,” International Journal of Environment and Climate Change, Dec. 2022, 876–882, doi: 10.9734/ijecc/2022/v12i121527.

[17] M. Ismanov, P. Francis, C. Henry, and L. Espinoza, “Relations among Sap Flow, Soil Moisture, Weather, and Soybean Plant Parameters in High Water Demand and Final

Growth Stages," Agricultural Sciences, vol. 10, no. 03, 2019, 371–385, doi: 10.4236/as.2019.103030.

[18] P. Pawara, "Plant recognition, detection, and counting with deep learning", doi: 10.33612/diss.156115978.

[19] A. D. A. Aldabbagh, C. Hairu, and M. Hanafi, "Classification of Chili Plant Growth using Deep Learning," 2020 IEEE 10th International Conference on System Engineering and Technology (ICSET), Nov. 2020, doi: 10.1109/icset51301.2020.9265351.

[20] J. R. Ubbens and I. Stavness, "Corrigendum: Deep Plant Phenomics: A Deep Learning Platform for Complex Plant Phenotyping Tasks," Frontiers in Plant Science, vol. 8, Jan. 2018, doi: 10.3389/fpls.2017.02245.

[21] "PREDICTION OF TOMATO PLANT GROWTH AND YIELD IN GREEN HOUSE ENVIRONMENT USING ANN AND DEEP LEARNING," International Research Journal of Modernization in Engineering Technology and Science, Aug. 2023, doi: 10.56726/irjmets43938.

[22] L. C. Lei Chen and Y. Y. Yuan Yuan, "An image dataset for field crop disease identification," Science Data Bank Datasets. Computer Network Information Center, Chinese Academy of Sciences. doi: 10.11922/sciencedb.745.

[23] T. Akase, H. Nakao, and L. Zhang, "Preprocessing Method for Training Dataset in Character Recognition using Convolutional Neural Network," Proceedings of The 7th International Conference on Intelligent Systems and Image Processing 2019, 2019, doi: 10.12792/icisip2019.035.

[24] J. Chaki and N. Dey, "Other Applications of Image Preprocessing," A Beginner's Guide to Image Preprocessing Techniques, Oct. 2018, 83–97, doi: 10.1201/9780429441134-7.

[25] C. Kosaraju, C. Nama, Y. Deepthi, C. Ramanjamma, and P. Chandrakala, "Mirchi Crop Yield Prediction based on Soil and Environmental Characteristics using modified RNN," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Feb. 2023, doi: 10.1109/sceecs57921.2023.10063004.

[26] J. Patel, B. Vala, and M. Saiyad, "LSTM-RNN Combined Approach for Crop Yield Prediction On Climatic Constraints," 2021 5th International Conference on Computing

Methodologies and Communication (ICCMC), Apr. 2021, doi: 10.1109/iccmc51019.2021.9418231.

[27] N. Chakraborty, "Testing RNN-LSTM Forecasting with Simulated Time-Series: Exploring Univariate Sensitivity," Aug. 2023, doi: 10.20944/preprints201907.0241.v2.

[28] S. M. Kuriakose and T. Singh, "Indian Crop Yield Prediction using LSTM Deep Learning Networks," 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Oct. 2022, doi: 10.1109/icccnt54827.2022.9984407.