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LSTM-POWERED SMART GROWTH CHAMBER FOR RICE SEEDLING OPTIMIZATION

Dr. CHAITRALI CHAUDHARI
Assistant Professor, Department of Computer Engineering, Lokmanya Tilak College of Engineering, Navi Mumbai, Mumbai University, Maharashtra, India. Email: chaitralichaudhar13@gmail.com

Dr. SANJIVANI DEOKAR
Assistant Professor, Department of Computer Engineering, Lokmanya Tilak College of Engineering, Navi Mumbai, Mumbai University, Maharashtra, India. Email: sanjivanideokar@gmail.com

SHIRIN MATWANKAR
Assistant Professor, Department of Computer Engineering, Lokmanya Tilak College of Engineering, Navi Mumbai, Mumbai University, Maharashtra, India. Email: shirinmatwankar@gmail.com

Abstract

Considering the global crisis for food supply, machine learning applications have a significant impact on agriculture and the global economy by transforming the methods for data processing and decision making. This research presents an intelligent system designed to optimize rice cultivation using automated growth chambers managed by Long Short-Term Memory (LSTM) models. The setup employs an IoT-enabled microcontroller integrated with sensors that continuously monitor key environmental parameters such as temperature, humidity, light intensity, CO_2 concentration, and soil moisture. The real-time sensor data is processed by the LSTM model to predict and dynamically adjust environmental conditions for optimal plant growth. This adaptive control system enhances seedling development while reducing resource consumption. The approach minimizes reliance on external weather conditions and ensures efficient use of agricultural inputs, leading to improved crop yield and quality. Furthermore, the system is scalable and adaptable for implementation in diverse and non-traditional agricultural settings. By leveraging machine learning and precision farming techniques, this study contributes to the advancement of sustainable and data-driven agricultural practices that hold potential for application to a wide range of crops in the future.

Keywords: Machine Learning, LSTM, Rice, Prediction, Deep Learning, Smart Growth Chamber, Optimization.

1. INTRODUCTION

As a crucial and staple food for more than half of the global population, rice plays a critical role in ensuring food security, nutrition, highlighting the need for its efficient and consistent cultivation. However, conventional rice farming methods are heavily influenced by natural environmental conditions such as temperature, humidity, and soil moisture, often resulting in variable yields and inefficient resource utilization.

Additionally, the growing impact of climate change, limited water availability, and unpredictable weather patterns have intensified the challenges faced by traditional farming techniques, highlighting the need for more precise and adaptive agricultural solutions.

This research introduces an intelligent growth chamber system that integrates Internet of Things (IoT)-enabled sensors with Long Short-Term Memory (LSTM) deep learning

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models to optimize rice seedling development. The system continuously tracks critical environmental parameters and uses predictive modeling to dynamically adjust internal conditions, ensuring optimal growth settings in real time. By combining automated sensor-based monitoring with AI-driven decision-making, the proposed solution reduces reliance on external environmental factors, enhances crop quality, and conserves valuable resources.

Through the use of smart automation and data-driven insights, this study aims to transform rice cultivation practices by improving efficiency, scalability, and adaptability across various agricultural environments. Moreover, the flexible design of the system allows for its application to a wide range of crops, thereby extending its potential benefits beyond rice farming.

2. LITERATURE REVIEW

The integration of Artificial Intelligence (AI) and Internet of Things (IoT) in agriculture optimizes crop yield. It has a significant contribution in resource management and its consumption as well as reducing waste. Specific applications include Crop Classification, Irrigation Optimization, Disease Detection, Soil Analysis, Weed Detection, Pest Management etc.

Models like Long Short-Term Memory (LSTMs) and Recurrent Neural Networks (RNNs) can analyze time-series data like weather patterns and soil conditions to predict future environmental conditions and their impact on crop growth which can lead to intelligent decision-making.

Models like CNNs when used along with LSTMs enable prediction of crop yields based on a variety of inputs like weather data, soil information, and crop health data. Since the environment is continuously changing it makes a huge effect year by year and on various locations in crop production. Under such circumstances, prediction of accurate yield is very beneficial to global food production. The research has extensively analysed how machine learning methods have influenced several aspects of agricultural activities and discussed as below.

2.1. Machine Learning for Crop Growth Prediction

Machine learning techniques have been increasingly adopted to predict and enhance crop growth. Alhnaity et al. (2019) have done the prediction formulations by deploying a deep recurrent neural network model along with Long Short-Term Memory neuron model. A real-time monitoring of plant development is done in the greenhouse environment, to improve crop tracking accuracy.

To model the targeted growth parameters, RNN architecture utilizes former yield, growth and stem diameter values, as well as the microclimate conditions. Similarly, Alibabaei et al. (2021) focused on climate-driven data and irrigation scheduling, showing that predictive analytics can play a critical role in managing crop yield effectively.

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They have tested the application of this technique for tomato and potato yields at a site in Portugal. Researchers have also developed a Random Forest-based system for crop yield forecasting using multispectral imagery and weather data, emphasizing the effectiveness of ensemble learning in agriculture. Suiyun Tan et. al presented automatic approaches to detect rice seedling of three critical stages, BBCH11, BBCH12, and BBCH13. Zachary C. Lipton et al

2.2. LSTM Applications in Agriculture

LSTM networks, known for their strength in handling time-series data, have proven particularly useful in agricultural applications. Castro Filho et al. (2020) applied LSTM and Bi-LSTM architectures to Sentinel-1 satellite imagery to detect rice crops, showcasing the model's strength in sequential data analysis.

Chaithanya et al. (2020) employed RNN-based models for rice yield prediction, outperforming conventional regression models. In another study, Some researchers have used LSTM networks to forecast temperature and humidity within greenhouses, enabling precise climate control for plant growth. LSTM’s capacity for long-term soil moisture prediction has been proved crucial for irrigation planning.

2.3. IoT-Driven Precision Agriculture

IoT technology is rapidly developing and enabling real-time monitoring along with automation, to form the backbone of smart farming systems. Anguraj et al. (2021) proposed a crop recommendation system using IoT-enabled soil analysis and machine learning algorithms, improving farming decisions.

Chandgude et al. (2018) provided a comprehensive review of ML techniques applied to agriculture, emphasizing their benefits in pest control, irrigation management, and yield forecasting.

Some researchers have involved deploying a smart irrigation system using IoT sensors and cloud-based analytics to reduce water usage and enhance crop health. A sensor-based greenhouse monitoring system is built that dynamically adjusts environmental parameters based on IoT sensor feedback.

2.4. Limitations of Existing Systems

While recent innovations in precision agriculture show considerable promise, both traditional methods and some contemporary practices continue to face significant challenges. A primary concern is their dependency on weather conditions, which makes them vulnerable to unpredictable climatic variations and often results in inconsistent crop yields.

Additionally, these systems tend to suffer from inefficient resource utilization due to the absence of intelligent management mechanisms, leading to excessive water and energy consumption. Furthermore, the limited incorporation of automation in environmental control processes hampers the scalability and adaptability of these cultivation techniques.

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3. METHODOLOGY

Decision-making systems powered by machine learning algorithms can be used in agriculture throughout the cultivation and harvesting cycle. They can make decisions by using increasingly large amounts of data, and extracting features from them automatically. This study utilizes an intelligent growth chamber integrated with IoT devices and a Long Short-Term Memory (LSTM) deep learning model to optimize the growth of rice seedlings. The methodology comprises the design of the smart chamber, development of the LSTM model, real-time optimization techniques, and performance evaluation is demonstrated through controlled experiments in many researches.

3.1. Smart Growth Chamber Design

The system architecture includes a network of environmental sensors and a microcontroller to facilitate automated monitoring and control.

3.1.1 Hardware Components

The system employs a comprehensive array of environmental sensors to monitor and regulate the agricultural setup effectively. These include a temperature sensor to track ambient conditions, a soil moisture sensor to assess irrigation needs, a humidity sensor for maintaining optimal atmospheric moisture levels, a CO_2 concentration sensor to gauge the air quality for plant respiration, and a light intensity sensor to ensure adequate illumination for photosynthesis. At the core of the system is a Raspberry Pi microcontroller, which serves as the central processing unit responsible for integrating sensor data, executing control logic, and managing data acquisition tasks in real time.

3.2. LSTM Model Development

The LSTM model is designed to predict optimal environmental conditions for rice seedling growth based on historical data.

Development Framework:

TensorFlow

Training Process:

Historical environmental data is used to train the model

Input features include temperature, humidity, CO_2 levels, light intensity, and soil moisture

The model learns to predict the ideal conditions required for optimal plant development

Optimization Techniques:

Hyperparameter tuning to improve model performance

Loss function minimization to enhance prediction accuracy

3.3. Optimization and Real-Time Control

To dynamically manage the environment within the growth chamber, advanced optimization algorithms are employed.

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Algorithms Used:

- Genetic Algorithms (GA) is used for hyperparameter optimization as it offers a robust and automated approach, saving time and resources while enhancing model performance.
- Reinforcement Learning is used for adaptive environmental control as it can learn from the real-time feedback from the environment, and adapt to changing conditions like weather patterns, energy demand, or resource availability.

IoT Automation:

- Real-time sensor data is processed by the LSTM model
- The system automatically adjusts environmental parameters based on predictions to maintain optimal conditions

3.4. Testing and Validation

The system's effectiveness is evaluated through comparative experiments and performance analysis.

Experimental Setup:

- Rice seedlings are cultivated under two conditions: AI-optimized growth chambers and conventional environments

Performance Metrics:

- **Root Mean Square Error (RMSE):** Used to measure the accuracy of LSTM predictions
- **Growth Rate Comparison:** Analyzed between AI-controlled and traditional setups to assess improvements in seedling development

Scalability Assessment:

- The system’s potential to support different crop types and adapt to varied agricultural environments is also tested

4. Experimental Setup and Results

The Architecture of the model consist of:

1. A growth chamber
2. Sensors connected to raspberry pie will provide the real time data
3. Actuators will alter the data to provide optimal Parameters
4. Raspberry Pi which will collect data and analyze for best performance

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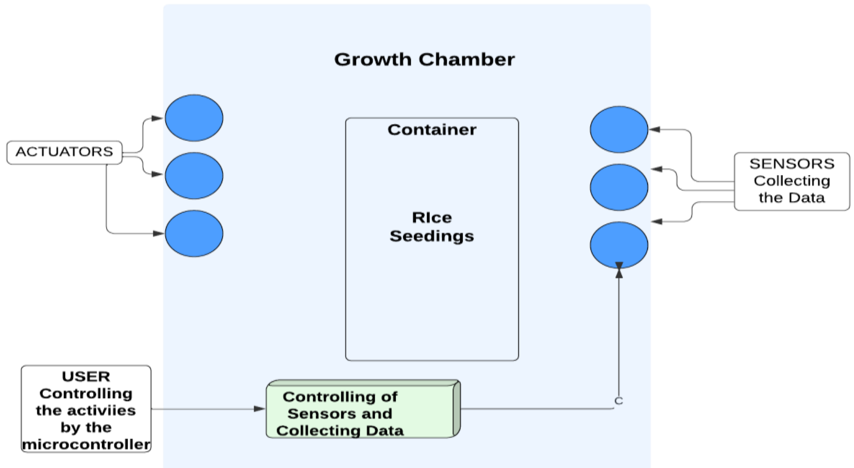

Fig. 1: Rice Seedling Growth Chember

Following figure 2 shows the proposed neural network architecture used by Hamid Ghaffari et.al., in their research paper 'LSTM Modeling and Optimization of Rice (Oryza sativa L.) Seedling Growth using an Intelligent Chamber'. The model has three main layers. The input layer is used to receive the raw data, processed and transferred to the hidden layer along with weights and biases. The information is transferred from the hidden to the output layer. The architecture is as shown below.

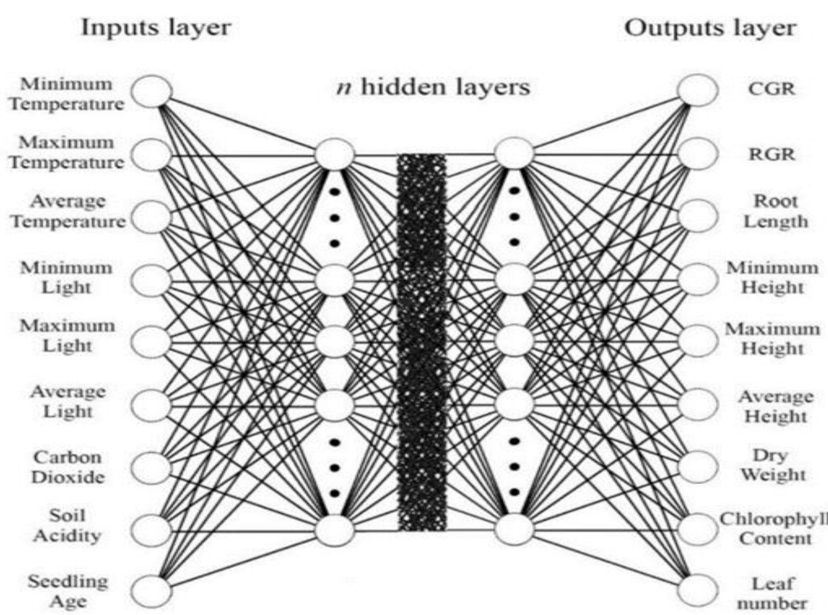

Fig. 2: A Neural Network Architecture

Inspired by the above architecture, the model was developed and the experimentations were carried out on the sample dataset using deep learning techniques enabled with IoT.

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4. EVALUATION AND RESULTS

4.1 Evaluation Metrics

To evaluate the performance of the LSTM-based rice growth optimization system, the following metrics were employed:

Accuracy:

Measures the proportion of correctly predicted optimal environmental conditions (e.g., temperature, humidity) relative to the total predictions made.

Precision:

Determines the proportion of true positive predictions among all positive predictions made by the model, reflecting the accuracy of the model in identifying optimal conditions without false alarms.

Recall:

Indicates the model's ability to correctly identify all relevant instances of optimal parameters, showing how effectively the model captures suitable growth conditions.

4.2 Experimental Results

To validate the proposed system, experiments were carried out using real-time and historical environmental data collected over a one-year period (365 days). The LSTM model was trained and tested on this dataset to forecast ideal environmental conditions for rice seedling growth.

4.2.1 Optimal Parameter Prediction

The model successfully identified and adjusted environmental parameters such as temperature, humidity, CO_2 levels, soil moisture, and light intensity to within optimal ranges. Key observations include:

- Consistent prediction accuracy above 90% for temperature and humidity conditions
- High precision in maintaining stable CO_2 levels and light intensity thresholds
- Reliable recall values, indicating the model's effectiveness in detecting necessary adjustments in real-time

These outcomes demonstrate the capability of the system to accurately monitor, predict, and adjust critical factors for rice cultivation, resulting in more efficient and controlled plant development.

Index	Optimal Temperature (°C)	Optimal Humidity (%)
0	26.837217	75.016296
1	33.380543	50.387547
2	28.128906	70.179886
3	25.966379	62.686356
4	34.772064	47.731361

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Index	Optimal Light Intensity (lux)	Optimal CO2 Levels (ppm)
0	15439.12109	545.510986
1	32792.30859	657.321594
2	23403.06836	727.650635
3	29490.55664	537.2901
4	19433.02148	412.076782

Index	Optimal Soil Moisture (%)
0	27.998589
1	22.197342
2	28.206324
3	44.638561
4	36.096371

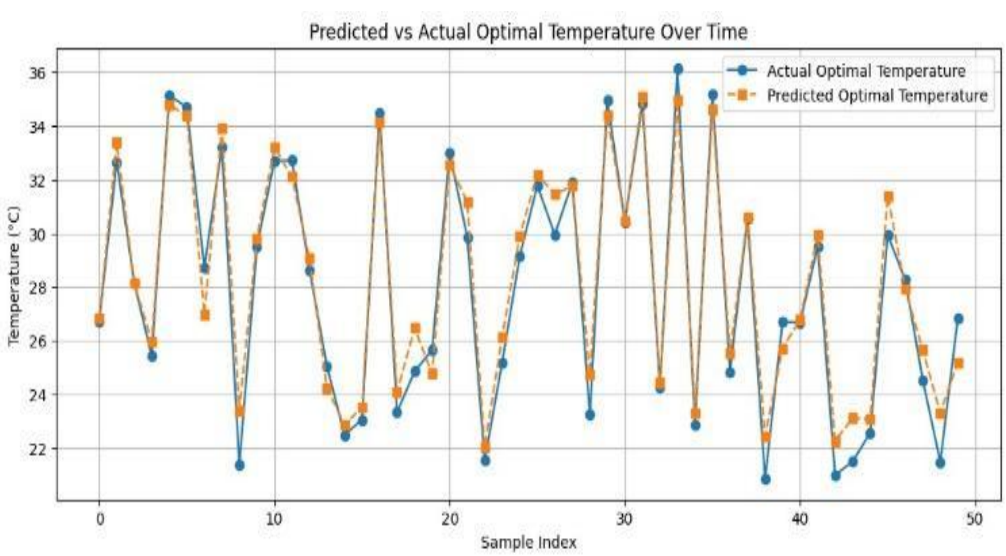
Index	Optimal Water Supply (L/day)
0	1.964456
1	1.491503
2	2.206589
3	1.870729
4	0.743733

Index	Optimal Nutrient Concentration (%)
0	3.146767
1	2.085659
2	4.192884
3	1.6333
4	2.543426

Table 1: Performance Metrics of the model

Implementation

Following figures show the predicted versus optimal temperature recorded over time.



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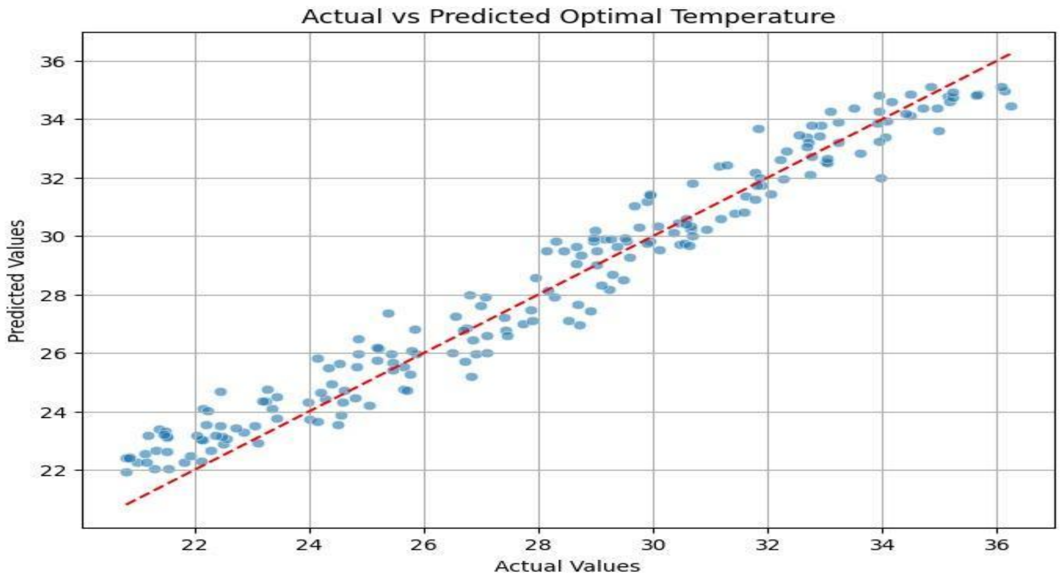

Fig. 3: Predicted versus Optimal Temperature

5. APPLICATIONS

The intelligent rice growth chamber presents a range of impactful applications across agricultural, educational, and research domains:

1. Enhanced Crop Productivity

By maintaining ideal environmental parameters such as temperature, humidity, light intensity, and soil moisture, the system ensures a stable microclimate conducive to rice cultivation. This results in higher yields and improved crop quality.

2. Support for Agricultural Research

The controlled environment of the growth chamber allows researchers to systematically study the influence of various factors on rice development. This facilitates experimentation and breeding programs aimed at creating climate-resilient rice varieties.

3. Advancement in Precision Agriculture

The integration of sensor networks and AI-based control enables precise monitoring and dynamic adjustment of growth parameters. These capabilities can be scaled to larger farming setups, improving efficiency and reducing resource wastage.

4. Educational Utility

The chamber can be utilized in academic settings to demonstrate core concepts in plant biology, environmental science, automation, and artificial intelligence. It serves as an effective teaching aid for students in agriculture and technology fields.

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5. Data-Driven Crop Improvement

The continuous collection of environmental and plant growth data supports the identification of growth traits linked to specific conditions. This data can be used in genetic research and the development of superior, high-yield rice cultivars.

6. CHALLENGES AND FUTURE WORK

6.1 Challenges

Despite the advantages offered by the system, several practical limitations continue to hinder its effectiveness. One significant issue is sensor accuracy, as prolonged exposure to environmental conditions can cause sensors to drift or degrade, thereby compromising data quality and system reliability.

Hardware constraints also pose a challenge; although cost-effective components make the system more accessible, they often lack the durability and computational capabilities required for sustained or commercial use. Furthermore, managing the large volumes of sensor data generated by the system proves difficult, especially in terms of efficient storage, real-time processing, and meaningful analysis.

Another drawback lies in the high power consumption associated with the continuous operation of pumps, sensors, and control units, which raises concerns regarding energy efficiency and sustainability. Additionally, while the chamber effectively replicates optimal environmental conditions, it falls short of capturing the complex variability found in outdoor environments, thus limiting its direct applicability to real-world farming scenarios.

6.2 Future Enhancements

To overcome these challenges and enhance overall usability, several improvements are being considered. Introducing remote monitoring and control through a mobile or web-based application would empower users to interact with the system more conveniently and in real time.

Efforts are also underway to scale the system for larger installations, such as extensive greenhouse or open-field setups, to facilitate commercial-level farming applications. Integrating renewable energy sources like solar panels would further address the issue of high power consumption, contributing to a more sustainable and eco-friendly operation.

Moreover, transitioning to a cloud-based infrastructure for data storage and real-time analytics would significantly improve accessibility, enable more sophisticated data interpretation, and streamline control mechanisms across diverse agricultural setups.

Future research should consider the direction of study and experimentation employing more cultivars, climatic conditions, different crops, and more growth stages recognition as well as other factors shall be investigated to further verify and optimize the algorithms used in this domain.

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7. CONCLUSION

The proposed intelligent rice growth chamber offers a robust solution for modernizing agricultural practices through sensor-based automation and AI-driven environmental control. By ensuring optimal growth conditions irrespective of external weather variations, the system enhances both yield and quality of rice crops. It also supports research, educational activities, and large-scale adoption of precision farming techniques.

While the system demonstrates strong potential, challenges such as sensor reliability, energy consumption, and limited real-world simulation need to be addressed. Future improvements—such as the use of renewable energy, cloud connectivity, and remote access—can further enhance its effectiveness and scalability. Ultimately, this research contributes to the development of sustainable, intelligent agricultural systems capable of meeting the demands of global food security in the face of climate change.

References

1) Suiyun Tan, Jingbin Liu, Henghui Lu, Maoyang Lun, M L Approaches for Rice Seedling Growth Stages Detection , Publication (2022)
2) B. Alhnaity, S. Pearson, G. Leontidis, and S. Kollias, “Using deep learning to predict plant growth and yield in greenhouse environments,” International Symposium on Advanced Technologies and Management for Innovative Greenhouses, vol. 1296, pp. 425-432, 2019.
3) K. Alibabaei, P. D. Gaspar, and T. M. Lima, “Crop yield estimation using deep learning based on climate big data and irrigation scheduling,” Energies, vol. 14, no. 11, 2021.
4) K. Anguraj, B. Thiyaneswaran, G. Megashree, J. P. Shri, S. Navya, and J. Jayanthi, “Crop recommendation on analyzing soil using machine learning,” Turkish Journal of Computer and Mathematics Education, vol.12, no. 6, pp. 1784-1791, 2021.
5) H. C. D. Castro Filho, O. A. D. Carvalho Júnior, O.L. F. D. Carvalho, P. P. D. Bem, R. D. S. D. Moura, A.O. D. Albuquerque, and R. A. T. Gomes, “Rice crop detection using LSTM, Bi-LSTM, and machine learning models from sentinel-1 time series,” Remote Sensing, vol. 12, no. 16, 2020.
6) S. Chaithanya, A. Punith Raj, N. Rajeshrahul, H.Sujatha, and D. Veena, “Rice crop yield prediction using recurrent neural networks,” International Research Journal of Engineering and Technology (IRJET), vol. 7,2020.
7) A. Chandgude, N. Harpale, D. Jadhav, P. Pawar, and S. M. Patil, “A review of machine learning algorithms used for a crop monitoring system in agriculture,” International Research Journal of Engineering and Technology (IRJET), vol. 5, no. 4, 2018.