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The utilization of IoT-based humidity monitoring method and convolutional neural networks for orchid seed germination

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Abstract. This research endeavors to advance orchid seed germination efficiency through the development of an Internet of Things (IoT)-based humidity monitoring system integrated with Convolutional Neural Networks (CNN). Recognizing the pivotal role of proper humidity in orchid seed sowing, the proposed system employs humidity sensors connected to an IoT platform for real-time data collection. The collected data undergoes analysis and prediction by CNN, elucidated through graphical representations such as histograms, line charts, and scatterplot charts. By synergizing IoT technology with artificial intelligence, this innovative system contributes positively to orchid seed sowing efficiency, empowering farmers and orchid cultivators to optimize plant growth conditions. Furthermore, the adaptability of this approach extends beyond orchids, making it applicable to various crop seeding applications through parameter modifications tailored to specific needs.

Introduction

Smart farming is taken from the word 'smart' in smart city, smart farming which was originally called 'precision farming' will become a mandatory agricultural concept in the future due to limited land. Smart farming utilizes technology such as big data, GPS, and the Internet of Things (IoT) to improve the quality and quantity of production in the agricultural industry. Things like this should help simplify and streamline all agricultural processes from production to marketing [1].

The Smart Farming concept began to be developed as an effort to increase the efficiency and productivity of the agricultural sector which is still dominated by traditional methods. Rapid technological developments enable farmers to utilize technological information and communication in agricultural land management, production and marketing of agricultural products. Smart Farming has many benefits, including increasing the efficiency of using resources such as air and energy, increasing the quality and quantity of harvests, reducing production costs, and minimizing negative impacts on the environment. Apart from that, Smart Farming can also help farmers integrate and control the agricultural environment in real-time, which can help in overcoming problems that arise quickly and in a timely manner [2][3].

Convolutional Neural Networks (CNN) is a method of smart farming. CNN itself is a type of neural network commonly used on image data. CNN can be used to detect and recognize objects in an image. CNN is a technique inspired by the way mammals — humans, produce visual perception.

In general, a Convolutional Neural Network (CNN) is not much different from a regular neural network (NN). NNs typically transform input by passing it through a series of hidden layers. Each layer consists of a collection of neurons, where each layer is fully connected to all the neurons in

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the previous layer. Finally, a fully connected layer (output layer) is used to represent the predictions. The CNN consists of neurons that have weights, biases and activation functions. Convolutional layers also consist of neurons arranged in such a way as to form a filter with length and height (pixels) and CNN utilizes the convolution process by moving a convolution kernel (filter) of a certain size to an image, the computer obtains new representative information from the results of multiplying parts of the image depending on the filter used [4][5]. CNN is used for sowing orchid seeds, because CNN can help with visual analysis, such as identifying problems, and providing information for the maintenance and development of orchid seeds.

The paper is organized into distinct sections to present the research on utilizing an Internet of Things (IoT)-based humidity monitoring system combined with Convolutional Neural Networks (CNN) for efficient orchid seed germination. The abstract succinctly introduces the research, highlighting the integration of humidity sensors with CNN analysis for optimal orchid seeding conditions. The introduction outlines the significance of smart farming, emphasizing the role of technology, particularly CNN, in agricultural advancements. The literature review delves into the importance of real-time humidity monitoring, the challenges in orchid cultivation, and the application of IoT and CNN in the context of smart farming. The methodology section details the problem identification process, the seven research stages, and the selection of evaluation metrics, showcasing the comprehensive approach taken. Device design elucidates the essential tools—NodeMCU, Water Pump DC 12V, and DHT11—employed in the research. Algorithm design provides a visual representation of the analysis method used in the Temporary Immersion System. The results section showcases temperature and humidity data, with a focus on accuracy testing using CNN and comparisons with other methods. The conclusion summarizes key findings, emphasizing the high accuracy of the IoT and CNN-based humidity monitoring methods and their potential applications in optimizing orchid seed sowing.

Literature Review

Moisture Monitoring. Monitoring soil moisture is very important in crop cultivation, especially at the time of planting. Proper soil moisture can increase the success of plant growth and reduce the risk of growth failure. The use of IoT sensor technology can monitor soil moisture in real-time and accurately [6][7].

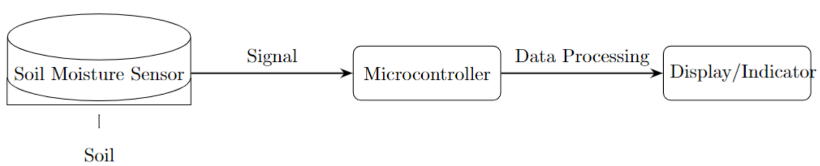

Fig. 1 Humidity Monitoring [6].

Orchid Cultivation. Orchids are a type of ornamental plant that is very popular and has high economic value. However, orchid cultivation requires careful care and supervision, especially when sowing seeds. Real-time and accurate monitoring of humidity can help increase the success of sowing orchid seeds.

Internet of Things (IoT). IoT is a concept where electronic devices connected to the internet can communicate with each other and exchange data. In this case, the use of IoT sensor technology can monitor soil moisture in real-time and send data to a server that can be accessed from anywhere.

Convolutional Neural Network (CNN). CNN is one of the most popular types of Deep Learning algorithms in image processing. CNN can learn complex patterns in images and classify images into appropriate categories based on the learned features. In this case, CNN can be used to process humidity data from IoT sensors and classify humidity status to predict the success of orchid seed sowing [8][9].

Methodology
Identification of problems. The utilization of Root Mean Square Error (RMSE) is imperative in addressing the inherent challenges associated with orchid seed germination, particularly the unpredictability in factors influencing orchid growth outcomes. Orchid seeds pose unique difficulties in prediction due to various uncontrollable variables. Traditional prediction methods often fall short in accurately foreseeing the results of observed plant behavior, leading to suboptimal predictions. RMSE serves as a valuable metric, specifically gauging plant quality, enabling researchers to set high expectations for seeds predicted to be superior while discerning and discarding those anticipated to yield damaged or compromised outcomes. This strategic application of RMSE not only enhances predictive accuracy but also aids in making informed decisions regarding seed quality and subsequent plant development.

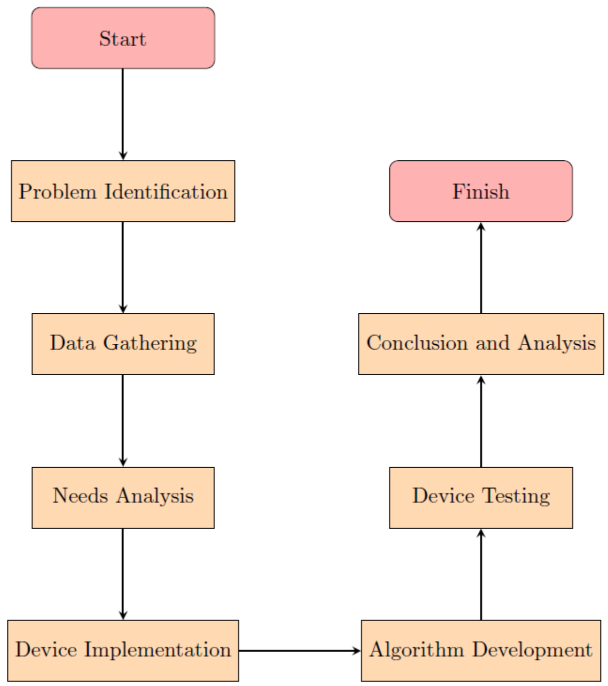

Fig. 2 Research Flow Diagram.

Research Stages. This research includes seven research stages which can be seen in Fig. 2. The beginning of this research is the problem identification process. After that, the data collection stage is carried out to process the information, then analyze the requirements needed to design the tool, including hardware, sensors and other components, with the aim of preventing errors when making the tool. After the tool has been successfully created, the research will proceed to the testing stage using the Convolutional Neural Network (CNN) method and making comparisons with other methods.

Method Selection. Mean Squared Error (MSE) is not a direct part of Convolutional Neural Networks (CNN), but MSE is one of the evaluation metrics commonly used in training and evaluating CNN models. Root Mean Square Error (RMSE) is a standard way to measure the error of a model in predicting quantitative data.

$$RMSE = \sqrt{\sum_{k=1}^{K} \frac{(\hat{y}_k - y_k)^2}{K}} \qquad (1)$$

MAE is one of the evaluation methods commonly used in data science. MAE calculates the average of the absolute differences between predicted and actual values.

$$MAE = \frac{1}{K}\sum_{k=1}^{K}|\hat{y}_k - y_k| \qquad (2)$$

R^2 is basically used to see how adding independent variables helps explain the variance of the dependent variable.

$$R^2 = 1 - \frac{SSR}{SST} \qquad (3)$$

where R^2 is the coefficient of determination, RSS is the sum of squares of residuals, and TSS is total sum of squares.

Device Design. Following items are some of the tools needed in designing:

NodeMCU [10] (Fig. 3a) is an open source IoT platform. Consists of hardware and software. The hardware is a development board integrated with an ESP8266 microcontroller and a USB to serial communication chip. The software is firmware that is compatible with the Arduino IDE.
Water Pump DC 12V (Fig. 3b). This type of pump is operated by immersing it in water and cannot work outside the water. The water pump in this design is designed to flow air from tank 1 to tank 2 periodically.

DHT11 [11] (Fig. 3c) is a sensor that can detect temperature and humidity around the area where the sensor is placed. This sensor consists of a thermistor which functions to measure temperature and a capacitive sensor which is used to measure humidity levels. Generally, this sensor is integrated in a module which is equipped with sensors and chips to convert analog signals into digital signals.

(a) (b) (c)

Fig. 3 Components (a) NodeMCU, (b) Water Pump, and (c) DHT11

Algorithm Design. In analyzing the impact of the time and frequency of watering in the Temporary Immersion System on the growth of orchid seeds and sowing orchid seeds, the algorithm method as depicted in Fig. 4 is used.

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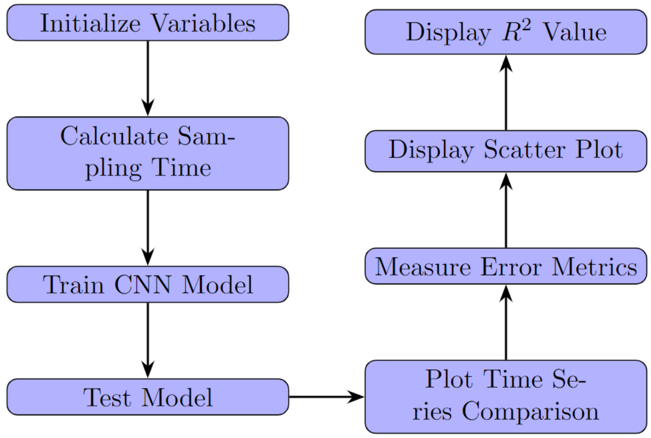
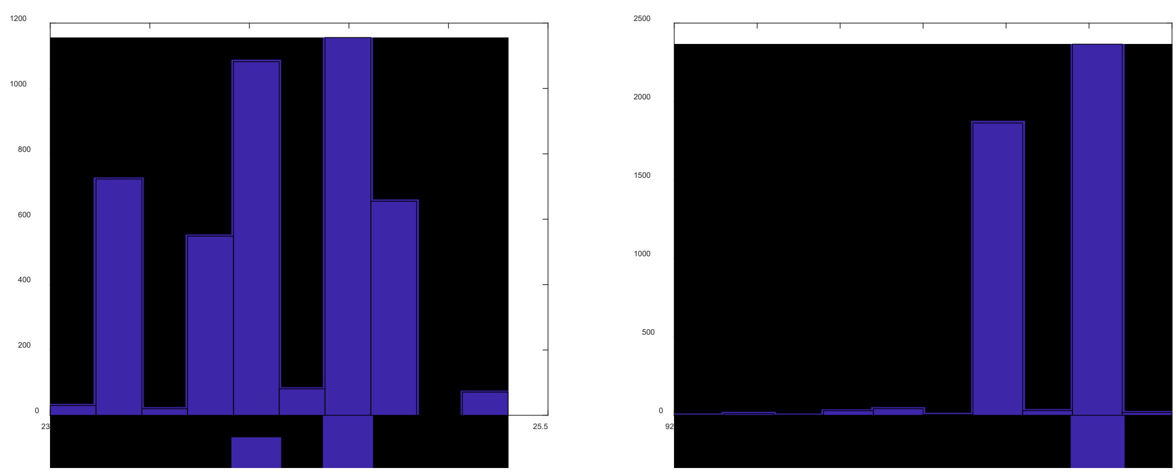


Fig. 4 Research Algorithm.

Based on the algorithm in Fig. 4, it can be explained that the code uses the predict() function to predict air humidity for each data in Xts. This function returns predicted values in vector form. The code uses the functions mse(), nmse(), rmse(), nrmse(), mae(), and mbe() to calculate various error measures between predictions and actual data. The first plot shows the actual and predicted humidity values for the first 500 minutes. The second plot shows the actual and predicted humidity values for the first 200 minutes. The R-squared value calculated with the code is 0.95, which means that the machine learning model can predict humidity with high accuracy.

Result and Discussion

Measurement results. During the period from 7 to 10 November 2023, measurements were carried out periodically every 10 seconds using the ESP32 device. A total of 4000 data were collected to record the temperature and humidity in vessel 1. The aim of this observation was to gain deeper insight into changes in temperature and humidity, especially in the context of vessel 1. The data processing was carried out using the Matlab application.



(a) (b)

Fig. 5 Histogram of (a) Temperature and (b) Humidity Data.

Fig. 5(a) depicts a detailed graphical representation of the results of temperature measurements in vessel 1 during the observation period. The recorded temperature range was between 23° to 25.5° Celsius, providing a comprehensive picture of the temperature variations in the room. The peak frequency occurred at a temperature of 24.5° Celsius, with the amount of data reaching 1150,

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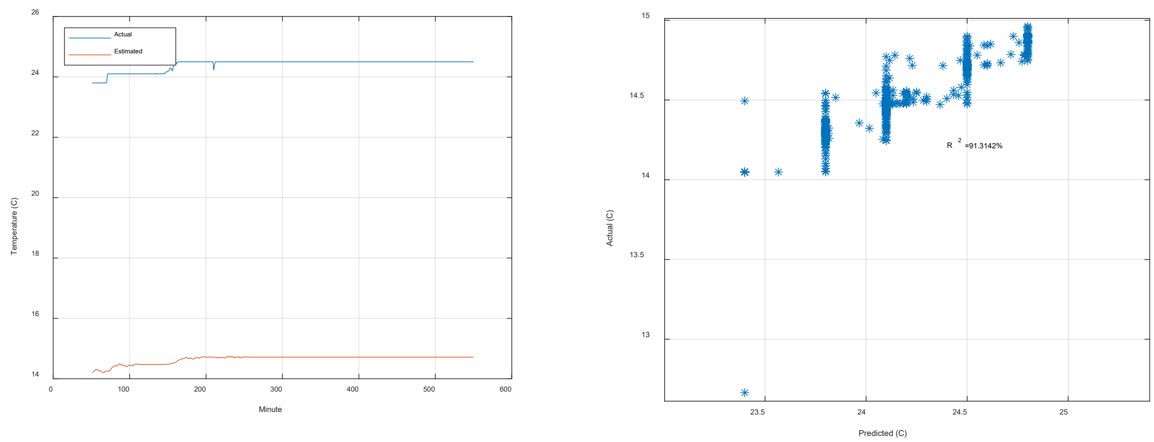
followed by a temperature of 24° Celsius which reached a frequency of 1100 data. Apart from that, a temperature of 23.3° Celsius was also recorded with a frequency of 750 data.

Fig. 5(b) depicts a detailed graphical representation of the measurement results of humidity in vessel 1. The data presented via a histogram highlights the humidity value range between 92% to 98%. From the analysis carried out, it can be seen that the dominant humidity in vessel 1 reached 97%, with a measurement frequency reaching 2400 data. Apart from that, humidity at the 96% level also shows significance, measured by a measurement frequency of 1800 data.

Accuracy Test Results Using CNN. In the framework of this research, accurate measurements were carried out using the CNN method, and the results were compared with several other methods. The goal of this comparison is to gain a thorough understanding of the performance of tree regression methods on accuracy measurements.

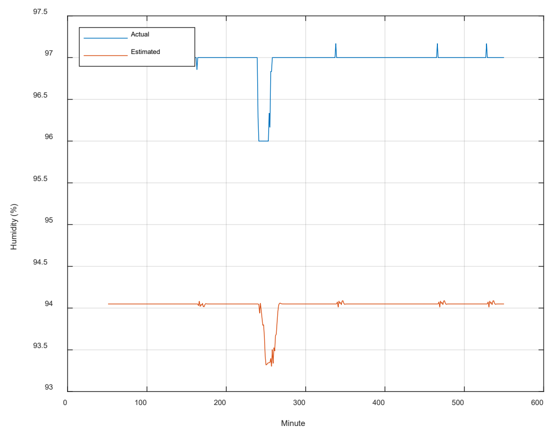


(a) (b)

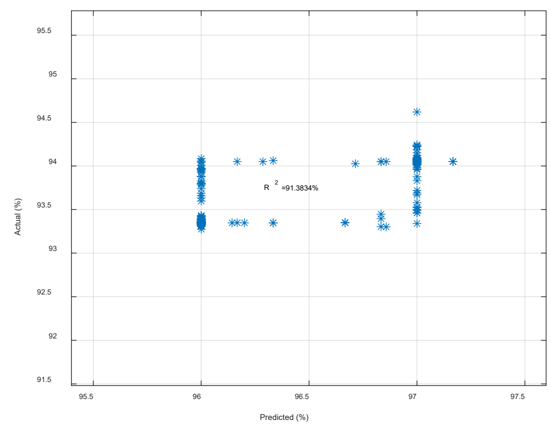
Fig. 6 (a) Comparison of Estimated Temperature Prediction Results Using CNN and (b) its Scatter Plot

The graph presented in Figure 6(a) illustrates a discrepancy between actual and predicted temperatures at the 50th minute, with the actual temperature recorded at 23.8 Celsius and the predicted temperature at 14.2 Celsius. The actual temperature exhibited a gradual increase, in contrast to the forecasted temperature, which rose in an erratic manner. By the 250th minute, both temperatures had stabilized, with the actual temperature reaching 24.5 Celsius and the forecasted temperature leveling off at 14.7 Celsius. The graph features a red line representing the predicted temperature, which does not run parallel to the blue line that indicates the actual temperature, highlighting the inaccuracy of the temperature predictions. Furthermore, the temperature prediction scatter plot, as shown in Figure 6(b), reveals that the CNN method's tests display a general trend of rising actual temperature values in conjunction with increases in estimated temperatures, despite the fluctuations in this ascent.

In Figure 7(a), during the 50th minute, 9 different tests were conducted, revealing a discrepancy between the actual and the predicted humidities, despite their nearly identical graphical representations. The actual humidity was recorded at 97%, while the predicted humidity was slightly lower at 94.05%. Both humidities experienced a decline at the 237th minute, with the actual humidity dropping to 96% and the predicted humidity to 93.3%. By the 250th minute, humidities began to rise, eventually stabilizing at the original levels by the 270th minute. This pattern indicates a slight increase in the second humidity measurement before it too stabilized at the initial level, suggesting that the predictions do not perfectly align with the actual humidities. The Scatter Plot of the humidity prediction is shown in Fig. 7(b). The humidity accuracy test appears almost rectangular, with humidity values fluctuating between 93.3% and 94.2%, and reaching a peak at 94.6%. Concurrently, the CNN method achieved a high accuracy level, attaining 91.383%. Scatterplot analysis indicates a positive correlation between the actual and estimated humidity values.



(a)



(b)

Fig. 7 (a) Comparison of Humidity Prediction using the CNN Method and (b) its Scatter Plot.

Comparison of Results. Table I demonstrates that the training method outperforms the testing method in forecasting temperature and humidity levels. This superiority is evidenced by the higher values of R2, MSE, RMSE, MAE, MBE, NRMSE, and NMSE for the training method compared to those for the testing method. The overall analysis of the table within the figure suggests that the R2 method is more effective in predicting air temperature and humidity.

Table 1. Comparison of Results.

Method	Temperature			Humidity		
	Train	Validation	Test	Train	Validation	Test
R2	0.95	0.71	0.91	0.94	0.5	0.91
MSE	93.3	1.81	93.7	7.74	8.65	8.07
RMSE	9.66	13.4	9.68	2.78	93.01	284
MAE	9.65	13.4	9.68	2.77	93.01	28.3
MBE	-9.65	13.4	-9.68	-2.77	93.01	-28.3
NMSE	0.15	2.01	0.15	8.33	8.84	8.64
NRMSE	4.2	3.09	6.91	0.55	9.11	2.43

Conclusion

In conclusion, this study successfully demonstrates the efficacy of an Internet of Things (IoT) and Convolutional Neural Networks (CNN)-based air humidity monitoring approach for enhancing orchid seed germination. The research findings affirm that the integrated system, utilizing real-time data collection and CNN analysis, achieves a notable accuracy level, particularly highlighted by a 91.383% success rate in humidity prediction. The insights gained from this study offer valuable information for farmers, enabling them to make informed decisions about optimal watering schedules and nutrient supplementation, thereby increasing the likelihood of successful orchid seed sowing. Moreover, the adaptability of this method for broader agricultural applications underscores its potential as a transformative tool in smart farming practices. By promoting increased productivity, improved crop quality, and reduced risks of failure, the IoT and CNN-

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based humidity monitoring approach emerges as a promising avenue for sustainable agricultural practices.

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