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Weather Monitoring and Prediction System for Rice Cultivation in Mandalay Using IoT and Machine Learning

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Article Information	Abstract
Received : 20 Feb 2025 Revised : 24 Feb 2025 Accepted : 28 Feb 2025	The purpose of this research is to monitor and predict temperature, humidity and carbon-dioxide with the objective of increasing rice yields in the rice fields located east of Mandalay. This research focuses on monitoring the temperature and humidity of rice fields near MTU. The data are displayed on
Keywords ESP 32, DHT11, DM118, Arduino UNO, LSTM, AWS Lightsail	a LCD and uploaded to a server to ensure timely access for farmers. Monthly weather forecasts are provided to assist farmers in making advance preparations. The energy generated by the solar system is sufficient to meet the system's low power consumption requirements. An ESP32 collects weather data from DHT11 sensor. CO2 data from the DM118 sensor is sent to the ESP32 via Arduino UNO using the UART protocol. These data are uploaded to the AWS Lightsail server. LSTM well-suited for time-series and
	sequence prediction tasks. Additionally, the data is presented in the farmers' native language to ensure readability for non-English speakers.

A. Introduction

Rice is the main agricultural product of Myanmar, and is also the main food crop of many Asian countries, and Southeast Asia. The nutritional value and quality of rice depend heavily on the climate and CO2 levels in the field. For enhance rice yield and quality, the temperature required is between 20°C and 35°C [1], and the required humidity is between 70% and 80%. The CO2 levels below 350ppm can slow down photosynthesis, resulting in slower growth and lower yields. Between 700 and 1000ppm, photosynthesis peaks, resulting in vigorous plant growth, better grain filling, and higher yields. These requirements are being addressed through monitoring and forecasting using modern technologies based on IoT and machine learning, aligned with the principles of Industry 4.0. farmers are being informed in real-time through automated systems.

In this research, ESP32 is used as the microcontroller and the data from DHT11 sensor is sent to ESP32. Since the DM118 only has analog output, it is converted to digital using the built-in ADC in the Arduino UNO and the data is sent to the ESP32 using the UART protocol. The obtained data is displayed on the 16×2 LCD in real-time using the ESP32 and uploaded to an AWS Lightsail server through WebSocket and Socket I.O. Then, the weather data is predicted using an LSTM machine learning model implemented with NumPy and Keras in Jupyter Notebook.

By providing the server ID and password to farmers in the project area near the MTU, farmers can easily view weather information in real time from the LCD and the server. This research provides weekly forecasts of temperature, humidity, and CO2, and the server provides information in both English and Burmese, so farmers who do not speak English can easily read and understand and prepare for their paddy fields.

Manzhu Yu, Fangco Xu, Weiming Hu, Jian Sun [1] did research on temperature forecasting for urban areas. In this research, a comparison of temperature prediction was conducted using various time series prediction techniques, including persistence model, historical average, ARIMA, feedforward neural networks (FNN), and Long Short-Term Memory (LSTM). Among these methods, LSTM is the best performance. When comparing performance, LSTM is divided into IoT data-only LSTM GeoTab and LSTM GeoTab+WU with five years of data. In LSTM architecture, the model is 90% trained and 10% validated. Performance evaluation was calculated by using RMSE and bias error. LSTM GeoTab has the best RMSE, it has 5.5% missing data.

Shivanshu, Palash Nagwanshi, and Anamika Chau [2] researched the weather forecasting system. In this research, humidity data from DHT22, and temperature data from LM35 sensor are sent to Arduino UNO and displayed on 16×2 LCD display. The Arduino uploads the collected data to the server via the ThingSpeak platform. Weather data is displayed using linear regression and multiple regression algorithm. In this research, there are two experiments with and without the use of the Levenberg-Marquardt Algorithm (LMA). This paper shows that the output without outliers is more stable than the output with outliers.

Wenhua Li, Lili Yi, and Xiang Yin [3] are used STM32F103C8T6 as main control board and ZH03B for dust sensor and SHT30 for temperature and humidity sensor. In this research, the M5310-A module was utilized as an interface due to its compatibility with Narrowband IoT (NB-IoT) communication. The weather data is transmitted to Alibaba cloud via the M5310-A module, where it undergoes predictive analysis using an LSTM (Long Short-Term Memory) network. In this research, PM2.5, PM10, temperature and humidity are detected. These data can be predicted for the next few hours.

In this research, not only temperature and humidity but also CO_2 are monitored and predicted. Moreover, the most effective prediction method, the Long Short-Term Memory (LSTM) method is used. Therefore, this research has an accuracy of over 92%, making it effective in monitoring and predicting weather for rice fields.

B. Methodology

This research uses renewable energy source. The ESP32 is used as the main microcontroller for data collection and transmission.

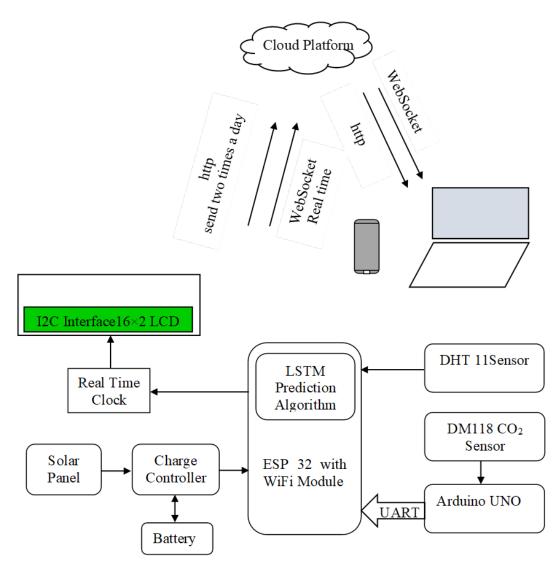


Figure 1. Block Diagram of the Weather Monitoring and Prediction System

The DHT11 sensor is used for measuring temperature and humidity. The DM118 sensor is used for measuring CO2 levels. The program is written in Arduino IDE to transmit it to a server using HTTP requests or WebSocket. Flask and Socket I.O are used for handling the data sent from the ESP32. The data is uploaded to the server through the internet connection provided by the SIM card inserted into the ESP32. Farmers can monitor the data on a smartphone or laptop devices. It is used as a controller. Real Time Clock RTC used to operate in real time application [5]. This allows the I2C 16×2 LCD to display values in real time and upload to the cloud for monitoring and data logging. This process is shown in Figure 1. The pin diagram of the temperature and humidity system is shown in Figure 2.

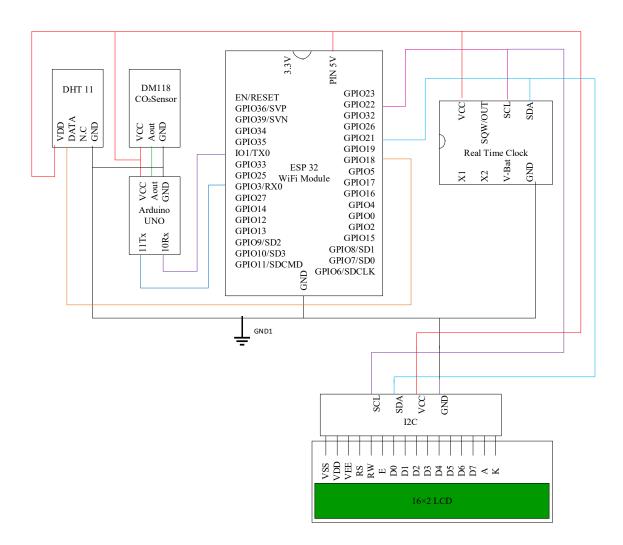


Figure 2. Pin Diagram of the Weather Monitoring System

The flow-chart of the temperature and humidity monitoring system is shown in Figure 3. The process begins by initializing the controller and sensors. Once initialized, the sensors are activated and ready to collect data. The system then verifies the functionality of the sensors. If the sensors are operational, data collection commences. Real-time data from the sensors (temperature, humidity, and CO2 levels) is gathered and stored. Finally, these weather data are displayed to the 16×2 LCD.

The LSTM method is used to predict the temperature, humidity and carbon-dioxide data. The flow chart illustrates the processes involved in weather forecasting, highlighting the application of Long Short-Term Memory (LSTM) machine learning models.

In this research, the accuracy of temperature and humidity measurements was determined by comparing the data obtained from the Department of Meterology and Hydrology (DMH) [4] sensor with reference values. The accuracy of CO_2 measurements was evaluated by comparing the data from the DM118 sensor from Environmental Conservation Department (ECD) [5].

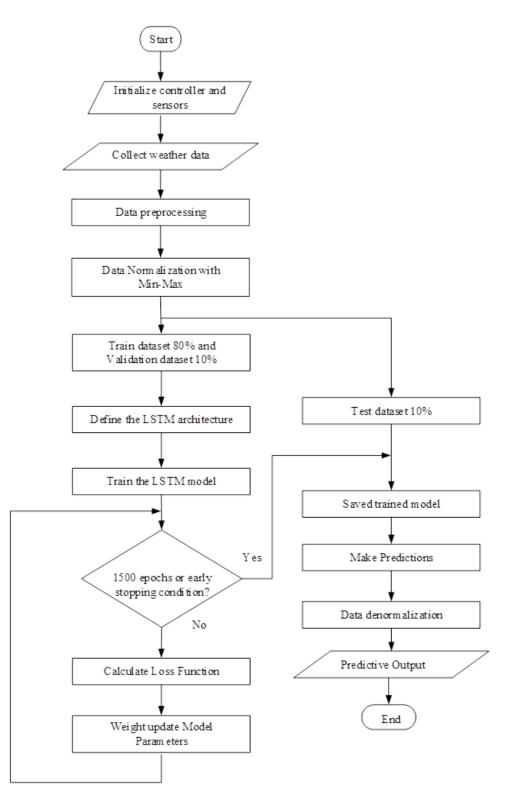


Figure 3. Flow-Chart of the Weather Monitoring System

The rice fields, where this research was conducted, are situated near Mandalay Technological University. Tables 1, 2, and 3 list the CO2 levels, temperature levels, and humidity levels specified for display on the server, and the effects of those values in both local and English. It is intended to be convenient for farmers who only speak the local language. In this research, LSTM algorithm is used to predict temperature, humidity, and carbon-dioxide data.

Table 1. CO ₂ rating and impact chart [6,7]			
CO2 level (ppm)	Effect	အကျိုးသက်ရောက်မှု	
<350ppm	Healthy outside air level	ကျန်းမာသော ပြင်ပလေထုအဆင့်။	
≥350 and <600	Healthy indoor air level	ကျန်းမာသော အိမ်တွင်းလေထုအဆင့်။	
≥600 and <800	Acceptable level	လက်ခံနိုင်သော လေထုအဆင့်။	
≥800 and <1000	Ventilation required	လေဝင်လေထွက် လိုအပ်သောအခြေအနေ။	
≥1000 and <1200	Ventilation necessary	လေဝင်လေထွက် မဖြစ်မနေလိုအပ်။	
≥1200 and <2000	Negative Health Effects	အနုတ်လက္ခဏာ ကျန်းမာရေး သက်ရောက်မူ။	
≥2000 and <5000	Hazardous prolonged	ကြာရှည်နေလျှင် အန္တရာယ်ရှိသော အခြေအနေ	
	exposure		

Table 1. CO ₂ rating and impact	chart [6,7]
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Table 2. Temperature rating and impact chart [8]			
Temperature level ('C)	Effect	အကျိုးသက်ရောက်မှု	
<10	Cold	အေးခဲသည်။	
≥10 and <17	Cool	အေးမြသည်။ -	
≥17 and <30	Warm	နွေးထွေးသည်။	
≥30 and <35	Hot	ပူသည်။	
≥35 and <40	Very hot	အလွန်ပူသည်။	
≥40 and <45 ≥45	Extreme hot Lethal heat	အလွန်အမင်းပူနေသည်။ သေနိုင်လောက်သောအပူဖြစ်သည်။	

Table 2. T	'emperature	rating and	impact	chart	[8]	
	cmperature	i uting unu	mpuce	chart		

Table 3. Humidity rating and impact chart [9]		
CO2 level (ppm)	Effect	အကျိုးသက်ရောက်မှု
<25	Poor low humidity levels	စိုထိုင်းဆနိမ့်သော အဆင့်ဖြစ်သည်။
≥25 and <30	Fair	စိုထိုင်းဆ သင့်တင့်သည်။
≥30 and <60	Healthy levels	ကျန်းမာစေသော အဆင့်ဖြစ်သည်။
≥60 and <70	Fair	စိုထိုင်းဆ သင့်တင့်သည်။
≥70	Poor high humidity levels	စိုထိုင်းဆမြင့်သော အဆင့်ဖြစ်သည်။

C. Hardware Requirements

This research use TTGO Call ESP32 Wi-Fi module, DM 118 carbon-dioxide sensor, LCD display, and RTC. It is slightly different from Greenwich Mean Time because PythonAnywhere is a free server. Therefore, Real Time Clock (RTC) is used to keep the Myanmar Standard Time.

TTGo Call ESP32 with Wi-Fi Module

The TTGo Call ESP32 with Wi-Fi module is a dual-core microcontroller that supports programming in both the Arduino IDE and Python. It features built-in Wi-Fi and Bluetooth connectivity, along with GSM support at frequencies of 850, 900, 1800, and 1900 MHz, making it suitable for various IoT applications. The TTGO call ESP 32 microcontroller is illustrated in Figure 4.



Figure 4. TTGO Call ESP 32 Wi-Fi Module [10]

DM118 Carbon-dioxide Sensor

The DM18 CO2 sensor is operational within a temperature range of -10°C to 50°C and a relative humidity range of 0% to 95%. It is capable of measuring CO2 concentrations across a range of 0 to 10,000 ppm. DM118 carbon-dioxide sensor is shown in Figure 5.



Figure 5. DM118 Carbon-Dioxide Sensor [11]

DHT11 Temperature and Humidity Sensor

The DHT11 sensor operates with a power supply range of 3V to 5V. It provides a temperature accuracy of $\pm 2^{\circ}$ C within the range of 0°C to 50°C and a humidity accuracy of $\pm 5\%$ within the range of 20% to 80%. Figure 6 shows the DHT11 sensor.



Figure 6. DHT11 Temperature and Humidity Sensor [12]

Arduino UNO

The Arduino UNO has a clock speed of 16 MHz and requires an operating voltage of 5V. The Arduino UNO is shown in Figure 7.



Figure 7. Arduino UNO [13]

I2C Interface Module

The I2C interface simplifies the 16-pin configuration of the 16*2 LCD display to a 4-pin setup, utilizing VCC, GND, SDA, and SCL for power and communication. The I2C interface module for 16*2 LCD is shown in Figure 8.



Figure 8. I2C Interface Module [14]

16×2 LCD Module

The DHT11 sensor operates with a power supply range of 3V to 5V. It provides a temperature accuracy of $\pm 2^{\circ}$ C within the range of 0°C to 50°C and a humidity accuracy of $\pm 5\%$ within the range of 20% to 80%. Figure 9 shows the DHT11 sensor.



Figure 9. 16×2 LCD Module [15]

Real Time Clock RTC

The RTC includes a digital temperature sensor with a $\pm 3^{\circ}$ accuracy and the device communicates via the I2C interface. A real time clock RTC is shown in Figure 10.



Figure 10. Real Time Clock RTC [16]

D. Software Requirements

This research use TTGO Call ESP32, DM 118 carbon-dioxide sensor, DHT11 temperature and humidity sensor, Arduino UNO, 16*2 LCD display with I2C interface and Real Time Clock (RTC). Real Time Clock (RTC) is used to keep the Myanmar Standard Time.

Arduino IDE Software

In this research, Arduino UNO is used UART to send data from DM118 sensor to the ESP32, and Arduino IDE software is also used for the ESP32. The logo of Arduino is shown in Figure 11.



Figure 11. Arduino IDE [17]

Python with NumPy and Keras

In this research, Python with NumPy and Keras are used machine learning and deep learning frameworks for AI. Figure 12 shows the logo of NumPy and Figure 13 shows the logo of Keras.



Figure 12. NumPy Logo [18]



Figure 13. Keras Logo [19]

Jupyter Notebook

Jupyter Notebook is used for developing LSTM model by using NumPy libraries. The LSTM time-series prediction model is built using Keras in a Jupyter Notebook, where data is manipulated using NumPy. Jupyter Notebook logo is shown in Figure 14.



Figure 14. Jupyter Notebook Logo [20]

WebSocket and Socket I.O

WebSocket provides for real-time communication, while Socket.IO enhances it by adding additional features and reliability across platforms. Figure 15 shows the logo of WebSocket and Socket.IO.



Figure 15. WebSocket and Socket I.O Logo [21]

E. Result and Discussion

In this research, data from the last week of December 2024 is used for training, and predictions were made for the first week of January, 2025 and estimated over 1500 epochs to predict the temperature, humidity, and carbon-dioxide values. Figure 16 shows the testing of weather monitoring and prediction system.

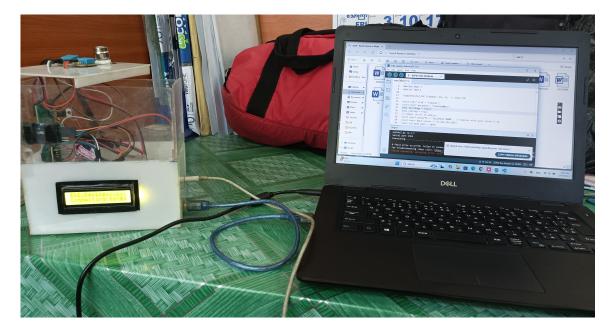


Figure 16. Testing of the Weather Monitoring and Prediction System

This research uses Jupyter Notebook. The default Transmission Control Protocol (TCP) port for this Jupyter Notebook is 8888 for IoT application. Additionally, 8889 is used as an alternative port for the MQTT service. Database and analytics tools are used port 8889. Figure 17 shows the home page of 8889.

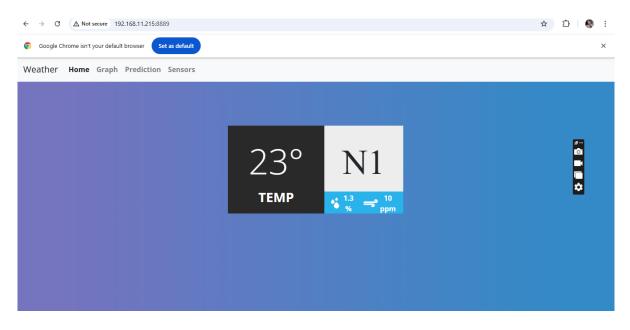


Figure 17. Home page of 8889 port

When making predictions with LSTM, 80% of the dataset is trained with 1500 epochs. Each epoch step takes $10 \sim 13$ ms. Since there are 7batches per epoch, the approximately time per epoch would be 7×12 ms (average per step) =84ms per epoch. For 1500epochs, the total time would be 1500×84 ms=126s=2m6s. LSTM machine learning model is used to predict the weather for a week. The predicted values are then uploaded to the AWS Lightsail server, as illustrated in Figure 18.

Date	Humidity(Day)	Humidity(Night)	Temperature(Day)	Temperature(Night)	Carbon(Day)	Carbon(Night)
1/1/2025	83.76	75.28	30.00	18.72	620.58	896.57
1/2/2025	83.83	75.27	30.00	18.73	621.38	896.59
1/3/2025	83.84	75.23	30.00	18.72	621.70	896.40
1/4/2025	83.84	75.21	30.00	18.72	621.95	896.26
1/5/2025	83.84	75.20	30.00	18.72	622.14	896.13
1/6/2025	83.84	75.20	30.01	18.73	622.29	896.01
1/7/2025	83.84	75.21	30.01	18.73	622.41	895.89

Figure 18. Predicted data on the AWS Lightsail Server

Tables 4, 5, and 6 show the measured humidity, temperature, and carbon-dioxide values respectively. Day refers to 9.30 am and night refers to 6:30 pm.

Table 4. Humi	dity values measured at 9	:30 am and 6:30 pm		
Date	Humidity (Day)	Humidity (Night)		
1/1/25	80	78.2		
1/2/25	79.8	79.5		
1/3/25	82	80.4		
1/4/25	83.4	74.5		
1/5/25	79.4	72.3		
1/6/25	85.2	77.9		
1/7/25	84.3	79.8		
Table 5 Tompor	ature values measured at	9.30 am and 6.30 nm		
Date	Temperature (Day)	Temperature (Night)		
1/1/25	27.2	17		
1/2/25	31.3	17.3		
1/3/25	28.1	16.9		
1/4/25	27.9	17.1		
1/5/25	27.2	17.4		
1/6/25	31.3	18.34		
1/7/25	28.4	18.52		
	Table 6. CO_2 values measured at 9:30 am and 6:30 pm			
Date	CO ₂ (Day)	CO ₂ (Night)		
1/1/25	621.5	854.1		
1/2/25	630.9	850.6		
1/3/25	635.2	831.6		
1/4/25	637.4	853.8		
1/5/25	616.4	859.2		
1/6/25	645.3	834.3		
1/7/25	637.2	902.6		

The predicted data in Figure 18 and the real-time monitoring data from Tables 4, 5, and 6 were substituted into Equation 1 to compute the percentage error at the first week of January, 2025. Subsequently, the accuracy was determined using Equation 2. The obtained accuracy values of humidity, temperature, and carbon-dioxide are shown in Table 7, 8, and 9, respectively.

$$PE = \frac{|y_i - \hat{y}_i|}{|y_i|} \tag{1}$$

Where, PE=Percentage Error y_i = real data, y_i = predict data

Table 7. Prediction accuracy values of humidity at 9:30 am and 6:30 pm				
Date	Humidity (Day)	Humidity (Night)		
1/1/25	95.511	96.27		
1/2/25	95.193	94.68		
1/3/25	97.76	93.57		
1/4/25	99.475	99.05		
1/5/25	94.408	95.99		
1/6/25	98.404	96.53		
1/7/25	99.451	94.248		

Table 8. Prediction accuracy values of temperature at 9:30 am and 6:30 pm

Date	Temperature (Day)	Temperature (Night)
1/1/25	90.67	89.88
1/2/25	95.67	92.37
1/3/25	93.24	90.278
1/4/25	92.47	91.35
1/5/25	89.71	92.414
1/6/25	95.88	97.87
1/7/25	94.33	98.87

Table 9. Prediction accuracy values of Carbon-dioxide at 9:30 am and 6:30 pm

Date	CO ₂ (Day)	CO ₂ (Night)
1/1/25	99.85	95.263
1/2/25	98.49	94.87
1/3/25	97.91	92.208
1/4/25	97.576	95.027
1/5/25	99.069	95.702
1/6/25	96.43	92.603
1/7/25	97.68	99.257

As indicated in Tables 7, 8, and 9, the lowest accuracy in predicting the data for the first week of January, 2025 was observed for the temperature value during the day on the 5th, recorded at 89.71%. The highest accuracy was achieved for the humidity during the day on the 7th, recorded at 99.4513%. Since the lowest accuracy value is 89.71%, it

conclude that the LSTM-based prediction model in this research demonstrates a high level of reliability and performance.

The predicted data were compared with the measured data to calculate the accuracy of the prediction system. This research compares the weather data from Department of Meteorology and Hydrology (DMH, Mandalay) for temperature and humidity and data from Environmental Conservation Department (ECD, Mandalay) for CO_2 to calculate the accuracy of the weather monitoring system. Figure 19 shows a comparison of humidity, Figure 20 shows a comparison of temperature, and Figure 21 shows a comparison of CO_2 for the first week of January, 2025.

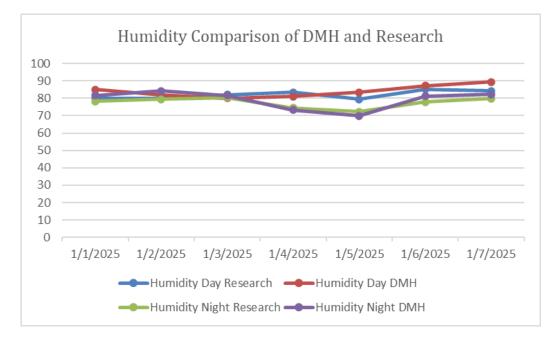


Figure 19. Humidity Comparison of Research and DMH Data

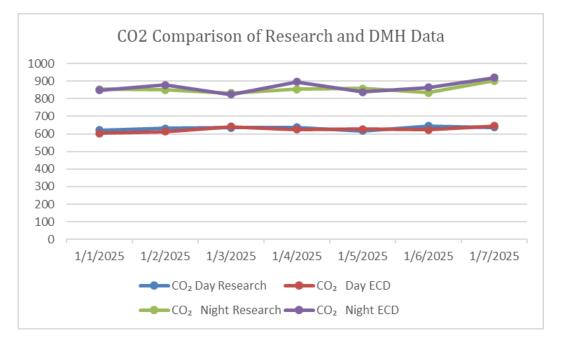


Figure 20. Temperature Comparison of Research and DMH Data

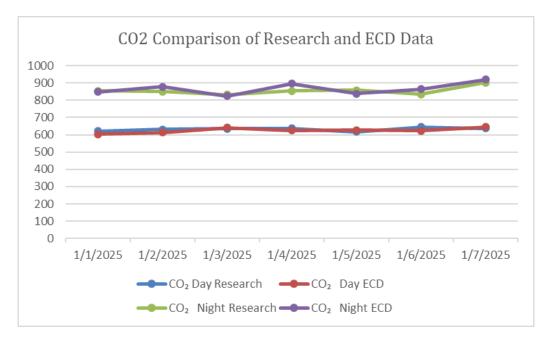


Figure 21. CO2 Comparison of Research and DMH Data

The accuracy results of the weather monitoring system developed in this research are compared in Figure 22. Accuracy values exceeding 99% were observed for one day in daytime CO_2 and two days in nighttime CO_2 . Accuracy values exceeding 98% were observed for two days in nighttime humidity and one day in nighttime CO_2 . In daytime conditions, accuracy exceeded 98% for two days in temperature and three days in CO_2 . The lowest accuracy for real-time monitoring system was 93.75% and 93.95% for daytime humidity, and 93.96% for nighttime humidity and 93.64% for nighttime temperature, so this research considered as good and reliable.

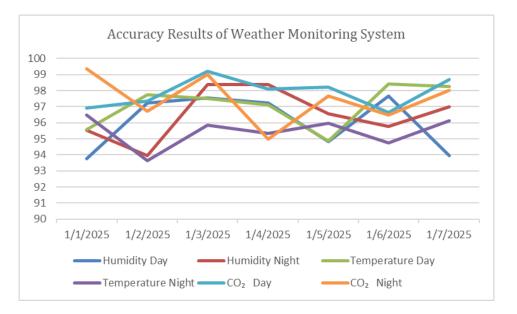


Figure 22. Accuracy Results of weather monitoring system

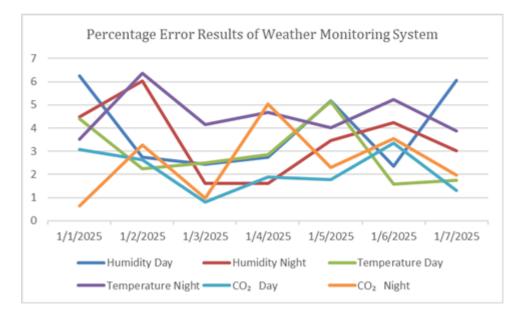


Figure 23. Percentage error results of weather monitoring system

A comparison of the percentage error of the weather monitoring system is shown in Figure 23. Accuracy and percentage error are used to calculate system performance. According to Equation 2, the inverse relationship is that as percentage error increases, the accuracy decreases. The highest percentage error is over 6 with an accuracy of over 93%. The prediction is for daytime temperatures to be 89.71% and nighttime temperatures to be 89.88%. Therefore, this research said to be able to conveniently monitor and approximate the temperature, humidity, and CO_2 levels required by farmers for rice cultivation.

F. Conclusion

The research focuses on monitoring and predicting temperature, humidity, and CO2 levels essential for rice plant cultivation. The current and forecasted data are uploaded to an AWS Lightsail server, enabling local farmers to access the information using the provided server ID and password. Weather conditions are displayed in both English and the local language to enhance usability for farmers. The accuracy of the predictions exceeds 89% ensuring the reliability and convenience of the system.

G. Acknowledgement

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