APPLICATION OF INTERNET OF THINGS AND GATED RECURRENT UNIT FOR TEMPORARY IMMERSION SYSTEM

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Abstrak

Aplikasi teknologi Internet of Things (IoT) dan Gated Recurrent Unit (GRU) dalam sistem Temporary Immersion System (TIS) yang dapat digunakan untuk budidaya anggrek. Anggrek, sebagai tanaman hias dengan nilai ekonomi tinggi dan banyak diekspor di Indonesia, menghadapi tantangan dalam produksi yang tidak sebanding dengan permintaan pasar yang terus meningkat. Keterbatasan ini disebabkan oleh persyaratan ketat terhadap kondisi lingkungan seperti suhu, kelembaban, dan intensitas cahaya. Metode TIS yang dipadukan dengan IoT dan pembelajaran mesin menggunakan GRU untuk memprediksi suhu dan kelembaban dalam metode TIS dapat memantau suhu dan kelembaban di inkubator TIS selama pertumbuhan anggrek. Sensor akan digunakan untuk mengumpulkan data lingkungan, yang kemudian diproses untuk mengontrol kondisi inkubator secara real-time. Pembelajaran mesin GRU, sebagai model jaringan saraf buatan yang digunakan untuk memprediksi kebutuhan lingkungan. Implementasi IoT dan GRU dalam metode TIS diharapkan tidak hanya meningkatkan efisiensi dan kualitas kultur jaringan anggrek, tetapi juga memberikan kontribusi terhadap penelitian di bidang agronomi dan botani. Penelitian ini mencakup identifikasi masalah, pengumpulan data, analisis kebutuhan, pembuatan alat, pembuatan algoritma, pengujian alat, dan pembuatan laporan. Evaluasi akurasi prediksi kondisi inkubator TIS menggunakan GRU akan dilakukan dengan metrik seperti RMSE, MAE, MAPE, dan R^2. Hasil penelitian ini diharapkan dapat memberikan perspektif baru dalam penggunaan teknologi canggih di bidang pertanian dan menawarkan solusi untuk meningkatkan produksi anggrek di Indonesia.

Kata kunci: *Machine Learning, IoT, GRU, TIS*

Abstract

Application of Internet of Things (IoT) and Gated Recurrent Unit (GRU) technology in the Temporary Immersion System (TIS) system which can be used for orchid cultivation. Orchids, as ornamental plants with high economic value and widely exported in Indonesia, experiencing challenges in production that are not in line with increasing market demand. This limitation is caused by strict requirements for environmental conditions such as temperature, humidity, and Light intensity. TIS method combined with IoT and machine learning using GRU to predict temperature and humidity in the method TIS can monitor the temperature and humidity in the TIS incubator during orchid growth. Sensors will be used to collect environmental data, which is then processed to control incubator conditions in real-time. GRU machine learning, as an artificial neural network model used to predict environmental needs. Implementation of IoT and GRU The TIS method is expected to not only increase efficiency and quality orchid tissue culture, but also contribute to research in fields of agronomy and botany. This research includes problem identification, data collection, analysis requirements, tool creation, algorithm creation, tool testing, and manufacturing report. Evaluation of the accuracy of predictions of TIS incubator conditions using GRU will be done with metrics such as RMSE, MAE, MAPE, and R^2. Results of this research is expected to provide a new perspective on the use of advanced technology in agriculture and offers solutions to increase orchid production in Indonesia.

Keywords : Machine Learning; Internet of Thing; Gated Reccurent Unit; Temporary Immersion System; Tissue Culture; Environment Prediction.

1. Introduction

Orchids are highly favored ornamental plants among plant enthusiasts, cherished for their beautiful flowers and relatively high prices. Orchids constitute the highest exported plant species in Indonesia, significantly impacting the country's economy. However, orchid production has been relatively slow compared to market demands due to the meticulous monitoring required for factors such as temperature, humidity, and light intensity [1].
To address this, the Temporary Immersion System (TIS) method is proposed. TIS utilizes a liquid medium to stimulate large-scale plant tissue culture automatically. This method allows precise control of the culture environment, including nutrients, humidity, and gas exchange tailored to the plant's needs. TIS also reduces contamination risks as plants are not directly exposed to the external environment during the culture process [2], [3].
A study introduced a new model using Gated Recurrent Unit Neural Networks to predict sea surface temperatures in the Bohai Sea. This model captures temporal regularities and improves prediction accuracy and stability. Accurate sea surface temperature predictions have applications in marine climate management, production optimization, and sea protection [4].

Another study used Gated Recurrent Units (GRU) to predict PM2.5 concentrations in Beijing using meteorological data from 2010 to 2014. The GRU method accurately predicted pollutant concentrations, employing logistic sigmoid functions for calculations and z-score normalization for data preparation. Results indicate potential for broader pollutant prediction applications, contributing to environmental monitoring and management [5].
In 2019, Aniruddha Dutta, Saket Kumar, and Meheli Basu utilized advanced machine learning to predict Bitcoin prices. They found that the GRU approach outperformed other models, with internet search data and Ripple price proving significant predictors. This study sheds light on Bitcoin's potential as an alternative investment [6].
In 2020, Wuyan Li et al. used the GRU model to predict dissolved oxygen levels in hairy crab ponds in Yixing, China, showing its effectiveness. They noted similar success in predicting river water quality in Qiantang using RNN-based approaches. This highlights the potential of deep learning models for improving fishery production and health [7].
In 2019, Mohammad Obaidur Rahman et al. used modified GRUs to predict stock prices, achieving high accuracy. However, their focus on one method and limited dataset may affect generalizability. Also, future accuracy cannot be guaranteed as it's based on historical data [8].
In 2020, Edmund Pok Leng Shiang et al. explored using GRU models for real-time mobile network traffic prediction, addressing challenges posed by 5G and big data. Their research highlights the potential benefits of neural networks in improving traffic control and offers insights into innovative solutions [9].
In another study, Ning Dai et al. introduced Attention-GRU to improve cotton yarn quality prediction, resulting in significant accuracy enhancements. This has crucial implications for the textile industry, enabling better production efficiency through optimized cotton blending and spinning parameters. Their study provides a strong foundation for further research in this area [10].

We know that GRU is good for prediction from several previous researches which used GRU algorithm.To enhance environmental control within the TIS system, a combination of Internet of Things (IoT) and Gated Recurrent Unit (GRU) is proposed. IoT employs an Arduino UNO microcontroller to automate irrigation using DHT11 temperature and humidity sensors. GRU, as an effective type of artificial neural network for sequence data modeling, predicts the next environmental requirements and identifies patterns not easily discernible by human observation. These predictions are then used to regulate the TIS system to maintain optimal temperature and humidity for orchid growth.

2. Material and Methods

2.1 Block Diagram Tool

By integrating IoT and GRU into TIS, it is expected to improve efficiency and quality in orchid cultivation, reduce human intervention, and offer new insights in agronomy and botany by gaining a deeper understanding of the complex interactions within plant growth systems.

The tool made is a pump that uses an Arduino Uno microcontroller and Temperature and humidity monitoring tool that uses ESP32. Arduino UNO will control the watering process by activating the pump via a relay and carrying out five times watering the vessel every hour and suctioning after five hours. The ESP32 will separately collect temperature and humidity data from its sensors placed in the vessel and send it to the cloud via Wi-Fi to be carried out in the training process.

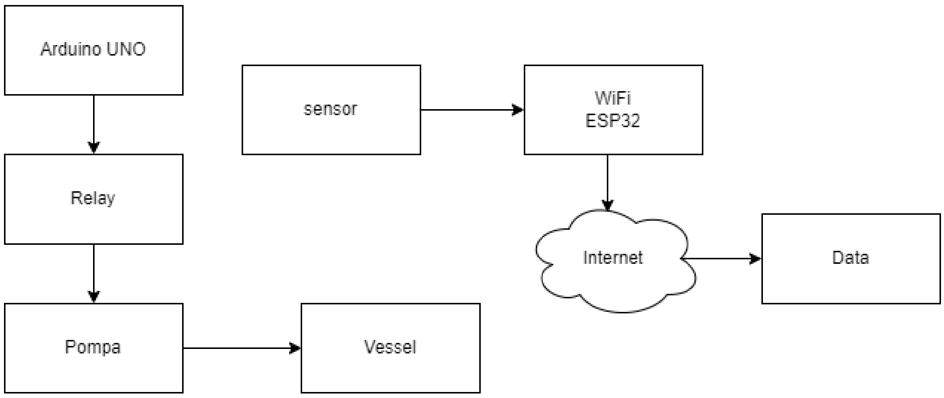

Figure 1 Block Diagram Tool

2.1.1 Pump Equipment

The pump tool was made using Arduino UNO as microcontroller to regulate the ignition of the pump using a relay, The relay will be connected to pin 12 on the Arduino UNO "in" on the relay, pin "3.3v" for the “vcc” pin, and the “gnd” pin for the “gnd” pin. Relays are used for controls and supplies electricity to the pump, the "com" pin is used on the relay to flow electric current from a source with a voltage of 9v, and the pin is "on" connected to positive current on both pumps. Both pumps will be used to pump water from both "reservoir" tubes and tubes "incubator", so that the pump can be turned on at certain time intervals determined and configured by Arduino UNO. To drain the water there are 4 The hose used is the same length, namely 30 cm, the hose is used to drain water from the reservoir to the incubator and from the incubator to the container.

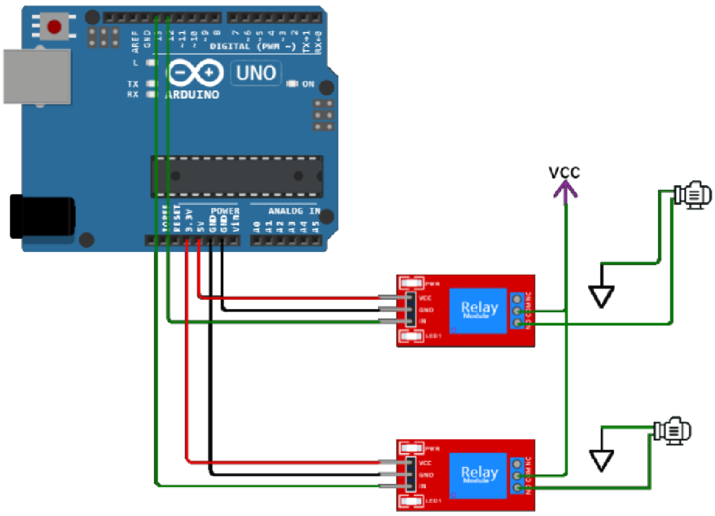

Figure 2 Pump Equipment

2.1.2 Temperature and Humidity Monitoring Tool

The temperature and humidity monitoring tool is made using a microcontroller ESP32 and uses a DHT11 sensor, the DHT11 sensor will be inserted into the tube incubator to take temperature and humidity data. The data that has been retrieved will be sent using wifi and entered into the spreadsheet.

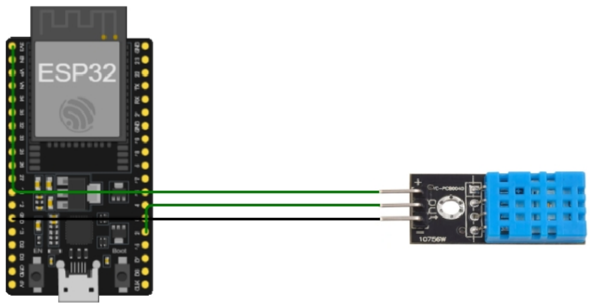

Figure 3 Temperature and Humidity Tool

2.2 Data Accumulation

The data collected is temperature and humidity data. Humidity and temperature measurements were carried out over a period of 7 consecutive days using the ESP32 device. During the data collection period, which was taken every 10 seconds, a total of 64,904 data entries were collected, each of which included time, temperature and humidity columns.

2.3 Measurement

2.3.1 RMSE

RMSE (Root Mean Square Error) is a metric used to measure how well the regression model predicts actual values. RMSE calculates the average deviation between the value predicted by the model and the actual value by calculating the difference between the value predicted by the model and the actual value, then the result squared, added, divided by the amount of data, and taken the square root of the results and obtain the RMSE value, which is a measure of the average deviation between values predicted with actual values. RMSE provides a useful measure of the magnitude of the model error, by giving more weight to errors that are larger, making it very sensitive to outliers [11].

$$RMSE=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i-Y_i)^2} \quad (1)$$

where m is the number of samples, X_i is predicted value for i-th sample, and Y_i is the actual value for the i-th sample.

2.3.2 MAE

MAE (Mean Absolute Error) is an evaluation metric used to measure how well the regression model predicts actual values. MAE calculates the average of the absolute difference between the value predicted by the model and the actual value with calculate the absolute difference between the value predicted by the model and the actual value, then the results are added up and divided by the amount of data and the MAE value is obtained, which is the average measure of the deviation between the predicted value and the value actual. A lower MAE value indicates that the model is better at predicting actual values. MAE is more resistant to outliers in comparison with RMSE, because MAE uses a softer L1 norm than the norm L2 used by RMSE [11].

$$MAE=\frac{1}{m}\sum_{i=1}^{m}\left|X_i-Y_i\right| \quad (2)$$

where m is the number of samples, X_i i-the predicted value, and Y_i is i-the actual value.

2.3.3 MAPE

MAPE (Mean Absolute Percentage Error) is an evaluation metric used to measure how well the regression model predicts values relatively actual. MAPE calculates the average of the absolute percentage differences between the value predicted by the model and the actual value by calculating the absolute percentage difference between the value predicted by the model and the value actual, then the results are added up and divided by the number of data and The MAPE value is obtained, which is an average measure of the percentage deviation between the predicted value and the actual value. Lower MAPE value shows that the model is better at predicting actual values 18 relatively. However, MAPE has the weakness that it can only be used on data which has a positive value and tends to give a biased assessment towards low prediction. Therefore, MAPE is often used together with other evaluation metrics to provide a more complete picture of model performance [11].

$$MAPE=\frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i-X_i}{Y_i}\right| \quad (3)$$

Where m is the number of samples, X_i i-th predicted value, and Y_i is i-the actual value.

2.3.4 R^2

Coefficient of determination or R^2 is the evaluation metric used to measure how well the regression model fits the observed data. R^2 measures how much variation in the response variable can be explained by a regression model by comparing the variability of the predicted values by the model with variability from the actual value. R^2 has a value range between 0 to 1, where a value of 1 indicates that the model is able to explain all variability of the data, while a value of 0 indicates that the model is not capable of explaining any variability at all. Higher R^2 indicates that the model is better at explaining variations in the data. However, R^2 also has weaknesses, namely not being able to provide information about model suitability if the model is too complex or if there are multicollinearity problems [11].

$$R^2 = 1 - \frac{\sum of\ Residual(SSR)}{Total \sum of\ Square(SST)} \tag{3}$$

Where **Sum of Squares of Residuals (SSR)** is the sum of squares of residuals, i.e the difference between the observed value and the value predicted by the model. SSR calculated by formula $\sum_{i=1}^{m} (Y_i - \hat{Y}_i)^2$ where Y_i is the observation value and $\hat{Y}_i$ is predicted value. Total Sum of Squares (SST) is the total variance in the observed data, calculated by formula $\sum_{i=1}^{m} (Y_i - \underline{Y})^2$ where $\underline{Y}$ is the average of the observation value Y_i .

2.4 Temporary Immersion System (TIS)

Temporary Immersion System (TIS) is a plant tissue culture system which uses liquid media and is designed to produce tissue cultures in large quantities. TIS allows controlling microenvironmental conditions, such as nutrient supply and gas transfer, so as to improve efficiency tissue culture production. TIS can also solve some of the related problems with tissue culture, such as hyperhydric and contamination [2], [3].

2.5 Internet of Things (IoT)

Internet of Things (IoT) is a technology that creates objects around us, including electronic devices, to connect to the internet network. This concept expands the benefits of continuous internet connectivity connected, so it is able to connect various devices, both machines or other physical objects, using sensors, networks and actuators thus collecting and processing data as well as managing device performance independently, can collaborate across devices and act based on independently acquired new information, which can be controlled from long distance [12].

2.6 DHT11 Sensor

The DHT11 sensor is a temperature and humidity sensor used in humidity and temperature monitoring projects. This sensor is capable of measuring internal temperature range -20°C to 50°C with an accuracy of ±2°C, as well as internal humidity range from 20% to 90% with an accuracy of ±5%. The DHT11 sensor uses a digital signal to transfer temperature and humidity data to the microcontroller [12].

2.7 Gated Recurrent Unit (GRU)

GRU (Gated Recurrent Unit) is a type of artificial neural network architecture network used to process sequence data such as text, sound, and video. GRU is a development of RNN (Recurrent Neural Network) and is similar to LSTM (Long Short-Term Memory), but with fewer parameters and faster training. The GRU combines several operations in one unit, including update gate, reset gate, and current memory content, which allows it to store values in memory for a certain period of time and use those values to carry forward information at the time of need [13].

3. Result and Discussion

3.1 Measurement Result

Humidity and temperature measurements were carried out over a period of 7 consecutive days using the ESP32 device. During the data collection period, which was taken every 10 seconds, a total of 64,904 data entries were collected, each of which included time, temperature and humidity columns. This intensive data collection is carried out to ensure that temperature and humidity patterns and trends can be tracked with high accuracy. The collected data is very useful in further analysis of environmental conditions measured by ESP32. The abundant availability of data allows for in-depth statistical analysis, as seen in temperature and humidity histograms.

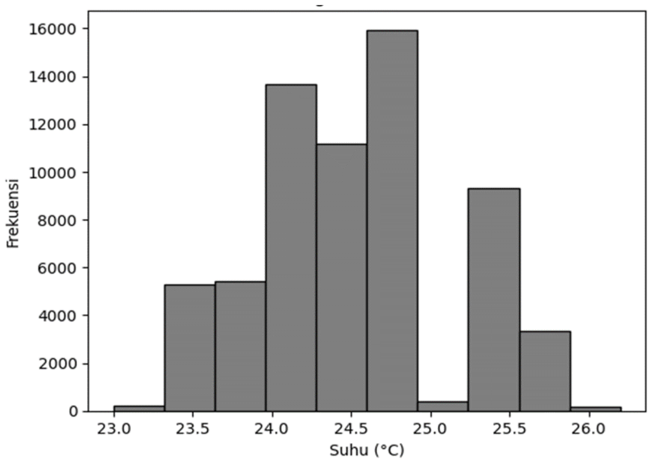

Figure 4 Temperature Data Histogram

Figure 4 Histogram shows the distribution of temperature data measured in the range 23.0°C to 26.0°C. The X axis shows the temperature value (°C) with intervals of 0.5°C, while the Y axis shows the frequency, namely the amount of data measured at each temperature interval. Based on the histogram, the majority of data (around 12,000) is concentrated in the temperature range 24.0°C - 24.5°C. This shows that temperatures of 24.0°C - 24.5°C are most often measured in incubators. The data frequency then decreases in the temperature range below 24.0°C and above 25.0°C. There is little data (under 2,000) in the temperature ranges 23.0°C - 23.5°C and 25.5°C - 26.0°C. The most frequently measured temperature in vessel 1 was between 24.0°C and 24.5°C. There is quite small temperature variation, with little data measured outside the 24.0°C - 25.0°C range.

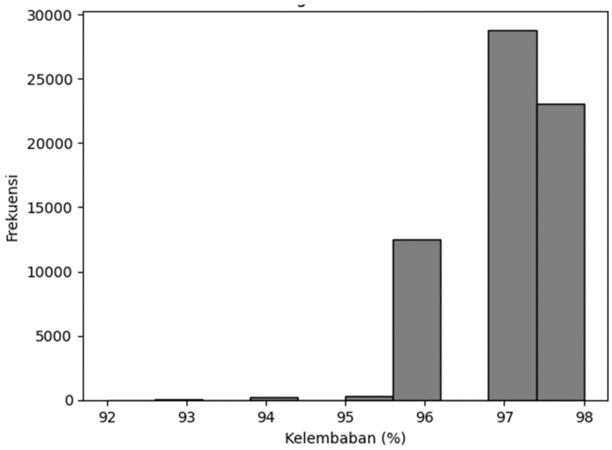

Figure 5 Humidity Histogram

In Figure 5, the histogram shows the distribution of humidity data measured in the humidity range of 92% to 98%. The X axis displays the humidity value in percentage (%) with 1% intervals, while the Y axis shows the frequency, namely the number of measurements recorded in each humidity interval. From this histogram, the majority of data is concentrated in the 97% - 98% humidity range, where this range has the highest frequency exceeding 25,000 measurements. This indicates that humidity in the range of 97% - 98% is most frequently recorded. The measurement frequency then decreases in the humidity range below 97% and slightly lower in the 96% range. There was a significant number of measurements, around 10,000, at 96% humidity. Measurements for the 92% - 95% humidity range are the lowest, indicating that humidity rarely drops below 96%. Thus, the most frequently measured humidity is between 97% and 98%. There is relatively little variation in humidity, with most data concentrated above 96%.

3.2 GRU Accuracy Testing Result

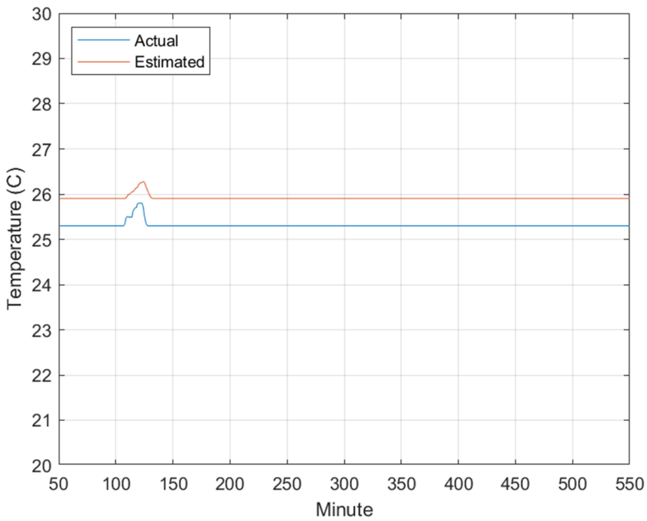

Figure 6 Comparison of estimated temperature prediction results using the GRU method

Temperature values are measured in degrees Celsius. From this graph, it can be seen that the actual temperatures show little fluctuation during the test period, especially between the 100th and 200th minutes. In contrast, the temperatures estimated by the GRU (Gated Recurrent Unit) algorithm appear to be quite stable and do not capture the fluctuations shown by the actual data. Although there is a slight difference between the actual values and the estimated values, the algorithm seems to do a pretty good job of averaging the temperature across the period tested.

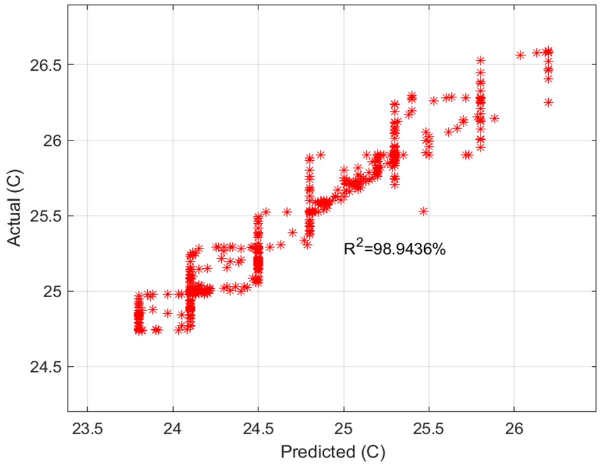

Figure 7 Temperature Prediction Scatterplot

Figure 7 shows the correlation between actual values between Actual (C) and Predicted (C). The dots on the scatter graph show the relationship between the independent variable (actual value (C)) and the dependent variable (predicted value (C)). The coefficient of determination, or R-squared, in this graph is 98.9436%, which indicates that 98.9436% of the variation in the dependent variable (predicted value (C)) can be explained by the linear regression model that was built showing that the linear regression model is very fits the data used so that the independent variable (Actual (C)) can explain most of the variability in the dependent variable (Predicted (C)). Variations in the dependent variable (predicted values (C)) appear consistent across the spectrum of the independent variables (actual values (C)). The remainder, which is the difference between the predicted value and the actual value, is scattered randomly around the regression line without showing any particular pattern or trend. This shows the fulfillment of basic assumptions in the linear regression model such as independence, homoscedasticity and normal distribution of residuals. Based on the very high R-squared value and the data distribution pattern on the scatter graph, it can be concluded that the linear regression model provides a very good representation of the data, where the independent variable (actual value (C)) succeeds in explaining most of the variation in the dependent variable (value prediction (C)).

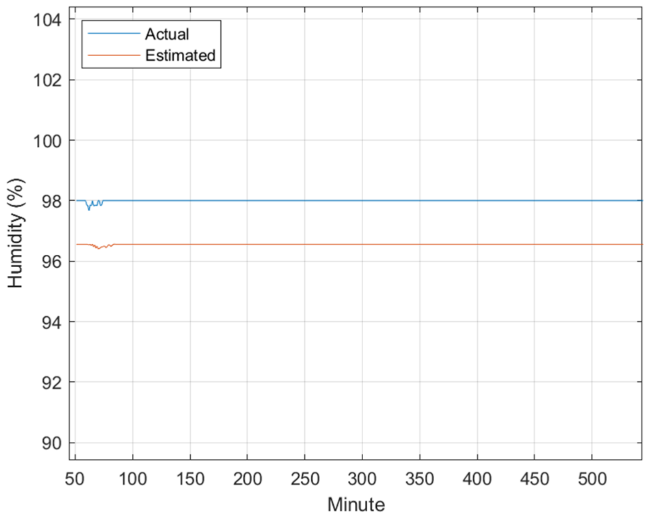

Figure 8 Comparison of Estimated Humidity Prediction Results Using the GRU Method

Humidity values are measured in percentage. From this graph, it can be seen that the actual humidity experienced slight variations during the test period, especially between the 50th and 100th minutes. The humidity values estimated by the GRU (Gated Recurrent Unit) algorithm appear to be very stable and do not reflect the fluctuations present in the actual data. Although there is a slight difference between the actual and predicted values, the algorithm appears to be quite effective in predicting the average humidity throughout the test period. This shows that while the algorithm may not capture sharp or rapid changes in humidity, it is able to provide a consistent estimate of the long-term trend of the measured humidity.

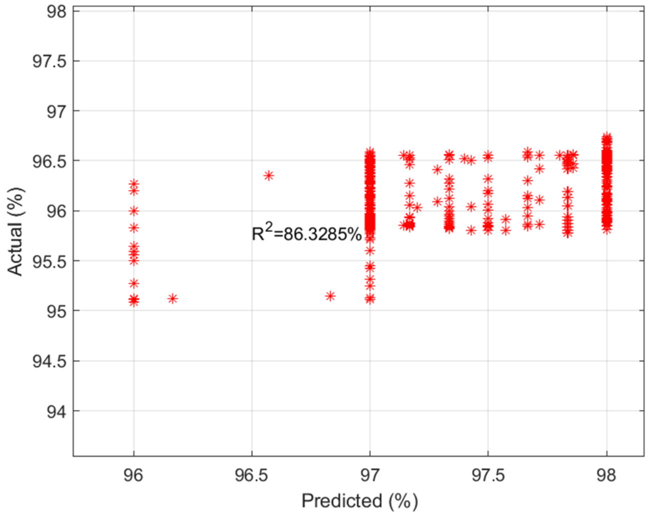

Figure 9 Humidity Prediction Scatterplot

The R^2 value of 86.3285% shows that the model has quite good performance but is not perfect in predicting humidity. This scatter plot reveals a fairly wide spread of points around the line that would represent a perfect prediction, indicating that there is variability in prediction error, and the possibility of some outlier values or inaccurate predictions.

3.3 Comparison of Result

Table 1 Comparison of Result

Metode	Temperature			Humidity		
	Training	Validation	Testing	Training	Validation	Testing
MAE	0.8614	0.7333	24.4484	1.0408	1.3627	94.9633
MBE	0.8614	0.7333	24.4484	-1.0408	-1.3624	94.9633
MSE	0.7575	0.5563	597.9385	1.1211	1.8960	9018.2559
NMSE	0.0015	0.0009	627.9623	0.0001	0.0002	9173.9780
NRMSE	0.3784	0.3108	234.9324	0.2118	0.6885	4653.2601
RMSE	0.8703	0.7458	24.4528	1.0588	1.3770	94.9645
R^2	0.9870	0.9894	0.9923	0.9366	0.8633	0.9491

Table 1 shows the estimation results using the Gated Recurrent Unit. Based on the table, it can be seen that GRU produces better performance on training data compared to validation data. This is indicated by the lower MAE, MBE, MSE, NMSE, NRMSE, and RMSE values in the training data. The high R^2 values in both data sets indicate that GRU is able to explain most of the data variation. The results of training and validation of temperature data show excellent performance with very high R^2 (> 0.98), which shows a good fit of the model to the data. However, in the testing phase, even though R^2 was still high (0.9923), the MSE and RMSE values jumped significantly, indicating the possibility of overfitting or diversity in the testing data that was not captured during the training phase. Performance in the training and validation phases of humidity data shows a fairly good R^2 (more than 0.86). In the testing phase, the metrics show significant increases in MAE, MBE, and especially MSE and NMSE, indicating that the model may not perform well on previously unseen data.

4. Conclusions

The results of humidity and temperature measurements using the ESP32 device for 7 days produced 64,904 data entries. Data analysis shows that the most frequently measured temperature is in the range of 24.0°C - 24.5°C, while humidity is most often recorded in the range of 97% - 98%. The data show small variations in temperature and humidity, indicating relatively stable environmental conditions during the measurement period. Testing the accuracy of the GRU model for temperature and humidity shows different results. The GRU model provided stable temperature estimates with little fluctuation, demonstrating the model's ability to average temperatures across the test period even though it does not fully capture actual temperature fluctuations. The temperature prediction scatterplot shows a very high coefficient of determination (R-squared) (98.9436%), indicating an excellent fit of the model to the data. However, for humidity, although the GRU model is quite effective in predicting average humidity, the model cannot accurately reflect actual humidity fluctuations, as shown by the R2 value of 86.3285% in the humidity prediction scatterplot. Comparison of accuracy testing results using GRU shows better performance on training data compared to validation data, with a very high R2 value indicating good model suitability. However, in the testing phase, especially for humidity, there was a decrease in performance which was marked by a significant increase in MSE and NMSE, indicating the potential for overfitting or the model's inability to generalize to new data. Overall, the results show that the GRU model is effective in predicting temperature.

5. Acknowledgements

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References

[1] N. Anggraeni, “POTENSI ANGGREK INDONESIA DI TENGAH PANDEMI COVID-19,” *Mimbar Agribisnis: Jurnal Pemikiran Masyarakat Ilmiah Berwawasan Agribisnis*, vol. 8, p. 639, Dec. 2022, doi: 10.25157/ma.v8i2.7171.

[2] V. Georgiev, A. Schumann, A. Pavlov, and T. Bley, “Temporary immersion systems in plant biotechnology,” *Eng Life Sci*, vol. 14, Dec. 2014, doi: 10.1002/elsc.201300166.

[3] L. CARVALHO, A. Ozudogru, M. Lambardi, and L. Paiva, “Temporary Immersion System for Micropropagation of Tree Species: a Bibliographic and Systematic Review,” *Not Bot Horti Agrobot Cluj Napoca*, vol. 47, p. 269, Dec. 2018, doi: 10.15835/nbha47111305.

[4] Z. Zhang, X. Pan, T. Jiang, B. Sui, C. Liu, and W. Sun, “Monthly and Quarterly Sea Surface Temperature Prediction Based on Gated Recurrent Unit Neural Network,” *J Mar Sci Eng*, vol. 8, p. 249, Dec. 2020, doi: 10.3390/jmse8040249.

[5] X. Zhou, J. Xu, P. Zeng, and X. Meng, “Air Pollutant Concentration Prediction Based on GRU Method,” *J Phys Conf Ser*, vol. 1168, no. 3, p. 32058, Feb. 2019, doi: 10.1088/1742-6596/1168/3/032058.

[6] A. Dutta, S. Kumar, and M. Basu, “A Gated Recurrent Unit Approach to Bitcoin Price Prediction,” *Journal of Risk and Financial Management*, vol. 13, p. 23, Dec. 2020, doi: 10.3390/jrfm13020023.

[7] W. Li, H. Wu, N. Zhu, Y. Jiang, J. Tan, and Y. Guo, “Prediction of Dissolved Oxygen in a Fishery Pond Based on Gated Recurrent Unit (GRU),” *Information Processing in Agriculture*, vol. 8, Dec. 2020, doi: 10.1016/j.inpa.2020.02.002.

[8] M. Rahman, Md. S. Hossain, T.-S. Junaid, M. Forhad, and M. Hossen, “Predicting Prices of Stock Market using Gated Recurrent Units (GRUs) Neural Networks,” vol. 19, pp. 213–222, Dec. 2019.

[9] E. Shiang, W.-C. Chien, and C.-F. Lai, “Gated Recurrent Unit Network-based Cellular Trafile Prediction,” Dec. 2020, pp. 471–476. doi: 10.1109/ICOIN48656.2020.9016439.

[10] N. Dai, H. Jin, K. Xu, X. Hu, Y. Yuan, and W. Shi, “Prediction of Cotton Yarn Quality Based on Attention-GRU,” *Applied Sciences*, vol. 13, p. 10003, Dec. 2023, doi: 10.3390/app131810003.

[11] D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” *PeerJ Comput Sci*, vol. 7, p. e623, Jul. 2021, doi: 10.7717/peerj-cs.623.

[12] R. A. Najikh, M. Hannats, H. Ichsan, and W. Kurniawan, “Monitoring Kelembaban, Suhu, Intensitas Cahaya Pada Tanaman Anggrek Menggunakan ESP8266 Dan Arduino Nano,” 2018. [Online]. Available: http://j-ptiik.ub.ac.id

[13] G. Shen, Q. Tan, H. Zhang, P. Zeng, and J. Xu, “Deep Learning with Gated Recurrent Unit Networks for Financial Sequence Predictions,” *Procedia Comput Sci*, vol. 131, pp. 895–903, Dec. 2018, doi: 10.1016/j.procs.2018.04.298.