Prediction of Timing and Amount of Houseplants Watering by an Echo State Network on Jetson

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Abstract

Cultivating of houseplants in biophilic designed spaces requires appropriate timing and amount of watering. However, determining them is challenging, as fluctuations in ambient temperature can influence these factors. We develop a system capable of predicting ambient temperature changes and determining the appropriate timing and amount of watering. The system acquires ambient data using sensors connected to a Jetson Nano and processes the data using a neural network for the prediction and determination. We adopt an echo state network, a lightweight neural network, enabling a power-efficient system capable of running on edge devices. Additionally, we implement a function to notify the user of the timing and amount of watering via a chat service whenever the soil moisture content drops below a predefined threshold.

Keywords: Biophilic-design, Echo State Network, Edge device

1. Introduction

Houseplants have various effects on our lives [1]. For example, they clean the air and give relaxation as interior decorations. Recently, biophilic design has gained attention. This is a methodology for designing building environments that achieve long-term sustainability by restoring and enhancing people's positive relationship with nature [2]. It is wide-ranging, for example, nature restoration design in artificial environments [3][4][5][6], biomimicry design, and greening buildings to improve people's well-being. Using houseplants is a key component of biophilic design for indoor building environments, and its function and benefits are reported [7][8]. To maintain a biophilic design space, it is important to properly manage the environment for houseplants, such as lightning and watering conditions.

However, managing the environment to grow houseplants is difficult because plants placed indoors depend on sunlight from outside and artificial lighting for their light supply. Sunlight from outside is affected by factors, such as the building structure, the sun angle depending on the region, seasonal changes, and weather. Additionally, artificial lighting often results in uneven light distribution indoors when buildings are designed based only on human needs. Lighting schedules are also controlled by human activities, with lights being turned on and off, making it difficult to manage optimal light conditions for houseplants. For water supply, the required amount of water changes depending on the plant's photosynthesis, transpiration, growth, and the indoor temperature and humidity. Even in indoor environments, the temperature and humidity can become uneven due to heating, cooling, ventilation, and humidity control from air conditioning systems. To address these issues, many studies focus on selecting plant types suitable for indoor greenery, mainly from the perspective of light supply. However, managing houseplants manually requires a lot of effort fundamentary. Also, not all caretakers have knowledge about plants, making it hard to provide the right amount of light and water at the right time.

Therefore, we develop a system to manage houseplants using AI that senses and predicts environmental data and notifies the user of the best watering time for the plants. For the hardware to run this system, we adopt the Jetson Nano [9], a device with an interface to connect sensors. Additionally, Jetson Nano is equipped with a graphics processing unit (GPU) and has a compact size, making it suitable for implementing edge AI. Since Jetson Nano has limited processing power, we cannot implement AI models with high computational load on it. Based on this, we build a system using a lightweight AI model, reservoir computing (RC).

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2. Technologies and Equipments

This study adopts RC as a prediction model for environment data because RC is lightweight and suitable for time-series processing, such as environment data. We implement an echo state network (ESN) [10] for the RC model.

The proposed system collects various environmental data such as temperature and soil moisture in real-time, analyzes them, and makes watering decisions. In this experiment, we use BME280 sensor [11], which measures temperature, humidity, and pressure, and Adafruit STEMMA Soil Sensor [12], which measures soil moisture.

3. Proposed Method

The proposed system consists of an environmental prediction part and a user notification part. This section describes these parts, respectively.

3.1. *Environmental prediction*

Generally, the optimal watering frequency for houseplants is approximately once every 4-5 days in spring and autumn, every 2-3 days in summer, and once every 1-2 weeks in winter. Therefore, we aim to implement a system that can predict environmental data a few days ahead.

For the environmental data prediction, we focus on temperature data among the environmental data. The proposed system feeds the temperature data into the ESN and trains it so that the ESN predicts one step ahead data. After the training, sequential forecasting, where the ESN output is fed to the ESN again to predict future steps, is available.

3.2. *User notification system*

When soil moisture remains below the proper range for a long time, plants may show mild stress signs, such as wilting leaves. Therefore, we focus on soil moisture here and develop the user notification system via LINE [13] when soil moisture decreases.

In this system, when the value from the soil moisture sensor falls below the threshold of 600, which was experimentally determined by obtaining the value when the soil becomes dry, the ESN predicts the temperature 10 minutes later. The value from the soil moisture sensor is a capacitance, with a range from approximately 200 (very dry) to 2000 (very wet). If the predicted temperature is higher than the current temperature, the system notifies the user to water the plants more. If the predicted temperature is lower than the current temperature, the system notifies the user to water the plants less. These notifications act as a guideline for users to determine the appropriate amount of watering, helping them avoid overwatering or underwatering. Figure 1 shows the flowchart of the system.

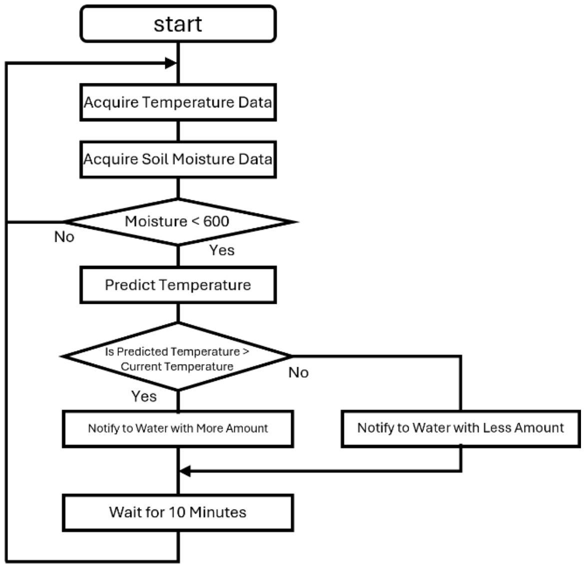


Fig 1. Flowchart of the system

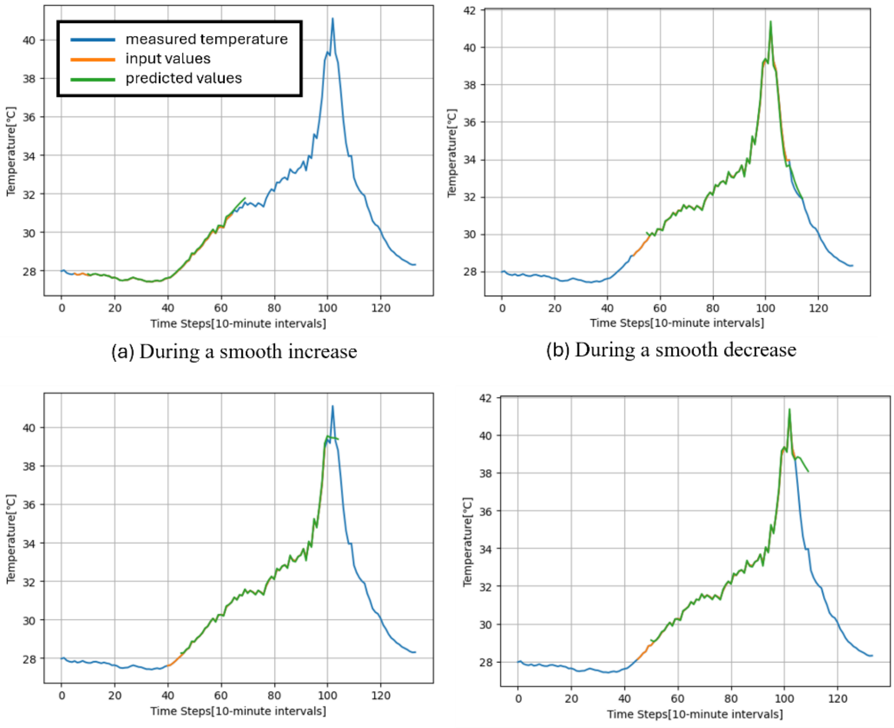
4. Experimental Method
4.1. *Environmental prediction*

First, we created the training data using long-term observation data [14] published by the Japan Meteorological Agency. The long-term observation data consists of temperature records at 10-minute intervals. We created the training data by selecting 10 consecutive steps (100 minutes) from the 800 step (8000 minute) long-term data, resulting in a total of 790 sets of 10 steps.

Next, we trained the ESN using the created training data by the ridge regression. The reservoir layer in the ESN consisted of 100 nodes. The connection weights for each node were randomly set values between -1 and 1, and the connection density was set to 0.5. Then, the connection weights were scaled so that the spectral radius became 0.99. The input layer had one node, and the connection weights from input to reservoir layer are randomly set between -0.3 and 0.3. The output layer had one node, and the connection weights from output to reservoir layer are randomly set between -0.01 and 0.01. The leak rate was set to 0.75. After the training, we verified the performance of the trained the ESN by giving untrained environmental dataset to it and comparing the predicted values with the actual values. Specifically, we fed 10 steps of untrained data into the ESN and compared prediction and the actual value.

4.2. *Sequential environmental prediction*

In this experiment, we used the model from Section 4.1 and temperature data observed on a specific day to evaluate the performance of sequential forecasting up to 10 steps ahead. First, we fed the actual values into the



(a) During a smooth increase (b) During a smooth decrease

(c) During a rapid increase (d) During a rapid decrease

Fig 3. Evaluation results

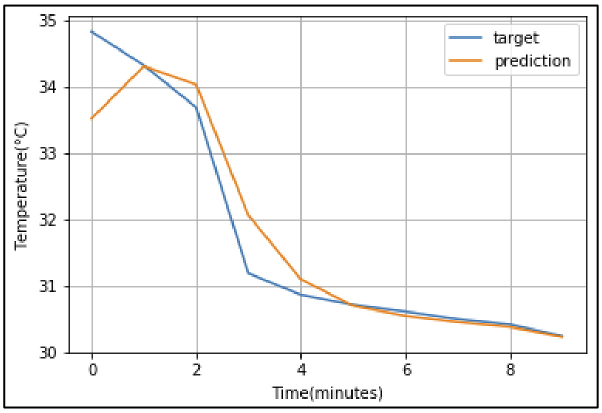


Fig 2. Temperature prediction using ESN

ESN up to a certain time. Then, starting from a specific time, we fed the predicted value from the ESN into the ESN for the next time as input and continue updating the reservoir state. A specific time refers to points where the data shows clear trends, such as smooth increases, smooth decreases, sharp rises, and sharp drops. This allows us to evaluate the performance of the prediction model under various conditions.

4.3. *Comparison of power consumption*

We measured the total power consumption in the system using a wattmeter [15]. We measured power consumption in two cases: when the system was in idle state (with no prediction model running) and when it run the temperature prediction using the ESN.

5. Results

5.1. *Environmental prediction*

We input measured temperature data for 10 steps into the trained ESN to check which step allows accurate prediction of the temperature data 10 minutes ahead.

Figure 2 shows an example of temperature prediction results. The blue line in the graph represents the data from the sensor, and the orange line represents the predicted data. In this example, from the 5th step, the sensor data and predicted data are almost the same, confirming that the temperature can be roughly predicted 10 minutes ahead.

5.2. *Sequential environmental prediction*

Figure 3(a) shows the prediction results for a smooth increase in temperature, Figure 3(b) shows the results for a smooth decrease, Figure 3(c) shows the results for a rapid increase, and Figure 3(d) shows the results for a rapid decrease. The blue line represents the measured temperature of the day, the orange line represents the input values to the ESN, and the green line represents the predicted values. Between time steps 65 and 70 in Figure 3(a) and between time steps 110 and 115 in Figure 3(b), the green line roughly follows the blue line. In contrast, between time steps 100 and 105 in Figure 3(c) and between time steps 105 and 110 in Figure 3(d), the green line does not follow the blue line and shows significant deviations. These results suggest that sequential

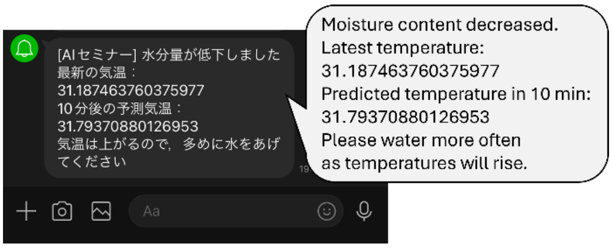


Fig 4. Execution results of the user notification system

forecasting can predict smooth changes, but it may be difficult to predict sudden changes.

5.3. *Comparison of power consumption*

The average power consumption in idle state was 35.85 [W], and the average power consumption during temperature prediction with ESN was 43.95 [W]. From this result, it was confirmed that when predictions using the ESN were made at short intervals of 1 second, the power consumption difference for each state was 8.1 [W]. In the system developed in this study, predictions using the ESN are made at 10-minute intervals, so the impact on power consumption by the ESN is small.

5.4. *Development of the user notification system*

Figure 4 shows the screenshot of the user notification system. The notification includes information about the decreased moisture level, the current temperature, the predicted temperature after 10 minutes, and the suggested watering amount. From this result, we confirmed that the notification system for the user worked correctly.

6. Conclusion

This study developed a system that predicts the timing and amount of watering for houseplants, which can run on an edge device using Jetson Nano. Specifically, the system uses an ESN for lightweight environmental prediction and sends appropriate notifications to the user based on data from sensors. Experimental results showed that this system accurately collects environmental data and can respond flexibly to changes in soil moisture. Additionally, predictions using the ESN can be performed with low power consumption on the edge device.

In the future, we introduce a function to predict sensor values for environmental factors other than temperature, such as humidity, light levels, and CO2 concentration. Additionally, we will analyze the growth of plants, including leaf color and shape, using image processing. This information be used as training data for a model that automatically adjusts the timing and amount of watering, aiming to further improve system accuracy. Moreover, we will enhance the system by predicting the optimal watering timing for each plant individually. As an application in biophilic design spaces, we develop robots with functions such as moving plants to watering stations based on the predicted environmental data.

References

1. V.-I. Lohr and C. H. Pearson-Mims, "Effects of Indoor Plants on Human Functions: A Systematic Review with Meta-Analyses," International Journal of Environmental Research and Public Health, vol. 19, no. 12, 2022.
2. S. R. Kellert, J. Heerwagen, and M. Mador, "Biophilic Design: The Theory, Science, and Practice of Bringing Buildings to Life," John Wiley & Sons, Inc. 2008.
3. K. Ito, T. Sudo, K. Ishimatsu, and H. Hasegawa, "Design and Ecological Management Process of Fishway and Surroundings." In: K. Ito (Eds.) Urban Biodiversity and Ecological Design for Sustainable Cities. Springer, 2021, pp.105-121.
4. K. Ito, T. Sudo, and I. Fjørtoft, "Ecological design: collaborative landscape design with school children." In Murnaghan, A.M.F. and Shillington, L.J. (Eds.) Children, Nature, Cities. UK: Routledge, 2016, pp. 95-209.
5. K. Ito, I. Fjørtoft, T. Manabe, and M. Kamada, "Landscape Design for Urban Biodiversity and Ecological Education in Japan: Approach from Process Planning and Multifunctional Landscape Planning," In: N. Nakagoshi, and J.A. Mabuhay, (Eds) Design Low Carbon Societies in Landscapes, Ecological Research Monographs. Springer, 2014, pp. 73-86.
6. K. Ito, I. Fjørtoft, T. Manabe, K. Masuda, M. Kamada, and K. Fujiwara, "Landscape Design and Children's Participation in a Japanese Primary School – Planning Process of School Biotope for 5 Years". In: Müller et al., (Eds.) Urban Biodiversity and Design. Willey-Blackwell, 2010, pp441-453.
7. F. Liu, L. Yan, X. Meng, C. Zhang, "A review on indoor green plants employed to improve indoor environment," J. Build. Eng., 53, 2022, 104542.
8. P. Chatakul, and S. Janpathompong, "Interior plants: Trends, species, and their benefits," Building and Environment, 2022, 222, 109325.
9. NVIDIA Corporation, "Jetson Nano Developer Kit," [Online]. Available: https://developer.nvidia.com/embedded/jetson-nano-developer-kit. Accessed: Dec. 8, 2024.
10. H. Jaeger, "The 'echo state' approach to analysing and training recurrent neural networks-with an erratum note," GMD Technical Report 148, German National Research Center for Information Technology, 2001.
11. Bosch Sensortec, "BME280 Combined Humidity and Pressure Sensor," [Online]. Available: https://www.bosch-sensortec.com/products/environmental-sensors/humidity-sensors-bme280/. Accessed: Dec. 8, 2024.
12. Adafruit Industries, "Adafruit STEMMA Soil Sensor - I2C Capacitive Moisture Sensor," [Online]. Available: https://www.adafruit.com/product/4026. Accessed: Dec. 8, 2024.
13. LINE Corporation, "LINE," [Online]. Available: https://line.me. Accessed: Dec. 8, 2024.
14. Japan Meteorological Agency, "Historical Weather Data Download," [Online]. Available: https://www.data.jma.go.jp/gmd/risk/obsdl/. Accessed: Dec. 8, 2024.
15. Sanwa Supply Co., Ltd., "TAP-TST10N Watt Monitor USB (2P, 1 Socket, White)," [Online]. Available: https://www.sanwa.co.jp/product/syohin?code=TAP-TST10N. Accessed: Dec. 8, 2024.

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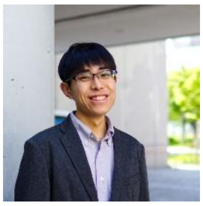

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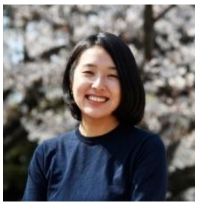

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