Smart Flowerpot as an IoT Device for Automatic Plant Care

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***Abstract*— Indoor plants provide many benefits but maintaining a healthy indoor plant can be difficult for some people as they may forget to water the plant regularly. In this research, we present design of a initial prototype smart flowerpot as an Internet of Things (IoT) device for automatic plant care. The device can retrieve weather data over the Internet and record sensor readings. Three control modes: manual, automated, and smart care with machine learning, were tested. Plants were kept alive in all modes, but the smart care mode achieved the same results with much less water usage. In all modes, maintaining steady soil moisture level proved to be challenging.**

Keywords—IoT Devices, Machine Learning, Automated Plant Care

I. Introduction

Potted plants and herbs are very common in indoor spaces and provide many benefits such as improved aesthetics, air purification, food source, and positive effects on people's mental health [1]. However, maintaining the health of the plant can be difficult for some people as they may forget to water the plant regularly, or they may need to leave the plant unattended for extended periods of time due to travel, potentially exposing the plant to drought conditions that affect its health or even result in the death of the plant.

There is a great deal of research addressing the many applications of IoT and machine learning in agriculture. However, little research is available applying these technologies to the care of indoor container plants.

Researchers have explored how these technologies can be used to determine watering needs, monitor crop state, distribute water to crops, and more [2]. In 2022, a virtual soil moisture sensor was presented that used deep learning (Long Short-Term Memory) to predict the soil moisture from other parameters (ambient temperature, soil temperature, relative humidity of the air, light radiation, and rainfall) [3].

In 2020, an IoT system was developed that used machine learning (Gradient Boosting Regression Trees) to learn the irrigation habit of a plant without previous data [4]. The system used data from sensors (air temperature, humidity, and soil moisture) and requires a small set of manual irrigation instances to learn the irrigation schedule and can continue that schedule autonomously with accuracy. In 2022, a solar-thermophysical irrigation (STI) instrument for potted plants was designed [5] . The system effectively provided the plants with micro-irrigation over the course of an eight-hour period driven by the naturally occurring isobaric thermal expansion and contraction processes occurring in the STI instrument as a result of irradiation by sunlight. Their results showed that plants watered by the STI system showed increased growth compared to periodically watered plants. The primary advantage of this system was the passive delivery of water over time However, the volume of water delivered is affected by the capacity of the instrument.

In this paper, we present an initial prototype flowerpot that was developed to evaluate sensor data, develop the capability to retrieve weather data and to test three control approaches. The prototype design includes sensors to monitor the ambient light, ambient temperature, relative humidity, and soil moisture of the plant environment. The data is made available over the Internet in a Google Sheet for a remote user. Additionally, the device can collect local weather information which is also added to the Google Sheet. The device performance was evaluated in three operation modes: (1) Manual care with operator pressing button to water, (2) Automated care according to a schedule and target soil moisture level, and (3) Smart care using machine learning.

II. Design of the Prototype Flowerpot

A. Device Design

The device consists of two nested pots (Figure 1). The white top pot contains drainage and holds the soil and plant. The clear pot has a reservoir at the bottom with a submersible pump and water.

Fig. 1. Photographs of the smart flowerpot.

The submersible pump (HiLetGo, JT-DC3-6V) is secured to the bottom of the water reservoir and a silicone tubing is connected to the pump outlet to deliver water to the top pot.

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The nested pots are placed on a rotating base (black round piece in Fig. 1). The base can rotate the flowerpot to any position within +/- 180 degrees so that different parts of the plant can be exposed to sunlight for even lighting and growth. The gray cover under the rotating base is where all the electronics and a Raspberry Pi 4 are located. An analog-to-digital converter (Adafruit, PCF8591) for the light and soil moisture sensors was used. Sensors for ambient light (dfRobot, DFR0026), and temperature and humidity (Adafruit, AHT20) were secured to the platform which also features a push-button, to initiate manual watering, and a kill-switch to allow immediate shutdown of the system without damaging the controller. A capacitive soil moisture sensor is inserted into the soil penetrating to a depth of 3 inches and located approximately half-way between the plant (located at the center of the nursery pot) and the edge of the nursery pot.

B. *Control Algorithms*

The smart flowerpot control algorithms were written in Python programming language. Three operation modes were designed and are described below.

Automated Care: All sensor data are collected every 30 minutes and recorded to a cloud document (Google Sheets). Watering need is evaluated every 2 days. If the soil moisture sensor indicates that the soil is drier than a desired target soil moisture level, the pump is activated for 2 seconds; otherwise, no action is taken, and the need for watering is re-evaluated after the next 2 days.

Manual Care: All sensor data are collected every 30 minutes and recorded to a cloud document. Watering occurs only by activation of the pump by human intervention (button press). Every 2 days, a researcher checks the soil moisture by inserting a finger in the soil and uses the flowchart in Figure 2 to make a watering decision based on observed plant state and local weather forecast.

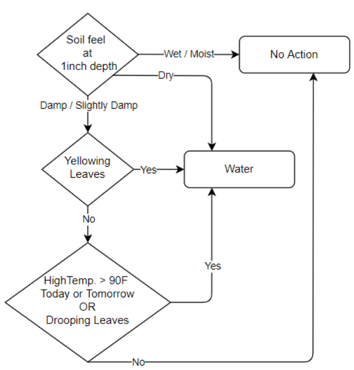

Fig. 2. Flowchart for manual care.

Smart Care: When water is added to a pot of soil, it takes a while for it to infiltrate into the soil. At the same time, some evaporation occurs, especially if the plant is located near a window with sunlight. In this approach, two machine learning (ML) algorithms are used: (1) Evaporation ML, and (2) Infiltration ML. Both models use Random Forest Regression. Every 30 minutes, all sensor and weather data are collected, and the evaporation ML model is used to output a predicted soil moisture (PSM) value. The model inputs were: previous soil moisture (PSM-1), time since the plant was last watered, if the sun has set, current date and time as well as the timestamp, temperature, dewpoint, visibility, relative humidity, and cloudiness from the most recent NOAA hourly observation. When the smart flowerpot is first turned on, no PSM-1 exists, therefore, the first PSM value is generated using a real soil moisture sensor value as PSM-1. After that, every 2 days, the algorithm determines if watering is needed. If the PSM value predicts that the soil is drier than a desired soil moisture target, the pump is activated for 2 seconds. After each watering instance, the infiltration ML model is used to output a new PSM from a set of inputs (time since watered = 15 minutes, previous soil moisture, date and time).

Data were collected to train the two ML models:

1. *Evaporation model data collection and training:* We first collected data for how soil moisture decreases over time as water evaporates from the soil. Two pots of soil were completely saturated with water, and each was placed inside smart flowerpots next to a window. The sensor readings on the smart flowerpot as well as the most recent hourly weather data a local airport near the university were retrieved by the flowerpots from the National Oceanic and Atmospheric Administration (NOAA) server every 30 minutes. Data were collected for 11 days from August 17-28.

   The data were then processed by parsing the date string into separate numerical values, and by assigning numerical values (0-6) to the cloud cover data, such as cloudy (0), sunny, partly cloudy, clear skies (6), etc.

2. *Infiltration model data collection and training:* We set a fresh pot of soil next to a window and watered it once. Then, every half hour the moisture sensor was checked to see if the reading reached a certain level. If so, another watering was done and the reading was repeated. The data collected was then processed to be used in training the ML model.

III. Experiments and Results

As mentioned earlier, three control strategies were tested. The performance of the flowerpot was evaluated using the following metrics: ability to (1) maintain a soil moisture target level, (2) keep the plant alive, and (3) support continued growth of the plant measured as increase in number of spinach leaves and greatest height increase of the lentil seedlings during the experiment.

A. *Plant preparation*

First, six nursery pots were prepared with All Purpose Potting Mix, then we planted two lentil sprouts (Lens culinaris) and one spinach plant (Spinacia oleracea) into each nursery pot. The spinach plant was placed in the center of the pot while the lentil sprouts were placed half-way between the center and the edge of the nursery pot on opposite sides of the spinach. The plants were then watered with 100mL of water, observations were recorded, and the plants were allowed to drain overnight. On the next day, each nursery pot was placed into a smart flowerpot and the irrigation tube and soil moisture sensor were added.

B. Observation categories

Every 2 days throughout the experiment, photos were taken to monitor the height of the spinach plants and lentil seedlings. In all experiments, the goal was to main a target moisture level reading of 23. The value read from the sensor goes up as the soil gets drier. Additionally, the following observation categories were recorded for each plant:

- Soil feel – in order of decreasing moisture perception: wet, moist, damp, slightly damp, dry, dry & hard.
- Leaf & stem position – upright, slight droop, drooping
- Leaf color – green, green-yellow, yellow-green, yellow
- Mature leaf texture – smooth, sticky, floppy
- Whether or not the 24hr forecast predicts outdoor temperatures to exceed 90°F.
- Number of mature leaves
- Number of immature/new growth leaves
- Number of dead leaves
- Number of leaves with pest damage
- Number of leaves with other damage

C. Treatment groups

Six smart flowerpots were divided into 3 treatment groups with two smart flowerpots assigned to each group (Figure 3). The three treatment groups correspond to the three control algorithms discussed earlier in Section II. Smart flowerpots F-10 and F-13 were assigned to the manual care treatment group. Smart flowerpots F-5 and F-12 were assigned to the automated care treatment group. Smart flowerpots F-1 and F-4 were in the smart care treatment group.

Smart flowerpots were placed indoors in front of windows and the experiment began by initiating the appropriate control algorithm for each smart flowerpot. For a total of 19 days, data were collected every 30 minutes and researcher observations were recorded every 2 days.

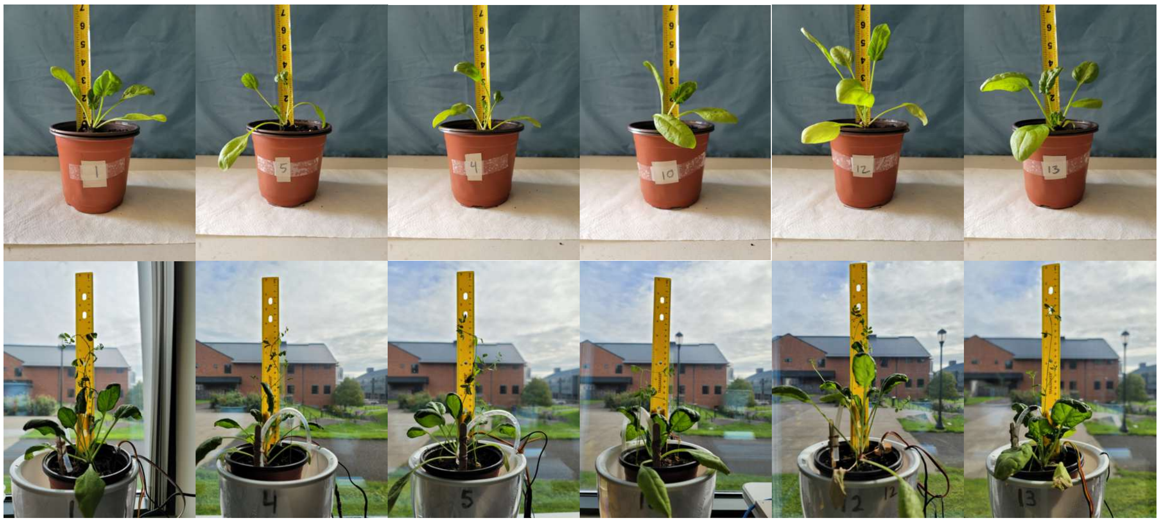

Fig. 3. Photos of spinach plants and lentil seedlings in nursery pots one day before beginning the experiment. (*top*) Photos of smart flowerpots on day 19 of the experiment. (*bottom*)

D. Manual care results

As shown in Figure 4, the manual care operation mode failed to achieve and maintain the target soil moisture level. Soil moisture readings at the beginning of the experiment were 27.84 for F-10 and 26.67 for F-13. Watering of F-10 was initiated on 80% of observation days, while F-13 was watered on 90% of observation days.

Both F-10 and F-13 kept the spinach plant and lentil seedlings alive for the duration of the experiment. F-10 developed 5 new leaves, while F-13 developed 4 new leaves. The greatest lentil seedling height increase for F-10 was 15.24cm, and it was 20.96cm for F-13.

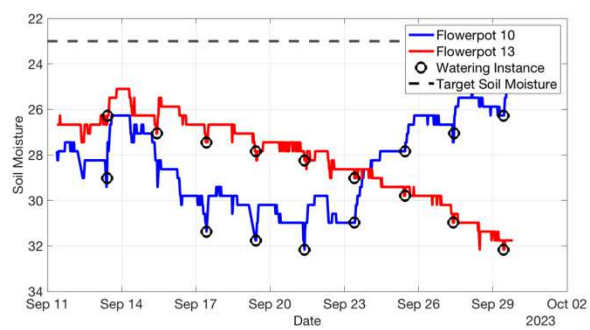

Fig. 4. Soil moisture over time for manual care flowerpots.

The circles highlight each time the plant was watered while the dashed line shows the target soil moisture value that was chosen as the ideal humidity for the spinach plants.

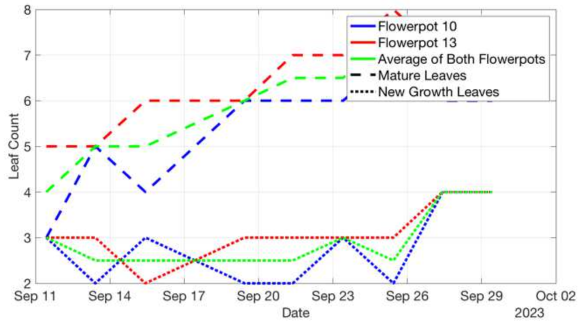

Fig. 5. Mature and new leaf count over time for manual care flowerpots.

Both flowerpots F-10 and F-13 started at very close soil moisture levels and initially decreased at a similar rate until September 24. F- 10 soil moisture then began to increase gradually through the rest of the experiment. F-13 however continued to lose moisture. Throughout the experiment, both flowerpots stayed relatively dry below the desired moisture level.

In Figure 5, the dashed lines represent the rate in which leaves matured for both flowerpots. The dotted lines are the count of new growth leaves. The green lines show the average leaf count between both flowerpots for each leaf category. Both flowerpots F-10 and F-13 had a very similar count of mature and new leaves throughout the experiment. The mature leaf count had steadily grown while the new leaf count stayed about the same with a small yet sudden increase after September 26.

E. Automated care results

As shown in Figure 6, the automated care operation mode achieved the soil moisture target for F-12 on day 3, but on day 4, the soil became slightly drier than the target soil moisture level. F-5 steadily approached the target soil moisture and got close to it although eventually remained below it. Soil moisture readings at the beginning of the experiment were 27.06 for F-5 and 26.27 for F-12. Watering occurred on 100% of watering decision days for both F-5 and F-12.

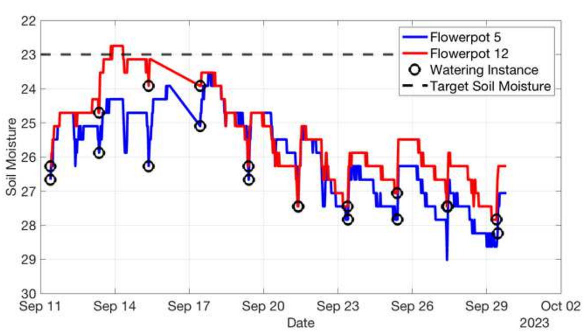

Fig. 6. Soil moisture over time for automated care flowerpots.

Both flowerpots maintained consistent and similar soil moisture with the automated care approach. Both increased at the start and began to steadily lose moisture from September 20th until the 23rd.

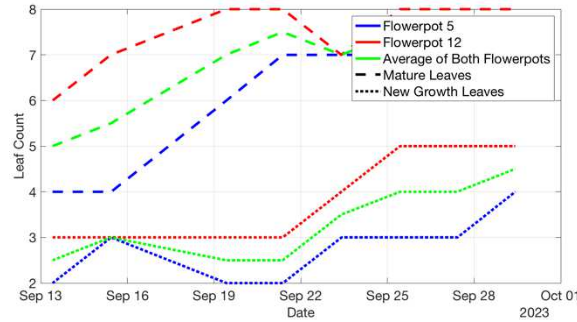

Fig. 7. Mature and new leaf count over time automated care flowerpots.

As seen in Figure 7, both F-5 and F-12 kept the spinach plant and lentil seedlings alive for the duration of the experiment. F-5 and F-12 both developed 6 new leaves during the experiment. The greatest lentil seedling height increase for F-5 was 17.78cm, and 18.42cm height increase was measured for F-12.

F. Smart care results

The performance of the smart care mode was similar the automated care case.

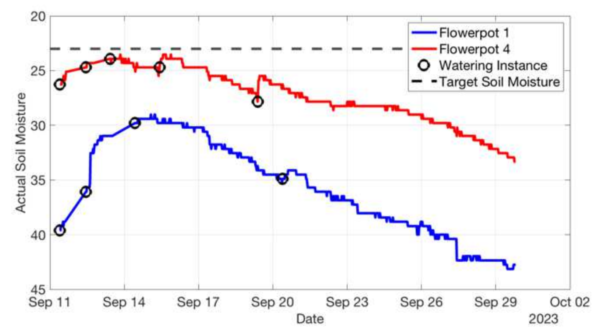

Fig. 8. Actual soil moisture over time for smart care flowerpots.

Figure 8 shows the actual soil moisture readings from the sensor in the soil because of the watering decisions made by the ML algorithms. However, these real sensor readings were not used by the ML algorithms in making watering decisions. Instead, the predicted soil moisture from the ML algorithms shown in Figure 9 were used to make the watering decisions.

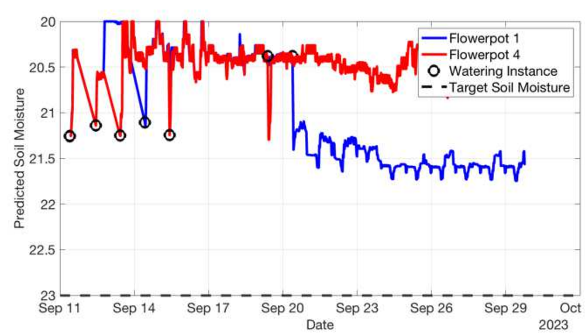

Fig. 9. Soil moisture predicted by ML over time for smart care flowerpots.

As shown in Figure 8, F-4 steadily approached the target soil moisture and got to 23.53 on days 3 and 5 although eventually remained below it. Soil moisture readings at the beginning of the experiment were 39.61 for F-1, and 26.27 for F-4. Watering of F-1 occurred on 40% of observation days, while F-4 was watered on 45.45% of observation days.

Both F-1 and F-4 kept the spinach plant and lentil seedlings alive for the duration of the experiment (Figure 10). F-1 developed 6 new leaves, while F-4 developed 7 new leaves during the experiment. The greatest lentil seedling height increase for F-1 was 15.87cm, and it was 15.88cm for F-4.

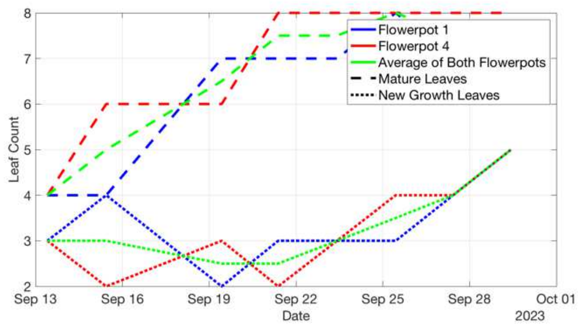

Fig. 10. Mature and new leaf count over time for smart care flowerpots.

IV. Conclusions

In this research, we have presented the design of a first prototype smart flowerpot as an IoT device for automatic plant care. The smart flowerpot performance was evaluated in three operating modes: manual care, automated care, and smart care. The device was evaluated for its ability to maintain target soil moisture levels, keep a plant alive, and support continued growth of a plant measured as increase in number of leaves and height increase for the tallest lentil seedling.

The results showed that all flowerpots were able to keep a spinach plant and two lentil seedlings alive for 19 days. Overall, it is hard to maintain a consistent soil moisture as seen in the manual experiment, even if you remember to water your plants. Same challenge was true for the smart care with ML and automated care modes. But in these modes, the moisture levels got near the desired target and remained near it for a period although ultimately the moisture in the soil was less than desired like the manual case. The leaf growth and count increased slower in the manual case than the automatic cases. The smart care with ML had a similar performance in soil moisture levels to the automated care but with much less frequent watering and hence water usage. It used significantly less water (40-45%) than the manual case (80-90%) to achieve the same plant health as in the manual case. It may be possible to further improve the performance of the ML model using more training data for closer predictions to the real moisture sensor readings.

The device as a first prototype provided valuable insights into the relations between various sensor data and enabled testing automatic algorithms. The future versions of the flowerpot will have less expensive processor and simpler design to reduce overall cost. In addition, experiments will be conducted for a longer period of time with increased watering amounts, which would likely improve the ability of the smart flowerpot to reach and better maintain target soil moisture.

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