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IOT IN INDOOR PLANTING

Vukota Đokić1*, Nikola Ivanović

Faculty of Agriculture, University of Belgrade, Belgrade, Serbia

*Corresponding author: vukotadjokic@gmail.com

Abstract. Nowadays, it is impossible to imagine a world without automation. A frequently used system that enables automation processes is the Internet of Things (IoT). The IoT is a system that brings together multiple technologies and techniques to create a connected network of devices. IoT devices find their way into homes through smart watches, air conditioners, cars, etc. The application in agriculture is also significant. Indoor cultivation of microgreens is often a side business, and growers don't have the whole day to monitor the microgreens. The question that arises is how to improve and smartly manage the cultivation of microgreens. According to that, the main goal of this project is to use the IoT for tracking parameters that are important, and sending them to the web for analysis and further control. In order to do that, microcontroller boards such as Raspberry Pi and Arduino Nano as well as the sensors DHT 11 and a capacitive soil moisture sensor are employed. The Raspberry Pi is used as the main brain of the project, while the Arduino Nano is used for listening and executing orders. The DHT 11 sensor is used to measure air temperature and humidity, and a capacitive soil moisture sensor is used for soil moisture. LED lights and a step motor are controlled through a web interface and can be accessed from anywhere. The Raspberry Pi V2 camera is placed on the edge of the rotating axis, and determines the stages of the microgreens by means of a Machine Learning (ML) model. In this way, two modes can always be used, automatic and manual, so that the growers can customize their own growing experience. This physical network of devices is especially useful for those people who want to grow their food but don't have enough time to keep an eye on everything, so it is easier for them if someone gives them exact data on what they need to do and when. This is exactly what this smart IoT project offers. It is necessary to connect the IoT project to the internet and track the desired data. In addition, a trained ML model helps to decide which stage a microgreen is in and what to do next.

Keywords: Indoor planting, IoT, Raspberry Pi, Arduino Nano and sensors

1. INTRODUCTION

Microgreens have become increasingly popular in recent years. People grow them in their basements, and small to mid-sized companies grow them on indoor farms. Whatever the growing method, there are challenges in actively measuring their status. The commonly used method for monitoring the growth of microgreens involves the use of: visual inspection, sensors and Internet of Things (IoT).

The first method is most commonly used because it doesn't require investment in expensive equipment. However, if you rely only on your eyes, you may notice problems too late, since you can't watch your microgreens all day. Low-cost sensors help, but they mostly provide surface-level information. Using the Internet of Things is best because it provides real-time, accurate information on microgreen status and can actively change that status, making an independent system that doesn't rely on human presence. This paper emphasizes using the fast-developing field of artificial intelligence, machine learning and deep learning, to improve the monitoring of microgreens. By implementing these technologies, you can track microgreens by color, determine their current growth stage, and identify what they need most to grow well.

The goal of this paper is to implement a deep learning model to analyze the stage of microgreens. In this way, we can track their growth stage and provide what they need in a timely and appropriate manner.

2. MATERIAL AND METHODS

In our work, for the experimental setup, we use:

- Raspberry Pi 4 Model B (8 GB RAM) as a master;
- Arduino Nano (ATmega328P) - as a slave;
- Raspberry Pi Camera Module v2 (Sony IMX219, 8 MP) for image acquisition;
- DHT11 digital sensor (data acquisition to Arduino);
- Aideepen capacitive soil-moisture sensor (analog output);
- 5 V LED grow strip (for plant illumination); and
- 3D-printed electronics enclosure (project-specific).

Figure 1. Overview of experimental IoT system.

The Raspberry Pi acts as the master and represents the main core of IoT projects, while the Arduino Nano acts as the slave. In automation terms, the master performs high-level decision-making, while the slave reports measurements and executes commands. In experimental setup, the camera and the Arduino are connected to the Raspberry Pi (USB serial). The Arduino handles all low-level I/O: two sensors (air temperature/humidity and soil moisture), LED strip and stepper motor. The LED strip and the stepper motor are powered by an external power supply, with a common ground, to prevent unintended resets caused by voltage drops. The process works in two phases: ZERO and INTERVENTION.

ZERO phase is the term for the first cycle that the shaft makes. In this phase, it goes one full circle while taking images, and then returns, still taking images. In total, it takes 24 images (12 on the forward pass and 12 on the return). Each captured image is analysed using a MobileNetV2 model [1]. When the entire cycle is completed, deap learning model counts how many images belong to each growth stage and determine the current stage of the microgreens based on the percentage. Based on this decision, we proceed to the Intervention phase. The Intervention phase is divided into three stages: GR - Germination, GP - Growth and PH - Pre-harvest.

In the germination stage, the microgreens are still dark/black and at this stage, they require a dark environment with slightly higher temperature and humidity. The temperature should be between 22-25°C, while the humidity reaching from 65-80 % of relative humidity. Accorcing to the capacitive sensor, the soil moisture should be between 250-400 of its raw reading. When the Deep Learning model decides that the microgreens are in this stage, we turn off the LED light and indicate in the app that the plants are in the Germination stage, which means that they need darkness and a slightly higher temperature and humidity.

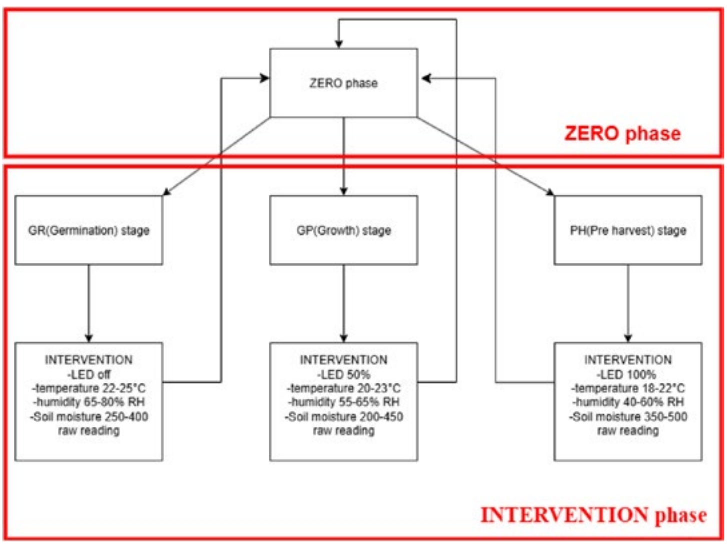

Figure 2. Workflow Diagram.

During the growth stage, the microgreens require 55-65% relative humidity and a temperature of 20-23°C. At this stage, the stepper motor slowly rotates one full cycle of the shaft and then returns shaft to its original position, while the LED light is set to 50% of maximum power (PWM 128). Raw values of the capacitive sensor should be 200-450.

In the pre-harvest stage (PH), the microgreens are green and fully developed, and before harvest it is neceserly wait a few more days. For this reason, the LED is set to full power, which means PWM is 255. The temperature should be 18–22°C and the relative humidity 40-60%. Raw values of the capacitive sensor should be 350–500.

Each stage lasts exactly 10 minutes, after which the model automatically returns to the ZERO phase and restarts the decision-making process. In this way, we reduce time in each stage and increase the precision of the system.

3. RESULTS AND DISCUSSION

3.1 Deep Learning Model

In our work, we used a convolutional neural network, MobileNetV2 pre-trained with the ImageNet dataset. We fine-tuned this model for our three microgreen stages. This transfer-learning setup uses features learned from ~1.2 million images (edges, textures, shapes), and was further tuned to our stages, enabling efficient training with a small dataset [1,2]. We labelled 300 images and split them into training and validation folders. Each of these folders has 3 subfolders with images of our stages. In the training folder, there are 3 subfolders labelled as our stages and each has 80 images, while the training folder has 20 images per stage. We trained a model to decide which stage our microgreen is in, and the resulting classifier achieves an accuracy of 73% on the held-out test set.

```
Overall accuracy: 73.33%

Confusion matrix (rows=true, cols=pred):
            GP      GR      PH
     GP     18       0       2
     GR      0      20       0
     PH     14       0       6
```

Figure 3. Accuracy of model.

After fine-tuning, the model was exported to TensorFlow Lite, a lightweight version of TensorFlow optimized to run on devices with lower memory and processing power.

3.2 Accuracy of the Deep Learning Model

The achieved accuracy of 73% is to be expected given the small amount of fine-tuning. Even though the model was pretrained with the large ImageNet dataset, it still needs more images per stage to better distinguish between the stages. However, even without adding more images to our dataset, there are other ways to increase the accuracy: data augmentation (brightness/contrast, small rotations, blurring [3]) and training refinements (cosine learning-rate decay, label smoothing [4]).

3.3 Discussion

Deep learning in this work is the perception module within a broader IoT system. Running on the Raspberry Pi, the model classifies the plant's growth stage from images, and the IoT controller uses that decision to adjust light, moisture, and temperature-closing the loop from sensing to actuation. It is expected that deep learning-based decision support in IoT systems will become increasingly widespread in the coming years.

4. CONCLUSIONS

In this work, the beginning of implementing Sony IMX219 camera in small indoor microgreens production is presented. A camera is used to capture images of microgreens, which are then processed by a convolutional neural network MobileNetV2. This is all part of the IoT system we are developing that can make the determination of the stage the microgreens are in. For future work, we will analyse two directions of development:

1. A scientific approach to building a better and more accurate system; and
2. A commercial approach.

For a scientific approach we would try a few things:

- Increasing the accuracy of our model with techniques discussed earlier;
- Switching from an RGB to a multispectral camera;
- Trying different types of processors to increase efficiency;
- Developing an algorithm that will make decisions based on multiple input parameters acquired from different sensors; and
- Adding actuators that react after deciding what the problem is.

All these approaches need more time and knowledge, as well as a bigger team that will work on them. For a commercial approach, it is necessary to analyse the market for this type of device, and, based on that, correct the device presented in this paper.

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