Development of IoT-based camera system for automated in-field monitoring to support crop breeding Programs

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ABSTRACT

Automated monitoring and evaluation systems for plant phenotyping are one of the keys to advance and strengthen crop breeding programs. In this study, the improvements of the camera-based sensor system and a weather station from a previous study—assembled mainly from Raspberry Pi products – board with dual cameras (RGB and NoIR) providing high spatial and temporal resolution data—is outlined. Hardware for the internet connection and the power supply system of the sensor were upgraded. Previously, the sensor could automatically capture plant images following user-defined time points; thus, an image processing algorithm (edge computing) was developed and installed to extract digital phenotypic traits from the images after capturing process. With the development, the new sensor system could be integrated with the internet, and a cloud server was configured to store data online (digital traits and raw images). A real-time monitoring system was created to visualize the time series data of a trait development and plant images throughout the season. With such a system, plant breeders will be able to monitor multiple trials for timely crop management and decision-making process, which is also resources efficiency.

Keywords: Internet of things; sensor; high-throughput phenotyping; Raspberry Pi; edge computing; Node-RED, Microsoft Azure; vegetation indices.

1. INTRODUCTION

In crop breeding programs, precise plant phenotypic data, individually or related to key performance traits, such as yield potential, disease resistance, and drought tolerance, are needed. These specific requirements are to ensure that plant varieties/cultivars with high performance are selected before distribution to farmers.[1,2] However, traditional field phenotyping tools/methods in crop breeding programs can be subjective and sometimes laborious and time-consuming.[3,4]

Internet-of-Things (IoT) based sensor is one of the platforms that can be utilized for field-based high-throughput phenotyping[5,6] application, in addition to the unmanned aerial vehicle (UAV)[7,8] and low-orbiting satellite[9,10] platforms. IoT technology, in general, has become the essential technical support tool for decision-making in various disciplines because of the ability to get massive amounts of timely information that can be computed to extract valuable data automatically on the system.[11,12] In crop breeding, IoT technology can significantly improve the phenotype evaluation quality/process efficiency by allowing close monitoring of plants and high temporal resolution in data collection (continuous crop monitoring) with exact weather information (micro-climate data). Besides, with internet communication and computation power, resource utilization such as personnel/travel can be improved as the technology enables an automated process to compute valuable traits and provide online data visualization.[13,14] Raspberry Pi products (https://www.raspberrypi.org, accessed on 20 October 2022) have been applied for different plant phenotyping applications. Plant traits such as size/shape/height[15,16], color[17], phenological stage[18], and disease[19], including vegetation indices (VIs) to evaluate plant health[20] can be extracted from the images captured by the Rasberry Pi camera; red-green-blue (RGB) and no infrared (NoIR) cameras. The Raspberry

Pi board is a microprocessor used to control the IoT-based sensor, such as capturing the Raspberry Pi camera and processing the images to extract plant features. The board is internet-enabled; therefore, the extracted data can be sent and monitored in real-time by breeders/researchers.

This study improved and developed the IoT platform for automated in-field phenotyping to acquire high-frequency data on wheat breeding programs using Raspberry Pi products based on Sangjan et al. (2021)[20]. Two Raspberry Pi cameras: RGB and NoIR, were integrated to allow the extraction of normalized difference vegetation index (NDVI)[21] representing wheat's crop vigor and health status. A microclimate sensor was also installed to evaluate crop growth and development dynamics. With the internet connection in the field, the data transfer system was developed to pass extracted data and images from the sensor system to a cloud platform utilized to store the data online and centralize a host of the website for data visualization.

2. IMPROVEMENTS TO THE PREVIOUS SENSOR SYSTEM

The sensor in the previous version was primarily developed to capture two images (from RGB and NoIR cameras) simultaneously in a single shot and was arranged to display on one screen and installed during the field season of 2020[20]. In the new sensor version (AGIcam), major hardware and software improvements were made in both the backend and frontend, and re-installed in the 2021 and 2022 field seasons on both spring and winter wheat trial fields in Washington State (Figure 1a).

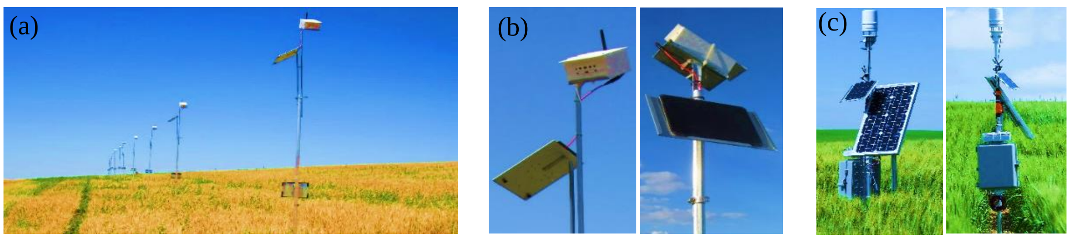

Figure 1. AGIcam sensor and weather station. (a) AGIcam installed in spring wheat field trial in the 2021season; (b) AGIcam sensor; and (c) weather station.

2.1. System hardware

Each AGIcam was equipped with a universal serial bus (USB) WiFi antenna to connect the sensor to the internet (Figure 1b). The antenna supports the Linux operation system on the Raspberry Pi compute module 3+ lite board used in the sensor. A power supply system was upgraded by using the 6W, 6V Voltaic solar panel (Voltaic Systems, Brooklyn, NY, USA) to charge the 6,400 mAh Voltaic V25 USB battery (Figure 1b). A 5V regulator was connected between the solar panel and battery to charge the power safely, not overcharging, to protect the battery and the sensor as the battery was placed inside the enclosure with the board and cameras.

An Arduino Uno board was applied to connect with the weather station ATMOS41 (Meter Inc., Pullman, WA, USA) through the serial digital interface at 1200 baud (SDI-12) communication protocol (Figure 1c). The weather data was then transferred to store in a Raspberry Pi 4 board via the serial wire type USB, and the board sent the data to the cloud. Witty Pi 3 mini board (UUGear, Prague, Czech Republic) was installed on the Raspberry Pi 4 to manage the power (similar power supply system with AGIcam) and operation of ATMOS41 to collect the data following the AGIcam's operation schedule.

A 4G long-term evolution (LTE) WiFi router (Linovision, Zhejiang, China) with a subscriber identity module (SIM) card slot was installed in the field close to the sensors (at the exact location as the weather station) to provide the internet signal to the sensors and weather station (Figure 1c). A SIM card from T-Mobile with 30 GB/month of data was used. The router could operate with the power supplied from an external 12 VDC battery and charging with energy from a 30W solar panel (Figure 1c).

2.2. Backend of the system

The primary operating system of AGIcam was similar to the first sensor version. The sensor's operation system (Linux-based operating system Raspbian Buster), software for powering on-off the sensor automatically from Witty Pi, and time-lapse imaging algorithm created from Python 3 for capturing images were mainly utilized in AGIcam. However, the image processing algorithm to extract digital traits from captured images was developed and installed in the Raspberry Pi board (microprocessor unit) of AGIcam. Similar steps of the image processing algorithm to extract NDVI presented in Sangjan et al. (2021)[20] was coded by Python 3 and run after the time-lapse imaging algorithm. The NDVI values (max, median mean, standard deviation, 95th percentile, 90th percentile, and 85th percentile) were extracted, including the timestamp data. The last algorithm's section was to convert the extracted data to javascript object notation (JSON) file format and store them in the sensor's secure digital (SD) card onboard before transfer to the cloud storage.

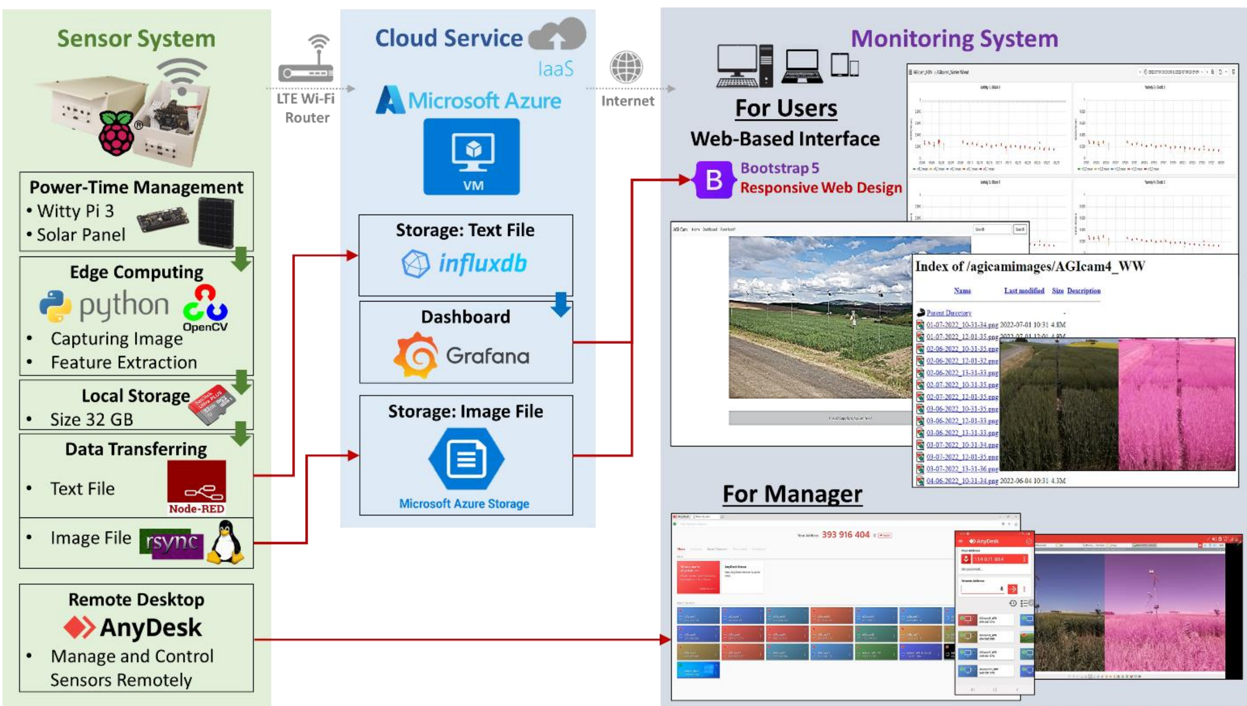

Figure 2. The IoT framework comprises the sensor, cloud service, and monitoring systems.

The weather and the NDVI data (JSON file format) were stored in their local storage, and then Node-RED software (https://nodered.org/, accessed on 20 October 2022) on the AGIcam/weather station (Raspberry Pi 4) took and wrote these data to InfluxDB (https://www.influxdata.com/, accessed on 20 October 2022) on the cloud through the internet communication, as shown in Figure 2. Node-RED is a flow-based development platform connecting different hardware and software, and InfluxDB is a database used for aggregated time-series data. In this data transfer, a JavaScript (https://www.javascript.com/, accessed on 20 October 2022) was coded and run in a custom node on Node-RED to organize/match the data with specific plot information and specify the destination to store data on the InfluxDB database. With the image files, the Remote sync (Rsync) command in Linux over the secure shell (SSH), a secure protocol for data transfer, was utilized to transfer the images to another database on the cloud (Figure 2). The Rsync was applied as the advantage of syncing files to/from a remote server/storage, meaning the targeted storage will update only new data when running the command. The cloud service was the infrastructure as a service (IaaS) type in this study because only the storage (InfluxDB and database for image files) and networking (for web-based interface) facilities were utilized. Thus, virtual machine (VM) based Linux from Microsoft Azure (https://azure.microsoft.com/en-us/, accessed on 20 October 2022) was implemented (Figure 2).

2.3 Frontend of the system

Grafrana (https://grafana.com/, accessed on 20 October 2022), interactive visualization web application software, was installed on the VM to draw the NDVI data from InfluxDB for displaying in a graphic view. Bootstrap 5 (https://getbootstrap.com/, accessed on 20 October 2022) with a hypertext markup language (HTML5) was a framework to create a web-based interface for users. The framework enables the basics for responsive web development. Therefore, the website's design format and two contents: graphics—embedded from the Grafana dashboard and images—drawn from the storage in VM, could show in different sizes of display (desktop computer, laptop, tablet, and smartphone). Another monitoring system was for the manager/administrator level. AnyDesk software (https://anydesk.com/en, accessed on 20 October 2022), a remote desktop application, was installed in each AGIcam, which was used to access the sensor remotely to modify/check operations, including time-laps and image processing algorithms. In addition, the dashboard from Anydesk was utilized to monitor the operating status of the AGIcam (Figure 2).

3. RESULTS AND DISCUSSION

The results of image quality and image analysis from the AGIcam were similar to those described in Sangjan et al. (2021).[20] With the improvement in the hardware, AGIcam could connect to the internet via the antenna; however, the wireless network signal range and strength should be considered to improve because of the far distance (> 50 m) from the router, the weak signal was received on the AGIcam. A high-performance router and antenna, a strong internet signal (5G, satellite internet), or the equipment to expand the internet signal range (long-range wide-area network (LoRaWAN)) can be options for a better internet connection. The AGIcam in the 2021 and 2022 seasons could operate for the whole season (~four months) after upgrading the power supply system with the conditions of capturing images three to four-time points a day. The issue was found only at the beginning of the season because the three-four rainy days in a row resulted in the solar panel not producing power for the battery. The monitoring system (AnyDesk) helped to check this issue directly; therefore, the manual charging was done after the sensors shut down for only one day. As a result of the backend development, the two algorithms for capturing the image and extracting NDVI could be operated smoothly and automatically, including the data transfer system for the whole season. The only issue was that at the beginning of the software installation (the two Python algorithms, Node-RED) needed specific configured depending on the plot to label the plot information correctly match with NDVI data. The sensor preparation process then took a lot of time and created confusion sometimes when the sensor needed to be fixed. The global positioning (GPS) module should be considered to connect to the sensor to provide the position of the plot where the sensor is located. The frontend development in this 2022 season should be further improved to show more content, as data visualization only display the time series of NDVI result.

4. CONCLUSION

The proposed IoT platform has a high potential for supporting crop breeding programs as a low-cost platform; all backend and frontend software is open source except for Microsoft Azure (3 USD per month in this study). It also has a low energy consumption and is compact with the appropriate sensors remotely from any place in the world. Researchers can benefit from this IoT system to revolutionize crop breeding programs and improve reproducibility in experimentation tasks with a high impact on resource utilization.

DATA AVAILABILITY STATEMENT

The data presented in this study are available on request from the corresponding author after published.

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