Enhancing Plant Health with AI Using Thermal and Image Processing

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***Abstract*— The paper proposes an integrated system for plant disease detection and classification, aiming to address the challenges posed by plant diseases in agriculture. The system combines deep learning techniques with environmental sensors to provide comprehensive and automated disease assessment. Thermal imaging technology is utilized to capture leaf temperature and calculate Vapor Pressure Deficit (VPD), while an environmental humidity sensor (AHT10) measures humidity. By integrating these environmental parameters, the system offers a comprehensive approach to disease detection and management. A deep learning framework based on convolutional neural networks (CNN) is employed for accurate disease classification using visible and thermal plant images. Real-time testing of the AI model is enabled through frame extraction from a video feed obtained using a USB camera. The system demonstrates high accuracy in identifying and classifying various plant diseases, aiding in early risk identification. It also utilizes VPD calculations to assess irrigation needs and provides insights into plant water requirements. The proposed system offers benefits such as real-time disease detection, non-invasive monitoring, and scalability, making it valuable for farmers, agronomists, and researchers in mitigating plant diseases and ensuring sustainable crop production.**

Keywords*— *Plant Disease Detection, Deep Learning, Convolutional Neural Networks, Environmental Sensors, Thermal Imaging, Vapor Pressure Deficit (VPD), Disease Risk Assessment, Automated System

I. Introduction

Traditionally, plant disease detection has relied on manual inspection and visual examination by experts, which can be time-consuming, labor-intensive, and prone to human error. However, with the continuous evolution of agriculture and the adoption of technological advancements, there is a growing demand for automated systems that can quickly and reliably detect plant diseases, enabling early intervention and minimizing crop damage.

In recent years, artificial intelligence (AI) and deep learning techniques have revolutionized automated plant disease detection. Deep learning, specifically Convolutional Neural Networks (CNNs), has demonstrated remarkable capabilities in image recognition and classification tasks. By harnessing these techniques, researchers and scientists can train AI models to analyze plant images and accurately identify the presence of diseases.

However, effective disease management requires considering environmental factors and conditions that significantly influence disease development and progression. Parameters such as temperature, humidity, and vapor pressure deficit (VPD) play vital roles in the growth and spread of plant diseases. Integrating and monitoring these environmental factors in disease detection systems can provide a more comprehensive and accurate assessment of disease risks, empowering farmers to make informed decisions regarding disease control strategies.

Thermal imaging technology has emerged as a valuable tool in plant disease detection and management. By capturing the infrared radiation emitted by plant leaves, thermal cameras can measure leaf temperature, which serves as an indicator of plant health and stress. Combining thermal imaging with AI algorithms enables the detection of subtle temperature variations associated with disease symptoms, offering early indications of disease presence.

Vapor Pressure Deficit (VPD) is another crucial parameter in plant disease management. VPD represents the difference between the actual vapor pressure in the air and the saturation vapor pressure at a specific temperature. High VPD values indicate a dry atmosphere, which can increase water stress on plants and create favorable conditions for certain diseases. Monitoring VPD and integrating it with disease detection systems allows farmers to assess the need for irrigation and adjust watering practices accordingly, optimizing water usage and reducing the risk of diseases caused by excessive moisture.

The integration of deep learning techniques with environmental sensors, such as thermal cameras and humidity sensors, provides a comprehensive approach to plant disease detection and management. By combining image analysis with environmental data, these integrated systems offer real-time disease monitoring, automated disease classification, and valuable insights into disease risks and irrigation needs. This integration reduces reliance on manual inspection, enhances disease management practices, and contributes to sustainable and efficient crop production.

The proposed system aims to overcome the limitations of traditional disease detection methods by harnessing the power of deep learning and environmental sensing. By providing real-time disease monitoring, accurate disease classification, and insights into environmental parameters, the system empowers farmers, agronomists, and researchers to make informed decisions, take timely actions, and effectively manage plant diseases. This integrated approach holds immense potential for improving agricultural practices, enhancing crop yields, and ensuring global food security amidst the increasing pressures of plant diseases.

II. RELATED WORKS

The authors of Cheng et al. (2020)'s paper "Integrating Deep Learning and Internet of Things for Smart Plant Disease Diagnosis" use deep convolutional neural networks (CNNs) as the primary part of their disease detection strategy. CNNs have demonstrated outstanding performance in numerous computer vision applications and are frequently employed in image processing jobs. In this study, CNNs are taught to identify and categorize plant illnesses using pictures of infected plant parts like leaves or stems. To precisely identify various diseases, the deep learning model learns from a big dataset of annotated photos. The system integrates IoT technology by using environmental sensors in the setup to improve the disease diagnosing process. In particular, temperature and humidity sensors are employed to gather information in real-time about the environment around the plant which our team will also be implementing. The system intends to give precise and rapid diagnosis of plant illnesses by merging the image-based disease detection capabilities of deep learning with real-time environmental data gathered from IoT sensors. IoT technology integration enables proactive disease management and prompt responses by offering continuous plant health monitoring.

There has also been another study made in “Leaf disease detection of cucurbits using CNN” by Isha Agrawal. In the study, they implemented image pre- processing and identification of leaf diseases using CNN Algorithm in the backend and UI is designed using Flask. In their paper, they emphasized the use of large datasets for more accurate detections. For their image pre-processing, they used a formula for RGB to grayscale for the images, and moved onto image segmentation. They also used CNN as their classifier to categorize the diseases. This step is quite difficult and needs good computational power.

III. SYSTEM DESIGN

The hardware integration, consisting of the Jetson Nano, thermal camera, AHT10 sensor, USB camera, and laptop, establishes a comprehensive and potent system for plant disease detection and management. Each component contributes distinct functionalities, facilitating precise temperature and humidity measurements, VPD calculations, efficient image processing, and reliable development and testing capabilities.

Fig. 1. System map

The combined hardware setup empowers researchers and plant scientists to monitor and analyze plant health in a reliable and advanced manner, harnessing the capabilities of both the embedded system and the development platform.

A. Hardware Components

The hardware components utilized in the implementation of the smart plant irrigation and health monitoring system are described in this section.

NVIDIA Jetson Nano 4GB The NVIDIA Jetson Nano 4GB is a high-performance single-board computer specifically designed for AI edge applications. It features a powerful NVIDIA 128 CUDA core Maxwell GPU, enabling efficient parallel computations. The Jetson Nano supports 4K video encoding at 30 fps or multiple sources at lower resolutions. It provides seamless connectivity with two CSI ports for IMX219/477 camera drivers, a 40-pin header for GPIO, i2c, is2, and spi interfaces, and four USB ports for peripherals. The Jetson Nano is equipped with either 16GB onboard eMMC memory with preinstalled JetPack OS or an SD card slot for easy OS flashing and swapping.

Raspberry Pi Cam v2.1 NoIR The Raspberry Pi Cam v2.1 NoIR features an IMX219 RGB Camera with an 8-megapixel resolution. It supports video capture at a maximum rate of 30 frames per second. The camera utilizes the MIPI CSI-2 interface, ensuring seamless connectivity with the Jetson Nano. Mounted as a video source, it provides frames at a resolution of 1280x720p for pose recognition.

Thermal Imaging Cameras Thermal imaging cameras leverage infrared thermography to detect levels of infrared radiation emitted by objects. While they are not accurate in directly measuring temperature due to multiple infrared radiation sources, proper calibration using environmental data significantly improves accuracy. The system incorporates two types of thermal imaging cameras:

MLX90640: Manufactured by Melexis, the MLX90640 thermal camera captures thermal images at a resolution of 32x24 pixels. It provides accurate temperature measurements at close distances.

Lepton 3.5: The Long Wave Infrared Thermographic Camera from TELEDYNE FLIR offers a five times higher resolution than the MLX90640. It includes radiometry features for easy calibration and increased temperature accuracy. The Lepton 3.5 offers increased flexibility in camera placement without compromising temperature accuracy, compared to the MLX90640, which experiences drastic drop-off in the instantaneous field of view with distance.

Temperature Humidity Sensor The system incorporates a temperature and humidity sensor to gather environmental data. Specifically, the AHT10 sensor is utilized for measuring temperature and humidity. It interfaces easily with the system using I2C communication and the Adafruit Circuit Python library.

These hardware components, including the NVIDIA Jetson Nano 4GB, Raspberry Pi Cam v2.1 NoIR, thermal imaging cameras (MLX90640 and Lepton 3.5), and AHT10 temperature humidity sensor, form the backbone of the implemented smart plant irrigation and health monitoring system.

B. Software Components:

The project utilizes a variety of AI algorithms and software tools to facilitate the detection and analysis of plant diseases. These components are crucial for the development, training, and deployment of the deep learning model, as well as for data processing and visualization. The key AI algorithms and software tools employed in the project are as follows:

- Deep Learning Model: The project's AI capabilities revolve around a deep learning model that utilizes algorithms like Convolutional Neural Networks (CNNs) to learn and identify patterns in plant images. By training these models with extensive datasets of labeled plant images, accurate classification and identification of plant diseases can be achieved.
- TensorFlow: TensorFlow is a widely adopted open-source deep learning framework that provides a comprehensive ecosystem for developing and training deep neural networks. It offers a range of tools and libraries that simplify the implementation of complex models and streamline the training process. In this project, TensorFlow is used to construct and train the deep learning model for plant disease detection.
- Keras: Built on top of TensorFlow, Keras is a high-level neural networks API written in Python. It offers a user-friendly interface for building deep learning models, providing pre-built layers and models that simplify the design and training of deep neural networks. Keras is utilized in the project to build and configure the architecture of the deep learning model.
- OpenCV: OpenCV (Open-Source Computer Vision Library) is a powerful open-source computer vision library that offers a collection of algorithms and functions for image and video processing. It includes tasks such as image filtering, feature extraction, and object detection. In this project, OpenCV is employed for image preprocessing tasks like resizing, normalization, and augmentation, enhancing the quality and diversity of the training data. Additionally, OpenCV is used for interpolating and finding the offset of the IR and RGB frames, enabling accurate thermal readings, as well as creating demo videos through frame extraction.
- NumPy: NumPy is a fundamental library for numerical computing in Python, providing robust tools for handling large multi-dimensional arrays and matrices, along with mathematical functions for array operations. NumPy plays a crucial role in the project for efficient data manipulation, preprocessing, and transformation tasks, facilitating seamless integration with deep learning frameworks.
- Jupyter Notebook: Jupyter Notebook is an interactive computing environment that allows the creation and sharing of documents containing live code, equations, visualizations, and narrative text. It serves as a convenient platform for developing and prototyping the AI algorithms used in the project. Jupyter Notebook supports iterative experimentation, data exploration, and collaborative development, promoting an efficient workflow.
- Matplotlib: Matplotlib is a widely used data visualization library in Python, offering various functions for creating plots and charts. It enables effective visualization of data and model performance. In this project, Matplotlib is utilized to generate visualizations of training and validation metrics such as accuracy and loss curves, aiding in the analysis and interpretation of the deep learning model's performance.
- NVIDIA Jetpack OS: NVIDIA Jetpack OS (4.6.3, Linux 32.7.3) is a customized Ubuntu-based operating system designed specifically for Jetson boards. It comes with various AI development packages, including GPU CUDA core acceleration toolkits. This enables accelerated AI processing on the Jetson Nano.
- Adafruit CircuitPython: Adafruit CircuitPython is a Python library that simplifies the implementation of a wide range of sensors. It offers a comprehensive collection of sensor drivers and supports easy i2c interfacing. In this project, Adafruit CircuitPython was used to integrate the AHT10 temperature humidity sensor and the MLX90640 IR camera seamlessly. Adafruit also provides supplementary information resources and tutorials for straightforward implementation.
- UVC Library: The UVC library(libuvc) enables communication with the capture library over USB using the UVC protocol, ensuring seamless data

- transfer and control between the Lepton 3.5 camera and the system.
- Jetson Inference: Jetson Inference is a library specifically designed for deep learning inference on the NVIDIA Jetson platform. It provides pre-trained deep learning models and tools for deploying and running them on Jetson devices. In this project, Jetson Inference was utilized for real-time object detection and inference tasks.

Python was chosen as the programming language for the project due to its rich ecosystem of libraries and tools for AI and data science. Python offers simplicity, readability, and strong community support, which facilitates development and troubleshooting. Additionally, Python's versatility allows seamless integration with various AI frameworks and libraries. Although other programming languages like R or MATLAB could be used for similar tasks, Python's combination of ease-of-use and wide adoption within the AI community made it the preferred choice.

C. *Coding Methodology:*

To develop a comprehensive system for plant identification and disease detection, four main coding methodologies were employed. This section discusses the methodologies used for data extraction, video processing, and plant identification, as well as the significance of Vapor Pressure Deficit (VPD) in the context of the project.

Data Output from Thermal Camera and AHT10 Sensor: To gather essential data from the thermal camera and AHT10 sensor, a Data Extraction Program was developed, which involved three scripts.

The first script, "AHT.py," captures humidity and temperature data using the AHT10 sensor via I2C communication. It creates a CSV file named "humidity_data.csv" and continuously reads the humidity and temperature values, calculating the Vapor Pressure Deficit (VPD) and saving the data with timestamps in the CSV file every 2 seconds.

The second script, "PT2_Lep_Temp_Array.py," reads thermal data from a PureThemal2 board (IR camera) via USB UVC (USB Video Class). It defines a callback function that receives the captured frame as a NumPy array, and it continuously retrieves thermal data from the camera, printing it as a temperature map represented by a NumPy array.

The third script, "uvc-types.py," provides necessary ctypes structures and functions for the USB Video Class (UVC) communication used in "PT2_Lep_Temp_Array.py." It loads the appropriate shared library for the operating system and defines the required structures and constants for interacting with the UVC device and frames.

Video Processing from the USB Camera: The video processing component of the system relies on the utilization of OpenCV, a popular computer vision library. OpenCV is used to convert the video feed from the USB camera into individual frames. Two code snippets demonstrate different functionalities related to video capture, image processing, and thermal imaging using OpenCV and the Pure Thermal 1 camera.

In the first snippet, "Plant Disease Detection with Webcam," the code captures frames from the webcam, converts them to grayscale, thresholded to obtain a binary image, calculates the percentage of black pixels in the image, and saves frames meeting certain criteria to a test directory.

The second snippet, "OpenCV Capture from Pure Thermal 1," defines a class called "OpenCvCapture" that encapsulates the capture state from the Pure Thermal 1 camera. It continuously captures and displays frames from the camera until the ESC key is pressed.

The third snippet, "Thermal Imaging with Pure Thermal 1 Camera," imports necessary libraries and defines functions for temperature conversion and image processing of the captured frames.

Plant Identification and Disease Detection: The core functionality of plant identification and disease detection is achieved through a Python program utilizing Keras, an open-source deep learning library integrated within the Tensorflow framework. The coding methodology includes importing necessary libraries, defining data directories, image size, functions for image preprocessing and loading, creating the base MobileNet model, setting model training properties, defining data generators for training and validation, training the model, plotting and saving training history, saving and loading the trained model, and making predictions on test images.

Vapor Pressure Deficit (VPD): VPD plays a pivotal role in irrigation practices and is a crucial parameter in evaluating the drying power of the atmosphere. To calculate VPD, a Python script imports the "math" module and defines a function, "calculate_vpd()," which takes temperature and humidity as inputs and calculates the VPD based on the Clausius-Clapeyron equation.

Another function, "check_irrigation_needed()," interacts with the user to obtain temperature and humidity inputs and compares them with predefined VPD and humidity thresholds to determine if irrigation is needed.

D. *Security Issues:*

The proposed integrated system for plant disease detection and management brings significant benefits and advancements to agriculture. However, it also introduces potential security challenges that need to be carefully addressed. The following are security concerns that may arise in the project:

- Data Privacy and Confidentiality: The project involves collecting and analyzing sensitive data, such as plant images, environmental sensor readings, and potential location information. Safeguarding the privacy and confidentiality of this data is crucial to protect the interests of farmers and users. To achieve this, measures such as encryption, access controls, and secure communication protocols should be implemented for data storage, transmission, and access.
- Network and Communication Security: The system relies on networks and communication channels to transmit data between devices, servers, and end-users.

However, these networks are susceptible to interception, eavesdropping, or unauthorized access. Mitigating these risks involves implementing secure network protocols, strong encryption, and conducting regular security audits.

- Device and System Authentication: To prevent unauthorized access and tampering, the system should employ authentication mechanisms to ensure that only authorized users and devices can access it. Enhancing system security can be achieved through the use of strong passwords, multi-factor authentication, and secure device registration processes.
- Malicious Attacks: The integration of AI algorithms, data processing, and communication infrastructure creates opportunities for various malicious attacks. These attacks may include denial-of-service (DoS) attacks, data manipulation, injection of malicious code, or exploitation of software or hardware vulnerabilities. Regular security assessments, code reviews, and software updates are essential to mitigate these risks.
- Data Integrity and Trustworthiness: Maintaining the integrity and trustworthiness of the data used for disease detection and decision-making is critical. Compromised data integrity can lead to incorrect disease classifications or misguided management strategies. Implementing data validation techniques, checksums, and data verification mechanisms can help ensure data integrity.
- Physical Security: Adequate physical security measures must be implemented to protect the devices and infrastructure involved in the project. Unauthorized physical access to servers, sensor installations, or computing devices can result in data breaches, tampering, or system disruptions. To mitigate these risks, it is necessary to establish physical access controls, surveillance systems, and secure storage facilities.
- System Resilience and Disaster Recovery: The project's system should be designed with resilience in mind to withstand potential security incidents, system failures, or natural disasters. Regular backups, redundancy measures, and disaster recovery plans are essential to maintain system availability and minimize the impact of security breaches.
- User Awareness and Training: Users of the system, including farmers, agronomists, and researchers, should be educated about potential security risks, best practices, and their roles in maintaining system security. Conducting user awareness campaigns, providing training materials, and offering ongoing support can foster a security-conscious user community.

Addressing these security issues requires a comprehensive approach encompassing secure design principles, robust software development practices, regular security audits, and a commitment to staying updated with the latest security standards and technologies. By prioritizing security throughout the project's lifecycle, the integrated system can provide reliable, trusted, and secure disease detection and management capabilities for the agricultural community.

IV. IMPLEMENTATION

Using the NVIDIA Jetson Nano as the computing core and the mounted RGB camera, this project successfully performed object detection on plants. The primary objective was to detect the plant, identify its specific type, and determine the leaf/canopy region. Unfortunately, due to time constraints, the trained leaf disease detection algorithm could not be implemented on the Jetson Nano. Therefore, a key focus for future work should be on extracting individual leaves for detection and processing as soon as the Jetson platform can support the required libraries.

In addition to the RGB camera, the project incorporates a thermal imaging camera to capture temperature data. The thermal imaging cameras include the Melexis MLX90640 (32x24 matrix) and the Lepton 3.5 (160x120 matrix). These cameras provide frames in the form of temperature values, allowing for the assessment of temperature distribution across the plants. Calibration of the RGB and thermal images will be conducted by computing a transformation matrix to ensure accurate correspondence between the temperature array and RGB camera pixel positions.

To gather environmental data, the project will integrate a temperature humidity sensor. This sensor will provide readings of air temperature and humidity, offering valuable information about the plant's surrounding conditions.

By combining the RGB and thermal imaging data, along with the environmental data, the project creates a comprehensive picture of the plant's health and environmental conditions. This information will enable more precise irrigation decisions tailored to the individual plant's needs.

It is important to note that irrigation controls are not explicitly mentioned in the summary. However, with the data obtained from the RGB camera, thermal imaging cameras, and temperature humidity sensor, the project provides the necessary components to inform and optimize irrigation practices. By understanding the plant's type, leaf/canopy region, and temperature distribution, the project lays the foundation for implementing smart irrigation strategies based on the specific requirements of each plant.

Overall, the project combines advanced technologies, including the Jetson Nano, RGB camera, thermal imaging cameras, and temperature humidity sensor, to monitor, analyze, and ultimately optimize plant health and environmental conditions. By leveraging these components, the project aims to optimize irrigation practices and contribute to sustainable and efficient water use in crop production.

V. RESULTS

Our project sought to implement a thermal camera and RGB camera to showcase their functionality and capabilities to recognize objects. Taking high-resolution images of the plants, the RGB camera worked in conjunction with a thermal camera to measure the environmental temperature, effectively monitoring the plant's health. A model to detect disease was successfully implemented with RGB images, which proved to be promising when providing new data. This highlights the potential for identifying crop diseases.

TABLE 1. DIEASE DETECTION MODEL TRAINING

Epochs	Training Model		
	Total Time	***Loss***	***Accuracy***
5	101m 24.2s	14.39%	95.37%
10	202m 55.6s	9.76%	96.71%
25	500m 7.4s	6.91%	97.72%

The final version of our system provides a monitoring solution, allowing us to design and evaluate various irrigation strategies. Using both the Jetson Nano's Inference DetectNet to detect leaf regions along with an AHT10 temperature and humidity sensor, we were able to obtain real-time data regarding the plant's environmental conditions. These components were used in conjunction with a Lepton camera, which was used to calculate the temperature average of the detected leaf regions. All these system features provide successful irrigation management and plant health monitoring.

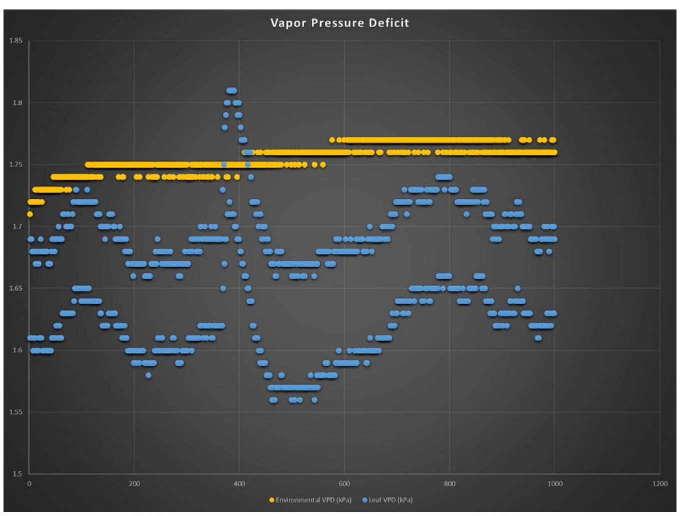

Fig. 2. VPD values obtained from the thermal leaf regions (2) blue and the environment (1) over a short period of time.

It's important to note that this system does have certain limitations. Our disease detected model was not fully optimized to work on the Jetson Nano due to time constraints, which limited the system edge computing capabilities. Future work would focus on fully optimizing and adapting the disease detection model, since this could easily improve overall health outcomes.

Although the system gave accurate readings for detecting leaf regions, future work would focus on defining specific regions, such as fruit bearing areas of the plant or the trunk. Furthermore, advanced image processing may enable simultaneous analysis for different parts of the plant. The capabilities of the Lepton camera were limited and suboptimal since at a distance, resolution was subpar. This indicates that a better camera should be considered for future works to achieve accurate region identification.

VI. CONCLUSION

The research concludes by presenting an integrated system that combines deep learning methods with environmental sensors to address the issues related to plant diseases in agriculture. The device gathers essential environmental information for thorough illness assessment by utilizing thermal imaging technology and an environmental humidity sensor. A comprehensive approach to disease identification and management is made possible by this combination. Using both visual and thermal plant pictures, the system achieves accurate disease classification using a deep learning framework based on convolutional neural networks (CNNs). Real-time testing of the AI model is made possible through the extraction of frames from a video feed collected using a USB camera. The outcomes show the system's excellent accuracy in recognizing and categorizing different plant diseases, allowing for the early detection of risk.

Additionally, the system uses Vapor Pressure Deficit (VPD) computations to evaluate irrigation requirements and offer perceptions into plant water needs. This feature improves methods for managing water, which results in better resource allocation and less water waste. The suggested integrated system has a number of advantages. First of all, it makes real-time disease diagnosis possible, enabling quick response to stop the spread of diseases and reduce crop losses. Second, the non-invasive monitoring strategy eliminates the need for labor-intensive physical inspections. The method is also adaptable and may be used in a variety of agricultural contexts, which is advantageous to researchers, agronomists, and farmers alike.

ACKNOWLEDGMENT

We would like to acknowledge Dr. Jafar Saniie, Xinrui Yu, Mikhail Gromov for supporting us and providing guidance throughout the entirety of the project.

REFERENCES

[1] Agrawal, Isha. *Plant Leaf Disease Detection and Classification Using Deep Learning* ..., www.researchgate.net/publication/364821944_Plant_Leaf_Disease_Detection_and_Classification_Using_Deep_Learning_Technique. Accessed 29 June 2023.

[2] "Advances in Remote Sensing." SCIRP. Accessed May 17, 2023. https://www.scirp.org/journal/ars/.

[3] Application of infrared thermography for irrigation scheduling of ... Accessed May 17, 2023. https://www.researchgate.net/publication/355906427_Application_of_Infrare

d_Thermography_for_Irrigation_Scheduling_of_Horticulture_Plants.
[4] Author links open overlay panel Olivier Debauche a b, a, b, c, d, and Abstract Overcoming population growth dilemma with less resources of soil and water. "Edge Ai-IoT Pivot Irrigation, Plant Diseases, and Pests Identification." Procedia Computer Science, November 11, 2020.
https://www.sciencedirect.com/science/article/pii/S1877050920322742.
[5] Cloud of things in smart agriculture: Intelligent ... - IEEE xplore. Accessed May 18, 2023.
https://ieeexplore.ieee.org/document/7879140.
[6] Thermal imaging for Smart Agriculture Irrigation System to support ir 4 ... Accessed May 18, 2023.
https://www.researchgate.net/profile/Aznida-Abu-BakarSajak/publication/344862746_Thermal_Imaging_for_Smart_Agriculture_Irrigation_System_t_support_IR_40_Initiative/links/5f945127299bf1b53e40d24d/Thermal-Imagingfor-Smart-Agriculture-Irrigation-System-to-support-IR-40-Initiative.pdf