Detection of Water Stress in Vegetable Crops Using Deep Learning

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Abstract. Properly monitoring plant health in hydroponic farming is crucial as the plants rely solely on mineral water flowing through their roots as a growth source. One of the main challenges is the early detection of wilt in plants due to water stress. If not addressed promptly, water stress can lead to crop failure. One approach used to detect the plant wilting level is by applying deep learning technology. This paper presents a novel approach to data collection and classification in the context of vertical aeroponic agriculture. To effectively monitor the condition of crops within this setup, a custom data collection system using a simple robotic arm was developed. Images of bok choy crops were captured in both fresh and wilted conditions. The proposed deep learning model processes three-channel images with a resolution of 128×128 pixels. Results show that the proposed deep learning model achieved a high overall accuracy of 90% in distinguishing between fresh and wilted conditions. The model correctly classified 131 out of 138 fresh samples and 107 out of 125 wilted samples, resulting in only 25 misclassifications out of 263 total samples.

Keywords: Image Classification, Machine Learning, Wilt Detection

1 Introduction

The world population is expected to reach around 9.7 billion by 2050 (UN, 2022), and this condition will pose significant challenges related to global food availability (Miladinov, 2023; van Dijk et al., 2021). In this regard, the agricultural sector has proven to make an essential contribution to providing food for the world population (Pawlak & Kołodziejczak, 2020). However, agricultural production can be unstable due to a variety of complex and dynamic factors, including climate conditions, markets, and public policies that are beyond the control of farmers (Martin et al., 2013).

Considering the limitations of arable land, scarcity of water resources, environmental impact, and increasing awareness of sustainable development, it is necessary to seek alternatives to open-field farming systems (Stein, 2021). One proposed alternative to open-field farming is hydroponic farming (Martin et al., 2019;

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Rajendran et al., 2024). The hydroponic farming system uses clean water enriched with essential dissolved minerals necessary for plant growth (Velazquez-Gonzalez et al., 2022). Plants can efficiently absorb the required nutrients since these nutrients are available in the water solution. Applying a hydroponic farming system allows plants to use their energy more effectively, as there is no need for extensive effort to develop roots to penetrate soil or rocks to obtain minerals.

Water stress in vegetable crops is a critical issue affecting the hydroponic farming system worldwide (Tripathi et al., 2015). As global population growth drives the demand for increased food production, efficient management of water resources has become a priority. Traditional methods of detecting water stress in crops, such as visual inspection and manual measurements, are labor-intensive and often subjective (Virnodkar et al., 2020). A plant condition monitoring system involving information technology, such as computer vision, is essential to help farmers reduce disturbances in hydroponic plants, one of which is wilting (Fravel & Larkin, 2002). Early prevention of plant wilting using information technology has the potential to avoid crop failure and reduce human resource costs. One of the latest technologies used for classifying digital images is deep learning (Xin & Wang, 2019). Recent advancements in deep learning have opened new avenues for automated, accurate, and scalable solutions to monitor crop health and detect water stress. In this context, deep learning techniques have already shown significant promise in various image classification tasks and offer a powerful tool for advancing agricultural monitoring systems.

The application of deep learning in agriculture has received considerable attention, with researchers exploring its potential to address various challenges, including disease detection, crop yield prediction, and environmental monitoring (Albahar, 2023). For instance, Convolutional Neural Networks (CNNs) have been effectively utilized for classifying crop diseases from leaf images (Sladojevic et al., 2016) and UAV-based imagery analysis for large-scale monitoring (Zhang et al., 2019). However, the specific water stress detection in vegetable crops, particularly in controlled environments like vertical aeroponic systems, remains open to be explored. This research aims to fill this gap by leveraging deep learning techniques to detect water stress conditions in vegetable crops, focusing on fresh and wilted states.

Our study introduces a novel approach to data collection and analysis in the context of vertical aeroponic agriculture. Unlike traditional flat-field farming, vertical aeroponic systems grow crops in vertically stacked layers, providing a controlled environment that optimizes space and resource usage. To effectively capture the condition of crops within this setup, we developed a custom data collection system involving a simple arm robot. This robotic arm, equipped with a camera module, offers flexibility in capturing images from various angles and heights, ensuring comprehensive coverage of the crops' conditions. By automating the data collection process, we aim to reduce manual labor and enhance the consistency and accuracy of the data.

The primary novelty of our research lies in creating and utilizing a unique dataset comprising images of vegetable crops under fresh and wilted conditions collected within a vertical aeroponic system. This dataset is the foundation for training a deep learning model designed to classify crop conditions effectively. This paper addresses the specific challenges in detecting water stress and demonstrates the broader potential for integrating robotics and deep learning in precision agriculture.

2 Methodology

2.1 Dataset Collection

Images of bok choy (*Brassica rapa* subsp. *chinensis*) were collected in fresh and wilted conditions. Each image is 128 × 128 pixels and was captured using a camera module attached to a Raspberry Pi Zero W single-board computer. The bok choy was grown in a vertical farming system using an aeroponic tower, which cultivates crops in vertically stacked layers.

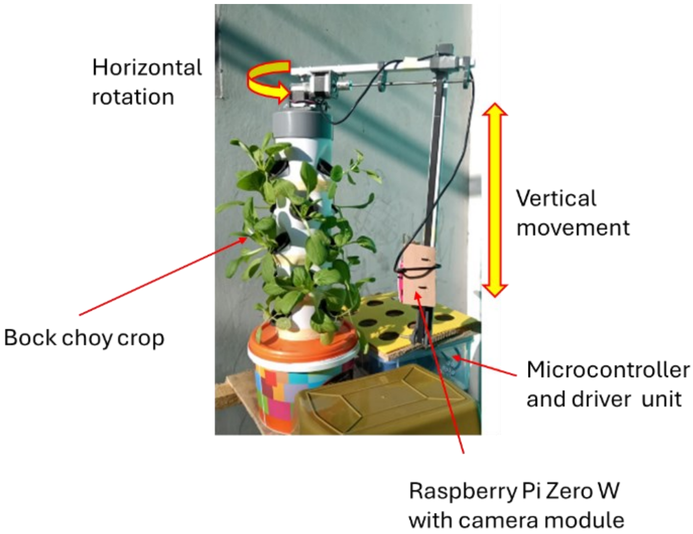

Figure 1. Data collection setting

As shown in Figure 1, a simple arm robot mechanism is performed to move the camera module. A strategy is needed to capture the crop condition as the crops are grown in a vertical tower. This research used two stepper motors to move the camera module horizontally (through rotation) and vertically (through translation). This mechanism provides a chance to capture all crop images grown in the stacked layer of the vertical tower.

Figure 2 illustrates the module's communication workflow. As shown in the figure, a camera module is mounted on the Raspberry Pi Zero. The Raspberry Pi board connects wirelessly to the ESP32 microcontroller module and communicates through the HTTP post-request protocol. The ESP32 module controls the drivers that move the motors. The HTTP post-request protocol is operated wirelessly and was chosen to minimize the number of wires connected to the central processing board (the Raspberry Pi). The board is part of a moving arm and is connected only with a power cable. The crop images were stored in two locations. First, the images were saved in the internal memory of the Raspberry Pi module. Since the captured images are relatively small (128×128 pixels), storing them internally on the SD card mounted to the Raspberry Pi does not require significant space. Second, as the board was connected to an internet modem, the images were also uploaded to the cloud as a backup.

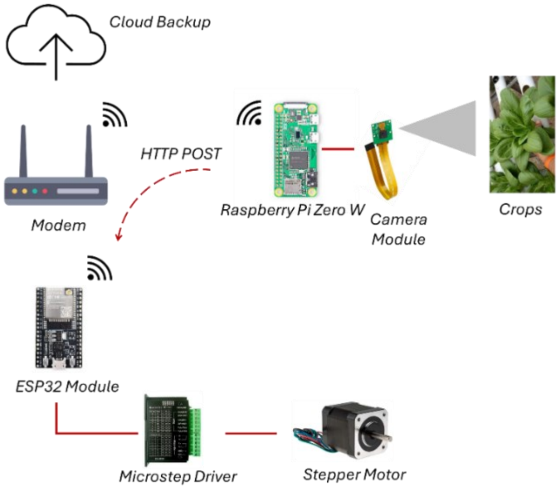

Figure 2. Module's communication workflow

Examples of crop condition images are shown in Figure 3. Water stress in crops causes wilting, as illustrated in the lower row of the figure. In contrast, the upper row displays fresh leaves. The camera module did not capture images of individual crops; instead, a single image might contain overlapping leaves from multiple crops with varying conditions. However, if images include a single wilting leaf, this paper labeled those images as wilt.

Figure 3. Example of crop conditions: fresh (upper row) and wilt (lower row)

2.2 Deep Learning Model

Figure 4 visualizes the proposed deep learning model. The model accepts three-channel images of 128×128 pixels. The inputs are then processed through multiple pairs of convolutional and pooling layers before being flattened and classified using dense layers. The proposed deep learning model is implemented using TensorFlow 2.11 and designed for image classification. The model contains a sequential architecture with multiple layers. The proposed deep model begins with a two-dimensional convolutional layer containing 32 filters of size 4×4 and utilizes a rectified linear unit (ReLU) activation function. A max-pooling layer with a pool size of 3×3 follows this first convolutional layer. The max-pooling layer helps reduce the spatial dimensions. The second convolutional layer with 64 filters of size 3×3, ReLU activation function and another max-pooling layer with a pool size of 2×2 is included. Then, a third convolutional layer with 128 filters of size 3×3 is combined, followed by another 2×2 max-pooling layer. The output from the convolutional layers is flattened into a one-dimensional vector, which is then processed by a dense layer with 128 units and ReLU activation. A dropout layer with a dropout rate of 0.5 is included to prevent overfitting. Finally, the model concludes with a dense layer. The dense layer (equipped with a sigmoid activation function) contains one unit suitable for classifying the input images into two categories. In total, there are 1,142,753 trainable parameters.

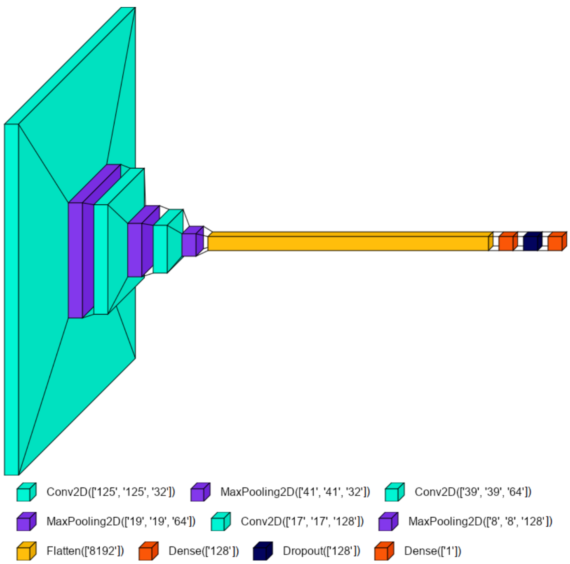

Figure 4. Proposed deep learning model

2.3 Model Training

The model was compiled using the Adam optimizer. During training, binary cross-entropy was used as the loss function, and accuracy was used as the evaluation metric. An early stopping callback was selected to improve the training process, monitoring the validation loss with the patience of 5 epochs and restoring the best weights upon stopping. Early stopping is a regularization method utilized in deep learning to avoid overfitting during training. Early stopping involves monitoring the model's performance on a validation dataset and stopping the training process once its performance stops improving. The model was trained on the dataset for up to 50 epochs, leveraging this early stopping mechanism to prevent overfitting and ensure optimal performance. The model was fitted to the training data generator and validated against the test data generator as part of the training process.

3 Results and Discussion

Figure 5 shows the model accuracy and loss during training. Based on the figure, the model demonstrated substantial improvement in both training and validation accuracy, particularly in the early stages of training. The training process of the deep learning model using early stopping resulted in significant improvements in both training and validation accuracy over the epochs. The model showed a notable increase in validation accuracy from 73.38% in the first epoch to 90.49% by the 35th epoch, with a corresponding decrease in validation loss from 0.5631 to 0.2272. The training accuracy improved consistently, reaching 88.40% by the 38th epoch. Despite slight fluctuations, such as in epochs 3 and 10, where the validation accuracy dipped, the overall trend was positive, indicating the model's robustness and effectiveness. Early stopping involves monitoring the model's performance on a validation dataset and stopping the training process once its performance stops improving. Early stopping consists of monitoring the model's performance on a validation dataset and stopping the training process once its performance stops improving. The early stopping strategy effectively prevented overfitting, as evidenced by the high validation accuracy and low validation loss achieved.

Figure 5. Model accuracy and loss during training

Table 1 and Figure 6 show the classification report and confusion matrix on the test data. Based on the experiments, the deep learning model achieved a high overall accuracy of 90% in distinguishing between fresh and wilted conditions. The model showed strong performance with precision, recall, and f1-score values for the 'fresh' class at 0.86, 0.98, and 0.92, respectively. For the 'wilt' class, precision, recall, and f1-score values were 0.97, 0.82, and 0.89, respectively. The confusion matrix revealed that the model correctly classified 135 out of 138 fresh samples and 103 out of 125 wilted samples, with only 25 misclassifications out of 263 samples. These results underscore the model's strong ability to accurately classify conditions with balanced performance across both classes.

Table 1. Classification report

Class	Precision	Recall	F1-score	Support
fresh	0.86	0.98	0.92	138
wilt	0.97	0.82	0.89	125
Parameters				
accuracy			0.90	263
macro avg	0.92	0.90	0.90	263
weighted avg	0.91	0.90	0.90	263

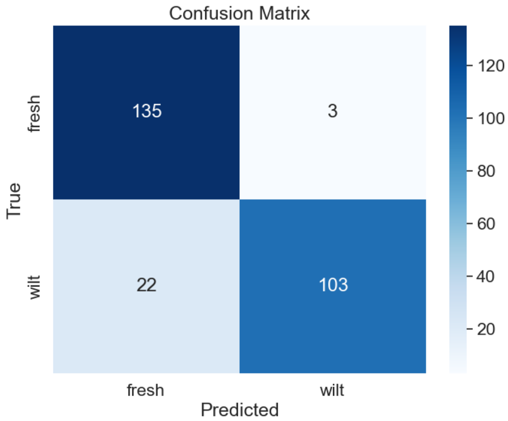

Figure 6. Confusion matrix on test data

4 Conclusion

Using a binary classification approach, this paper demonstrates a method for detecting wilt in crops due to water stress. The proposed data collection and deep learning model can classify whether the crops are fresh or wilted with an accuracy of 90% on the test data. The model correctly classified 135 out of 138 fresh samples and 103 out of 125 wilted samples, resulting in only 25 misclassifications out of 263 samples. These results highlight the model's strong ability to classify conditions with balanced performance across both classes accurately.

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