MSc Report for EE5003

Project Title: Detecting Plant Growth Stages By Machine Learning

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ABSTRACT: This project focuses on developing an AI-based system for accurately detecting and classifying different growth stages of plants. By leveraging computer vision techniques and deep learning algorithms, the system aims to accurately monitor and evaluate the process of plant growth, which can be valuable in various fields such as agriculture and plant research.

DECLARATION: I affirm that the contents contained in this report is original and there is no plagiarism. Any resemblances to existing works are purely coincidental.

ACKNOWLEDGEMENT: I am grateful to Dr Zhang Jianwen for his consistent support and insightful counsel throughout the conception and implementation of this project.

Contents

1 INTRODUCTION

The development of innovative technology becomes vital in response to the need for sustainable food production and food security, especially in metropolitan contexts like Singapore with limited land resources. This report outlines a project aimed at developing an AI-based system for accurately detecting and classifying different growth stages of plants, with a focus on lettuce, and then expand the system to identify abnormal leaves. The goal is to contribute to the enhancement of urban farming capabilities and support Singapore's '30 by 30' target outlined in the Singapore Green Plan 2030.

1.1 Project background

When it comes to locating places for farming, commercial centers and HDB multi-story parking lots' rooftops are viable options for productive farms. As seen in Figure 1, a 1,900 square meter urban vertical farm built by Citiponics is situated on the rooftop of a HDB parking garage. Up to four tonnes of pesticide-free green vegetables are grown there each month[1].

Figure 1: Urban multi-storey carpark rooftop farm @ Citiponics.

In order to effectively track the growing status, technology is required. Controlled environmental farming systems and cameras allow for the real-time tracking of plant growth status for timely harvesting, as well as the monitoring and adjustment of planting area variables like temperature and humidity to guarantee ideal conditions for plant growth.

1.2 Project Objectives

- **Acquire Well-Labeled Datasets**: Well-labeled dataset of plant images representing different growth stages.
- **Develop Deep Learning Models:** Engineer deep learning models capable of precisely detecting and classifying plant growth stages.
- **Visualize Detected Results:** Implement visualization techniques to present the detected growth stages in a clear and interpretable manner.

2 DATASET CREATION

2.1 Lettuce Growth Stages Dataset

The existing dataset on the growth stage of lettuce is insufficient to meet the data requirements of this project. In order to improve the dataset, I planted lettuce myself and collected images as the data source for the dataset.

Growing lettuce in Singapore need to consider the tropical climate and high temperatures in the region. Choose heat-tolerant lettuce varieties such as loose-leaf types. The natural sunlight is insufficient in Singapore due to the rainy season, supplement with LED grow lights. Select the hydroponic approach because lettuce grown hydroponically grows more quickly and is more resilient than lettuce grown in soil. The aperture of the cultivation board is 3.2cm, and the planting density is 10cm by 10cm; Apply the soaked seeds directly onto the surface of the sponge block, and after germination, insert the cultivated seedlings into the holes of the cultivation board. Regularly change the nutrient solution.

As shown in Figure 2, take photos at a fixed point every day to make sure that the light and angle are the same, and the background is clean. Crop the original image and adjust its size to fit the image size and pixel values in the dataset.

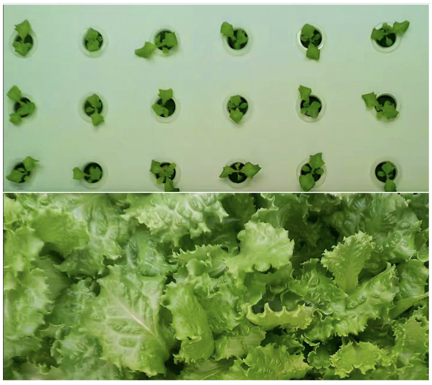


Figure 2: Photos of self-grown hydroponic lettuces

The final dataset consists of **self-grown hydroponic lettuce** and **Online Challenge Lettuce Images** from open source 3rd Autonomous Greenhouse Challenge[2].

- **Classes**: 'Seedling', 'Growth', 'Mature'
- **Train set**: For each class, 80 images from self-grown hydroponic lettuce, 24 images from Online Challenge Lettuce Images.
- **Test set**: For each class, 20 images from self-grown hydroponic lettuce, 6 images from Online Challenge Lettuce Images.

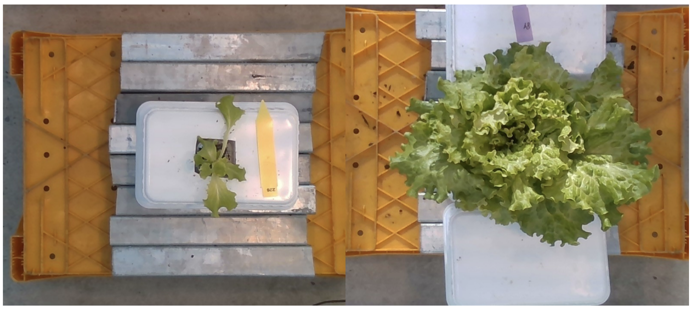


Figure 3: Photos from open source lettuce database

2.2 Abnormal Leaves Dataset

Use the Lettuce NPK dataset[3] which contains the following categories of Diseased lettuce: Fully Nutritional('FN'), Nitrogen Deficient('-N'), Phosphorus Deficient('-P') and Potassium Deficient('-K').

- **Classes**: '-K', '-N', '-P', 'FN'
- **Train set**: For '-K', '-N', '-P' classes, 40 images. For 'FN' classes, 10 images.
- **Test set**: For '-K', '-N', '-P' classes, 8 images. For 'FN' classes, 2 images.

3 METHODOLOGY

3.1 Develop model capable of accurately detecting different growth stages

3.1.1 Image Preprocessing

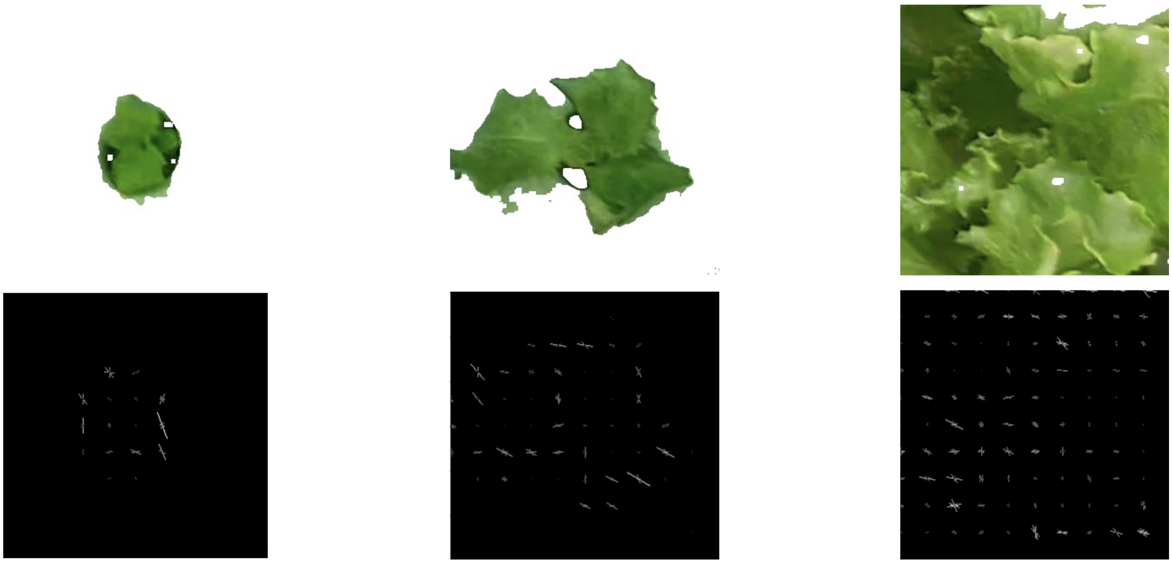
Preprocess the image of lettuce to separate it from the background and improve its quality for further analysis. It defines a specific color range corresponding to lettuce leaves in the HSV color space and applies this range to create binary masks. Then, morphological operations are used to refine the mask, and the background area is extracted. Finally, separate the lettuce leaves from the background and cover them on a white background to generate an image suitable for subsequent processing and analysis. The image preprocessing results are shown in Figure 4.

(a) Before preprocessing (b) After preprocessing

Figure 4: Comparison before and after image preprocessing

3.1.2 HOG Feature Extraction and SVM Classification

Load and preprocess images from Lettuce Growth Stage Dataset, resizing them to a uniform size and applying gamma correction for contrast enhancement. Then, as shown in Figure 5, Histogram of Oriented Gradients (HOG)[4] features are computed for each preprocessed image, capturing local intensity gradients.



(a) Seedling (b) Growth (c) Mature

Figure 5: Images from different stages and their extracted HOG features

These features captured by HOG, along with corresponding labels indicating the growth stage of each image (e.g., seedling, growth, and mature), are used to train a Support Vector Machine (SVM) classifier. The SVM classifier is instantiated with a linear kernel and a regularization parameter (C) set to 1.0. Once trained, the SVM model is saved as "$SVM\_Detect\_growth\_stages.pkl$" for later use. This approach enables the classification of new images into distinct growth stages with satisfactory accuracy.

During testing stage, load the pre-trained SVM classifier from "$SVM\_Detect\_growth\_stages.pkl$" and utilizes it to classify lettuce images into different growth stages. It prepares test data by resizing and loading lettuce images from specified directories. Then, it employs a sliding window approach to extract regions of interest from each image and computes Histogram of Oriented Gradients (HOG) features for classification. Using the SVM model, it predicts the growth stage of each region and calculates confidence scores. Non-maximum suppression is applied to refine the detections.

Finally, the detected regions are visualized on the original images, and the accuracy of the classifier is computed by comparing the predicted labels with the ground truth labels of the test dataset.

Generating a confusion matrix for visualization of the SVM classification performance across different lettuce growth stages classes and calculate the classification accuracy.

As seen in Figure 6, the plot displays the confusion matrix with labels for true and predicted classes. The color intensity of each cell represents the number of instances, with darker shades indicating higher counts. Additionally, text annotations inside each cell show the exact count. The classes are represented as 'Seedling', 'Growth' and 'Mature'. As shown in Figure 7, accuracy of SVM classification on different lettuce growth stages is 80.77%.

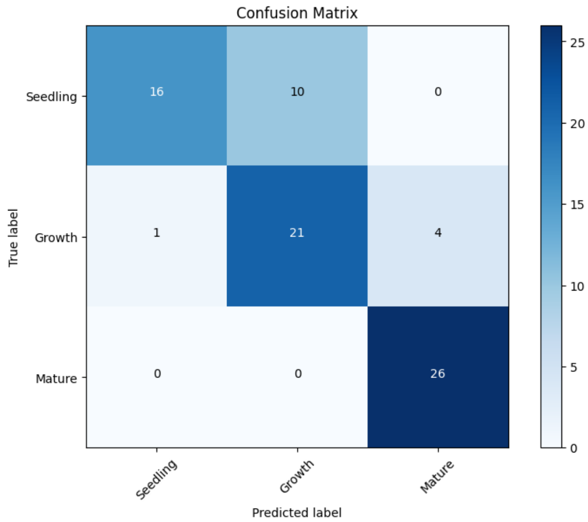


Figure 6: Confusion matrix of SVM classification on different growth stages

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✓ 0.4s

Load SVM model from SVM_Detect_growth_stages.pkl!
Accuracy of SVM classification : 80.77%
```

Figure 7: Accuracy of SVM classification on different growth stages

3.1.3 CNN Classification

Implements a Convolutional Neural Network (CNN) using PyTorch for multi-class image classification[5]. The architecture of the CNN model comprises two convolutional layers, two max-pooling layers, and two fully connected layers. Data loading and transformation functions are defined to prepare the training and testing datasets, including resizing, cropping, and normalization. The model is trained over a specified number of epochs(e.g., 50) using a training loop, where batches of data are iterated, and forward and backward passes are performed to update the model parameters using the Adam optimizer. Following training, it evaluates the model on the test dataset, computing the classification accuracy. Finally, the trained model parameters are saved to a file named "$Detect\_growth\_stages.pth$" for future use, providing a complete pipeline for image classification tasks.

Generating a confusion matrix for visualization of the CNN model's performance across different lettuce growth stages classes and calculate the classification accuracy. As seen in Figure 8, The classes are represented as 'Seedling', 'Growth' and 'Mature'. As shown in Figure 9, accuracy of CNN classification on different lettuce growth stages is 97.44%.

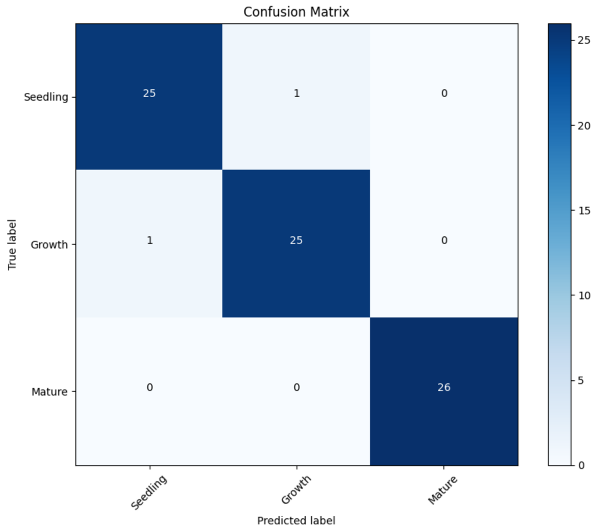

Figure 8: Confusion matrix of CNN classification on different growth stages

```
Load CNN model from Detect_growth_stages.pth!
Final Classification Accuracy: 97.44%
```

Figure 9: Accuracy of CNN classification on different growth stages

3.2 Develop model capable of accurately detecting abnormal leaves

The algorithm logic of accurately detecting abnormal leaves[6] is similar to the CNN described earlier, it loads the Lettuce NPK dataset for training and testing, defines the CNN architecture with two convolutional layers and two fully connected layers, trains the model using the Adam optimizer and Cross Entropy loss function, and evaluates the final classification accuracy on the test set.

Generating a confusion matrix for visualization of the CNN model's performance across different classes and calculate the classification accuracy.As seen in Figure 10. In this specific case, the classes are represented as '-K', '-N', '-P', and 'FN'. As shown in Figure 11, accuracy of CNN classification on abnormal leaves is 92.31%.

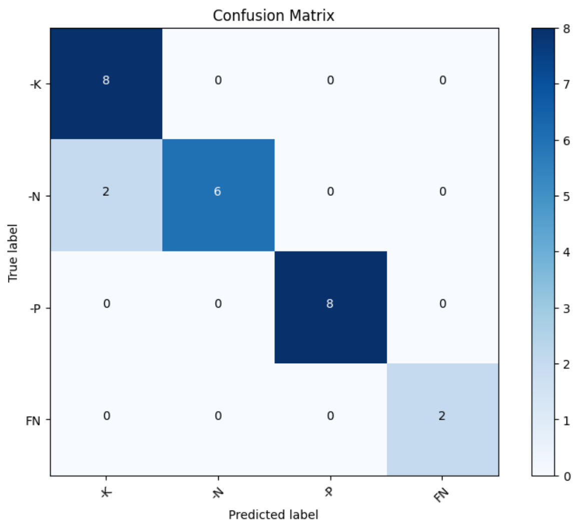

Figure 10: Confusion matrix of CNN classification on abnormal leaves

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✓ 8.3s

Load CNN model from Detect_abnormal_leaves.pth!
Accuracy of CNN classification: 92.31%
```
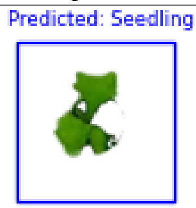
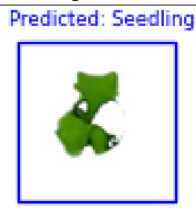
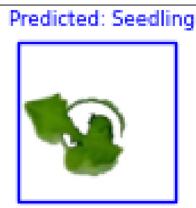
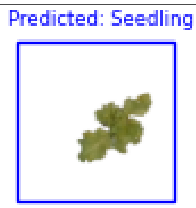
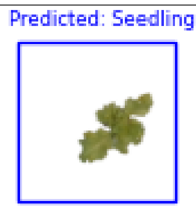

Figure 11: Accuracy of CNN classification on abnormal leaves

3.3 Visualize the detected results

During the model testing phase, the model's performance can be assessed by computing the classification accuracy numerically by comparing the predicted labels with the true labels. Additionally, colored rectangles with label text are created around the objects in the image to illustrate the prediction results, with each color denoting a different prediction class. This provides a more intuitive representation of the model classification findings.

As shown in table 1, randomly select 3 test images for each growth stages class to demonstrate the visualization of growth stages detection results. As we can see, Test images 2 and 5 are correctly classified by CNN, but they are misclassified by the SVM classification.

<table>
<tr><th>/</th><th>Real Class</th><th>Original_image</th><th>SVM_prediction</th><th>CNN_prediction</th></tr>
<tr><td>Test images 1</td><td>Seedling</td><td></td><td>
</td><td>
</td></tr>
<tr><td>Test images 2</td><td>Seedling</td><td></td><td>
</td><td>
</td></tr>
<tr><td>Test images 3</td><td>Seedling</td><td></td><td>
</td><td>
</td></tr>
<tr><td>Test images 4</td><td>Growth</td><td></td><td>
</td><td>
</td></tr>
</table>

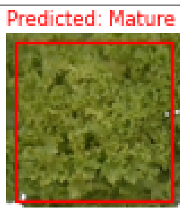
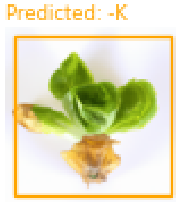
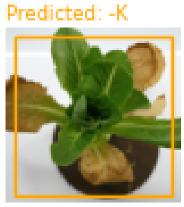
/	Real Class	Original_image	SVM_prediction	CNN_prediction
Test images 5	Growth			
Test images 6	Growth			
Test images 7	Mature			
Test images 8	Mature			
Test images 9	Mature			

Table 1: Visualization of growth stages detection results

As shown in table 2, randomly select 2 test images for each diseased lettuce class to demonstrate the visualization of abnormal leaves detection results. We can observe that, due to the smaller number of "FN" samples compared to other classes in the Abnormal Leaves Dataset, CNN classification incorrectly classified the fully nutrition Test image 7 as nitrogen deficient. In the mean time, CNN's classification of other test images in the table is correct.

/	Real Class	Original_image	CNN_prediction
Test images 1	-K		
Test images 2	-K		
Test images 3	-N		
Test images 4	-N		
Test images 5	-P		
Test images 6	-P		

/	Real Class	Original_image	CNN_prediction
Test images 7	FN		
Test images 8	FN		

Table 2: Visualization of abnormal leaves detection results

4 SUMMARY

In this project, I leveraged both traditional computer vision techniques and deep learning algorithms to address the tasks of plant growth stage classification and abnormal leaf detection. Firstly, I utilized histogram of oriented gradients (HOG) feature extraction combined with support vector machine (SVM) classification to classify plant growth stages. This approach involved preprocessing the images, computing HOG features, and training an SVM classifier. The SVM classification achieved an accuracy of 80.77% on the test set.

Subsequently, I employed a Convolutional Neural Network (CNN) model for both plant growth stage classification and abnormal leaf detection. The CNN model was trained on the same dataset used for the SVM classification, achieving a significantly higher accuracy of 97.44% for plant growth stage classification. Additionally, the CNN model was trained on a separate dataset for abnormal leaf detection, achieving an accuracy of 92.31% on the test set.

This experiment proved the accuracy with which deep learning models, particularly convolutional neural networks, can classify plant growth stages and identify aberrant leaves. Convolutional neural networks outperformed classic computer vision approaches, demonstrating the power of deep learning in handling complicated picture categorization problems.

References

[1] SFA. (2021). A foodie haven with no food is a recipe for disaster. Food for Thought. Retrieved from https://www.sfa.gov.sg/food-for-thought/article/detail/a-foodie-haven-with-no-food-is-a-recipe-for-disaster.

[2] S. (Silke) Hemming; H.F. (Feije) de Zwart; Elings, A. (Anne); monique bijlaard; Bart Marrewijk, van et. al. (2021): 3rd Autonomous Greenhouse Challenge: Online Challenge Lettuce Images. Version 1. 4TU.ResearchData. dataset. https://doi.org/10.4121/15023088.v1

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[5] Gang MS, Kim HJ, Kim DW. Estimation of Greenhouse Lettuce Growth Indices Based on a Two-Stage CNN Using RGB-D Images. Sensors (Basel). 2022 Jul 23;22(15):5499. doi: 10.3390/s22155499. PMID: 35898004; PMCID: PMC9331482.

[6] Yang, R., & Wu, Z., et al. (2023). Detection of abnormal hydroponic lettuce leaves based on image processing and machine learning. Information Processing in Agriculture, 10(1), 1-10. https://doi.org/10.1016/j.inpa.2021.11.001.