MSc Report for EE5003

Project Title: Detecting Plant Growth Stages By Machine Learning

Wu Yutong - A0279693E

Dept of Electrical & Computer Engineering, NUS

2024

ABSTRACT: This project focuses on designing an AI-based system for accurately detecting and classifying different growth stages of lettuce. By utilizing computer vision technology and deep learning algorithms, this system aims to accurately monitor and evaluate plant growth processes, which is valuable for fields such as agriculture and plant research.

DECLARATION: I declare that this report is the result of independent research and writing under the guidance of my supervisor. The content mentioned in the report is original and there is no plagiarism.

ACKNOWLEDGEMENT: I am grateful to Dr. Zhang Jianwen for providing me with guidance throughout the implementation process of the project. His support and useful suggestions are essential for me to successfully complete the project research.

Contents

1 INTRODUCTION **3**

1.1 Project background 3

1.2 Project Objectives 3

2 DATASET CREATION **4**

2.1 Lettuce Growth Stages Dataset 4

2.2 Abnormal Leaves Dataset 5

3 METHODOLOGY **5**

3.1 Develop model capable of accurately detecting different growth stages 5

3.1.1 Image Preprocessing 5

3.1.2 HOG Feature Extraction and SVM Classification 5

3.1.3 CNN Classification 7

3.2 Develop model capable of accurately detecting abnormal leaves 10

3.3 Method comparison 11

3.4 Visualize the detected results 12

4 SUMMARY **15**

1 INTRODUCTION

Applying technology to agriculture is crucial for meeting the needs of sustainable food production and food security, especially in urban environments with limited land resources such as Singapore. This project aims to develop an artificial intelligence based system for accurately detecting and classifying different growth stages of lettuce, and then expand the system to identify abnormal leaves during the growth process. 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

In terms of site selection for urban agriculture, commercial centers and HDB rooftops are good choices to improve land use efficiency. Figure 1 shows a 1900 square meter urban vertical farm built by Citiponics on the roof of an HDB parking lot. Up to four tons of pesticide free green vegetables can be planted here every month. [1].

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

This new type of smart agriculture requires technological support to effectively track the growth status of plants in the long term. A controlled camera and multi-sensor system can track the growth status of plants in real time for timely harvesting, and can also monitor and adjust variables such as temperature and humidity in the planting area to maintain the ideal conditions for plant growth.

1.2 Project Objectives

- **Acquire Well-Labeled Datasets**: Well-labeled dataset of lettuce growth stages, including plant images from different growth stages, as well as well-labeled dataset of abnormal leaves, which includes categories of diseased lettuce.
- **Develop Deep Learning Models:** Design algorithm models that can accurately detect and classify plant growth stages and detect abnormal leaves.
- **Visualize Detected Results:** Visualize the detection results and present the detected growth status 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 requires consideration of the tropical climate and high temperatures in the region. Choose heat-resistant lettuce varieties, such as loose leaf type. Due to the rainy season in Singapore, there is insufficient natural light and LED lights are needed to supplement the lighting. 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 in the dataset.

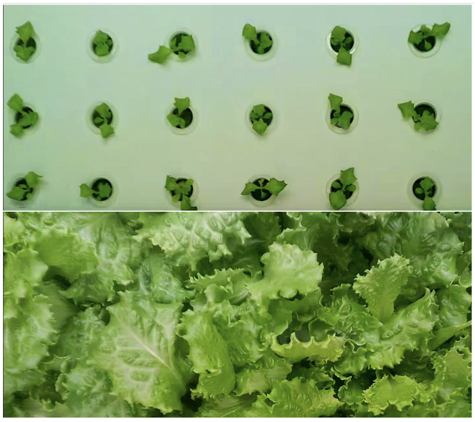


Figure 2: Photos of self-grown hydroponic lettuces

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.

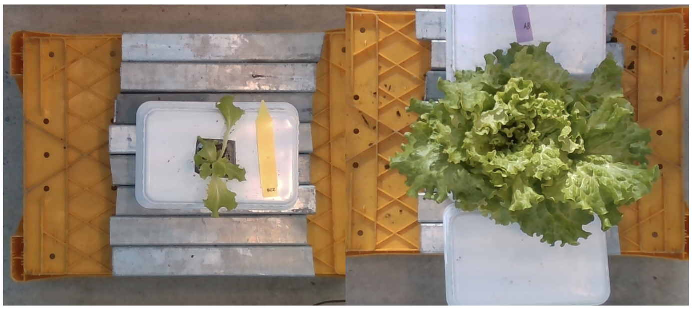


Figure 3: Photos from open source lettuce database

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

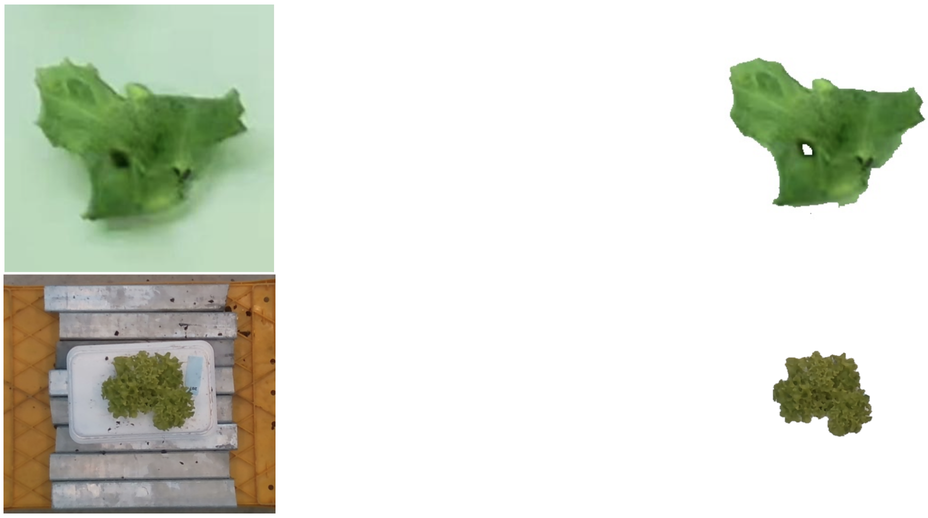
3.1 Develop model capable of accurately detecting different growth stages

3.1.1 Image Preprocessing

In the process of image preprocessing, the image of lettuce is separated from its background and its quality is improved to facilitate further analysis. Create a binary mask with a specific color range corresponding to lettuce leaves in the HSV color space. Then, use morphological operations to refine the mask and extract the background area. Finally, separate the lettuce from the background and place it on a white background to generate an image suitable for subsequent processing and analysis. The image preprocessing results are shown in Figure 4.

3.1.2 HOG Feature Extraction and SVM Classification

Load and preprocess images from the lettuce growth stage dataset, and apply gamma correction to enhance the contrast of the images. Then, as shown in Figure 5, calculate the gradient oriented histogram[4] features for each preprocessed image and capture the local intensity gradient.



(a) Before preprocessing (b) After preprocessing

Figure 4: Comparison before and after image preprocessing

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

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

Support Vector Machine (SVM) is a universal supervised machine learning algorithm widely used for classification tasks. Its core is to pursue the optimal hyperplane that can effectively separate data points belonging to different categories. When executing SVM, kernel type and regularization parameters (C) are two key parameters that must be defined. For case, linear kernels are suitable for directly segmenting information, while radial basis function (RBF) kernels are more general and allow for complex nonlinear information segmentation. The regularization parameter (C) determines the trade-off between maximizing edges and minimizing classification errors. Lower C emphasizes more attention to edges, which may lead to more misclassification. A higher C value allows for fewer misclassifications, but may result in tighter edges, which may lead to overfitting. In this project, an SVM classifier with a linear kernel and regularization parameter (C) equal to 1.0 can meet the classification requirements.

Use the features captured by HOG, as well as the corresponding labels for the growth stages of each image (such as seedlings, growth, and maturity), to train this Support Vector Machine (SVM) classifier. After training, the SVM model is saved as "$SVM\_Detect\_growth\_stages.pkl$" for future use. This method can classify the input lettuce images into different growth stages.

In the testing phase, load a pre trained SVM classification model from "$SVM\_Detect\_growth\_stages.pkl$" and use it to classify the input lettuce images into different growth stages. It uses a sliding window method to extract regions of interest from loaded lettuce images, and uses the computed gradient oriented histogram (HOG) as image features for classification. Calculate the confidence score for the prediction results of the SVM classification model. Finally, visualize the detected areas on the original image and compare the predicted labels with the true labels on the test dataset to calculate the accuracy of the classifier.

Generating a confusion matrix for visualizing 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 real classes and predicted classes. The color intensity of each cell represents the number of images, the darker the shadow, the higher the count. 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%.

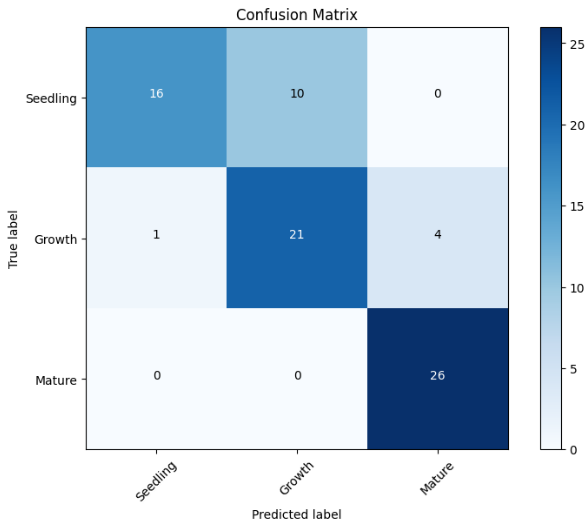


Figure 6: Confusion matrix of SVM classification on different growth stages

```
✓ 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

The Convolutional Neural Network (CNN) architecture is designed using the PyTorch toolkit to effectively process and recognize complex patterns in images, which are necessary for accurately classifying lettuce plants at different growth stages[5]. Figure 8 shows that CNN includes a multi-layer structure that utilizes convolution, activation, pooling, and fully connected layers to extract features and perform classification prediction.

When training the CNN model, the input image first enters the convolutional layer. The convolutional layer applies a learnable filter to the input image, performs convolution operations on the image, and extracts local patterns and features that are crucial for distinguishing different growth stages. In this CNN architecture design, the first convolutional layer consists of 20 filters, while the subsequent layers use 50 filters, each with a kernel size of 5x5. The output feature maps of the convolutional layers is shown in Figure 9.

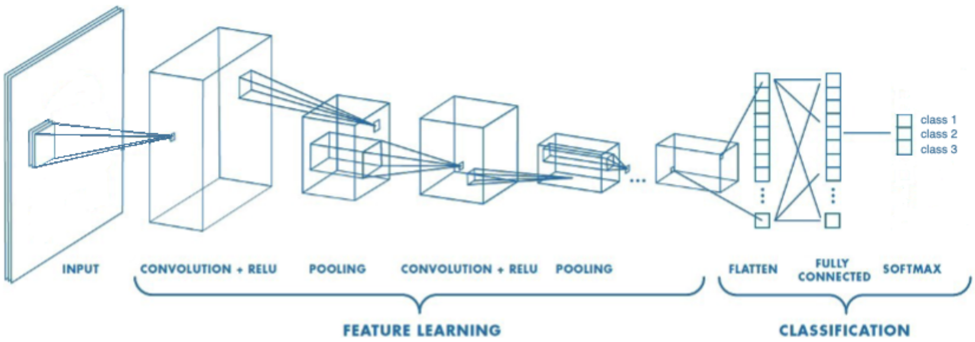


Figure 8: Architecture of Convolutional Neural Network

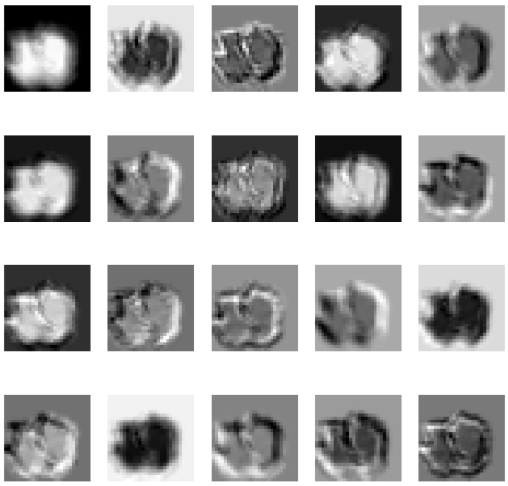


Figure 9: Convolutional output feature maps

Corrected Linear Unit (ReLU) is an activation function that outputs zero for any negative input value, while the output of positive values remains unchanged. Due to its ability to zero negative values without changing positive values, this introduces nonlinear characteristics into the model. After each convolutional layer, placing the ReLU activation function can enable the model to capture further complex structures present in the image, enhancing the model's ability to accurately distinguish different growth stages.

In order to reduce the spatial dimension of image data or feature maps while preserving the most important information, a max-pooling layer needs to be integrated after each convolutional layer. It downsamples the feature map by selecting the maximum value within each pooling region. This reduces the computational complexity of the model and helps to reduce the risk of overfitting.

The output from the convolutional layers is flattened and passed through two fully connected layers. The first fully connected layer consists of 500 neurons, which further process the extracted features. The final layer comprises three neurons, corresponding to the three different growth stages of lettuce plants. These fully connected layers enable the network to perform high-level reasoning and classification based on the learned features.

Data loading and transformation functions are defined to prepare the training and testing datasets, including resizing, cropping, and normalization. During the training phase, the CNN is optimized using the Adam optimizer with a learning rate of 0.001. The model minimizes the Cross-Entropy Loss function, which quantifies the disparity between predicted and actual class labels. Through backpropagation, the model iteratively adjusts its parameters to minimize this loss. The model is trained over a specified number of epochs(e.g., 50) using this training loop.

Following training, it evaluates the model on the test dataset. The trained model is saved as "$Detect\_growth\_stages.pth$" for future use. 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 10, The classes are represented as 'Seedling', 'Growth' and 'Mature'. As shown in Figure 11, accuracy of CNN classification on different lettuce growth stages is 97.44%.

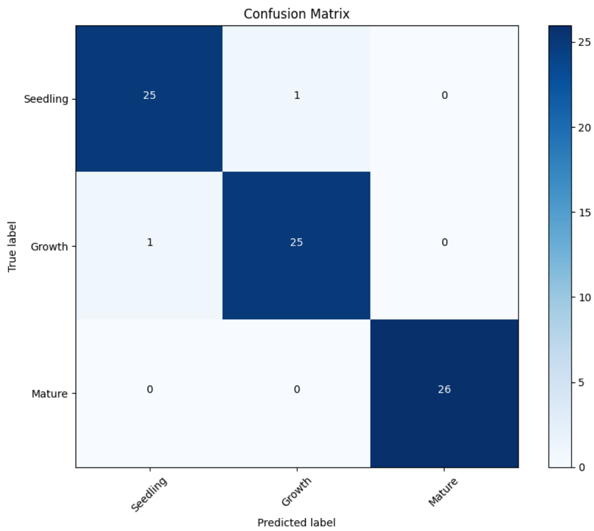


Figure 10: Confusion matrix of CNN classification on different growth stages

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

Figure 11: Accuracy of CNN classification on different growth stages

To verify the robustness of the CNN model, use all self-grown hydroponic lettuce images as the training set, and all Online Challenge Lettuce images as the testing set.

- **Classes**: 'Seedling', 'Growth', 'Mature'
- **Train set**: For each class, 100 images from self-grown hydroponic lettuce.

- **Test set**: For each class, 30 images from Online Challenge Lettuce Images.

Use this new dataset, train the CNN model again. After evaluating using the test set, the new confusion matrix for visualization of the CNN model's performance across different lettuce growth stages classes is as shown in Figure 12. The CNN model trained solely on self-grown hydroponic lettuces has a classification accuracy of 90.00% for Online Challenge Lettuce images. The accuracy has slightly decreased, but it still has good performance on classifying lettuces from different growth stages.

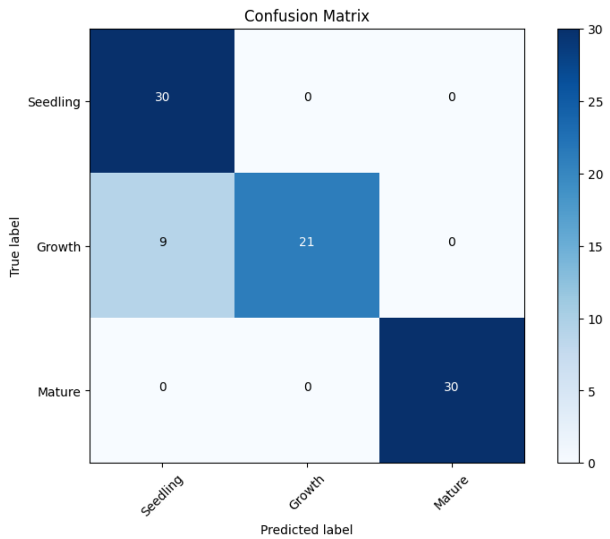


Figure 12: Confusion matrix of CNN trained solely on self-grown hydroponic lettuces

```
Load CNN model from Detect_growth_stages.pth!
Final Classification Accuracy: 90.00%
```

Figure 13: Accuracy of CNN trained solely on self-grown hydroponic lettuces

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 14. In this specific case, the classes are represented as '-K', '-N', '-P', and 'FN'. As shown in Figure 15, accuracy of CNN classification on abnormal leaves is 92.31%.

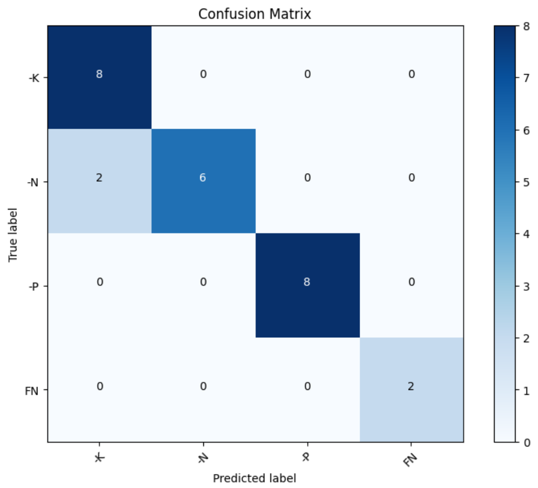


Figure 14: Confusion matrix of CNN classification on abnormal leaves

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

Figure 15: Accuracy of CNN classification on abnormal leaves

3.3 Method comparison

By comparing the results obtained from the above methods, I found that both traditional computer vision techniques and deep learning algorithms are effective in detecting plant growth stages. However, the classification accuracy of Convolutional Neural Network (CNN) models is superior to traditional classification methods that combine Gradient Histogram (HOG) and Support Vector Machine (SVM).

As shown in Table 1, the CNN achieved an accuracy rate of 97.44% for plant growth stages classification and 92.31% for abnormal leaves detection. In contrast, the HOG+SVM approach yielded lower accuracy rates, indicating the superior performance of deep learning methods in this context.

Method	Accuracy
HOG+SVM for plant growth stages classification	80.77%
CNN for plant growth stages classification	97.44%
CNN for abnormal leaves detection	92.31%

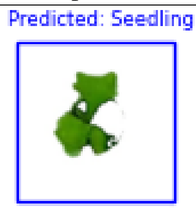
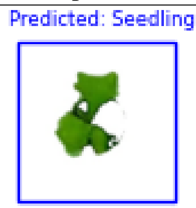
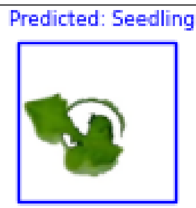
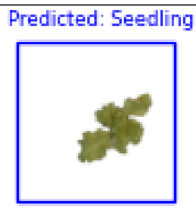
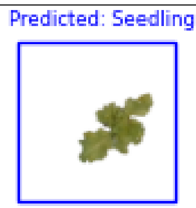
Table 1: Comparison of method accuracy

Compared with manual feature extraction methods such as HOG, the success of CNN can be attributed to its ability to automatically learn hierarchical features from input images using convolutional layers, which enables it to more effectively capture complex information in images. In addition, CNN is the most suitable choice for the AI-based plant growth monitoring system in this project, as it increases the flexibility and scalability of the project.

3.4 Visualize the detected results

In the model testing phase, in addition to evaluating the performance of the model by comparing predicted labels with real labels and calculating classification accuracy digitally, colored rectangles with labeled text can also be created around the image to illustrate the prediction results. Print the input image and draw different colors and text on it to represent different predicted categories. This provides a more intuitive representation of the model classification results.

As shown in Table 2, 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.

/	Real Class	Original_image	SVM_prediction	CNN_prediction
Test images 1	Seedling			
Test images 2	Seedling			
Test images 3	Seedling			
Test images 4	Growth			
Test images 5	Growth			

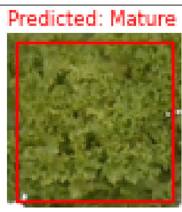
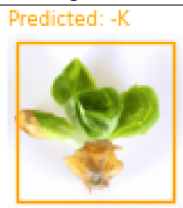
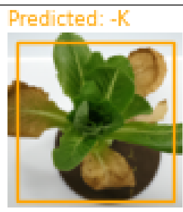
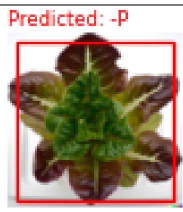
/	Real Class	Original_image	SVM_prediction	CNN_prediction
Test images 6	Growth			
Test images 7	Mature			
Test images 8	Mature			
Test images 9	Mature			

Table 2: Visualization of growth stages detection results

As shown in Table 3, 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 3: Visualization of abnormal leaves detection results

4 SUMMARY

In this project, I utilized traditional computer vision techniques and deep learning algorithms to solve the tasks of plant growth stage classification and abnormal leaf detection. Firstly, a method combining gradient histogram (HOG) feature extraction with support vector machine (SVM) classification is used to classify plant growth stages. This method includes preprocessing images, calculating HOG features, and training SVM classifiers. The accuracy of SVM classification on the test set is 80.77%.

Subsequently, I used a Convolutional Neural Network (CNN) model for plant growth stage classification and abnormal leaf detection. Training CNN models on the same dataset used for SVM classification achieved a higher accuracy of 97.44% in plant growth stage classification. In addition, training a CNN model on the dataset of abnormal leaves for abnormal leaf detection achieved an accuracy of 92.31% on the test set.

This project demonstrates that the AI-based convolutional neural network model can more accurately classify plant growth stages and identify abnormal leaves. The performance of convolutional neural networks is superior to traditional computer vision methods, demonstrating the power of deep learning in dealing with complex image classification 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

[3] Ramimalik782. (2023). Lettuce NPK Dataset. Retrieved from Kaggle: https://www.kaggle.com/datasets/baronn/lettuce-npk-dataset

[4] H. Rachman, Y. Purwanto and C. Setianingsih, ”Detection of Lettuce Plant Conditions Based on Images using Back-propagation Method,” 2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), Sakheer, Bahrain, 2022, pp. 593-597, doi: 10.1109/3ICT56508.2022.9990758.

[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.