Carrot Cure: A CNN Based Application to Detect

Carrot Disease

3.1.1 System Description

The current state of lettuce crop management is largely reliant on traditional methods which include manual inspection and conventional pest control strategies. These methods are labor-intensive, time-consuming, and often prone to human error, leading to suboptimal crop health and yield. The system under development aims to enhance the efficiency and accuracy of lettuce crop management through the application of advanced machine learning techniques, particularly convolutional neural networks (CNNs).

The proposed system is a web-based application that leverages CNNs to identify and classify diseases in lettuce plants. By analyzing images of lettuce leaves, the system can detect the presence of bacterial, fungal, and other types of diseases. The integration of this technology aims to provide farmers with a reliable tool to monitor crop health in real-time, enabling timely intervention and reducing the overall impact of diseases on crop yield.

2.2 Dataset construction

In this study, the defective leaves of hydroponic lettuce were

divided into four categories: Decayed, Broken, Yellow and Wilting,

the color of broken leaves is the same as that of healthy leaves, and

the color of yellow leaves, wilting and decayed defects becomes

yellow, dark green and black, respectively, as shown in Figure 3.

Secondly, the leaf texture of hydroponic lettuce in different states

was also different, the texture of yellow leaves did not change

significantly. The wilted leaves were wrinkled due to water loss,

but basically maintained the shape of the leaves. The decayed leaves

became soft, the leaf texture disappeared, and there is no fixed

shape; The broken leaf texture was destroyed, with obvious cracks

or holes.

The defective leaves in the image were annotated by LabelImg

image annotation software, with Decayed as D (No.0), Broken as B

(No.1), Yellow as Y (No.3), and Wilting as W (No.4). After

annotation, an xml file in VOC format is generated, which

contains the image size, the coordinate position of the defective

leaves, and various label names. Then, the xml file was converted

into the txt file corresponding to the YOLO model. Finally, the

images of lettuce and the labeles were divided into a training set and

a test set in an 8:2 ratio, and placed in images and labels

folders, respectively.

2.3 Data augmentation

Deep learning algorithm training requires a large dataset to

continuously extract and learn features, but the data collectionprocess is very time-consuming. Therefore, offline data

augmentation was conducted on the original dataset before model

training, aiming to increase the number and diversity of samples on

the basis of limited data, and improve the robustness and

generalization ability of the network model. In the experiment,

the augmentation methods adopted include: translation, mirror,

cropping, Gaussian noise and brightness adjustment, etc. A total of

3600 images are obtained after enhancement.

In addition to offline augmentation operations, the model

training process also uses Mosaic data augmentation technology.

Randomly read 4 images in the training set for random cropping,

rotation, scaling, and other operations, and then concatenate them

into one image as training data.