Utilizing UAV Data for Neural Network-based Classification of Melon Leaf Diseases in Smart Agriculture

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***Abstract*—Integrating unmanned aerial vehicle (UAV) technology with plant disease detection is a significant advancement in agricultural surveillance, marking the beginning of a transformational era characterised by innovation. Traditionally, farmers have had to rely on manual visual inspections to identify melon leaf diseases, which proves to be a time-consuming and costly process in terms of labour. This paper aims to use UAV technology for plant disease detection to achieve notable progress in agricultural surveillance. Incorporating UAV technology, specifically utilising the You Only Look Once version 8 (YOLOv8) deep-learning model, is revolutionary in precision agriculture. This study uses UAV imagery in precision agriculture to explore the utility of YOLOv8, a powerful deep-learning model, for detecting diseases in melon leaves. The labelled dataset is created by annotating disease-affected areas using bounding boxes. The YOLOv8 model has been trained using a labelled dataset to detect and classify various diseases accurately. Following the training, the performance of YOLOv8 stands out significantly compared to other models, boasting an impressive accuracy of 83.2%. This high level of accuracy underscores its effectiveness in object detection tasks and positions it as a robust choice in computer vision applications. It has been shown that rigorous evaluation can help find diseases, which suggests that it could be used for early intervention in precision farming and to change how crop management systems work. This has the potential to assist farmers in promptly identifying and addressing plant issues, hence altering their crop management practices.**

Keywords*—Smart agriculture; plant disease; melon leaf disease; image processing; neural network; UAV

I. INTRODUCTION

The melon, scientifically known as Cucumis melo L., is a significant horticultural commodity thriving in Malaysia, categorized within the Cucurbitaceae family. Its cultivation is widespread globally, particularly on subtropical and tropical regions [1], [2]. Melons are esteemed for their delightful sweet tastes, crisp textures, and distinct fragrances [3]. The flesh of the melon is also very good for you because it is full of ascorbic acid (vitamin C), which is a water-soluble vitamin that is known to be one of the safest and most effective nutrients [4], [5]. Numerous farmers extensively cultivate melon, a high-value fruit commodity. Cultivating melons is challenging due to the prevalence of various diseases associated with melon plants. Leaf diseases in melon plants result in economic losses for melon growers. Melon plant diseases are classified into two categories according to their causes: insects and viruses.

One of the insects is called a leaf miner. Various polyphagous leafminer flies pose a potential threat to vegetable crops, and occasionally, even melons are susceptible to these pests. Then, mines show up on the leaflets. The worst-affected leaves may become yellow, wilt, and dry out. These leaves might occasionally contain up to 20 larvae per. Thus, during an infestation, a plant's photosynthetic activity, growth, and yields can all be significantly decreased [6]. Other than leaf miners, aphids are also one of the insects that can form colonies on the young leaflets of melon leaf. They usually establish colonies when they develop on melon. They are particularly dangerous since they can spread many viruses. Nutritional punctures cause chlorotic punctures, which can deform young, rolled-up, and somewhat bloated leaves.

To tackle this challenge, image processing, machine learning (ML), and deep learning (DL) methods offer a solution for categorising plant disease levels on melon leaves, aiding farmers in effectively managing these issues. These techniques have been widely employed in identifying, detecting, and classifying different types of leaf diseases. Scholars have initiated investigations into applying deep learning models for plant detection and counting. This includes the utilization of popular models such as you only look once (YOLO) [7], faster region-based convolutional neural network (Faster R-CNN) [8], and EfficientDet [9]. Several scholars have also implemented a series of enhancements to achieve the objectives of plant detection and counting jobs [10], [11]. Different methods were used to classify leaf diseases: DenseNet and Inception categorized four diseases for bananas, with DenseNet showing better accuracy at 84.73% [12]. Grape leaves were classified into healthy and leaf spot categories using deep forest, achieving 96.25% accuracy [13]. Cucumber leaf diseases were segmented to identify disease points, reaching 97.23% accuracy using an improved saliency method and deep feature selection [14]. Detecting and categorising leaf diseases involves extracting features, which are then used for classification [15].

This research presents a novel approach to disease detection in melon plants through a neural network using drone imagery and an effective method known as YOLO. It is a novel strategy for handling melon problems from above, assisting farmers in more accurately identifying and controlling crop diseases. The contributions of this paper are as follows:

- The research proposes a unique methodology for disease detection in melon plants by employing a neural network trained on drone imagery. This innovative approach aims to address the identified gap in the literature and contribute to advancing agricultural monitoring.

- The study employs the YOLOv8 and YOLOv5 methods, demonstrating their effectiveness as an efficient and accurate tool for identifying diseases in melon plants.
- The research contribution lies in its potential to significantly improve the overall management of melon plants by introducing a novel combination of unmanned aerial vehicle (UAV) imagery and the YOLO method.

As a result, this paper presents a novel method for identifying diseases in melon plants, addressing the gap in current investigations using the YOLO model. This method can significantly improve the process by which farmers detect and manage infections in melon crops, representing a notable advancement in agricultural techniques.

II. Related Works

In precision agriculture, drones have been applied in various ways, and new applications are always being investigated. Numerous drone applications have been created for various uses, including soil analysis, pest detection, crop yield estimation, yield spraying, water stress detection, land mapping, plant nutrient deficiency identification, livestock control, weed detection, and protection of agricultural products [16]. Using UAVs to detect plant leaf diseases has grown in popularity over the past few years due to the industry's rapid growth in machine vision and UAV manufacture [17].

The effective use of DL technology in plant disease categorization in recent years has given researchers a fresh perspective on the topic. Traditionally, disease diagnosis in farming has depended on unaided eye observation, which is costly, time-consuming, and highly skilled [18]. It is possible that deep learning methods could help solve problems in feature extraction, classification, and expert system development. This could help farmers grow better fruit plants that produce more fruit. Models like DenseNet-121 [19], ResNet-50 [20], and MobileNet [21] are well-known and have been used in many previous studies to find and classify images in the field of diagnosing and identifying plant diseases. Sladojevic et al. introduced a method for identifying plant diseases utilizing a Convolutional Neural Network (CNN) within the Caffe DL framework [22]. They gathered images from diverse origins and employed data augmentation methods such as affine transformation, perspective transformation, and rotation to create additional images.

The YOLO model has gained considerable attention due to its remarkable combination of accuracy and speed. Regression-based object detection models commonly used are Single Shot Multi-box Detector (SSD) [23], and YOLO [24]. YOLO is a basic neural network that can simultaneously predict bounding box coordinates and related class probabilities. Also, YOLO frame detection is seen as a regression problem because it finds targets from start to finish without the need for a complicated pipeline [24], making it very efficient. Moreover, YOLO outperforms other real-time systems regarding mean average precision (mAP) [25]. Goyal et al. proposed a model based on the YOLOv5 object detection system to sort fruit for fruit detection and quality detection [26]. For fruit detection, the model's mAP was 92.80% in the first stage and 95.60% and 93.10% for apples and bananas, respectively, in the second stage. For pear counters, Parico and Ahamed employed depth sorting and the YOLOv4 model to recognize and count pear fruit in real time [11]. YOLOv8, the most recent iteration in the YOLO series, not only retains its predecessors' strengths but surpasses them, thereby emerging as a powerful instrument for professionals in plant science.

Besides, no existing methods are designed to detect disease in this melon, representing a research gap in using DL with UAV images for melon diseases. Although DL methods and UAV imagery have been utilized in research to detect diseases in other plants, melon diseases have not received as much attention as they should. The realised gap highlights the lack of thorough investigation into the potential advantages of using UAV images for disease detection in melon crops. This highlights the need for targeted research in this specific area. Utilising deep learning to identify plant diseases may overcome the drawbacks of manually selecting disease spot characteristics. This approach enhances the objectivity of plant disease feature extraction and accelerates research efficiency and technological transition.

III. Proposed Approach

This study used a neural network model and an image processing technique to develop a method for identifying melon leaf diseases. Fig. 1The proposed approach. shows the proposed approach. The details of the proposed method will be discussed in the next section.

A. Data Acquisition

A dataset of melon leaf images was gathered from KMK Agro Global Sdn. Bhd., Banting, Selangor, with the leaves seen in their natural environment under a controlled greenhouse. Moreover, the dataset has been extracted specifically for analysing colour. The flowchart in Fig. 2The flowchart of the system for disease detection using UAV images. describes a systematic process for combining UAV-captured imagery and the DL model YOLOv8 to detect diseases in melon leaves. First, information is gathered using a UAV to take recordings of the melon greenhouse. Pre-processing operations are performed on the collected data, such as consistent image expansion, image removal, and extracting video recordings into their component frames for analysis. The images are then labelled by highlighting spots that indicate illnesses on the rock melon leaves and annotating locations of interest with bounding boxes. The labelled dataset becomes the foundation for training the YOLOv8 model. During this phase, the model learns to recognise and classify different diseases affecting the leaves. After training, the model is rigorously tested using a different set of images. This evaluation step uses performance metrics like accuracy, precision, and recall to see how well the model can reliably find and classify illnesses in rock melon leaves.

The melon dataset was collected using a high-resolution UAV, DJI Mavic Air 2s. Fig. 3 illustrates the UAV, DJI Mavic

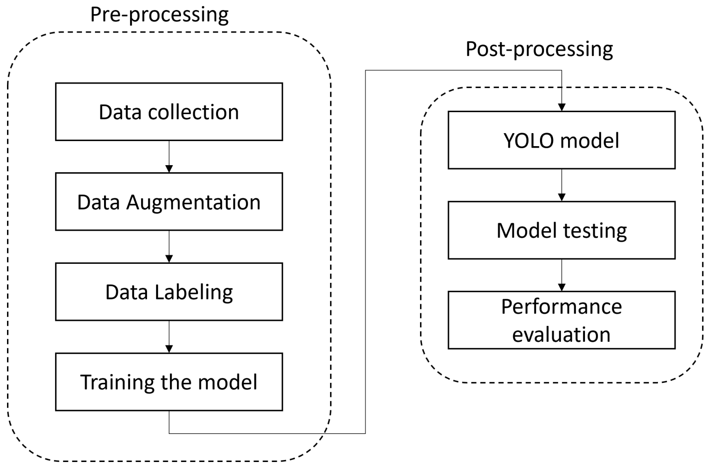

Fig. 1. The proposed approach.

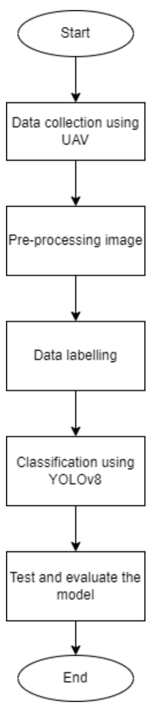

Fig. 2. The flowchart of the system for disease detection using UAV images.

Fig. 3. DJI Mavic Air 2s.

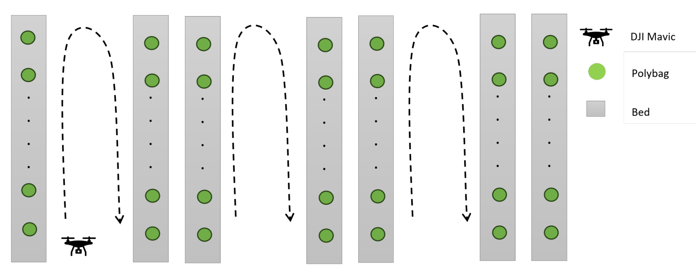

Fig. 4. The layout and drone flying direction in the KMK Agro Global Sdn. Bhd. greenhouse for data collection.

Air 2s used during data collection. The UAV specifications are shown in Table IDrone Specifications. When engaging in the photographic documentation of melon leaves, it becomes imperative to factor in technical intricacies. This involves maintaining a precise distance centred on the leaf object, within 15 cm to 20 cm. Ensuring that the leaf object remains well-contained within the camera frame is crucial. From the aerial perspective, the drone's movement will be orchestrated upward and downward along the plant, meticulously scrutinising for any signs of disease. The height of the plant varied from 1.5 m to 2.0 m. The drone captured images of healthy plants and plants with diseases. The images captured must be within 20 cm of the plant so that the leaves are visible in the drone's field of view (FOV).

Fig. 4 illustrates the greenhouse layout and the direction in which the drone is flying. The recording is in 4K and at normal speed to ensure the high quality of the images. The UAV flies facing the plant and moves along the row. Throughout the data collection, a UAV captured data in 4K resolution during a 30-minute recording session. The video will be broken down into frames to extract images of the melon plant at five-second intervals. Fig. 5 depicts some of the images captured by UAV.

B. Data Augmentation

After data collection, frames were extracted from the video every five seconds to obtain appropriate images for training. The dataset collected from the farm for melon plant disease exhibits an imbalance, which may compromise the

TABLE I. DRONE SPECIFICATIONS

No	Feature	Specification
1.	Drone	DJI Mavic Air 2s
2.	Video Resolution	4K: 3840 x 2160 at 24/25/30/48/50/60fps
3.	Max Flight Time	Up to 34 Minutes
4.	Camera Sensor	1/2-inch CMOS, 48 MP

Fig. 5. Images of melon plants collected from UAVs before dataset training.

accuracy of the YOLO model. Data augmentation enhances the model's performance by generating diverse variations of the training data. This reduces the problem of overfitting and enhances the model's capacity to form generalisations. In this study, ImageDataGenerator by Keras library is used for data augmentation. Using the ImageDataGenerator class in Keras makes it easy to set up and apply random transformations to image data, such as rotations, shifts, flips, and normalisation operations. These changes can be made without interrupting the training pipeline, which makes the model more flexible and good at what it does.

C. Data Annotation

After the data augmentation, the preprocessing stage aimed to identify plants with diseases for the training process. Once all the images were selected, the labelling process began. When labelling images in computer vision, bounding boxes annotate objects or regions of interest by enclosing them with rectangles or other shapes. Neural network models find it easier to locate, localise, and recognise items when using these bounding boxes, which accurately show the location and bounds of certain objects. Labelling is challenging as it involves addressing imbalances in disease images, which could impact training accuracy. Balancing diseased plant images with normal ones ensures the YOLO model functions effectively. Fig. 6Data labelling process: Annotated markings highlighting disease-affected areas on melon leaf. shows the labelling process of the melon leaf.

Fig. 6. Data labelling process: Annotated markings highlighting disease-affected areas on melon leaf.

For this melon plant, five classes were utilized in the labelling process. These classes include normal, unknown, mosaic, leafminer, and aphid. All these types of diseases commonly affect melon plants. Fig. 7(a) Aphid (b) Leafminer (c) Mosaic (d) Unknown. displays the diseases that typically affect melon plants. For a normal melon plant, the leaves are green and devoid of white or yellow spots.

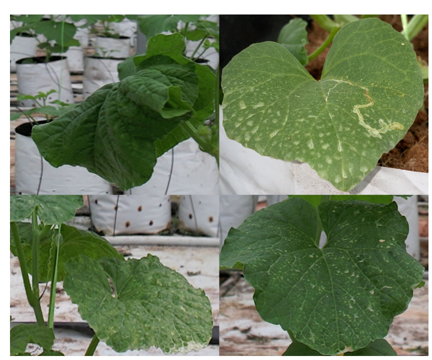

Fig. 7. (a) Aphid (b) Leafminer (c) Mosaic (d) Unknown.

D. Training the Dataset

The dataset has been divided into three distinct sections: training, testing, and evaluation, each accounting for 80%,

TABLE II. Parameters before Dataset Training

Training Images	1200
Test Images	150
Size Images	640x640
Epoch	100
Class	5 classes
GPU	NVIDIA GPU

10%, and 10%, respectively. Before the training phase, the images undergo augmentation techniques to increase their quantity. This involves resizing them uniformly to 640x640 and introducing rotations within the range of +15° and -15°. The training dataset comprises 1200 images, while 150 images have been allocated for testing and evaluation. This process sets the stage for the model to excel in identifying elusive diseases nestled within melon leaves.

1) YOLOv8 Model: YOLOv8 is the latest cutting-edge model within the YOLO series, suitable for object detection, image classification, and instance segmentation tasks. The influential and industry-shaping YOLOv5 model's creators, Ultralytics, are also responsible for creating the YOLOv8, a significant advancement in this field. Consider utilizing YOLOv8 for your upcoming computer vision endeavour for several compelling reasons. Firstly, its accuracy, assessed via common objects in context (COCO) and Roboflow 100 metrics, stands notably high. Secondly, YOLOv8 boasts a range of developer-friendly features, including an intuitive CLI and a well-structured Python package, enhancing usability. A robust community within the YOLO framework, particularly around the YOLOv8 version, supports the model. This means that people who work in computer vision can get much help and advice. Notably, YOLOv8 demonstrates robust performance on COCO benchmarks, exemplified by the YOLOv8m model achieving a 50.2% mAP. Table IIParameters before Dataset Training displays the comprehensive set of parameters employed specifically for training the YOLOv8 model.

IV. Result and Discussion

After the training process, the model is tested and evaluated. Performance metrics considered in this study are mean average precision (mAP), precision, and recall. The results are shown in Table IIIPerformance Evaluation for Plant Disease. From Table IIIPerformance Evaluation for Plant Disease, YOLOv8 outperforms YOLOv5. The dataset used during the training is the same. The superiority of YOLOv8 over YOLOv5 is evident through substantial enhancements. YOLOv8 exhibits an mAP of 83.2%, precision at 84.3%, and a recall of 73%. YOLOv8 performs better than YOLOv5 because of several significant improvements and optimizations. These enhancements could include improved network architectures, feature extraction strategies, sophisticated training approaches, or hyperparameter adjustments. It is possible that YOLOv8's more complex or effective backbone architecture allowed it to extract more significant features from the data.

Furthermore, YOLOv8 experienced extensive training procedures using bigger and more varied datasets, which improved its capacity to generalize and precisely identify objects and resulted in greater precision and recall scores. Compared to YOLOv5, YOLOv8 performs better overall because of these enhancements combined. Once the model is ready, it undergoes rigorous testing to evaluate its performance and accuracy. Fig. 8Results of using YOLOv8 on test images to spot diseases in melons. depicts the output of the detection process, showcasing the model's performance. The evaluation of the system for categorization included metrics such as mAP, precision, and recall to measure its efficacy. MAP is a metric used to evaluate the performance of object detection models. It measures the average precision of an algorithm across multiple classes or object categories. It considers the precision and recall of the model's predictions, offering a comprehensive assessment of how accurately and completely the model detects objects in an image across different categories.

After the training, other parameters can be employed to evaluate the effectiveness of YOLOv8 detection algorithms. Once the dataset training is over, there is a difference in the accuracy of class identification. In particular, the classes related to mosaic illness and the unknown condition in this investigation showed noticeably lower accuracy scores of are 75% and 76%, respectively, as shown in Fig. 9The outcomes observed for each class after the training phase.. This decreased accuracy is because several diseases have remarkably similar traits, making it difficult for the model to discriminate between them. These particular diseases are difficult to classify accurately due to their intricate visual traits and similarities, which is why these classes' accuracy levels are lower. The area under the precision-recall curve at different detection thresholds is called AP. The mAP shows how accurate the system is for each of the n object classes.

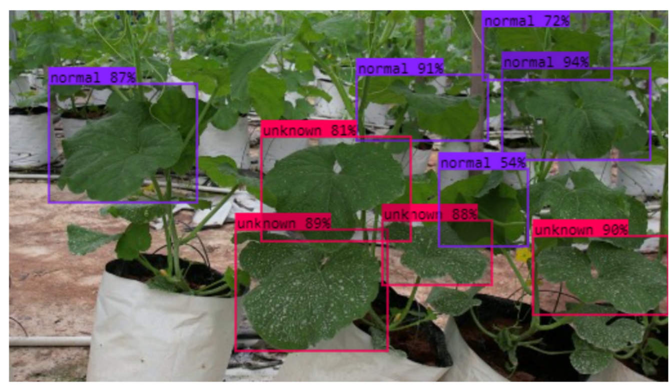

Fig. 8. Results of using YOLOv8 on test images to spot diseases in melons.

Fig. 9. The outcomes observed for each class after the training phase.

The mAP% can be calculated using the equation [27]

TABLE III. PERFORMANCE EVALUATION FOR PLANT DISEASE

Model	Number of Images	mAP	Precision	Recall
YOLOv5	1200	72.7%	83.3%	65.7%
YOLOv8	1200	83.2%	84.3%	73%

$$\text{mAP} = \frac{\sum_i^n AP_i}{n}. \tag{1}$$

$$\text{AP} = \int_0^1 x\, dy \tag{2}$$

Precision and recall can be measured using true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) indicators. The equation to calculate precision x, and recall y are given by:

$$x = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{3}$$

and

$$y = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{4}$$

where x is precision and y is recall.

Other than YOLOv8, this study compares its performance with YOLOv5. The YOLOv8 proposed method leaves the use of predefined anchor boxes and instead employs an anchor-free strategy to achieve enhanced item localization accuracy, particularly for smaller objects. The Path Aggregation Network (PANet) integrates several network-level features, enhancing detection accuracy using multi-scale contextual information. Fig. 10YOLOv5 training development graph, highlighting recall, precision, and accuracy metrics during training. and Fig. 11YOLOv8 training development graph, highlighting recall, precision, and accuracy metrics during training. show the training graph for YOLO. The training process involves iterating through the dataset 100 times, each iteration known as an epoch. During these 100 epochs, the model learns and refines its understanding of the data, gradually improving its performance and accuracy through repeated exposure to the information provided in the dataset.

Moreover, the convolutional block attention module (CBAM) has been enhanced to improve the feature extraction process. The dynamic adjustment of feature importance achieves this by effectively suppressing noise and improving the clarity of distinctions. The efficient backbone network of YOLOv8 successfully preserves accuracy by reducing parameters and enhancing inference performance. The proposed approach effectively separates the responsibilities of object prediction and categorization, resulting in improved precision. The system attains accelerated convergence and enhanced stability by employing network pruning, varied data augmentation techniques, mixed precision training, and an enhanced training framework. The unified architecture of YOLOv8 enables its compatibility with many vision tasks, establishing it as a robust and versatile tool for applications involving object identification and image recognition.

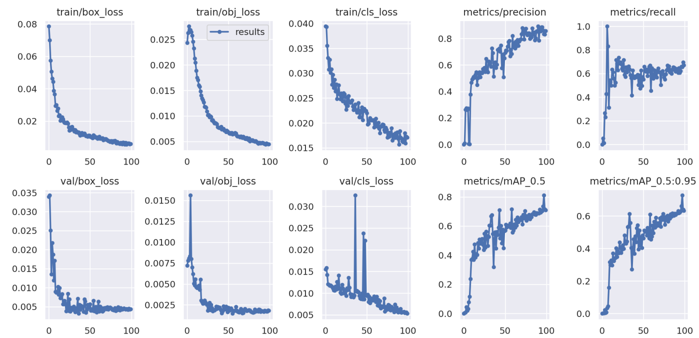

Fig. 10. YOLOv5 training development graph, highlighting recall, precision, and accuracy metrics during training.

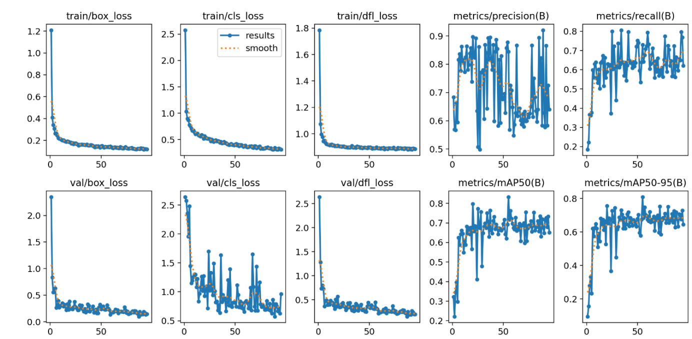

Fig. 11. YOLOv8 training development graph, highlighting recall, precision, and accuracy metrics during training.

V. LIMITATIONS OF THIS STUDY

The study highlights certain limitations that should be recognised. Firstly, a limited annotated dataset was utilised for training the YOLOv8 model. Using a restricted dataset raises concerns regarding the possibility of overfitting, wherein the model may exhibit good performance on the training data but encounter difficulties in efficiently applying its knowledge to new, real-world farming situations. Furthermore, in this study, the influence of environmental factors was considered by conducting data collection in a controlled atmosphere. Climatic conditions might impact the quality of UAV footage and the precision of the YOLOv8 model's forecasts, underscoring the necessity to tackle these obstacles for real-world implementations. Furthermore, it is necessary to carefully examine the possible impact of environmental variables, such as changes in lighting, on the performance of the UAV and YOLOv8 model.

VI. CONCLUSION

In summary, this study has used UAV footage to highlight the strong performance of YOLOv8 in detecting diseases in rock melon leaves. The deep learning model exhibits notable levels of accuracy and efficiency, highlighting its potential as a useful asset in precision agriculture. While acknowledging problems like limited datasets and the effect of changes in the environment on the performance of models, the study has highlighted the strong features of YOLOv8 as a major step forward in finding illnesses in agricultural settings. Overall, YOLOv8 emerges as a pivotal technological advancement, promising significant enhancements and advancements in agricultural practices.

This study offers numerous tangible benefits for the agricultural industry. Combining UAV data with a neural network-based classification system greatly improves the identification of melon leaf illnesses, allowing farmers to detect problems at their initial stages. The efficiency of this technology is especially advantageous for monitoring extensive agricultural regions, resulting in time and labour savings compared to conventional manual techniques. The neural network enables rapid identification, timely intervention, and effective disease management. The technology's capacity to scale allows it to be easily adjusted for large-scale farming operations, and the data-driven decision-making process provides farmers with vital knowledge to manage crops effectively. The research has the potential to fundamentally transform disease control, resulting in higher crop productivity, enhanced quality, and the adoption of more sustainable farming methods in smart agriculture.

Further studies may considerably improve the performance of the neural network-based classification system using other types of DL models. Actively focusing on diversity in the training dataset is one important approach. This study can incorporate samples from various geographic regions, meteorological conditions, and growing seasons to create a more comprehensive dataset. This diversity would strengthen the model's robustness and generalizability across many agricultural contexts, as well as its capacity to adjust to various environmental conditions. Then, further research could examine how UAV data can be integrated with other cutting-edge sensing technologies. For example, drones have been added to monitoring systems. This multidisciplinary strategy might result in a more comprehensive and precise disease detection solution for smart agriculture. Combining different sensing technologies could lead to a more comprehensive understanding of crop health and, ultimately, a more advanced and efficient precision agriculture system.

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