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Deep Learning-based Leaf Segmentation and Disease Classification

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***Abstract*— Timely and precise diagnosis of tomato foliar diseases is crucial to minimize crop losses and enhance productivity in the farming sector. Yet deep learning models that are trained on controlled data sets are not as effective in field settings because they are unable to tackle background clutter, lighting changes and multiple objects in a field scene. To overcome these problems, the present study suggests a deep learning-based system which segments leaf regions prior to disease diagnosis. The images of tomato leaves from PlantVillage dataset are preprocessed using YOLOv8 to detect the leaf and Segment Anything Model (SAM) to segment the leaves and remove noises. The segmented leaf images are then used to train an EfficientNetV2 classifier for nine tomato disease classes. To evaluate real-world applicability, the trained model is tested on the PlantDoc dataset. Since complex backgrounds negatively affect classification performance, U2-Net is employed to segment leaf regions from PlantDoc images prior to classification. Experimental results show a validation ac curacy of 95% on the PlantVillage dataset and a real-world accuracy of 55.76% on the PlantDoc dataset after segmentation, compared with approximately 30% accuracy without segmentation. The results demonstrate that leaf segmentation significantly improves disease classification performance in challenging field conditions**

***Index Terms*— Tomato leaf disease classification, Leaf segmentation, YOLOv8, Segment Anything Model (SAM), Efficient NetV2term.**

I. INTRODUCTION

Tomato is one of the most important vegetable crops worldwide; however, it is highly susceptible to several leaf diseases that can significantly reduce crop yield and quality. Early and accurate disease identification is therefore essential for effective crop management and sustainable agriculture [1, 2]. Traditional disease diagno sis relies on manual inspection by farmers or experts, which is time-consuming, sub jective, and difficult to scale. Recent advances in computer vision and deep learning have enabled automated plant disease detection systems with improved efficiency and accuracy [3]. CNNs have been performing well on the controlled datasets like PlantVillage. But, models trained with these datasets are poor on real field images because of complex background, variable illumination, occlusion and noise [4]. Field data sets like Plant Doc contain more realistic field settings with greater difficulty for disease classification [5]. Recent research has been conducted on segmentation of leaves prior to classification, in order to enhance robustness. Segmentation en ables models help to ignore irrelevant background information and focus only on disease characteristics, such as spots, discoloration, and texture variations [6].

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This paper applies the YOLO leaf detection model to segment out leaf areas and employs the Segment Anything Model (SAM) to segment leaf areas and then trains an EfficientNetV2 disease model. The proposed model is trained and tested on the PlantVillage and PlantDoc datasets, respectively, to evaluate the real-world performance of the model. In order to achieve further cross dataset generalization, U2Net based segmentation is used prior to classification on PlantDoc images. The study examines the effect of leaf isolation on disease recognition performance as well as its suitability for practical applications in agriculture [8, 9].

II. Related Work

A. Plant Disease Detection and Datasets

From the traditional image processing method to the approach based on deep learning, plant disease detection has developed. Previous research used features like color, shape, and texture to classify images which were created by hand. Ferentinos presented the effectiveness of machine learning and deep learning techniques for crop disease detection and Zhao et al. enhanced tomato disease classification using an attention-based convolutional neural network [1, 2]. Models trained under controlled conditions, however, fail to perform well in the field because of background clutter, change of illumination and variations in leaf [10].
The availability of public datasets has greatly facilitated research in this area. The PlantVil lage dataset contains images of diseases taken in controlled laboratory conditions and is extensively used for deep learning model training [11]. The PlantDoc dataset, on the other hand, comprises of pictures taken in the field, which feature intricate backgrounds, diverse lighting and occlusions making the task of disease classification much more challenging [12].

B. Detection, Segmentation and Classification Approaches

In recent years, disease classification has been boosted with the use of object detection and segmentation. Currently, many models based on YOLO have been developed to achieve good localization accuracy for leaves in complex scenes [13, 14, 15]. To achieve leaf segmentation, U2-Net has achieved good results in salient object extraction; the Segment Anything Model (SAM) can generate segmentation masks with high quality, and only needs a few samples to be trained for the specific task [16, 6]. Segmentation eliminates parts of the image that are irrelevant and allows the classifiers to concentrate on the disease symptoms. EfficientNetV2 has proved to be a good performer in image classification problems thanks to its efficient feature extraction and training process [17] among the deep learning architectures. Many studies performed the classification of the image directly, without properly identifying the leaf region, although great advances have been made. Recent research suggests that combining detection, segmentation, and classification into a unified pipeline can improve robustness and generalization on real-world datasets [8]. Motivated by these findings, this work proposes a multi-stage framework consisting of YOLOv8 based leaf detection, SAM-based segmentation, and EfficientNetV2-based disease classification

III. Proposed System

The proposed framework combines leaf detection, segmentation, and disease classification to improve tomato leaf disease recognition in real-world conditions. The overall workflow is shown in pipeline diagram.

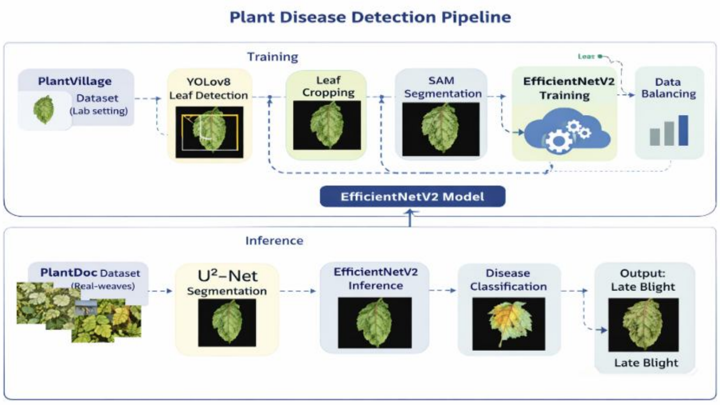

Fig. 1 Overall workflow of the proposed method

A. Dataset Description

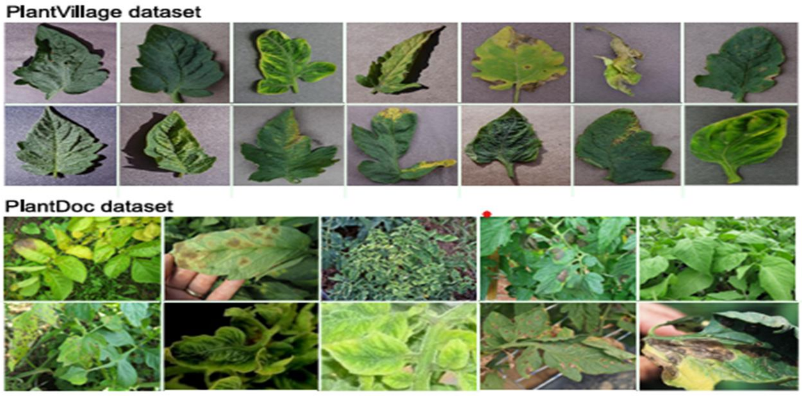

Fig. 2 Plantvillage and PlantDoc dataset images

Two publicly available datasets were used in this study.
PlantVillage Dataset: PlantVillage contains tomato leaf images captured under controlled laboratory conditions with clean backgrounds. Nine tomato disease cate gories were selected for training and validation using an 80:20 train-test split. Dataset Link: https://www.kaggle.com/datasets/emmarex/plantdisease
PlantDoc Dataset: PlantDoc contains field images with varying illumination, background clutter, and occlusions. The dataset was used to evaluate the generaliza tion capability of the trained model. Dataset Link: https://github.com/pratikkayal/PlantDoc-Dataset

B. Leaf Detection and Segmentation

YOLOv8 was used to detect and crop leaf regions from PlantVillage images. The cropped images were then segmented using the Segment Anything Model (SAM) to Deep Learning-Based Leaf Segmentation and Disease Classification 5 remove background information. For PlantDoc images, U2-Net segmentation was applied before classification to isolate leaf regions from complex field backgrounds.

TABLE I

Class	Precision	Recall	F1-score	Support
Tomato Bacterial Spot	0.57	0.15	0.24	78
Tomato Early Blight	0.24	0.85	0.37	99
Tomato Late Blight	0.52	0.56	0.54	87
Tomato Leaf Mold	0.56	0.31	0.40	70
Tomato Septoria Leaf Spot	0.66	0.32	0.43	96
Tomato Spider Mites (Two-Spotted)	0.80	0.80	0.80	5
Tomato Yellow Leaf Curl Virus	0.88	0.39	0.54	172
Tomato Tomato Mosaic Virus	0.74	0.40	0.52	35
Tomato Healthy	0.93	0.50	0.65	28
Accuracy	0.56			
Macro Avg	0.66	0.48	0.50	670
Weighted Avg	0.63	0.44	0.46	670

C. Disease Classification

EfficientNetV2 was employed as the classification model due to its efficient feature extraction capability. The model was tested and trained on segmented PlantVillage images and tested on PlantDoc images to see the model's real-time performance.

D. Performance Evaluation Metrics

The model was evaluated using Accuracy, Precision, Recall, and F1-score.

$$\text{Acuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1} = 2 * \frac{precision*recall}{precision+recall}$$

Before and after segmentation model performance was compared using these metrics:.

IV. Results and Evaluation

The proposed framework has been trained on PlantVillage dataset and tested on the actual PlantDoc dataset. The aim was to study the effectiveness of leaf detection and segmentation for the improvement of disease classification in field conditions.

A. Leaf Detection and Segmentation Results

Prior to classification, the regions containing leaves were detected and cropped using the YOLOv8 model. This pre processing step minimised noise at background level and retained the disease related features for further analysis. The quality of segmentation was evaluated using manually annotated samples. The Segment Anything Model (SAM) achieved an Intersection over Union (IoU) score of 0.95 and a Dice score of 0.96, indicating accurate separation of leaf regions from the background.

$$\text{IoU} = \frac{|P \cap G|}{|P \cup G|}$$

$$\text{Dice} = \frac{2|P \cap G|}{|P| + |G|}$$

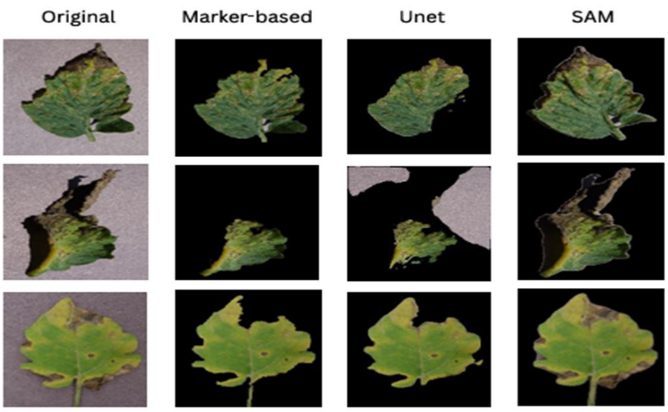

Fig. 3. Comparison of segmentation outputs.

B. Disease Classification Performance

EfficientNetV2 was trained using segmented PlantVillage images belonging to nine tomato disease categories. The model achieved a validation accuracy of 95.16% on the PlantVillage dataset. When directly tested on PlantDoc images, the classification accuracy decreased to 31.76% because of background clutter, varying illumination, and complex field conditions. To address this issue, U2-Net segmentation was applied before classifi cation to isolate leaf regions and remove irrelevant background information. After segmentation, the classification accuracy improved to 55.76%, demonstrat ing the importance of leaf isolation in improving real-world disease recognition.

TABLE II: Laboratory (PlantVillage) and Real-World (PlantDoc) Classification Performance

Model	Dataset	Accuracy (%)	Drop
EfficientNetV2	PlantVillage	95.16	-
EfficientNetV2	PlantDoc	31.76	63.40
Proposed Pipeline	PlantVillage	95.16	-
Proposed Pipeline	PlantDoc	55.76	39.4

C. Comparison with Existing Methods

Table 1 compares the proposed framework with existing studies evaluated on real world datasets. Previous research has reported a significant performance drop when models trained on controlled datasets are tested on field images. The proposed pipeline achieved 55.82% accuracy on PlantDoc images after seg mentation, compared with 31.76% accuracy without segmentation. This improve ment confirms that combining leaf detection, segmentation, and classification im proves cross-dataset generalization and reduces the impact of complex backgrounds. Deep Learning-Based Leaf Segmentation and Disease Classification 7 The results indicate that segmentation-based preprocessing is an effective strat egy for enhancing tomato disease classification performance in practical agricultural environments

TABLE II. COMPARISON OF MODEL PERFORMANCE WITH EXISTING STUDIES ON FIELD (REAL-WORLD) DATASETS

Study	Dataset	Accuracy (%)	Notes
[9]	PlantDoc	66-88	Large performance drop under real world conditions.
[26]	Field Dataset	27.81	Evaluated on a narrow field test set.
[24]	Synthetic (corruption shifted)	15.40	Evaluation performed on synthetic corrupted images rather than real-world data.
[25]	PlantDoc subset	26.00	Evaluation conducted on only 24 test samples.
Proposed (Ours)	PlantDoc	55.76	U2-Net based leaf segmentation applied before EfficientNetV2 classification to improve robustness on complex field images.

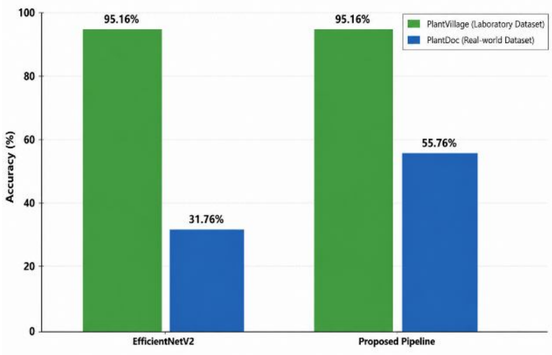

Fig. 3 Comparison of classification accuracy on PlantVillage and PlantDoc datasets

V. DISCUSSION

The experimental results show that the proposed deep learning-based pipeline for leaf segmentation and disease classification has the potential of accurately detecting tomato leaf diseases and enhances robustness in real-world agricultural settings. After leaf segmentation, the proposed framework validated with a PlantVillage dataset and obtained an accuracy of 95.16% while it obtained an accuracy of 55.76% on the PlantDoc dataset. This finding suggests that the system is capable of extracting visual information associated with specific diseases from controlled laboratory images while at the same time achieving reasonable performance on challenging images from the field. One of the important findings from the experiments is the effect of the segmentation of leaves on the classification accuracy. The accuracy was only 31.76% when we used the EfficientNetV2 Classifier directly on PlantDoc images due to background noise, lighting differences, overlapping leaves and noise in the environment. The leaf segmentation accuracy was improved to 55.76% by using U2-net based leaf segmentation, which is a significant improvement under practical conditions. This reveals that even though there is irrelevant background information, counting the leaf area before classification helps the model identify disease rather than background features. YOLOv8, SAM, and EfficientNetV2 are crucial components of the proposed pipeline. YOLOv8 can accurately locate the leaf region in the image, and SAM can accurately segment the background part of the PlantVillage images during training, excluding unnecessary background content. EfficientNetV2 is efficient and accurate in extracting features and classifying them at a relatively low computational cost. All these elements form a solid multi-layered system for detecting tomato leaf disease. The proposed method performs competitive in comparison to the previous studies on real world data sets. There has been considerable reported degradation in performance when models developed from a controlled set of images are applied to images collected in the field. The proposed system improves cross-dataset generalization by employing leaf segmentation prior to classification, and reduces the adverse affects of complex background. The outcome validates the importance of segmentation based pre-processing for the gap between lab and field environment. The proposed approach also finds practical application in applications for smart agriculture. Early disease detection can be achieved using automated disease identification which can help farmers to minimize crop losses and act promptly. The methodology can be incorporated into agricultural monitoring systems to support the assessment of crop health in real-time, in either mobile or cloud-based versions.Although it has shown good performance, it still has a number of drawbacks. The model was primarily trained by the images of PlantVillage, which might not be diverse enough to reflect the variability of field conditions under which plants grow in agricultural settings. In addition, only nine classes of tomato diseases were included in this study. Further testing of the method on larger and more representative datasets from other geographical areas and environmental conditions is needed to confirm the robustness of the approach.Future research will involve improving generalisation across datasets using sophisticated data augmentation, domain adaptation, and larger real world training sets. Further enhancing the system's practical application in the field of precision agriculture with the integration of EAI techniques and the deployment onto mobile devices, for real-time disease diagnosis, can further increase the practicality of the proposed system.

VI. CONCLUSIONS

This work provided a model that uses learning to classify diseases in tomato leaves. The model does this in steps. It first finds the leaves then it separates them from the rest of the picture. Finally it figures out what disease the leaf has. This is a -stage process, for classifying tomato leaf diseases using deep learning. The model uses leaf detection, segmentation and classification techniques to do this. Tomato leaf disease classification is the goal of this work. The proposed method integrated YOLOv8 for leaf detection, SAM and U2 Net for leaf segmentation, and EfficientNetV2 to determine diseases. The goal of the study was to enhance the robustness of the plant disease classification models when used in real agricultural environment. The outcomes of the experiments conducted on the PlantVil lage dataset demonstrated that EfficientNetV2 can achieve high accuracy in controlled settings. A major performance loss was found when the model was tested on real-world PlantDoc images, as they were taken against complex backgrounds, with different light conditions, and with background noise. When using segmentation based preprocessing to separate the leaf area from the image before classification, the accuracy of PlantDoc increased significantly to 55.76% from 31.76%. Results show that background removal and correct leaf isolation are important to boost the performance of cross dataset generalization and real-world disease detection. The proposed pipeline was able to successfully eliminate the in fluence of irrelevant background information, which allowed the classifier to focus more effectively to the visual patterns related to the disease. Moving forward, more realistic datasets and more sophis ticated domain adaptation methods can be used to further enhance the generalization ability. There are many other possibilities for improvement, such as lightweight models for mobile use and real-time disease detection systems for use in practical agriculture.

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