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SAM-IE: SAM-enabled image enhancement for segmentation of infected cucumber leaves

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Abstract

The synthesis of compounds in plants with the aid of radiant energy is essential for plant growth and crop yield. However, the leaves through which this synthesis of compounds occurs, when infected, cannot perform this function optimally and thus negatively impact plant growth and crop yield. Symptoms of cucumber disease are observed on the cucumber leaves. The main objective of this paper is to facilitate automated detection systems for the segmentation of infected cucumber leaves from healthy leaves by proposing a novel SAM-IE (Segment Anything Model-Image Enhancement) model using ResNet50 and CNNs. The SAM-IE model is a hybrid of an existing SAM model and a novel IE method. All the data collection and processing steps were explored. Moreover, experiments were performed, and competitive results were obtained with detailed analysis as follows: ResNet50 with SAM-IE obtained 0.885 accuracy, 0.894 F1-Score, and a processing time of 112 (ms). ResNet50 without SAM-IE obtained 0.883 accuracy, 0.845 F1-Score, and a processing time of 121 (ms). CNNs with SAM-IE obtained 0.872 accuracy, 0.831 F1-Score, and a processing time of 115 (ms). CNNs without SAM-IE obtained 0.772 accuracy, 0.821 F1-Score, and a processing time of 123 (ms). To further validate these results, we compared them with the existing results from K-means clustering, Fuzzy C-means clustering, Expectation Maximization (EM), and Superpixels + EM. The practical implications of the findings in this paper are essential for the horticulture industry. Horticulture farming systems that incorporate deep learning not only enhance plant growth but also ensure high crop yield via automated management and monitoring, reducing crop vulnerability to disease and increasing economic gain.

Keywords: CNNs, Cucumber leaf disease, Image enhancement, ResNet50, SAM, Segmentation.

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1. Introduction

Among the factors that can affect cucumber production are rising costs of production and damage caused by cucumber diseases [1]. Accurate diagnosis of these factors for cucumber crop protection is a significant challenge for farmers. Cucumber is low in calories and high in fiber, making it a great combination for healthy eating and digestion [2]. Due to various infectious plant diseases, cucumber yield has significantly decreased both in quality and quantity [3]. Pathogens such as fungi and bacteria are disease-producing agents that increasingly militate against cucumber plants and severely affect their production [4]. The production of cucumbers is thwarted not only by pests and diseases but also by a decline in quality, which hinders the increase in production [5].

Most countries' households and their economies depend on agriculture, but this is often curtailed due to the negative impact of diseases on crop plants. The detection of diseases by farmers has been done through manual methods, which are labor-intensive, time-consuming, and inaccurate. Moreover, manually detected diseases often lead to the destruction of healthy cucumber plants due to the use of incorrect chemicals. To detect diseases in cucumber crops, there is a need to employ a low-cost method that produces good results. However, existing foundational methods have their weaknesses and limitations, among which are high computation costs and low capabilities for disease detection that negatively influence the increase in system costs [6-8].

Recently, computer-aided plant disease diagnosis has gained wide acceptance from the machine-learning research community [9]. When it comes to the detection of cucumber plant diseases, computer-aided systems have demonstrated great potential for their identification and classification [10]. Images of cucumber plants comprise both foreground and background objects from which key features are extracted for effective disease detection. The handcrafted method was one of the early computer-aided approaches designed for extracting and analyzing features from an image [11]. However, there are notable limitations with the handcrafted features, such as a lack of robustness and effectiveness. Convolutional neural networks (CNNs), among other deep learning models, have shown significant performance in feature extraction tasks, such as the extraction of features of interest from images of plants.

Features are learned and extracted automatically from images by CNNs, thus ensuring high accuracy in the detection of infected cucumber leaves [12]. The capability of CNNs to extract and learn relevant features from images makes the model promising for their application in the diagnosis of plant diseases for the overall management and monitoring of cucumber crops. Built on the foundation of CNNs, we proposed a novel SAM-IE (Segment Anything Model-Image Enhancement) model for the segmentation of infected cucumber leaves from healthy leaves in an image [13]. SAM, a foundation model, was proposed by Kirillov, et al. [14] and immediately gained wide acceptance by the scientific community; this feat was achieved due to the fusion of its three components, which are a prompt for the task, a model, and the SAM dataset.

SAM was pretrained on datasets whose features were composed of information that is spatially and semantically rich, useful for the segmentation of images [15]. Moreover, SAM has been applied to different agricultural tasks, such as automatic extraction of mask regions in livestock monitoring [16], fast-tracking the revolution of smart farming [17], identifying corn rows [18], and water body segmentation [19]. All these applications of SAM to agricultural tasks validate its application for the segmentation of infected cucumber leaves from healthy leaves in an image. In this paper, SAM's prompt-driven approach is proposed for the segmentation of infected cucumber leaves in an image. The approach in promptable segmentation involves returning a valid mask for each segmented object when provision is made for any segmentation prompt.

A prompt specifies the target object in an image for segmentation, which can include textual or spatial information useful for the identification of the object. When prompts are in moderation, SAM's generated masks and stability scores are essential resources for cucumber leaf image segmentation and classification. The SAM-IE method is distinguished from the traditional IE method primarily by one important factor, which is the traditional IE method's low level of operation. This level is below the high-level requirement needed to reconstruct and recover an original image [20]. This is one of the targets that SAM-IE aims to achieve in this study. Increasing SAM's semantic structures led to the feat that SAM-IE attained. The adaptation of SAM-IE to SAM for image enhancement is easy, thus enabling its application for the detection and segmentation of infected cucumber leaves from healthy leaves.

In this paper, in order to evaluate the SAM-IE, ResNet50 [21] and CNNs were employed. Research has revealed that the performance and efficiency of downstream models built for image segmentation can be improved by employing the prior maps produced from the integration of original images and SAM's generated images for the enhancement of network inputs [15]. This revelation motivated the concept of SAM-IE, which is achieved by applying SAM's generated masks and stability scores. The enhanced images facilitate the identification of regions of infected leaves in the original images, thus furnishing the classification models with attention maps for an enhanced classification of cucumber leaf images. The SAM-IE techniques enable the effective detection and segmentation of objects in images.

The work carried out in this paper is a step towards facilitating automated detection systems for the segmentation of infected cucumber leaves from healthy leaves by proposing a novel SAM-IE (Segment Anything Model-Image Enhancement) model using ResNet50 and CNNs. The practical implications of the findings in this paper are essential for the horticulture industry. Horticulture farming systems that incorporate deep learning not only enhance plant growth but also ensure high crop yield via automated management and monitoring, reducing crop vulnerability to disease and increasing economic gain. The contributions of this paper are:

- This study demonstrates the novelty of using the SAM model to address infected cucumber leaves.
- Hybrid of an IE model and a SAM model to facilitate automated detection systems for segmentation of infected cucumber leaves from the healthy leaves in an image.

The rest of the paper is organized as follows: Section 2 presents the materials and methods. Section 3 presents the experiments and evaluation metrics. Section 4 presents the results and discussions. Section 5 concludes the study.

2. Materials and Methods

2.1. Dataset of Infected Cucumber Leaf

The dataset of infected cucumber leaves [22] was employed to perform the experiment in this study. The dataset, comprising 1000 cucumber leaf images (RGB) with other heterogeneous background objects was augmented and divided into two datasets, 80% as a training dataset and 20% as a testing dataset for the powdery mildew disease segmentation and classification. In addition, the pre-trained backbone weights based on the SA-1B dataset [14] were also adopted to facilitate and accelerate the model training process. The SA-1B dataset comprises 11 million diverse, high-resolution, licensed, and privacy-protecting images and 1.1 billion mask annotations. Figure 1 shows the flowchart of the training and testing phases of the models using the dataset.

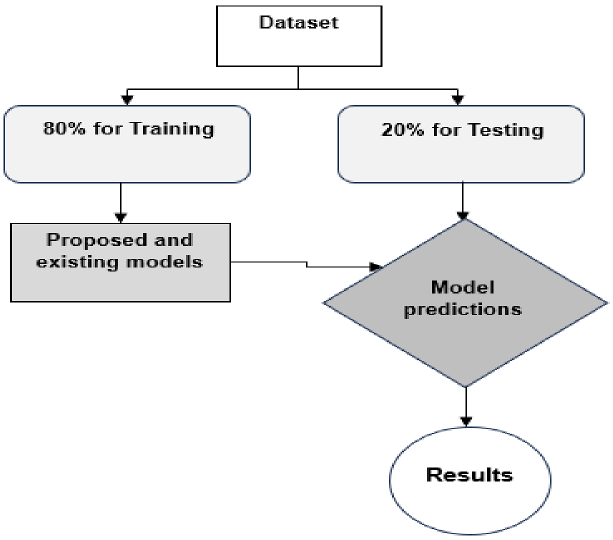

Figure 1.
Flowchart of training and testing phases of the models.

2.2. Processing Methods

Making use of techniques of image processing for the segmentation and classification of infected cucumber leaves in a complex environment is the main focus of this study. The images acquired in this study were preprocessed for further analysis.

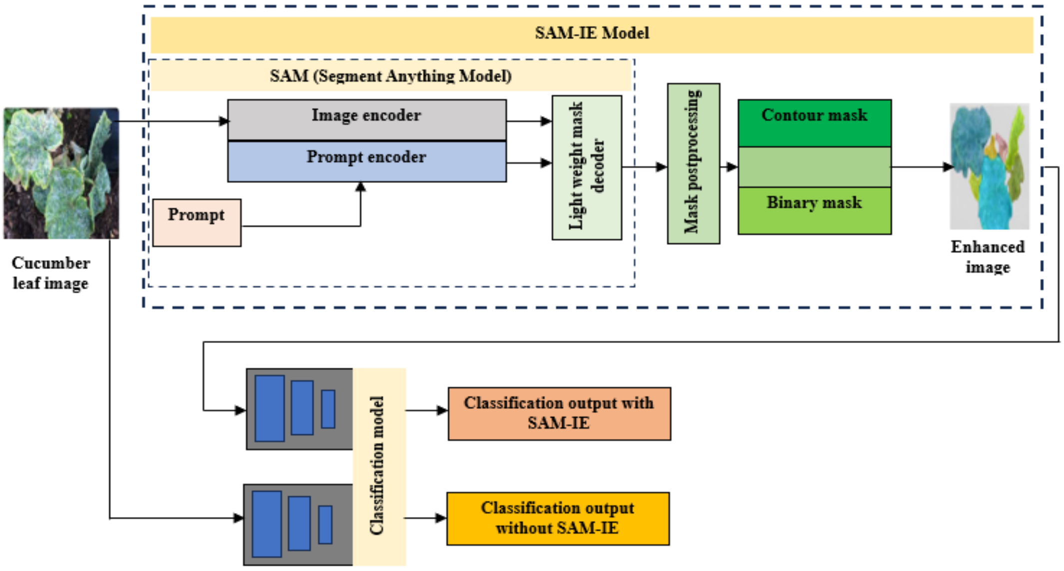

Figure 2.
Workflow of SAM-IE for segmentation of infected cucumber leaves from the healthy leaves.

The primary method of detecting cucumber leaf disease is by identifying its symptoms, such as the effects of powdery mildew in the images. ResNet50 and CNNs were employed as the classification models in this study. Specifically, the SAM-IE method is utilized for image enhancement prior to classification by the models. The application of SAM-IE is for segmenting the area of interest in order to facilitate target analysis. Upon completing the segmentation, an analysis of each segment is carried out to classify the infected cucumber leaves from the healthy leaves. Figure 2 demonstrates the workflow of the proposed approach.

3.3 Image Enhancement and Classification Models

The generation of segmentation masks for cucumber leaf images is made possible by applying the pre-trained SAM, also, by applying the SAM, the segmentation masks and stability scores can be generated for the entire regions in a cucumber leaf image without prior prompts; this is also applicable to both binary and contour masks generation, after this, a procedure is performed for the generation of enhanced images as shown in Figure 3. There are two tasks involved in the segmentation of cucumber leaf images, the task involves extracting the foreground objects and the task involves retaining the unwanted background objects. Given set $\{(c_1, d_1), (c_2, d_2), (c_3, d_3), \ldots, (c_n, d_n)\}$ as the original dataset for training, where $c_i \epsilon \mathbb{R}^{w\times h\times 3}$, $c_1 \epsilon \{0, 1\}$ denotes the classification label of the cucumber leaf image c_i. By applying SAM-IE to each cucumber leaf image in the training dataset, set $\{(c_1^{IE}, d_1), (c_2^{IE}, d_2), (c_3^{IE}, d_3), \ldots, (c_n^{IE}, d_n)\}$ is produced as a new enhanced training dataset, where $c_i^{IE} \epsilon^{\mathbb{R}w\times h\times 3}$ denotes the enhanced image c_i of cucumber leaf image. We applied ResNet50 and CNNs (M denotes CNNs) so that the training sets that were not enhanced by SAM-IE can be learned from them. M parameters optimization is as follows.

$$\sum_{i=1}^{n} loss(M(c_i), d_i) \quad (1)$$

The objective of the new learning, in essence, is to reduce the target based on M parameters:

$$\sum_{i=1}^{n} \alpha loss(M(c_i), d_i) + \theta loss(M(c_i^{IE}), d_i) \quad (2)$$

where the value of the training loss for original images and enhanced images is put under check by α and θ; When α=1 and θ=0, Equation 2 would be modified to Equation 1. However, both α and θ in this paper, have the same number 1, this is to enable assigning equal weight to the original images and the enhanced images. To construct the loss function, which is expressed in Equation 1 and Equation 2, the cross-entropy loss is used. For model testing, Equation 3 is used and this is expressed as follows:

$$q=f(M(p)) \quad (3)$$

3. Experiments and Evaluation Metrics

The experiment in this study was performed using (1) Windows 11 Home, on which the following were executed: Google Colab, GPU, OpenCV, Python 3.x, and its libraries such as NumPy, Flask, and Matplotlib. The following parameters were set for ResNet50 and CNNs: ResNet50 has a 0.01 initial learning rate and a batch size of 70. CNNs have a 0.001 initial learning rate and a batch size of 40. Performance comparison was carried out between the results obtained from using an open dataset in carrying out the classification experiment and the results obtained from using the SAM-IE enhanced dataset in carrying out the classification experiment. In this study, Precision, Average Precision (AP), and Recall were used as the metrics for evaluating the proposed model's performance. Equation 4 denotes Precision, Equation 5 denotes Recall, Equation 6 denotes AP, and Equation 7 denotes IOU, which stands for Intersection Over Union.

$$P = \frac{True\ positive}{True\ positive + False\ positive} \quad (4)$$

$$R = \frac{True\ positive}{True\ positive + False\ negative} \quad (5)$$

$$AP = \sum_{n=1}^{N} [R(n) - R(n-1)].maxP(n) \quad (6)$$

where *N* is the calculated number of PR points produced.

$$IOU = \frac{A \cap B}{A \cup B} \times 100 \quad (7)$$

4. Results and Discussions

In this study, we achieved image enhancement for the cucumber leaf image datasets by using SAM-IE. This is evident in Figure 3, which is a sample of the difference between the original images and the SAM-IE's enhanced images. The enhanced images were obtained from the processed contour and binary masks. Performance comparison was carried out between the results obtained from using the open dataset in carrying out the classification experiment and the results obtained from using the SAM-IE enhanced dataset in carrying out the classification experiment.

Figure 3.
(a) Original image of infected cucumber leaf with heterogeneous background, (b) Enhanced image of infected cucumber leaf using SAM-IE. The white powdery spots indicate symptoms of powdery mildew fungal disease.
Source: Nelson [23].

It is evident from the results obtained that SAM is efficient and has performed significantly in the segmentation of natural images, and will perform more in other applications with little enhancement for prompt-able segmentation. The performance of SAM in segmenting infected cucumber leaves from the healthy leaves is on par with the best. The results of ResNet50 and CNNs on the original dataset of infected cucumber leaf and SAM-IE enhanced dataset of infected cucumber leaf are graphically represented in Figure 4. Moreover, it is evident that SAM performance could be extended and applied to the region of the infected cucumber leaf (region of interest) in an image simply by fine-tuning the confidence level of the region segmented.

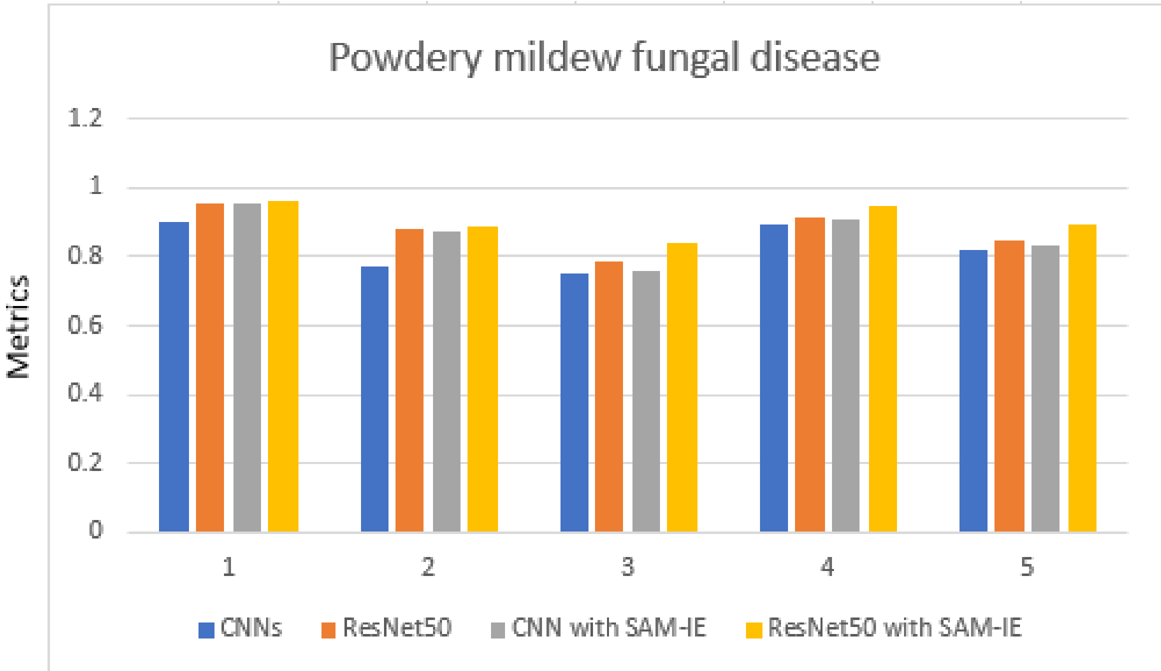

Figure 4.
The results of ResNet50 and CNNs on original dataset of infected cucumber leaf and SAM-IE enhanced dataset of infected cucumber leaf.

Figure 5 depicts the segmentation by masking individual infected cucumber leaves using the proposed SAM-IE model. The SAM-IE model for segmentation of individual infected cucumber leaves with the bounding boxes, the masks, and the class is shown in Figure 6.

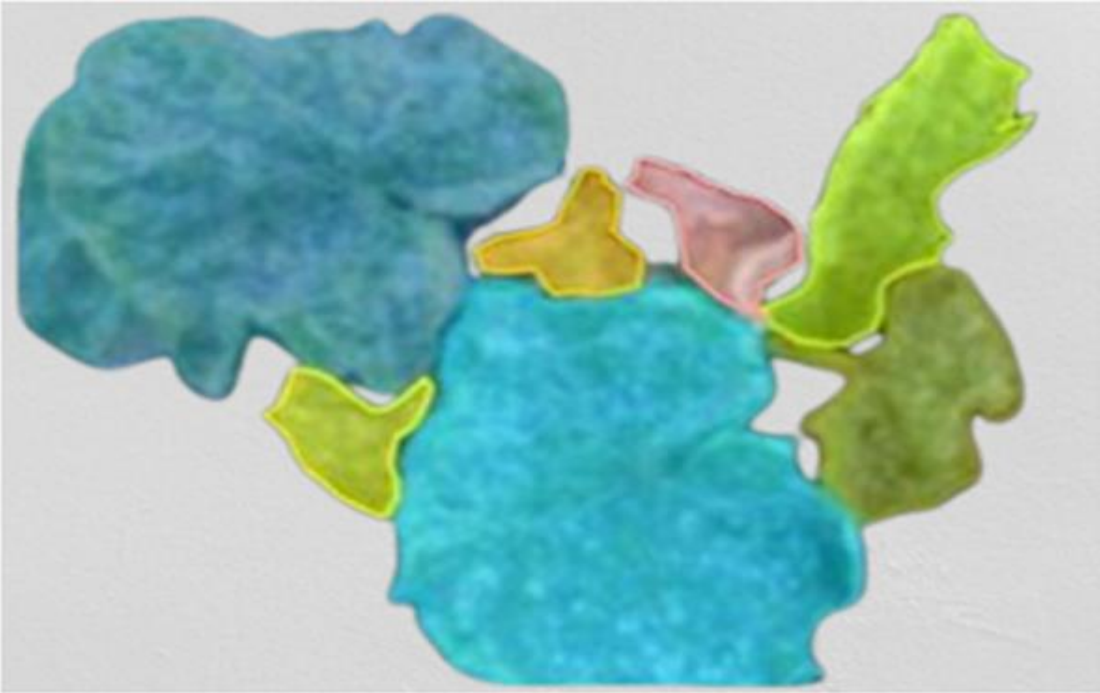

Figure 5.
Segmentation by masking individual infected cucumber leaves using the proposed SAM-IE model.

The K-means clustering method for segmenting lesions from cucumber leaf images is shown in Figure 7. The Fuzzy C-means clustering method for segmenting lesions from cucumber leaf images is shown in Figure 8. The Expectation Maximization (EM) method for segmenting lesions from cucumber leaf images is shown in Figure 9. The Superpixels + EM method for segmenting lesions from cucumber leaf images is shown in Figure 10.

Figure 6.
SAM-IE model for segmentation of individual infected cucumber leaves shows the bounding boxes, the masks, and the class.

Table 1 shows the comparison of results for the proposed models and benchmark models for the segmentation of infected cucumber leaves from healthy leaves.

As depicted in Figure 7 to Figure 10, the K-means clustering method, Fuzzy C-means clustering method, EM method, and Superpixels + EM method were able to detect the lesions in the image, however, they could not classify the cucumber disease unlike the proposed model, which is able to detect, segment, and classify the infected cucumber leaves from the healthy leaves using the mask as shown in Figure 6.

Table 1.
The Results of Resnet50 and CNNS on Original Infected Cucumber Leaf Dataset and Sam-IE Enhanced Infected Cucumber Leaf Dataset.

Dataset	MODEL	AUC	Accuracy	Precision	RECALL	F1-Score	Processing time (MS)
Powdery mildew fungal disease	CNNs	0.901	0.772	0.752	0.897	0.821	123
	ResNet50	0.953	0.883	0.785	0.912	0.845	121
	CNNs with SAM-IE	0.959	0.872	0.762	0.907	0.831	115
	ResNet50 with SAM-IE	0.961	0.885	0.843	0.952	0.894	112
	K-means clustering	-	-	-	-	-	325
	Fuzzy C-means clustering	-	-	-	-	-	371
	EM	-	-	-	-	-	234
	Superpixels + EM	-	-	-	-	-	168

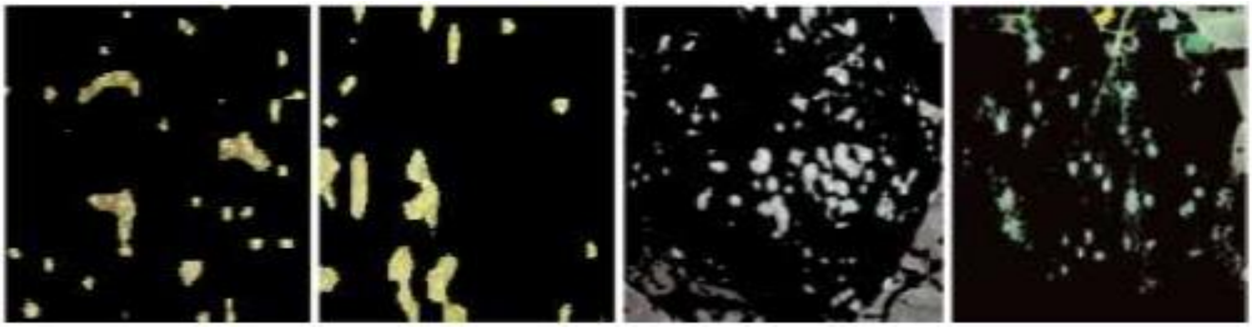

Figure 7.
K-means clustering method for segmenting lesion from cucumber leaf image.
Source: Zhang, et al. [24].

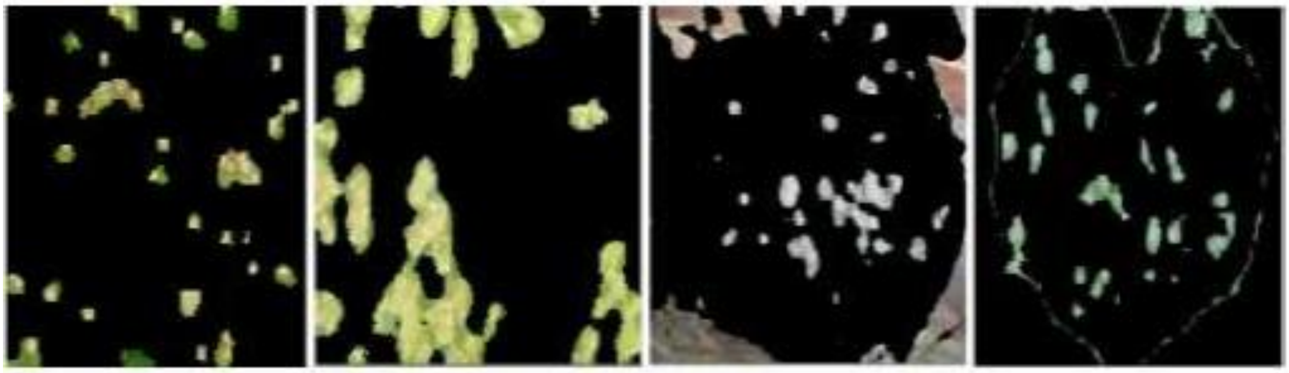

Figure 8.
Fuzzy C-means clustering method for segmenting lesion from cucumber leaf image.
Source: Zhang, et al. [24].

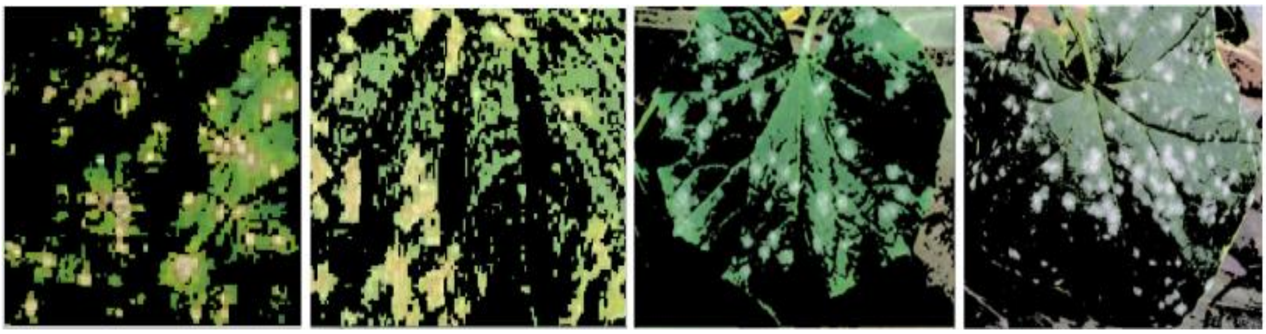

Figure 9.
EM method for segmenting lesion from cucumber leaf image.
Source: Zhang, et al. [24].

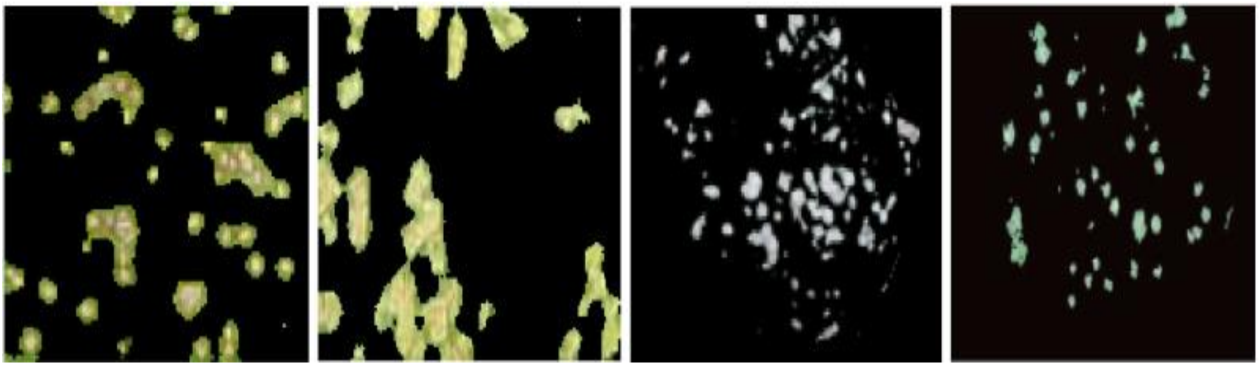

Figure 10.
Superpixels + EM method for segmenting lesion from cucumber leaf image.
Source: Zhang, et al. [24].

5. Conclusion

SAM-enabled image enhancement for the segmentation of infected cucumber leaves has been proposed in this paper. The results were obtained from the segmentation and classification experiments performed on publicly available datasets of infected cucumber leaves. ResNet50 with SAM-IE obtained 0.885 accuracy, 0.894 F1-Score, and processing time of 112 (ms). ResNet50 without SAM-IE obtained 0.883 accuracy, 0.845 F1-Score, and processing time of 121 (ms). CNNs with SAM-IE obtained 0.872 accuracy, 0.831 F1-Score, and a processing time of 115 (ms). CNNs without SAM-IE obtained 0.772 accuracy, 0.821 F1-Score, and a processing time of 123 (ms).

The results are evidence of the high performance of SAM-IE in enhancing the images of infected cucumber leaves for the employed classification models. The practical implications of the findings in this paper are essential for the horticulture industry. Horticulture farming systems that incorporate deep learning not only enhance plant growth but also ensure high crop yield via automated management and monitoring, reducing crop vulnerability to disease and increasing economic gain. Future work will dwell on collecting cucumber leaves infected with different diseases for optimum model performance.

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