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Intelligent agricultural robotic detection system for greenhouse tomato leaf diseases using soft computing techniques and deep learning

Thi Thoa Mac, Tien-Duc Nguyen✉, Hong-Ky Dang, Duc-Toan Nguyen & Xuan-Thuan Nguyen

The development of soft computing methods has had a significant influence on the subject of autonomous intelligent agriculture. This paper offers a system for autonomous greenhouse navigation that employs a fuzzy control algorithm and a deep learning-based disease classification model for tomato plants, identifying illnesses using photos of tomato leaves. The primary novelty in this study is the introduction of an upgraded Deep Convolutional Generative Adversarial Network (DCGAN) that creates augmented pictures of disease tomato leaves from original genuine samples, considerably enhancing the training dataset. To find the optimum training model, four deep learning networks (VGG19, Inception-v3, DenseNet-201, and ResNet-152) were carefully compared on a dataset of nine tomato leaf disease classes. These models have validation accuracy of 92.32%, 90.83%, 96.61%, and 97.07%, respectively, when using the original PlantVillage dataset. The system then uses an enhanced dataset with ResNet-152 network design to achieve a high accuracy of 99.69%, as compared to the original dataset with ResNet-152's accuracy of 97.07%. This improvement indicates the use of the proposed DCGAN in improving the performance of the deep learning model for greenhouse plant monitoring and disease detection. Furthermore, the proposed approach may have a broader use in various agricultural scenarios, potentially altering the field of autonomous intelligent agriculture.

Keywords Soft computing, Fuzzy control, Tomato plant disease classification, DCGAN, Precision agriculture

Over the last few decades, the demand for high-quality agriculture products has increased significantly, leading to the cultivation of more plants in greenhouses within a monitored environment[1]. Several techniques have been developed for greenhouse production, including radio frequency identification (RFID)[2], computer vision[3,4], and deep learning[5]. Early detection of plant diseases is a fundamental factor in precision agriculture in greenhouses, as it can help reduce the spread of diseases, minimize economic losses, and enhance production quality[6,7]. To achieve this, a mobile robot can be employed, and computer vision and deep learning techniques can assist smart agriculture, improving production quality and decision-making processes such as early leaf disease detection and classification and ripe fruit detection for harvesting[6].

Machine learning and deep learning methods are commonly employed in precision farming applications[8]. In the field of image processing, hand-crafted feature extraction and classification algorithms in machine learning, such as Back Propagation (BP) networks, Support Vector Machine (SVM), Random Forest (RF), K-Nearest-Neighbors (KNN), and Naïve Bayes (NB), have achieved quite good results in disease and weed detection[9]. Since 2015, various researchers in the domain have investigated deep learning algorithms for early disease detection in plants for intelligent agriculture purposes, enabled by High-Performance Computing (HPC) and Graphics Processing Unit (GPU) technology[10]. Convolutional Neural Networks (CNNs) are one of the most effective approaches for early disease detection in plant images[11], GoogLeNet[12], AlexNet[13], VGG[14], ResNet[15], and Inception[16] are some of the most well-known CNN models, which learn to identify and locate objects visually by studying various samples, similar to the human brain's process. However, CNNs heavily rely on the size of the training dataset; thus, a sufficiently large dataset is required to obtain good results. Otherwise, the model may suffer from overfitting or perform poorly. Therefore, various image data augmentation techniques

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have been applied, including traditional augmentation methods, deep learning approaches, and meta-learning search algorithms[17]. Generative Adversarial Networks (GANs) are one of the most powerful unsupervised neural network techniques for image augmentation[18]. GANs are commonly used when the training images are inadequate and traditional augmentation techniques prove ineffective.

This work proposes presents a highly effective approach for enhancing autonomous navigation systems in greenhouses through the combination of a fuzzy control algorithm for robot tracking row in the green house and a deep learning-based disease classification model. The key innovation, the improved Deep Convolutional Generative Adversarial Network (DCGAN), plays a critical role in augmenting the training dataset by generating synthetic images of diseased tomato leaves, which dramatically improves model accuracy. The improved DCGAN network includes several enhancement techniques: (i) Using Residual Blocks in the Generator helps preserve information through the deep layers of the network, improving the ability to generate detailed and complex features; (ii) Spectral Normalization in the Discriminator is used to stabilize the Discriminator's training process by normalizing weights in Conv2D layers, aiding the model in avoiding gradient issues and improving convergence; (iii) Mixed Precision Training utilizes both 16-bit and 32-bit floating-point numbers during training to accelerate computation and reduce memory usage while maintaining model accuracy, making the model more robust and efficient. The system's high validation accuracy using the PlantVillage dataset demonstrates its strong potential for automatic disease detection and classification in real-time agricultural environments, providing a valuable tool for intelligent agriculture. The experiments are conducted a thorough comparison of four deep learning networks VGG19: 92.32% accuracy, Inception-v3: 90.83% accuracy, DenseNet-201: 96.61% accuracy, ResNet-152: 97.07% accuracy with original dataset. After the DCGAN enhancement, the accuracy of ResNet-152 increased to 99.69%, demonstrating a significant boost in performance. This approach shows how integrating DCGAN with deep learning models can not only optimize crop monitoring but also contribute to precision farming techniques.

This paper is structured as follows: Section Literature review introduces related works; Section Methodology presents the proposed methodology, including dataset and data augmentation as well as model structure; Section Experimental results and discussions consists of experimental results and discussions, and the last section provides conclusions and future works.

Literature review

Robot navigation is a crucial issue in various applications[19–21]. In greenhouse robot systems, the most common solution for navigation is guide rail navigation[22] due to its simplicity. However, this method has limitations in movement and is expensive. Magnetic navigation and ribbon navigation are other options for greenhouse robots based on detecting electromagnetic signals on the ground[23]. The advantage of this method is low installation cost and space-saving. However, the movement is still restricted by fixed routes. Vision-based navigation has been developed to solve this problem[24]. Recently, simultaneous localization and mapping (SLAM) has been implemented in agriculture robots for localization and map building without prior knowledge of the working environment[25].

Regarding machine learning and deep learning in precision farming applications, a survey paper emphasizes the potential of a real-time decision support system to enhance plant growth, which in turn improves productivity, quality, and economic value[26]. The paper surveys various studies that implement computer vision and soft computing methods for identifying and classifying plant diseases through leaf images. By combining computer vision with soft computing techniques, such as neural networks, fuzzy logic, and genetic algorithms, the agricultural domain benefits from automated solutions for disease detection, resource management, and yield optimization. The use of Artificial Neural Networks (ANN) and machine learning techniques for the classification of plant leaf diseases is summarized and discussed[27]. By integrating Digital Image Processing with neural network models, there is significant potential to enhance plant diagnosis, improving time efficiency, segmentation accuracy, and minimizing errors in classification. In the past decade, several deep learning techniques, such as convolutional neural networks (CNNs)[28,29], attention-embedded residual CNN[8], region-based fully convolutional network (R-FCN)[30], VGG[31], Bayesian deep learning[32], have been proposed for disease detection and classification. The use of a CNN model to classify six different plant species—Ashwagandha, Black Pepper, Garlic, Ginger, Basil, and Turmeric is proposed[33]. With an accuracy of 99%, the CNN model outperforms traditional machine learning models like logistic regression, decision tree, random forest, Gaussian naïve Bayes, and support vector machines (SVM), showing the clear benefits of using deep learning for complex visual data such as plant characteristics. An automatic web-facilitated leaf disease segmentation system for mango trees using a neural network (NN) is proposed[34] with four key stages (Image Acquisition, Preprocessing and Feature Extraction, Neural network Training Optimization, Disease Segmentation). The system achieves high segmentation accuracy, with specificity at 91,15% and sensitivity at 90,86%, demonstrating its efficacy in detecting diseased areas. Additionally, a comparison with other state-of-the-art methods shows the advantages of this approach. In other work[35], the segmentation and classification of leaf diseases for two specific plants is investigated. The study uses a novel superpixel clustering-based hybrid neural network to segment diseased regions in plant leaf images. The classification is based on extracted features such as color, texture, and shape. A nature-inspired algorithm (e.g., genetic algorithms or particle swarm optimization) is used to optimize the connection weights in the neural network, improving the learning rate and segmentation performance. Another approach using a firefly algorithm with a fuzzy-based function network (FBFN) and incorporates Scale-Invariant Feature Transform (SIFT) for the detection of galls on the leaves of Alstonia Scholaris plants is presented in the research paper[36] of S.S. Chouhan et al. The work emphasizes the economic importance of automatic plant disease diagnosis and offers a real-time computer vision system based on the Internet of Things (IoT).

To improve the results, popular data augmentation techniques, such as rotation, scaling, flip, brightness adjustment, affine transformation, and Gaussian noise, can be implemented. Nithish Kannan E et al. investigated an approach for detecting tomato leaf diseases using transfer learning[37]. Three augmentation techniques (rotation, flip, and combine) were implemented to increase the dataset to 4 times, and the model achieved an accuracy of 97%. However, traditional data augmentation has the disadvantage of generating images with similar semantic information, which cannot improve dataset diversity. A. Paymode et al. presented data augmentation by turning, translation, and randomized transformation to enhance dataset volume and achieve better model performance and hyperparameter tuning with the VGG model, with an accuracy of 95.71% for tomatoes[31]. A novel approach to classifying pepper diseases by utilizing a concatenated neural network model, which combines the strengths of VGG16 and AlexNet is proposed[38]. The process begins with essential steps like dataset collection, image preprocessing, noise removal, and segmentation to prepare the images for analysis. The features extracted by VGG16 and AlexNet are then combined and fed into fully connected layers for classification. The model achieved 100% training accuracy, 97.29% validation accuracy, and 95.82% testing accuracy.

To avoid overfitting in the deep learning process, the conditional generative adversarial network (C-GAN) was used to increase the dataset size[39]. Using this technique and the DenseNet model, an approach for tomato leaf disease detection was developed[40]. The DCGAN network was used to implement data augmentation, and the AlexNet, GoogLeNet, VGG16 networks, and ResNet were used as deep learning models[41]. The obtained accuracy of this approach was 94.33%. A deep threshold multi-feature extraction convolution GAN with Mixed Attention and Markovian Discriminator (MMDGAN) for tomato disease leaf classification was first introduced[42]. This module improves the extraction of features from tomato disease leaves, potentially enhancing the quality and diversity of generated images. Combines cross-attention and a fused features-highlighting module to improve the generation of images by focusing on relevant features and their relationships. Utilizes Markovian principles to enhance the judgment of local texture similarities in generated images, leading to more realistic and high-quality synthetic images with 97.12% accuracy and a 97.78% F1 score.

GoogleNet CNN was proposed for disease detection[10]. In a similar study, the AlexNet, GoogleNet, and ResNet structures were investigated[41], where the highest accuracy (97.28%) was obtained. A proposed image fusion algorithm based on ResNet-152 was presented[43] by decomposing both the infrared (IR) and visible (VIS) images into their low-frequency (LF) and high-frequency (HF) components using an average weighting approach. The fusion technique helps in blending the smooth features of both images. In addition, multiply the high-frequency components with the maximum weight layer obtained from the ResNet-152 processing to form a new high-frequency component.

Methodology

This section comprises three subsections, each of which explains the different components involved in developing an agricultural robot for tomato plants.

Trajectory design based on fuzzy controller for an agricultural robot

The agricultural robot was designed to travel easily between tomato rows, as shown in Fig. 1. The tomato plant's maximum height is about 1.2 m, and the distance between rows is 60 cm, while the distance between tomato plants is 40 cm. The robot includes a basement with a dimension of 40×40 cm, MPU 6050, and ultra-sonic sensor SRF04 to avoid low-position obstacles. Additionally, a camera was used for navigation and learning purposes. A 2D camera was used to take pictures of the tomato leaf, while the Intel RealSense depth camera D435 was used to implement the simultaneous localization and mapping (SLAM) task. The proposed navigation was implemented in the Ubuntu 16.04 LTS operating system running on the Robot Operating System (ROS) Kinetic.

For the navigation task, the robot starts at the first corner of the greenhouse and fully travels through all tomato rows to take pictures and monitor the tomato plant. Fuzzy control is used, with the inputs being the angle error and the derivative of angle error. The angle error (angle_error) and the derivative of angle error is designed with physical values from -900 to 900, including seven linguistic values corresponding to seven membership functions: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positve Small), PM (Positve Medium), PB (Positve Big) as shown in Figs. 2 and 3, respectively.

Corresponding to the two input variables angle error (angle_error) and angle error derivative (d_angle_error) is the output variable angular velocity with a physical value range from -1.2 rad/s to 1.2 rad/s, including 7 linguistic values corresponding to 7 membership functions: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PM (Positive Medium), PB (Positive Big) as shown in Fig. 4. The fuzzy associative memory (FAM) table is presented in Table 1, while the fuzzy curve is shown in Fig. 5.

Dataset and improved DCGAN

For this study, we utilized the PlantVillage dataset[44], which consists of ten groups with healthy leaves and nine different leaf diseases (Bacterial spot, Early blight, Late blight, Leaf Mold, Septoria leaf spot, Two spotted spider mite, Target Spot, YellowLeaf Curl Virus, Tomato mosaic virus). Each image in the dataset has a resolution of 256×256 pixels, RGB color space, and is in JPG format. The original dataset was divided into two sets, a training set, and a validation set, in an 80:20 ratio for each class. Figure 6 shows examples of the ten classes in the original dataset.

GANs were first introduced in 2014[45], which consist of two models: a generator G and a discriminator D. The generator generates images for training purposes, while the discriminator distinguishes between real training images and generated images, as shown in Fig. 7. In this study, we proposed DCGAN for data augmentation. Figure 8 illustrates the structure of the two models, generator and discriminator, in the proposed improved DCGAN. The details of Generator and Discriminator are presented as follows:

Generator structure.

Input layer Receives a random noise vector.

Fig. 1. Robot design (left) and real robot (right).

Dense layer Converts this noise vector into a 3D tensor of larger size (16 × 16 × 512). This creates a small "image" but with many feature maps.

Reshape layer Converts the tensor from vector form to spatial form to be processed by convolutional layers.

Conv2DTranspose layers These layers perform "upsampling" (enlarging) of the image, gradually increasing the spatial dimensions (from 16 × 16 to 128 × 128). Conv2DTranspose is used with different filter sizes to progressively create a higher resolution image.

Residual blocks with concatenation: Includes two residual blocks, each performing a series of steps: Conv2D -> BatchNormalization -> LeakyReLU -> Conv2D -> BatchNormalization. The output of the block is then concatenated with the original input to retain the original information. These blocks help the model learn deeper features and retain information from previous layers.

Concatenate & upsampling After the Residual Blocks, features from these blocks are combined and the size is further increased.

Output layer The final layer is Conv2DTranspose with a tanh activation function, producing an RGB image of size 128 × 128 × 3. The tanh function normalizes the output values to the range [-1, 1], suitable for the Discriminator's input format.

Discriminator structure:

Input layer Receives an image of size 128 × 128 × 3 (RGB).

Conv2D layers Used to progressively reduce the image size while extracting important features.

Spectral normalization Applied to the Conv2D layers to normalize the spectral norm of the weight matrix, helping stabilize the training process and avoid gradient issues.

LeakyReLU Used after each Conv2D layer to introduce non-linearity into the model, helping the model learn more complex features. LeakyReLU is chosen over ReLU to avoid the dead neuron problem.

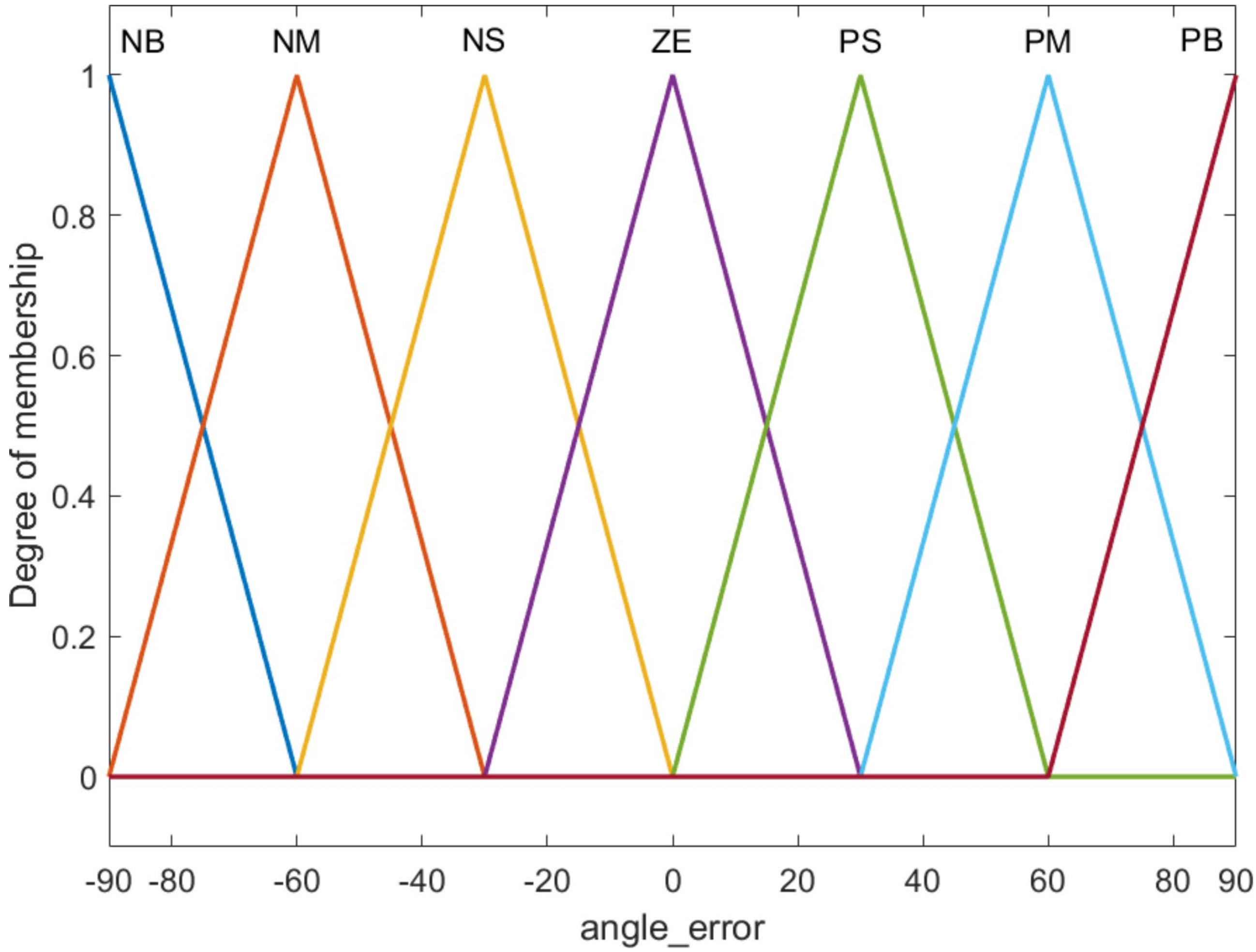

Fig. 2. The angle error triangular membership functions.

Dropout layers Used after convolutional layers to minimize overfitting by randomly dropping some connections in the network.

Flatten layer After the Conv2D layers, the image is flattened into a vector before being fed into the final layer.

Output layer The final layer is a single Dense layer, with the output being a scalar value representing the model's confidence that the input image is real or fake.

The proposed improved DCGAN network includes several enhancement techniques:

Using Residual Blocks in the Generator helps preserve information through the deep layers of the network, improving the ability to generate detailed and complex features. In addition, spectral Normalization in the Discriminator is used to stabilize the Discriminator's training process by normalizing weights in Conv2D layers, aiding the model in avoiding gradient issues and improving convergence. Moreover, Mixed Precision Training utilizes both 16-bit and 32-bit floating-point numbers during training to accelerate computation and reduce memory usage while maintaining model accuracy.

After DCGAN is trained on the original dataset, it is used to generate 500 images for each class. The generated images have the same resolution as the original image, PNG format, and RGB color space. Examples of synthetic images are shown in Fig. 9. Each class added 500 images after generating data using DCGAN, resulting in a total of 21,012 images (16204 for training and 4808 for validation). The classes of the augmented dataset and class-wise image distribution are represented in Table 2.

Model training

We investigated four different transfer learning models, namely VGG-19, Inception-v3, DenseNet-201, and ResNet-152, on the original dataset, and selected the best model to train on the dataset enriched with improved DCGAN. After training the models on the initial dataset, we obtained the training curves and the accuracy of the models. The training curves of the models are shown in Figs. 10, 11, 12 and 13. The values of validation accuracy for these models are 92.32%, 90.83%, 96.61%, and 97.07% respectively with the original dataset for nine tomato

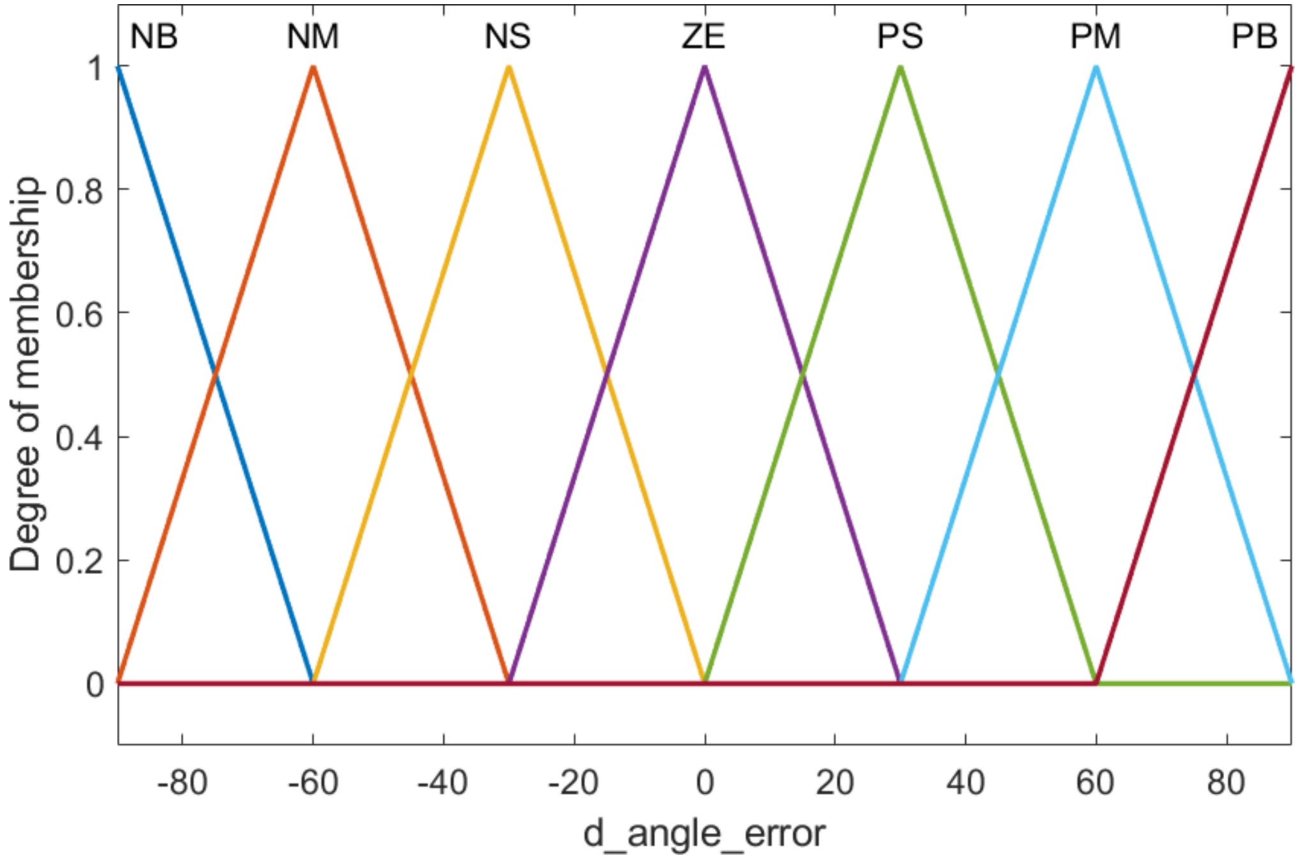

Fig. 3. The angle error derivative triangular membership functions.

leaf disease classes. As a result, we chose ResNet-152 to build a disease leaves classification model with data enriched by improved DCGAN.

Experiments and results

In this study, we present a novel solution for autonomous robots in greenhouses that uses fuzzy control for autonomous navigation and early detection of tomato leaf disease based on an improved DCGAN for data augmentation, followed by classification using the ResNet model. The results obtained with the trajectory design based on a fuzzy controller in the real robot system are presented in Fig. 14. The robot starts at the first corner of the greenhouse and successfully travels to monitor tomato plants while ensuring efficient coverage of all rows and minimal plant disruption. Our main objective is to utilize the improved DCGAN to enhance the dataset, resulting in improved accuracy for the tomato leaf disease classification model. We implement the proposed method in two main steps: using the improved DCGAN to generate images and then applying the ResNet-152 model for classification. The discriminator and generator use convolutional and convolutional transpose layers explicitly.

We train the ResNet-152 model on the augmented dataset using transfer learning, and our results show that the accuracy of the classification model increased from 97.07% on the original dataset to 99.69% on the augmented dataset. Compared to other works in the field of detecting diseases on tomato leaves, our proposed method proves to be more effective with a higher accuracy of the model. The learning curves of ResNet-152 on the augmented dataset are shown in Fig. 15. We implement the model in Python using Keras and TensorFlow as deep learning frameworks. Training is executed on a Google server (Kaggle) with a powerful Graphics Processing Unit (GPU) to accelerate the experimental process. System specifications are listed in Table 3.

Figure 16(a) depicts the ResNet152 model's confusion matrix, whereas Fig. 16(b) depicts the same ResNet152 model with an updated dataset based on the proposed improved DCGAN network. In terms of overall accuracy (diagonal values), both charts show a high number of right predictions for each class. However, when utilizing the updated dataset created by the proposed DCGAN, these values increase dramatically, particularly in classes such as EB (from 268 to 294) and TS (from 395 to 419). This suggests that the ResNet152 model using the argument dataset increases classification accuracy across several classes. As for the confusion between classes (Off-diagonal values), in the confusion matrix of ResNet152 using the original dataset, there is some confusion between classes, such as BS and EB, LB and LM. However, when using the enhanced dataset, these misclassifications have either been reduced or eliminated, showing that the enhanced dataset has improved class differentiation. A clear example is the reduction in confusion between EB and LB (from 13 in Fig. 16(a) to 1 in Fig. 16 (b)). The enhanced dataset has strengthened the differentiation of smaller classes. Classes with fewer data,

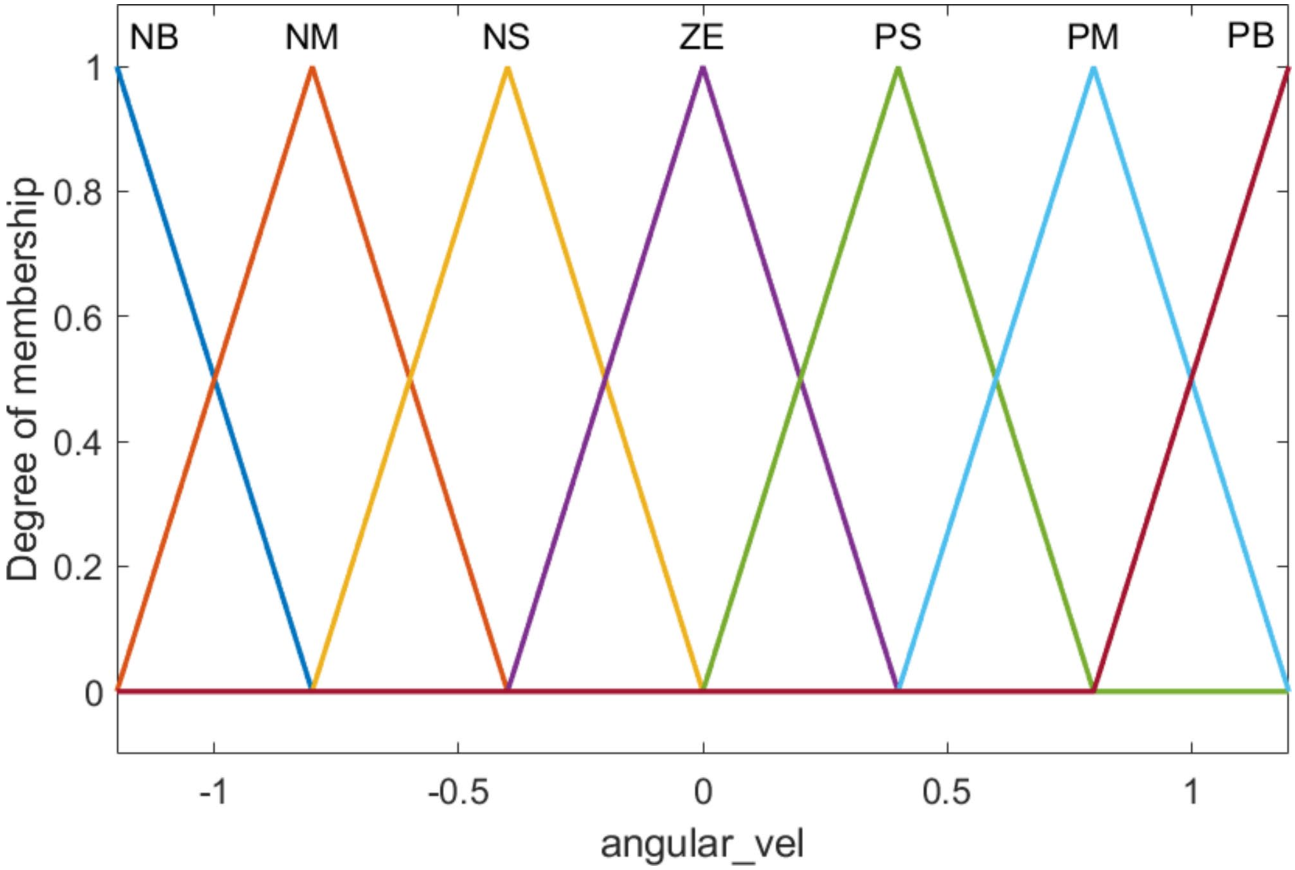

Fig. 4. The angular velocity triangular membership functions.

	Angle error							
		NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
Derivative of angle error	**NB**	NB	NB	NB	NB	NM	NS	ZE
	NM	NB	NB	NB	NM	NS	ZE	PS
	NS	NB	NB	NM	NS	ZE	PS	PM
	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NM	NS	ZE	PS	PM	PB	PB
	PM	NS	ZE	PS	PM	PB	PB	PB
	PB	ZE	PS	PM	PB	PB	PB	PB

Table 1. FAM table present the composite of angular velocity rules based on the two input variables.

such as H, saw reductions in misclassifications when using the enhanced dataset (from 474 to 478). Overall, the use of the enhanced dataset improves the performance of the ResNet152 model, reducing confusion between classes and enhancing classification accuracy for individual classes.

The system for classifying tomato leaf diseases was assessed using four key metrics: accuracy, precision, recall, and F1-score. These metrics are defined by Eqs. (1–4) as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = 2 \times \frac{Precision \times \ Recall}{Precision + Recall} \tag{4}$$

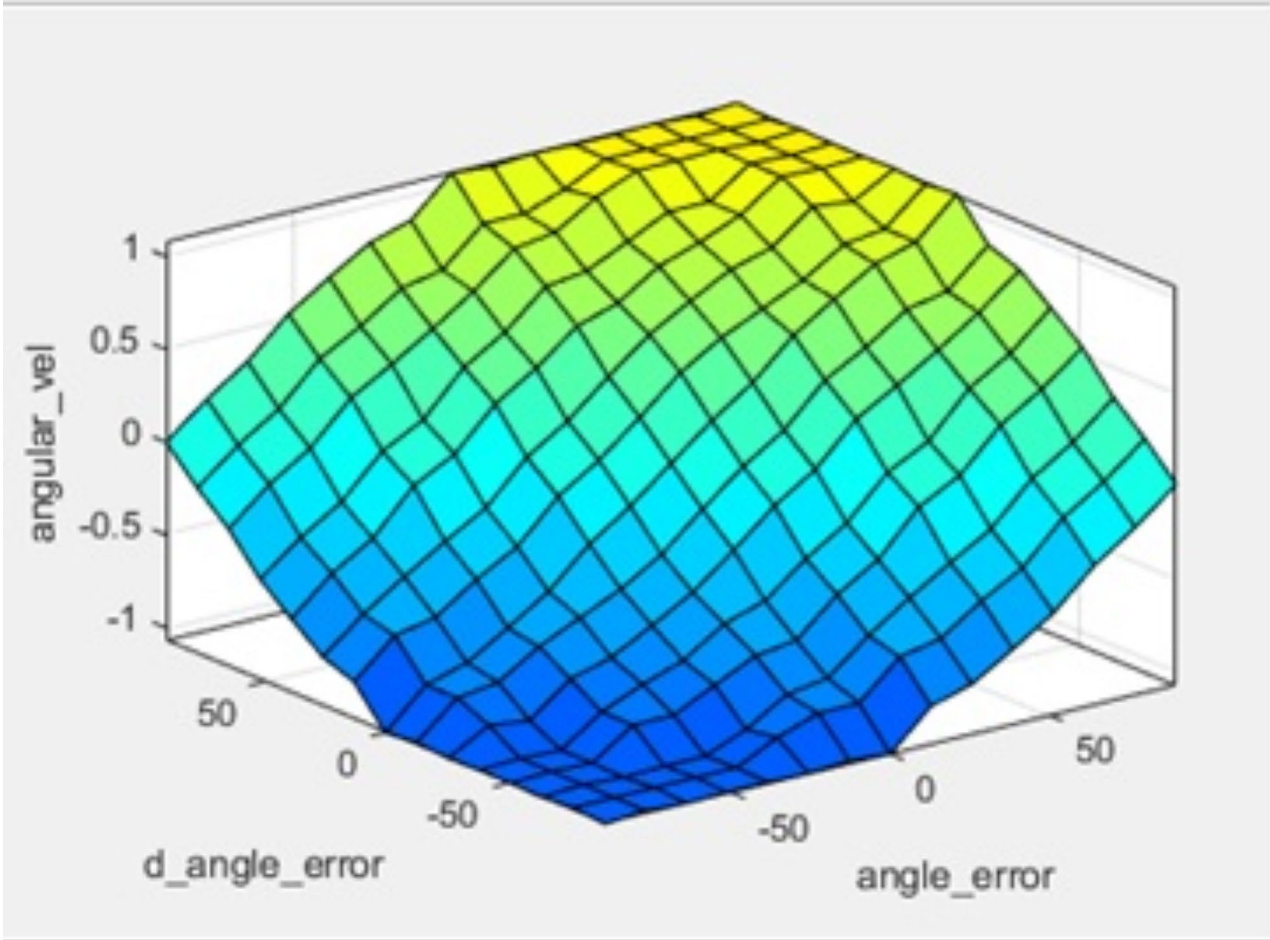

Fig. 5. The fuzzy curve of the composite of angular velocity rules based on the two input variables.

where accuracy measures the model's overall correctness. It is calculated by taking the ratio of correctly predicted instances (true positives and true negatives) to the total number of predictions. Precision is the ratio of true positive predictions to the total number of positive predictions. This metric indicates how well the model avoids making false positive errors. Recall is the proportion of true positives identified from all actual positive cases. It measures the model's ability to detect positive instances. The F1 score is the harmonic mean of precision and recall. This score offers a balanced evaluation by considering both false positives and false negatives.

The comparison of these metrics between normal and enhanced training is presented in Table 3. Detail performance on each class is presented in Table 4.

From Table 3, it is evident that the accuracy of the ResNet152 model is 97.07%, while when combined with the proposed improved DCGAN network, the accuracy increases to 99.69%. This shows that data augmentation using the proposed DCGAN significantly improves the model's performance. Additionally, the values of precision, recall, and F1-score all increase significantly when using the proposed DCGAN:

- Precision: from 97.56 to 99.67%.
- Recall: from 97.67 to 99.61%.
- F1-score: from 97.61 to 99.64%.

This improvement reflects that using the proposed improved DCGAN helps the model make more accurate predictions across classes, reduces bias, and enhances overall classification capability.

Table 5 provides a comparison of the model's performance on each class with and without using the proposed improved DCGAN during training. Precision, recall, and F1-score for each class all increase significantly when combined with the improved DCGAN. For example:

- Early blight (EB): Precision increases from 94.04 to 99.32%, recall from 89.33 to 98.00%, and F1-score from 91.62 to 98.66%.
- Late blight (LB): Precision increases from 96.64 to 99.30%, recall from 95.46 to 99.65%, and F1-score from 96.05 to 99.48%.

Fig. 6. Examples of original dataset.

This growth shows that the model not only improves its ability to accurately identify (precision), but also increases its ability to detect true instances belonging to a class (recall), leading to an improvement in the F1-score, which is an overall measure of the model's performance. Classes with less data, such as Mosaic virus (MV) and Healthy (H), achieve excellent performance when using the improved DCGAN, with precision, recall, and F1-score all reaching a maximum value of 1.0000. This demonstrates that the proposed DCGAN has helped the model handle more challenging or underrepresented classes more effectively. When compared, it can be seen that with the enhanced data using the proposed DCGAN, the performance disparity between classes has decreased, and the average metrics across classes are very high and close to perfect. This means that the model with the proposed improved DCGAN has overcome the shortcomings of class bias and performs more uniformly across all classes. Thus, the use of the proposed DCGAN network has significantly improved the performance of the ResNet152 model on both the overall dataset and individual classes, particularly in classes with less data.

To compare our proposed method with other approaches, we consider Networks, dataset, training, testing, and classification model accuracy in Table 6, which includes the results of other works[6,8,18,28,30,31,46,47]. Our proposed approach has the highest accuracy of 99.69%.

Conclusion

This study proposes a methodology for an intelligent robotics system in a greenhouse for autonomous navigation and tomato leaf disease detection using soft computing techniques. Specifically, a fuzzy control algorithm is developed for row trajectory tracking the greenhouse environment, and a deep learning algorithm with an improved DCGAN is used to increase the diversity of the dataset and improve the accuracy of detecting nine types of tomato leaf diseases. The improved DCGAN network includes several enhancement techniques: (i) Using Residual Blocks in the Generator helps preserve information through the deep layers of the network, improving the ability to generate detailed and complex features; (ii) Spectral Normalization in the Discriminator is used to stabilize the Discriminator's training process by normalizing weights in Conv2D layers, aiding the

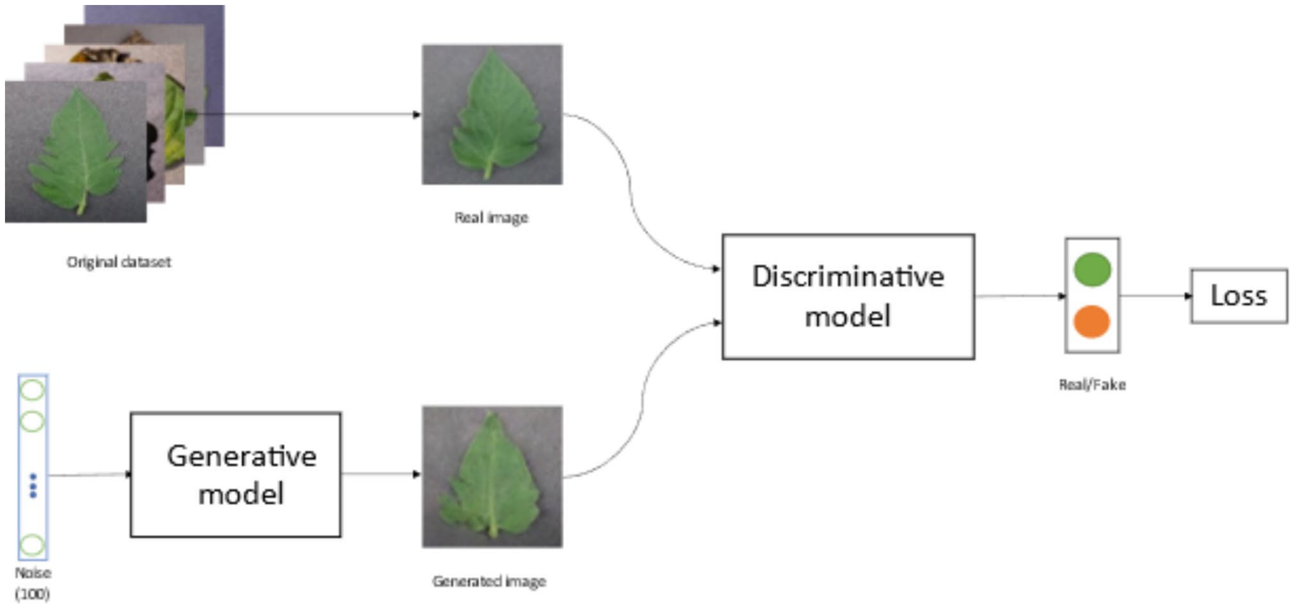

Fig. 7. Main steps of GAN.

model in avoiding gradient issues and improving convergence; (iii) Mixed Precision Training utilizes both 16-bit and 32-bit floating-point numbers during training to reduce memory usage while maintaining model accuracy, making the model more robust and efficient. Several state-of-the-art convolutional neural network architectures, including VGG-19, Inception-v3, ResNet-152, and DenseNet-201, have been tested on the original dataset, which is a subset of the open dataset PlantVilla. Among them, ResNet-152 has achieved the highest accuracy. In our proposed approach, the augmented dataset based on an improved DCGAN, generated by combining the original dataset and the generated dataset, is then used to train the ResNet-152 model. Precision, recall, and F1-score for each class all increase significantly when combined with the improved DCGAN. For example: Early blight (EB): Precision increases from 94.04 to 99.32%, recall from 89.33 to 98.00%, and F1-score from 91.62 to 98.66%; Late blight (LB): Precision increases from 96.64 to 99.30%, recall from 95.46 to 99.65%, and F1-score from 96.05 to 99.48%. Over all, the accuracy of the classification model has increased from 97.07% on the original dataset to 99.69%, demonstrating the effectiveness of the proposed method. In future work, the real-world dataset and perform data augmentation can be explored and improved to further increase the model's classification accuracy. In addition, the proposed approach is not only implemented in greenhouses but also in outdoor agricultural environments to deal with uncertainties, different light conditions, and unknown obstacles. In summary, this work offers a promising solution for automating the monitoring and detection of tomato leaf diseases in greenhouse environments, which can ultimately lead to increased crop yield and improved food security.

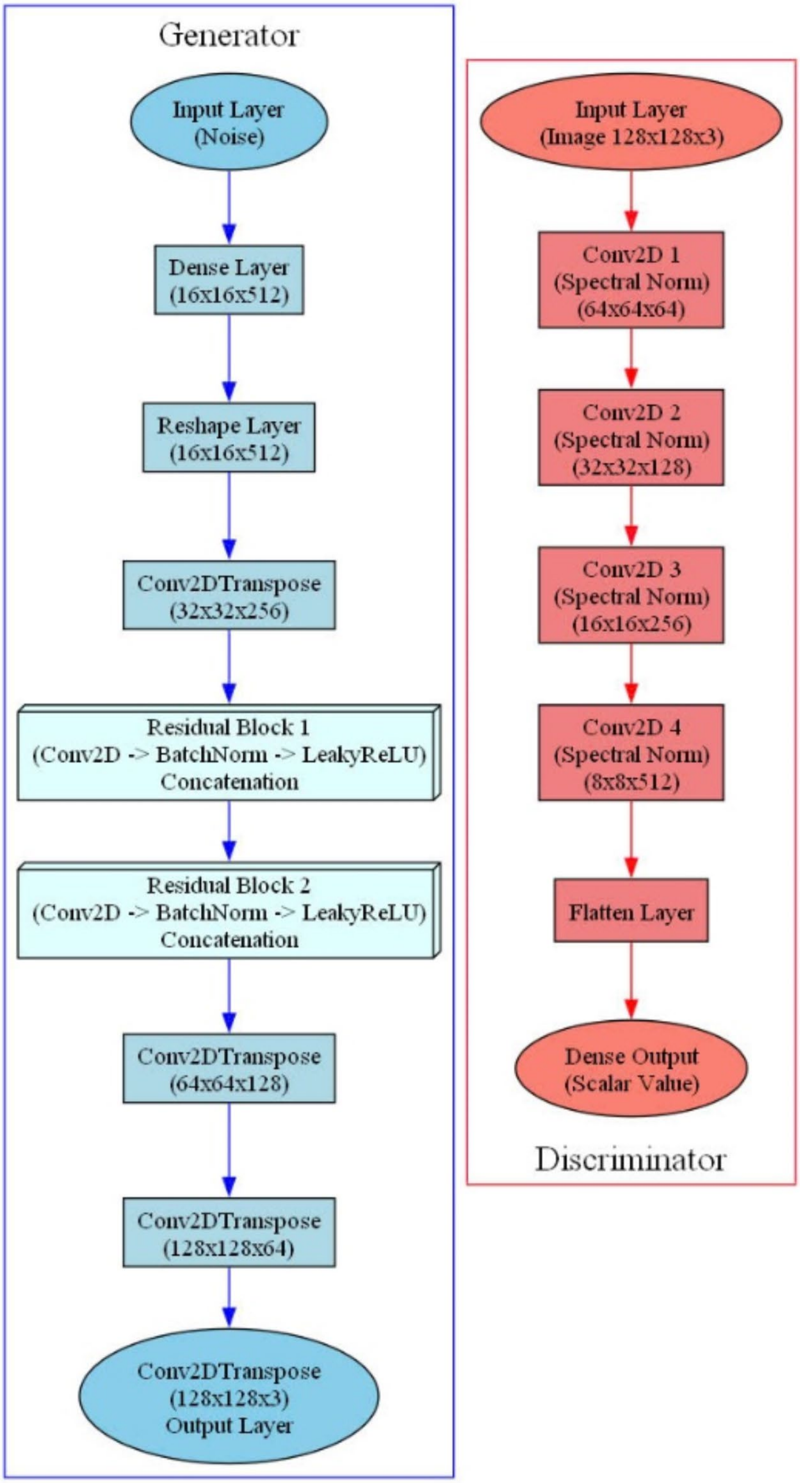

Fig. 8. Improved DCGAN processing.

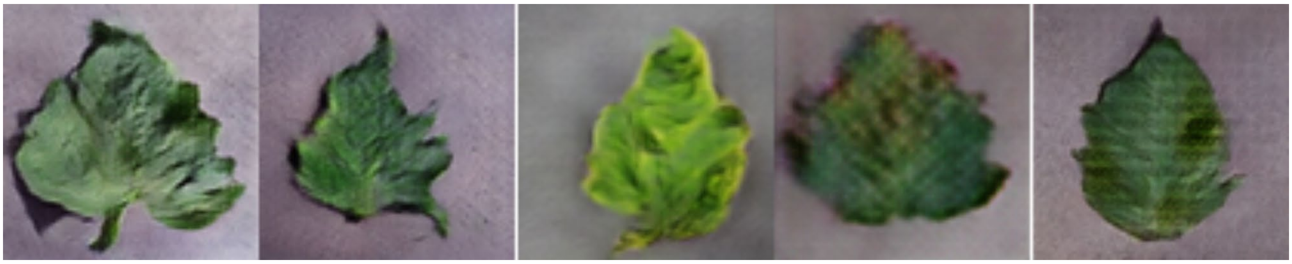

Fig. 9. Examples of synthetic images.

Order	Class	Training	Validation
1	Bacterial spot	1488	639
2	Early blight	700	300
3	Late blight	1336	573
4	Leaf Mold	666	286
5	Septoria leaf spot	1239	532
6	Two spotted spider mite	1173	503
7	Target Spot	982	422
8	YellowLeaf Curl Virus	2246	963
9	Tomato mosaic virus	261	112
10	Healthy	1113	478
	Total	11,204	4808

Table 2. Original dataset.

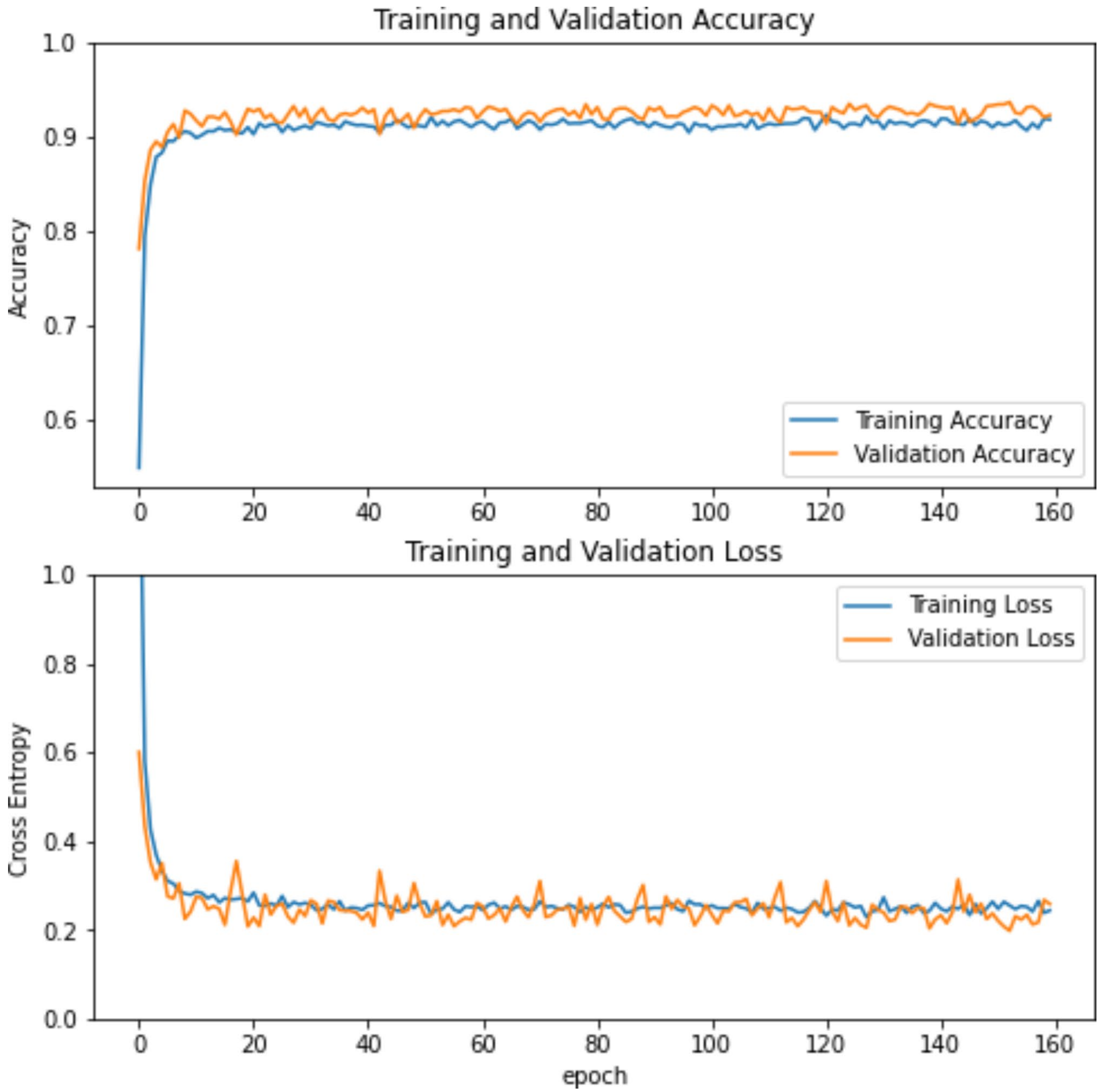

Fig. 10. VGG19 classification models results.

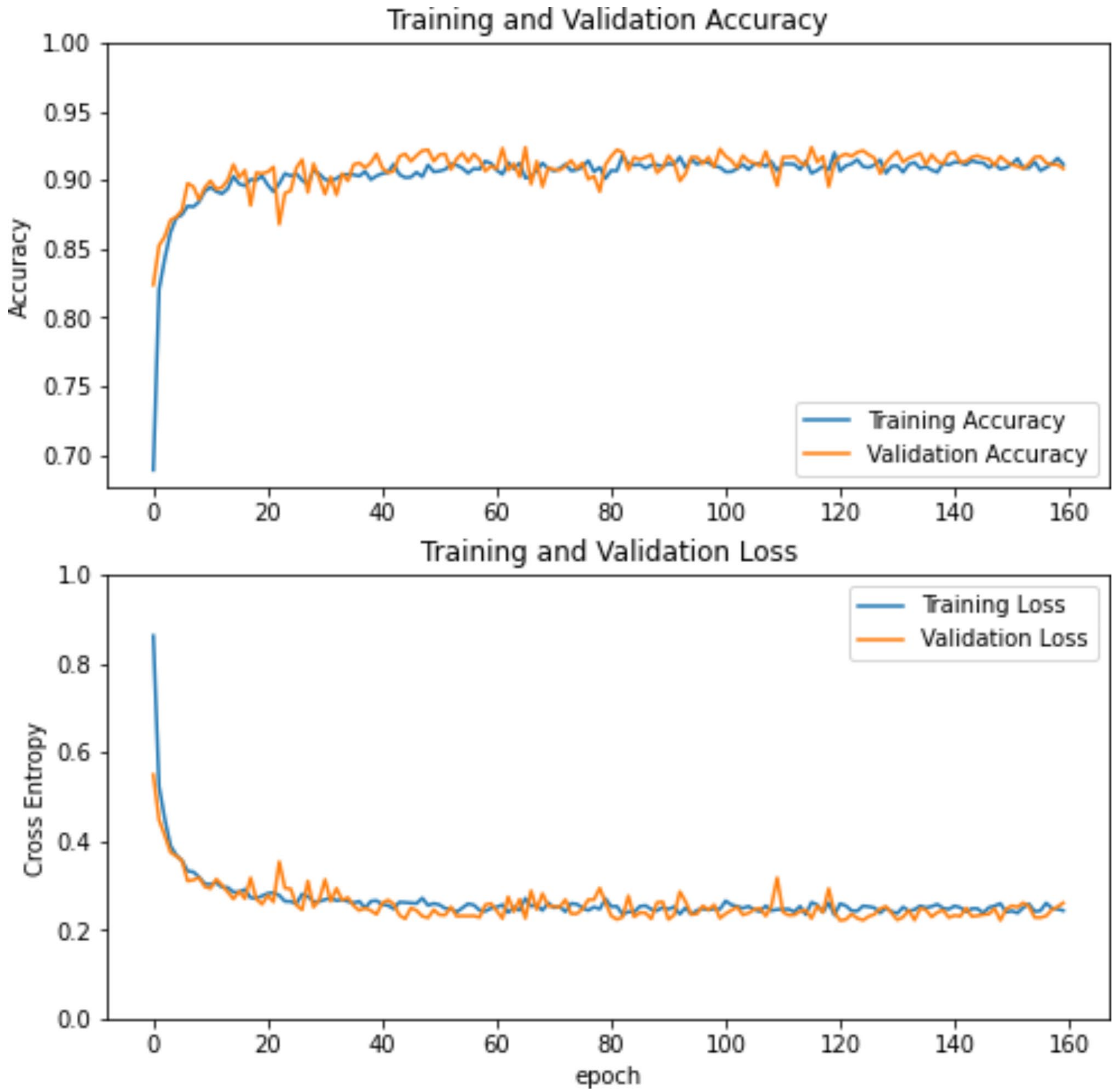

Fig. 11. Inception-V3 classification models results.

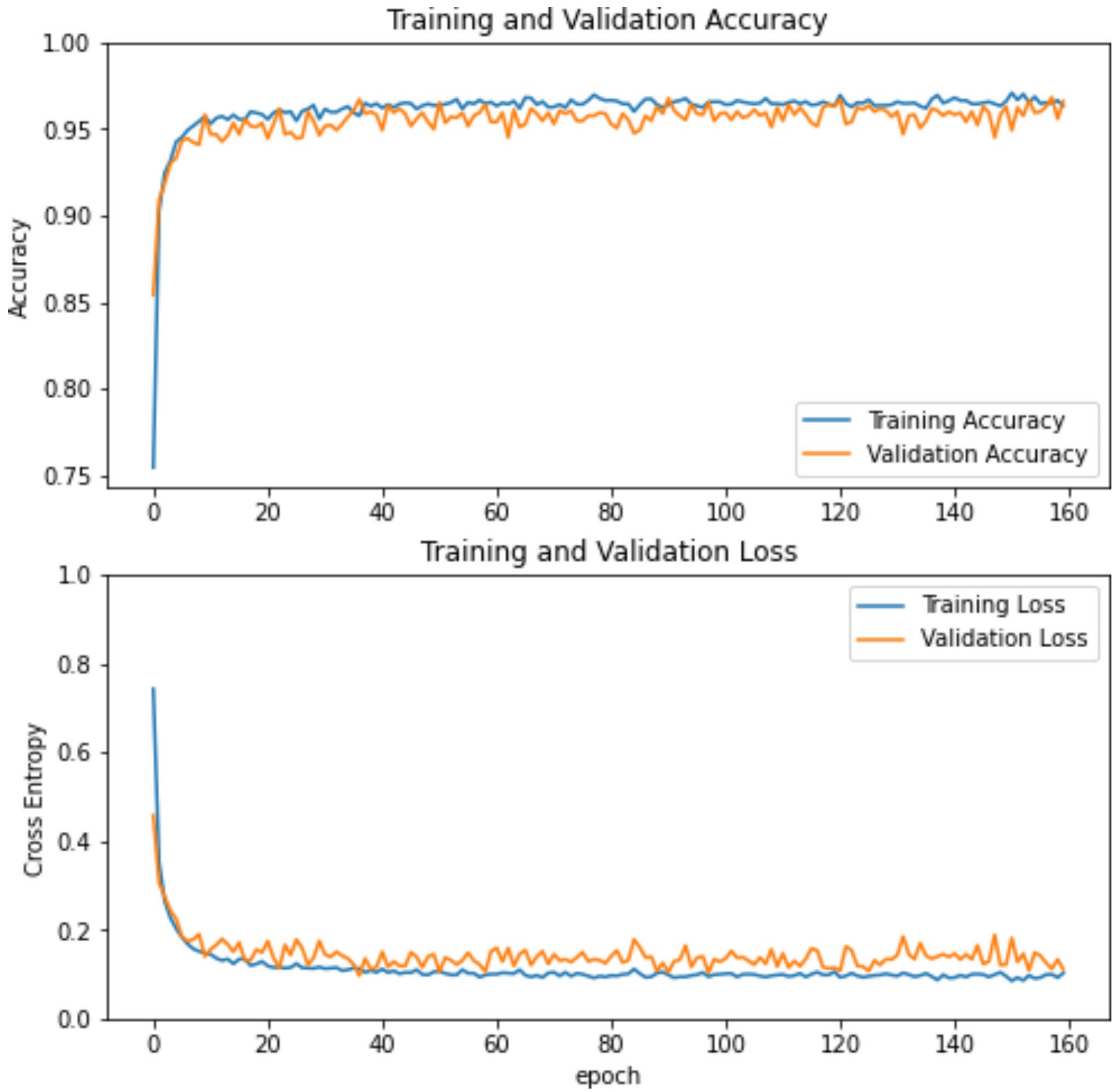

Fig. 12. DenseNet 201 classification models results.

Fig. 13. ResNet-152 classification model results.

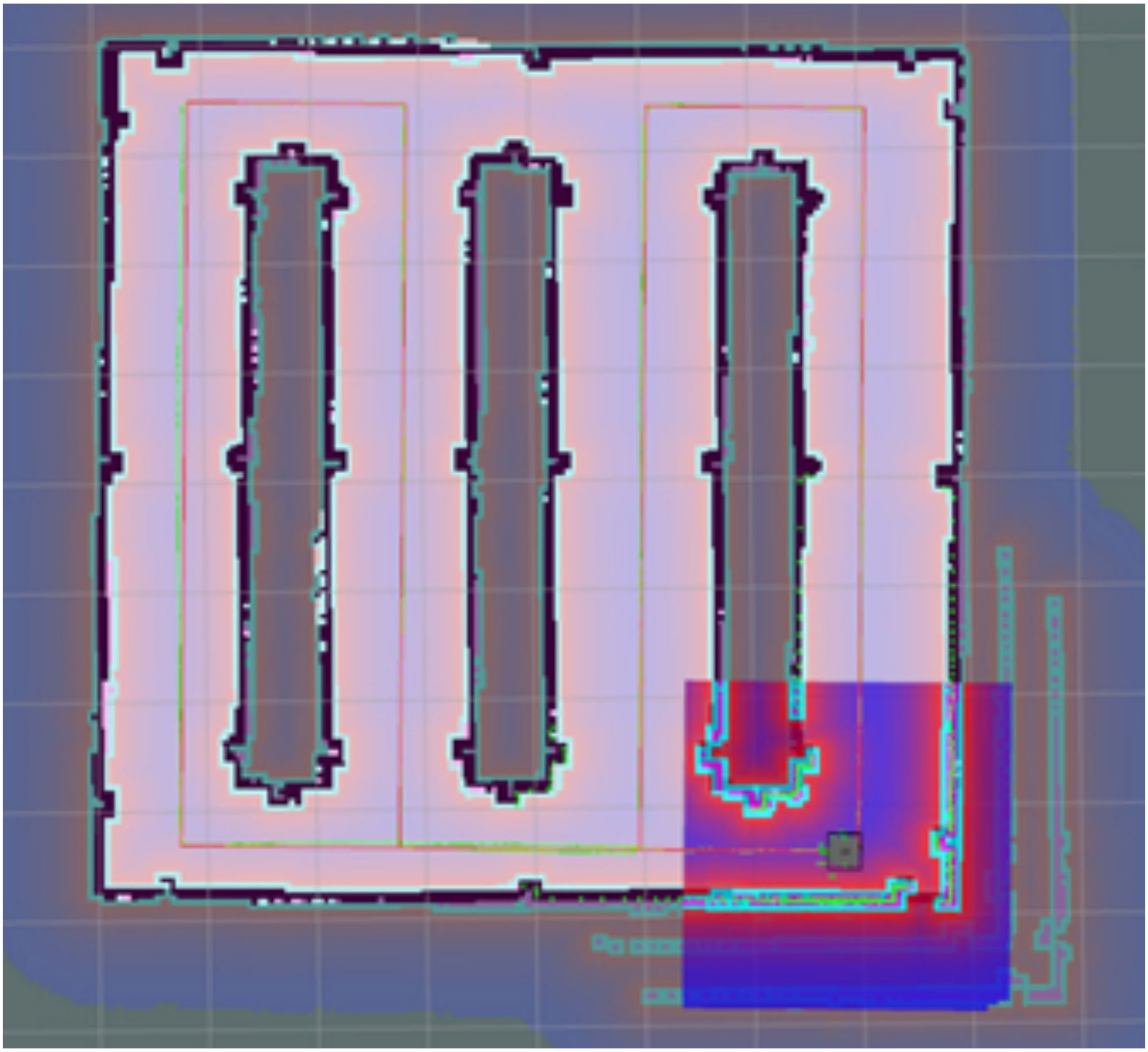

Fig. 14. Fuzzy control in tomato greenhouse.

Fig. 15. Learning curves of ResNet-152 on augmented dataset.

CPU	RAM	GPU	Operating system	Computing platform	Software library
Intel(R) Xeon(R) Gold 6138	64 GB	NVIDIA GeForce RTX 4080	Windows-10	CUDA version: 11.7.64	TensorFlow version: 2.8.0

Table 3. System specifications.

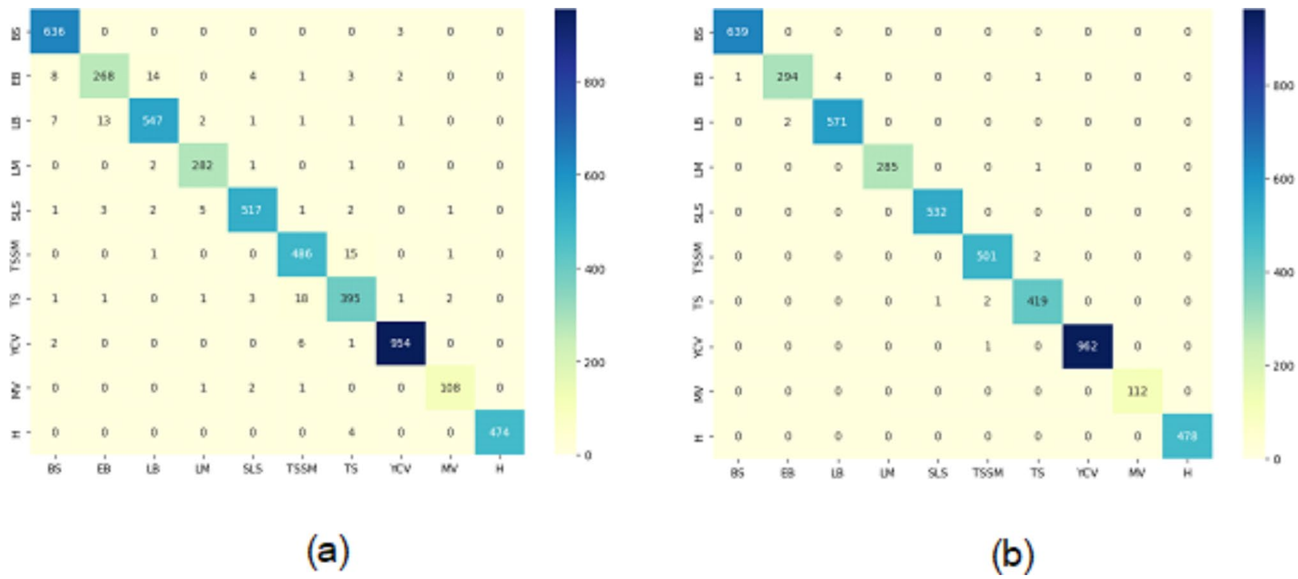

Fig. 16. Confusion matrices of the model. (**a**) Resnet152, (**b**) Resnet152 with enhanced dataset.

	Accuracy	Precision	Recall	F1-score
Resnet152	97.07%	96.65%	96.50%	96.56%
Resnet152 + DCGAN	99.69%	99.67%	99.61%	99.64%

Table 4. Average metrics comparison with vs. without DCGAN.

Class	Resnet152			Resnet152 + DCGAN		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Bacterial spot (BS)	97.10%	99.53%	98.30%	99.84%	100.00%	99.92%
Early blight (EB)	94.04%	89.33%	91.62%	99.32%	98.00%	98.66%
Late blight (LB)	96.64%	95.46%	96.05%	99.30%	99.65%	99.48%
Leaf mold (LM)	96.91%	98.60%	97.75%	100.00%	99.65%	99.82%
Septoria leaf spot (SLS)	97.92%	97.18%	97.55%	99.81%	100.00%	99.91%
Two spotted spider mite (TSSM)	94.55%	96.62%	95.58%	99.40%	99.60%	99.50%
Target spot (TS)	93.60%	93.60%	93.60%	99.05%	99.29%	99.17%
Yellow Leaf curl virus (YCV)	99.27%	99.07%	99.16%	100.00%	99.90%	99.95%
Mosaic virus (MV)	96.43%	96.43%	96.43%	100.00%	100.00%	100.00%
Healthy (H)	100.00%	99.16%	99.58%	100.00%	100.00%	100.00%
average	96.65%	96.50%	96.56%	99.67%	99.61%	99.64%

Table 5. Comparison of model performance with and without DCGAN.

Year	Ref	Networks	Dataset	Training	Testing	Accuracy
2021	[6]	DenseNet121 and C-GAN	PlantVillage	–	–	98.65%
2020	[18]	DCGAN + CNN	PlantVillage	1500	–	94.33%
2018	[28]	CNN	PlantVillage	6300	2700	95.54%
2017	[46]	Faster RCNN + VGG16 + Resnet-X	Self-collected	4000	1000	86%
2020	[30]	Attention Residual CNNs + Residual CNN	PlantVillage	70%	30%	98%
2019	[47]	Multi-Scale + AlexNet	PlantVillage	5766	–	92.70%
2021	[31]	VGG16	PlantVillage	54,303	–	95.71%
2020	[8]	Attention Residual CNNs + Residual CNN	PlantVillage	70%	30%	98%
2024	Our Method	ResNet-152 + improved DCGAN	PlantVillage	11,204	4808	99.69%

Table 6. Comparison of deep learning techniques for tomato leaf disease classification.

Data availability

The datasets used and/or analyzed during the current study are available at link to the dataset and code (https://drive.google.com/drive/folders/1-OF4MAJAMPxKiNEAip0Zw76XpKyMAy-h).

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Author contributions

T.T.M. and T.D.N. conducted data analysis and edited the paper. X.T.N and T.T.M. provided guidance on the methodology and analyzed the data. T.D.N. conceptualized the study. H.K.D. and T.T.M. conducted the analysis on the evaluation of conceptualized. X.T.N. and T.T.M. conducted data analysis and experimental results. T.D.N. and D.T.N. contributed to article revisions.

Declarations

Competing interests

The authors declare no competing interests.

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