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# Enhanced Leaf Disease Detection Using Multi-Stage Segmentation and GAN-Based Classification Techniques

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## ABSTRACT

The primary source of financial loss in the global agriculture and farming sector is plant diseases. It's a significant factor as it lowers crop quality and yield potential. Therefore, it's imperative that various plant diseases be categorized and identified, and it demands the utmost care. Fruits are the vital nutrients rich source for plants worldwide, however the quantity and quality of fruits are negatively impacted by number of diseases. Results, early detection and classification of leaf disease are made possible by the application of efficient machine vision technologies.We put out a novel generative adversarial networkbased disease detection model for grape leaf. The industryis expanding positively. With an emphasis on limited grape leaf training images of illnesses, this study presents a unique model called Leaf GAN, which is based on generative adversarial networks (GANs), to generate pictures of four distinct disease images of grape for training of identification models. The deep connectivity approach and instance normalisation are integrated into an efficient discriminator model to identify realistic and fake images by using their excellent feature extraction capability on grape leaf lesions. Initially, a generator model framework with a decreasing count of channels is developed to generate diseased grape leaf images. Utilizing their advanced capability to capture details from grape leaf lesions, the approach employs dense connectivity in conjunction with instance normalization.The consistency and durability of the suggested method are also tested.After rigorous simulation, the proposed or developed modelachieves a classified accuracy of 87.26% percent.The accuracy of the suggested work is better comparative to conventional machinelearning techniques.

*Index Terms*—**Convolutional neural networks, deep learning, identification of grape leaf disease, real-time detection, and data augmentation.**

## I. INTRODUCTION

A key focus area in precision agriculture is the detection of diseases through plant leaf images. Artificial intelligence, image processing, and graphical processing units (GPUs) can all help to increase and improve plant protection and growth. Most plant diseases produce visible symptoms, therefore learning models should have high observation abilities to recognize the symptoms of any disease. Among the most widely cultivated fruits globally, with Rich in nutrients and therapeutic value is Grapes. This leads to considerable economic losses as numerous diseases impact apple production
on a large scale.Leading to prompt and accurate diagnosis of leaf diseases is critical for the apple industry's continued growth and has became popular resarch topic in field of agricultural informatics.However, due to subjective perception,there is a chance of inaccuracy. Various spectroscopic and imaging approaches for identification of plant diseases have been discovered. They do, however, necessitate accurate equipment and large sensors, resulting in high costs and low efficiency. With the widespread adoption of digital cameras and other electronic devices in few years, automatic plantdisease diagnosis via machine learning has became an viable alternative.

Conventional machine learning techniques such as (SVM) and K-means clustering, on, typically need complicated imagepre-processing and extraction of features stages, which impair disease diagnostic efficiency. Machine learning algo's are better to identifying uniform-background plant photos collectedin a controlled laboratory environment.The dataset of grape leafs was created to provide a strong guarantee to the proposed model's generalisation capacity. To begin, diseased grape photos with homogeneous and tough backgrounds are collected not only in the labs but also from the agricultural fields to boost the resilience of CNN model. Furthermore, natural diseased grape photos are processed to provide adequate training images via data augmentation technology to face the issue of insufficient diseased grape leaf images and prevent overfitting of the CNN-based model during training .It is suggested that a GAN Leaf model be utilized to generate pictures of diseased grape leaf. The generator model is initially reconstructed usingprogressive channel layers to meet the requirements for training with large image datasets. Given its enhanced feature extraction abilities, the discriminator framework model is then optimizedwith dense connectivity and normalization techniques to differentiate between genuine and synthetic disease images.

A robust GAN based augmentation techinque model termed Leaf Generative Adversarial Networks is implemented in current paper to perform process of augmentation of data for disease detection of diseased grape leaf photos and jump the

identification model's overfitting problem. For distinct trainingmodels, the suggested data augmentation strategy can give enough and high-quality photos of grape leaf disease.The dataset generated through GAN contains 8,124 images of dieased grape leaf, is developed using the proposed data augmentation method.The most common classification modelsdemonstrate improved recognition performance when trained.The proposed paper can provide amazing solution for data augmentation process of diseased images of grape leaf andcan increase image disease detection accuracy.

## II. Literature Survey

A substantial body of literature exists on different plant and leaf and fruit Disease Identification using different techniques.Various papers are suggesting the variousimplementation ways as illustrated and discussed below.

Saleem, P., Arif, M., et al., proposed the work on DiseaseDetection and Classification of plant leaf by Deep Learning.Inthis Paper,A more efficient means of seeing disease spots inplants should be developed because it will save money byreducing the use of fungicides, pesticides, and herbicides thataren't needed. Because the severity of plant diseases varies overtime, DL models should be enhanced or adjusted to allow themto identify and categorise illnesses during their entire life cycle.Boulent J., Foucher S., et al. discuss the use of convolutional neural networks for automatically identifying diseases inplants.In their research ,recognised some of the significantconcerns and flaws in previous work that used CNNs toautomatically diagnose agricultural diseases in this publication.The research demonstrates the applicability of deep learningmethods for identifying agricultural diseases. Their findingshold a lot of promise for the development of new agriculturaltools that could help to production of food more secure and sustainable.

A. P. J and G. G. et.al.,,proposed the work based on Detection of plant leaf disease through a deep neural network with nine layers, In this study, the model obtains an average accuracy of 96.46 percent was classified in testing dataset of leaf images, with individual class accuracy ranging from 92 percent to 100 percent. The number of training epochs, batch size, and dropoutall had a **bigger** impact on the outcomes. The maximum poolingmethod outperforms the average pooling method. The proposedDeep CNN model surpasses alternative machine learning approaches in predictive accuracy and overall performance. M. A. Khan et al. suggested an automatic system for segmenting and recognizing diseases in fruit crops, utilizing correlation coefficients and deep CNN features.In this study, the researchers employed a method that combines a number of phases such as contrast stretching, illness segmentation, deep feature extraction, and classification. The main goal of contraststretching is to help the segmentation process reliably detect diseased regions by combining the correlation coefficient process with texture and color data, also H.M and M.D.

S. Zhang,et.al.,proposed the work based on TCCNN.in this paper,Instead of laborious preprocessing, lesion segmentation,and hand-crafted feature extraction, TCCNN can extract highlevel discriminant characteristics directly from the colour diseased leaf image. The developed method eliminates the needfor lesion segmentation and hand-crafted feature creation. The Experimental results displays that multi-channel CNN is both effective and practicable.

Jiang P., Y. Chen,et.al., proposed disease detection method for detecting apple leaf in real-time, utilizing a deep learning approach with enhanced convolutional neural networks.In this study, a total of 26,377 images with uniform and tough backgrounds was collected from the labs and in a real apple field and generated using data augmentation process to enhancethe model's effectiveness and the adequacy of the apple diseaseimage dataset.

K. P. Ferentinos,proposed Disease detection and diagnosis ofplant leaf based on Deep learning models.In this study, Deep learning method has showcased considerable promise in its effectiveness. therefore, it's a matter of increasing the quantityand quality of available data to improve the system and increase the count of plant species and diseases that can be identified, aswell as making it more robust in real-world conditions.

S.Wu, G. Deng,Enhancing Triple,et.al.,GAN for semisupervised conditional instance synthesis and classification.The HEMS, which contains the battery and CL, CD, EWH, EV, was explored for halfhour RO. To implement RO, three ways were investigated: CR, FLC and MILP. The proposed approach for local cost optimization of these integrated devices within HEMS may serve as a foundational step toward developing services for helping energy reserve market.

Ge, C., Gu, I. Y.-H., et al.,Enhaned training set of data by pairing it by GANs for Tumor Detection Based on Molecular Data classification.In this paper,A unique approach for the analysis of remote sensing data based on EFs in this research. An EP constituted series of thinning and thickening modifications performed to a grayscale image is proposed. Thesuggested method is capable of efficiently performing a multilevel decomposition on the image using EFs. In addition, first time in the community of remote sensing, we have incorporated a few additional properties, such as volume and height.

Z. Zhong,Gu,et.al.,Random erasing data augmentation.In this study,We saw a significant improvement in object detection and re-identification of people, suggesting that our system is capable of performing well in a variety of recognitiontasks. We want to adapt our method to other CNN recognition problems in the future, such as image retrieval, face recognition, and fine-grained categorization.

## III. PROPOSED SYSTEM

In this Deep learning techniques, and in particular Convolutional Neural Networks (CNNs), led to significant progress in image processing.Because of the lack of conformance, the trained models may have poor generalisationskills for unknown data sets and/or imaging settings, limiting their usefulness. Their findings hold a lot of promise for the development of new agricultural tools that could help to make production of food more secure and sustainable. In this ExistingSystem, it need to broaden our plant disease identification target beyond plant leaves to include other sections of the plant, suchas flowers, fruits, and stems. We also intend to investigate the training process without the use of annotated photos.

In previous paper research, a novel approach for the analysis ofremote sensing data based on EFs is provided. We want to examine the application of EP for additional types of remote sensing data and compare the efficacy of different classifiers for the categorization of EP characteristics.It was needed to beresearched how to make smart home devices appropriate for application of auxiliary services in the reference of smart grid in this article. Despite the widespread utilization of convolutional neural networks employed in field ofidentification of disease, detection of object has not been initialized on to the realtime monitoring of leaf diseases, whichis of great practical relevance for agricultural applications.

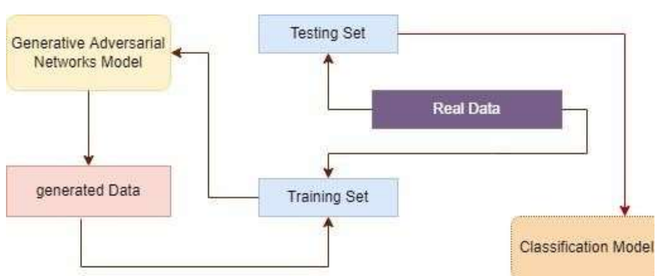
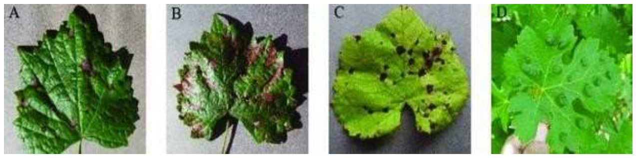



Fig. 1. Flowchart of Data Augmentation

Data augmentation process is depicted in flowchart form in Fig 1: The dataset was partitioned into testing and training datasets with ratio 9:1. For testing of classification model.The suggested data augmentation approach, which is GAN based, its expected to perform well on a different models.

### A. System Model

1. Data Acquisition process For Grape Leaf Disease images: Plant-Village provided total 4,062 photographs of grapes leavesexhibiting typical symptoms, including Black rot




images(1,180), Esca measles images(1,383,) Leaf spot images(1,076,) and healthy leaf images(423). The original collection consists of photographs of grapes leaf disease at a resolution of 256 256 pixels.

Fig. 2. Types of Diseased grape leaf. (a) Black rot (b) Esca measles (c) Leaf spot (d) Healthy

Figure 2 illustrates the key differences among the four grape leaf disease types. Grape leaves affected by disease named as Black rot display small brown lesions, appearing as spots. Escadisease is characterized by yellow or dark red streaks on the leaves, which turns necrotic and dry. Leaves with spot disease exhibit a yellowing appearance with minute black spots. Grapeleaves with a vibrant green color are considered as Healthy. Additionally, two distinct models have been developed for analyzing disease of grape leaf images: The structures of the Generator and Discriminator models are illustrated..

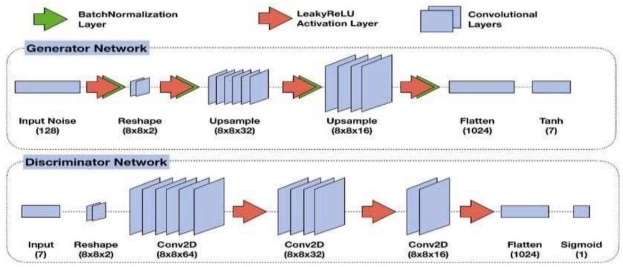



Fig. 3. Generator Discrimintor Model Architecture

The Generator Framework Analyzing Disease of Grape Leafimages:Esca measles is difficult to distinguish from Black rot measles because the spots are identical. For the model to work,it needs to be capable to generate highly distinct lesions. Maintaining equilibrium between the generator and discriminator frameworks is crucial during training to ensure the generator continuously produces distinct features.Resulting, a generated model is used that is comparable to the DCGAN. The model gives the infected RGB grape images as output with a 256x256 pixels resolution, thanks to 7 layers of deconvolution that reduce the no. of channels across layers. Aside from that, the conventional ReLU is been Activated by trial and error.A sequence of deconvolution layers make up a generator model. A 128 x1 x1 latent vector taken from an gaussian distribution is used as the model's input. First layer deconvolution reduces the input vector size to 2048x 4 x4. Thechannels is then reduced, and deconvolution is performed one by one to yield features of disease in a seamless manner. Each deconvolution layer's is halfed the number, while doubling thetensor output. Finally, the activation layer outputs the final created image.

b.The Discrimintor Model For Diseased Grape Leaf images:The lesions in photographs are unreadable features thataffect the outcomes of identification models. Discriminator model should be capable to extract the microscopic lesions effectively. Deep connectivity offers significant flexibility for utilizing the extracted features and reusing previous data. Due to one of the issues impeding the GAN's training process is the vanishing gradient of discriminator model, the deep connectivity technique is meant to help stabilise the training ofmodel. The discriminator framework is designed as a compact DenseNet to minimize memory usage and training time, whichcan be significant when training the generator and discriminator framework. The suggested discriminator framework consists oftwo blocks with sufficient layers.The overall information gained by batch normalisation will not help with picture production problems. Instance normalisation extracts data froma one image in order to preserve the instance of each image. Normalization can enhance the detection of lesions by highlighting distinct boundary and angular features.

*B. Algorithm*

1. Convolutional Neural Network (CNN) structure containstwo layers. The extraction layer connects each neuron's input to the preceding layer's local ready fields and extracts the localfeature. Once extraction of local feature is done, the positionalrelationship between them and other features will be displayed.Other is the feature map layer; each computing layer from the network takes advantage from the feature map. Every feature map is a plane, the weight of the neurons in the plane are same.The structure of feature plan uses the sigmoid function as activation function of the convolution network, which makes the feature map have shift in difference.

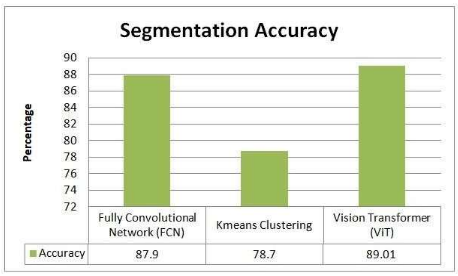
2. Fully Convolutional Network (FCN) This model has theability to process image of any size and output spatial

maps. It’s achieved by replacing fully connected layers in a conventionalCNN with convolutional layers. This helps in segmenting an entire image pixel by pixel.

## IV. Result and Discussion

The Experiments are implemented by personal computer with configuration: Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GB memory, Windows 7, MySQL 5.1 backend database and JDK 1.8. The application uses web application tool for design code in Eclipse and execute on Tomcat server.

Positive (P) : Observation is positive.
Negative (N) : Observation is not positive. True Positive (TP) :Observation is positive, and is predicted to be positive.
False Negative (FN) : Observation is positive, but is predictednegative.
True Negative (TN) : Observation is negative, and is predictedto be negative.
False Positive (FP) : Observation is negative, but is predictedpositive.
Accuracy = [TP + TN] / (Total Observation) Where Total Observation = [TP + FP + TN + FN]
Precision = TP / [TP + FP]
Recall = TP / [TP + FN]




F1-Measure = 2 * Precision * Recall / (Precision + Recall).

Fig. 4. Multi stage Segmentation Results

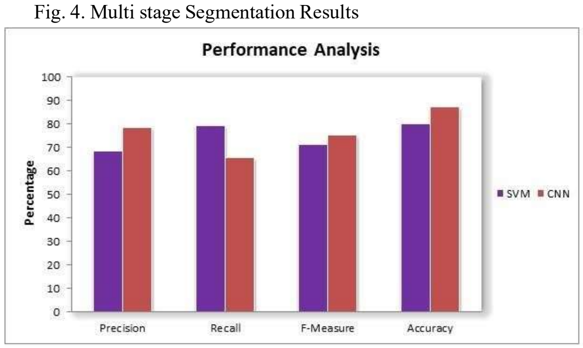
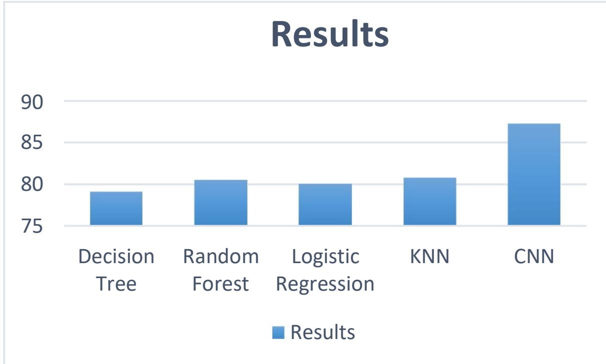



Fig. 5. Classification Results

| Algorithm | Accuracy |
|---|---|
| Decision Tree | 79.10 |
| Random Forest | 80.50 |
| Logistic Regression | 80.00 |
| K-Nearest Neighbors | 80.75 |
| Proposed System (CNN) | 87.26 |




## V. Conclusion

In this paper, we used the data augmentation process to create Generative Adversarial Networks (GAN) models for diagnosisof disease for grape leaf. The proposed model effectively generated a sufficient number of training images for detecting disease of grape leaf. By utilizing a generator with a progressively reduced number of channels, this approach produced high-quality images of diseased grape leaf with cleardisease lesions and enhanced feature utilization.As measured

by the Frechet inception´ distance evaluation criteria, the new model's average score is higher comparative to the old one. Thedataset from Leaf GAN demonstrates significantly higher overall recognition accuracy compared to traditional and otherGAN-driven augmentation techniques. Specifically, test accuracy reached an impressive average of 98.70 percent in certain cases. The retrieved results from experiment, shows thatthe suggested GAN leaf model can effectively produce a sufficient number of leaf images of grapes as output withnoticeable lesions, suggesting that it is a workable remedy for the current scarcity of training model on images for diseased grape leaf.

## References


[1] CHANGJIAN ZHOU, ZHIYAO ZHANG, SIHAN ZHOU, JINGE XING, QIUFENG WUAND JIA SONG"Identification of grape leaf spotswith limited samples using a fine-grained" IEEE Access 2021.

[2] Saleem, P., & Arif, M., "Detection and Classification of Plant Diseases Using Deep Learning Techniques," *Plants*, vol. 8, no. 11, article 468, October 2019.

[3] J. Boulent, S. Foucher, J. Theau, and P.-L. St-Charles, "Convolutional´ neural networks for the automatic identification of plant diseases," *Frontiers in Plant Science*, vol. 10, article 941, July 2019.

[4] G. G. and A. P. J., "Identification of plant leaf diseases using a nine layer deep convolutional neural network," Computer Electrical. Eng., vol. 76,pp. 323–338, Jun. 2019.

[5] M. A. Khan, T. Akram, M. Sharif, M. Awais, K. Javed, H. Ali, and T. Saba, "CCDF: An Automated System for Fruit Crop Disease Segmentation and Recognition Using Correlation Coefficient and Deep CNN Features," *Computers and Electronics in Agriculture*, vol. 155, pp.220–236, December 2018.

[6] Zhang, S., Huang, W., & Zhang, C. (2019). Utilizing Three-Channel Convolutional Neural Networks for Recognizing Diseases in Vegetable Leaves," *Cognitive Systems Research*, vol. 53, pp. 31-41

[7] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," IEEE Access, vol. 7, pp. 59069– 59080,2019.

[8] ] K. P. Ferentinos, "Deep learning models for plant disease detection anddiagnosis," Comput. Electron. Agricult., vol. 145, pp. 311–318, Feb. 2018.

[9] S. Wu, G. Deng, J. Li, R. Li, Z. Yu, and H.-S. Wong, "Enhancing Triple GAN for Semi-Supervised Conditional Instance Synthesis and Classification," presented at the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2019, pp. 10091–10100.

[10] Ge, C., Gu, I. Y.-H., Jakola, A. S., & Yang, J. (Year). Expanding trainingdatasets through pairwise GANs for classification of brain tumors based on molecular data. *IEEE Access*, vol. 8.pp. 22560–22570, 2020.

[11] Z. Zhong, L. Zheng, G. Kang, S. Li, and Y. Yang, "Random Erasing DataAugmentation," in Proceedings of the AAAI Conference on Artificial Intelligence, 2020, pp. 1–10.

[12] New Standards to Curb the Global Spread of Plant Pests and Diseases. [Online]. Available: http://www.fao.org/news/ story/en/item/1187738/icode/

[13] A. A. Bharate and M. S. Shirdhonkar, "Classification of grape leaves using KNN and SVM classifiers," in Proc. 4th Int. Conf. Comput. Methodologies Commun. (ICCMC), Erode, India, Mar. 2020, pp. 745– 749, doi: 10.1109/ICCMC48092.2020.iccmc-000139.

[14] J. Zhu, A. Wu, X. Wang, and H. Zhang, "Identification of grape diseasesusing image analysis and BP neural networks," Multimedia Tools Appl.,vol. 79, nos. 21–22, pp. 14539–14551, Jun. 2020, doi: 10.1007/s11042018-7092-0.

[15] S. M and S. V. Uma, "Adaptive machine learning approach for grape leafsegmentation," in Proc. Int. Conf. Smart Syst. Inventive Technol. (ICSSIT), Tirunelveli, India, Nov. 2019, pp. 482–487, doi: 10.1109/ICSSIT46314.2019.8987971.

[16] S. M. Jaisakthi, P. Mirunalini, D. Thenmozhi, and Vatsala, "Grape leaf disease identification using machine learning techniques," in Proc. Int.

Conf. Comput. Intell. Data Sci. (ICCIDS), Chennai, India, Feb. 2019, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/ 8862084/authorsauthors, doi: 10.1109/ICCIDS.2019.8862084.

[17] Kirti and N. Rajpal, "Black rot disease detection in grape plant (Vitisvinifera) using colour based segmentation machine learning," presentedat the 2nd International Conference on Advanced Computing,Communication, and Control Networks (ICACCCN), December 2020,pp.976-979.Availableonline.able: https://ieeexplore.ieee.org/document/9362812/authorsauthors, doi:10.1109/ICACCCN51052.2020.9362812.

[18] Sinha A. and S. Shekhawat, "Detection, quantification and analysis of neofabraea leaf spot in olive plant using image processing techniques," presented at the 5th International Conference on Signal Processing, Computing, and Control (ISPCC), October 2019

[19] Khitthuk C, Kumsawat P, Srikaew A, and K. Attakitmongcol, "Plant leafdisease diagnosis from color imagery using co-occurrence matrix and artificial intelligence system," presented at the International Electrical Engineering Congress (iEECON), March 2018, pp. 1-4. DOI: 10.1109/IEECON.2018.8712277.

[20] X. Zhao, H. Shao, X., Z. He and X. Zhong, "Ensemble transfer CNNs driven by multi-channel signals for fault diagnosis of rotating machinerycross working conditions," published in *Knowledge-Based Systems*, vol. 207, November 2020, Article 106396. DOI: 10.1016/j.knosys.2020.106396.

[21] C. Zhou, J. Song, S. Zhou, Z. Zhang, and J. Xing, "COVID-19 detectionbased on image regrouping and resnet-SVM using chest X-ray images," IEEE Access, vol. 9, pp. 81902–81912, 2021, doi: 10.1109/ACCESS.2021.3086229.

[22] X. Xie, Y. Ma, B. Liu, J. He, S. Li, and H. Wang, "A deep-learningbasedreal-time detector for grape leaf diseases using improved convolutional neural networks," Frontiers in Plant Science*, vol. 11, article 941, Jun 2020*, doi: 10.3389/fpls.2020.00751.

[23] K. Thet, K. Htwe, and M. Thein, "Grape leaf diseases classification usingconvolutional neural network," in Proc. Int. Conf. Adv. Inf. Technol. (ICAIT), 2020, pp. 147–152, doi: 10.1109/ICAIT51105.2020.9261801.

[24] B. Liu, C. Tan, S. Li, J. He, and H. Wang, "A data augmentation methodbased on generative adversarial networks for grape leaf disease identification," IEEE Access, vol. 8, pp. 102188–102198, 2020, doi: 10.1109/access.2020.2998839

[25] X. Liu, W. Min, S. Mei, L. Wang, and S. Jiang, "Plant disease recognition: A large-scale benchmark dataset and a visual region and loss reweightingapproach," IEEE Trans. Image Process., vol. 30, pp. 2003–2015, 2021, doi: 10.1109/TIP.2021.3049334.

[26] L. Kouhalvandi, E. O. Gunes, and S. Ozoguz, "Algorithms for speedingup the deep neural networks for detecting plant disease," in Proc. 8th Int. Conf. Agro-Geoinformat. (Agro-Geoinformat.), Jul. 2019, pp. 1–4, doi: 10.1109/Agro-Geoinformatics.2019.8820541.

[27] S. S. Chouhan, A. Kaul, U. P. Singh, and S. Jain, "Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology," IEEE Access, vol. 6, pp. 8852–8863,2018, doi: 10.1109/ACCESS.2018.2800685.

[28] M. Chanda and M. Biswas, "Plant disease identification and classification using back-propagation neural network with particle swarm optimization," in Proc. 3rd Int. Conf. Trends Electron. Informat. (ICOEI), Apr. 2019, pp. 1029–1036, doi: 10.1109/ICOEI.2019.8862552.

[29] C. Senthilkumar and M. Kamarasan, "Optimal segmentation with backpropagation neural network (BPNN) based citrus leaf disease diagnosis," in Proc. Int. Conf. Smart Syst. Inventive Technol. (ICSSIT), Nov. 2019, pp. 78–82, doi: 10.1109/ICSSIT46314.2019.8987749.

[30] A. Forster, J. Behley, J. Behmann, and R. Roscher, "Hyperspectral plant disease forecasting using generative adversarial networks," in Proc. IEEEInt. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2019, pp. 1793–1796, doi: 10.1109/IGARSS.2019.8898749.

[31] S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant leaf detection and disease recognition using deep learning," in Proc. IEEE Eurasia Conf. IoT, Commun. Eng. (ECICE), Oct. 2019, pp. 579–582, doi: 10.1109/ECICE47484.2019.8942686