Tomato Leaf Disease Detection Using Convolution Neural Network

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***Abstract*—The quality and quantity of the crop are significantly affected by numerous diseases in plants. In this regard, an early detection of such diseases is highly effective. Tomato is one of the important crops that is produced in large quantities with high commercial value. Several types of tomato diseases affect the crop at an alarming rate. In this paper, we deployed two Convolution Neural Network (CNN) based models i.e. GoogLeNet and VGG16 for tomato leaf disease classification. The proposed work aims to find the best solution to the problem of tomato leaf disease detection using a deep learning approach. VGG16 obtained 98% accuracy while GoogLeNet obtained 99.23% on Plant Village dataset containing 10735 leaf images. The proposed system can be used in tomato fields for early detection of disease to avoid production loss.**

Keywords—Tomato Disease; Deep Features; Image Processing; Late and Early Blight; Bacterial Spot.

I. Introduction

Plant diseases are cause of significant crop destruction which is detrimental to the economy. The plant diseases are not only harmful to humans but also for animals. According to an estimate, about 40% of the crops are lost due to the diseases in plants [1]. In agricultural countries, most of the population depends upon the agricultural sector, therefore, disease detection in plants plays an indispensable role in boosting the economy by expanding the crop yield. According to a report by the Food and Agriculture Organization (FAO), it is estimated that the population of the whole world will approximately increase up to 9 billion in a few years. However, the production within the agricultural sector needs to be increased to at least 70% in order to satisfy the food demands of human beings [2]. The pathogens can also affect the plants and cause destruction to crops, so early-stage disease detection is important to help scale back economic loss.

Farmers from poor countries usually observe their plants through naked eye which is time consuming and inefficient. Such inspection is ineffective for diseases having similar patterns. But from the last decade, new techniques for disease detection are introduced that not only minimize the error rate but are being used commercially. Capturing the leaf images and identifying diseases is considered to be one of the attractive solutions to sight diseases. The leaf images are analyzed using computer vision or image processing techniques. Last two decades witness the extensive use of Deep Learning (DL) applications in agriculture sector. Artificial Intelligence (AI) and Machine Learning (ML) can help in analysis and diagnosis of plant diseases [3]. Developing an image processing solution, one must remember that in fields plant leaf images usually contains noise which causes poor segmentation, poor feature extraction and then poor overall performance of the system. Due to incorrect analysis and diagnosis, farmers either uproot the plants or excessively use pesticides that badly affect the health of plants. The rest of the paper is organized as follows: Section I presents the related work. Proposed method is presented in Section II. Experimental results are explained in Section III, and Conclusion in Section IV.

II. Literature Review

Several computer vision-based plant disease identification methods are summarized in this section.

In [3], the authors proposed a method that detects grapevine yellows in grapes on datasets from GitHub and Plant Village. The method employs Otsu Threshold for segmentation whereas automatic features were extracted using CNN. The proposed system implemented six neural network architectures i.e. ResNet-101, ResNet-50, Alex Net, Squeeze Net, GoogLeNet, and Inception V3. The system obtained 98.96% sensitivity and 99.40% specificity through deep learning. In another study [4], proposed a crop disease detection system to detect different diseases like Downey mildew, Powdery mildew, and Black rot. The system employs segmentation through the Grab cut Algorithm and obtained 95% overall accuracy.

In [5], the authors designed a neural-network-based system to detect plant diseases like bacterial speck, target spot, late blight, early blight, mosaic virus, and Septoria leaf spot. The proposed model employed a three-channel convolution neural network and achieved a total accuracy of 89.29%. [6] proposed an automatic system to detect diseases in cucumber leaves. The system uses K-Means clustering based segmentation and obtained 85.70% accuracy. The authors in [7] proposed a CNN-based system to authors identify maize diseases through DL models like GoogLeNet and Cifar10 achieved 98.90% overall accuracy. The authors in [8], presented a plant disease detection system to detect fungal rust in pea plants.

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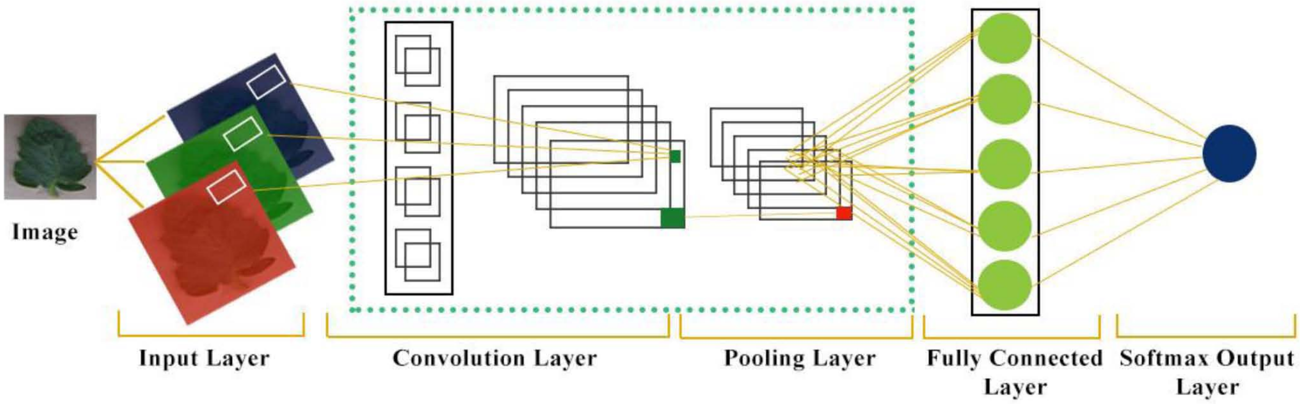


Fig. 1. Deep Neural Network Architecture

The images were segmented using the binary threshold and SVM for classification. The system obtained an overall accuracy of 89.60%.

In studies [9, 10], the authors presented a DL based plant disease detection system. [9] obtained 95.60% accuracy using GoogLeNet and 93.60% using AlexNet. Whereas [10] achieved an accuracy of 98.02%, 81.92%, 99.99%, 100% using Inception V4, VGG, ResNet, DenseNet on Plant Village dataset respectively. The authors in [11-13], gave an idea of a neural network based plant disease identification system. The accuracy obtained by [11] was 97.59%. The authors in [13] obtained 88.00% accuracy using VGG16. [14] presented a system to detect Cercospora Leaf spot in sugar beet. SVM was used for classification and the system achieved 87.00% accuracy. The authors in [15] presented a plant disease detection system. Shape and texture features were extracted before classification. The classification of diseases is done using the minimum distance criterion using K-mean clustering and SVM. The system achieved accuracy between 86.54% to 95.71%.

The studies [16, 17] presented plant disease detection and classification systems. The authors in [16] detected leaf spot diseases in cotton and obtained 97.10% accuracy. Whereas [17] AlexNet, GoogLeNet, and VGG16 to detect diseases in apple leaves. The authors in [18] presented a deep learning-based plant disease severity estimation system. The system focuses on estimating the severity of disease in apple leaves. VGG16 achieved the best accuracy of 90.40%. The details of some existing systems are shown in Table 1.

III. MATERIALS AND METHODS

A typical CNN consists of an input layer, various hidden layers, and a classification layer. CNNs include hidden layers like convolution layers, pooling layers, fully connected layers etc. The structure of the deep neural network is presented in Fig. 1. The proposed system employs CNN models like GoogLeNet and VGG16 to detect diseases in plants using the Plant-Village dataset.

TABLE I. DETAILS OF SOME EXISTING PLANT DISEASE DETECTION SYSTEMS

Ref	Crop Culture	Focused Disease	Classifiers	Acc %
[3]	Grapes	Grapevine Yellows	SoftMax	96.3
[4]	vine leaves	Downey mildew, Powdery Mildew and Black Rot	One Class SVM	95.0
[5]	Tomato	Powdery Mildew, Gray Mold, Downey, Early & Late Blight	SoftMax	89.2
[6]	Cucumber	Powdery Mildew, Gray Mold, Downey, Anthracnose	SVM, NN	85.7
[11]	Wheat	Leaf Blotch, Powdery Mildew, Stripe Rust, Leaf Rust, Black Chaff	SoftMax	89.0
[13]	Tomato	Tomato Late & Early Blight, Leaf Curl Virus, Bacterial Spot, Target spot, Gray spot	SoftMax, SVM	89.0
[17]	Apple	Mosaic Rust, Brown & Alternaria Leaf Spot	SoftMax	97.6
[19]	Tomato	Leaf & Gray Mold, Canker, Miner, Powdery Mildew	SoftMax	83.0
[20]	Tea leaf	Tea red scab, tea red leaf spot and tea leaf blight	SVM	90.0

TABLE II. SAMPLE LEAF IMAGES FROM PLANT VILLAGE DATASET

Disease	Disease Number of Samples
Bacterial Spot	3398
Late Blight	3476
Early Blight	2034
Healthy Leaves	1827
Total Images	10735

A. Dataset

The proposed model is trained and assessed using the state-of-art Plant Village dataset [21]. The dataset is composed of a total of 10735 images of tomato leaves. The image distribution is presented in Table II. The dataset is divided into training and testing sets. The training set comprises of 70% of total images where the testing set contains 30% images of the total.

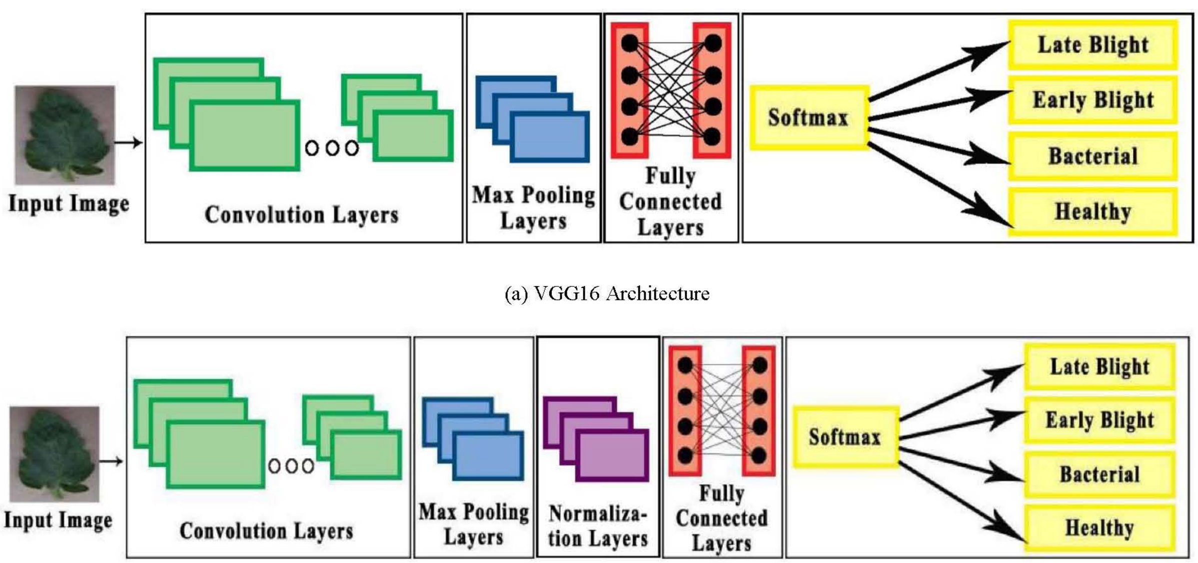
B. Image Pre Processing

The dataset is composed of RGB images of various sizes. Before feeding the leaf images into the CNN, two preprocessing steps are performed. First, the images are resized in order to match the size of the input layer of CNN. The sizes are standard for architecture to architecture, here the images are resized to 225x225. Secondly, images are denoised using Gaussian Blur Filter. Fig. 2 shows sample images denoised using Gaussian blur filter.

Fig. 2. Preprocessed Sample Images (a) Bacterial Spot (b) Late Blight (c) Early Blight (d) Healthy

C. Transfer Learning

Transfer learning is the improvement of learning new knowledge from the source task that has already been learned. Usually in transfer learning the algorithm is already trained with sufficient data samples, so the model is retrained with another dataset. The CNN architecture is composed of multiple layers and every layer performs a specific task like segmentation, feature extraction, edge detection, etc. Fig. 3a shows the VGG16 architecture that consists of Convolution layers, Max-pooling layers, ReLU activation function, Fully connected layers, and Softmax layer and Fig. 3b shows the GoogLeNet architecture.



(a) VGG16 Architecture

(b) GoogLeNet Architecture

Fig. 3.VGG16 Architecture V/S GoogLeNet Architecture

There are many state-of-the-art deep learning frameworks in Python and Matlab. For this research, CNN frameworks from Matlab were used, along with the weights learned on ImageNet dataset. The convolution layer is an essential building block of CNN. This layer generates feature maps by using filters called convolution filters. The image pixels are convoluted with the filters by dot product between kernel pixels and image pixels. In VGG16 kernel size of 3x3 is applied and K=64, 128, 256, 512 where K is the number of filters. Whereas in GoogLeNet architecture the kernel size of 1x1, 3x3, 5x5 and 7x7 is applied. Each convolution layer is followed by ReLU activation function. CNN with ReLUs train many times faster than with any other activation function. ReLU is defined in Eq. 1.

$$f(x) = \max(0, Z^x) \quad (1)$$

where x is the input to the activation function f on the x^{th} channel.

The layer that follows the Convolution Layer is a Pooling layer. In this layer the output obtained by the convolution layer is in fact input for the pooling layer. This layer reduces the size of the images. In max-pooling max filter is applied to non-overlapping sub-regions in the image. VGG16 uses pooling layer of kernel size 2x2. Whereas pooling layer of size 3x3 is applied in GoogLeNet.

Fully connected layer contains feature vectors extracted from previous layers. These vectors are essential for image classification. VGG16 contains three FC layers and the first two FC layers contain 4096 channels whereas the last layer contains 1000 channels and GoogLeNet contains one FC layer with 1000 channels.

The output layer makes use of the feature vectors from the fully-connected layer to classify the images into their predefined categories. For training a CNN, data is split into train and test set, then the model is trained using training set and new instances are predicted using the test set that determine the accuracy of the model. . In our proposed method images were smoothened using Gaussian Blur filter and then supplied to the CNN models for disease classification. The deep feature vector from the CNN models was also supplied to multiple classifiers for system evaluation. For evaluating the predictive model, 5-fold cross validation technique was used.

IV. Results and Discussion

A. Evaluation Metrics

The efficiency of the algorithm is evaluated using Specificity, Sensitivity, Precision, F1-score and MCC.

Sensitivity (SEN) also called true positive rate or recall, is calculated in Eq. 2 where TP is number of True Positives and FN is number of False Negatives. Specificity (SPE) is calculated in Eq. 3 here TN is a number of True Negatives and FP is the number of False Positives. Precision (PRE) is the ratio of the total number of TP and a total number of predicted positives as shown in Eq. 4. F1-Score seeks a balance between precision and recall. It is calculated in Eq. 5. Mathews Correlation Coefficient (MCC) measures the quality of binary classification. It is calculated using Eq 6.

$$Recal\ Rate = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \quad (2)$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN + FP}} \quad (3)$$

$$Precision\ Rate = \frac{TP}{TP + FP} \quad (4)$$

$$F1\text{-}Score = 2 * \frac{(Precision * Recall)}{Precision + Recall} \quad (5)$$

$$MCC = \frac{(TP*TN) - (FP*FN)}{[(TP+FP)*(FN+TN)*(FP+TN)*(TP+FN)]} \quad (6)$$

B. Results

In our proposed method, two different transfer learning models i.e. VGG16 and GoogLeNet are trained on Plant-Village dataset. Then the deep feature vector is supplied to other classifiers like Cubic SVM, Ensemble Bagged Tree, Fine KNN and Medium Gaussian SVM. The accuracy of the proposed method employing GoogLeNet is 99.23% whereas the accuracy percentage obtained through VGG16 is 98.00%. Table III shows performance of the plant disease classification method employing GoogLeNet. Different performance evaluation metrics like TP, TN, FP, FN and ACC are calculated. Whereas Fig. 4 graphically presents the PRE, F1-Score, MCC, SEN and SPE. The results clearly depict that all the classifiers performed better except Cubic SVM in terms of the different evaluation metrics.

The results of VGG16 as well as other classifiers i.e. Cubic SVM, Ensemble Bagged Tree, Fine KNN and Medium Gaussian SVM are depicted in Table IV measured through different performance metrics. Fig. 5 depicts PRE, F1-Score, MCC, SEN and SPE obtained through VGG16 and other classifiers. It is visible that CSVM and Medium Gaussian SVM achieved better results as compared to Fine KNN and Ensemble Bagged Tree. Result wise comparison of the proposed system with existing techniques is presented in Table V, which shows that proposed method outperforms the existing techniques in term of classification accuracy.

TABLE III. Performance evaluation using GoogLeNet

	TP	TN	FP	FN	ACC %
GoogLeNet	3219	9728	25	25	99.2
Cubic SVM	7000	19669	572	572	92.4
Ensemble Bagged Tree	7569	22713	3	3	99.9
Fine KNN	7568	24042	4	4	99.9
Medium Gaussian SVM	7546	22701	8	7	99.9

TABLE IV. Performance evaluation using VGG16

	TP	TN	FP	FN	ACC %
VGG16	3256	9612	44	64	98.0
Cubic SVM	7369	22369	128	164	98.1
Ensemble Bagged Tree	7169	22390	446	446	94.1
Fine KNN	7033	22062	480	482	93.8
Medium Gaussian SVM	7340	21570	175	175	97.8

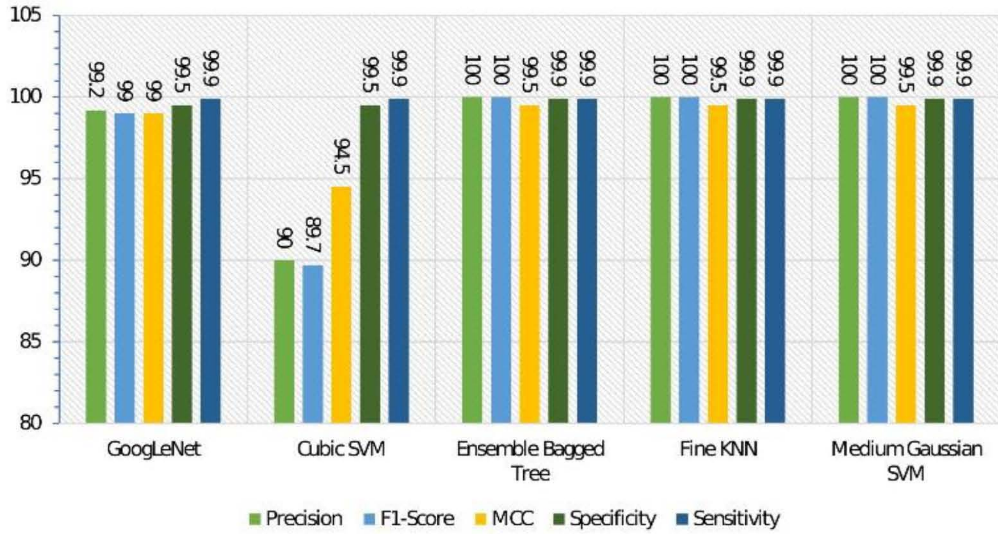


Fig. 4. Precision, F1-Score, MCC, Sensitivity, Specificity using GoogLeNet

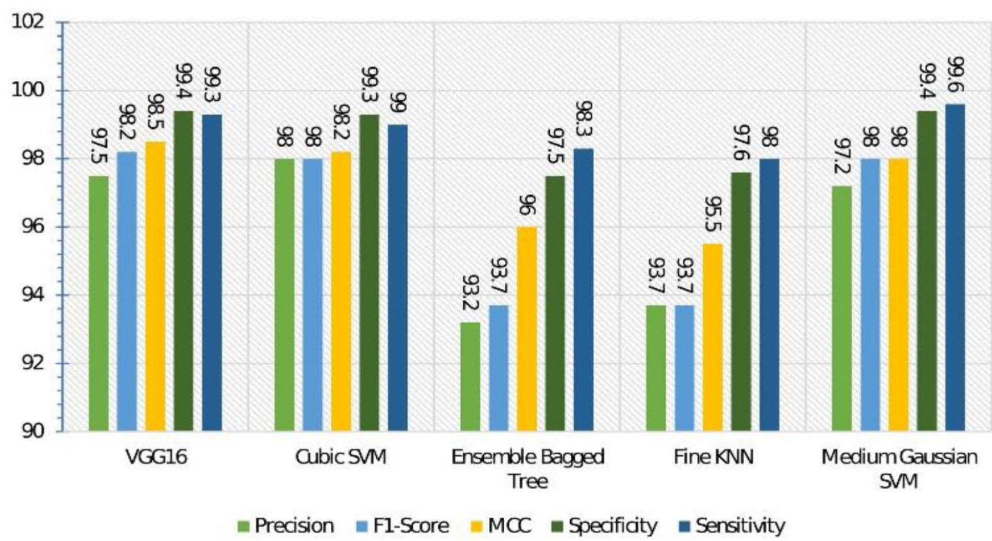


Fig. 5. Precision, F1-Score, MCC, Sensitivity, Specificity using VGG16

TABLE VI. Performance evaluation using VGG16

GoogLeNet			**VGG16**		
Ref	**Year**	**Acc %**	**Ref**	**Year**	**Acc %**
[3]	2019	96.3	[10]	2018	81.9
[7]	2018	90.1	[11]	2017	93.2
[9]	2016	98.2	[13]	2017	89.0
[22]	2017	97.7	[18]	2017	90.4
[23]	2018	96.6	[19]	2017	83.0
[24]	2019	96.6	[20]	2019	90
Proposed method	2020	99.2	**Proposed method**	2020	98.0

V. Conclusion

Computer vision based systems are being widely employed in different agricultural sectors. These systems can help in automating laborious tasks to produce adequate data for future analysis. In our proposed method two deep learning models i.e. VGG16 and GoogLeNet are employed to classify diseases in tomato leaf images. VGG-16, achieved a success rate of 98.00%. Whereas, GoogLeNet achieved 99.23% accuracy. It is evident from the results that the CNN is highly suitable for the automated detection of plant diseases.

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References

[1] L. Han, M. S. Haleem, and M. Taylor, "A novel computer vision-based approach to automatic detection and severity assessment of crop diseases," in *2015 Science and Information Conference (SAI)*, 2015, pp. 638-644.

[2] FAO, "Declaration of the world summit on food security," ed: World Summit on Food Security Rome, 2009, pp. 1-7.

[3] A. Cruz, Y. Ampatzidis, R. Pierro, A. Materazzi, A. Panattoni, L. De Bellis, *et al.*, "Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence," *Computers and electronics in agriculture,* vol. 157, pp. 63-76, 2019.

[4] X. E. Pantazi, D. Moshou, and A. A. Tamouridou, "Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers," *Computers and electronics in agriculture,* vol. 156, pp. 96-104, 2019.

[5] S. Zhang, W. Huang, and C. Zhang, "Three-channel convolutional neural networks for vegetable leaf disease recognition," *Cognitive Systems Research,* vol. 53, pp. 31-41, 2019.

[6] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," *Computers and electronics in agriculture,* vol. 134, pp. 135-141, 2017.

[7] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identification of maize leaf diseases using improved deep convolutional neural networks," *IEEE Access,* vol. 6, pp. 30370-30377, 2018.

[8] K. Singh, S. Kumar, and P. Kaur, "Support vector machine classifier based detection of fungal rust disease in Pea Plant (Pisam sativam)," *International Journal of Information Technology,* vol. 11, pp. 485-492, 2019.

[9] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in plant science,* vol. 7, p. 1419, 2016.

[10] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture,* vol. 161, pp. 272-279, 2019.

[11] J. Lu, J. Hu, G. Zhao, F. Mei, and C. Zhang, "An in-field automatic wheat disease diagnosis system," *Computers and electronics in agriculture,* vol. 142, pp. 369-379, 2017.

[12] H. Durmuş, E. O. Güneş, and M. Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning," in *2017 6th International Conference on Agro-Geoinformatics*, 2017, pp. 1-5.

[13] J. Shijie, J. Peiyi, and H. Siping, "Automatic detection of tomato diseases and pests based on leaf images," in *2017 Chinese Automation Congress (CAC)*, 2017, pp. 2537-2510.

[14] R. Zhou, S. i. Kaneko, F. Tanaka, M. Kayamori, and M. Shimizu, "Disease detection of Cercospora Leaf Spot in sugar beet by robust template matching," *Computers and electronics in agriculture,* vol. 108, pp. 58-70, 2014.

[15] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Information processing in Agriculture,* vol. 4, pp. 41-49, 2017.

[16] P. Revathi and M. Hemalatha, "Classification of cotton leaf spot diseases using image processing edge detection techniques," in *2012 International Conference on Emerging Trends in Science, Engineering and Technology (INCOSET)*, 2012, pp. 169-173.

[17] B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," *Symmetry,* vol. 10, p. 11, 2018.

[18] G. Wang, Y. Sun, and J. Wang, "Automatic image-based plant disease severity estimation using deep learning," *Computational intelligence and neuroscience,* vol. 2017, 2017.

[19] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors,* vol. 17, p. 2022, 2017.

[20] G. Hu, H. Wu, Y. Zhang, and M. Wan, "A low shot learning method for tea leaf's disease identification," *Computers and Electronics in Agriculture,* vol. 163, p. 104852, 2019.

[21] D. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," *arXiv preprint arXiv:1511.08060,* 2015.

[22] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," *Applied Artificial Intelligence,* vol. 31, pp. 299-315, 2017.

[23] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture,* vol. 145, pp. 311-318, 2018.

[24] Y. Li, H. Wang, L. M. Dang, A. Sadeghi-Niaraki, and H. Moon, "Crop pest recognition in natural scenes using convolutional neural networks," *Computers and Electronics in Agriculture,* vol. 169, p. 105174, 2020.