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A Review of Plant Disease Prediction Methods for Agricultural Applications

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***Abstract:** Due to the decrease in plant quality and productivity, plant diseases seem to be responsible for significant economic losses in the world. As a result, farmers nowadays consider plant disease prediction to be an important area of research. To help an accurate prediction of plant disease, numerous techniques have been detailed in the literature. To highlight the many issues with current approaches for problem-solving predictions, we will evaluate various literary works that are focused on plant disease prediction in the agricultural industry. Based on several variables, including different datasets, year of publication and journals, performance metrics, and other considerations, the analyses of various approaches are enhanced in this case, and include the advantages and disadvantages based on the analysis of the methods. Finally, the paper concludes by discussing future research areas and difficulties in improving prediction performance for the plant disease prediction techniques used in the growing agricultural process.*

***Keywords:** Plant Disease Prediction, Agricultural Application.*

I. INTRODUCTION

Agriculture production is extremely important to India's economy. When plant diseases are not identified on time, food insecurity increases because they have a significant negative influence on agricultural production. [1] [2]. As a result, it is critical to detect plant illnesses. Malignant viruses, bacteria, and fungi cause these plant diseases. If correct treatment is not given on time, the crop may suffer [3]. To minimize the occurrence of illnesses, increase productivity, and maintain agricultural sustainability, enhanced disease detection is required to prevent crop damage. As a result, researchers are very interested in predicting plant illnesses and preventing them. Early disease detection and control strategies can assist farmers in saving their crops. These measures include ways of detecting diseases that are either direct or indirect. Laboratory-based techniques are the most common direct detection methods, while hyperspectral, fluorescence imaging and optical sensors for thermography techniques are used in indirect detection methods [4] [5] [4]. Specifically, determining which traits are ideal and resilient for disease detection from the many extracted features is difficult.

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Furthermore, most approaches fail to successfully separate the leaf and accompanying lesion picture from its backdrop under complicated background settings, resulting in unsatisfactory disease recognition results [2].

A generalized architecture of plant disease detection, starting with a review of numerous diseases in plants and plant pathology section). The computational complexity and accuracy of illness detection systems are largely determined by feature extraction, feature descriptor selection, and feature selection. The feature descriptors algorithm is defined as the extraction of feature vectors from the image of a plant leaf [6]. The techniques that have been used by several researchers are image processing, K-means clustering, radial basis function (RBF), and support vector machine (SVM) classifier. Deep learning approaches such as convolutional neural networks are gaining popularity and attention in the scientific community these days [7]. Plant disease prediction models have been built using a variety of prediction methodologies, including support vector machine (SVM), generalized regression neural network (GRNN), and traditional multiple regression (REG) [8] [9]. In Plant disease classification grape and wheat illness has been identified using probabilistic neural networks (PNNs), and GRNNs [10]. Based on high-resolution multispectral stereo images, pixel-wise classification using K nearest neighbor classifiers (KNN) has been utilized to categorize leaf diseases automatically. [11]. Plant disease recognition utilizing multiple illness symptoms is also done using models like the multi-layered perceptron model (MLP) for real-time visual diagnosis [12]. Partial least square regression (PLSR) and Multivariate linear regression (MLR) are two more approaches for estimating the severity of plant disease using hyperspectral data [13] [4].

This research paper mentions the survey of the actual research papers which is included in the prediction of numerous crops and prediction of various diseases which affects the growth in agricultural application. In this survey, various existing researchers' absorption is depending on analyzing the prediction along with different segmentation methods and put forward innumerable limitations of the conventional techniques for prediction issues. The estimation of numerous conventional methods utilized a variety of elements, including performance measures, various segmentation method achievements, year of publication and disease detection, and so on.

The article is structured as follows: Section 2 provides a comprehensive examination of the reviews. Section 3 of this article examines and discusses the prediction of plant disease in relation to agriculture.

The difficulties and constraints of research are discussed in Section 4. The paper concludes with a summary in section 5.

II. RELATED WORKS

The review of the conventional methods enumerated in this section is as follows. Manish Kumar *et al.* [4] presented a machine learning model which includes soil and environmental monitoring sensors. The datasets involve various features splitting them into trained and testing data based on this the neural network is trained. By utilizing the cost-effective sensors and neural network models the different types of plant diseases are easily detected although the sensors are in a limited manner.

Junde Chen *et al.* [2] used transfer learning in the deep convolutional neural network for plant disease identification. It achieves high accuracy although in complicated background conditions. When the epochs are increased, the training loss of the utilized approach is very low than other conventional approaches. Mobile devices and computer-aided diagnosis are examples of real-time applications where it is not suitable.

Koushik Nagasubramanian *et al.* [14] applied explainable deep learning in the hyperspectral images, which makes the network more suitable for plant disease identification. The applied network involves feature extraction and classification using a pre-trained module and extended layers. The specific hyperspectral wavelengths differentiate the disease affected and the healthy stem though they consider only a smaller dataset.

Konstantinos P. Ferentinos [15] utilized a model for the prediction of accurate disease in plants using a convolutional neural network and a deep learning network to diagnose simple healthy and disease-affected leaves. The performance of success rates for classification varies, in field conditions, it achieves better success rates, and solely the success rate is quite low.

Aditya Khamparia*et al.* [7] integrated both auto encoder and CNN to develop a deep convolutional neural network named as convolutional encoder network. To collect the characteristics from the input photos, many layers were used. This hybrid network is utilized to classify and estimate plant diseases in addition to the computer vision method and the developed model is fine-tuned using such hyper parameters. There is a limitation in the dataset relying upon the hardware.

Punam Bedi and Pushkar Gole [16] presented a hybridized model for automatic plant disease identification using a convolutional auto encoder and convolutional neural network. Firstly, CNN extracts different features from the raw images and its major role is to classify the images also plays a prominent role in computer vision tasks. Utilizes a greater number of training parameters which slightly reduces the accuracy of the conventional methods.

Parminder Kaur *et al.* [3] introduced a fractional order Zernike moment accompanied by SVM to easily diagnose plant diseases. Without affecting the prediction accuracy, it reduces the time complexity, and later than preprocessing the FZM images are commutated. Then the training matrix for SVM is extracted and used as training data. In the comparison analysis, the acquired accuracy is lower than the conventional methods.

Ang Wu *et al.* [17] utilized an automatic disease detection system that depends on BP neural network and Wavelet Wiener filtering method. In the image extraction process, the disease-affected region is isolated from the sample leaf image for classification and segmentation by an otsu method. The Prewitt operator performs better to analyze the horizontal and vertical edges in an image. The images are interrupted by noise and irregular lighting exists in experimentation.

S. Hernandez and Juan L. Lopez [18] employed a Bayesian deep learning probabilistic programming method to predict plant illness. The developed model achieves a better classification performance which is utilized for fine-tuning the developed deep learning model. It evaluates diagnostic problems in the posterior density and predicts the unreliability in out-of-sample where sometimes there happens misclassification.

Chen Jun-De *et al.* [19] developed a classification and automatic detection-based technique for plant disease in leaves. A prediction model is based on image processing which involves feature engineering inspection, where the comparative methods are performed using the features handled by the group method data handling-logistic model. In the initial testing time, the recall rate is very low compared to other existing techniques.

Yafeng Zhao *et al.* [20] utilized a double generative adversarial network to balance the unhealthy datasets and produce high-resolution images, super-resolution generative adversarial and Wasserstein networks performed separate training. Pertaining helps to reduce the error in a second between the raw and the obtained image. Subsequently in the DoubleGAN expansion obtained average accuracy is low.

A. Umamageswari*et al.* [21] developed a deep learning model which includes preprocessing, classification, feature extraction, and segmentation. Both the segmentation and classification of plant disease are done by fuzzy-based progressive neural architecture search and chameleon swarm algorithm. Computational time is high in Progressive neural architecture search.

Kamal KC *et al.* [22] proposed a model for detecting plant diseases that involve depth wise separable convolution architecture. For accurate detection, a variety of deep learning techniques are applied, in which the MobileNet outperforms the other conventional methods. Time consumption is high when it is implemented in a large number of databases.

E. Vamsidhar*et al.* [23] developed a K-means clustering based on the segmentation technique for the classification and detection of various plant diseases. The data is trained using the obtained features, and several classification techniques are utilized to diagnose conditions. The K-means clustering technique for segmentation achieves low accuracy compared to the SVM classifier.

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Anakha Krishnakumar and Athi Narayanan [24] developed an approach to provide the severity measures by classifying the variety of diseases caused by the plant cucumber using the technique called image processing. The major concern is based on disease-affected regions and classification using segmentation and image preprocessing. The prediction is accurate though the preventive measure is not implanted at a suitable time.

M. S. Mustafa *et al.* [25] introduced a hybridized-based model for predicting and recognizing the possibility of disease occurring earlier. It combines the characteristic of the NB classifier, PNN, and SVM with FIS for species recognition. For early disease recognition, both the feature extraction and processing method are significant. The combination of several classifiers spends some more computational time than the solo classifier.

Shiv Ram Dubey and Anand Singh Jalal [26] introduced an image processing related method that involves various steps are segmentation, feature extraction, combining the extracted features, and last training in addition the classification is performed using MSVM. The disease can be recognized and classified based on image processing methods. For severe diseases, the obtained accuracy is low compared to the normal class.

Umit Atila*et al.* [27] developed a deep learning-based architecture called Efficient Net for plant disease classification and it involves image processing and pattern recognition. Using the transfer learning method the deep learning models and Efficient Net architecture are trained. For the original database, the acquired precision rate is less than the augmentation database.

SayleeGharge and Priyanka Singh[28] introduced an algorithm for the classification and detection of plant diseases using an image enhancement technique. The methods involve preprocessing, cluster selection, classification, and disease estimator. Neural networks are used for classification and K-means are used for segmentation. A limited number of diseases is considered for the classification of diseases.

Vaibhav Tiwari *et al.* [29] demonstrated a deep learning-based method for detecting and classifying plant diseases using images captured at various resolutions. The utilized model achieves high accuracy to classify the various types of plant leaf diseases efficiently. Fewer classes than those involved in the prediction of existing diseases affect plant leaves. K. Thaiyalnayaki and Christeena Joseph [30] used an SVM and deep learning algorithms for soybeans disease classification in which the datasets are classified using an SVM classifier. The accuracy of the deep learning classifier is increased by optimizing the layers in the architecture. Misclassification highly occurs in the initially adopted classifier. Kemal Adem and Mehmet Metin Ozguven[31] combined a region proposal network with the CNN-dependent classifier, named the faster R-CNN model. Using the collected images determines the disease's severity, and modifications to CNN also show which speed up the Faster R-CNN model's performance. Several datasets are still required to enhance prediction accuracy.

S. Ashwinkumar*et al.* [32] introduced an optimal mobile network-based convolutional neural network that automatically detects and classifies plant leaf diseases. It involves classification; feature extraction, segmentation, and preprocessingto enhance the performance of the OMNCNN model. Image segmentation methods are incorporated to further improve the efficiency of disease prediction.

S. Nandhini and K. Ashok kumar [33] classified the different diseases in plant leaves using a CNN-based method. Using the Improved Crossover-based Monarch Butterfly Optimization (ICRMBO) technique, a binary solution encoding scheme is used to minimize the complexity of CNN. It helps the information extraction and automatic disease classification from images. The model is to be enhanced along with its severity level for various diseases in a variety of crops.

K. Deeba and B. Amutha [34] developed a deep learning-based disease classification and identification in vegetable leaves. For testing and training, public datasets and real-time data are gathered from the varying agricultural field where the resulting accuracy for real-time data is low. It still does not improves the preprocessing techniques for the accuracy of real-time applications.

III. DISCUSSION AND ANALYSIS

The results of the analysis show the significance of plant disease prediction in agricultural applications after evaluating the overview of tools, metrics including methods utilized in the research articles.

A. Analysis based on achievements of segmentation methods

Table 1 delineates the analysis of the research papers and the achievements under the segmentation methods utilized for the prediction of plant disease in the agricultural process. The existing studies frequently used neural networks, Otsu segmentation, FCMCSA, K-means clustering, and Kapur's thresholding. The most popular dataset for use with the various plant disease prediction techniques is K-means clustering. Among the 25 papers, 4 papers utilize K-means clustering segmentation. Figure 2 illustrates the chart based on the analysis of the different segmentation methods for plant disease prediction.

Table 1: Prediction of Plant Diseases by Analysis Based on Various Segmentation Techniques

Segmentation Method	Research paper	Metrics used
Neural Network	[4]	Accuracy
Otsu segmentation	[17]	Accuracy
FCM-CSA	[21]	Accuracy
FCM-CSA	[21	Sensitivity
FCM-CSA	[21	Specificity
FCM-CSA	[21	Precision
K-means clustering	[23], [26], [28]	Accuracy
K-means clustering	[23]	Precision
K-means clustering	[23]	Recall
K-means clustering	[23]	F-measure
K-means clustering	[24]	Severity
Kapur's thresholding	[32]	Accuracy
Kapur's thresholding	[32]	Precision
Kapur's thresholding	[32]	Recall
Kapur's thresholding	[32]	F-score

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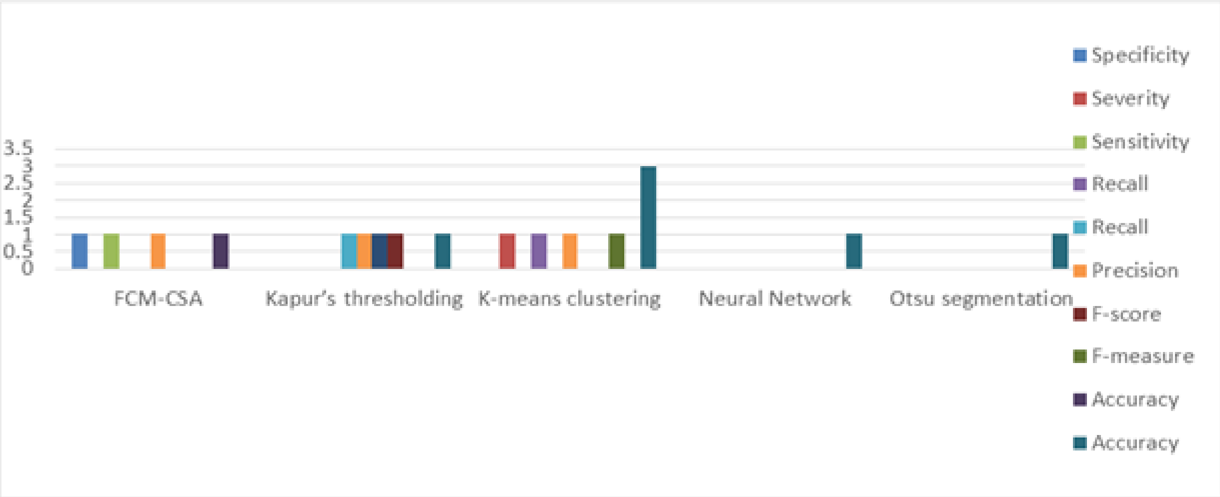

Figure1. Prediction of plant disease using various methods of segmentation

B. Plant Disease Evaluation Depending on Publication Period

Table 2 organizes the evaluation of the research papers depending on the publication year. From the years 2018 to 2021, the majority of review papers were published. The chart analysis of publications year for review papers is illustrated in figure 2.

Table 2: Year of Publication

Year of publication	Research paper
2016	[26] [28]
2017	[35]
2018	[15] [36] [17] [37] [24]
2019	[14] [3] [22] [23] [31]
2020	[4][2][7][38][18][19][25][34]
2021	[6] [16] [20] [21] [27] [29] [30] [32] [33]

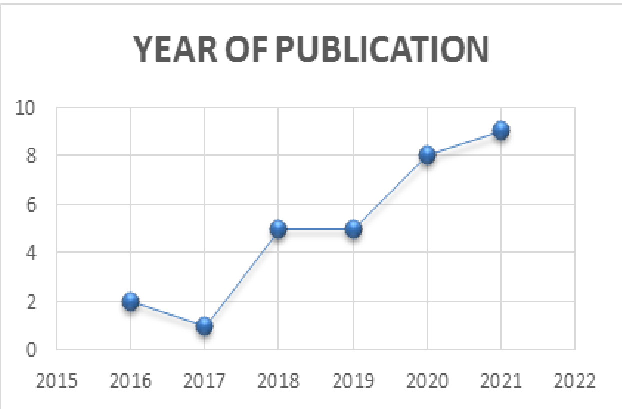

Figure2. For Plant Disease Detection, The Analysis Made Based on The Publication Year

C. Analysis based on achievements of the disease detection models

The study of research articles and accomplishments with the classifier used to predict plant disease in agricultural processes are shown in Table 3. Among the 25 papers, 11 papers depend on the accuracy metric.

Table 3: Prediction of Plant Diseases Using Analysis Based on Different Classifiers

Classifier used	Reference paper	Achievements %
MLP	[4]	Accuracy> 98
Transfer learning based on deep CNN	[2]	Accuracy 92
HCEN	[7]	Precision - 91
HCEN	[7]	Recall - 91
HCEN	[7]	F1-score - 91
HCEN	[7]	Accuracy - 100
CNN	[16]	Accuracy - 98
SVM	[3]	Accuracy - 97
GMDH - Logistic	[19]	Recall - 86
DoubleGAN	[20]	Accuracy - 99
PNAS	[21]	Accuracy - 97
PNAS	[21]	Sensitivity -97
PNAS	[21]	Specificity -97
PNAS	[21]	Precision -96
SVM (linear kernel)	[23]	Accuracy - 95
SVM (linear kernel)	[23]	Precision - 92
SVM (linear kernel)	[23]	Recall - 95
SVM (linear kernel)	[23]	F-measure - 94
SVM (RBF kernel)	[23]	Accuracy - 94
SVM (RBF kernel)	[23]	Precision - 91
SVM (RBF kernel)	[23]	Recall - 94
SVM (RBF kernel)	[23]	F-measure - 93
SVM (polynomial kernel)	[23]	Accuracy - 95
SVM (polynomial kernel)	[23]	Precision - 92
SVM (polynomial kernel)	[23]	Recall - 95
SVM (polynomial kernel)	[23]	F-measure - 95
SVM	[24]	Severity - 24
MSVM	[26]	Accuracy - 95
EfficientNet	[27]	Accuracy –99
EfficientNet	[27]	Sensitivity - 98
EfficientNet	[27]	Specificity - 99
EfficientNet	[27]	Precision - 98
BPNN	[28]	Accuracy - 93
Faster R-CNN	[31]	Sensitivity - 95
Faster R-CNN	[31]	Specificity - 95
OMNCNN	[32]	Accuracy - 98
OMNCNN	[32]	Precision - 98
OMNCNN	[32]	Recall - 98
OMNCNN	[32]	F-score - 98
ResNet	[34]	Accuracy – 96

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D. Prediction of plant diseases using evaluation of performance metrics

The performance measures used within the plant disease detection approach are evaluated using 25 publications in Table 4 to show how well they performed. The most commonly used performance metrics are Accuracy, Prediction, Recall, F-measure, Sensitivity, Specificity, F-score, F1-score, and Severity. The accuracy is one of the most used metrics for estimating plant disease prediction methods.

Table 4: Performance Metrics Utilized for The Plant Disease Prediction

Performance metrics	Research papers
Accuracy	[4] [2] [7] [16] [3] [20] [21] [23] [26] [27] [28] [32] [34]
Precision	[7] [21] [23] [27] [32]
Recall	[7] [19] [23] [32]
F-measure	[23]
Sensitivity	[21] [27] [31]
Specificity	[21] [27] [31]
F-score	[32]
F1-score	[7]
Severity	[24]

IV. CHALLENGES AND RESEARCH GAP

The problems of the evaluated strategies from various kinds of literature are discussed in this section.

A. Challenges in Plant Disease Prediction

The major challenges of the methods are enumerated as follows:

- A significant amount of information must be acquired for a variety of optical sensing systems, and processing that data is difficult. To efficiently use this technique, excessive setup and high computational cost is required in addition to the data analytics and statistical methods [4].
- In an artificially designed feature, it requires valuable work and well-skilled knowledge. Determination of optimal features and which is powerful for disease detection from numerous extracted features is complicated [2].
- Many methods fail to efficiently segment the leaf and unrelated sored image from its background under the complicated surrounding conditions thus resulting in irresponsible disease prediction analysis. On account of the difficulty of disease-affected leaf images, the task of automatically identifying images of damaged plants is quite difficult. [2].

B. Challenges in Segmentation Methods Associated with Plant Disease Prediction

- The time it takes to diagnose plant diseases is still significantly impacted by the prediction of plant diseases and their segmentation using digital images [29].
- Several images were structured by inter-class and intra-class differences along with complicated tasks which are proceeded by the neural network-based segmentation [29].
- In Otsu-based segmentation, there still exists an unwanted noise, segmentation error, and small holes included in the image [17].
- The major issue in the FCM segmentation involves when operating complicated diseases in leaves, it is mostly confined by the local minima [21].

C. Challenges Associated with the Feature Extraction Strategies for Plant Disease Prediction

- Neural Network-based back propagation network involved in feature extraction to classify the samples provided for training, the processing time is quite low for to be trained [24].
- A difficult operation that directly affects classification performance in the machine learning process is feature extraction. [27].
- The system's performance is significantly impacted by its dependency on manual features in machine learning and statistical techniques [29].

V. CONCLUSION

To highlight the many flaws in existing approaches for problem-solving predictions, we will evaluate various literary works that are focused on plant disease prediction in the agricultural industry. Based on a number of parameters, including different datasets, journals' year of publication and performance measures, the analysis of diverse methodologies is made easier here. As an alternative, the approaches' analysis in terms of their advantages and limitations will be discussed. The report concludes by discussing future study topics and difficulties in improving forecast accuracy for the plant disease prediction techniques used in the evolving agricultural process.

REFERENCES

1. Faithpraise, F., Birch, P., Young, R., Obu, J., Faithpraise, B., and Chatwin, C., "Automatic plant pest detection and recognition using k-means clustering algorithm and correspondence filters," Int. J. Adv. Biotechnology Res., vol.4, no.2, pp.189–199, 2013.
2. Chen, J., Chen, J., Zhang, D., Sun, Y., and Nanehkaran, Y.A., "Using deep transfer learning for image-based plant disease identification," Computers and Electronics in Agriculture, vol.173, pp.105393, 2020. [CrossRef]
3. Kaur, P., Pannu, H.S. and Malhi, A.K., "Plant disease recognition using fractional-order Zernike moments and SVM classifier. Neural Computing and Applications," vol.31, no.12, pp.8749-8768, 2019. [CrossRef]
4. Kumar, M., Kumar, A., and Palaparthy, V.S., "Soil Sensors Based Prediction System for Plant Diseases using Exploratory Data Analysis and Machine Learning," IEEE Sensors Journal, 2020. [CrossRef]
5. K. Golhani, S. K. Balasundram, G. Vadamalai and B. Pradhan, "A review of neural networks in plant disease detection using hyperspectral data," Information Processing in Agriculture, vol.5, pp. 354–371, 2018 [CrossRef]
6. Vishnoi, V.K., Kumar, K., and Kumar, B., "Plant disease detection using computational intelligence and image processing," Journal of Plant Diseases and Protection, vol.128, no.1, pp.19-53, 2021. [CrossRef]
7. Khamparia, A., Saini, G., Gupta, D., Khanna, A., Tiwari, S., and de Albuquerque, V.H.C., "Seasonal crops disease prediction and classification using deep convolutional encoder network," Circuits, Systems, and Signal Processing, vol.39, no.2, pp.818-836, 2020. [CrossRef]
8. R. Kaundal, A. S. Kapoor and G. P. Raghava, "Machine learning techniques in disease forecasting: a case study on rice blast prediction," BMC Bioinformatics, pp.47–58, 2006. [CrossRef]

9. Y. Chtioui, S. Panigrahi and L. Francl, "A generalized regression neural network and its application for leaf wetness prediction to forecast plant disease," Elsevier, Chemometrics and Intelligent Laboratory Systems, vol.48, pp.47–58, 1999. [CrossRef]
10. H. Wang, G. Li, Z. Ma and X. Li, "Image recognition of plant diseases based on principal component analysis and neural networks," In proceedings of 8th International Conference on Natural Computation, pp.246–251, 2012. [CrossRef]
11. S. Bauer, F. Korc and W. Forstner, "The potential of automatic methods of classification to identify leaf diseases from multispectral images," Precision Agriculture, vol.12, pp. 361–377, 2011. [CrossRef]
12. G. Stegmayer, D. H. Milone, S. Garran and L. Burdyn, "Automatic recognition of quarantine citrus diseases," Expert Systems with Applications, vol.40, pp.3512–3517, 2013. [CrossRef]
13. J.-C. Zhang, R. liang Pu, J. hua Wang, W. jiang Huang, L. Yuan and J. hua Luo, "Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements," Computers and Electronics in Agriculture, vol.85, pp.13–23, 2012. [CrossRef]
14. Nagasubramanian, K., Jones, S., Singh, A.K., Sarkar, S., Singh, A., and Ganapathysubramanian, B., "Plant disease identification using explainable 3D deep learning on hyperspectral images," Plant methods, vol.15, no.1, pp.1-10, 2019. [CrossRef]
15. Ferentinos, K.P., "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol.145, pp.311-318, 2018. [CrossRef]
16. Bedi, P., and Gole, P., "Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network," Artificial Intelligence in Agriculture, vol.5, pp.90-101, 2021. [CrossRef]
17. Wu, A., Zhu, J. and He, Y., "Computer Vision Method Applied for Detecting Diseases in Grape Leaf System," In International Symposium on Artificial Intelligence and Robotics, Springer, Cham, pp. 367-376, 2018. [CrossRef]
18. Hernandez, S., and Lopez, J.L., "Uncertainty quantification for plant disease detection using Bayesian deep learning," Applied Soft Computing, vol.96, pp.106597, 2020. [CrossRef]
19. Chen, J., Yin, H., and Zhang, D., "A self-adaptive classification method for plant disease detection using GMDH-Logistic model," Sustainable Computing: Informatics and Systems, vol.28, pp.100415, 2020. [CrossRef]
20. Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., and Zhang, Z., "Plant Disease Detection using Generated Leaves Based on DoubleGAN," IEEE/ACM Transactions on Computational Biology and Bioinformatics,2021. [CrossRef]
21. Umamageswari, A., Bharathiraja, N. and Irene, D.S., "A Novel Fuzzy C-Means based Chameleon Swarm Algorithm for Segmentation and Progressive Neural Architecture Search for Plant Disease Classification," ICT Express, 2021. [CrossRef]
22. Kamal, K.C., Yin, Z., Wu, M., and Wu, Z., "Depthwise separable convolution architectures for plant disease classification," Computers and Electronics in Agriculture, vol.165, pp.104948,2019. [CrossRef]
23. Vamsidhar, E., Rani, P.J., and Babu, K.R., "Plant disease identification and classification using image processing," Int. J. Eng. Adv. Technol, vol.8, no.3, pp.442-446, 2019.
24. Krishnakumar, A., and Narayanan, A., "A system for plant disease classification and severity estimation using machine learning techniques," In International Conference on ISMAC in Computational Vision and Bio-Engineering, pp. 447-457, Springer, Cham,2018. [CrossRef]
25. Mustafa, M.S., Husin, Z., Tan, W.K., Mavi, M.F., and Farook, R.S.M., "Development of automated hybrid intelligent system for herbs plant classification and early herbs plant disease detection," Neural Computing and Applications, vol.32, no.15, pp.11419-11441, 2020. [CrossRef]
26. Dubey, S.R., and Jalal, A.S., "Apple disease classification using color, texture and shape features from images," Signal, Image and Video Processing, vol.10, no.5, pp.819-826, 2016. [CrossRef]
27. Atila, U., Ucar, M., Akyol, K. and Ucar, E., "Plant leaf disease classification using EfficientNet deep learning model," Ecological Informatics, vol.61, pp.101182, 2021. [CrossRef]
28. Gharge, S., and Singh, P., "Image processing for soybean disease classification and severity estimation," In Emerging research in computing, information, communication and applications, pp. 493-500, Springer, New Delhi,2016. [CrossRef]
29. Tiwari, V., Joshi, R.C., and Dutta, M.K., "Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images," Ecological Informatics, vol.63, pp.101289, 2021. [CrossRef]
30. Thaiyalnayaki, K., and Joseph, C., "Classification of plant disease using SVM and deep learning," Materials Today: Proceedings,2021. [CrossRef]
31. Ozguven, M.M., and Adem, K., "Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms," Physica A: Statistical Mechanics and its Applications, vol.535, pp.122537, 2019. [CrossRef]
32. Ashwinkumar, S., Rajagopal, S., Manimaran, V., and Jegajothi, B., "Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks," Materials Today: Proceedings,2021. [CrossRef]
33. Nandhini, S., and Ashokkumar, K., "Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convolutional neural network," Multimedia Tools and Applications, vol.80, no.12, pp.18583-18610, 2021. [CrossRef]
34. Deeba, K., and Amutha, B., "ResNet-deep neural network architecture for leaf disease classification," Microprocessors and Microsystems, pp.103364, 2020. [CrossRef]
35. P. Barre, B.C. Stover, K.F. Muller and V. Steinhage, "LeafNet: a computer vision system for automatic plant species identification," Ecol. Inform. vol.40, pp.50–56, 2017. [CrossRef]
36. Barbedo, J.G., "Factors influencing the use of deep learning for plant disease recognition," Biosystems engineering, vol.172, pp.84-91, 2018. [CrossRef]
37. Thomas, S., Kuska, M.T., Bohnenkamp, D., Brugger, A., Alisaac, E., Wahabzada, M., Behmann, J., and Mahlein, A.K., "Benefits of hyperspectral imaging for plant disease detection and plant protection: a technical perspective," Journal of Plant Diseases and Protection, vol.125, no.1, pp.5-20, 2018. [CrossRef]
38. Nagaraju, M., and Chawla, P., "Systematic review of deep learning techniques in plant disease detection," International Journal of System Assurance Engineering and Management, vol.11, no.3, pp.547-560, 2020. [CrossRef]

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