A Comprehensive Study of Crop Disease Detection Using Machine Learning Classification Techniques

Chapter · May 2023

DOI: 10.1007/978-3-031-31153-6_41

2 authors:

Sanjeela Sagar
VSIT

Jaswinder Singh
Guru Jambheshwar University of Science and Technology

A Comprehensive Study of Crop Disease Detection Using Machine Learning Classification Techniques

Sanjeela Sagar[1](✉) and Jaswinder Singh[1,2]

[1] Vidyalankar School of Information Technology, Mumbai, India
sanjeela.sagar@vsit.edu.in
[2] Guru Jambheshwar University of Science and Technology, Hisar, India

Abstract. Agriculture is the main livelihood of India. About 58% of total population livelihood of India is based on agriculture. India is world's sixth largest market in the terms of food and grocery. Due to the rapid growth of population and demand for more food results into increase in the yield of crop. Around 30%–40% crop gets affected due to crop diseases. It can be prevented by using crop disease detection methods or techniques. Machine learning techniques can be used to identify or classify crop diseases. This paper presents the comprehensive study of various machine learning techniques used for crop disease identification and the various stages of general crop disease detection methods. In this study, it is observed that multi-layer CNN (Convolution Neural Network) gives more accuracy and detects a greater number of diseases.

Keywords: Crop disease detection · Machine learning techniques · Classification methods

1 Introduction

The agriculture is called as the backbone of India's economy as it accounts for 18% of India's GDP [1]. Farmers selects the crop based on the weather and soil condition including availability of water. According to FAO, 30- 40% of the crop gets affected to crop diseases. According to the Government of India report, India lost 5.04 million hectares (MHA) of crop area to cyclonic storms, flash floods, floods, landslides, and cloudbursts till November 25, 2021.

In the absence of crop protection, yield losses of up to 70% can occur across many major food crops, with weeds at 30%, followed by animal pests and pathogens at 23% and 17%.

Now due to new bill of the Government, industries started invested into farming and with the use of technology like Smart farming is booming up. Due to smart farming, the major highlight is of precision farming where best decisions will be made by using technology to increase the yield of the crop. A farmer uses pesticides to prevent the crop disease and it results in low production of crop. To increase the production of crop, it is necessary to identify the crop diseases on time.

L. Garg et al. (Eds.): ISMS 2022, LNNS 671, pp. 509–525, 2023.
https://doi.org/10.1007/978-3-031-31153-6_41

In India, crop disease is identified by experts. Farmers recognize it by continuously monitoring by using their naked eyes and based on their experience or they send samples to the experts, and it becomes a lengthy and expensive process. The Fig. 1 below shows the various types of crop diseases. These diseases are the main causes behind low production of crops. To minimize the risk of these diseases, there is a need to identify the diseases by automating methods so that prevention can be done on right time.

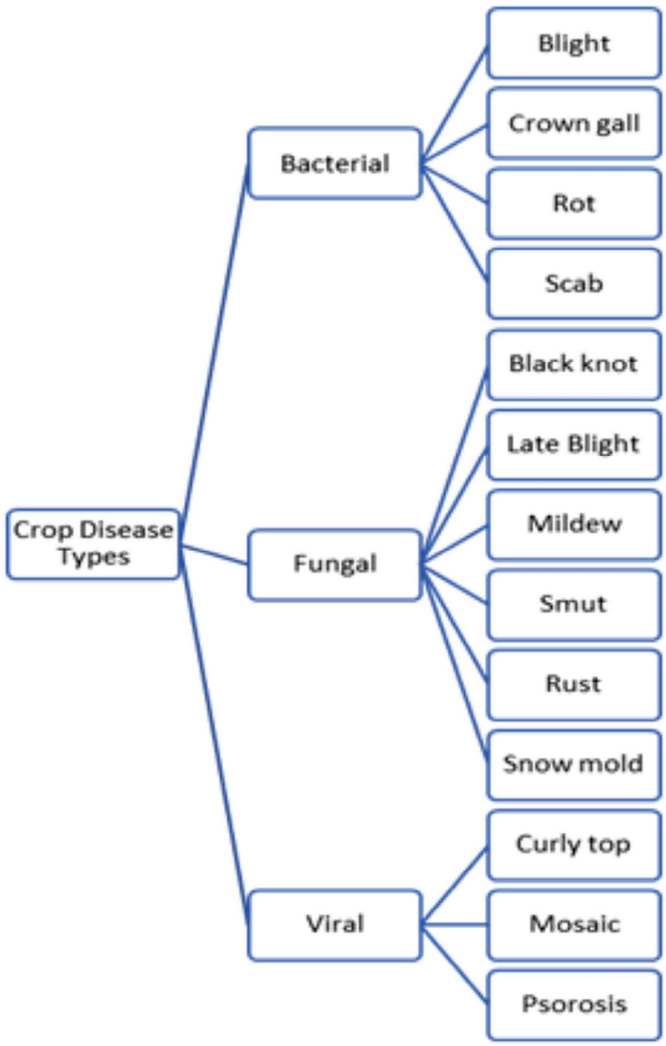

Fig. 1. Various types of Crop Diseases [2]

In this paper we are going to analyze different machine learning techniques used to classify these crop diseases and to find the correct algorithmic technique via which the risk of these diseases can be minimized.

The following section of the paper contains the steps of crop disease detection methods and review on machine learning techniques used to identify and classify crop diseases.

Machine Learning algorithm is divided into two phases:

1. Training phase: A huge amount of data is provided to the machine to learn different patterns, features or characteristics of data. And then with the help of a model, the machine can find the correlation between various features of data.
2. Testing phase: Once, the machine is trained, and then its testing starts. Testing is done with predetermined data to verify the working of the machine. Once, it starts giving accurate results, it is developed fully and will become ready for use in real world.

Machine Learning algorithms are categorized into following types as given in the Fig. 2:

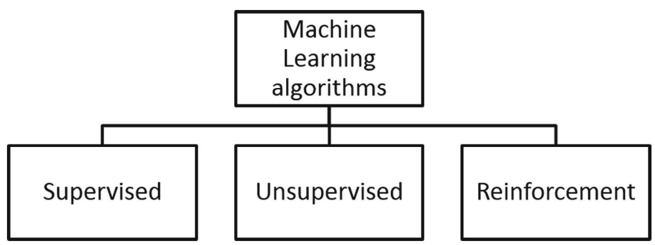

Fig. 2. Categorization of Machine learning algorithms

1. Supervised: In this type, the Input and output are known. The function which maps the input to the output which is desired called as the supervisor and the learning that happens is called as supervised learning.

   In this type of learning algorithm, the algorithm training is done with the input dataset and their respective expected output. Here, machine will be trained using various images of crop diseases so that machine can be used to classify the disease more accurately than humans. The main Machine learning algorithms that fall in this category are SVM, FFNN, Naive Bayes, KNN, LR, CNN, etc.
2. Unsupervised: In unsupervised learning, the target output is not known. Algorithm has to identify the hidden pattern by itself. There is no supervisor who can tell what the output is. This type of machine learning is known as self-organizing learning or learning without supervisor. The main machine learning algorithms that fall in this category are pattern matching like K-means, Hierarchical clustering, PCA, Apriori etc.
3. Reinforcement: Reinforcement learning is behavior based. In this type of learning, learning happens through rewards and punishments. The elements of reinforcement learning are agent, environment, reward, state and action. For example, in

autonomous car, the car is a agent, the road on which it is going to run is its environment. Suppose there is red signal, then car has to change its run state to stop state and if the car stops, this is the action taken by the car on seeing red signal. The main machine learning algorithms that fall in this category are Markov Decision Process, Q learning, state-Action-Reward-State-Action algorithm, Deep Q-network, etc.

In this paper, the study is done on supervised machine learning methods/ techniques used to identify/ classify crop diseases.

2 Crop Disease Detection Method

The crop diseases are identified by different parts of the crop like leaves, root and stem of the plant. The digital image processing can be used to detect these diseases. The basic steps in digital image processing to identify crop diseases are (Fig. 3):

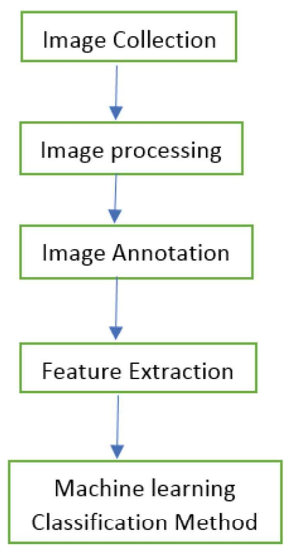

Fig. 3. Crop Disease Detection Method

- Image Collection: Images can be collected from various open sources like PlantVillage, UCI Repository, Kaggle, etc.
- Image Processing: Image processing can be done using various image processing methods like rotation, contrast, clip, blur to identify the proper location of the diseases. Then image segmentation can be applied to identify the diseases in the different parts of the plants.
- Image Annotation: knowledge base dataset can be created for collected images with different classes.

- Feature extraction: Various methods of feature extraction like color co-occurrence, texture, shape, blend vision, etc. can be used to identify the diseases.
- Machine learning classification method: Finally, one of the algorithms will be selected from various classification algorithms available like Naïve Bayes, Support Vector Machines, KNN (K Nearest Neighbor), ANN (Artificial Neural Network), CNN (Convolution Neural Network), etc. to classify the various diseases of crops

3 Literature Survey

The authors did extensive study to compare crop disease detection and classification using machine learning techniques. Following Machine learning algorithms were studied SVM, FFNN (Feed forward Neural network), Naïve Bayes, KNN, Logistic Regression and CNN methods used in detection of crop diseases.

3.1 SVM Classification

SVM is supervised machine learning algorithm used for classification of data. Following authors used SVM to classify crop diseases.

[3] Bakanae disease in rice seedlings was detected with an accuracy of 87.9%. Grape Plant diseases were classified using Opposite Colour Local Binary Pattern Feature with an accuracy of 89.3% [4]. [5] Apple Blotch, Apple rot and Apple scab diseases of apple were classified using multi-class SVM with an accuracy of 95.4%. Late blight, Early blight Potato Diseases using Image Segmentation were detected with 95% accuracy [6]. Big pest like snake, mouse, spider, mongoose, and small pest like green leafhopper, Stem-borer, Mealy Bug, Hispa were identified in Paddy Plant [7].

3.2 FFNN (Feed Forward Neural Network)

Feed Forward neural networks work in one direction i.e., they move in forward direction. 6 texture features: moment, mean, variance, contrast, entropy, and correlation of leaf images were extracted in [8] and then used K means and FFNN for classification and achieved more efficient results. K Muthukannan and his team in 2015 [9] used FFNN and Quantization algorithm for bean leaf and bitter gourd leaf disease classification and found that FFNN has given more accuracy over Quantization algorithm.

3.3 Naïve Bayes

Pattern matching for crop pest/ disease prediction using Naïve Bayes algorithm was done by Hemantkumar Wani in 2017 [10] by taking exterior and interior temperature of soil samples.

Naives Bayes algorithm was used in [11] to differentiate unhealthy leaves of plants from healthy ones using color conversion, segmentation, and feature extraction with an accuracy of 97%. Also, disease was classified. Rotten palm oil leaves were detected using Naïve Bayes in with [12] an accuracy of 80% and an expert system was built to identify to find the various disease symptoms on leaves. Fungal disease Cercospora and insect larva leaf miner diseases in bean were identified using Naive Bayes with Gaussian in 2018 [13].

3.4 KNN

KNN was used by the study in Bangladesh for Classification of Soil [14] and by using Soil series data, 92.93% accuracy was achieved. In June 2018, the study was done in Bristol, UK [15] for weed detection using various machine learning algorithms and one of then was weighted KNN which has given almost 84% accuracy. Bacterial Blight, Alternaria, Cercospora Leaf Spot, Anthracnose, all these cotton plant diseases were recognized using various machine learning algorithms [16] and KNN was compared, and it was found that improved KNN can give better accuracy.

3.5 Logistic Regression

A study on broad leaf weed detection was done in UK funded by InnovateUK in 2018 where regression was proved better tan KNN, SVM and Ensemble methods [13]. Logistic regression was also suggested in the study of tomato disease prediction that LR with SVM has achieved accuracy of 92.37% where SVM was used to remove noise and LR was used to classify and detect the disease [17].

3.6 CNN

Convolution neural networks was developed in 1994 and it has shown a remarkable improvement in detecting plant diseases over a period of time. Basic study of Viral Plant Disease detection was done in Japan [18] where CNN has proved accuracy upto 94.9%. Later in 2017, A study was done for "Rural Development Administration, Republic of Korea" where 5K images [19] were collected from different farms to understand the different types of fungal diseases on tomato leaf plants using different CNN models. CNNs with 10-fold cross – validation strategy was trained to identify 10 common rice diseases by taking 500 natural images [20] of diseased and healthy rice leaves and stems and achieved 95.48% accuracy. Crop pest classification was done by NIT, India [21] using NBAIR dataset for three classes of insects and the accuracy 96.75, 97.47, and 95.97% was achieved for three datasets. A study on "Plant disease identification from individual lesions and spots" was done in Brazil with 14 plant species and 79 diseases and accuracy was improved by 12% using CNN [22]. Mohit A and his team did a study on Tomato leaf disease detection using CNN variants VGG16, MobileNet and Inception V3 and found that accuracy varies from 76% to 100% [23] with respect to different classes of diseases.

Residual learning and attention mechanism were used on PlantVillage tomato leaf dataset with CNN and achieved almost 98% accuracy [24] (Figs. 4 and 5).

Bibliometric Analysis on Scopus Database:

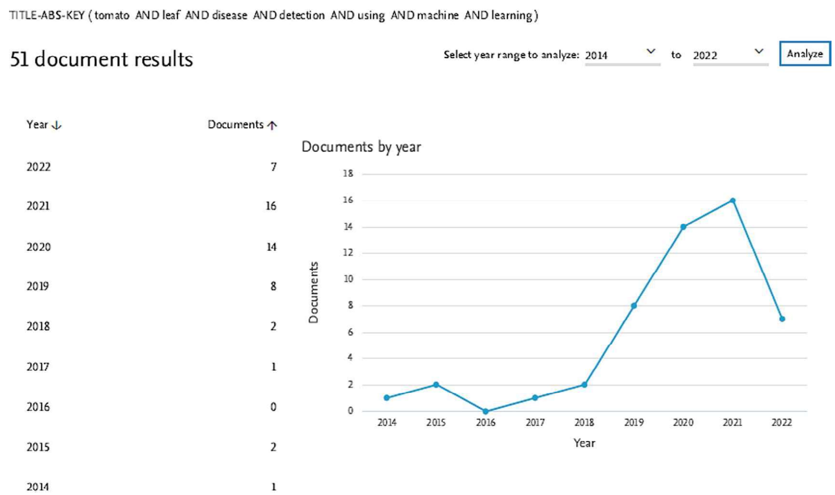

Fig. 4. Bibliometric analysis on Scopus Database

Fig. 5. Documents by source, Documents by author, Documents by affiliation and Documents by country/territory

Bibliometric analysis shows that not much research is done in this area. There is a need to explore more (Table 1).

Summary of the study:

Table 1. Summary of the comprehensive study of crop disease detection and classification using machine learning methods**.**

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[3]	Seeds were incubated and two cultivators were selected	Selection of essential traits done via genetic algorithms and SVM classifiers were used for optimal model parameters	A predictive value of 91.8% with 87.9% accuracy was achieved
[4]	Plant images were captured in.jpg format by using a digital camera	Image Resize, Image segmentation using background subtraction, Features were extracted using properties like correlation, homogeneity, color, contrast, and energy. SVM was used as a classification method	89.3% average accuracy was achieved
[5]	Google Image set on Apple diseases was taken. Blotch (80), Non-diseased Apple(80), rot apple(80), and scab disease (80)	The following feature-based descriptors were used: (1) color-based— histogram and coherence vector (2) ZM for shape-based and 3) LBP and completed LBP for texture-based. For defect segmentation, K-means was used and MSVM was used for classification	Average of 95.4% accuracy achieved
[7]	Used Live data	SVM	The system was able to identify both big and small pests like a snake, mouse, spiders, Hispa, Greenhopper, and few more

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[8]	Images of the plant stem and plant leaves were taken	RGB to HSI color space conversion methods was used. K-means clustering with squared Euclidean distance method used. Six texture features: mean, moment, contrast, variance, entropy, and correlation of leaf images were extracted. FFNN is used for classification	K-means with FFNN enhanced efficacy
[10]	Two data set Crop Data set and Pest Data Set from website of agriculture which is a government portal was taken	To detect the pest both interior and exterior temperatures were taken whereas to detect the diseases of plants; the exterior temperature of soil samples was used. Naïve Bayes used for classification	Output is pattern matching
[14]	Soil series of Khulna district's 6 upazillas from Bangladesh were taken for the study	SVM with Gaussian-based, KNN, and bagged trees methods were used for the classification of soil	SVM is better and given 94.95% followed by KNN 92.93% and Bagged Trees at 90.91%
[15]	Live data feed was used to collect data from a farm field	Near about 6K images were collected which were divided into grass images weed image patches. Then various variants of SVM with KNN, LR, and Ensemble methods were applied	An accuracy of 96.88% was achieved to detect weeds in different pastures
[16]	Anthracnose, Bacterial Blight, Alternaria, Cercospora Leaf Spot were collected	GLCM, HoG, HIST, SVM, KNN	Improved SVM and KNN

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[18]	Data collected from a research Center	Square crop and square deformation were used as preprocessing methods. The image dataset was increased by rotating the image at 10 degrees extended 36 times. 4-fold cross–validation used. CNN is used for classification	92.5% accuracy achieved
[19]	A dataset of near about 5K images was collected from farms located in Korean Peninsula	Geometrical transformations and intensity transformations were used namely rotation, flipping, resizing, brightness, color, noise. CNN and Faster-CNN were used	Comparison of various CNN models was done
[20]	Dataset of approximately 500 images of infected and non-diseased rice stems and leaves was captured from a rice experimental field	10 common rice diseases were identified by using trained CNNs	The proposed CNNs-based model was used with a 10-fold cross-validation strategy and an accuracy of 95.48% was achieved
[21]	Three datasets were taken from the NBAIR dataset	CNN	For NBAIR an accuracy of 96.75%, for Xie1 97.47% and for Xie2 95.97% was achieved
[22]	Images were categorized into 3 sets: a) actual images; b) images with removed background; c) extended dataset	CNN	The output was improved consistently by using images of infected plants with spots and lesions marked on them except for soybean and cotton

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[25]	Gamma correction, Image augmentation, rotation, etc. were used to get the dataset	Deep CNN model was trained with different batch sizes, training epochs, and dropouts	Accuracy was then compared, where SVM (50.6%), DT(72.23%), LR(80.99%), KNN(87.9%), and proposed model has shown the highest accuracy of 96.46%
[26]	Remote sensing was used to collect the dataset	Images with their RGB values were compared against the threshold images The canny edge detection method was used	Various ML models were used to identify plant diseases
[27]	Dataset consists of 12 plant species, each with different characteristics like no. of samples, no. of diseases, and other conditions	Cassava, Citrus, Common Bean, Coconut tree, Coffee, Cashew tree, Corn, Cotton, Grapevines, Sugarcane, Soybean, Wheat are used. The images were used with a removed background and CNN algorithm was applied	This study concluded that CNNs are better than any other algorithm to deal with the problems of plant pathology
[28]	Dataset was prepared from diseased rice plant images with four disease classes and twenty-five features	Particle swarm optimization with an incremental technique-based classifier was used	Classification rules were then generated both in static and real-time environment
[29]	Sixty images were collected with a camera which was divided into four categories	For computing, the attribute color co-occurrence method was used. And then the four categories were classified	The accuracy of the system developed was improved by 7% as compared to CNN

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[30]	A public dataset with approximately 54K images of fourteen crops and twenty-six diseases was used	The pre-processing methods used were: Segmentation, Feature extraction: GLCM, Blend vision. ML methods SVM, ANN, KNN, Fuzzy, CNN were used	The model was able to identity Soybean plant diseases namely Downy Mildew, Septoria using CNN. And achieved 99.32% accuracy
[31]	A digital platform in the form digital knowledge database was used for the data	ML methods were used to learn and evaluate the health of the crop and later based on learning can predict the future occurrence of the events/diseases	Methods to overcome knowledge engineering challenges were suggested
[32]	Sensors were used to collect the data. Following four diseases were collected: leaf spot, fruit rot, and spot and bacterial blight	Hidden Markov method used with 75th likelihood. That means the output generated should be at least correct by seventy-fifth	Farmers will be alerted by the system and preventive measures will be taken on time
[33]	750 mango images were taken which were then divided into three types equally: Red, Yellow, and green	Gray Scale, Edge detection were used. SVM and Naïve Bayes were used for classification. Classification was done on RGB values and diameter	The system worked for a particular surface area
[34]	The model was divided into four phases: Data discovery, Data Preparation, Analytical, and Visualization Phase		Farmer can get updates about the weather forecast and the market for their goods
[35]	Different soils data from different regions of India	LR, SVM	The system proposed to send an SMS to the farmer as soon as the anomaly is detected

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
	A dataset of about 300 images from Plant Village of potato leaves was taken. Late blight, non-diseased potato leaf and early blight images were collected	Image segmentation was used as preprocessing and color and texture statistical feature extraction were used and then SVM multiclass classifier is used	95% testing accuracy was achieved
[36]	Data set of rice leaves infected with blast and brown spot was acquired from the farms of West Bengal, India	Following texture features of the infected regions were computed namely Correlation, Contrast, Homogeneity, Energy, and Entropy	Almost 15 different classifiers that were available in the WEKA tool were used. Among these EVI and VI have given the better average result with 84% accuracy
[37]	Dataset was taken from International Rice Research Institute	Various image pre-processing and segmentation methods were studied. Also, various ML methods were analyzed	The study was done on the leaf images
[38]	Data of Soyabean plant collected using a digital camera in a farm	Conversion from RGB to HSV was done. Multithresholding was used to get a region of interest. Segmentation was done using color and cluster-based techniques. SVM is used for classification	The average accuracy of 93.79% achieved
[39]	Dataset collected from a farm	Crop Selection Method	The algorithm was able to predict the sequence of crops with which production per day can be increased in the season

(*continued*)

Table 1. (*continued*)

Ref. No.	Dataset Used	Methodology/Algorithms Used	Output
[40]	Dataset of chilly plant was collected from 3 farms	Images were resized, flipped and cropped to reduce the background noise. 80–20% Train-test split was used. CNN with Inception v3 was used	VGG16, InceptionV3, and EfficientNetB0 were used to classify the diseases and Inception v3 shown the higher accuracy of more than 98%
[41]	Kenaf plant leaf blight, sundapteryx, mites were collected from the farm	Images were collected with three different camera result in different sizes. They are were then brought to the same size. Faster RCNN was used and compared with CNN	Faster RCNN has shown more accuracy as compared to CNN
[42]	Dataset of strawberry healthy and leaf scorch disease from open source Kaggle was taken	Data augmentation was used to annotate the images. 80–20% train split method was used. Proposed Op-CNN was compared with other CNN methods	OP-CNN has given 100% accuracy
[43]	Dataset was collected from a farm	Images were contrasted and augmented. Six CNN models were compared	DenseNet201 has given the highest accuracy
[44]	200 images of rice plant were used	Image analysis and color feature extraction	Coarse tree used and an accuracy of 100% is achieved

4 Conclusion

A comparative study is done in this review for six machine learning algorithms namely SVM, FFNN, NB, KNN, LR, and CNN for crop disease detection. SVM, KNN was used by many authors. These classification techniques performed differently when applied to different tools for different datasets. These classification techniques have some pros and cons when applied for classifying plant diseases. The result shows that deep learning methods CNN and its variants detect crop diseases with more accuracy. In the future, multilayer deep CNN can be explored to detect the crop disease and then compared with other classification methods.

References

1. India Brand Equity Foundation: Agriculture in India: Information About Indian Agriculture & Its Importance. An initiative of the Ministry of Commerce & Industry, Government of India (2020). https://www.ibef.org/industry/agriculture-india.aspx. Accessed 23 Dec 2020
2. The Editors of Encyclopaedia Britannica: List of plant diseases (2016). https://www.britannica.com/topic/list-of-plant-diseases-2033263
3. Chung, C.L., Huang, K.J., Chen, S.Y., Lai, M.H., Chen, Y.C., Kuo, Y.F.: Detecting Bakanae disease in rice seedlings by machine vision. Comput. Electron. Agric. **121**, 404–411 (2016)
4. Waghmare, H., Kokare, R., Dandawate, Y.: Detection and classification of diseases of Grape plant using opposite colour Local Binary Pattern feature and machine learning for automated Decision Support System. In: 3rd International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India (2016)
5. Dubey, S.R., Jalal, A.S.: Apple disease classification using color, texture and shape features from images. Signal Image Video Process. **10**(5), 819–826 (2015). https://doi.org/10.1007/s11760-015-0821-1
6. Islam, M., Dinh, A., Wahid, K., Bhowmik, P.: Detection of potato diseases using image segmentation and multiclass support vector machine. In: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada (2017)
7. Agnihotri, V.: Machine learning based pest identification in paddy plants. In: 2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India (2019)
8. Tripathi, G., Save, J.: An image processing and neural network based approach for detection and classification of plant leaf diseases. Int. J. Comput. Eng. Technol. (IJCET) **6**(4), 14–20 (2015)
9. Muthukannan, K., Latha, P., Selvi, R.P., Nisha, P.: Classification of diseased plant leaves using feed forward neural network and learning vector quantization algorithm. Int. J. Eng. Res. Technol. (IJERT) TITCON **3**(16) (2015)
10. Wani, H., Ashtankar, N.: An appropriate model predicting pest/diseases of crops using machine learning algorithms. In: 2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India (2017)
11. Mohanapriya, K., Balasubramani, M.: Recognition of unhealthy plant leaves using Naive Bayes. In: IOP Conference on Series: Materials Science and Engineering, First International Conference on Materials Science and Manufacturing Technology, Coimbatore, Tamil Nadu, India, 12–13 April 2019, vol. 561, p. 012094 (2019)
12. Nababan, M., et al.: The diagnose of oil palm disease using Naive Bayes method based on expert system technology. In: International Conference on Mechanical, Electronics, Computer, and Industrial Technology, Prima, Indonesia, 6–8 December 2017 (2017)
13. Magdy, A., Ali, H., Ashraf, E.: Using the machine learning Gaussian Naive Bayes classifier to detect the Cercospora and leaf miner diseases in bean. In: Third Student Conference for Innovation and Creativity, Beni-Suef University, Beni-Suef (2018)
14. Rahman, S.A.Z., Mitra, K.C., Islam, S.M.: Soil classification using machine learning methods and crop suggestion based on soil series. In: 2018 21st International Conference of Computer and Information Technology (ICCIT), Dhaka, Bangladesh (2018)
15. Zhang, W., et al.: Broad-leaf weed detection in pasture. In: 2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC), UK (2018)
16. Prashar, K., Talwar, R., Kant, C.: CNN based on overlapping pooling method and multi-layered learning with SVM & KNN for American cotton leaf disease recognition. In: 2019 International Conference on Automation, Computational and Technology Management (ICACTM), London, UK, 29 July 2019 (2019)

17. Bhatia, A., Chug, A., Singh, A.P.: Hybrid SVM-LR classifier for powdery mildew disease prediction in tomato plant. In: 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India (2020)
18. Kawasaki, Y., Uga, H., Kagiwada, S., Iyatomi, H.: Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. In: Bebis, G., et al. (eds.) ISVC 2015. LNCS, vol. 9475, pp. 638–645. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-27863-6_59
19. Fuentes, A., Yoon, S., Kim, S.C., Park, D.S.: A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sens. Agric. (2017)
20. Lu, Y., Yi, S., Zeng, N., Liu, Y., Zhang, Y.: Identification of rice diseases using deep convolutional neural networks. Neurocomputing **267**, 378–384 (2017)
21. Thenmozhi, K., Reddy, U.S.: Crop pest classification based on deep convolutional neural network and transfer learning. Comput. Electron. Agric. **164**, 104906 (2019)
22. Barbedo, J.G.A.: Plant disease identification from individual lesions and spots using deep learning. Biosyst. Eng. **180**, 96–107 (2019)
23. Agarwal, M., Singh, A., Arjaria, S., Sinha, A., Gupta, S.: ToLeD: tomato leaf disease detection using convolution neural network. Procedia Comput. Sci. **167**, 293–301 (2020). https://doi.org/10.1016/j.procs.2020.03.225
24. Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A., Menaka, R.: Attention embedded residual CNN for disease detection in tomato leaves. Appl. Soft Comput. **86**, 105933 (2020)
25. Geetharamani, G., Pandian, A.: Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput. Electr. Eng. **76**, 323–328 (2019)
26. Badage, A.: Crop disease detection using machine learning: Indian agriculture. Int. Res. J. Eng. Technol. (IRJET) **05**(09), 867–869 (2018)
27. Barbedo, J.G.A.: Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Comput. Electron. Agric. **153**, 46–53 (2018)
28. Sengupta, S., Das, A.K.: Particle swarm optimization based incremental classifier design for rice disease prediction. Comput. Electron. Agric. **140**, 443–451 (2017)
29. Jenifa, A., Ramalakshmi, R., Ramachandran, V.: Classification of cotton leaf disease using multi-support vector machine. In: 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), Tamilnadu, India, 09 January 2020 (2020)
30. Shruthi, U., Nagaveni, V., Raghavendra, B.: A review on machine learning classification techniques for plant disease detection. In: 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore, India (2019)
31. Nery, M., Santos, R., Santos, W., Lourenco, V., Moreno, M.: Facing digital agriculture challenges with knowledge engineering. In: 2018 First International Conference on Artificial Intelligence for Industries (AI4I), Laguna Hills, CA, USA (2018)
32. Pawara, S., Nawale, D., Patil, K., Mahajan, R.: Early detection of pomegranate disease using machine learning and internet of things. In: 2018 3rd International Conference for Convergence in Technology (I2CT), Pune, India (2018)
33. Nandi, C.S., Tudu, B., Koley, C.: A machine vision technique for grading of harvested mangoes based on maturity and quality. IEEE Sens. J. **16**(16), 6387–6396 (2016)
34. Sumathi, K., Santharam, K., Selvalakshmi, N.: Data analytics platform for intelligent agriculture. In: 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India (2018)
35. Varghese, R., Sharma, S.: Affordable smart farming using IoT and machine learning. In: 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India (2018)

36. Phadikar, S., Goswami, J.: Vegetation indices based segmentation for automatic classification of brown spot and blast diseases of rice. In: 3rd International Conference on Recent Advances in Information Technology (2016)
37. Shah, J.P., Prajapati, H.B., Dabhi, V.K.: A Survey on Detection and Classification of Rice (2016)
38. Dandawate, Y., Kokare, R.: An automated approach for classification of plant diseases towards development of futuristic decision support system in Indian perspective. In: 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Kochi, India (2015)
39. Kumar, R.: Crop selection method to maximize crop yield rate using machine learning technique. In: 2015 International Conference on Smart Technologies and Management, TN, India (2015)
40. Rozlan, S., Hanafi, M.: Efficacy of chili plant diseases classification using deep learning: a preliminary study. Indonesian J. Electr. Eng. Comput. Sci. **25**(3), 1442–1449 (2022)
41. Rakhmandasari, A., Mahmudy, W.F., Yulianti, T.: Kenaf plant pest and disease detection using faster regional based convolutional neural network. Indonesian J. Electr. Eng. Comput. Sci. **24**(1), 198 (2021). https://doi.org/10.11591/ijeecs.v24.i1.pp198-207
42. Belattar, S., Abdoun, O., Haimoudi, E.: Performance analysis of the application of convolutional neural networks architectures in the agricultural diagnosis. Indonesian J. Electr. Eng. Comput. Sci. **27**(1), 156 (2022). https://doi.org/10.11591/ijeecs.v27.i1.pp156-162
43. Rajbongshi, A., Khan, T., Pramanik, M.M.R.A., Tanvir, S.M., Siddiquee, N.R.C.: Recognition of mango leaf disease using convolutional neural network models: a transfer learning approach. Indonesian J. Electr. Eng. Comput. Sci. **23**(3), 1681–1688 (2021)
44. Geollegue, K.W.V., Arboleda, E.R., Dizon, A.A.: Seed of rice plant classification using coarse tree classifier. IAES Int. J. Artif. Intell. (IJ-AI) **11**(2), 727 (2022). https://doi.org/10.11591/ijai.v11.i2.pp727-735