JournalsPub

International Journal of
Image Processing and
Pattern Recognition

ISSN: 2456-6985
Volume 10, Issue 1, 2024
January—June
DOI (Journal): 10.37628/IJIPPR

https://journalspub.com/journal/ijippr

Review IJIPPR

The Implementation of Machine Learning in the Search to Fight Plant Disease

Mohit Batra[1,*], Neha Bathla[2]

Abstract

The agriculture business loses money and time due to plant diseases. Diagnosing disease accurately takes skill and devotion. Infected plants may have spots or streaks of a different color on their leaves. Several fungal, bacterial, and viral species can also infect plants. Individual plant disease signs and indications are assessed. Neural network applications are growing. Recent research studies have determined how well machine learning reviews traditional plant disease diagnosis methods. Deep learning, a subset of machine learning, may increase plant disease identification accuracy with a convolutional neural network model.

Keywords: Machine learning, plant disease, detection, deep learning, convolutional neural network (CNN), accuracy parameter

INTRODUCTION

Possible applications of image processing techniques for plant disease diagnosis include edge detection and picture compression. Images may be processed in two dimensions or three. In order to train and test a convolution neural network, it is necessary to first compress and identify edges in the images of plant illnesses. Two-dimensional computer graphics emerged with the introduction of vector graphics devices in the 1950s. The next decades saw the progressive replacement of these tools by raster-based alternatives. The advent of the X Window System and the PostScript language has had a profound impact on the industry. In order to express various numerical forms, electronic visuals, and typeset raster images, several image attributes are used. In computer graphics, scaling is a technique for altering the size of an image. Reducing one's living space is not an easy task. It is essential to find a happy medium between rapidity, fluency, and clarity. When using bitmap graphics, image details become more apparent when image size is increased or decreased. The averaged image loses some of its own character. In order to re-render vector pictures, it may be necessary to allocate a smaller portion of the available computing resources. In computer-generated animation, it manifests as slow rendering in two ways: frame skipping and lower frame rates. Both lossy and lossless methods of compressing images are now in use. When dealing with tasks of a historical nature, lossless encoding is preferable.

*__Author for Correspondence__
Mohit Batra
E-mail: mohitbatra484@gmail.com

[1]Student, Department of Computer Science & Engineering, Yamuna Institute of Engineering & Technology (YIET), Gadholi, Yamnunagar, Haryana, India
[2]Assistant Professor, Department of Computer Science & Engineering, Yamuna Institute of Engineering & Technology (YIET), Gadholi, Yamunanagar, Haryana, India

Received Date: December 04, 2023
Accepted Date: January 04, 2024
Published Date: May 30, 2024

Citation: Mohit Batra, Neha Bathla. The Implementation of Machine Learning in the Search to Fight Plant Disease. International Journal of Image Processing and Pattern Recognition. 2024; 10(1): 25–34p.

Image Processing

Modifying a digital picture using a computer and an algorithm is known as digital image manipulation (IM). The benefits of digital image processing over analog image processing are considerable. Digital image processing is a specialized area of application for digital signal processors. The possibility of many algorithms processing the input data lessens the risk of issues like noise and distortion building up. Digital image processing may be seen as a multidimensional system, since pictures are often specified in more than two dimensions. The development of computing and mathematics are only two of the many variables that have aided the expansion of digital image processing.

LITERATURE REVIEW

In 2016, Mohanty et al. [1] reported a technique for diagnosing plant diseases using a trained convolutional neural network (CNN). CNN model has been trained on 14 different plant species to distinguish between healthy and diseased plants. The model's accuracy was 99.35% on the validation data. On 31.4% of test photos from reputable internet sources, the system performs better than a random selection model, although it may need more training data to really shine. If alternative models or NN training approaches can improve accuracy, this might pave the door for broad use of plant disease diagnoses [1].

Work on image segmentation and soft calculated algorithms for disease detection in plant leaves was given by Singh and Misra [2]. Some automated equipment for detecting plant diseases was useful since it eliminated the need for regular monitoring in vast agricultural farms and caught symptoms of sickness on the leaves of plants as soon as they appeared. For the purpose of automating the diagnosis and classification of leaf diseases, the authors of this study provide an image segmentation approach. In addition, a discussion of the various disease classification techniques that may be used to plant leaf disease detection was provided. Image segmentation, a necessary stage in the diagnosis of plant leaf diseases, was performed using the genetic technique [2]. In their 2017 study, Marathe et al. [3] zeroed down on the digital image processing and global system for mobile disease detection in plants. The first is the loss of crops and plantations by pests and diseases, while the second is the damage caused by natural catastrophes such as floods, earthquakes, droughts, famines, etc. The former accounts for almost all (98%) of the harm, and just 2% may be attributed to natural calamities and the rest are illnesses. Therefore, the capacity to recognize plant diseases is a crucial factor. The standard methods were ineffective and full of flaws. Based on the findings of these research, image processing (IP) has been used into the analysis of leaf samples for the detection of plant diseases. Different leaf markings and patterns might serve as diagnostic indicators. The adoption of digital image processing was another breakthrough that helped provide more accurate results. Credible sources such as IEEE and international conferences and journals were combed by researchers who found no effective treatments for the plant disease [3].

The IP was first developed by Sujatha et al. [4] to detect diseases in leaves. The identification of plant diseases has become a prominent research topic in the field of computer science. Intelligent systems may aid in the correct diagnosis of diseases. The leaves are the primary target for microorganism attacks. The goal of this research was to detect plant illnesses using just the images supplied. Disease detection requires a number of steps, including transforming photos from RGB (red, green, blue) to grayscale. Adaptive histogram equalization (AHE) is used to improve image contrast. You may get the 13 most important features by utilizing a feature extraction method called GLCM (gray level co-0ccurrence matrix). On the output screen, [4] you can see the results of training the support vector machine (SVM) classifier using the gold-standard benchmark images.

In their 2017 review, Kaushal and Bala [5] examined the use of a GLCM and KNN (K-nearest neighbor)–based algorithm for plant disease identification. To analyze and make sense of digitally collected visual data, image processing was developed. Plant disease detection using photography (PDD) was the technique employed. In this research, we use techniques for extracting, segmenting, and classifying textures. Textural information in the picture was extracted using the GLCM technique. We employ the k-means clustering method to segment input images. In the present method, the SVM classifier was utilized to split the input image in half. To make the existing technique more effective, the SVM classifier was replaced with the KNN classifier. The accuracy of disease diagnosis was improved by further subdividing the data into multiple groups [5].

Research on the use of GLCM and SVM for disease detection in leaves was given by Namrata et al. [6]. The goal of this suggested activity was to develop an automated system for diagnosing illnesses in plant leaves. In this instance, plant diseases were detected using image processing. pictures were acquired, pre-processed, segmented, features were extracted, and ultimately, the pictures were classified. Classification in this work was accomplished using SVM, and both training and testing datasets were made available. Extracting raw data from the IP webcam is the first order of business. This image will then be preprocessed to remove noise and sharpen the focus. A classifier will then provide a disease categorization to the image based on the extracted characteristics [6]. The image will then be split into smaller clusters, each of which will comprise only the sick region.

Sridhathan and Senthil Kumar [7] surveyed the state of image processing-based plant illness detection. The conventional method was far more time- and labor-intensive. Early detection of plant diseases using automation tools might help huge farms save some crops. In this study, the authors provide an automated approach to visual disease identification in plants utilizing IP techniques. There are image processing algorithms that can recognize certain leaf color traits, which are then used to diagnose plant illnesses and diseases. We employed the GLCM method to classify diseases, while the K-means algorithm was used to divide colors into distinct groups. A vision-based plant infection strategy was shown to be successful and promising [7].

Bensaadi and Louchene [8] used a low-cost CNN to assess the categorization of diseases affecting tomato plants. They provide a CNN architecture with minimal complexity that may be utilized to speed up online categorization of plant diseases. During the course of the training process, almost 57,000 PCs were used. To facilitate the training process, nine distinct classes of tomato leaves were shot in their native environments and utilized without any background reduction. The suggested model demonstrated a high degree of accuracy in differentiating between diseases with a classification accuracy of 97.04% and an error rate of less than 0.2%.

Haridasan et al. [9] presented a deep learning–based method for identifying and categorizing rice plant diseases. The suggested method for the detection of rice plant illnesses takes a computer vision-based approach, using IP, machine learning (ML), and deep learning (DL), to safeguard paddy crops from the five principal diseases that regularly affect the Indian rice fields. After initial image processing, the affected area of the paddy plant was extracted using image segmentation. The aforementioned infections were identified just by their outward appearance. Researchers have integrated a support vector machine classifier with CNN to detect and categorize many rice plant diseases. When employing the ReLU and softmax functions, the suggested DL-based method attained its highest validation accuracy (0.9145). A predictive treatment was recommended after diagnosis, which might aid persons in the agricultural sector in fighting the ailment.

Tugrul et al. [10] first reported that DL models were effective in identifying plant leaf diseases. In this research, they provide cutting-edge CNN architectures for disease detection in leaves. As part of this study, a potato leaf database was compiled for future use in both training and testing. They sent the input images from the given training dataset into a CNN, which then extracted the characteristics needed for disease classification. The model was trained using 1700 photos of potato leaves, and then around 600 of those images were used for testing. Disease diagnosis was done in citrus groves using CNN, DL, baseline, and TL. The suggested architecture improves upon the present state-of-the-art ResNet models in terms of training, testing, and experimental correctness, reaching a level of 99.62%.

Research Gap

Agriculture has been cited as a major source of personal income in several nations [1]. Natural circumstances of the land and local needs guided farmers in their efforts to cultivate food crops. The scarcity of water and the danger of natural disasters are two of the most pressing issues farmers face. [2].

There is a need for more investigation on paddy leaf detecting difficulties. Since such a technique may increase food output [3], consulting a specialist is not necessary. There is a growing need for research in plant disease diagnosis [4]. The most challenging component of the job is recognizing and detecting plant diseases. Plant diseases must be identified if agricultural output and yields are to be preserved. Researchers believe that plant disease detection research might reveal disease trends in plants [6]. Hand-made plants are tough to keep track of in terms of health. Plant disease detection and image processing methods are frequently employed since manual processing involves a lot of time and expertise [7]. Data retrieval has involved the gathering of pictures to diagnose and track down diseases. A picture must first be split and pre-processed before it can be used. Characteristics are ultimately retrieved to categorize the objects in question. For polluted plants, these methods may be helpful [11]. Leaves from a variety of species have been linked to a wide range of diseases. According to the kind of plant that is infected, the disease's symptoms will be different. Plant pathogens come in many shapes, sizes, and colors. It has been shown that plant leaves may cause a variety of illnesses, from allergies to cancer. Some plant diseases seem pink, while others appear brown, according to experts [12]. Tumors may seem the same from the outside, but their colors may vary drastically on the inside. On the other side, some share a hue but have a unique shape. Following segmentation, some of the disease-related traits may be recovered [13]. To identify plant diseases, scientists have traditionally looked at the plants with their eyes, which takes longer and costs more on large-scale farms [14, 15]. Performing this procedure is an uphill battle. In the process of diagnosing a specific illness, mistakes might be made [16]. The severity of plant leaf diseases must be taken into account in light of the decrease in rice output [17].

RESEARCH METHODOLOGY

The traditional definition of research is an exhaustive, systematic inquiry. It is capable of searching for data on any topic imaginable. The emphasis is on a certain area of study. There are six parts to this chapter. In the first part, we discuss the applied study methodology, which equips researchers with the know-how to pick appropriate processes, scientific instruments and methodologies, and study materials. The methods and equipment that went into the study are broken out in further detail in the second part. In the third part, we introduce MATLAB, a software package integral to the presented tools and technologies. CNN technique utilized to represent the various graphical qualities. where a more efficient edge detecting technique is named and the relevance of the parameter is revealed.

Case Study Method

In this study, we used the experimental method of research. The study has examined the effectiveness of the suggested nutrition prescription model and the impact of clustering on unstructured nutritional data. The .net and MATLAB modules were built for simulation purposes. In the current study, we gather data for sentiment analysis from the outset as shown in Figure 1.

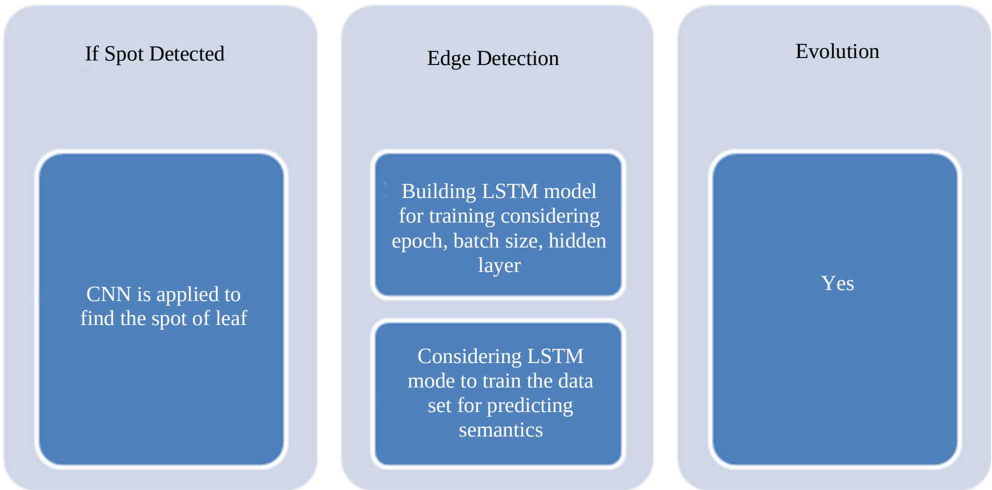

Figure 1. Process flow of proposed work.

PROPOSED MODEL

Now, we are trying to figure out how to spot infections in paddy leaf plants. Severe disease causes destruction to the leaf in a characteristic pattern. This tends to indicate that a diagnosis of the disease is required. By applying image processing techniques in advance, tasks like resizing, compressing, and discovering patterns using an edge detection approach have become possible. An edge detection component has been added to the detection process, which successfully eliminates the colored, irrelevant sections of the image. Improvements in efficiency result from the elimination of such obstructions. There are several approaches to edge detection, such as Previtt, Sobel, Robert, and Canny. Smart edge detection was used, and now the suggested task is of higher quality.

Working of CNN Model for Classification

One such approach is the use of a traditional neural network for training and evaluating images. There is a separate database for pictures of healthy leaves, and another for pictures of leaves that are unwell. Parameters such as epochs, hidden layers, classification algorithm, iterations, batch size, connected layers, and so on must be set up before a CNN model can be initialized. To train the model, 70% of the photos were utilized, whereas just 30% were used for testing.

A confusion matrix was generated for the first situation by training and testing using baseline graphics. After that, we calculate metrics like accuracy, precision, recall, and f1.

The second technique creates a one-of-a-kind confusion matrix by considering edge-detected photos in both the training and testing phases. Finally, the edge detected image's generated accuracy characteristics are compared to industry norms.

PROBLEM STATEMENT

NNs have been employed in the field of plant disease diagnosis, while others have recommended using image processing and feature extraction. A flaw in current approaches is that accuracy in plant disease classifications is not being adequately addressed. It would also be helpful to have better categorization and prediction skills [18]. The suggested study suggests using picture compression and edge detection techniques to reduce file sizes and enhance plant disease diagnosis performance and accuracy. Therefore, it is necessary to utilize an edge identification technique to remove clutter from the plant disease picture. This would allow for more efficient processing of images throughout the categorization and prediction stages. It is also important to assess the level of plant disease. Depending on how severe a plant disease is, it may or may not be curable.

Inception-Based CNN for Plant Disease Detection

As the world's population and consequent hunger rise [19–21], so does the risk of plant diseases and the severity of their impact on farmers. Early diagnosis of plant diseases might ensure food security and decrease economic losses. Examining images of sick plants may sometimes help determine what's wrong with them. CNN's tagging skills are used to attain pinpoint accuracy [22]. Specifically, Google's 'Inception v3' model from their pre-training library is used. A model for plant disease identification is trained using Inception v3 and the 'Plant Village Dataset' [23]. The new detection system's efficiency is evaluated. In this study [24, 25], the author uses a CNN-based technique to classify diseases on leaves, as shown in Figure 2. Building a reliable neural network is challenging. The use of transfer learning has the potential to increase output. The Inception v3 model may be used for instantaneous image classification and can be further trained to detect additional classes [26]. As a result, Inception v3 has potential to be a helpful tool for making accurate diagnoses of plant diseases quickly. In order to ensure that the model is properly trained for all features [27], the contour method of categorizing the dataset may be used to pick a training set. In this scenario, feature extraction is enhanced compared to what may have been achieved with unstructured data labelling. When the procedures outlined in the article were carried out to the letter, positive results were obtained [28–30]. These classification schemes for plant diseases may assist mitigate their effects on agricultural production.

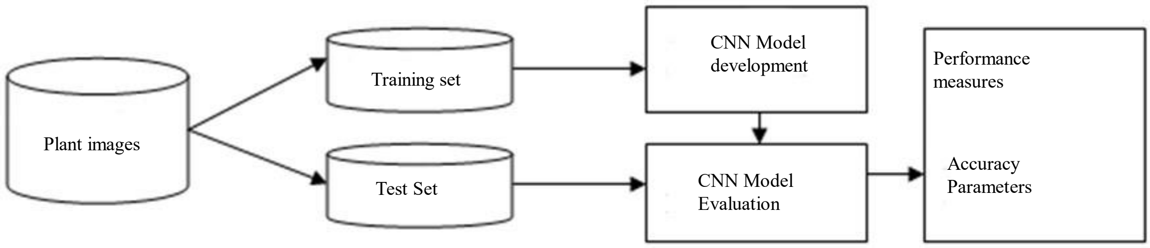

Figure 2. Training and testing of plant images for classification.

Figure 3. Plant images.

RESULTS AND DISCUSSION

Acquisition of Images

In a rural setting, a high-resolution digital camera was used to capture images of the rice plant's leaves. In order to use the photos for illness diagnosis, they must be transferred to a computer. This location is where the strategy is put into action. The bulk of this archive is devoted to pictures of ill days. Photos were taken at the scene of the crime. Moreover half of the pictures are healthy, but the other half show symptoms of the bacterial plague [31]. There are 170 pictures in all, and they show everything from explosions to sheath rot. As can be seen in Figure 3, the collection includes 150 images of brown spots.

Simulation of the Previous Model [7]

Deep Neural Network (DNN), artificial neural network (ANN), and DE noising auto encoders were predicted to perform worse than traditional methods like DNN JOA. Scientists examined their findings across several diseases, including some that are rather prevalent. Seventy percent of the photos were utilized for training, 20% for testing, and 10% for verification as shown in Table 1 [32].

Table 2 displays data matrices generated by the aforementioned procedure [33]. This confusion matrix may be used to forecast true positive, false positive, and false negative values.

Results

True positive: 87
Overall accuracy: 72.5%

Simulation of the Proposed Model

CNN and edge detection tools in MATLAB are utilized to put the suggested technique to the test. Brown spot, bacterial blight, the norm, sheath rot, and blast disease are all included in this evaluation.

The dataset was split into thirds and used for training, testing, and validation, respectively, as shown in Table 3.

The outcomes of generating a confusion matrix in the aforementioned manner are shown in Table 4. Negative values and genuine positives are both predicted by this confusing matrix.

Results

True positive: 105
Overall accuracy: 87.5%

Comparison Analysis

Here, we show the differences between the filtered and unfiltered data sets side by side.

Accuracy

Table 5 displays the results of an accuracy comparison.

Table 1. Confusion matrix of previous work.

	Blast	Bacterial Blight	Brown Spot	Normal
Blast	22	2	4	2
Bacterial blight	3	21	2	4
Brown spot	2	2	25	1
Normal	5	3	3	19

Table 2. Accuracy parameter of confusion matrices of previous work.

Class	*n* (Truth)	*n* (Classified)	Accuracy	Precision	Recall	F1 Score
1	32	30	85%	0.73	0.69	0.71
2	28	30	86.67%	0.70	0.75	0.72
3	34	30	88.33%	0.83	0.74	0.78
4	26	30	85%	0.63	0.73	0.68

Table 3. Confusion metrics of proposed work.

	Blast	Bacterial Blight	Brown Spot	Normal
Blast	26	1	2	1
Bacterial blight	2	25	1	2
Brown spot	1	1	28	0
Normal	2	1	1	26

Table 4. Accuracy parameter of confusion matrices of proposed work.

Class	*n* (Truth)	*n* (Classified)	Accuracy	Precision	Recall	F1 Score
1	31	30	92.5%	0.87	0.84	0.85
2	28	30	93.33%	0.83	0.89	0.86
3	32	30	95%	0.93	0.88	0.90
4	29	30	94.17%	0.87	0.90	0.88

Table 5. Comparison of accuracy in both cases.

Class	Previous Work	Proposed Work
1	85%	92.5%
2	86.67%	93.33%
3	88.33%	95%
4	85%	94.17%

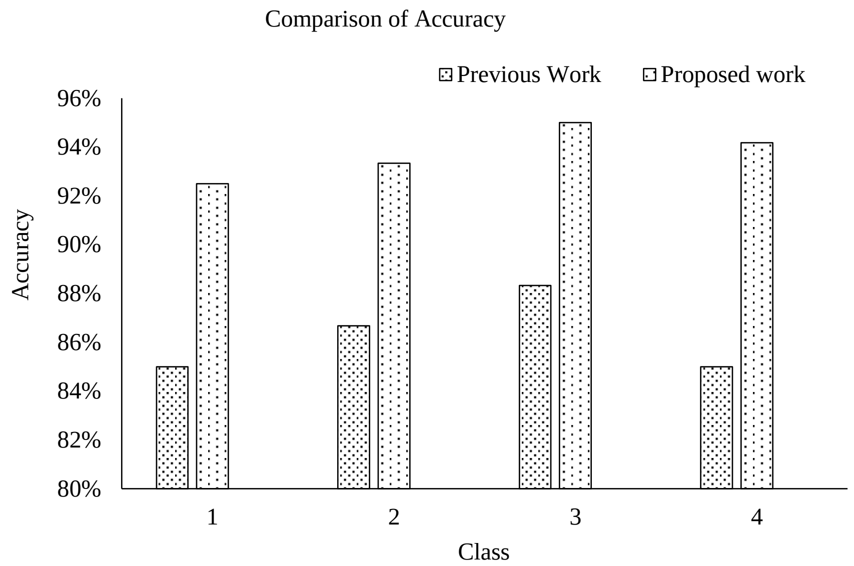

Figure 4. Comparison of accuracy.

With Table 5 as a guide, we can now compare the success and failure rates of the unfiltered dataset to those of the filtered one, as shown in Figure 4. The accuracy of filtered datasets has been shown to be higher than that of non-filtered datasets.

CONCLUSION

In this research, we aimed to better understand how to identify plant diseases. Observations have shown that severely diseased leaves follow a certain pattern. This pattern emphasizes the significance of establishing a diagnosis. Preprocessing images using image processing techniques allows for further scaling, compression, and pattern identification with edge detection systems. The detection performance of the edge detection method is enhanced by cutting off the colorful, less significant parts of the image. When such things are taken out, things run smoother. The suggested research has considered intelligent edge detection because of its higher quality compared to other edge detection procedures. The suggested approach has very high precision when it comes to diagnosing plant diseases. The proposed approach for plant disease identification is more precise, flexible, and extensible than the existing method. Moreover, a remedy for the severe symptoms of the disease was found. The model accurately predicts plant disease spread. Simulated findings suggest that compressed and edge-detected images are more accurate than standard ones. The proposed work has produced a system that is scalable, adaptable, and trustworthy.

Future Scope

The suggested study is meant to provide more precise findings and a perfect, scalable solution. There is potential for the integration of CNN and edge detection methods to dramatically improve future projects needing picture categorization. The employment of more sophisticated processes in future studies might be fruitful. It may be used for any purpose, not only to image processing studies linked to precision agriculture. Research of this kind may find future use in many fields, including business, medicine, and the classroom. It is possible to use lossless compression methods that are more robust. Additionally, CNN methods should be improved to boost efficiency and dependability. This research holds the potential to bring advantages to businesses, healthcare facilities, and schools in the future. If more reliable compression techniques were used, the output may be lossless. There is also room for development in CNN techniques to make them more effective and trustworthy. There has been a lot of research done on the topic of plant disease detection, but it can always be better. The extent of previous studies shows that the problem of detecting plant diseases was only partially addressed. Thus, more precise measurements are needed. Future research might improve plant disease detection systems' efficiency and accuracy.

REFERENCES

1. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016; 7: 1419.
2. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques. Inform Process Agric. 2017; 4 (1): 41–49.
3. Marathe PS, Raisoni GH, Phule S. Plant disease detection using digital image processing and GSM. Int J Eng Sci Comput. 2017; 7 (4): 10513–10515.
4. Sujatha R, Kumar YS, Akhil GU. Leaf disease detection using image processing. J Chem Pharm Sci. 2017; 10 (1): 670–672.
5. Kaushal G, Bala R. GLCM and KNN based algorithm for plant disease detection. Int J Adv Res Electr Electron Instrum Eng. 2017; 6 (7): 5845–5852.
6. Namrata KP, Nikitha S, Saira Banu B, Wajiha Khanum PK. Leaf based disease detection using “GLCM and SVM”. Int J Sci Eng Technol. 2017; 7: 1–4.
7. Sridhathan C, Senthil Kumar M. Plant infection detection using image processing. Int J Mod Eng Res. 2018; 8 (7): 13–16.
8. Bensaadi S, Louchene A. Low-cost convolutional neural network for tomato plant diseases classification. IAES Int J Artif Intell. 2023; 12 (1): 162.
9. Haridasan A, Thomas J, Raj ED. Deep learning system for paddy plant disease detection and classification. Environ Monitor Assess. 2023; 195 (1): 120.
10. Tugrul B, Elfatimi E, Eryigit R. Convolutional neural networks in detection of plant leaf diseases: a review. Agriculture. 2022; 12 (8): 1192.
11. Boulent J, Foucher S, Théau J, St-Charles PL. Convolutional neural networks for the automatic identification of plant diseases. Front Plant Sci. 2019; 10: 941.
12. Rinu R, Manjula SH. Plant disease detection and classification using CNN. Int J Recent Technol Eng. 2021; 10 (3): 152–156.
13. Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E. Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics. 2021; 10 (12): 1388.
14. Patil BV, Patil PS. Computational method for cotton plant disease detection of crop management using deep learning and internet of things platforms. In: Suma V, Bouhmala N, Wang H, editors. Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2020. Singapore: Springer; 2021. pp. 875–885.
15. Bari BS, Islam MN, Rashid M, Hasan MJ, Razman MA, Musa RM, Ab Nasir AF, Majeed AP. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. PeerJ Computer Sci. 2021; 7: e432.
16. Sujatha R, Chatterjee JM, Jhanjhi NZ, Brohi SN. Performance of deep learning vs machine learning in plant leaf disease detection. Microprocessors Microsyst. 2021; 80: 103615.
17. Pushpa BR, Ashok A, Shree Hari AV. Plant disease detection and classification using deep learning model. In 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, September 2–4, 2021. pp. 1285–1291.
18. Cap HQ, Suwa K, Fujita E, Kagiwada S, Uga H, Iyatomi H. A deep learning approach for on-site plant leaf detection. In: 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), Penang, Malaysia, March 9–10, 2018. pp. 118–122.
19. Ahmed AA, Reddy GH. A mobile-based system for detecting plant leaf diseases using deep learning. AgriEngineering. 2021; 3 (3): 478–493.
20. Negi A, Kumar K, Chauhan P. Deep neural network-based multi-class image classification for plant diseases. In: Choudhury A, Biswas A, Prateek M, Chakrabarti A, editors. Agricultural Informatics: Automation Using the IoT and Machine Learning. New York, NY, USA: Wiley; 2021. pp. 117–129.
21. Krishnamoorthy N, Prasad LN, Kumar CP, Subedi B, Abraha HB, Sathishkumar VE. Rice leaf diseases prediction using deep neural networks with transfer learning. Environ Res. 2021; 198: 111275.

22. Latha RS, Sreekanth GR, Suganthe RC, Rajadevi R, Karthikeyan S, Kanivel S, Inbaraj B. Automatic detection of tea leaf diseases using deep convolution neural network. In: 2021 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, January 27–29, 2021. pp. 1–6.
23. Bedi P, Gole P. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. Artif Intell Agric. 2021; 5: 90–101.
24. Akshai KP, Anitha J. Plant disease classification using deep learning. In: 2021 3rd International Conference on Signal Processing and Communication (ICPSC), Coimbatore, India, May 13–14, 2021. pp. 407–411.
25. Nuanmeesri S. A hybrid deep learning and optimized machine learning approach for rose leaf disease classification. Eng Technol Appl Sci Res. 2021; 11 (5): 7678–7683.
26. Rashid J, Khan I, Ali G, Almotiri SH, AlGhamdi MA, Masood K. Multi-level deep learning model for potato leaf disease recognition. Electronics. 2021; 10 (17): 2064.
27. Li L, Zhang S, Wang B. Plant disease detection and classification by deep learning—a review. IEEE Access. 2021; 9: 56683–56698.
28. Khan RU, Khan K, Albattah W, Qamar AM. Image-based detection of plant diseases: from classical machine learning to deep learning journey. Wireless Commun Mobile Comput. 2021; 2021: Article 5541859.
29. Roy AM, Bhaduri J. A deep learning enabled multi-class plant disease detection model based on computer vision. AI. 2021; 2 (3): 413–428.
30. Applalanaidu MV, Kumaravelan G. A review of machine learning approaches in plant leaf disease detection and classification. In: 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, February 4–6, 2021. pp. 716–724.
31. Patil AB, Sharma L, Aochar N, Gaidhane R, Sawarkar V, Fulzele P, Mishra G. A literature review on detection of plant diseases. Eur J Mol Clin Med. 2020; 7 (7): 1631–1637.
32. Yadav MM, Nennuri R, Rajeshwari D, Rishitha V, Puneeth T. Identification of plant leaf diseases using machine learning algorithms. Ann Romanian Soc Cell Biol. 2021; 25 (6): 6866–6875.
33. Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. Plant Methods. 2021; 17: 1–8.

