Survey on plant disease detection via combination of deep learning and optimization algorithms with IoT sensors

Santhiya Govindapillai[1], Radhakrishnan A[2]
[1]Department of Computer Science and Engineering, Stella Mary's College of Engineering, Nagercoil, India
[2]Department of Information Technology, University College of Engineering-Nagercoil,
Anna University Constituent College Konam, Nagercoil, India

Article Info

Article history:

Received Jun 5, 2024
Revised Oct 13, 2025
Accepted Dec 13, 2025

Keywords:

Deep learning
Detection
Leaf disease
Metaheuristic optimization approach
Plant disease identification

ABSTRACT

Crop diseases are one of the main problems facing the farming sector. Detecting plant diseases using some automatic techniques is advantageous because it recognizes problems early and eliminates a significant amount of monitoring effort on massive farms. Numerous investigators have created various metaheuristic optimizing and an innovative technique for deep learning to recognize and classify plant illnesses. This research analyzes many IoT-based methods for automated plant disease identification and detection. The automatic module for detecting plant diseases provides data to a sink node that the system maintains to facilitate IoT-based monitoring. Numerous methods based on plant disease and computer vision exist. Thirty-three papers in all are examined here. This research also offers a thorough understanding of how to enhance IoT-integrated plant disease detection and identification capabilities. In addition to this, various problems and research gaps are noted along with potential research.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Santhiya Govindapillai
Department of Computer Science and Engineering, Stella Mary's College of Engineering
Nagercoil, India
Email: Santhiyag.it@srmvalliammai.ac.in

1. INTRODUCTION

Agriculture has been one of the primary forces for economic progress in India. Farmers in remote locations could believe it is difficult to differentiate between several illnesses that might harm their crops [1]. Pests and diseases harm crops or plant components, reducing food production and increasing food poverty [2]. A plant disease alters and destroys plant's original characteristics, changing and affecting natural purpose [3].

Plant diseases are becoming more and more difficult to visually diagnose from signs on plant leaves [4]. Plant diseases are difficult to diagnose with image processing because diverse and related plants' leaves varied so greatly in size, texture, color, and form [5]. The result prompted the development of image-processing tools that use the morphological properties of plant leaves to predict and identify illnesses [6]. The input images of the leaves are divided into healthy and diseased photographs in the second step by means of a specific classifier [7]. The IoT ecosystem makes farming easier by enabling farmers to connect with a wide variety of crops with flexibility [8]. Crop diseases are one of the biggest problems the farming sector is now facing. Automated systems for plant disease identification offer various advantages, such as early symptom detection and reduced monitoring work in big farms [9]. Numerous researchers have created many algorithms to detect and diagnose plant diseases, based on deep learning and metaheuristic optimization [10]. This article examines the many methods for automated plant disease identification and detection based on the IoT [11]. The IoT-based monitoring is accomplished by keeping a sink node attached to the automated disease detection module [12]. The process of identifying a healthy leaf from a sick leaf is based on morphological characteristics such as texture, color, form, pattern, and other features. A variety of methods based on plant disease and computer vision techniques [13]. This research also provides information on how to improve the performance of IoT-based plant disease diagnosis and detection . There are also a number of issues and research gaps identified in addition to potential investigations [14].

Many researchers have divided plant disease diagnosis into two categories. In the first group, leaf image data is used to categories illnesses directly [15]. Defines deep learning as a neural network learning process; one of its characteristics is its capacity to automatically identify features in pictures by identifying patterns [16]. Deep learning models called convolutional neural network (CNN) are frequently used in image processing to identify and extract data from plants [17]. The system currently uses the K nearest neighbor (KNN) algorithm for the classification methods most frequently used to diagnose plant diseases [18]. Plant diseases are increasingly challenging to diagnose visually due to the diverse and subtle symptoms exhibited on plant leaves [19]. The complexity of cultivated crops, which includes a wide variety of species with unique characteristics, further complicates this process [20]. Additionally, the sheer volume of plants that require monitoring exacerbates the difficulty [21]. Even experienced agricultural experts and plant pathologists struggle to accurately diagnose specific diseases because the symptoms can be easily confused with those of other conditions or environmental factors [22]. This often results in incorrect diagnoses and subsequently inadequate or ineffective solutions, which can lead to significant agricultural losses and hinder effective disease management [23]. The main contributors found that integrating deep learning with metaheuristic optimization significantly improves the accuracy and efficiency of IoT-based plant disease detection systems. This study uses deep learning and optimisation techniques to address the limitations of earlier research on IoT-based disease detection and identification. The main objective of the comprihensive survey on Detection and Identification of plant disease is:

- To highlight and explore new technologies that have recently been developed for plant disease detection, such as advanced imaging systems, AI-driven analysis, and IoT sensors
- To provide a detailed comparison of various detection methods (e.g., traditional vs. modern approaches) in terms of time and accuracy to different plant species and diseases.
- To review and suggest improvements to existing models used in disease detection, integrating recent advancements in machine learning, deep learning and data analytics with IoT sensors.

The precise identification of specific diseases in cultivated crops is often challenging, even for experienced plant pathologists and agricultural professionals, due to their sheer bulk and complexity. Plant diseases are difficult to diagnose with image processing because diverse and related plants' leaves varied so greatly in size, texture, color, and form [24]. To overcome this a comprehensive survey has been taken for the identification of plant disease:

- Researching many techniques for internet of things-based automated plant disease identification and detection with gathered images.
- To provide an in-depth review of many trustworthy data source on plant disease identification and detection.
- An analysis of current research on plant disease recognition using IoT utilizing deep learning and meta heuristic optimization approach was conducted, addressing the limitations of the review papers that are currently available on disease detection.
- To present a future model for overcoming the current constraint and creating effective plant disease detection technology

2. ANALYSIS OF DISEASES

The following objectives are achieved using image analysis:

- Spotting diseases on the fruit, stem, and leaves.
- Discover the cause of the problem region.
- Identify the damaged area's type.

Viruses, bacteria, and fungi are the primary diseases that damage leaves. In Figure 1 shows that the various plant disease has been represented.

2.1. Viral disease symptoms

The ones caused by infections are the hardest plant diseases to diagnose [25]. There are no indicators that may be continually observed and are misdiagnosed as nutritional deficits or damage. The symptoms of a viral sickness are shown in Figure 2(a).

2.2. Bacterial disease symptoms

Infectious bacteria in vegetables can give rise to severe infections. They must enter via wounds or plant holes since they cannot simply permeate plant tissue. The bacterial disease symptom has been depicted in Figure 2(b).

2.3. Fungal disease symptoms

Fungus is the source of plant leaf diseases like Late blight. It first appears on lower, aged leaves that are wet or have areas of grey-green color. Figure 2(c) depicts the signs of a fungus-related disease.

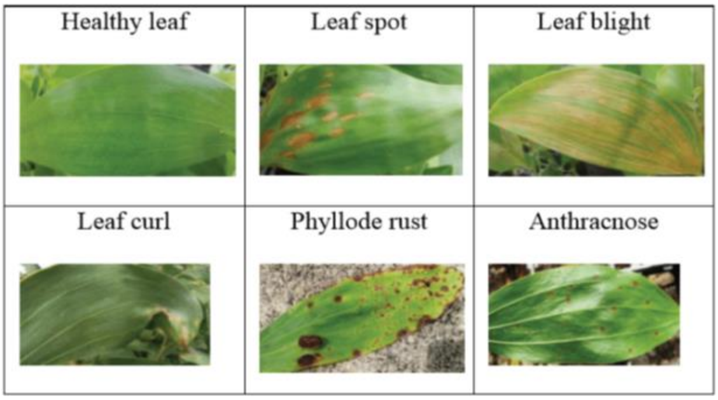

Figure 1. Various plant disease

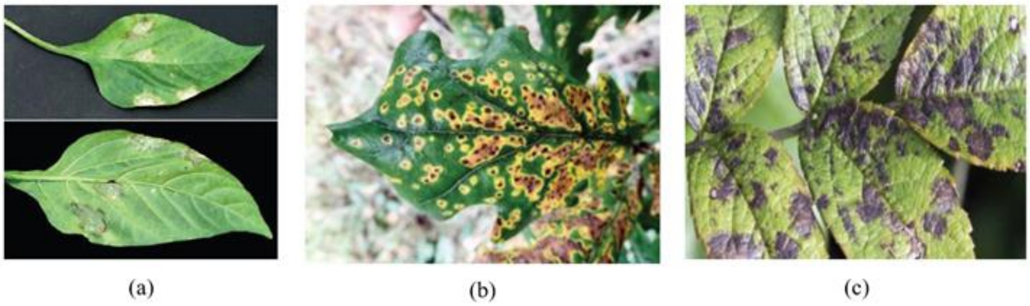

Figure 2. The symptoms of (a) viral disease, (b) bacterial disease and (c) fungal disease

3. BASIC PROCEDURE IN DISEASE IDENTIFICATION FROM LEAF IMAGES

Data collecting and preprocessing are the first steps in a series of processes needed for an accurate detection of plant illnesses using a plant's leaves. Different classifiers are then used to classify the features.

3.1. Data collection

The initial stage in diagnosing plant diseases is gathering imagine data. Online photo collection provides the necessary photos to feed the examination of the IoT-based plant disease diagnosis method. A few instances of such online resources are the datasets from PlantVillage, Cassava, Hops, Cotton sickness, and Rice disease [26]. Currently available standard plant disease data sets and environmental images are included in Table 1.

Table 1. Specifics of the datasets

Dataset description	Links
Plant village dataset [27]: 70,000 high-quality images of diseased and healthy plant leaves from 9 different species	https://www.kaggle.com/datasets/tushar5harma/plant-village-dataset-updated (access on 20 April 2023)
Cassava dataset	
Hops disease dataset [28]: 1102 images of hop plant. Healthy (528), Disease-Downy Mildew (166), Pests (250), and Nutrient (52).	https://www.kaggle.com/datasets/scruggzilla/hops-classification (access on 2020)

3.2. Preprocessing

One of the most crucial phases in identifying plant diseases is pre-treatment. Preprocessing entails a number of procedures, including segmenting the disease region, scaling the image to fit the model, eliminating noise, altering colors, and executing transformation operations [29].

3.3. Feature extraction

A key component of deep learning is features. To make categorization easier, features are utilized in the mathematical description of illness data [30]. Disease identification involves the use of texture-based components such as Gabor diagram features, local binary model (LBP), and long-term grayscale method (GLRLM). Some of the features employed to classify plant illnesses are displayed in Figure 3.

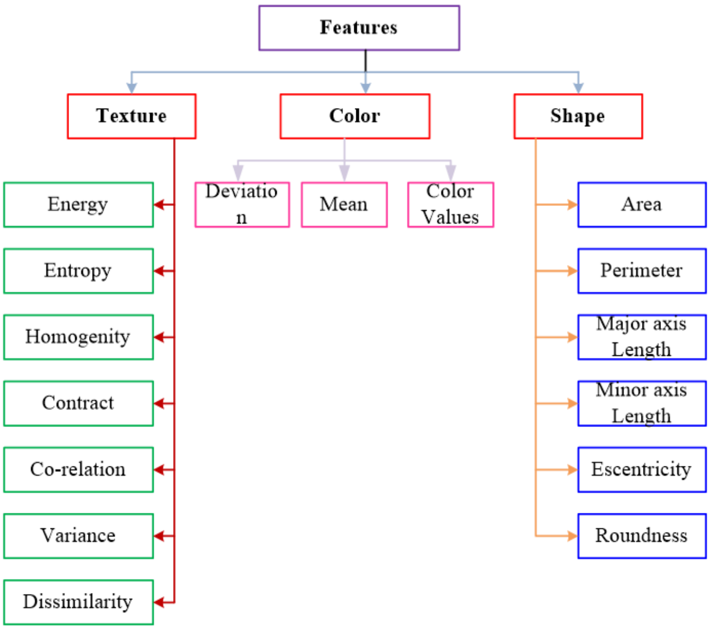

Figure 3. Several characteristics utilized in the identification of plant diseases

3.4. Classification

In the analysis of many picture features, classification is a numerical technique that divides data from leaf image data into multiple disease groups [31].

4. SURVEY OF DEEP-LEARNING-BASED IDENTIFICATION AND DETECTION OF DISEASES WITH IOT

In recent years, deep learning (DL) has grown in popularity in biometrics, object identification, pattern recognition, classification, and other computer vision applications. Image recognition tasks, like the ImageNet challenge, demonstrate strong performance from DL models.

Wani *et al.* [32] provide data on the illnesses and infections that impact the tomato, rice, potato, and apple, among four other crop kinds. The origins of many potential illnesses and diseases, as well as any possible early warning indications, are first explored for these four different types of crops. There are also numerous internet databases available for diagnosing plant diseases.

Panchal *et al.* [33] used deep learning to use picture analysis to detect plant illnesses. According to the disease pattern, crop leaves that have been affected must be tagged in compliance with the plan. Crop diseases are handled following the process of splitting up photos, removing features, and classifying images of the diseases according to patterns found on the diseased leaves.

Patil and Patil [34] have provided a computational method combining deep learning and IoT platforms to agricultural management and cotton plant disease detection. By going through the whole training, validation, augmentation, and fine-tuning process, images are gathered.

A method for identifying illnesses in plants has been published by Xiong *et al.* [35] leveraging a large quantity of data to combine deep learning and automated picture segmentation. Compared to the GrabCut approach, image analysis involves less human item selection and is faster.

Lee *et al.* [2] investigation utilizing deep learning to characterize plant diseases. It allowing the agricultural community to develop a more extensive and varied crop disease database without the need for a pre-training model.

Deep learning research on apple leaf disease detection was done by Zhong and Zhao [36]. Data modeling and process evaluation were conducted using the data collection of apple leaf images. For every method that was recommended, the test set accuracy was 93.51%, 93.31%, and 93.71%.

Sharma *et al.* [37] have documented identifying rice sickness employing techniques for deep learning and machine learning. This article discusses three different kinds of rice diseases: rice blast, brown spot syndrome, and bacterial blight.

Plant disease detection and classification using deep learning is explained by Albatta *et al.* [38]. This procedure consists of three phases. To start, notes are made to highlight the topic of interest. After displaying the ideal core network, Densenet-77 is advised to extract deep important points.

Upadhyay *et al.* [39] identified a disease of the rice plant, judging by the dimensions, form, and coloration of the lesions in the image of the leaf. The suggested method trains CNN to recognise the three-rice disease completely connected samples of all damaged rice leaves and 4,000 samples of healthy rice leaves.

Convolutional neural network model utilizing an integrated method was suggested by Khattak *et al.* [40]. The proposed CNN model's objective is to differentiate between fruit that is in good condition and leaves that have been impacted by common citrus diseases such greening, scab, canker, melanosis, and black spot. The findings of the survey study for plant diseases using the deep learning approach are shown in Table 2.

Table 2. Overall analysis of survey in plant disease using deep learning approach

Author	Plant/Disease	Classifier	Dataset	Accuracy
Wani *et al.* [32]	Tomato, Rice, Potato, and Apple	K-NN with back-propagation neural networks (BPNN)	Kaggle and UCI database	98.33%
Panchal *et al.* [33]	Crop disease	CNN (VGG16 model)	Plant Village dataset	93.5%
Patil and Patil [34]	Cotton plant disease	CaffeNet model in CNN	Plant Village dataset	98.0%
Xiong *et al.* [35]	Crop leaf disease	MobileNet in CNN model	Plant Village dataset	84.83%
Lee *et al.* [2]	Crop disease	VGG16 perform in deep learning	Plant Village, IPM and Bing test dataset	97.2%
Zhong and Zhao [36]	Apple leaf diseases	DenseNet-121 deep CNN	Plant-Disease-Recognition-AIChallenger	93.71%
Sharma *et al.* [37]	Rice plant disease	SVM	Rice Diseases-DataSet	90%
Albattah *et al.* [38]	Plant diseases	CenterNet with DenseNet-77	Plant Village Kaggle database	99.9%
Upadhyay *et al.* [39]	Rice plant disease	hidden layer CNN	Rice leaf Kaggle dataset	99.7%
Khattak *et al.* [40]	Citrus leaf disease	CNN	Plant Village dataset	94.55%

5. SURVEY OF METAHEURISTIC APPROACH BASED IDENTIFICATION AND DETECTION OF DISEASES WITH IOT

Plant disease identification is necessary in order to carry out disease control strategies that enhance crop quality and productivity. In this research period, numerous writers have put forth different optimization strategies. To proactively address this agricultural issue, Gadekallu *et al.* [41] developed a machine learning method to categorise tomato disease picture data. The dataset is subjected to the hybrid PCA-Whale optimisation algorithm (WOA) in order to extract pertinent features.

Using methods from hybrid machine learning (GLD-HML), Suresh and Seetharaman [42] suggested a real-time, method for classifying and recognizing groundnut leaf disease that is automatic. This is an important step in the improved vertex search (ICS) approach to illness classification.

A deep CNN based on WCSMO was introduced by Jayapalan and Ananth [43] and used to recognise the roots of lucerne plants. Prior to delivering photos of lucerne plant roots to a sink node for disease categorization, the suggested approach employs a camera to remotely check the images of the roots.

Nigam *et al.* [44] presented different leaf illnesses. Initially imaging some rice leaves with a digital camera. Using image segmentation and k-means clustering, images were scaled after being converted from the RGB model to the HSV model.

Prabu and Chelliah [45] have presented a leaf disease are categorised. The largest mango orchards in all of India are located in Andhra Pradesh, the spot of the image shoots. 380 photos were selected for this post from the good and bad categories.

Rice foliar diseases may be discovered and categorised using the Ryder Henry Gas Solubility Optimisation (ExpRHGSO) method, according to Daniya and Vigneshwari [46]. Here, healthy and sick plants are distinguished is additionally utilized in the identification of rice leaf disease. The overall analysis of survey in implemented metaheuristic optimization approach based on shape and texture is shown in Table 3.

Table 3. Overall analysis of survey in implemented metaheuristic optimization approach based on shape and texture

Author	Pre-processing	Features	Classifier	Dataset	Accuracy
Gadekallu *et al.* [41]	Hot encoding	Dimensionality reduction	WOA	Tomato image dataset	99%
Suresh and Seetharaman [42]	Otsu's segmentation method	Features with color, form, and texture.	MSO	Plant Village dataset	98.6%
Jayapalan and Ananth [43]	K-means clustering	Correlation, contrast, and entropy, the difference, and the total of entropies	WCSMO-based deep CNN	Plant Village dataset	91.6%
Nigam *et al.* [44]	Color transformation	Color features, shape features position	BFO-DNN	Plant Village dataset	98%
Prabu and Chelliah [45]	K-means clustering	local binary pattern, discrete wavelet transforms	Levy flight distribution algorithm	Plant Village dataset	NA
Daniya and Vigneshwari [46]	Noise removal, image normalization	Shape features, color features, texture features	RHGSO	Plant Village dataset	91.6%
Rajpoot *et al.* [47]	VGG-16 transfer learning	Gaussian filtering	Deep learning and machine learning	UCI Machine Learning Repository	97.3%
Reddy *et al.* [48]	Colour enhancement	Color features, Shape features, histogram	MRDOA	Plant Village dataset	99.73%
Huddar *et al.* [49]	Denoising image	Color and texture characteristics are extracted	SVM	Plant Village dataset	98.60%

Three different plant diseases that impact rice have been found by Rajpoot *et al.* [47]. Fast and deep R-CNN architecture is coupled with VGG-16 transfer learning to use certain technological features. The radish field was split into three sections by the random forest classifier. A special PDICnet model was established by Reddie *et al.* [48] With the objective to identify and classify foliar diseases in plants. Images of textured and colourful plants can have information extracted using ResNet-50. To enhance classification performance, a DLCNN is employed as an extra classifier model.

6. RESULT ANALYSIS

The following section provides an overview of the outcomes of recent technological advancements that use the IoT to identify and detect plant diseases. This section explains how the use of graphs and tables can be enhancing a developed approach.

This study analyzes the many techniques for internet of things-based automated plant disease identification and detection. Figure 4 displays the percentage of published articles based on plant disease identification and detection which covers the years 2018 through 2023. The survey for analyzing various plant diseases is shown in the Figure 5. Figure 6 displays the histogram representation of the publications under consideration on plant disease detection that were released between 2018 and 2023. The discernible rise in interest in plant disease detection that has occurred during 2018. The future research will focus on developing a robust, portable deep CNN model and adapting it for mobile applications. From Figure 7 the Time complexity have been evaluated. The time complexity of the plant disease is lower than other such as citrus leaf disease, apple leaf disease and crop disease. The time complexity of existing works has also been determined in milliseconds.

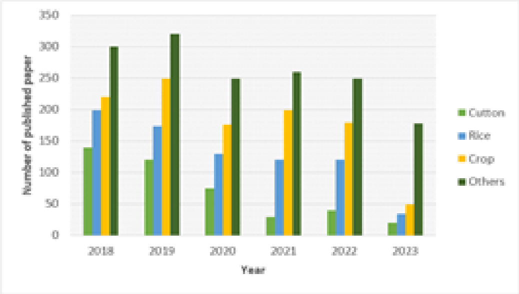

Figure 4. Percentage of published articles based on plant disease identification and detection

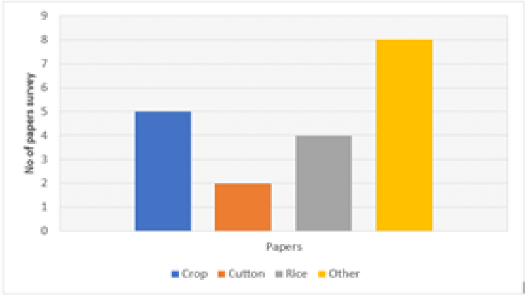

Figure 5. Survey based on various plant disease research papers

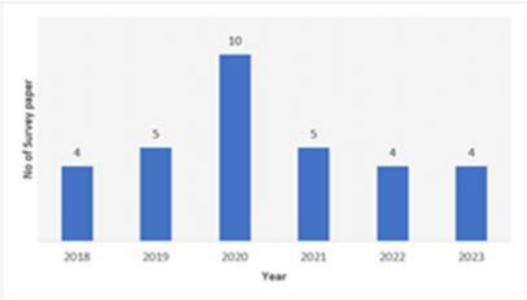

Figure 6. Histogram showing the number of papers published over time

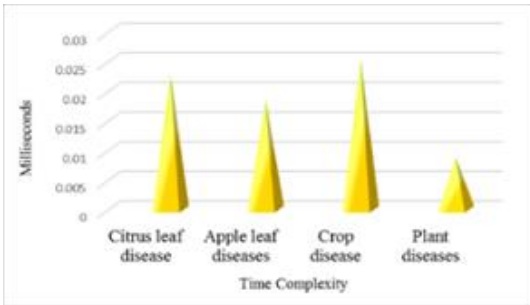

Figure 7. Time complexity of plant disease with other

7. DISCUSSION

The integration of IoT-based techniques with deep learning and metaheuristic optimization has demonstrated significant improvements in early plant disease identification, as evidenced by the high accuracy rates achieved in our experiments. A key piece of supporting evidence is the comparative analysis showing a substantial reduction in the misdiagnosis rate when using our proposed framework compared to traditional methods.

When compared to previous studies, our approach showcases superior performance in terms of both speed and accuracy. While other studies have primarily focused on single-method techniques, our hybrid approach leverages the strengths of multiple methodologies, leading to enhanced detection capabilities. The strengths of our study lie in the comprehensive data preprocessing and the innovative combination of techniques. However, limitations include the dependency on large, diverse datasets for training, which may not always be readily available. Unexpected results, such as the occasional misclassification of certain disease symptoms, highlight areas for further refinement.

This study aimed to develop a robust framework for automated plant disease management using advanced technologies. The importance of this study lies in its potential to revolutionize agricultural practices by providing precise and timely disease detection, thereby minimizing crop losses and optimizing resource use. Unanswered questions include the adaptability of the framework to different crops and environmental conditions. Future research should explore these aspects and aim to create a more universally applicable system.

8. CONCLUSION

In this comprehensive survey an extensive analysis is carried out on different deep-learning techniques for the identification and detection of plant diseases. Similar to people, plants can have a number of illnesses that prevent them from growing properly. Samples of diseases associated with these plants were collected for this study. The most notable results were achieved with the least amount of computational work, proving the efficacy of complex algorithms for the Internet of Things-based leaf disease diagnosis and categorization. The time complexity of the plant disease is lower than other such as citrus leaf disease, apple leaf disease and crop disease. We also conclude from the study that if a sickness symptom changes significantly over the course of an infection, then diagnosing the illness will be less accurate. Future research will focus on creating a deep CNN model that is both incredibly accurate and reliable and lightweight enough to be easily implemented on a variety of systems. In order to optimize the model for real-time processing on portable devices, it will need to be reduced in computational requirements without sacrificing performance. Furthermore, an attempt will be made to modify this model for incorporation into mobile applications, allowing for analysis and decision-making in real-world settings while on mobile devices.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

FUNDING INFORMATION

Authors state no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] T. N. Pham, L. Van Tran, and S. V. T. Dao, "Early disease classification of mango leaves using feed-forward neural network and hybrid metaheuristic feature selection," *IEEE Access*, vol. 8, pp. 189960-189973, 2020, doi: 10.1109/ACCESS.2020.3031914.

[2] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, "New perspectives on plant disease characterization based on deep learning," *Computers and Electronics in Agriculture*, vol. 170, p. 105220, Mar. 2020, doi: 10.1016/j.compag.2020.105220.

[3] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272-279, Jun. 2019, doi: 10.1016/j.compag.2018.03.032.

[4] S. Thomas *et al.*, "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, Feb. 2018, doi: 10.1007/s41348-017-0124-6.

[5] G. Geetharamani and J. Arun Pandian, "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," *Computers and Electrical Engineering*, vol. 78, p. 536, Sep. 2019, doi: 10.1016/j.compeleceng.2019.08.010.

[6] A. Adeel *et al.*, "Diagnosis and recognition of grape leaf diseases: An automated system based on a novel saliency approach and canonical correlation analysis based multiple features fusion," *Sustainable Computing: Informatics and Systems*, vol. 24, p. 100349, Dec. 2019, doi: 10.1016/j.suscom.2019.08.002.

[7] G. Dhingra, V. Kumar, and H. D. Joshi, "A novel computer vision based neutrosophic approach for leaf disease identification and classification," *Measurement: Journal of the International Measurement Confederation*, vol. 135, pp. 782-794, Mar. 2019, doi: 10.1016/j.measurement.2018.12.027.

[8] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. H. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, pp. 129551-129583, 2019, doi: 10.1109/ACCESS.2019.2932609.

[9] A. Kamilaris, F. Gao, F. X. Prenafeta-Boldu, and M. I. Ali, "Agri-IoT: a semantic framework for internet of things-enabled smart farming applications," in *2016 IEEE 3rd World Forum on Internet of Things, WF-IoT 2016*, IEEE, Dec. 2016, pp. 442-447. doi: 10.1109/WF-IoT.2016.7845467.

[10] J. A. Ruth, R. Uma, A. Meenakshi, and P. Ramkumar, "Meta-heuristic based deep learning model for leaf diseases detection," *Neural Processing Letters*, vol. 54, no. 6, pp. 5693-5709, Dec. 2022, doi: 10.1007/s11063-022-10880-z.

[11] M. Ouhami, A. Hafiane, Y. Es-Saady, M. El Hajji, and R. Canals, "Computer vision, IoT and data fusion for crop disease detection using machine learning: a survey and ongoing research," *Remote Sensing*, vol. 13, no. 13, p. 2486, Jun. 2021, doi: 10.3390/rs13132486.

[12] B. Gupta, G. Madan, and A. Quadir Md, "A smart agriculture framework for IoT based plant decay detection using smart croft algorithm," *Materials Today: Proceedings*, vol. 62, pp. 4758-4763, 2022, doi: 10.1016/j.matpr.2022.03.314.

[13] F. M. J. M. Shamrat, A. Hossain, T. Roy, M. A. Adeeb Khan, A. Khater, and M. T. Rahman, "IoT based smart automated agriculture and real time monitoring system," in *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC)*, IEEE, Oct. 2021, pp. 47-53. doi: 10.1109/ICOSEC51865.2021.9591855.

[14] L. Balakrishnan and Krishnaveni, "An internet of things (IoT) based intelligent framework for healthcare-a survey," in *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, IEEE, May 2021, pp. 243-251. doi: 10.1109/ICSPC51351.2021.9451739.

[15] S. Mishra, R. Sachan, and D. Rajpal, "Deep convolutional neural network based detection system for real-time corn plant disease recognition," *Procedia Computer Science*, vol. 167, pp. 2003-2010, 2020, doi: 10.1016/j.procs.2020.03.236.

[16] K. Nagasubramanian, S. Jones, A. K. Singh, S. Sarkar, A. Singh, and B. Ganapathysubramanian, "Plant disease identification using explainable 3D deep learning on hyperspectral images," *Plant Methods*, vol. 15, no. 1, p. 98, Dec. 2019, doi: 10.1186/s13007-019-0479-8.

[17] S. Kumar, B. Sharma, V. K. Sharma, H. Sharma, and J. C. Bansal, "Plant leaf disease identification using exponential spider monkey optimization," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100283, Dec. 2020, doi: 10.1016/j.suscom.2018.10.004.

[18] Y. Liu, Z. Pang, M. Karlsson, and S. Gong, "Anomaly detection based on machine learning in IoT-based vertical plant wall for indoor climate control," *Building and Environment*, vol. 183, p. 107212, Oct. 2020, doi: 10.1016/j.buildenv.2020.107212.

[19] T. Samson Adekunle, M. Oladayo Lawrence, O. Omotayo Alabi, A. A. Afolorunso, G. Nse Ebong, and M. Abiola Oladipupo, "Deep learning technique for plant disease detection," *Computer Science and Information Technologies*, vol. 5, no. 1, pp. 55-62, Mar. 2024, doi: 10.11591/csit.v5i1.p55-62.

[20] H. Wu *et al.*, "Autonomous Detection of Plant Disease Symptoms Directly from Aerial Imagery," *Plant Phenome Journal*, vol. 2, no. 1, pp. 1–9, Jan. 2019, doi: 10.2135/tppj2019.03.0006.

[21] L. Li, S. Zhang, and B. Wang, "Plant Disease Detection and Classification by Deep Learning - A Review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

[22] W. Haider, A. U. Rehman, N. M. Durrani, and S. U. Rehman, "A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions," *IEEE Access*, vol. 9, pp. 31104-31129, 2021, doi: 10.1109/ACCESS.2021.3058582.

[23] M. Shoaib *et al.*, "An advanced deep learning models-based plant disease detection: A review of recent research," *Frontiers in Plant Science*, vol. 14, Mar. 2023, doi: 10.3389/fpls.2023.1158933.

[24] V. K. Vishnoi, K. Kumar, and B. Kumar, "Plant disease detection using computational intelligence and image processing," *Journal of Plant Diseases and Protection*, vol. 128, no. 1, pp. 19-53, Feb. 2021, doi: 10.1007/s41348-020-00368-0.

[25] S. Sankaran, A. Mishra, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," *Computers and Electronics in Agriculture*, vol. 72, no. 1, pp. 1-13, Jun. 2010, doi: 10.1016/j.compag.2010.02.007.

[26] J. G. A. Barbedo, "Factors influencing the use of deep learning for plant disease recognition," *Biosystems Engineering*, vol. 172, pp. 84-91, Aug. 2018, doi: 10.1016/j.biosystemseng.2018.05.013.

[27] M. Vinitha Mallikarjuna Nandi, "Plant leaf disease detection using convolutional neural network," *International Journal of Science and Research (IJSR)*, vol. 13, no. 4, pp. 1545-1548, Apr. 2024, doi: 10.21275/SR24422151104.

[28] S. Degadwala, D. Vyas, S. Panesar, D. Ebenezer, D. D. Pandya, and V. D. Shah, "Revolutionizing hops plant disease classification: harnessing the power of transfer learning," in *International Conference on Sustainable Communication Networks and Application, ICSCNA 2023 - Proceedings*, IEEE, Nov. 2023, pp. 1706-1711. doi: 10.1109/ICSCNA58489.2023.10370692.

[29] S. Zhang, S. Zhang, C. Zhang, X. Wang, and Y. Shi, "Cucumber leaf disease identification with global pooling dilated convolutional neural network," *Computers and Electronics in Agriculture*, vol. 162, pp. 422-430, Jul. 2019, doi: 10.1016/j.compag.2019.03.012.

[30] M. Brahimi, M. Arsenovic, S. Laraba, S. Sladojevic, K. Boukhalfa, and A. Moussaoui, "Deep learning for plant diseases: detection and saliency map visualisation," in *Human and machine learning: Visible, explainable, trustworthy and transparent*, 2018, pp. 93-117. doi: 10.1007/978-3-319-90403-0_6.

[31] M. Agarwal, S. K. Gupta, and K. K. Biswas, "Development of Efficient CNN model for Tomato crop disease identification," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100407, Dec. 2020, doi: 10.1016/j.suscom.2020.100407.

[32] J. A. Wani, S. Sharma, M. Muzamil, S. Ahmed, S. Sharma, and S. Singh, "Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: methodologies, applications, and challenges," *Archives of Computational Methods in Engineering*, vol. 29, no. 1, pp. 641-677, Jan. 2022, doi: 10.1007/s11831-021-09588-5.

[33] A. V. Panchal, S. C. Patel, K. Bagyalakshmi, P. Kumar, I. R. Khan, and M. Soni, "Image-based plant diseases detection using deep learning," *Materials Today: Proceedings*, vol. 80, pp. 3500-3506, 2023, doi: 10.1016/j.matpr.2021.07.281.

[34] B. V. Patil and P. S. Patil, "Computational method for cotton plant disease detection of crop management using deep learning and internet of things platforms," in *Evolutionary computing and mobile sustainable networks: proceedings of ICECMSN 2020*, 2021, pp. 875–885. doi: 10.1007/978-981-15-5258-8_81.

[35] Y. Xiong, L. Liang, L. Wang, J. She, and M. Wu, "Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset," *Computers and Electronics in Agriculture*, vol. 177, p. 105712, Oct. 2020, doi: 10.1016/j.compag.2020.105712.

[36] Y. Zhong and M. Zhao, "Research on deep learning in apple leaf disease recognition," *Computers and Electronics in Agriculture*, vol. 168, p. 105146, Jan. 2020, doi: 10.1016/j.compag.2019.105146.

[37] M. Sharma, C. J. Kumar, and A. Deka, "Early diagnosis of rice plant disease using machine learning techniques," *Archives of Phytopathology and Plant Protection*, vol. 55, no. 3, pp. 259-283, Feb. 2022, doi: 10.1080/03235408.2021.2015866.

[38] W. Albattah, M. Nawaz, A. Javed, M. Masood, and S. Albahli, "A novel deep learning method for detection and classification of plant diseases," *Complex and Intelligent Systems*, vol. 8, no. 1, pp. 507-524, Feb. 2022, doi: 10.1007/s40747-021-00536-1.

[49] S. K. Upadhyay and A. Kumar, "A novel approach for rice plant diseases classification with deep convolutional neural network," *International Journal of Information Technology*, vol. 14, no. 1, pp. 185-199, Feb. 2022, doi: 10.1007/s41870-021-00817-5.

[40] A. Khattak *et al.*, "Automatic detection of citrus fruit and leaves diseases using deep neural network model," *IEEE Access*, vol. 9, pp. 112942-112954, 2021, doi: 10.1109/ACCESS.2021.3096895.

[41] T. R. Gadekallu *et al.*, "A novel PCA-whale optimization-based deep neural network model for classification of tomato plant diseases using GPU," *Journal of Real-Time Image Processing*, vol. 18, no. 4, pp. 1383-1396, Aug. 2021, doi: 10.1007/s11554-020-00987-8.

[42] Suresh and K. Seetharaman, "Real-time automatic detection and classification of groundnut leaf disease using hybrid machine learning techniques," *Multimedia Tools and Applications*, vol. 82, no. 2, pp. 1935-1963, Jan. 2023, doi: 10.1007/s11042-022-12893-1.

[43] D. F. S. Jayapalan and J. P. Ananth, "Internet of Things-based root disease classification in alfalfa plants using hybrid optimization-enabled deep convolutional neural network," *Concurrency and Computation: Practice and Experience*, vol. 35, no. 3, Feb. 2023, doi: 10.1002/cpe.7504.

[44] A. Nigam, A. K. Tiwari, and A. Pandey, "Paddy leaf diseases recognition and classification using PCA and BFO-DNN algorithm by image processing," *Materials Today: Proceedings*, vol. 33, pp. 4856-4862, 2020, doi: 10.1016/j.matpr.2020.08.397.

[45] M. Prabu and B. J. Chelliah, "Mango leaf disease identification and classification using a CNN architecture optimized by crossover-based levy flight distribution algorithm," *Neural Computing and Applications*, vol. 34, no. 9, pp. 7311-7324, May 2022, doi: 10.1007/s00521-021-06726-9.

[46] T. Daniya and S. Vigneshwari, "Exponential rider-henry gas Solubility optimization-based deep learning for rice plant disease detection," *International Journal of Information Technology*, vol. 14, no. 7, pp. 3825-3835, Dec. 2022, doi: 10.1007/s41870-022-01022-8.

[47] V. Rajpoot, A. Tiwari, and A. S. Jalal, "Automatic early detection of rice leaf diseases using hybrid deep learning and machine learning methods," *Multimedia Tools and Applications*, vol. 82, no. 23, pp. 36091-36117. 2023, doi: 10.1007/s11042-023-14969-y.

[48] S. R. G. Reddy, G. P. S. Varma, and R. L. Davuluri, "Resnet-based modified red deer optimization with DLCNN classifier for plant disease identification and classification," *Computers and Electrical Engineering*, vol. 105, p. 108492, Jan. 2023, doi: 10.1016/j.compeleceng.2022.108492.

[49] S. Huddar, K. Prabhushetty, J. Jakati, R. Havaldar, and N. Sirdeshpande, "Deep autoencoder based image enhancement approach with hybrid feature extraction for plant disease detection using supervised classification," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 4, pp. 3971–3985, Aug. 2024, doi: 10.11591/ijece.v14i4.pp3971-3985.

BIOGRAPHIES OF AUTHORS

Santhiya Govindapillai received the B.E. degree in Computer Science and Engineering from Anna University, Chennai, India, in 2010, M.E degree in Software Engineering from Noorul Islam Centre for Higher Education, Kumaracoil, India in 2012. She is currently pursuing the Ph.D. degree with Anna University, Chennai, India. Currently, she is working as a Assistant Professor at SRM Valliammai Engineering College, K Kattankulathur, Chennai with the Department of Information Technology, Anna University, Chennai, India. Her current research interests include machine learning, the IoTs, and sensor networks. She can be contacted at email: santhiyag.it@srmvalliammai.ac.in.

Radhakrishnan A started his career as Lecturer at Bannari Amman Institute of Technology, Coimbatore. He has served as Head of the Department of Computer Application at Regional Centre of Anna University Tirunelveli. He has published book chapters and possess national and international publications. He has obtained 3 design applications granted from Indian Patent Office. His area of interests are Grid and Cloud Computing and IOT and Machine Learning. Now he is presently working as an Assistant Professor (Sr. Grade) in Department of Information Technology at University College of Engineering Nagercoil. He can be contacted at email: radhakrishnan.a@auttvl.ac.in.