FGS Press

Journal of Computer Allied Intelligence
ISSN: 2584-2676
Vol.03(01), February 2025, pp.48-56

Research Article

Plant Disease Detection Using Machine Learning

Swathi.S[1,*]

[1]MCA First Year Student, Department of Computer Applications, Karpaga Vinayaga College of Engineering and Technology, Chengalpattu, Tamil Nadu-603308, India.

[*]Corresponding Author: Swathi. S. Email: swathisahadev151@gmail.com

Received: 05/01/2025; Revised: 10/02/2025; Accepted:18/02/2025; Published: 28/02/2025.
DOI: https://doi.org/10.69996/jcai.2025005

Abstract: Agricultural productivity is significantly affected by crop pathogens and pests, with unpredictable climatic conditions intensifying the challenge. This growing threat to global food security highlights the need for efficient plant disorder detection methods. Traditionally, naked eye observation is used for identifying plant disorders, but it requires continuous expert presence and struggles with visually similar symptoms. Existing automated detection approaches often rely on simple background datasets like Plant Village, which may not perform well in real-world conditions with complex backgrounds and occlusions. To address these limitations, non-invasive, image-based detection methods are proposed. These approaches are simple, effective, and eliminate the need for in-situ data collection. The models are tested on various datasets, using handcrafted feature extraction techniques and novel image segmentation methods that calculate super pixels. To enhance performance, thermal imaging is employed for detecting water stress, an abiotic disorder. Additionally, a residual module-based deep learning model is developed to improve generalization and mitigate overfitting, surpassing traditional feature-based methods. These approaches show promise in accurately detecting both biotic and abiotic plant disorders, contributing to early intervention and improved crop management. The integration of advanced imaging and deep learning techniques holds potential for practical, real-world agricultural applications.

Keywords: Agriculture, Disease Detection, Automation, Machine Learning, Image Processing.

1.Introduction

This study focuses on addressing the growing and urgent need for automated detection systems for plant diseases in the agricultural sector. Agriculture, being a fundamental source of food and economic stability, faces significant threats from various factors, including pathogens, pests, and unpredictable climatic conditions. These challenges not only decrease crop productivity but also jeopardize global nutritional security. A decline in both the quality and quantity of plant yields can have far-reaching consequences, particularly in countries where agriculture forms the backbone of the economy.

Traditional methods of plant disease identification rely heavily on manual observation and expert knowledge, making them time-consuming, labor-intensive, and costly. These conventional techniques often involve physically inspecting crops for symptoms, which may not always be accurate due to human error or delayed recognition. Moreover, not all farmers have access to experienced agricultural experts, especially in rural areas. Therefore, there is an urgent requirement for advanced, cost-effective solutions that can quickly and accurately identify plant diseases.

To address these challenges, this research aims to develop an automated system capable of detecting plant diseases through the use of image processing technologies and the advancements in machine learning algorithms. The proposed approach involves capturing images of plant leaves and analyzing them to identify visual indicators of disease. By leveraging modern machine learning models, the system can efficiently process large datasets and improve detection accuracy, allowing farmers to take timely, proactive measures.

One of the major advantages of automated systems is their ability to provide early-stage detection, which is crucial for preventing the spread of diseases and minimizing crop damage. This research emphasizes the importance of non-invasive methods, ensuring that plants remain unaffected during the detection process. Early recognition can significantly reduce treatment costs and improve the overall quality of agricultural produce.

The key components of the proposed solution include several critical stages:

1. **Image Acquisition:** High-quality images of plant leaves are captured under various environmental conditions to ensure diverse and robust data collection.
2. **Image Segmentation:** This step isolates the region of interest—typically the infected portion of the leaf—from the background, enhancing the focus on disease-specific features.
3. **Feature Extraction:** The system analyses essential characteristics such as colour, texture, and shape to differentiate between healthy and diseased tissues.
4. **Classification:** Using machine learning algorithms, the extracted features are classified to accurately identify the type and severity of the plant disease.

By seamlessly integrating these components into a unified system, the study aims to enhance the precision and efficiency of plant disease detection. Automated systems equipped with these features can provide farmers with timely information, enabling informed decision-making regarding crop management, pest control, and the application of fertilizers or pesticides.

The broader goal of this research is to contribute to sustainable agricultural practices by reducing crop losses, improving yield quality, and promoting environmental safety. By minimizing the excessive use of chemicals through accurate diagnosis, the system supports eco-friendly farming and preserves soil health. In turn, these improvements can positively affect the global food supply chain, helping to alleviate hunger and malnutrition, especially in vulnerable regions.

This study holds particular significance for countries like India, where agriculture plays a pivotal role in the economy and ensuring food security remains a pressing concern. Indian farmers, many of whom work on small-scale farms with limited resources, can greatly benefit from accessible, easy-to-use automated detection systems. By providing early warnings about potential disease outbreaks, these technologies can help safeguard harvests and stabilize farmers' incomes, ultimately strengthening the agricultural sector.

2.Related Works

Deep learning has revolutionized image-based plant disease detection by enabling automatic feature extraction from raw images, improving accuracy over traditional methods. Key techniques include convolutional neural networks (CNNs), data augmentation, transfer learning, and ensemble methods that enhance model performance and adaptability across various crops and conditions. Robust training data and transfer learning help detect subtle disease symptoms efficiently. Integrating deep learning with technologies like remote sensing and IoT further strengthens disease monitoring, enabling early diagnosis, reducing crop losses, and supporting global food security and agricultural sustainability [1-3].

Artificial intelligence (AI) techniques play a vital role in enhancing plant disease detection through imaging technology. AI methods, including machine learning algorithms, neural networks, and fuzzy logic systems, improve accuracy and efficiency over conventional approaches. These techniques handle diverse imaging data, automate detection processes, and save time and resources. Early disease identification using AI enables timely interventions, reduces crop losses, and supports agricultural sustainability and global food security [4-6].

The review explores various image processing techniques for early plant disease detection to enhance food security and agricultural productivity. It covers traditional methods and advanced machine learning algorithms for analysing plant images to identify diseases. High-quality image acquisition and preprocessing are emphasized for accurate diagnosis. Challenges like environmental variations and plant diversity are addressed with potential solutions. The integration of technologies like drones, smartphones, crowdsourcing, and citizen science aids remote plant health monitoring. The review concludes with a call for continued research to develop scalable, cost-effective detection solutions [7-10].

Computer vision techniques offer an efficient solution for automated plant disease detection, addressing the limitations of manual observation. Key methods include image preprocessing, feature extraction, and classification algorithms. Challenges like plant appearance variations and environmental factors are tackled through machine learning approaches to improve accuracy and scalability. These technologies enable early disease detection, timely interventions, and better crop management, supporting food security and sustainable agriculture [11-13]

This review explores digital imaging methods for effective plant disease detection, emphasizing early diagnosis to prevent crop loss and economic damage. It highlights the benefits of digital imaging, including non-invasiveness, cost-effectiveness, and scalability over traditional methods. The methods are categorized into machine learning-based approaches, image processing techniques, and spectral imaging, with detailed discussions on their principles, strengths, and limitations. Challenges like environmental variability, image quality, and data collection are addressed with potential solutions and future research directions for real-world agricultural applications [14-16].

This review examines machine learning algorithms for plant disease detection, emphasizing early diagnosis to reduce crop loss and ensure food security. It highlights machine learning's advantages over traditional methods, including handling large datasets, learning complex patterns, and adapting to varying environments. The methods are categorized into supervised, unsupervised, and semi-supervised learning, with detailed discussions on algorithms like support vector machines, random forests, and convolutional neural networks. The review addresses each approach's strengths, limitations, data needs, computational complexity, and interpretability for effective disease detection [17]

The paper reviews traditional and modern plant disease detection methods, highlighting their strengths and limitations. Traditional techniques like visual inspection and laboratory assays are fundamental but can be subjective and time-consuming. Modern approaches, including image processing, machine learning, and molecular diagnostics, offer more precise and efficient detection. The review emphasizes early disease detection's importance for agricultural sustainability and food security. It advocates integrated methods combining various techniques for accurate disease management and explores future directions to enhance detection accuracy and practicality in real-world applications.

3.Proposed System

The proposed system integrates an image-based approach and machine learning technology to develop automatic detection of system diseases. The system uses the progress of image processing. The system captures images of plant leaves and performs segmentation to separate leaves from the background and other unwanted elements. It then uses distinctive extraction techniques to extract related characteristics from segmented images such as colors, textures, and shapes. These properties serve as inputs for machine learning models for classification where algorithms are trained to distinguish healthy and diseased plants. Figure 1 showing proposed method.

Critical components of the proposed system include image absorption, segmentation, characteristic extraction and classification. New image segmentation techniques and machine learning models are being developed to improve the accuracy and efficiency of disease recognition. By automating the recognition process, the system can provide farmers with good time and accurate information about plant health and take proactive measures to mitigate the effects of disease on yields. Overall, the proposed system aims to revolutionize disease detection in agriculture, support sustainable agricultural practices, and contribute to global nutrition security.

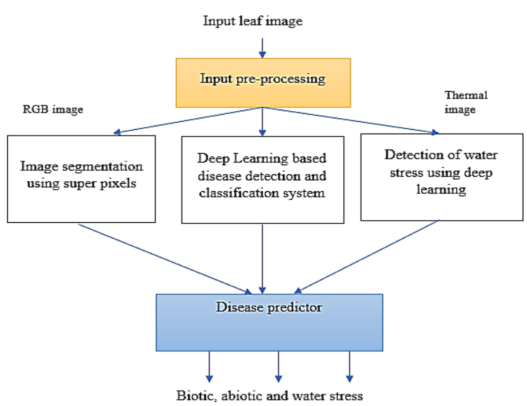

Figure 1: Methodology

4.Modules

4.1 Image Acquisition Module

This module is responsible for capturing high-quality images of plant leaves using suitable imaging devices such as cameras or drones. It may involve controlling the imaging parameters like resolution, lighting conditions, and angle to ensure optimal image quality for subsequent processing steps.

4.2 Image Preprocessing Module

Before further analysis, acquired images often undergo preprocessing to enhance their quality and remove noise. This module may include operations like noise reduction, contrast enhancement, and image resizing to standardize the input images for subsequent processing steps.

4.3 Image Segmentation Module

The segmentation module partitions the preprocessed images into meaningful regions, separating the plant leaves from the background and other unwanted elements. Techniques such as thresholding, edge detection, or region-growing algorithms are commonly used for this purpose.

4.4 Feature Extraction Module

This module extracts relevant features from the segmented images to represent distinctive characteristics of healthy and diseased plant leaves. Features may include color histograms, texture descriptors, shape properties, or spatial statistics, depending on the requirements of the classification task.

4.5 Classification Module

The classification module employs machine learning algorithms to classify the extracted features into predefined categories, such as healthy or diseased. Common classification algorithms include support vector machines (SVM), decision trees, random forests, or convolutional neural networks (CNNs), depending on the complexity of the classification problem and the available dataset

5. Results

Here figure 2 gives the Feature segmentation Procedure and fig 3 gives the selected image.

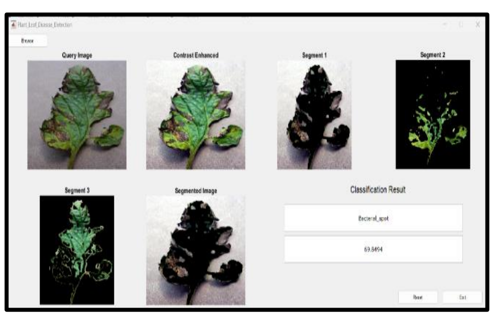

Figure 2: Feature Segmentation

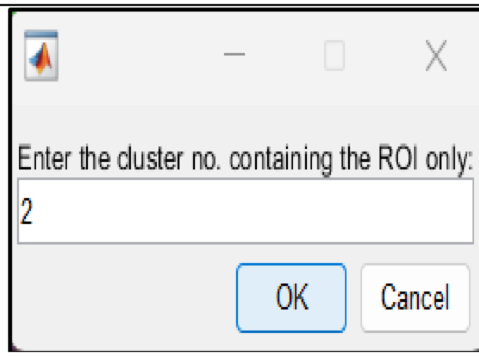

Figure 3: Selection of Segmented Image

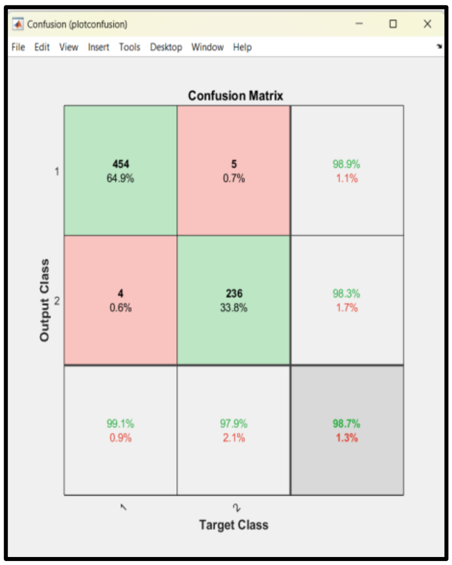

Figure 4: Confusion Matrix

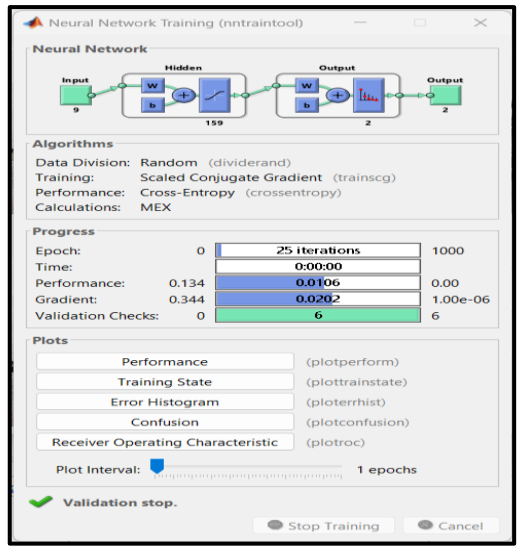

Figure 5: Neural Network Training

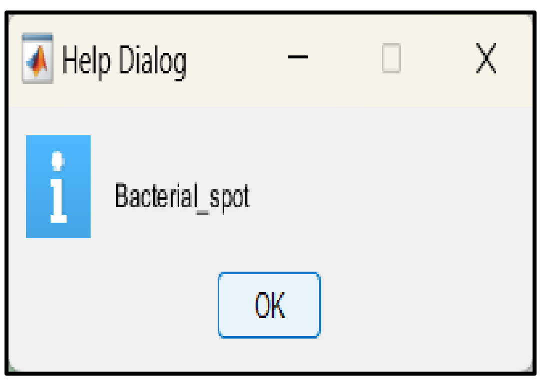

Figure 6: Diseases Prediction

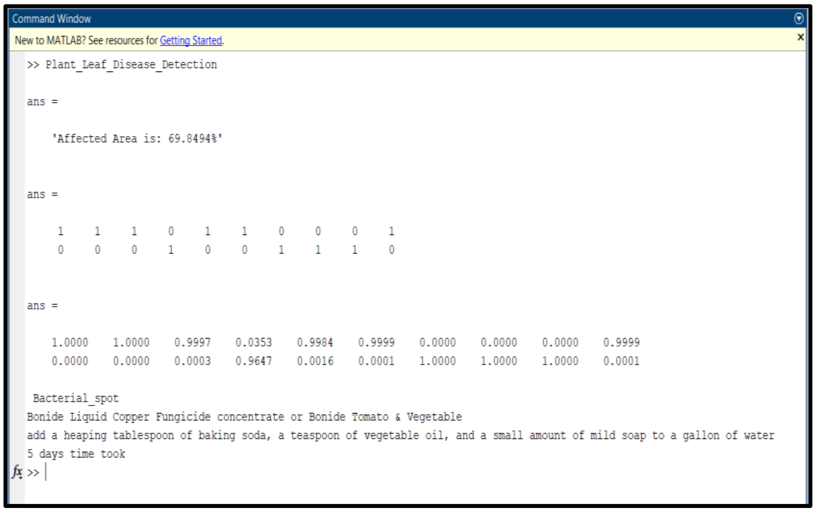

Figure 7: Report and Solution for Treatment

Figure 4 showing confusion matrix, figure 5 showing neural network training, figure 6 showing diseases prediction and finally figure 7 showing report and solution for treatment.

6.Conclusion

Finally, the development and use of automated detection of plant diseases will revolutionize plant management practices and significantly further development of agricultural technologies with the potential to improve nutritional certainty around the world. It represents. By integrating image processing technology, machine learning and advanced hardware algorithms, these systems provide scalable and efficient solutions to the challenges arising from harvesting diseases, pests and environmental factors. It is overestimated, particularly in relation to increased global food demand and increased risks of climate change. These systems allow farmers to provide information about plant health quickly and accurately, enable these systems to provide positive strategies for disease management, reduce crop losses, and improve overall agricultural productivity I will. To ensure their reliability and accuracy with real attitudes. Performance rating metrics such as accuracy, recall, and F1 scores provide valuable insight into the skills of your system and help identify areas of improvement. Furthermore, the importance of continuous maintenance, updates and user support for long-term success and sustainability of these systems is extremely important.

One of the most important advantages of automated detection systems is that they can analyse large quantities using algorithms for machine learning and identify subtle patterns indicating the presence of disease. Through continuous learning from new data and adaptation to changing conditions, these systems improve their accuracy and effectiveness over time, providing farmers with reliable insights into harvests at any given time. It may be limited for small farmers in developing countries where agriculture expertise and access to resources is adequate. These systems can strengthen farmers, improve lives and contribute to the fight against poverty by providing equipment for affordable users-diagnosis and management. It's not a panacea for all agricultural challenges. They should be seen as part of a broader toolkit for sustainable harvest management that complements traditional practices and the knowledge of agricultural professionals. Furthermore, ethical considerations such as data protection, algorithm distortion and fair access to technology are cautionary to ensure that automated disease detection benefits everything involved in the agricultural value chain. You need to be treated. Potentially promote technologies with significant improvements in agricultural productivity, sustainability and nutritional certainty. Through continuous research, innovation and collaboration, we can maximize the potential of these systems to address the complex challenges of global agriculture and pave the way for a more resistant and sustainable future.

Acknowledgment: Not Applicable.
Funding Statement: The author(s) received no specific funding for this study.
Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

References

[1] A. Singh, B. Ganapathy Subramanian, A.K. Singh and S. Sarkar, "Deep Learning for Plant Disease Detection and Diagnosis," *International Journal of Mathematics Statistics and Computer Science,* vol.2, 2019.
[2] D. Singh and U.Singh, "Advances in Deep Learning Techniques for Image-Based Plant Disease Detection," 2019.
[3] P. Baranowski, M. Jedryczka, W. Mazurek, D. Babula-Skowronska, A. Siedliska and Kaczmarek. "Review of Artificial Intelligence Techniques in Imaging for Plant Disease Detection," 2015.
[4] S. Ghosal, D. Blystone, A.K. Singh and Ganapathy Subramanian, "Review on Detection of Plant Diseases Using Image Processing Techniques," 2020.
[5] S.P. Mohanty, D.P. Hughes and M. Salathé, "Computer Vision Techniques for Plant Disease Detection," 2021.
[6] A. Mehta, A. Bansal and A.Saxena, "Review of Methods for Detecting Plant Diseases from Digital Images," 2022.
[7] A. Fuentes, S. Yoon, S.C. Kim and D.S. Park, "Plant Disease Detection Using Machine Learning Algorithms: A Review," 2022.
[8] S. Ghosal, A. Singh, B. Ganapathysubramanian, A.K. Singh and S. Sarkar, "Review on Various Methods for Detection of Plant Diseases," 2021.
[9] Wang, L L , Xiong, Y., Wang, Z., and Qiao, Y. (2015). Towards good practices for very deep two-stream ConvNets. arXiv preprint arXiv:1507.02159., 1-5. doi: 10.48550/ arXiv.1507.02159
[10] Wang, Z, and Zhang, S. (2018). Segmentation of corn leaf disease based on fully convolution neural network. Acad. J. Comput. Inf Sci. 1, 9-18. doi: 10.25236/ AJCIS. 010002

[11] Wiesner-hanks, T., Wu, H., Stewart, E., Dechant, C., Kaczmar, N., Lipson, H., et al. (2019). Millimeter-level plant disease detection from aerial photographs via deep learning and crowdsourced data. Front. Plant Sci. 10, 1-11. doi: 10.3389/ fpls. 2019.01550

[12] Xie, X., Ma, Y., Liu, B., He, J., Li, S., and Wang, H. (2020). A deep-Learning-Based real-time detector for grape leaf diseases using improved convolutional neural networks. Front. Plant Sci. 11, 1-14. doi: 10.3389/fpls.2020.00751

[13] Xu, J., Chen, J., You, S., Xiao, Z., Yang, Y., and Lu, J. (2021). Robustness of deep learning models on graphs: A survey. AI Open 2 (December 2020), 69-78. doi: 10.1016/ aiopen.2021.05.002

[14] Yalcin, IL., and Razavi, S. (2016). "Plant dassification using convolutional neural networks," in 2016 Fifth International Conference on Agro-Geoinformatics (AgroGeoinformatics). (Tianjin, China: IEEE), 1-5. doi: 10.1109/ AgroGeoinformatics.2016.7577698

[15] Yoosefzadeh-Najafabadi, M., Earl, H. J., Tulpan, D., Sulik, J., and Eskandari, M. (2021). Application of machine learning algorithms in plant breeding: Predicting yield from hyperspectral reflectance in soybean. Front. Plant Sci. 11 (January). doi: 10.3389/ fis. 2020.624273

[16] Zhang, S., Huang, W., and Zhang, C. (2019). ScienceDirect three-channel convolutional neural networks for vegetable leaf disease recognition. Cogn. Syst. Res. 53, 31-41. doi: 10.1016/j.cogsys.2018.04.006

[17] Zhao, S., Wu, Y., Ede, J. M., Balafrej, I., and Alibart, F. (2021). Research on image classification algorithm based on pytorch research on image classification algorithm based on pytorch. Journal of Physics: Conference Series, 4th International Conference on Computer Information Science and Application Technology (CISAT 2021). 2010, 1-6. doi: 10.1088/1742-6596/2010/1/012009