International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

# A Review on the Advancements in Plant Disease Detection Using Deep Learning

**Divya Kanwar, Dy HOD Assistant Professor Uday Pratap Singh**
Dept. Artificial Intelligence and Data Science
Poornima Institute of Engineering and Technology, Jaipur

**Abstract- The use of DL algorithms revolutionizes the approach towards the detection of plant disease, making this most critical agricultural technology develop towards accuracy and efficiency that were not possible even with earlier methods. Apart from the benefits that an automated system may have over a manual intervention one, such as quicker identification of disease and less manual efforts, DL techniques, and CNNs in particular, allow the diagnosis of the diseases on plants with precision. The potential of AI-powered systems for plant disease detection is the ability to automatically analyze a plant image to recognize the symptoms and classify diseases with high accuracy. These systems also have the potential to provide real-time support by analyzing complex images and suggesting management recommendations for diseases. Thus, with DL algorithms, the system can identify diseases in plants, detect slight changes in texture and color, and recommend the corrective action to optimize crop health. Further, with the recent advancement in optimized models like YOLOv5 and hybrid techniques by integrating CNN with traditional classifiers such as Support Vector Machines (SVMs), the accuracy in detection has increased. Although the approaches present promising outcomes, challenges abound, especially in dealing with complex image backgrounds, low-quality datasets, and computational efficiency. This paper discusses approaches designed to overcome these hurdles, thus indicating the future direction of plant disease detection systems. This work will, therefore contribute towards the advancement of AI-driven agricultural solutions in terms of the accuracy and speed of plant disease detection and enable better crop management practices around the world.**

**Index Terms- AI, Deep Learning, Plant Disease Detection, Convolutional Neural Networks (CNN), YOLOv5, Hybrid Models, Real-time Decision Support, Agricultural Imaging.**

## I. INTRODUCTION

The use of DL techniques has drastically transformed plant disease detection into an improved accuracy while being more efficient in the determination of plant health disorders. In the past, most traditional agriculture for disease diagnosis depended highly on manual inspections, which were time-consuming and even prone to human errors. This challenge is particularly critical in large-scale farming, because timely detection of disease can minimize crop losses. The complexity of plant diseases has increased, and hence the need for automated systems that can sort through a large amount of data and distinguish between relatively minor symptoms of the disease.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in automating the process of plant disease detection. CNNs can learn hierarchical features from images, enabling them to identify a wide range of diseases based on subtle differences in texture, shape, and color. In agricultural applications, these models have proven promising, with solutions developed to result in significantly less dependency on manual labour compared to prior accuracies in disease classification. Furthermore, hybrid models combined CNNs and traditional machine learning techniques, like SVMs, have increased detection accuracy and computational efficiency. Attention mechanisms-a more recent addition, such as the Convolutional Block Attention Module (CBAM)-enable the systems to focus on relevant parts of a plant image, further enhancing detection capabilities.

This paper reviews the latest advances in deep learning techniques in detecting plant diseases, with particular emphasis on CNN architectures, hybrid models, and attention mechanisms.

It also attempts to highlight the challenges going forward, especially those related to variability issues in datasets, computational complexity, as well as real-time applications in agricultural settings. The paper focuses on providing an in-depth understanding of the work done in this area of research

International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

and establishes possible lines of future enhancement of plant disease detection systems in order to carry out crop management and disease prevention with better efficiency.

## II. LITERATURE REVIEW

**Literature Review-I**

**A Novel Hybrid CNN Methodology for Automated Leaf Disease Detection and Classification.**

The presence of plant diseases is a significant blow to crop quality and production. Traditionally, such identification relies upon visual observation by farmers, which is subjective and prone to error. With time, Machine Learning (ML) and Deep Learning (DL) techniques have emerged as potent weapons to automate disease detection processes, thus achieving higher precision and efficiency.

Early works were mainly in the usage of simple ML techniques towards disease detection. Such techniques, though accurate, found difficulties in having high variability in the same disease, such as shape, color, and texture, which made hard classification accuracy. In the recent development of DL, especially with CNNs, has brought better capability in the detection and classification ability of a plant disease. The CNNs perform very well in imaging tasks because they can learn hierarchical patterns.

A few works have successfully utilized CNNs for the purpose of detecting leaf diseases

Using AlexNet and GoogLeNet in PlantVillage, impressive accuracies are obtained in the detection of multiple diseases against various crops.

Fine-grained disease symptoms can be identified using ResNet architectures with greater accuracy. Models such as ResNet-50 and ResNet-101 depict the potential to detect diseases in crops with impressive precision.

Recent methods combine CNNs with traditional machine learning classifiers, such as SVMs, offering enhanced classification accuracy by using the feature extraction capabilities of CNN and the strength of SVM in classification tasks. Attention mechanisms, such as the Convolutional Block Attention Module or CBAM, further improve the models by focusing on crucial parts of an image, thereby enhancing the detection of disease symptoms.

However, the data requirements and computational complexity will be big challenges for the model. Models like DenseNet, VGG, and others have proved partially successful with various trade-offs between accuracy and computational efficiency.

This paper proposes a hybrid methodology based on the combination of CNN, SVM, and CBAM for improving both detection accuracy and computational efficiency. In this context, it is improved to counter the pitfalls existing in previous methods and gives a ground breaking leap into the area of automated leaf disease detection.

This review forms the basis for the current research work, which highlights the need to combine multiple state-of-art DL techniques to meet the challenges of leaf disease detection and classification.

**Literature Review-II**

**Optimized Lightweight YOLOv5 Model-Based Method for Plant Disease Detection and Classification**

Plant diseases are a major threat to agriculture, causing significant global losses. Traditional diagnosis methods rely on expert knowledge, which can be time-consuming and error prone. To address these issues, machine learning, particularly deep learning, has been applied to plant disease detection. Early methods like KNN and multi- feature machine learning techniques have shown promise but require complex manual feature extraction, which is inefficient for large-scale deployment.

In recent years, object detection technologies such as YOLO (You Only Look Once) gained great popularity with the rapidity of their detection and classification of diseases on images. Very effective and balanced between speed and accuracy in plant disease classification is the lightweight version YOLOv5. However, most of the existing models, fast as they might be, often have weaknesses, especially in the detection of small objects against complex backgrounds in images.

In an attempt to deal with these constraints, this paper proposes an optimized version of YOLOv5 model incorporating the improvements like IASM, GhostNet, and BiFPN. All these improvements enhance the model's accuracy, shrink the model's size, and accelerate processing, making it more viable for disease detection within a variety of agricultural environments.

This review gets into the field of shifting from manually extracted features to automated deep learning approaches, and YOLOv5 is one of the state-of-the-art solutions for efficient plant disease detection.

**Literature Review -III**

**Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques**

The detection and classification of plant leaf diseases are even more relevant in agriculture, since traditional determination by human senses requires time, could be prone to error, and employs expertise. Recent advances in deep learning and image processing bring about more efficient and accurate automated solutions. Currently, the use of Convolutional Neural Networks (CNNs) has been very effective for automating such tasks; this only comes with high accuracy in the classification of various plant diseases from images.

Previous works include that of Prajwala et al., who have imposed CNN-based model in the detection of tomato leaf diseases with a perceived accuracy of around 95%.

Atabay examined deep residual learning and resolved higher performance while classifying disease using pre-trained models such as VGG. Various work, similar to Kawasaki et al., set up CNN applications to detect the viral infection in cucumber leaf at an accuracy of 94.9%.

Although these approaches are promising, many focused on one or two species and were somewhat limited in scope. The current work elaborates on previous works by using a bigger dataset from the repository Plant Village, which contains 20,636 images of three of the major crops, namely tomatoes, potatoes, and peppers, distributed into 15 disease classes.

A CNN designed for this paper has classed 98.029%, many more than most previous methods. This actually proves the capabilities of CNN to work effectively on multiple plant disease detection and classification in different species.

This review highlights the shift from the conventional, labor-intensive approach to the advanced, efficient deep learning models for the identification and classification of plant disease.

**Literature Review-IV**

**From Traditional Approach to Deep Learning in Identifying Plant Diseases**

This paper discusses the transformation in the methodology of plant disease detection from its traditional image processing approach to the solutions that rely on deep learning. The findings are as follows:

- Traditional approaches including K-means clustering, SVMs reached an accuracy of 93% to 98% while diagnosing only specific diseases like apple scab, banana leaf spot, and rice blight.
- Deep learning models mainly ConvNets have the ability to process large volumes of data while eliminating the need to extract features.
- Challenges include a high dependence on quality datasets, computational costs, and a need to be in real-time. The study highlights the need for adopting more advanced visualization techniques such as Grad-CAM for deeper insights into model predictions.

## III. METHODOLOGIES

**1. Literature Survey**

**Criteria for Selection**

Conduct a search for relevant research papers based on the following:

- **Keywords:** plant disease detection, classification, CNN, YOLOv5, hybrid methods, image processing, deep learning.
- **Sources:** Peer-reviewed journals, conference papers, and technical reports.
- **Timeframe:** Focus on recent works for, for example, from the last 5–10 years.1.2. Categorization of Studies

Classification of Studies Classification of studies into:

- **Classical Machine Learning Methods:** KNN, SVM, K-means clustering.
- **Deep Learning Methods:** CNN, YOLOv5, DenseNet, ResNet.
- **Hybrid and Optimized Methods:** CNN + SVM, YOLOv5 with GhostNet, CBAM.

**2. Comparison of Methods**

**Metrics used in Comparison between Studies**

- Accuracy
- Precision and recall
- F1-score
- Processing speed and model size
- Computational efficiency

**Data Sources**

Datasets utilized in the respective studies:

- Private datasets, images from the field, or PlantVillage.
- Characteristics of datasets: size, diversity, and annotation quality.

**Feature Extraction Techniques**

- Compare traditional methods (Manual feature extraction) with automated approaches (Hierarchical feature learning in CNN).

**3. Proposed Framework**

**Hybrid Methodology**

CNN based feature extraction plus the addition of:

- **SVM:** This will improve the classification accuracy of the system.
- **CBAM:** This will help a focus on the critical regions inside the image.
- Advantage of the hybrid technique over individual techniques.

**Optimized Lightweight Models**

- Discuss the advantages of light models, such as YOLOv5, for real-time applications.
- Use the following techniques:
- GhostNet: to simplify the model
- BiFPN: for better feature features

**Benchmarking**

- Devise testing against classical and state- of-the-art solutions to determine performance improvements.

**4. Challenges and Gaps**

Identify the unsolved challenges

- Large and varied datasets with annotations are needed.
- High computational demands.
- Difficulty in detecting illness with similar symptoms.

## IV. CONCLUSION

Deep techniques in machine learning, specifically Convolutional Neural Networks (CNNs), have improved the accuracy and efficiency of plant disease detection systems. This review illustrates how the merging of CNN-based techniques with hybrid and optimized models, including YOLOv5, SVMs, and attention mechanisms, such as CBAM, has dramatically impacted the accuracy achieved in comparison to previous studies. More precise feature extraction, improvements in the accuracy for classification, and optimized computational performance are some of the developments facilitated by these state-of-the-art methodologies.

While these technologies are able to address many problems in traditional approaches, there are still some unresolved issues: the requirement for diverse, high-quality datasets, dealing with complex image backgrounds, and ensuring real-time computational efficiency to deploy at scale.

This study contributes to the burgeoning body of knowledge on AI-driven solutions in agriculture, suggesting a roadmap for further research that enhances the robustness, scalability, and applicability in field deployment of plant disease detection systems. With hybrid frameworks and lightweight models in focus, the findings open up the way to construct practically implementable real- time solutions that could revolutionize modern agriculture practices and bring about healthier crops and better productivity.

## REFERENCES

1. Prajwala, P., et al. (2021). "CNN-based detection of tomato leaf diseases." Journal of Agricultural Informatics, 12(3), 45–56.
2. Atabay, A. (2020). "Deep Residual Learning for Plant Disease Detection." International Journal of Computer Vision and Applications, 8(4), 112–125.
3. Kawasaki, T., et al. (2019). "Detection of Viral Infections in Cucumber Leaves Using CNNs." Computers and Electronics in Agriculture, 164, 104932.
4. Redmon, J., et al. (2020). "YOLOv5: Object Detection for Real-Time Applications." ArXiv Preprint.
5. Misra, D., et al. (2021). "GhostNet: Reducing Model Complexity for Efficient Object Detection." IEEE Transactions on Image Processing, 30, 1395–1408.
6. Woo, S., et al. (2018). "CBAM: Convolutional Block Attention Module." Proceedings of the European Conference on Computer Vision (ECCV), 3, 3–19.
7. Mohanty, S.P., et al. (2016). "Using Deep Learning for Image-Based Plant Disease Detection." Frontiers in Plant Science, 7, 1419.
8. Krizhevsky, A., Sutskever, I., & Hinton, G.E. (2012). "ImageNet Classification with Deep Convolutional Neural Networks." Advances in Neural Information Processing Systems, 25, 1097–1105.
9. Simonyan, K., & Zisserman, A. (2015). "Very Deep Convolutional Networks for Large-Scale Image Recognition." ArXiv Preprint.
10. Hughes, D.P., & Salathé, M. (2015). "An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics." PeerJ, 3, e354