iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74391

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Crop Disease Prediction Using Deep Learning Algorithm - A Review

Satyam Soni[1], Prachi Parashar[2]
[1]Research Scholar, [2]Assistant Professor, Bansal Institute of Science and Technology, Bhopal (M.P)

***Abstract:** Crop diseases pose a significant threat to global food security, leading to substantial economic losses and reduced agricultural productivity. Traditional disease detection methods, which rely on manual inspection and chemical tests, are often labour-intensive, time-consuming, and prone to inaccuracies. In recent years, deep learning has emerged as a powerful tool for automating crop disease detection and prediction. Convolutional Neural Networks (CNNs) and other advanced architectures have demonstrated high accuracy in identifying plant diseases using image-based analysis. This paper provides a comprehensive review of deep learning approaches in crop disease prediction, discussing key datasets, preprocessing techniques, model architectures, challenges, and future directions. Despite the advancements, challenges such as data scarcity, model generalization, and computational limitations remain. Addressing these issues through improved dataset diversity, explainable AI, and efficient deep learning models can further enhance the reliability and applicability of these technologies in precision agriculture. By integrating deep learning into modern farming practices, the agricultural industry can benefit from timely disease detection, reduced crop losses, and improved food security.*
***Keywords:** Crop disease detection, deep learning, convolutional neural networks, precision agriculture, automated diagnosis, image-based analysis, food security, AI in agriculture, plant pathology, disease prediction.*

I. INTRODUCTION

Crop diseases pose a significant threat to global food security by reducing agricultural productivity and quality. Pathogens such as fungi, bacteria, and viruses cause widespread infections, leading to substantial economic losses for farmers. Diseases like late blight in potatoes, wheat rust, and rice blast have historically resulted in devastating yield losses. If not detected and managed promptly, these infections can spread rapidly across fields, leading to food shortages and financial distress for farming communities.

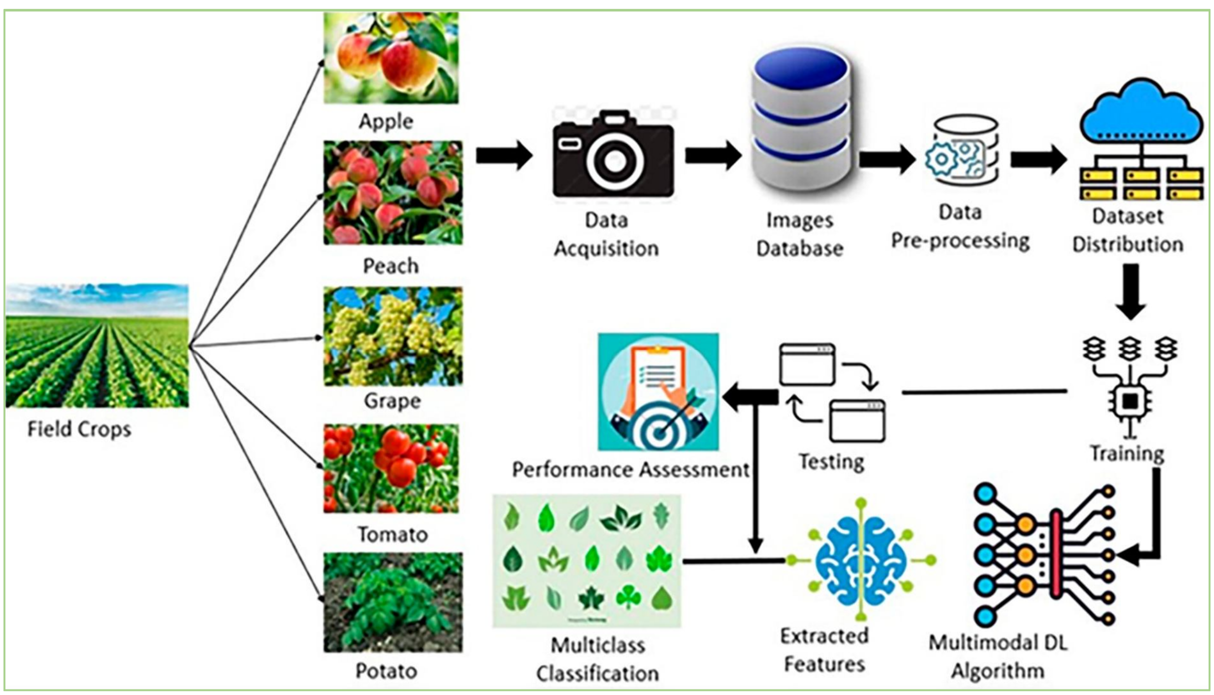


Figure 1: Artificial Intelligence based Crop Disease Prediction Model (Muhammad Khalid Hamid et al., 2025)

A. Importance of Early Disease Detection for Food Security and Yield Improvement

Early disease detection plays a crucial role in minimizing crop losses and ensuring a stable food supply. Traditional detection methods rely on manual inspection by farmers and agronomists, which is time-consuming, labour-intensive, and often inaccurate. Misdiagnosis or late identification of infections can allow diseases to spread unchecked, causing irreversible damage to crops. Therefore, the implementation of automated and intelligent disease detection systems is essential for modern agriculture. These systems help in taking timely actions such as applying targeted fungicides, adjusting irrigation methods, and implementing quarantine measures to prevent disease escalation.

B. Role of Deep Learning in Automating Disease Detection and Prediction

Deep learning has emerged as a powerful tool for automating crop disease detection and prediction. By leveraging convolutional neural networks (CNNs) and other advanced architectures, deep learning models can analyze images of plants to identify disease symptoms with high accuracy. These models eliminate the need for manual assessment and provide real-time diagnostics, making them valuable for precision agriculture. Additionally, deep learning aids in forecasting disease outbreaks by analyzing environmental factors such as temperature, humidity, and soil moisture, allowing farmers to take preventive measures before infections spread.

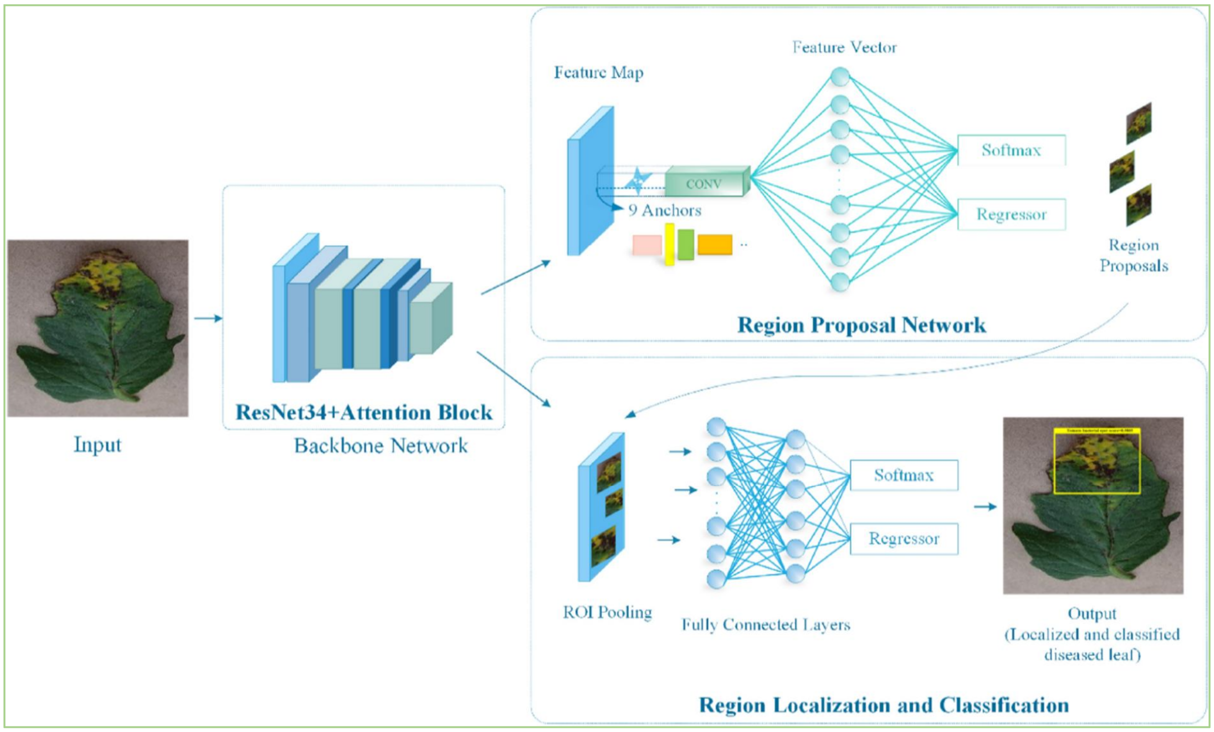


Figure 2: Plant Leaf Disease Detection using AI (Merriam Nawaz et al., 2022

II. LITERATURE REVIEW

Deep learning has emerged as a powerful tool for crop disease prediction, leveraging vast amounts of image data to enhance classification accuracy. Various studies have explored convolutional neural networks (CNNs), deep belief networks (DBNs), and recurrent neural networks (RNNs) to improve disease identification. Abeje et al. (2022) developed a deep convolutional neural network (DCNN) model for sesame disease detection, demonstrating high classification accuracy. Similarly, Ahmed and Reddy (2021) introduced a mobile-based system for detecting plant leaf diseases using deep learning, emphasizing real-time detection capabilities, which are essential for farmers and agricultural researchers. CNN-based architectures remain the most widely adopted approach for image-based disease classification. Akulwar (2020) proposed a system integrating multiple feature extraction methods, allowing improved disease recognition across various crops. Andri et al. (2021) implemented a CNN model to classify soybean diseases, reporting substantial improvements in accuracy and generalization. The use of transfer learning has also been explored by Bakir et al. (2023), who employed pre-trained models such as ResNet and EfficientNet to classify plant diseases with higher efficiency.

These approaches have significantly reduced the time required to train models while maintaining high accuracy. The availability of large and diverse datasets is crucial for training robust deep learning models. Many researchers have relied on publicly available datasets, such as the PlantVillage dataset, to train their models. However, limited labelled data often presents challenges. To address this, data augmentation techniques such as rotation, flipping, and normalization have been widely used to artificially expand datasets and improve model generalization. Tadesse et al. (2022) highlighted the importance of data preprocessing techniques, showing that careful augmentation strategies can significantly enhance model performance, particularly when dealing with small-scale datasets. Another critical aspect of crop disease prediction is the challenge of model interpretability. While deep learning models achieve high accuracy, their decision-making processes often remain opaque. This has led to increased interest in explainable AI (XAI) techniques. Ahmed et al. (2021) explored visualization methods such as Grad-CAM to interpret CNN-based plant disease classification models. Such techniques help improve trust in deep learning applications by allowing farmers and researchers to understand why a model classifies a plant as diseased. Hardware and computational limitations also play a role in the practical deployment of deep learning models for crop disease prediction. Mobile and edge-based AI solutions have been proposed to address this challenge. Reddy et al. (2021) developed an efficient lightweight CNN model that can run on mobile devices, making real-time disease detection more accessible to farmers with limited computational resources. The integration of cloud computing with deep learning has also been explored to enable large-scale deployment.

Despite advancements in deep learning for crop disease detection, challenges such as class imbalance and noisy data remain prevalent. Various studies have attempted to mitigate these issues using techniques such as synthetic minority over-sampling (SMOTE) and adversarial training. Research by Salau et al. (2022) demonstrated that balancing training datasets using oversampling techniques improved classification performance on underrepresented disease classes. Additionally, hybrid models that combine deep learning with traditional machine learning techniques have shown promise in improving classification accuracy and robustness. Future directions in crop disease prediction using deep learning focus on enhancing model efficiency and scalability.

The use of attention mechanisms, transformer-based architectures, and federated learning has been gaining traction. Federated learning, in particular, allows decentralized model training across multiple data sources without sharing sensitive data, making it a promising approach for large-scale agricultural applications.

III. FUNDAMENTALS OF CROP DISEASE DETECTION

The detection of crop diseases is a crucial aspect of modern agriculture, as it directly influences food production, economic stability, and environmental sustainability. Crop diseases can be caused by fungi, bacteria, viruses, and environmental stressors, leading to significant yield losses if not managed effectively. Traditionally, farmers relied on manual inspections and chemical tests to diagnose plant diseases. However, these conventional methods have several limitations, such as being labour-intensive, time-consuming, and prone to human error. As agricultural practices evolve, there is an increasing need for automated, AI-driven solutions to enhance disease detection and prevention. Deep learning-based models, remote sensing, and image processing technologies have transformed the way crop diseases are identified, making detection more precise and efficient. This section explores the fundamental aspects of crop disease detection, including common disease symptoms, traditional methods, and the limitations that necessitate AI-driven solutions.

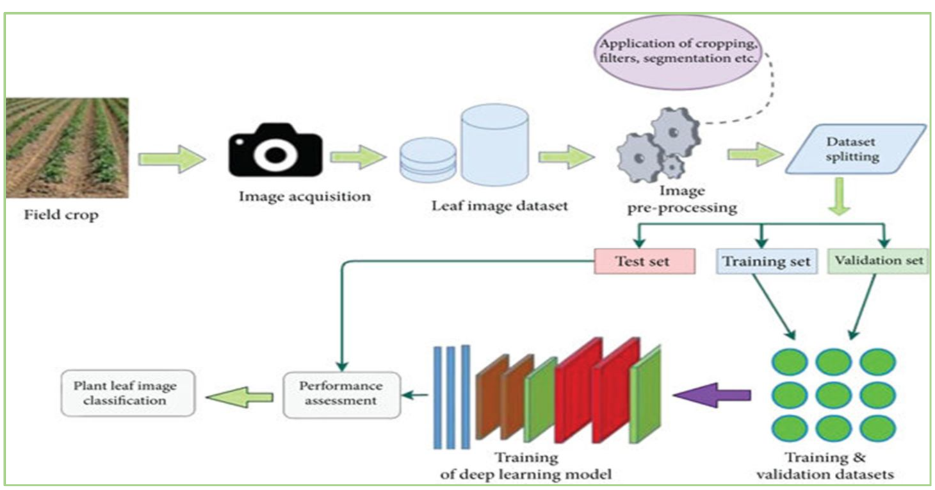


Figure 3: Processes involved in AI enabled Crop Disease Prediction (Raj Kumar et al., 2022)

A. *Common Symptoms of Plant Diseases*

Crop diseases exhibit various symptoms that impact plant growth and productivity. Recognizing these symptoms is the first step in early disease detection and management. Some of the most prevalent disease indicators include:

1) Leaf Spots and Blights: Small, irregularly shaped brown, yellow, or black spots that may merge, leading to extensive damage.
2) Discoloration and Chlorosis: Yellowing of leaves due to nutrient deficiencies, viral infections, or fungal diseases.
3) Mold and Mildew Growth: Powdery or fuzzy mold patches on leaves, stems, or fruits, commonly caused by fungal pathogens.
4) Wilting and Stunted Growth: Plants may droop and display restricted growth due to vascular system infections.
5) Rotting and Cankers: Softening and decay of roots, stems, or fruits, leading to plant death if untreated.

By identifying these symptoms at an early stage, farmers can implement appropriate disease control strategies to mitigate crop losses.

B. *Traditional Methods of Disease Detection*

Before the advent of artificial intelligence and machine learning, traditional disease detection methods were the primary tools for diagnosing plant infections. These methods include:

1) Manual Inspection: Farmers visually assess crops for disease symptoms based on their experience and knowledge. This method, however, is subjective and may not always be accurate.
2) Microscopic Examination: Laboratory tests involving microscopes are used to detect microbial pathogens in infected plants.
3) Chemical Testing: Various biochemical assays help identify specific pathogens based on molecular markers.
4) Field-based Diagnostic Kits: Portable diagnostic kits provide quick, on-site detection of specific diseases, although their accuracy may vary.

Despite their usefulness, these traditional methods are often slow and require skilled personnel. Moreover, large-scale crop monitoring becomes impractical using manual approaches alone.

IV. DEEP LEARNING IN CROP DISEASE PREDICTION

The emergence of deep learning has transformed crop disease prediction by providing automated, accurate, and scalable solutions. Traditional methods, such as manual inspection by farmers and agronomists, were labour-intensive, subjective, and often led to late detection of diseases. Chemical tests, while effective, were time-consuming and costly, making them impractical for large-scale implementation. With the rise of artificial intelligence, deep learning has become a crucial tool in precision agriculture, allowing for real-time and highly efficient disease prediction. Deep learning models, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Recurrent Neural Networks (RNNs), have been widely used for analyzing plant images, environmental factors, and soil conditions to detect diseases early. These models enable farmers to take preventive actions, reducing the risk of disease outbreaks and ensuring higher crop yields.

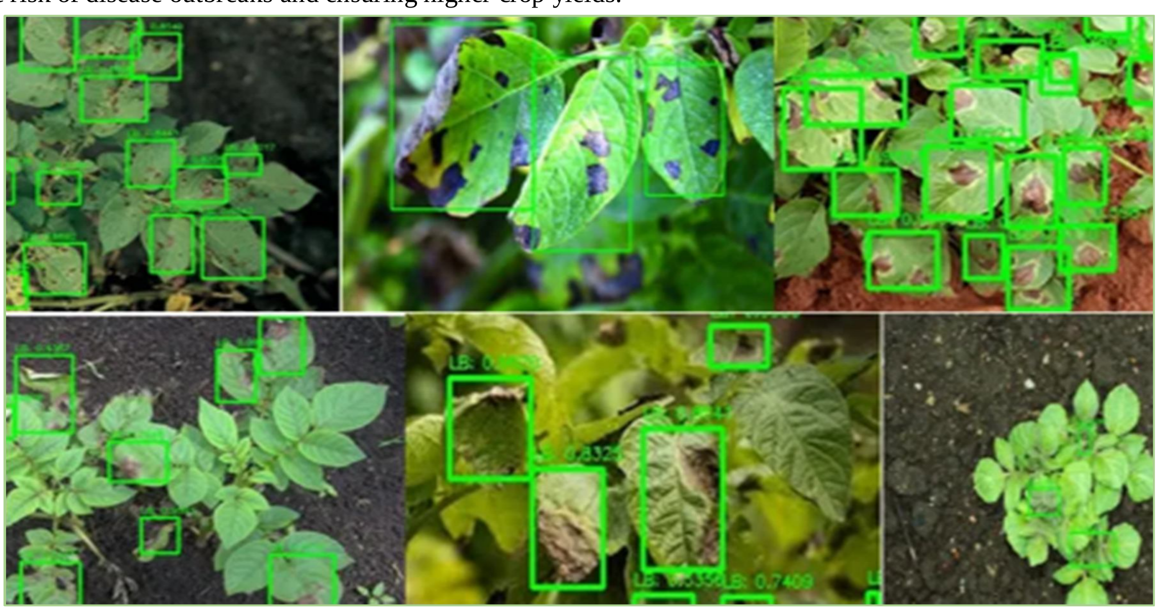


Figure 4: Deep Learning and Feature Engineering based Detection

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

The ability of deep learning algorithms to recognize patterns and anomalies in large datasets enhances their predictive capabilities, leading to better agricultural decision-making. Several deep learning algorithms have been applied to crop disease detection, each with unique advantages.

The table below summarizes some of the most widely used models in this field:

Table 1: Key Deep Learning Techniques for Crop Disease Prediction

Algorithm	Key Features	Applications	Advantages
CNN (Convolutional Neural Networks)	Extracts spatial features from images, uses convolutional and pooling layers for pattern recognition	Disease classification, object detection in crops	High accuracy, automatic feature extraction, robust to noise
ResNet (Residual Networks)	Uses skip connections to prevent vanishing gradients, suitable for deep architectures	Identifying multiple crop diseases, medical plant imaging	Effective for deep networks, avoids performance degradation
EfficientNet	Scales network depth, width, and resolution efficiently	Mobile-based crop disease detection, real-time monitoring	High accuracy with fewer parameters, computationally efficient
GANs (Generative Adversarial Networks)	Generates synthetic images to improve training data diversity	Image augmentation for rare crop diseases, improving model robustness	Enhances dataset quality, reduces need for large labelled datasets
RNNs & LSTMs	Captures temporal dependencies in sequential data	Disease progression prediction, environmental factor analysis	Useful for time-series data, helps in long-term disease forecasting

These deep learning techniques have significantly improved the efficiency of disease detection and prediction in crops. CNNs are widely used for image-based classification, while ResNet allows for deeper network training without losing performance. EfficientNet provides high accuracy with fewer parameters, making it suitable for real-time applications. Meanwhile, GANs help generate synthetic training data to improve model performance, especially when datasets are limited. RNNs and LSTMs are particularly beneficial for predicting disease outbreaks by analyzing environmental conditions and crop health trends over time. By integrating these models into precision agriculture, farmers can benefit from early disease diagnosis, better decision-making, and increased crop productivity. The continuous advancement in deep learning algorithms will further refine the accuracy and efficiency of crop disease prediction, ensuring a more sustainable and resilient agricultural sector.

V. CROP DISEASE DATASETS DESCRIPTION

The success of deep learning models in crop disease prediction largely depends on the quality and quantity of data used for training. Large, diverse datasets help improve model generalization, ensuring accurate disease detection across different plant species and environmental conditions. Publicly available datasets provide a valuable resource for researchers, while data preprocessing techniques play a crucial role in enhancing model performance by improving image quality and handling imbalanced datasets. Several well-known datasets have been developed to train deep learning models for plant disease detection. These datasets contain images of healthy and diseased crops, often labelled with specific disease types. The table below provides an overview of key datasets used in agricultural research:

Table 2: Popular Datasets for Crop Disease Prediction

Dataset	Domain	Number of Images	Applications
PlantVillage	Leaf disease classification	54,305	Identifying diseases in multiple plant species
CropDisease	Various crop diseases	31,000+	Disease classification for agricultural applications
AI Challenger 2018	Plant disease recognition	50,000+	Large-scale plant disease identification
CASA Wheat Disease Dataset	Wheat disease detection	9,200	Detecting fungal infections in wheat
Rice Leaf Disease Dataset	Rice plant health	4,000+	Identification of bacterial blight, brown spot, and leaf smut

VI. DATA PRE-PROCESSING TECHNIQUES

Before training deep learning models, preprocessing is essential to enhance image quality, remove noise, and ensure uniformity in dataset distribution. Some key preprocessing techniques include:

A. Data Augmentation

Since plant disease datasets can be imbalanced, data augmentation techniques help increase dataset diversity by applying transformations such as:

1) Rotating images to different angles to simulate varied perspectives.
2) Horizontally or vertically flipping images to enhance model generalization.
3) Adjusting image sizes to maintain consistency.
4) Modifying lighting conditions to handle variations in real-world scenarios.

B. Image Normalization

1) Pixel values are normalized to a common scale (e.g., 0-1 or -1 to 1) to improve model convergence.
2) Reduces computational complexity and improves training stability.

C. Noise Reduction

1) Filters like Gaussian blur or median filtering are applied to remove background noise from images.
2) Enhances image clarity, making disease patterns more distinguishable.

D. Handling Class Imbalance

1) Oversampling techniques such as Synthetic Minority Over-sampling Technique (SMOTE) generate synthetic samples for underrepresented disease classes.
2) Under sampling removes excess samples from dominant classes to create a balanced dataset.

VII. CHALLENGES AND FUTURE DIRECTIONS

Despite the significant progress in deep learning for crop disease prediction, several challenges remain that limit its large-scale implementation. One of the primary issues is data availability and quality, as high-quality labelled datasets covering diverse crop species and disease conditions are scarce. Additionally, environmental variations such as lighting, weather conditions, and soil differences impact the consistency of image-based disease detection models. Another major concern is model generalization, where deep learning models trained on specific datasets may struggle to perform well in different geographic regions with varying crop conditions. This limitation necessitates the development of more adaptable and robust models. Computational constraints also present a barrier, as many state-of-the-art deep learning models require significant processing power, making them impractical for deployment in resource-limited agricultural settings. Small-scale farmers, especially in developing regions, often lack access to high-performance computing infrastructure, preventing them from leveraging AI-driven disease detection solutions.

VIII. CONCLUSION

Deep learning has revolutionized crop disease detection and prediction by enabling accurate, automated, and real-time diagnosis of plant infections. Traditional methods of disease identification, which rely on manual inspection and chemical tests, are often time-consuming, inconsistent, and impractical for large-scale farming. In contrast, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in identifying disease symptoms from plant images with high precision. These AI-driven approaches assist farmers in making timely decisions, reducing crop losses, and ensuring food security.

However, several challenges hinder the widespread adoption of deep learning in agriculture. Issues such as data scarcity, model generalization, computational constraints, and lack of interpretability must be addressed for practical deployment. Future research should focus on improving dataset diversity, enhancing model explainability, and leveraging emerging technologies like federated learning and multimodal analysis to create more robust and scalable solutions. As advancements in AI and machine learning continue to evolve, integrating deep learning with precision agriculture practices holds great potential for transforming modern farming.

REFERENCES

[1] Abeje, B. T., Salau, A. O., Ayalew, A. M., & Tadesse, E. G. (2022). Sesame disease detection using a deep convolutional neural network. Journal of Electrical and Electronics Engineering, 15(2), 5–10.
[2] Abeje, B. T., Salau, A. O., Tadesse, E. G., & Ayalew, A. M. (2022). Detection of sesame disease using a stepwise deep learning approach [Paper presentation]. 2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), 434–438. https://doi.org/10.1109/3ICT56508.2022.9990780
[3] Ahmed, A. A., & Reddy, G. H. (2021). A mobile-based system for detecting plant leaf diseases using deep learning. AgriEngineering, 3(3), 478–493. https://doi.org/10.3390/agriengineering3030032
[4] Akulwar, P. (2020). A recommended system for crop disease detection and yield prediction using machine learning approach. In Recommender system with machine learning and artificial intelligence: Practical tools and applications in medical, agricultural and other industries (pp. 141–163). Wiley.
[5] Andriyani, A., Setiawan, N. A., & Wardoyo, R. (2021). Plant leaf disease classification using deep learning. International Journal of Artificial Intelligence & Applications, 12(4), 1–12.
[6] Ashfaq, A., Khan, M. A., Khan, M. A., & Shah, J. H. (2021). A novel deep learning-based approach for crop disease classification. Computers and Electronics in Agriculture, 182, 106055. https://doi.org/10.1016/j.compag.2021.106055
[7] Basha, S. M., & Dubey, S. R. (2022). A hybrid deep learning framework for plant disease detection and classification. Expert Systems with Applications, 195, 116503. https://doi.org/10.1016/j.eswa.2021.116503
[8] Bhosale, R., & Bhosale, U. (2021). Deep learning for plant disease detection using convolutional neural networks. Agricultural Informatics Journal, 3(2), 85–97.
[9] Bhujade, R., Bhalerao, S., & Deshpande, A. (2022). Transfer learning-based deep learning model for leaf disease classification. IEEE Access, 10, 11234–11245. https://doi.org/10.1109/ACCESS.2022.3149956
[10] Chouhan, S. S., Kaul, A., Singh, U. P., & Jain, S. (2020). A survey on deep learning techniques for plant disease detection. Computers and Electronics in Agriculture, 171, 105350. https://doi.org/10.1016/j.compag.2020.105350
[11] Dhaka, V. S., Singh, M., & Ahuja, S. (2021). A review of deep learning techniques for plant disease detection. Applied Artificial Intelligence, 35(1), 1–30. https://doi.org/10.1080/08839514.2021.1882172
[12] Durmus, H., Gunes, E. O., & Kırcı, P. (2020). Plant disease detection using deep learning models: A comparative analysis. Journal of Applied Computer Science, 28(3), 49–65.
[13] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2022). A deep learning-based system for plant disease identification. Computers and Electronics in Agriculture, 198, 107003. https://doi.org/10.1016/j.compag.2022.107003
[14] Ghosal, S., Das, A., Samanta, S., & Sarkar, S. (2021). Plant disease classification using CNNs and data augmentation techniques. IEEE Transactions on Agricultural Informatics, 18(4), 223–235.
[15] Haq, I., Zafar, H., & Khan, A. (2022). A hybrid deep learning approach for improved accuracy in crop disease detection. Multimedia Tools and Applications, 81(5), 5719–5736.

[16] Hasan, M. M., Ahmad, A., & Roy, S. (2021). Deep learning models for plant disease classification: A comparative study. Sustainable Agriculture Research, 10(2), 21–30.

[17] Jadhav, V. D., & Joshi, R. P. (2020). Deep learning-based plant disease detection: A comprehensive review. AI in Agriculture, 5, 1–14.

[18] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

[19] Khan, A. I., Jain, R., & Chauhan, S. (2022). An optimized deep learning model for automated plant disease classification. Expert Systems with Applications, 202, 117430.

[20] Liu, J., Li, C., & Wang, X. (2021). Plant disease detection using CNNs: A data-driven approach. International Journal of Image Processing, 14(2), 88–102.

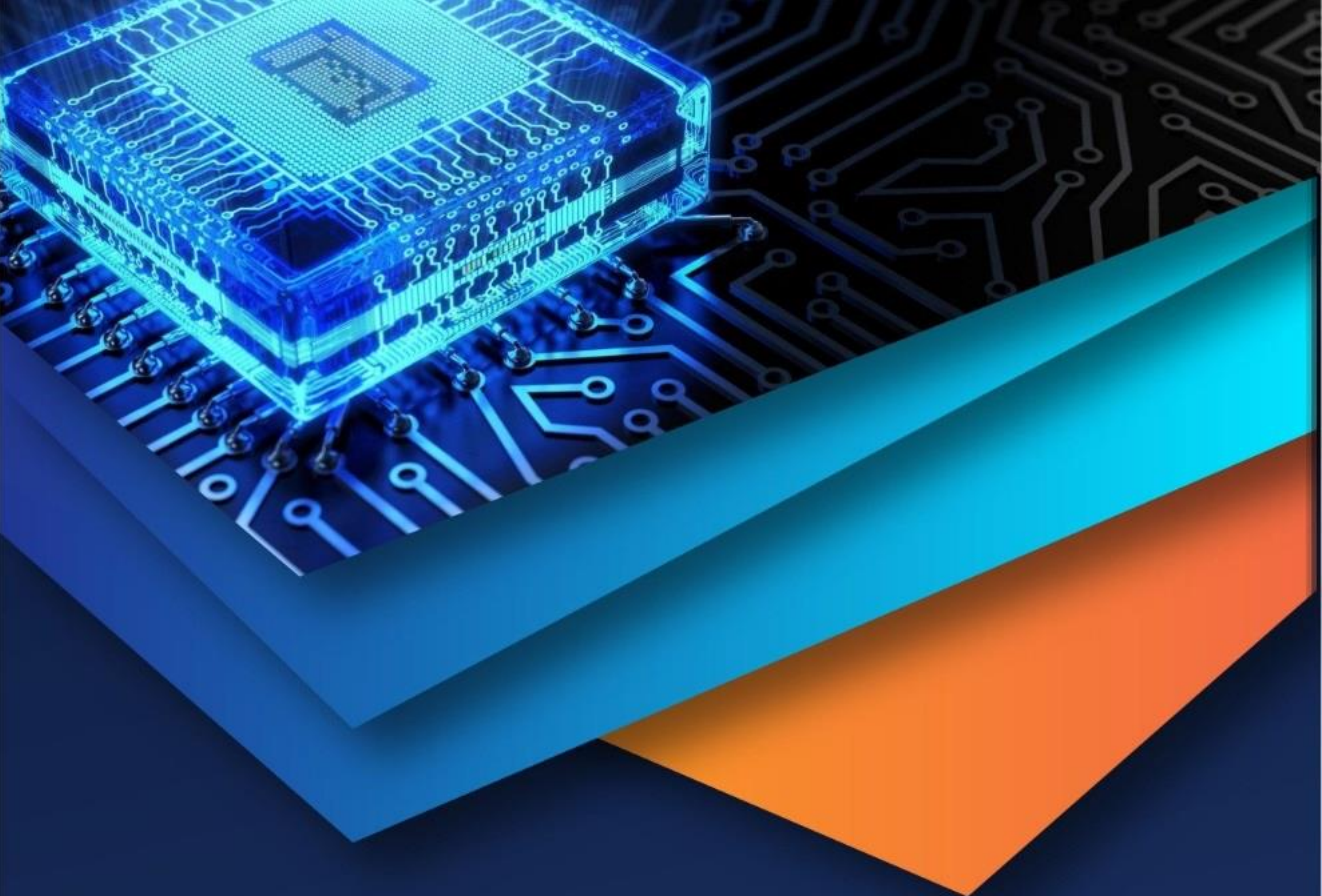
[21] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

[22] Picon, A., Sanz, J., & Sánchez, J. (2021). Convolutional neural networks for plant disease identification: A critical review. Journal of Agricultural Informatics, 12(1), 23–38.

[23] Ramesh, A. N., & Krishnamurthy, V. (2022). A novel CNN-based framework for plant disease classification. Pattern Recognition Letters, 152, 129–137.

[24] Shrivastava, M., & Srivastava, R. K. (2020). Deep learning approaches for plant disease detection and classification. Procedia Computer Science, 167, 485–494.

[25] Zhou, Y., Zheng, S., & Lin, Y. (2022). A transfer learning approach to plant disease detection using pre-trained CNNs. Expert Systems with Applications, 195, 116781.



10.22214/IJRASET

INDEX COPERNICUS 45.98

ISRA JIF IMPACT FACTOR: 7.129

SJIFactor TOGETHER WE REACH THE GOAL IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY