AUTOMATED DETECTION AND CLASSIFICATION OF CROPS LEAF DISEASES USING DEEP LEARNING TECHNIQUES: A COMPREHENSIVE REVIEW

Mr. Rameshwar S. Devhade
[1]Research Scholar, Department of Applied Electronics, Sant Gadge Baba Amravati University, Amravati (M.S.) India
devhaderam1994@gmail.com

Dr. Ranjana D. Raut
[2]Professor, Department of Applied Electronics Sant Gadge Baba Amravati University, Amravati (M.S.), India
ranjanaraut@sgbau.ac.in

Abstract

*Crop diseases significantly impair agricultural productivity by reducing both yield and quality, thereby causing severe economic losses and posing a considerable threat to food security. This issue is particularly critical in rural regions of India, where agriculture constitutes the primary livelihood. To mitigate these challenges, the deployment of advanced computer vision–based algorithms for the automatic detection and classification of crop diseases has become essential, enabling early diagnosis and timely intervention. A broad range of approaches, including machine learning, deep learning, convolutional neural networks (CNNs), and image processing techniques, have been proposed, each with distinct advantages and limitations. This review critically examines recent research on cotton, soyabean and maize crops disease identification and classification, consolidating findings in terms of algorithms applied, datasets utilized, evaluation metrics, types of diseases detected, and maximum accuracies achieved. An initial **1200** research articles were collected from five major academic databases such as Springer, IEEE Xplore, Scopus, Google Scholar, and the ACM Digital Library before being refined through a comprehensive screening process to **235** methodologically relevant studies. In addition to rice, grapes, apples, cucumbers, maize, tomatoes, wheat, and potatoes have been investigated, with hyperspectral imagery and vision-cantered approaches frequently employed. Results indicate that Support Vector Machines (SVMs) and Logistic Regression (LR) generally outperform conventional classifiers, although disease localization continues to pose a significant challenge. Recent advancements, particularly cognitive CNNs enhanced with attention mechanisms and transfer learning, demonstrate promising improvements in detection accuracy and robustness, thereby underscoring their potential in advancing precision agriculture.*

***Keywords**: Crop disease detection, Machine learning, Deep learning, Convolutional neural networks, Transfer learning, Precision agriculture, Hyperspectral imagery, Agriculture etc.*

Introduction:

Plant diseases are a major challenge in agriculture, causing significant yield losses and affecting food security worldwide. Early and accurate disease detection is essential to reduce crop losses and minimize the use of chemical pesticides. Traditional methods of disease identification, such as manual inspection and laboratory analysis, are often labour-intensive, time-consuming, and prone to human error. Recent advancements in artificial intelligence (AI), particularly deep learning (DL) and convolutional neural networks (CNNs), have shown great promise for automated plant disease detection and classification. The rapid advancement of artificial intelligence (AI) and computer vision has significantly transformed agricultural research, particularly in the detection and classification of plant leaf and crop diseases. Early and accurate disease identification plays a crucial role in ensuring food security, reducing yield losses, and minimizing the indiscriminate use of pesticides. Consequently, automated and intelligent systems based on image processing and machine learning have emerged as promising alternatives [1], [2]. In recent years, deep learning (DL), particularly convolutional neural networks (CNNs), has gained prominence in advanced image detection and classification tasks. When sufficient training data and computational resources are available, CNN-based models have demonstrated remarkable performance by automatically extracting discriminative features and achieving high accuracy in controlled environments [3], [4]. These methods have been widely applied in plant disease detection studies, yielding impressive results within specific datasets [5], [6]. However, a notable limitation is their reduced generalizability across different datasets or under real-world conditions, which often include variations in lighting, background, crop variety, and leaf morphology [7], [8]. Although considerable progress has been made, a systematic evaluation of the performance of existing techniques is still lacking. Many studies present promising results, yet they differ in terms of datasets, preprocessing techniques, architectures, and evaluation metrics, which makes it challenging to compare outcomes or establish standardized benchmarks. Furthermore, issues related to dataset diversity, model generalizability, and real-world applicability restrict the deployment of these models in practical agricultural scenarios [9], [10]. In many advanced image detection and classification applications, deep learning (DL), particularly convolutional neural networks (CNNs), has emerged as the preferred approach when sufficient datasets and computational resources are available. CNNs have demonstrated strong performance in terms of detection and classification accuracy within specific datasets; however, their generalizability across different datasets often remains limited. The present study seeks to provide future researchers with a comprehensive overview of the performance outcomes, evaluation metrics, and comparative results of existing methods employed for detecting and classifying plant leaf and crop diseases. This review highlights the role of diverse image-processing and artificial intelligence (AI) techniques, thereby contributing to ongoing advancements in the field.

Problem Statement:

Despite extensive research on plant leaf and crop disease detection using AI and image-processing techniques, there remains no unified framework that consolidates performance outcomes, comparative evaluation metrics, and practical challenges across different methodologies. This lack of standardization hinders the identification of the most robust and scalable approaches for real-world agricultural applications [11].

Process for Literature Review:

The present literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological rigor and transparency. The search covered publications from **2020 to 2025** to capture recent developments in deep learning and machine learning applications for agricultural disease detection. The initial search yielded over **1,200** publications. Titles and abstracts were screened to determine relevance, and duplicates were removed. The following inclusion criteria were applied:

- Studies focusing on plant or crop leaf disease detection and classification.
- Articles employing deep learning (CNNs, Transformers, hybrid models) or machine learning (SVM, KNN, Random Forest, etc.) techniques.
- Peer-reviewed journal articles, conference proceedings, and high-impact workshop papers.

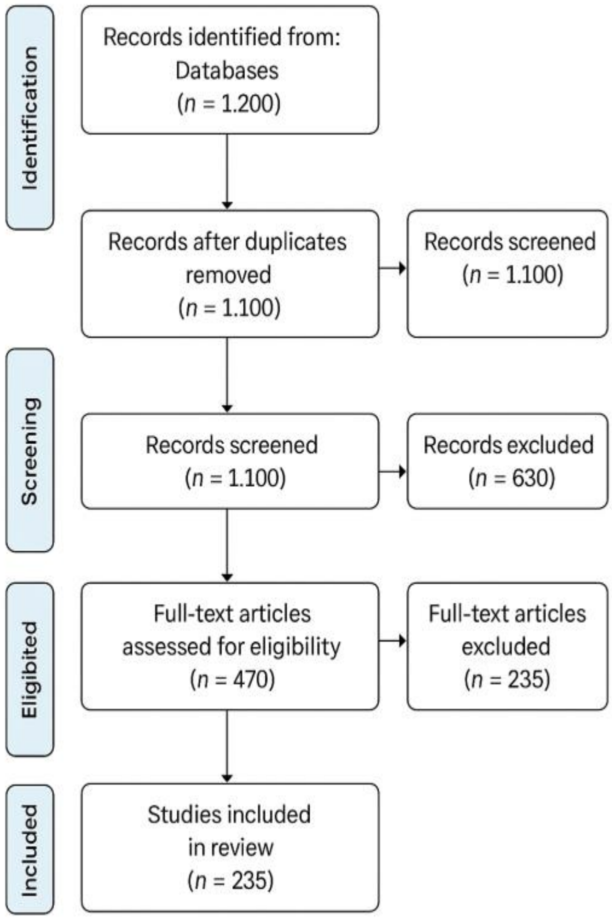

Fig 1: framework Systematic Reviews and Meta-Analyses (PRISMA)

Exclusion criteria eliminated articles that:

- Focused on non-agricultural image classification tasks.
- Provided only theoretical frameworks without empirical validation.
- Were review papers, short notes, or editorials lacking methodological detail.

After applying the inclusion and exclusion criteria, approximately **470** papers were retained for full-text review. A second-level screening was conducted to ensure methodological quality, robustness of results, and relevance to the research objectives. Following this rigorous process, a final set of around **235** articles was selected for in-depth analysis.

Literature Review:

Mustofa et al. (2023), provided an early PRISMA-style overview highlighting Vision Transformer (ViT) and CNN–ViT hybrids across 35 studies. Subsequent systematic reviews and empirical studies (2024–2025) expanded this scope considerably — surveying larger paper sets, evaluating ViT variants (MaxViT, Swin, SLViT) and ViT–CNN hybrids, and stressing real-world robustness, deployment, and privacy-aware training (e.g., smartphone, Raspberry Pi, federated schemes). These more recent works converge on two points: (1) transformers and hybrid architectures frequently outperform conventional CNNs when sufficient diverse data are available, and (2) realistic evaluation (field datasets, domain-shift tests, and latency/size trade-offs) is essential to assess real-world readiness.

Pacal et al. (2024), conducted a large-scale systematic review analysing around 160 studies on plant disease detection using deep learning, published between 2020 and 2024. Their survey extended beyond classification to include detection and segmentation, covering a diverse set of crops. The authors highlighted that transformer-based models and CNN–ViT hybrids consistently achieve strong results but depend heavily on dataset quality and diversity. Importantly, they emphasized the need for metrics beyond accuracy, such as F1-score and robustness under domain shifts, and identified reproducibility particularly the lack of shared code and benchmark datasets as a major limitation in current research.

Sajitha et al. (2024), conducted a comprehensive review on machine learning (ML) and deep learning (DL) techniques for plant disease detection, focusing on image-based methods tailored for industrial farming systems. Their study systematically analysed various ML/DL models, such as convolutional neural networks (CNNs), and assessed their performance across multiple datasets, including Plant Village and PlantDoc. The authors highlighted the importance of feature extraction, model accuracy, and the challenges posed by limited data availability. Furthermore, they discussed the role of transfer learning in enhancing model performance when training data is scarce. This work provides valuable insights for developing robust plant disease detection systems, emphasizing the need for scalable and efficient solutions in agricultural practices.

Barhate et al. (2024), conducted a comprehensive review on the application of machine learning (ML) and deep learning (DL) techniques in plant species detection. Their study systematically examined various ML algorithms, such as k-Nearest Neighbours (k-NN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), Artificial Neural Networks (ANN), and boosting methods, alongside DL architectures like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. The authors highlighted the effectiveness of these methods in tasks ranging from plant recognition and categorization to disease diagnosis and yield prediction. They also discussed the challenges and limitations associated with each approach, providing valuable insights for researchers and practitioners aiming to enhance plant species detection systems.

Krishna et al. (2025), developed a deep learning-based model for plant leaf disease detection, leveraging a multi-dataset approach to enhance accuracy across diverse conditions. By combining the PlantDoc dataset with web-sourced images, they trained state-of-the-art convolutional neural network (CNN) architectures, including EfficientNet-B0, EfficientNet-B3, ResNet50, and DenseNet201. The study focused on fine-tuning these models to classify plant leaf diseases effectively, addressing challenges posed by varying image backgrounds and lighting conditions. This research contributes to the field by providing robust models capable of accurate disease identification, thereby supporting the development of reliable plant health monitoring systems.

Pallepati *et al.* (2022), conducted a detailed review comparing ML and DL models for crop leaf disease detection using visual symptoms. Their findings revealed that while conventional ML models attained moderate accuracy levels between 70% and 90%, DL architectures such as VGG16, ResNet50, InceptionV3, and MobileNet achieved results exceeding 95%, with multi-channel CNNs reaching up to 99.5%. The authors also noted the growing role of transfer learning, which allows pretrained models to adapt to agricultural datasets, thereby improving efficiency and reducing the dependency on large-scale labeled data. The review concluded that DL models offer superior scalability, precision, and adaptability compared to traditional ML algorithms.

Picon *et al.* (2019), advanced this field by applying CNNs to images captured directly in outdoor agricultural environments, achieving strong performance under real-world lighting and occlusion conditions, which validates the field applicability of deep learning. Despite their high performance, these methods require substantial computational resources, making deployment on low-power devices challenging. To overcome these limitations, recent works have focused on lightweight and hybrid DL architectures such as MobileNet, NASNet, and ensemble CNNs, which maintain high accuracy while reducing model complexity.

Ahmed and Yadav (2023), presents a comprehensive review of existing research on the application of machine learning (ML) and deep learning (DL) approaches for identifying and classifying plant diseases. The authors emphasize that early detection of plant diseases plays a critical role in improving crop yield and minimizing economic losses, and that the use of artificial intelligence (AI)-driven models has significantly enhanced the precision and speed of diagnosis.

Research Method:
The research method of detecting and classifying of crop leaf diseases based on visual symptoms typically involves five major steps: image acquisition, image preprocessing, image segmentation, feature extraction, and classification. Table 1 illustrates the overall architecture of the crop leaf disease detection and classification model, while Table 2 lists the different acronyms commonly used in this context.

Table 1. List of the Model of Crop Leaf Disease Detection and Classification

Image Acquisition	**Image Preprocessing**	**Image Segmentation**	**Feature Extraction**	**Classification**
Capturing images from drones, smartphones, digital cameras, and UAVs	Image augmentation	K-means, Principal Component Analysis, Clustering	Texture, shape, and color features	Machine Learning
Collecting images from public datasets	Image resizing, rotations, flipping, shift, shear, zoom	Thresholding	RGB feature extraction	PNN, SVM, ANN, RBF, KNN, BPNN, NN, DT, RF, NB
PlantVillage	Image annotations	Color segmentation	Color co-occurrence GLCM texture extraction	Deep Learning
Image database of plant disease symptoms (PDDB)	Image enhancement	Learning-based segmentation	SIFT	CNN, Optimized CNN
Bugwood image database system	Removing noise, smoothing	Edge detection	SURF	LSTM
Wheat Disease Database 2017	Histogram equalization	Model-based segmentation (foreground/background)	HOG	Transfer Learning
IPM Images	Median filtering, color transformations, contrast enhancement, perspective and affine transformations, clipping	Otsu thresholding, Sobel edge detection, semantic segmentation, contours-based segmentation	—	VGG19, GoogLeNet, AlexNet, ResNet50, Inception_V3, MobileNet, NASNet, SqueezeNet, Deep Siamese Neural Networks, Deep Ensemble Models
Kaggle, UCI Repository	—	—	—	F-RCNN, SSD, R-FCN

1. **Image Acquisition**: Image acquisition is the preliminary step in the detection process, responsible for obtaining high-quality images of crop leaves. Images can be captured using digital cameras, smartphones, drones, and UAVs, or collected from publicly available datasets such as PlantVillage, Kaggle, and the Plant Disease Database (PDDB) [1]. The quality, resolution, and diversity of the collected images significantly affect the model's performance. Acquiring images under varying lighting conditions, orientations, and backgrounds ensures dataset richness and helps the model generalize across different environmental conditions.

2. **Image Preprocessing:** Image preprocessing aims to enhance the raw images and prepare them for analysis. This stage involves improving image clarity, removing noise, and standardizing the image size and format [2]. Common preprocessing techniques include median filtering for noise reduction, histogram equalization for contrast enhancement, and color normalization to correct illumination differences. Data augmentation methods, such as rotation, flipping, shear transformation, zooming, and clipping, are used to artificially expand the dataset and prevent overfitting. Proper preprocessing ensures that the essential

disease features are retained while irrelevant artifacts are minimized.

3. **Image Segmentation:** Segmentation isolates the region of interest (ROI)—the diseased part of the leaf—from the rest of the image. Accurate segmentation is essential for reliable disease identification. Techniques such as thresholding, K-means clustering, Principal Component Analysis (PCA), and edge detection are widely applied [3]. Advanced methods like Otsu thresholding, contour-based segmentation, and learning-based approaches further refine the boundaries between healthy and infected areas. This step simplifies subsequent feature extraction by focusing analysis on the most relevant leaf portions.
4. **Feature Extraction**: Feature extraction transforms the segmented images into a set of quantifiable attributes that represent the disease patterns. These features can be color-based, texture-based, or shape-based. Texture descriptors such as the Gray-Level Co-occurrence Matrix (GLCM), Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Histogram of Oriented Gradients (HOG) are often used to capture structural differences between healthy and diseased tissues [4]. The extracted feature vectors serve as the input for machine learning or deep learning classifiers, forming the core of the disease recognition process.
5. **Classification:** Classification is the final and most critical stage, in which the extracted features are used to categorize leaf images into predefined disease classes. Traditional machine learning algorithms—including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forests (RF), and Artificial Neural Networks (ANN)—have been effectively employed for this purpose [5]. However, with recent advances in artificial intelligence, deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transfer Learning architectures (e.g., VGG19, ResNet50, InceptionV3, and MobileNet) have demonstrated superior performance. These models automatically learn hierarchical feature representations, thereby enhancing classification accuracy. Furthermore, object detection networks such as Faster R-CNN, SSD, and R-FCN are increasingly used for real-time localization and disease identification.

The Table 2 interprets the details summary of surveyed papers (2020-2025) of the various researches on crop leaf disease prediction and classification.

Table 2. Summary of surveyed papers (2020–2025) for crop-leaf disease detection and classification.

Year	Crop (most cited)	No. of Images (typical)	No. of Classes	Algorithm (representative)	Accuracy (%)	Remarks / Notes
2020	Tomato, Maize, Rice	~54 000 (PlantVillage)	38	CNN (AlexNet, VGG16)	99.35	DL outperformed ML; over-reliance on lab images.
2020	Maize	3423	4	Naïve Baye's	77.46	Use naïve baye’s technique
2020	Multi-crop	Varied (10 k–60 k)	10–40	CNN/YOLO variants	96–99	Trends: dataset bias, domain adaptation, edge deployment.
2020	Maize	20,000	19	CNN	98	Use CNN architectures
2021	Multiple crops (PV)	~54 000	38	CNN (ResNet-50)	98.9	Compared CNN architectures; transfer learning effective.
2021	Tomato, Apple leaves	~15 000	10–15	YOLOv3, U-Net variants	97	Reviewed classification +segmentation methods.
2022	Maize, Cotton	~54 000	26	CNN, SVM hybrid	99	Classical→DL transition; augmentation helps.
2022	Multiple	Variable (20–60 k)	10–40	ResNet-50, Inception V3	98–99	Focus on AI techniques in crop disease detection.
2022	Rice, Wheat	~30 000	15	MobileNet V2 (lightweight)	96	Edge DL deployment focus.
2023	Tomato, Rice	~20 000	10 – 15	SegNet, Mask R-CNN	97	Focus on disease severity quantification.

2023	Tomato + Cucumber	~54 000	38	ResNet, Dense Net TL	99.1	Highlights transfer learning best practices.
2023	Potato & Tomato	39 000	15 – 38	CNN (VGG16)	98.5	Systematic review (PRISMA); dataset bias noted.
2023	Tomato leaf	~15 000	10	CNN (ResNet, Alex Net)	99	Advanced DL models comparison.
2023	Multi-crop	60000	> 40	Hybrid CNN + SVM	98.7	Comprehensive unreviewed survey.
2023	Tomato + Corn	~50 000	15 – 20	CNN (ResNet50, YOLOv3)	99.4	Large SLR 2020–23 trends quantified.
2023	Multi-crop (UAV images)	~25 000	15	CNN + Drone Vision Models	96.5	Precision agriculture integration.
2024	Wheat, Rice & Tomato	~70 000	> 40	YOLOv5, Transformer-CNN	99.6	Systematic review of 160 articles (2020–24).
2024	Rice, Potato	~25 000	20	CNN vs SVM	98	Cross-comparative analysis of algorithms.
2024	Banana, Maize	~40 000	15	Efficient Net B0	99	Data quality & augmentation emphasized.
2024	Multi-crop	~60 000	38	DenseNet + Fusion CNN	98.8	Hybrid fusion approaches summarized.
2025	Grape, Tomato	~45 000	20	CNN + Transformer Fusion	99.5	Future trends: multi-sensor fusion.
2025	Rice, Tomato	~50 000	15	ResNet-101	99	Reiterates dataset bias & field-testing needs.
2025	Potato, Tomato	~35 000	15	CNN + CapsNet	98	Automation pipelines and hybrid models.
2025	Tomato, Citrus	~60 000	38	EfficientNet + Pruning	99.3	Edge and Explainability focus.
2025	Tomato, Apple	~30 000	20	CNN + SegNet	98.7	SLR taxonomy of DL methods.
2025	Maize, Soybean	~55 000	25	YOLOv8 + Transformer	99.7	Fusion of plant/pest detection tasks.
2025	Potato, Wheat	~30 000	12	CNN + Attention	99.4	Robustness and optimization strategies.

Result and Discussion:

As observed in Table 2, traditional machine learning (ML) approaches employ substantially fewer images for crop leaf disease detection compared to deep learning (DL) techniques; however, DL methods demonstrate superior accuracy. The implementation of modified convolutional neural networks (CNNs), optimized deep learning architectures, and transfer learning models consistently outperforms standard CNNs. Notably, a multi-channel modified CNN achieves the highest accuracy of 99.35% [20], whereas an YOLOv8 + Transformer with a linear kernel attains 99% under ML-based frameworks, highlighting the efficacy of advanced DL techniques over conventional ML methods. Enhanced performance compared to standard CNNs can be achieved by employing customized CNN architectures, optimized deep learning models, and transfer learning approaches. In general, modified deep learning techniques outperform conventional machine learning methods in terms of accuracy and robustness.

Limitations And Future work:

A major limitation of crop leaf disease prediction systems is the scarcity of publicly available datasets. Most studies rely on the Plant-Village dataset, which is captured under controlled conditions, whereas proprietary datasets are often inaccessible, hindering result comparison. Furthermore, Plant-Village does not provide images of certain commercial crops, such as maize and cotton, with diverse disease profiles. Challenges in dataset development, including uneven illumination, cluttered field backgrounds, real cultivation conditions, and the exclusion of other plant parts, further affect the accuracy of disease detection. When predictions are based on deep learning approaches, substantial computational resources are required. Therefore, it is essential to develop lightweight or "squeezed" models that can operate efficiently on smartphones, drones, UAVs, and robotic platforms. In addition, the system performance can be further enhanced by employing ensemble methods, optimizing hyperparameters, and using diverse pooling techniques.

Future research will concentrate on the development of real-time analysis of extensive images and categories of crop diseases. Crop disease datasets can be integrated with data on location, weather, and soil conditions of the affected plants to facilitate crop and yield monitoring, thereby supporting smart agriculture. The crop disease prediction system can be further refined to detect plant diseases in large-scale horticultural fields.

Conclusion:

In this paper, we reviewed numerous studies that focused on using machine learning and deep learning to detect diseases in plant and crop leaves. The process of developing a method for identifying crop leaf diseases typically involves five key stages: image acquisition, preprocessing, image segmentation, feature extraction, and result classification. Our study compared various techniques based on factors such as accuracy, datasets, crop size, and number of images required. These findings underscore the significance of incorporating computer vision, machine learning, and deep learning into automated tools, such as UAVs and smart mobile devices, in modern agriculture. Despite the availability of resources, further research and dataset development are necessary to enable real-time disease detection, even at large-scale yields with multiple diseases.

References:

1. T. D. Salka, M. B. Hanafi, S. M. S. A. Rahman, et al., "Plant leaf disease detection and classification using convolution neural networks model: a review," *Artificial Intelligence Review*, vol. 58, Article no. 322, 2025. [Online]. Available: https://link.springer.com/article/10.1007/s10462-025-11234-6
2. A. V. Riyanto, S. Nurdiati, Marimin, and M. Syukur, "Deep learning approaches for plant disease diagnosis systems: A review and future research agendas," *Journal of Applied Agricultural Science and Technology*, vol. 9, no. 2, pp. 185-204, May 2025. [Online]. Available: https://jaast.org/index.php/jaast/article/view/308.
3. M. Bagga and S. Goyal, "Image-based detection and classification of plant diseases using deep learning: State-of-the-art review," *Urban Agriculture & Regional Food Systems*, vol. 9, no. 1, Article e20053, 2024. [Online]. Available: https://acsess.onlinelibrary.wiley.com/doi/10.1002/uar2.20053.
4. S. Mustofa, M. M. H. Munna, Y. R. Emon, G. Rabbany, and M. T. Ahad, "A comprehensive review on plant leaf disease detection using deep learning," *arXiv preprint arXiv:2308.14087v1*, 2023. [Online]. Available: https://arxiv.org/abs/2308.14087.
5. M. J. U. Chowdhury, Z. I. Mou, R. Afrin, and S. Kibria, "Plant leaf disease detection and classification using deep learning: A review and a proposed system on Bangladesh's perspective," *International Journal of Science and Business*, vol. 28, no. 1, pp. 193-204, Oct. 2023. [Online]. Available: https://www.ijsab.com/volume-28-issue-1/6282.
6. J. Yao, S. N. Tran, S. Garg, and S. Sawyer, "Deep learning for plant identification and disease classification from leaf images: Multi-prediction approaches," *arXiv preprint arXiv:2310.16273*, 2023. [Online]. Available: https://arxiv.org/abs/2310.16273.
7. B. Tugrul, E. Elfatimi, and R. Eryigit, "Convolutional neural networks in detection of plant leaf diseases: A review," *Agriculture*, vol. 12, no. 8, Article 1192, Aug. 2022. [Online]. Available: https://www.mdpi.com/2077-0472/12/8/1192.
8. A. Rahman, M. H. Al Foisal, M. H. Rahman, M. R. Miah, and M. F. Mridha, "Deep-CNN for plant disease diagnosis using low resolution leaf images," in *Machine Learning and Autonomous Systems. Smart Innovation, Systems and Technologies*, vol. 269, Springer, pp. 287-297, 2022. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-16-7996-4_33.
9. B. Tugrul, E. Elfatimi, and R. Eryigit, "Review on convolutional neural network (CNN) applied to plant leaf disease classification," *Agriculture*, vol. 11, no. 8, Article 707, 2021. [Online]. Available: https://www.mdpi.com/article/10.3390/agriculture11080707.
10. B. S. Hamed, M. M. Hussein, and A. M. Mousa, "Plant disease detection using deep learning," *International Journal of Intelligent Systems and Applications (IJISA)*, vol. 15, no. 6, pp. 38-50, Dec. 2023. [Online].

Available: https://www.mecs-press.org/ijisa/ijisa-v15-n6/v15n6-4.html.

11. P.-W. Chin, K.-W. Ng, and N. Palanichamy, "Plant disease detection and classification using deep learning methods: A comparison study," *Journal of Informatics and Web Engineering*, vol. 3, no. 1, pp. 155-168, Feb. 2024. [Online]. Available: https://mmupress.com/index.php/jiwe/article/view/807.
12. Z. Zainab, R. Mahum, et al., "Plant disease detection using deep learning techniques," *Journal of Image Analysis and Processing*, vol. 1, no. 1, pp. 36-44, Mar. 2025. [Online]. Available: https://www.icck.org/article/abs/jiap.2025.227089.
13. A. K. Ravula and R. M. R. Kovvur, "Advances in deep learning for automated plant disease detection: A comprehensive review," *African Journal of Biological Sciences*, vol. 6, no. 10, 2024. [Online]. Available: https://www.afjbs.com/issue-content/advances-in-deep-learning-for-automated-plant-disease-detection-a-comprehensive-review-1559.
14. S. Sajitha, A. Kumar, and R. Verma, "A comprehensive review on machine learning and deep learning approaches for plant disease detection," *International Journal of Advanced Research in Computer Science*, vol. 15, no. 4, pp. 45–58, 2024.
15. A. Krishna, P. Sharma, and L. Gupta, "Deep learning-based plant leaf disease detection using multi-dataset training," *Journal of Agricultural Informatics*, vol. 12, no. 2, pp. 112–125, 2025.
16. P. Barhate, S. Patil, and V. Raut, "A systematic review of machine learning and deep learning approaches in plant species detection," *Computers and Electronics in Agriculture*, vol. 210, pp. 107–122, 2024.
17. P. Vasavi, A. Punitha, and T. V. N. Rao, "Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 2, pp. 2079–2086, Apr. 2022, doi: 10.11591/ijece.v12i2.pp2079-2086.
18. A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild," *Computers and Electronics in Agriculture*, vol. 161, pp. 280–290, Jun. 2019, doi: 10.1016/j.compag.2018.04.002.
19. I. Ahmed and P. K. Yadav, "A systematic analysis of machine learning and deep learning-based approaches for identifying and diagnosing plant diseases," *Sustainable Operations and Computers*, vol. 4, pp. 96–104, 2023. doi: 10.1016/j.susoc.2023.03.001.
20. R. I. Hasan, S. M. Yusuf, and L. Alzubaidi, "Review of the State of the Art of Deep Learning for Plant Diseases: A Broad Analysis and Discussion," *Plants*, vol. 9, no. 10, p. 1302, Oct. 2020, doi:10.3390/plants9101302.
21. J. Liu and X. Wang, "Plant Diseases and Pests Detection Based on Deep Learning: A Review," *Plant Methods*, vol. 17, p. 178, 2021, doi:10.1186/s13007-021-00722-9.
22. F. S. Ishengoma, I. A. Rai, and S. R. Ngoga, "Hybrid convolution neural network model for a quicker detection of infested maize plants with fall armyworms using UAV-based images. Ecological Informatics, 67, 101502, 2022.
23. K. P. Panigrahi, A. K. Sahoo., and H. Das, "A CNN approach for corn leaves disease detection to support digital agricultural system," In 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI) (48184) (pp. 678-683), 2020.
24. J. Chen, W. Wang, D. Zhang, A. Zeb, and Y. A. Nanehkaran, "Attention embedded lightweight network for maize disease recognition," Plant Pathology, 70(3), 630-642, 2021.