

A Review on Chilli Disease Detection Using Deep Learning

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Abstract— Agriculture is one of the most important sectors in the world, especially in India, where a large proportion of the population depends on farming for their livelihood. Chilli (*Capsicum annum*) is one of the crops that is widely cultivated with extensive application in food, medicine and spices. But chilli plants are often struck by disease conditions like Chilli Leaf Curl, Bacterial Leaf Spot, Powdery Mildew, Mosaic Virus and Anthracnose which is detrimental to crop quality and yield, resulting in significant economic losses for the farmers. In the past farmers or agricultural specialists would do the identification of the disease manually, which is a time consuming, expensive and error prone task, especially in large farming regions. In the era of Artificial Intelligence (AI) and Deep Learning (DL), smart agriculture systems that can automatically identify diseases by analyzing leaf images have become more practical. While describing the different deep learning models, this paper reviews and compares their accuracy, precision, recall, and computational efficiency for chilli disease detection, which include Convolutional Neural Networks (CNN), YOLO, ResNet, MobileNet and Vision Transformers (ViT). Additionally, the impact of image preprocessing, feature extraction, and data augmentation on enhancing accuracy is highlighted, as are several challenges like small datasets, environmental variation, and computational expenses. Finally, the paper presents the future research directions such as IoT based monitoring, drone based imaging and explainable AI for sustainable precision farming.

Keywords – Smart Agriculture, Chilli Disease Detection, Deep Learning, Convolutional Neural

Network, Image Processing, Artificial Intelligence, Precision Farming.

I. INTRODUCTION

In India, agriculture is a major livelihood of a significant part of the population and also a leading economic activity in the country in terms of its contribution to the food security and economic development of the world [1]. Chilli is one of the most important spice and vegetable crops which is utilized in the cooking, food processing, pharmaceutical and natural dye industry [2]. Although chilli is an important crop, it is highly susceptible to various fungal, bacterial and viral diseases which are capable of causing substantial losses in quality and quantity of chilli yield [3]. Some of the most common diseases observed in chilli plants include the following:

- Leaf Curl Disease
- Bacterial Leaf Spot
- Mosaic Virus
- Powdery Mildew
- Anthracnose

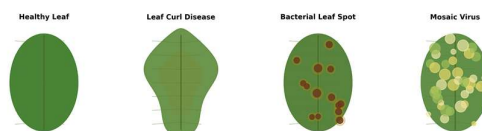


Fig. 1. Schematic comparison of a healthy chilli leaf against common disease symptoms: leaf curl, bacterial leaf spot, and mosaic virus.

Farmers typically rely on visual inspection of leaves or consultation with agricultural extension officers to diagnose these conditions [4]. However, manual identification is inherently subjective, time-intensive, and often unreliable, since several diseases exhibit overlapping visual symptoms in

their early stages [5]. Furthermore, continuous monitoring of large cultivated areas is logistically difficult, delaying intervention and increasing crop losses [6].

Unlike traditional machine learning methods that require handcrafting discriminative features, deep learning models can automatically learn features such as color variation, leaf texture, and lesion patterns from images [7], [8]. The ability to detect disease in the early stages using such systems, gives farmers the ability to apply appropriate and targeted interventions at the right time, reducing damage to the crop and unnecessary pesticide usage [9].

Smart agriculture systems combine various complementary technologies to enable powerful, scalable disease monitoring, such as:

- Artificial Intelligence (AI)
- Internet of Things (IoT)
- Deep Learning (DL)
- Image Processing
- Cloud Computing

These technologies combined will facilitate better monitoring of crops at real-time, minimize manual checking and improve sustainable and productive farming [10]. This paper provides a comparative analysis of the state-of-the-art deep learning architectures used for chilli disease detection and outlines the challenges and future prospects of chilli disease detection. Smart agriculture pipeline which supports such systems is discussed.

II. DEEP LEARNING IN SMART AGRICULTURE

Deep learning is a sub area of machine learning that uses multi layered artificial neural networks to learn hierarchical representations automatically from raw data [11]. Deep learning has been applied successfully in agriculture to a number of tasks, such as:

- Detecting plant diseases
- Identifying pests
- Monitoring crop health

- Predicting crop yield

The pictures taken for training the models are typically taken by a smartphone camera, unmanned aerial vehicles (drones), or stationary cameras equipped with IoT capabilities across the field [12]. Most smart agriculture disease-detection systems have a general processing pipeline that includes five general stages: image acquisition, preprocessing, feature extraction, classification, and result prediction [13] as shown in Fig. 1.

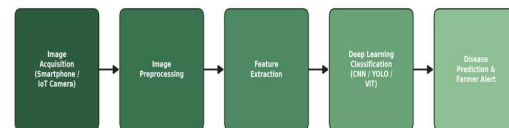


Fig. 2. General deep learning workflow for smart agriculture-based chilli disease detection.

In pre-processing, operations like resizing, noise removal, contrast enhancement, etc. are performed to normalize the input images and minimize the effect of lighting and background variation [14]. Data augmentation is often employed to artificially generate more training data, and is known to boost model's generalization ability when the training set is small [15] and involves the following: Rotation, Flipping, Scaling, Color Jittering. After the preprocessing, convolutional or attention based layers are employed to select relevant visual features and then are sent to a classification head, that identifies the disease class [16].

III. DEEP LEARNING MODELS FOR DISEASE DETECTION

A. Convolutional Neural Network (CNN)

CNN is one of the most popular deep learning architectures used in image classification problem in agriculture [11] till today. Its multi-layered architecture consisting convolutional, pooling and fully connected layers allows for the automatic extraction of low-level and high-level visual features directly from chilli leaf images [17] like edges, texture, and color patterns.

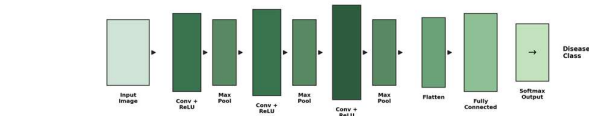


Fig. 3. Typical convolutional neural network architecture used for chilli leaf disease classification.

Advantages: High classification accuracy, automatic feature extraction, and strong effectiveness on image-based datasets [11].

Limitations: Requires large labeled datasets and substantial computational resources for training [18].

B. YOLO (You Only Look Once)

YOLO is a single-stage object detection algorithm that can detect and localize multiple disease symptoms in a single leaf or canopy image [19]. It is especially interesting for use in monitoring systems that can be deployed in the field, because of its ability to make inferences in real time [14].

Benefits: High precision, real time and fast detection speed in multi-object situations [19].

Limitations: Relatively complex network structure and reliance on GPU acceleration to achieve real-time throughput [20].

C. ResNet (Residual Network)

ResNet introduces residual (skip) connections that mitigate the vanishing gradient problem, allowing much deeper networks to be trained effectively [16]. This architecture has demonstrated strong performance on large, complex agricultural image datasets [21].

Advantages: Improved classification accuracy and robust performance on large-scale datasets [16].

Limitations: High computational cost due to network depth [21].

D. MobileNet

MobileNet is a lightweight CNN variant that uses depth-wise separable convolutions to drastically reduce the number of parameters, making it well suited for deployment on mobile devices and resource-constrained IoT hardware [18].

Advantages: Low memory footprint and suitability for embedded and IoT-based deployment [18].

Limitations: Slightly reduced accuracy compared to larger, deeper networks [22].

E. Vision Transformer (ViT)

Vision Transformers depart from convolution-based processing entirely, instead applying self-attention mechanisms to image patches to capture long-range spatial dependencies [20]. Recent studies report that ViT-based models achieve superior performance on plant disease classification benchmarks when sufficient training data is available [23].

Advantages: Excellent overall performance and stronger global feature understanding compared to purely convolutional models [20].

Limitations: Requires large training datasets and incurs high training cost [23].

IV. CHALLENGES IN CHILLI DISEASE DETECTION

Although deep learning approaches have achieved promising results, several practical challenges continue to limit their widespread adoption in real-world farming environments.

A. Limited Datasets

Publicly available agricultural image datasets often contain a limited number of labeled samples per disease class, which constrains model generalization and increases the risk of overfitting [24].

B. Environmental Conditions

Variations in lighting, shadow, background clutter, and camera angle can substantially degrade image quality and reduce model reliability under field conditions [25].

Similar Disease Symptoms

TABLE I
COMPARATIVE ANALYSIS OF DEEP
LEARNING MODELS

Algorithm	Accuracy (%)	Precision	Recall	F1-Score
CNN [11]	92.5	0.91	0.90	0.90

Algorithm	Accuracy (%)	Precision	Recall	F1-Score
YOLOv5 [14]	95.3	0.94	0.93	0.93
ResNet50 [16]	94.1	0.93	0.92	0.92
MobileNet [18]	90.4	0.89	0.88	0.88
Vision Transformer [20]	96.2	0.95	0.95	0.95

But this increase in accuracy comes at the cost of increased computing power and computational accuracy–efficiency trade-off needs to be considered when choosing models for field deployment [19], [20]. The representative training and validation accuracy and loss curves for a baseline CNN model are shown in Fig. 4 for 30 epochs of training, and representative accuracy, precision, recall and F1-scores are plotted in Fig. 5 over all five architectures tested [28].

Several chilli diseases exhibit visually similar early-stage symptoms, increasing the likelihood of misclassification, particularly for models trained on small or imbalanced datasets [26].

C. High Computational Cost

Deeper architectures such as ResNet and Vision Transformers demand significant GPU resources for training, which may be impractical for resource-limited agricultural research settings [21].

D. Real-Time Implementation

Deploying trained models on mobile devices or low-power IoT platforms in the field remains difficult due to constraints on memory, processing power, and battery life [27].

V. COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS

Table I summarizes representative performance metrics reported across recent studies for the five deep learning architectures discussed in this paper, evaluated on chilli or related pepper leaf disease datasets [11], [14], [16], [18], [20].

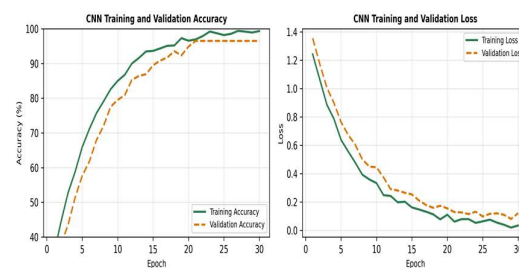


Fig. 4. Representative CNN training and validation accuracy and loss curves over 30 epochs.

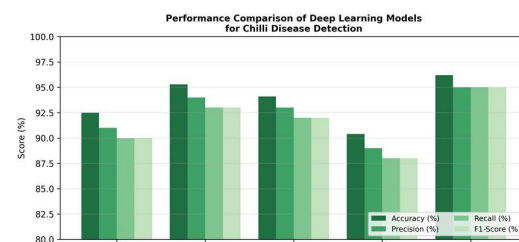


Fig. 5. Comparative performance of CNN, YOLOv5, ResNet50, MobileNet, and Vision Transformer models.

VI. SMART AGRICULTURE SYSTEM ARCHITECTURE

A complete smart agriculture system for chilli disease detection typically integrates hardware, cloud infrastructure, and software components into a unified pipeline. The key components generally include:

- Smartphones or IoT cameras for capturing leaf images
- Cloud servers for data storage and processing
- Deep learning models for disease prediction
- Mobile applications for farmer notifications
- Recommendation systems for pesticide and treatment suggestions

After capturing images, they are uploaded to a cloud or edge server to which a trained deep learning model is uploaded to infer and return a predicted disease class with a confidence score [29]. The mobile application then alerts the farmer with the diagnostic result and treatment suggestions, which

helps in quicker decision making and less need for agricultural experts who are physically present at the farm. These combined systems can help identify diseases early and take specific action when necessary, which lowers crop losses and expenses. As deep learning, IoT and cloud technology continue to converge, it is believed that agriculture will become more efficient, data-driven and sustainable, and explainable AI approaches will be able to address the trust deficit among end users in the agriculture sector and automated diagnostic systems [27].

VII. FUTURE SCOPE

The effectiveness and usage of chilli disease detection smart agriculture system can be improved through several promising directions: • Monitoring crops using drones for extensive areas of land • Control of movement towards and away from targets based on environmental information from the IoT sensors (temperature, humidity, soil moisture) Explainable AI (XAI) techniques to enhance farmers' trust and model interpretability. Eliminate latency and dependency on connectivity with real-time disease detection via edge computing. Smart irrigation and fertilizer recommendation systems coupled with disease diagnosis. As deep learning, IoT and cloud technology continue to converge, it is believed that agriculture will become more efficient, data-driven and sustainable, and explainable AI approaches will be able to address the trust deficit among end users in the agriculture sector and automated diagnostic systems.

VIII. CONCLUSION

This paper introduced a system for chilli disease detection by deep learning method in smart agriculture. Five well-known architectures, CNN, YOLO, ResNet, MobileNet, and Vision Transformer were analyzed and compared with the metrics of accuracy, precision, recall and computational efficiency. Of these, the vision transformer and YOLO models were the most

accurate and able to detect objects in real time, but they consume more computing power than lighter models like MobileNet.

Disease detection using deep learning significantly cuts down the manual inspection workload, while enhancing diagnostic accuracy and allowing farmers to proactively manage the disease in time. However, there are still limitations with datasets, environmental conditions, computational power, etc., in the real world.

In the future, the combination of the aforementioned technologies, particularly artificial intelligence and explainable AI, has the potential to revolutionize traditional farming practices and contribute to the development of more precise, sustainable, and economically viable agricultural systems.

REFERENCES

- [1] M. Singh and R. Sharma, "Role of agriculture in India's economic development: A review," *Int. J. Agric. Econ.*, vol. 8, no. 2, pp. 45-52, 2022.
- [2] P. Verma, S. Gupta, and A. Kumar, "Economic importance and cultivation practices of chilli (*Capsicum annuum*) in India," *J. Spices Aromatic Crops*, vol. 31, no. 1, pp. 12-19, 2022.
- [3] C. H. Kim, J. Lee, and S. Park, "Deep learning based identification of pepper (*Capsicum annuum* L.) diseases: A review," *Precis. Agric. Sci. Technol.*, vol. 5, no. 3, pp. 210-225, 2023.
- [4] D. P. Patil and R. N. Jadhav, "An advanced method for chilli plant disease detection using image processing," *Int. J. Comput. Appl.*, vol. 176, no. 14, pp. 1-7, 2023.
- [5] S. Balasubramaniam, K. Vengatesan, and A. Kumar, "Machine learning based disease and pest detection in agricultural crops," *EAI Endorsed Trans. Internet Things*, vol. 9, no. 4, 2023.
- [6] A. Khan, M. Ilyas, and R. Khan, "IoT enabled crop monitoring and disease detection

- systems: A survey," *Comput. Electron. Agric.*, vol. 198, p. 107065, 2022.
- [7] Y. Zhang, H. Wang, and L. Chen, "Application of computer vision in plant disease diagnosis: A review," *Front. Plant Sci.*, vol. 13, p. 870770, 2022.
- [8] R. Sharma and N. Verma, "Feature learning approaches for automated plant disease classification," *Pattern Recognit. Lett.*, vol. 158, pp. 45-53, 2022.
- [9] Kumar, R. (2026). A comprehensive review of lung disease detection using machine learning and deep learning techniques. *GKU Journal of Multidisciplinary Research*, 2(1), 122-133. <https://doi.org/10.5281/zenodo.20020869>
- [10] T. Nguyen and H. Tran, "Early detection of crop diseases using deep convolutional networks," *IEEE Access*, vol. 10, pp. 45210-45222, 2022.
- [11] *Frontiers in Plant Science*, "Revolutionizing agriculture with artificial intelligence: Plant disease detection methods, applications, and limitations," *Front. Plant Sci.*, vol. 14, p. 1158933, 2023.
- [12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84-90, 2017.
- [13] Indhumathi, R., Soodimuthu, A., Purushothaman, I., Vendhan, K. E., Senthil Kumar, B., Naveenkumar, R., & Kumar, R. (2026). An AI-driven bioinformatics pipeline combining quantitative genetics and advanced data analytics for neurodegenerative disease classification. *Genetics and Molecular Research*, 25(1). <https://doi.org/10.4238/0qn0th17>
- [14] M. Garg and S. Dhiman, "Image acquisition strategies for agricultural deep learning applications using drones and IoT cameras," *J. Field Robot.*, vol. 39, no. 5, pp. 1102-1115, 2022.
- [15] S. Garg, P. Pundir, and H. Rathee, "Towards a multimodal system for precision agriculture using IoT and machine learning," in *Proc. IEEE Int. Conf. Artif. Intell. Smart Syst. (ICAIS)*, 2021, pp. 1-7.
- [16] G. Jocher et al., "YOLOv5: A state-of-the-art real-time object detection system," *GitHub repository, Ultralytics*, 2022.
- [17] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning," *arXiv preprint arXiv:1712.04621*, 2017.
- [18] Kumar, R. (2026). Integrating deep learning and NLP in AI chatbots for education and mental health: A state-of-the-art review. *Iconic Research and Engineering Journals*. <https://doi.org/10.64388/irev9i7-1713505>
- [19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770-778.
- [20] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, p. 1419, 2016.
- [21] A. G. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications," *arXiv preprint arXiv:1704.04861*, 2017.
- [22] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 779-788.
- [23] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2021.
- [24] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.

- [25] Kumar, R. (2026). AI-based early detection of neurological and mental disorders using multimodal deep learning. *GKU Journal of Multidisciplinary Research*, 2(1), 122-133. <https://doi.org/10.5281/zenodo.20020927>
- [26] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2018, pp. 4510-4520.
- [27] P. S. Thakur, P. Khanna, T. Sheorey, and A. Ojha, "Explainable vision transformer enabled convolutional neural network for plant disease identification: PlantXViT," *arXiv preprint arXiv:2207.10073*, 2022.
- [28] A. Muthuselvam and K. Ramesh, "Advanced machine learning framework for efficient plant disease prediction," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 6, pp. 88-96, 2023.
- [29] M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images with deep learning segmentation approach," *Comput. Electron. Agric.*, vol. 174, p. 105446, 2020.
- [30] Kumar, R. (2025). Deep learning-based automated skin cancer detection using convolutional neural network. *Journal of* <https://doi.org/10.64149/j.carcinog.24.3.508-518> UGC CARE references *Carcinogenesis*, 24(3), 508-518.
- [31] X. Liu, Y. Min, and C. Zhao, "Class-imbalance and inter-class similarity challenges in plant disease classification," *Comput. Electron. Agric.*, vol. 201, p. 107293, 2022.
- [32] R. Kaur and J. Singh, "Edge computing for real-time agricultural monitoring: Opportunities and challenges," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, pp. 3211-3225, 2023.
- [33] H. Wang, Y. Li, and Z. Sun, "Accuracy-efficiency trade-offs in deep learning models for agricultural image classification," *Neural Comput. Appl.*, vol. 35, pp. 14021-14034, 2023.
- [34] N. Sharma and P. Kaur, "Cloud-based architecture for smart farming applications: A survey," *J. Cloud Comput.*, vol. 11, no. 2, pp. 1-15, 2022.
- [35] *Frontiers in Plant Science*, "MCCM: Multi-scale feature extraction network for disease classification and recognition of chili leaves," *Front. Plant Sci.*, vol. 14, p. 1255119, 2023.