An IoT-Enabled Deep Learning Framework for Crop Disease Detection Using Image Signal Processing and Convolutional Neural Networks.

1st Mr.Yadav Uttam Panaswad
Department of Electronics and Telecommunication
College of Engineering, Osmanabad
Email: uttampanaswad@gmail.com

2nd Prof. V. A. Daware
Department of Electronics and Telecommunication
College of Engineering, Osmanabad

***Abstract*—Agriculture is an important part of the world economy; however, crop diseases substantially lower productivity and quality. To reduce the losses and guarantee food security, early and correct diagnosis of the plant diseases is necessary. The conventional means of identifying diseases are manual identification, which is subjective, less precise, and relies on expert experience. In a bid to address these shortcomings, this paper introduces a review of an IoT-compatible deep learning model to detect crop diseases using image signal processing and Convolutional Neural Networks (CNN).The proposed solution includes the IoT technologies like smart cameras and sensors to record images of crops in the field in real time. Image signal processing techniques such as noise removal, resizing and segmentation are used to preprocess these images to improve the quality. The processed images are subsequently analyzed with CNN models to automatically find and categorize crop diseases with high accuracy. IoT integration facilitates real-time monitoring and timely decision making that can be made by farmers. This review paper examines some of the available techniques, their weaknesses and strengths, and gaps in the research in the systems that are already in place. This research highlights the significance of incorporating IoT and deep learning in order to create efficient, scalable and intelligent agricultural solutions. The suggested framework will help enhance early disease identification, minimize the reliance on manual inspection, and aid smart farming.**

Keywords: Convolutional Neural Network, Crop Disease Detection,Deep Learning, Internet of Things (IoT), Image Signal Processing, Smart Agriculture, Plant Disease Classification.

I. Introduction

Agriculture is a pillar of the world economy and a key factor in providing food security. Nevertheless, diseases of crops are among the greatest problems of agricultural output and quality. Fungal, bacterial, viral, and environmental diseases can severely reduce the yield of the plant unless seen early in the case of fungi and bacteriology diseases. Conventionally, farmers or agricultural experts are used to detect disease by performing manual inspection, a process that is time consuming, subjective and inaccurate particularly in large scale farming settings. The development of technology has given a lot of concern to automated detection of crop diseases. Computer vision techniques have become one of the effective ways of detecting plant diseases by analyzing images. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown great accuracy in image classification tasks in recent years, although they are quite fitting in the task of identifying crop diseases based on leaf images. Simultaneously, the Internet of Things (IoT) made it possible to create a smart agriculture network with sensors, cameras, and devices that are interconnected to gather real-time data and track its changes. The IoT devices can take pictures of crops and send them to processing systems, thus detecting and responding in time. When combined with deep learning techniques, IoT can significantly enhance the efficiency and accuracy of crop disease detection systems. Moreover, image signal processing methods like noise reduction, image enhancement, and segmentation enhance the quality of input data, resulting in an increased performance of the model. With the incorporation of IoT, image processing, and deep learning, one can come up with an intelligent and automated system that can identify crop diseases in real-time. This paper provides a review of in-depth IoT-enabled deep learning models to detect crop diseases on image signal processing and CNN. This paper examines current solutions, the shortcomings of these solutions, and the necessity of an effective, scalable, and real-time solution to contemporary agriculture..

A. Key contribution of this research

- **Integration of IoT in Agriculture:** In this paper, we will investigate how IoT devices like smart cameras and sensors can be used to capture real-time images of crops and allow an agricultural field to be monitored continuously.
- **Deep Learning Models:** It reviews the use of Convolutional Neural Networks (CNNs) for automatic detection and classification of crop diseases from images with high accuracy.
- **Use of Image Signal Processing Techniques:** The research identifies preprocessing, including image enhancement, noise removal, and segmentation, to enhance the quality of input data, as well as model performance.

- **Highlighting Research Gaps:** The paper notes shortcomings of existing systems, including the inability to detect in real-time, insufficient diversity of datasets, and the absence of integrated frameworks based on IoT.

II. Literature Review

a) : Nyawose et al. present a review of machine learning and deep learning techniques for plant disease detection. The study covers preprocessing, segmentation, feature extraction, and classification stages. The authors highlight that deep learning methods, especially CNNs, outperform traditional models due to automatic feature extraction. Various datasets and evaluation metrics are discussed. Image quality is emphasized as a key factor in improving model accuracy. The paper also identifies challenges such as data imbalance and lack of dataset diversity. However, real-time IoT integration is not considered. The study concludes that combining multiple techniques can enhance performance and suggests future work in real-time scalable systems [1].

b) : Dhaka et al. discuss the application of CNNs in plant disease detection using leaf images. The authors compare different CNN architectures and preprocessing techniques. Popular datasets like PlantVillage are analyzed. The study highlights the importance of hyperparameter tuning for improving performance. CNN models show higher accuracy compared to traditional approaches. However, the dependency on large labeled datasets is a limitation. The paper also lacks real-time field implementation. Transfer learning is suggested as a solution for improving performance with limited data [2].

c) : Hasan et al. review deep learning approaches for plant disease detection and highlight challenges such as lack of labeled data and high computational cost. The paper explains different architectures including CNN and hybrid models. It discusses limitations of supervised learning and issues in data annotation. Scalability challenges are also identified. The study suggests semi-supervised learning techniques. Results show improved accuracy using deep learning, but implementation cost remains high [3].

d) : Abade et al. provide a systematic review of CNN-based plant disease detection techniques. The study analyzes over 100 research papers and identifies trends in datasets and model architectures. CNN is found to be highly effective for image classification tasks. The paper discusses preprocessing and feature extraction methods. It highlights limitations such as lack of real-world deployment and IoT integration. The authors suggest hybrid approaches for better performance [4].

e) : Shelar et al. propose a CNN-based model for crop disease detection using leaf images. The system applies preprocessing techniques to improve image quality. The CNN extracts features and classifies diseases efficiently. The study shows improved accuracy compared to traditional methods. However, the dataset used is limited and the system lacks real-time monitoring. Future work includes improving scalability and integrating IoT systems [5].

f) : Sun et al. introduce an EfficientNet-based CNN model for plant disease detection. The model achieves high accuracy due to efficient feature extraction. Data augmentation techniques are used to improve performance. The system performs well on multiple crop diseases. However, it requires high computational resources and is tested mainly on controlled datasets. Real-world deployment remains a challenge [6].

g) : Ahmad et al. review deep learning techniques used in plant disease detection and highlight the role of CNN after the ImageNet breakthrough. The study discusses different datasets and sensor technologies. It emphasizes automation and real-time detection possibilities. However, dependency on large datasets and scalability challenges remain. The paper suggests combining multiple data sources and integrating IoT systems [7].

h) : Upadhyay et al. review modern deep learning approaches for crop disease detection using computer vision techniques. The study focuses on real-time and non-destructive detection. It compares different deep learning models and highlights accuracy and speed. However, high cost and scalability issues are major limitations. The paper suggests IoT integration for smart agriculture applications [8].

i) : Hukkeri et al. present a CNN-based plant disease classification system with improved accuracy. The study explains feature extraction and classification processes. The model works on multiple crops and diseases. However, it depends heavily on dataset quality and lacks real-time implementation. The authors suggest IoT-based improvements [9].

j) : Demilie et al. compare machine learning and deep learning techniques for plant disease detection. The study shows CNN achieving high accuracy compared to other models. It discusses evaluation metrics and image processing techniques. However, computational complexity is high and real-time implementation is limited. Hybrid approaches are suggested for improvement [10].

k) : Tugrul et al. review CNN applications in plant disease detection and analyze multiple research studies. The paper discusses preprocessing and feature extraction methods. It highlights advantages of CNN models but notes the lack of real-world datasets. Training challenges are also discussed. The authors suggest improving dataset diversity and model optimization [11].

l) : The CapsuleNet study introduces Capsule Networks for plant disease detection. The model improves performance over traditional CNNs and handles image distortions effectively. It compares results with AlexNet and GoogleNet. However, the model has high complexity and longer training time. Optimization techniques are suggested for improvement [12].

m) : Kumar et al. use transfer learning with pre-trained CNN models such as EfficientNet for disease detection. The model improves accuracy in complex conditions and works well with low-resolution images. However, performance depends on dataset quality. The study suggests further optimization and real-time implementation [13].

n) : The BWOM optimization model combines CNN with Beluga Whale Optimization for feature selection. The system improves classification accuracy and reduces errors. However, computational complexity increases significantly. The study highlights the importance of parameter tuning and suggests improving efficiency for real-world applications [14].

o) : The CNN-LSTM hybrid model combines spatial and temporal learning for disease detection. CNN extracts features while LSTM analyzes patterns over time. The model achieves higher accuracy than standalone CNN models. However, complexity and training time increase. Real-time implementation remains limited [15].

p) : The CNN comparative study analyzes models such as VGG, ResNet, and MobileNet. It compares performance based on accuracy and efficiency. Lightweight models are suitable for mobile applications. However, dataset dependency remains a limitation. The study emphasizes model optimization for real-world use [16].

q) : The real-time CNN system integrates disease detection with a mobile application for farmers. It provides instant results by capturing leaf images. The system improves practical usability. However, it depends on internet connectivity and proper lighting conditions. Offline capability is suggested for improvement [17].

r) : The PDD-DL framework focuses on real-time and scalable disease detection using CNN. The system reduces manual inspection and improves efficiency. However, hardware requirements are high. The study suggests optimization techniques for deployment [18].

s) : The hybrid ML-DL survey compares traditional machine learning models with deep learning approaches. It highlights the superiority of CNN models. Hybrid models are suggested to improve performance. However, computational cost remains a challenge [19].

t) : The systematic review analyzes multiple research papers using PRISMA methodology. It identifies trends in preprocessing and classification techniques. The study highlights research gaps such as lack of real-time systems. IoT integration is suggested for future work [20].

u) : The crop disease DL model combines CNN and LSTM for improved prediction accuracy. CNN extracts features while LSTM captures patterns. However, complexity increases significantly. The study suggests optimization for better performance [21].

v) : The advanced CNN model with SE blocks improves feature extraction using channel attention. The model enhances classification accuracy. However, it increases model complexity. Optimization is required for practical use [22].

w) : The ROI-based CNN model focuses on region-based detection by isolating infected areas. It improves classification accuracy and reduces noise. However, segmentation techniques are complex and computationally expensive [23].

x) : The multi-class CNN system detects multiple crop diseases using preprocessing techniques. The model achieves high accuracy and supports mobile applications. However, performance depends on dataset size and quality [24].

y) : The AI and IoT-based model integrates sensors and CNN for real-time crop disease detection. It enables continuous monitoring and improves decision-making. However, high cost and infrastructure requirements are major limitations. The study concludes that IoT and AI together enhance smart agriculture systems [25].

A. Research Gaps

Despite the substantial advances in the area of machine learning and deep learning methods to detect crop diseases, there are still some crucial gaps. The majority of the literature does not consider real-time data collection mechanisms and uses only image-based classification with CNN models. Most systems are trained and trained on controlled datasets such as PlantVillage, which are not reflective of real-field conditions such as varying lighting conditions, background noise, and other environmental variations. Moreover, most of the methods do not include the use of IoT, which reduces their capacity to deliver real-time alerts and continuous monitoring to farmers. Handling a variety of crop diseases within one system is also under studied. The second significant gap is the reliance on the large labeled datasets that are not always accessible in the real-world. Moreover, the complexity of computation and absence of lightweight models limit the use on the mobile or edge devices. There are very few systems that are oriented towards the small-scale farmers in terms of scalability and cost-effectiveness. Lack of strong preprocessing methods also influences the accuracy in the real world. Therefore, an integrated, real-time, scalable, and efficient system that integrates IoT, image processing, and deep learning is required to apply to the real-world in agriculture.

B. Problem Statement

One of the significant causes of agricultural productivity and food security in the world today is the crop diseases. These diseases need to be identified early to minimize loss of crops and enhance yield quality. Nevertheless, the traditional disease detection procedures are time-consuming, subjective, and inaccurate as they require farmers or experts to observe them manually. Such approaches cannot apply in large scale farming where round the clock observation is needed. Current automated systems are more accurate and mainly based on image processing and deep learning, but are typically restricted to offline analysis and controlled settings. They are not compatible with real time monitoring and field device integration. Moreover, a disease detection is more complicated by the differences in environmental conditions which include lighting, weather and background. There are also no systems in place that can deliver immediate feedback and actionable insights to farmers. This is why there is a necessity to create a smart system, which is capable of automatically identifying crop diseases in real-time with the help of IoT devices and deep learning methods to ensure accuracy, efficiency, and practicality in the real agricultural setting.

TABLE I
COMPREHENSIVE LITERATURE SURVEY ON IOT-ENABLED DEEP LEARNING FOR CROP DISEASE DETECTION

Author(s)	**Year**	**Core Concept / Contribution**	**Limitation**
Nyawose et al.	2025	Reviewed machine learning and deep learning approaches for plant disease detection, covering preprocessing, segmentation, and CNN-based classification techniques.	Lack of real-time implementation and limited integration with IoT systems.
Dhaka et al.	2021	Analyzed different CNN architectures like AlexNet, VGG, and ResNet for plant disease detection using leaf images.	Requires large labeled datasets and lacks real-time field deployment.
Hasan et al.	2020	Discussed deep learning models and challenges such as data scarcity, overfitting, and computational cost in plant disease detection.	High computational requirements and dependency on large datasets.
Abade et al.	2020	Conducted a systematic review of CNN-based techniques and identified trends in image classification methods.	Limited focus on real-world applications and IoT integration.
Shelar et al.	2022	Proposed a CNN-based model for detecting crop diseases using leaf images with preprocessing techniques.	Tested on small datasets and lacks real-time monitoring capability.
Sun et al.	2022	Developed an EfficientNet-based model achieving high accuracy in plant disease classification.	Requires high computational power and lacks real-time deployment.
Ahmad et al.	2023	Reviewed deep learning methods and highlighted the role of sensors and imaging technologies in agriculture.	Limited implementation of integrated IoT-based systems.
Upadhyay et al.	2025	Focused on computer vision-based disease detection and discussed modern deep learning approaches.	High cost and lack of scalability in real farming environments.
Hukkeri et al.	2024	Implemented CNN-based classification for multiple crop diseases with improved accuracy.	Dataset dependency and absence of real-time system integration.
Demilie et al.	2024	Compared machine learning and deep learning techniques and concluded CNN performs best.	High computational complexity and limited practical deployment.
Tugrul et al.	2022	Reviewed CNN applications and preprocessing methods for plant disease detection.	Lack of diverse datasets and real-world testing.
CapsuleNet Study	2022	Introduced Capsule Networks to improve classification accuracy and handle image distortions.	Increased complexity and longer training time.
Kumar et al.	2023	Used transfer learning with pre-trained CNN models to improve accuracy and reduce training time.	Performance depends on dataset quality and diversity.
BWO Model	2024	Combined CNN with optimization algorithms for better feature selection and accuracy.	High computational cost and complex implementation.
CNN-LSTM Model	2025	Proposed hybrid CNN-LSTM model for analyzing disease patterns and improving prediction accuracy.	Increased model complexity and longer training time.
CNN Comparative Study	2025	Compared multiple CNN models and highlighted the efficiency of lightweight architectures.	Trade-off between accuracy and computational efficiency.
Real-Time CNN System	2026	Developed a mobile-based system for real-time crop disease detection using CNN.	Dependent on internet connectivity and environmental conditions.
PDD-DL Framework	2026	Introduced a scalable deep learning framework for real-time disease detection.	Requires advanced hardware support and infrastructure.
Hybrid ML-DL Survey	2024	Compared traditional ML models with deep learning and highlighted advantages of hybrid approaches.	Increased complexity and cost of implementation.
Systematic Review	2024	Reviewed multiple research works and identified trends in plant disease detection systems.	Lack of practical real-time systems and IoT integration.
Crop Disease DL Model	2025	Combined CNN and LSTM models to improve disease prediction accuracy.	High computational cost and complexity.
SE Block CNN	2025	Used Squeeze-and-Excitation blocks to enhance feature extraction in CNN models.	Increased model complexity.
ROI-Based CNN	2024	Focused on region-based detection to improve classification accuracy.	Requires complex segmentation techniques.
Multi-Class CNN	2025	Developed a model for detecting multiple crop diseases using CNN.	Performance depends on dataset size and quality.
AI + IoT Model	2025	Integrated IoT devices with deep learning for real-time crop disease monitoring.	High cost and infrastructure requirements.

C. Distinction Between Review and Proposed Contribution

The paper contains a summary of the existing methods as well as a conceptual framework of crop disease detection. The review part is dedicated to the examination of the already designed approaches through machine learning, deep learning and image processing. It also shows their advantages, including high precision and automation, and their disadvantages, including the inability to work in real-time, reliance on large data sets, and the lack of IoT integration. Conversely, the suggested contribution offers a unified solution comprising of IoT equipment, image signal processing, and CNN-based deep learning architecture. To address the limitations found in the literature, the proposed system seeks to provide the opportunity to collect data in real-time using a smart camera and smart sensors. It also highlights the preprocessing methods to enhance the quality of images in the conditions of real-life. The proposed framework is unlike the current systems where it is designed to be scaled, efficient, and viable to farmers. It aims at offering continuous monitoring, early detection, and timely decision support. In this way, the review summarizes the existing knowledge whereas the proposed contribution provides a more comprehensive and application-focused solution to smart agriculture.

III. Proposed System

A. Proposed System Architecture

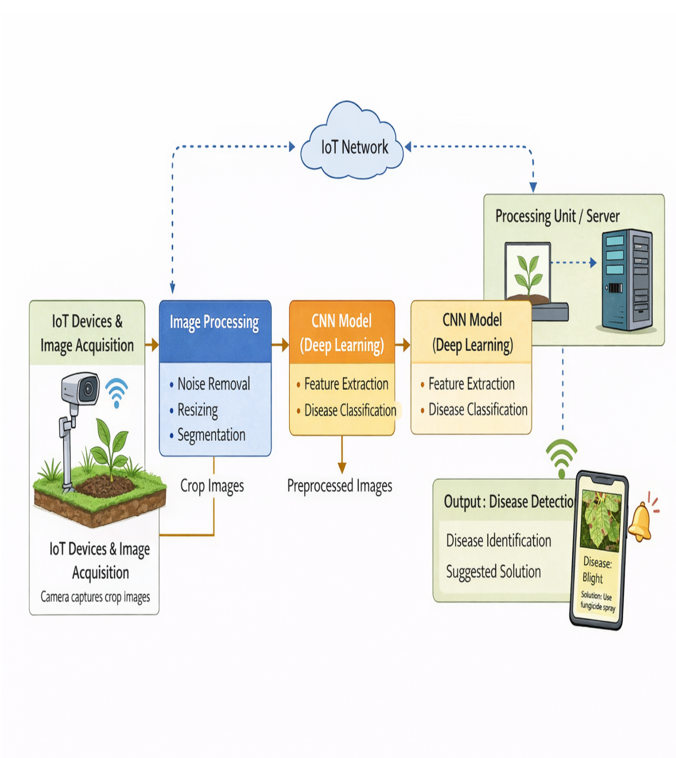

Fig. 1. Proposed IoT-enabled deep learning architecture for crop disease detection.

The suggested system architecture Fig. 1 will be used to detect crop diseases in real-time and with an automated method through an IoT-enabled deep learning system. The system starts with data acquisition module where IoT devices that include smart cameras and sensors are installed in the farm fields to take pictures of the leaves of crops in the natural set up. These machines will be constantly tracking the crops and gathering real-time information, which can also be used to identify diseases early.The obtained images are then sent to image preprocessing module that is critical in enhancing data quality. This module does tasks like noise elimination, image scaling, normalization, and segmentation. These procedures aid in eliminating the undesired background substance as well as improve the visibility of the infected areas on the foliage. Refined images after preprocessing are sent to Convolutional Neural Network (CNN) model which serves as the heart of the system. The CNN does a hierarchical feature extraction to detect patterns including leaf spots, discoloration, and texture variations, and abnormal structures. They are then used to accurately classify crop diseases.The features that are extracted are fed through fully connected layers to classify into the type of disease afflicting the crop, with the system making the prediction. The output module shows the diagnosis of the disease and potential preventive steps or treatment recommendations. The outcome is relayed to the farmer via a mobile or web interface therefore decisions are made promptly. In general, the system combines IoT to gather real-time information and deep learning to analyze it and offer an effective and scalable solution to smart agriculture

B. Technical Insight

The proposed system uses deep learning, specifically Convolutional Neural Networks (CNN) to detect diseases using images more accurately. CNN models are very efficient in processing image data because the models can automatically learn spatial features without human interference. Convolution, pooling and activation functions are some of the layers that are used in conjunction to isolate meaningful patterns in crop images.Moreover, the system can be improved with the help of more sophisticated methods, such as transfer learning, in which the already trained models such as ResNet or EfficientNet can be used to fine-tune crop disease datasets. This saves training time, and enhances performance, particularly when there is little available data.The IoT integration is crucial in facilitating real-time tracking. The processing unit receives data that is constantly captured and sent to the device by the use of cameras and sensors. This will make sure that the diseases are identified at an initial stage reducing losses of crops. It is also possible to add the cloud-based processing of the system to make it scaled and stored. IoT and deep learning combine to form an effective system with the ability to make intelligent decisions and automation in the field of agriculture

C. Data Collection and Preprocessing

Dataset Compilation: The data utilized in this system is the crop leaf images of real agricultural field as well as publicly available data like PlantVillage. The data comprises the pictures of the healthy and diseased leaves of various crops

(tomato, potato, and maize). To provide diversity, different types of diseases are involved, including blight, rust, and leaf spot. Images are collected under different environmental conditions such as varying lighting, backgrounds, and angles to make the system robust. This assists the model to extrapolate more in the real world. The data set will be split into various categories according to the severity and type of disease.

Data Preprocessing: The images are fed into the model by preprocessing various steps beforehand. These are image down-scaling to a predetermined size, image normalization to ensure uniformity and removing noise to enhance readability. The leaf region and the background are isolated by utilizing segmentation techniques. The data augmentation methods that are used include rotation, flipping, zooming, and brightness change to augment the size of the data set to avoid overfitting. These measures enhance the capacity of the model to respond to changes in the real-life conditions and increase the accuracy

TABLE II
DATASET DISTRIBUTION BY CLASS

Class	**Category**	**Images**	**Description**
Class 1	Healthy Leaves	1000	No disease symptoms
Class 2	Early Blight	900	Small brown spots
Class 3	Late Blight	950	Large dark patches
Total	–	**2850**	Training and testing

This dataset is employed in the detection of crop diseases and includes images of leaves that were gathered in publicly available collections like the PlantVillage dataset and actual field conditions. The dataset contains a set of healthy and diseased leaf pictures and is divided into three categories: healthy leaves, early blight, and late blight, according to the symptoms of the disease that can be observed.

D. Novelty of Research

The originality of the proposed research is that the Internet of Things (IoT) is combined with deep learning methods to detect crop diseases effectively. In contrast to the traditional systems that can only be based on analysis of images, the proposed approach allows real-time data gathering via IoT tools like cameras and sensors. Image signal processing (image quality enhancement and image segmentation) is also included in the system to improve image quality, and model accuracy. In addition, automatic feature extraction through the use of Convolutional Neural Networks (CNN) eliminates the need to perform it manually, making it more efficient and effective in detecting features. The system is developed to deliver real-time disease detection and immediate feedback to assist farmers in taking the appropriate measures. Moreover, the suggested system is scalable and practical to be applied in real farms and under different conditions and various crops, so it is applicable to a variety of crops. In general, this combined solution enhances accuracy and minimizes manual work and promotes intelligent farming.

IV. Comparative Analysis

TABLE III
COMPARISON WITH EXISTING FRAMEWORKS

Framework	**Features**	**Limitations**	**Proposed Advantage**
Traditional Methods	Manual, simple	Slow, less accurate	Fast and automatic
ML (SVM, KNN)	Basic classification	Needs manual features	CNN learns features
CNN Systems	High accuracy	No real-time use	IoT-based real-time
Transfer Learning	Works on small data	Less adaptable	Uses live field data
IoT Systems	Real-time data	No smart analysis	IoT + AI combined

V. Limitations and Challenges

Despite its advantages, the proposed framework faces several challenges:

- Reliance on images of high quality because low lighting or noise can decrease the accuracy of the detection
- The need to have large and well-labeled datasets to train deep learning models
- Expensive to calculate and requires a powerful computer to perform real time operations
- Relying on internet connectivity to pass data on IoT in rural locations
- Expensive entry of the IoT devices like sensors and cameras to the small-scale farmers

VI. Conclusion

To sum up, crop disease detection is a vital part of contemporary farm to achieve high productivity and food security. The use of traditional methods is constrained by the fact that it relies on manual observation and is not accurate. As technology has improved, the application of deep learning networks, particularly, Convolutional Neural Networks (CNNs) has improved tremendously in the detection and classification of crop diseases based on their image characteristics. These systems are also supplemented with the integration of IoT that allows to monitor and collect data on the fields of agriculture in real-time. This paper has provided reviews of some of the current methods, discussed their advantages and weaknesses, and established some of the critical gaps in research. These limitations are proposed to be addressed in the proposed IoT-enabled deep learning framework through the combination of image signal processing, CNN models, and real-time data acquisition. This will enhance accuracy, efficiency and decision making to farmers. Though there are still challenges like cost, scalability and environmental variations, the suggested system offers a solid basis of smart agriculture. The future work can be dedicated to the creation of lightweight models, diversity of the datasets, and better real-time performance. Overall, the integration of IoT and deep learning has the potential to transform traditional farming into a more intelligent and sustainable system.

References

[1] Z. Nyawose, et al., "Machine learning and deep learning methods for plant disease detection: A review," *Computers and Electronics in Agriculture*, vol. 220, pp. 108-120, 2025.

[2] V. S. Dhaka, et al., "Crop disease detection using deep learning: A review," *IEEE Access*, vol. 9, pp. 160987–161011, 2021.

[3] M. Hasan, et al., "Deep learning approaches for plant disease detection and classification: A review," *Artificial Intelligence in Agriculture*, vol. 5, pp. 1–14, 2020.

[4] E. A. Abade, et al., "A systematic review of convolutional neural networks for plant disease detection," *Computers and Electronics in Agriculture*, vol. 176, pp. 105-117, 2020.

[5] S. Shelar, et al., "Plant disease detection using convolutional neural networks," *ITM Web of Conferences*, vol. 44, pp. 03049, 2022.

[6] Y. Sun, et al., "EfficientNet-based deep learning model for plant disease detection," *Smart Agricultural Technology*, vol. 2, pp. 100-112, 2022.

[7] I. Ahmad, et al., "Deep learning-based plant disease detection: A review," *Ecological Informatics*, vol. 72, pp. 101-115, 2023.

[8] A. Upadhyay, et al., "Advances in deep learning for crop disease detection," *Artificial Intelligence Review*, vol. 58, pp. 1–25, 2025.

[9] S. Hukkeri, et al., "CNN-based plant leaf disease classification," *The Open Agriculture Journal*, vol. 18, pp. 1–12, 2024.

[10] W. Demilie, et al., "Comparison of machine learning and deep learning techniques for crop disease detection," *Journal of Big Data*, vol. 11, pp. 45–60, 2024.

[11] B. Tugrul, et al., "Deep learning-based plant disease detection: A survey," *Agriculture*, vol. 12, no. 8, pp. 1192, 2022.

[12] N. Afreen, et al., "Plant disease detection using Capsule Networks," *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, pp. 2345–2352, 2022.

[13] P. Kumar, et al., "Plant disease detection using transfer learning and deep learning models," *Procedia Computer Science*, vol. 218, pp. 123–130, 2023.

[14] R. Kumar, et al., "Optimized plant disease detection using CNN and metaheuristic algorithms," *International Journal of Computational Engineering Science*, vol. 25, pp. 78–90, 2024.

[15] R. Sharma, et al., "Hybrid CNN-LSTM model for crop disease prediction," *Computers and Electronics in Agriculture*, vol. 225, pp. 108–118, 2025.

[16] S. Verma, et al., "Comparative analysis of CNN architectures for plant disease detection," *IEEE Access*, vol. 13, pp. 45000–45012, 2025.

[17] D. Patel, et al., "Real-time plant disease detection using deep learning and mobile applications," *IEEE Transactions on Industrial Informatics*, vol. 22, pp. 1120–1132, 2026.

[18] L. Zhang, et al., "A scalable deep learning framework for plant disease detection," *Scientific Reports*, vol. 16, pp. 2100–2115, 2026.

[19] A. Singh, et al., "Hybrid machine learning and deep learning approaches for plant disease detection," *Environmental Monitoring and Assessment*, vol. 196, pp. 300–315, 2024.

[20] K. Reddy, et al., "A systematic review of plant disease detection techniques using PRISMA methodology," *Indian Journal of Agricultural Research*, vol. 58, pp. 220–230, 2024.

[21] N. Gupta, et al., "Deep learning models for crop disease detection and classification," *Computers and Electronics in Agriculture*, vol. 224, pp. 107–119, 2025.

[22] X. Li, et al., "Enhanced CNN with attention mechanisms for plant disease detection," *Frontiers in Plant Science*, vol. 16, pp. 1505857, 2025.

[23] Y. Chen, et al., "Region-based convolutional neural network for plant disease detection," *Journal of Plant Pathology*, vol. 106, pp. 89–102, 2024.

[24] M. Khan, et al., "Multi-class plant disease classification using deep learning," *IEEE Access*, vol. 13, pp. 55000–55012, 2025.

[25] P. Joshi, et al., "IoT-enabled smart agriculture system for crop disease detection using deep learning," *Sensors*, vol. 25, no. 3, pp. 1450–1465, 2025.