



# International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.699**

**Volume 15, Issue 3, March 2026**

# **IoT Based Crop Disease Detection using Edge AI**

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**ABSTRACT:** Agriculture faces pressing challenges such as climate change, water scarcity, and crop diseases, demanding efficient and sustainable solutions. This research presents a smart farming system that integrates IoT sensors, edge computing, and artificial intelligence for real-time monitoring and decision-making. Environmental factors like soil moisture, temperature, humidity, and pH are continuously tracked, while on-site crop leaf images enable disease detection. A deep learning model deployed on edge devices ensures offline functionality, reducing reliance on internet connectivity. The system transitions from MobileNetV2 to the more accurate EfficientNetB3 architecture, achieving improved performance without sacrificing efficiency. This integration enhances productivity, optimizes water usage, and supports timely interventions. Designed for scalability and cost-effectiveness, it offers practical benefits to small and mid-scale farmers. By merging AI with IoT-based sensing, the approach transforms traditional agriculture into a smarter, more resilient practice.

**KEYWORDS:** Edge AI, IoT, Precision Agriculture, Crop Disease Detection, Real-Time Monitoring

## **I. INTRODUCTION**

Agriculture is a determinant factor in global food security, economic growth, and rural livelihood, particularly in low- and middle-income nations. As the world population continues to rise and is estimated to be 9.7 billion by 2050, there is mounting pressure on agricultural systems to be more productive and minimize losses [1]. Among the most important causes of crop loss is the epidemic of plant diseases that can greatly lower yield and quality. It is estimated that plant diseases account for about 20–40% of crop production loss around the world every year [2]. For this reason, early and precise detection of plant disease is imperative to reducing these losses and maintaining sustainable agricultural production. Conventional methods of disease detection—like field observation by hand, laboratory analysis, and distant specialist advice—tend to be time-consuming, expensive, and susceptible to human error. These drawbacks limit extensive monitoring, particularly in rural or far-off agricultural areas with restricted access to specialist agronomists or laboratory facilities. In addition, visible signs of plant illness usually become manifest only after significant internal damage has been done, and thus reactive measures are less successful [3]. Current innovations in Artificial Intelligence (AI), the Internet of Things (IoT), and Edge Computing provide new opportunities for creating smart systems that can monitor plant diseases in the field in real time. IoT-based networks can continuously track environmental and plant parameters via sensors (e.g., leaf moisture, temperature, humidity, spectral imaging), whereas Edge AI permits direct deployment of machine learning models on low-power embedded devices such as Raspberry Pi, Jetson Nano, ESP32-CAM, and Coral Edge TPU [4], [5]. The interplay between the two facilitates near-instant decision-making, reduces dependence on internet connectivity, and maintains data privacy through local processing of sensitive agricultural data [6].

### **1.2. OUTLINE OF THE PROJECT**

Agriculture plays a crucial role in ensuring global food security, but crop diseases significantly reduce agricultural productivity and yield. Traditional disease detection methods rely on manual inspection by agricultural experts, which is time-consuming, costly, and often inaccurate. Recent advancements in Internet of Things (IoT), Artificial Intelligence (AI), and Edge Computing have enabled real-time monitoring and automated detection of crop diseases directly in the field.

Several researchers have explored the integration of IoT sensors, edge devices, and machine learning algorithms to detect crop diseases efficiently.

Nyakuri et al. developed an AI and IoT-powered edge device for crop pest and disease detection using a lightweight convolutional neural network called Tiny-LiteNet. The system used a camera for image acquisition, Raspberry Pi for edge processing, and GSM communication for data transmission. The proposed model achieved 98.6% accuracy while maintaining low power consumption and fast inference time, making it suitable for real-time agricultural applications.

Bharathi et al. proposed a Smart Agro-IoT system with Edge AI for crop leaf disease detection and precision irrigation. Their system integrates environmental sensors such as soil moisture, temperature, humidity, and pH sensors with deep learning models like MobileNetV2 and EfficientNet deployed on edge devices. This approach enables real-time disease detection without requiring continuous internet connectivity and improves crop productivity through timely intervention.

Madiwal et al. conducted a comprehensive survey on Edge AI and IoT for real-time crop disease detection. The study highlighted the importance of decentralized computing where AI models run directly on edge devices such as Raspberry Pi, Jetson Nano, and embedded systems. The survey also identified several research challenges including limited datasets, scalability issues, energy efficiency, and secure communication between IoT devices.

Recent studies have also focused on developing lightweight deep learning models suitable for edge devices. Moges et al. proposed a Dynamic Meta-Ensemble Framework that combines multiple lightweight CNN models to improve disease detection accuracy while maintaining low computational requirements. The framework achieved high classification accuracy on plant disease datasets and demonstrated efficient performance on resource-constrained IoT devices.

Another study introduced a hybrid knowledge distillation approach that transfers knowledge from complex transformer models to lightweight CNN models for IoT-based agricultural systems. This technique significantly reduces computational complexity while maintaining high accuracy in plant disease classification, making it suitable for real-time edge deployment.

Researchers have also explored advanced deep learning models such as Vision Transformers and CNN hybrids for plant disease detection. These models provide improved feature extraction and classification performance while maintaining a lightweight architecture suitable for IoT-based smart farming applications.

Despite significant advancements, existing systems still face several limitations such as dependency on large datasets, limited adaptability to multiple crop types, and energy constraints in edge devices. Therefore, further research is required to develop more efficient, scalable, and cost-effective crop disease detection systems using IoT and Edge AI technologies.

## II.LITERATURE SERVEY

### 1. IoT and Edge AI for Smart Crop Disease Detection

Recent studies show that combining IoT sensors with edge-based AI models allows crop disease detection directly on devices such as Raspberry Pi or Jetson Nano without requiring cloud connectivity. A system proposed by Jean Pierre Nyakuri and colleagues developed an IoT-based device that uses a lightweight CNN model called Tiny-LiteNet for detecting crop pests and diseases. The system integrates a camera for leaf image capture, an edge device for local processing, and GSM communication for remote monitoring. The model achieved 98.6% accuracy with only 80 ms inference time, making it suitable for real-time field deployment.

This approach reduces latency, energy consumption, and dependency on internet connectivity while providing farmers with immediate feedback.

### 2. Edge AI-Based Smart Agriculture Systems

Another research work presented a **Smart Agro-IoT system with Edge AI** that integrates environmental sensors and deep learning models to monitor crop conditions. The system collects parameters such as soil moisture, humidity, temperature, and pH while simultaneously analyzing leaf images using convolutional neural networks like

**MobileNetV2 and EfficientNet.** The use of edge devices allows data processing locally, ensuring faster decision making and improved farm productivity.

This integration of sensor data and AI models helps farmers take timely actions such as irrigation control and disease treatment.

### **3. Survey on Edge AI and IoT for Crop Disease Detection**

A comprehensive survey conducted by **Abhishek S. Madiwal and researchers** analyzed recent trends in crop disease detection systems using Edge AI and IoT. The study highlighted the transition from centralized cloud processing to decentralized edge computing architectures. Lightweight deep learning models and compact hardware platforms enable autonomous disease monitoring in agricultural environments. However, challenges remain in areas such as dataset availability, model generalization across different crops, and secure communication between IoT devices.

The survey also emphasized the importance of integrating multiple sensors and improving energy-efficient AI models for field deployment.

### **4. Deep Learning Models for Edge-Based Plant Disease Detection**

Several studies focus on designing lightweight deep learning architectures for deployment on resource-constrained devices. For example, a research work on plant disease detection proposed an ensemble of lightweight CNN models such as **MobileNetV2, NASNetMobile, and InceptionV3** optimized for edge devices. The approach achieved classification accuracies of **99.53% for potato diseases and 96.61% for maize diseases** while maintaining low computational cost.

Similarly, hybrid models combining Vision Transformers and CNNs have been proposed to improve accuracy while maintaining efficiency for IoT devices.

### **5. Vision-Based Disease Identification for IoT Agriculture**

Another line of research uses image-based plant disease identification models optimized for IoT systems. Lightweight architectures combining CNN and transformer networks can detect multiple plant diseases from leaf images with high accuracy.

## **III. IMPLEMENTATION**

Climate change exacerbates the challenges of maintaining crop health by influencing invasive pest and disease infestations, especially for cereal crops, leading to enormous yield losses. Consequently, innovative solutions are needed to monitor crop health from early development stages through harvesting. While various technologies, such as the Internet of Things (IoT), machine learning (ML), and artificial intelligence (AI), have been used, portable, cost-effective, and energy-efficient solutions suitable for resource-constrained environments such as edge applications in agriculture are needed. This study presents the development of a portable smart IoT device that integrates a lightweight convolutional neural network (CNN), called Tiny-LiteNet, optimized for edge applications with built-in support of model explainability. The system consists of a high-definition camera for real-time plant image acquisition, a Raspberry-Pi 5 integrated with the Tiny-LiteNet model for edge processing, and a GSM/GPRS module for cloud communication. The experimental results demonstrated that Tiny-LiteNet achieved up to 98.6% accuracy, 98.4% F1-score, 98.2% Recall, 80 ms inference time, while maintaining a compact model size of 1.2 MB with 1.48 million parameters, outperforming traditional CNN architectures such as VGGNet-16, Inception, ResNet50, DenseNet121, MobileNetv2, and EfficientNetB0 in terms of efficiency and suitability for edge computing. Additionally, the low power consumption and user-friendly design of this smart device make it a practical tool for farmers, enabling real-time pest and disease detection, promoting sustainable agriculture, and enhancing food security.

### **EXISTING SYSTEM**

- Crop diseases are mainly detected manually by farmers through visual inspection.
- Farmers often consult agricultural experts or laboratories for proper diagnosis
- Some systems use cloud-based AI models for disease detection.
- These methods are slow, less accurate, and require internet connectivity.

### 3.1. DISADVANTAGES OF EXISTING SYSTEM

- Limited accuracy in real-time field conditions
- High computational load on edge devices
- Insufficient and less diverse training datasets
- Poor performance under varying lighting and weather conditions
- Dependency on internet/cloud for processing or model updates
- High power consumption and energy constraints

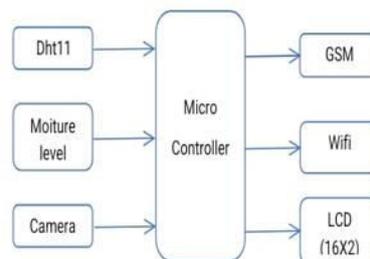
### 3.2. PROPOSED SYSTEM

- Camera captures crop leaf images.
- IoT sensors collect environmental data.
- Edge AI device processes data locally.
- AI model detects disease in real time.
- Alert is sent to farmer immediately.

#### 3.2.1. ADVANTAGES

- Reduced latency and faster decision making
- Minimal internet dependency
- Lower operational and data transmission costs
- Improved reliability in remote farming areas
- Enhanced data privacy and security
- Efficient and scalable agricultural monitoring

BLOCK DIAGRAM:



### WORKING

Agriculture plays a vital role in sustaining the global economy, and plant health directly influences crop productivity and food security. However, plant diseases often go undetected at early stages due to the limitations of manual inspection, which requires expert knowledge and is prone to human error. To address this challenge, the proposed project introduces an intelligent plant disease detection system based on machine learning and image processing techniques. The system operates by acquiring leaf images, which are then preprocessed through resizing, normalization, and noise reduction to enhance visual quality. Advanced deep learning models such as Convolutional Neural Networks (CNN) are employed to automatically extract relevant patterns and classify leaf images into healthy or diseased categories. A labeled dataset containing multiple plant species and disease variants is used to train and evaluate the model for high accuracy and generalization. Once trained, the model is integrated into a user-friendly interface, allowing farmers or agricultural professionals to upload or capture images using a mobile or web application and receive instant diagnostic results along with suggested remedies. This automated solution significantly reduces dependency on expert consultation, minimizes economic loss due to late detection, and promotes precision agriculture. Moreover, the system can be continuously improved by expanding the dataset to support additional crops and diseases, making it scalable and sustainable for real-world deployment. Overall, this project demonstrates an efficient, low-cost, and technology-driven approach to plant disease management, enabling smarter decision-making and contributing to global agricultural resilience.

## IV. CONCLUSION

Agriculture remains the backbone of the global economy, and the health of crops plays a crucial role in ensuring food security and farmer welfare. However, plant diseases often spread rapidly and remain undetected until severe damage has already occurred, leading to significant yield loss and economic setbacks. Traditional disease detection methods rely on manual examination by agricultural specialists, which is time-consuming, subjective, and often inaccessible to small and remote farming communities. With the advancement of artificial intelligence and computer vision, automated plant disease detection has emerged as a powerful alternative. Modern deep learning architectures such as YOLO (You Only Look Once), Vision Transformers (ViT), and MobileNet variants enable real-time image-based diagnosis with high accuracy, even on mobile and edge devices. In this project, an intelligent detection system is developed where leaf images are captured or uploaded, preprocessed, and then analyzed using advanced AI models to classify diseases and suggest corrective actions. Unlike conventional CNN-based approaches, the integration of Edge AI and Transformer-based architectures offers faster inference, lightweight deployment, and improved generalization across multiple crop varieties. This technology-driven approach not only empowers farmers with instant diagnosis but also supports large-scale precision agriculture, enabling proactive monitoring, reduced pesticide misuse, and sustainable crop protection. Thus, AI-powered disease detection represents a transformative step toward smart farming and digital agriculture.

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