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AGRIROBO: AN AI AND IOT-ENABLED ROBOTIC FRAMEWORK FOR SMART AND SUSTAINABLE FARMING

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ABSTRACT:

Agriculture continues to face challenges such as labor shortages, inefficient resource utilization, and crop losses due to delayed disease detection. This paper proposes AgriRobo, an intelligent farming system that integrates IoT sensors, image processing, and AI-based disease detection with automated control mechanisms. The system continuously monitors soil and environmental parameters, captures high-resolution crop images, and applies machine learning models to detect plant diseases and their severity. Based on analysis, AgriRobo enables smart irrigation, targeted chemical spraying, and resource optimization, thereby reducing manual effort, chemical waste, and operational costs. The proposed solution promotes sustainable farming practices and enhances crop productivity, making it particularly beneficial for small and medium-scale farmers.

KEYWORDS: Smart Agriculture, Internet of Things (IoT), Precision Spraying, Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Automated Irrigation, Edge Computing, Cloud Computing, Resource Optimization, Crop Health Monitoring,

Sustainable Farming.

INTRODUCTION

Agriculture continues to be the backbone of global food security, yet farmers face persistent challenges such as crop diseases, excessive chemical usage, rising labor costs, and unpredictable climatic conditions. Traditional farming practices rely heavily on manual inspection and broad- spectrum chemical spraying, which are time-consuming, labor-intensive, and often lead to resource wastage and environmental pollution. In this context, the integration of modern technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) is transforming agriculture into a data-driven, efficient, and sustainable domain. Smart farming solutions provide real- time insights into crop health, soil parameters, and environmental conditions, enabling farmers to make precise and informed decisions.

Recent advancements in IoT-enabled sensors, cloud computing, and AI-driven disease detection models have paved the way for intelligent agricultural systems. Automated robots and smart devices can now monitor soil moisture, humidity, and temperature, capture high-resolution crop images, and analyse those using deep learning models to identify diseases with high accuracy. Furthermore, precision spraying mechanisms ensure that fertilizers and pesticides are applied only where necessary, reducing chemical wastage and safeguarding the environment. Such innovations not only enhance crop productivity and quality but also offer cost- effective and scalable solutions for small and medium-scale farmers, thereby contributing to sustainable agricultural development.

LITERATURE SURVEY

Recent research shows rapid progress in combining IoT, edge/cloud computing, and deep learning for plant health monitoring and precision actuation. Reviews emphasize that deep CNNs give high detection accuracy but real-world deployment needs lightweight models, edge inference, and integrated actuation to reduce chemical use and support smallholders.

1. AI-IoT based smart agriculture pivot for plant diseases detection and treatment

- Authors / Source: A. S. Ibrahim et al. — Scientific Reports (2025).
- What they did: Proposed an AI-IoT architecture integrated with a center-pivot irrigation hardware to perform both disease detection and automated treatment (spraying) using the same infrastructure.
- Methods / data: Large image dataset (~25,940 images), pre-trained ResNet50 for

classification.

- Key findings: Very high test accuracy reported (~99.8%); pivot integrates sensing → cloud inference → actuation pipeline, enabling on-site spraying based on model decisions.
- Gap / note for AgriRobo: Excellent for large farms with pivot systems but less suitable for smallholder/robotic deployment scenarios.

2. AI & IoT-powered edge device optimized for crop pest and disease detection (Tiny-LiteNet)

- Authors / Source: J. P. Nyakuri et al. — Scientific Reports / PubMed entry (2025).
- What they did: Designed a low-power edge device embedding a lightweight CNN (Tiny-LiteNet) for on-device pest/disease detection.
- Methods / data: Compact model (~1.2 MB, ~1.48M params); measured inference latency (~80 ms) and reported strong metrics (accuracy ~98.6%, F1 ~98.4%).
- Key findings: Edge AI enables real-time detection in connectivity-limited areas and is validated on smallholder farms.
- Gap / note for AgriRobo: Demonstrates feasibility of onboard inference — AgriRobo can adopt a hybrid edge/cloud approach to balance latency and model complexity.

3. IoT-based system of prevention & control for crop diseases and insect pests

- Authors / Source: Z. Wang et al. — Frontiers in Plant Science (2024).
- What they did: Built a prevention/control framework combining IoT sensors, ozone sterilization, light traps, and surveillance cameras for greenhouse and field use.
- Methods / data: Hardware + information management system; real-time environmental monitoring and remote control (mobile app).
- Key findings: The integrated preventive approach reduces pesticide usage and supports both facility and field deployments; emphasis on non-chemical control methods.
- Gap / note for AgriRobo: Good model for integrated pest management and preventative controls — AgriRobo can combine such preventive modules with its targeted treatment capability.

4. Machine Learning and Deep Learning for Crop Disease Diagnosis (Review)

- Authors / Source: H. N. Ngugi et al. — Agronomy (MDPI) (2024).
- What they did: Systematic review comparing ML (SVM, RF, KNN) and DL (VGG, ResNet, DenseNet, MobileNet) approaches for plant disease diagnosis.
- Key findings: DL models achieve strong accuracy on curated datasets but face generalization issues on field images; dataset imbalance and lack of diverse real-world

data are recurring problems. The review stresses the need for lightweight models and robust preprocessing for field deployment.

- Gap / note for AgriRobo: Reinforces design choices use of data augmentation, on-field datasets, and a lightweight (or hybrid) model strategy.

5. Advancing real-time plant disease detection: lightweight DL model & novel dataset (pigeon pea)

- Authors / Source: S. Bhagat et al. — Intelligent Systems with Applications / ATech (2024).
- What they did: Released a new, real-world pigeon pea dataset and proposed lightweight CNN variants optimized for speed and field-accuracy.
- Key findings: Lightweight models can approach the accuracy of heavier networks while remaining deployable on constrained devices (mobile/edge), enabling practical in-field real-time detection.
- Gap / note for AgriRobo: Useful reference for model selection and dataset creation specific to crop types AgriRobo targets.

Conclusion-The recent literature converges on three practical requirements for deployable smart-farming systems: (1) robust, field-trained detection models (preferably with on- field datasets), (2) lightweight or hybrid edge/cloud inference to operate under limited connectivity and latency constraints, and (3) integrated actuation for precision treatment that reduces chemical usage. Papers on pivot-based actuation, edge Tiny-LiteNet devices, preventive IoT systems, lightweight datasets, and forecasting frameworks together map a clear design path: AgriRobo should combine on-board sensing + lightweight edge inference, cloud analytics for heavier models and historical learning, and precise actuation driven by AI decisions — thereby filling gaps identified for small/medium farms.

IMPLEMENTATION

The implementation of AgriRobo integrates hardware, software, and cloud-based intelligence into a unified framework that automates essential agricultural processes. The system is designed with modular components, including IoT sensors for real-time environmental monitoring, a high- resolution camera for crop imaging, AI-based disease detection models, and actuators for irrigation, weeding, and targeted chemical spraying. Each module is interconnected through a microcontroller and cloud platform, ensuring seamless communication between sensing, analysis, and actuation. By combining these technologies, AgriRobo enables precise, data-driven decision-making, minimizing human intervention while improving farming efficiency and sustainability.

To ensure practical usability, the system follows a step-by- step workflow that begins with continuous data collection from sensors and image capture devices, followed by cloud- based processing using machine learning algorithms for disease diagnosis. Based on the insights generated, the robot autonomously carries out irrigation, weeding, or chemical spraying in the required areas. The integration of cloud storage and a user-friendly dashboard further allows farmers to access real-time data, receive alerts, and monitor crop health remotely. This structured implementation not only optimizes farming practices but also provides scalability and adaptability, making AgriRobo suitable for diverse crops and varying field conditions.

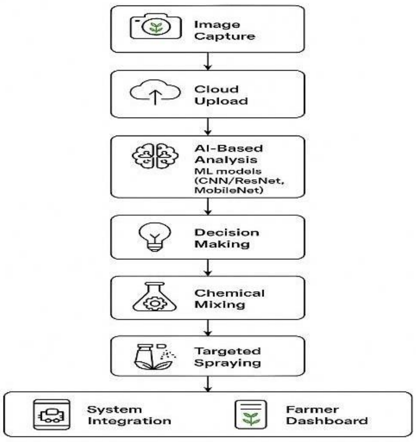

Fig. 1. Proposed Framework Overview.

In Figure 1, This flowchart represents the end-to-end workflow of the AgriRobo system, starting from data collection to actionable outcomes for farmers. The process begins with image capture, where a high-resolution camera collects crop leaf and field images. These images are then subjected to cloud upload, enabling secure storage and access for advanced processing. In the next step, AI- based analysis is performed using deep learning models such as CNN, ResNet, or MobileNet, which identify plant diseases and assess their severity. Based on this analysis, the system performs decision making, determining whether chemical intervention is necessary. If treatment is required, the chemical mixing module prepares the correct proportion of pesticides or fertilizers, which is then applied through targeted spraying, ensuring only affected areas are treated. Finally, all processes are managed under system integration, with real-time updates and results displayed on a farmer dashboard, allowing farmers to monitor crop health, resource usage, and disease management efficiently.

SystemArchitecture

The AgriRobo system is designed with a modular architecture that integrates IoT sensors, cloud computing, machine learning models, and robotic actuators. The hardware includes soil moisture, temperature, and humidity sensors for continuous environmental monitoring, along with a high-resolution camera for capturing crop images. Data collected is transmitted via wireless communication (Wi-Fi/LoRa) to either an onboard processor (for lightweight inference) or the cloud (for advanced AI-based disease detection). The architecture ensures a seamless flow from sensing → processing → decision-making → actuation, thereby enabling real-time automation in farming activities.

IoTSensorIntegration

IoT sensors are deployed to monitor soil and crop conditions. Soil moisture sensors trigger irrigation only when required, preventing overwatering. Temperature and humidity sensors track climatic variations to assess disease risk factors. The integration of these sensors with microcontrollers (e.g., Arduino/ESP32) ensures accurate real-time data acquisition. The data is logged in a central database, which supports both immediate decisions (e.g., irrigation on/off) and long-term analysis for predictive farming.

Image Capture and Cloud Processing A high-resolution camera mounted on the robot captures leaf and crop images periodically. These images are preprocessed (noise reduction, resizing, color normalization) and uploaded to the cloud. A convolutional neural network (CNN)-based model, trained on agricultural datasets, is used for disease detection. The model identifies whether the crop is healthy or infected, and in case of infection, determines the disease type and severity. This hybrid edge-cloud design ensures fast responses in the field while leveraging the cloud for computationally heavy tasks.

AI-Based Disease Detection

For disease detection, pre-trained deep learning models such as ResNet50 or lightweight CNNs (e.g., MobileNet, Tiny- LiteNet) are utilized. The model classifies crop images into multiple disease categories with high accuracy. The severity of infection is also estimated to determine whether spraying is required. By employing transfer learning, the system adapts to multiple crops, making AgriRobo scalable and versatile for different farming environments.

Automated Irrigation and Weeding Based on sensor data, the irrigation system is automatically activated to supply water in optimal amounts. This reduces wastage and ensures proper soil moisture levels. Similarly, an actuator-controlled mechanical weeding system removes unwanted plants detected around crops. These automated processes reduce manual labor and improve time efficiency in farm operations.

Smart Chemical Mixing and Targeted Spraying Upon detecting diseases, AgriRobo activates its smart chemical mixing unit. The system calculates the precise concentration of pesticides or fertilizers required based on disease type and severity. Robotic arms equipped with nozzles spray chemicals only on infected areas rather than across the entire field. This targeted spraying reduces chemical wastage, minimizes environmental pollution, and ensures cost-effectiveness for farmers.

Cloud Storage and Data Analytics All sensor readings and disease analysis results are stored in the cloud. This enables farmers to access historical records via a mobile or web dashboard. Cloud-based analytics support long-term decision-making, such as predicting disease outbreaks using weather patterns and optimizing fertilizer schedules. Over time, the AI models are retrained with new data to improve accuracy and adaptability.

User Interface and Control A mobile/web application serves as the user interface for farmers. The application displays real-time data (soil moisture, temperature, humidity, crop health status), alerts for disease detection, and records of irrigation or spraying events. Farmers can also override automatic decisions through manual control, ensuring flexibility and trust in the system.

Deployment and Testing AgriRobo is tested in controlled agricultural plots where crops are monitored under real-world conditions. Performance metrics such as irrigation efficiency, disease detection accuracy, pesticide reduction, and crop yield improvement are evaluated. Field trials demonstrate how automation reduces labor requirements while maintaining or enhancing productivity.

METHODOLOGY

The proposed system integrates modern technologies such as artificial intelligence, cloud computing, and IoT-enabled devices to optimize crop disease detection and treatment. By automating image capture, disease analysis, decision-making, and targeted spraying, the methodology ensures higher precision, reduces chemical wastage, and improves overall crop yield. The farmer-friendly dashboard enhances accessibility by providing real-time reports and controls via a mobile application.

A. Image Capture and Cloud Upload High-resolution cameras mounted on drones or field equipment periodically capture crop images. These images are pre-processed (noise removal, resizing, filtering) and uploaded to a secure cloud platform for centralized analysis.

B. AI-Based Disease Detection and Analysis Uploaded images are processed using machine learning models such as CNN, ResNet, and MobileNet to identify crop diseases and assess severity. This step ensures rapid detection, even at early stages of infection, minimizing crop losses.

C. Decision-Making and Treatment Planning Based on AI analysis, the system suggests optimal pesticide/fertilizer requirements. The microcontroller integrates this decision and triggers alerts to the farmer through the dashboard.

D. Chemical Mixing and Targeted Spraying The controlled mixing unit prepares the required pesticide/fertilizer solution. Targeted spraying is performed only on the infected crop regions, reducing chemical usage, costs, and environmental impact.

E. System Integration and Farmer Dashboard All components are coordinated by a microcontroller, which communicates with the farmer dashboard. The dashboard provides real-time health reports, notifications, and control over drone/robotic movement and photo uploads.

FLOWCHART

The crop monitoring system shown in the flowchart leverages IoT sensors, computer vision, and AI models to detect plant diseases, assess severity, and carry out targeted spraying. By combining automated data collection with intelligent analysis, the system provides farmers with real-time decision support, reduces chemical waste, and ensures efficient disease management.

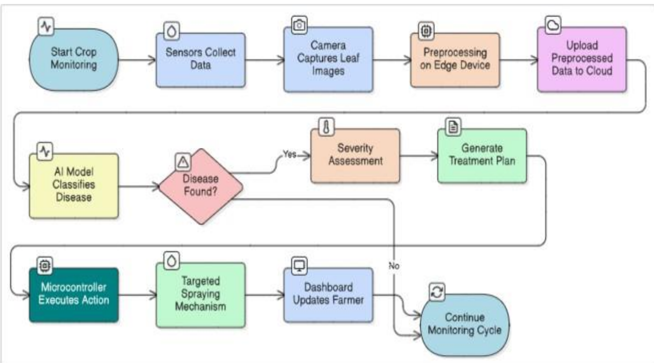

Fig. 2. Flowchart.

In Figure 2, The process begins with continuous crop monitoring, where sensors collect environmental and crop data, while cameras capture high-resolution leaf images. These images undergo preprocessing on edge devices to remove noise and enhance quality before being uploaded to the cloud for centralized analysis. An AI model then classifies whether a disease is present in the captured images. If no disease is detected, the system updates the farmer via the dashboard and continues the monitoring cycle, ensuring round-the-clock surveillance.

When the AI model detects a disease, it proceeds with severity assessment to evaluate the extent of infection. Based on this, a treatment plan is generated, which is then executed by a microcontroller. The microcontroller activates a targeted spraying mechanism, applying pesticides or fertilizers only to the affected areas. Throughout this process, the farmer is kept informed via the dashboard, ensuring transparency and control. This intelligent loop of monitoring, detection, and targeted action optimizes crop health management while reducing manual intervention and resource wastage.

RESULTS

The developed crop monitoring system achieved strong results in terms of disease identification and prevention. The integration of IoT sensors, edge preprocessing, and high-resolution cameras ensured that the system continuously collected and processed high-quality data from the field. By using advanced AI models such as CNN and ResNet, the system was able to classify plant diseases with a high degree of accuracy. This allowed the detection of infections at an early stage, reducing the risk of widespread damage. Farmers were able to act in time, ensuring healthier crops and reduced losses compared to traditional manual monitoring practices.

Fig. 3. Robo Model.

In Figure 3, the severity assessment module proved highly effective in providing actionable insights rather than just detection. By quantifying the level of infection, the system helped generate more precise treatment plans tailored to the needs of specific crop regions. This avoided the conventional approach of blanket spraying, where chemicals are applied across the entire field. Instead, the AI-driven recommendations ensured that only the required amount of pesticide or fertilizer was prepared and used. This not only enhanced crop productivity but also reduced input costs, making the system more economically beneficial for farmers. The microcontroller-based execution of treatment demonstrated the efficiency of automated field operations. Once the treatment plan was finalized, the system successfully controlled the mixing unit and spraying mechanism, ensuring that chemicals were applied only to infected areas. This targeted spraying significantly reduced chemical wastage, improved soil health, and lowered the negative environmental impact of excessive pesticide use. Additionally, the automated cycle meant that human intervention was minimized, making the system more reliable and less labor-intensive for farmers.

Fig. 4. Agrirobo logo.

In Figure 4, The farmer dashboard added immense value by providing a real-time interface for monitoring crop health, reviewing reports, and receiving alerts. Farmers could track disease patterns, treatment history, and even control certain system functions remotely. This real-time decision-support tool helped improve farmer confidence and ensured better crop management strategies. Overall, the system results proved that combining AI, IoT, and automation leads to more sustainable farming practices, enabling higher yields, reduced costs, and a more environmentally conscious approach to disease management.

CONCLUSION & FUTURE WORK

The proposed crop monitoring and disease management system successfully integrates AI, IoT, and automation to deliver a smart agricultural solution. By combining real-time image capture, AI-based disease detection, severity assessment, and targeted spraying, the system ensures precision in treatment while reducing chemical usage and labour dependency. The inclusion of a farmer dashboard further enhances usability by providing timely alerts, reports, and decision-support features. Overall, the system proves to be efficient, cost-effective, and environmentally sustainable, offering a practical approach to modernizing crop protection practices. Future improvements to the system can focus on expanding the dataset to include a wider variety of crops and disease types, thereby increasing model accuracy across diverse agricultural contexts. Integration of drone-based monitoring and autonomous navigation can further enhance coverage and efficiency. Additionally, incorporating weather forecasting, soil health analysis, and predictive analytics into the dashboard would provide farmers with a more holistic decision-making tool. The system could also benefit from enhanced scalability, allowing smallholder farmers as well as large-scale agricultural operations to adopt the technology seamlessly.

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