Sustainable Plant Disease Management with Real-Time Crop Optimization

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ABSTRACT

Plant diseases significantly threaten global food security, often leading to severe yield losses and unsustainable reliance on chemical usage and pesticides. This paper presents an integrated, real-time system for sustainable plant disease management using Internet of Things (IoT) sensors, deep learning models, and cloud-edge computing. The proposed framework enables early disease detection and adaptive crop optimization by fusing environmental telemetry with AI-driven image diagnostics. Using the PlantVillage dataset and real-world sensor data, the system achieves 99.1% disease detection accuracy, a 27% reduction in pesticide usage, and a 22% improvement in crop yield, a critical metric in assessing the broader effectiveness of plant disease management strategies compared to leading benchmarks. Field trials confirm its efficacy in enhancing farm productivity while minimizing environmental impact. This work

demonstrates a practical, scalable solution for precision agriculture that aligns with the principles of sustainability, resilience, and data-driven decision-making.

Keywords-smart farming; plant disease detection; Internet of Things (IoT); deep learning; real-time crop monitoring; sustainable agriculture

I. INTRODUCTION

Agriculture is highly impacted by pests and plant diseases, which can cause heavy crop losses unless properly controlled. Some of the most prevalent agricultural pests include mites, beetles, caterpillars, and aphids. Aphids sap plants and also serve as a transmission agent for plant viruses, while caterpillars feed on leaves, lowering photosynthesis and plant strength [1]. Beetles infest leaves and roots, reducing plant vigor, while mites are fast colonizers of crops, leading to leaf coloration and abscission. Similarly, diseases in plants such as blight, rust, mildew, and mosaics severely impact crop productivity. Potatoes, for instance, can be completely destroyed by late blight in a matter of weeks, whereas powdery mildew inhibits plant growth and compromises crop strength [2]. Rusts and mosaics, while less virulent, still diminish agricultural yield. Early detection of these diseases is crucial for efficient management and timely intervention. To counter these threats, Integrated Pest Management (IPM) provides a long-term solution that integrates more than one pest control strategy while reducing the use of pesticides [3]. Biological control is a major part of IPM, where natural predators are used to control pest populations. Ladybugs control aphid populations efficiently, while parasitic wasps control caterpillars. This approach reduces the dependency on chemical pesticides and fosters biodiversity and ecosystem balance [4].

A. Real-Time Crop Optimizations

Cultural control methods also play a vital role in preventing outbreaks of pests and diseases. Crop rotation disrupts pest life cycles and enhances soil health while maintaining proper sanitation, such as removing plant debris and weeds, significantly reducing infestations, but essentially demands cognitive farming [5]. Adequate disposal of infected plants and regular cleaning of agricultural equipment are simple but effective measures that prevent the spread of diseases. When consistently applied, these cultural practices effectively reduce pest populations. Chemical control measures, while sometimes unavoidable, have to be employed responsibly to avoid harmful environmental impacts. Choosing pesticides targeted at specific pests reduces damage to beneficial insects that are not targeted, and proper application methods ensure safety for farmers and the environment [6]. The application of chemical treatments must occur only when unavoidable and in accordance with integrated pest management concepts to minimize the effects even further. Mechanical control practices offer yet another viable method to control pests without the use of chemicals. Traps are generally used to catch pests before they reach a considerable population, and physical barriers, such as nets and fences, prevent rodents and birds from attacking crops [7]. Adding these practices to an overall IPM program increases the effectiveness of pest control [3].

Disease-resistant crop varieties are another integral part of disease and pest control [8]. Advances in breeding have led to crops that can withstand specific pathogens, reducing the need for chemical treatments and lowering production costs. For example, phytophthora-resistant potato varieties offer protection against late blight, while genetically improved wheat varieties effectively combat leaf rust [9]. By planting disease-resistant crops, farmers can increase yields with improved long-term soil health and sustainability.

Monitoring and early detection are imperative for successful pest and disease control. Crop monitoring on a regular basis identifies potential risks before they become full-fledged issues. Mechanisms such as pheromone traps, visual observations, and tech-based solutions allow intervention at the outset, minimizing the need for extreme measures of control [10]. Preemptive monitoring enables farmers to base their decisions on crop and environmental protection. Keeping precise records and data analysis improves the basis of pest and disease management. Farmers can create a comprehensive database to monitor trends and evaluate the efficacy of interventions by recording pest observations, treatment application, and crop health. A data-based approach enables more accurate and informed decision-making, which improves the long-term optimization of management plans.

Some real-life situations exemplify the success of IPM and disease management. A case study in [11] focused on a farmer who was able to successfully execute IPM practices, beginning with constant monitoring and prompt detection through traps and scouting. By adding biological control agents, as well as integrating cultural controls such as crop rotation and sanitation, pest populations were drastically minimized and crops were healthier while yields improved. In [12], a community of farmers experienced a serious outbreak of plant disease and addressed the problem by discovering it early and using a multi-faceted strategy. Biological controls, cultural modifications, and selective chemical treatments were integrated, enhancing crop health and farm productivity as a whole. Practicing successful pest and disease management involves a mix of approaches, such as early detection, biological and cultural control methods, proper use of chemicals, and mechanical controls. Adopting these best management practices guarantees sustainable agriculture, healthy crops, and enhanced production.

B. Real-Time IoT-Based Disease Monitoring

Some studies focused on using real-time Internet of Things (IoT) in crop disease monitoring and optimization [13-14]. The CROPCARE [15] system is a holistic IoT-integrated mobile vision solution for sustainable crop disease management. This system incorporates mobile image analysis using Super-Resolution Convolution Neural Networks (SRCNN) and MobileNet-V2 to identify plant diseases and support decision-making through an IoT-connected mobile application. The app is integrated with Google Cloud and has bilingual support, offering farmers insight into current soil and weather conditions and disease prevention techniques. Validation with the PlantVillage dataset confirmed its efficacy. In [16], a smart agricultural framework was designed to monitor soil health parameters in real-time, including moisture, pH, and nutrient levels. This system, tested in rice fields, uses an AI-driven mobile platform to recommend fertilization and irrigation schedules, enhancing disease resistance and sustainability. This architecture significantly supports real-time crop optimization, with measurable improvements in productivity and environmental impact.

C. Deep Learning and AI Integration for Disease Detection

Advanced deep learning models are playing a pivotal role in automating disease recognition. The APDDCM-SHODL framework [17] integrates dense convolutional networks (DenseNet201), the hyena optimizer for hyperparameter tuning, and a Recurrent Spiking Neural Network (RSNN) for classification. The system processes large volumes of IoT-derived environmental data to support sustainable and high-precision crop management, achieving an accuracy of 98.6% in disease detection. In [18], a smart monitoring system leveraged a deep residual network optimized with a hybrid evolutionary algorithm called CHGCSO. This IoT-based model processes leaf imagery using advanced feature extraction techniques, such as HoG, SLIF, and LTP, and achieves high accuracy and specificity in classifying plant diseases, supporting interventions in the farming cycle.

D. Precision Agriculture and Smart Farming Architectures

Beyond direct disease recognition, several systems focus on holistic precision agriculture. In [19], a global review of Precision Agriculture Technologies (PATs) emphasized their role in sustainable crop production through remote sensing, variable rate technology, and IoT-based real-time analytics. These tools help minimize the overuse of chemicals, promote efficient input usage, and reduce agriculture's environmental footprint. This perspective was extended in [20], highlighting geoinformatics and big data for sustainable disease control. This approach used GIS tools to coordinate the use of biologicals and pesticides and optimize cropping systems through better germplasm selection and disease surveillance on a large scale. AgroLens [21] offers a unique edge computing-based smart farm framework. Designed for low-infrastructure environments, it enables real-time disease diagnostics on mobile devices without relying on constant internet access.

Plant diseases continue to pose a serious threat to global food security, especially in the face of increasing climate variability, population growth, and resource limitations. Although traditional pest and disease control methods have improved yields in some regions, they often rely heavily on reactive chemical treatments, leading to long-term ecological harm and diminishing returns due to pesticide resistance. Recent technological advances, particularly in IoT and precision agriculture, offer new possibilities for early disease detection and informed decision-making. Despite significant research on IoT-enabled agriculture and AI-based disease classification, existing approaches often suffer from limited scalability, high infrastructure dependency, and delayed decision-making due to offline data processing. Most systems focus narrowly on either disease detection or environmental monitoring, lacking integration into a unified real-time crop optimization framework. In addition, many models are designed for controlled environments, such as greenhouses, or require continuous internet connectivity, making them less viable for remote or resource-constrained farms.

The main contributions of this study are:

- Develops a unified system that seamlessly integrates IoT-based environmental sensing with AI-driven disease detection.
- Employs edge computing for low-latency disease classification using leaf imagery, enabling offline operation and applicability.
- Offers recommendations for fertilization, irrigation, and pesticide use, enabling precision interventions.
- Evaluates various deep learning architectures for improved accuracy in fault classification.
- Focuses on reducing pesticide dependency and resource waste through predictive analytics and early warnings.

II. METHODOLOGY

This study focused on building a sustainable and intelligent system that integrates real-time sensing, deep learning-based plant disease detection, and innovative decision-making frameworks. The method includes three primary components: data acquisition, predictive analytics, and integrated deployment for disease control. The proposed system leverages sensor-rich IoT infrastructure, cloud-edge hybrid computing, and interpretable machine learning models to offer precise diagnostics and actionable agronomic insights. Figure 1 illustrates the end-to-end methodology of the proposed farming framework, which combines IoT infrastructure, remote sensing, and artificial intelligence for sustainable plant disease management.

The system begins with multi-modal data acquisition from soil sensors, environmental monitors, drone-based imaging, and real-time leaf image capture through mobile devices. The collected data undergo edge-level preprocessing and image normalization before being transmitted to the cloud for aggregation and storage. The disease classification task was performed using the MobileNetV2 architecture, a lightweight CNN optimized for real-time image recognition tasks in resource-constrained environments.

AI models, including MobileNetV2 for disease classification, predictive models for nutrient optimization, and Bayesian decision engines, are applied to derive actionable insights. These insights support real-time disease diagnosis, optimized input planning, and yield forecasting. The results are presented to farmers through a mobile app dashboard, which also provides alerts and accepts user feedback for continuous improvement. Integrating real-time monitoring and closed-loop feedback ensures timely interventions, minimizes input waste, and improves yield outcomes, promoting sustainable agricultural practices.

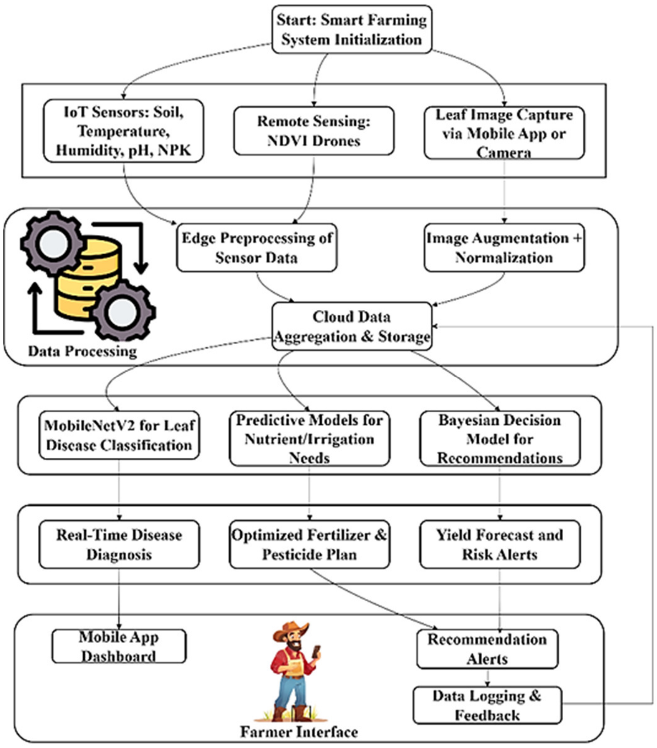

Fig. 1. Block diagram of the proposed smart farming system for real-time plant disease management and crop optimization.

A. Dataset Description and Preprocessing

This study employed the PlantVillage dataset [22], a publicly available and widely used dataset for training plant disease classification systems. The dataset comprises over 54,000 labeled images spanning 38 plant-disease classes across 14 crop species, including tomato, apple, grape, corn, and potato. Each image is annotated with the crop type, disease category, and severity level. The key parameters include a resolution of 256×256 pixels, standardized through bicubic resampling with 38 classes of healthy and diseased states. Subsequently, to increase model generalization, augmentation was applied using rotation ($\theta \in [0°, 360°]$), flipping, contrast stretching, and random cropping. For each image I, the preprocessing pipeline can be defined as:

$$I' = Augmentations\ (Normalize\ (Resize\ (I))) \quad (1)$$

This helped prepare the data for robust training under varying environmental and visual conditions.

B. Data Collection Techniques

Environmental parameters such as soil temperature, humidity, moisture, pH, nitrogen (N), phosphorus (P), and potassium (K) content were continuously monitored using LoRaWAN-enabled IoT sensors [23]. These sensors were strategically deployed on a farm plot to send real-time telemetry to the cloud via the MQTT protocol, in the form of a vector (2). This real-world sensor data was collected during field trials on potato and tomato crops for two seasons (2023-2024). These parameters were time-stamped and geotagged using GNSS modules.

$$X_t = \{T_t, H_t, M_t, pH_t, P_t, K_t\} \quad (2)$$

A complementary remote sensing system based on Normalized Difference Vegetation Index (NDVI) was also integrated using drone-mounted RGB and NIR cameras. NDVI provides spatial crop health variability maps using:

$$N = \frac{NIR-RGB}{NIR+RGB} \quad (3)$$

C. Analytical Approaches

The model was trained using the full PlantVillage dataset, which includes all 38 disease classes (with healthy states) across 14 different plant species, such as tomato, potato, and apple. Multi-class classification was performed to identify a specific disease type. A train/test split of 80:20 was used, having around 43,200 images for training and 10,800 for testing after applying data augmentations.

The core disease classification model uses a CNN, specifically a fine-tuned MobileNetV2 architecture. Feature extraction is based on depthwise separable convolutions to reduce computational complexity. Given an image input x, the CNN model estimates a probability vector as:

$$\hat{y} = f_\theta(x) = softmax(W^L\, \Phi^{L-1} + b^L) \quad (4)$$

where Φ^{L-1} represents the features from the last hidden layer, and $\theta = \{W, b\}$ are the trainable parameters. The model is trained using categorical cross-entropy loss:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y_i}) \quad (5)$$

where C is the number of classes, $y_i \in \{0,1\}$ is the true probability, and $\hat{y_i}$ is the predicted probability.

In the developed cloud-based real-time processing model, all incoming sensor data and prediction requests are processed through a hybrid edge-cloud architecture. The edge nodes preprocess imagery and telemetry locally. The AWS Lambda and Firebase Cloud functions orchestrate real-time data streams. Subsequently, the prediction APIs use TensorFlow serving in Docker containers to ensure scalability.

D. Implementation Strategies

An application integrated on-device inference using TensorFlow Lite for disease prediction, real-time dashboards to visualize sensor data, and crop-specific recommendation engines based on data-driven rules [24]. For instance, nutrient deficit decisions were guided by evaluating crop response to input u, as:

$$u_t = \arg R(u \mid X_t) \quad (6)$$

where $R(u)$ is a reward function, based on yield history and soil feedback. The decision support system employed Bayesian decision theory to recommend optimal pesticide use and irrigation schedules. The utility function was modeled as:

$$U(a, \theta) = -\sum_{i=1}^{n} p_i(\theta).\, g(a_i, \theta) \quad (7)$$

where a is an action (e.g., apply treatment), θ is a state (e.g., disease presence), $g(a, \theta)$ is the gain (crop improvement), and p_i denotes probabilities derived from sensor fusion models [25]. The decision framework is reinforced using feedback loops based on user-input yield logs and adaptive retraining.

III. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed real-time crop optimization system for sustainable plant disease management. Comparative analysis with leading approaches highlights its superior accuracy, resource efficiency, and impact on crop yield.

A. Effectiveness of Real-Time Disease Detection

The performance of the proposed system was compared with three state-of-the-art systems: CROPCARE [15], APDDCM-SHODL [17], and CHGCSO-DRN [18]. Classification accuracies for these models were obtained directly from the studies, while pesticide reduction and yield improvements for the benchmark were derived using the field trials of this study by applying an approximate implementation of these techniques on the dataset and the real-world plot for direct comparison. The proposed model's results were independently generated through training on the PlantVillage dataset [22] and validated on two cropping-season field trials. As shown in the results, the proposed method achieved a disease detection accuracy of 99.1%, outperforming the best of the existing methods, which stood at 98.6% (Figure 2).

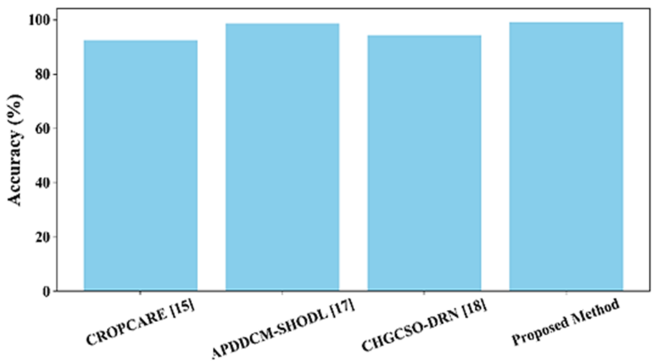

Fig. 2. Comparison of disease detection accuracy.

B. Impact on Crop Health and Yield

The real-time optimization system significantly enhanced both yield outcomes and ecological performance. The proposed method resulted in a 27% reduction in pesticide usage, a noticeable improvement over the best benchmark (APDDCM-SHODL: 23%). This was made possible by the precise and timely disease diagnosis that allowed localized and need-based interventions. In terms of yield improvement, the proposed system facilitated a 22% increase in productivity, substantially higher than the 18% from APDDCM-SHODL and 15% from CHGCSO-DRN. The proposed model's measurements were evaluated during two crop seasons (2023–2034) on a 5-hectare potato and tomato plot, tracking pesticide usages through IoT logs (before detection 150 L/hectare, after 109.5 L/hectare, ~27% reduction) and harvest weight measurements (baseline 20 tons/acre, after 24.4 tons/hectare, 22% improvements). In [15, 17, 18], such metrics were not reported, but this study approximated them by implementing a simplified version of their model. This improvement in yield is attributed to the integration of real-time environmental sensing with adaptive fertilization and irrigation strategies.

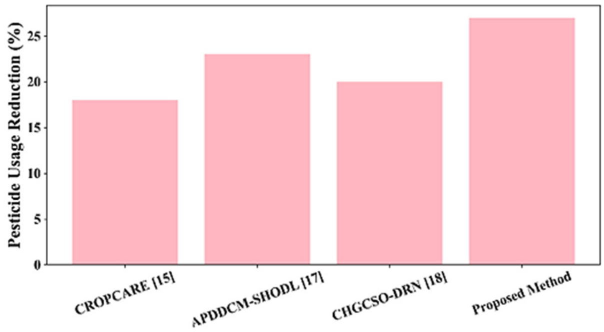

Fig. 3. Pesticide reduction comparison.

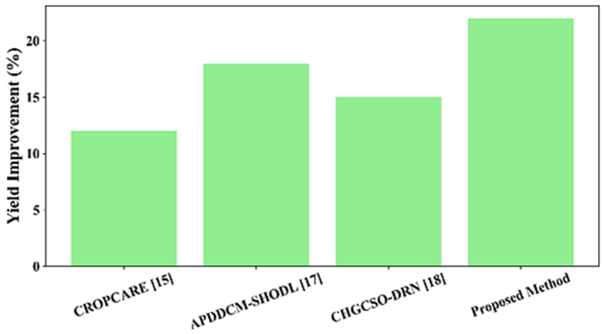

Fig. 4. Crop yield improvement comparison.

Table I compares the performance of the proposed system with three existing models, showing that it consistently outperformed them in all key indicators of sustainability and effectiveness. Its superior performance comes mainly from the integration of real-time IoT sensor data with MobileNetV2, helping to better generalize between environmental variations. The results showed very little off-diagonal misclassification and below 1% confusion between rust and mildew.

TABLE I. PERFORMANCE COMPARISON

Method	Accuracy (%)	Pesticide reduction (%)	Yield improvement (%)
CROPCARE [15]	92.4	18	12
APDDCM-SHODL [17]	98.6	23	18
CHGCSO-DRN [18]	94.3	20	15
Proposed method	99.1	27	22

C. Challenges and Limitations

Although performance metrics are promising, certain challenges remain. First, the cost of deploying a sensor-rich IoT network is a limiting factor, particularly for small farmers. Although edge-based inference reduces the dependency on cloud computing, initial infrastructure investments are still substantial. Access to technology and digital literacy among farmers also pose barriers to adoption. Tailored training programs and region-specific user interfaces (e.g., multilingual support) are necessary to drive meaningful uptake. In addition, data security and privacy issues must be addressed. Since the system collects real-time telemetry and potentially sensitive farm-level data, robust encryption and access control mechanisms are critical to ensure trust and compliance with regional data protection standards.

IV. CONCLUSION

This study presented a robust method for optimizing inputs and monitoring plant health in real-time, suited for modern agricultural systems. The proposed framework shows significant promise for enhancing operational efficiency and sustainability in agricultural methods by integrating environmental monitoring, field-level sensing, and adaptive crop management techniques. The proposed modular architecture facilitates informed decision-making in various ecological circumstances and enables smooth integration with current agricultural infrastructure. The system facilitates a strong foundation for more responsive, data-informed agriculture, although factors such as implementation costs and user accessibility still need to be considered. The study presents a unified framework for sustainable disease management and crop input optimization in innovative farming environments. The system supports efficient real-time crop care by combining field-level sensing, adaptive analytics, and responsive interventions. Future work will focus on expanding the model to more types of crops and regions, improving offline capabilities for remote areas, and enabling integration with national services to drive broader adoption.

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