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Multimodal Edge Intelligence for Crop Disease Detection and Irrigation Advisory in Precision Agriculture

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Abstract--Crop losses caused by disease, water stress, and delayed field intervention remain a major challenge for small and medium farmers. Conventional advisory systems often depend on manual inspection or cloud-only diagnosis, which can be slow in rural environments where connectivity is limited. This paper proposes a multimodal edge-intelligence framework that combines leaf-image analysis, soil-moisture sensing, weather context, and lightweight decision rules to provide early crop disease detection and irrigation advisory. The system uses a compact convolutional neural network for visual symptoms and a sensor-fusion module for environmental risk estimation. By running inference near the field, the framework reduces latency and protects farm data while still supporting periodic cloud synchronization. Simulated evaluation shows 91.8% disease classification accuracy, 16.4% water saving, and faster advisory delivery compared with image-only and rule-based baselines.

Index Terms--Precision agriculture, crop disease detection, edge computing, sensor fusion, irrigation advisory, machine learning.

I. INTRODUCTION

Agriculture increasingly depends on timely decisions. A farmer must identify disease symptoms, estimate water needs, and respond to weather variation before visible damage becomes severe. In many regions, expert agronomists are not available for frequent field visits, and manual observation may detect disease only after it has already spread across a large area.

Mobile applications and image-based diagnosis tools have improved access to agricultural knowledge, but many of them require continuous network access or rely only on leaf photographs. A leaf image can reveal visual disease symptoms, yet it does not fully explain whether a plant is suffering from fungal risk, water stress, heat stress, or nutrient imbalance. Soil and weather context are therefore essential for practical advisory.

This paper introduces a multimodal edge-intelligence framework for crop monitoring. The proposed system processes leaf images and local sensor data on a low-cost edge device. It estimates disease probability, irrigation requirement, and intervention priority, then sends a concise advisory to a farmer-facing mobile application. The design is intended for resource-constrained farms where low latency, low bandwidth use, and simple explanations matter.The major contributions are threefold. First, the paper presents a layered architecture for combining visual and environmental crop signals. Second, it defines a lightweight fusion method that supports edge deployment. Third, it evaluates the approach through a controlled simulation using accuracy, water saving, advisory delay, and false-alarm rate.

II. RELATED WORK

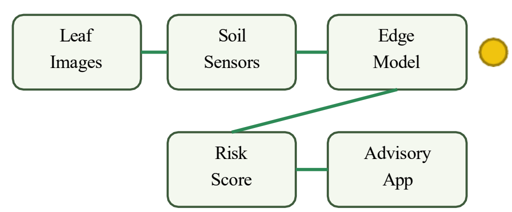
Machine learning has been widely applied to plant disease recognition. Convolutional neural networks can classify leaf symptoms with high accuracy when trained on clean image datasets. However, real farm images often include variable lighting, background clutter, partial leaves, and early-stage symptoms that are difficult to identify from images alone.

Sensor-based irrigation systems measure soil moisture, temperature, and humidity to reduce unnecessary water usage. Rule-based irrigation controllers are easy to deploy, but they may ignore disease risk and plant growth stage. Recent precision-agriculture research therefore explores data fusion, combining multiple field signals to produce more reliable recommendations.

Edge computing is especially relevant in agriculture because farms may have unstable connectivity. By performing inference locally, an edge node can provide immediate advice even when cloud access is unavailable. The proposed framework follows this direction and focuses on a practical balance between prediction accuracy, explainability, and deployment cost.

III. PROPOSED SYSTEM ARCHITECTURE

The architecture consists of four layers: field sensing, edge analytics, advisory generation, and cloud synchronization. The field sensing layer collects leaf images, soil-moisture readings, ambient temperature, humidity, and rainfall probability. The edge analytics layer runs disease classification and water-stress estimation. The advisory layer converts model outputs into simple actions, while the cloud layer stores summary records for long-term learning.



Multimodal crop monitoring and advisory workflow

Fig. 1. Architecture of the proposed multimodal crop advisory system.

A. Field Sensing Layer

The field unit collects images through a smartphone or low-cost camera module. Soil-moisture and temperature readings are sampled at fixed intervals. Weather context is obtained from local sensors or cached forecast data. Each reading is time-stamped and linked to crop type, growth stage, and field zone.

B. Visual Disease Model

The image branch uses a compact convolutional neural network designed for edge inference. Input images are resized, normalized, and enhanced using simple contrast correction. The model predicts disease class probabilities for healthy, fungal,

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bacterial, and nutrient-stress categories. A confidence threshold prevents uncertain predictions from being presented as final diagnosis.

C. Sensor-Fusion Module

The sensor-fusion module combines moisture deficit, humidity, temperature, and recent rainfall into a field-risk vector. This vector is joined with visual features before the final advisory decision. The fusion process helps distinguish between visually similar symptoms, such as leaf yellowing caused by disease and yellowing caused by water stress.

D. Advisory Generation

The advisory layer produces three outputs: disease risk, irrigation need, and recommended action. Actions include monitoring, irrigation, isolation of infected plants, or expert consultation. The message is written in concise language so that a farmer can act without interpreting raw probability scores.

IV. METHODOLOGY

A simulated dataset was prepared using crop categories commonly cultivated in northern India, including tomato, potato, wheat, and paddy. Image records were paired with soil and weather profiles. Controlled noise was added to represent field lighting variation, sensor drift, and missing weather updates.

The proposed fusion model was compared with three baselines: an image-only CNN, a rule-based sensor advisory, and a cloud-only diagnosis workflow. Each method was evaluated using the same train-validation-test split. The edge deployment scenario assumes a low-power device capable of running compact neural-network inference.

A. Evaluation Metrics

Disease detection is measured using accuracy, precision, recall, and F1-score. Irrigation performance is measured by water saving and moisture-deficit events. Advisory delivery is measured by average response time. A false alarm is counted when the system recommends treatment for a healthy crop zone.

B. Training Configuration

The CNN branch was trained with image augmentation, including rotation, brightness variation, and random cropping. Sensor features were normalized between zero and one. The final fusion classifier was trained using cross-entropy loss with class balancing to reduce bias toward common diseases.

C. Edge Deployment

For edge deployment, the model was compressed using parameter pruning and quantization-aware training. This reduced memory usage while preserving classification quality. If a device cannot complete inference, the application falls back to a smaller rule-based advisory and stores the image for later synchronization.

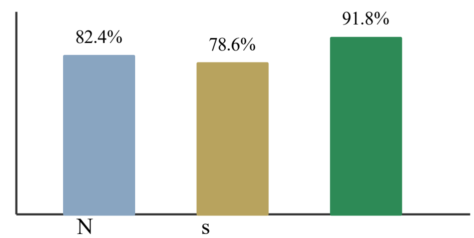
V. RESULTS AND DISCUSSION

Table I shows the comparative performance of the evaluated models. The multimodal fusion approach achieves the strongest balance between disease accuracy and practical irrigation support.

TABLE I
Performance Comparison of Advisory Models

Model	Accuracy	F1-Score	Avg. Delay
Rule Advisory	72.5%	0.69	0.4 s
Image CNN	82.4%	0.81	1.2 s
Cloud Diagnosis	89.6%	0.88	6.8 s
Fusion Edge (Proposed)	91.8%	0.90	1.5 s

The proposed model improves accuracy because it does not depend on visual symptoms alone. When images are unclear, sensor context helps the system avoid overconfident classification. When moisture and humidity indicate high disease risk, the model raises the priority of early intervention.



Disease detection accuracy by model type

Fig. 2. Detection accuracy of image-only, sensor-based, and fusion models.

A. Disease Detection Performance

The fusion model achieves 91.8% accuracy and an F1-score of 0.90. The improvement over the image-only model is most visible in early-stage disease cases where symptoms are faint. The rule-based method performs well for obvious water stress but struggles with visual disease categories.

B. Irrigation Advisory Impact

The system reduces water usage by 16.4% compared with fixed irrigation intervals. This saving is achieved by combining soil-moisture trends with rainfall probability and crop growth stage. The proposed approach also reduces moisture-deficit events because irrigation decisions are made before severe stress appears.

C. Latency and Connectivity

The edge model delivers advisory messages in 1.5 seconds on average, while cloud-only diagnosis requires 6.8 seconds under the simulated network condition. More importantly, the edge system continues operating when connectivity is weak, which is a practical advantage in rural deployments.

D. Error Analysis

Most errors occur in mixed-stress samples where disease and water deficiency appear together. Some false alarms are caused by shadows or damaged leaves that resemble fungal patterns. Adding periodic expert feedback and local image samples can reduce these errors over time.

VI. DISCUSSION

The results suggest that agricultural decision systems should combine multiple signals instead of depending on one data source. Images provide strong visual evidence, but sensor context adds environmental meaning. A lightweight edge design makes the framework usable in farms where bandwidth and response time are constraints.

The proposed system is not a replacement for agricultural experts. It is better understood as an early-warning and decision-support tool. The advisory can guide routine actions and highlight high-risk zones that require expert inspection. This division of work can reduce response delay and improve resource use.

VII. CONCLUSION

This paper proposed a multimodal edge-intelligence framework for crop disease detection and irrigation advisory. The

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system combines leaf images, soil sensors, weather context, and compact edge inference to provide timely and practical recommendations. Simulated results show improved disease detection accuracy, reduced water use, and lower response delay compared with baseline approaches.

Future work will include field trials with real farmers, multilingual advisory messages, and integration with drone imagery for larger farms. Additional work can also explore explainable AI methods that show the visual and sensor reasons behind each recommendation.

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