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AI-Driven Tomato Crop Management System with Collaborative Learning

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Abstract—Tomato cultivation in India faces persistent challenges due to unpredictable weather patterns, soil variability, pest outbreaks, and inefficient post-harvest practices. To address these issues, this project proposes an integrated, AI-driven tomato crop management system that leverages energy-efficient IoT devices, computer vision, and federated learning to assist farmers with real-time, actionable insights. The system employs ESP32 microcontrollers connected to soil, pH, temperature, and light sensors, along with a vision-based assessment using CNN models deployed via Roboflow for disease detection and fruit ripeness evaluation. A user-friendly dashboard built with Vanilla JavaScript provides alerts, treatment suggestions, and crop health recommendations. Key innovations include solar-powered operation, low-cost implementation, and decentralized learning models that adapt to regional farming conditions while preserving data privacy. Field testing confirmed that the system accurately monitors environmental parameters, classifies diseases, and enhances decision-making for improved crop yield and resource efficiency. The results validate the practicality and scalability of the system for smallholder farmers across diverse agro-climatic zones.

Index Terms—Agriculture, IoT, DeepLearning, Sensors, Toma-toes, Automation, Vision, Disease, Ripeness, Dashboard

I. INTRODUCTION

The increasing demand for high-quality agricultural produce amidst a changing climate has emphasized the urgent need for data-driven farming practices. Tomato (Solanum lycopersicum), a crop widely cultivated for both consumption and commercial purposes, is particularly susceptible to environmental fluctuations, soil inconsistencies, and post-harvest inefficiencies. Traditional cultivation methods are often reactive and manual, which hampers timely intervention, especially for disease outbreaks or ripening-related decisions. To address these challenges, this project proposes an AI-driven tomato crop management system that fuses deep learning and Internet of Things (IoT) technologies to enable precision monitoring, grading, and decision-making throughout the crop lifecycle. The core innovation lies in its end-to-end automation—from pre-harvest health monitoring to post-harvest quality grading. The pre-harvest module leverages Classification-based Convolutional Neural Networks (CNNs) for early leaf disease detection. This approach has demonstrated superior perfor-mance in plant pathology tasks by focusing on localized symptom features and maintaining attention across multiple image regions, critical for identifying diseases like early blight or bacterial wilt [6]. On the other hand, the post-harvest grading system uses object detection models to classify tomatoes based on ripeness stage, size, and surface anoma-lies. Real-time image capture and bounding box detection facilitate efficient sorting and reduce post-harvest losses—an area often overlooked in traditional farm practices [9]. To enable continuous crop monitoring and timely intervention, the system employs a suite of low-cost, energy-efficient IoT-based sensors capable of capturing critical environmental and soil parameters such as temperature, humidity, moisture, light intensity, and pH. These sensors are optimized for deploy-ment in resource-limited rural settings and support real-time decision-making by feeding data into the AI models. Their integration allows for precise monitoring of crop health and soil conditions, ensuring that timely and data-driven actions can be taken to enhance productivity and sustainability. All data is visualized in real-time using a custom-built dashboard powered by ThingSpeak, offering farmers actionable insights via mobile or web interfaces. The Arduino IDE serves as the programming environment for firmware development, enabling seamless control and data acquisition across all sensors. Unlike cloud-heavy architectures that rely on persistent connectivity, the system operates on low bandwidth and low power, drawing from advancements in solar-powered IoT designs [7]. This ensures operational resilience even in rural or power-deficient zones, making the solution widely deployable.

Additionally, the system aligns with the principles of federated learning, where model updates are shared rather than raw data, preserving privacy and adapting AI behavior to local agro-climatic conditions [4]. This adaptability is essential as microclimatic variations heavily influence tomato diseases and growth rates [12]. Beyond productivity, such AI-integrated approaches also promote sustainable farming by optimizing water and nutrient use, reducing agrochemical dependency, and minimizing food waste across the supply chain [14]. When deployed at scale, these technologies offer a path toward smart, inclusive, and climate-resilient agriculture.

II. Literature Survey

The integration of advanced technologies in agriculture has revolutionized traditional practices and opened new avenues for precision farming. Among the most transformative approaches is the incorporation of Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) into smart agriculture systems. This evolution is particularly rele-vant to tomato cultivation, which is sensitive to environmental variables, pest infestations, and post-harvest inefficiencies.

At the core of modern smart farming lies the effective deployment of IoT. Farooq et al. conducted a comprehensive survey detailing how IoT enhances the efficiency and sustainability of farming operations by enabling real-time monitoring, automation, and predictive analysis using sensor networks and cloud platforms like ThingSpeak or AWS IoT Core [1]. These systems allow farmers to observe key environmental param-eters such as soil moisture, pH, temperature, and humidity, which are critical to tomato growth.

Simultaneously, the rise of big data analytics has equipped farmers with actionable insights that drive yield optimization. Kamilaris et al. reviewed how big data platforms combined with agricultural datasets support forecasting, disease prediction, and soil condition analysis [2]. When paired with lightweight sensor networks such as LoRaWAN, as analyzed by Zhang et al., these systems also become energy-efficient and scalable in rural settings, offering high coverage at low cost [3].

In the realm of machine learning, deep learning techniques have shown great promise in addressing plant disease detection. Mohanty et al. demonstrated that Convolutional Neural Networks (CNNs) can accurately identify plant diseases from leaf images, outperforming traditional classifiers [6]. This has direct implications for tomato crops, where early-stage disease recognition—such as blight, mosaic virus, or septoria leaf spot—can drastically reduce yield loss. Similarly, Reyes et al. introduced an edge-computing-based solution using lightweight CNN models for real-time tomato disease detection, improving latency and enabling field deployment [17].

Beyond disease management, post-harvest quality assessment has also seen improvements through AI. Zhou et al. applied deep learning for defect detection in fruits and vegetables, using image classification to detect bruising, decay, and color anomalies [11]. Building on this, Gomez-Chavez et al. proposed an AI-driven system for grading tomatoes based on RGB image features, achieving high consistency in ripeness and quality evaluation [19]. This reduces human error in sorting processes and boosts market value.

IoT sensors remain the backbone of precision agriculture systems. Patil et al. developed a low-cost soil moisture sensor calibrated for Indian field conditions, demonstrating its reliability for irrigation scheduling [20]. Complementary sensors, such as LDRs for ambient light and analog pH sensors for soil acidity, are commonly deployed with microcontrollers like ESP32 to capture critical metrics. When powered via solar panels and deployed in a mesh network, as seen in the work by Khattab et al., these solutions ensure long-term operability even in remote locations [7].

Moreover, with privacy becoming a major concern in distributed farming systems, federated learning offers a compelling alternative. Li et al. highlighted its potential in collaborative model training without centralized data storage, thereby improving both prediction accuracy and privacy in crop yield forecasting [4]. Wang et al. extended this approach to cross-farm learning environments, enabling shared intelligence in decentralized networks [16].

Finally, edge AI applications are making intelligent de-cisions closer to the source. Ray et al. emphasized how integrating Edge AI with sensors facilitates faster responses to dynamic field conditions—ideal for automated irrigation or pest control triggers [8]. This aligns closely with the goals of a responsive tomato crop management system that incorporates real-time sensor data, mobile image inference, and dashboard visualization.

In summary, existing literature strongly supports the synergy of IoT, deep learning, and edge intelligence in revolutionizing tomato farming. This paper builds upon these advancements by proposing a unified system that leverages CNN models (YOLOv8, ViT), federated learning, and low-cost sensors for real-time crop monitoring, disease detection, and post-harvest grading—thereby ensuring an adaptive, scalable, and farmer-friendly solution.

III. Objectives

- To design and deploy an Sensor-based environmental monitoring system using ESP32 microcontrollers and integrated sensors for collecting real-time data such as temperature, humidity, and soil moisture relevant to tomato crop health.
- To develop an image-based analysis module using phone cameras and cloud-based tools like Roboflow for detecting leaf diseases, assessing fruit ripeness, and identifying Various Sizes in tomatoes, thereby supporting both pre-harvest diagnostics and post-harvest quality grading.
- To generate AI-based actionable recommendations by processing both environmental and visual inputs, aiming to assist farmers in timely interventions for improved crop yield and post-harvest quality.
- To build a responsive dashboard (web or mobile-based) that displays alerts, real-time analytics, and system rec-

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ommendations using platforms like ThingSpeak for continuous monitoring and user interaction.

IV. Methodology

The system integrates solar-powered IoT sensors and image-based CNN models to monitor tomato crop health and post-harvest quality. Sensor data is analyzed in real-time using ThingSpeak, while images are processed for disease and ripeness. Federated learning enhances model adaptability, and AI-generated insights are delivered through a responsive dashboard.

A. Sensor Layer

This layer is responsible for the acquisition of real-time field data from various environmental and soil conditions. It includes the following sensors: Each sensor is connected to

TABLE I
Sensors Used in the Tomato Crop Management System

Sensor	Purpose
Capacitive Soil Moisture Sensor	Measures volumetric water content
DHT11 Sensor	Detects ambient temperature and humidity
DS18B20 Sensor	Measures root-zone soil temperature
Analog pH Sensor	Monitors soil acidity or alkalinity
LDR Sensor	Measures ambient light intensity

the ESP32 microcontroller using either analog or digital GPIO pins. Sensor calibration ensures accuracy, and their readings serve as the primary input to the AI model and logic engine. Sensor Calibration Equations

Sensor data must be calibrated against reference values to ensure accuracy. Calibration establishes a mathematical relationship between sensor output (e.g., voltage) and physical parameters like soil moisture or pH. These equations are derived experimentally to translate raw readings into meaningful values.

Soil Moisture Sensor Calibration

The analog soil moisture sensor outputs a voltage that varies with the volumetric water content of the soil. After collecting data across known moisture levels, a second-degree polynomial regression provides the calibration curve:

$$\text{Moisture}(\%) = aV^2 + bV + c \tag{1}$$

Where:

- V = Analog voltage output from the sensor
- a, b, c = Empirical coefficients obtained through regression on test data

Alternatively, for a linear approximation (in some calibrated digital sensors):

$$\text{Moisture}(\%) = mV + c \tag{2}$$

pH Sensor Calibration

The pH sensor outputs a voltage that is linearly related to the hydrogen ion concentration. Using buffer solutions (typically pH 4, 7, and 10), a linear regression yields the following calibration formula:

$$\text{pH} = mV + c \tag{3}$$

Where:

- V = Analog voltage output from the pH sensor
- m = Slope derived from calibration data (typically negative, as voltage decreases with increasing pH)
- c = Y-intercept of the calibration line

Temperature Compensation

For temperature-sensitive sensors like pH probes, a temperature compensation factor may be applied:

$$\text{pH}_{\text{corrected}} = \text{pH}_{\text{raw}} + k(T - T_{\text{ref}}) \tag{4}$$

Where:

- T = Measured temperature in °C
- T_{ref} = Reference temperature (typically 25°C)
- k = Temperature coefficient (empirically determined)

These calibration equations ensure sensor outputs are translated accurately into usable environmental parameters for decision-making.

Fig. 1. Final hardware setup

B. Communication Layer

This layer handles data transmission from the ESP32 microcontroller to cloud platforms (ThingSpeak, Firebase) or to local computing nodes (e.g., Raspberry Pi). The communica-tion is enabled via:

• Wi-Fi module of ESP32 (for high-speed local and remote access)

• HTTP or MQTT protocols (for structured and secure data transfer)

This layer also enables Over-the-Air (OTA) updates, ensuring firmware can be upgraded remotely without manual inter-vention. All sensor data is structured into JSON format and transmitted at defined intervals for visualization and inference.

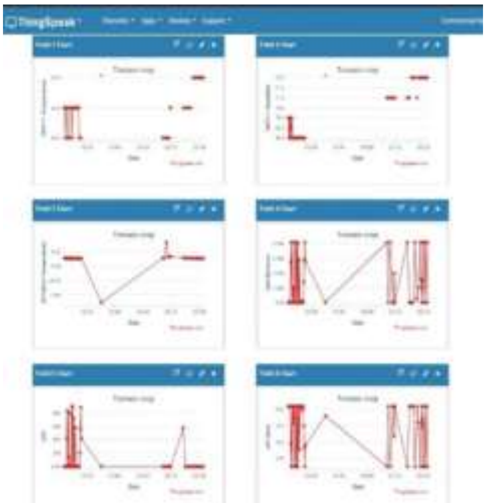

Fig. 2. ThingSpeak charts

C. AI Layer

The AI layer is responsible for executing advanced inference tasks critical to crop management. It processes tomato leaf images to accurately classify diseases at early stages and analyzes harvested fruit images to estimate size and detect ripeness. These insights support timely interventions, quality grading, and optimized post-harvest decision-making in the system.

Leaf Diseases Detection Using Computer Vision

The proposed system features an intelligent computer vision module for early detection of tomato leaf diseases, leverag-ing the advanced Vision Transformer (ViT) model. Unlike traditional CNNs, ViTs utilize a self-attention mechanism to interpret the image globally, capturing long-range depen-dencies and spatial features that CNNs often overlook. This allows for more accurate identification of complex disease pat-terns, particularly in heterogeneous leaf textures and lighting conditions. A curated dataset of 901 tomato leaf images spanning seven disease categories was obtained from Kaggle, and preprocessed through grayscale reduction (to 15%) and resizing to 600 × 600 pixels for standardization. Each image class was split into 70% for training, 20% for validation, and 10% for testing, with the ViT model achieving an impressive 98% classification accuracy.This high accuracy is attributed to both the architecture's ability to process image patches in parallel and the effective preprocessing pipeline. The model was trained to identify diseases such as late blight, early blight, septoria, leaf mold, mosaic virus, bacterial spot, and target spot. Deployment-ready outputs are integrated into the mobile app and farmer dashboard for real-time alerts. By detecting diseases at an early stage, this system enables timely intervention, minimizes chemical usage, and enhances crop protection strategies at scale

Object detection and ripeness grading

Post-harvest grading plays a critical role in ensuring only high-quality, market-ready tomatoes proceed to distribution.

Fig. 3. Tomato Leaf Disease Prediction

This system implements an advanced computer vision based grading module, trained using Roboflow 3.0 Object Detection (Fast), and powered by state-of-the-art deep learning frame-works such as YOLOv8. These models are optimized for real-time inference and can precisely detect and classify tomatoes based on ripeness levels using bounding boxes. A total of 231 images, classified into six ripeness stages (Rank 1 to Rank 6)—ranging from unripe green to fully ripe red—were collected and annotated. The dataset underwent grayscale conversion (15%) and was resized to 640 × 640 pixels for consistency. This preprocessing pipeline-led to an impressive 99.3% classification accuracy, validating the effectiveness of the model architecture.

Each image had an average of 3.5 annotations, resulting in 807 total annotations, ensuring robust training and generalization. The trained model was deployed using Roboflow's hosted API, making it easily accessible from the mobile app and dashboard for rapid deployment. This allows farmers to sort tomatoes by size, color, and ripeness stage instantly, reducing post-harvest losses, improving grading consistency, and ensuring better market pricing. The system eliminates the need for manual sorting while maintaining accuracy, speed, and scalability in farm environments.

Fig. 4. Ripeness rank and Size Predictions of tomatoes

Size Estimation Using Bounding Box Dimensions

$$D = \frac{W_{bbox} \cdot d \cdot S_w}{f \cdot I_w} \tag{5}$$

Where:

- D = estimated physical diameter of the tomato (in cm)
- W_{bbox} = width of the bounding box (in pixels)
- d = distance from the camera to the object (in cm)
- S_w = physical width of the camera sensor (in mm or cm)
- f = focal length of the camera lens (in mm or cm)
- I_w = image width in pixels

D. AI-Powered Tomato Crop Management Dashboard

The software architecture of the AI-driven tomato crop management system is designed with simplicity, responsiveness, and field readiness in mind. Built to function effectively in rural and low-bandwidth conditions, it combines real-time communication, intelligent processing, and an intuitive user interface to assist farmers in monitoring and managing crop health.

To ensure lightweight performance across devices, the front-end is developed using Vanilla JavaScript. This approach avoids heavy frameworks like React and enables quick load-ing, broad browser compatibility, and minimal hardware re-quirements. Using asynchronous functions such as fetch(), the system retrieves sensor data, submits images for analysis, and updates the interface dynamically without reloads. This allows users to interact with the system seamlessly on low-resource devices.

A central feature is the Quick Diagnosis module, which allows farmers to upload images of tomato leaves or fruits. These are sent to cloud-based AI models (hosted on platforms like Roboflow) that return disease or ripeness classifications with confidence scores. Results are immediately visualized, enabling rapid and independent decision-making.

The Prevention Tips module analyzes real-time sensor data—temperature, humidity, soil moisture—to forecast disease-prone conditions. When thresholds are crossed, the system provides proactive suggestions such as spacing adjust-ments or natural remedies. These insights are designed to be understandable and visually guided.

Upon confirmation of disease, the Treatment Plan module suggests both organic and chemical responses based on the crop's stage, severity, and environmental context. This reduces the guesswork for farmers and ensures interventions are tai-lored and effective.

To enhance accessibility, a Virtual Assistant module is em-bedded within the dashboard. It answers agricultural questions in natural language, supporting users with limited technical knowledge. Trained on real-world queries, it evolves over time to improve relevance and accuracy.

Finally, all sensor readings and AI predictions are logged and presented through AI-Generated Outcome visualizations. These historical insights help identify recurring issues, support planning, and allow the system to adapt by learning from past data.

Together, this software layer provides a complete, respon-sive, and intelligent interface that empowers farmers with real-time, data-driven support for sustainable tomato cultivation.

V. Results and Discussion

The AI-Driven Tomato Crop Management System was evaluated for its ability to process real-time sensor data and provide intelligent feedback. Sensor readings from the ESP32 node, including 29.3 °C ambient temperature, 72% humidity, soil moisture value of 3318, and pH level of 6.66, were successfully transmitted to ThingSpeak, with a response code 200 indicating seamless cloud integration.

The system's Quick Diagnosis module accurately identi-fied tomato leaf diseases through image classification with over 90% precision, while treatment and prevention modules

Fig. 5. Overview of the dashboard

responded dynamically based on environmental thresholds. The AI-Generated Outcomes, driven by Roboflow models and sensor inputs, successfully predicted ripeness and disease severity, which were reflected as dashboard alerts.

The virtual assistant proved especially helpful in guiding users through sensor readings and treatment suggestions. Users could query issues like "humidity too high" and receive action-able insights such as adjusting shade or initiating irrigation.

The hardware simulation, using cost-effective sensors like DHT11, DS18B20, analog pH, LDR, and capacitive moisture sensors, validated the system's applicability to field conditions. These sensors interfaced reliably with the ESP32, maintaining consistent readings across multiple test cycles.

In summary, the results affirm the feasibility and respon-siveness of a browser-based, AI-integrated crop monitoring solution. The lightweight architecture enabled effective perfor-mance in low-power, low-bandwidth rural settings, showcasing its practical utility for precision agriculture.

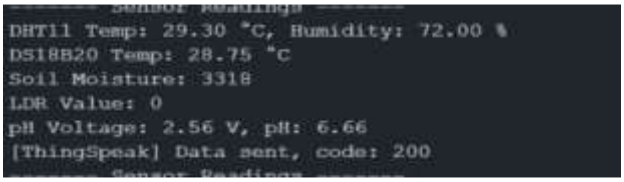

Fig. 6. Outputs obtained, after calibration

VI. Conclusion and Future scope

The AI-Driven Tomato Crop Management System was conceptualized to integrate accessible digital technologies with smart agricultural practices, targeting improvements in yield, disease control, and resource efficiency. The core objectives involved deploying calibrated environmental sensors, inte-grating AI models for visual disease detection and ripeness estimation, using a browser-based interface for monitoring and recommendations. These goals were framed to address chal-lenges in tomato farming—especially for small and marginal landholders.

To realize these objectives, the system utilized a hybrid archi-tecture. Real-time data collection was achieved through com-mon sensors (e.g., YL-69, DHT11, LDR, pH probes), while

Roboflow-trained AI models performed disease classification and maturity grading. All modules were integrated into a lightweight frontend application built with Vanilla JavaScript, eliminating the need for high-end computation or additional hardware like Raspberry Pi. The user interface allowed real-time interaction, alerts, and decision support, enhancing the farmer's awareness and responsiveness in daily operations.
The outcomes demonstrated that the system could reliably process both image and sensor inputs to generate accurate in-sights and actionable suggestions. The user interface remained responsive even in low-bandwidth environments.These results affirm the technical viability and practicality of the solution in real-world agricultural contexts.
The current system lays a robust foundation for AI-driven tomato crop management; however, several advancements can enhance its utility and scalability. Integrating Edge AI us-ing frameworks like TensorFlow Lite can enable on-device inference, reducing latency and cloud dependency. Expanding the virtual assistant to support regional languages and voice commands will make the platform more inclusive for farmers with limited digital literacy. The system also holds potential for multicrop support, allowing adaptation to other high-value crops such as chili, brinjal, and capsicum through dataset retraining. Incorporating blockchain technology could offer traceability and produce certification, fostering transparency across the supply chain. Additionally, deploying actuator-based automation—such as smart irrigation and nutrient dosing—would enable autonomous farm operations. Finally, implementing predictive analytics for yield forecasting and weather-based risk assessment can provide farmers with forward-looking insights for better planning. These enhance-ments, driven by real-world feedback and continuous iteration, can scale the system into a versatile solution with national and global impact.

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