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YOLO Vision-Sensor Hybrid Approach for Automated Nutrient Actuation in Smart Greenhouse Melons

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ABSTRACT

Cultivating hydroponic melons requires precise nutrient management to avoid crop failure. While farmers traditionally rely on visual inspections, this manual approach is subjective and prone to human error. Conversely, relying solely on single-source automated systems—using either cameras or water sensors alone—often causes incorrect automated actions in dynamic greenhouse environments. To bridge this gap, this study introduces RANUM, a smart agriculture system combining advanced edge AI with reliable hardware actuation. The Raspberry Pi 5 is used as the master controller for processing visual data, while the ESP32 serves as the microcontroller to execute the pump actuation logic, RANUM acts as both the eyes and the brain of the greenhouse. The AI was trained on a real-world dataset of 1,000 images, utilizing the optimal "best.pt" checkpoint to maintain continuous accuracy and prevent overfitting. During field tests, the hardware demonstrated exceptional precision, recording minimal average errors of just 0.021 for pH and 1.11 ppm (0.13%) for Total Dissolved Solids (TDS). What makes RANUM truly unique is its hybrid cross-validation approach. Using a strict AND logic protocol, the system takes action only if the visual AI detects a leaf anomaly and the physical sensors confirm a nutrient imbalance. This dual-check mechanism successfully filters out visual false positives. In integration testing, this architecture achieved 100% decision-making accuracy, completely preventing premature triggers for the AB Mix and pH dosing pumps. Supported by an interactive real-time web dashboard, this multimodal framework eliminates technical noise, offering modern farmers a highly reliable and accurate smart agriculture solution.

INTRODUCTION

Premium melon (Cucumis melo L.) cultivation within greenhouse ecosystems is a high-value agribusiness sector that demands stringent precision management(Loredo-Treviño et al., 2026)(Sugeru, Wibowo, Musa, Harahap, & Harmanto, 2025). The success of this crop's production heavily relies on optimal fertigation management from the vegetative to the generative phases, where inaccuracies in nutrient composition can trigger nutrient deficiencies (stunting) and increase susceptibility to pathogen attacks(Sood, Kapoor, Kaur, Hussain, & Sood, 2025). Plant health monitoring in large-scale cultivation still generally depends on manual visual observations by farmers (Shafay et al., 2025). This approach is not only limited by subjectivity and prone to human error, but it also frequently leads to delayed interventions during critical plant growth phases(Chandel, Chakraborty, Jat, & Chouhan, 2024), (H. Yang, Jin, Jiang, Lu, & Wen, 2025). Given the large plant population and the required intensity of supervision, conventional methods remain a major bottleneck in achieving optimal yield efficiency and stability.

Along with the digitalization of the agricultural sector, the adoption of Internet of Things (IoT) technology has been widely implemented to improve land-use efficiency through automated irrigation and microclimate control(Lakhiar et al., 2024), (Abiri, Rizan, Balasundram, Shahbazi, & Abdul-Hamid, 2023). The majority of existing in premium melon cultivation systems still operate in a blind-control mode, where automated actions are limited to monitoring water quality parameters such as pH and Total Dissolved Solids (TDS)(Agustina, Susetyoko, Trisniani, & Anggraini, 2025), (Karimzadeh, Li, & Ahamed, 2025), a fundamental limitation of this approach is the system's inability to capture the real-time biological responses of the plants(Phankaen & Kumpanuch, 2025). In fact, the most valid indicators for determining nutrient adequacy and plant health are the physical conditions of the leaves, such as the presence of chlorosis symptoms or necrotic spots that signify specific nutrient deficiencies or pest infestations(Ghimirey, Chaurasia, & Marahatta, 2024), (Bell, 2023). Current automated risk executing mistargeted nutrient and causing delayed disease detection, which is often only realized after the plant damage has become severe(Dhavale, Aiwale, & Sarnobat, 2025), (Hu et al., 2026). Research question arises regarding how to directly integrate plant biological feedback into automated fertigation control systems to achieve optimal nutrient efficiency.

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To address these challenges, this study proposes the development of RANUM, an intelligent system that integrates deep learning-based visual detection capabilities with a plant-needs-based IoT control architecture. Unlike conventional systems, RANUM does not solely rely on physical sensors, it also deploys the YOLO (You Only Look Once) object detection algorithm to identify leaf morphological patterns, such as chlorosis and necrosis symptoms, in real time(Preanto, Ahad, Emon, Mustofa, & Alamin, 2024), (Maqbool, Nazeer, Basit, & Zahra, 2023), (Chutichaimaytar, Zongqi, Kaewtrakulpong, & Ahamed, 2025). The primary novelty of this research lies in its hybrid control logic mechanism, where nutrient pump actuator activation decisions are executed through the cross-validation of visual data from cameras and physical parameter readings from environmental sensors(Sadik, Abdelhadi, Youssef, Houda, & Samir, 2026), (Subeesh, Chauhan, & Kushwaha, 2025). By employing this approach, hopefully the system delivers precise, proactive, and corrective actions, thereby significantly optimizing nutrient use efficiency and mitigating the risk of crop failure associated with delayed diagnostic interventions.

Based on the identified urgency and technological gap, this research aims to design and develop system as a comprehensive precision agriculture automation solution. The main contributions of this study encompass three strategic aspects: (1) developing a system integration architecture that combines physical sensors and smart cameras for the early detection of growth anomalies(Jaramillo-Alcazar, Govea, & Villegas-Ch, 2023); (2) designing a hybrid control algorithm capable of translating YOLO visual data into automated corrective actions within the irrigation system (closed-loop system)(T. Yang et al., 2026); and (3) implementing an interactive web dashboard that visualizes environmental data while providing early notification features for farmers(Kumari, Pandey, & Tiwari, 2024), (Wirasena, Fakhrurroja, & Pramesti, 2025). Through this approach, this research is expected to serve as an adaptive and efficient model for edge intelligence implementation, while making a tangible contribution to the modernization of the IT-driven agribusiness sector.

METHOD

This study adopts an experimental engineering research design aimed at developing a dual-validation automated smart agriculture control system. The architectural framework is structured around a dual-controller paradigm to separate high-level vision computing from real-time sensory-actuator hardware management. A Raspberry Pi 5 is designated as the core edge computing unit tasked with running the YOLO object detection model for plant health assessment. Concurrently, an ESP32 microcontroller functions as the field-level control node responsible for continuous sensor data acquisition and relay operations. This design incorporates a strict logic validation matrix (AND gate) to bridge the visual data and physical parameters, effectively eliminating false-positive actuator triggers and ensuring precise automated dosing. To provide a comprehensive overview of the instrument's operational mechanism, the overall system workflow is designed based on the flowchart in Figure 1. This figure details the step-by-step process of the parallel data acquisition, the hybrid AND-logic cross-validation, and the final automated pump actuation.

As depicted in Figure 1, the process initiates with the activation of all hardware modules during the system initialization stage, process initiates with the activation of all hardware modules during the system initialization stage (Initialization System). Subsequently, data processing is executed via two independent and simultaneous pathways including visual processing pathway and physical sensor reading pathway.

Visual processing pathway is the camera captures the real-time visual data of the plant leaves (Input Visual Leaf Data by Camera). This image is then processed using the YOLO-based algorithm model (Leaf Condition Detection using the YOLO Model). The system evaluates the health status of the leaves through a decision node (Are the leaves healthy?). If the leaves are classified as healthy (Yes), the system assigns the parameter value to Set Variable State Leaf = 0. Conversely, if the leaves are identified as unhealthy or nutrient-deficient (No), the parameter is configured as Set Variable State Leaf = 1. The final classification output is then transmitted wirelessly from the vision processing unit to the ESP32 microcontroller (Send the Result of Leaf Condition to ESP32 via WiFi).

Physical Sensor Reading Pathway is Simultaneously, the system establishes the minimum and maximum threshold parameters for PPM and pH values (Set parameter minimum and maximum PPM and PH). Following parameter definition, the TDS and pH sensors measure the real-time physical attributes of the plant nutrient solution (Input Data from TDS and PH Sensor).Upon receiving both data streams (visual and sensory data), the ESP32 microcontroller performs inference processing using a combined AND logic operation (ESP32 process inference leaf condition from sensor and leaf visual by AND logic). This logic application functions as a dual-validation mechanism, ensuring that the actuator pumps are only triggered when the visual deficiency indication aligns with the deviation in the physical water quality parameters.

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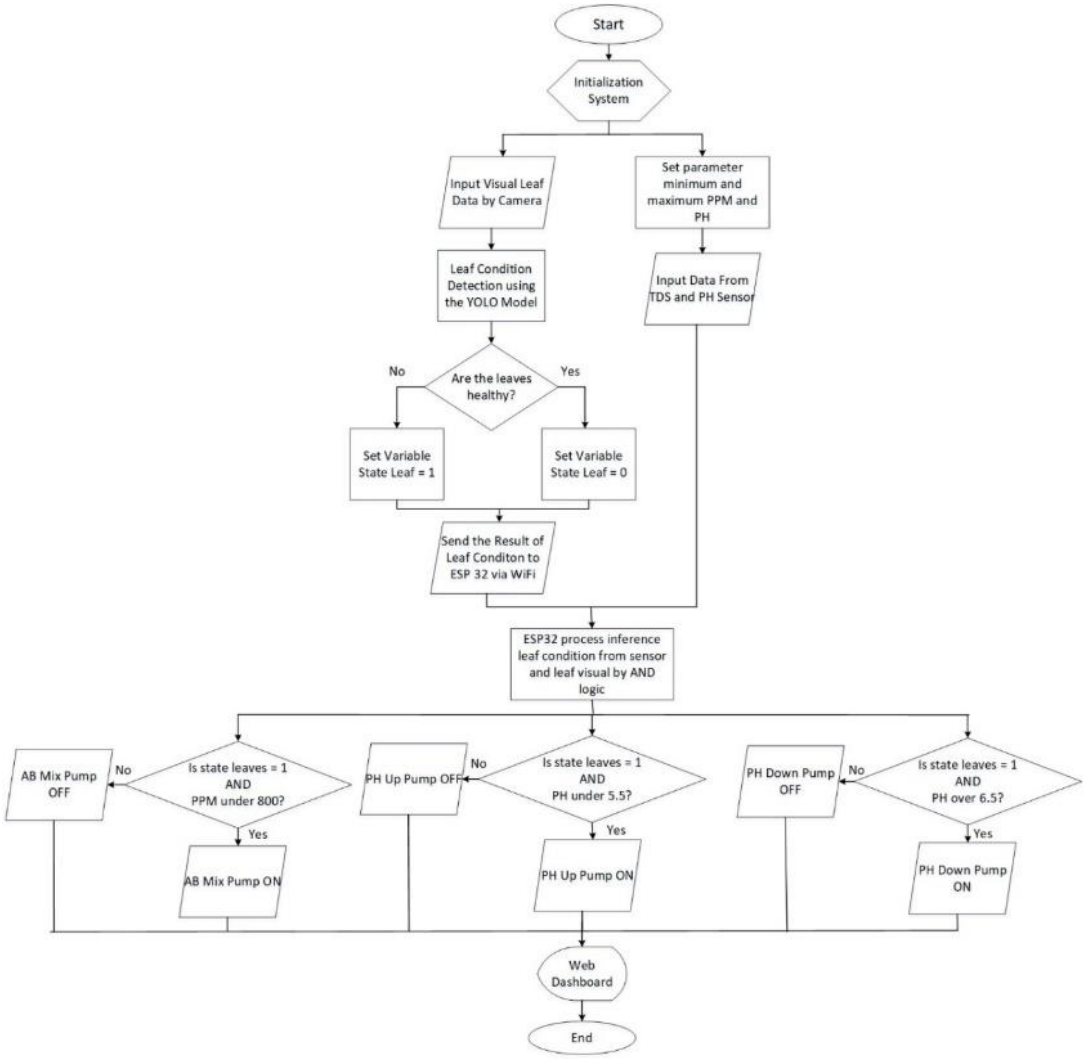


Figure 1. Device Operation Flowchart

Based on the outcomes of the AND logic inference, the ESP32 routes control instructions into three decision branches to regulate each actuator pump. AB Mix Pump working when the system evaluates whether State Leaf = 1 (unhealthy leaf) AND the PPM value is below 800 (PPM under 800?). If both conditions are validated as true (Yes), the nutrient pump is turned on (AB Mix Pump ON). Otherwise (No), the pump is deactivated or remains off (AB Mix Pump OFF). PH Up Pump working when the system evaluates whether State Leaf = 1 AND the pH value is below 5.5 (PH under 5.5?). If true (Yes), the pH Up pump is activated (pH Up Pump ON). If the criteria are not met (No), the pump is turned off (pH Up Pump OFF), PH Down Pump working when the system evaluates whether State Leaf = 1 AND the pH value exceeds 6.5 (PH over 6.5?). If satisfied (Yes), the pH Down pump is activated (pH Down Pump ON) to reduce water acidity. If the conditions are not satisfied (No), the pump is kept in an off state (pH Down Pump OFF).

All real-time operational telemetry is transmitted and synchronized with the interactive web monitoring application (Web Dashboard). The dashboard serves as a centralized graphical user interface (GUI) that visualizes a live video feed and object detection results, displaying the leaf condition with bounding boxes and classification confidence scores generated by the YOLO model. Additionally, the interface integrates live text overlays and parameter widgets rendering active physical water parameters, such as real-time TDS values (in ppm), pH levels, direct visual indicators display the current activation status of each dosing pump. Finally, the dashboard features auxiliary diagnostic panels indicating the real-time connection status of the ESP32 alongside interactive progress bars representing the remaining stock percentages for the pH Up, pH Down, and AB Mix solution reservoirs.

RESULT

The training process of the YOLOv8n object detection model was conducted using a dataset of 1,000 images of hydroponic melon leaves, categorized into two target classes: "Healthy Leaves" and " Nutrient-deficient Leaves". The training was executed for 100 epochs to observe the model's convergence patterns and stability. The evaluation results of the performance metrics and loss values during the training process are presented in Figure 2 below,

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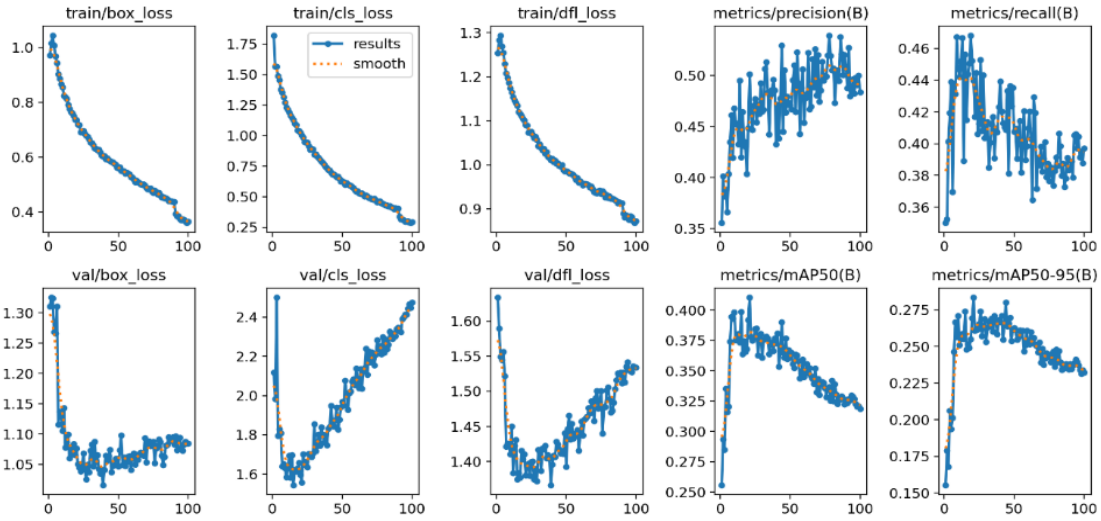


Figure 2. Training Curves and Evaluation Metrics of the YOLOv8n Model over 100 Epochs

As illustrated in Figure 2, the training results exhibit distinct metric trajectory characteristics between the initial and final phases of the training process. In the top row of the graphs, the training loss components comprising train/box_loss, train/cls_loss, and train/dfl_loss demonstrate a consistent and gradual decline towards the final epoch. The sharp drop observed at epoch 90 is attributed to the internal optimization protocol of YOLOv8, which deactivates the mosaic augmentation feature during the final 10 epochs to stabilize object bounding box regression.

The second row of the graphs (validation loss) indicates the onset of overfitting after the model surpasses the 20th epoch. Specifically, the val/cls_loss metric representing validation classification performance exhibits a significant upward trend after reaching its lowest point between epochs 15 and 20. This behavior directly correlates with the trajectory of the accuracy metrics plotted in the metrics/mAP50(B) and metrics/mAP50-95(B) graphs. The model achieves its peak performance near epoch 20, registering mAP50 value of approximately 41% (0.41) and mAP 50-95 of 26.5% (0.265). Beyond this optimal point, the mAP values undergo gradual degradation, ultimately settling at approximately 32% by epoch 100. To mitigate the accuracy degradation caused by overfitting during real-world system implementation, the final model weights from epoch 100 (last.pt) were bypassed. Instead, the deployment process utilizes the optimal weights automatically preserved at the peak performance checkpoint (best.pt) around epoch 20. By leveraging this checkpointing strategy, the hybrid IoT control system is consistently supplied with visual feedback operating at the maximum mAP50 of 41%, which is deemed highly sufficient for detecting plant macronutrient anomalies within a greenhouse ecosystem.



Figure 3. Qualitative object detection results (validation batch prediction) for hydroponic melon leaves.

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Figure 3 illustrates the qualitative analysis of the validation image prediction samples associated with the training phase presented in Figure 2. In general, the YOLOv8n model utilizing the optimal weights (best.pt) demonstrates excellent leaf localization capabilities under both controlled conditions with an isolated white background (mini-studio) and the actual greenhouse environment (as shown in the second row, fourth column). Furthermore, the model successfully identifies distinct morphological features representing both "Healthy Leaves" (characterized by homogenous green color patterns) and "Nutrient-Deficient Leaves" (characterized by yellowish chlorosis and brownish necrosis along the leaf margins).

The performance evaluation of the pH sensor was conducted to assess the measurement accuracy and reliability of the instrument by benchmarking its readings against a standard digital pH meter as a reference. This testing protocol comprised nine distinct observation points encompassing three acidity regimes specifically acidic, neutral, and alkaline with each chemical state represented by three individual samples. The test solutions utilized featured a comprehensive range of chemical properties, spanning acidic solutions, plant nutrient solutions, buffer solutions, and alkaline solutions.

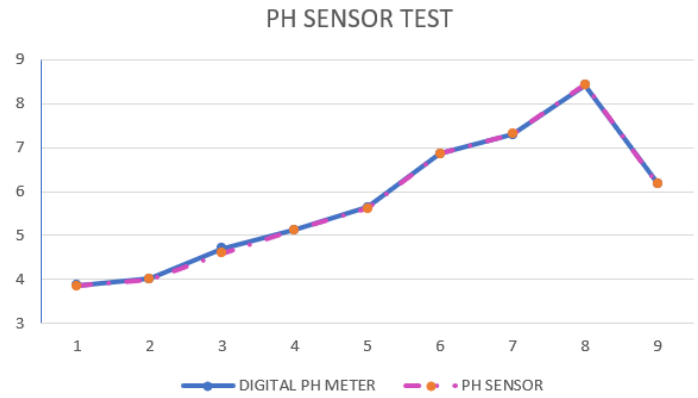


Figure 4. PH Sensor Test Results Graph

Based on the data visualization in Figure 4, the pH sensor reading curve exhibits a linear trend that precisely aligns with the reference instrument. The quantitative values generated by the sensor demonstrate minimal deviation from the reference values, with measurement discrepancies ranging from only 0.00 to 0.10. Statistical analysis indicates that the calculated mean error is a mere 0.021. This near-zero error value verifies the exceptionally high accuracy of the sensor in detecting the acidity levels of the solution. Consequently, the experimental data are declared valid, successfully satisfying the acceptable tolerance limits required for the implementation of the automated crop control system.

Performance testing of the Total Dissolved Solids (TDS) sensor was conducted to evaluate the accuracy, linearity, and response of the ESP32 microcontroller-based instrument. This evaluation was performed by directly comparing the real-time data acquired from the sensor against a calibrated digital TDS meter, which served as the standard reference instrument. To simulate the real-world operational conditions of a hydroponic system, the testing protocol involved nine samples of AB Mix nutrient solutions, comprehensively varied across low (deficient), normal (ideal), and high (excessive) nutrient concentration ranges. The baseline mapping procedure initiated with raw water (devoid of nutrients) and scaled up to a highly concentrated nutrient solution. The measurement discrepancy and alignment between the reference instrument and the ESP32 sensor readings across these nine observation points are visually plotted in Figure 5 below:

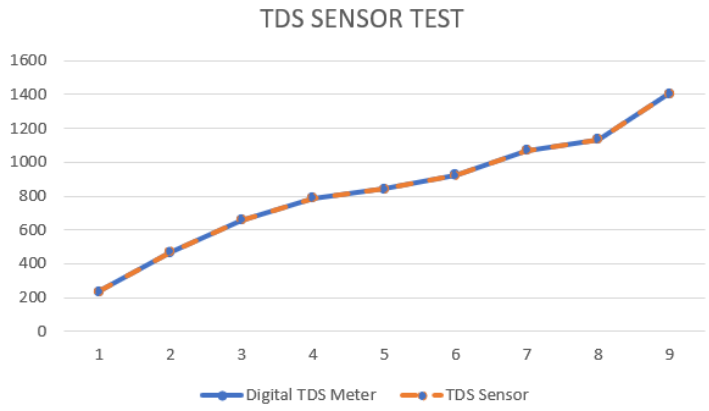


Figure 5. TDS Sensor Test Results Graph

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Based on the curve visualization in Figure 5 and the quantitative data detailed in Table 1, the TDS sensor demonstrates an exceptionally high degree of linearity, consistently aligning with the reference measuring instrument across the entire testing range. Statistical analysis of the complete dataset yields a mean error of 1.11 ppm, with a remarkably low relative error of 0.13%. These quantitative findings substantiate the reliability and consistency of the TDS sensor in accurately representing nutrient solution concentrations, thereby rendering it highly valid and suitable for integration as a critical system input parameter.

The final phase of this study involves a comprehensive, end-to-end system integration test to validate the performance of the decision-making algorithm governed by AND logic operations between sensory and visual leaf inputs. This testing protocol was designed to guarantee that the synchronization of real-time visual data from the YOLO model (characterizing leaf physical states) and quantitative telemetry from the multi-sensor array (pH and TDS) can drive the actuator pumps precisely in accordance with the predefined decision matrix. Under this experimental scenario, the system was evaluated on its capacity to execute a dual-validation mechanism, whereby corrective chemical adjustments by the dosing pumps are strictly triggered only when the visual indication of leaf distress directly correlates with chemical deviations in the water quality parameters. This functional validation incorporated five randomized testing conditions representing deficient, optimal, and excessive nutrient regimes. The resulting centralized inference processing executed by the ESP32 microcontroller, alongside the real-world operational responses of the AB Mix, pH Up, and pH Down dosing pumps, are comprehensively summarized in Table 1.

Table 1. Results of Integration Testing

Parameter	**Testing**				
	1	**2**	**3**	**4**	**5**
PH	5.96	3.77	7.7	5.8	7.5
TDS	366	828	1300	700	900
Visual					
AB Mix Pump	ON	OFF	OFF	OFF	OFF
PH Up Pump	OFF	ON	OFF	OFF	OFF
PH Down Pump	OFF	OFF	ON	OFF	OFF

Based on the functional data presented in Table 1, the implementation of the AND logic gate successfully executed control instructions with 100% accuracy across all test scenarios. A detailed analysis of each condition is outlined below:

In Tests 1, 2, and 3: The camera detected a visual condition identified as "Nutrient-Deficient Leaf" (State Leaf = 1). In Test 1, because the measured TDS value was low (366 ppm, or < 800 ppm), the system successfully activated the AB Mix Pump (ON). In Test 2, when the pH sensor read an extremely acidic value (3.77, or < 5.5), the system responsively activated the pH Up Pump (ON). Meanwhile, in Test 3, a pH spike to 7.7 (> 6.5) successfully triggered the activation of the pH Down Pump (ON).

In Tests 4 and 5: The advantage of the dual-validation feature is clearly evident. Although physical sensor data indicated parameter deviations specifically, the TDS value in Test 4 fell below the threshold (700 ppm) and the pH value in Test 5 exceeded the threshold (7.5)—all actuator pumps remained in the OFF state. This occurred because the YOLO model classified the visual condition as "Healthy Leaf" (State Leaf = 0).

This logical combination proves that the system is capable of preventing false-positive triggers, which frequently occur in conventional single-sensor-based control systems. Consequently, the integration test results are declared valid and successful, demonstrating that the proposed intelligent system possesses high reliability in automatically and efficiently maintaining nutrient quality stability in hydroponic cultivation. All physical parameter data, visual classifications, and actuator operational statuses obtained from the integration testing are transmitted and synchronized in real-time to a web-based monitoring application (Web Dashboard), as illustrated in Figure 6.

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Figure 6. Dashboard Monitoring

The seamless data synchronization between computer vision processing on the Raspberry Pi and the ESP32 controller underscores that the system's Web Dashboard functions not merely as a passive monitoring tool, but rather as a transparent, responsive, and adaptive control and information hub for precision farming for hydroponic farmers.

DISCUSSION

Developing this hybrid IoT setup highlights why combining computer vision with precise physical sensors is what actually makes automated hydroponics work reliably. The YOLOv8n model handled leaf localization and symptom tracking well, though its training curves made a strong case for early checkpointing around epoch 20. Stopping at that point kept overfitting and preserved a peak mAP50 of 41%. Working alongside these visual diagnostics, the physical hardware performed almost identically to calibrated reference instruments, with the pH and TDS sensors recording minimal mean errors of just 0.021 and 1.11 ppm, respectively. These tight error margins gave the underlying control algorithm a dependable stream of physical data from the start.

The real practical strength of the system comes down to its dual-validation logic, which achieved 100% accuracy in preventing the false-positive triggers common in single-sensor setups. By applying an AND logic rule, dosing pumps for AB Mix, pH Up, or pH Down only turn on when a water quality deviation directly matches visual evidence of leaf distress. If pH or TDS levels drift off-target while the camera marks the leaves as healthy, the system keeps the pumps shut off, saving chemical inputs and avoiding unnecessary stress on the plants. Syncing these decisions to a real-time web dashboard moves the system beyond passive monitoring into a practical, self-correcting manager for hydroponic farms.

CONCLUSION

This study successfully developed and validated the RANUM system, a comprehensive precision agriculture automation solution that addresses the critical technological gap in smart hydroponics. By establishing a dual-controller integration architecture, the system effectively bridges high-level edge intelligence (YOLO on Raspberry Pi 5) with low-level sensory-actuator hardware (ESP32). The empirical results demonstrate exceptional sensor accuracy, with the pH sensor achieving a remarkably low mean error of 0.021, and the TDS sensor exhibiting a mean error of just 1.11 ppm (0.13%). More importantly, the system integration testing confirmed 100% decision-making accuracy through an AND-logic-based dual-validation mechanism that successfully eliminated false-positive actuator triggers, ensuring that dosing pumps (AB Mix, pH Up, and pH Down) are only activated when visual leaf distress correlates with physical water parameter deviations. Crucially, the entire automated control cycle is seamlessly synchronized with an interactive web dashboard that serves as a centralized telemetry hub. This interface successfully visualizes real-time leaf health diagnostic overlays, live physical sensor readings, current pump activation states, and auxiliary solution stock percentages, thereby guaranteeing absolute operational transparency for greenhouse management. Ultimately, this methodology introduces a novel paradigm in closed-loop agricultural control: relying solely on physical sensors often leads to premature chemical dosing, whereas consolidating physical measurements with visual AI diagnostics and real-time IoT monitoring ensures a highly resource-efficient, biologically accurate, and adaptive crop management workflow that safeguards the root environment.

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