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VERDE: IoT-Based Hydroponics System with Sensor–Vision Fusion for Plant Health Monitoring and Nutrient Management

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THIS IS JUST A SAMPLE.

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LIST OF ABBREVIATIONS

The following abbreviations are used in this study:

ADC – Analog-to-Digital Converter
AI – Artificial Intelligence
CNN – Convolutional Neural Network
CSI – Camera Serial Interface
EC – Electrical Conductivity
GPIO – General-Purpose Input/Output
GSM – Global System for Mobile Communications
HTML – HyperText Markup Language
IoT – Internet of Things
LED – Light-Emitting Diode
mAP – Mean Average Precision
ML – Machine Learning
NFT – Nutrient Film Technique
NTU – Nephelometric Turbidity Unit
OS – Operating System
pH – Potential of Hydrogen
RAD – Rapid Application Development
RF – Random Forest
RRL – Review of Related Literature
SDG – Sustainable Development Goals
SDLC – System Development Life Cycle
SMS – Short Message Service
SPI – Serial Peripheral Interface
TDS – Total Dissolved Solids
USB – Universal Serial Bus
VERDE – Vegetation Environment Recognition and Detection Engine
Wi-Fi – Wireless Fidelity
YOLO – You Only Look Once

ABSTRACT

This study presents a brief investigation into the development and evaluation of a digital energy monitoring system designed to improve household electricity awareness and reduce unnecessary power consumption. Rising electricity costs and limited access to real-time usage data often result in inefficient energy habits among residential users. To address this issue, the researchers developed a prototype system that tracks energy consumption in real time and provides users with visual feedback through a simple interface.

The system was designed using accessible hardware sensors and a software application that records, processes, and displays energy usage data. A testing phase was conducted with selected participants to assess usability, accuracy of readings, and user perception of energy awareness before and after exposure to the system. Results indicated that users became more conscious of their electricity usage patterns and demonstrated improved energy-saving behaviors after interacting with the system.

Findings suggest that real-time monitoring tools can play a significant role in promoting energy efficiency at the household level. The study highlights the potential of integrating low-cost monitoring technologies into everyday environments to encourage responsible energy consumption. THIS IS A 250 WORD COUNT SAMPLE.

Keywords: energy monitoring system, electricity consumption, real-time tracking, energy efficiency, user awareness

CHAPTER 1

INTRODUCTION

The increasing demand for sustainable food production, combined with challenges brought by urbanization and changing environmental conditions, has encouraged the development of alternative agricultural technologies. Among these innovations, hydroponics has gained attention as a soil-less cultivation method capable of supporting efficient crop production through controlled nutrient delivery systems. Hydroponic systems integrated with Internet of Things (IoT) technologies have demonstrated the ability to automate the monitoring of important water-quality parameters such as pH, electrical conductivity (EC), turbidity, and water temperature, together with environmental parameters such as ambient humidity, improving system management and reducing the need for constant manual observation [1][2]. Lettuce (*Lactuca sativa*) has become one of the most widely cultivated crops in hydroponic setups owing to its short growth cycle, shallow root structure, and sensitivity to fluctuations in water-quality parameters such as pH and electrical conductivity, making it both a commercially viable crop and a suitable model plant for prototype-scale research involving automated monitoring and control systems [3]. Its consistent demand in urban and peri-urban food markets further reinforces its relevance as a focus crop for studies targeting sustainable and technology-driven agricultural practices [4].

In the Philippines, several studies have explored smart greenhouse and hydroponic technologies using IoT-based monitoring and automation systems [5][6], yet most existing systems primarily focus on environmental monitoring or automation processes without integrating sensor-based water-quality analysis with computer vision-based plant health assessment within a single

operational framework, a gap confirmed through an interview conducted with a practicing small-scale hydroponic lettuce farmer in Bulacan as part of this study. Recent developments in intelligent agriculture have introduced machine learning and computer vision techniques into hydroponic environments. Convolutional neural networks and YOLO-based object detection models demonstrated effectiveness in monitoring plant conditions and identifying visible signs of plant stress or disease under controlled growing setups [7][8], while research on multimodal deep learning highlights the importance of combining multiple data sources to improve monitoring accuracy and reliability in plant-care applications [9].

To address this, the study proposed VERDE (Vegetation Environment Recognition and Detection Engine), an integrated hydroponic monitoring and control system that combined IoT-based water-quality classification with YOLOv8-based plant condition and pest detection, using lettuce as the target crop for system development and evaluation. The system utilized a dual-mode operational design consisting of Full Automation Mode and Semi-Automation Mode, contributing to the goals of SDG 2 (Zero Hunger) and SDG 11 (Sustainable Cities and Communities) through sustainable, technology-driven agricultural practices applicable to controlled farming environments.

1.2. Significance of the Study

This study benefited the following:

1.2.1 Educational Institutions

Schools offering agricultural technology or computer engineering programs could use this research as a reference for curriculum development in precision agriculture, demonstrating how embedded systems and computer vision converged into deployable decision-support tools.

1.2.2 Academic Researchers

This study contributed baseline metrics on fusion accuracy, alert response latency, and decision reliability in prototype hydroponics settings. Future researchers could build on these findings to explore fully autonomous nutrient control, multi-crop generalization, or edge-deployment optimizations for resource-constrained environments.

1.2.3 Engineering and Agriculture Students

The system served as a concrete case study in IoT integration, edge machine learning deployment, and responsible automation design. Students gained practical exposure to hardware-software co-design, model training workflows, and the engineering trade-offs between automation and human oversight.

1.2.4 Agricultural Technology Developers

The sensor-vision fusion methodology demonstrated in this study offered a replicable architecture for multimodal agricultural monitoring. Developers could adapt the confidence-scoring framework to other crops, integrate additional environmental sensors, or extend the decision logic to more complex control scenarios without rebuilding the core system from scratch.

1.2.5 Small-Scale Hydroponics Farmers

Farmers operating hydroponic systems in peri-urban areas such as Bulacan and Batangas currently rely on manual water testing or basic sensor alarms with limited diagnostic context. This study provided them with a confidence-based alert

system that cross-checked water chemistry against plant appearance, reducing unnecessary farm visits, distinguishing true nutrient deficiencies from sensor anomalies, and guiding precise manual interventions. The result was lower crop loss risk without requiring dedicated technical staff.

1.3. Statement of the Problem

How could IoT-based water quality sensors and computer vision be integrated with sensor-vision fusion within a dual-mode automated system to effectively monitor and manage lettuce health in a hydroponic environment?

1.4. Objectives

1.4.1. General Objectives

To develop and evaluate VERDE, an IoT-based hydroponics system with sensor-vision fusion, dual-mode automated control, and a web dashboard for plant condition monitoring, pest detection, environmental monitoring, and nutrient management.

1.4.2. Specific Objectives

1. To detect the condition of lettuce plants using computer vision.
2. To detect the presence of pests on the lettuce and send an SMS alert.
3. To measure the pH, electrical conductivity, temperature, and turbidity of the water.
4. To classify the water quality as Optimal, Suboptimal, or Critical based on pH, electrical conductivity, temperature, and turbidity, providing the basis for the corresponding system response.

5. To monitor ambient humidity independently and generate dashboard warnings when levels fall outside the defined range.
6. To automatically dispense pH-Up solution when the pH level falls below the Optimal range.
7. To automatically dispense pH-Down solution when the pH level rises above the Optimal range.
8. To automatically switch the system between Full Automation Mode and Semi-Automation Mode based on the detected sensor status and plant condition.
9. To display monitoring data and alerts through a web dashboard.
10. To achieve at least a 90% success rate for the system.

1.5. Scope and Limitations

This study focused on developing VERDE (Vegetation Environment Recognition and Detection Engine), an integrated hydroponic monitoring and control system designed specifically for the cultivation of Butterhead (*Lactuca sativa* var. *capitata*) and Looseleaf (*Lactuca sativa* var. *crispa*) lettuce in a prototype-scale, home-based hydroponic setup. The system combined IoT-based water quality classification with computer vision-based plant health detection through a sensor-vision fusion engine, supported by a dual-mode operational framework consisting of Full Automation Mode and Semi-Automation Mode.

VERDE monitored four core water quality parameters: pH, electrical conductivity (EC), water temperature, and turbidity, classifying the nutrient solution condition as Optimal, Suboptimal, or Critical based on predefined threshold ranges established for lettuce cultivation. The pH, EC, water temperature, and turbidity parameters were directly integrated into the machine

learning water quality classifier. Water temperature and ambient humidity were monitored as environmental parameters only, as no physical corrective actuators for these parameters were included in the current prototype.

Turbidity was continuously monitored as an indicator of nutrient solution clarity. The system processed the sensor values and checked whether turbidity fell within the acceptable range. If turbidity was normal, monitoring continued. If it was not, the system displayed a dashboard warning and logged the event in the system records. No automatic corrective actuator was implemented for turbidity in the current prototype. These four water quality parameters were prioritized based on the expert interview conducted with the participating small-scale hydroponic farmer *(see Appendix L – Transcript of Interviews*), who identified pH, EC, and water temperature as the primary indicators monitored in practice, while turbidity was included based on its relevance to nutrient solution clarity and root health. Parameters such as dissolved oxygen and ammonia were outside the scope of this study.

For plant health assessment, the system used a trained YOLOv8 model to classify Butterhead and Looseleaf lettuce foliage into four plant conditions into four plant conditions: Harvest-Ready, Healthy, Yellowing, and Wilting. In addition, the YOLOv8 model detected the presence of insects or pests on the lettuce foliage and triggered an SMS notification alert; the system did not identify or classify pest species. Prototype testing and evaluation of the pest detection functionality were conducted using simulated pest representations (e.g., artificial or toy pests) under controlled conditions to avoid ethical concerns associated with the use of live insects during experimentation.

The trained YOLOv8 model was intended to detect the presence of pests on lettuce foliage during system operation; however, validation using live insects under real cultivation conditions was outside the scope of this study. Prototype testing and evaluation were conducted using Butterhead and Looseleaf lettuce grown under controlled indoor hydroponic conditions. The study did not evaluate additional lettuce cultivars or other crop species; therefore, the reported performance was limited to the selected lettuce varieties within the prototype environment. Detection was performed through a camera module positioned at a fixed angle above the lettuce plants under controlled LED lighting. Detection accuracy was optimized under stable and sufficient artificial lighting conditions; performance under low-light, heavily shadowed, or highly variable lighting environments was not guaranteed and fell outside the scope of this study.

The YOLOv8 model was trained exclusively using images of Butterhead (*Lactuca sativa* var. *capitata*) and Looseleaf (*Lactuca sativa* var. *crispa*) lettuce to classify foliage into the four defined plant condition classes (Healthy, Yellowing, Wilting, and Harvest-Ready) and to detect the presence of pests. The model did not extend to other crop species or plant disease diagnosis beyond the defined plant condition and pest detection classes.

The predefined threshold ranges for pH, EC, water temperature, turbidity, and humidity were evaluated independently. For water temperature, the Optimal range of 18–24°C was established based on controlled hydroponic lettuce research [12]. In practice, the Philippine tropical climate and the absence of a physical cooling actuator in the current prototype limited temperature management to monitoring and alerting only. The Critical upper threshold of 35°C reflected the operational ceiling recommended by the participating small-scale hydroponic farmer (*see Appendix L – Transcript of Interviews*). The lower critical temperature bound is not established

for this study, as the system operated in a controlled indoor environment where cold stress conditions were not applicable.

Ambient humidity was monitored and was reported for informational purposes only; no corrective actuation was triggered by humidity readings. Butterhead (*Lactuca sativa* var. *capitata*) and Looseleaf (*Lactuca sativa* var. *crispa*) belong to the same lettuce species (*Lactuca sativa*); therefore, the same water quality threshold ranges were applied throughout prototype development and evaluation. The sensor-vision fusion confidence level framework, which mapped all possible combinations of sensor status and plant condition outputs to a descriptive reliability classification (High, Medium, or Low), was presented in Table 3 (Chapter 2, Section 2.1.10). Actuator control and SMS alert triggering were driven by the detected condition rather than the confidence level.

VERDE did not monitor dissolved oxygen, ammonia, or any water quality parameter beyond the four defined above. The system did not identify pest or insect species; pest detection produced a notification only. Temperature and humidity deviations were addressed through dashboard warnings only; no physical actuators for environmental temperature or humidity correction were included. The YOLOv8 model did not diagnose specific plant diseases beyond the four defined plant condition classes and the binary pest-detected class. The system did not support large-scale multi-bed deployment, outdoor weather-adaptive monitoring, cloud synchronization, or long-term autonomous learning. Dashboard access required local network connectivity; WiFi interruptions might affect remote monitoring functions without disrupting local edge-based inference and automated control operations. The prototype was intended for demonstration and research evaluation purposes only.

VERDE operated under two modes: Full Automation Mode, where the system autonomously managed the nutrient management process by continuously monitoring water quality, classifying the detected condition, automatically dispensing pH-Up solution when the pH fell below the Optimal range, dispensing pH-Down solution when the pH rose above the Optimal range, performing EC adjustment when required, and controlling the circulation pump without farmer intervention. Semi-Automation Mode required manual farmer confirmation through the web dashboard before pH and EC dosing recommendations were executed, while circulation pump control remained automatic. Parameters without deterministic corrective actuators were limited to monitoring, dashboard warnings, and event logging according to their corresponding system conditions. Among these parameters, Critical turbidity readings and computer vision detection events generated SMS notifications when applicable, while water temperature and ambient humidity remained limited to dashboard warnings only. The system automatically overrode to Semi-Automation Mode upon detecting a Critical, Faulty Sensor, or Faulty Vision condition, regardless of the active setting.

During prototype testing and evaluation, water quality sensor readings were acquired every 5 to 10 seconds while the camera module captured lettuce foliage images every 30 seconds, at which point the accumulated sensor readings were processed, fused with the plant health detection output, and the web dashboard was updated with the resulting confidence score and system status. Operational monitoring intervals for deployment were determined following prototype evaluation.

SMS notifications were dispatched upon detection of predefined system events, including Critical, Faulty Sensor, Faulty Vision, Harvest-Ready, and Pest Detected conditions, through a GSM module operating independently of internet connectivity. System testing and evaluation were conducted using a single-unit home-based hydroponic setup operated by a small-scale hydroponic

farmer who participated in the initial requirements interview (*see Appendix L – Transcript of Interviews*). This study did not include large-scale multi-bed deployment, outdoor weather-adaptive monitoring, or long-term autonomous learning capabilities.

1.6. Conceptual Framework

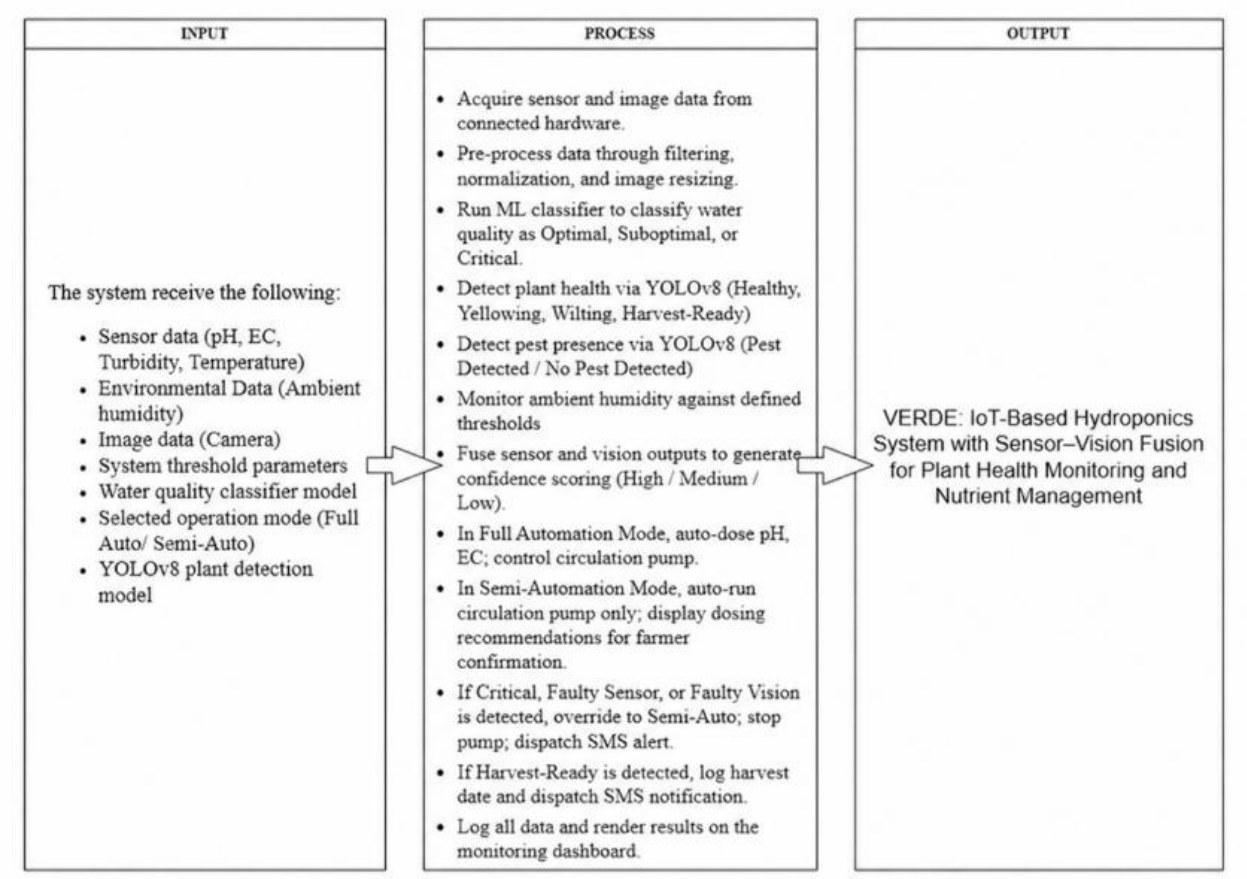


Figure 1. Input-Process-Output Diagram

As shown in Figure 1, this framework outlined the approach for developing VERDE, an integrated hydroponic monitoring and control system combining IoT-based water quality classification with computer vision-based plant health detection. On the input side, the system received sensor data covering pH, electrical conductivity (EC), turbidity, water temperature, and ambient humidity readings, image data from the camera module, system threshold parameters, the

water quality classifier model, the selected operational mode, and the YOLOv8 plant detection model.

These inputs were processed by the microcomputer through two parallel pipelines. Sensor data was first preprocessed through filtering and normalization before being passed to the Random Forest machine learning classifier, which categorized the water quality status as Optimal, Suboptimal, or Critical. Simultaneously, camera images were preprocessed through resizing before being passed to the YOLOv8 model, which classified the visible plant condition as Healthy, Yellowing, Wilting, or Harvest-Ready, while also detecting the presence of insects or pests. The outputs of both pipelines were integrated through the sensor-vision fusion engine, which generated a confidence level as a descriptive remark indicating the degree of agreement between the two data streams.

Based on the detected condition and the selected operational mode, the system responded accordingly. In Full Automation Mode, the system autonomously dispensed pH and EC corrections and controlled the circulation pump. In Semi-Automation Mode, only the circulation pump was automatically controlled while dosing recommendations were displayed on the web dashboard for manual farmer confirmation. Turbidity was not paired with any physical actuator; when a Critical turbidity reading was detected, the system only generated a dashboard warning and logged the event, recommending manual inspection and nutrient solution replacement by the farmer.

Upon detection of a Critical, Faulty Sensor, or Faulty Vision condition, the system overrode to Semi-Automation Mode, halted the circulation pump, and dispatched an SMS alert to the farmer regardless of the active setting. Upon detection of a Harvest-Ready or Pest Detected plant condition, the system dispatched a separate SMS notification, while Harvest-Ready detections

were additionally logged for harvest monitoring. All sensor readings, classification outputs, detection results, fusion confidence levels, actuator logs, and alert records were continuously logged and rendered on the locally hosted web dashboard.

1.7. Definition of Terms

Condition-Based Alert - VERDE's alert mechanism that triggers SMS notifications and Semi-Automation Mode override upon detecting a Critical, Faulty Sensor, or Faulty Vision condition, with a separate SMS notification dispatched upon detection of a Harvest-Ready plant condition or a Pest Detected output. Dashboard warnings are displayed for all detected anomalies, while the confidence level serves only as a descriptive remark on the agreement between sensor and vision outputs.

Confidence Level - A descriptive fusion output indicating the degree of agreement between sensor status and plant condition results, categorized as High, Medium, or Low, serving as a data reliability indicator that informs the farmer of how trustworthy the current system output is before deciding on a course of action.

Critical Condition - Water-quality classification indicating sensor readings have exceeded survivable thresholds for lettuce growth, prompting immediate intervention.

Dual-Mode Operation Design - VERDE's operational framework supports Full Automation or Semi-Automation Mode based on user selection and system conditions.

Electrical Conductivity (EC) - Measurement of nutrient concentration in the hydroponic solution (mS/cm), used to evaluate nutrient balance and classify water quality.

Full Automation Mode - An operating mode where VERDE automatically regulates pH, EC, and circulation via actuators based on detected sensor and plant condition outputs.

Harvest-Ready - YOLOv8 classification indicating a lettuce plant has reached optimal harvest maturity based on visual foliage characteristics.

Humidity Monitoring - Measurement of ambient relative humidity within the hydroponic growing environment, used to inform the farmer of environmental conditions that may contribute to plant stress or disease where deviations trigger dashboard warnings.

Latency - The elapsed time from sensor data acquisition and image capture initiation to the completion of dashboard update and alert generation within the VERDE system.

Machine Learning Classifier - Random Forest model that processes normalized pH, electrical conductivity (EC), turbidity, and water temperature readings to classify water quality as Optimal, Suboptimal, or Critical.

Suboptimal - Water-quality classification indicating sensor readings are outside the optimal range but within survivable limits, requiring corrective monitoring.

Optimal Range - The defined value range for a given water quality parameter (pH, electrical conductivity, temperature, or turbidity) within which the hydroponic nutrient solution is considered most favorable for lettuce cultivation, as established in Table 1 and used as the baseline for Suboptimal and Critical classification boundaries.

Pest Detected - A YOLOv8 detection output indicating the presence of insects or pests on the lettuce foliage, without classifying pest species, which triggers an SMS notification and dashboard alert prompting the farmer to inspect the setup and take appropriate action.

pH - Measurement of acidity/alkalinity (0 - 14 scale) of the nutrient solution, used to evaluate nutrient absorption and trigger corrective dosing.

pH-Up Dosing Condition - A condition in which the measured pH level of the hydroponic nutrient solution falls below the Optimal range of 5.5 defined in Table 1, prompting the VERDE system to dispense pH-Up solution to raise it back to the ideal range.

pH-Down Dosing Condition - A condition in which the measured pH level of the hydroponic nutrient solution rises above the Optimal range of 6.5 defined in Table 1, prompting the VERDE system to dispense pH-Down solution to lower it back to the ideal range.

Plant Condition - Visual classification output from YOLOv8 analyzing lettuce foliage, categorized as Healthy, Yellowing, Wilting, or Harvest-Ready.

Semi-Automation Mode - Operating mode where only circulation is automated; pH and EC corrections are displayed as dashboard recommendations requiring manual farmer confirmation.

Sensor Status - Water quality condition assigned by the machine learning classifier based on pH, EC, turbidity, and temperature sensor readings, categorized as Optimal, Suboptimal, Critical, or Faulty Sensor.

Sensor-Vision Fusion - An analytical process that combines water-quality classifications and YOLOv8 plant-health results to generate fusion confidence levels as descriptive remarks on the agreement between both data streams.

System Performance - The composite evaluation of VERDE across three metrics: water quality classification accuracy (covering pH, EC, turbidity, and temperature), plant health detection mAP, and system response latency. The system meets its performance target when classification accuracy reaches at least 90%, mAP reaches at least 85%, and response latency does not exceed five (5) seconds.

Turbidity - A measurement of the optical clarity of the hydroponic nutrient solution, used as a fourth water quality parameter alongside pH, EC, and temperature to detect contamination or sediment presence, and integrated into the machine learning water quality classifier alongside the other monitored parameters, though monitored without a corrective actuator, unlike pH and EC.

VERDE - Vegetation Environment Recognition and Detection Engine. IoT-based hydroponics monitoring and control system.

Water Quality - A classification of the hydroponic nutrient solution's condition, determined by the machine learning classifier based on four measured parameters: pH, electrical conductivity (EC), water temperature, and turbidity, and categorized as Optimal, Suboptimal, or Critical according to the threshold ranges defined in Table 1.

Web Dashboard - Locally hosted interface displaying continuous sensor readings, YOLOv8 outputs, fusion levels, historical logs, actuator controls, mode settings, and alerts.

YOLO (You Only Look Once) - YOLOv8 object detection model is used to analyze lettuce foliage images and classify plant conditions based on visual features.

CHAPTER 2

REVIEW OF RELATED LITERATURE

2.1. Foreign Related Literature

2.1.1. Optimizing Electrical Conductivity, pH and Cultivar Selection to Enhance Yield and Nutritional Quality of Hydroponic Lettuce

This study evaluated the combined effects of electrical conductivity, pH levels, and cultivar selection on the growth, yield, and nutritional quality of hydroponic lettuce under subtropical conditions, testing EC levels ranging from 1.8 to 2.2 dS/m and pH levels from 5.5 to 7.5 across multiple lettuce varieties. Results identified optimal parameter ranges that maximized vegetative growth, biomass, and nutritional quality, confirming the sensitivity of lettuce to precise EC and pH management in hydroponic nutrient solutions. [10] The optimal EC range of 1.2-1.8 mS/cm and pH range of 5.5-6.5 established in this study directly informed VERDE's water quality threshold classifications, serving as the scientific basis for defining Optimal, Suboptimal, and Critical EC and pH boundaries used by the machine learning water quality classifier.

Table 1. Water Quality Parameter Threshold Classifications for Hydroponic Lettuce

Parameter	Optimal	Suboptimal	Critical	Reference
pH	5.5 - 6.5	Below 5.5 or above 6.5	Below 4.5 or above 8.0	A, B
EC (mS/cm)	1.2 - 1.8	Below 1.2 or above 1.8	Below 0.5 or above 4.0	A, C
Temperature (°C)	18 - 24	Below 18 or above 24	Exceeds 35	D
Turbidity	< 5 NTU	5-20 NTU	> 20 NTU	E

Legends:
A - Optimizing Electrical Conductivity, pH and Cultivar Selection to Enhance Yield and Nutritional Quality of Hydroponic Lettuce [10]
B - Hydroponic Nutrient Solutions [11]
C - Yield and nutrient use efficiency of lettuce grown at different electrical conductivity levels of hydroponic solutions [12]
D - Effects of root zone temperature of hydroponic lettuce affects plant growth, nutrient uptake, and vitamin A content [17]
E - Internet of Things-Based Hydroponic Monitoring and Threshold-Controlled Recirculation for Lettuce Under Open-Field Thermal Stress [28]

Table 1 shows that for plant health assessment, the system used a trained YOLOv8 model to classify lettuce foliage into four plant conditions, as defined in Table 2. Detection was performed through a camera module positioned at a fixed angle above the lettuce plants under controlled LED lighting. Detection accuracy was optimized under stable and sufficient artificial lighting conditions; performance under low-light, heavily shadowed, or highly variable lighting environments was not guaranteed and fell outside the scope of this study.

The predefined threshold ranges for pH, electrical conductivity, and water temperature are presented across three classification categories. Each parameter was evaluated independently, and the resulting classification reflected the most critical condition detected among all monitored parameters. The Optimal ranges were defined as 5.5-6.5 for pH [10][11], 1.2-1.8 mS/cm for electrical conductivity [12], and 18-24°C for water temperature [17], with Suboptimal and Critical boundaries established beyond these ranges. Turbidity was included as a fourth water quality parameter, with an Optimal range of below 5 NTU, a Suboptimal range of 5-20 NTU, and a Critical classification above 20 NTU, based on thresholds adopted from an IoT-based plant monitoring system for water clarity assessment [28]. Turbidity served as an indicator of nutrient solution clarity, with elevated readings suggesting the presence of algae growth, decaying organic matter, or sediment buildup that may affect nutrient availability and root health.

The Optimal temperature range of 18-24°C was established based on controlled hydroponic lettuce research [17]. In practice, however, the Philippine tropical climate and the absence of a physical cooling actuator in the current prototype limited the system's temperature management to monitoring and alerting only. The Critical upper threshold of

35°C reflected the operational ceiling recommended by the participating small-scale hydroponic farmer (*see Appendix L – Transcript of Interviews*), beyond which lettuce survival was no longer reasonably assured. The lower critical temperature bound was not established for this study, as the system operated in a controlled indoor environment where cold stress conditions were not applicable.

2.1.2. Hydroponic Nutrient Solutions

Cabrera-Garcia established that the optimum pH for most hydroponic crops fell within the range of 5.5 to 6.5, noting that pH levels outside this range affected nutrient solubility and availability, potentially preventing plants from absorbing nutrients in the solution or causing toxic concentrations [11]. The pH threshold validated in this study directly informed VERDE's pH classification boundaries, defining the Optimal range of 5.5–6.5 used by the machine learning water quality classifier to distinguish Optimal from Suboptimal pH conditions. The Bulacan farmer's practiced minimum of 6.0 further corroborated the practical relevance of this range within a Philippine tropical farming context, ensuring that VERDE's pH classification boundaries were grounded in established nutrient science rather than empirical observation alone.

2.1.3. Yield and Nutrient Use Efficiency of Lettuce Grown at Different Electrical Conductivity Levels of Hydroponic Solutions

Jalal et al. investigated the effects of varying electrical conductivity levels on lettuce yield and nutrient use efficiency under tropical conditions, finding that EC levels between 0.9 and 1.4 dS/m produced the highest fresh and dry matter accumulation, with EC 1.3 dS/m identified as most suitable for lettuce cultivation, as excessive EC was found to increase saline stress and reduce both lettuce growth and nutrient uptake [12]. Being

conducted under tropical conditions, this study was particularly relevant to VERDE's Philippine deployment context, with its findings directly informing the lower bound of 1.2 mS/cm established in VERDE's EC classification threshold, as defined in Table 2.

2.1.4. Effects of Root Zone Temperature of Hydroponic Lettuce on Plant Growth, Nutrient Uptake, and Vitamin A Content

This study examined the effects of varying root zone temperatures on hydroponic lettuce growth, nutrient uptake efficiency, and vitamin A content, establishing that temperatures within the range of 18-24°C supported optimal lettuce development while deviations negatively affected both growth rates and nutritional quality [17]. The temperature thresholds established in this study directly informed VERDE's water temperature classification boundaries, defining the Optimal range of 18-24°C and the Critical upper threshold of 35°C used by the machine learning water quality classifier to categorize nutrient solution conditions. This scientific grounding ensured that VERDE's temperature-based classifications reflected physiologically meaningful boundaries for lettuce cultivation rather than arbitrary thresholds.

2.1.5. Water IoT Monitoring System for Aquaponics Health and Fishery Applications

This study presented a cost-effective IoT-based water monitoring system for aquaponics applications, demonstrating how multiple water-quality sensors combined with low-power communication technologies enabled automated monitoring, data transmission, and energy efficiency across scalable sensor network architectures [18]. The multi-parameter sensor integration approach adopted in this study informed VERDE's water quality monitoring architecture, informed the design of combining pH, EC, turbidity, and temperature sensors into a unified IoT-based acquisition system for continuous hydroponic nutrient solution assessment. This approach ensured that all four water quality parameters

were acquired through a single integrated pipeline, reducing latency between sensor reads and classification inputs in VERDE's monitoring cycle.

2.1.6. Enhancing Hydroponic Farming with Machine Learning: Growth Prediction and Anomaly Detection

This study explored machine learning applications in precision hydroponic farming using an NFT lettuce system, evaluating models including linear regression, neural networks, and Random Forest classifiers on collected pH, EC, and temperature data. The Random Forest classifier achieved 94.45% accuracy in classifying hydroponic growth conditions, confirming the effectiveness of ML-based classification for multivariate sensor data in controlled agricultural environments. [13] This study directly informed VERDE's adoption of the Random Forest classifier for water quality classification, with the 94.45% benchmark serving as a reference for evaluating VERDE's own classifier performance against the same parameter inputs. Additionally, the study's classification of hydroponic growth conditions into distinct states, including anomalous conditions observable through yellowing and wilting symptoms, informed the definition of VERDE's Yellowing and Wilting plant condition categories used in the YOLOv8 detection model.

2.1.7. An IoT-Based Data-Driven Real-Time Monitoring System for Control of Heavy Metals to Ensure Optimal Lettuce Growth in Hydroponic Set-Ups

This study presented a low-cost IoT-based monitoring and actuation system for lettuce hydroponics that combined water quality sensors with a machine learning classifier to predict tolerable nutrient levels and trigger corrective dispensing actions through a closed-loop control system, demonstrating the viability of integrating IoT sensing with ML-driven classification for automated nutrient management. [19] The closed-loop sensor-to-actuator design adopted in this study informed VERDE's water quality classification

pipeline and dual-mode nutrient dosing control system, where sensor readings processed by the Random Forest classifier directly determined corrective actuator responses. This confirmed that automated actuation driven by ML classification was a viable and reliable approach for nutrient management, directly justifying VERDE's dual-mode dosing control architecture.

2.1.8. Lettuce Plant Trace-Element-Deficiency Symptom Identification via Machine Vision Methods

This study demonstrated that machine vision methods could reliably identify and classify visible nutrient deficiency symptoms in lettuce foliage under controlled growing conditions, with deep learning models achieving over 99.5% accuracy in distinguishing deficiency classes from foliage images collected across multiple growth stages [16]. The image-based foliage classification approach validated in this study supported VERDE's use of computer vision for plant health assessment, confirming that visible lettuce stress conditions could be reliably detected and categorized from foliage images, directly applicable to VERDE's YOLOv8-based classification of lettuce conditions as Harvest-Ready, Healthy, Yellowing, or Wilting. This confirmed that image-based foliage analysis was sufficiently reliable for automated plant condition assessment, justifying VERDE's reliance on computer vision as an independent data stream in the sensor-vision fusion engine.

Table 2. VERDE Plant Condition Classification Categories

Plant Condition	Description	Reference
Harvest-Ready	Lettuce foliage displays visual characteristics consistent with full maturity and readiness for harvest, including full rosette formation, adequate head size and spread, and sufficient leaf density, as assessed through trained image-based detection.	A
Healthy	Lettuce foliage shows no visible signs of stress; color, texture, and structure are within normal appearance for the current growth stage	B
Yellowing	Lettuce foliage displays discoloration characterized by yellowing of leaves, indicating possible nutrient deficiency or environmental stress	C

Wilting	Lettuce foliage shows visible drooping or loss of turgor, indicating possible water stress, root damage, or severe environmental imbalance	C
Legends: A - Combining computer vision and deep learning to enable ultra-scale aerial phenotyping and precision agriculture: A case study of lettuce production [15] B - YOLO-based deep learning framework for real-time multi-class plant health monitoring in precision agriculture [14] C - Lettuce plant trace-element-deficiency symptom identification via machine vision methods [16]		

Table 2 shows the four plant conditions used by the YOLOv8 detection model were defined based on observable foliage characteristics. Each condition represented a distinct visual state of the selected Butterhead and Looseleaf lettuce varieties. Although these cultivars exhibit differences in leaf morphology, the defined condition classes were based on observable foliage characteristics common to both varieties, allowing the YOLOv8 model to learn generalized visual features for plant condition assessment. The use of computer vision for classifying plant health conditions including healthy states and visible stress symptoms such as yellowing and wilting was supported by existing literature [13][14], and the application of image-based detection for identifying harvest readiness based on visual foliage characteristics was further validated by studies demonstrating the viability of computer vision in assessing lettuce maturity for harvest [15].

2.1.9. Comparative Analysis of YOLOv8 and YOLOv9 Models for Real-Time Plant Disease Detection in Hydroponics

This study presented a comparative evaluation of YOLOv8 and YOLOv9 for plant disease detection in hydroponic environments, with YOLOv8 achieving a mean Average Precision of 87.22% under controlled conditions, confirming the suitability of YOLO-based architectures for automated plant health assessment in hydroponic setups. [6] This study directly informed VERDE's selection of YOLOv8 as the plant health detection model, with its validated performance in hydroponic plant detection supporting deployment for classifying lettuce foliage conditions as Harvest-Ready, Healthy,

Yellowing, or Wilting, while the 87.22% mAP served as a reference benchmark for evaluating VERDE's own detection performance.

2.1.10. Sensor Fusion Based Intelligent Hydroponic Farming and Nursing System

This study proposed a sensor fusion-based smart hydroponic system combining multiple environmental sensors with a Random Forest algorithm to autonomously determine and regulate priority parameters, demonstrating that sensor fusion paired with machine learning enabled intelligent, energy-efficient autonomous control in hydroponic environments [20]. The sensor fusion architecture and ML-based classification approach adopted in this study informed VERDE's fusion engine design, confirming that cross-referencing multiple independent data streams through a unified classification framework was a viable approach for generating priority-based system responses in intelligent hydroponic monitoring systems.

Table 3. VERDE Sensor-Vision Fusion Confidence Level

Sensor Status	Plant Condition	Confidence	Reasoning
Optimal	Harvest-Ready	High	Both agree - normal condition
Optimal	Healthy	High	Both agree - normal condition
Optimal	Yellowing	Medium	Conflict - vision detects problem
Optimal	Wilting	Medium	Conflict - vision detects problem
Suboptimal	Harvest-Ready	Medium	Single signal - vision only
Suboptimal	Healthy	Medium	Conflict - sensors detect problem
Suboptimal	Yellowing	High	Both agree - problem condition
Suboptimal	Wilting	High	Both agree - problem condition
Critical	Harvest-Ready	Medium	Conflict - sensors critical
Critical	Healthy	Medium	Conflict - sensors critical
Critical	Yellowing	High	Both agree - problem condition
Critical	Wilting	High	Both agree - problem condition
Faulty Sensor	Harvest-Ready	Low	Hardware or data reliability issue
Faulty Sensor	Healthy	Low	Hardware or data reliability issue
Faulty Sensor	Yellowing	Low	Hardware or data reliability issue
Faulty Sensor	Wilting	Low	Hardware or data reliability issue
Optimal	Faulty Vision	Low	Hardware or data reliability issue
Suboptimal	Faulty Vision	Low	Hardware or data reliability issue
Critical	Faulty Vision	Low	Hardware or data reliability issue
Faulty Sensor	Faulty Vision	Low	Hardware or data reliability issue
Legends: Medium - Sensor status and plant condition outputs are in conflict, or detection relies on a single data stream. Low - Sensor input is faulty or unavailable; system reliability cannot be confirmed			

Faulty Sensor - A sensor whose output is absent, unreadable, or beyond physically plausible bounds, rendering it unreliable for fusion processing.
Faulty Vision - A condition where the camera or image processing module fails to produce a valid plant classification, rendering visual data unavailable for fusion processing.

In Table 3, the confidence level logic of the sensor-vision fusion engine was presented across all combinations of sensor status and plant condition outputs. A High confidence level indicated agreement between both data streams, Medium indicated a conflict or reliance on a single data stream, and Low indicated a Faulty Sensor or Faulty Vision condition where one or both inputs were unreliable or unavailable. The confidence level classifications represented an original sensor-vision fusion framework developed by the researchers, designed to provide interpretable system outputs for non-technical end users. Rather than serving as a decision-making indicator, the confidence level functioned as a descriptive remark and data reliability indicator, informing the farmer of the degree of agreement between sensor and vision outputs so that they could assess the trustworthiness of the system output before deciding on a course of action. Actuator control, Semi-Automation Mode override, and SMS alert notifications were triggered by the detected condition, specifically upon identifying a Critical, Faulty Sensor, or Faulty Vision state, with a separate SMS notification dispatched upon detection of a Harvest-Ready plant condition. The use of fusion-based scoring as a reliable approach for synthesizing multi-source outputs in intelligent monitoring systems was supported by [9] and [16].

2.1.11. Technology Design to Improve Plant Quality with IoT-Based Plant Temperature and Humidity Monitoring System

This study presented an Internet of Things (IoT)-based monitoring system that continuously measured ambient temperature and relative humidity to support lettuce cultivation under controlled environmental conditions. Using environmental sensors

integrated with a wireless communication platform, the system enabled real-time monitoring through a web-based interface, allowing growers to observe environmental changes that might affect plant growth. The study reported that maintaining relative humidity within the range of 65–78% contributed to favorable growing conditions for lettuce while reducing the need for frequent manual observation. This study informed VERDE's implementation of ambient humidity monitoring by providing a reference range for defining humidity thresholds and supporting the integration of dashboard warnings whenever humidity deviated from the established operating range [26].

2.1.12. Internet of Things Approaches for Monitoring and Control of Smart Greenhouses in Industry 4.0

Bersani *et al.* reviewed Internet of Things (IoT)-based smart greenhouse systems, emphasizing the importance of continuously monitoring environmental parameters such as temperature, relative humidity, light intensity, carbon dioxide concentration, and ventilation to improve crop productivity and operational efficiency. The study highlighted that integrating multiple environmental sensors enabled real-time monitoring, timely decision-making, and sustainable greenhouse management by providing growers with continuous situational awareness of the cultivation environment. This study supported VERDE's environmental monitoring architecture by justifying the inclusion of ambient humidity as an additional monitored parameter alongside water quality sensing. Although the current prototype did not perform automatic humidity regulation, the study validated the use of continuous humidity monitoring through the web dashboard to assist farmers in identifying environmental conditions that might contribute to plant stress and required manual intervention [27].

2.1.13. Internet of Things-Based Hydroponic Monitoring and Threshold-Controlled Recirculation for Lettuce Under Open-Field Thermal Stress

Becerra-Suarez *et al.* developed an Internet of Things (IoT)-based hydroponic monitoring system for lettuce that integrated multiple water quality sensors, including pH, electrical conductivity (EC), nutrient solution temperature, dissolved oxygen, and turbidity, into a threshold-controlled recirculation framework with near-real-time monitoring through a web interface [28]. The system continuously collected sensor data and used predefined threshold values to regulate nutrient solution recirculation while monitoring water quality indicators throughout the cultivation period. The study demonstrated that integrating multiple water quality parameters with threshold-based monitoring was technically feasible and supported improved crop management under varying environmental conditions. This study directly supported VERDE's implementation of turbidity as an additional monitored water quality parameter alongside pH, EC, and water temperature. Furthermore, it validated the use of threshold-based monitoring, continuous dashboard visualization, and real-time sensor acquisition as part of VERDE's hydroponic monitoring architecture.

2.1.14. Identifying the Growth Status of Hydroponic Lettuce Based on YOLO-EfficientNet

Wang *et al.* proposed a computer vision approach for identifying the growth status of hydroponic lettuce using a combination of the YOLOv8n object detection model and the EfficientNet-v2s classification model [29]. The study addressed the challenges of manually identifying healthy plants, pest infestations, and disease conditions in large-scale hydroponic lettuce production by automatically detecting individual lettuce plants and classifying them into Healthy, Diseases, and Pests. Using a dataset consisting of 2,240

original images expanded into 12,000 cropped lettuce images, the proposed method achieved approximately 99% object detection accuracy and recall, while the classification model obtained 94.68% testing accuracy and an F1-score of 96.18%, demonstrating the effectiveness of deep learning for automated hydroponic lettuce monitoring. This study supported VERDE's implementation of computer vision for monitoring lettuce conditions and validated the feasibility of detecting the presence of insects or pests through image-based analysis. While VERDE limited pest detection to notification without pest species classification, the study provided a strong foundation for integrating AI-assisted visual monitoring into hydroponic management systems.

2.1.15. Deep Learning for Sustainable Agriculture: A Systematic Review on Applications in Lettuce Cultivation

Qin *et al.* conducted a systematic review of deep learning applications in lettuce cultivation, examining the use of convolutional neural networks (CNNs) and YOLO-based object detection models across various precision agriculture tasks, including pest and disease diagnosis, crop condition monitoring, growth stage classification, yield prediction, weed management, and irrigation and fertilization management [30]. The review concluded that deep learning had significantly improved the efficiency, accuracy, and automation of lettuce production by enabling intelligent image-based monitoring and reducing dependence on manual crop inspection. Furthermore, the authors identified computer vision as an essential component of sustainable lettuce cultivation because it supported timely detection of crop abnormalities while optimizing resource utilization. This study supported VERDE's implementation of a YOLOv8-based computer vision system for monitoring lettuce conditions and detecting the presence of insects or pests. It

further validated the use of deep learning as a practical approach for intelligent hydroponic monitoring and reinforced the integration of AI-assisted visual analysis within the proposed sensor-vision fusion framework.

2.2. Local Related Literature

2.2.1. A hybrid Internet of Things-based smart system performs better than a purely wireless sensor in monitoring indoor hydroponics farms

This study implemented a hybrid wired-wireless IoT sensor network for indoor hydroponic monitoring, demonstrating significant improvements in data reliability over purely wireless systems, with packet loss reduced from 12.23% to 0% under continuous traffic conditions, confirming that hybrid connectivity approaches substantially improved sensor data integrity in hydroponic monitoring applications [21]. The reliability improvements demonstrated in this study informed VERDE's system architecture and local network connectivity design, supporting the decision to prioritize stable local network communication for consistent sensor data acquisition and dashboard accessibility. This was particularly critical for VERDE, where dashboard accessibility and uninterrupted sensor data flow were essential for timely confidence-based alert generation and actuator control.

2.2.2. Automated Monitoring of Aquaponics with Biofiltration System

This study presented a pilot-scale aquaponics system with a centralized sensory chamber that automated the monitoring of physicochemical water parameters across multiple grow chambers, demonstrating that automated water quality monitoring improved productivity and system balance in Philippine aquaponic environments [22]. This study established a local technical precedent for automated water parameter monitoring that VERDE built upon, confirming the practical viability of centralized sensor-based water quality assessment within Philippine-controlled farming contexts.

2.2.3. AQUAMAG: Smart Water Quality Monitoring through Internet of Things

This study presented AQUAMAG, an IoT-based water quality monitoring device with a web dashboard that provided automated alert notifications and sensor data visualization, with an ISO 25010 evaluation confirming high end-user acceptance among local users due to the system's accuracy and practicality [23]. The web dashboard design and automated alerting approach validated in this study directly informed VERDE's dashboard-driven alert framework, confirming that sensor visualization with automated notifications was a well-accepted and practical design approach for Filipino end users in IoT-based monitoring systems.

2.2.4. Bloomigo: A Wireless IoT-Based Hydroponics Control System for Efficient and Sustainable Farming

This study introduced Bloomigo, a wireless IoT-based hydroponics automation system with three operational control modes: Manual, Automation, and Machine Learning, deployed across three greenhouse sites in Cebu, Philippines, demonstrating high sensor accuracy, rapid actuator response, and strong user satisfaction among small-scale Filipino farmers [24]. The multi-mode operational control design validated in this study informed VERDE's Dual-Mode Operation Design, confirming that offering farmers a choice between different levels of system control was both technically feasible and practically accepted within the Philippine small-scale hydroponic farming context. This validated VERDE's design decision to implement both Full Automation and Semi-Automation modes rather than a single fixed operational mode, ensuring the system accommodated varying farmer preferences and monitoring scenarios.

2.2.5. Developing an automated IoT-based indoor farming system with optimal LED light quality control for leafy vegetable growth

This study presented an automated IoT-based indoor farming system for Philippine lettuce cultivation integrating a Raspberry Pi as the central controller with sensor modules, actuators, and a web dashboard for automated monitoring and light control, confirming the economic feasibility and technical viability of IoT-based automation and web dashboard monitoring for small-scale indoor hydroponic lettuce production [25]. While this study established IoT automation and dashboard monitoring as viable for Philippine indoor hydroponics, it did not incorporate machine learning water quality classification, computer vision-based plant health assessment, or sensor-vision fusion, which resembled the gap that VERDE was designed to address, making this study both a local technical foundation and a direct justification for VERDE's development.

2.3. Synthesis

IoT-based multiparameter sensor networks confirmed the feasibility of automated pH, electrical conductivity (EC), temperature, turbidity, and humidity monitoring in hydroponic environments, while dedicated agronomic studies provided the scientifically validated threshold values for each monitored parameter: the optimal pH range of 5.5–6.5 validated by Cabrera-Garcia [11], the EC range of 1.2–1.8 mS/cm established through the subtropical findings of Singh et al. [10] and the tropical conditions study of Jalal et al. [12], which was particularly relevant to VERDE's Philippine deployment context, the temperature range of 18–24°C confirmed by Moccio et al. [17], and the turbidity thresholds supported by the threshold-controlled recirculation framework of Becerra-Suarez et al. [28], collectively defining the Optimal, Suboptimal, and Critical nutrient solution conditions used by the machine learning water quality classifier. Ambient humidity was

monitored independently using the reference range of 65–78% established by Setiawan et al. [26] and further reinforced by tipburn-focused research identifying elevated humidity as a risk factor for lettuce quality [31], with deviations triggering dashboard warnings to assist farmers in identifying environmental conditions requiring manual intervention without serving as a classifier input or automated actuation trigger. The demonstrated accuracy of Random Forest classifiers on multivariate hydroponic sensor data validated VERDE's water quality classification pipeline, and both YOLO-based object detection and machine vision studies confirmed that image-based plant health detection and visible symptom identification in hydroponic lettuce environments were feasible and reliable, with YOLOv8 specifically validated at 87.22% mAP under controlled conditions. Research on deep learning further demonstrated that computer vision could effectively detect the presence of insects or pests in hydroponic lettuce while supporting automated crop monitoring, validating VERDE's implementation of pest detection through image-based analysis [29], [30]. Research on sensor fusion and multimodal integration further reinforced that cross-referencing independent data streams improved monitoring accuracy and system reliability, directly informing VERDE's sensor-vision fusion engine design.

Local literature confirmed the relevance of VERDE within the Philippine agricultural context. Studies on hybrid IoT connectivity, automated aquaponic monitoring, web dashboards with automated alerting, and multi-mode operational control collectively demonstrated that sensor-based automated monitoring, dashboard-driven alerts, and flexible operational frameworks were technically viable and well accepted by small-scale Filipino farmers, directly informing VERDE's system architecture, alert design, and Dual-Mode Operation Design. However, no existing Philippine hydroponic implementation

integrated machine learning water quality classification across pH, EC, temperature, and turbidity, ambient humidity and pest monitoring, computer vision-based plant health detection, computer vision-based pest detection, and sensor-vision fusion into a unified dual-mode control framework, the precise gap that VERDE was designed to address.

Across the reviewed literature, no single study integrated continuous IoT-based water quality classification with computer vision-based plant health detection and pest detection within a unified confidence-scoring framework. Isolated capabilities such as computer vision-based pest detection had been independently demonstrated in specific hydroponic lettuce contexts [29], confirming the feasibility of this approach, but such implementations did not incorporate machine learning-based water quality classification, sensor-vision fusion, or dual-mode automation. Systems that relied solely on sensor data could identify environmental deviations but could not confirm whether the plant had already manifested visible stress or whether insects or pests were present. Systems that relied solely on vision could detect surface symptoms and pest presence but could not determine the underlying environmental or water-quality conditions contributing to these observations. By combining both modalities through a sensor-vision fusion engine, VERDE uniquely enabled cross-validation between environmental readings and plant appearance, allowing the system to distinguish true nutrient deficiencies from sensor anomalies, provide pest presence notifications, reduce false intervention triggers, and generate confidence-based alerts that neither approach could produce independently. This integration represented the primary contribution of the present study to the existing body of hydroponic monitoring research.

2.4. Research Gap

The following table summarized how VERDE compared to related systems across key technical features, identifying the specific capabilities that existing implementations lacked and that this study introduced.

Table 4. Research Gap

Related Literatures	System Features							
	IoT water quality monitoring	Web dashboard & alerts	Lettuce-specific scope	ML water quality classification	Computer Vision Plant Health Detection	Computer Vision Pest Detection	Sensor-vision fusion	Dual-mode automation
A	✓	✗	✓	✗	✗	✗	✗	✗
B	✓	✗	✓	✗	✗	✗	✗	✗
C	✓	✗	✓	✗	✗	✗	✗	✗
D	✓	✓	✗	✗	✗	✗	✗	✗
E	✓	✗	✗	✓	✗	✗	✗	✗
F	✓	✗	✓	✓	✗	✗	✗	✗
G	✗	✗	✓	✗	✓	✗	✗	✗
H	✗	✗	✗	✗	✓	✗	✗	✗
I	✓	✗	✗	✓	✗	✗	✗	✗
J	✓	✓	✓	✗	✗	✗	✗	✗
K	✗	✗	✓	✗	✗	✓	✗	✗
L	✓	✓	✗	✗	✗	✗	✗	✗
M	✓	✓	✗	✗	✗	✗	✗	✗
N	✓	✓	✗	✗	✗	✗	✗	✗
O	✓	✓	✗	✗	✗	✗	✗	✗
P	✓	✓	✓	✗	✗	✗	✗	✗
VERDE	✓	✓	✓	✓	✓	✓	✓	✓

Legends:

✓ - Present in existing research

✗ - Not present in existing research

Foreign Related Literature:

A - Optimizing Electrical Conductivity, pH and Cultivar Selection to Enhance Yield and Nutritional Quality of Hydroponic Lettuce [10]
B - Hydroponic Nutrient Solutions Yield and Nutrient Use Efficiency of Lettuce Grown at Different Electrical Conductivity Levels of Hydroponic Solutions [11]
C - Effects of Root Zone Temperature of Hydroponic Lettuce on Plant Growth, Nutrient Uptake, and Vitamin A Content [17]
D - Water IoT Monitoring System for Aquaponics Health and Fishery Applications [18]
E - Enhancing Hydroponic Farming with Machine Learning: Growth Prediction and Anomaly Detection [13]
F - An IoT-Based Data-Driven Real-Time Monitoring System for Control of Heavy Metals to Ensure Optimal Lettuce Growth in Hydroponic Set-Ups [19]
G - Lettuce Plant Trace-Element-Deficiency Symptom Identification via Machine Vision Methods [16]
H - Comparative Analysis of YOLOv8 and YOLOv9 Models for Real-Time Plant Disease Detection in Hydroponics [6]
I - Sensor Fusion Based Intelligent Hydroponic Farming and Nursing System [20]
J - Internet of Things-Based Hydroponic Monitoring and Threshold-Controlled Recirculation for Lettuce Under Open-Field Thermal Stress [28]
K - Identifying the Growth Status of Hydroponic Lettuce Based on YOLO-EfficientNet [29]

Local Related Literature:

L - A Hybrid Internet of Things-Based Smart System Performs Better than a Purely Wireless Sensor in Monitoring Indoor Hydroponics Farms [21]
M - Automated Monitoring of Aquaponics with Biofiltration System [22]
N - AQUAMAG: Smart Water Quality Monitoring through Internet of Things [23]
O - Bloomigo: A Wireless IoT-Based Hydroponics Control System for Efficient and Sustainable Farming [24]
P - Developing an Automated IoT-Based Indoor Farming System with Optimal LED Light Quality Control for Leafy Vegetable Growth [25]

CHAPTER 3

METHODOLOGY

This research project represented the integration of knowledge and competencies acquired throughout the Bachelor of Science in Computer Engineering program of FEU Institute of Technology. Concepts and technical skills learned from various academic courses were applied in the design, development, and implementation of VERDE (Vegetation Environment Recognition and Detection Engine), demonstrating the practical application of theoretical foundations in embedded systems, computer vision, machine learning, automation, Internet of Things (IoT), and web-based monitoring systems.

Insights from COE0057 (Design Thinking for Engineers) guided the researchers in identifying real-world challenges in hydroponic monitoring and automation, particularly in developing a system capable of improving water-quality management, environmental monitoring, and plant-health and pest monitoring through intelligent decision support. Concepts from CPE0043 (Methods of Research for CPE) strengthened the researchers' capability to conduct systematic investigation, technical documentation, data gathering, and proper academic writing throughout the development of the study.

For the hardware implementation of VERDE, foundational courses such as CPE0005 (Fundamentals of Electrical Circuits Lecture and Laboratory), CPE0011 (Fundamentals of Electronic Circuits Lecture and Laboratory), CPE0019 (Fundamentals of Mixed Signals and Sensors), and CPE0021 (Logic Circuits and Design Lecture and Laboratory) provided the researchers with the necessary background in circuit analysis, sensor interfacing, relay integration,

signal handling, and hardware communication. These concepts were essential in integrating the pH sensor, electrical conductivity (EC) sensor, water temperature sensor, turbidity sensor, humidity sensor, relay modules, pumps, and actuator systems into the hydroponic automation framework. Knowledge from CPE0025 (Feedback and Control System) also contributed to the implementation of automated corrective actions and operational control logic for nutrient dosing and circulation management, as well as the monitoring-and-alert logic applied to parameters such as humidity that did not have a corresponding corrective actuator in the current prototype.

Lessons from CPE0035 (Embedded Systems Lecture and Laboratory) were applied in assembling and interfacing the microcomputer, sensors, camera module, and automation devices into a functional embedded monitoring and control system. Through CPE0029 (Microprocessors Lecture and Laboratory), the researchers gained proficiency in configuring and utilizing embedded computing platforms, which was applied in using the microcomputer as the central processing unit responsible for sensor acquisition, automation control, machine learning inference, and dashboard hosting. Concepts from CPE0037 (Computer Architecture and Organization Lecture and Laboratory) and CPE0031 (Computer Networks and Security Lecture and Laboratory) also contributed to understanding system architecture, network communication, and secure local dashboard connectivity. Knowledge from operating-system-related concepts under CPE0037 enabled the researchers to efficiently manage the Linux-based Debian environment used for deploying system services and artificial intelligence models.

The software development aspect of the study was supported by CPE0007L (Computer Programming for CpE), CPE0017L (Object Oriented Programming), and CPE0033L (Data Structures and Algorithms for CPE), which provided the necessary programming foundations for implementing sensor processing, automation logic, and system integration. CPE0039L

(Introduction to Database) contributed to the development of the historical logging and monitoring database used for storing sensor readings, plant-health and pest detection results, and alert records.

Computer vision and artificial intelligence components of the study were supported by concepts from CPE0013 (Numerical Methods for CPE), CPE0009 (Discrete Mathematics for CPE), and COE0011 (Engineering Data Analysis), which strengthened the researchers' understanding of data processing, algorithmic logic, and machine learning principles. These concepts were applied in implementing the Random Forest machine learning classifier for water-quality assessment across pH, EC, turbidity, and water temperature, while independently implementing ambient humidity monitoring and the YOLOv8-based plant-health and pest detection model. Image preprocessing techniques, including normalization, resizing, and frame handling, were applied to improve computer vision performance during continuous lettuce condition and pest detection.

Through the integration of these academic learnings, the researchers were able to conceptualize, design, develop, and evaluate VERDE as an intelligent IoT-based hydroponics monitoring and control system integrating sensor-driven water-quality classification, computer vision-based plant-health and pest detection, dual-mode automation, and confidence-based decision support for hydroponic farming applications.

The development process of VERDE followed the four primary phases of the RAD model: Requirement Planning, User Design, Rapid Construction, and Cutover.

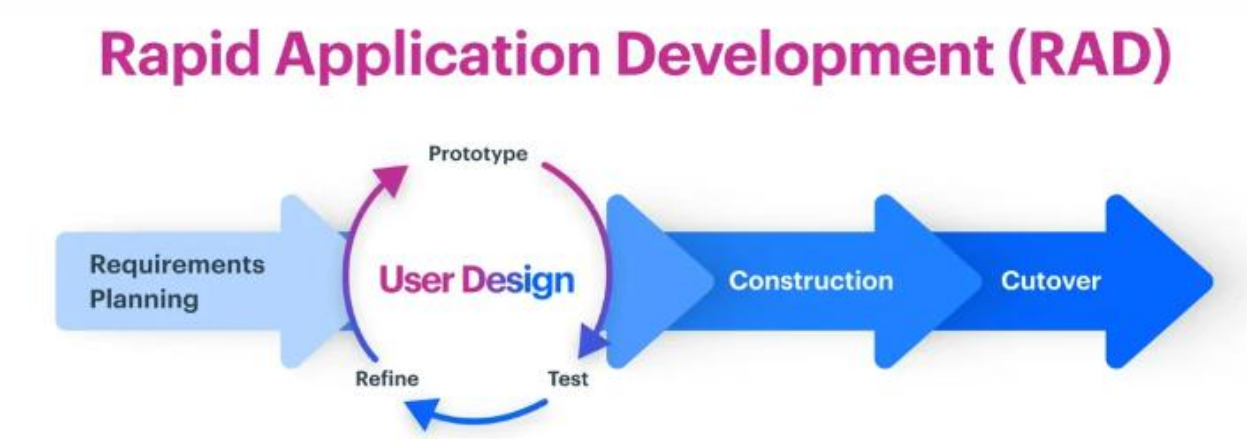


Figure 2. Rapid Application Development

The development process of VERDE follows the four primary phases of the RAD model: Requirement Planning, User Design, Rapid Construction, and Cutover.

- **Requirement Planning** - The Requirement Planning phase involved identifying the functional and technical requirements of the proposed hydroponics monitoring and control system. During this phase, the researchers analyzed the common challenges in hydroponic farming related to water-quality monitoring, environmental monitoring, plant health and pest assessment, delayed intervention, and automation limitations, informed by an interview conducted with a practicing small-scale hydroponic lettuce farmer. The required system components and functionalities were identified, including pH, electrical conductivity (EC), water temperature, and turbidity monitoring for water quality classification; ambient humidity monitoring; YOLOv8-based lettuce condition detection and pest detection; sensor-vision fusion processing; web dashboard visualization; SMS alert notification; and dual-mode automation control. Operational parameter threshold ranges for lettuce hydroponics were also defined across Optimal, Suboptimal, and Critical

classifications to serve as the basis for water-quality classification and condition-based corrective actions, alongside independent threshold ranges for ambient humidity monitoring.

- **User Design -** During the User Design phase, the researchers developed the initial architecture and interface designs of VERDE. This phase included the design of the system block diagram, operational flowchart, sensor integration framework, database structure, automation logic, and web dashboard interface. The researchers also designed the sensor-vision fusion framework, which combined the outputs of the Random Forest water-quality classifier and the YOLOv8 plant health detection model to generate a confidence level as a descriptive remark on the agreement between the two data streams. Prototype dashboard layouts, condition-based alert mechanisms, and operational controls for Full Automation Mode and Semi-Automation Mode were also planned and refined during this phase, including the logic for Semi-Automation Mode override upon detection of a Critical, Faulty Sensor, or Faulty Vision condition.
- **Rapid Construction** - The Rapid Construction phase focused on the actual development and integration of the system components. A microcomputer was configured as the main processing unit responsible for sensor acquisition, machine learning inference, YOLOv8 detection, automation control, and dashboard hosting. The pH, EC, water temperature, and turbidity sensors were integrated for continuous water quality monitoring, the humidity sensor was integrated for independent environmental monitoring, and the camera module was integrated for plant image acquisition. The Random Forest classifier was developed to categorize water-quality conditions as Optimal, Suboptimal, or Critical based on pH, EC, water temperature, and turbidity readings, while the YOLOv8 model was trained and

deployed to classify plant conditions of Butterhead and Looseleaf lettuce as Healthy, Yellowing, Wilting, or Harvest-Ready, while independently detecting the presence of simulated pests on the lettuce foliage. The sensor-vision fusion engine was implemented to cross-reference both outputs and generate confidence levels across all sensor status and plant condition combinations. The web dashboard, SMS alert notifications, humidity dashboard warnings, and Semi-Automation Mode override logic were implemented and configured accordingly. Continuous debugging, calibration, and prototype refinement were conducted throughout this phase to improve system reliability and performance.

- **Cutover -** The Cutover phase involved system deployment, testing, evaluation, and final refinement of the VERDE prototype. Prior to testing, the trained YOLOv8 model weights were transferred from the training machine to the Raspberry Pi 5, and all system services including sensor acquisition, machine learning inference, fusion engine processing, and web dashboard hosting were configured to initialize automatically upon device startup. The Raspberry Pi 5 was configured to broadcast a local wireless hotspot, enabling the web dashboard to remain accessible to the farmer through a phone or computer browser without requiring external internet connectivity. This configuration supported the system's primary design goal of continuous unattended operation, allowing VERDE to monitor the hydroponic environment and dispatch SMS alerts independently of the farmer's physical presence or active dashboard interaction. The integrated system was then tested under controlled hydroponic conditions using Butterhead and Looseleaf lettuce plants to evaluate sensor accuracy, plant health and pest detection performance, humidity monitoring behavior, automation response, dashboard functionality, and sensor-vision fusion output consistency.

The researchers conducted repeated testing procedures to assess the reliability and responsiveness of both Full Automation Mode and Semi-Automation Mode, including the automatic override behavior triggered by Critical, Faulty Sensor, and Faulty Vision conditions. System response latency, condition-based alert behavior, actuator operation, and detection consistency were also evaluated. Errors and inconsistencies identified during testing were corrected through recalibration, software refinement, and adjustment of automation logic to improve the final implementation of the system.

3.1. Block Diagram

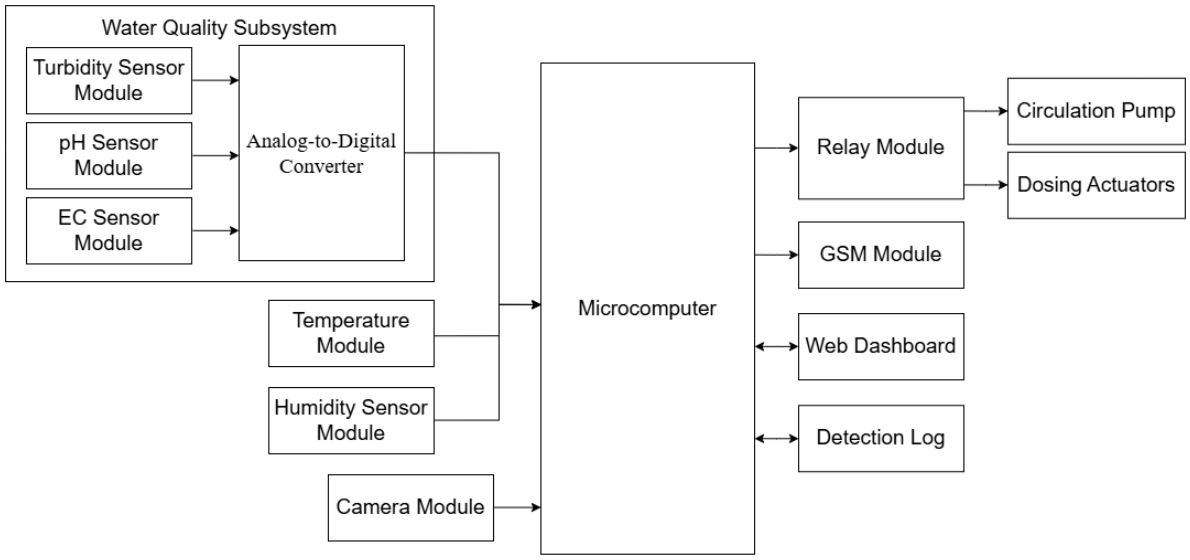


Figure 3. System Block Diagram

As shown in Figure 3, the block diagram presents the hardware architecture and signal flow of VERDE. On the input side, the pH, EC, and Turbidity Sensor Modules were grouped under the Water Quality Subsystem, with their analog outputs passed through an Analog-to-Digital Converter before reaching the microcomputer, which did not natively support analog input. The Temperature, Humidity, and Camera Modules connected directly to the microcomputer via their respective digital interfaces. The microcomputer served as the central processing unit, executing

the necessary processing and inference tasks, and issuing control signals to the Relay Module, which drove the Circulation Pump and Dosing Actuators for automated nutrient management. Alert notifications were dispatched through the GSM Module upon detection of the appropriate conditions, while the Web Dashboard and Detection Log operated bidirectionally, supporting continuous monitoring and user input on the dashboard side, and data storage and retrieval on the log side.

3.2. System Flowchart

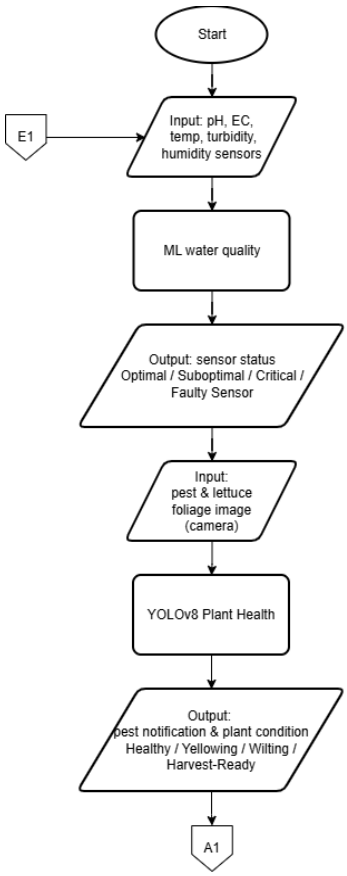


Figure 4.0. System Flowchart - Data Acquisition and Plant Health Detection

In Figure 4.0, the data acquisition and plant health detection phase of VERDE is presented. The process began at START, where the system acquired inputs from the pH, EC, temperature, and

turbidity sensors for water quality classification, while the humidity sensor was acquired and monitored independently as a separate environmental parameter. The pH, EC, temperature, and turbidity readings were processed by the machine learning water quality classifier, which output the sensor status as Optimal, Suboptimal, Critical, or Faulty Sensor. Simultaneously, the camera module captured a lettuce foliage image, which was passed through the YOLOv8 model to classify the visible plant condition as Healthy, Yellowing, Wilting, or Harvest-Ready, and separately to detect the presence of pests as an independent camera-vision output. Both the water quality classification output and the plant condition output were then forwarded to the sensor-vision fusion engine through connector A1. The E1 connector represented the system reinitialization path, returning to the input acquisition stage upon cycle retry or manual intervention.

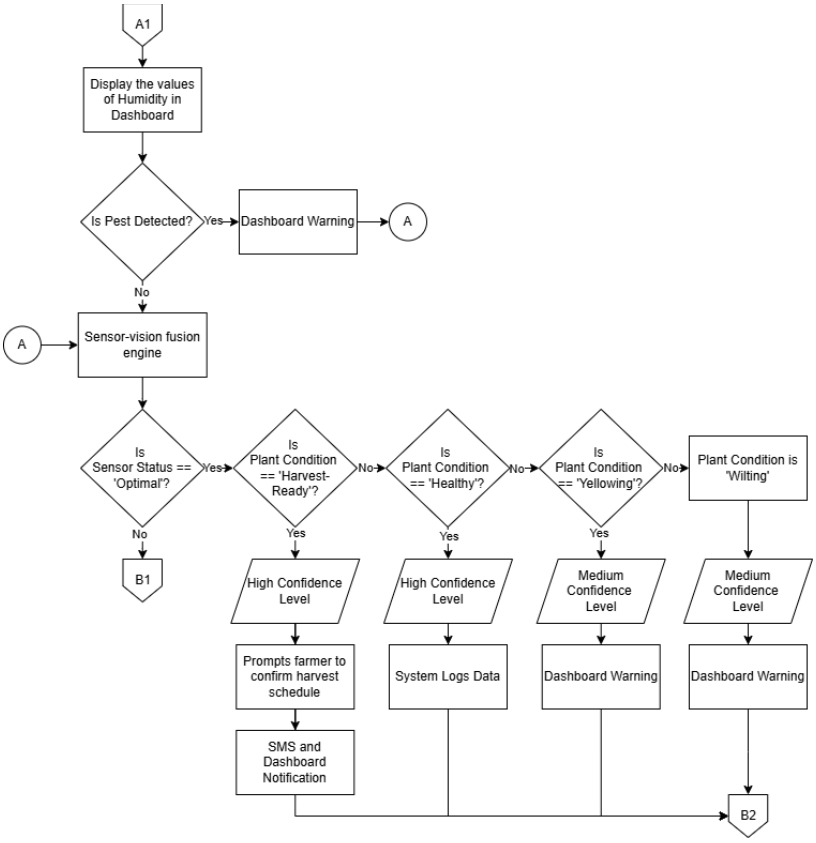


Figure 4.1. System Flowchart - Pest Detection and Sensor-Vision Fusion Engine Optimal Sensor Status (cont.)

In Figure 4.1, the system first checked whether a pest had been detected from the YOLOv8 output. If pest presence was detected, the system generated a Dashboard Warning and dispatched an SMS notification before proceeding to connector A. If no pest was detected, the system proceeded directly to connector A, where the sensor-vision fusion engine evaluated the sensor status and plant condition combination. If the sensor status was Optimal, the system evaluated the detected plant condition. If the plant condition was Harvest-Ready, the system generated a High Confidence Level, prompted the farmer to confirm the harvest schedule, and dispatched an SMS and Dashboard Notification before proceeding to connector B2. If the plant condition was Healthy, the system generated a High Confidence Level and logged the data silently before proceeding to connector B2. If the plant condition was Yellowing, the system generated a Medium Confidence Level and triggered a Dashboard Warning before proceeding to connector B2. If the plant condition was Wilting, the system generated a Medium Confidence Level and triggered a Dashboard Warning before proceeding to connector B2. If the sensor status was not Optimal, the system proceeded to connector B1.

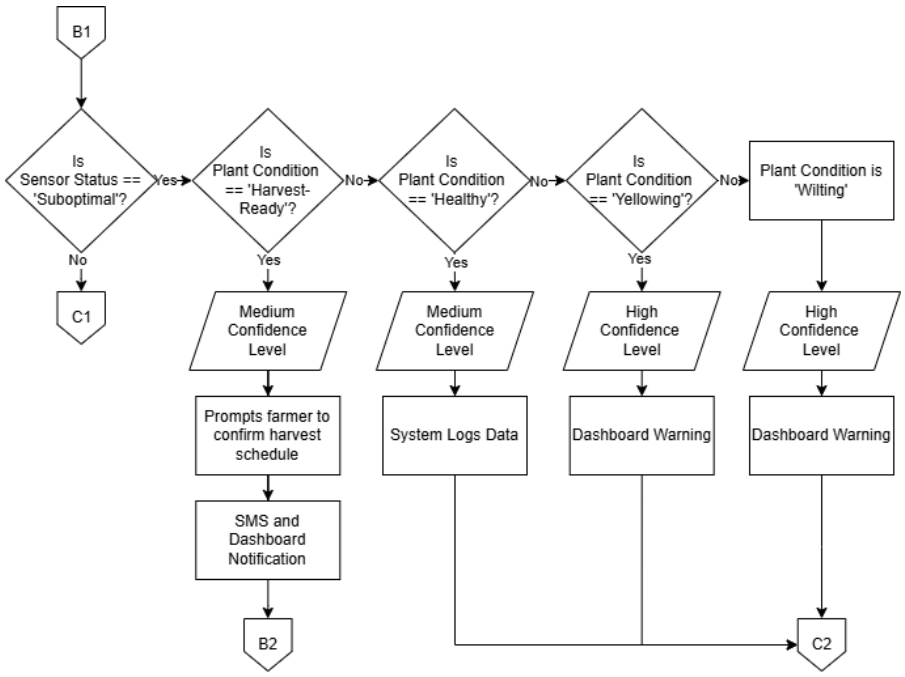


Figure 4.2. System Flowchart - Sensor-Vision Fusion Engine Suboptimal Sensor Status (cont.)

In Figure 4.2, the sensor-vision fusion engine evaluated all possible plant condition combinations under a Suboptimal sensor status. If the plant condition was Harvest-Ready, the system generated a medium confidence level, prompted the farmer to inspect before confirming harvest, and dispatched an SMS and Dashboard Notification before proceeding to B2. If the plant condition was Healthy, the system generated a medium confidence level reflecting a conflict between the detected water quality deviation and the visually healthy plant appearance and generated a Dashboard Warning before proceeding to connector C2 for corrective dosing. If the plant condition was Yellowing or Wilting, the system generated a high confidence level as both data streams agreed a problem condition existed, generated a Dashboard Warning, and proceeded to C2 for corrective action.

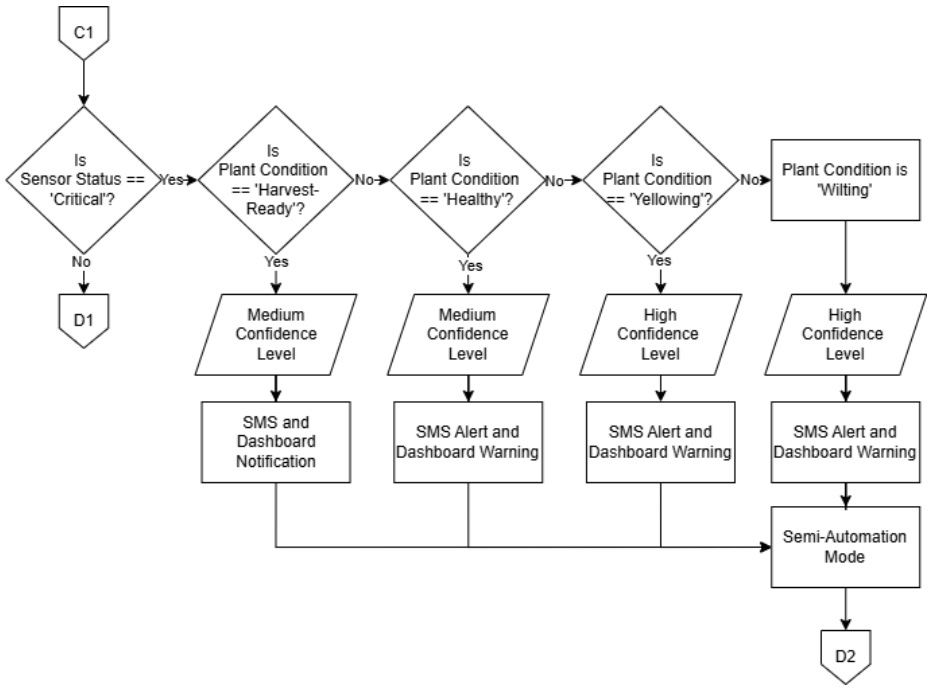


Figure 4. 3. System Flowchart - Sensor-Vision Fusion Engine Critical Sensor Status (cont.)

In Figure 4.3, the sensor-vision fusion engine evaluated all possible plant condition combinations under a Critical sensor status. If the sensor status was Critical, the system evaluated the detected plant condition. If the plant condition was Harvest-Ready, the system generated a Medium Confidence Level and dispatched an SMS and Dashboard Notification before proceeding to Semi-Automation Mode. If the plant condition was Healthy, the system generated a Medium Confidence Level and dispatched an SMS Alert and Dashboard Warning before proceeding to Semi-Automation Mode. If the plant condition was Yellowing, the system generated a High Confidence Level and dispatched an SMS Alert and Dashboard Warning before proceeding to Semi-Automation Mode. If the plant condition was Wilting, the system generated a High Confidence Level and dispatched an SMS Alert and Dashboard Warning before proceeding to Semi-Automation Mode. All paths under Critical sensor status converged to Semi-Automation

Mode before proceeding to connector D2 for farmer confirmation and corrective action. If the sensor status was not Critical, the system proceeded to connector D1.

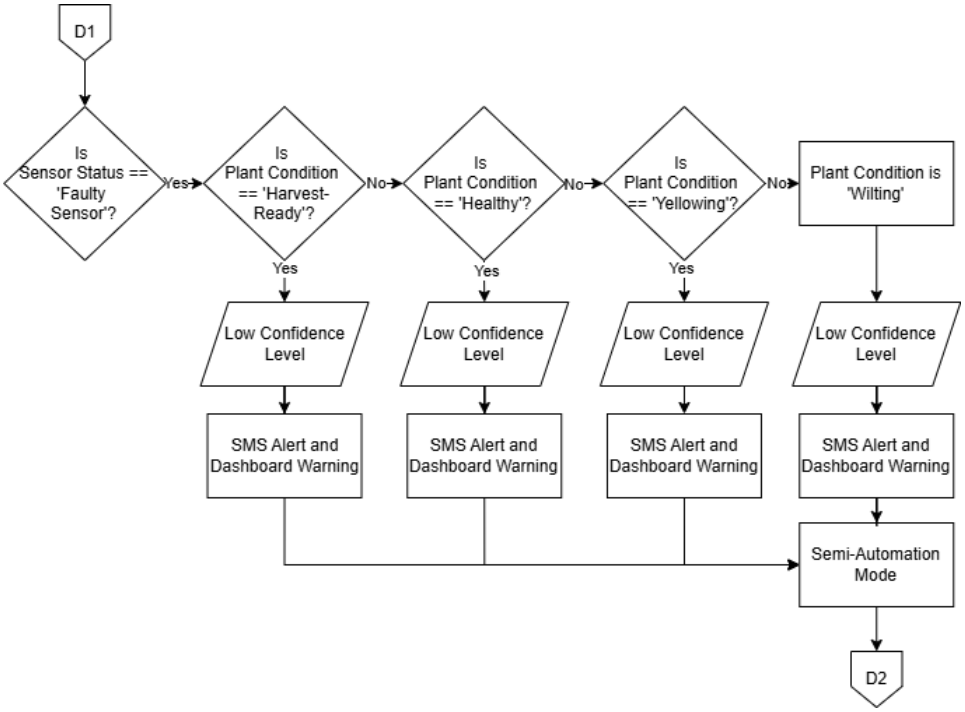


Figure 4.4. System Flowchart - Sensor-Vision Fusion Engine Faulty Sensor Status (cont.)

In Figure 4.4, the sensor-vision fusion engine evaluated all possible plant condition combinations under a Faulty Sensor status. Upon receiving a Faulty Sensor status from connector D1, the system checked the plant condition sequentially. Regardless of the detected plant condition, all paths generated a Low confidence level, indicating that sensor input was unavailable or unreliable and that system decisions could not be fully trusted. A Harvest-Ready plant condition dispatched an SMS and Dashboard Notification, while Healthy, Yellowing, and Wilting plant conditions each dispatched an SMS Alert and Dashboard Warning. All paths proceeded to Semi-Automation Mode before continuing to connector D2, ensuring that no automated corrective actions were executed without farmer confirmation when sensor reliability could not be confirmed.

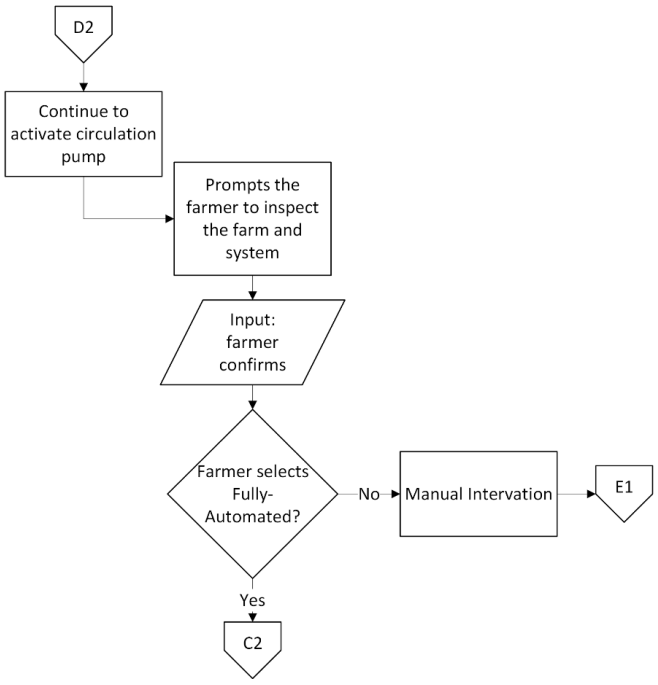


Figure 4.5. System Flowchart - Semi-Automation Mode and Farmer Confirmation (cont.)

In Figure 4.5, the system response under Semi-Automation Mode is presented. Upon entering from connector D2, the circulation pump continued to operate to maintain nutrient solution flow while the system prompted the farmer to inspect the farm and system. The farmer provided confirmation through the dashboard input. If the farmer selected Full Automation Mode, the system proceeded to connector C2 to initiate the corrective dosing sequence. If the farmer did not select Full Automation, the system registered a Manual Intervention and reinitialized through connector E1, returning to the data acquisition phase for a fresh monitoring cycle while retaining the current operational mode.

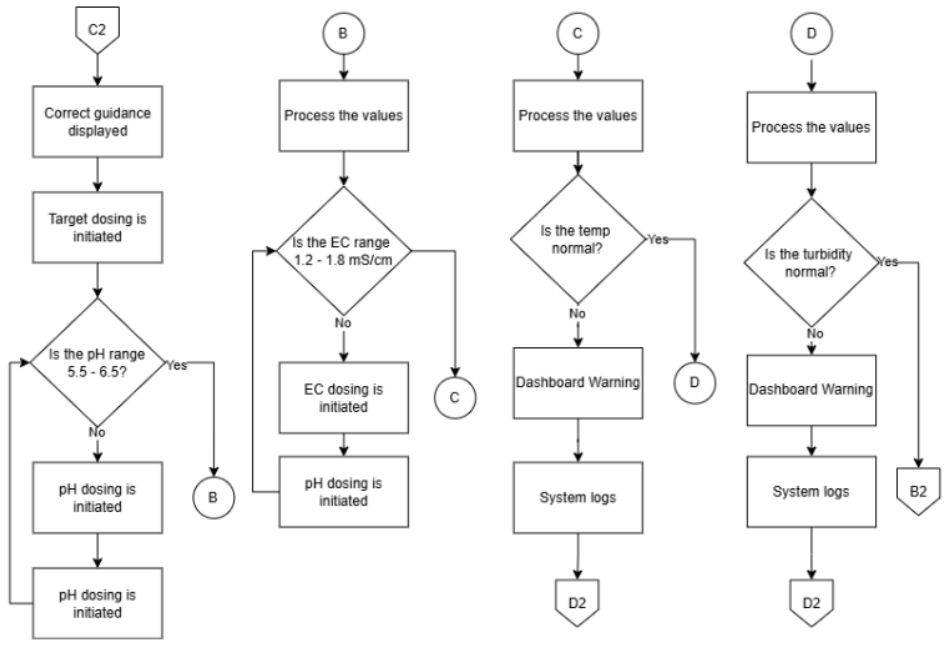


Figure 4.6. System Flowchart - Automated Dosing and Actuator Control (cont.)

In Figure 4.6, the automated dosing and monitoring control sequence of VERDE is presented. Upon entering from connector C2, the system first displayed the appropriate corrective guidance on the web dashboard and initiated the corresponding target dosing process. The system then evaluated whether the measured pH value fell within the optimal range of 5.5 to 6.5. If the pH level was outside the defined range, the appropriate pH dosing operation was initiated before the system proceeded to connector B. If the pH level was already within the optimal range, the system proceeded directly to connector B without performing corrective dosing.

At connector B, the system processed the electrical conductivity (EC) reading and evaluated whether it fell within the optimal range of 1.2 to 1.8 mS/cm. If the measured EC value was outside the defined range, the appropriate nutrient dosing operation was initiated before

proceeding to connector C. Otherwise, the system proceeded directly to connector C without corrective action.

At connector C, the system processed the water temperature reading and determined whether it remained within the predefined operating range. If the temperature was outside the acceptable range, the system generated a Dashboard Warning, recorded the event in the system log, and proceeded to connector D2. Since no physical temperature control actuator was implemented in the current prototype, no automatic corrective action was performed. If the temperature remained within the defined range, the system proceeded to connector D.

At connector D, the system processed the turbidity reading and evaluated whether it remained within the acceptable threshold. If abnormal turbidity was detected, the system generated a Dashboard Warning, dispatched an SMS notification to the registered user, recorded the event in the system log, and proceeded to connector D2, where manual inspection and nutrient solution replacement might be performed by the farmer when necessary. If the turbidity level remained within the acceptable range, the system proceeded directly to connector B2 to begin the data logging and cycle completion phase.

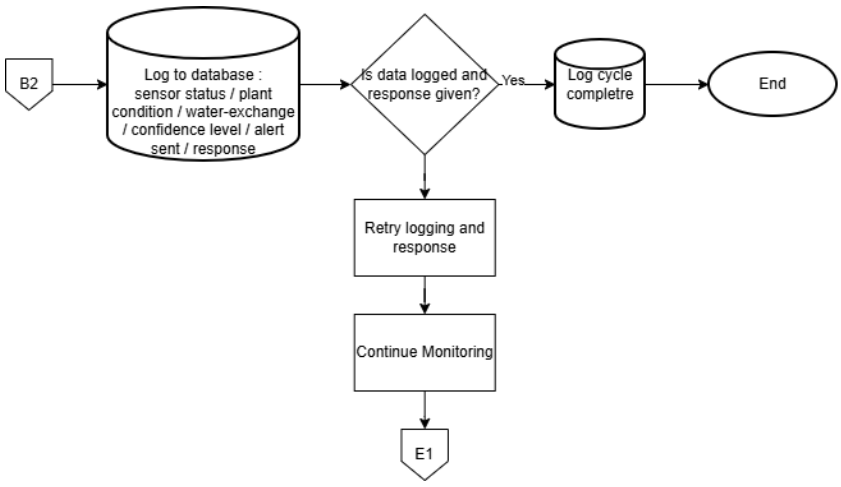


Figure 4.7. System Flowchart - Data Logging and Cycle Completion (cont.)

In Figure 4.7, the data logging and cycle completion phase of VERDE is presented. Upon entering from connector B2, the system logged all relevant monitoring data to the database, including sensor status, plant condition, water exchange records, confidence level, alert sent, and system response. The system then checked whether the data had been successfully logged and a response had been given. If confirmed, the system marked the log cycle as complete and proceeded to END, concluding the current monitoring cycle. If logging or response confirmation was unsuccessful, the system retried the logging and response step, continued monitoring, and reinitialized through connector E1, returning to the data acquisition phase for a fresh monitoring cycle.

3.3. Proposed System

3.3.1. Hardware System

The hardware system of VERDE consisted of a microcomputer that processed data from water quality sensors, a camera module, and connected actuators. It featured a web dashboard for continuous monitoring and user interaction and includes a GSM module for

remote alert notifications. The system operated under two modes: Full Automation and Semi-Automation, managed through relay-controlled pumps and a stable power supply.

3.3.1.1. Microcomputer

It served as the primary edge computing unit, running all ML inference (water quality classifier and YOLOv8 model), executing the sensor-vision fusion engine, managing dual-mode control logic, and hosting the local web dashboard server.

3.3.1.2. pH Sensor Kit

It measured the acidity of the hydroponic nutrient solution on a 0-14 scale. Output an analog voltage signal read through an Analog-to-Digital Converter interfaced with the microcomputer. Evaluated against the lettuce-specific optimal pH range of 5.5 - 6.5.

3.3.1.3. EC Sensor Module

It measured the electrical conductivity (EC) of the nutrient solution in milli Siemens per centimeter (mS/cm), converted from total dissolved solids (TDS) readings. Interfaced with the microcomputer via an analog-to-digital converter over SPI. Evaluated against the lettuce-specific optimal EC range of 1.2 - 1.8 mS/cm.

3.3.1.4. Temperature Sensor

It measured the nutrient solution water temperature in degrees Celsius, evaluated against the lettuce-specific optimal range of 18 - 24°C, interfaced with the microcomputer.

3.3.1.5. Humidity Sensor

It measured the relative humidity (%) of the ambient air within the hydroponic Humidity readings were monitored continuously and displayed on the web dashboard; deviations beyond the defined threshold range triggered dashboard warnings. No corrective actuation as performed based on humidity readings in the current prototype.

3.3.1.6. Turbidity Sensor

It measured the optical clarity of the hydroponic nutrient solution in Nephelometric Turbidity Units (NTU) by detecting light scattering caused by suspended particles. Interfaced with the microcomputer through the Analog-to-Digital Converter alongside the pH and EC sensors. Turbidity readings were evaluated as a fourth water quality parameter, integrated into the machine learning water quality classifier alongside pH, EC, and temperature to classify the nutrient solution condition as Optimal, Suboptimal, or Critical. Elevated turbidity may indicate sediment accumulation, algal growth, or contamination in the nutrient reservoir.

3.3.1.7. Analog-to-Digital Converter (ADC)

It converted analog voltage outputs from the pH and EC/TDS sensor modules into digital signals readable by the microcomputer.

3.3.1.8. Camera Module

The camera module captured high-resolution images of lettuce foliage at regular intervals for YOLOv8-based plant health classification and pest detection. Provided native integration with the microcomputer.

3.3.1.9. Peristaltic Dosing Pumps (Dosing Actuators)

Three peristaltic pumps were used in Full Automation Mode to deliver precise volumes of pH adjustment solution or nutrient concentrate to the reservoir in response to classified deviations. Controlled through relay modules connected to the microcomputer pins.

3.3.1.10. Submersible Water Pump (Circulation Pump)

It maintained nutrient solution flow throughout the hydroponic system. Controlled automatically in both operation modes ran on schedule under normal conditions and was stopped immediately upon detection of a Critical, Faulty Sensor, or Faulty Vision condition.

3.3.1.11. 4-Channel Relay Module

It served as the interface between the microcomputer outputs and the high-current actuators (dosing pumps and circulation pumps), providing electrical isolation and safe switching.

3.3.1.12. GSM Module

It enabled SMS notification transmission to the farmer's registered mobile number upon detection of a Critical, Faulty Sensor, Faulty Vision, or Critical Turbidity condition, with separate SMS notifications dispatched upon detection of a Harvest-Ready plant condition or pest presence, operating independently of internet connectivity.

3.3.1.13. Power Supply Unit

It provided stable, regulated power to the microcomputer, sensor circuits, relay module, and GSM module. Actuator pumps were powered from a separate supply appropriate to their voltage and current requirements.

3.3.2. Software System

The software system of VERDE consisted of an operating system environment running on the microcomputer that supported all processing layers, including sensor data acquisition, machine learning inference, fusion-based decision-making, and actuator control logic. It featured a locally hosted web dashboard for continuous monitoring and user interaction and integrated an SMS alerting interface for remote notifications independent of internet connectivity. The system operated under two modes: Full Automation and Semi-Automation, managed through software-driven control logic.

3.3.2.1. Microcomputer OS

It served as the operating system running on the microcomputer, providing the runtime environment for all software components, including sensor drivers, machine learning inference, web server, and control scripts.

3.3.2.2. Sensor Interface Libraries

These libraries handled communication between the microcomputer and the connected sensors. They managed analog signal reading through the ADC over SPI for the pH and EC sensors and 1-Wire protocol communication for the temperature sensor, converting raw hardware signals into usable numerical values for further processing.

3.3.2.3. Web Dashboard

It served as the primary user interface for continuous monitoring and control of the hydroponic setup, hosted locally on the microcomputer. Through this web-based interface, users could view live sensor readings, observe plant health detection outputs, check fusion confidence levels as data reliability indicators, manage actuator controls, and switch between Full Automation and Semi-Automation modes. The dashboard persistently always displayed the current active operational mode, ensuring the farmer remained informed of the system's operational state, including following any automatic override to Semi-Automation Mode. Implemented using Flask for backend routing and local network hosting, Jinja2 for dynamic HTML template rendering, OpenCV for live camera capture and bounding box overlay on plant detection outputs, NumPy for array-based image and sensor data computations, HTML/CSS/JavaScript for frontend design including time-series graphs and manual actuator override controls, SQLite for timestamped storage of sensor readings, classifications, detections, actuation records, and alert history, and an SMS Alert Library for interfacing with the GSM module.

3.3.2.4. Machine Learning Model

The system employed two machine learning models working in parallel. The first was a Random Forest classifier trained using Scikit-learn, which processed normalized pH, EC, water temperature and turbidity sensor readings to classify the water quality status as Optimal, Suboptimal, or Critical. The second was a fine-tuned YOLOv8 object detection model initialized from pretrained COCO dataset weights and trained on a custom lettuce dataset of Butterhead (*Lactuca sativa* var.

capitata) and Looseleaf (*Lactuca sativa* var. *crispa*) lettuce, which analyzed captured lettuce foliage images to classify plant conditions into four classes: Healthy, Yellowing, Wilting, and Harvest-Ready, and separately detected the presence of pests or insects on the foliage without classifying pest species.

The YOLOv8 plant health detection model was trained on a dataset comprising approximately 2,200 annotated The YOLOv8 plant health detection model was trained on a dataset comprising approximately 2,200 annotated Butterhead and Looseleaf lettuce foliage images representing the four classification classes images across four classification classes: Healthy, Yellowing, Wilting, and Harvest-Ready. The base dataset was sourced from Kaggle's publicly available lettuce disease and plant health image repositories, supplemented by self-collected photographs of Butterhead and Looseleaf lettuce taken directly from the research participant's hydroponic lettuce farm in Bulacan to ensure class representation relevant to the study's deployment context, particularly for the Harvest-Ready condition. The combined base dataset of approximately 700 images was expanded to 2,200 images through data augmentation techniques applied via Roboflow, including horizontal flipping, rotational adjustments of up to ±15 degrees, brightness and contrast variation of ±20%, random cropping, and Gaussian blur. The final dataset was partitioned into training, validation, and testing splits of 70%, 20%, and 10% respectively, yielding approximately 1,540 training images, 440 validation images, and 220 testing images. All images were captured under controlled indoor lighting conditions consistent with the system's operational environment.

The YOLOv8 pest detection model was trained on a separate annotated dataset comprising Butterhead and Looseleaf lettuce foliage images labeled for the presence or absence of insects or pests, without pest species classification. The base dataset was sourced from Kaggle's publicly available pest image repositories, supplemented by self-collected photographs of Butterhead and Looseleaf lettuce taken directly from the research participant's hydroponic farm from the research participant's hydroponic lettuce farm in Bulacan to ensure representation of pest conditions relevant to the study's deployment context. The combined base dataset of approximately 600 images was expanded to approximately 2,000 images through data augmentation techniques applied via Roboflow, including horizontal flipping, rotational adjustments of up to ±15°, brightness and contrast variation of ±20%, random cropping, and Gaussian blur. The final dataset was partitioned into training, validation, and testing splits of 70%, 20%, and 10%, respectively. All images were captured under controlled indoor lighting conditions consistent with the system's operational environment.

The YOLOv8 model was trained on a laptop equipped with an NVIDIA GTX 3050 GPU using the PyTorch framework with CUDA acceleration, which significantly reduced training time compared to training directly on the microcomputer. Upon completion of training, the resulting model weights file was exported and transferred to the Raspberry Pi 5 for edge deployment, where the microcomputer performed inference only, keeping the computational load within the Raspberry Pi's operational capacity during continuous system operation. The YOLOv8 model

operated on the PyTorch deep learning framework, which provided the computational support for efficient inference.

The outputs of the Random Forest water quality classifier and the YOLOv8 plant condition detection model were then passed to the Sensor-Vision Fusion Engine, which implemented the Rule-Based Decision Matrix (RBDM). Rather than functioning as a trained machine learning model, the RBDM operated as a deterministic rule-based lookup matrix that cross-referenced the Random Forest classifier's water quality classification output (Sensor Status) with the YOLOv8 model's plant condition output using the predefined mappings in Table 3. The corresponding confidence level was assigned and returned without requiring additional inference or model training. The fusion computation was executed once per monitoring cycle, immediately after both the water quality classification and plant condition detection outputs became available, ensuring that the confidence level was generated within the same 30-second monitoring cycle. The confidence level served solely as a descriptive indicator of the degree of agreement between the two independent data streams. It did not directly determine actuator control, automation mode transitions, or alert generation. Instead, corrective actions, automation mode transitions, and notification logic were governed independently by the sensor status and plant condition outputs according to the system's predefined operational rules.

Sensor readings were flagged as unreliable and triggered a Low confidence output based on bounds defined by the research team according to the physical operating limits of the sensor modules used. These included: a pH reading outside the range

of 0–14, an EC reading below 0 mS/cm or exceeding the sensor module's rated upper limit, a temperature reading outside the operational range of the waterproof temperature sensor, a null or missing value returned by any sensor, or a failure of the YOLOv8 model to return a valid detection output within the defined inference window.

3.3.2.5. Random Forest Classification Methodology

The Random Forest classifier served as the primary water quality classification engine within the VERDE system. It operated on the microcomputer as an edge-deployed model, processing sensor inputs to classify hydroponic nutrient conditions without requiring external network connectivity.

The classifier received four normalized input features: pH level, electrical conductivity (EC), water temperature, and turbidity. These values were acquired from the sensor modules, converted to digital signals through the ADC, and normalized to a standard scale before inference. The model output one of three classification states: Optimal, Suboptimal, or Critical, based on the predefined threshold ranges for lettuce hydroponics (pH 5.5–6.5, EC 1.2–1.8 mS/cm, water temperature 18–24°C, and turbidity below 5 NTU for Optimal, 5–20 NTU for Suboptimal, and above 20 NTU for Critical).

The Random Forest model was implemented using Scikit-learn and configured with 100 estimators and a maximum depth of 10. The ensemble structure was selected for its robustness against sensor noise, ability to rank feature importance, and computational efficiency suitable for resource-constrained edge deployment, with

class boundaries derived from the Optimal, Suboptimal, and Critical parameter ranges defined in Table 2.

Upon classification, the model output, consisting of the predicted class and its associated prediction score, was passed to the sensor-vision fusion engine, where it was cross-referenced with the YOLOv8 plant health detection result to generate a unified system response based on the detected condition.

3.3.2.6. Camera Module

The camera module's software function provided an image feed that enabled continuous monitoring and analysis of lettuce plant conditions. It captured images at regular intervals, which were preprocessed and passed through the YOLOv8 model to classify the visible health condition of the lettuce foliage and to detect the presence of pests or insects on the foliage.

3.3.2.7. pH Sensor

The software processed the pH readings and evaluated them against the lettuce-specific optimal range of 5.5–6.5, utilizing the values as a key parameter in water quality classification and fusion-based decision making.

3.3.2.8. EC Sensor

The software processed the electrical conductivity readings and evaluated them against the lettuce-specific optimal range of 1.2 - 1.8 mS/cm, utilizing the values as a key parameter in water quality classification and fusion-based decision-making.

3.3.2.9. Temperature Sensor

The software processed the water temperature readings and evaluated them against the lettuce-specific optimal range of 18 - 24°C, utilizing the values as a key parameter in water quality classification and alert generation.

3.3.2.10. Humidity Sensor

Humidity data was continuously logged in the system database, displayed on the web dashboard, and triggered dashboard warnings whenever readings fell outside the predefined threshold range.

3.3.2.11. Turbidity Sensor

The software processed turbidity readings from the sensor module via the ADC and evaluated them as a fourth water quality parameter in the Random Forest water quality classifier alongside pH, EC, and temperature. Turbidity data was logged in the system database and displayed on the web dashboard.

3.3.2.12. Dosing Pumps

The software controlled the activation and duration of the pH-Up, pH-Down, and nutrient dosing pumps through relay switching commands issued by the dual-mode control logic, executing corrective dosing actions based on the fusion engine output in Full Automation Mode or upon manual confirmation in Semi-Automation Mode.

3.3.2.13. Circulation Pump

The software automatically managed the circulation pump in both operational modes, maintaining scheduled nutrient flow under normal conditions and

immediately halting pump operation upon detection of a Critical, Faulty Sensor, or Faulty Vision condition.

3.3.2.14. GSM Module

The software interfaced with the GSM module to monitor alert trigger conditions and dispatch SMS notifications to the farmer's registered mobile number upon detection of a Critical, Faulty Sensor, Faulty Vision, or Critical Turbidity condition, with separate SMS notifications dispatched upon detection of a Harvest-Ready plant condition or pest presence, operating independently of internet connectivity.

3.3.2.15. Turbidity Monitoring Logic

The software continuously monitored the measured turbidity value acquired from the turbidity sensor. When the measured turbidity exceeded the predefined Critical threshold, the system generated a dashboard warning, logged the timestamp and corresponding turbidity reading, and recommended farmer inspection and manual nutrient solution replacement when necessary. No relay activation or actuator control was performed for turbidity.

3.3.3. Data Gathering Procedure

Data collection for this study was conducted across two phases: the requirements interview phase, conducted before system development, and the system evaluation phase, conducted upon prototype completion.

3.3.3.1. Requirements Interview Phase

A semi-structured interview was conducted with the research participant, a practicing small-scale hydroponic lettuce farmer, before system development to

validate the relevance and practicality of VERDE's proposed features. The interview was conducted in-person, audio-recorded with the participant's written consent, and subsequently transcribed for reference during system design. The interview was guided by six key questions addressing the following:

1. Whether farmers encounter cases where water quality readings appear normal, but plants already show visible stress symptoms such as yellowing or wilting, which directly informed the need for the sensor-vision fusion engine.
2. How frequently farmers misdiagnose plant symptoms without water chemistry context, which validated the importance of cross-referencing sensor data with plant visual detection.
3. Whether farmers currently rely on manual testing, basic sensor alarms, or both, and what limitations they encounter, which informed the system's automated monitoring and alert design.
4. Whether farmers would benefit from a Full Automation Mode that independently controls pH, EC, and circulation pumps during extended absences, which guided the Full Automation Mode operational logic.
5. Whether a Semi-Automation Mode, where only the circulation pump runs automatically while nutrient dosing requires manual confirmation, would better suit farmers who prefer collaborative decision support during active management, which shaped the Semi-Automation Mode design.
6. Whether VERDE's approach of cross-referencing sensor data with plant vision detection addresses a real gap in current hydroponics monitoring practice, which served as overall validation of the study's proposed system concept.

3.3.3.2. System Evaluation Phase

Upon prototype completion, a survey instrument was administered to the research participant to assess overall system performance and user acceptance. The survey collected both quantitative and qualitative data covering the following areas:

1. Accuracy and reliability of sensor readings and water quality classifications (covering pH, EC, temperature, and turbidity)
2. Correctness and usefulness of plant health detection outputs

3. Correctness and usefulness of pest detection outputs
4. Clarity and interpretability of fusion confidence levels as data reliability indicators
5. Responsiveness and usability of the web dashboard interface
6. Appropriateness and timeliness of condition-based SMS alert notification
7. Adequacy of humidity monitoring and dashboard warning behavior
8. Overall satisfaction with the dual-mode operational framework

In addition to the survey, system-generated data were automatically collected and logged by VERDE's database during prototype testing. This included timestamped sensor readings (pH, EC, temperature, turbidity, and humidity), water quality classification outputs, plant health and pest detection results, fusion confidence scores, actuator activation logs, and alert records. Observational notes were also recorded by the researchers to document system behavior, anomalies, and user interactions during evaluation sessions.

3.3.3.3. Comparative Data Collection

To establish a baseline for evaluating system validity, traditional hydroponics monitoring data were gathered from the research participant before system deployment, reflecting the manual monitoring practices currently employed. This baseline data, consisting of manually recorded water quality readings and visual plant assessments, were compared against VERDE's automated sensor readings, classification outputs, and detection results under the same growing conditions. The comparison served to assess whether VERDE's automated monitoring and classification pipeline produced outputs consistent with and more reliable than conventional manual observation, providing a practical measure of system validity in a real farming context.

3.3.3.4. Confidence Level Validation

The correctness of the sensor-vision fusion engine's confidence level classifications was validated by simulating all possible sensor status and plant condition input combinations defined in Table 3 and comparing the system-generated confidence level against the expected output in the VERDE Sensor-Vision Fusion Confidence Level matrix. For each combination, the generated confidence level was recorded and checked against the expected classification. Consistency and correctness rates were computed across all tested combinations to determine the reliability of the fusion logic. Additional validation was conducted by cross-referencing High and Medium confidence outputs against actual observed sensor and plant condition states during prototype testing to confirm that the confidence level accurately reflected the agreement or disagreement between both data streams.

3.3.3.5. Nature of Data

The data collected in this study were primarily quantitative in nature, consisting of numerical sensor measurements, classification outputs, pest detection outputs, fusion confidence scores as data reliability indicators, and system performance metrics including accuracy, mAP, and response latency. Qualitative data were also gathered through the requirements interview and survey instrument, capturing the participants' firsthand experiences with hydroponic monitoring, perceived challenges, and preferences regarding system automation and alert mechanisms.

The quantitative data served as the basis for evaluating the system against the performance targets defined in the study's specific objectives: at least 90% overall system performance, at least 85% mean Average Precision (mAP) for the YOLOv8

plant health detection model, and a system response latency of no more than five seconds. The qualitative data informed the design decisions related to the dual-mode operational framework and dashboard interface and contributed to the overall assessment of system usability and practical relevance.

3.3.3.6. Purpose of Data Collection

Data collected during this study served the following purposes:

1. To validate whether the sensor-vision fusion approach addressed a real and recurring gap in current hydroponic monitoring practice, based on the firsthand experiences of an active hydroponics practitioner.
2. To identify the specific limitations of existing manual and sensor-based monitoring methods encountered by small-scale hydroponic farmers, which informed the design of VERDE's automated monitoring and alert system.
3. To confirm the practical relevance of the Dual-Mode Operation Design by understanding how farmers manage their systems during both active monitoring periods and extended absences.
4. To evaluate the classification accuracy of the Random Forest water quality classifier against labeled sensor test datasets covering pH, EC, temperature, and turbidity.
5. To evaluate the detection performance of the YOLOv8 plant health detection model against annotated test image datasets.
6. To evaluate the detection performance of the YOLOv8 pest detection model against annotated test image datasets.
7. To assess the responsiveness of humidity monitoring in generating dashboard warnings when readings deviated from the defined range.
8. To assess the reliability of the sensor-vision fusion engine in generating appropriate confidence levels across all sensor and plant condition combinations.
9. To measure system response latency from sensor reading and image capture to dashboard update under prototype testing conditions.
10. To document and analyze the operational behavior of the Dual-Mode Operation Design under controlled testing conditions.

3.3.3.7. Ethical Considerations

The conduct of this study observed both legal and ethical standards in the collection, handling, and disposal of research data.

Before the requirements interview, the research participant was provided with an informed consent form explaining the purpose of the study, the nature of the data to be collected, how it would be used, and their right to withdraw participation at any time without consequence. The participant's written consent was obtained before any data collection activity was conducted. Ethics review forms required by the institution were completed and filed in accordance with the applicable research ethics protocols.

To protect the privacy and confidentiality of the research participant, the participant's name and exact location are withheld from this report and all appendices. Throughout this manuscript, the individual is referred to only as "the research participant." Any descriptions of the study site are limited to the level of detail necessary to support the research without revealing personally identifiable information.

The camera module used in this study was dedicated exclusively to capturing images of Butterhead and Looseleaf lettuce foliage together with simulated pest representations (e.g., artificial or toy pests) for plant condition classification and pest presence detection. It was installed at a fixed position above the hydroponic setup and was not directed toward the research participant or any other individual

during prototype testing. Consequently, all image data collected consisted solely of the selected lettuce varieties and simulated pest representations and did not contain personally identifiable visual information. The use of simulated pest representations during prototype testing avoided the need to introduce live insects for experimental purposes while allowing controlled evaluation of the system's pest detection functionality.

Interview recordings and transcripts were used exclusively for research documentation purposes and were not shared beyond the research team. All raw data, including audio recordings, transcripts, survey responses, and system-generated logs, were stored in password-protected storage accessible only to members of the research team throughout the duration of the study.

System-generated data logged by the SQLite database during prototype testing were not modified, filtered, or selectively excluded after collection. All logged entries, including outlier readings and failed detection instances, were retained and considered in the evaluation to ensure the integrity and completeness of the reported results.

Upon completion of the study and after all required documentation has been submitted and approved, all personally identifiable information and raw data collected from the research participant will be securely disposed of in accordance with the institution's data retention and disposal policies. The researchers exercised due diligence in ensuring that all reported performance metrics accurately reflect

the system's behavior under prototype testing conditions without misrepresentation or selective reporting.

3.3.3.8. Data Analysis

Data gathered during both the requirements interview phase and the system evaluation phase were analyzed using the following approaches:

- Qualitative Analysis - Interview responses and survey feedback were reviewed and analyzed thematically to identify recurring challenges, preferences, and insights expressed by the research participant regarding current hydroponic monitoring practices and system usability. Key themes extracted from the transcript and survey, such as the limitations of manual water testing, the difficulty of diagnosing plant symptoms without chemistry context, and preferences between Full and Semi-Automation modes, were used to validate design decisions and confirm the practical relevance of VERDE's proposed features.

- Water Quality Classifier Performance - The performance of the Random Forest water quality classifier was evaluated using the held-out test split of the labeled sensor dataset covering pH, EC, temperature, and turbidity. The following metrics were computed to assess classification performance: accuracy, the proportion of correctly classified instances out of all test instances; precision, the proportion of true positive classifications out of all positive predictions per class; recall, the proportion of true positive classifications out of all actual positive instances per class; and F1-Score,

the harmonic mean of precision and recall, was used to assess overall classification balance across the four water quality classes.

- Plant Health Detection Performance - The performance of the YOLOv8 plant health detection model was evaluated using the held-out test image split of the annotated lettuce dataset. Mean Average Precision at IoU threshold 0.5 (mAP@0.5) was computed across all four plant condition classes: Harvest-Ready, Healthy, Yellowing, and Wilting, to assess overall detection performance. Results were evaluated against the target threshold of at least 85% mAP.

- Pest Detection Performance - The performance of the YOLOv8 pest detection model was evaluated using the held-out test image split of the annotated pest dataset. Detection accuracy and recall were computed to assess the model's ability to correctly identify the presence of pests on lettuce foliage without evaluating species classification.

- Fusion Engine Evaluation - The correctness of the sensor-vision fusion engine was assessed by comparing the system-generated fusion confidence levels against the expected outputs defined in the VERDE Sensor-Vision Fusion Confidence Level matrix in Table 3. For each tested sensor-vision combination, the generated confidence level was recorded and checked against the expected classification. Consistency and correctness rates were computed across all tested combinations to determine the reliability of the fusion decision logic.

- System Response Latency - System latency was measured by recording the elapsed time from simultaneous sensor data acquisition and image capture initiation to the completion of dashboard update and alert generation across a minimum of thirty timed trials. The average and maximum latency values were computed and evaluated against the target threshold of no more than five seconds.

3.3.4. Testing Procedure

This section presents the procedures that were used to evaluate the VERDE system. Each test corresponds directly to the specific objectives of the study, ensuring that all functional, performance, and integration requirements were properly validated under a controlled hydroponic environment.

3.3.4.1. To detect the condition of lettuce plants using computer vision

Objective 1: To evaluate the ability of the plant health detection model to correctly detect and classify lettuce plant conditions as Harvest-Ready, Healthy, Yellowing, or Wilting using camera-captured images of Butterhead and Looseleaf lettuce foliage with and without simulated pest representations.

Materials:

- Microcomputer
- Camera module
- Trained YOLOv8 plant health detection model
- Butterhead and Looseleaf lettuce plants grown in a hydroponic setup
- Web dashboard

- Controlled lighting setup

Procedure:

1. Position the camera module facing the lettuce plants at a fixed angle above the foliage.
2. Ensure the trained YOLOv8 plant health detection model is properly loaded into the system.
3. Activate the VERDE plant detection module.
4. Capture images of lettuce plants representing each of the four condition classes. Harvest-Ready images were captured from plants confirmed at harvest maturity by the research participant based on observable foliage characteristics, including full rosette formation, head size, and leaf density.
5. Run the captured images through the YOLOv8 detection model.
6. Record the predicted plant condition class and the model's internal detection confidence for each image, noting that this refers to YOLOv8's prediction confidence and is separate from the system's fusion confidence level.
7. Display results on the web dashboard with bounding boxes and class labels.
8. Compare model outputs against actual plant conditions through direct visual inspection.
9. Repeat the process under different growth stages to evaluate detection consistency.

3.3.4.2. To detect the presence of pests on the lettuce and send an SMS alert

Objective 2: To evaluate the ability of the pest detection model to correctly identify the presence of simulated pests on lettuce foliage and to verify that corresponding SMS and dashboard notifications were dispatched upon detection.

Materials:

- Microcomputer
- Camera module
- Trained YOLOv8 pest detection model
- Butterhead and Looseleaf lettuce plants grown in a hydroponic setup, with and without simulated pest representations
- Simulated pest representations (e.g., artificial or toy pests)
- GSM module
- Web dashboard

Procedure:

1. Position the camera module facing the lettuce plants at the same fixed angle used for plant health detection.
2. Ensure the trained YOLOv8 pest detection model was properly loaded into the system.
3. Place the simulated pest representations on or near the lettuce foliage under controlled testing conditions.
4. Capture images of lettuce foliage with and without simulated pest representations.
5. Run the captured images through the YOLOv8 pest detection model.

6. Record whether the system correctly outputs a Pest Detected or No Pest Detected result for each image, without evaluating pest species classification.
7. Verify that an SMS notification was dispatched to the farmer's registered mobile number upon a Pest Detected result.
8. Verify that a corresponding dashboard alert was displayed upon a Pest Detected result.
9. Repeat the test across multiple foliage samples from both Butterhead and Looseleaf lettuce and simulated pest placements to evaluate detection consistency.

3.3.4.3. To measure the pH, electrical conductivity, temperature, and turbidity of the water

Objective 3: To evaluate the accuracy and reliability of the pH, EC, temperature, and turbidity sensors in measuring the condition of the hydroponic nutrient solution.

Materials:

- Microcomputer
- pH sensor kit
- EC sensor module
- Water temperature sensor
- Turbidity sensor
- Analog-to-Digital Converter (ADC)

- Hydroponic nutrient solution reservoir
- pH and EC calibration reference solutions
- Reference handheld pH meter, EC meter, thermometer, and turbidity meter
- Web dashboard

Procedure:

1. Install the pH, EC, temperature, and turbidity sensors into the hydroponic nutrient solution at their appropriate positions.
2. Connect the pH, EC, and turbidity sensors to the microcomputer through the ADC, and the temperature sensor via the 1-Wire protocol.
3. Calibrate the pH, EC, and turbidity sensors using their respective standard reference solutions.
4. Run the VERDE data acquisition system.
5. Collect sensor readings from all four sensors, acquired at 5 to 10 second intervals during the testing period.
6. Store and log all sensor outputs in the system database.
7. Display sensor readings on the web dashboard, updated every 30 seconds in synchronization with the fusion cycle.
8. Repeat measurements under varying nutrient solution conditions for each parameter.
9. Validate each sensor's readings against its corresponding reference instrument.

3.3.4.4. To classify the water quality as Optimal, Suboptimal, or Critical, providing the basis for corresponding system response

Objective 4: To evaluate the accuracy of the machine learning classifier in categorizing hydroponic water quality based on pH, electrical conductivity, temperature, and turbidity sensor readings.

Materials:

- Microcomputer
- Random Forest water quality classifier model
- Labeled sensor dataset (pH, EC, temperature, turbidity)
- Web dashboard

Procedure:

1. Collect sensor data from the pH, EC, temperature, and turbidity sensors.
2. Preprocess and normalize the input values.
3. Load the trained Random Forest water quality classifier model.
4. Input the normalized sensor data into the classifier for prediction.
5. Generate the water quality classification output.
6. Store classification results in the system database.
7. Display classification results on the web dashboard.
8. Compare classifier outputs against predefined threshold-based classification rules.
9. Repeat tests under different nutrient solution conditions representing all three classification categories.

3.3.4.5. To monitor ambient humidity and generate dashboard warnings when levels are abnormal.

Objective 5: To evaluate the accuracy of the humidity sensor and the system's ability to generate dashboard warnings when ambient humidity deviates from the defined threshold range.

Materials:

- Microcomputer
- Humidity sensor
- Reference hygrometer
- Web dashboard

Procedure:

1. Install the humidity sensor within the hydroponic growing environment.
2. Connect the humidity sensor to the microcomputer via its digital interface.
3. Run the VERDE data acquisition system.
4. Collect humidity readings from the sensor at regular intervals.
5. Store and log humidity outputs in the system database.
6. Display humidity readings on the web dashboard.
7. Simulate or observe humidity conditions both within and outside the defined threshold range.
8. Verify that a dashboard warning is generated when readings fall outside the defined range.
9. Validate sensor readings against a reference hygrometer

3.3.4.6. To automatically dispense pH-Up solution when the pH level falls below the Optimal range

Objective 6: To evaluate the system's ability to automatically activate the pH-Up dosing pump when the measured pH level falls below the Optimal range of 5.5.

Materials:

- Microcomputer
- pH sensor kit
- pH-Up dosing pump
- 4-channel relay module
- Hydroponic nutrient solution reservoir
- Web dashboard

Procedure:

1. Set the system to Full Automation Mode.
2. Prepare a nutrient solution with a pH level below 5.5 to simulate a below-Optimal condition.
3. Allow the pH sensor to acquire and transmit the below-threshold reading to the system.
4. Confirm that the water quality classifier registers the condition as Suboptimal or Critical.
5. Observe and record whether the system automatically activates the pH-Up dosing pump through the relay module.
6. Measure and record the duration of the dosing action executed by the system.
7. Monitor the pH level following the dosing action to evaluate corrective effectiveness.
8. Log the actuator activation event in the system database.
9. Repeat the test under multiple below-Optimal pH conditions to evaluate response consistency.

3.3.4.7. To automatically dispense pH-Down solution when the pH level rises above the Optimal range

Objective 7: To evaluate the system's ability to automatically activate the pH-Down dosing pump when the measured pH level rises above the Optimal range of 6.5.

Materials:

- Microcomputer
- pH sensor kit
- pH-Down dosing pump
- 4-channel relay module
- Hydroponic nutrient solution reservoir
- Web dashboard

Procedure:

1. Set the system to Full Automation Mode.
2. Prepare a nutrient solution with a pH level above 6.5 to simulate an above-Optimal condition.
3. Allow the pH sensor to acquire and transmit the above-threshold reading to the system.
4. Confirm that the water quality classifier registers the condition as Suboptimal or Critical.
5. Observe and record whether the system automatically activates the pH-Down dosing pump through the relay module.
6. Measure and record the duration of the dosing action executed by the system.
7. Monitor the pH level following the dosing action to evaluate corrective effectiveness.

8. Log the actuator activation event in the system database.
9. Repeat the test under multiple above-Optimal pH conditions to evaluate response consistency.

3.3.4.8. To automatically switch the system between Full Automation Mode and Semi-Automation Mode based on the detected sensor status and plant condition.

Objective 8: To evaluate the system's dual-mode operational design through Full Automation Mode, which autonomously executes corrective actions, and Semi-Automation Mode, which requires manual farmer confirmation before dispensing.

Materials:

- Microcomputer
- pH-Up, pH-Down, and nutrient dosing pumps
- Circulation pump
- 4-channel relay module
- Web dashboard

Procedure:

1. Activate Full Automation Mode.
2. Allow the system to autonomously control all dosing actuators and the circulation pump based on water quality classification and fusion outputs.
3. Observe and record system responses to different sensor and plant condition output combinations, including corrective pH dosing, nutrient dosing, and circulation pump scheduling.
4. Verify that the system automatically overrode to Semi-Automation Mode upon detection of a Critical, Faulty Sensor, or Faulty Vision condition, regardless of the active setting.

5. Switch to Semi-Automation Mode.
6. Verify that corrective dosing recommendations for pH and EC were displayed on the web dashboard and required manual farmer confirmation before execution.
7. Confirm that the circulation pump continued to operate automatically under Semi-Automation Mode under normal conditions and halted upon detection of a Critical, Faulty Sensor, or Faulty Vision condition.
8. Compare system response behavior between the two modes.
9. Record all actuator activation logs and evaluate the effectiveness of both modes in maintaining hydroponic stability.

3.3.4.9. To display monitoring data and alerts through the web dashboard

Objective 9: To evaluate the performance of the web dashboard in displaying sensor readings, plant health and pest detection outputs, fusion confidence levels, humidity status, and system alerts accurately and consistently.

Materials:

- Microcomputer
- Web dashboard
- Connected sensor modules
- Camera module
- Plant health and pest detection modules
- Fusion engine module
- GSM module

Procedure:

1. Launch the VERDE web dashboard on the local network.
2. Connect the system to sensor and camera modules operating at the defined testing intervals.
3. Monitor sensor readings, including humidity, displayed on the dashboard, updated every 30 seconds in synchronization with the fusion cycle.
4. Observe plant health detection outputs with bounding boxes and condition class labels.
5. Observe pest detection outputs and verify correct display of Pest Detected status when applicable.
6. Check fusion confidence level updates displayed on the dashboard as data reliability indicators reflecting the degree of agreement between sensor and vision outputs.
7. Verify system alert displays, including dashboard warnings and condition-based notifications for water quality, humidity, and pest detection.
8. Confirm that SMS alerts were dispatched via the GSM module upon detection of a Critical, Faulty Sensor, or Faulty Vision condition, and that separate SMS notifications were dispatched upon detection of a Harvest-Ready plant condition, or pest presence.
9. Verify that the current active operational mode was persistently displayed on the web dashboard during system operation, including after an automatic override to Semi-Automation Mode.
10. Test dashboard updates under continuous system operation.
11. Validate the correctness of all displayed data against the system database records.

3.3.4.10. To achieve at least 90% overall system performance

Objective 10: To evaluate VERDE's overall System Performance, defined as the composite evaluation across water quality classification accuracy, plant health detection mAP, and system response latency.

Materials:

- Microcomputer
- Labeled test dataset for water quality classification
- Annotated test image dataset for plant health detection
- System timing and logging tool
- Web dashboard

Procedure:

1. Prepare labeled test datasets for the water quality classifier and the plant health detection model.
2. Run the Random Forest water quality classifier on the labeled test dataset and compute accuracy, precision, recall, and F1-score across all three classification categories, covering pH, EC, turbidity, and temperature.
3. Run the YOLOv8 plant health detection model on the annotated test image dataset and compute mAP@0.5 across all four plant condition classes.
4. Record all prediction outputs and compare against ground truth labels.
5. Measure system response latency from sensor reading acquisition and image capture initiation to dashboard update and alert generation, evaluated across a minimum of thirty timed trials conducted at the defined testing intervals of 5 to 10 second sensor reads and 30 second fusion cycles.
6. Compute the average and maximum latency values across all trials.
7. Compare all results against the defined System Performance targets: water quality classification accuracy of at least 90%, plant health detection mAP of at least 85%, and system response latency not exceeding five (5) seconds.

8. Analyze and document whether the system met all three System Performance targets.

3.3.5. Design Constraints

3.3.5.1. Technical

The system monitored four water quality parameters, pH, electrical conductivity (EC), water temperature, and turbidity, and did not monitor additional parameters such as dissolved oxygen or ammonia. Ambient humidity was monitored independently of the water quality classifier and did not factor into water quality classification. The plant health detection model was scoped to four lettuce-specific condition classes and did not extend to other crop species or comprehensive plant disease diagnosis. Pest detection was limited to identifying the presence of insects or pests on the lettuce foliage and did not classify pest species or severity. Detection accuracy depended on consistent and adequate lighting conditions; performance under low-light or highly variable lighting environments was not guaranteed. The system operated on a local network and did not support real-time cloud synchronization.

3.3.5.2. Manufacturability

The prototype is designed with practicality and ease of construction in mind. The prototype was designed with practicality and ease of construction in mind. The system was modular, allowing components to be assembled, replaced, or reconfigured with relative ease. All components were selected for local availability and were accessible from local electronics suppliers or

online marketplaces, ensuring reproducibility for small-scale or community-level production. The prototype was designed for single-unit evaluation and was not optimized for multi-bed or large-scale hydroponic deployments. Physical temperature, humidity, and turbidity control actuators were not included in the current prototype due to budget limitations; temperature and humidity deviations were therefore managed exclusively through dashboard warnings rather than automated corrective dispensing. Turbidity, similar to ambient humidity, was limited to monitoring rather than automatic correction. However, unlike ambient humidity, Critical turbidity additionally generated a dashboard warning and SMS notification recommending manual inspection and nutrient solution replacement by the farmer when necessary. The prototype did not include hardware for automatic turbidity adjustment. Similarly, pest detection did not trigger any automated corrective action, as the system was limited to notification only.

3.3.5.3. Economic

All components were selected for cost-efficiency without compromising functional accuracy, including sensors, processing units, and actuators sourced within the study's budget constraint. To further reduce overall system costs, the system architecture was optimized to run all processing, inference, and dashboard hosting natively on the microcomputer, eliminating the need for a separate external server and avoiding the

operational expenses associated with maintaining a cloud-based or server-based setup.

3.3.5.4. Legal and Ethical

The conduct of this study adhered to the Data Privacy Act of 2012 (Republic Act No. 10173). Only operationally necessary data was collected and transmitted through the system, and no personal information beyond the farmer's registered mobile number for SMS alert notifications was stored. All data collected during system testing were used exclusively for research evaluation purposes and were not shared with third parties. The identity of the research participant was kept confidential throughout the study in accordance with the ethical considerations outlined in Section 3.3.3.7.

3.3.6. Design Revisions

3.3.6.1 Block Diagram

The revision focused on improving the accuracy of the hardware representation by removing internal software processing modules from the block diagram, regrouping sensor components, and adding GSM Module, Relay Module and Dosing Actuators to complete the hardware configuration.

a. Previous

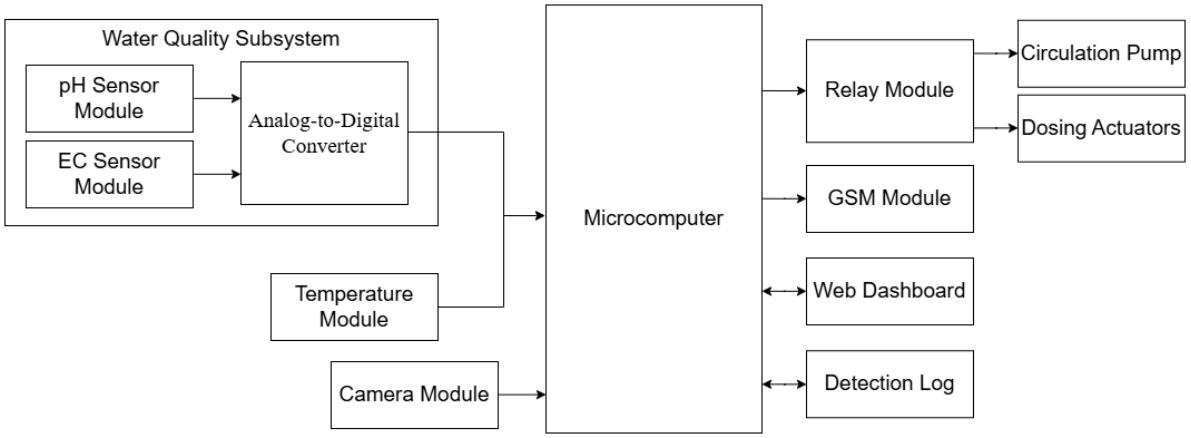


Figure 5. Previous Block Diagram

Figure 5 shows the original block diagram of VERDE, illustrating the hardware configuration and signal flow of the proposed hydroponic monitoring and control system. The pH and EC Sensor Modules are grouped under a Water Quality Subsystem, with their analog outputs passing through an Analog-to-Digital Converter (ADC) before being transmitted to the microcomputer, which does not natively support analog input. The Temperature Module and Camera Module connect directly to the microcomputer through their respective digital interfaces. Acting as the central processing unit, the microcomputer processes sensor and image data, then sends control signals to the Relay Module, which operates the Circulation Pump and Dosing Actuators. Alert notifications are transmitted through the GSM Module, while the Web Dashboard and Detection Log maintain bidirectional communication with the microcomputer to support continuous monitoring,

user interaction, and data storage. This original block diagram represents the baseline hardware architecture prior to the integration of the turbidity and humidity sensors introduced in the revised design.

b. Current

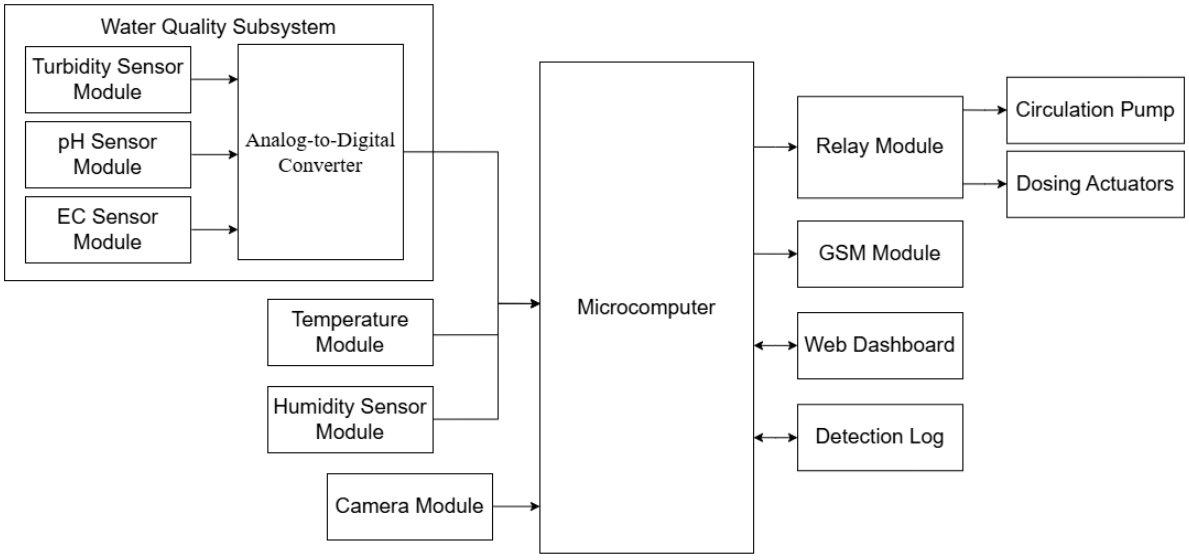


Figure 6. Current Block Diagram

Figure 6 shows the revised block diagram of VERDE, illustrating the updated hardware architecture and signal flow of the proposed hydroponic monitoring and control system. The Turbidity Sensor Module, pH Sensor Module, and EC Sensor Module are grouped under the Water Quality Subsystem, with their analog outputs passing through an Analog-to-Digital Converter (ADC) before being transmitted to the microcomputer, which does not natively support analog input. The Temperature Module, Humidity Sensor Module, and Camera Module connect directly to the microcomputer through their respective digital interfaces. Acting as the central processing unit, the microcomputer processes sensor and image data, executes machine learning inference and control logic, and issues control signals to the Relay Module, which operates the Circulation Pump and

Dosing Actuators for automated nutrient management. Alert notifications are transmitted through the GSM Module, while the Web Dashboard and Detection Log maintain bidirectional communication with the microcomputer to support continuous monitoring, user interaction, data visualization, and historical record storage. Compared to the previous design, the revised block diagram incorporates the Turbidity Sensor Module and Humidity Sensor Module, expanding the system's monitoring capabilities. Turbidity readings are processed by the microcomputer and displayed on the web dashboard, but no dedicated actuator is implemented for turbidity correction in the current prototype; when turbidity exceeds the Critical threshold, the system generates a dashboard warning and SMS notification recommending manual inspection and nutrient solution replacement by the farmer, while the overall hardware architecture and signal flow otherwise remain preserved.

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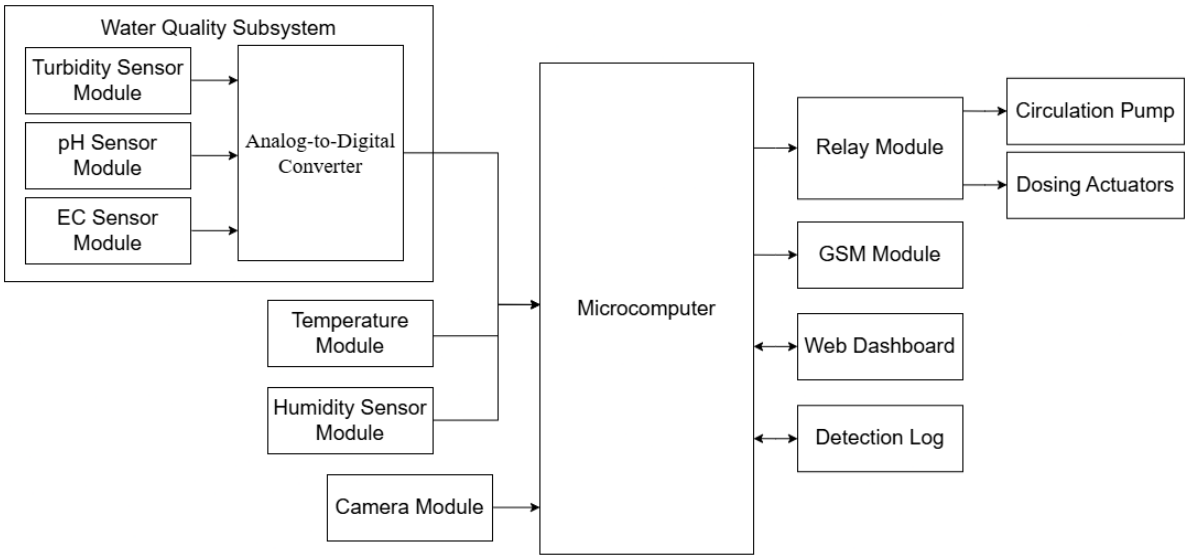
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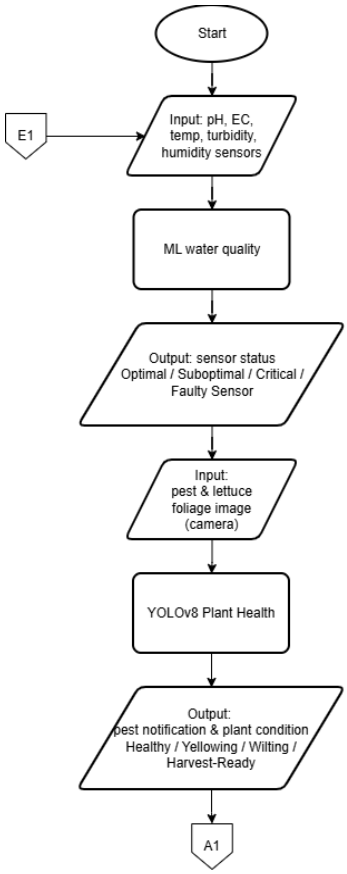
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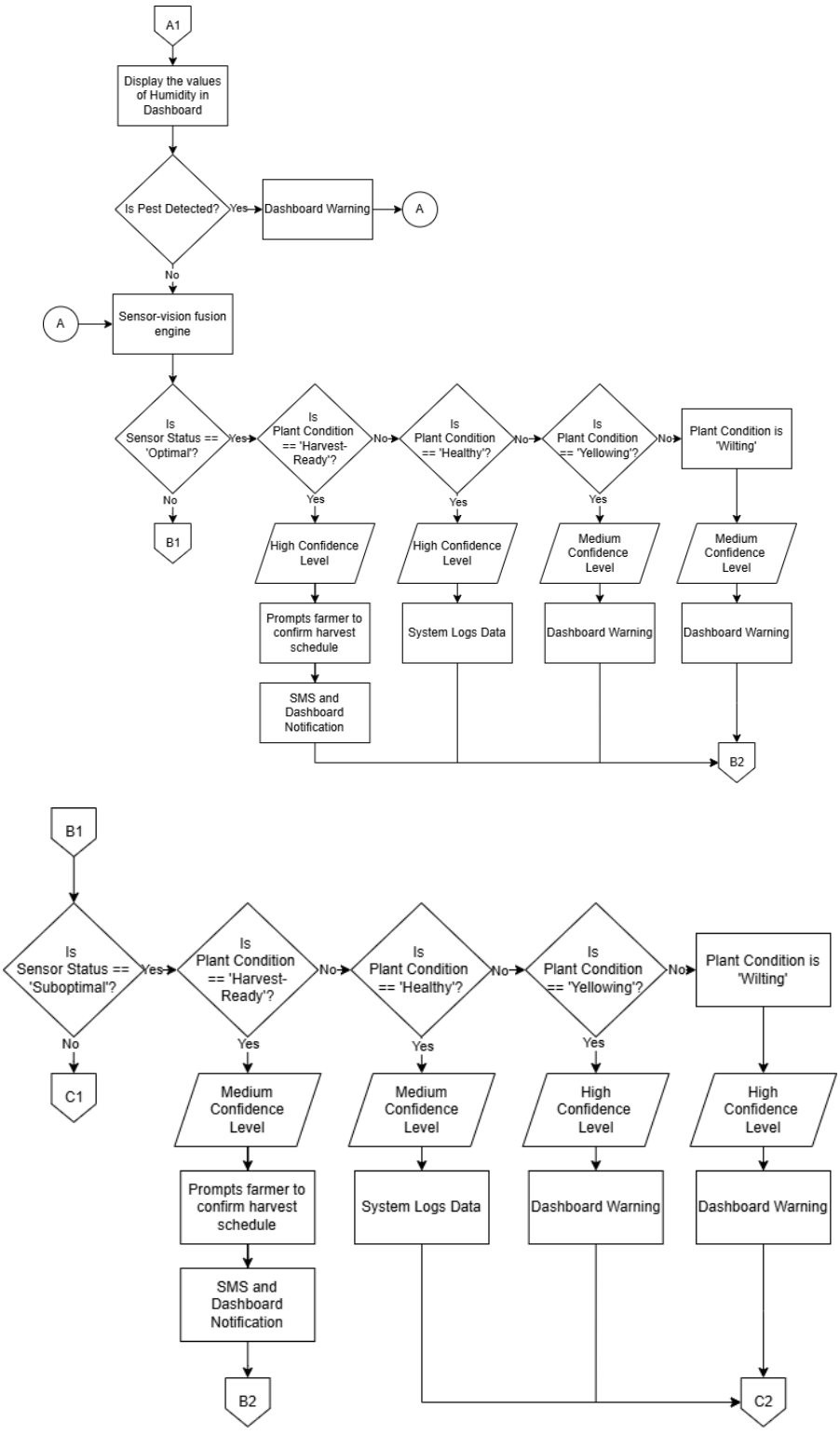
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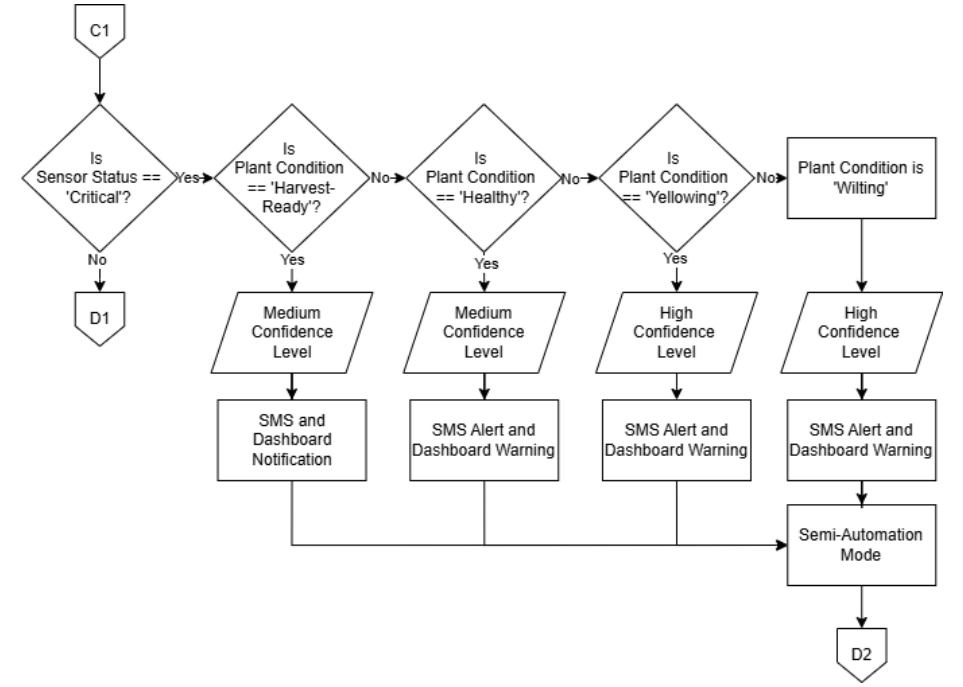
APPENDIX B: BLOCK DIAGRAM

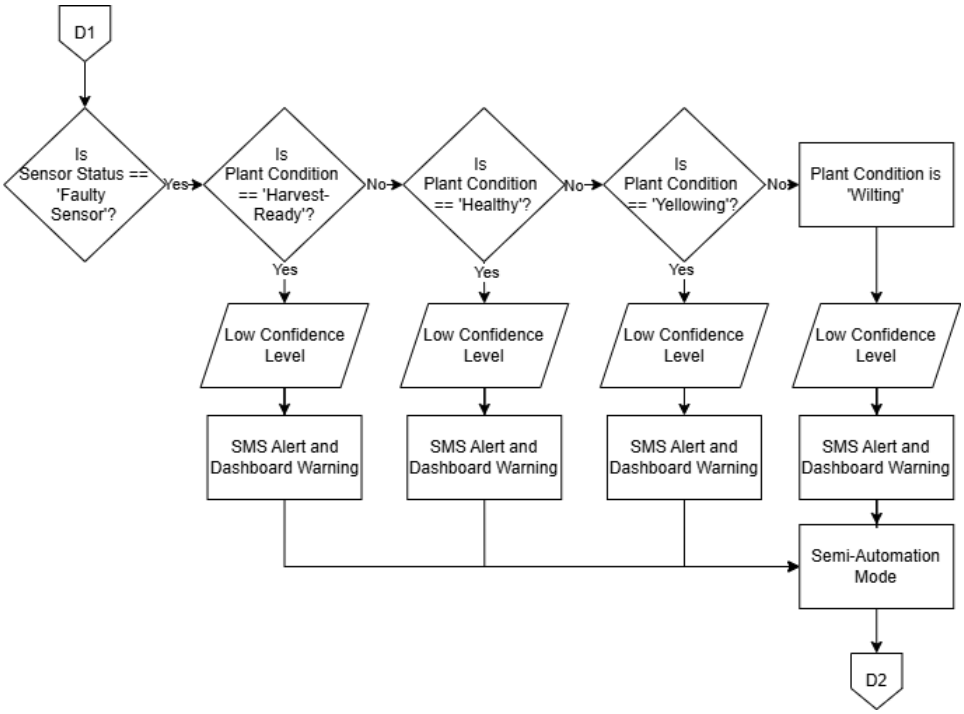


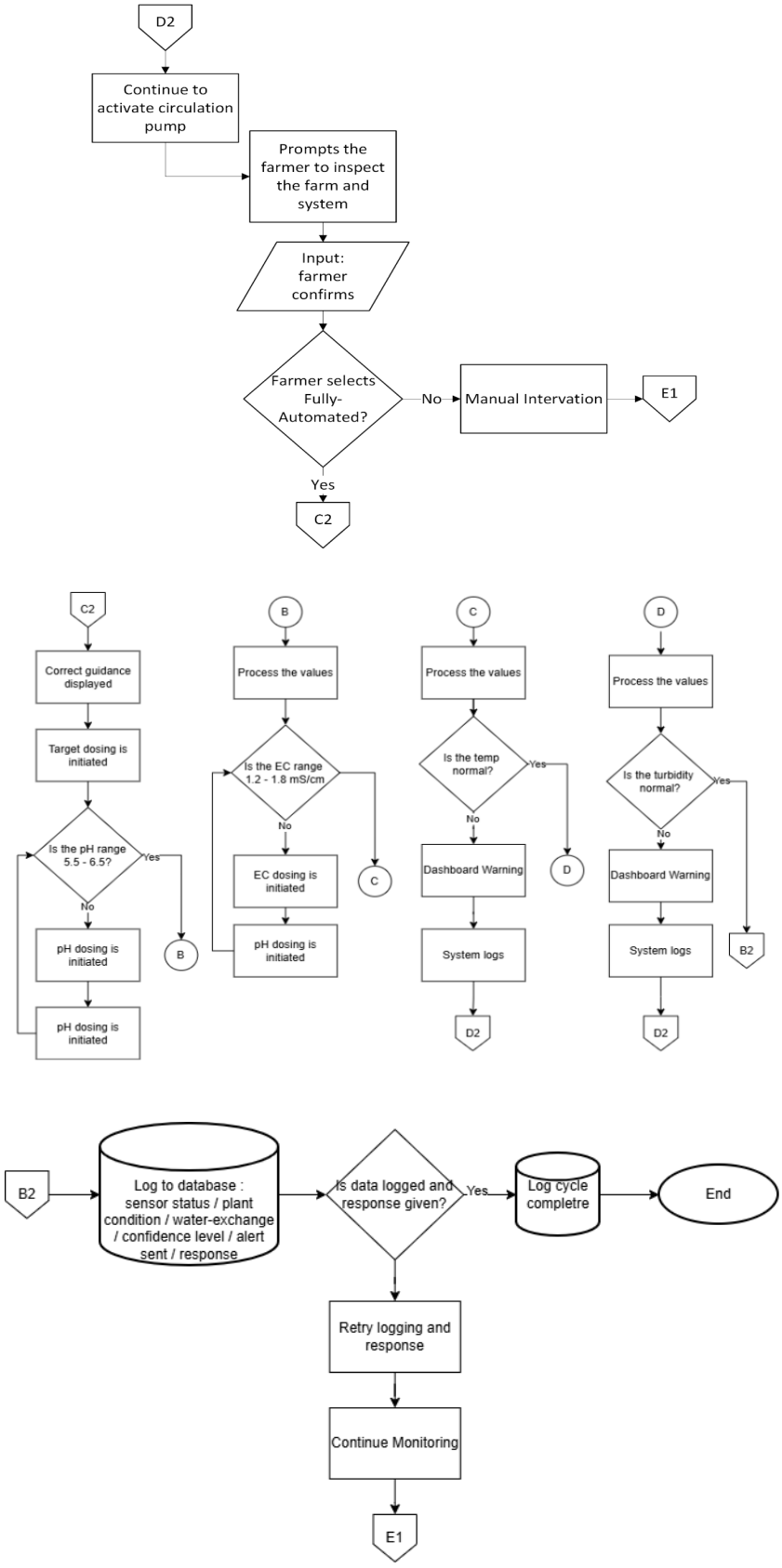
APPENDIX D: SYSTEM FLOWCHART




A1
Display the values of Humidity in Dashboard
Is Pest Detected?
Yes
Dashboard Warning
A
No
A
Sensor-vision fusion engine
Is Sensor Status == 'Optimal'?
Yes
Is Plant Condition == 'Harvest-Ready'?
No
Is Plant Condition == 'Healthy'?
No
Is Plant Condition == 'Yellowing'?
No
Plant Condition is 'Wilting'
No
Yes
Yes
Yes
B1
High Confidence Level
High Confidence Level
Medium Confidence Level
Medium Confidence Level
Prompts farmer to confirm harvest schedule
System Logs Data
Dashboard Warning
Dashboard Warning
SMS and Dashboard Notification
B2
B1
Is Sensor Status == 'Suboptimal'?
Yes
Is Plant Condition == 'Harvest-Ready'?
No
Is Plant Condition == 'Healthy'?
No
Is Plant Condition == 'Yellowing'?
No
Plant Condition is 'Wilting'
No
Yes
Yes
Yes
C1
Medium Confidence Level
Medium Confidence Level
High Confidence Level
High Confidence Level
Prompts farmer to confirm harvest schedule
System Logs Data
Dashboard Warning
Dashboard Warning
SMS and Dashboard Notification
B2
C2


C1
Is Sensor Status == 'Critical'?
Yes
No
D1
Is Plant Condition == 'Harvest-Ready'?
No
Yes
Medium Confidence Level
SMS and Dashboard Notification
Is Plant Condition == 'Healthy'?
No
Yes
Medium Confidence Level
SMS Alert and Dashboard Warning
Is Plant Condition == 'Yellowing'?
No
Yes
High Confidence Level
SMS Alert and Dashboard Warning
Plant Condition is 'Wilting'
High Confidence Level
SMS Alert and Dashboard Warning
Semi-Automation Mode
D2


D1
Is Sensor Status == 'Faulty Sensor'?
Yes
Is Plant Condition == 'Harvest-Ready'?
No
Yes
Low Confidence Level
SMS Alert and Dashboard Warning
Is Plant Condition == 'Healthy'?
No
Yes
Low Confidence Level
SMS Alert and Dashboard Warning
Is Plant Condition == 'Yellowing'?
No
Yes
Low Confidence Level
SMS Alert and Dashboard Warning
Plant Condition is 'Wilting'
Low Confidence Level
SMS Alert and Dashboard Warning
Semi-Automation Mode
D2


D2
Continue to activate circulation pump
Prompts the farmer to inspect the farm and system
Input: farmer confirms
Farmer selects Fully-Automated?
No
Manual Intervation
E1
Yes
C2
C2
Correct guidance displayed
Target dosing is initiated
Is the pH range 5.5 - 6.5?
Yes
No
pH dosing is initiated
pH dosing is initiated
B
B
Process the values
Is the EC range 1.2 - 1.8 mS/cm
No
EC dosing is initiated
pH dosing is initiated
C
C
Process the values
Is the temp normal?
Yes
No
Dashboard Warning
System logs
D2
D
D
Process the values
Is the turbidity normal?
Yes
No
Dashboard Warning
System logs
D2
B2
B2
Log to database : sensor status / plant condition / water-exchange / confidence level / alert sent / response
Is data logged and response given?
Yes
Log cycle completre
End
Retry logging and response
Continue Monitoring
E1

APPENDIX L: TRANSCRIPT OF INTERVIEWS

Transcription:

Researcher Ah ayan. So ayun, good afternoon po ulit. Ah unang questions po namin is ah may mga customer po ba kayo na ano naka-experience ng mga case na yung water quality readings po kapag po chine-check nila is normal pero po yung mga halaman is nagpapakita po ng iba pang mga stress. Kunyari po ah medyo naninilaw na or medyo wilting na sila.

Interviewee Yes. O, actually talagang naranasan namin talaga yun ah kasi maraming factor ah. Yung yung ating kung bakit nagkakaganun kung okay naman yung parameter, yung water natin, yung pH niya, yung potential of hydrogen, ppm, yung parts per million is okay naman. Pero yung temperature, yung humidity hindi siya maganda kasi nagma-matter po lahat yan eh.

Interviewee Hindi kasi pwedeng magba-balance lang tayo sa isang, let's say ah kino-correct mo yung pH. Okay yung regarding sa question mo, okay naman yung quality ng water natin. Hindi pwedeng doon lang tayo magbase sa isa. Nagma-matter yung pH natin, nagma-matter yung temperatura. Yun kasi napakaimportante. And then yung system, kung ang system natin ay hindi maganda, yun yung mangyayari.

Researcher Ah bale, ano po yung doc nag-mention po kayo ng tatlo sa apat po, kung sasama po yung ppm, alin po doon sa apat yung parang pinaka-priority niyo na unahin na ayusin po?

Interviewee Actually ang number one na kailangang ayusin yung system, yung greenhouse. Yan yung pinaka number one na importante. Yung greenhouse natin ah, kung kasing sa pH madali lang siyang i-monitor eh. So kung ang system natin ay hindi magiging maayos, kahit i-correct mo yung pH, kahit i-correct mo yung ppm, wala rin.

Interviewee Sobra nga eh, ka nalilinis, sobrang pag lumaki yung pH niya, kapag nako-correct mo siya, the problem yung humidity, yung temperatura is ganun pa din. Wala rin, hindi mo pa rin masosolusyunan yung mga maaaring magiging problema mo. Yun kasi napakaimportante.

Interviewee To follow na lang yung pH, yung EC, yung ppm, to follow na lang. Bale parang kailangan po talaga combine siya, tine-taking consideration, hindi po pwedeng paisa-isa lang.

Researcher Oo, mm, yun siya opo.

Interviewee Yun yung kailangan natin. Kasi sir okay naman pH namin, okay naman pero yun nga yung humidity yung temperatura, mainit. Yung greenhouse kasi number one nating kailangan i-consider yung greenhouse natin. Okay? Kasi nasa mainit na lugar tayo eh. So kapagka yun ay hindi natin na-practice, wala rin.

Researcher Ah next po is, gaano po kadalas ah nami-misdiagnose po ng mga customer niyo yung mga symptoms nung plant, ah kapag po walang chemistry context or hindi po nila masyadong naiintindihan po yung mga ano meaning nung mga values.

Interviewee Yes. Exactly. Dun sa question mo, meron kasi tayong hit na basic. Ito yung walang meter. So ayan. Hindi nila mada-diagnose kung ano ba yung kulang kasi hindi nila nasusukat. Although naggo-grow naman sila. Pero yun nga, kapagka yung tanim natin ay nagkasakit, hindi natin alam kung ano yung source ng sakit niya kasi hindi tayo gumagamit ng meter.

Interviewee Unlike doon sa isang complete set, meron siyang kasamang meter. Alam mo kung mababa or mataas yung pH niya kaya siya hindi lumalaki, kasi mabagal yung uptake niya ng nutrients. Kung okay naman yung temperatura, okay naman yung greenhouse mo pero wala kang system nung pH para ma-correct mo yung potential of hydrogen, ma-correct mo yung ppm. Yun yung mangyayari sa kanya. So hindi rin siya maggo-grow properly.

Interviewee Pero may time naman na, kaya nga dalawa yung kit natin eh. May time naman na kahit wala yung meter na yon naggo-grow yung mga tanim natin. So ganun yung nangyayari. Ayon. So yung ah pangmeasure po ng mga values, manual testing pa rin po ba, or like ah may mga sensors or yung manual po na paisa-isa lang po talaga? Combine siyang 4-in-1 meter siya, meron siyang meter yan.

Interviewee Ayan, andiyan siya lahat. So sasawsaw mo lang sa tubig. Ayan na siya. Nakikita mo na, monitor mo na siya.

Researcher Pwede po naming matanong kung ano pong device ito?

Interviewee Ito yung tinatawag nating 4-in-1 TDS meter. Total Dissolved Solids meter.

Researcher So ano pong limitations nila kapag po yan yung ginagamit?

Interviewee Ito mas nabibigay mo yung tamang pagkain para doon sa halaman kasi sa science to eh. So alam mo kung ano yung needs nila, kung mababa yung pH. Kasi kapag alkaline or acidity yung water natin in terms of hydroponics, mabagal yung uptake ng nutrients ng ating mga halaman. So ganun po yun.

Researcher Ah next po is, magbe-benefit po ba yung mga customer niyo if meron po tayong fully automated na mode kung saan po automatic niyo na pong kino-control yung pH, yung EC, and yung temperature, pati na rin po yung circulation ng tubig, habang ah kunyari po nagre-rest, hindi po kayang physically na bantayan.

Interviewee Actually meron naman na ganon, sobrang mahal lang. Pero meron ng gumawa ng mga estudyante na nagche-thesis sa akin na nagawa sila nung automation na correction ng pH, correction ng ppm. So meron silang ginawa. Ano ba, university yata yun, mga estudyante ng ibang university. Ayun. So malaking benepisyo yun. The problem lang yung market value niya, sobrang mahal, 50,000.

Interviewee So ako ang inaalok sa akin ng Chinese supplier, pinakamababa na yung pH, 45,000 na pang-automated na pH tsaka PPM. Siya na yung mag-a-adjust kapag mababa or mataas yung pH.

Researcher So kung kayo po ang papipiliin, ano po yung mas magiging beneficial, yung fully automated po ba or semi-automated? Ang semi-automated po is automatic pa rin po yung circulation ng pump pero yung mga dosing po nung pH, nung EC, kailangan pa rin po ng confirmation nung farmer sa dashboard app or website. Alin po yung mas prefer niyo?

Interviewee Syempre mas sa akin yung automated dosage na siya. Yun na yung pinaka-best. Kasi kung naka-semi-automated ka rin naman, bayt hindi ka pa pumunta doon sa upgraded na version. Kaya naka-upgrade ka na nga pero parang parang bumili ka ng isang bagay pero may kailangan kang idagdag. So parang hindi rin siya masyadong gamit. So additional ka pa na nagagawa. So ganon.

Researcher Pero kung reading po nung mga sensor is parang critical range na po, ang prefer niyo pa rin po ba na fully automated po siya or farmer na po muna yung magha-handle if critical?

Interviewee Kasi kung yun kasing siguro kung magkakaroon ng problema, kailangan talaga pero yung device kasi na yun is accurate yun. Nakita ko na kasi sa mga malalaking farming eh. So kapag yun ay hindi naging tama yung function niya, ibig sabihin may problema yung device kasi hindi niya ma-correct yung pH sa kanyang sarili. Pero yun yung trabaho niya, hindi siya nagpa-function ng properly yung machine na nilagay natin. So yun yun. So ima-manual ng farmer.

Researcher Ay yung machine po na yun, paano po yung checking nung mga value, naka-connect sa cellphone?

Interviewee Oo.

Researcher Ah meron po silang mga notification kapag tumataas, bumababa, may history din po.

Interviewee Meron siya.

Researcher What if po, mayroon na rin siyang vision, ico-compare niya po yung sensor readings plus po yung live condition nung plants po, na fully sensors lang?

Interviewee Mas maganda yun. Mas high tech yun, although wala pa nung sa mga farm na, wala pa. Pero mas ang pinaka, yung highest na yon, isang upgrade na system yan.

Researcher Mas gugustuhin niyo po ng ganon kaysa po sa sensors lang?

Interviewee Syempre, kanya yan eh, kumbaga fully upgraded.

Researcher Then yung app niya po is full history din po, included po yung sensors, ratings and yung status po nung plant.

Interviewee Oo. Parang yung nakaraan, dito may nakalagay silang camera, may data sila daily. Nagba-base sila kung gaanong inches yung nilaki, kung ilang centimeter yung nilaki nung halaman. Parang ganun siya. May camerang ginawa diyan. Puro camera.

Researcher So doon po sa nabanggit po namin, parang may initial thought po ba kayo na posible pong maging problema ng system if mag-combine po kayo ng sensor connection ng WiFi?

Interviewee Mostly dito naman sa atin sa Pilipinas eh ang nagkakaroon tayo ng problema, hindi yung internet connection natin eh. Yun lang naman eh, kasi magfa-function ng, eh kung nagawa nating properly yan, the problem dito sa atin sa Pilipinas yung internet connection. Kasi once na nawalan ng connection ng WiFi, doon magkakaproblema. Yun yung nakikita kong problema doon – WiFi connection, internet.

Interviewee Yun kasi yun nga, unpredictable. Minsan ba, na-experience sa bahay natin, tulad ko, may time PLDT walang signal, di ba, yung Converge walang signal. So yun lang yun, yung possible na nakikita ko pwedeng nagkaroon ng problema.

Researcher So yung sa last question po namin, based po sa experience niyo, yung approach po namin ng system which is nagco-cross reference po nung sensor pati po nung plant vision, may ina-address po ba siyang gap sa current po na manual monitoring ng mga hydroponic systems?

Interviewee Meron. Bale yung sa inyo, kasi magkagandahan sa sa inyo, kung hindi ka makapaglista kung kailan mo siya iha-harvest, kayang ma-detect nung machine niyo na ganitong date for harvest na siya. Dadagdag natin siya. Let's see. O nagtanim ako ngayon dito. Meron akong tanim ako ngayon dito, wala lang ako. Nakalimutan ko siya kung kailan ko siya tinanim. So yung yung machine niyo, made-detect niya kung kailan siya pwedeng i-harvest. Yun yun.

Researcher Okay. So ah, pwede po namin siya i-take, bale ang magiging system po namin is iche-check niya po yung plant kung normal ba or nagwi-wilting. And yung additional po is if possible na po siya ma-harvest. Yes. Pwede po namin siya i-take.

Researcher Tsaka po, bale yung ano namin, yung system po namin, sensor po siya na ano, may computer vision. Yung nagagawa po ng computer vision is ayun nga po, parang it-train po namin yung camera na may AI, YOLO, na may AI na ite-train po namin siya na healthy yung lettuce, i-co-compare po namin sa parang nanlalata yung parang hindi na healthy na lettuce. Ganun po yung process ng system namin.

Researcher So ayan po, parang mas ano po, mas reliable po yung ano system kasi po dalawa po yung comparison nya, kasi yun nga po yung add po namin, yung sinabi niya pong predicting yung kailan po ma-harvest.

Interviewee O kasi mostly minsan yung ibang farmer tsaka nakaligtaan, nakalimutan e. Tulad ko, lalo na kung busy. Kasi yung akin dito yung mga tanim ko dito is for viewing lang din talaga, minsan ah hindi ko alam kung kailan po iha-harvest. Ayan kasi, pag may mga tanim na. Ayan siya nasa taas. Ayan siya.

Researcher Opo. Parang mahirap po siya bantayan. So ayan. Yan yung setup ko dito kapag punong-puno ng tanim.

Interviewee Yan yung setup ko dito kapag punong-puno ng tanim.

Researcher Ayan yung nasa gilid. So bale dagdag question na lang po. Ah nasa technical site po, ah yung normal values po nung pH, EC, pati po yung temperature para po sa lettuce.

Interviewee Oo. So pH natin at least 6.0. 6.0. Oo. Yung EC natin, 1.2 yan. Then yung PPM around 800 to 900. And then yung temperature natin, huwag lang lalagpas ng 40, nasa, hindi naman kasi kaya talaga 35. Oo, 35 siya, yun yung kailangan nating attain. Doon sa 35. Ayan, okay.

Researcher Tsaka ah, hindi na po siya question pero parang request na lang po. Kapag po nag-testing, kasi po yun nga po, magbe-base po tayo sa sensor at saka po sa vision. Bale medyo madami po tayong kailangan. Ah i-ask lang po namin yung guidance niyo since ah ang AI po kasi dito yung vision is parang binabasa niyo po yung pattern. Kunyari po ah yung pH po is unti-unti siyang nataas or nababa pero yung temperature niya is normal, EC is normal, pero may sudden changes po doon sa plant.

Researcher Aalamin po nung system natin, combined po yung sensor, yung changes po nung sensor pati po yung plant, aalamin niya po ano po yung tamang status. Oo. Habang hindi pa po siya nakakarating doon po sa status na medyo grabe na po pala yung change ng pH, dapat habang unti-unti siyang nagbabago, alam na po ng system.

Interviewee Maganda yun.

Researcher Ah ang ire-request lang po namin is guidance po para po tama po yung pag-measure namin para ma-determine kung ano po yung tamang status ng halaman. Yun lang po ang request.

Interviewee Maayos naman, anong course? Computer Engineering din yung mga nagthesis sa akin din. Saan niyo ilalagay yung kwan? Sa saan niyo planong i-put?

Researcher Actually yung una po namin naisip is small lang siya for testing, if possible po kahit sa bahay. Pwede po sa bahay.

Interviewee Oo.

Researcher Or kailangan po nasa maayos na po siya.

Interviewee Okay lang naman doon pero kailangan naaarawan siya. So kailangan mag-build ng isang maliit na setup.

Researcher Kasi po for testing hindi po namin kailangan yung mahahabang system, kahit po yung maliit lang.

Interviewee Oo, styro lang yung ganyan.

Interviewee Ano ba requirement sa inyo? Basta system NFT or wala naman.

Researcher Hindi pa tayo nakakasearch, sa ngayon po is Thesis 1 paper po, parang proposal.

Interviewee Oo. Huwag niyong kunin yung aquaponics.

Researcher Napakahirap nga po e. Opo. Yun po yung sinimula namin, tsaka nagbago po kami. Kasi mahirap po yung ano, pagde-depensa na yung prototype.

Interviewee Nakaaquaponics ako before, ang hirap niyang i-maintain. Tapos ang dami mong sinusukat doun. Kailangan alam mo yung amount nung isda na ilalagay mo doun sa halaman. Tapos parang dagdag mo pa gagastusin niyo doon. Sa aquaponics, pag hindi niyo pa alam alagaan yung isda, malalagot pa kayo. Mahirap.

Researcher Ayun lang naman po yung mga tanong namin.

Interviewee Wala na, okay na kayo?

Researcher Opo, okay na po.

APPENDIX M: LETTERS

FEU INSTITUTE OF TECHNOLOGY

May 26, 2026

Green Pasture Hydroponics Supply
Guiguinto, Bulacan

To the Management of Green Pasture Hydroponics Supply,

Good day!

We are Computer Engineering students at FEU Institute of Technology taking Thesis 1. We are finalizing our thesis concept, **VERDE** — an IoT-based smart hydroponics system that fuses **sensor data** (pH, EC, temperature) with **YOLO-based plant health detection** (Healthy, Yellowing, Wilting) to generate confidence-scored alerts and automate nutrient management.

Key Features:

- **Dual-Mode Operation: Full Automation (pump + dosing) or Semi-Automation (pump auto, dosing with manual confirmation)**
- **Sensor–Vision Fusion: Cross-checks water chemistry against plant appearance to reduce false alerts and detection lag**
- **Real-time Alerts: Dashboard + SMS with High/Medium/Low confidence scoring**

We believe Green Pasture Hydroponics Supply would be a valuable beneficiary, given your role in supporting local hydroponics growers. We seek your insights on whether VERDE addresses real farmer needs.
We request an interview on May 27, 2026, or any convenient day at your preferred time.

Attached below are some of the interview questions for your review:

1. Do your customers experience cases where water quality readings appear normal, but plants already show visible stress (yellowing, wilting)?
2. How often do your customers misdiagnose plant symptoms (e.g., confusing nitrogen deficiency with iron lockout or natural senescence) without water chemistry context?
3. Do your customers currently rely on manual testing, basic sensor alarms, or both? What limitations do they encounter with these methods?
4. Would your customers benefit from a **Full Automation Mode** that independently controls pH, EC, temperature dosing, and circulation pumps during extended absences?
5. Would a **Semi-Automation Mode**, where only the circulation pump runs automatically while nutrient dosing requires manual confirmation, better suit farmers who want collaborative decision support during active management?
6. Based on your experience with growers, does VERDE's approach of cross-referencing sensor data with plant vision detection address a real gap in current hydroponics monitoring?

Thank you for your time and kind consideration. We are hoping for your positive response.

Respectfully yours,

Joseph Emmanuel V. Landeza

Kim Marwin S. Roque

John Benedict C. Pantalla

Brian James S. Sager

MOISES F. JARDINIANO
Thesis Adviser

FEU INSTITUTE OF TECHNOLOGY

VERDE Hydroponics System - Participant Consent Form

Title of Study: VERDE: IoT-Based Hydroponics System with Sensor-Vision Fusion for Plant Health Monitoring and Nutrient Management

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Purpose of the Interview

You are invited to participate in an interview to provide feedback on VERDE, an IoT-based smart hydroponics system that combines water quality sensors (pH, EC, temperature) with computer vision (YOLO-based plant health detection) to automate nutrient management and generate confidence-based alerts. The purpose is to understand real-world hydroponic monitoring practices, challenges, and whether VERDE addresses actual farmer needs.

Participation Details

- Participation is **voluntary**. You may refuse to answer any question or withdraw at any time without penalty.
- The interview will take approximately **30–45 minutes.**
- Interviews will be conducted **face-to-face** at your preferred location.
- With your permission, the interview may be **audio-recorded** for accurate documentation. Recordings will be deleted after transcription.

Procedures

- You will be asked questions about your current hydroponic monitoring practices, challenges with manual testing or basic sensors, and your thoughts on automated features such as Full Automation Mode and Semi-Automation Mode.
- Notes and optional audio recording may be taken to document the session.
- If you agree to prototype testing in a separate phase, the VERDE system will be temporarily installed in your hydroponic setup for evaluation. *(This is optional and requires separate agreement.)*
- No personally identifiable information will be published. You will be referred to as "Participant A" or described by your general role (e.g., "small-scale hydroponic farmer").

Risks and Benefits

- **Risks:** There are no anticipated risks beyond normal conversation. The time commitment is minimal, and you may stop at any time.
- **Benefits:** Your feedback will help develop VERDE, potentially improving hydroponic monitoring and nutrient management for small-scale Filipino farmers. You will also receive early access to the prototype during testing.

Confidentiality

All information will be kept confidential. Summarized responses may be used in reports or presentations, but your identity will not be disclosed without your explicit permission. Data will be stored securely and accessed only by the research team and faculty adviser.

Consent

By signing below, you indicate that:

- You have read and understood the purpose of this interview.
- You voluntarily agree to participate.
- You understand that you can withdraw at any time.

Participant Name / Initials: ARCIE KING MACOPAGAL

Signature: _____

Date: May 26, 2026

Interview Conducted By: Landeza, Pantalla, Roque, Sager