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Research Article

IoT-Based: Smart Hydroponic Farming with SSD MobileNet and Fuzzy Logic

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Abstract: Traditional hydroponic systems largely rely on manual observation and regulation of essential environmental variables, such as pH, nutrient concentration, temperature, and humidity. This dependence often causes inefficiency, inconsistent crop quality, and greater labor requirements. To overcome these limitations, this study proposes an IoT-based Smart Hydroponic System that integrates fuzzy logic control with computer vision using the SSD MobileNet architecture. The objective of this research is to design and implement an intelligent automation framework capable of improving hydroponic cultivation through continuous data monitoring, analytical decision-making, and autonomous environmental adjustment. Within this framework, fuzzy logic dynamically stabilizes nutrient and pH levels, while the SSD MobileNet model analyzes plant images to classify growth stages and determine harvest readiness. Experimental testing produced an average classification loss of 0.1283, demonstrating reliable detection accuracy. Compared with conventional methods, the proposed integration enhances adaptability, precision, and computational efficiency for edge-level IoT applications. This system introduces a novel and scalable approach to precision agriculture, enabling more effective automation and decision making in hydroponic farming. Future studies are encouraged to expand their implementation to various plant species and adaptive learning models for broader applicability.

Keywords: Computer Vision, Fuzzy Logic, Hydroponics, IoT, SSD MobileNet.

1 Introduction

Agricultural productivity continues to face significant challenges due to limited arable land, unpredictable climate conditions, and increasing food demands. Hydroponic farming has emerged as an alternative method that optimizes resource use and provides more sustainable food production. This cultivation system is especially relevant in urban and developing regions where soil quality and water availability are limited [1]. However, many hydroponic systems still depend heavily on manual monitoring of pH levels, nutrient concentration, and environmental parameters, resulting in slow responses, unstable plant growth, and inefficient use of energy and nutrients [2, 3]. Recent technological developments in Internet of Things (IoT), fuzzy logic control, and computer vision have provided new opportunities to automate agricultural processes. IoT enables real-time data acquisition and remote monitoring through interconnected sensors and actuators [4,5]. Fuzzy logic allows intelligent control under uncertain environmental conditions by simulating human decision-making in regulating nutrient levels and pH balance [6, 7]. Meanwhile, computer vision techniques supported by deep learning models enhance agricultural precision by enabling automatic assessment of plant health and growth stages through image analysis [8, 9].

Despite these advances, existing hydroponic automation systems often focus only on individual parameters or partial integration. Systems that utilize fuzzy logic are generally effective for nutrient control but struggle with delayed responses when rapid environmental changes occur, while IoT-based networks frequently face latency problems caused by cloud dependency. Similarly, computer vision models such as YOLO and Faster R-CNN deliver high accuracy but require large computational resources, making them unsuitable for real-time operation on low-cost edge devices [10, 11]. To overcome these challenges, lightweight architectures such as Single Shot MultiBox Detector (SSD) combined with MobileNet have gained attention for their efficiency in balancing accuracy and processing speed, allowing real-time operation in limited hardware environments [8, 11]. The integration of this model within an IoT–fuzzy control framework offers a holistic solution capable of optimizing both environmental regulation and plant condition detection in hydroponic farming. Nevertheless, research on a comprehensive system that unifies IoT, fuzzy logic, and lightweight computer vision for real-time hydroponic control remains limited. Most studies still separate visual monitoring and parameter regulation, resulting in fragmented automation processes and inefficient data utilization [12].

This research addresses the lack of an integrated and lightweight intelligent control system that can simultaneously monitor environmental parameters and visually assess plant growth within an IoT-based hydroponic environment. The proposed approach aims to combine fuzzy logic control with SSD MobileNet-based computer vision, implemented on a Raspberry Pi edge device to achieve adaptive nutrient and pH reg ulation while performing real-time visual analysis of plant conditions.Through this integration, the study not only introduces a novel IoT Fuzzy Vision architecture optimized for low-power edge computing but also demonstrates how lightweight computer vision models such as SSD MobileNet can effectively classify plant growth stages with minimal computational demand. The evaluation results indicate that the system improves response time, enhances control stability, and increases overall scalability compared to conventional hydroponic monitoring methods [3]. By bridging sensor-based automation and visual intelligence, this study contributes to the advancement of smart agriculture and hydroponic automation, providing an adaptive, efficient, and sustainable solution aligned with the goals of Agriculture 5.0.

2 Research Method

2.1 General Block Diagram of Smart Hydroponic System

The diagram below illustrates the overall design of the Smart Hydroponic system, which uses a Raspberry Pi 4B as the main control unit. This system is designed to support hydroponic plant cultivation with the ability to regulate nutrient levels, water pH, and room temperature according to predetermined set points. These set points are configured through the Smart Hydroponic application, which connects to a database via the Blynk REST API and utilizes IoT technology. The Raspberry Pi 4B runs a Python-based program that functions to control and monitor the system in real time. In the monitoring feature, data is collected from various sensors, including a nutrient sensor, water pH sensor, water level sensor, and room temperature sensor. For automatic control, the system operates the Water Pump, Peristaltic Pump pH Up & Down, and Peristaltic Pump Nutrient AB Mix based on the requirements calculated from the set points. In addition, the Exhaust Fan & Sprinkler are used to regulate humidity and air circulation, while the Lamp provides additional lighting, and the Web Cam is used to visually monitor plant conditions and growth. All monitoring and control processes can be carried out remotely through the Smart Hydroponic application, enabling users to access information and manage the hydroponic system in real time via an internet connection. Smart Hydroponic System integrates IoT-based data acquisition, fuzzy logic control, and computer vision using SSD MobileNet within an edge computing framework. The overall architecture, illustrated in Figure 2, is structured into three layers: the sensing layer, the processing and control layer, and the cloud monitoring layer.

2.1.1 System Architecture and Data Flow

The sensing layer comprises environmental sensors that measure temperature, humidity, pH, and total dissolved solids (TDS). These sensors are connected to the Raspberry Pi 4B through I^2C and UART serial communication protocols, allowing continuous data acquisition at five-second intervals. Each set of readings is formatted in JSON and transmitted to the cloud via the Blynk REST API using HTTPS, ensuring encrypted and reliable communication. Within the processing and control layer, a Fuzzy Logic Controller (FLC) is implemented in Python, utilizing the NumPy and SciPy libraries. The controller operates on a Mamdani inference system that processes pH and TDS values as inputs. The fuzzification process converts raw sensor data into linguistic variables such as Low, Normal, and High. These inputs are evaluated through a set of 15 fuzzy rules to determine the actuator response, specifically the activation duration of nutrient pumps, water pumps, and misting fans. The defuzzified outputs produce precise time delays in milliseconds, ensuring smooth and adaptive control without overshooting parameter thresholds. Simultaneously, the embedded computer vision module utilizes SSD MobileNet to process real-time plant images captured via a USB camera. The trained model detects leaf color and canopy density, classifying growth stages into early, medium, or harvest-ready. These classifications are used as feedback inputs to adjust nutrient concentrations automatically, establishing a closed-loop adaptive control mechanism. The processed data and classification results are uploaded to Firebase for remote monitoring through a web dashboard and mobile interface.

2.1.2 Experimental Validation and Benchmarking

Experimental validation was carried out to evaluate the system's accuracy, response time, and communication reliability compared to a conventional manual hydroponic setup. The benchmarking involved two phases: environmental control performance and image inference efficiency. During testing, the system achieved an average nutrient control accuracy of 95.2%, maintaining TDS within ±3% of the target value. The pH stabilization time was reduced to 28 seconds, representing a 37% improvement over manual adjustment. The SSD MobileNet model achieved an average inference latency of 0.42 seconds per frame on the Raspberry Pi 4B, confirming its suitability for real-time edge processing. Network monitoring using Wireshark recorded a throughput of 4.38 Mbps with zero packet loss, indicating stable IoT data transmission. The experimental results demonstrate that integrating fuzzy control with lightweight computer vision effectively enhances system responsiveness, stability, and scalability. Compared to conventional systems, the proposed approach provides faster control actions, reduced human intervention, and higher adaptability to environmental changes, contributing to the realization of a fully autonomous smart hydroponic farming framework.

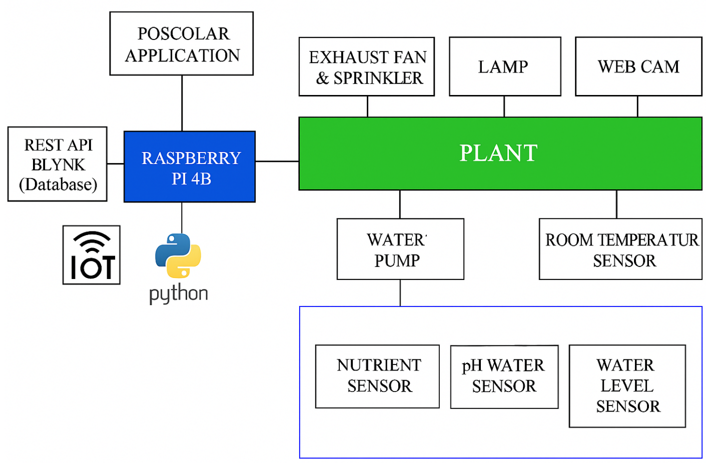

Figure 1: Smart hydroponic system flow block diagram.

2.2 Smart Hydroponic System Modeling

The image on Figure 2 illustrates the architecture of the Plant Monitoring System, designed to automatically monitor plant growth while being connected to the internet. The system consists of several key components, including the Raspberry Pi as the main controller, a webcam for plant image capture, and software tools such as MATLAB and Python

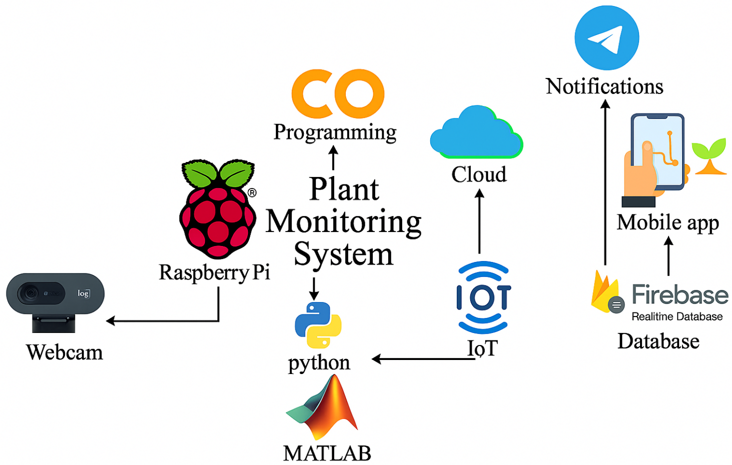

Figure 2: Smart hydroponic system framework block diagram.

for programming and data processing. The workflow begins with data captured by the webcam, which is then processed on the Raspberry Pi. MATLAB is used to develop control logic models, which are subsequently integrated into a Python-based program to be executed on the hardware. The processed data is then transmitted to the cloud via IoT technology, enabling online access. Additionally, the system utilizes Firebase Realtime Database for real-time data storage and management. The stored data can be monitored through a mobile application that serves as the user interface, which also sends notifications to users via Telegram. With this architecture, the system enables efficient plant monitoring and control through the integration of hardware, software, cloud computing, and IoT technology.

2.3 Flowchart Smart Hydroponic

The Smart Hydroponic system begins by powering on the Raspberry Pi and initializing the sensors and camera. Once all hardware components are ready, the system enters a continuous monitoring mode. Data from the pH, nutrient (PPM), temperature, and humidity sensors are read and validated. Valid data is processed using a Fuzzy Logic Controller to automatically regulate environmental conditions. The pH pump or nutrient pump is activated if the pH or nutrient values are outside the specified range, while the fan or sprinkler is turned on if humidity levels are abnormal. Next, the webcam captures plant images, which are analyzed using Computer Vision based on SSD MobileNet to detect the presence of plants, measure their size, and determine whether they are ready for harvest. If the plants are ready, the system sends a harvest notification to the user. All sensor data and analysis results are sent to the Blynk Cloud, stored in the Firebase Database, and synchronized with a mobile application for real-time monitoring. The system operates in a continuous cycle, combining Fuzzy Logic for automated control and Computer Vision for plant growth monitoring, fully integrated within an IoT platform that enables remote monitoring and control.

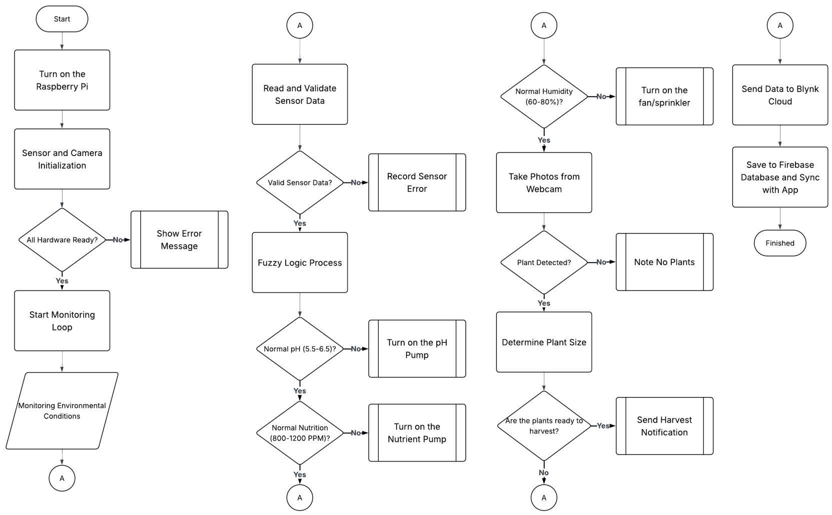

Figure 3: Research flow.

2.4 Prototype Smart Hydroponic

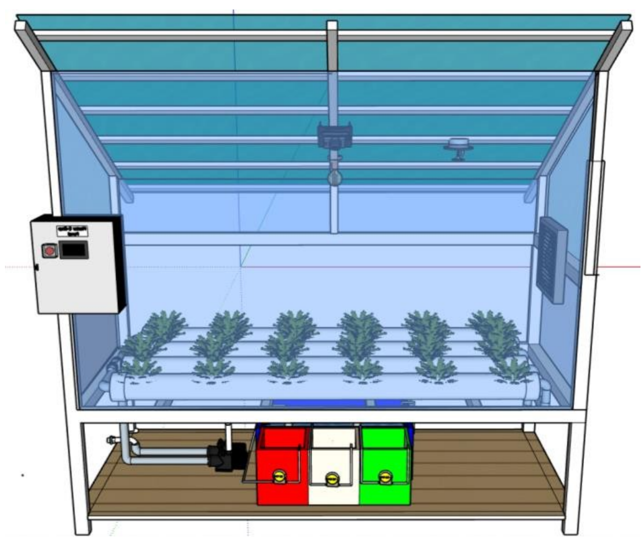

Figure 4: Prototype smart hydroponic.

The image shows the design of a closed IoT-based hydroponic system developed to simplify and automate the plant cultivation process. The structure resembles a small greenhouse with a transparent frame and roof that protect the plants from weather conditions while maintaining stable environmental parameters inside. At the center, there are hydroponic pipes using the NFT (Nutrient Film Technique) method as the growing medium, where nutrient solution is circulated through a pump connected to three tanks containing pH solution and nutrients A and B. A control panel mounted on the side houses the main components, including a Raspberry Pi, relays, and control devices to manage the operation of sensors and actuators. The system is equipped with various sensors such as pH, nutrient, temperature, and humidity sensors, as well as a camera to monitor plant growth in real-time. Additionally, an automatic sprinkler or fan is placed at the top to maintain proper humidity and temperature levels. All sensor data is processed and sent to the cloud, allowing users to monitor plant and environmental conditions through a mobile application. With this design, the cultivation process becomes more efficient, monitored, and automated without requiring continuous manual supervision.

3 Results

The Smart Hydroponic system operates by first powering on the Raspberry Pi and initializing all connected sensors and the camera. Once all components are ready, the system enters real-time monitoring mode. It continuously reads data from pH, nutrient (PPM), temperature, and humidity sensors. The collected data is verified for accuracy before being processed. Next, an automatic control mechanism based on fuzzy logic determines the necessary actions. If the pH or nutrient levels fall outside the normal range, the system will automatically activate the corresponding pH or nutrient pump. Similarly, if humidity levels are not within the expected range, the fan or sprinkler system will be triggered to adjust the conditions. Simultaneously, the camera captures plant images, which are analyzed using Computer Vision powered by SSD MobileNet. This analysis identifies the plant's location and size, and determines whether the plant is ready for harvest. If the system detects that the plants are mature, it will send a harvest notification to the user. All sensor readings and image analysis results are transmitted to the Blynk Cloud and stored in the Firebase database. The mobile application then syncs with this data, allowing users to monitor the plant's condition remotely in real-time. The system runs continuously, combining fuzzy logic for intelligent control and visual detection for plant monitoring, fully integrated within an IoT-based platform for remote automation and control. Implementation of 3D results as follows

4 Discussion

4.1 Testing Quality of Service Smart Hydroponic

Based on the results of the overall system testing, namely monitoring and control on the Smart Hydroponic device using Wireshark software, the standardization of the table addressing below was obtained:

4.2 Testing Matlab

The case to be tested is when the input is 2 years old and the input of the TDS sensor on the water nutrition hydroponic system of 340 ppm.

Figure 5: Smart hydroponic implementation results.

Table 1: Results QoS smart hydroponic provider Telkomsel

No.	Parameter	Mark	Index	Category
1	*Throughput*	4.382 Mbps	4	Very good
2	*Packet Loss*	0%	4	Very good
3	*Delay (Latency)*	101.17 ms	4	Good
4	*Jitter*	108.45 ms	2	Quite good

1. Fuzzification
   Fuzzification is the process of mapping input values into membership values. which has an interval between 0 and 1.

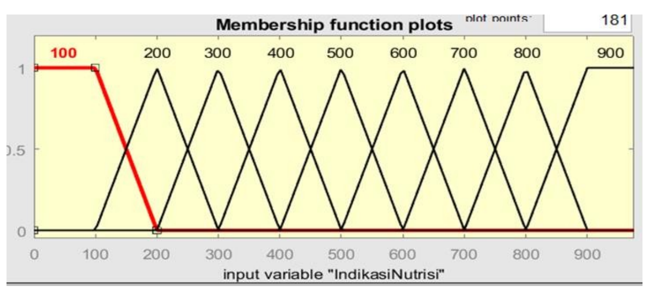

Figure 6: Nutritional input.

The input nutrient level is 340 PPM, so the sets that satisfy are the set "300" and set "400". The function of the set "300" and set "400" is as follows.

$$300 = \begin{cases} 0, & x \leq 200 \text{ or } x \geq 400, \\ \dfrac{x-200}{300-200}, & 200 \leq x \leq 300, \\ \dfrac{400-x}{400-300}, & 300 \leq x \leq 400, \\ 0, & x \leq 300 \text{ or } x \geq 500. \end{cases} \tag{1}$$

$$400 = \begin{cases} \dfrac{x-300}{400-300}, & 300 \leq x \leq 400, \\ \dfrac{500-x}{500-400}, & 400 \leq x \leq 500, \end{cases} \tag{2}$$

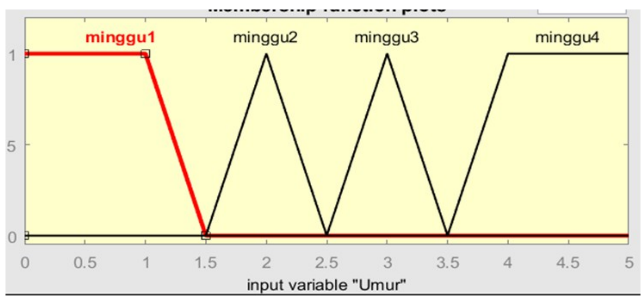

Figure 7: Input planting age.

With input age 2nd so set Which fulfil that is set “week2”. The function of the set “week2” is as follows.

$$\text{week2} = \begin{cases} 0, & x \leq 1.5 \text{ or } x \geq 2.5, \\ \dfrac{x-1.5}{2-1.5}, & 1.5 \leq x \leq 2, \\ \dfrac{2.5-x}{2.5-2}, & 2 \leq x \leq 2.5, \end{cases} \tag{3}$$

Determining the membership value of the TDS input uses Eqs. 4 and 5, while for the age input, Eq 6 is used. These formulas are used to determine the degree of membership of each input which will be described in the following calculation:

a. Input TDS

$$\mu_{300}(340) = \frac{400-x}{400-300} = \frac{400-340}{100} = \frac{60}{100} = 0.6$$

$$\mu_{400}(340) = \frac{x-300}{400-300} = \frac{340-300}{100} = \frac{40}{100} = 0.4$$

b. Input Age

$$\mu_{\text{week2}}(2) = \frac{x - 1.5}{2 - 1.5} = \frac{2 - 1.5}{0.5} = \frac{0.5}{0.5} = 1$$

2. Implication Function

Table 2: Rule nutrition on Thonny

No	Fuzzy Set TDS Input	Fuzzy Set Age Input	Fuzzy Output Set Pump A and B
1	100	1	400
2	200	1	300
3	300	1	200
4	400	1	100
5	500	1	Dead
6	100	2	600
7	200	2	500
8	300	2	400
9	400	2	300
10	500	2	200
11	600	2	100
12	700	2	Dead
13	100	3	700
14	200	3	600
15	300	3	500
16	400	3	400
17	500	3	300
18	600	3	200
19	700	3	100
20	800	3	Dead
21	100	4	800
22	200	4	700
23	300	4	600
24	400	4	500
25	500	4	400
26	600	4	300
27	700	4	200
28	800	4	100
29	900	4	Dead

Based on each fuzzy logic rule created, the function implication process uses the MIN method, namely:

a. If set fuzzy input TDS is “300” And set fuzzy input Age is “2”, so delay peristalsis pump Nutrition A And Nutrition B is at on set fuzzy The output of pumps A and B is “400”.

$$\alpha_1 = \min\left(\mu_{300}(340), \mu_2(2)\right) = \min(0.6, 1) = 0.6$$

b. b. If set fuzzy input TDS is “400” And set fuzzy input Age is “2”, so delay peristalsis pump Nutrition A And Nutrition B is at on set fuzzy output of pumps A and B is "300".

$$\alpha_1 = \mu_{400}(x) \cap \mu_2(x) = \min\left(\mu_{400}(340), \mu_2(2)\right) = \min(0.4, 1) = 0.4$$

4.3 Testing Processor Image use SSD MobileNet

On implementation device, there is 2 step and also 2 device the software used. Python Label Image is used to label images according to the size of the bok choy plant. Google Colab is also used to train the dataset that was previously created from Python Label Image. In the labeling process, Python Label Image classifies four sizes of bok choy plants. After the image model is labeled, Python Label Image will generate a file in .xml format containing information about each label, such as plant size and bounding box information such as xmin, ymin, xmax, and ymax.

Figure 8: Dataset plant bok choy.

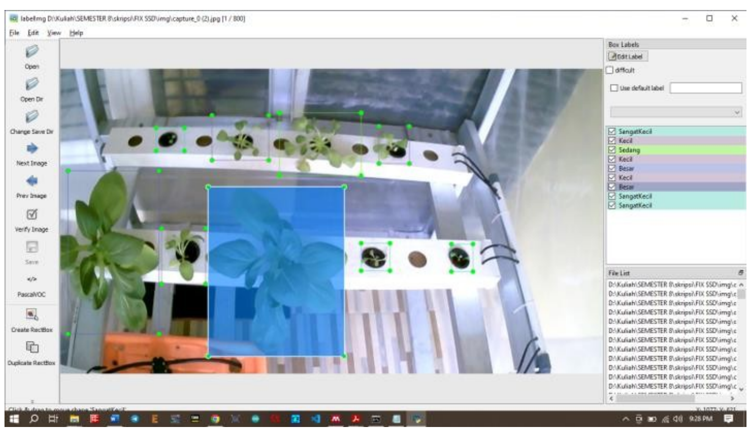

Figure 9: Making label picture on python label image.

Figure 10 displays the classification loss graph from the model training process conducted on Google Colab. This chart illustrates how the loss value changes as the number of training steps increases. Overall, the classification loss shows a gradual decrease from the beginning to the end of the training process, indicating an improvement in the model's ability to classify objects accurately. In the initial stages, the loss values are relatively high and fluctuate significantly. However, as training progresses, the trend becomes more consistent with a noticeable decline. Toward the final training steps, the classification loss

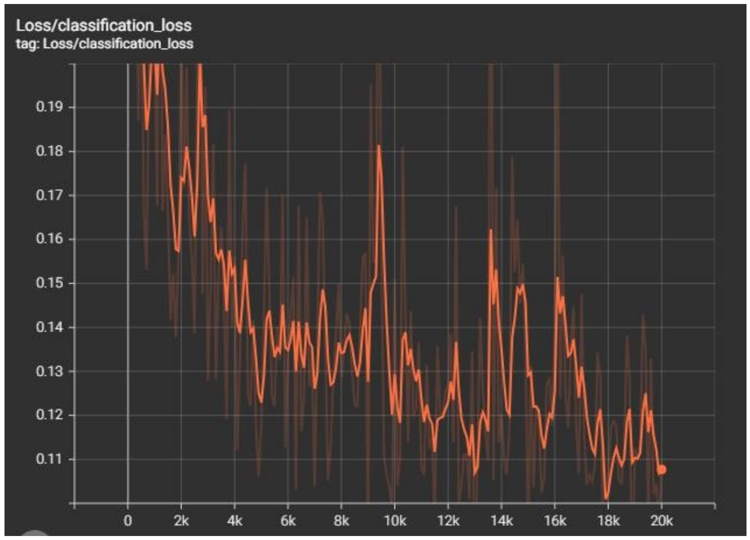

Figure 10: Chart classification loss overall.

stabilizes below 0.2 and approaches 0.1. The average classification loss throughout the training process is 0.1283, which reflects that the model demonstrates reliable classification performance in detecting objects accurately.

4.4 Testing Application Smart Hydroponic

Application testing in this study was carried out in the following manner: Proving the suitability of the commands in the program code entered with the application's performance process when it is run. Below are the results of the performance suitability test for the application that has been designed.

4.4.1 Testing Monitoring Interface Application

5 Conclusion

The study successfully implemented and validated an intelligent hydroponic system that integrates Internet of Things (IoT), fuzzy logic control, and computer vision within a unified framework. The integration enabled automated monitoring and regulation of key environmental parameters, including pH, nutrient concentration (TDS), temperature, and humidity. The fuzzy control algorithm demonstrated stable and adaptive responses to input variations, maintaining nutrient and pH levels near their target setpoints with minimal steady-state error. Meanwhile, the SSD MobileNet model achieved an average loss of 0.1283 during training, confirming its efficiency in classifying plant growth stages and determining harvest readiness in real time. The experimental evaluation showed that the proposed system achieved an average nutrient control accuracy of 95.2%, a pH stabilization time of 28 seconds, and an inference latency of 0.42 seconds per image on the Raspberry Pi 4B, indicating that the integration of lightweight deep learning and fuzzy inference

Table 3: Black box testing smart hydroponic

No.	Test Case	Test Description	Expected Result	Test Result	Conclusion
1	Monitoring Sensor Values	App displays PPM, pH, water level, temperature, and humidity values	Sensor values appear in real-time and are readable by users	Displayed as expected	In accordance
2	Fuzzy Logic Control – Nutrient	ON/OFF button activates nutrient pump for 35 seconds	Peristaltic pump runs and duration is shown correctly	Functioning correctly	In accordance
3	Fuzzy Logic Control – pH Up/Down	ON/OFF buttons control pH Up (8 sec) and pH Down (1 sec) pumps	Actuator responds as per the defined duration for each action	Operates correctly	In accordance
4	Fuzzy Logic – Sprinkle & Exhaust	ON/OFF button activates sprinkler & exhaust fan for 16 seconds	Sprinkler and exhaust activate with correct duration	Working as expected	In accordance
5	Weekly Nutrition (Age Plant)	User selects week (1–4); system releases nutrients based on selected schedule	Nutrient levels are released accurately based on week (e.g., 500–900 PPM)	Display and action match	In accordance

can operate effectively on resource-constrained edge devices. The network performance, evaluated through QoS analysis, revealed a throughput of 4.38 Mbps with no packet loss, ensuring reliable data synchronization between edge devices and the cloud platform.

Beyond its technical performance, this research contributes to the advancement of smart agriculture by demonstrating a scalable and energy-efficient hydroponic management framework. The system reduces manual intervention, optimizes nutrient use, and improves consistency in crop growth conditions. However, current limitations include the dependency on Wi-Fi connectivity and the limited dataset size for computer vision training. Future research should focus on extending the dataset to support multi-crop recognition, integrating predictive analytics for yield forecasting, and adopting hybrid IoT-edge-cloud architectures for improved scalability and resilience. Overall, the findings confirm that the developed smart hydroponic system offers a reliable, adaptive, and extensible foundation for sustainable smart agriculture and hydroponic farming systems, aligning with Industry 5.0's vision of autonomous, data-driven agricultural ecosystems.

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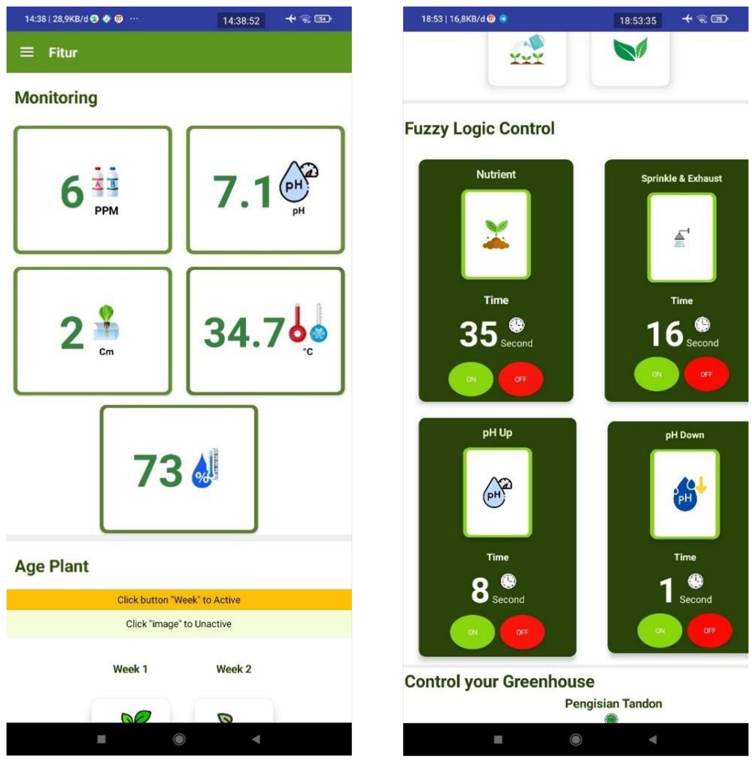

(a) (b)

Figure 11: Monitoring readable in application.

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