SMART AQUAPONIC SYSTEM USING FUZZY LOGIC AND CONVOLUTIONAL NEURAL NETWORK (CNN)

XUE, C. L.[1] – NOOR, A. M.[1*]

[1] *Faculty of Electronic Engineering & Technology, Universiti Malaysia Perlis, Perlis, Malaysia.*

**Corresponding author*
e-mail: anasnoor[at]unimap.edu.my

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Abstract. Aquaponics is an innovative and sustainable farming method that combines aquaculture (fish farming) and hydroponics (soilless plant cultivation) in a symbiotic environment. While aquaponics offers significant advantages, such as reduced water usage and efficient nutrient recycling, it faces challenges, including the need for precise monitoring, early disease detection, and optimal resource management. Traditional systems often lack real-time data analysis and predictive capabilities, leading to inefficiencies, crop losses, and increased operational risks. To address these limitations, this study introduces a smart aquaponic system that integrates fuzzy logic, convolutional neural networks (CNNs), and IoT technologies to enhance yield and resource management. The proposed system employs sensor-based monitoring to collect real-time data on critical parameters such as water quality, temperature, pH levels, and nutrient concentrations. A fuzzy logic model evaluates the health of fish and plants using predefined rules, effectively managing uncertainties in biological systems. Additionally, a CNN-based plant disease detection module achieves exceptional performance, with a precision of 93%, recall of 91%, and an accuracy of 92%, enabling early identification and mitigation of diseases. The system is accessible via a mobile application, providing farmers with user-friendly tools for remote monitoring and management. By enhancing real-time monitoring, predictive analytics, and disease detection, this research supports global sustainability goals, offering a scalable solution for modernizing aquaponics and advancing food security..
Keywords: *aquaponics, smart farming, IoT monitoring system, sustainable farming, plant disease detection, fuzzy logic prediction*

Introduction

Aquaponics in rice paddies, which took place in ancient China, gave rise to aquaponics (Wan et al., 2022). An aquaponic system combines hydroponics and aquaculture to produce fish and plants that are nutritious food sources (Danner et al., 2019). It is a technology that can recycle fish wastes into nutrients that plants need following the nitrification process. In an aquaponic system, microorganisms and nitrifying bacteria convert fish waste, which is ammonia, to nitrites and subsequently nitrates (Nicolae et al., 2015). *Figure* 1 illustrates the complete cycle of an aquaponic system. Chemical fertilizers are not necessary in an aquaponic system since it is a natural, chemical-free system. In addition, because aquaponics uses less water than other agricultural techniques, it can help cut down on water usage. An examination of the benefits of aquaponics systems in agricultural output through a comparison with hydroponics and conventional methods. Aquaponics lessens its ecological footprint while producing great agricultural products (Ezzahoui et al., 2021). The Food and Agriculture Organization (FAO) of the United Nations forecasts that there will be approximately nine billion people on the planet in 2050, marking a critical turning point in human history. 17 Sustainable Development Goals (sdgs), which were adopted by the United Nations General Assembly (UNGA) in 2015 as a "shared blueprint for peace and

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prosperity for people and the planet, now and into the future. "By 2030, it is projected that these sustainable development goals will have been achieved. Among the objectives we may achieve with this project are SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-Being) and SDG 13 (Climate Action).

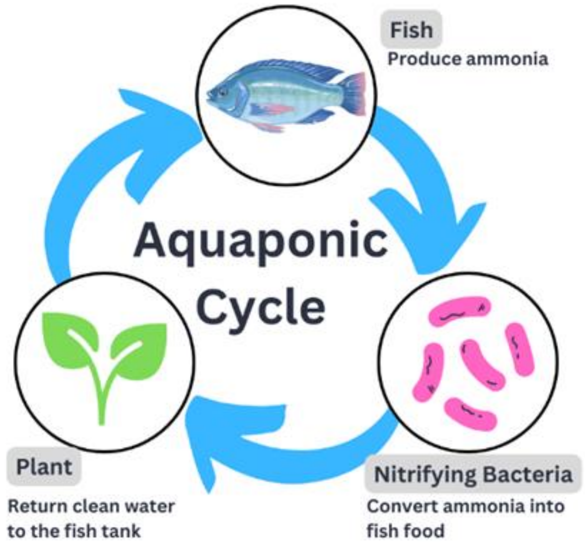

Figure 1. *Aquaponic cycle.*

The current government now promotes food security. Malaysia intends to increase the percentage of fish produced by aquaculture from 26% to 60% over the course of the next two to seven years. The National Food Security Policy Action Plan 2021-2025 and the National Agrofood Policy 2021–2030 are being implemented as part of the effort to enhance food production by utilizing modern technologies and economies of scale. The government also supports sustainable farming methods and works to fortify the food supply chain. It is hoped that as Internet-connected devices monitor and perform duties on farms, the usage of iot in agriculture would grow and aid in resolving concerns related to food security (Le et al., 2020). One of the significant challenges in urban aquaponic farming is resource management which is further complicated by spatial constraints and the reliance on manual monitoring (Angotti, 2015; Pfeiffer et al., 2015). Conventional urban aquaponic systems often lack real-time monitoring capabilities for key parameters such as water quality, ph levels, and the health of aquatic life (Ibrahim et al., 2023b; Yep and Zheng, 2019; Goddek et al., 2015). This absence of continuous oversight can lead to suboptimal practices, higher operational costs, and increased risks to plant and fish health (Ibrahim et al., 2023b; Monsees et al., 2019).

Previous studies have highlighted the potential of aquaponics to enhance crop yields and optimize resource management, addressing challenges like nutrient utilization and water quality (Colt et al., 2022; Yanes et al., 2020; Kloas et al., 2015). Further research demonstrates that integrating advanced technologies into aquaponic systems, such as macroalgae for improved nutrient management and water quality, can significantly boost yield and resource efficiency (Zhang et al., 2022). Building on these insights, our system offers real-time monitoring and adaptive management, leading to better resource utilization and increased crop productivity. This approach supports the sustainability of urban aquaponic farming by enhancing both efficiency and environmental stewardship.

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Numerous studies have been conducted to enhance aquaponic systems through the integration of sensor-based monitoring, fuzzy logic and machine learning. Wan et al. proposed a modular IoT-based monitoring system for aquaponics, incorporating edge computing to optimize resource management and achieve higher productivity (Wan et al., 2022). However, this study lacked predictive analytics for disease detection, limiting its capability to pre-emptively address potential system issues. Similarly, Ezzahoui et al. introduced IoT technologies into hydroponic and aquaponic farming for real-time monitoring and automation (Ezzahoui et al., 2021). Despite the advantages in operational efficiency, this approach did not employ fuzzy logic for health prediction, resulting in less nuanced assessments of plant and fish conditions. Ibrahim et al. (2023a) developed a smart home aquaponic system with IoT-enabled monitoring and control via a mobile application, focusing on user convenience and real-time parameter tracking. While effective in improving accessibility, the study did not include advanced machine learning models for plant disease detection, limiting its application to broader farming contexts. Zou et al. examined the effects of pH on nutrient transformations in aquaponic systems, proposing optimal ranges for improved nitrogen utilization (Zhou et al., 2016). However, their work did not integrate automated monitoring solutions to maintain these ranges dynamically. Furthermore, Zhang et al. (2022) explored the use of macroalgae in aquaponics for nutrient optimization, demonstrating improved resource efficiency and yield. While innovative, this study did not leverage IoT or machine learning, making the system less adaptable to urban farming settings with spatial constraints. Monsees et al. compared aquaponic and hydroponic systems, showcasing aquaponics' environmental benefits and similar yields (Monsees et al., 2019). However, their analysis did not include the implementation of advanced monitoring systems, limiting its practical relevance in technology-driven farming.

Despite significant advancements, existing studies on aquaponic systems lack a comprehensive integration of sensor-based monitoring, fuzzy logic, and machine learning to address the critical challenges of urban farming, such as real-time disease detection, resource optimization, and predictive analytics. Current approaches often focus on isolated solutions-such as IoT-enabled monitoring or nutrient management-without combining these elements into a holistic system. Additionally, most studies do not incorporate user-friendly interfaces that enable farmers to access actionable insights for proactive decision-making. This work aims to fill these gaps by developing a smart aquaponic system that seamlessly integrates IoT, fuzzy logic, and convolutional neural networks (CNNs) for real-time monitoring, predictive analytics, and plant disease detection. The proposed solution offers a mobile application with an intuitive interface, granting users comprehensive control and valuable insights that support sustainable and efficient farming practices. It addresses the limitations identified in previous studies and provides a robust framework for future advancements in agriculture.

Materials and Methods

Proposed system

System architecture

The Internet of Things (IoT) smart aquaponic system is built on an advanced distributed architecture precisely designed to maximize utility and efficiency. Fundamentally, a network of sensors carefully collects essential data from the aquaponic environment, such as water temperature, pH, and Total Dissolved Solids (TDS) levels. The main processing unit of the system, NodeMCU ESP32, handles this raw data with convenience. Through smooth connectivity with the mobile application and cloud-based database, the microcontroller gives users real-time monitoring and control over the system's functions. The cloud-based database acts as a reliable storehouse for processed data, allowing for remote access and ongoing performance monitoring of the aquaponic system. Firebase is chosen as our cloud database. With the help of a user-friendly mobile application interface, users may make well-informed decisions to maximize performance and guarantee long-term growth by gaining thorough insights into system metrics. Furthermore, the system's capabilities are enhanced by the addition of a camera for the purpose of detecting plant diseases. The camera serves as an extra sensor, taking detailed pictures of the plants that are analysed using advanced computer vision techniques. This makes it possible for users to proactively manage plant health and reduce any hazards by enabling the quick diagnosis of diseases or irregularities. All things considered, the Internet of Things smart aquaponic system is a prime example of how distributed architectures can revolutionize contemporary agriculture. The system optimizes efficiency, scalability, and convenience through the seamless integration of sensors, microcontrollers, cloud-based databases, and mobile applications. *Figure 2* shows the diagram of the system architecture.

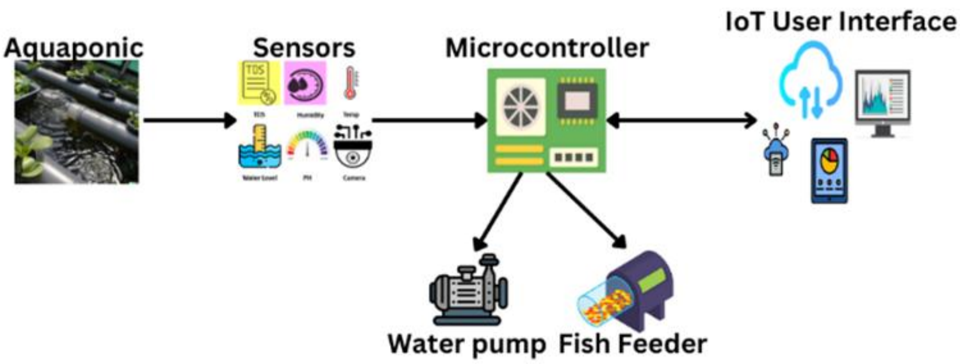

Figure 2. *System architecture.*

Software integration and platform implementation

This project integrates multiple software and platforms to optimize the performance and user experience of the smart aquaponic monitoring system. The Arduino IDE is utilized to program the NodeMCU ESP32 microcontroller, enabling precise execution of tasks such as sensor data collection and real-time system control. Firebase, a cloud-based database, serves as the central repository for sensor data, ensuring secure and scalable storage and facilitating seamless data communication with other components. For data visualization, Google Sheets is employed to automatically plot trends over time, while Google Apps Script automates data retrieval from Firebase at regular intervals, enhancing efficiency and minimizing manual intervention. MATLAB’s Fuzzy Logic Toolbox is instrumental in developing health prediction models for plants and fish, allowing the system to provide accurate and actionable insights based on real-time environmental parameters. The mobile application, developed using MIT App Inventor, offers an intuitive interface for users to monitor system performance, access historical data trends, and manage system controls. It also integrates plant disease detection capabilities by processing captured images and presenting the results directly within the

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app. This seamless integration of software and platforms ensures robust system functionality, user engagement, and informed decision-making. Additionally, plant disease detection is bolstered through image capture and processing, with results seamlessly integrated into the mobile app for user review. This integration of software and platforms provides a robust solution for data monitoring, analysis, and user engagement. *Figure 3* illustrates the architectural flow of these integrations.

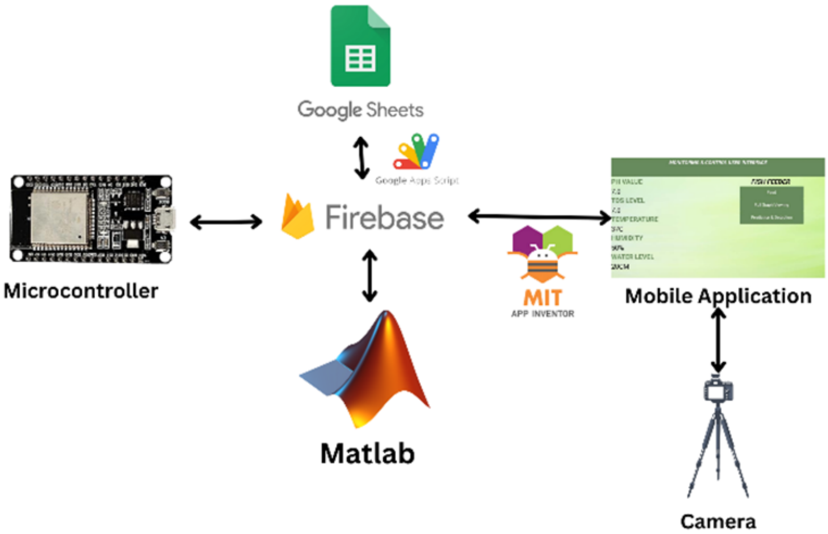

Figure 3. *System software and platforms.*

Prediction of plant and fish health status using fuzzy

Fuzzy logic is a mathematical framework that deals with reasoning that is approximate rather than precise, allowing for a more nuanced understanding of complex systems like ecosystems. The fuzzy logic approach in our system begins with the fuzzication process, where crisp input values, such as pH levels, Total Dissolved Solids (TDS), air humidity and temperature are converted into fuzzy sets using memberships functions. For instance, the membership function for the "optimal pH" fuzzy set is defined as in Eq. (1):

$$\mu_{optimal_{pH}}(x) = \begin{cases} 0 & if\ x \leq 5.5\ or\ x \geq 7.5 \\ \frac{x-5.5}{6-5.5} & if\ 5.5 < x \leq 6 \\ \frac{7.5-x}{7.5-7} & if\ 7 < x \leq 7.5 \end{cases} \quad \text{Eq. (1)}$$

This function assigns a degree of membership to each crisp input, enabling the representation of concepts like "acidic", "optimal" and "alkaline". Logical operations such as AND, OR, and NOT are then applied to combine fuzzy sets according to predefined rules. These operations are mathematically defined as in Eq. (2), Eq. (3), Eq. (4):

AND (Minimum)

$$\mu_{AND}(A, B) = min(\mu_A, \mu_B) \quad \text{Eq. (2)}$$

OR (Maximum)

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$\mu_{OR}(A,B) = max(\mu_A, \mu_B)$ Eq. (3)

NOT (Complement)
$\mu_{NOT}(A) = 1 - \mu_A$ Eq. (4)

When multiple rules are triggered simultaneously, their output are aggregated by taking the maximum value of the overlapping fuzzy sets as in Eq. (5):

$\mu_{aggre}(y) = \max(\mu_{rule1}(y), \mu_{rule2}(y), \dots, \mu_{ruleN}(y))$ Eq. (5)

The final step in fuzzy logic process is defuzzication, where aggregated fuzzy set is converted into a crisp output. In our proposed system, we use the centroid method for defuzzication, which calculates the center of gravity of the aggregated fuzzy set as in Eq. (6):

$y_{crisp} = \frac{\int y \cdot \mu_{aggregated}(y)dy}{\int \mu_{aggregated}(y)dy}$ Eq. (6)

The crisp value represents the overall health status of the plants or fish. To provide actionable insights, this health status is scaled to a percentage as in Eq. (7):

$Health\ status\ (\%) = \left(\frac{y_{crisp}}{y_{max}}\right) \times 100$ Eq. (7)

Where ymax is the maximum possible output value. Optimal conditions are indicated by a green status with the respective percentage, while deviations from the ideal range are clearly flagged. Fuzzy based rules are based on the IF-THEN statement. The first step in fuzzy is the fuzzification process for each data entered. The data is then processed in accordance with predetermined rules based on certain conditions. The rule is also related to the logic of AND and OR operations (Elkano et al., 2018). In the purposed system, we define key parameters that are crucial for the well-being of plants and fish, such as pH levels, Total Dissolved Solids (TDS), air humidity, and temperature. Each parameter is assigned a range of values that are considered optimal for the health of the organisms. Using fuzzy logic, we assign linguistic variables to these parameters, representing concepts like "acidic", "alkaline" and "optimal" These linguistic variables are then mapped to fuzzy sets, which represent the degree of membership of a value in the given linguistic variable. For example, a pH level of 6.5 might have a high degree of membership in the linguistic variable "optimal pH," indicating that it is within the ideal range for the organisms. Next, we define fuzzy rules that govern how these linguistic variables interact with each other. For instance, a rule might state that if the pH level is high and the temperature is low and humidity is low, then the health status of the plant is in severe. Once the linguistic variables, fuzzy sets, and rules are defined, we use fuzzy inference to compute the overall health status of the organisms. This involves aggregating the fuzzy sets according to the defined rules and applying fuzzy reasoning to determine the degree to which the organisms are healthy.

The output of the fuzzy inference process is a quantitative assessment of the health status, represented in a value of 1-100 which represents percentage. Optimal conditions are indicated by a green status, accompanied by the respective percentage indicating

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how closely the current conditions match the ideal range. Deviations from the optimal range are clearly indicated, allowing users to identify areas where adjustments may be necessary to improve the health of the organisms. Overall, our platform provides a sophisticated yet user-friendly tool for assessing the health status of plants and fish, leveraging the power of fuzzy logic to capture the complexity of ecosystem dynamics and provide actionable insights for users. *Figure 4(a)* shows the fuzzy inference system for inputs and output while *Figure 4(b)*, *Figure 4(c)* and *Figure 4(d)* shows the membership function of each parameter.

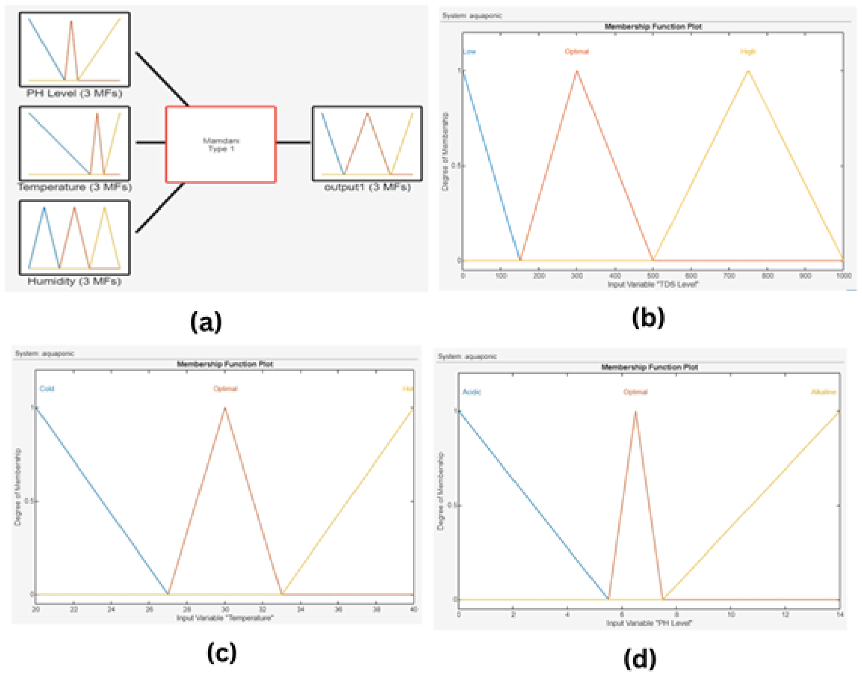

Figure 4. *Fuzzy system. (a) Fuzzy inference system inputs and output, (b) TDS level membership function, (c) temperature membership function, (d) pH level membership function.*

Several literature reviews have been conducted to determine the ideal range of parameters for our systems. Following thorough study and testing, it was determined that a temperature range of 27-33°C is suitable for optimal growth of both plants and fish (Fabula et al., 2023; Ula et al., 2022; Le et al., 2020). In aquaponics systems, maintaining pH around 6.0 results in a maximum nitrogen usage efficiency of 50.9% (Zhou et al., 2016). Additionally, research suggests that pH value of 5.5-7.2 optimized phosphorus availability and uptake by plants (Da Silva Cerozi and Fitzsimmons, 2016). Therefore, the pH range for fish welfare is established in 5.5 to 7.5 (Mustapha and Atolagbe, 2018; El-Sherif and El-Feky, 2009). As different types of crops can be planted in our system, a relative humidity of 60% to 80% has been designated our system (Carmassi et al., 2022; Solis-Toapanta et al., 2020a; 2020b). Comparing to a hydroponic system which need a high total dissolved solids (TDS) level, a lower TDS value ranging from 200 to 400 ppm is acceptable for plant growth, as the nutrients are generated continuously (Rakocy, 2012). *Table 1* summarize the ideal parameters for both fish and plants that are used. Based on our previous experiments and observations, we developed the appropriate fuzzy logic rules used in our prediction system, as presented in *Table 2*. These fuzzy logic rules are important to maintain the optimal water quality in our aquaponic system, ensuring the health of both fish and plants. When

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these rules are not met, fish and plant may experience stress, illness, or even fatality. For example, High pH stress impacts root form and function, leading to nutrient deficiencies that limit plant growth, and may cause aboveground symptoms (Turner et al., 2020), and high or low temperatures can prevent development and reproduction. Excessive TDS levels can stress fish osmotically and hinder plants' ability to absorb nutrients. Therefore, adhering to these guidelines is essential for accurately predicting and preventing potential issues, facilitating proactive management, and ensuring the well-being of aquatic life.

Table 1. *Ideal parameters conditions for fish and plant.*

Category	pH level		TDS level (ppm)		Temperature (°C)		Humidity (%)	
	Plant	Fish	Plant	Fish	Plant	Fish	Plant	Fish
Optimal	6.0-7.0	5.5-7.5	200-400	150-500	27-33	27-33	60-80	N/A
Low	<6.0	<5.5	<200	<150	<27	<27	<60	N/A
High	>7.0	>7.5	>400	>500	>33	>33	>80	N/A

Table 2. *Proposed fuzzy logic rules.*

Rule	pH level	Temperatures	TDS	Output
1	Optimal	Optimal	Optimal	Optimal
2	Optimal	Optimal	Low	Acceptable
3	Optimal	Optimal	High	Acceptable
4	Acidic	Optimal	Optimal	Acceptable
5	Alkaline	Optimal	Optimal	Acceptable
6	Optimal	Cold	Optimal	Acceptable
7	Optimal	Hot	Optimal	Acceptable
8	Acidic	Cold	Low	Severe
9	Alkaline	Hot	High	Severe
10	Alkaline	Hot	Optimal	Severe
11	Alkaline	Hot	Low	Severe
12	Acidic	Hot	Low	Severe
13	Acidic	Hot	Optimal	Severe
14	Acidic	Hot	Optimal	Severe
15	Acidic	Hot	High	Severe
16	Acidic	Cold	Optimal	Severe
17	Acidic	Cold	High	Severe
18	Acidic	Optimal	Low	Severe
19	Acidic	Optimal	High	Severe
20	Optimal	Cold	Low	Severe
21	Optimal	Cold	High	Severe
22	Optimal	Hot	Low	Severe
23	Optimal	Hot	High	Severe
24	Alkaline	Cold	Low	Severe
25	Alkaline	Cold	Optimal	Severe
26	Alkaline	Cold	High	Severe
27	Alkaline	Optimal	Low	Severe
28	Alkaline	Optimal	Wet	Severe

Plant disease detection

Data collection and pre-processing

A data collection of plant disease images has been collected for our model training. Images included 5 classes which included few common diseases that occur on lettuce plants which are bacterial leaf spot, powdery mildew, downy mildew, septoria leaf spot and healthy leaves. Each class contains a substantial number of images to ensure the quality for training and validation purposes as shown in *Table 3*. Preprocessing steps include resizing all images to a uniform size of 224x224 pixels and normalizing pixel values to the range [0,1]. Besides that, data augmentation techniques were applied to augment the training set to enhance the model's ability to generalize across variation in leaf appearance. Data augmentation techniques included rotating, shifting, shearing, zooming and horizontal flipping.

***Table 3**. Distributions of leaf images in training, validation and testing sets.*

Leaf type	Training set	Validation set	Testing set
Bacterial	56	32	8
Powdery	56	32	8
Downy	56	32	8
Septoria	56	32	8
Healthy	56	32	8

Model selection and architecture

The architecture used for this project is MobileNet. MobileNet is an efficient, light-weight convolutional neural network (CNN) model for object detection and recognition in computers, mobile, and embedded vision (Sinha and El-Sharkawy, 2019). We chose to leverage a pre-trained MobileNet model that was pre-trained on the ImageNet dataset. By utilizing transfer learning, we leveraged the learned features from ImageNet to improve the model's performance on our task. The MobileNet architecture is based on depthwise separable convolutions (DSC), which decompose a standard convolution operation into two steps. Using the Depthwise Convolution as shown in Eq. (8).

$$Y_{i,j,k} = \sum_{m=1}^{M} \sum_{n=1}^{N} X_{i+m,j+n,k} \cdot W_{m,n,k} \qquad \text{Eq. (8)}$$

Where X is the input feature map, W is the depthwise filter, and Y is the output feature map. Each channel of the input is convolved independently. And the Pointwise Convolution as shown in the Eq. (9).

$$Z_{i,j,l} = \sum_{k=1}^{K} Y_{i,j,k} \cdot V_{k,l} \qquad \text{Eq. (9)}$$

Where V is the pointwise filter, K is the number of input channels, and Z is the final output feature map. This operation combines the depthwise convolution outputs to produce the desired number of output channels. Figure 5 below illustrates the overall architecture used in this project. This model is implemented using Matlab software.

Training process and optimization

The training of our model was conducted using the Adam optimizer with a learning rate of 0.001. We employed a batch size of 32 and trained the model for 50 epochs. During training, the categorical cross-entropy loss function was optimized to minimize the discrepancy between predicted and actual class labels. To prevent overfitting, we monitored the model's performance on a separate validation set and applied early stopping when the validation loss ceased to decrease for a certain number of epochs. Additionally, we incorporated data augmentation techniques during training to expose

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the model to diverse variations of the input images and enhance its robustness against real-world scenarios.

Model evaluation and performance matrics

Following the training process, we evaluated the trained model on a held-out validation set to assess its performance. We computed several metrics to gauge the model's efficacy, including accuracy, precision, recall, and F1 score. These metrics provided insights into the model's ability to correctly classify diseased and healthy lettuce leaves. Moreover, we visualized the model's performance through accuracy over epochs, loss over epochs and confusion matrices, allowing for a more comprehensive understanding of its behavior across different disease classes. Precision is defined as the ratio of all instances that are displayed to be relevant to a given class as shown in the Eq. (10). The percentage of relevant instances that a machine learning model correctly predicts is known as recall. It is obtainable as in Eq. (11)

$$precision = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Eq. (10)}$$

$$Sensitivity = \frac{TP}{TP+FN} \qquad \text{Eq. (11)}$$

Internet of Things

The IoT utilized in this work focuses on a smart aquaponics monitoring system specifically designed for sustainable farming (Sfar et al., 2017). The IoT implementation includes a distributed network of sensors that measure critical parameters such as water temperature, pH and Total Dissolved Solids (TDS). This system also incorporates a NodeMCU ESP32 microcontroller for data processing and real-time communication with a cloud-based database (Firebase) and a mobile application. Additionally, IoT devices enable integration with vision-based monitoring for plant disease detection, leveraging cameras and machine learning algorithms to enhance resource management and yield optimization in aquaponics systems.

Design of the aquaponic model

Figure 5 illustrates the isometric view of a hardware design featuring a 3 layered plant system utilizing the Nutrient Film Technique (NFT). NFT is widely used by the farmers due to its efficency in promoting plant growth. Besides that, NFT can also save 70-90% of water (Sharma et al., 2018). This system segregates the fish tank from the plant system, facilitating separate feeding of fish and easier maintenance works. Additionally, a sump tank equipped with filtration system is integrated. This filtration system can helps to remove impurities such as excess fish food and waste. In fitration system, the nitrifying bacteria will then convert harmful ammonia into nutrients for plants. Once filtration completed, it will then pump into the highest pipe of plant system. From there, it will gradually move downwards to lower pipe, eventually return to the fish tank. This circulation system enables plants to receive water and nutrients while maintaining optimal water quality in fish tank.

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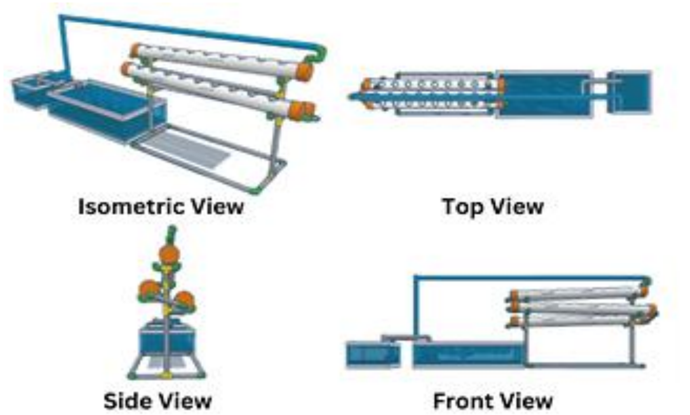

Figure 5. *Aquaponic with 3 layered plant system.*

Results and Discussion

Mobile application

The mobile application offers a stable interface with several features for aquaponic system management. Users undergo authentication using a secure username and password procedure upon login *(Figure 6 (a)*, guaranteeing access control to the system. If users enter the wrong information, a popup quickly alerts them to the problem, protecting the integrity of the system's security procedures. The Tank Monitor Selection Interface *(Figure 6 (b)* is then displayed to users, allowing them to carefully choose individual tank systems in their aquaponic system for real-time monitoring. After selecting, users are shown the Monitoring & Control Interface *(Figure 6 (c)*, which provides the most recent information on critical parameters like pH, total dissolved solids (TDS), temperature, humidity, and water level. For user convenience, simple features like fish feeding are also effortlessly incorporated. The application offers a Parameter Graph *(Figure 6 (d)* for further research, which makes it easier to see trends over time for important parameters and helps users identify trends and possible problems in their system. Additionally, the application provides a page called "Optimal Reading for Plants" *(Figure 6 (e)* that gives users comprehensive information about the ideal growing circumstances for different types of vegetables. This information allows for exact environmental control based on crop requirements. Lastly, the Prediction & Disease Detection Interface *(Figure 6 (f)* uses algorithms to proactively identify problems in the health of plants and fish. This allows for the fast management necessary to preserve system integrity and maximize output by sending quick alerts and notifications to users. The mobile app provides unmatched oversight and control over aquaponic systems with its extensive feature set, equipping users with the means to promote sustainable growth.

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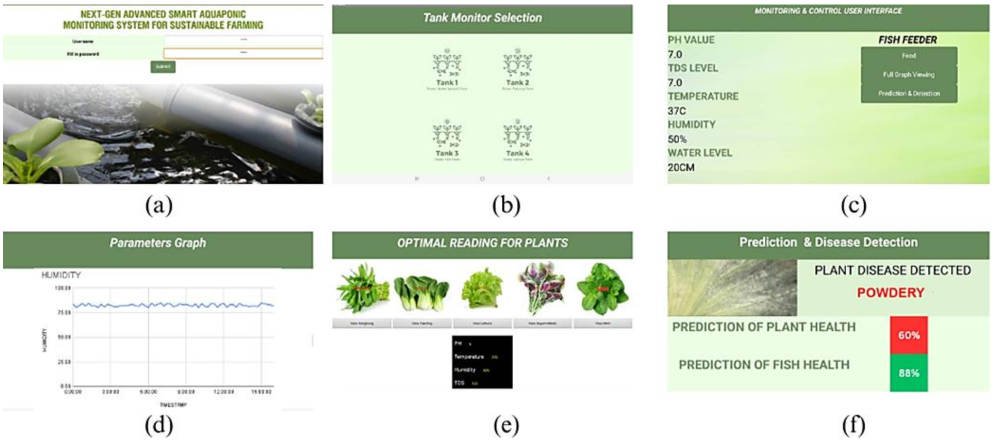

Figure 6. *Mobile application User Interface. (a)Login page, (b) Tank monitor, (c) Real-time sensing data, (d) continuous monitoring data, (e) Plants information, (f) Plant imaging disease detection and prediction.*

Fuzzy logic system output

The fuzzy inference system (FIS) was tested with multiple datasets to evaluate its predictive accuracy. *Table 4* illustrates sample data logs collected during monitoring. Simulations demonstrated that the FIS effectively categorized input parameters into optimal, acceptable, and severe ranges based on 28 predefined fuzzy rules. 3 ranges which indicates Optimal (75-100), Acceptable (50-75) and Severe (0-50) from the 28 fuzzy-rules proposed. The fuzzy inference system (FIS) was tested using multiple sets of data through a simulation as illustrate in *Figure 7*. Different values of input were entered into the FIS rule viewer to get the output result. For example, Dataset 1 yielded an output of 100, indicating optimal conditions as all input parameters fell within the ideal ranges. Dataset 2 returned an output of 89.5, categorized as optimal but slightly lower due to minor deviations. Dataset 3 produced a result of 7.5, indicating severe conditions, highlighting the system's ability to identify critical issues. *Figure 7* provides a graphical representation of the results. As the model is trained across 50 epochs, *Figure 8* shows the accuracy and loss of both training and validation. Both the training and validation accuracies show a sigmoid trend in the accuracy chart. As the model learns from the training set, they steadily rise. The speed of rise slows down as they reach their peak, suggesting a possibility of overfitting. The loss decreases dramatically at first and then steadily until it stabilizes in the second subplot, which shows loss over epochs. The validation loss steadily stays higher and drops more slowly than the training loss, indicating that the model has difficulty generalizing to new data.

Table 4*. Example of data logging of the sensors.*

Timestamp	Humidity (%)	pH	TDS (ppm)	Water level (cm)	Temperature (°C)
10:00:00	80.00	6.97	415	109	32
12:00:00	79.00	7.12	391	110	32
14:00:00	76.00	7.23	396	110	34
16:00:00	82.00	7.28	394	113	34
18:00:00	81.00	7.23	419	102	29
20:00:00	82.00	7.20	414	117	28
22:00:00	84.00	7.22	415	108	29
0:00:00	75.00	6.91	404	113	30
2:00:00	76.00	7.25	395	109	31

4:00:00	81.00	7.05	390	116	30
6:00:00	83.00	6.91	393	109	30
8:00:00	76.00	7.16	400	110	29

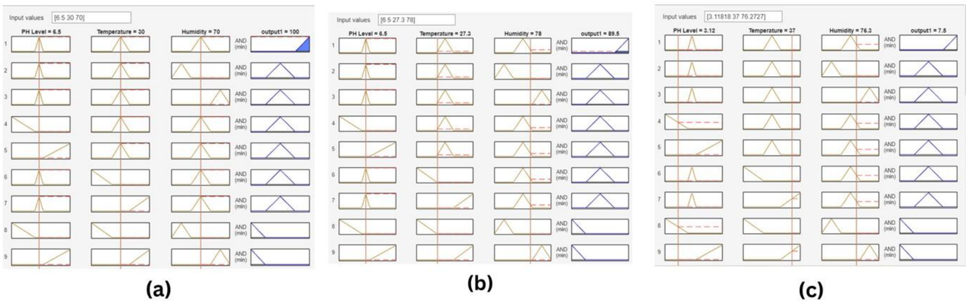

Figure 7. *Example of the result form 28 rules fuzzy-logic proposed.*

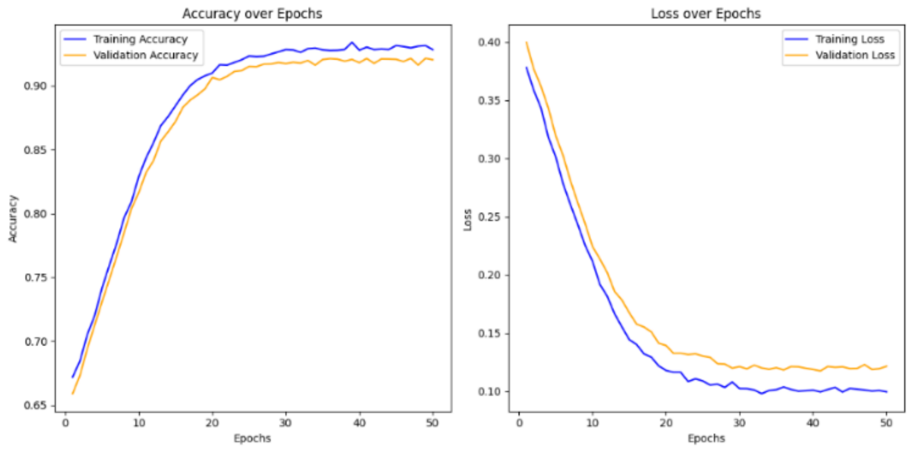

Figure 8. *The graph of accuracy & loss over epochs.*

Plant disease detection model performance

Table 5 presents the performance metrics for different classes which included Bacterial, Powdery, Downy, Septoria and Healthy. The metrics evaluated are precision, accuracy and F1-score for both training and validation datasets. A strong performance across all classes with a result of 0.85 to 0.93 in both training and validation datasets for precision and accuracy values. The F1-score, which measures classification capabilities, ranges from 0.84 to 0.92. This indicates that the model is working well in classification capabilities. It achieves high precision, recall, and F1-scores for Septoria and Healthy class, which means it can accurately classify them with very few mistakes. The model also performs well for Bacterial and Powdery leaf types, showing consistent precision and recall metrics. However, the Downy class doesn't perform as well as the other classes, but it still has reasonable accuracy. *Figure 10 (a)* shows the confusion matrix of training and *Figure 10 (b)* shows the confusion matrix of validation. In both training and validation sets, the results are acceptable. For every class, only an image was misclassified, indicating high accuracy of model. Misclassifications occur when the model mixes up the leaves classes that look similar.

Table 5*. Performance metrics of the plant disease classification model.*

Plant disease	Train precision	Train recall	F1-score	Validation precision	Validation recall	Validation F1-score

Bacterial	0.88	0.83	0.85	0.86	0.89	0.87
Powdery	0.89	0.85	0.87	0.87	0.85	0.86
Downy	0.85	0.88	0.86	0.83	0.86	0.84
Septoria	0.93	0.91	0.92	0.91	0.93	0.92
Healthy	0.91	0.89	0.9	0.89	0.91	0.9

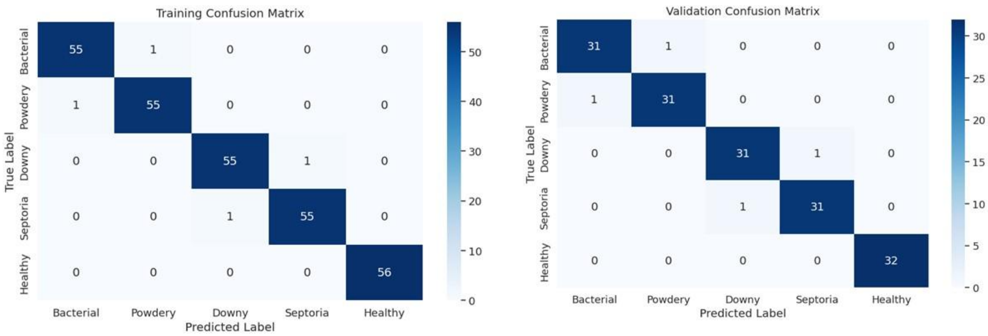

Figure 10. *Prediction model confusion matrix. (a) training, (b) validation.*

Conclusion

This research highlights the transformative potential of integrating sensor-based monitoring, fuzzy logic, and machine learning into traditional aquaponic monitoring systems. The purposed system demonstrates significant advancements in urban farming by overcoming the limitations of manual monitoring. The system provides comprehensive real-time monitoring, predictive analytics, and plant disease detection, crucial for enhancing yield and managing resources effectively. The application of fuzzy logic enables precise assessment of fish and plant health based on defined rules, which enhances monitoring accuracy. The machine learning model shows impressive performance, with recall value of 0.91 and precision value of 0.93. Additionally, the plant disease detection algorithm achieves an accuracy rate of 92%, ensuring reliable identification of potential issues. In addition, the mobile application interface facilitates user-friendly access to real-time data and predictive alerts, empowering farmers with the information needed for informed decision-making and proactive management. These advancements contribute to optimizing resource efficiency, minimizing risks, and maximizing yields, aligning with global sustainability development goals such as food security and resource efficiency. Further research should concentrate on enhancing these technologies, broadening their applications, and investigating new solutions to advance sustainable farming practices. Ongoing innovation in this domain will foster the development of more effective and resilient agricultural systems, thereby making substantial contributions to global sustainability goals.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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