Chapter

Automation and Control for Adaptive Management System of Urban Agriculture Using Computational Intelligence

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Abstract

It has been predicted by the United Nations that the world population will increase to 9.8 billion in 2050. This causes agricultural development areas to be transformed into urban areas. This urbanization and increase in population density cause food insecurity. Urban agriculture using precision farming becomes a feasible solution to meet the growing demand for food and space. An adaptive management system (AMS) is necessary for such farm to provide an artificial environment suitable to produce cultivars effectively. This research proposes the development of a computational intelligence-based urban farm automation and control system utilizing machine learning and fuzzy logic system models. A quality assessment is employed for adjusting the environmental parameters with respect to the cultivars' requirements. The system is composed of sensors for data acquisition and actuators for model-dictated responses to stimuli. Data logging was done wirelessly through a router that would collect and monitor data through a cloud-based dashboard. The model intended for training from the acquired data undergo statistical comparative analysis and least computational cost analysis to optimize the performance. The system performance was evaluated by monitoring the conditions of the sensors and actuators. Experiment results showed that the proposed system is accurate, robust, and reliable.

Keywords: urban agriculture, precision farming, adaptive control, automation, aquaponics, computational intelligence

1. Introduction

Increasing population density reduces land availability and quality [1–2]. There is evidence that areas having higher population densities are correlated with having smaller farm sizes [3]. The correlation is highly apparent in urban areas. Urbanization has been rapid in the recent decades with the transformation or rural regions into urban areas [4]. Thus, as the population density increases, rural areas, which where agricultural land were originally based, are being rapidly developed into cities for accommodating the increasing demand of spaces for shelter and industrial infrastructures. It has been gradually noticeable that food production had not met the rural areas' expectation on its crucial role in different sectors [5], further proving that urbanization may impose challenges such as food insecurity [6].

Insufficiency in food production is a global challenge that needs to be addressed as emphasized by United Nation Sustainable Development Goal (SDG 12) with responsible consumption and production [7]. One of the most feasible solutions is the establishment of farms in urban areas (UA) to contribute for food security. The idea promotes the planting and cultivating of crops within cities [8, 9]. Moreover, it also involves complex systems that consider indoor food production inside factories with an artificial environment suitable for cultivation [10], which applies the discipline of a controlled environment agriculture (CEA) [11, 12].

The limited availability of space in urban is addressed by one of the common forms: the aquaponics (AP) system. Such a system is considered to be an emerging technique for combining intensive production with waste recycling and water conservation [13]. Common AP systems do not control their environment [14]. However, one usual challenge in AP is the management of nutrients in the water being shared by the crops and fish [15, 16]. This leads to the concept of using technological control and automation of the environmental parameters affecting growth and cultivation implementing the concept of CEA in AP systems. It is proven that since AP has a hydroponic component that does not require soil for cultivation, the use of CEA can optimize production and energy conservation [17].

Controlled environment agriculture is an intensive method for managing plant growth and development through taking advantage of technological advancements and innovations in horticulture [18]. Another issue to consider is that even though AP addresses conservation, CEA consumes a lot of energy for operations due to the use of innumerable devices from sensors to controllers [19]. Efficiency in farm performances is quantified from sustainable intensification defined to be the maximum ability of the system to produce [20]. Sustainable intensification models were proven to increase production and upgraded profits per unit of energy invested while maintaining the same consumption of energy [21]. There are numerous responses relating to sustainable intensification, involving the application of innovative technology to enhance control over factors such as nutrient use efficiency to reduce attribute-derived environmental risk [22]. Automating systems in the farming community are commonly operated with an expert system (ES) that is a computer program designed to emulate the logic and reasoning of a human expert through if-then rules as a tool for decision-making support [23]. ES-based automation is bound to a static configuration set by the programmer, resulting in a fixed control that does not respond on the real-time necessity of the system. The integration of urban agriculture principles and intelligent controller and automation may be beneficial down to the community level [24–31].

The specifc objectives of this study are as follows: (1) to implement wireless sensor nodes for irrigation control, nutrient mixture automation, adaptive temperature maintenance, and lighting systems between the hydroponic chambers and the pond for aquaculture; (2) to develop a smart control and automation on actuators based on the collected data from the sensors; (3) to wirelessly send the data acquired from the sensors to a common router node for cloud-based monitoring; (4) to develop a computational intelligence-based model in evaluating the performance of the smart automation system with respect to crop productions; and (5) to evaluate the developed model by determining the exhibited accuracy and sensitivity.

2. Developments of urban agriculture with its control and automation technologies

2.1 Urban agriculture perspective

Land resources for agricultural utilization are rapidly decreasing as they are developed and transformed into cities for accommodating the increasing demand of food due to drastic population growth [28]. Urbanization has both become a solution and a problem as it addresses land space issues for residential and industrial purposes, while causing lack of available land area for agriculture.

A study [30] on the success of urban farming concluded that city-adjusted farms in comparison with their counterpart are better in terms of three parameters: economic farm situations, positive farm prospects, and farm succession development. This results to foreseeing that urban agriculture (UA)-based businesses have small probabilities of decline and closure. The effectivity of UA in food production and business profitability has been evident. However, there are still questions on UA's capability to contribute in securing food demand. To further improve city farming performances, most of its advances are credited to the innovative technology for UA (ITUA), defined to be the integration of control and automation technological advancement for optimizing food production in open or closed systems [31]. Among different forms of ITUA, Aquaponics systems (AP) earned the most attention of researchers. Even though this is the case, the economic sustainability and feasibility of such systems remain an open research area and still require further extensive studies.

Utilizing control and automation technology and innovation in UA was proven to be beneficial in expanding access to food and agriculture [32]. Aside from automated food production, ITUA has been relevant in treating waste. Hydroponics systems (HD), which falls under ITUAs, was proven to enable and control decentralization of wastewater treatment, which in turn could provide nutrients for crops being cultivated in HDs using technology-based efficient removal of unnecessary nutrients (i.e., nitrogen and phosphorus) to sustain crop growth [33].

A new discipline identified as biosystems engineering (BE) is determined to be a major necessity to deal with ITUA as bioproducts and bioenergy will be produced through series of structures, operations, machines, converters that are well systematized on which most of the applications are biological in nature [34]. This concept applies with the feasibility of ITUA for food production and environmental sustainability; thus, application of technology in farming is enabled through BE.

Farming in urban contexts by default is not that sustainable for the environment because it is dependent on high-energy consumption and intensive capital needs particularly in controlled environment agriculture (CEA). The need for CEA relies on its advantage for being capable of optimized year-round production, higher yields, and improved water usage efficiency [35–43]. This, hence, focuses on production efficiency while neglecting environmental sustainability, which contradicts the feasibility of UA. Synthesizing the presented technologies, CEA should be operated through BE making it an ITUA-founded farming, which could result to improving energy consumption and maximizing financial capital while maintaining high-production performance despite CEA's heavy operational requirements.

2.2 Intelligent controller and automation applications for urban agriculture

The emerging advancements of CEA allowed to solve agricultural concerns ranging from climate change to food insecurity. One environmental parameter that remarkably affects growth of crops is humidity. Controlling such parameter is a necessity for overall productivity, sustainability, and energy efficiency in a CEA. A liquid desiccant system integrated with arrays of triple-bore hydrophobic hollow fiber membranes was developed to control humidity levels for maintaining an optimal environment suitable for plant cultivation [44]. Temperature is another noteworthy attribute that could influence plant growth. An fuzzy logic-based cooling system for tomato cultivation was developed in a soil-based close system to vary temperature of the environment based on growth stage and the time of the day for increasing crop productivity [45].

Artificial lighting systems have become a research focus of many studies to optimize and alternatively replace sunlight's contribution for photosynthesis in a close environment. One research aimed on exploring the consequences of a multichromatic light-emitting diode (LED) spectrum in a controlled environment chambers with regard to nutritive primary metabolites in green and red leaves of lettuce being cultivated [46]. The study concluded with identifying that metabolic plasticity of cultivars determines lettuce crops' sensitivity to lighting spectrum. Reduction of power consumption and attainment of optimal plant growth were put into consideration [47] in an automated indoor farming that utilizes far-red LED treatment. The technology produces variable lighting intensity through a micro-controller, solid state relay, and dimmable LED light for controlling flowering process and stem elongation.

Nutrient assessment up to production quality analysis is usually done in a CEA. A demonstration of altering macro-cation proportions in the nutrient solution (K/Ca/Mg proportions) was done to prove that it is possible to increase or enhance the concentration of the respective macro-minerals and key phytochemicals in lettuce crops and reduce anti-nutritional components such as nitrate regardless of crop genotype [48]. This was implemented through targeted modulation of cationic proportions in the nutrient solution, especially through the application of proportionally elevated magnesium. The development can deal with the demand for crops needing to have high nutritional value and enhanced bioactive content. Image analysis technique was utilized for measuring plant growth properties that are commonly grown in a CEA *via* a smartphone integrated to a local desktop [49]. The application contributes in monitoring and assessing quality of cultivated plants in a challenging controlled environment.

Water irrigation from recycling and reusing mixed mackerel and brown seaweed wastewater for cultivating lettuce crops was implemented in a hydroponic environment. Samples were measured from installed pH probes to determine high chlorophyll and carotenoid content and high antioxidant activity from lettuce to determine the effects of wastewater, therefore, ensuring crop quality and maximizing water resources [50]. A study on vision-based lettuce phenotype model using fuzzy logic controller integrated with fertigation system showed excellent nutrient efficacy and lower chemical wastewater emissions compared with manual fertigation [51].

Farming automation is the language used in technology-based urban agriculture whether in an open or a closed system, especially in a data-driven era. Agricultural economists are challenged with handling and analyzing big data that can determine specific actions or logical responses from the information obtained [52].

Recent research focuses on developing CEA that are fully automated. A study implemented a prediction model and was imparted for irrigation scheduling and automation to manage water usage for optimizing water resources through adjusting water content to the actual volume explored by the crops' roots [53]. The method involved estimating the root depth attained from digital photographs of the vegetation cover to analyze gains and losses of water to determine soil water status.

Another study focused on farm management that uses a multi-level automation for information system [54]. It was done by implementing three automation levels that improve farm management information systems (FMIS) *via* provision of solutions relating to the acquisition of fragmented-missing data and time-consuming data entry. It has contributed to effective financial analyses and assessment, task formulation, and profitability analyses. A fully automated hydroponics was also setup with the use of multiple sensors and microcontrollers. Android and iOS devices were also used to remotely monitor information from the sensors and provide analyses [55]. This significantly contributes to farming in remote places, which could be a basis for future research on places where agriculture is not usually set.

Monitoring automatically through wireless network communication is also becoming relevant in CEA. Internet of things (IoT) have made tremendous breakthroughs in farm automation. IoT provides the possibility of connecting all things to the Internet for various advantages such as remote monitoring and control, large data storage, and information accessibility. The use of IoT in agriculture is becoming more relevant. The performance of an indoor micro-climate horticulture farming was developed with the use of IoT for gathering data from sensors and for acquiring weather information from a meteorological agency for automating environmental factors in the farm [56]. Integrating IoT to unmanned aerial vehicles (UAV) is also used in open system or traditional agriculture to transform it to precision agriculture (PA) [57]. A study proved this technique to further improve crop yield and quality, reduce cost, and mitigate ecological footprint for traditional farming [58]. Data from the agricultural industry are contributing enormously in problem-solving as IoT opened ways for easy access of these. However, agricultural data can be messy, which could provide uncertain data quality resulting to inaccurate analyses. Preserving data in a secure storage was developed in helping farmers [59].

Aquaponics (AP) is the integration of hydroponic-based vegetable crop cultivation with an aquaculture unit for an innovative smart and sustainable production system, which plays a crucial role in the future of environmental and socioeconomic sustainability in smart cities [60]. The emerging AP systems have the potential to achieve high success rate. However, intensive monitoring, control, and management are essential to properly provide a conducive environment for all cultivars grown in both the hydroponics and the aquaculture systems [61]. Challenges in AP systems are difficult to address as a major factor involves the recirculating water from the marine system that is used for irrigation and gives nutrients to the crops planted in the hydroponics chambers, which in turn feeds back the water again to the aquaculture unit with different substances and nutrient concentration. An example of this phenomena is the fish wastewater, provided through recirculating aquaculture system (RAS), may cause to contain high amounts of microorganism that can compete with plants for oxygen [62], therefore not sufficiently providing the nutrients needed by the crops.

Performance assessment is a relevant AP research concept. A study [63] conducted focused on assessing how the three different AP systems carry out with its operation for small-scale production. The three configurations experimented with were Nutrient Film-Technique (NFT), floating raft, and vertical felt living wall system. Statistical analyses with SPSS 24 statistical package were performed. A comparative analysis was also done through one-way ANOVA and Shapiro–Wilk test assessed the normality of the data. Results showed that among the three systems, the NFT outperformed the rest in terms of crop production and water consumption. With regard to fish production, no significant differences in performance were observed. Through statistical analyses, results showed that nitrogen transformation, which includes water nitrogen retention, and nitrous oxide emission, is affected by the plant-fish (P/F) biomass ratio [64].

Since AP falls under the classification of CEA, automation plays a crucial role on operating such systems reliably. A recent study [65] aimed on including an innovative and sustainable AP system solution, a modular solution for an adaptable and a scalable local condition, and an optimal way of reusing water resources, and Supervisory Control and Data Acquisition (SCADA) and Manufacturing execution systems (MESs) were the techniques that operated the configuration. Through these, the collection of software and hardware components enabled the management to automate fish and crop production. An indoor farming configured with an automated AP system was designed and implemented [66] that can monitor and control the system through a mobile phone which resulted in highly successful vegetable yield. Further integrating the BE concept, an automated solar-powered AP system was developed [67]. Water quality, greenhouse environmental conditions, solar energy conversion status, and cooling and heating parameters were controlled and monitored through NI LabVIEW that was successful in considering the environmental impact of the setup while providing optimal yield.

The majority of automation systems in agriculture rely on expert system and static programming for control. Those systems are limited to the fixed standards of environmental parameters needed in the ecosystem. Applying adjustment in accordance to the real-time needs of the cultivars is not addressed. This may result to not catering the immediate necessity of produce, which yields to production and operation inefficiency. Nonetheless, automation is still an integral part of an IUAs, especially to CEAs. A quantitative research based on case studies and desk researchers analyzed existing data to present the need of a multisystem and multifaceted approach [67] to address the problem with regard to farmers not realizing that their decisions and actions toward agriculture are causing a reduction on economic efficiency, making automation play an important role for farming.

Optimizing automation relies on adaptivity. An adaptive management has long been known to ecology and conservation. Classical methods in biological conservation do not usually consider uncertainties in the state of a system and the model describing its dynamics [68]. The study included a solution for adaptive management of ecological systems. It is a significant strategy in addressing complex issues in natural resource management, which corresponds to decision making under uncertainty and uncertainty reduction through learning from arrival of new data. A sample application of the study involved fisheries' population mass is used to adjust harvest decisions.

Monitoring automation can also apply adaptive management system (AMS). A smart farm that applies remote monitoring adapts or adjusts to what wireless communication technology to be used between LoRaWAN and IEEE802.11 ac depending on their respective advantages [69–70]. A classification application used in an adaptive farm topology develops a Naïve Bayes model for accurately identifying on which to allocate agricultural fields into different farm types [71].

Agriculture automation is an emerging concept in the industry. Together with the use of machine visions (MV) and its subsets: machine (ML) and deep learning (DL), has shown potential in solving different challenges in agriculture [72]. A lot of difficulties arise in the field such as crop pests, crop diseases, lack of irrigation control, weed, water, and storage mismanagement, and plant misclassification. Due to these, expert system-based control and automation are becoming less appropriate for addressing agricultural complications as this is limited to thinking processes. This gave birth to the use of an intelligent machine powered by the discipline of artificial intelligence (AI). AI is a field of computer science and engineering that ventures to reversing the human brain and is capable of maximizing rate of success for solving such problems by providing analytical decisions to determine the most suitable environment for sustaining plant growth based on learning from past experiences [73].

Advancing biosystems engineering with AI can enable agriculture machinery engines for a more comprehensive automation especially in CEA. Various machine learning techniques have been engaged in precision agriculture for both supervised learning and unsupervised learning in assessing plant health status and condition and invasive plant species recognition through the use of spectral signatures and optical features [74]. According to the study, there are three major contributions to agriculture that data analytics-based ML can provide. These are as follows:

1. Crop status for optimal production can be done by fusing information from spatial, spectral, and time series of crop parameters for detecting trends related to the condition of crops.

2. Hardware sensors and actuators can also be improved by making them compact and embeddable in field-deployable devices. Integrating with the discipline makes use of the devices for acquiring big data for real-time analysis, which can allow event-based decision algorithm to automatically respond for managing crop conditions on a real-time basis.

3. Accurate and reliable models can be trained from the data gathered for assessing and predicting future potential states within the field. Applications from weather projections to soil maps can be made possible for determining crop suitability in the examined fields.

With the presented contributions, studies have shown specifically the important use of AI in different agricultural applications. A smart pesticide sprayer was designed and developed with the use of AI and MV in a traditional agriculture. The sprayer was attached to an all-terrain vehicle autonomously driving itself with the aid of a global positioning system. The MV systems function as the target detector. Once a target is locked in with the system processing, the algorithm, which uses YOLOv3 and convolutional neural network (CNN), instructs the end effector to spray [75]. The study is fully automated and does not require a farmer to manually spray pesticides to each of the crops with defects.

A deep reinforcement learning, an AI subset, was used merging with IoT to enable a smart farm to make immediate decisions such as determining the amount of water that needs to be irrigated for enhancing the environment where the crops are cultivated. The IoT was utilized for gathering data from environmental attributes: air temperature and humidity, carbon dioxide concentration, soil moisture and temperature, and light intensity. The data from IoT are then analyzed through different AI models for adjusting the environment for crop growth [76]. Another hydroponic setup for lettuce production utilizes an automatic control of pH and nutrient solution concentration. The system used sensors for gathering data, microcontrollers for data processing and actuators for responding based on the results of AI algorithm to effectively adjust the nutrient parameters autonomously [77]. These studies applied AI for AMS in a CEA.

A machine vision system (MVS) was implemented for automatic classification of different leaves if they have defects or diseases. For this MVS, Haralick algorithm was used for extracting texture features. The features build the dataset for training different ML algorithms: artificial neural network, Naïve Bayes, random forest, and support vector machine; to meet the objective in determining if leaves are in good condition or not [57].

It is established that controlled environment agriculture is one of the most common applications of innovative urban agriculture (IUA), which uses the discipline of biosystems engineering for ensuring efficient crop production and energy consumption while considering environmental sustainability. Among the various CEAs, aquaponics is the most relevant research focus on the recent years. However, there are research gaps involving AP performances that need to be filled as this system has numerous challenges as it involves cultivars of different species sharing the same medium for nutrient consumption. One of the pressing issues in an AP system is the difficulty to maintain recirculating water that provides the right number of substances for both fish culture and the vegetable crop. Therefore, controlling these kinds of parameter significantly contributes for the effectiveness of such systems. Agricultural automation enables remote controlling and monitoring, which eliminates the need to have complex procedures for maintaining a suitable environment for growth. Moreover, agricultural automation for a smart aquaponics system can perform better when considering an adaptive management system (AMS), enabling the automation to adjust the environmental factors affecting cultivation based on the real-time condition and status of the cultivars. In this way, optimum results can be achieved in terms of overall success determinant. An adaptive AP system is done by integrating artificial intelligence or computational intelligence as it is capable to respond accurately and immediately as it pre-learned the situations or circumstances in the ecology.

3. Processes involve in formulating computational intelligence-based adaptive management system for urban agriculture (CIAMSUA)

Figure 1 shows the conceptual framework of the proposed CIAMSUA aquaponics platform. The framework consists of five phases on which each phase composed of detailed methods for integrating from the software to the hardware prototype. Phase 1 involves the implementation of sensor nodes to the four environmental systems. The first phase includes calibrating the sensors, programming them for data acquisition, and design and development of sensor node implementation. The second phase is the development of control and automation through programming of the actuators based on logical response from data and the construction of systems for the control and automation processes. Data transmission and acquisition comprise phase three, it integrates and embeds the wireless communication programs in the microcontroller nodes. As these data are transmitted to the cloud, it will be effectively acquired from the cloud for data processing. Data from cloud will not be limited from the sensors, which would also include data from the machine vision systems. Modeling the performance of controls based on production is done at the fourth phase. This is going to be implemented though training machine learning algorithms and adapting them in the system.

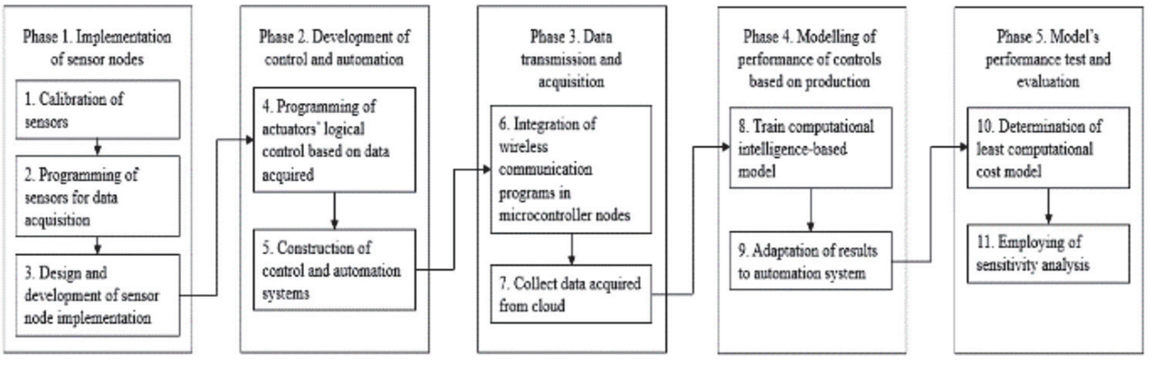


Figure 1.
Developmental framework of computational intelligence-based adaptive management system for urban agriculture (CIAMSUA).

3.1 Sensor programming for data acquisition

Data read and acquired from sensors may vary even if they were produced with the same manufacturers. There could be slight differences in the values yielded for each sensor detecting the same parameter and environment, which leads to inaccuracy and inconsistency. This is very critical and significant to consider as computational intelligence heavily rely on data for training to effectively perform. To accurately gather data, sensors are calibrated in the same external factors to adjust their readings. After calibration, sensors are programmed to acquire or read data where they are deployed. In this research, Arduino integrated development environment (IDE) will be used for embedding the software codes to the hardware through a microcontroller. Specifically, the code will be written in C ++ as this is the language used by the Arduino IDE.

The code will be composed of initiating libraries to efficiently apply existing functions so the program can simply call the specific operation to logically provide the responses. Pin configurations will be setup for assigning sensors to which pin in the microcontroller will be connected. Variables will then be initialized depending on what type (i.e., integer, float) of data they are. Void setup will then be programmed to activate variables as pins and determine which pins will be used as an input or output mode. This will also include initiating serials and sensor reading operations. The void loop will be written with sensor reading programs for the different environmental factor systems. The code will then be embedded to the microcontroller to a universal serial bus (USB). Specifically, shown in **Figure 2**, ESP32 will be used as a microcontroller as it has a Wi-Fi module integrated with the chip at an inexpensive price. Data to be acquired will be from four different systems of CIAMSUA. The following are the list of environmental factors to be monitored:

1. For nutrient mixture, conditioning, and drain tank automation,

    a. Power of Hydrogen (pH) Level

    b. Electrical Conductivity (EC)

    c. Dissolved Oxygen (DO) Level

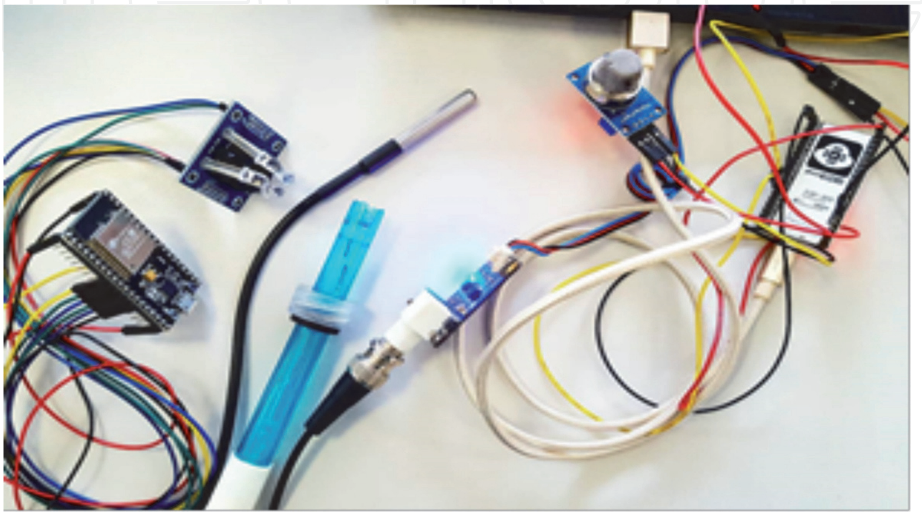


Figure 2.
Programming sensors for data acquisition with ESP32 board.

   d. Ammonia (NH3) Level

   e. Water Temperature

2. For irrigation control,

   a. Water level in a tank

3. For artificial lighting systems,

   a. Real-time basis

4. For temperature control,

   a. Environment temperature

   b. Environment humidity

The CIAMSUA will be focused and implemented in the hydroponics chamber platform. The irrigation control concentrates on managing the water from fishpond to be properly distributed in the chambers for the hydroponics unit to effectively produce lettuce crops.

3.2 Sensor node implementation

The schematic diagram shown in **Figure 3** is one of the sensor nodes for the nutrient mixture automation, the conditioning tank, and the irrigation control.

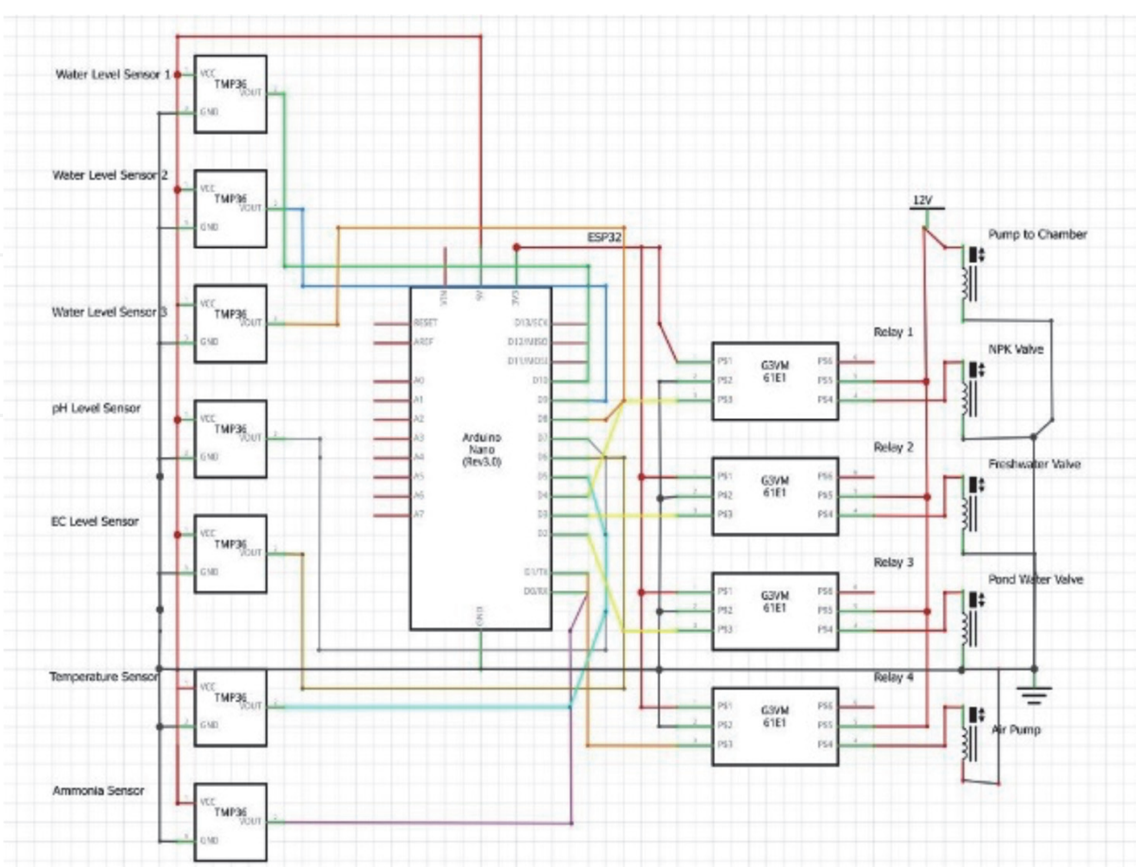


Figure 3.
Nutrient mixture, conditioning tank, and irrigation control node schematic acquisition.

There are three water-level sensors placed at the input side. Four more sensors are also assigned as input, and these are pH level sensor, EC level sensor, water temperature sensor, and ammonia sensor. Logical controls are embedded on the ESP32. The outputs are connected to an electronic mechanical relay, which response to trigger the microcontroller to switch on and off the solenoid valves, the water pump, and the air pump for appropriate water flowing and mixing.

Figure 4 shows the schematic diagram of the node to be placed in the drain tank. As noticed, there are no actuators in the node as the purpose of this is only to acquire data to determine the difference between the limnological parameters in the water before and after the lettuce crops consumed the water being irrigated in the racks of the chambers. The sensors included are the same as the sensors shown in **Figure 3**; that way, a model can be derived to determine how much nutrients of the crops do intake in different life stages.

Figure 5 shows the node that both control the NPK solution tank and the freshwater tank. The control is done for allowing the liquid to pass through the hose leading to the solenoid valves connected in the nutrient mixture and the conditioning tank. The sensors are not connected to the control and will only be used for monitoring the tank levels so that a manual refill can be made if the tanks are empty and manual drainage if the tanks are full.

Sensor node for temperature control is shown in **Figure 6**. It has three temperature sensors for acquiring real-time temperature in different areas of the hydroponics chamber. The output side is a relay that is electronically triggered to switch on or off the exhaust fan. The relay also functions to isolate the low DC voltage of the input and microcontroller side from the high AC voltage of 220 V that is required to operate the exhaust fan.

The artificial lighting system schematic diagram is shown in **Figure 7**. The ESP32 is not connected to any input devices as this automation depends on time duration. A delay function would be embedded to switch on or off the relays connected to lights at a specific amount of time.

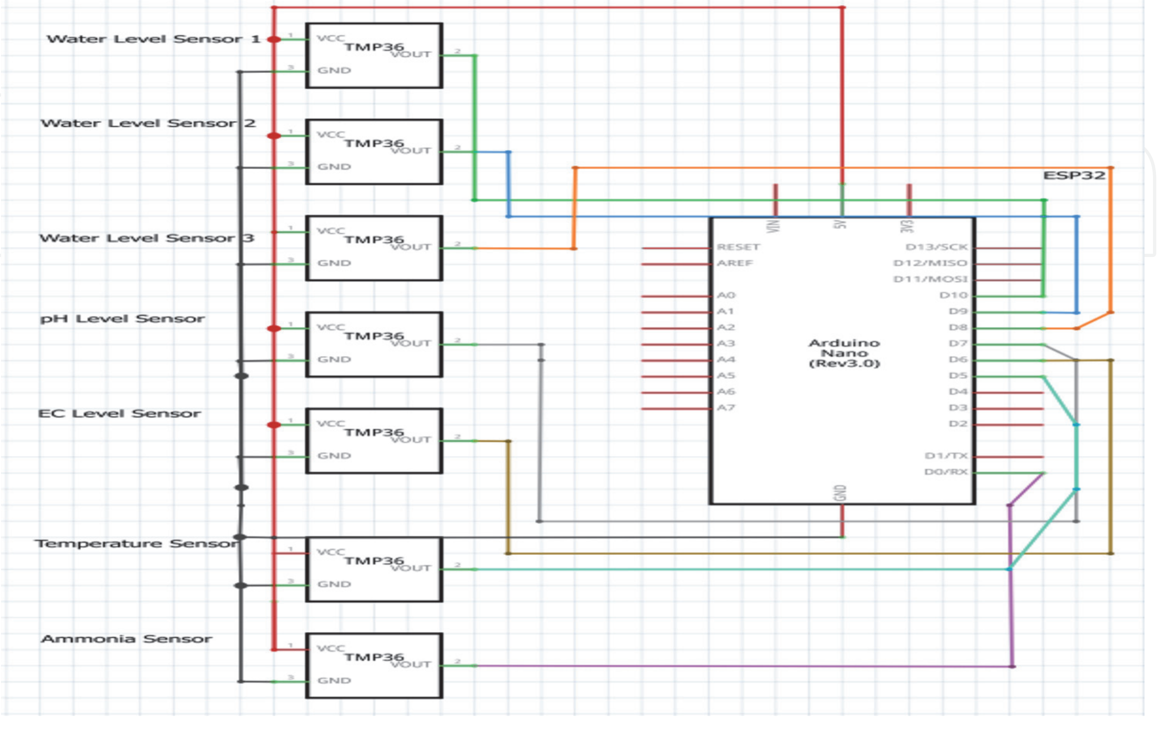


Figure 4.
Drain tank control node schematic diagram.

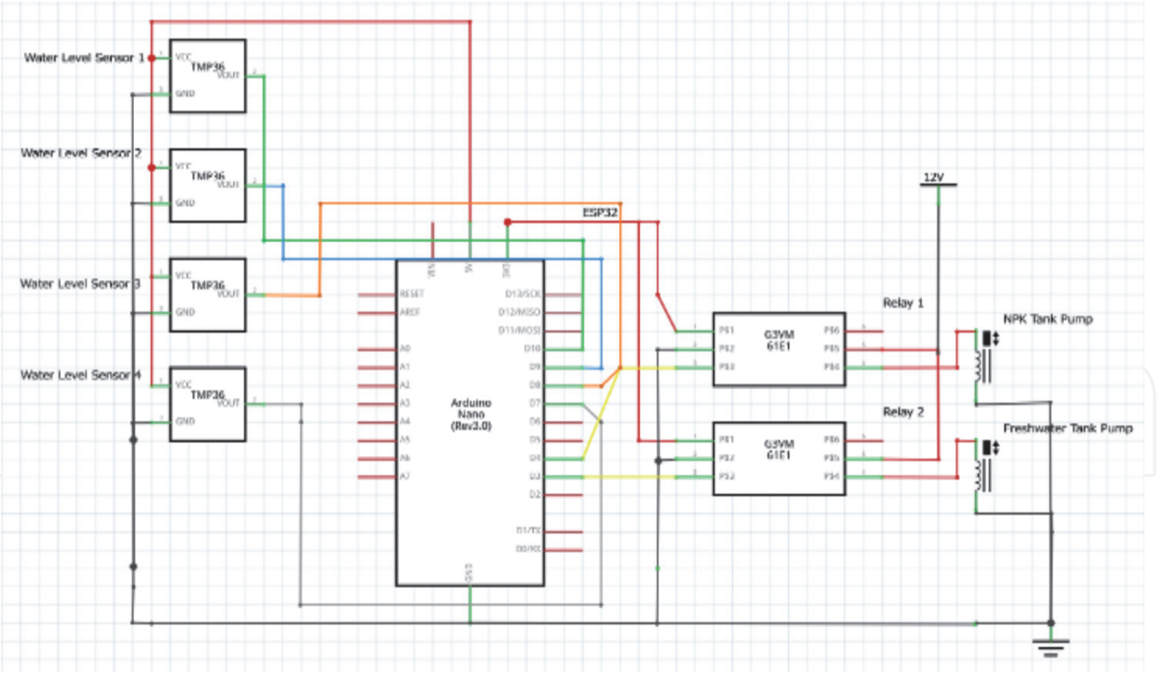


Figure 5.
NPK and freshwater tank control.

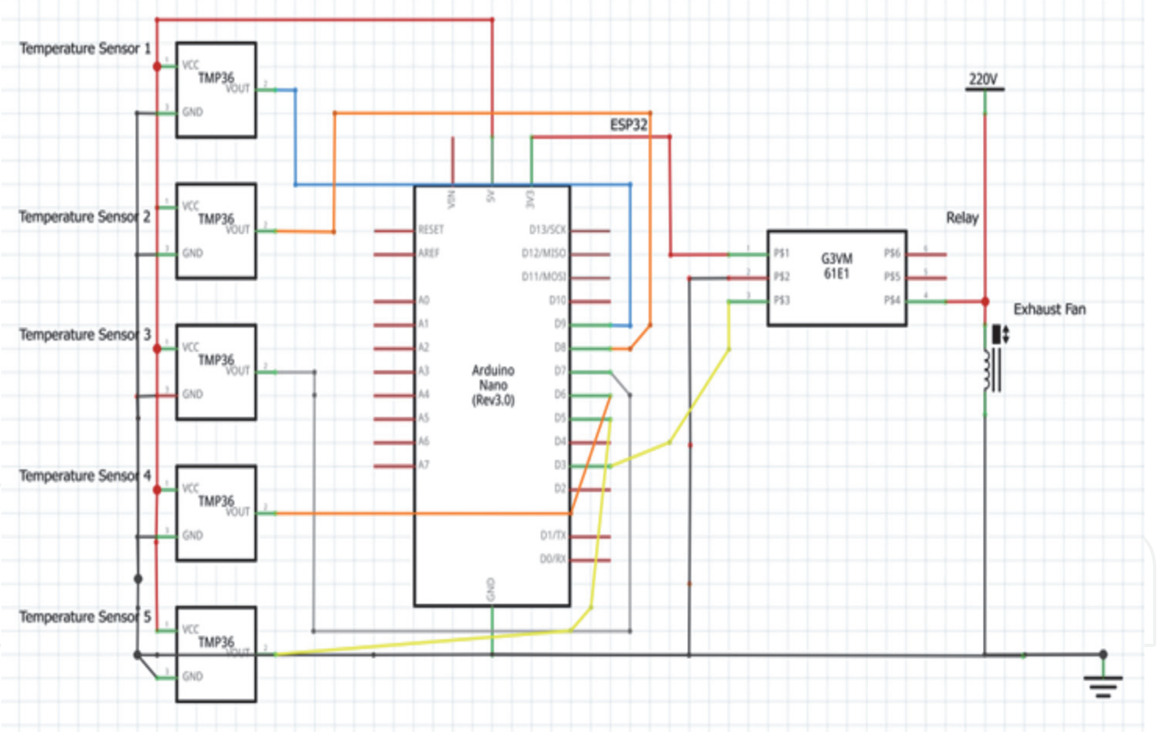


Figure 6.
Temperature and humidity maintenance node schematic diagram.

Actuators will be logically programmed in accordance with the data acquired from the sensors. The truth table only presents the system for the nutrient mixture automation and irrigation control as shown in **Table 1**. The truth table developed to visualize all the eight possible combinations of water-level sensors status and the corresponding responses of the five actuators involved in the nutrient mixture automation and irrigation control. Out of eight combinations, only four are realistically possible as the water-level sensors are placed in different levels in the water tank, resulting to only considering combinations that correspond to water filling from the bottom of the tank up to the top consecutively.

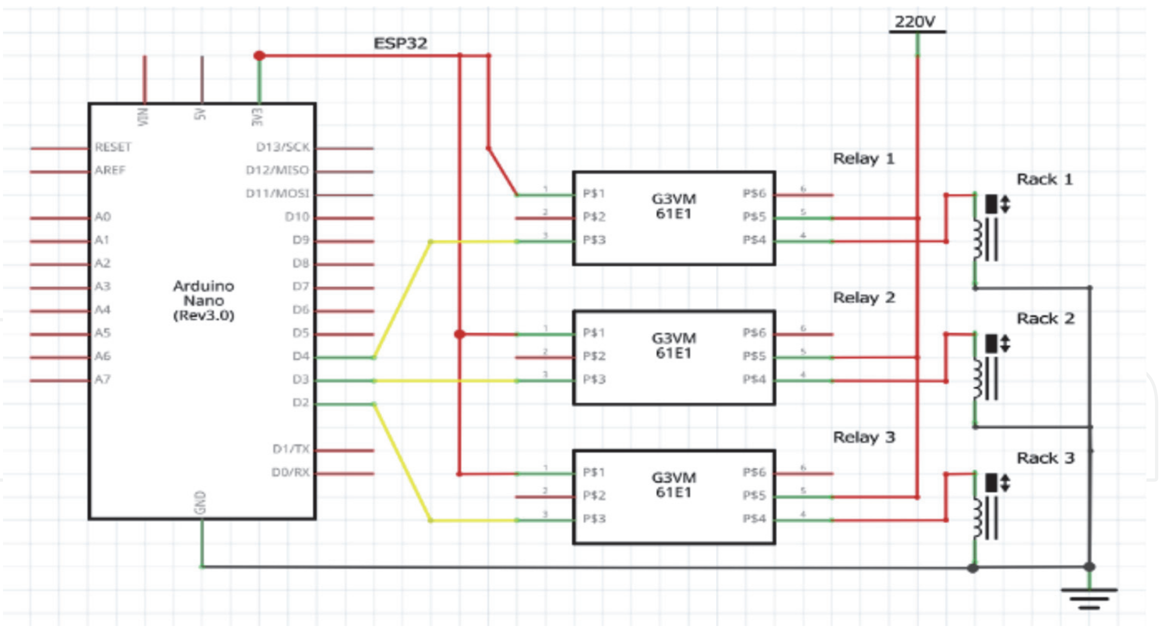


Figure 7.
Artificial lighting system node schematic acquisition.

The first combination, 0–0-0, means that the water in the tank is at the bottom level, not reaching any of the three sensors. With this, the pond water valve and the pump supplying water to the chamber from the tank should be on. At 0–0-1, the water level is being detected by the sensor placed at the lowest level. The 0–1-1 combination shows that the two sensors placed at the bottom and at the middle of the tank are turned on, representing that the tank is half full; thus, valve for pond water should be turned off to avoid overfilling. The top half of the tank should only be filled with either freshwater or NPK solution to control the pH and EC level of the tank mixture. The combination 1–1-1 means that the water sensor at the top-most level of the tank has been reached, remarking it as full; therefore, the source water from the pond should be stopped. The combination 0–1-0 is not possible to take place as the water cannot only be at the middle part of the tank and not at the bottom. The same is true for the three remaining truth table combinations.

Readings from pH, EC, temperature, and ammonia sensors should always be activated, representing a logic 1 to continuously acquire data at any water level. The pump-distributing water to the chambers should always be turned on as well at any level, to consistently supply water to the lettuce racks. Air pump on the other hand follows an OR logic, on which it will turn on only if one of the valves is on.

3.3 The CIAMSUA fuzzy logic controller

Figure 8 shows the fuzzy logic controller (FLC) that is use in this study. Data that were transmitted to a cloud-based dashboard will be automatically downloaded in MATLAB. From there, they would be used as new dataset for the pretrained network that is connected to the FLC. The output of the computational intelligence-based models, which are specifically the fresh weight and the phytopigments of the lettuce crops, will be used as input to a fuzzy inference system for determining how long will the NPK valve, freshwater valve, and air pump should turned on or off. The truth table and the FLC function together as a nested condition of the actions for irrigation controls to determine the control of the air pump, NPK, freshwater, and pond water valves.

The membership functions of the input and output for the fuzzy logic control of the freshwater and NPK solenoid valves are shown in **Figure 9**. The fresh weight of

	Tank status			Remarks						Actuators' Response		
H_2O level top	**H_2O level middle**	**H_2O level bottom**	**Remarks**	**pH**	**EC**	**Temp**	**NH_3**	**NPK valve**	**Fresh H_2O valve**	**Pond H_2O valve**	**Pump to chamber**	**Air pump**
0	0	0	No to very low level water	1	1	1	1	0 or 1	0 or 1	1	1	0 only if NPK and fresh H_20 valves are 0
0	0	1	Water level at lowest sensor (3)	1	1	1	1	0 or 1	0 or 1	1	1	0 only if NPK and fresh H_20 valves are 0
0	1	0	Cannot happen	—	—		—	—	—	—	—	—
0	1	1	Tank halfway full	1	1	1	1	0 or 1	0 or 1	0	1	0 only if NPK and fresh H_20 valves are 0
1	0	0	Cannot happen	—	—	—	—	—	—	—	—	—
1	0	1	Cannot happen	—	—	—	—	—	—	—	—	—
1	1	0	Cannot happen	—	—	—	—	—	—	—	—	
1	1	1	Tank full	1	1	1	1	0	0	0	1	0 only if NPK and fresh H_20 valves are 0

Table 1.
Irrigation control truth table.

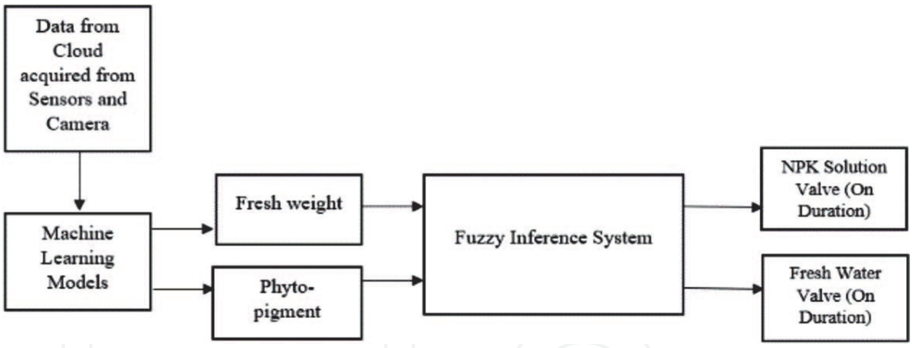


Figure 8.
Nutrient mixture tank fuzzy logic controller.

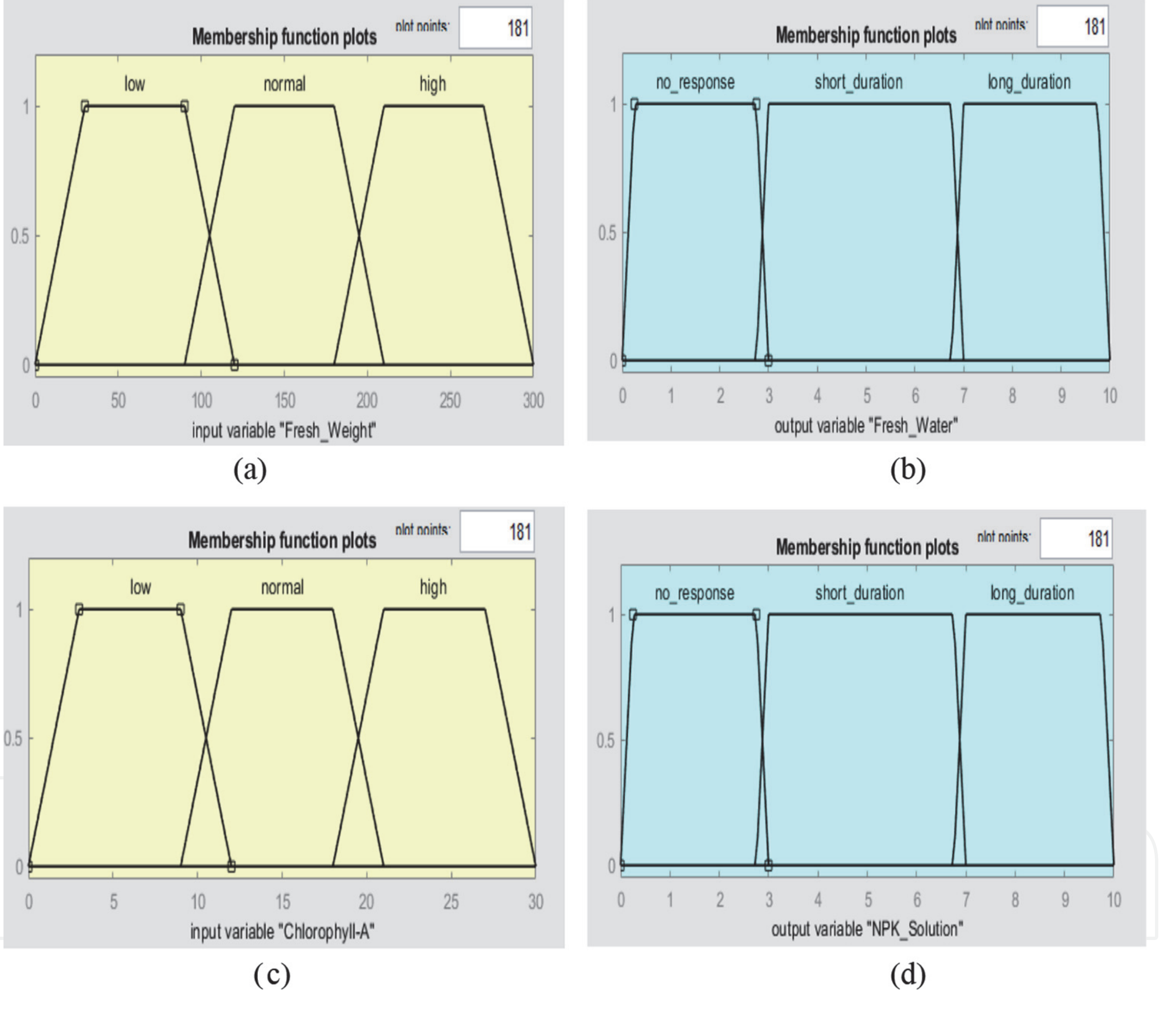


Figure 9.
(a) Fresh weight, (b) freshwater, (c) chlorophyll-A, and (d) solenoid valves membership functions.

the lettuce is used as input in **Figure 9a** representing the 0 to 300 mg range of change in weight per day. **Figure 9c** represents the membership function for the 0 to 30 mg/L range of changes of chlorophyll-A per day. The output crisps represent the duration for how long the valves: freshwater **Figure 9b** and NPK solution **Figure 9d** are on, which ranges from 0 to 10 seconds.

The rule viewer for the fuzzy inference system (FIS) is shown in **Figure 10**. Based on the given sample values of the input parameters, having 269 mg of change in fresh weight in a day and 23.2 mg/L change of chlorophyll-A in a day, the freshwater valve will turn on for 8.37 seconds. Another system was implemented to round it off to

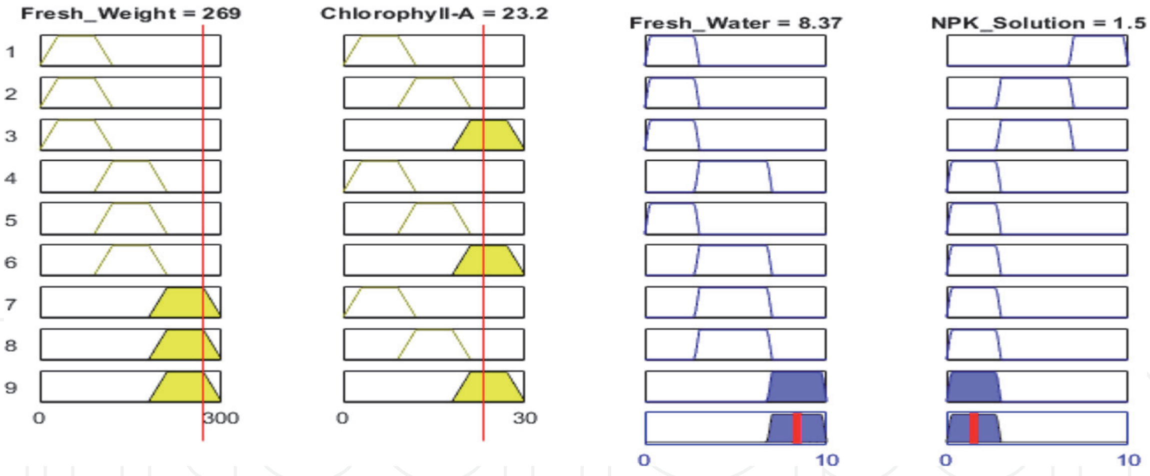


Figure 10.
Fuzzy inference system rule viewer with nine rules.

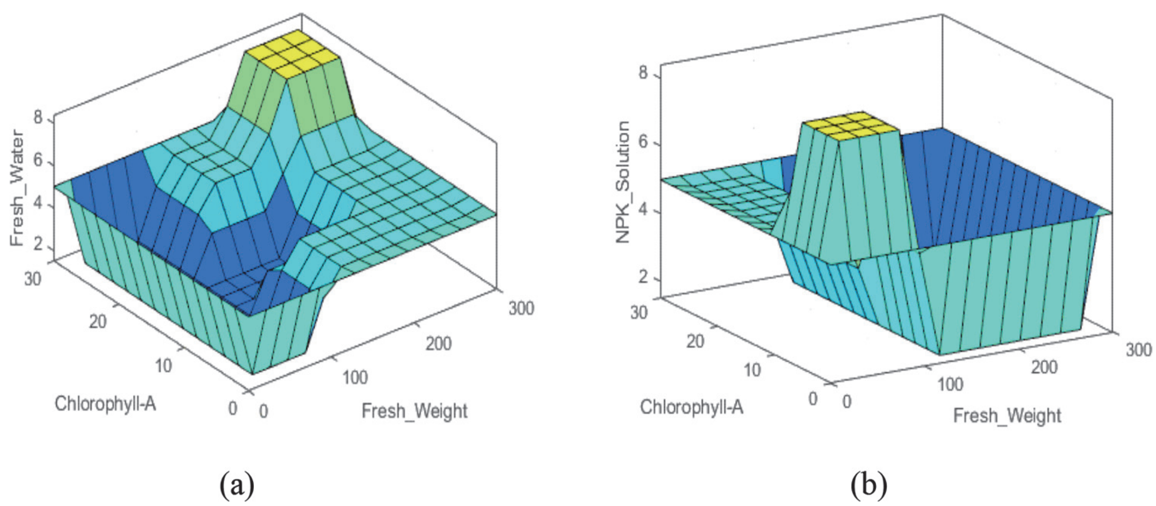


Figure 11.
Fuzzy inference system surface viewer for lettuce phenotypes: (a) fresh water, chlorophyll a and fresh weight interrelated dynamics; and (b) NPK solution, chlorophyll and fresh weight interrelated dynamics.

10 seconds, while the NPK solution valve is turned off for the day's cycle. Thus, this sample adds 660 mL of freshwater into the hydroponics growth bed.

Figure 11 represents the Surface Viewer of the FIS. It can be interpreted from both figures that as the fresh weight and chlorophyll-A values increase, it is necessary to turn the solenoid valve on for the freshwater longer and turn the NPK solution valve off.

The inference systems using freshwater and the other two phytopigments: chlorophyll-B and vitamin C follow the exact same membership function, ranges, and sets of rules used. Thus, only one set of FLC is represented.

The artificial lighting systems will be controlled depending on photoperiod, which is reliant on a time duration input. Various durations will be assigned for each layer of lettuce rack for experimentation. By default, the test cases will be set to 9, 12, and 16 hours, respectively. This will then change depending on the results of the performance evaluation or sensitivity analysis from the output of the models developed so that permanent photoperiod control could be integrated in the system.

The temperature is programmed through a fuzzy logic controller to maintain the temperature adequate for the plant's excellent growth. **Figure 12** shows the block diagram for the adaptive control of the temperature and humidity maintenance based on the fresh weight and phytopigments of lettuce crops. The system follows the similar approach with the nutrient mixture control. However, there is a

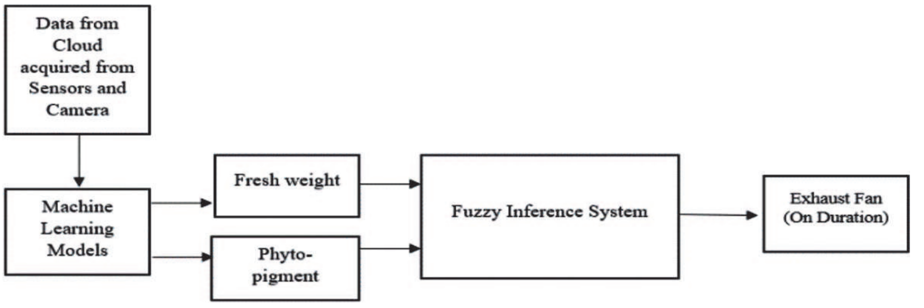


Figure 12.
Temperature fuzzy logic controller.

significant difference on how it was implemented. For the temperature and humidity control, the FLC was embedded to the microcontroller through the Arduino IDE, unlike with the nutrient mixture control which uses the Simulink.

Listed below are the actuators that will be implemented for each of the four systems:

1. For nutrient mixture tank automation,
    a. Freshwater solenoid valve.
    b. NPK solenoid valve.
    c. Freshwater solenoid valve.
    d. Air pump
2. For irrigation control,
    a. Water pumps
3. For artificial lighting systems,
    a. Photoperiod control
4. For temperature control,
    a. Exhaust fan.

3.4 Data acquisition for CIAMSUA

The aquaponics system was constructed following the layout in **Figure 13**. The control nodes were placed accordingly to where it is needed the nearest to avoid long-wiring connections. **Figure 13a** shows the front view of the hydroponic chamber on which the drain node, artificial lighting system, and temperature and humidity controls are visible. **Figure 13b** shows the back of the hydroponic chamber on which the fishpond for the aquaculture unit is located. Two nodes were placed, which are the nutrient mixture and the NPK solution tank nodes. **Figure 13c** and **d** shows additional isometric views that further provide understanding on where the nodes were implemented and placed in the chamber. The 3D model was only limited to represent the adaptive management system. **Figures 14** to **18** show how the hardware nodes for the automation are constructed in terms of wiring

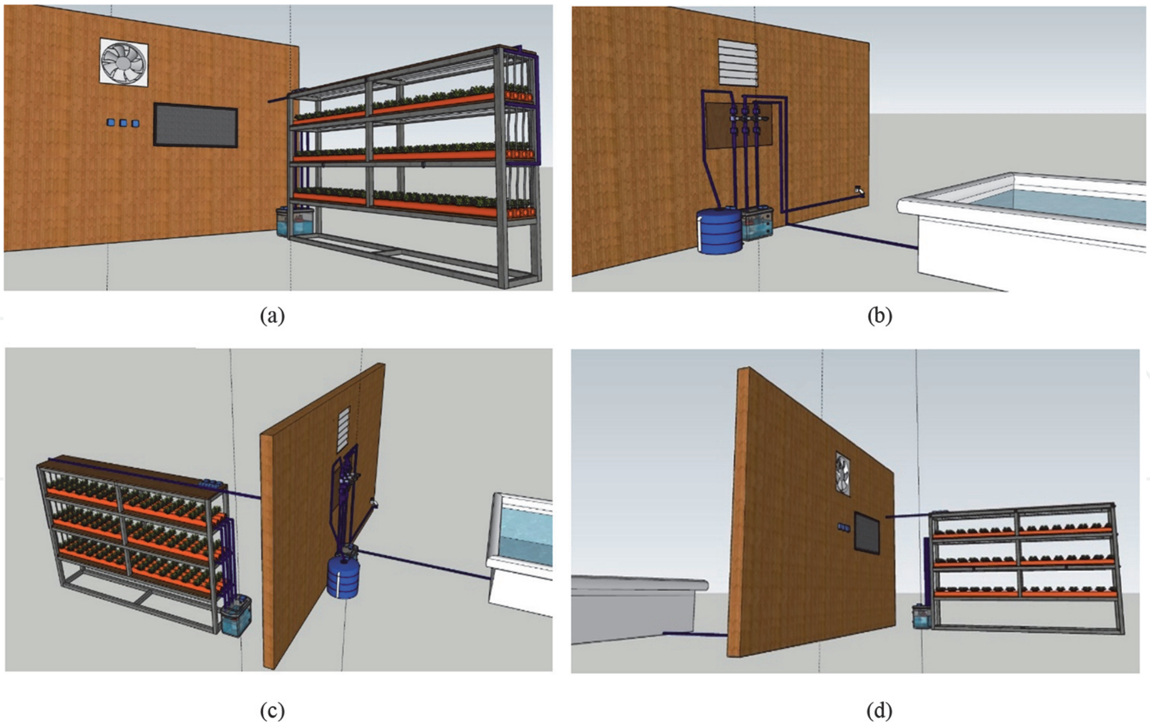


Figure 13.
Hardware implementation of the aquaponics setup: (a) front view of the aquaponic chamber with emphasis on the installed exhaust fan and grow bed, (b) mixing tank connected to an artificial fish pond, (c) drain tank connection from the vertical grow bed, and (d) connection from artificial fish pond to the grow bed.

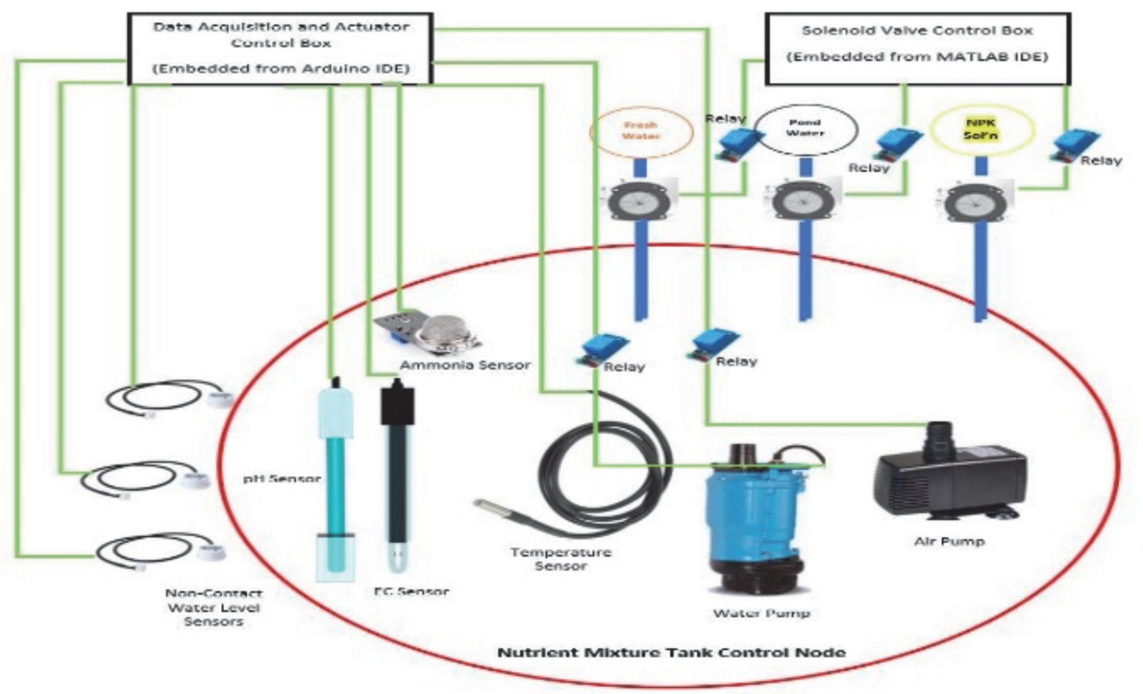


Figure 14.
Nutrient mixture tank control node.

diagram as reflected in the schematics. The details of its programs are already discussed in the previous sections.

Aside from controlling the actuators, monitoring of the sensor and actuator status was implemented to determine whether the acquired data match the actuators responses. The status of each device, whether they are active or not, was transmitted alongside with the data from the sensors to the cloud to a wireless network.

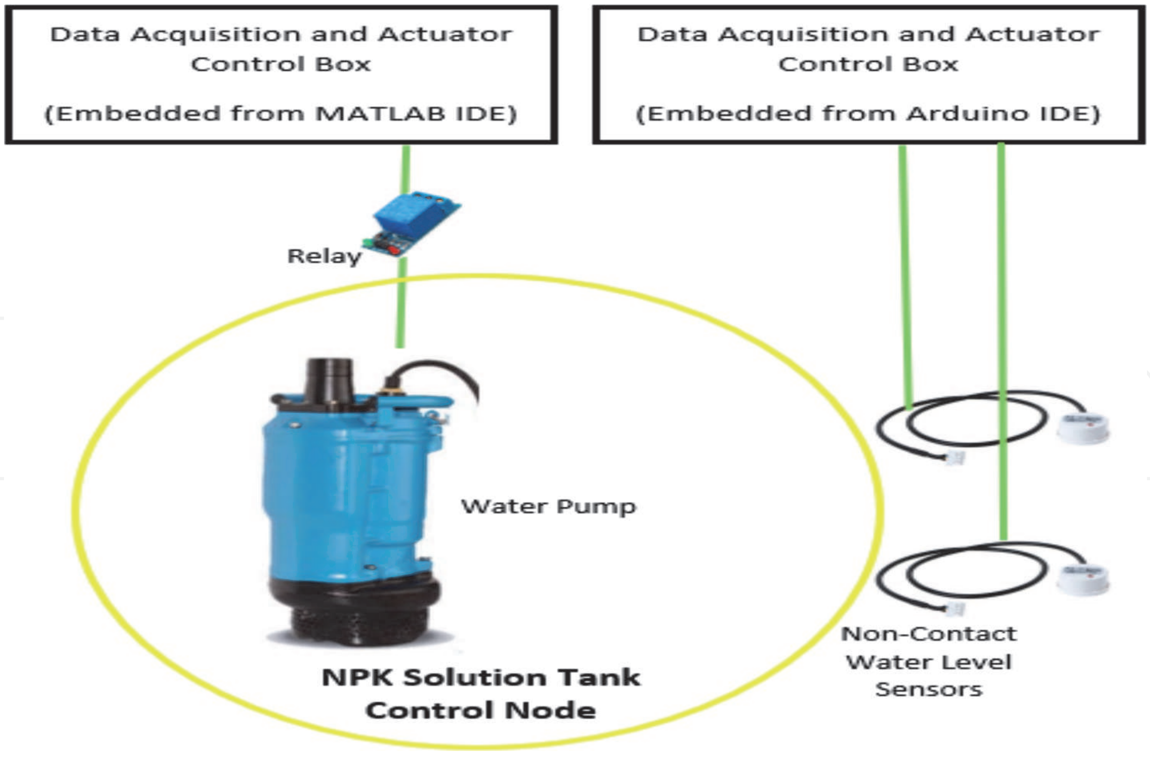


Figure 15.
Freshwater and nutrient solution tank control node.

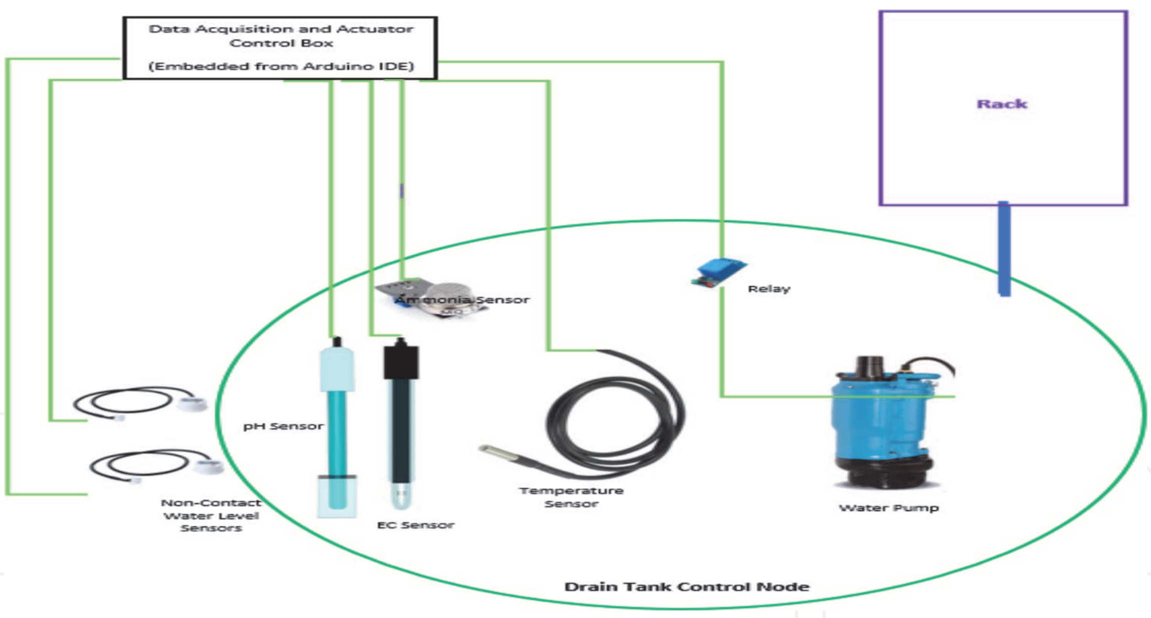


Figure 16.
Drain tank control node.

The data acquired from the sensors were transmitted *via* wireless communication network. This is done by embedding programs that activate the Wi-Fi module of the ESP32 and selectively send the data to a common router. The common router is responsible for collectively sending data to the cloud. Data will be collectively displayed on a cloud dashboard for remote monitoring. The data printed from the dashboard will be exported to csv files to present a tabular form of dataset. **Figure 19** shows a sample monitoring dashboard for displaying the data acquired.

Spectrophotometry was done to obtain the response variables that are the chlorophyll-A, chlorophyll-B, and vitamin C for a given input image. This is the technique used to carry out the discipline of spectroscopy. It is a method for

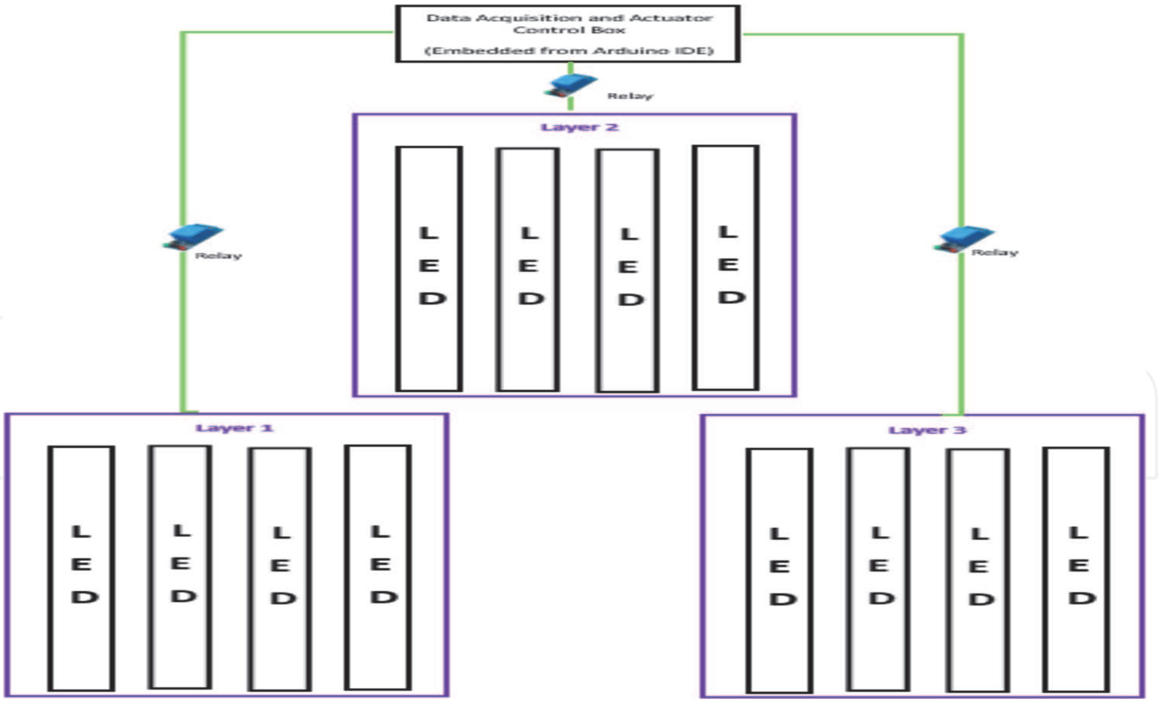


Figure 17.
Artificial lighting system control node.

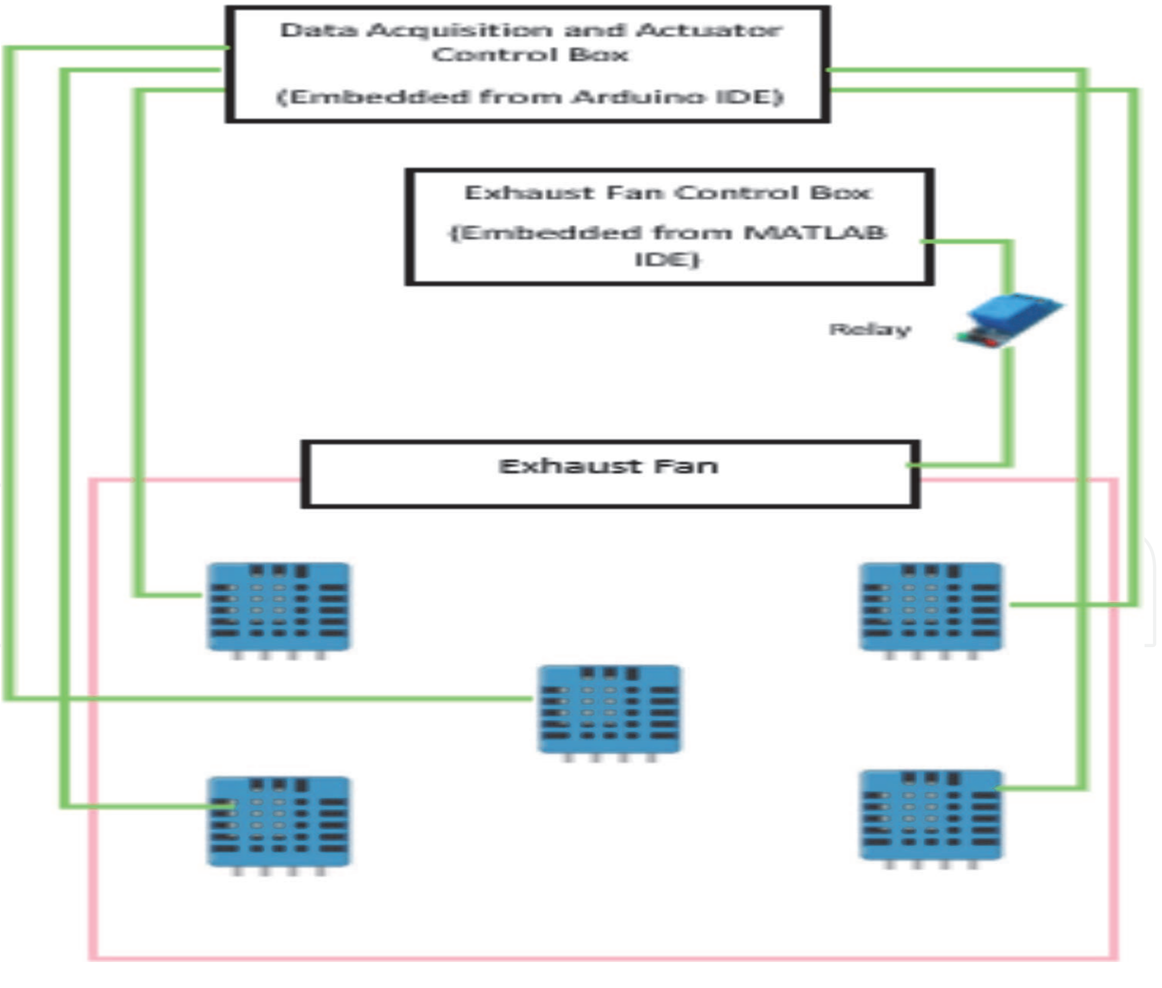


Figure 18.
Temperature control node.

quantitatively measuring the light spectra reflection as dispersed in the concept of spectroscopy and its interaction to the properties of materials' transmission relative to the wavelength. It measures the light's relative intensity at a specific wavelength,

DOI: http://dx.doi.org/10.5772/intechopen.102775

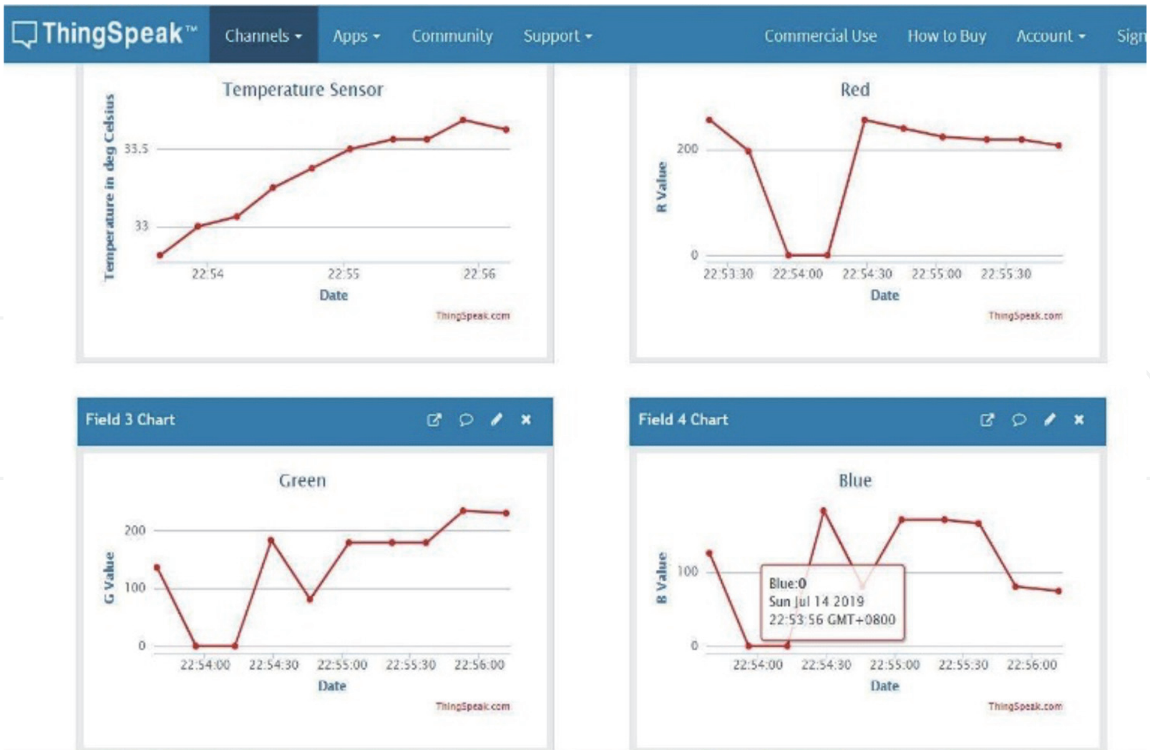
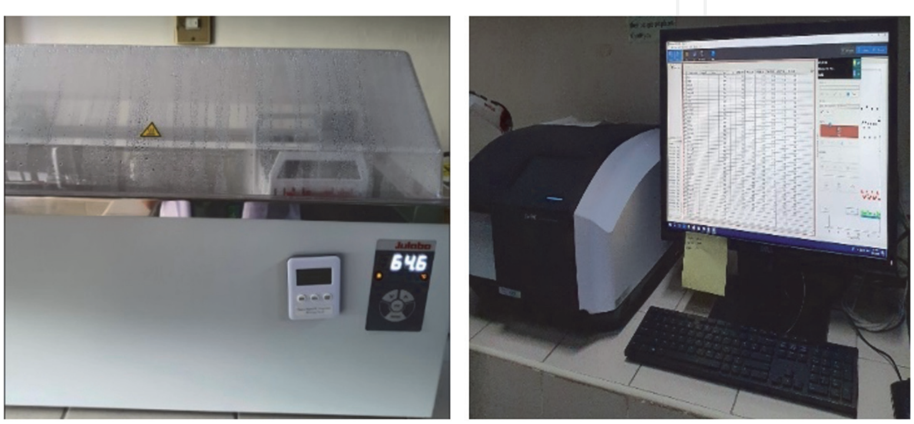


Figure 19.
Sample cloud dashboard for data acquisition.

(a) (b)

Figure 20.
Sample test tubes during pigment extraction from (a) leaf tissue samples mixed with ethanol and (b) collection of test tubes containing different concentrations of dissolved leaf pigments.



(a) (b)

Figure 21.
(a) Hot bathing and (b) spectrophotometry for pigment assay.

which supports spectroscopy on determining the relationship of the spectrum absorption properties of substances. **Figure 20a** and **b** show the test tubes that contain a leaf sample for every lettuce per day. These were then heated at 65°C as shown in **Figure 21a** before undergoing spectrophotometry in **Figure 21b**.

Image processing was done to resize the images to the compatible input sizes of a given transfer learning network. These transfer learning networks were used in predicting the fresh weight, chlorophyll-A, chlorophyll-B, and vitamin C given a lettuce image as input. InceptionV3 were used for predicting the fresh weight, chlorophyll-B, and vitamin C, while MobileNetv2 was used in predicting chlorophyll-A. For Inceptionv3, the required image size is 299x299x3 pixels, while for the MobileNetv2 it is at 224x224x3 pixels. Hence, the captured images were resized to those values. These networks were preselected based on multiple trial and error on determining which networks would yield the highest accuracy in performing the regression. **Figure 22a** display the original image captured, while **Figure 22b** is a sample of an image resized to 299x299x3 to be used as input in transfer learning. The output on the other hand is the corresponding data gathered from spectrophotometry. The data created were split into 70% training datasets and 30% testing datasets. The training dataset was used to model four regression networks.

3.5 CIAMSUA model performance

The modeled algorithms were evaluated to determine its performance through the "unseen" data or the testing data to validate if the models do not overfit to the training data alone. **Figure 23** shows the transfer learning network. The first dataset is bigger than the dataset used in the study as it would be used to pre-train a more generalized model. The target domain in the study used segmented lettuce images. The source model transfers knowledge to a target model to perform prediction of phyto-morphological features. The models were developed while considering hyperparameter optimization to further increase the algorithm's performance. Training options were predetermined and set before training the model. The parameters and their values are as follows:

1. Optimizing algorithm—Stochastic Gradient Descent with Momentum

2. Mini Batch Size—32

(a) (b)

Figure 22.
Sample input image (a) at t1 = 0 hr and (b) at t2 = t1 + 24 hrs.

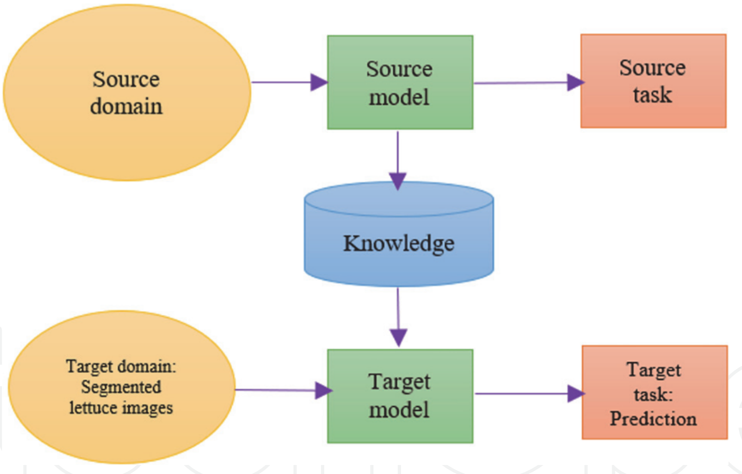


Figure 23.
Transfer learning network.

3. Initial Learning Rate—0.000001

4. Maximum Epochs—10

After training the models, a complete cultivation of lettuce was conducted on which images were captured each day for the six-week cultivation. The capture images were used as input to predict the fresh weight and the three phytopigments.

Table 2 shows the predicted values of the fresh weight and the three phytopigments daily. The average of the dataset was obtained which served as the ground truth for the standard values for the fresh weight, chlorophyll-A, chlorophyll-B, and vitamin C as summarized in **Table 3**. The values in the table were also fed back to the fuzzy logic controller to be used as parameters for the input of the inference system. The change of values per day was obtained to be set as ranges for the membership functions.

Evaluating the system's performance will be reliant on machine vision algorithms and the data acquired from sensors to determine the quality of the crops produce. From the results of quality assessment, it will determine the response of the automation and control system to produce the environmental factors need by the crops to improve their quality. This therefore adjusts the nutrients being supplied to the crops, the pressure of water flow feeding the crops, the amount of light intensity and photoperiod, and the temperature of the surroundings resulting to an adaptive and managed system. The system adaptation will be done by integrating MATLAB, which is capable of machine vision and machine learning algorithm to be embedded in the microcontroller.

To further improve the system models developed, least computation cost was implemented. This finds out which systems have the least mean-squared error (MSE) and least learning time for training while maintaining a high performance. **Figures 24–26** are examples of the adjustment that were conducted for the number of neurons for determining which model would yield the least MSE, least-learning time, and high accuracy.

Sensitivity analysis is a way to determine how the dependent variables, which are the fresh weight and phytopigments, are being affected by the independent variables that are the amount of NPK solution, freshwater, environmental temperature and humidity, and the photoperiod control. The experiment for this phase would be to measure the amount of NPK solution and freshwater for the short and long duration as produced by the fuzzy logic controller (FLC). The process also

Day	Image no	Fresh weight (g)	Chl-a (mg/L)	Chl-b (mg/L)	Vit C (mg/L)
1	1	0	87.221	135.623	290.369
2	2	0.45	97.143	157.623	336.39
3	3	0.52	100.449	174.236	369.125
4	4	0.78	139.874	189.623	377.36
5	5	0.84	147.869	209.143	382.898
6	6	0.856	157.41	220.32	387.27
7	7	0.88	167.84	226.52	395.369
8	8	0.906	167.902	234.63	397.739
9	9	0.914	169	236.041	400.321
10	10	0.925	169.227	241.356	401.376
11	11	0.937	170.914	248.73	402.36
12	12	0.97	171.265	253.559	403.013
13	13	1.019	173.415	265.325	405.694
14	14	0.986	175.347	271.143	410.364
15	15	1.03	177.846	285.694	418.395
16	16	1.167	191.623	297.137	426.375
17	17	1.354	215.412	309.67	439.657
18	18	1.497	229.654	327.65	444.36
19	19	1.524	245.562	350.571	456.949
20	20	1.74	257.027	376.197	468.791
21	21	1.929	278.974	387.462	479.765
22	22	1.974	282.475	394.273	481.367
23	23	2.004	294.613	401.657	487.673
24	24	2.194	301.214	415.193	492.317
25	25	2.201	303.415	436.874	495.769
26	26	2.313	309.919	468.198	498.185
27	27	2.461	314.95	491.257	507.769
28	28	2.61	321.54	505.056	519.469
29	29	2.899	347.618	516.243	523.076
30	30	3.164	374.512	547.35	531.176
31	31	3.334	391.147	587.367	542.176
32	32	3.447	407.874	598.38	554.007
33	33	3.656	417.843	617.978	561.073
34	34	3.779	431.512	628.367	570.312
35	35	3.962	467	654.328	587.675
36	36	4.219	498.184	690.143	668.447
37	37	4.675	502.634	739.165	708.98
38	38	4.914	520.21	784.361	781.142
39	39	5.389	529.347	800.35	815.6
40	40	5.759	564.955	816.646	831.194

Day	Image no	Fresh weight (g)	Chl-a (mg/L)	Chl-b (mg/L)	Vit C (mg/L)
41	41	6.119	575.695	837.361	854.989
42	42	6.221	592.314	865.32	872.994

Table 2.
Fresh weight and phytopigments.

	STANDARD			
Week	Freshweight (g)	Chl-a (mg/L)	Chl-b (mg/L)	Vit C (mg/L)
1	0.618	128.258	187.584	362.683
2	0.951	171.01	250.112	402.981
3	1.463	228.014	333.483	447.756
4	2.251	304.018	444.644	497.507
5	3.463	405.358	592.859	552.785
6	5.328	540.477	790.478	790.478

Table 3.
Phytopigments standard values of lettuce per week.

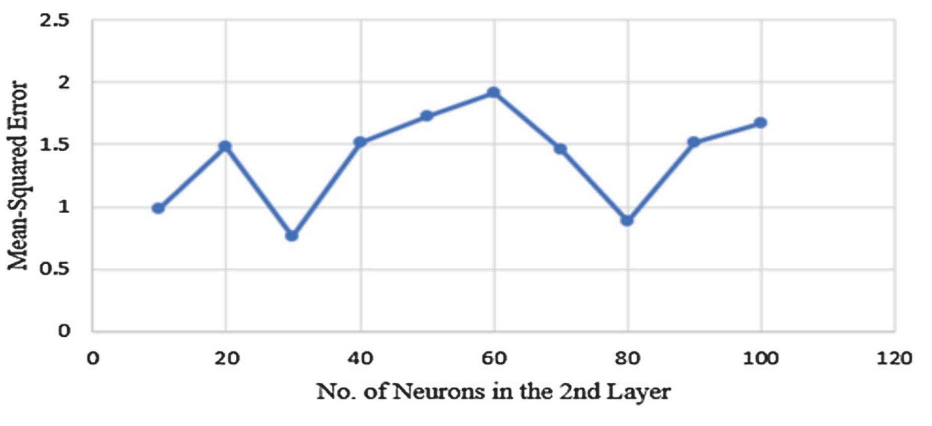


Figure 24.
Number of neurons versus mean-squared error.

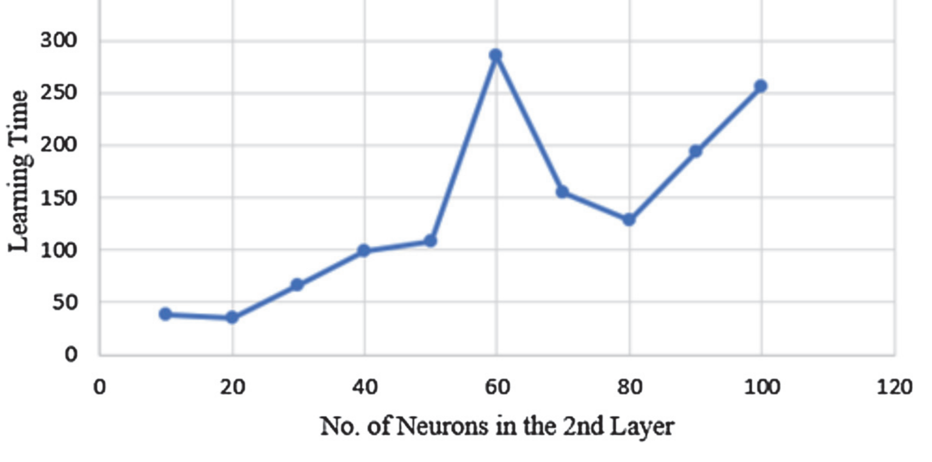


Figure 25.
Number of neurons versus learning time.

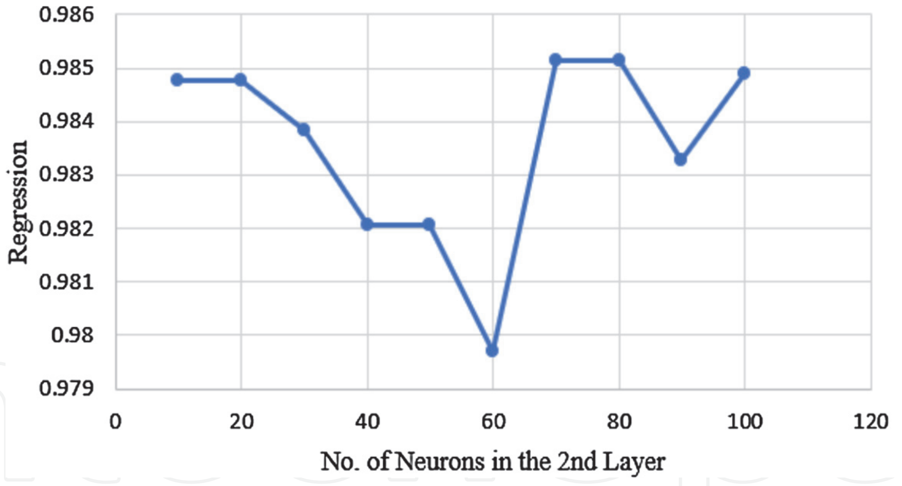


Figure 26.
Number of neurons versus regression.

includes the following: a) determine the temperature, humidity, and the corresponding photoperiod of artificial lights, b) measure crop parameters, c) record the FLC conditions and crop parameters for the whole crop cycle, and d) determine whether crop features improve from the given FLC condition.

4. Results and discussion

This chapter details the results of the experimentation conducted as followed from the methodology and the discussions for supporting the validity of achieving the objectives. For the nutrient mixture, conditioning tank and irrigation control, sensitivity analysis was done to determine the response of the control system based on the data acquired from lettuce images. The artificial lighting system was experimented with the aid of the test case from **Table 4**. The temperature and humidity maintenance node was tested by determining the response of the fuzzy logic controller given with simulated environment temperature and humidity. Automating the system adaptively follows standard target values to provide the necessary amount of nutrients that are needed to sustain the standard phytopigment values for optimal lettuce crop growth. The lettuce crops, fresh weight, chlorophyll-A, chlorophyll-B, and vitamin C should be at least 5.328 g, 540.48 mg/L, 790.48 mg/L, and 790.48 mg/L, respectively, during the harvesting stage at week six.

	Rack with 9 hours of on state in a photoperiod	Rack with 12 hours of on state in a photoperiod	Rack with 16 hours of on state in a photoperiod
Fresh weight on Day 42	4.923 g	5.328 g	5.013 g
Chlorophyll-A on Day 42	481.914 mg/L	540.477 mg/L	545.896 mg/L
Chlorophyll-B on Day 42	619.847 mg/L	790.48 mg/L	708.367 mg/L
Vitamin C on Day 42	611.598 mg/L	790.48 mg/L	756.284 mg/L

Table 4.
Phytopigments values during harvest stage on different cultivation photoperiods.

	Freshwater										
Day	**0**	**1140**	**2280**	**2760**	**5220**	**5700**	**7320**	**7800**	**8940**	**9420**	**10,080**
1	0	0.052946	0.105892	0.128185	0.203424	0.225717	0.317675	0.362261	0.415207	0.4375	0.468153
2	0.024974452	0.07792	0.130866	0.153159	0.228398	0.250691	0.34265	0.387236	0.440182	0.462475	0.493128
3	0.049948903	0.102895	0.155841	0.178134	0.253373	0.275666	0.367624	0.41221	0.465156	0.487449	0.518102
4	0.074923355	0.127869	0.180815	0.203108	0.278347	0.30064	0.392599	0.437185	0.490131	0.512424	0.543077
5	0.099897807	0.152844	0.20579	0.228083	0.303322	0.325615	0.417573	0.462159	0.515105	0.537398	0.568051
6	0.124872258	0.177818	0.230764	0.253057	0.328296	0.350589	0.442548	0.487134	0.54008	0.562373	0.593026
7	0.14984671	0.202793	0.255739	0.278032	0.35327	0.375563	0.467522	0.512108	0.565054	0.587347	0.618
8	0.209700413	0.27321	0.336719	0.36346	0.45371	0.480451	0.590757	0.644238	0.707747	0.734488	0.771257
9	0.239657614	0.303167	0.366676	0.393417	0.483667	0.510408	0.620714	0.674195	0.737705	0.764445	0.801214
10	0.269614816	0.333124	0.396634	0.423374	0.513624	0.540365	0.650671	0.704152	0.767662	0.794403	0.831171
11	0.299572018	0.363081	0.426591	0.453332	0.543582	0.570322	0.680628	0.73411	0.797619	0.82436	0.861128
12	0.32952922	0.393039	0.456548	0.483289	0.573539	0.60028	0.710585	0.764067	0.827576	0.854317	0.891086
13	0.359486422	0.422996	0.486505	0.513246	0.603496	0.630237	0.740543	0.794024	0.857533	0.884274	0.921043
14	0.389443623	0.452953	0.516462	0.543203	0.633453	0.660194	0.7705	0.823981	0.887491	0.914231	0.951
15	0.528632023	0.608682	0.688732	0.722438	0.836193	0.869898	1.008933	1.076343	1.156393	1.190099	1.236443
16	0.566391453	0.646442	0.726492	0.760197	0.873952	0.907658	1.046692	1.114103	1.194153	1.227858	1.274203
17	0.604150883	0.684201	0.764251	0.797956	0.911712	0.945417	1.084451	1.151862	1.231912	1.265617	1.311962
18	0.641910314	0.72196	0.802011	0.835716	0.949471	0.983177	1.122211	1.189622	1.269672	1.303377	1.349722
19	0.679669744	0.75972	0.83977	0.873475	0.987231	1.020936	1.15997	1.227381	1.307431	1.341136	1.387481
20	0.717429174	0.797479	0.877529	0.911235	1.02499	1.058695	1.19773	1.26514	1.34519	1.378896	1.425241
21	0.755188604	0.835239	0.915289	0.948994	1.06275	1.096455	1.235489	1.3029	1.38295	1.416655	1.463
22	1.03335233	1.137672	1.241991	1.285915	1.434159	1.478083	1.659269	1.747117	1.851437	1.895361	1.955756

DOI: http://dx.doi.org/10.5772/intechopen.102775

	Freshwater										
Day	**0**	**1140**	**2280**	**2760**	**5220**	**5700**	**7320**	**7800**	**8940**	**9420**	**10,080**
23	1.082559584	1.186879	1.291199	1.335123	1.483366	1.52729	1.708477	1.796325	1.900644	1.944568	2.004964
24	1.131766838	1.236086	1.340406	1.38433	1.532573	1.576497	1.757684	1.845532	1.949851	1.993775	2.054171
25	1.180974092	1.285294	1.389613	1.433537	1.581781	1.625705	1.806891	1.894739	1.999059	2.042983	2.103378
26	1.230181346	1.334501	1.43882	1.482744	1.630988	1.674912	1.856098	1.943946	2.048266	2.09219	2.152585
27	1.2793886	1.383708	1.488028	1.531952	1.680195	1.724119	1.905306	1.993154	2.097473	2.141397	2.201793
28	1.328595853	1.432915	1.537235	1.581159	1.729402	1.773326	1.954513	2.042361	2.14668	2.190604	2.251
29	1.838344307	1.977533	2.116723	2.175328	2.373124	2.431729	2.673479	2.790691	2.92988	2.988486	3.069069
30	1.903999461	2.043189	2.182378	2.240984	2.438779	2.497385	2.739134	2.856346	2.995535	3.054141	3.134724
31	1.969654615	2.108844	2.248033	2.306639	2.504434	2.56304	2.804789	2.922001	3.06119	3.119796	3.200379
32	2.035309769	2.174499	2.313688	2.372294	2.570089	2.628695	2.870444	2.987656	3.126845	3.185451	3.266035
33	2.100964923	2.240154	2.379343	2.437949	2.635744	2.69435	2.9361	3.053311	3.192501	3.251107	3.33169
34	2.166620076	2.305809	2.444998	2.503604	2.701399	2.760005	3.001755	3.118967	3.258156	3.316762	3.397345
35	2.23227523	2.371464	2.510653	2.569259	2.767054	2.82566	3.06741	3.184622	3.323811	3.382417	3.463
36	3.12125033	3.310309	3.499368	3.578972	3.847634	3.927238	4.255603	4.414811	4.60387	4.683473	4.792929
37	3.210428911	3.399488	3.588547	3.66815	3.936813	4.016417	4.344782	4.503989	4.693048	4.772652	4.882107
38	3.299607492	3.488666	3.677725	3.757329	4.025991	4.105595	4.433961	4.593168	4.782227	4.861831	4.971286
39	3.388786072	3.577845	3.766904	3.846507	4.11517	4.194774	4.523139	4.682347	4.871405	4.951009	5.060464
40	3.477964653	3.667023	3.856082	3.935686	4.204349	4.283952	4.612318	4.771525	4.960584	5.040188	5.149643
41	3.567143234	3.756202	3.945261	4.024865	4.293527	4.373131	4.701496	4.860704	5.049763	5.129366	5.238821
42	3.656321815	3.845381	4.034439	4.114043	4.382706	4.46231	4.790675	4.949882	5.138941	5.218545	5.328

Table 5.
Freshweight sensitivity analysis from freshwater.

A duration-based control using fuzzy logic system was developed to translate the output amplitude of the nutrient solution automation into a time dimension. This controls the duration of the solenoid valve in turning on and off for the NPK solution to flow. For the short duration, the solenoid valve should be on for 5 seconds to give 480 mL liquid concentration. For the long duration, the solenoid valve should be on for 10 seconds to give 660 mL liquid concentration. This process only occurs once a day as the system was set to capture image information on daily basis only. The artificial lighting system was tested at different photoperiods of 9, 12, and 16 hours, on layers 1, 2, and 3 of growth beds, respectively. Results of these are shown in **Table 5**. The phytopigments were measured for one sample of every layer. It was observed from the result that the optimal photoperiod is at 12 hours. Hence, the light setting of the system should be continuously on for 12 hours and off for the next 12-hour cycle.

Sensitivity analysis has proven to be a significant tool in determining the effectivity of models used in eco-systems. The response of the actuators for nutrient, conditioning, and irrigation control was measured on how effective they were on taking automation controls based on the changes on the input data. The analysis contains eight tables of information for the four phytopigments considered such as fresh weight, chlorophyll-A, chlorophyll-B, and vitamin C. The performance of the actuators was measured based on cumulative freshwater volume and cumulative NPK solution volume. The two actuator measurements were used since the time the crop was first planted to determine the changes of the four phytopigments that resulted to eight combinations of sensitivity analysis dataset. The dataset contains 42 samples representing every phytopigment value captured each day for the six-week cultivation. The samples were defined through what if analysis from 42 days of measuring the amount of NPK solution and freshwater added to the hydroponics unit each day from the fuzzy logic controller that operates once every 24 hours. This results to a 42-by-42 dataset on which the measured amount of liquid is added cumulatively for each sample. To simplify the representation, the 42 measured liquid substances added to the system were summarized into 11 samples that were proportionately parted to represent the whole dataset. Note that at day 42, the standard value for the lettuce crops at week 6 for harvest was accurately obtained. **Table 5** shows sample fresh weight sensitivity analysis from freshwater. When a total of 10,800 mL of freshwater was added on the water inflowing to the hydroponics growth bed, the freshweight obtained was 5.328 g. It is interesting to mention that the required standard value for the lettuce crops at week 6 for harvest is obtained accurately in all experiment results.

5. Conclusions and recommendations

The wireless sensor nodes for irrigation control, nutrient mixture automation, adaptive temperature maintenance, and lighting systems between the hydroponic chambers and the pond for aquaculture were effectively implemented for the automation and control of the adaptive management system. The water flow as controlled by the irrigation system successfully recirculates from the pond to the mixing tank and then flows through the hydroponics chamber back to the pond through the drain and conditioning tank. The nutrient mixture automation depends on the machine vision system data, deep learning models, and fuzzy logic controller to determine the amount of nutrient solutions to be added on the liquid concentration before it flows to the growth beds. The adaptive temperature maintenance as controlled by fuzzy logic maintains the standard temperature and humidity for optimal crop growth. Lighting the crops is dependent on an artificial real-time clock setup that has a photoperiod of 9, 12, and 16 hours, respectively, for each layer of the growth beds.

Data acquired from the wireless sensor nodes were utilized to determine the responses of the actuators. For the irrigation control, each of the tanks contains a pump or solenoid valves that are reliant to the water level and nutrient sensors. For the nutrient mixing tank, there are three water-level sensors that control the solenoid valve for the pond water to control if the inflow should be stopped while there is a continuous outflow of water to the hydroponics chamber. Mixing tanks are controlled to determine whether the tank should be filled with nutrient concentrations. The outflow, however, is not controlled by the irrigation control but by the nutrient mixture automation. The conditioning tank has the same irrigation control with the nutrient mixing tank. The drain irrigation, however, is only controlled by two water-level sensors that turn on the pump if the tank is almost full and turn off the pump as the tank almost empties. The nutrient mixture automation relies on data acquired from the vision systems. Maintaining the temperature suitable for lettuce growth is reliant on the temperature and humidity data acquired from five sensors across the chamber.

Transmission of data that are used for determining the actuators' response is done wirelessly to store them on a database and to present them on a cloud-based monitoring system through a common router node. Sending the data to the common router node is integrated with the use of the built-in WIFI module of the ESP32 through the wireless transmission program developed in each of the sensor nodes.

Machine vision acquires image data that are wirelessly sent to the cloud-based database and monitoring as the input for the crop growth optimization based on the phytochemical and phytopigment and fresh weight models. The models were trained using computational-based algorithms. Lettuce crop images underwent image processing techniques to obtain the data that are used as response variables to be predicted by the deep learning networks. Predictions made by the models from newly acquired data that were not yet seen or used by the model are integrated to a fuzzy logic controller to determine the duration of solenoid valve opening once per day. This controls the nutrient concentration added to the mixing tank per day to adaptively adjust the nutrients to be absorbed by the plants based on its yield from the previous day. The adaptive management system on the nutrient mixture automation both in the mixing and conditioning tank is using the models to automatically set the required nutrients needed by the cultivars in the hydroponics chamber and the aquaculture pond.

Sensitivity analysis was then used to determine whether the adaptive management system responds timely and accurately based on the input data from the wireless sensor networks and the machine vision systems. The analysis determines whether the amount of nutrients cumulatively added per day result in the needed concentration for the crops. According to the standard values from **Table 4**, the system was able to obtain the necessary amount of phytopigments per cultivation week as the nutrients were adjusted accordingly. During the harvesting stage, the lettuce crops, fresh weight, chlorophyll-A, chlorophyll-B, and vitamin C were at 5.328 g, 540.48 mg/L, 790.48 mg/L, and 790.48 mg/L, respectively, that were the optimal values to harvest the crops at its optimal yield.

For future works, it is recommended that an adaptive management system for different crops will be implemented in a single-smart aquaponics system. The concept underlies a way for switching an AMS that can produce an optimal yield for different cultivars that can be cultivated in a single system of hydroponics unit and aquaculture unit. This will address the limitation of study that solely focuses on lettuce crops. Other ecological and environmental factors aside from the four aspects covered in the study can be added to the AMS as well such as gas system emission control to determine the crops' growth effect as well to other surrounding cultivars that will be added in the system.

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