# Development of Integrated Real Time Iot-Based Monitoring System for Optimal Ipomoea Aquatica Indoor Cultivation

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## ABSTRACT

With the emphasis of smarter, more efficient crop growing methodologies coupled with advances in sensors, Internet of Things (IoTs) and artificial illumination especially at the urban areas propel the development of indoor farming to another level as never been seen before as per compared to open and large-scale farming. However, there is a relatively big void in term of reference data availability for soilless indoor farming i.e. precision farming, level of nutrients, light irradiances, yield improvement and etc. This study is primarily aims at design and implement IoT system for real-time multi nodes parameters monitoring for indoor farming using related sensors and related components to tap on real time indoor farming critical parameters. Edge computing solutions and a cloud-based storage/computing to be applied accordingly as tools to facilitate data monitoring and storage. This study will involve installation of various sensors aiming at sensing parameters and functionality of nutrient quality monitoring (nutrient sensors, pH, Electrical Conductivity (EC), nutrient temperature), climates monitoring (humidity, indoor room temperature, $CO_2$ gas) and irrigation (flow, level and turbidity). All of these data then shall be transmitted accordingly to relevant processors, monitoring system and then being stored at clouds. The methodology is structured in a way that the system could be scaled-up for larger space and modular setting. This study also aims at collecting real-time data for future yield improvement purposes. Technically, this study will contribute a real-time monitoring system of closed-loop automated nutrient quality management, climates and irrigation for soilless indoor farming on top of useful data/trend for future indoor leafy agricultural studies and improvement particularly in Sarawak, Malaysia.

**Keywords:** Indoor farming, Internet-of-Things (IoT), Raspberry Pi, real-time monitoring, sensors, Ipomoea Aquatica (water spinach)

## INTRODUCTION

While large area and open space agriculture practices are very much common in the non-urban area, with the rapid migration to the cities and/or urban areas, the globe is experiencing unbalance development in term of food production while trying to sustain the livelihood of humanities in general. This created an upward pressure on the food supply chain on top of existing limited urban resources compounded with shrinking of arable land as well as exposure to political instability, geographic and limitation of manpower. Innovative agriculture practices could be very much key points to overcome the above challenges and limitations. Indoor farming coupled with the advances in technologies for example sensors and Internet-of-things (IOT) is a promising approach to overcome these challenges in term of land and water shortage, shrinking arable agricultural land due to various climates impacts, shortage of manpower as well as highly adoptable to be implemented in urban areas. Typically, urban

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areas are well connected to power source/electricity and internet connection are reliable and stable thus providing a good platform for indoor farming.

The scope of this study is to develop a cost-effective system for indoor application, specifically for water spinach (Ipomoea Aquatica). The system will provide real-time monitoring of the nutrient solution and environmental conditions in an indoor setting with parameters such as pH level, total dissolved salt (TDS), water temperature, reservoir level and turbidity level as well as the ambient temperature, humidity and carbon dioxide concentration are being monitored respectively and individually.

**Background**

Indoor farming refers to utilizing an indoor space or enclosure for farming with artificial lighting as photosynthesis sources. It could be hydroponic-based or other soilless-based approaches and normally on fertigation or continuous pumping irrigation modes [1, 2]. Recent development of indoor farming were highly motivated with the advances in lighting or illumination sources and growing trend/demand in controlled environments for agricultural activities [3]. Literature compilation on studies and developments on this area mainly involved the adaptation of complex components and functionality such as artificial intelligent algorithms [4], various sensors and actuators [5-7], IoT components [8-10] and multi-spectral systems storage element [11-13] for monitoring [14, 15], precision farming [16], yield optimization [17, 18], automated control and detection applications [4, 5].

However, there is a noticeable void in term of literature on IoT based indoor farming related parameters particularly in Sarawak as most available references are mainly based on open space and large area farming. In addition, the adaptation, direct scaling and modularity of IoT solutions for real practical indoor farming is yet to be widely implemented or seen in indoor farming.

## METHODOLOGY

The IoT monitoring system follows a four-layer architecture based on IoT principles, consisting of the following layers (a) perception layer, (b) edge computing, (c) processing layer and (d) application layer as summarized in Figure 1. This modular IoT architecture ensures efficient data flow, scalability and robust system performance.

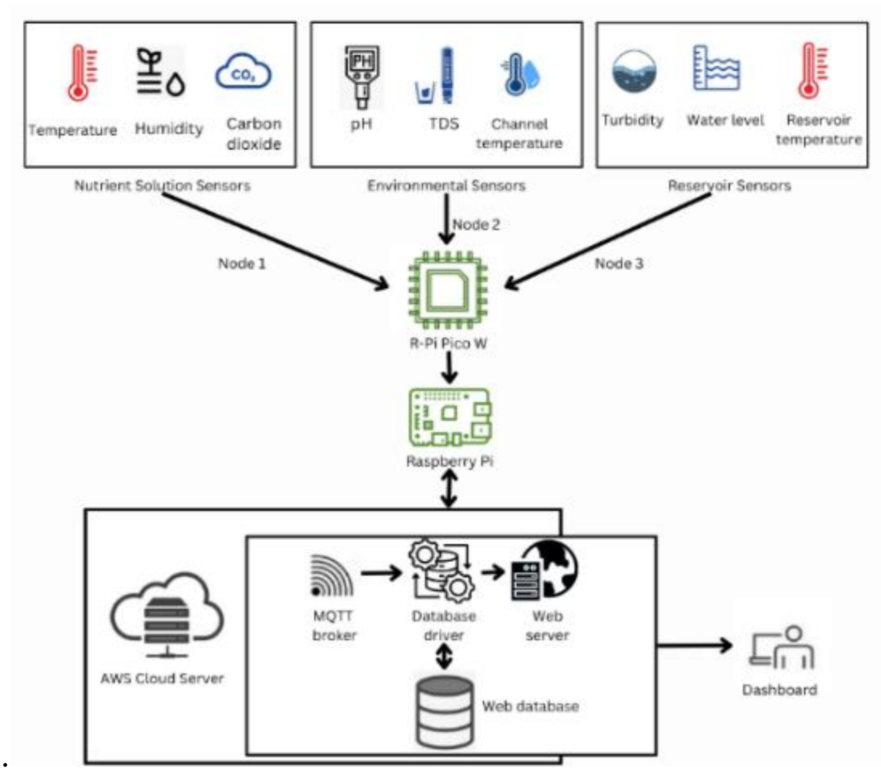


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Figure 1: Block diagram illustrating a four-layer architecture based on IoT principles in this study.

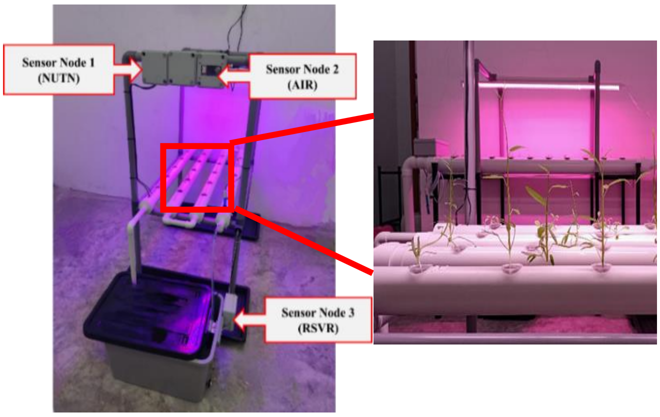


Figure 2: Real time fully integrated IoT monitoring system for Soilless Indoor Cultivation with subset showing Ipomowa *Aquatica* in growth.

The perception layer consists of different sensors connected to the microcontrollers. These sensors measure the indoor farming environment parameters and these data will be collected and stored in the local database in the microcontroller. In the processing and edge computing layer, the data is pre-processed before sending to the global server within a Wi-Fi network. The synchronization between the local and global databases is achieved using MQTT protocol on the global server side. Data visualizations will be taken over in the application layer such as presenting the line graphs, tables or gauges to provide an intuitive representation of real-time data. It provides comprehensive understanding to the user. The block diagram of the overall operation of the monitoring system is illustrated in Figure 1. Figure 2 shows a complete integrated four-layer architectures of IoT system for indoor farming system in this research which utilizes Nutrient Film Technique (NFT) and Deep Water Culture (DWC) systems

The system is 150 x 57 x 120 cm in size and has four channels that are arranged horizontally and have holes that are 5 x 32 mm. The reservoir is capable to hold a maximum of 33 L of nutrient solution in it. Periodically, a nutrient solution is injected into the first channel, permitted to overflow and return back to the reservoir. Instead of having a slope, the channels are designed to submerge half of the growing medium in the nutrient solution. The system is intended for indoor use and is equipped with full spectrum LED lights that replicate sunlight by turning on from 8 am to 8pm. Three sensor nodes are installed at the hydroponics set. The first node is used to measure the readings of pH, total dissolved solids, and water temperature in the nutrient solution. Environmental readings such as temperature, humidity, and carbon dioxide concentration in the air are collected by the second node. The third node gathers data in the reservoir, including turbidity level, water level, and water temperature.

Several sensors were installed at designated point in order to track different environment parameters. Analog pH sensor was used to measure the acidity or alkalinity of the nutrient solution. Meanwhile, analog total dissolved solids (TDS) sensor and analog turbidity sensor were used to monitor the water quality of the cultivation beds whereas MQ135 air quality sensor was used to monitor the surrounding air quality. Next, waterproof DS18B20 digital temperature sensor was commissioned to measure the nutrient solution temperature. For measurement of the surrounding relative humidity and temperature, the DHT22 sensor was used. Lastly, ultrasonic sensor (HC-SR04) was used to detect the water level of the nutrient solution. These sensors are integrated with a Raspberry Pi Pico W microcontroller, supported by the Raspberry Pi Model B Plus, which functions as a local server for data processing and management.

In configuring the monitoring system which primarily consisting of two primary parts which are local server operation and web database synchronization. It involves real-time acquisition of environmental parameters from all connected sensors (various nodes). In this study, the first line is to connect to a Raspberry Pi Pico W due to its incorporated wireless communication capabilities through built-in Wi-Fi. This addition makes the Pico W particularly suitable for Internet of Things (IoT) applications, enabling seamless integration with online databases, cloud services, and remote monitoring systems. Subsequently, Raspberry Pi Pico W was then connected to a Raspberry Pi. This strategy offers offloading benefits especially when Raspberry Pi is expected to manage higher level operation such as data processing, storage and graphical user interface (GUI) as well as working and over a long period of data collection. By connecting the two, the strengths of both devices, the Raspberry Pi's processing

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power and networking capabilities, combined with the Pico W's efficient GPIO handling and real-time response could be maximally utilized. The communication flows between the sensor nodes with a local server (Raspberry Pi) starts with initializing the local server and sensor nodes. The sensor nodes connected to the router via Wi-Fi and established a link with the Mosquitto MQTT broker hosted on the local server. Once connected, data was gathered and transmitted to the broker. In case of a connection loss, the sensor nodes attempt to re-establish connectivity. The local server receives the transmitted data, which is stored in a database for monitoring and analysis while the connection remains active. This cycle continues indefinitely unless the MQTT broker is disrupted.

The synchronization process between a local database and a cloud-based web database was meant to ensure seamless data consistency and accessibility. The web database resides on a cloud server configured using Amazon Elastic Compute Cloud (EC2), a scalable computing service offered by Amazon Web Services, Inc. (AWS). This setup provides reliable storage and processing capabilities. The MQTT broker, a lightweight messaging protocol commonly used in IoT systems, acts as the intermediary between the local server and the cloud server. The cloud server periodically retrieves the latest data from the MQTT broker to update its records. This allows the web database to reflect the most recent local data. Synchronization was first initiated by comparing and aligning the latest entries in the local and web databases. This process ensures that discrepancies are resolved, and both databases maintain consistent and updated records. The synchronization of the web server with the local server enables IoT features for data visualization, ensuring that the data is current and available.

## RESULT AND DISCUSSION

### Real-time data visualization

In an IoT system, data visualization plays a vital role by transforming raw, unstructured data into an easily interpretable format at the same time allows users to identify trends and make informed decisions based on the insights presented. For this study, three different visualization dashboards were developed on a cloud server, each offering distinct data visualization capabilities as illustrated in Figure 3. The first dashboard as shown in Figure 3(a) shows the gauge-based monitoring updates for all tracked parameters. Meanwhile, in Figure 3(b), the second dashboard sumarized the latest 20 data points for a particular parameter in a tabular format. Lastly, a line graph as illustrated in Figure 3(c) provides a trendline for pH level in the nutrient solution. These dashboards enable for the real-time monitoring for all environment parameters as mentioned previously and all day long.

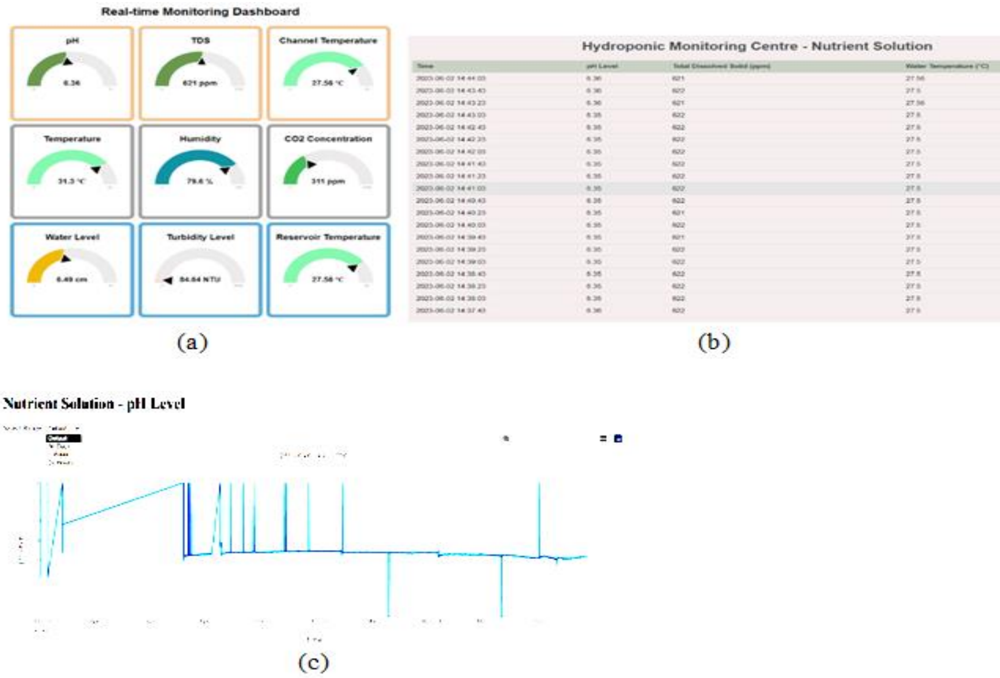


Figure 3: Real time data visualization on a cloud server (a) Gauge-based dashboard, (b) Table-based dashboard, (c) A line graph dashboard

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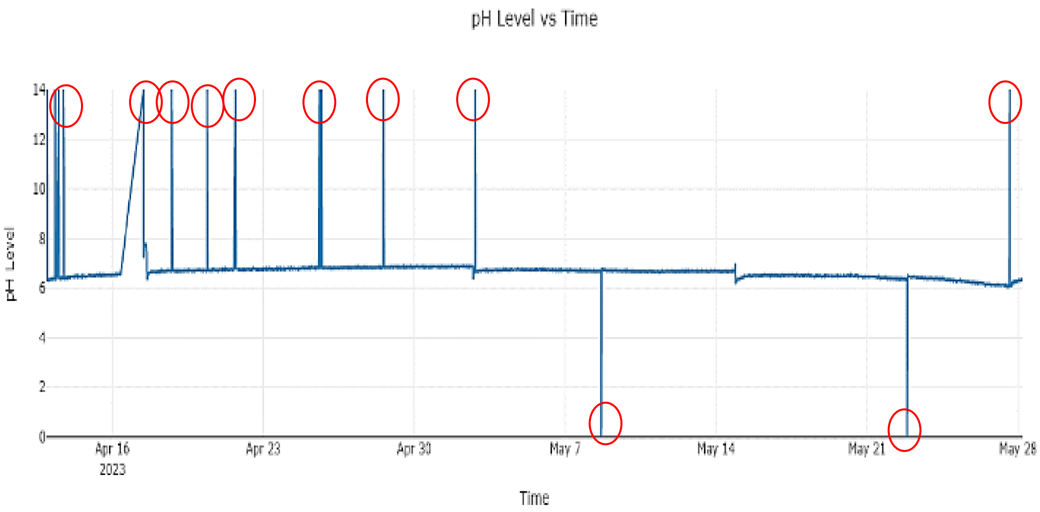


Figure 4: A line graph showing pH data collected for the duration of 45-days.

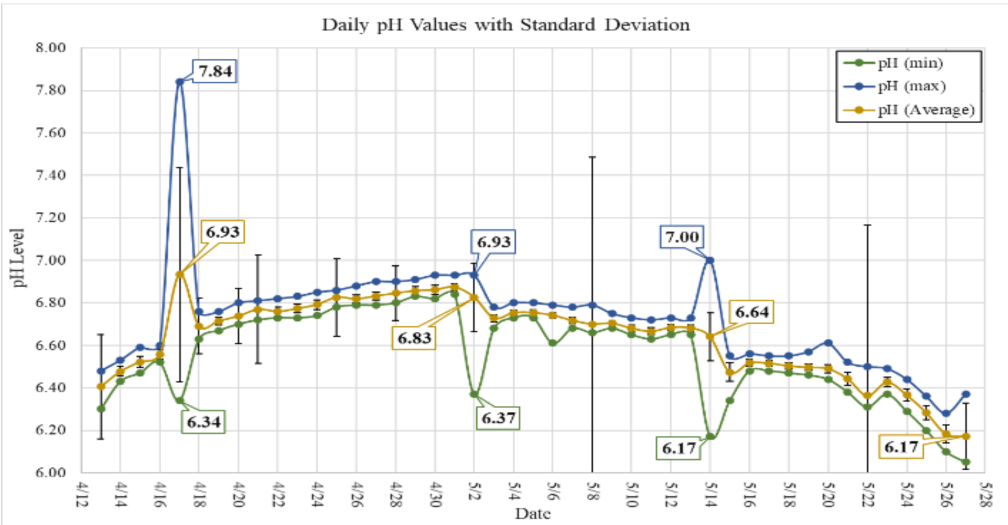


Figure.5: Daily pH values with corresponding Standard Deviation values

The monitoring of the pH level of the nutrient solution was monitored accordingly for the period and plotted in a line graph as shown in Figure 4. The ideal pH level should be between 6.0 and 7.0 for optimum growing condition of green leaves plant or any equivalent species [20]. Overall trend of the pH level is within the expected optimum growing pH level as suggested in the literature. However, drifting and some extreme data points were observed (pH 0 and pH 14). Spikes to a pH of 14 occurred during debugging or system restarts, while sudden drops to zero on May 8th and May 22nd happened when the pH sensor was disconnected for maintenance. In both cases, soaking the pH probe in potassium chloride (KCl) buffer solution will gradually restoring its sensitivity, the pH of the nutrient solution gradually stabilized, dropping to 6 by the final data collection date. To better analyze trends, the daily minimum, maximum, and average pH values were plotted using a line graph which using standard deviation error bars to show data variability, as seen in Figure 5. The average pH per day was calculated by averaging all daily measurements, and the standard deviation (SD) was determined using the STDEV() function.

Based on Figure 5, the fluctuation of average pH values over time, with a minimum value of 6.17 on May 27$^{th}$ and a maximum value of 6.93 on April 17$^{th}$ with an overall reducing trend were observed. The main causes of the longer error bars seen was due to regular nutrient refilling, pH probe maintenance and system restarts for troubleshooting. These planned sporadic occurrences were spotted on April 27$^{th}$, May 2$^{nd}$, 14$^{th}$ and 27$^{th}$. Dry nutrient residues deposited over times on the pH sensor's interface could be one of the causes to the reducing trend. This could contribute to the pH probe sensitivity is decreasing over time and is not suitable for long-term measurement. In addition, the pH value between 6.0 to 7.0 ranges is ideal for the development of the crops.

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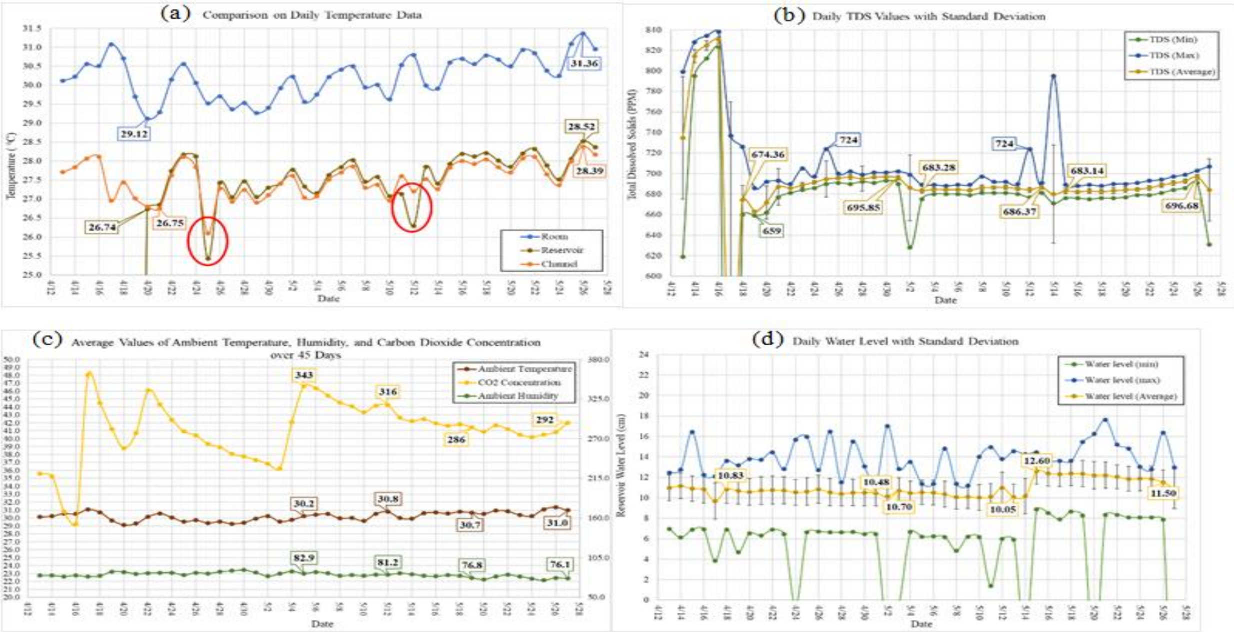


Figure 6: Real-time measurement data ranging from 13th April until 27th May (45 days) for each corresponding parameters with (a) daily average temperature recorded at room ambient temperature, channel temperature and reservoir temperature, (b) daily TDS values with SD, (c) average values of ambient temperature, humidity and CO2 concentration and (d daily reservoir water level with corresponding standard deviation values

Figure 6(a) summarizes the average temperature recorded in-situ and was sensed at room ambient temperature, channel temperature and reservoir temperature. The trend lines for these three observations showed similar patterns, with the room temperature consistently being 2-3 °C higher than the channel and reservoir temperatures. It was demonstrated that the channel temperature was normally lower than the reservoir temperature. This can be explained by the amount of surface area the nutrient solution has in contact with the air; the greater the surface area, the more effectively the nutrient solution dissipates heat. Two unusual data which hits to the maximum SDs of 2.27 °C was recorded on April 25th and May 12nd, which are below the overall average value suspected due to the algae growth in the reservoir. There is a correlation between ambient temperature and the water temperature in the reservoir and channel. The coldest water temperatures were noted on April 20th, when the lowest room temperature of 29.12 °C was noted, with the reservoir recorded a reading of 26.74 °C and the channel the next day at 26.75 °C. Similar to the maximum room temperature of 31.36 °C, highest water temperatures of 28.52 °C in the reservoir and 28.39 °C in the channel were also recorded on May 26th.

On the other hand, Figure 6(b) shows a gradual increase in the average TDS value after each water change. The average TDS value was calculated by calculating the difference between the first value after a water change and the value before the next water change. There is a minimum increased value of 3.09ppm recorded between May 3rd and May 13th and the maximum changed value of 23.49ppm of TDS value between April 18th and May 1st recorded, and the total average TDS value was calculated to be 691.98 ppm by taking the mean of all average daily TDS values. Two maximum TDS value of 724 ppm were recorded on April 25th and May 12th due to the events of low water temperature, eventually affecting the sensor readings since it is related to the calculation formula used for the TDS sensor. Figure 6(c) shows the line graphs illustrated the trend lines for the average values of ambient temperature within a range from 20 °C to 50 °C while for humidity and CO2 concentration were plotted within a range from 50 to 380. From the trend lines, the CO2 concentration varied significantly for the first 10 points before decreasing consistently until May 4th. This is because the issues with MQ135 sensor, including a coding problem and low sensitivity caused by the on-board resistor. When considering only the data points from May 6th, the CO2 concentration is inconsistently reduced which may due to the growth of the leafy plants and increased use of carbon dioxide for photosynthesis. The temperature remained relatively stable over the period while the humidity can be said is fluctuated more widely than the temperature, but both of these parameters shows they have not direct impact on the CO2 concentration. Figure 6(d) shows the trend line of the reservoir water level, plotted with the summarized minimum and maximum water level of the reservoir. Regular water changes were made on April 17th, May 2nd, 14th and 27th over the 45-day data collecting period. The data shows that water usage varied over time. With a 0.35 cm drop in reservoir water level prior to the second water change, the water quantity be consumed is the least. The most water was used by looking into the 1.1cm drop in reservoir water level was recorded after the third water change.

**Corresponding Pilot Ipomoea Aquatica Growth Run**

In this closed-loop pilot run together with the real time IoT integrated system, 10 seeds were germinated since April 12th and transplanted onto the indoor farming system on April 19th. Parallel data were recorded simultaneously and presented below. As a record of the plant growth, the length and number of leaves on the plants were jot down every two days. The changes were visualized using line graphs as shown in Figure 7 and Figure 8 respectively. For further differentiation and analysis, all the plants were labelled with capital letters from A to J. Based on the graphs, all of the plants except 'E' exhibits constant progressive growth rate in the first month. Plant E was found wilted due to an unknown reason, therefore new seeding was substituted. After that, rapid growth rate for all plants were observed, with significant increases in both plant height and number of leaves. The most notable increase in height was observed for plant 'B', while the most notable increase in the number of leaves was observed for plant 'J' due to the development of a new branch. However, when the harvesting period is approaching, a slight decrease in height was observed for several plants. This was due to some plants were growing fast and too close to the light source, causing the tips to burn out.

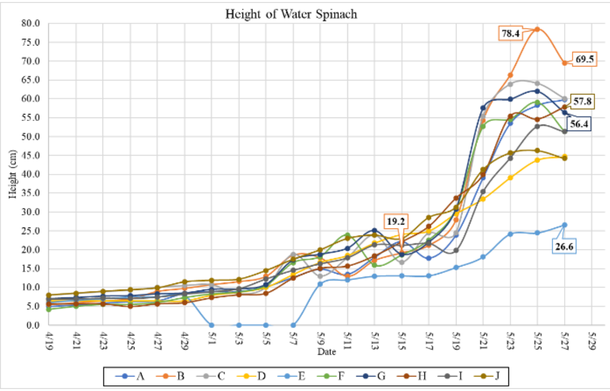


Figure 7: Observed visually height changes in plant height labelled A to J over the cultivation period of time

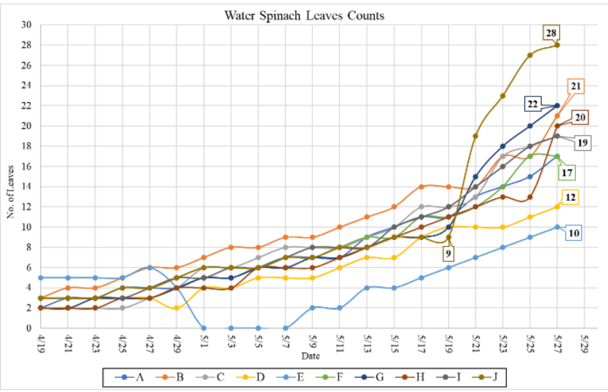


Figure 8: Corresponding increase in number of the leaves for the plants labelled A to J over the cultivation period of time

# CONCLUSION

In conclusion, this project successfully demonstrated an IoT-based monitoring system tailored for indoor farming with the objective of enhancing crop yield and promoting urban food sustainability lifestyles. The system monitored critical parameters such as nutrient solution quality and environmental conditions for leafy green cultivation, supported by cloud-based dashboards that enabled real-time visualization and tracking. Analysis of the collected data provided important insights into plant growth conditions, while the IoT system design enabled data tracking, system reliability, fault occurrences and the ability to operate continuously under varying conditions over 45 days non-stop data collection. Overall, the results highlight how the IoT technology can improve efficiency, robustness, and long-term sustainability in indoor farming systems, aligning with the goals of Agriculture 4.0 and contributing meaningfully to future global food security.

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