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Internet of things based seasonal auto regression integrated moving average model for hydroponic water quality prediction

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ABSTRACT

Technological progress significantly impacts agriculture, with the rapid expansion of industrial and residential areas leading to a scarcity of agricultural land. Modern farming techniques like hydroponics have emerged as a solution, allowing plant growth with water as a medium. Real-time monitoring of water quality is crucial for hydroponic systems. Lettuce (Lactuca sativa) is particularly compatible with hydroponics due to its short growth cycle and nutritional value. Key factors for successful cultivation include maintaining pH, temperature, and nutrient levels within optimal ranges. To address water quality monitoring complexities, internet of things (IoT) technology offers a promising solution. IoT devices autonomously gather environmental metrics such as temperature, pH, humidity, and nutrient concentrations. This study integrates an IoT-driven hydroponic water quality monitoring system using the seasonal auto-regressive integrated moving average (SARIMA) algorithm and the ESP32 microcontroller. This approach allows real-time water quality management, enhancing lettuce cultivation efficiency and productivity. The proposed model achieved 98.6% accuracy, effectively predicting water quality.

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1. INTRODUCTION

In the contemporary era, technological progress significantly impacts various sectors, including agriculture. However, the rapid expansion of industrial, commercial, and residential areas has resulted in a scarcity of agricultural land. This trend stems from the increasing demand for land for industrial, commercial, and residential purposes. Consequently, agricultural lands previously allocated for food and crop production are diminishing as they are converted into industrial, commercial, or residential zones.

This land scarcity creates a challenge to the development of sustainable and self-sufficient agriculture. One notable advancement is the adoption of modern farming techniques like hydroponics, which are increasingly popular in rural and urban settings [1]. These systems enable plant growth without soil, allowing cultivation indoors using water as a medium. In hydroponic setups, water quality plays a crucial role in influencing plant growth. Hence, precise and real-time monitoring of water quality is imperative for hydroponic farmers to maintain optimal conditions for plant growth.

Not all plants can live in a hydroponic system. Bigger plants might not fit. Some vegetables like lettuce have more compatibility with the hydroponic system compared to others. Lettuce plants (known as Lactuca sativa) are popular green leafy vegetables with minerals and vitamins [2], [3]. Lettuce plants have soft leaves with a shape resembling animal leaves or triangles. In addition, lettuce plants have a short growth cycle and require a shorter waiting time for harvest.

In the hydroponic cultivation of lettuce plants, several factors affect the lettuce growth such as pH, temperature, and nutrients. These factors must be maintained at appropriate levels. The optimal value ranges for the cultivations are pH 6-7 for water acidity, the temperature within 17-25 °C, and nutrients (total dissolved solids (TDS)) must be within 560-840 ppm. Unable to maintain these levels may lead to slow growth, lower vegetable nutrients, or dead plants [4], [5].

To address the complexities associated with hydroponic water quality monitoring, the utilization of internet of things (IoT) technology emerges as a promising solution due to its notable efficiency [6]-[8] in many sectors including internet security as an example [9], [10]. By leveraging IoT capabilities, interconnected devices autonomously gather vital environmental metrics including temperature, pH, humidity, and TDS nutrient concentrations within the water. This implementation employs the Blynk platform, a cloud-based application development tool tailored for IoT applications, as an intuitive user interface [11], [12]. Through seamless integration with mobile devices, the Blynk platform facilitates real-time monitoring and operational control of the system [13].

In the past, numerous studies have aimed to monitor water quality in hydroponic cultivation employing diverse technologies. In 2021, a proposed model was capable of accurately detecting nutrient content and maintaining optimum water quality conditions [14]. Within the same year, there was also a different model capable of controlling water nutrition. Using Arduino mega 250 and TDS sensor to monitor the nutrient content with an error rate maximum of 2% [15]. In the next year 2022, there was another model that implemented different sensors like waterproof temperature, dissolved oxygen, and pH sensors to control the water quality. The proposed model successfully monitors every 5 seconds through 28 days non-stop [16], [17]. The improvement of hydroponic monitoring was not in that year. In 2023, there was a model equipped with an Android app to control and monitor the model. With that improvement, human intervention is no longer needed [18]. Also in 2023, there was another model of hydroponic monitoring that used ESP32 as the main processor. The monitoring system was connected to internet-based platforms like ThingsBoard to monitor sensor data, presenting it through numeric and graphical displays [19]. Despite these efforts, only data transmission and display functionalities are addressed. These systems did not integrate advanced algorithms to forecast future water conditions, thus failing to provide proactive recommendations or preventive measures.

Because of those reasons, this study endeavors to combine an IoT-driven hydroponic water quality monitoring system, employing the seasonal auto-regressive integrated moving average (SARIMA) algorithm and anchored by the ESP32 microcontroller as its pivotal element. By employing SARIMA as the prediction algorithm for the proposed model, the farmer will receive more accurate predictions compared to another algorithm [20]. SARIMA excels at capturing seasonal patterns in time series data. By explicitly accounting for seasonality, SARIMA can often provide more accurate forecasts than algorithms that do not consider seasonal variations. For example, SARIMA can be implemented to forecast the COVID-19 epidemic [21] and stock [22]. Unlike other supervised learning that relies on normal datasets, this algorithm is based on time-series (historical) data. Thus, the model will understand the history of the water quality and predict the water quality with that data. The main contribution of this study is to implement the SARIMA machine learning algorithm and predict the water quality condition based on the water's historical data.

Through this initiative, hydroponic cultivators will seamlessly monitor and regulate water quality in real time. The envisaged implementation aims to empower farmers to undertake timely measures to sustain optimal conditions conducive to lettuce plant growth, thereby enhancing efficiency and productivity in hydroponic farming. Furthermore, insights gleaned from preceding research endeavors will be leveraged to foster the development of a more comprehensive and effective solution for hydroponic water quality monitoring. To explain the proposed model in detail with the SARIMA prediction algorithm, this study provides more information about the method to prepare the proposed model, the evaluation's results, and the discussion about what the evaluation obtained in the following sections.

2. RESEARCH METHOD

In this study, a methodology was employed to address the issue at hand. This section discusses how this study starts the research by gathering the data, planning, designing, and evaluating the proposed model. The research methodology utilized in this study is illustrated in Figure 1.

Figure 1 depicts the stages involved in crafting a variable control system for hydroponic applications. The progression of establishing an IoT-driven lettuce hydroponic water quality monitoring system employing the SARIMA algorithm encompasses several pivotal stages. These steps are important to ensure this study is reproducible in the next study. Improperly following the method may produce incorrect results which is different from this study. These stages encompass problem analysis, identification, planning, implementation, and testing.

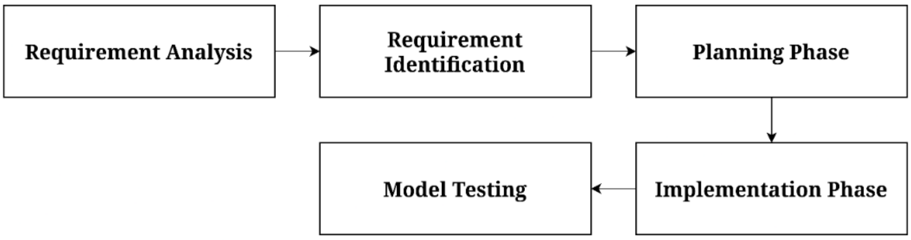


Figure 1. Model development phases

The first step is to identify the hydroponic problem. As explained in the first section, the problem with the hydroponic is about manual measurement that requires precision to keep water quality [15], [23], [24]. After identifying the problem, this study then identifies what is required to solve the problem. To decrease human labor to do manual measurement, the IoT-based approach is used. By implementing multiple sensors like temperature, acidity, and TDS sensors, the proposed model can monitor water conditions and predict the water quality. Table 1 contains the needed hardware for the proposed model.

Table 1. The proposed model's specification

0	Components	Purpose
1	ESP32	Mainboard
2	LCD 4×120 I2C	Display monitoring results
3	pH-4502C module	Measuring the pH of water
4	TDS sensor module	Measuring the nitrous concentration of water
5	DS18D20 sensor module	Measuring water temperature

Table 1 contains the proposed model's specifications. This model consists of ESP32 as the main board, liquid crystal display (LCD) to display the result, PH-4502C sensor for pH detection (this kind of sensor is often used in many studies like wastewater treatment monitoring [25]), TDS sensor for detecting the concentration within the water, and DS18B20 sensor for temperature detection (this sensor offers more accurate detection than digital humidity and temperature (DHT) sensor [26], [27]). Everything is connected with jumper cables following the ESP32 pinout guidance. The installation process is crucial when building the physical model of the IoT-based model. Human error that occurs during the installation process may break the IoT board or the sensors. Serious injuries like burns may also happen if a short circuit occurs. Thus, cable installation must be taken seriously. All components are then assembled into a lettuce hydroponic water monitoring system, comprising four primary components: input, process, output, and IoT. The input segment integrates various sensors, including the ESP32 DOID DevKit V1 for program processing, device control, and sensor data collection [28], [29]. Additionally, it incorporates a pH-4502C sensor for acidity/alkalinity measurement, a DS18b20 temperature sensor for precise water temperature measurement, and a TDS meter V1 for dissolved nutrients within water. For real-time monitoring via smartphone or website and display of sensor readings and program outputs, the Blynk 2.0 platform is employed. Furthermore, a 20×4 I2C LCD is utilized to present sensor and program output results, while indicator LED lights indicate specific system conditions.

To allow prediction with the proposed model, this study used fuzzy Mamdani to map water quality and the SARIMA for prediction. By combining these two algorithms, the proposed model may achieve better accuracy compared to another algorithm. To create the fuzzy Mamdani model, there are several steps to do.

The first step is to create a fuzzy input membership with pH, temperature, and TDS. The pH membership with acid (range 0-7), neutral (value 7), and alkaline (range 7-14). Meanwhile, the temperature membership with cold (range 0-17), mild (range 15-27), and warm (25-35). The TDS membership contains low (range 0-550), middle (range 500-900), and high (850-1000) concentrations. After creating the input membership functions, the next step is to make the output membership that decides the water quality.

In this case, this study chooses the range 0-2 (where 0 is low, 1 is medium, and 2 is high) as the quality indicator. The result of the output is between three choices and it is impossible to get decimal value from this range. The next step is to create a SARIMA model based on the dataset mapped with the fuzzy Mamdani model. The first step is to capture the dataset with the previously designed IoT node. With this device, this study obtained more than 5000 rows of data with a 1 second interval. However, this data is not usable yet as SARIMA data training. To make this data trainable, this study used fuzzy logic to map the output into human interpretation. Table 2 contains the monitoring data with the mapped water quality from the fuzzy Mamdani model.

Table 2. Sample data with mapped water quality

Timestamp	Temperature	pH	TDS	Water quality
2024-04-19 10:00:00	32	6	653	1
2024-04-19 10:00:01	34	7	716	1
2024-04-19 10:00:02	32	6	689	1
	...			
2024-04-20 09:59:57	25	6	696	1
2024-04-20 09:59:58	34	7	832	1
2024-04-20 09:59:59	35	7	650	1

Table 2 is the result of data mapping with fuzzy logic. Table 2 contains Timestamps that indicate when the data was obtained, temperature, pH, TDS, and the water quality level. All columns except the water quality level will be used as the training model for the SARIMA algorithm. On the contrary, the water quality level is the target of the algorithm. The next step is to create the SARIMA parameter according to the data's behavior. Hence, the proposed model must be identified first before training the model. The first parameter is the p-order which contains the seasonal autoregression part of SARIMA. The d-order parameter is the differencing order. Meanwhile, the q-order parameter is the moving average components. After the differencing process with partial autocorrelation function, this study found the p-order value is 1. Meanwhile, the autocorrelation function produced the q-order value of 1. The process to obtain d order is different from p-order and q-order. The augmented Dickey-Fuller (ADF) formula is used to get the d-order value. Since the p-value of the ADF formula is already under 0.05, differencing is not required at all. Thus, the d-order value is 0. After obtaining the p, d, and q order values, the next process is to train the model. This study uses the labeled dataset as the training data. To make sure the model is reusable in the clouds, this study dumps the model into a binary Python pickle. Once the model has been completed, this study is ready to implement the prediction model. Figure 2 is the wiring diagram for the proposed IoT prototype that reflects the installation of the sensors.

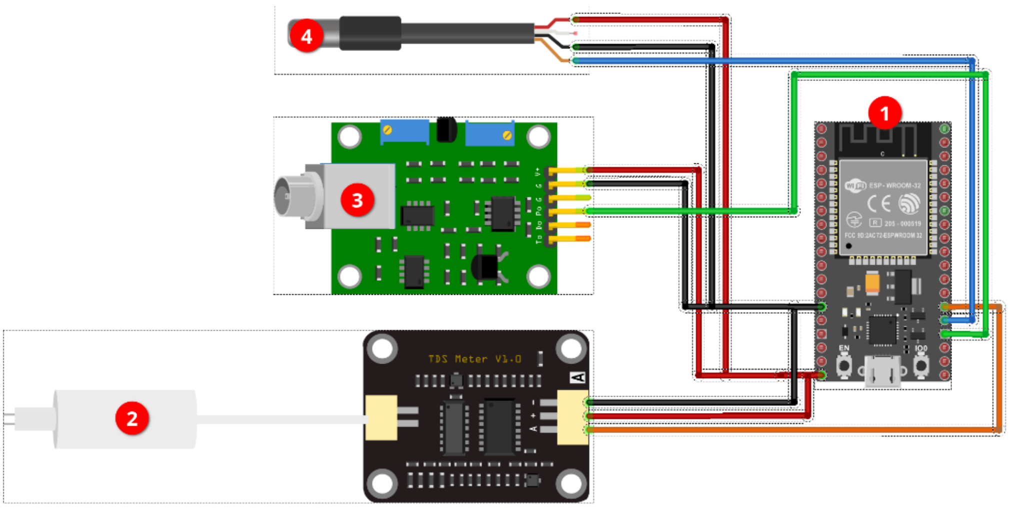


Figure 2. Model's wiring diagram

To make the IoT prototype work, proper wiring is required. Figure 2 explains how this study wires the sensors into the processing board. Within the circuit, there are four main components used to monitor the environment's conditions. The first component is the main processing board called ESP32. This board has better performance than its predecessor: ESP8266. The second component is a TDS sensor to read water concentration. The third component is PH-4502C (a pH measurement sensor). The last component is DS12B20 which has the job of detecting temperature within the water. The wiring setup is quite simple. The TDS sensor is connected via an analog-to-digital (ADC) pin, this pin is usually located at the GPIO4 pin. This sensor uses 5 V provided by the board. Meanwhile, PH-4502C is similar to the previous sensor. However, this sensor is connected via ADC in GPIO15. The DS12B20 sensor is connected to the ADC interface that is available in GPIO02.

After designing and implementing the wiring diagram into a prototype, the next step is to program the IoT board. This step is important to ensure that the board reads the sensors' values and sends them to the server for prediction. The following flowchart serves as a visual depiction of sequential steps or processes in diagrammatic form, aiding in illustrating information flow, decision-making, or a series of actions within a system or procedure. Utilizing graphical symbols connected by arrows, flowcharts depict the sequence of actions or decisions to be executed. In this context, Figure 3 presents the flowchart detailing the operations of the IoT-based lettuce hydroponic water quality monitoring tool.

The flow process in Figure 3 starts from activating the node's internet connectivity via a wireless network. The next process is to read the water conditions through temperature, pH, and TDS sensors. These data are the main variables in the next training and prediction process. After obtaining the data, the model will try to predict the water quality with a SARIMA-trained model. After completing the prediction model with fuzzy Mamdani and SARIMA, this study then implements the model to a hydroponic system for the evaluation phase.

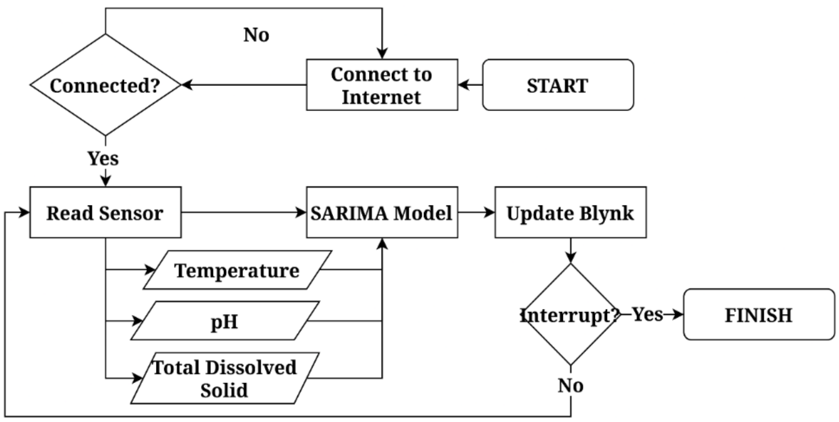


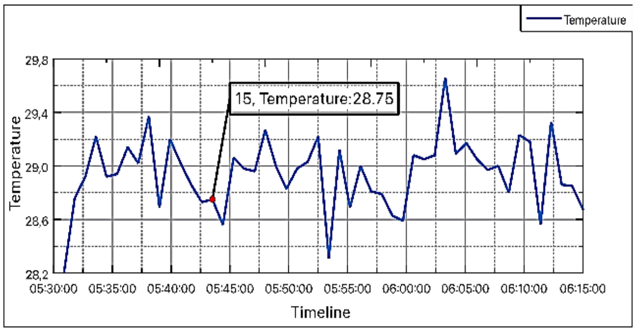
Figure 3. Model's process flowchart

3. RESULTS AND DISCUSSION

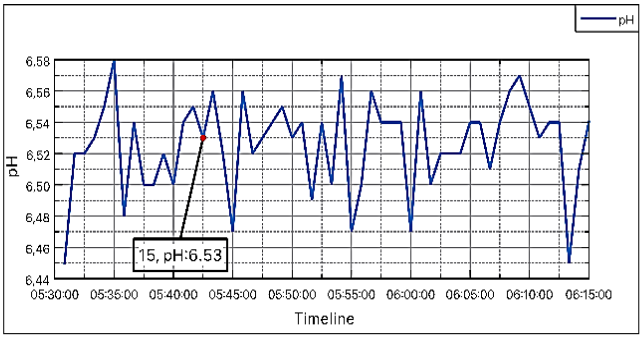
This section explains the result of the evaluation phases with the proposed model. This section is divided into two subsections the first subsection contains the proposed model's result and evaluation and the second one contains the discussion of overall evaluation. Figure 4 shows the illustrations during the monitoring process based on sample data taken from the Blynk app.

Figure 4 is the compilation of monitoring results for temperature, pH, and TDS. Each subfigure contains a piece of information at a certain time. For example, in Figure 4(a) the temperature at 06:40 am reached 28.75 °C. At the same time, pH reached 6.53 (Figure 4(b)), and TDS 701.84 (Figure 4(c)). After obtaining the monitoring data, the next step is to evaluate the accuracy of the SARIMA model. Table 3 is the result of the water quality prediction with the SARIMA model.

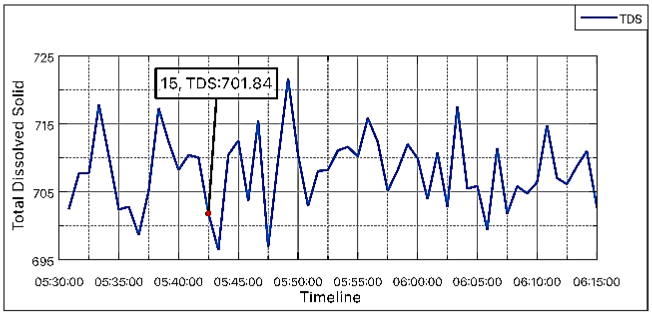
Table 3 contains the monitoring and prediction results with the SARIMA model with as many as 16000 rows. However, this result is too many to illustrate. Thus, this study reduces the data rows with the data reduction averaging method. The next step is to calculate the accuracy of SARIMA with a confusion matrix. This study used the following equation to calculate the multi-class accuracy of the SARIMA model.



(a)



(b)



(c)

Figure 4. Monitoring result where (a) temperature, (b) pH, and (c) TDS

Table 3. Water quality monitoring and prediction result

Time	Temp	pH	TDS	Actual	Prediction
05:30:00	28.21	6.45			
05:35:00	28.76	6.52			
			...		
09:50:00	29.21	6.51			
09:55:00	28.55	6.54			

Equation (1) consists of several components where: acc (%) is the SARIMA's accuracy as percent, TP is the correct prediction against actual data, and Z is the data in the confusion matrix. The summation of TP is based on the i index for each actual and prediction result. Then, the result is divided by the total sum of every data based on the i and j indices. The last step is multiplying the result by 100% to obtain the percentage. The calculation with equation x produces accuracy in the bar graph shown in Figure 5.

Figure 5 is the calculation result from the confusion metric. According to the graph, the model has an accuracy of 98.6% and an error of 1.4%. This result means that the proposed model successfully predicted the water quality. This statement is proved by Wang *et al.* [30], where SARIMA has statistically higher performance. The second subsection of this study is a discussion. This study focused on predicting water quality with a machine-learning algorithm. On the contrary, the previous models are only used for monitoring water quality. This is a clear gap between the previous models with the current proposed models. According to the evaluation, this study found that the model has dynamic monitoring results as shown in Figure 4. The temperature result could be caused by the season in the local region. If the temperature within the area is colder, the water also gets colder, and vice versa.

$$Accuracy(\%) = \left(\frac{\sum_{i=1}^{n} TP_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} z}\right) * 100\% \tag{1}$$

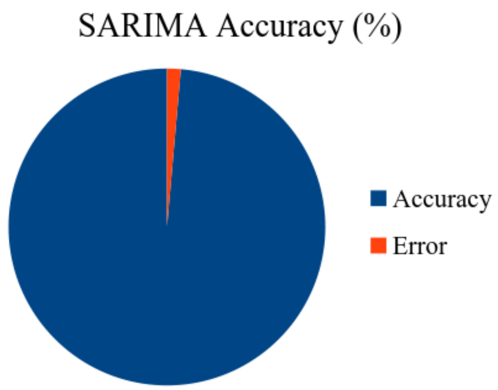


Figure 5. Accuracy and error result

Another parameter is about pH level. The factor that affects the pH is the external nutrient given by the farmer. Some plant nutrients have acidic properties and lower the pH level in the water. Meanwhile, the TDS factor is affected by solid nutrients dissolved in water. Besides that, this study also found an accuracy of 98.6% and an error rate of 1.4%. The model's accuracy is closer to 100% is proof that SARIMA is capable of predicting water quality. Since the SARIMA model is implemented externally, this will not affect the model's performance. Thus, it is easy to implement the prediction algorithm on many kinds of IoT boards. This model also benefits all low-cost users that afraid of higher costs to purchase expensive IoT boards to load prediction algorithms like SARIMA.

However, despite how high the accuracy was. There were several weaknesses with the model. The limitation of this model is the prediction algorithm. This algorithm has a dependency on seasonality. If the seasonality changes drastically, it will also impact the prediction and make the model unusable. Re-gathering and re-training the data will solve this problem. The second limitation is the prediction model's implementation. Since the prediction model was implemented externally, a server is required to handle prediction requests from IoT devices. Without this server, the prediction must be made internally and requires higher model specifications.

According to the previous paragraph, this study found that there are possibilities to improve the proposed model. For example: using neural-network-based algorithms that might be better than SARIMA. Besides that, using better sensors also could improve the prediction's result. With these discussions, this study concluded that the proposed model is better than the previous model. Not only does it have high prediction accuracy but also cheaper cost to implement with an external prediction mechanism. Thus, this model is friendly toward low-cost users.

4. CONCLUSION

Water quality monitoring in hydroponic cultivation is an activity that requires precise observation to ensure the quality is within the threshold. In larger sites, manual monitoring was not effective due to wider area compared to smaller cultivation. For that reason, this study designed a model with the SARIMA algorithm to predict the water quality based on parameters such as temperature, pH, and TDS. According to the results, this study found that the model performed well, with an accuracy of 98.6% and an error percentage of 1.4%. Meanwhile, the monitoring's result is dynamic. For example, at 06:40, the model read the condition with the temperature reaching 28.75 °C, pH reached 6.63, and TDS reached 701.84. However, these numbers were unstable and relatively going up and down due to water flow.

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