Multi-Layer Perceptron Neural Network and Internet of Things for Improving the Realtime Aquatic Ecosystem Quality Monitoring and Analysis

https://doi.org/10.3991/ijim.v16i06.28661

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Abstract—This research proposes improving the aquarium environment for ornamental fish farming for small enterprises raising ornamental fish for sale during the COVID-19 Pandemic with an automatic aquarium system capable of forecasting the optimum environment for fish using Multi-Layer Perceptron Neural Network. Since the amount of the collected data was limited, it was also employed to adjust the imbalanced dataset by applying the Synthetic Minority Over-Sampling Technique to increase forecasting accuracy. Subsequently, the developed system is based on Internet of Things devices in conjunction with sensors for measuring the indicators that affect the aquarium environment, including temperature, turbidity, total dissolved solids, the potential of hydrogen ions, dissolved oxygen, and nitrate ion. Further, the mobile application was developed and collaborated with sensors and devices to facilitate entrepreneurs monitoring and controlling this automatic system. The results showed that the accuracy of the developed water environment forecasting model was 97.31% and gave the highest level of automation efficiency. Therefore, the developed automated aquarium system could be applied to reduce fish mortality and maintain environmental conditions to grow adequately over the fish life span.

Keywords—aquatic ecosystem, Internet of Things, MLPNN, SMOTE

1 Introduction

Raising fish as a pet has been very popular since the first time when interacted with animals. By raising fish that can help reduce stress and blood pressure. It is found that raising fish also helps treat adolescents with diabetes better to control the disease [1]. In the COVID-19 Pandemic, social distancing is the restriction that causes most to stay home. As a result, people are interested in raising more beautiful fish. Furthermore, fish farming in Thailand is also widespread, causing the business of selling ornamental fish to continue to gain attention. The prices are depended on the fish species and specialty, such as the colors and patterns of the fish. Businesses that raise fish or fish farming for sale ornamental fish often encounter inadequate fish care. The reason might be insufficient staff or caretakers for the number of fish or ponds or fish tanks in the COVID-19

Pandemic. Otherwise, without thorough supervision and appropriate water quality for each fish species causing fish fatalities are prone to death. Otherwise, without thorough supervision and appropriate water quality for each fish species causing fish fatalities are prone to death.

For fish to survive for a long time, there are many factors such as water temperature, turbidity, total dissolved solids (TDS), the potential of hydrogen ion (pH), oxidation-reduction potential (ORP), electrical conductivity (EC), the oxygen level in the water or dissolved oxygen (DO), nitrate and phosphate waste. Some studies have found that some values have a direct relationship, for example, the ORP values are related to DO, and pH [2], and EC values vary according to TDS [3]. Therefore, some factors might represent each other in which these factors directly affect the quality of the aquarium water in which fish live. However, water replacement is another way to improve the quality of water. The frequency of water replacement affects the quality of water and the quality of life of fish directly.

Nowadays, many different technologies help improve the quality of life, such as the internet, computer technology, and especially the Internet of Things (IoT). This technology encourages tools and equipment that can be fabricated and utilized in various ways at a low cost. There are many kinds of IoT boards, such as Arduino UNO, ESP8266, and ESP32. These boards are open-source microcontroller boards and support the programmer in developing any internet connection system. Therefore, this work purposed to develop the automatic aquarium system for water quality monitoring and automatic water replacement using deep learning based on IoT for ornamental fish farmers and small entrepreneurs.

2 Related work

The related works for applying the aquatic ecosystem quality monitoring and analysis toward developing real-time aquatic ecosystem quality monitoring and analysis using Multi-Layer Perceptron Neural Network and Internet of Things were described as follows.

2.1 Properties of water

1) Water temperature: The water temperature affects the fish's livelihood a lot because fish are cold-blooded animals. The body of fish temperature or metabolic processes changes depending on the water temperature [4]. These temperatures were related to inhibiting the growth [5] and fish breeding directly.

2) Nitrate ion: Normally, nitrate is a polyatomic ion that molecule formula of the nitrate ion (NO−3). Nitrate is a nitrogen oxoanionic formed of nitric acid. It is produced from the nitrogen cycle caused by humus or fish waste. Beginning with fish feces or wastes from any uneaten foods were turned into ammonia (NH3), then benefits bacteria convert ammonia to nitrites (NO−2), and finally in the form of nitrates. The nitrogen cycle in the aquarium is shown in Figure 1. Nitrates directly impact fish by causing their blood hemoglobin levels to drop, resulting in the oxygen intake system failing to die eventually [6]. Usually, water replacement systems such as rain or partial water change in the aquarium remove nitrates.

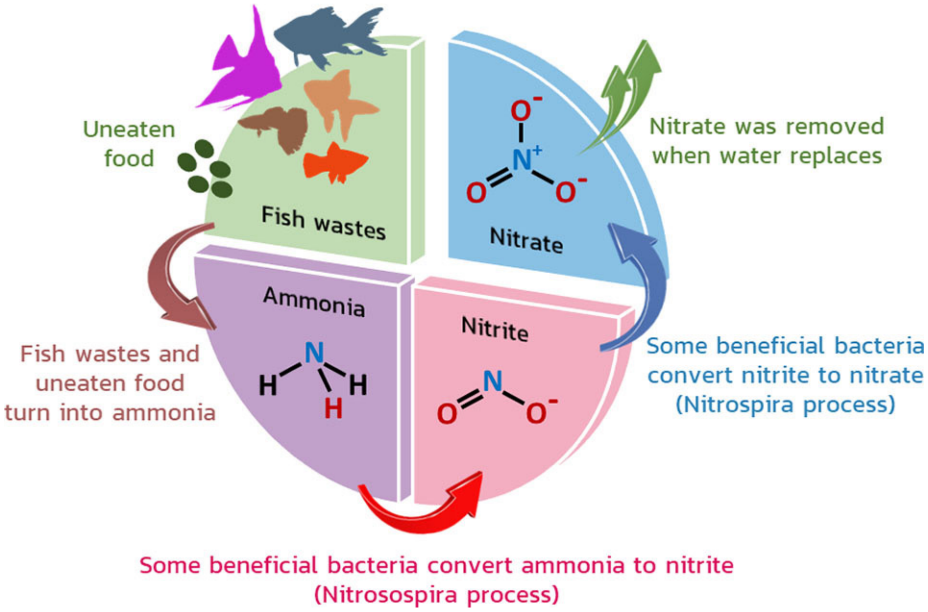

Fig. 1. The nitrogen cycle in the aquarium

3) Turbidity: Water turbidity is the cloudiness in the water. It consists of suspended solids, organic and inorganic substances in the water. The turbidity will affect the water's light-blocking and clarity and clog the fish respiratory system [7]. Moreover, its effects on the feeding and growth of fish [8]. Generally, turbidity can be measured by the 90-degree distribution of the beam in the water in a unit of measurement called Nephelometric Turbidity Units (NTU).

4) The potential of hydrogen ion: The potential of the hydrogen ion of a substance is an indicator of how many hydrogen ions it contains. It refers to the concentration of hydrogen ions ($H+$) of water ionization. The negative logarithm of the concentration of hydrogen ions ($H-$) was called pH. Generally, a pH value at 7.0 is neutral, below 7.0 is acidity, and over 7.0 is alkalinity. Some studies suggested that suitable pH for fish is between 6.5 and 9.0 [9].

5) Dissolved oxygen: Oxygen is necessary for aquatic animals such as fish. The oxygen is generated from the atmosphere and green plants. Therefore, it can dissolve in the water. Some studies showed that the water quality standard for fish production, in general, is the minimum DO values between 4.0 and 5.0 milligrams per liter (mg/L) for many varieties of fish [9].

6) Total dissolved solids: TDS is the concentration of dissolved ions containing organic and inorganic substances, which has benefits and toxicity to aquatic animals. It can cause toxicity by increased salinity [10], a factor in fish metabolism and reproduction.

2.2 Synthetic minority over-sampling technique

Synthetic Minority Over-Sampling Technique (SMOTE) is a technique that helps to resynthesize data by growing the dataset size with a small amount of class data [11] to be consistent with the largest dataset. It is a simple and widely used technique to solve the issue of data imbalance. This is achieved by generating a random value and measuring the distance between it and other values to determine the closest value.

2.3 Multi-layer perceptron neural network

The Multi-Layer Perceptron Neural Network (MLPNN) is one of the Artificial neural networks (ANNs) built from several processing elements connected by weights for optimizing classification [12]. Basically, MLPNN has three layers: input layer, hidden layer, and output layer. The work of MLPNN is inserting data into the input layer to estimate and deliver the results to the output layer. The estimation requires a sum of input data multiplied by weight value, as the output of each state is shown in (1) [13].

$$n = \sum_{i=1}^{k} W_i X_i + b \tag{1}$$

Where n represents the output of the output layer, k represents the number of neurons from the previous layer, i represents each neuron, X_i represents the input vector which is the output of each neuron from the previous layer, W_i represents the weight of each layer, and b represents the bias vector. The hidden layer output was sent to the output layer, where there is a comparison between the estimated outputs and the target outputs. If different values cannot be accepted, the outputs will get into the backpropagation process then go back to the hidden layer and input layer sequentially. Concurrently, the weight adjustment process will find the acceptable value to be tested with the data. Afterward, the output is estimated with the sigmoid function [14] based on the logistic function, as shown in (2) [15].

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Where x represents the input, and f represents the output of the sigmoid function.

2.4 Literature review

Currently, the IoT is the new technology of electronic devices that can connect to the internet or networks. Most research studied and developed several features based on IoT to monitor and control water quality related to fish aquariums or tanks, as in Table 1 and Table 2. There are twelve features on monitoring water conditions and improving the fish aquarium's water quality. Although the mentioned related works are based on IoT, they do not present machine learning or data mining for automatic prediction to advise what is needed for aquaculture.

Table 1. The research studies related to fish aquarium monitoring IoT-based

IoT Features	Research Studies
Temperature*	[9][16][17][18][19][20][21][22][23][24][25]
pH*	[9][16][17][18][19][20][21][22[23][24][25][26]
DO*	[9][16][18][19][20][22][25][26][27]
Ammonia/Nitrite/Nitrate*	[17][20]
TDS*	[22]
Turbidity*	[23]
Lighting*	[20][22]
Food/Feed level*	[21]
Water level*	[9][16][21][22][23][24][25][26][28]
Auto water replacement*,**	[25]
Message notification*	[20][22][25]
Real-time access*	[16][19][20][22][23][26][25]

Notes: *The proposed features in this work. **This work applied the neural network approach to IoT features.

Table 2. The research studies related to fish aquarium controlling IoT-based

IoT Features	Research Studies
Temperature*	[9][16][17][21][22][25]
DO*	[9][16][18][22]
Lighting*	[16][20][22][28]
Food/Feed level*	[16][21][22][28]
Water level*	[9][21] [22][25][28]
Auto water replacement*,**	[25]
Real-time access*	[22][25]

Notes: *The proposed features in this work. **This work applied the neural network approach to IoT features.

3 Methodology

The development of improving the real-time aquatic ecosystem quality monitoring and analysis consists of 6 stages, including 1) data acquisition, 2) adjustment of imbalanced data by SMOTE, 3) model development by Multi-Layer Perceptron Neural Network, 4) The effectiveness evaluation of the model, 6) Internet of Things development and 6) application development of the real-time automatic aquarium system, as following:

3.1 Data acquisition

The authors collected the data from these different ornamental fish farms and focused on Thailand's five favorite kinds of tropical fish. There are angelfish, goldfish, guppy, platy, and Sumatran tiger barb. The data was gathered by observing an interview with the fifteen fish farmers or entrepreneurs who volunteered and signed the ethical disclosure of this research. There are 1,592 records of data related to these parameters or features related to the water temperature, pH, turbidity, TDS, DO, nitrate ion, percentage of water replacement, and the period time of day. The collected data were prepared in the comma-separated values (CSV) file with ten features and one class to decide the water quality, as shown in Table 3.

Table 3. The features related to aquarium water quality analysis and automatic water replacement

Features	Descriptions
FishKind	Kind of fish (Angelfish, Goldfish, Guppy, Platy, and Sumatran tiger barb)
pH	The potential of hydrogen ion (0.0–14.0)
DO	The dissolved oxygen (mg/L)
TDS	The total dissolved solids (mg/L)
Nitrate	The nitrate ion (mg/L)
Temp	The water temperature (degree Celsius)
Turbidity	The water turbidity (NTU)
Percentage	The volume of water replaceable (0–100%)
Replace	Type of water replacement (none, partial, full)
PeriodTime	The period time of day (morning, noon, afternoon, evening, midnight)
Quality	The output class of water quality (good, poor)

3.2 Adjustment of imbalanced data

The SMOTE technique was used to correct the imbalanced data. The analyzed parameters of increasing the k-nearest neighbor were set to a value between 1 and 5. It was found that if k=5 and the randomSeed=1, the data could be balanced and upsized to 400%. Thus, the new dataset has increased from 1,592 to 2,578, 3,359, 4,532, and 5,469 records for balanced data using SMOTE at 100%, 200%, 300%, and 400%, sequentially.

3.3 Model development

This process applied the MLPNN to create the models for forecasting the water quality. Five datasets were prepared for building the model, including the original dataset, 100% of SMOTE, 200% of SMOTE, 300% of SMOTE, and 400% of SMOTE. The MLPNN model parameters were set in Python version 3.8.1 which supports deep learning. The parameters offered the highest effectiveness tested by 10-fold cross-validation, including six hidden layers with sigmoid activation function, five hundred epochs, batch size=auto, and early stopping=true. Furthermore, the adaptive moment optimization (Adam) was applied with a learning rate=0.005. Moreover, the model that gave the highest accuracy was selected to build the web application program interface (API) using the Flask framework based on Python. Finally, this web API was developed and set up on the central server as a service to forecast the water quality in the aquarium.

3.4 The effectiveness evaluation of the model

Each model was evaluated the training accuracy and error function, which was the Mean Square Error (MSE). The MSE is one of the loss functions applied to the neural network model. It was expressed as in (3) [29][30][31].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(t_i - y_i\right)^2 \tag{3}$$

Where N represents the number of patterns, t_i represents the target output for the pattern i, y_i represents the output obtained for the pattern i.

Moreover, the effectiveness of the models was evaluated using the 10-fold cross-validation process. Then, the procedure was repeated ten times more, with the test set changing each round until all ten sets were used as the test set. Finally, the confusion matrix was applied to measure the effectiveness of accuracy, sensitivity, and specificity, which were calculated in (4) to (6) [32][33][34][35][36], respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Where *TP* represents when the water quality is "Good," and the model predicts it as "Good," *FP* represents when the water quality is "Good," but the model predicts it as "Poor," *TN* represents when the water quality is "Poor," and the model predicts it as "Poor," and *FP* represents when the water quality is "Poor," but the model predicts it as "Good."

3.5 Internet of Things development

All the IoT and sensor devices designed in this work were illustrated in Figure 2 and described as follows:

1) ESP32 DevKitC: This developed kit board has twenty-six pins available for input and output signal, but this work requires over twenty-six pins to communicate with various sensors and devices to monitor and control water quality. Thus, integrated circuits (IC) 74HC165 and 74HC595 were used to extend the input and output pins. Further, the Wi-Fi component is built-in for this board and requires sending and receiving

information between IoT devices, the central server, and LINE Notification on the mobile application.

2) DS18B20 temperature sensor: It is 3-wires of the digital temperature sensor. In this system, the DS18B20 was connected in normal mode.

3) pH sensor: It is an analog sensor for measuring the pH in the aquarium. The pH values can be range from 0.0 to 14.0.

4) Dissolved oxygen sensor: This module measures the dissolved oxygen in the aquarium system with a probe in an analog signal.

5) Total dissolved solids sensor: It is used to measure the total concentration of dissolved substances or TDS in an analog signal.

6) Nitrate ion sensor: Nitrate ion can be detected and measured by this analog sensor. The output signal possible is 0, and up to 31,000 mg/L.

7) 5V-LED tube light: This Light-Emitting Diode (LED) is used to illuminate the interior of the aquarium at the right moment. The AD5171 digital potentiometer controlled the brightness.

8) Light dependent resistor (LDR) sensor: LDR was applied to measure light in the aquarium and measure the water turbidity with white LED.

9) 12V-water pump: It is used to drain the water from the aquarium.

10) 2-ways solenoid valve: It controls filling new water into the aquarium when the remaining water has a low water level.

11) Ultrasonic sensor: This sensor was applied for detecting and measuring the lowest level of water in the aquarium.

12) Horizontal water level sensor: It is used to detect and stop filling new water into the fish tank or aquarium.

13) 6V to 12V-air pumps: Two air pumps were controlled by the AD5280 digital potentiometer for increasing the dissolved oxygen in the water.

14) 12V-Cooling fans: Three air cooling fans were used to decrease the water temperature.

15) Water heater: At low temperature, this heater was activated to increase the water temperature.

16) 12V-step motor and A4988 stepper motor driver: This Direct Current (DC) step motor drives and controls the food volume for fish feeding.

17) Force sensor resistor (FSR): To quantify the remains of fish food level, the FSR was applied to calculate the food remaining inside the fish food container based on its weight or pressure.

18) Power Supply 5V-DC: This primary power source supplies a whole system (excluding the water heater).

19) MT3608 DC-DC step up: It was applied for boosting the current from 5V to 12V.

20) 5V-single channel relay: Five 5V-single channel relays were used to control devices, consisting of a water heater, cooling fans, air pumps, water pump, and 2-ways solenoid valve.

21) MicroSD card module: All system configurations were read and written from ESP32 into a microSD card via this module for logging data.

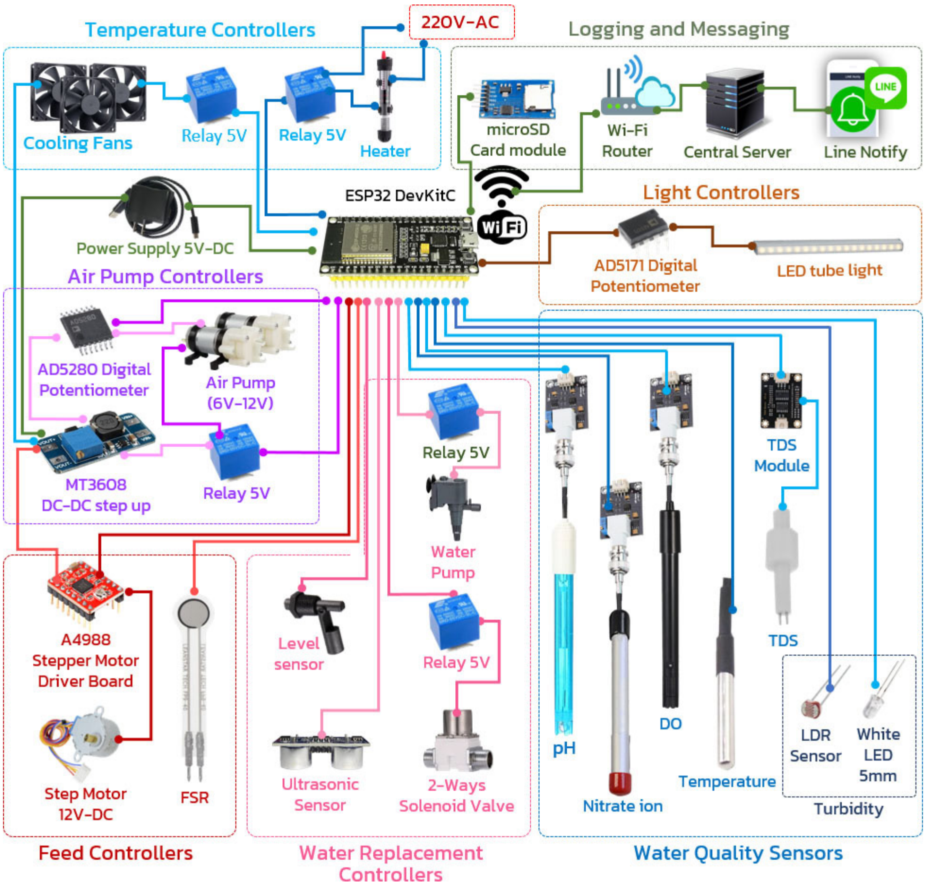

Fig. 2. The IoT and sensor devices designed for an automatic aquarium system

In this work, the authors develop the turbidity sensor by applying the white LED and LDR sensor, illustrated in Figure 3, to detect and calculate the voltage output (V_{out}) in (7).

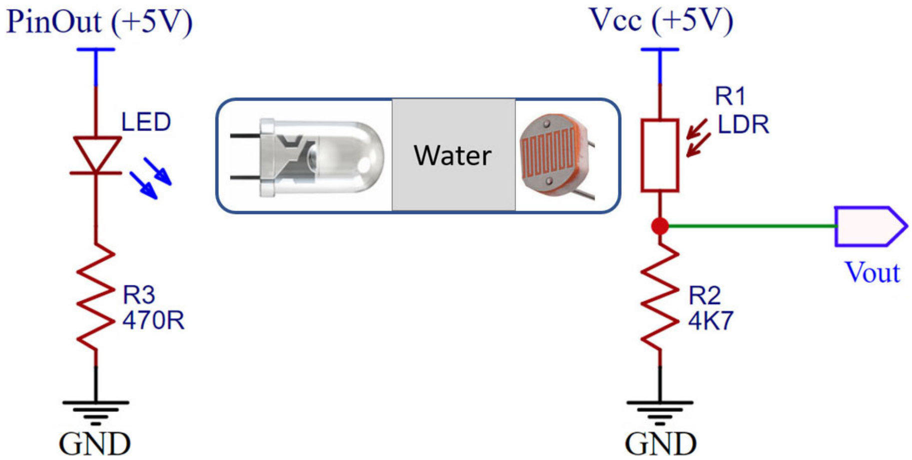

Fig. 3. The turbidity measurement LDR-based with white LED

$$V_{out} = \frac{R_1}{R_1 + R_2} V_{cc} \tag{7}$$

Where R_1 represents the resistance of LDR, R_2 represents the resistance was fixed at 4,700 ohms, and V_{cc} represents the source voltage was fixed at 5V.

In the experiment, the clear water (turbidity value is zero NTU) gave the V_{out} at 4.56V, while the maximum turbidity value was 2,982 NTU when the V_{out} was 2.50V. The turbidity output is related to the voltage output of LDR, as shown in Figure 4. These output values are similar to the quadratic equation in (8) with coefficients (*a*, *b*, and *c*). Thus, the coefficient values were solved where the *a* is –702.705, *b* is 3,513.526, and *c* is –1,409.908. Therefore, the turbidity in this work could be calculated as NTU in (9).

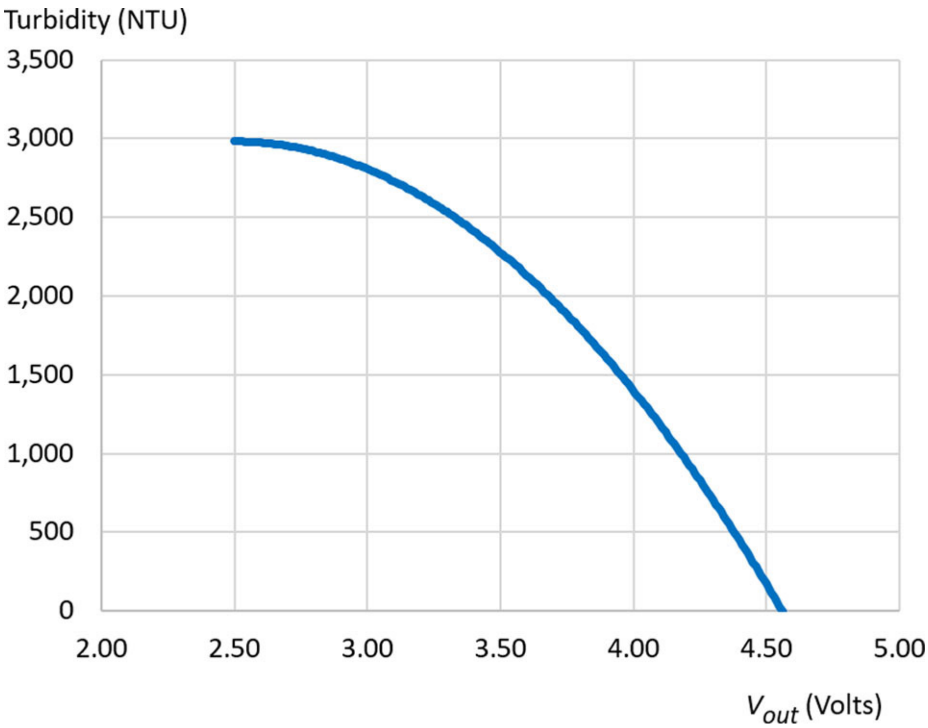

Fig. 4. The turbidity values related to the voltage output of LDR

$$NTU = aV_{out}^2 + bV_{out} + c \tag{8}$$

$$NTU = -702.705V_{out}^2 + 3513.526V_{out} - 1409.908 \tag{9}$$

3.6 Automatic aquarium system development

The development of the automatic aquarium system relies mainly on the Apache web server for communication between the smartphone and the ESP32 controller located in the aquarium or fish tank. The Arduino IDE version 1.8.9 was used to develop the aquarium controller system. It was written in the C++ programming language to control and send all data from sensors to the central server based on PHP5 and Python3 script. All data was stored in the MySQL database. The application developed for smartphones to connect to the aquarium system is designed under the Bootstrap framework that works with HTML5, CSS3, and JavaScript. In order to query the current aquarium environment in real-time, the web server sends communication commands to the ESP32 web server to request data from the sensors. Furthermore, users can also retrieve historical data stored in the database. In addition, the analysis and prediction of water quality derived from the MLPNN model were executed through the Flask framework, which is the Python micro web framework. The developed application infrastructure is illustrated in Figure 5. The example of user interfaces of the system is shown in Figure 6. There are nine main processes of automatic aquarium system as follows.

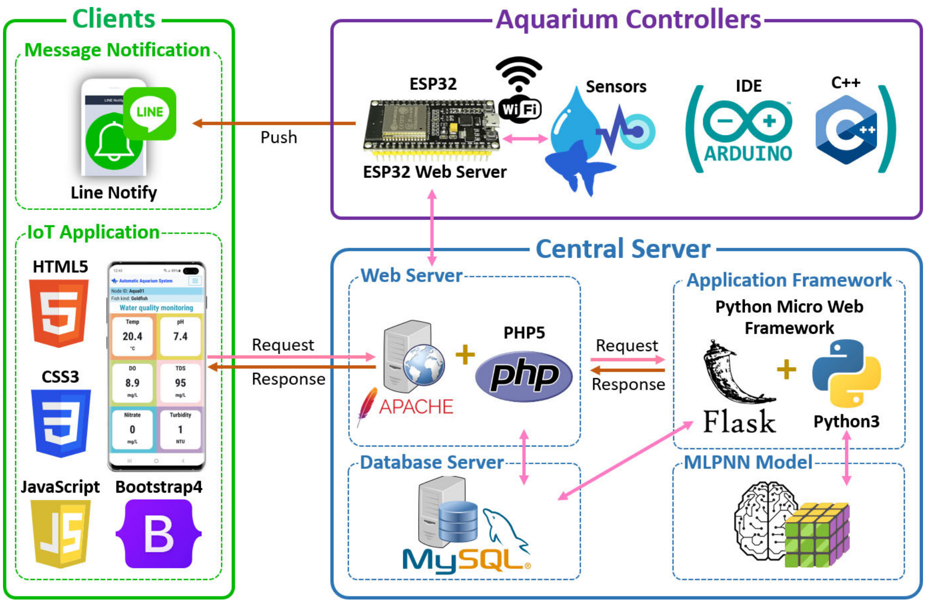

Fig. 5. The infrastructure of an automatic aquarium system

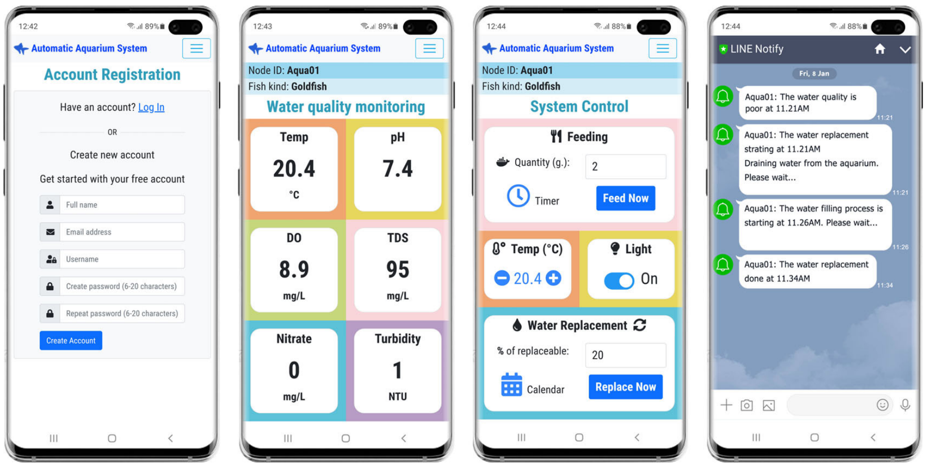

Fig. 6. The IoT application interfaces of automatic aquarium system

1) System configuration and registration: This process was developed for a new system registration for each node of the ESP32 board. The ESP32 will connect to the central server then load all necessary system configuration into itself by default, such

as temperature. However, the users can adjust the system configuration related to each kind of ornamental fish.

2) Automatic water quality monitoring: By default, the water temperature and DO were measured every five minutes, while other water quality parameters such as pH, TDS, nitrate ion, and turbidity were measured every thirty minutes. These measured water quality values were sent to the central server to analyze and predict water quality. If water quality is critical or poor, the automatic water replacement process will begin and send a warning message to the fish farmer. In addition, the percentage of the volume of water replaceable will be returned from the central server to the ESP32 board for controlling the water replacement process. Moreover, fish farmers can monitor the water quality in real-time through the application.

3) Automatic temperature control monitoring: There are cooling fans and a water heater for controlling the water temperature. Although Thailand has a relatively hot climate, sometimes it may be necessary to use a water heater to help maintain the proper water temperature in the aquarium for the fish in some areas and seasons.

4) Automatic air pump control: The amount of DO might be changed depending on the properties of water and respiration rate for the fish's metabolism at different times of the day. When the DO is low, it can be automatic gaining up using the air pumps to control the voltage for boosting the amount of oxygen into the water.

5) Automatic water replacement: The data from the sensors were sent to a central server for logging then forecasted by the water quality analysis model. If the data meet the output class of the model as poor water quality, the system will start to replace the water. For example, while the water pump activates to drain the water in the aquarium, the ultrasonic sensor activates to monitor the current water level until the minimum water level has occurred. Then the water pump will stop working and activate the automatic water filling process.

6) Automatic water filling: The automatic water filling will be activated if the situation meets one of the two conditions. First, the water was evaporated in the natural life cycle of water, and the water pump does not activate to drain the water out of the fish tank. Second, the water quality is poor, which was the forecasting output class of the water quality analysis model. The solenoid valve will change status as open to fill the new water in the aquarium. Until the horizontal water level sensor detects the current water level has reached, the solenoid valve will turn the status as closed for stop water filling.

7) Automatic lighting control: The lighting and brightness can be controlled both automatically and manually. It depends on the environment and the time of the day. Additionally, the fish farmer can set the timer to automatically turn the lights on and off, such as the sleep or rest time of the fish.

8) Automatic food level and feeding control: Initially, users or fish farmers can calibrate the fish food container weight to zero. Then they can define the feeding schedule and the feeding quantity, which is expressed in grams. Once the fish meal has been added to the container, the FSR sensor will measure the pressure and calculate the weight of the food inside the container for monitoring food levels. Each time for feeding, the step motor rotates the holed undercover plate to release the food into the aquarium. It works co-operating with the FSR sensor to increase the accuracy of calculating each fish meal's quantity. Suppose the amount of food is running low or empty. In that

case, the system will send a notification message to inform the fish farmer to increase the accuracy of calculating each fish meal's quantity. If the amount of food is running low or empty, the system will send a notification message.

9) Automatic message notification: The IoT system will send the notification as a message into the LINE Notify application on the internet for all critical events occurring. The fish farmer can monitor the aquarium status by viewing the message from the mobile application.

4 Research results

In this research, the results of the model's effectiveness and application evaluation can be summarized as follows:

4.1 The evaluated results of the effectiveness of the models

The training accuracy and MSE were used to evaluate the effectiveness of the models which were stopped training at the 218th epoch. The results showed that the training accuracy obtained from the model developed from the 400% of SMOTE+MLPNN dataset was the highest at 98.11%, followed by models developed from 300% of SMOTE+MLPNN, 200% of SMOTE+MLPNN, 100% of SMOTE+MLPNN, and the original dataset. Furthermore, the MSE value obtained from the model developed from 400% of SMOTE+MLPNN is the lowest at 0.0154, respectively, as shown in Figure 7.

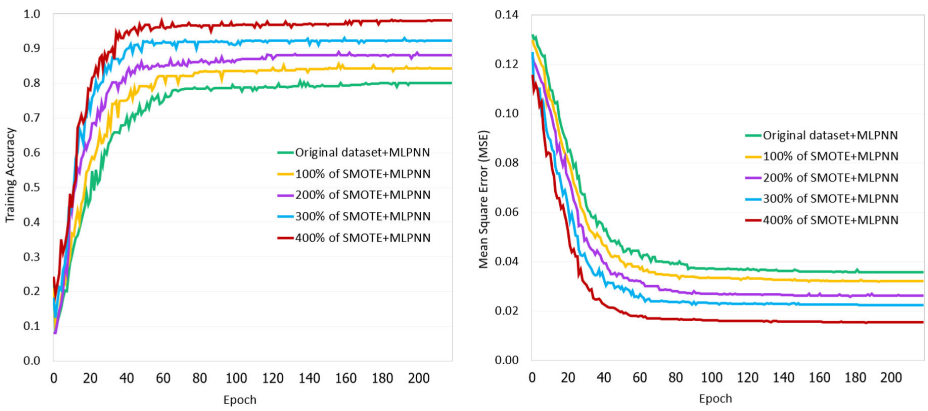

Fig. 7. The training accuracy and the MSE of the model

Moreover, the model's effectiveness of the 400% of SMOTE dataset built by MLPNN gave the highest accuracy at 97.31%, the sensitivity at 97.98%, and the specificity at 91.41%, as shown in Table 4.

Table 4. The evaluated results of the effectiveness of the models

Models	Data (records)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Original dataset+MLPNN	1,592	80.72	79.37	88.89
100% of SMOTE+MLPNN	2,578	82.82	82.32	87.71
200% of SMOTE+MLPNN	3,359	84.40	83.69	90.91
300% of SMOTE+MLPNN	4,532	93.60	93.92	91.26
400% of SMOTE+MLPNN	5,469	97.31	97.98	91.41

4.2 The accuracy results of the real-time automatic aquarium system

The data from the IoT system in microSD card, logging on a central server, and fish farmers were evaluated for each fish. The authors compared the system's logging data with the data recorded by the fish farmers or entrepreneurs of each ornamental fish farm to find the system's accuracy. The accuracy results of the automatic aquarium system are shown in Table 5.

Table 5. The accuracy results of the automatic aquarium system

Term of Evaluation	Accuracy (%)
Auto water quality monitoring	99.97
Auto temperature control	99.97
Auto air pump control	99.98
Auto lighting control	99.91
Auto water filling	99.92
Auto water replacement (low water quality)	99.56
Auto water replacement (schedule)	99.98
Auto food level control	99.83
Auto food feeding	99.95
Auto message notification	99.94
Online monitoring for user	99.78
Average	99.89

According to Table 5, there are results of evaluations that meet more than 99.50% accuracy for the automatic aquarium system, including auto water quality monitoring, auto temperature control, auto air pump control, auto water filling, auto food feeding, auto food level control, auto message notification, and auto water replacement (schedule). Other terms which have an accuracy of more than 99.80% are auto water replacement (low water quality), with 97.56% accuracy, respectively. For the online monitoring for users or fish farmers, the accuracy was 98.78%. Thus, for the overall system, the average accuracy was 99.89%. The author analyzed the factors and causes of the accuracy below 100.00%, which was found to be due to external factors and the different working processes of each fish farmer. For example, in automatic lighting control, the outdoor lighting conditions sometimes change slowly cause delaying the process of the brightness to the aquarium. In the case of auto water replacement, when the water quality is low or poor, some fish farmer needs to change the water to be clear and clean all the time to impress and motivate customers to buy fish. It is causing why the automatic aquarium system predicts good water quality, which is realistic but contrary to the requirements of the fish farmer. However, the water quality data for such fish could be further revised so that the model could be further learned later. For online monitoring to the aquarium water quality by users or fish farmers, sometimes the internet connection at the fish farm does not stable, for example, deficient speed or the Wi-Fi router disconnect from the internet services provider (ISP). However, the authors programmed the ESP32 board for rechecking and reconnecting to the Wi-Fi router when it disconnects from the network.

5 Conclusion

This work proposed improving the water quality analysis, which is the automatic water quality monitoring and water replacement based on IoT for ornamental fish entrepreneurs. The authors applied the SMOTE to solve the 1,592 records of imbalanced data related to fundamental water quality indicators and five tropical fish kinds in Thailand, including angelfish, goldfish guppy, platy, and Sumatran tiger barb. Five models are generated from these datasets for predicting water quality in fish tanks using MLPNN. The result showed that the model's effectiveness of the 400% of SMOTE dataset built by MLPNN gave the highest accuracy at 97.31%, the sensitivity at 97.98%, and the specificity at 91.41%. Thus, this model developed the automatic aquarium system for fish farms.

Each sensor in the automatic aquarium system measured the water quality factors, including temperature, pH, dissolved oxygen, total dissolved solids, turbidity, and the nitrate ion. These data from various sensors were processed to decide to control the system for replacing the water automatically. The model processed these data from various sensors to forecast the current water quality in an aquarium via API on a central server. If the forecasting shows that the water quality is poor, the system will automatically replace the appropriate volume of water to bring back the water quality to a reasonable level. The system gave an automatic water replacement accuracy of 97.56% when the water quality is poor from the real system testing and installation at fifteen fish farms for thirty days.

Further, the automatic aquarium system has also been developed for various automation capabilities, including auto temperature control, auto air pump control, auto lighting control, auto water filling, auto food level control, and auto food feeding. These automated processes deliver an accuracy of over 99.50%. In each process, a notification message was sent to the fish farmers via the LINE Notify application. Moreover, users or fish farmers can monitor water quality properties in their aquarium in real-time on mobile or web application with security to access their information.

Therefore, it can be concluded that the developed automatic aquarium system for water quality monitoring and water replacement using MLPNN could help reduce the burden of water maintenance for ornamental fish farmers. It is a developed system that can be configured to operate automatically to maintain the water environment, feed, and change the water, suitable for each kind of ornamental fish. Furthermore, fish farmers can monitor the water environment and control the system remotely. As a result, ornamental fish live longer and grow efficiently in the right environment, ready for sale and generating income for fish farmers.

For future work, the authors will expand the scope to cover several kinds of ornamental fish and fish farming from small-scale to large scale. Moreover, the authors plan to improve the communication network to reduce the number of ESP32 boards required for every node. It relies on a serial communication mixed wireless methodology to transfer data back to a central board capable of processing without a central dependence server. All sensor data is stored in cloud big data for sharing with other fish farmers. In addition, a model used to forecast water quality will be developed based on an adaptive learning model based on additional parameters such as the number of fish, tank size, amount of food supplied at each meal. This will help improve the predictive model efficiency and accuracy and be more suitable for each ornamental fish species.

6 Acknowledgment

We would like to be grateful to the Institute for Research and Development, the Faculty of Science and Technology, Suan Sunandha Rajabhat University, and Faculty of Information Technology and Digital Innovation, King Mongkut's University of Technology North Bangkok, who offered us the opportunity to conduct this research.

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Article submitted 2021-12-06. Resubmitted 2021-12-23. Final acceptance 2022-01-26. Final version published as submitted by the authors.