Computer Science Journal of Moldova, vol.**29**, no.3(87), 2021

Implementation of Internet of Things (IoT)-based Aquaculture System Using Machine Learning Approaches

Abdul Kadar Muhammad Masum

Abstract

The protein demand on the planet is increased rapidly with respect to the fast growth of the population and can't be met by meat. Fish is an amazing wellspring of protein that compares with meat even with minimal effort in production. The majority of consecutive fish farming and the subsisting intelligent system failed to produce anticipated amount of fish. The main aim of this research is to introduce an effective IoT-based low-cost fish farm which will also be high in the production of fish. A WEMOS D1 is actively involved in the determination of different basic water parameters such as temperature, oil layer, pH, water level, conductivity, oxygen level, turbidity, and fish behavior to anticipate their hunger status which significantly impacts on the quick fish growth. Via our built interactive smartphone application and Web interface, these pieces of information are transmitted to the end user. The D1 microcontroller works on the ESP8266 WIFI module through which the system sends the information to the mobile and web application. In the event of an abnormal situation, exceeding a predefined threshold value, the framework will inform the concerted authority to take immediate steps. In addition, the system is more remarkable and extraordinary as it can predict the amount of following day fish food and other constraints required for fish farmers to take a precautionary measure in advance. These characteristics would allow a fishery proprietor to grow a large number of fish via reducing the protein challenge.

Keywords: oil layer detection, pH sensor, Random Forest Regression (RFR), Support Vector Regression (SVR)

1 Introduction

At any pace, 70% more proteins are essential in 2100 with the increasing number of world population [1]. Seas, an exceptional resource of protein, is occupied around 2.5% more fish than what the sea usually would produce [2]. World Wildlife Fund (WWF) reported that 90% of fish caught around the world have evaporated from the sea since 1950 [3]. We are rising our burden on the sea, which is a threat for natural equalization. To satisfy the need, a substitute source should be considered without damaging the nature. According to FAO, aquaculture experienced a critical annual growth rate of 7.4% with increased meat needs.

Aquaculture-based fish cultivating is a great answer for this basic issue. Fish cultivating is so economical that to produce 1 pound of fish requires only 1.5 pounds of fish food, while to produce the same amount of meat requires 8000L of water and 8-9 pounds of feed for cow [1]. Furthermore, as regards monetary benefit, there was a huge difference towards IoT and non-IoT-based fisheries, which was noticed on a prior review. The speedy development of the fish depends on different components: environmental factors [2], production factors [3], and biotic factors [4]. It is conceivable to display and regulate a portion of those constraints.

The primary reason for this study is to create a sound structure for the control and monitoring of fish farms that can accurately evaluate various fundamental water parameters, such as temperature, oil layer density, pH, water level, and hungry fish level, by looking at fish behavior. A few information control systems such as mean, mode, information standardization have been followed to achieve a precise value. The obtained data such as estimating the possible oil layer, pH, water level, fish hungry level etc. is kept in the online storage server. If the specifications surpass the preset threshold point, the device will alert the consumer via the Mobile App. The cost is so small that fish farmers can adjust quickly and tackle the global protein challenge.

With the introduction, this paper is composed of five parts. Section 2 covers the literature review, and Section 3 contains methods for clarifying algorithm, smart fish observation, and the control procedure.

Section 4 shows the experimental outcomes. Section 5 addresses the analysis and future scope.

2 Related Work

Genetically altered fish having higher breeding competency has been composed by only a couple of researchers. But their rate of survival and degree of subsistence are lower than that of natural fish [5]. Exchange fish feeds are produced to control infections by providing lower synthetic compounds. These days the IoT (Internet of Things) is about the fourth Industrial Revolution. As a part of such a revolution, IoT elevates the fish growing system which contributes a huge part of the protein problem [6]. Conventional fish cultivating faces lots of issues like extraordinary climate, substantial precipitation, high temperature, constrained water and so on. SK Telecom has introduced an IoT-based fish farming device that identifies pH, temperature, oxygen and notifies users via their cell phones [7]. To inspect the water parameters, the conventional framework gathers a few samples from various areas to examine in the research center. In order to shrewd this approach, a group of researchers [8] built a decision support system based on Wireless Sensor Network (WSN), which detects different water properties and informs the user through cell phone. Likewise, another one built up a WSN based system [9]. The system grounded on Raspberry Pi endlessly determines the water attributes via fitted sensors and stores the information for further study in a cloud server [10]. In case of exceeding the trigger level of any attributes, automatically a SMS will be gone to the end user. LabView software was used to display the gathered data. But this system's prime downside is the extreme cost. Chy et al. [11] introduced a smart fish farm device to determine the following day fish food requirement, and in another work [12], they found that Support Vector Regression (SVR) performs better in fish feed prediction along with necessary water attributes related to the growth of fish. But they pursued basic analysis rather than considering a few significant highlights such as Biologically Oxygen Demand (BOD), turbidity and so on.

A system based on three layers of architecture is introduced in which the information is collected by a distant layer, the server layer transferred, and the information stored. The acquired data is seen in the user layer [13]. Similarly, the program is included with the device to show the sensor information. Furthermore, a huge segment of these system kinds may not know which sensors they have used or fitted expensive sensors that make the system hard to adapt to the fish farm. Moreover, most of the program gives the fish food after a certain time of ignoring feeding if they need it. Calculating the measurement of the necessary fish nutrition in the greater part of the structure is missing.

In the background of the aquaculture program in Bangladesh, a significant portion of the fish farm adopts the common ways of growing the fish. The cost ends up being high along these lines, but the outcome is not satisfactory. This is the fundamental undertaking, to the best of our knowledge, to establish a perfect observation and understanding of fish farms when fish need food by inspecting their behavior. Furthermore, predicting the amount of fish feed on the following day will help the fisherman to take an earlier protective step.

3 Methodology

How the fisheries information will be gathered and transmitted to the end user, an outline of the proposed system is demonstrated in Figure 1. The system measures various significant parameters of the water like temperature, oil layer, pH, oxygen level, turbidity, conductivity, water level as well as the development of the fish that greatly affect the quick advancement of a fish. After powering the system, it's activated and buy a couple of moments to prepare the sensor at the first time. pH sensor requires to shift continuously in purpose of assessing the pH estimation as it gives inappropriate value in stationary state. A servo motor with a pH sensor is attached to continuously move via turning 360 degrees in one direction and 360 degrees in the opposite one. For a more accurate pH meaning, it estimates the median and mean of five consequent pH values through Equations (1) and (2), where each value P is taken in 3 min intervals. To overcome the outlier problem, median is considered over mean. In the case of exceeding 0.5 of the absolute difference of median and mean, median is chosen as the pH value; else, mean (Equation (3)).

$$pH\_mean\& = \left(\sum_{i=1}^{5} P_i\right)/5 \tag{1}$$

$$pH\_median\& = Median\,(P_1, P_2, \cdots, P_n) \tag{2}$$

$$best\_pH = |(pH\_median – pH\_avg) < 0.5 ? ph\_mean : pH\_median| \tag{3}$$

Dense oil layer blocks fishes from reaching the sunrays and can also lead to death to the grown fish. The system tests the depth of the oil layer by an IR sensor and stores the data in the memory. Similar to the pH calculation, oil layer density is determined, and the value of 10 is set as a threshold. Typically, in a fish farm, fish foods are supplied in a certain period. Perhaps growing fishes require to feed early than the particular time, or even more food. As starved fish develop sluggishly, feeding fishes, while necessary, is an obligatory characteristic of a perfect fish farm. Our system can identify a fish's hunger level (intense or average or natural) so it can provide sufficient fish food. The abnormal movement of fishes will help us to identify the degree of hunger. Three ultrasonic sensors (x, y, z) were deployed to read six values after every 10 sec. The median and mean for each sensor are measured via Equations (4) and (6), where x corresponds to the location of a fish calculated by sensor x and y, z would be like x. For each sensor the best value is found by analyzing the mean and median value.

$$x\_avg = \left(\sum_{i=1}^{6} x_i\right)/6 \tag{4}$$

$$y\_avg = \left(\sum_{i=1}^{6} y_i\right)/6 \tag{5}$$

$$z\_avg = \left(\sum_{i=1}^{6} z_i\right)/6 \tag{6}$$

Then, the RMS value is calculated for each sensor using Equations (7) – (10). x_rms corresponds to sensor x, similarly, y_rms – to sensor y, and z_rms – to sensor z. The system can recognize the hunger level of fish from all these 3 RMS values. The hunger is extreme if the minimum threshold is exceeded by three RMS, if it is exceeded by two – the medium, else – the fish is satisfied.

$$x\_median = y\_median = z\_median = Middleofsortedvalues \tag{7}$$

$$\begin{aligned} x\_best &= compare(x\_avg, x\_median) \\ y\_best &= compare(y\_avg, y\_median) \\ z\_best &= compare(z\_avg, z\_median) \end{aligned}$$

$$x\_rms = \sqrt{(x_1 - x\_best)^2 + \cdots + (x_6 - x\_best)^2} \tag{8}$$

$$y\_rms = \sqrt{(y_1 - y\_best)^2 + \cdots + (y_6 - y\_best)^2} \tag{9}$$

$$z\_rms = \sqrt{(z_1 - z\_best)^2 + \cdots + (z_6 - z\_best)^2} \tag{10}$$

Excessively hot and cold temperatures are a factor behind fish's slow development. Like the previous estimation of the value, the system determines the temperature, and the absolute mean and median difference is taken as 0.5. Substantially, a fish farm is unsafe for frequent high and low water levels. To make the system relatively minimal-cost, the water level is determined by an ultrasonic sensor. Like for the previous value, for calculating water level, the absolute difference between the median and mean is assumed as 5. In water, the quantity of Biologically Oxygen Demand (BOD) also controls the growth of the fish and types of fish that live in it. Generally, the oxygen needs per unit weight decrease dramatically as the individual weight of fish is increasing. Turbidity is another important feature that demonstrates the cleanliness of the water, as the dirty water hinders the sunlight to come in contact with the fish. Water conductivity is another important feature that provides a measure of what is dissolved in water. Aquatic animals and plants are adapted for a certain range of salinity. Outside of this range, they will be negatively affected and may die. Wemos D1 passes the information to the fish owner. A smartphone application and an interactive web interface are combined with the framework to make the device more user friendly and track remotely. The information is graphically visualized and saved in the web server, which will enable to review the historical data. In addition, if the water attributes and fish behavior parameters cross the predetermined trigger value, the alarm will be turned on and the staff member will also be alerted through the mobile application.

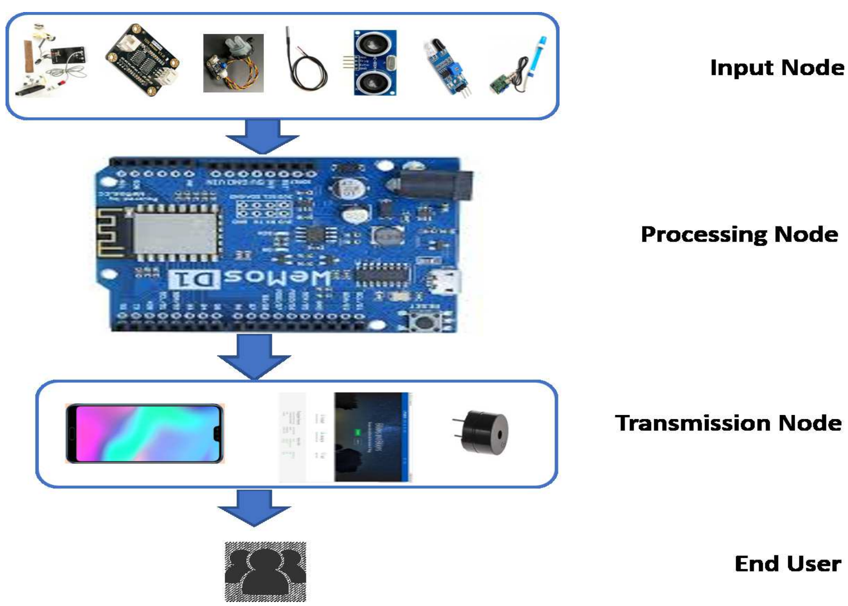

Figure 1. Overview of the proposed framework

3.1 Hardware

1) WEMOS D1 Microcontroller: a ESP8266 12E-based microcontroller board. The functional strategy is alike NODEMCU, except the hardware similar to Arduino UNO. In the efficiency and functioning speed context, WEMOS D1 is almost twice as potent as Arduino. The reason behind the selection of ESP8266 over ESP8285, as it is cheaper than ESP8285. Moreover, due to the huge community support and projects available online on ESP8266 rather than ESP8285, we selected ESP8266 for this research.

2) HC-SR04 Ultrasonic Sensors: HC-SR04 sensors are involved to calculate the fish hunger level and water level. It can detect an object at a frequency of 40 kHz ranging around 2 centimeters to 400 centimeters [14].

3) pH Sensor: To determine the acidity or alkalinity of a mixture, pH sensor is used, scaling from 0 to 14. On this scale, below 7 is considered as acidic, 7 – neutral, above 7 – alkalic. To measure the pH level, the TOL-00163 model is used in our system [15].

4) TDS Sensor: Arduino analog electrical conductivity and SEN0244 TDS sensor are utilized for evaluating and converting water conductivity to TDS [16].

5) BOD Sensor: LAZAR DO-166 Biologically Oxygen Demand (BOD) sensor is used to calculate the amount of dissolved oxygen in water with range from 0 to 20 ppm [16].

6) Turbidity Sensor: SEN0189 turbidity sensor integrates turbidity circuit and turbidity probe. Turbidity represents the cleanliness of water through the total amount of particles existing in the water. If the amount of solid particles increases, the turbidity level also increases [16].

7) IR Optical Sensor: The TCRT5000 IR is a transparent sensor that blends a photo-transistor in a lead box to block visible light [17].

3.2 Working Algorithm

Figure 2 demonstrates an overall working cycle of an ideal IoT based fishery. All sensor attributes are initialized at launch time. Servo motor oscillates between 30° left and right as pH sensor has to move for a decent performance. By applying pH formula, median, mean and comparing them, the best value is estimated from the pH sensor values. When the water's pH reaches the optimal pH range (7 – 8.5) [18], the system turns the alarms on and informs the user via the smartphone and web interface. Two optical IR sensors evaluate the layer of oil, where the output value provides a mixture of heat and noise. The method achieves the appropriate measurement by deducting the heat and noise from the sum. This sensor's best value from median and mean is determined using the corresponding formula. Less than 500 is an unstable situation for the oil layer. Similarly, temperature, BOD (Biologically Oxygen Demand), turbidity, water conductivity is determined by choosing the best value from their respective mean and median values. One research notes that 22°C to 27°C is a good value diapason for the fish's rapid growth [19], for BOD – 3–20 ppm, for turbidity – 10–20 mg/L [20], and for water conductivity – 45–57 mS/cm. Six Concurrent sensor readings shall be taken in one minute to recognize the frequency of movement of fish. The value of 4.5 centimeters for RMS is picked as a threshold for understanding the hungry fish stage. Wimos D1 microcontroller mounted on WIFI ESP8266 sends information to the smartphone application and interactive web interface from the system. Depending on these essential water parameters, the device forecasts how much fish feed will be required next day.

3.3 Forecasting the next day fish feed

Predicting numerous crucial water features makes the proposed framework more exceptional. For easiness, here only forecasting the following day fish food feature is undertaken. Like this approach, the system can be customized to predict other key attributes. Figure 3 is a general overview of the learning cycle of machines.

Dataset is the first and foremost requisite to develop a machine learning model. In this system, more than a year data has been collected from a local fish farm. Temperature, oil layer density, pH, water level, oxygen level, turbidity, water conductivity and fish starved level

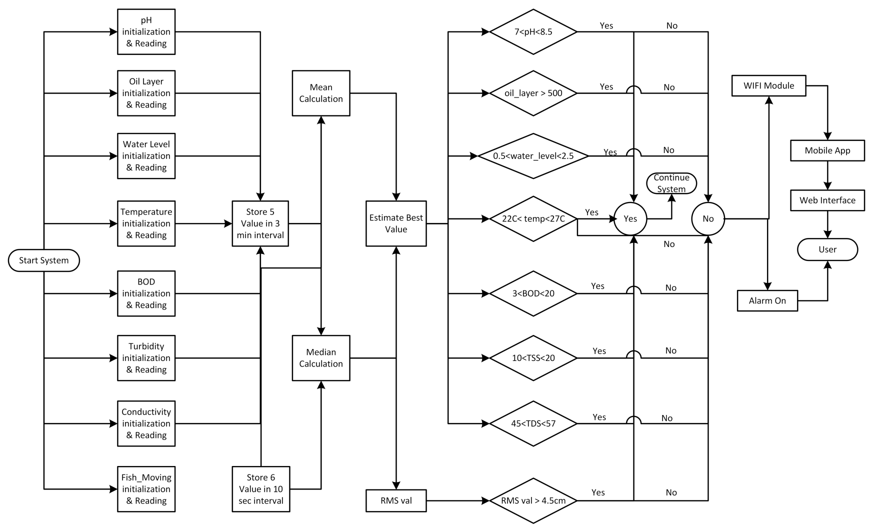

Figure 2. Working flow of the proposed framework

information are the key attributes for the training phase of the system. As the raw data set is not clean, there is the need to remove the noise and to preprocess. Two types of data processing techniques named feature scaling and one hot encoding are utilized upon the dataset. Feature scaling of the z-score normalization is used to render the standard deviation 1 and the mean zero. One hot encoding is adapted to the water level, in which 0 implies the water level isn't ok and 1 implies alright. Likewise, one-hot encoding is placed on the fish hunger level, in which 0 implies severe hunger, 1 – medium hunger, and 2 – fulfilled. Among various features which are the most important to build the predictive model, feature engineering plays a vital role. Backward elimination is integrated to find out the important features that mainly filter out the feature based upon the p value. The high p value of a feature refers it is less important. Figure 4 is the final stage of backward elimination, where, as a threshold value for p, we choose 0.005, and from 12 features only 8 ones are selected.

After selecting important features, from various types of machine

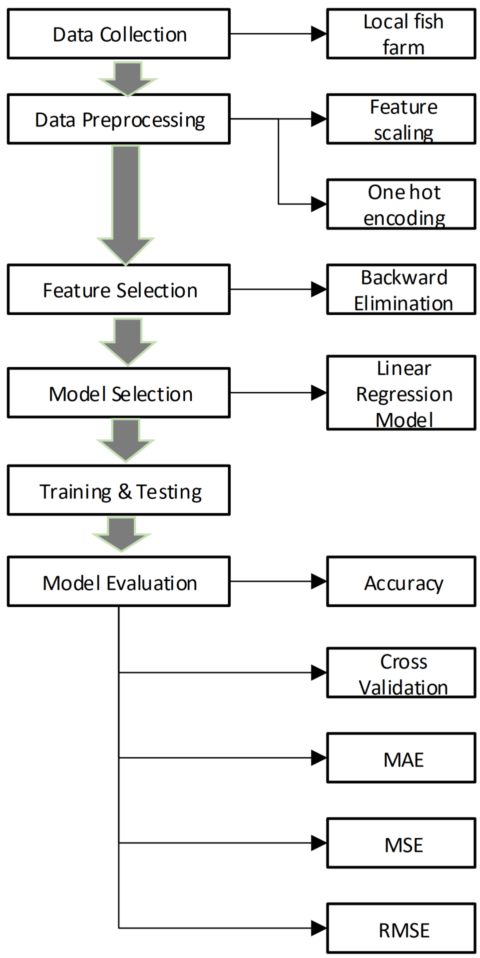

Figure 3. Machine Learning Model

	coef	std err	t	P>|t|	[0.025	0.975]
const	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x1	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x2	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x3	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x4	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x5	1594.1996	0.493	3232.754	0.000	1593.227	1595.172
x6	531.4074	4.406	120.608	0.000	522.718	540.097
x7	534.4032	4.545	117.580	0.000	525.440	543.366
x8	528.3890	4.306	122.724	0.000	519.898	536.880

Figure 4. Backward elimination Final stage

learning models, the linear regression model is chosen, as we want to predict the amount of the required fish food in the following day. Among the different regression models, some of the best regression models such as Linear Regression (LR), Polynomial Regression (PR), Decision Tree Regression (DTR), Random Forest Regression (RFR), Support Vector Regression (SVR), have been investigated to best train the model. Before feeding the whole data to the model, some data should be reserved to test the trained model. Here, the datasets are divided into 75% and 25%, where 25% is allocated to test the model being trained. After completion of machine learning training phase, the learning of the system is examined in terms of cross-validation, accuracy, MSE (Mean Squad Error), RMSE (Root Mean Squad Error) and Mean Absolute Error (MAE). SVR provides the best results by analyzing these outcomes for each regression model.

4 Experimental Outcomes

A prototype of the system appears in Figure 5, where temperature, oil layer, oxygen level, pH, water level, turbidity, conductivity, and the hunger level of a fish are the significant outcomes. To regulate various water parameters data remotely, the framework sends the information to the web server and to an interactive smartphone application interface via built in ESP8266 WIFI module. Also, for future analytics, information is stored to the cloud storage. The system turns on the alarm and informs the end user if any constraints surpassing the pre-set threshold value. A preview of the mobile app functionality is shown in Figure 6 (a), and an irregular condition is identified in Figure 6 (b), and the end consumer is notified via mobile app.

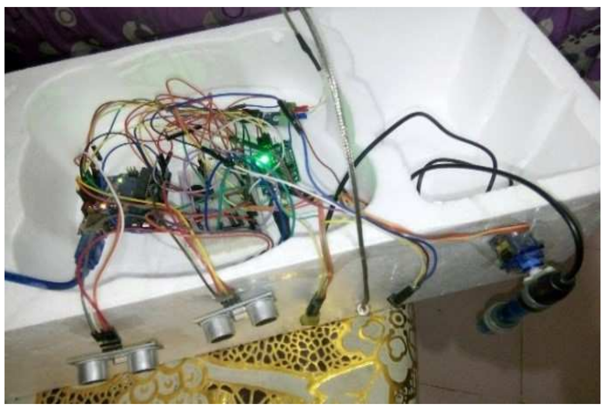

Figure 5. Photograph of the prototype

For the purpose of graphical visualization, the device sends the collected information to the web interface. Figure 7 displays the pH data representation over time and saves it to the web server's csv datasheet for potential analytics. The framework also shows oil density layer data (Figure 8), temperature (Figure 9), level of water (Figure 10), BOD level (Figure 11), turbidity level (Figure 12), water conductivity level (Figure 13) graphically.

Table 1 shows some sample prediction value of model after evaluation through the testing data via different LR, PLR, SVR, DTR, RFR model. Figure 15 is a line representation of the real value and different predictive model value in which each regression value is divided by another color.

Many techniques such as cross-validation, precision, RMSE, MSE,

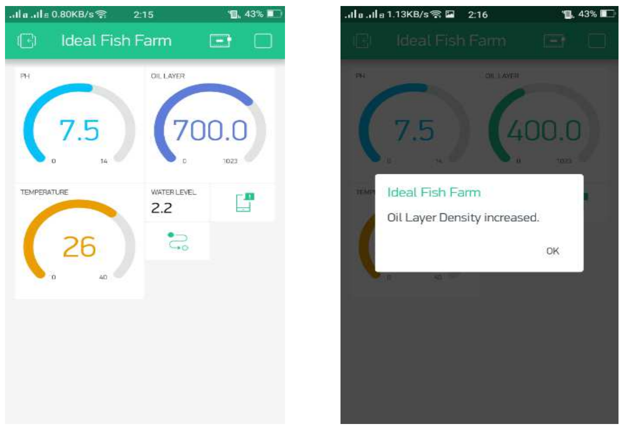

Figure 6. (a) Developed mobile application at usual state (b) At an abnormal state

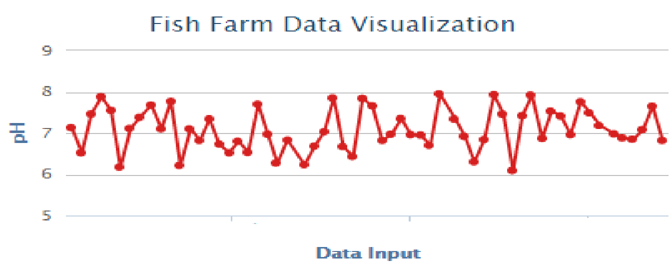

Figure 7. pH data visualization

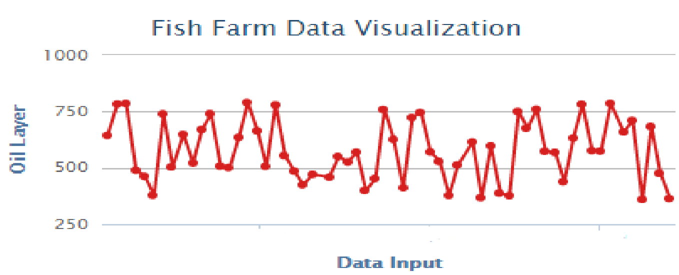

Figure 8. Oil Layer data visualization

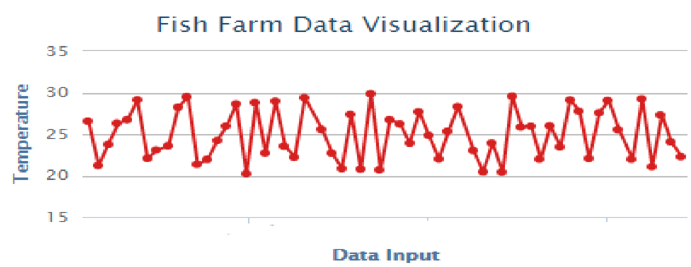

Figure 9. Temperature data visualization

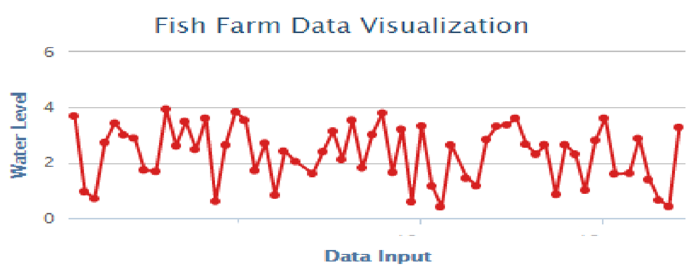

Figure 10. Water Level data visualization

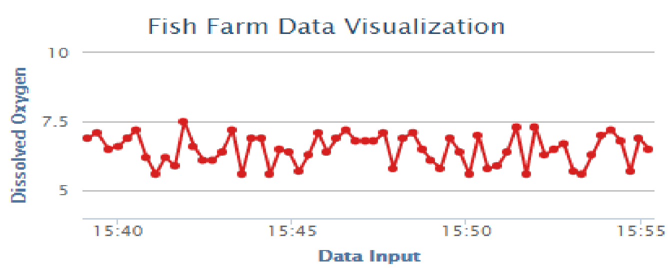

Figure 11. BOD data visualization

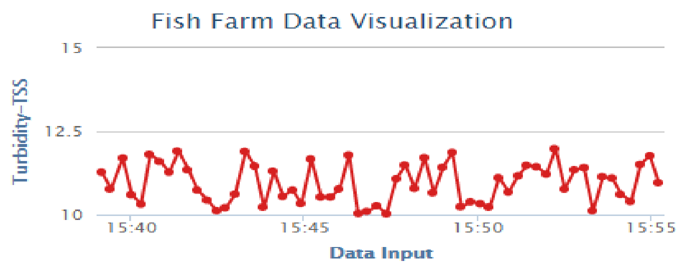

Figure 12. Turbidity data visualization

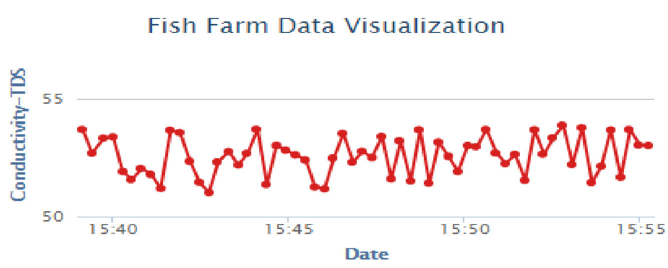

Figure 13. Conductivity data visualization

Table 1. Testing Data

Fish Food	LR	PLR	SVR	DTR	RFR
10016.13	10020.60	10013.14	10010.19	10034.50	10027.58
10181.10	10180.27	10107.86	10198.14	10192.47	10193.69
10065.23	10088.39	10088.56	10086.95	10081.69	10083.37

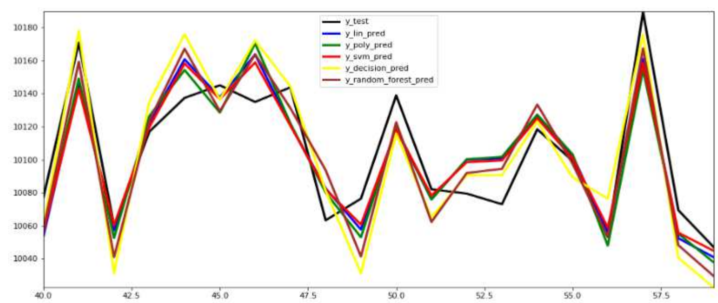

Figure 14. Testing and Predicted Value Visualization

MAE are regarded for evaluating the learned model displayed in Table 2. The five-fold ross-validation is used. The findings differ significantly from one regression to other regression, as the factors differ. Switching the polynomial regression (PLR) level to the third degree, an improved outcome than LR (linear regression) is obtained. SVR shows even much improved outcome than regression of the decision tree (DTR). But, in total, the efficiency of random forest regression (RFR) is to the satisfying point.

5 Conclusion

The fish production needs to be increased in preparation for the elevated amount of protein. Traditional fish farming system does not satisfy the protein requirement. This research introduces a smart fish monitoring system based on IoT, where numerous critical water constraints like pH, temperature, oxygen level, turbidity, conductivity, oil layer, water level, and fish performance are constantly determined and inform the end consumer at unstable condition. An interactive mobile app and web interface are developed to remotely interact with the system. Moreover, forecasting the following day's fish feed will assist the fish farmer to take a forward-thinking step. The system that has been developed is cheaper and more cost-effective than other modern

Table 2. Model Evaluation

Regression Evolution	**Model**	**LR**	**PLR**	**SVR**	**DTR**	**RFR**
Accuracy	Training	87.1	87.1	89.7	96.8	98.2
	Testing	84.6	83.2	87.6	78.7	88.2
Cross Validation		83.7	83.7	85.7	73.8	84.9
MAR	Training	12.6	11.7	12.5	4.69	6.61
	Testing	13.7	16.7	13.4	19.1	17.4
MSE	Training	267	269	257	29.1	43.1
	Testing	312	463	293	612	353
RMSE	Training	17.2	14.9	14.4	6.09	7.69
	Testing	18.5	20.3	16.5	23.3	16.5

systems and other smart systems. The potential scope of the present program is to add other essential features such as identifying the poison in the water, differentiating cost and image processing-based fish and non-fish species. The adoption of the proposed smart fishery surveillance system helps the fishery owner to increase fish production.

References

[1] 2013. [Online]. Available: http://hdl.handle.net/20.500.11822/8484

[2] V. Rubio, F. Sánchez-Vázquez, and J. Madrid, "Effects of salinity on food intake and macronutrient selection in european sea bass," *Physiology & behavior*, vol. 85, no. 3, pp. 333–339, 2005.

[3] M. A. Adewolu, C. A. Adeniji, and A. B. Adejobi, "Feed utilization, growth and survival of clarias gariepinus (burchell 1822) fingerlings cultured under different photoperiods," *Aquaculture*, vol. 283, no. 1-4, pp. 64–67, 2008.

[4] P. Kestemont, S. Jourdan, M. Houbart, C. Mélard, M. Paspatis, P. Fontaine, A. Cuvier, M. Kentouri, and E. Baras, "Size heterogeneity, cannibalism and competition in cultured predatory fish larvae: biotic and abiotic influences," *Aquaculture*, vol. 227, no. 1-4, pp. 333–356, 2003.

[5] J. A. Beardmore and J. Porte, "Genetically modified organisms in aquaculture," 2003.

[6] 2014. [Online]. Available: http://www.beechamresearch.com/files/BRL Smart Farming Executive Summary.pdf

[7] V. Bijalwan, V. Kumar, P. Kumari, and J. Pascual, "Knn based machine learning approach for text and document mining," *International Journal of Database Theory and Application*, vol. 7, no. 1, pp. 61–70, 2014.

[8] Z. Shareef, S. Reddy, and D. IGDTUW, "Design and development of iot based framework for aquaculture," in *National Conference on Product Design (NCPD 2016)*, Conference Proceedings.

[9] D. S. Simbeye and S. F. Yang, "Water quality monitoring and control for aquaculture based on wireless sensor networks," *Journal of networks*, vol. 9, no. 4, p. 840, 2014.

[10] K. R. S. R. Raju and G. H. K. Varma, "Knowledge based real time monitoring system for aquaculture using iot," in *Advance Computing Conference (IACC), 2017 IEEE 7th International*. IEEE, Conference Proceedings, pp. 318–321.

[11] M. K. A. Chy, A. K. M. Masum, M. E. Hossain, M. G. R. Alam, S. I. Khan, and M. S. Alam, *A Low-Cost Ideal Fish Farm Using IoT: In the Context of Bangladesh Aquaculture System*. Springer, 2020, pp. 1273–1283.

[12] A. K. M. Masum, M. Shahin, M. K. A. Chy, S. I. Khan, A. Shan-A-Alahi, and M. G. R. Alam, "Design and implementation of iot based ideal fish farm in the context of bangladesh aquaculture system," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*. IEEE, Conference Proceedings, pp. 1–6.

[13] M. Hua, D.-a. Zhao, W. Xia, Y. Zhu, and X. Liu, "The design

of intelligent monitor and control system of aquaculture based on wireless sensor networks," in *Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on*, vol. 2. IEEE, Conference Proceedings, pp. 9–12.

[14] 2018. [Online]. Available: http://www.electronicwings.com/sensorsmodules/ultrasonic-module-hc-sr04

[15] 2019. [Online]. Available: https://www.techshopbd.com/product-categories/meters/2576/ph-sensor-with-module-techshop-bangladesh

[16] H. MOHAMMED and I. AL-MEJIBLI, "Smart monitoring and controlling system to enhance fish production with minimum cost," *Journal of Theoretical & Applied Information Technology*, vol. 96, no. 10, 2018.

[17] 2019. [Online]. Available: https://www.techshopbd.com/product-categories/sensors-98778/977/reflective-optical-sensor-tcrt5000-techshop-bangladesh

[18] 2016. [Online]. Available: https://www.yokogawa.com/library/resources/application-notes/phin-fish-farming/

[19] 2019. [Online]. Available: http://www.tfhmagazine.com/aquarium-basics/temperature-control.htm

[20] N. Ezeanya, G. Chukwuma, K. Nwaigwe, and C. Egwuonwu, "Standard water quality requirements and management strategies for fish farming (a case study of otamiri river)," *International Journal of Research in Engineering and Technology*, vol. 4, no. 3, pp. 1–5, 2015.

Abdul Kadar Muhammad Masum,

Received June 3, 2020
Revised June 3, 2021
Accepted July 28, 2021

Department of Computer Science & Engineering (CSE),
International Islamic University Chittagong (IIUC),
Kumira, Sitakunda, Chittagong-4318, Bangladesh
E–mail: akmmasum@yahoo.com