Data Article

A dataset for internet of things based fish farm monitoring and notification system

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ARTICLE INFO

Article history:
Received 30 August 2020
Revised 14 October 2020
Accepted 20 October 2020
Available online 24 October 2020

Keywords:
Water quality factors
Fish farm monitoring
Real time monitoring
Digital sensors
Machine learning
Internet of things
Micro-controller
Notification system

ABSTRACT

Water quality depends on many factors. Some of them are essential for maintaining the minimum sustainability of water. Because of the great dependence of fishes on the condition of the aquatic environment, the water quality can directly affect their activity. Therefore monitoring water quality is a very important issue to consider, especially in the fish farming industry. In this paper a digital fish farm monitoring system is introduced and a collection of experimental data of water quality monitoring was presented, which were directly collected from a fish pond. As the quality factor of water affects its aquatic life form sustainability, therefore the quality factors of the water were measured using digital sensors. Temperature, pH factor and Turbidity were selected as the basic quality factors to measure. The dataset contains data recorded from two different water levels to analyze the aquatic environment more efficiently. Each level has 9623 sets of data of the selected parameters. Collection was continued all day long for several days. Later collected sensor data were analyzed as short period time series to find its properties. Machine Learning regression method was used to predict near future conditions. Moreover data were processed to find any repetitive patterns in its properties. This dataset represents the exact condition of the environment of the fish pond. Therefore it can be used to develop a system to monitor fish farms digitally. Using these data in machine learning,

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https://doi.org/10.1016/j.dib.2020.106457
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This dataset can be used for analyzing the condition of water in any fish farm to find its sustainability. Moreover, training machine learning regression method with it will help us to forecast the aquatic environment in the near future. Also any anomaly can be detected very quickly in the water quality factors by using the machine learning process. Automatic fish farm monitoring will be possible with it [2].

This dataset will be beneficial for the fish farming industry. It will be also beneficial for environmental scientists as it contains raw natural data.

Further these data can also be used for analyzing local geographical characteristics and discover new scopes of farming.

If such a data collection system is to be implemented in every fish farm throughout the country, a central monitoring and data base system can be built. It will help to compute the overall fish production in the country and help to make statistics of national profit, net productions, laggings, type of productions, possible productions, lag of any productions and many more.
1. Data Description

The dataset presented in this article is available in the Mendeley data repository [1]. The dataset has two data files which represents relative information from two different depths of water level. Table 1 and Table 2 show sample data of the dataset. The “Sensor data for 30 cm.xlsx” file includes Temperature sensor data, pH sensor data and Turbidity sensor data from 30 cm below the water surface. It has 9623 sets of data containing three data samples for each set of respective sensors. The “Sensor data for 60 cm.xlsx” file has Temperature and Turbidity sensor data from 60 cm below the water surface. It also has 9623 sets of data containing two data samples for each set of respective sensors. pH rating was not collected from 60 cm depth as changes in pH in a small area gets normalized quickly with respect to the surrounding area, so no significant changes are observed. For the both data files time samples are identical. Row-wise day and night time cycle over the experimental time period is presented in Table 3.

| Date and Time | Temperature (°C) | pH | Turbidity (NTU) |
|---------------|------------------|----|----------------|
| 2020-01-15 16:00:35 | 20.99 | 7.81 | 197 |
| 2020-01-15 16:01:33 | 20.99 | 7.81 | 197 |
| 2020-01-15 16:02:33 | 20.98 | 7.81 | 197 |
| 2020-01-15 16:03:22 | 20.98 | 7.81 | 197 |
| 2020-01-15 16:04:26 | 20.98 | 7.81 | 197 |
| 2020-01-15 16:05:21 | 20.97 | 7.81 | 197 |
| 2020-01-15 16:06:20 | 20.97 | 7.81 | 197 |
| 2020-01-15 16:07:17 | 20.95 | 7.81 | 197 |
| 2020-01-15 16:08:59 | 20.94 | 7.81 | 197 |
| 2020-01-15 16:10:00 | 20.93 | 7.81 | 197 |
| 2020-01-15 16:11:11 | 20.92 | 7.81 | 197 |

| Date and Time | Temperature (°C) | Turbidity (NTU) |
|---------------|------------------|----------------|
| 2020-01-15 16:00:35 | 22.54 | 134 |
| 2020-01-15 16:01:33 | 22.54 | 134 |
| 2020-01-15 16:02:33 | 22.54 | 134 |
| 2020-01-15 16:03:22 | 22.54 | 134 |
| 2020-01-15 16:04:26 | 22.54 | 134 |
| 2020-01-15 16:05:21 | 22.54 | 134 |
| 2020-01-15 16:06:20 | 22.54 | 134 |
| 2020-01-15 16:07:17 | 22.54 | 134 |
| 2020-01-15 16:08:59 | 22.54 | 134 |
| 2020-01-15 16:10:00 | 22.54 | 134 |
| 2020-01-15 16:11:11 | 22.54 | 134 |

| No. of experimental day | Row-wise Day time(6:00am-6:00pm) | Row-wise Night time(6:00pm-6:00am) |
|------------------------|--------------------------------|----------------------------------|
| 1                      | 2 (4:00pm)-116                   | 117-810                         |
| 2                      | 811-1445                        | 1446-2169                       |
| 3                      | 2170-2855                       | 2856-3633                       |
| 4                      | 3634-4410                       | 4411-5155                       |
| 5                      | 5156-5885                       | 5886-6553                       |
| 6                      | 6554-7189                       | 7190-7832                       |
| 7                      | 7833-8476                       | 8477-9077                       |
| 8                      | 9078-9624 (4:25pm)              | -                               |
sensor data from 30 cm underwater are presented graphically in Figs. 1–3 and raw sensor data from 60 cm underwater are presented graphically in Figs. 4–5. In these graphs X-axis represents the time series samples in minutes and Y-axis represents the data values. Table 4 shows the maximum and minimum values recorded by the sensors over the experimental time period. Table 5 shows the mean value of the parameters over the experimental time period.

Day and night time has different levels of temperature and pH rating and changes at a different rate. Temperature increases at the day time and decreases at the night time, where most of the time pH also has a tendency to increase at day time and slowly decrease at night time. Turbidity does not affect much by the day night cycle. With the increase of water depth temperature changes at a very slower rate. As a result the effect of day and night cycle is comparatively lower in the sensors 60 cm underwater. Fig. 6 and Fig. 7 show the changes in temperature and pH with respect to day and night cycle. In the graphs blue color denotes day time data from 6:00am to 6:00pm and red color denotes night time data from 6:00pm to 6:00 am. Table 6 shows the mean day and night time parameters over the experimental time period.
Temperature and turbidity values are not the same for both 30 cm and 60 cm levels. These two levels have difference in sensors values. Temperature increases with the depth of water level. As a result temperature rating in 60 cm underwater is warmer than 30 cm underwater. On the other hand turbidity level in 60 cm underwater is much lower than 30 cm underwater.

Furthermore the rate of change of parameters are not the same for both water levels also. Figs. 10–12 show the difference between adjacent values of each parameter for each water level depth. Near surface temperature of water level gets affected by the environmental temperature easily. As a result temperature in 30 cm underwater has a rapid changing rate and more fluctuation in the adjacent values. Temperature in 60 cm underwater does not change that rapidly. The rate of change is slow and steady. The adjacent values also show some periodic nature that repeats itself. Same properties are also found in turbidity values. Turbidity changes very slowly in 60 cm than 30 cm underwater. Yet, both level has a steady changing rate between the adjacent values. pH also has a steady changing rate between the adjacent values and changes slowly.

The experiment was conducted for seven days and among them there was a rainy day. In Fig. 13 and Fig. 14 data from 30 cm underwater are presented where dry day's data are
Fig. 5. Turbidity data from 60 cm underwater.

Table 4
Maximum and Minimum values recorded by the sensors over the experimental time period.

| S/N | Parameter Name                             | Maximum value | Minimum Value | Unit |
|-----|--------------------------------------------|---------------|---------------|------|
| 1   | Temperature sensor in 30 cm depth          | 23.81         | 15.6          | °C   |
| 2   | Temperature sensor in 60 cm depth          | 24.21         | 18.08         | °C   |
| 3   | pH sensor in 30 cm depth                  | 8.43          | 6.98          |      |
| 4   | Turbidity sensor in 30 cm depth           | 249           | 194           | NTU  |
| 5   | Turbidity sensor in 60 cm depth           | 154           | 134           | NTU  |

Table 5
Mean value of the parameters over the experimental time period.

| S/N | Parameter Name                             | Value         | Unit |
|-----|--------------------------------------------|---------------|------|
| 1   | Mean temperature value in 30 cm depth      | 20.0048       | °C   |
| 2   | Mean temperature value in 60 cm depth      | 21.5126       | °C   |
| 3   | Mean pH value in 30 cm depth               | 7.7579        |      |
| 4   | Mean turbidity value in 30 cm depth        | 216           | NTU  |
| 5   | Mean turbidity value in 60 cm depth        | 142           | NTU  |

Fig. 6. Change in Temperature in day and night time.
Table 6
Mean values of day and night time parameters over the experimental time period.

| S/N | Parameter Name                                      | Day time | Night time | Unit   |
|-----|------------------------------------------------------|----------|------------|--------|
| 1   | Mean temperature value in 30 cm depth               | 21.179   | 18.830     | °C     |
| 2   | Mean temperature value in 60 cm depth               | 21.979   | 21.047     | °C     |
| 3   | Mean pH value in 30 cm depth                        | 7.688    | 7.828      | -      |
| 4   | Mean turbidity value in 30 cm depth                 | 214      | 217        | NTU    |
| 5   | Mean turbidity value in 60 cm depth                 | 142      | 141.71     | NTU    |

Fig. 7. Change in pH in day and night time.

Fig. 8. Temperature difference between 30 cm and 60 cm underwater.

represented in blue color and the rainy day's data are represented as cyan color. During this period mean value of temperature decreased and turbidity increased than the other experiment days. The mean value of the parameters of dry days are described in Table 7 and the mean value of the parameters of the rainy day are described in Table 8.

Figs. 15–24 show the response plots and the corresponding error histogram plots of machine learning regression method (Support Vector Machine) of the dataset. 70% data of the dataset
Fig. 9. Turbidity difference between 30 cm and 60 cm underwater.

Fig. 10. Difference between adjacent values of Temperature.

Fig. 11. Difference between adjacent values of Turbidity.
Fig. 12. Difference between adjacent values of pH.

Fig. 13. Temperature and pH data of dry day and rainy day from sensors 30 cm underwater.

Fig. 14. Turbidity data of dry day and rainy day from sensors 30 cm underwater.
Table 7
Mean value of the parameters of dry days.

| S/N | Parameter Name                      | Value     | Unit  |
|-----|-------------------------------------|-----------|-------|
| 1   | Temperature sensor in 30 cm depth   | 19.8695   | °C    |
| 2   | Temperature sensor in 60 cm depth   | 21.3775   | °C    |
| 3   | pH sensor in 30 cm depth            | 7.6878    | -     |
| 4   | Turbidity sensor in 30 cm depth     | 217       | NTU   |
| 5   | Turbidity sensor in 60 cm depth     | 145       | NTU   |

Table 8
Mean value of the parameters of the rainy day.

| S/N | Parameter Name                      | Value     | Unit  |
|-----|-------------------------------------|-----------|-------|
| 1   | Temperature sensor in 30 cm depth   | 18.7704   | °C    |
| 2   | Temperature sensor in 60 cm depth   | 20.9467   | °C    |
| 3   | pH sensor in 30 cm depth            | 7.7256    | -     |
| 4   | Turbidity sensor in 30 cm depth     | 238       | NTU   |
| 5   | Turbidity sensor in 60 cm depth     | 144       | NTU   |

Fig. 15. Regression method response plot of Temperature sensor 30 cm underwater.

from each sensor was used for training the regression model and the rest 30% was used for testing. Figs. 15, 17, 19, 21 and 23 show the true data vs. predicted data plots where blue line represents true data and red line represents predicted data. Figs. 16, 18, 20, 22 and 24 show the error histogram plots of the corresponding response plots.

2. Experimental Design, Materials and Methods

Before developing the system's algorithm identifying the most important water quality factors is necessary. Factors that affect water quality the most are needed to be monitored. Hence several quality factors were analyzed that have the maximum impact in the aquatic environment of a fish farm [3,4]. Based on that the sensors were selected for monitoring the respective parameters. Selected water quality factors and respective sensors are described below:
2.1. Hardware and sensors

2.1.1. pH level and pH sensor
Water quality greatly depends on the pH factor, whether the water is acidic or nonacidic. Different fish like different kinds of pH conditions. So depending on which type of fish is being cultivated in the farm the pH factor can be observed to calculate the water suitability. Cellular membranes of a fish get damaged in high pH level like 9–14. Where low pH levels affects the rocks in the sediment resulting in release of metals. This increases water turbidity. Therefore a pH meter was used to collect the pH rating of the water.

2.1.2. Temperature level and temperature sensor
Maximum fresh water fishes have cold blood. That means they collect temperature from their surrounding water, thus synchronizing with the water temperature. Cold blooded animals are affected directly by its surrounding medium temperature. Temperature mainly affects their metabolism [5]. As a result rapid change in water temperature causes the fish stress and may
2.1.3. Turbidity level and turbidity sensor

If there is a lot of suspended material in the water or an excessive amount of food it may make the water dirty. Moreover high turbidity because of algae present in the water can harm fishes. Such as Trichodiniasis is a disease that happens due to parasites. Also turbidity affects the growth of fish eggs and larvae [6]. Furthermore light will not pass through a dirty water and organic materials may cause poisoning. For this reason two Turbidity sensors were used to measure the turbidity level of the water.

2.1.4. Arduino mega and supporting modules

To maintain the sensors, collect and store the data an Arduino Mega microcontroller board was used in this project. This board has enough input and output pin and processing power to support all the modules perfectly. To store data in the cloud storage an ESP8266 Wi-Fi Module
was used. And to store data in an electronic storage device a micro sd card reader module was used.

2.2. Methods

In the fish pond total number of deployed sensors were five divided into two sets. The first set includes a Temperature sensor, a pH sensor and a Turbidity sensor. This set of sensors were 30 cm underwater from the water surface. A second set of sensors were used in a different depth. Because the temperature and turbidity rating in water changes with respect to depth. The second set includes a Temperature sensor and a Turbidity sensor. This set was 60 cm underwater from the water surface. Both sets had the same horizontal alignment yet different depth. The sensors were immersed in the water where the microcontroller and the other modules were above the water surface attached to a floating structure. The microcontroller board read data from the sensors all together. Then uploaded the data in the cloud database and stored in the
storage device. Rate of data record on average was one set of data per minute. Later data was presented in a dedicated website for monitoring them from anywhere. For portable monitoring a mobile application had been developed. The website and the mobile application shows real time conditions of the water at any time. The mobile application is capable of notifying the user when any one of the parameters of the water quality factor crosses the safety limit. The overall data collection and storing system is presented in Fig. 25 and briefly described in Algorithm 1.

Algorithm 1: Algorithm for collecting and storing the sensor data

- Step 1: Delay 30 seconds for calibration of the sensors.
- Step 2: Read data X and Y from the Temperature sensors.
- Step 3: Read data Z from the pH sensor.
- Step 4: Read data P and Q from the Turbidity sensors.
- Step 5: Write the data X, Y, P, Q and Z in the electronic storage device.
- Step 6: Delay 200 ms.
- Step 7: Try to establish connection with the web host.
- Step 8: If connection is established go to Step 9, else go back to step 7.
Fig. 24. Error histogram plot of Turbidity sensor 60 cm underwater.

Fig. 25. Block diagram of the data collection and storing system.

- Step 9: Upload data in the database.
- Step 10: Delay 300 ms.
- Step 11: Go back to Step 2.

Fig. 26 illustrates the overall data collection and monitoring system. It shows how data were collected, stored and finally presented to the user.

2.3. Data collection and presentation

Data were presented in a dedicated website for monitoring the farm condition from anywhere and anytime. The cloud data collection and presentation system is shown in Fig. 27. The 'Home page' of the website let a user monitor each parameter individually in real time. It updates with new data in every minute. Fig. 27a shows the layout of the 'Home page' of the website. The previous data of the parameters can be found in the ‘Previous Data’ page. This page provides all the previous data in a descriptive manner. Fig. 27b shows the layout of the ‘Previous Data’ page of the website. Data were collected both from the database and the storage
device so that no data were missed. Fig. 27c shows the database of the work. A mobile application also supported in collecting data and made necessary notifications. Fig. 27d shows the layout of the mobile application.
2.4. Machine learning and prediction

Machine learning regression method was used to predict near future data and compare them with the true data. For this purpose we used the Gaussian kernel of Support Vector Machine (SVM) learning model. 70% of the data was used to train the regression model and 30% was
used to test it. Later prediction error was calculated by subtracting the predicted data from the true data.

Matlab’s script command “fitrsvm(x,y)” was used to train and test the SVM regression model. The script functions used for fitting is given below:

```matlab
mdl = fitrsvm(x,y,'KernelFunction','gaussian'); %Training the model with predictor x and response y
ypred = resubPredict(mdl); %Predicting data based on the trained model
e = y-ypred; %Calculating error
```

2.5. Arduino sketch

2.5.1. Reading data from the sensors

Fig. 28 shows the Arduino sketch for reading data from the three types of sensor used in this work.

Ethics Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships which have, or could be perceived to have, influenced the work reported in this article.

Acknowledgements

This work was supported by Electronics and Communication Engineering Discipline at Khulna University, Bangladesh.

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