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Potential of using Internet of Things (IoT) for Water Quality Monitoring in aquaculture: a case study in freshwater catfish culture in Rawang, Selangor, Malaysia

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Abstract:

Internet of Things (IoT) have significantly improved the way we deal with big data. Consequently, data mining enables us to understand patterns in data and their relationships. In this research, water quality from catfish pond has been analyzed using simple Expectation Maximization (EM) clustering. Parameters such as Total Dissolve Solid (TDS), Water Level, Turbidity, pH and Temperature have been collected via sensors connected to Raspberry Pi 3 Model B. Results analyzed using WEKA show that the minimum amount of TDS is 52 ppm and the highest is 60 ppm. The minimum value for Turbidity is 2776 NTU and maximum is 2776 NTU. Turbiditywill maintain low; hence, the existing setup is suitable for future IoT installation forfreshwater catfish, Clarias gariepinus culture.

Keywords: *Automation, Water QualityParameters,Aquaculture, Raspberry Pi, Sensor Node, NeatBeans, IoT, WEKA API, Data Mining, Simple Expectation Maximization (EM).*

I. Introduction

Internet of Things (IoT) have broughtsignificant improvement to technology that lead to the creation of huge volumes of data [1]. It propagates knowledge and management of large amounts of heterogenous data. It has turned into a noteworthy study area, that is, Data Mining. It involves examining huge volumes of data in order to derive new information, recognizing novel, conceivably useful, legitimate, and conclusively comprehensible patterns in data[2].

Previous studies have demonstrated related work; Automated Identification of Invasive Ladybirds [3], Anterior Cruciate Ligament injury classification system [4], Brown planthopper (BPH) detection [5] and Wheat yield prediction [6]. An advantage of using data mining is that the built models are based on historical data to predict the possible outcome [7].

Data mining is a useful way of studying water quality for human consumption, industrial and domestic use and environmental water quality

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[8].Data mining techniques can be classified into both supervised and unsupervised learning techniques. Supervised learning method concerns with constructing a model used in previous performance analysis, while unsupervised learning method is not driven by variable and does not generate a pre-analysis hypothesis based on appropriate models.

One of common method for unsupervised technique is Simple Expectation Maximization (EM) clustering technique. In this method, it will assign a probability distribution to each instance which indicates the probability of it belonging to each of the clusters.EM can decide how many clusters to create or how many clusters to produce [9].

Water quality is framed in terms of water's chemical, physical, biological content. Even though it is not affected by pollutions, it subjects to the changes it is not affected by pollutions, it subject to the changes of seasons and geographic regions. Guidelines on water quality provide fundamental science data on water quality parameters and ecologically appropriate toxicological threshold vales to safeguard water uses. Important physical and chemical parameters affecting the aquatic environment are water temperature, pH, Turbidity, Nitrates, Phosphates, Total DissolvedSolids, Chlorides, etc. The catfish could survive in pond water with dissolved oxygen levels of 0-1 mg / L, total ammonia nitrate (TAN) reaching 20 mg / L, 3-5 mg / L nitrite levels and BOD (Biological Oxygen Demand) values approximately 40-70 mg / L. The blue green algae found in the sample taken. Unfortunately, the toxic water quality condition increases the risk of infection to the catfish. Additionally, high densities of fish in the ponds contributes to the toxicity of ponds. Therefore, the toxic wastewater should be treated in the treatment pool first before being released to the environment. This is to avoid any severe pollution of the river which in turn causes the death of various species in the river[10].

This paper focuses on two important activities. Firstly, a WEKA in Raspberry Pi is installed using different platform for water quality analysis. Secondly, the relationship between different parameters using simple expectation maximization (EM) clustering technique will be defined. Data was collected at a commercial fishpond rearing catfish in Rawang, SelangorMalaysia.

II. LITERATURE REVIEW

Recent development in IoT, sensor technology, computer system and, Information Technology (IT), etc. have made it possible for automated system to be implemented. The data from environment parameter for water quality was collected using Raspberry Pi and analyzed using WEKA application.

A. *WEKA*

WEKA is an open source and independent platform. It can be used for supervised and unsupervised learning. There are three ways to use WEKA:

i. WEKA using common line.

ii. WEKA GUI.

iii. WEKA API.

In general WEKA sofware is relevant for water quality analysis. Many methods have been used, such as Decision Tree [11][12], Simple K-Means Clustering [13], Classification [14][15], and other Data Mining technique [16][17]

WEKA enables the comparison of various solutions approaches based on the same assessment method. Possibly identifying improvement in water qualitymonitoring in aquaculture.

B. *Raspberry Pi*

Raspberry Pi is a computer with the size of an passport with a dedicated version of Linux, the Raspbian, and it was developed by the Raspberry PiFoundation.Many applicationsuseRaspberry Pifor scientific purposes and prototype projects. In the recent decade it supports a special Internet of Things version.

Moreover, Raspberry Pi has been previously used for continuous water quality monitoring using Internet of Things (IoT). It has been used in water treatment plant [18], environment monitoring [19], agriculture [20], water resources [21], portable online water quality monitoring [22], fish culture [23], soft-shell farming [24], and aquatic ecosystem [25].

C. *Aquaculture Water Quality Parameters*

1. Water Temperature

The body temperature of fish is approximately t he same as the water temperature and varies with it. In the aquatic ecosystem, temperature effectsreproduction, feeding, metabolic activities,

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growth, distribution and migration behaviors of aquatic organisms [26].

With increased temperature, the solubility of gas in water will decrease [26]. Water temperature is influenced by daytime, temperatures can increase during the day and decrease at night. Pond temperatureforms stratification, epilimnion(surface level which is warmer and lighter), thermocline (barrier between two distinct parts)and hypolimnion (deep level). The average water temperature in bigger pond are more stable, compare to the smaller pond.

2. **pH**

pH parameter reflects the amount of hydrogen ions (H+) in the H_2O.It depends on other parameter such as CO_2, alkalinity and hardness.pH can be harmful to aquatic life when the water body influenced with hydrogen sulfide, cyanides, heavy metals, and ammonia [26].

Water may be acid, neutral or alkaline. Excessively low or high pH greatly affect fish production and reduce plankton growth. The pH threshold differs depending on fish size, fish species and other environmental factors. In general, at sunrise the most appropriate pH for pond fish range from pH 6.5 to 8.5.In addition, at pH below 5.5, fish reproduction can be affected while a pH greater than 9 is harmful to eggs and small fish. In aquaculture, most of the species will die in pH beneath 4.5 and equal/larger than 11 [26].The pH soil could influence the original pH of the water. However,the pH of pond water differs mainly because of photosynthesis (phytoplankton and water plant). The pH at during daytime is lowest as the light intensity rises. More carbon dioxide is removed from the water, which increases the pH. A peak pH value is obtained in the afternoon. During the nighttime, the phytoplankton engage in respiration thus, more carbon dioxide is form in the pond. This will causepH value to drop significantly until sunrise.In a full capacity pond, the daily pH fluctuation is higher due to higher fish respiration and photosynthesis (phytoplankton and water plant).The pH average of 9.5 will be consideredas normal in the afternoon.

3. **Turbidity**

The turbidity is caused by the presence of mineral (example silt and clay particles), plankton (example minute plants and animals), and Humic [26]. The increasing amount, of mineral and humic turbidity will increase the turbidity level, due to the penetration of light wave the surface of the water. Thus, it will reduce the photosynthesis activity and oxygen production, therefore, it will affect the growth of the fish and plankton [26]. Moreover, high mineral turbidity can injure fish respiration system, reduce growth, prevent their reproduction and reduce food (zooplankton).

4. **Total Dissolved Solid**

Total Dissolved Solid (TDS) is a measurement of inorganic salts (e.g. Cyanobacteria), organic matter (such as human activity e.g. from fertilizers like chromium and fish food pellets) and other dissolved materials in water (such as fish biproducts)[27].

In natural water, TDS concentration and composition are
influenced by geology, atmospheric and evaporation-precipitation [28]. In freshwater aquaculture, TDS are track water qualityfor plankton and indicator for chemical contaminants [29].

With these parameters, the relationship between different parameters for catfish in freshwater would be possibly to identified.

III. METHODOLOGY

The experiment is consisting of the following activities:

1. Installation of WEKA API in Raspberry Pi3 Model B (Stretch).
2. Installation of Total Dissolve Solid, Water Level, Turbidity, pH and Temperature Sensor to Raspberry Pi3 Model B.
3. Using simple expectation maximization clustering technique as the equation.

A. Installation of WEKA API in Raspberry Pi3 Model B (Stretch).

For this method, refer Fig. 1user is required to download the latest Netbeans packaged with the JDK from Oracle for Linux x64. Avoid installing Ask Toolbar or McAfee. Later, run IDE and create a new “Application_Name”. At “Application_Name” folder, extract weka.jar folder to JDK.

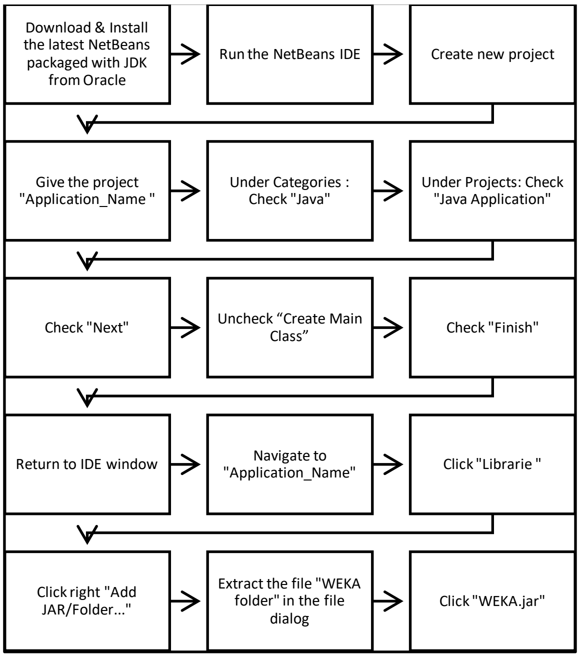

Fig. 1. Installation of WEKA API in Raspberry Pi 3 Model B (Stretch).

B. *RunningProgram*

A new Java class in the Default Package is created and the source code is uploaded.

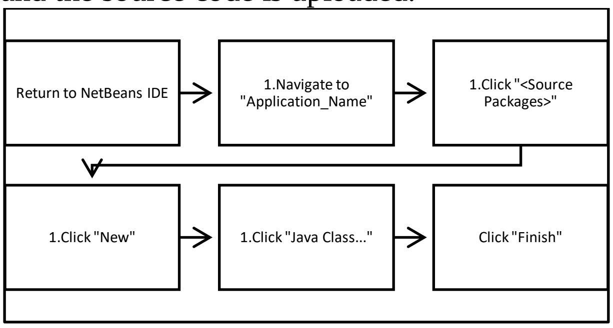

Fig. 2. Running Program

Data could be analyzed in Raspberry Pi using WEKA based on this method.

C. *Sensors Specification*

The following sensors were deployed during the experiment:

TABLE I. SENSORS MODEL AND SPECIFICATION [30]

Model	**Specification**
Gravity: Analog TDS Sensor/Meter (SKU: SEN0244)	Input: 3.3 ~ 5.5V Output: 0 ~ 2.3V Current: 3 ~ 6mA TDS Range: 0 ~ 1000 ppm TDS Accuracy: ± 10% F.S. (25 °C)
Gravity: Photoelectric Water/Liquid Level Sensor (FS-IR02)	Input: 5 VDC Current: 12 mA Temperature: -25 ~ 105 °C Low level output: < 0.1 V High level output: > 4.6 V Liquid level accuracy: ±0.5 mm Measuring range: No limit
Gravity: Analog Turbidity Sensor (SKU: SEN0189)	Operating Voltage: 5V DC Operating Current: 40mA (MAX) Response Time: <500ms Analog output: 0-4.5V Operating Temperature: 5°C~90 °C
Gravity: Analog pH Sensor(SKU: SEN161)	Range :0 – 14 pH Temperature: 0 - 60 °C Accuracy: ± 0.1pH (25 °C) Response Time: ≤ 1min
DS18B20 Digital Temperature (SKU: DFR0198)	Accuracy: minimum -10°C and maximum 85°C Temperature range: -55 to 125°C Query time is less than 750ms

D. *Simple Expectation Maximization (EM)*

Simple Expectation Maximization (EM) clustering technique is the hypothesis of maximum probability.

K = distributions

m_k= mean

σ_k= variance

h= hypothesis

In a single modal normal distribution,hypothesis isestimated directly from the data:

$$\tilde{m}=\sum_{i=0}^{N-1}\frac{x_i}{N} \qquad (1)$$

$\tilde{m}$ = estimated m

N = number of items in the population

x_i = data value at i

i = number at i

$$\sigma^2\sim=\sum_{i=0}^{N-1}\frac{(x_i-\tilde{m})^2}{N} \qquad (2)$$

$\sigma^2\sim$ =estimated σ^2

In Equation 1 and 2isthe trusted arithmetic average and variance. In a multi-modal distribution to estimate

$$h = [m_1,m_2,...,m_K;\sigma_1^2,\sigma_2^2,...,\sigma_K^2]. \qquad (3)$$

1. Initial estimate for each$\tilde{m}_k$and $\sigma_k^2\sim$.
2. The estimates can be taken from
   i. Earlier plots
   ii. Domain knowledge
   iii. Wild guesses (but not too wild)

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3. Use each data to answer the following questions
   - i. What is the probability that the data point was produced from a normal distribution with mean$\tilde{m}_k$ and $\sigma_k^2\sim$?
   - ii. Repeat task i. for each set in the distribution parameter.
   - iii. What is the probability that a data point x_i, i =1...N, was drawn from $N(\tilde{m}_1, \sigma_1^2\sim)$?
   - iv. What is the probability that it was drawn from$N(\tilde{m}_2,\sigma_2^2\sim)$?

   The normal density function is stated in Equation 4.

$$P(x_i \text{ belongs to } N(\tilde{m}_1,\sigma_1^2\sim)) = \frac{1}{\sqrt{(2\pi\sigma_1{}^2\sim)}}\, e^{\frac{-(x_i-\tilde{m}_i)^2}{(2\sigma_1{}^2\sim)}} \quad \text{\_\_\_ (4)}$$

$$P(x_i \text{ belongsto } N(\tilde{m}_2,\sigma_2^2\sim)) = \frac{1}{\sqrt{(2\pi\sigma_2{}^2\sim)}}\, e^{\frac{-(x_i-\tilde{m}_2)^2}{(2\sigma_2{}^2\sim)}} \quad \text{\_\_ (5)}$$

4. Classification: Probability that a data point x_i belongs to some class c_k:

$$P(x_i \text{belongs to } c_k) = \frac{\omega_k\sim P(x_i \text{ belongs to } N(\tilde{m}_1,\sigma_1^2\sim))}{\Sigma(\omega_1\sim P(x_i \text{ belongs to } N(\tilde{m}_1,\sigma_1^2\sim)))} \quad \text{\_\_\_ (6)}$$

$\omega_k\sim$ = The probability of picking k's distribution to draw the data point from.

In Equation 6, Each of clusters are equally likely to be picked. But like with $\tilde{m}_k$ and $\sigma_k^2\sim$. The value for these parameters is unknown. Therefore, our estimation is a part of our hypothesis:

$$h = [\, m_1, m_2, ..., m_K;\ \sigma_1^2, \sigma_2^2, ..., \sigma_K^2;\ \omega_1\sim, \omega_{2\sim}, ..., \omega_K\sim] \text{\_(7)}$$

In conclusion, the 2 steps of the Expectation Maximization are:

1. **E-step:** performs probabilistic assignments of each data point to certain class based on the current hypothesis *h* for the distributional class parameters;
2. **M-step:** update the hypothesis *h* for the distributional class parameters based on the new data assignments.

A complete IoT setup consisting of software and hardware has been performed. Possibly water quality parameter in catfish pond can be analyzed in Raspberry Pi3 Model B using simple Expectation Maximization (EM).

IV. Results

The following results define the relationship between the parametersthat have been retrieved from the deployment of sensors retrieved at the catfish pond.

A. *Time and Total Dissolve Solid*

In Figure3 shows the maximum amount of TDS is 60 ppm and the lowest is 52 ppm. Thus, it could be concluded that catfish and phytoplankton can live in this pond.

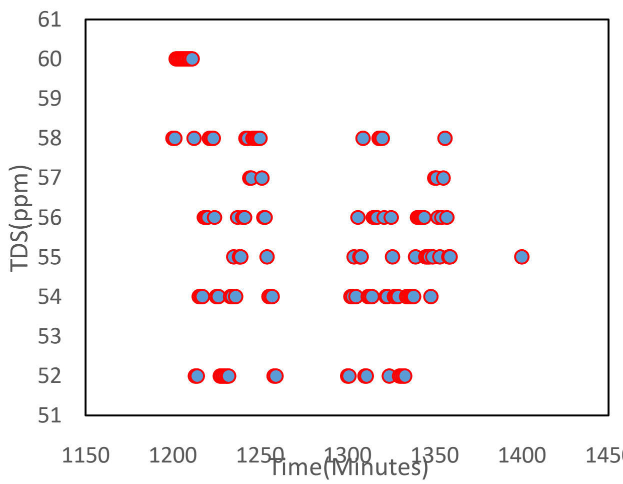

Fig. 3. Distribution of Time and Total Dissolve Solid (TDS)

B. *Time and Turbidity*

Figure 4 shows the maximum value for Turbidity is 782.5 NTU and minimum is 2776 NTU. Base on this measurement the precautions need to be taken thus the turbidity is expected to be decrease within the week otherwise the fish become stressed.

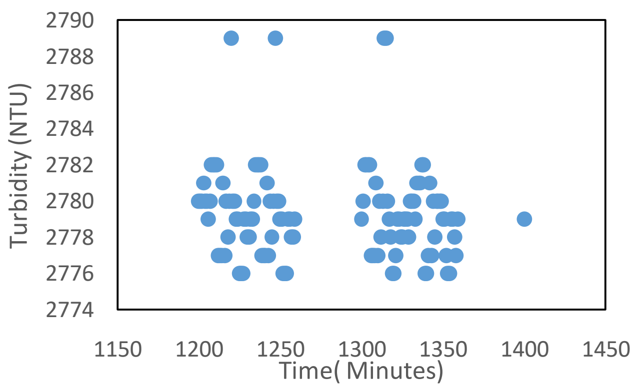

Fig. 4. Relationship between Time of Day vs Turbidity

C. *Total Dissolve Solid and Turbidity*

Result from Figure 5 shows the minimum TDS is 52 and the maximum TDS is 62 ppm. Thus, it shows that the greater Total Dissolve Solids content shall contribute to higher turbidity level.

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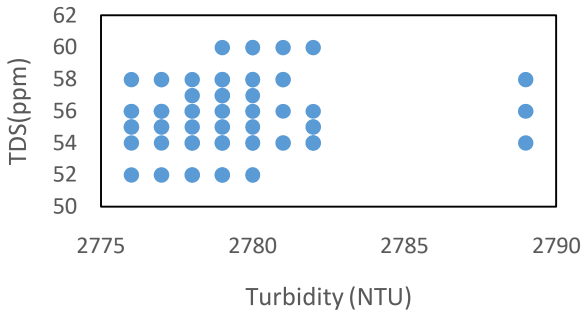

Fig. 5. Total Dissolved Solid and Turbidity

V. CONCLUSION

As a conclusion, theresearch shows a preliminary setup for an IoT system for water quality monitoring in aquculture. The WEKA have installedin Raspberry Piand the results is observed from our preliminary installation in a catfish farm. The existing setup is suitable for future IoT solution in freshwater fish farming industry for to increase the production. Potentially, we don't expect any abnormal observation in the actual deployment.However, for the future deployment, the Raspberry Pi will be linked to LoRa for the Data Analytics purpose.

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