Early Detection of Ammonia Gas Levels in the Air Using IoT-Based SVM

Lukman

Department of Electrical Engineering, Muhammadiyah University Makassar, Indonesia

E-mail: lukman@unismuh.ac.id

Abstrak

Saat ini diyakini bahwa pengenalan teknologi Internet of Things (IoT) akan membantu Generasi 4.0. Teknologi ini dapat digunakan, misalnya, untuk menyaring kualitas air di fasilitas pengolahan air limbah (IPAL) rumah sakit. Pengujian ini diperlukan untuk melindungi dan menghindari risiko yang terkait dengan paparan alkali yang tidak terkendali. Sampai saat ini, sebagian besar klinik medis memperkirakan file batas air menggunakan metode konvensional. Dalam pekerjaan ini, modul ESP8266-01 dan Arduino Nano digunakan untuk memperkirakan pengelompokan gas amonia di iklim IPAL. Suhu, pH, dan TDS diperkirakan batas untuk kualitas air. Data dikirim sebagai kumpulan data eksplorasi dari pekerja thingspeak. Data yang diperoleh dievaluasi menggunakan Support Vector Machine untuk menentukan peringkat tingkat kontaminasi amoniak (SVM). Analisis 20% dari data line approval menunjukkan bahwa presisi 98% adalah tingkat yang optimal. Investigasi ini karenanya dapat berfungsi sebagai template untuk klinik darurat yang menangani tingkat kontaminasi amonia.

Kata Kunci : SVM, Amoniak, Esp8266-01, Arduino Nano, Thingspeak ⊘

Abstract

It is currently believed that the introduction of Internet of Things (IoT) technology will aid Generation 4.0. This technology can be used, for instance, to screen the water quality at a hospital's waste water treatment facility (WWTP). This testing is required to protect against and avoid risks associated with uncontrolled alkali exposure. Until recently, the vast majority of medical clinics estimated the file of water boundaries using conventional methods. In this work, the ESP8266-01 and Arduino Nano modules were employed to estimate the ammonia gas grouping in the WWTP climate. Temperature, pH, and TDS are estimated limits for water quality. The data is sent as an exploration dataset from the thingspeak worker. The obtained data is evaluated using the Support Vector Machine to rank the degree of ammonia contamination (SVM). The analysis of 20% of line approval data indicates that 98% precision is the optimal level. This investigation can therefore serve as a template for emergency clinics dealing with ammonia contamination levels.

Keywords : SVM, Ammonia, Esp8266-01, Arduino Nano, Thingspeak

INTRODUCTION

Healthcare facilities generate the most wastewater. Diverse types of waste generated in emergency clinics and medical units can be hazardous and pose health risks to patients, visitors, and especially waste-handlers (N. Himayati, J. Joko, and H. L. Dangiran,2021). Alkali plays an important role in the solidity of biological systems. Nonetheless, the high alkali concentration in the water is harmful to living organisms. Hence, it is essential to screen ammonia measurements (L. P. Kim, O. Z. Xen, H. H. Eng, T. X. Yee, W. V. Yean, and H. Nisar, 2020). Alkali convergence is one form of WWTP contamination (TAN). Due to its toxicity, unregulated TAN has the ability to significantly alter the climate of the bulk of the ocean. TAN

is capable of influencing and modifying water quality components such as pH, temperature, ionic charge, salinity, and oxygen depletion [Ammonia Dan Bahayanya Di Perairan, 2021].

The Internet of Things refers to the organization of physical objects and technological improvements to connect and exchange data with numerous devices and systems over the internet. This item is commonly utilized in numerous industries, ranging from casual to contemporary equipment. Now, there are more than 7 billion connected IoT devices, and some analysts anticipate that figure will continue to rise until 2025 (What is the Internet of Things (IoT), 2021). As collaborations between machines, the Internet of Things (IoT) could move information throughout an organization (R. S. Sinha, Y. Wei, and S.-H. Hwang, 2017). The ESP8266 is one of several communication tools that can be utilized in Internet of Things applications. The ESP8266 NodeMCU module is used as a microcontroller to monitor or operate many types of modern home sensors (N. H. L. Dewi, M. F. Rohmah, and S. Zahara).

Several publications on the measurement of wastewater quality using multiple parameters of the same water quality have been published, but no additional analysis of the sensor's collected data has been conducted. M. Zhang's 2017 study, titled wastewater observing framework in modern workshop based on remote sensor network, aims to monitor wastewater removal in businesses based on the Wireless Sensor network by estimating temperature limits and the level of corrosiveness (pH) in wastewater released by businesses. The results indicate that the sensor's estimation may be sent efficiently via ZeegBee (M. Zhang and S. She, 2020). In the same year as (B. Xie, Y. Ma, J. Wan, Y. Wang, and Z), they also conducted a study to determine ammonia nitrogen online prediction in Anamox using the PCA-BP algorithm; measurement results revealed a determinant coefficient of 0.997 and an RMSE of 16-17%. This study makes accurate ammonia predictions, but does not incorporate IoT in its data collection process. In 2018, (S. I. Samsudin, S. I. M. Salim, K. Osman, S. F. Sulaiman, and M. I. A. Sabri, 2018) conducted additional study titled IoT Smart Water Monitoring System. In this investigation, the ESP 8266 module is employed to transmit data to the monitoring server. The ESP 8266 is a WiFi module that is more compact than other comparable devices utilized in prior research. Nonetheless, no expected examination was conducted in this inquiry. Vijayalahksmi et al. investigated monitoring ammonia gas leaks with the MQ-135 sensor in 2019; their findings indicated that the MQ-135 sensor was capable of detecting and providing early warning. Nonetheless, this work should be enhanced to provide a better understanding of the effects of ammonia estimations (J. Vijayalakshmi, G. Puthilibhai, and S. R. L. Siddarth, 2018).

We propose a study for predicting ammonia gas categorization using the Support Vector Machine method in order to provide early warning to hospital WWTP officials based on existing difficulties and past research.

RESEARCH METHODS

Arduino Nano board is a microcontroller board with an open-source design. This instrument can read sensors via a variety of digital and analog pinouts. This instrument is a diminutive variant of Arduino boards in general. The ATmega328-based Arduino Mini contains 14 digital input/output pins (6 of which can be used as PWM outputs), 6 basic data sources, a 16 MHz Crystal oscillator, a USB connection, a power port, an ICSP header, and a reset button.



Fig 1. Arduino Nano Board

ESP8266-01 is a complete chip containing a processor, memory, and GPIO access. This enables the ESP8266-01 to directly replace Arduino and enhances its capacity to support direct wifi connections, but it has fewer pins. In this study, the ESP8266-01 is used to transfer sensor values received by Arduino Nano to the Thingspeak server.



Fig. 2. ESP8266-01

DS18B20: DS18B20 is a temperature sensor with superior stability in temperature accuracy and measurement speed compared to LM35DZ. This sensor employs the 1-wire communication protocol for reading. The DS18B20 has three pins: + 5V, GND, and Data Input/Output. The DS18B20 temperature sensor operates between -55°C and +125°C. The output of the DS18B20 is digital data with an accuracy of 0.5oC over a temperature range of 10oC to +85oC, which makes it easier for the microcontroller to interpret. This sensor validation use a standard thermometer.



Fig. 3. DS18B20 Sensor

pH sensor: The pH sensor is a device that measures the acidity or alkalinity of a solution. A component of the pH sensor consists of an electrode rod and a glass negative. The electrode rod is formed of a glass material that has a positive effect, while the negative glass has thin walls and is negatively charged with respect to H+ ions. The pH sensor generates an output voltage. When the pH value increases, the sensor voltage decreases (may be negative), and vice versa, when the pH value decreases, the sensor voltage increases.



Fig. 4. pH Sensor

SEN0244 sensor: This sensor is a device for measuring the turbidity of a liquid. The turbidity sensor operates on the same principle as the light-based proximity sensors on the line-following robot. This instrument is validated using a conventional TDS/EC meter.



Fig. 5. SEN0244 (TDS Sensor)

MQ-137, this sensor can analyze air quality to determine the presence of Ammonia gas (NH3), sodium-(di) oxide (NOx), alcohol/ethanol (C2H5OH), benzene (C6H6), carbon dioxide (CO2), sulfur/sulfur gas hydroxide (H2S), and other vapors/gases. This sensor reports air quality findings as variations in the simple opposition value at the output pin. To be able to utilize this sensor optimally, it requires 24 hours of the most extreme warming interaction



Fig. 6. MQ-137

Based on the datasheet, to determine the value of ammonia, first determine the value of Rs with the following equation:

$$Rs = \frac{V_c \times R_l}{V_{rl}} - R_l \tag{1}$$

Furthermore, based on the sensitivity graph of this sensor, the ratio between the value of Rs and Ro is obtained in the equation below:

$$\frac{R_s}{R_0} = 2.6\tag{2}$$

Where Ro = sensor protection from clean air, Rs = sensor protection from ammonia gas. To ascertain the estimation of Ro, we need to compute the estimation of Rs as per condition (1). To determine the value of ammonia, the following equation is used.

$$y = mx + b \tag{3}$$

Where m = -0.26303440583, b = 0.42992639673, x = the voltage value at the MQ-137 output pin.

Source Layer: this layer is in the lowest position which is useful for collecting data on the sensor and ready to be forwarded to the database server. The components on this layer are sensors, Arduino Nano, ESP8266-01. To be able to send data to the server, the ESP8266-01 is connected to the modem via WiFi. Here are the prototypes of this layer.



Fig. 7. Prototype on Source Layer

Edge Layer: This layer is in the middle position which is useful for receiving data sent from the source layer. The data received is then analyzed and a notification is sent to the client app if the results of the analysis show an excessive level of ammonia classification. Algorithms such as Neural networks, SVM, K-NN can be used to perform predicting. In this study, we used the SVM algorithm.

Cloud layer: this layer will receive data from the edge layer that has been analyzed to be used as a user interface in monitoring the quality of wastewater. The following is a diagram proposed in this study:



Fig. 7. Proposed Architecture

All datasets that have been collected are pre-processed before they can be processed further. This process is carried out using python 3.7 to remove several rows of data that have a value of 0 in one of the tested water parameter values. In this study, we divided the ammonia contamination levels into 3 groups, namely :

- 1. Normal, which is a condition where ammonia levels range from 0 10 ppm. This condition is the threshold value in hospital waste management that has been set by the government.
- 2. Alert, which is a condition where the ammonia level ranges from 11 50.
- 3. Danger, which is a condition where the ammonia level ranges from 51 100.

This grouping aims to provide an early warning to the officers so that they can take precautions against water and environmental pollution as soon as possible. The dataset in this study amounted to 200 as shown in Table 1.

Row	such	ph	TDS	class_ammonia	ammonia					
0	21.3	7.3	88	0	16					
1	19.3	3.6	6	1	49					
2	17.8	3.6	26	2	68					
3	20.6	4.8	21	1	38					
4	22.4	7.1	46	0	8					
195	17.3	5.1	37	2	49					
196	24.3	5.8	40	0	49					
197	28.7	7.1	60	1	25					
198	29.0	8.0	56	1	47					
199	25.8	8.6	63	1	30					

Table 1. Dataset

Using a Support Vector Machine, categorize the ammonia levels from the three wastewater quality metrics, namely temperature, pH, and TDS/EC, from the dataset received on the database server.

Making predictions is one of the tasks, skills, and traits of the Support Vector Machine. SVM controls the capability to characterize and relapse for a given circumstance. In practice, SVM has an essential straight characterization standard, the definition of which is a case that can be isolated directly, but SVM has been expanded so that it can also handle non-straight problems by adding the bit concept to a high-dimensional workspace. Note that in highdimensional space, something known as a hyperplane that can increase the distance between several information classes will be sought.

In SVM, one of the four types of portions is the spread essential capacity (RBF) piece. While creating SVM with a Radial Basis Function (RBF) component, two boundaries, specifically C and gamma, must be considered. The low C boundary settles smoothly on the selection surface, but the high C will effectively characterize all preparation models. Gamma determines the impact of a single preparation model. The greater the gamma, the greater the likelihood that distinct examples will be influenced.

Fig. 9 illustrates the flow of the training process and parameter optimization for our proposed RBF kernel. Among the 200 datasets registered in the database, we allocated 160 datasets for training and 40 datasets for testing as such. We utilize Python 3.7-based Jupiterlab. In order to classify ammonia, the variables of temperature, pH, and TDS were trained using the supporting vector machine approach.



Fig. 9. Proses Training dan Testing pada SVM

Table 2 is the outcome of processing training data to predict ammonia classification using the SVM approach (without parameter optimization). These results indicate that the model's predictive accuracy for the three ammonia classifications is 90%.

Table 2. SVM Training and Testing Result									
classification	precision	recall	f1-score	support					
Normal (0)	0.83	1	0.91	10					
Waspada (1)	0.95	0.87	0.91	23					
Bahaya(2)	0.86	0.86	0.86	7					
Accuracy			0.9						

SVM Training and Tasting Pacult

In this paper, we use the RBF kernel type by setting the values of the C and gamma parameters. Adjustment of these parameters can produce a better level of system accuracy in solving non-linear classification problems (G. R and F. N. 2017).

 $k(x_i x_j) = (-\gamma ||x - x'||^2).\gamma$ (4)

In equation(4) it is realized that x = column information for preparing, and y = gamma. Consequently the initial step is to decide the estimation of boundary C, to be specific the edge distance, and y is the speed increase of the capacity. To get the hight expectation, we physically tried the C and y qualities to decide the ideal C and y values. The C qualities tried were 1,2,3,4, and 5. While the y values tried were 0.1, 0.01, 0.001, 0.0001. Retesting is carried out on the model by iterating the values of C and y specified above.

Table 3. Parameter Optimization							
γ γ	1	2	3	4	5		
0.1	95	96	97	98	98		
0.01	92	92	95	95	96		
0.001	90	90	90	90	90		
0.0001	92	90	90	90	90		

Table 3 shows the determination of the parameters C and y by trial and error where the optimum values of C = 2 and y = 0.1 are obtained, then the calculation of the RBF kernel is carried out using equation (4). After optimization of the kernel, the accuracy rate of the model increases to 97%, this shows that SVM can predict the level of ammonia classification in WWTP.

RESULTS AND DISCUSSION Data Visualization

After the prediction process is conducted at the edge layer, the data is sent to the Thingspeak database to visualize the parameters of temperature, pH, TDS, and classification of ammonia contamination levels. Fig. 10 shows the data visualization on the tingspeak side.



CONCLUSION

In this paper, the researcher proposes a Support Vector Machine method with RBF enhancements to predict the amount of Ammonia gas contamination levels. This method is used to verify wastewater quality in authentic wastewater treatment plants (WWTP). The results demonstrate that the prediction is more accurate if the RBF bit boundary is updated with an estimate of C = 2 and gamma = 0.01. Further research can be conducted to further enhance the system so that it can independently perform the analysis process and visualize the findings of the study as a unified system. For future study, it is intended that the system will provide a more satisfying level of performance in predicting the degree of ammonia gas pollution, which can then be adopted to facilitate the use of smart industry.

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