Retraction

Retraction: Surface Modeling Vehicle for Shrimp Ponds using Artificial Neural Network (IOP Conf. Ser.: Earth Environ. Sci. 980 012060)

Published 16 December 2022

This article has been retracted by IOP Publishing following an allegation that the work contains tortured phrases [1].

IOP Publishing has investigated and agrees the article contains a number of nonsensical phrases that feature throughout the paper, to the extent that the article makes very little sense.

It suggests the article may potentially have been created at least partly by artificial intelligence or translation software. IOP Publishing wishes to credit the Problematic Paper Screener for bringing the issue to our attention.

IOP Publishing Limited have been unable to contact the authors regarding this retraction, despite numerous attempts. The authors are encouraged to contact IOP Publishing Limited if they wish to comment on this retraction.

[1] Cabanac G, Labbe C, Magazinov A, 2021, arXiv:2107.06751v1
Retraction published: 16 December 2022
Surface Modeling Vehicle for Shrimp Ponds using Artificial Neural Network

P Destrianto 1*, K Agustianto 1, E Rosdiana 2, I G Wiryawan 1, E Mulyadi 1
1 Department of Information Technology, State Polytechnic of Jember, Indonesia
2 Department of Agricultural Production, State Polytechnic of Jember, Indonesia

* email: prawidya@polije.ac.id

Abstract. The worldwide frozen shrimp trade market in 2018 was recorded at the US $ 17.2 billion or around Rp.232.2 trillion. Indonesia is one of the principal exporters of frozen shrimp in the worldwide market. In light of this information, shrimp cultivating is a promising area, yet shrimp cultivating is particularly controlled by water quality. Water quality in shrimp cultivating consistently changes. Many variables impact changes in water quality (shrimp biomass, PH, and temperature). These components in the water should be inside the standard limit rank. Thusly, to accomplish the creation effectiveness of the shrimp business, it is important to robotize water quality control. This study aims to develop Surface Modeling Vehicles (SMV) for Shrimp Ponds utilizing an Artificial Neural Network. The test outcomes show an exactness pace of 94%, the expectation is that the instruments created by the exploration will want to acknowledge exact Vename Shrimp cultivating, so creation proficiency and expanded shrimp creation can be accomplished.

1. Introduction
The worldwide frozen shrimp trade market in 2018 was recorded at the US $ 17.2 billion or around Rp.232.2 trillion (swapping scale Rp.13,500/US$). Indonesia is one of the principal exporters of frozen shrimp in the worldwide market, to be careful, in the fourth spot after India, Ecuador, and Vietnam. The commodity worth of Indonesian frozen shrimp last year, as indicated by Worldtopexports.com, arrived at US$ 1.3 billion or Rp.17,55 trillion. Indonesia's frozen shrimp piece of the pie comes to 7.8%. Indonesia's frozen shrimp trade market incorporates, among others, the United States, Japan, and European Union nations [1]. In light of this information, shrimp cultivating is a promising area, yet shrimp cultivating is particularly controlled by water quality [2].

Water quality in shrimp cultivating consistently changes [2][3]. Many elements impact changes in water quality. Among them are the measure of broken down oxygen, the accessibility of phytoplankton as regular shrimp feed, the condition of shrimp biomass, PH, and temperature [2][3]. These elements in the water should be inside the standard limit rank. Hence, shrimp upkeep is exceptionally worried about controlling the nature of water each hour, consistently. Control of pool water quality decides the appropriateness of the pool the board measures. Appropriate support of shrimp incredibly decides the usefulness of reaped shrimp.

PT. Tanjung Sumber Rejeki has been raising shrimp beginning around 2017 covering a space of 26,200 m2. Super-concentrated support of 16 shrimp lakes. A professional and helped by 20 field laborers do manual controls. Up until this point, the organization utilized a few manual devices. The low skill of the labor force in utilizing the devices causes mistaken water quality control exercises.
Regularly it neglects to get precise information with the goal that it is twofold checked, requiring a somewhat longer time and expanding costs. In this manner, we wanted a cutting-edge versatile water quality control instrument for shrimp cultivating that is proper, present-day, proficient, and precise. Determined to help the quality shrimp creation industry, arriving at the size of shrimp as per global norms, expanding efficiency, augmenting the amount of traded shrimp, it is important to foster current designing advances that can illuminate shrimp biomass. The shrimp biomass data framework is required by the industry to decide effective and precise techniques for taking care of shrimp culture.

Understanding the creation proficiency of the shrimp business, it is important to mechanize versatile data on shrimp biomass. The robotization is done by embracing a water quality control gadget as down streaming the consequences of science and innovation and data innovation of the Jember State Polytechnic as ASV [4]. ASV is a device/vehicle equipped for working on the outer layer of the water without a team. The ASV device has demonstrated its capacity to deliver precise information on pH, temperature, DO (Dioxide Oxygen), carbon dioxide and turbidity, this is conceivable because ASV in its application is furnished with sensors comprising of a pH sensor, a temperature sensor, a turbidity sensor, a DO sensor, and a carbon dioxide sensor. The information acquired from the sensor is handled in the framework utilizing the Artificial Neural Network calculation. The information acquired from the sensor readings contained in the ASV are then handled with a class model framework. Class displaying is isolated into three, specifically: Good, Medium and Dangerous for every sensor marker. Class data is communicated on a Web-based data framework.

Research of the utilization of IoT has been grown, particularly compared to its capacity to help people in the entirety of their exercises, one of which is with regards to the climate. An examination led by [5][6][7][8][9]. Notwithstanding, the execution of WQM explicitly for the primary hydroponics of Vename Shrimp is as yet inadequate with regards to, this is shown by the connected examination found in IEEE [10][11].

This research is based on [2][3][10] and aim to foster Surface Modeling Vehicles (SMV) Using Artificial Neural Network Algorithm. The instrument created by this review (SMV) will utilize a similar sensor as ASV [4] however with an alternate class grouping, research is done alluding to coral reef guidelines yet in this review the reference is the ideal states of water to help development and advancement. Vename Shrimp. The expectation is that the instruments created by the examination will want to acknowledge exact Vename Shrimp cultivating, so creation productivity and expanded shrimp creation will be accomplished.

2. Related Work
Water quality in shrimp culture lakes consistently changes occasionally [2][3]. The variables that impact changes in water quality are different, including the measure of disintegrated oxygen, pH, and temperature [2][3]. These elements should be as per shrimp culture guidelines, to create great shrimp. So that shrimp upkeep is extremely worried about controlling water quality consistently, consistently (continuous). Control of pool water quality decides the suitability of pool the executive's measures. Legitimate support of shrimp enormously decides the usefulness of reaped shrimp. Hence we wanted an advanced method for controlling the Internet of Thing (IoT) water quality for shrimp cultivating that is fitting, current, effective, and exact. This is to help the quality shrimp creation industry, arriving at the size of shrimp as per global principles, boosting efficiency, expanding the amount of traded shrimp.

Research of the utilization of IoT has been grown, particularly compared to its capacity to help people in the entirety of their exercises, one of which is with regards to the climate. An examination led by [5][6][7][8][9]. Notwithstanding, the execution of WQM explicitly for the primary hydroponics of Vename Shrimp is as yet inadequate with regards to, this is shown by the connected examination found in IEEE [10][11].
This research is based on [2][3][10] and aim to foster Surface Modeling Vehicles (SMV) Using Artificial Neural Network Algorithm. The instrument created by this review (SMV) will utilize a similar sensor as ASV [4] shown by Figure 1, however with an alternate class grouping, research is done alluding to coral reef guidelines yet in this review the reference is the ideal states of water to help development and advancement. Vename Shrimp. The expectation is that the instruments created by the examination will want to acknowledge exact Vename Shrimp cultivating, so creation productivity and expanded shrimp creation will be accomplished.

3. Research Methods

This research method begins with a literature study, shown in Figure 2, this stage becomes very important in the context of ensuring the State of the Art (research position) [13], the research position found will be compared with the problems that arise in the field, the next step is identification and resolution, problems that are part of the purpose of the study. The next research stage is making rules, this rule will be used in the Artificial Neural Network [14] process on multi-sensors [4].

The utilization of the Artificial Neural Network technique expects to deliver a more precise perusing. The following stage is trying, which is to demonstrate that the sensor readings are proper [15][16],

---

**Figure 1. Previous ASV Research [4][12]**

**Figure 2. Research Methods**
testing in this review was completed upwards of 100 tests, at this stage, the exactness of the apparatus will likewise be acquired [17]. The test outcomes information is then acquired, this handling plans to assess the utilization of the Artificial Neural Network calculation which is carried out by the aftereffects of the perusing of the SMV water quality [12]. The eventual outcome of this exploration stage is the precision of the water quality class perusing of the SMV instrument. The aftereffects of information handling as apparatus precision are then contrasted and manual computations [18], to test the exactness by ground truth. The outcomes got at this stage will examine the variables that influence the exactness esteem got.

4. Discussion

4.1. SMV Development

The design of SMV based on [19][4][20] in this review is displayed in Figure 3 concerning the system block chart, Figure 3 shows a piece of the gadget containing a couple of sensors including a pH sensor what abilities to evaluate degrees Celsius of water, a temperature sensor what abilities to measure degrees Celsius of water, a turbidity sensor, what abilities to measure water turbidity even out and DO sensor what abilities to evaluate oxygen levels from water. SMV is a web-based noticing mechanical assembly that shows multi-sensor readings (pH, Dissolved Oxygen (DO), temperature, and turbidity) in shrimp lakes. The pH sensor limits the extent of the acridity of the water. Likewise, this sensor also abilities to change the non-electric sum for the present circumstance the degree of causticity (pH) into an electrical sum, specifically voltage. DO Sensors limits as an extent of the oxygen level of water, the DO regard is assessed as concentration, showing the proportion of oxygen (O2) available in water, the more essential the DO regard in water, exhibiting that the water has extraordinary quality, then again, if DO regard is low, it could be said that the water isn't satisfactory.

Then, the temperature sensor limits as an extent of the temperature of the water, the temperature showed will be changed over into Celsius which is the standard extent of temperature assessment in Indonesia [21]. Turbidity sensor limits the extent of the turbidity level of water, this sensor works by deciphering the infrared light communicated by the LED then the infrared light will go through the water and begotten by the phototransistor, the power got by the phototransistor is directly comparative with the turbidity level of the water. SMV execution using Thingspeak.

The Thingspeak application serves to show the delayed consequences of checking or data sent by sensors. The results got are taken care of again to make a graphical feature. In an instrument that scrutinizes water quality, this investigation uses Arduino Uno, which is in like manner the frontal cortex that examines and sends sensor readings similarly as giving requests to the motor driver which will move the propeller (orientation of development). This investigation uses the MCU center point. MCU
center points function as connectors and for web access, as an augmentation for data transmission. Using the Thingspeak application the data that has been taken by the sensor sent from the MCU center will be displayed as a reasonable diagram containing the four sensors used similarly as the Artificial Neural Network reasoning structure what abilities to choose water quality.

4.2. Artificial Neural Network Calculation

The information utilized in this exploration is quadrant information/sensor readings of water quality. The sensors utilized in this review incorporate temperature, pH, turbidity, and Dissolved Oxygen (DO) sensors. The yield on the sensor will then, at that point, be handled as a contribution to Artificial Neural Network, by considering the cutoff points acquired from the consequences of perceptions and meetings with ranchers, the worth norm and reaches are displayed in Table 1.

| Parameter | Quality Standards |
|-----------|-------------------|
| Temp.     | 28°C - 32°C       |
| pH        | 7.5 - 8.5         |
| DO        | > 3.0 mg/l        |
| Turbidity | 25-400 NTU        |

Each sensor is divided into three classes, but the labels for each class differ from one another, according to the type read/according to the type of sensor. From Table 1, the research then implements the tools developed, this implementation uses the Artificial Neural Network approach, which is reflected in Figures 4.

The input layer is the layer where the artificial neural network first receives data to be processed to produce output, shown by Figure 4. Input data may consist of 2 or more data depending on the number of variables used in a study. In this study, the input data [23][24] to be processed are data from several pond water parameters consisting of 4 parameters as follows: a) X1 is a pH parameter, b) X2 is the Temperature parameter, c) X3 is a parameter of Dissolved Oxygen (DO), and d) X4 is a parameter of Turbidity (Turbidity).

The hidden layer is a layer that receives data from the input layer, but the results cannot be observed directly. Then the data will be sent to the Output Layer to observe the results of the Artificial Neural Network processing. This study uses 1 Hidden Layer with 3 Nodes (nodes). Giving the number of Nodes is based on the level of data accuracy. The output layer is a layer that contains the results of the artificial neural network process. Consists of 1 Node (node) which is the result of predicting the value of water quality from all the parameters that are input. The following is an artificial neural network architecture design with 1 Input Layer, 1 Hidden Layer, and 1 Output Layer with the following learning parameters: a) Maximum Epoch = 1000, b) Learning Rate = 0.5, and c) Bias = 1.
Figure 4. Backpropagation Neural Network Architecture

The training data used in this study is 70% of the total data. The maximum and minimum data values are shown in Table 2, while the target calculation is shown by Equation 1, and the result shown by Table 3.

Table 2. Maximum and Minimum of Data Training

|        | pH   | Temp. | DO   | Turbidity | Target |
|--------|------|-------|------|-----------|--------|
| Maximum| 8.52 | 38    | 11.98| 192       | 232.14 |
| Minimum| 4.83 | 23.6  | 7.77 | 169       | 212    |

\[
y = 0.8 \left( \frac{x - \text{min}}{\text{max} - \text{min}} \right) + 0.1
\]

\[
\text{Target} = x_1 + x_2 + x_3 + x_4
\]

\[
y = 0.8 \left( \frac{2.21 - 4.83}{8.52 - 4.83} \right) + 0.1
\]

\[
y = 0.8 \left( \frac{3.38}{3.69} \right) + 0.1
\]

\[
y = 0.8 \cdot x + 0.1
\]

\[
y = 0.83279 \cdot 328
\]
Table 3. Normalization Result of Data Training

|       | pH        | Temp.     | DO        | Turbidity | Target     |
|-------|-----------|-----------|-----------|-----------|------------|
| 1     | 0.832791328 | 0.706896552 | 0.441605839 | 0.273913043 | 0.890243902 |
| 2     | 0.856639566 | 0.725287356 | 0.540875912 | 0.204347826 | 0.94498645  |
| 3     | 0.828455285 | 0.725287356 | 0.511678832 | 0.204347826 | 0.962872629 |
| 4     | 0.828455285 | 0.725287356 | 0.548175182 | 0.204347826 | 0.949322493 |
| 5     | 0.791598916 | 0.743678161 | 0.548175182 | 0.204347826 | 0.947696477 |

The calculation of the new weight Testing data that is stored for test data is the weight on the 1000th Epoch obtained from the data shown in Table 4 and Table 5.

Table 4. Table of final weight values from Input Layer to Hidden Layer

| K1  | K2  | K3  |
|-----|-----|-----|
| X1  | 0.706896552 | 0.441605839 | 0.273913043 |
| X2  | 0.725287356 | 0.540875912 | 0.204347826 |
| X3  | 0.725287356 | 0.511678832 | 0.204347826 |
| X4  | 0.725287356 | 0.548175182 | 0.204347826 |

Table 5. Final weight value from Hidden Layer to Output Layer

| L   |
|-----|
| K1  |
| K2  |
| K3  |
| 5.33 |
| -3.18 |
| -5.05 |

In this study, with the number of epochs and learning rates used referring to previous research, the MSE produced is classified as good: 0.000913127. So based on the results of the MSE, the research continues by processing the testing data (125 data) using the final weights that have been obtained from the Training data, calculation is shown by Equation 2.

\[
\text{Node Calculation} \quad \text{Output Calculation}
\]

\[
\begin{align*}
\text{Net } K1 &= V_{0j} + \sum_{t=1}^{n} X_t W_{ij} \\
&= \text{Bias} + X_1 V_{x1k1} + X_2 V_{x2k1} + X_3 V_{x3k1} + X_4 V_{x4k1} \\
&= 1 + 0.832791328 \cdot 0.66 + 0.706896552 \cdot 0.77 + 0.441605839 \cdot 0.12 \\
&= -0.9809471385 \\
K1 &= f(\text{Net } K1) \\
&= \frac{1}{1 + e^{-\text{Net } K1}} \\
&= 0.2727038911
\end{align*}
\]

\[
\begin{align*}
\text{Net } L &= V_{0j} + \sum_{t=1}^{n} X_t W_{ij} \\
&= \text{Bias} + K1 W_{k11} + K1 W_{k21} + K1 W_{k31} \\
&= 1 + 0.2727038911 \cdot 5.33 + 0.4269997047 \cdot 5.05 \\
&= 0.270783942 \\
L &= f(\text{Net } L) \\
&= \frac{1}{1 + e^{-\text{Net } L}} \\
&= 0.5672853515
\end{align*}
\]
\[
N_{NTT} = \sum_{t=1}^{n} X_i V_{ij} + V_{0j} + X_1 V_{x1k2} + X_2 V_{x2k2} + X_3 V_{x3k2} + X_4 V_{x4k2} = 1 + 0.832791328 \times -4.58 + 0.706896552 \times -2.13 + 0.441605839 \times -1.1 + 0.273913043 \times 0.08 = -4.783727317
\]

\[
K_2 = f(N_{NTT}) = \frac{1}{1 + e^{-NetK2}} = \frac{1}{1 + e^{5.95715025}} = 0.008295373834
\]

\[
N_{NTT} = \sum_{t=1}^{n} X_i V_{ij} + V_{0j} + X_1 V_{x1k3} + X_2 V_{x2k3} + X_3 V_{x3k3} + X_4 V_{x4k3} = 1 + 0.832791328 \times -2.96 + 0.706896552 \times 0.81 + 0.441605839 \times -1.43 + 0.273913043 \times 4.49 = -0.2941029105
\]

\[
K_3 = f(N_{NTT}) = \frac{1}{1 + e^{5.8406457734}} = \frac{1}{1 + e^{-0.8406457734}} = 0.4269997047
\]

The output value is then processed into fuzzy to form a class (good and bad), the fuzzy equation used in this study is shown by Equation 3. The class used in this study is intentionally made in two based on the threshold value from the Ministry of Maritime Affairs and Fisheries as shown in Table 1.

\[
\mu[Bad] = \begin{cases} 
0; & x \geq 0.4 \text{ at } x \leq 0.6 \\
(b - x)/(b - a); & 0.3 < x < 0.4 \\
(d - x)/(d - c); & 0.7 < x < 0.8 \\
1; & x \leq 0.3 \text{ dan } x \geq 0.8
\end{cases}
\]

\[
\mu[Good] = \begin{cases} 
0; & x \geq 0.8 \text{ dan } x \leq 0.3 \\
(x - a)/(b - a); & 0.3 < x < 0.4 \\
(x - c)/(d - c); & 0.7 < x < 0.8 \\
1; & 0.4 \leq x \leq 0.6
\end{cases}
\]

4.3. Testing and Result SMV

The development of this tool was successful, this is indicated by the Black Box testing, shown in Figure 8 and Table 3, where all the results obtained by the study were all successful (100%). Tests carried out in this study use the Ground Truth approach, where the output of the system is compared with expert judgment, shown in Table 4. If the results are the same, it will be calculated as accuracy, otherwise if there is a difference it will be counted as an error. In tests carried out on 100 data generated by sensors (tools), the study produced an accuracy value of 92%.
Table 6. Black Box Testing

| Number | Item                  | Func.                  | Result |
|--------|-----------------------|------------------------|--------|
| 1      | Node MCU             | Data Transmitting Arduino, Thingspeak | Success |
| 2      | Temperature Sensor   | Temperature Value      | Success |
| 3      | Turbidity Sensor     | Turbidity Value        | Success |
| 4      | pH Sensor            | pH Value               | Success |
| 5      | DO Sensor            | DO Value               | Success |

Table 7. Artificial Neural Network Testing Result

| Number | Temp. | pH  | Turbidity | DO  | Class | Expert |
|--------|-------|-----|-----------|-----|-------|--------|
| 1      | 7.64  | 29.8| 11.41     | 172 | Good  | False  |
| 2      | 7.64  | 29.8| 11.42     | 171 | Good  | True   |
| 3      | 7.63  | 29.8| 11.43     | 171 | Good  | True   |
| 4      | 7.63  | 29.9| 11.44     | 170 | Good  | True   |
| 5      | 7.62  | 29.9| 11.45     | 172 | Good  | True   |
| 6      | 7.61  | 29.9| 11.46     | 172 | Good  | True   |
| 7      | 7.61  | 29.9| 11.47     | 169 | Good  | True   |
| 8      | 7.6   | 29.9| 11.48     | 175 | Good  | True   |
| 9      | 8.1   | 30  | 11.49     | 175 | Good  | True   |
| ...    | ...   | ... | ...       | ... | ...   | ...    |
| 122    | 7.4   | 27  | 9         | 180 | Bad   | True   |
| 123    | 8.6   | 33  | 11        | 160 | Bad   | True   |
| 124    | 9     | 37  | 12        | 152 | Bad   | True   |
| 125    | 9     | 37  | 12        | 152 | Bad   | False  |

Figure 5. Testing

5. Conclusion
The conclusion obtained, the research has succeeded in developing a Real-time Surface Modeling Vehicle for Shrimp Ponds (SMV). This is indicated by an indication of the Black Box test results that result in system compatibility, with a value of 100%, or in other words all features are running well. Whereas in the test carried out with 125 data (7 false), an accuracy value of 94% was obtained. So that
these results are used as a reference that the tools produced in this study can be implemented in shrimp ponds and are expected to increase the accuracy of shrimp farming.

6. Acknowledgment
The authors would like to acknowledge the financial support of this work by grants from PNBP, Politeknik Negeri Jember. The author also thanked the P3M and Jurusan Teknologi Informasi, Politeknik Negeri Jember, which has provided support and assistance in completing this research.

References
[1] Data K 2019 Indonesia Eksporit Udang Beku Terbesar Keempat di
[2] Syafaat M N, Mansyur A and Tonnek S 2012 Dinamika kualitas air pada budidaya udang vannamei (Litopenaeus vannamei) semi-intensif dengan teknik perlirian pakan

Pros. Indoqua-Forum Inov. Teknol. Akuakultur 487–94
[3] Fuady M F, Supardjo M N and Haeruddin 2013 Pengaruh Pengelolaan Kualitas Air terhadap Tingkat Kelulushidupan dan Laju Pertumbuhan Udang Vannamei (Litopenaeus vannamei) di PT. Indokor Bangun Desa, Yogyakarta

Diponegoro J. Maquares Manag. Aquat. Resour. 2 155–62
[4] Wibowo N S, Destarianto P, Riskiawan H Y, Agustianto K and Kautsar S 2018 Development of low-cost autonomous surface vehicles (ASV) for watershed quality monitoring

2018 6th International Conference on Information and Communication Technology, ICoICT 2018 vol 0 (IEEE) pp 489–94
[5] Cao F, Jiang F, Liu Z, Chen B and Yang Z 2014 Application of ISFET Microsensors with Mobile Network to Build IoT for Water Environment Monitoring

Proceedings - 2014 International Conference on Intelligent Environments, IE 2014 pp 207–10
[6] Perumal T, Sulaiman N and Leong C Y 2015 Internet of Things (IoT) Enabled Water Monitoring System 2015 IEEE 4th Global Conference on Consumer Electronics (GCCE) Internet pp 86–7
[7] Pranata A A, Lee J M and Kim D S 2017 Towards an IoT-based Water Quality Monitoring System with Brokerless Pub / Sub Architecture
[8] Myint C Z, Gopal L and Aung Y L 2017 WSN-based Reconfigurable Water Quality Monitoring System in IoT Environment 2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON) pp 741–4
[9] Myint C Z, Gopal L and Aung Y L 2017 Reconfigurable Smart Water Quality Monitoring System in IoT Environment Proceedings - 16th IEEE/ACIS International Conference on Computer and Information Science, ICIS 2017 pp 435–40
[10] Muchtar E, Sanjaya F and Hariadi F I 2017 Human machine interface on e-Shrimp as smart control system for whiteleg shrimp pond 2017 Int. Symp. Electron. Smart Devices, ISESAD 2017 2018-Janua 24–9
[11] Sacasqui M, Sanchez I and Vasquez E 2017 Adaptive predictive control of dissolved oxygen concentration in a dynamic model of whiteleg shrimp culture 2017 Chil. Conf. Electr. Electron. Eng. Inf. Commun. Technol. CHILECON 2017 - Proc. 2017-Janua 1–6
[12] Agustianto K, Destarianto P and Dewanto W K 2020 Development of real-time motion autonomous surface vehicle controlling for coral reef conservation and fisheries

Proc. - 2017 Int. Conf. Sustain. Inf. Eng. Technol. SIET 2017 2018-Janua 374–8
[13] Kurnia D W, Kautsar S, Etikasari B and Khafidurrohman A 2018 A control scheme for typist robot using Artificial Neural Network

Proc. - 2017 Int. Conf. Sustain. Inf. Eng. Technol. SIET 2017 2018-Janua 374–8
[15] Destariantto P, Etikasari B and Agustianto K 2018 Developing Automatic Student Motivation Modeling System J. Phys. Conf. Ser. 953
[16] Dewanto W K, Agustianto K and Sari B E 2018 Developing thinking skill system for modelling creative thinking and critical thinking of vocational high school student J. Phys. Conf. Ser. 953
[17] Destariantto P, Riskiawan H Y, Agustianto K and Kautsar S 2018 Developing food sensory test system with preference test (Hedonic and Hedonic quality) wheat bread case study Proceedings - 2017 International Conference on Sustainable Information Engineering and Technology, SIET 2017 vol 2018-Janua
[18] Agustianto K and Destariantto P 2019 Imbalance Data Handling using Neighborhood Cleaning Rule (NCL) Sampling Method for Precision Student Modeling Proc. - 2019 Int. Conf. Comput. Sci. Inf. Technol. Electr. Eng. ICOMITEE 2019 1 86–9
[19] Agustianto K, Destariantto P and Dewanto W K 2020 Development of real-time motion autonomous surface vehicle controlling for coral reef conservation and fisheries IOP Conference Series: Earth and Environmental Science vol 411
[20] Farkan M and Setiyanto D D 2021 Development of realtime surface modeling vehicle for shrimp ponds ( ReSMeV-SP ) IOP Conf. Ser. Earth Environ. Sci.
[21] Science E 2021 Development of automatic temperature and humidity control system in kumbung (oyster mushroom) using fuzzy logic controller IOP Conf. Ser. Earth Environ. Sci.
[22] Kkp 2016 Peraturan Menteri Kelautan Dan Perikanan Republik Indonesia Nomor 75/Permen-Kp/2016 Tentang Pedoman Umum Pembesaran Udang Windu (Penaeus Monodon) Dan Udang Vaname (Litopenaeus Vannamei
[23] Choirunnisa S and Lianto J 2017 Hybrid Method of Undersampling and Oversampling for Handling Imbalanced Data 2018 Int. Semin. Res. Inf. Technol. Intell. Syst. 276–80
[24] Choirunnisa S, Meidyani B and Rochima S 2019 Software Defect Prediction using Oversampling Algorithm: A-SUWO 2018 Electr. Power, Electron. Commun. Control. Informatics Semin. EECCIS 2018 337–41