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Implementation of Extreme Learning Machine for Water Quality Control in Vannamei Shrimp Ponds

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Abstract: Based on the government's plan to increase shrimp production by 1,290,000 tons or experience a 250% increase, the application of science and technology knowledge is crucial in supporting the Indonesian Government's program, especially for increasing the production of Litopenaesus Vannamei shrimp. This research collaborates with shrimp pond farmers to develop technology that supports the cultivation of vaname shrimp. The water quality in the ponds can affect the harvest results, and water parameters such as pH, dissolved oxygen (DO), alkalinity, salinity, and temperature should be monitored and adjusted if they exceed the predetermined limits. Based on frequently encountered field conditions, water quality inspections are currently conducted manually with periodic checks, which can result in unstable water quality in the ponds. To address this, we have developed an Extreme Learning Machine-based water quality management system tailored to the geographic conditions of Indonesia. This tool uses sensors to read data from the pond water, which is then processed by a microcontroller and displayed in a web-based information system. This tool helps farmers determine the water conditions and address them accurately. Based on the experimental results, the data training error is 0.0001, and the error in the testing data is 0.1851. This indicates that the Extreme Learning Machine performs well in classifying water quality and determining the level of water quality controller in this research.

Kata Kunci: *Extreme Learning Machine; Litopenaesus Vannamei; Disolved Oxygen; pH.*

1. Introduction

In the implementation of the National Development Plan (National Priorities) RPJMN 2020-2024, the Ministry of Marine Affairs and Fisheries aims to increase shrimp production in Indonesia by 250% over a five-year period (2019-2024) [1]. To achieve this target, support is required from various aspects, including the application of science and technology, to support the government's Shrimp Pond Revitalization program. The role of information systems is expected to enhance the outcomes of shrimp ponds, and the use of monitoring systems is closely related to Industry 4.0, where monitoring can be conducted anywhere and at any time.

In this research, we collaborated with one of the shrimp farmers as an industrial partner to develop technology that supports the cultivation of vannamei shrimp in intensive shrimp ponds. In managing the vannamei shrimp with our partner, cultivation is carried out using an intensive management system in circular ponds with a diameter of 25 meters and a water depth of 1.5 meters. Additionally, there are significant factors that affect the harvest results of shrimp farmers, namely water quality [2]. Given the relatively high shrimp density, water conditions must be constantly monitored, and specific treatments must be promptly applied if any parameter exceeds the predetermined threshold [3]. This is done to maintain the quality of pond water, and the parameters that need to be maintained include alkalinity, salinity, temperature, dissolved oxygen, and pH [3]. Based on observations conducted with our industrial partner, the monitoring of water quality parameters is still conducted periodically following the SNI standards, with Water Temperature of 29 - 32°C checked twice a day, Salinity of 15 - 23 (adjusted to the partner's shrimp pond) checked daily, pH of 7.5 - 8.5, and dissolved oxygen checked every 2 days.

This approach may lead to adverse consequences if sudden changes in water quality parameters occur due to certain factors [4].

Based on these factors, we developed an Extreme Learning Machine-based water quality management system. In this tool, we obtain real-time readings from sensors, which are then processed by a microcontroller and displayed in a web-based information system. The aim of this tool is to facilitate shrimp farmers in determining water conditions, enabling them to cultivate vannamei shrimp more effectively.

2. Materials and Methods

The overall design process of Water Quality Control using the Extreme Learning Machine can be explained as a following flowchart in Figure 1. It can be understood that the research process begins with data preparation, followed by data preparation for training. The prepared data is then used for determining the model of the extreme learning machine. Subsequently, the training process is conducted to obtain appropriate bias and weight values. If after 5000 iterations, the suitable bias and weight values have not been obtained, the ELM model is revised, and the training process is repeated. Once the minimum error value for training data (0.00001) is achieved, the obtained values are transferred to the microprocessor for testing data generation.

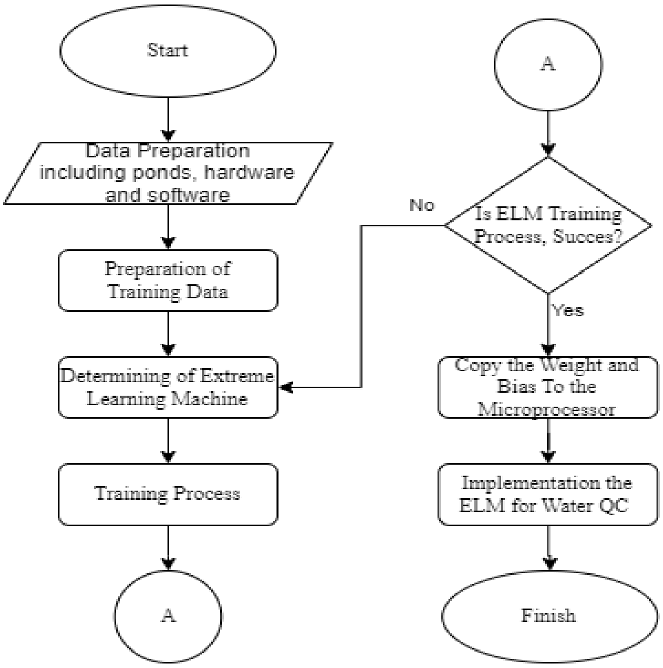

Figure 1. Flowchart of Design Water Quality Control

Figure 2. Shirmp Farm System

Figure 3. Standing Autofeeder

2.1. Experiment Data

Data used in this experiment consist of three components. The first component is shrimp ponds and the second component is Standing Auto Feeder (SAF) systems that contain sensors, processors, and actuators. The third components are treatment materials such as Molases, and Calcium Carbonate (CaCO3).

- **Shrimp Farm Data**

Shrimp Farm used in this experiment is circular a circular pond with a diameter of 10 m. The pond is also equipped with a piping system that is used for water circulation, to enter or remove water from the pond. The pool water level is in the range of 1.5 meters, so the volume of water in the pond is estimated at 736 m^3.

The figure of the pond can be seen in Figure 2. The pond's constituent materials consist of a concrete foundation, with an iron support frame, and water-retaining material made of tarpaulin.

- **Standing Auto Feeder (SAF)**

Standing Autofeeder is an automatic feeding tool and an automatic water quality regulator. I use the autofeeder to control the parameter automatically, to maintain the pH, Disolved Oxygen, Alkalinity, Salinity, Temperature value within its range. From the Figure 3 above, we can identify the components of the autofeeder, which include:

1. Solar panel, as the energy source for the autofeeder.
2. Feed tube, for storing the feed before it is dispensed.
3. Reservoir tank, for storing CaCO3 and molasses before spraying.
4. Feeder, for dispensing the feed into the pond.
5. Sprayer, for spraying molasses and CaCO3 into the pond.
6. Controller panel, for placing the PCB board, valve relay, aerator relay, and SAF controller.

- **Water Treatment Material**

In this research, there are two materials for water threatment, CaCO3 and Molasses. Both of them have their own functions, which are:

1. The first reservoir tank contains CaCO3 liquid, which is chosen as a pH and alkalinity increaser. It can be used to increase alkalinity, which helps to maintain the stability of the pH value [5].
2. The second reservoir tank contains Molasses, which is chosen as a natural and effective pH reducer to help maintain the stable and optimal conditions of the water for the shrimp living in it [5].

2.2. Extreme Learning Machine

In this study, an Extreme Learning Machine model was used. This model was chosen to classify the water quality in vannamei shrimp ponds and determine the necessary actions [6]. The structure of the Extreme Learning Machine can be seen in Figure 4 below.

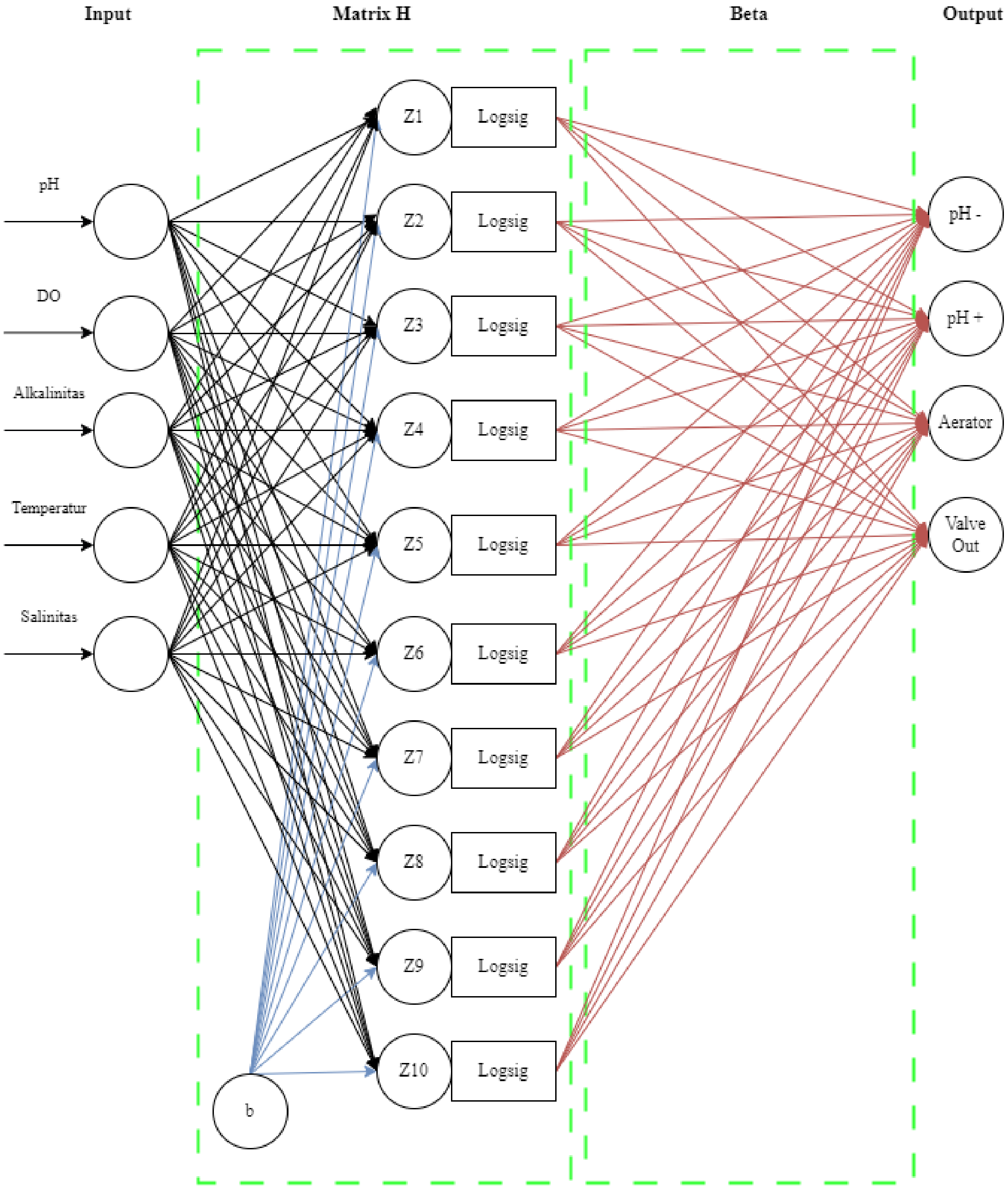

Figure 4. Extreme Learning Machine Structure

In the Figure 4 we can see the structure of the Extreme Learning Machine, The implementation of the Extreme Learning Machine (ELM) in this study utilized five input and a hidden layer composed of 10 neurons, with four output . The activeation function used in each hidden layer of the Extreme Learning Machine model was logsig. The activation function is chosen because no negative values are obtained in this operation. That is formula for training and testing the Extreme Learning Machine [6].

1. Data Normalization (minmax normalization)

   Data normalization is performed to scale the data so that the obtained values are in the range of 0 to 1. ELM uses random weights in the hidden layer, and when the input data has a wide range, these weights can become very large or very small. This can lead to numerical problems such as overflow or underflow, which can disrupt the model's performance and hinder efficient training.

$$d' = \frac{d - \min}{\max - \min} \quad (1) \tag{1}$$

d' = Data after normalization

d = Data before normalization

min = Smallest value from all data variable

max = Higest value from all data variable

2. Calculate hidden layer value (H_{init} & H^+)

The transposed of weght matrix is then multiplied with the matrix obtained from the output of the hidden layer with the usual activation function, which is called matrix H. Next step is to calculate the inverse of matrix H. After that, the Moore-Penrose Generalized Inverse of the output from the hidden layer with the activation function is computed. The following equation is used to calculate the values of the output weight and:

$$H_{init\,ij} = \left(\Sigma_{k=1}^{n} w_j \times x_{ik}\right) + b_j \tag{2}$$

$$H = \frac{1}{1 + e^{-H_{init}}} \tag{3}$$

$$H^+ = (H^T * H)^{-1} * H^T \tag{4}$$

H_{init} = Matriks keluaran hidden layer.

H^T = Matriks H Traspose.

H^+ = Matriks Moore-Penrose Generalized Invers from matrix H.

i = [1,2,….,N], where N is a total of data.

j = [1,2,…., Ñ], where Ñ is a total of hidden neuron.

n = Total of input neuron.

w = Weight.

x = Inpus.

b = Bias value.

3. Calculate output weight:

The value of βeta can be calculated by multiplying $H+$ with the target matrix, where the target matrix refers to the output from the training data.

$$\beta = H^{+} \times T \tag{3}$$

β = Output weight matrix.

H^+ = Moore-Penrose Generalized Invers from matrix H.

T = Matrix Target.

4. Testing Process

In this process, the aim is to evaluate the results of the ELM method from the previous training process. This process is carried out using the input weight, bias, and output weight obtained from the training process. The following are the steps in the testing process:

1. In the first stage, the initialization of the input weight and bias obtained from the training process is performed.

2. Then, the output of the hidden layer is computed using an activation function. One of the activation functions that can be used includes sigmoid, sin, hardlim.

3. The output weight values obtained in the training process are then used to calculate the output of the output layer, which represents the prediction result from ELM. The following equation is used to calculate the value of the output layer:

$$y = H\beta \tag{4}$$

y = Output layer
β = Output weight matrix.
H = Output from hidden layer and calculated using activation.

5. Denormalisasi data (minmax – denormalization)

Denormalization function is the inverse process of normalization, where the normalized values are reverted back to their original or pre-normalization range. Denormalization is necessary after the normalization process is completed, especially in the context of data analysis or machine learning.

$$d = d'(max - \min) + min \tag{5}$$

d' = Data before denormalization
d = Data after denormalization
min = Smallest value from all data variable
max = Higest value from all data variable

2.3. *Extreme Learning Machine Training and Testing Data*

In this study, the training and testing data were obtained from vannamei shrimp farmers in Modung, Bangkalan, Madura. Due to space limitations, not all data can be presented in this paper. However, I will provide a sample of the training and testing dataset used in this Extreme Learning Machine model.

Table 1. Input-Output Dataset

No.	Input					Output			
	pH	Alkalinity (mg/L)	DO (ppm)	Salinity (ppm)	Temperature (°C)	CaCO3 (mg/L)	Molases (mg/L)	Aerator (State)	Drain Valve (State)
1	8.4	133	8.5	16	27	0	0	Off	On
2	7.4	108	8.5	18	28	0	220.7812	Off	Off
3	8.3	136	8.1	16	26	0	0	Off	On
4	8.5	130	8.3	10	28	0	0	Off	On
5	8.4	138	8.1	10	26	0	0	Off	On
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
146	8.6	137	7.7	14	27	220.7812	0	Off	On
147	8.4	123	8	15	29	0	0	Off	Off
148	8.2	124	8.1	15	28	0	0	Off	Off
149	7.5	105	7.6	15	29	0	0	Off	Off
150	7.3	111	4.9	17	27	0	441.5625	On	On

In this study, there are five input parameters, namely pH, CaCO3, DO (Dissolved Oxygen), Salinity, and Temperature. Additionally, there are four output parameters, namely pH+ (CaCO3), pH- (Molasses), aerator relay, and central drain valve. CaCO3 is used to increase the pH value in order to maintain the pH range above the lower limit of 7. Furthermore, CaCO3 functions to regulate the alkalinity value, where a higher alkalinity value contributes to pH stability [8]. Moreover, molasses is used to lower the pH level in the pond when the pond's pH is higher than 8. The aerator is used to control the Dissolved Oxygen (DO) by creating air bubbles in the water; it will turn on if the DO is less than 5. Meanwhile, the Drain Valve is used to regulate the temperature to be maintained between 29 - 32°C and the salinity between 15 - 23 (adjusted according to the vannamei shrimp pond in Bangkalan, Madura). Periodic water changes will be conducted to address these two factors.

3. Results

3.1. Experimental Case Study

The aim of this paper is to test whether the Extreme Learning Machine model is suitable for classifying water quality parameters in shrimp ponds.

3.1.1. Extreme Learning Machine Training

Figure 5 shows the results of the Extreme Learning Machine testing, where the Google Colab platform was used for data analysis in the simulation. The error calculation was performed using the RMSE formula.

The error percentage in this research is represented by RMSE (Root Mean Square Error). Iterations are performed to obtain the best results for the learning process, which is used to find the appropriate weight and bias values for this ELM program. Furthermore, after the training process, weight values and bias values were obtained as shown in Tables 2 and 3 below.

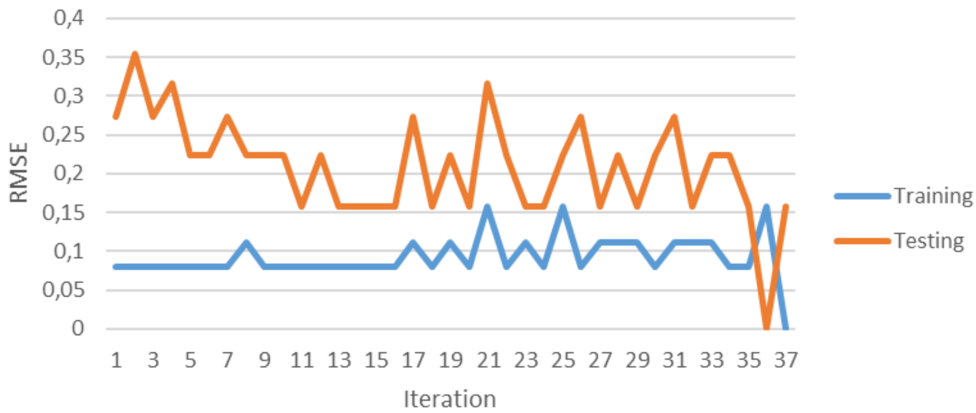

Figure 5. The error graph between training and testing results.

Table 2. Weight of Extreme Learning Machine

Weight									
-0.56673	0.585656	-0.17369	-0.06445	-2.35324	0.62695	0.708345	0.795255	1.443814	1.046769
0.616462	-0.42603	-1.47167	0.109994	2.230553	-1.55055	0.746343	-0.17574	0.539182	0.84859
-0.0172	0.574503	1.841321	-1.91592	0.471911	0.12081	1.18302	-1.57646	-0.01391	-0.12896
0.958257	2.033196	-0.55554	0.981786	1.88726	2.44978	1.525008	-0.28907	0.788142	0.656266
0.206519	-1.20659	-1.35798	-1.4047	1.345166	-1.04578	1.461619	1.477358	0.150207	0.246396

Tabel 3. Bias of Extreme Learning Machine

Bias									
1.615941	-0.7791	-2.03994	0.382376	-1.5076	-0.0182	0.768683	-0.8349	-0.5620	-0.74792

The weight and bias values mentioned above are then applied on a website to control the usage of pH, DO, salinity, alkalinity, and temperature.

4. Discussion

The final RMSE value from the training process is 0.0001, indicating that the Extreme Learning Machine model has found good weighting and bias parameters for the training data. Therefore, the obtained bias and weight values can be directly implemented in the system for testing purposes. However, the error graph in Fig 5 shows significant fluctuations in both training and testing values. Fluctuations of the value on the graph in Fig 5 are caused by randomly generated weights and biases, leading to random variations in the output results.

To improve the model's accuracy, steps such as adding additional datasets to the training data and increasing the number of neurons in the model can be taken. The testing results show an error value of 0.1581, indicating that there are still some errors in the predictions made by the Extreme Learning Machine model. This could be due to the limited amount of testing data available.

5. Conclusion

This research collaborates with shrimp pond farmers to develop technology that supports the cultivation of vaname shrimp. The experiment demonstrates that the Extreme Learning Machine model has provided reasonably good results in predicting the training data; however, further enhancements are required to achieve higher accuracy in predicting the testing data. Based on this research, it can be inferred that the Water Quality Control system performs quite well. This can be observed from the testing results, where the predicted output yields a relatively small root mean square error of 0.1851. Therefore, it can be concluded that the Water Quality Control system functions adequately.

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