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A comparative analysis of machine learning regression models of Whiteleg shrimp growth reared in eco-green aquaculture system

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ABSTRACT

The success of aquaculture business of whiteleg shrimp (*Litopenaeus vannamei)* depends on its growth throughout the cultured period. The whiteleg shrimp growth is highly influenced by the condition of water quality in aquaculture pond. However, the study of shrimp growth reared in eco-green aquaculture system is limited. Therefore, this study aims to compare and analyze shrimp growth in relation with water quality factors in eco-green system by using machine learning regression models, such as neural network multi-layer perceptron (NN-MLP), support vector regression (SVR), decision tree, and random forest. The data was collected from 2021–2023, including average daily growth of shrimp as well as eleven water quality variables that measured both in-situ and ex-situ. The results revealed that among the five machine learning techniques employed in this study, the models generated by decision tree and random forest surpassed those of NN-MLP and SVR on the training stage. Nonetheless, in the validation or testing phase, the outcomes were inverted. Furthermore, according to the modelling results, the water quality variables that have the biggest importance value on the daily growth prediction of shrimp in the eco-green system were dissolved oxygen and nitrate concentration, as well as total vibrio.

Keywords: coastal ecosystem; intensive system; prediction model; supervised learning; water quality.

INTRODUCTION

The growth performance of aquatic organisms is essential for the economic viability of the production of aquaculture. Researchers developed growth formulas to simulate the growth changes of the species of interest throughout its entire lifespan or during specific developmental stages within a particular cultural environment [Sun and Wang, 2024], while also modeling it as a function of water quality parameters [Musa et al., 2023]. In specific, water quality is critical in the intensive pond culture of whiteleg shrimp (*Litopenaeus vannamei*) concerning optimal growth and survival rates [Harlina et al., 2022]. Water quality is a term used to indicate the acceptability of water for a certain purpose or the ability of water to support diverse uses or processes [Mustafa et al., 2022]. Intensive whiteleg shrimp aquaculture operations frequently fail due to poor water quality during maintenance [Iqmah et al., 2022]. Poor water quality can contribute to the emergence of a wide range of diseases, causing shrimp stress and even death, while good water quality can improve shrimp growth, health, and production [Musa et al., 2020; Ritonga et al., 2021].

In principle, eco-green cultivation is intensive or superintensive shrimp cultivation with a pond arrangement design made using the "Silvofishery Komplangan models" and a cultivation system carried out using the "hybrid system" that integrated aquaculture ponds and mangrove ecosystems in coastal areas [Musa et al., 2020]. Ecogreen aquaculture is a system that utilizes the mangrove ecosystem to process incoming water before use or water that comes out after being used for cultivation, so this cultivation system is allegedly suitable for development in coastal areas that are experiencing degradation and whose water conditions are decreasing due to pollution [Fidari et al., 2020; Musa et al., 2023a]. Silvofishery is a fish farming system that combines aquaculture with mangrove forests to increase aquaculture production and preserve the environment [Rangkuti et al., 2015; Kusumaningtyas Perwitasari et al., 2020]. Meanwhile, the "komplangan model" itself is a more environmentally friendly construction of pond land, because the mangrove land as a conservation area is separate from the pond land as a cultivation area which is regulated by a water channel with two separate gates. The separation of mangrove land and pond land in the "komplangan model" is limited by an embankment between the two doors, so this pattern can be an environmentally friendly pond management solution [Paruntu et al., 2016]. Therefore, the application of environmentally friendly aquaculture such as eco-green aquaculture is more promising in coastal areas that have experienced degradation due to anthropogenic activities, such as industrial or domestic pollution and coastal development [Mahmudi et al., 2022].

In recent, the use of machine learning approach in aquaculture sectors has been popular. Machine learning empowers computers to assist humans in analyzing extensive and intricate data sets. This area of research emphasizes the development of models, the analysis of data, its classification, and the generation of predictions based on that information [Sarker, 2021]. This method has been utilized to classify the status of shrimp hatchery in Thailand [Panitanarak and Kaowleg, 2024], predicting shrimp growth in commercial setting [Yu et al., 2006], as well as controlling and intelligently monitor water quality in the shrimp pond [Lin et al., 2021; Kaur et al., 2023]. However, the application of Machine Learning in eco-green aquaculture is limited. Hence, this research aims to implement and compare several machine learning regression models to analyze the growth of whiteleg shrimp reared in eco-green aquaculture setting based on the condition of water quality aspects. This is important to promote the sustainability of shrimp aquaculture both economically and environmentally.

MATERIALS AND METHOD

Study area and data collection

The study was conducted at eco-green aquaculture whiteleg shrimp pond owned by Laboratorium Perikanan Air Payau dan Laut, Universitas Brawijaya located in Probolinggo Regency, East Java Province, Indonesia (Fig. 1). The data were collected from 2021 to 2023 and can be accessed at this following link: https://doi.org/10.6084/m9.figshare.28785923.v1

Techniques for measuring shrimp growth and water quality variables

Shrimp growth were measured as average daily growth (ADG; gram/day) by using the following formula

$$\mathrm{ADG} = \frac{W_{t+N} - W_t}{N} \tag{1}$$

where: W_{t+N} and W_t denotes average weight of shrimps measured at days $t + N$ and t,

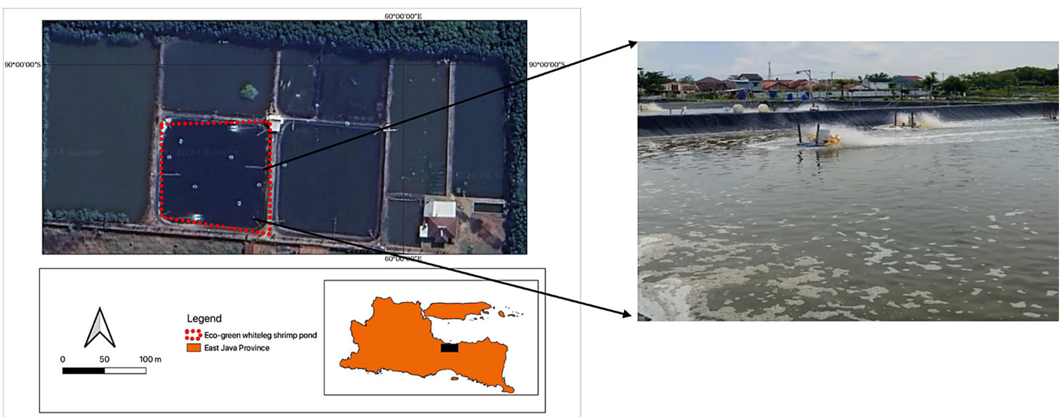

Figure 1. Research location map

respectively. Meanwhile, N is number of days between two weight measurement.

On the other hand, various water quality parameters were assessed through sample analysis. Instruments such as a Lutron PDO-520 DO meter were employed to record temperature (°C), pH, and dissolved oxygen (DO; mg/L). Transparency (m) and salinity (ppt) were evaluated using a secchi disc and refractometer, respectively. Test kits were utilized to determine concentrations of nitrate (mg/L) and ammonia (mg/L). Furthermore, phosphate (mg/L), total organic matter (TOM; mg/L), total suspended solid (TSS; mg/L) levels were analyzed using colorimetric, titrimetric, and gravimetric methods respectively in laboratory. In addition, total vibrio (CFU/mL) were counted by using total plate count technique.

Data analysis

Data pre-processing

Before the deployment of the machine learning techniques, the data underwent pre-processing step, which involved the elimination of missing values and data transformation. The listwise removal method was applied to eliminate any rows with missing values. Concurrently, the data underwent normal scale transformation to achieve zero mean and a standard deviation of 1.

Machine learning methods for prediction

Supervised learning is a machine learning technique that entails deriving a function that associates input with output, utilizing training data composed of labeled input-output pairs. An inferred function is generated from the examination of the designated training data and subsequently applied to novel, unseen instances. A prevalent method in this domain is regression, which employs an algorithm to elucidate the link between dependent and independent variables. Regression models facilitate the prediction of numerical values derived from several data sources. Table 1 presents instances of diverse regression methodologies employed in this approach.

Evaluation metrics for machine learning regression

A total of four metrics – mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R-square) – are taken into account when assessing the algorithms' performance. The higher the R-square and the lower MAE, MSE, as well as RMSE the better. We define these metrics as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (5)$$

where: n denotes sample size, y_i and $\hat{y}_i$ represent the i-th observed and predicted data, while $\bar{y}$ is mean of the observed data.

RESULTS AND DISCUSSION

Descriptive analysis of research variables

The summary statistics of the studied variables are displayed in Table 2 along with subsequently linked to the national standard values for

Table 1. Regression algorithm of supervised learning

No	Algorithm	Description
1	Neural network multi-layer perceptron (NN MLP)	MLP is a form of artificial neural network made up of an input layer, one or more hidden layers, and an output layer, with each layer consisting of connected neurons. It employs activation functions and backpropagation to learn patterns from data, making it suitable for regressions applications [Gardner and Dorling, 1998]
2	Support vector regression (SVR)	SVR is an enhancement to Support Vector Machines (SVM) that may be applied to regression situations. It optimizes a function by identifying a tube that corresponds to a continuous-valued function while minimising prediction error [Gambella et al., 2021]
3	Decision tree regression (DTR)	DTR is a nonparametric supervised machine learning technique that uses a tree-like structure to solve regression issues. It predicts the output value by learning basic decision rules from the input variables, resulting in a logical chain of decisions that leads to the final output prediction [Liu et al., 2016]
4	Random forest regression (RFR)	Random forest is a kind of ensemble machine learning technique employed for regression analysis as well as classification. It implements the concept of bagging (or bootstrap aggregation), which is a way for creating another set of data through replacement from a former sample [Borup et al., 2023]

Table 2. Descriptive statistics of research variables

Variable	Unit	Mean	Stdev	Min	Max	Standard
Average daily growth	mg/day	0.385	0.300	0.012	1.513	0.22
Temperature	°C	28.471	0.634	27.400	29.300	28–32
Transparency	cm	35.714	8.693	25.000	55.000	20–40
Total suspended solid	mg/L	224.857	45.751	140.000	277.000	< 50
Salinity	ppt	24.429	1.690	22.000	26.000	26–32
Dissolved oxygen	mg/L	5.714	0.862	4.200	6.700	> 3
Carbon dioxide	mg/L	49.736	13.964	24.257	67.062	< 5
Nitrate	mg/L	0.682	0.264	0.341	0.961	< 20
Phosphate	mg/L	0.256	0.223	0.010	0.711	< 5
Ammonia	mg/L	0.398	0.528	0.105	1.671	< 0.05
Total organic matter	mg/L	27.989	33.790	7.584	108.704	< 90
Total vibrio	CFU/mL	2385.714	1020.697	1000	3900	< 10000

aquaculture practices in Indonesia as stated in Government Regulation Number 22 of 2021 that can be accessed in the following link: https://peraturan.bpk.go.id/Details/161852/pp-no-22-tahun-2021. Most of the water quality metrics conform to the standard values, except salinity (below standard), carbon dioxide, and ammonia (above normal).

Whiteleg shrimp is recognized for its adaptability to a wide array of environmental conditions, including poor salinity. Prior research indicated that a salinity level even as low as 1 ppt in whiteleg shrimp ponds did not significantly impact the conversion rate of feed [Jaffer et al., 2020]. Furthermore, poor salinity conditions may substantially diminish the organism's growth rate early [Rahi et al., 2021]. On the other hand, prolonged ammonia exposure may impair normal growth and elevate the susceptibility of shrimp to numerous diseases [Liu et al., 2020]. Excessive carbon dioxide in the pond adversely impacted the development, survival, as well as wellness of shrimp. The shrimp subjected to elevated carbon dioxide levels exhibited impairment to the tubule structure of the hepatopancreas along with the cells that regulate diet digestion and absorption of nutrients [Casillas--Hernández et al., 2021].

Machine learning results in predicting Whiteleg shrimp's growth

The best hyperparameters for each machine learning approach were determined using a grid search strategy. A grid search technique entails systematically evaluating all potential parameter options in a loop and identifying the most effective parameter. This work employs cross-validation within the grid search strategy to validate model outcomes for every single hyperparameter arrangement, aiming to identify the optimum hyperparameters. After running cross-validation on all possible combinations of model parameters, we settled on the parameters with the smallest error metrics (RMSE) as the best ones. The chosen

Table 3. Selected hyperparameter of ML regression methods

ML methods	Hyperparameter optimization	
NN-MLP	Network topology	Hidden layer 1 : 6 neuron Hidden layer 2: 3 neuron Hidden layer 3: 5 neuron
	Activation function	Logistic
SVR	Kernel function	Polynomial
	C	0.5
	Scale	0.001
	Degree	3
Decision tree	cp	0.03446248
Random forest	mtry	7

hyperparameters for the machine learning regression methods are presented in Table 3.

Figure 2 presents the results of the training and testing (validation) phases for the implemented supervised learning regression method. This figure clearly demonstrates that the Random Forest model achieves the most favorable training results, with RMSE=0.327, MSE = 0.107, R-square=0.130, and MAE = 0.248. Conversely, the NN-MLP model produced the least favorable training outcomes, with RMSE=0.349, MSE = 0.122, R-square=0.072, and MAE = 0.274. The training results indicate that the SVR model outperforms the NN-MLP model, with metrics as follows: RMSE = 0.345, MSE = 0.119, R-Square = 0.065, and MAE = 0.269. The training results of the Decision Tree regression model are satisfactory, albeit marginally inferior to those of the Random Forest model (i.e., RMSE=0.329, MSE = 0.108, R-square=0.119, and MAE = 0.245).

In term of testing/validation result, contradictory outcomes are emerged compared to training results. Figure 2 shows that during validation phase, the best result obtained from NN-MLP with RMSE=0.606, MSE = 0.367, R-square=0.016, and MAE = 0.403. It is followed by the result of SVR model (i.e., RMSE=0.607, MSE = 0.368, R-square=0.001, and MAE = 0.399). Meanwhile, the other two model (Decision Tree and Random Forest) have lack metrics.

To mitigate overfitting issues, Figure 3 presents the learning curves of the implemented models on the training and testing samples. The results indicate that neither of these four models demonstrate overfitting. Nevertheless, the SVR model exhibits a reasonably excellent match; yet, its instability is a significant concern, since its performance can decline with a rise in the training sample size. Conversely, the NN-MLP along with Random Forest models demonstrate a strong fit and considerable consistency.

Figure 4 visualizes the overall importance of the 11 variables for accurate prediction of the shrimp growth. Both NN-MLP and SVR model indicate that DO, nitrate, and TOM as the top three important variables. Meanwhile, vibrio and nitrate have higher importance value based on the result of Decision Tree and Random Forest. By combining these finding, we can infer that DO, nitrate, and vibrio are the water quality variables which highly influence the prediction daily shrimp growth in studied area.

Re & Díaz (2011) showed that the capacity of shrimp to obtain energy and allocate it efficiently for growth is influenced by environmental factors. The level of oxygen is a critical factor that affects the metabolism of the organism. When the expenses related to the consumption and processing of ingested food exceed what can be supported by oxygen intake, shrimp cease feeding, prioritizing growth over the potential energy gain from food. Elevated oxygen levels enhance the feed conversion ratio as well as correlate with feed availability [Rahmawati et al., 2021]. Numerous

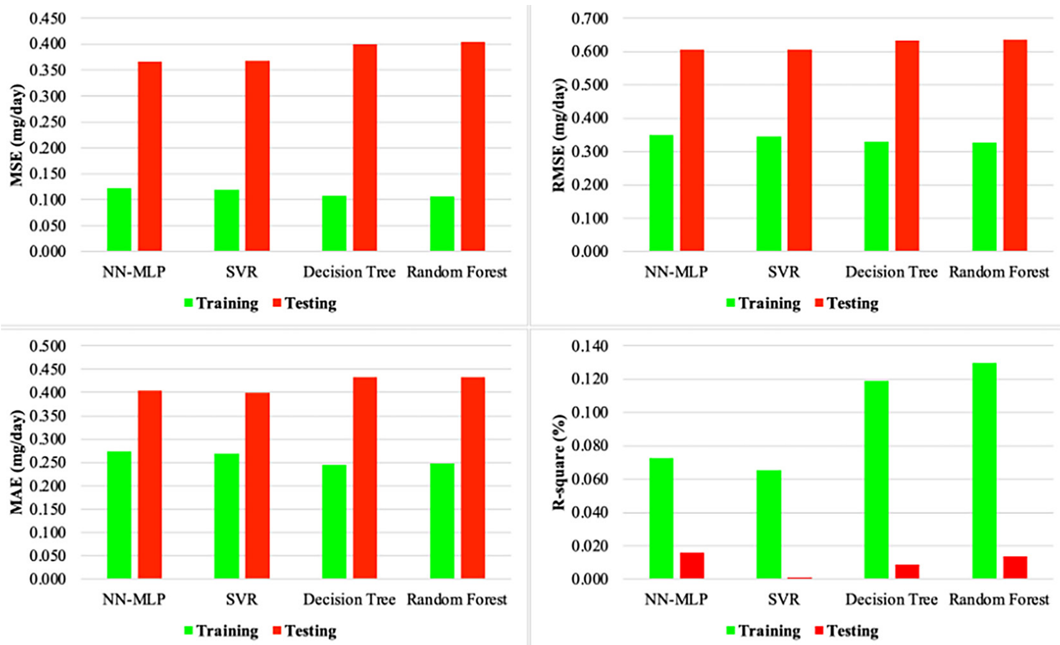

Figure 2. Evaluation metrics comparison of the applied machine learning regression models

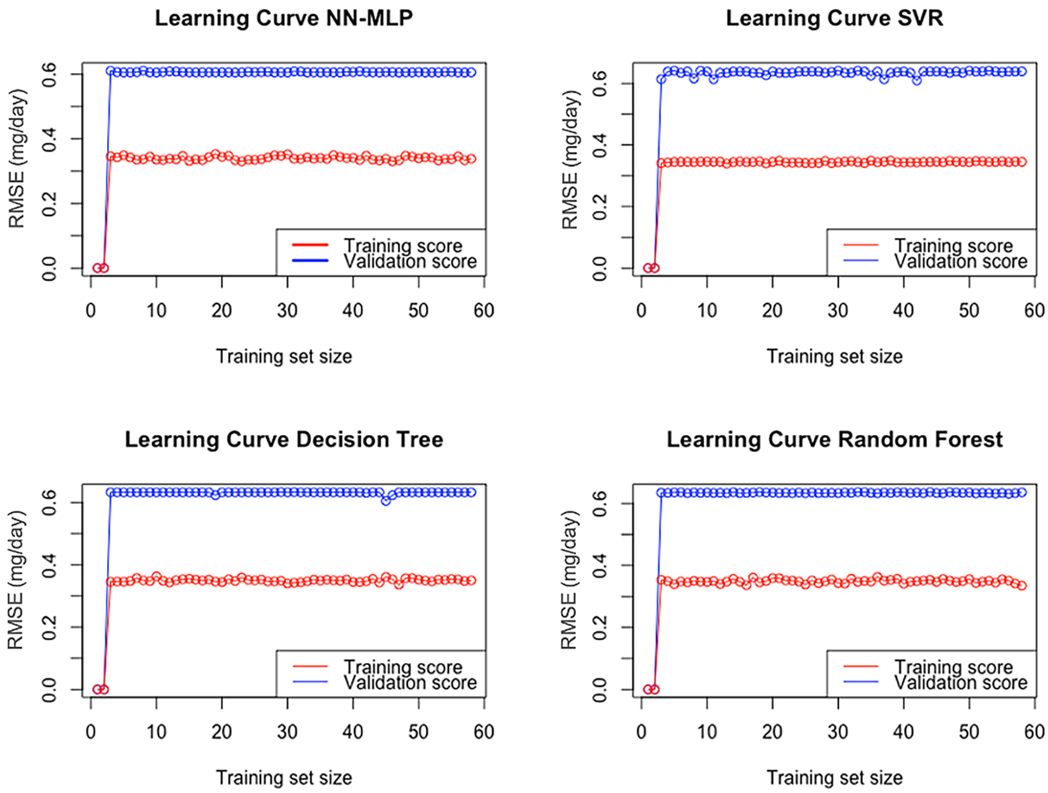

Figure 3. Learning curve of machine learning regression models

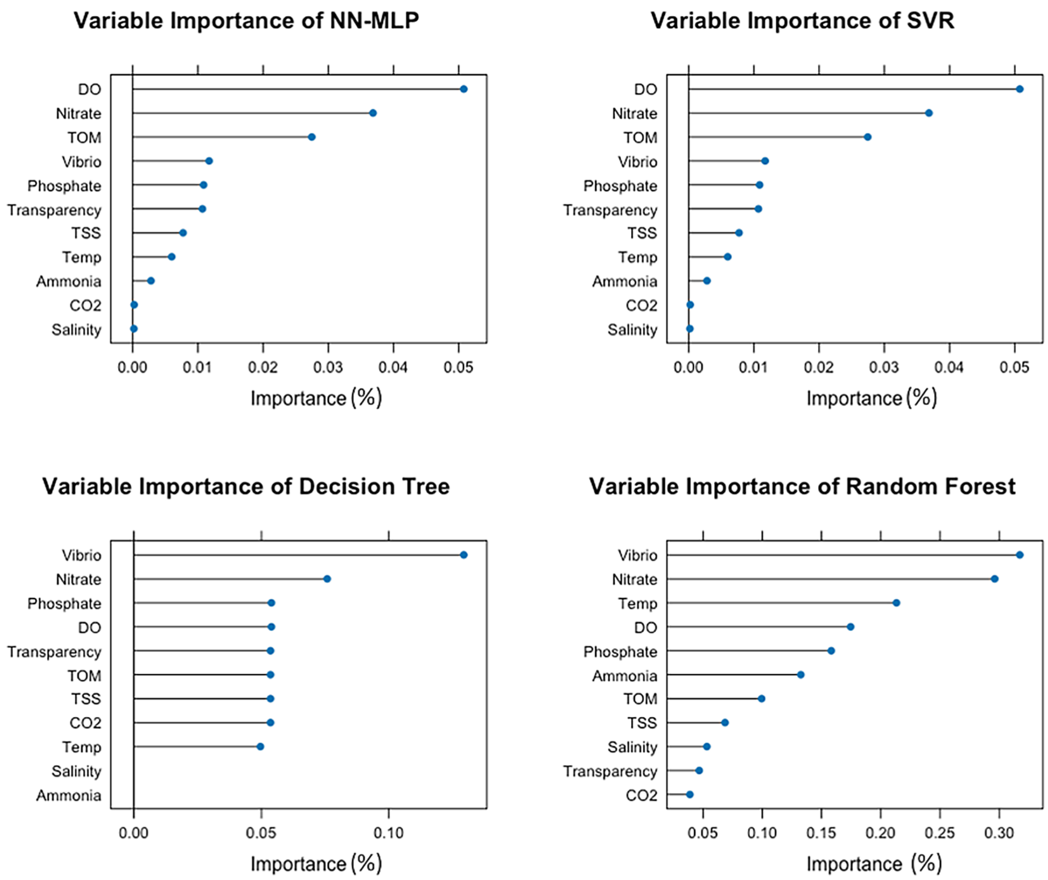

Figure 4. Water quality variable importance in predicting shrimp growth

investigations have shown that organisms in aquaculture have trouble metabolising food under low oxygen conditions, as oxygen is crucial for metabolic processes [Álvarez et al., 2023].

The setting up of elevated oxygen levels in the pond has significantly improved growth conditions by reducing total bacteria, viruses, and diseases, while also enhancing feed conversion efficiency, thus promoting optimal shrimp growth [Patkaew et al., 2024]. The study conducted by Nonwachai et al. (2011) indicated that increased oxygen levels lead to higher immune variable levels, evaluated via total haemocyte count, percentage phagocytosis, bactericidal activity, phenoloxidase activity, and superoxide dismutase activity. Shrimp exhibited effective physiological responses and demonstrated robust resistance to the pathogen when maintained at optimal stable oxygen levels. Elevated oxygen concentrations facilitate bacterial autolysis, improve biological lysis processes, and result in reduced sludge generation. The noticed conditions resulted in a decrease in entire vibrio as well as viral infection concentrations in shrimp [Ahmadi et al., 2018].

Moreover, a study performed by [Musa et al., 2024]reported the disease outbreak that occurred in eco-green aquaculture pond at 2022. The disease may cause by vibrio organism and resulted to early harvest at the eight weeks. The pond was identified by the emerging of blue-green algae dominance and thus making the shrimp more prone to viral infection [Anderson et al., 2012]. Therefore, the result if this study strengthen that the total vibrio factor highly determine the successfulness of shrimp aquaculture venture in eco-green system.

On the other hand, the high intensification of shrimp resulted in demanded high concentration of artificial feed and thus resulted to large number of feed left-over. This will cause the release of nitrogen compound in the environment, especially in shrimp-rearing pond [Musa et al., 2023b]. One of the substances from nitrogen in aquatic ecosystem is nitrate [Wasielesky et al., 2017]. Previous research indicated that prolonged exposure to risen nitrate levels (> 6.67 mg/L) adversely affects shrimp growth and disrupts immune function by compromising gut microbiota homeostasis [Prates et al., 2024]. Following nitrate exposure, the shrimp exhibited reduced growth; however, they subsequently regained their ability to grow when returned to control nitrate mechanisms [Huang et al., 2020].

CONCLUSIONS

Modelling whiteleg shrimp growth is important to ensure the profitability of this commodity's aquaculture venture. The shrimp growth can be modelled as the function of water quality variables. In this study, we used several machine learning regression models to analyze the effect of water quality factors on whiteleg shrimp growth reared in eco-green aquaculture system. The results showed that among the five machine learning technique that utilized in this study, model produced by decision tree and random forest outperformed those of NN-MLP and SVR during training phase. However, during validation or testing phase, the results were reversed. In further, the modelling results suggested that DO, nitrate levels, and Vibrio presence are the water quality variables that highly affect the daily growth predictions of shrimp in the eco-green system.

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