

Decision Tree-based Prediction of Hatching Efficiency in Mud Spiny Lobster (*Panulirus polyphagus*): Relative Importance of Body Weight, Carapace Length, and Water Quality

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ABSTRACT

Machine learning (ML) has been applied increasingly in aquaculture; however, its practical use in hatchery management remains limited due to challenges in model interpretability. This study developed an interpretable decision tree (DT) model to predict the hatching efficiency (HE) of mud spiny lobster (*Panulirus polyphagus*) in a hatchery system ($n = 72$), considering broodstock size indicators—carapace length (CL) and body weight (BW)—and key water quality parameters—temperature, salinity, dissolved oxygen (DO), pH, total ammonia nitrogen (TAN), nitrite (NO_2^-), and alkalinity). The objectives were to compare BW and CL performance, identify key factors affecting hatching success, and establish threshold-based decision rules for hatchery management. Preliminary regression analysis showed that simple linear models could not adequately capture the relationship between broodstock size and HE. However, BW performed relatively better than CL and was therefore selected for subsequent DT modeling. HE was classified into two groups using K-means clustering: low ($<40.5\%$) and high ($\geq 40.5\%$). The DT model achieved an overall classification accuracy of 62.50% based on 10-fold cross-validation of the complete dataset ($n = 72$), with variable classification performance between HE groups. In particular, the model showed limited ability to identify the high-HE group, with a recall of 0.11 and F1-score of 0.18. TAN, DO, and BW were identified as the most influential variables, with nitrite also contributing to the decision rules for hatchery management. Maintaining TAN below $0.14 \text{ mg-N}\cdot\text{L}^{-1}$ was associated with higher HE, particularly in broodstock weighing 819.5–895.6 g, while a higher TAN value was associated with reduced performance. In addition, DO levels above $4.95 \text{ mg}\cdot\text{L}^{-1}$ improved HE in larger broodstock ($>904 \text{ g}$). Based on these findings, the DT model may serve as an exploratory and interpretable decision-support tool for understanding HE patterns and informing broodstock and water quality management in sustainable lobster hatchery systems, while further model development and validation are needed before its use as a reliable predictive system.

Keywords: Lobster aquaculture decision support, Machine learning, Model prediction performance, Mud spiny lobster breeding

INTRODUCTION

Lobsters are an economically important aquatic resource, based on a high market value, strong consumer demand, and a wide geographic distribution across marine regions (Tuffley *et al.*,

2021; FAO, 2022). However, increasing demand has led to the continuous decline of wild lobster populations in many areas. Consequently, research efforts in both the public and private sectors have intensified to develop sustainable lobster aquaculture systems to compensate for reduced

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wild stocks and to ensure long-term production (Azra *et al.*, 2022).

In Southeast Asia, the mud spiny lobster (*Panulirus polyphagus* Herbst, 1793) has been studied widely in breeding, nursery, and grow-out systems (Petersen *et al.*, 2020; Nankervis and Jones, 2021; Oniam *et al.*, 2021; 2024; Arkronrat *et al.*, 2024). Despite these advancements, there remain major challenges in hatchery operations, particularly in understanding the relationships among environmental conditions, broodstock characteristics, and hatching performance. Variability in water quality parameters and broodstock size has been shown to influence hatching efficiency; however, often, these relationships are complex, nonlinear, and difficult to interpret, limiting effective decision-making and hindering the optimization of hatchery performance.

In more recent years, machine learning (ML) techniques have been applied increasingly in aquaculture to address such complexities. ML approaches can analyze multidimensional datasets and capture nonlinear interactions among variables, thereby improving predictive performance and enabling data-driven decision-making (Li *et al.*, 2020; Islam *et al.*, 2021). Applications of ML in aquaculture include environmental monitoring, feeding optimization, and production management (Jongjaraunsuk and Taparhudee, 2022; Zeng *et al.*, 2022; Imran *et al.*, 2025). Nevertheless, many advanced ML models, particularly deep learning and ensemble methods, often function as “black-box” systems, making their decision processes difficult to interpret and apply in practical aquaculture settings. Although these approaches can achieve high levels of predictive performance in many tasks, such as fish behavior analysis, water quality prediction, and intelligent feeding systems, their internal decision mechanisms remain largely opaque to end-users (Sun *et al.*, 2020; Wu *et al.*, 2025). This lack of transparency can limit their practical adoption, as aquaculture practitioners may find it difficult to understand, trust, and validate model outputs under real-world conditions (Alsakran *et al.*, 2025), thereby creating challenges in real-world implementation.

Model interpretability is critically important in aquaculture applications, especially in hatchery management. Farmers and hatchery operators require transparent and understandable decision rules to confidently apply model outputs in real-world conditions. Decision tree (DT) models provide a practical solution to this challenge, as they generate explicit, rule-based structures that clearly describe how input variables influence outcomes (Molnar *et al.*, 2020). In addition, DT models can identify key threshold values, such as dissolved oxygen, total ammonia nitrogen, and broodstock size, and translate complex relationships into actionable management guidelines (Huan *et al.*, 2020; Ryo *et al.*, 2020; Gkikas *et al.*, 2024). Other studies have demonstrated that DT-based approaches are effective at supporting aquaculture decision-making by identifying critical environmental thresholds and improving the understanding of factors influencing aquatic animal health and production performance.

Despite these advantages, there has been limited application of interpretable ML approaches in lobster hatchery management. In particular, there has been no clear relationship established regarding the relative importance of broodstock size indicators, such as body weight (BW) and carapace length (CL), in predicting hatching efficiency. Addressing this gap is essential for improving broodstock selection and optimizing hatchery outcomes. Therefore, the current study aimed to develop an interpretable DT model to evaluate the relationships between broodstock size and water quality parameters and the hatching efficiency of mud spiny lobster. Specifically, the objectives were: (i) to compare the predictive performance of BW and CL in relation to hatching efficiency, (ii) to identify the most influential variables affecting hatching success, and (iii) to establish threshold-based decision rules to support broodstock selection and water quality management. By emphasizing interpretability and practical applicability, this study should bridge the gap between machine learning techniques and real-world aquaculture practices, thereby supporting sustainable hatchery management and improving production efficiency.

MATERIALS AND METHODS

Study design and data sourcing

The data were obtained from a hatchery at the Klongwan Fisheries Research Station in Prachuap Khiri Khan Province, Thailand. Ovigerous female mud spiny lobsters were captured by local fishers using lobster traps in Thailand's Andaman Sea coastal region, transferred to the hatchery, and reared individually in 500 L fiberglass incubation tanks. The females were measured for carapace length (CL) in centimeters with vernier calipers and for body weight (BW) to the nearest gram. All lobsters were fed daily at approximately 4:00 pm with 4–5 live green mussels (*Perna viridis*) until hatching (Oniam *et al.*, 2021).

Fecundity was defined as the number of eggs per batch produced by a female and was estimated using a volumetric method. Briefly, three 100 mL aliquots from the hatching tank were counted for larvae, the average was calculated, and the total larvae per female was derived from the mean larvae per 100 mL. Fecundity was defined as the sum of newly hatched phyllosomal larvae and unhatched eggs, while the hatching rate was the percentage of larvae produced relative to the total number of eggs (Oniam *et al.*, 2021).

During the rearing period, approximately one-half of the water in each rearing tank was exchanged every three days after water quality measurements. Dissolved oxygen (DO) and temperature using an oxygen probe (Pro20i; YSI; USA), salinity was measured using a refractometer (Master-S10 alpha; Atago; Japan), pH using a portable pH meter (pH Testr30; Eutech; Singapore), and total ammonia nitrogen (TAN), nitrite, and alkalinity were determined using indophenol blue, colorimetric, and titration methods, respectively (APHA, AWWA, and WEF, 2023).

Data preprocessing

Model development was based on the CL, BW, and mean water quality parameters recorded during each hatching event as input variables. Data preprocessing was conducted to ensure data

quality and suitability for DT analysis, following standard practices in environmental and biological datasets (Brijith, 2023; Zhurakovskiy *et al.*, 2025).

Data quality assessment was performed to identify missing values and outliers. Missing data were handled using mean imputation or by excluding incomplete records, while outliers were evaluated based on biological plausibility to minimize bias and improve model reliability (Zhurakovskiy *et al.*, 2025). Categorical variables, if present, were converted into numerical forms for analysis. As DT models are non-parametric and insensitive to feature scaling (Ryo, 2022), normalization or standardization was not applied, thus preserving the original data distribution and enhancing interpretability.

Additionally, the K-means clustering was used to classify the hatching efficiency (HE) into two groups, where group 1 represented low performance (<40.5% HE), and Group 2 represented high performance ($\geq 40.5\%$ HE), following Omar *et al.* (2022). The 40.5% cutoff represented the boundary between the two clusters identified by the K-means analysis. This classification supported the development of an interpretable DT model capable of generating clear rule-based predictions for hatchery management.

Preliminary regression analysis

A preliminary regression analysis was conducted to evaluate the individual relationships between broodstock size indicators and HE, with HE specified as the dependent variable and BW or CL as the independent variable in separate regression models. Each variable was analyzed separately to assess its predictive performance prior to model development. Model performance was evaluated using the coefficient of determination (R^2) and mean squared error (MSE), which are standard metrics for regression analysis (Wang *et al.*, 2023). For each regression model, R^2 and MSE were evaluated using 10-fold cross-validation, with the cross-validated performance summarized across the folds. R^2 quantifies the proportion of variance in HE explained by the model, while MSE measures the average squared prediction error.

The results were used to compare the predictive capability of BW and CL and to guide the selection of the most appropriate variable for subsequent DT modeling.

Decision tree model development

The DT model was developed using a recursive partitioning algorithm, in which the dataset was iteratively split based on feature values that maximized class separation. The gain ratio criterion was used to select the optimal splitting variable at each node. Tree complexity was controlled using built-in pruning and pre-pruning techniques to improve model generalization while maintaining interpretability. The model was configured with a maximum tree depth of 10, a confidence level of 0.10, a minimum gain of 0.01, a minimum leaf size of 2, a minimum split size of 4,

and 3 pre-pruning alternatives. Model performance was evaluated using 10-fold cross-validation ($k = 10$) on the complete dataset ($n = 72$), and the average performance across the folds was used to estimate the model's cross-validated performance. Following cross-validation, the selected DT configuration was used to construct the final DT model using the complete dataset. The final model was then used to derive interpretable decision rules and identify the variables contributing to HE classification. These procedures provided a consistent evaluation of model performance while maintaining model interpretability (Ryo, 2022; Blockeel *et al.*, 2023).

The overall workflow of the DT modeling approach, including model implementation, training, and cross-validation procedures, is illustrated in Figure 1.

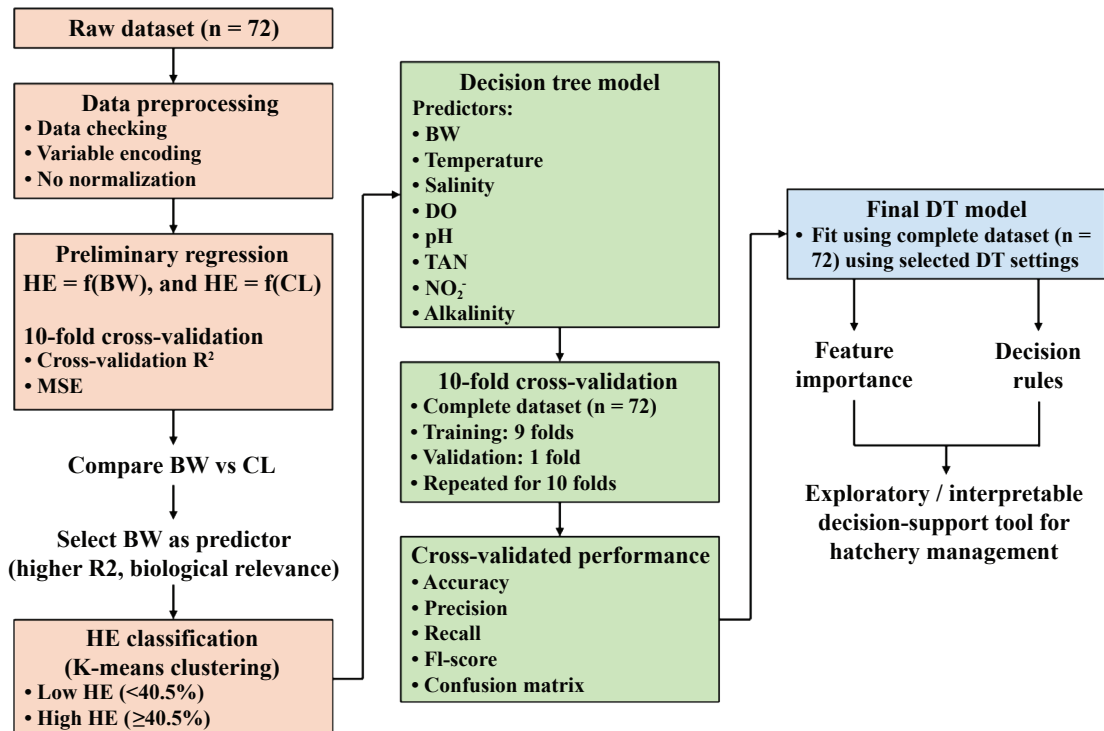


Figure 1. Overall workflow of the decision tree modeling approach, including data preprocessing, model implementation, training, and 10-fold cross-validation using the complete dataset ($n = 72$), model evaluation, and final model construction for classifying hatching efficiency (HE) in mud spiny lobster (*Panulirus polyphagus* Herbst, 1793).

Model evaluation and feature importance analysis

The performance of the DT model was evaluated using predictions from 10-fold cross-validation on the complete dataset with standard classification metrics (accuracy, precision, recall, F1-score), calculated using:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

where TP, TN, FP, and FN are the true positive, true negative, false positive, and false negative values, respectively.

A confusion matrix was generated to evaluate classification performance and identify misclassification patterns between low and high hatching efficiency groups. Model performance was evaluated using 10-fold cross-validation on the complete dataset. The confusion matrix was derived from the cross-validation predictions.

Feature importance was analyzed to identify the most influential variables contributing to HE classification. Variable importance was quantified based on the relative contribution of each predictor to the DT model, with higher importance scores indicating a greater influence on classification outcomes (Zhurakovskiy *et al.*, 2025). This analysis provided insights into the relative contributions of broodstock size (CL and BW) and key water quality parameters, supporting biological interpretation and practical decision-making in hatchery management.

Decision rule extraction and interpretation

Decision rules were extracted from the final tree structure in the form of “if–then” statements, linking threshold values of input variables to predicted hatching efficiency outcomes. These rules were used to identify critical thresholds for

key biological and environmental factors (Lundberg *et al.*, 2020), and were interpreted to provide practical guidance for broodstock selection and water quality management in hatchery systems.

Software and implementation

All data preprocessing, regression analysis, and model development were performed using Altair® AI Studio (Version 2025.1.0; Altair Engineering Inc., USA). Regression analysis was conducted to evaluate the relationships between broodstock size indicators (BW and CL) and hatching efficiency, with HE specified as the dependent variable, using 10-fold cross-validated R^2 and MSE as performance metrics. The DT model was implemented using built-in operators for classification, validation, and feature importance analysis. Data visualization, based on DT structures and performance plots, was generated to support result interpretation.

RESULTS

In total, 72 female mud spiny lobsters (*P. polyphagus*) were analyzed. The mean BW was 685.2 ± 198.6 g (range = 372.8–1,117.5 g), whereas the mean CL was 91.8 ± 9.2 mm (range = 74–110 mm), and the descriptive statistics of measured water quality parameters are summarized in Table 1.

Simple regression analyses were conducted using BW and CL as individual predictors to provide a preliminary assessment of their relationships with HE. Both BW and CL showed limited predictive performance based on the 10-fold cross-validated results, with R^2 values of -0.22 and -0.35, respectively. These negative R^2 values indicate that both regression models performed worse than a baseline model that predicts HE using its mean value. Because HE was used as the dependent variable in both regression models, the MSE values were expressed on the same response scale (HE^2) and were therefore directly comparable. BW was selected for subsequent decision tree modeling because it showed relatively better cross-validated performance than CL, as indicated by its higher R^2 value, and was considered more biologically relevant as an indicator of broodstock condition (Figure 2).

Table 1. Water quality parameters recorded during ovigerous female mud spiny lobster (*Panulirus polyphagus*) rearing and hatching, and used for decision tree model development (at 30 ‰ salinity).

Parameter	Mean±SD	Range
DO (mg·L ⁻¹)	5.53±0.92	4.21–7.50
Temperature (°C)	28.89±1.54	26.3–32.5
pH	8.30±0.13	8.07–8.70
TAN (mg·N·L ⁻¹)	0.11±0.05	0.02–0.21
Nitrite (mg·N·L ⁻¹)	0.02±0.07	0.01–0.37
Alkalinity (mg·L ⁻¹ CaCO ₃)	140.64±16.54	111.00–174.00

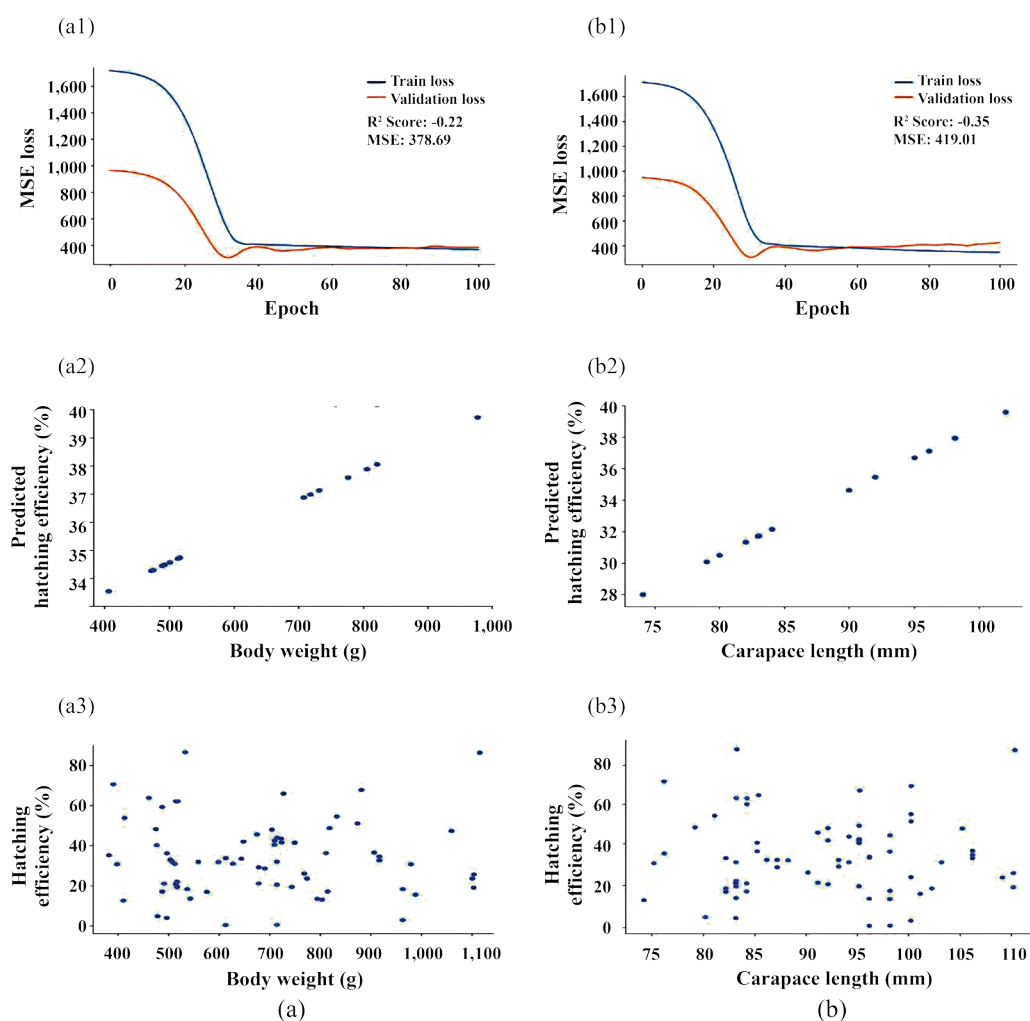


Figure 2. Regression analysis of (a) body weight (BW) and (b) carapace length (CL) in relation to hatching efficiency in mud spiny lobster (*Panulirus polyphagus*). Subpanels (a1–a3) and (b1–b3) represent training and validation loss curves, predicted HE in relation to BW or CL, and the corresponding HE relationships, respectively. Regression performance was evaluated using 10-fold cross-validation, with cross-validated R^2 values of -0.22 for BW and -0.35 for CL, indicating limited predictive performance.

Overall, CL alone showed poorer predictive performance than BW, although both regression models performed worse than a mean-based baseline. BW was therefore retained for subsequent DT modeling based on its relatively less negative cross-validated R^2 and greater biological relevance to broodstock condition, rather than on evidence of strong standalone predictive ability.

Following cross-validation, the selected DT configuration was used to construct the final model, from which the decision rules and key variables associated with HE classification were derived. It should be noted that this final model was trained on the complete dataset and is therefore structurally distinct from the ten individual models generated during cross-validation; the decision rules reported below thus represent the structure of the final model, while the accuracy, precision, recall, and F1-score reported are cross-validated estimates of the general modeling approach rather than of this specific final tree. The DT model classified HE into low (<40.5%) and high ($\geq$ 40.5%) groups. Based on the 10-fold cross-validation predictions, the confusion matrix analysis (Table 2) showed that the model achieved higher classification performance for the low HE group (Group 1), with a recall of 0.91 and a precision of 0.64. In contrast, the model showed limited ability to correctly identify high HE cases (Group 2), with a recall of only 0.11 and a precision of 0.42. This imbalance in precision and recall was reflected further in the F1-score, which was low for the high HE group (F1 = 0.18), indicating limited performance in

identifying high-HE cases. Based on these results, the model correctly classified most low-HE cases but had limited ability to detect high-HE cases, as reflected by the low recall for Group 2 (11%), with 23 high-HE observations misclassified as Group 1. Although the overall accuracy reached 62.50%, the discrepancy among the evaluation metrics suggested that model performance was more favorable for the more prevalent class (Group 1), and the model may therefore have limited reliability for identifying high-efficiency conditions. This highlighted the importance of using multiple evaluation metrics beyond accuracy when assessing classification models.

The DT model identified several key variables associated with HE classification: TAN, DO, broodstock BW, and nitrite. Among these, TAN, DO, and BW were the most influential factors, appearing at higher levels of the tree structure and indicating their greater contribution to the classification process. The relationships between BW and key water quality parameters (TAN, DO, NO_2^-) influencing HE, as predicted by the DT model, are illustrated in Figure 3.

Furthermore, the DT model revealed that TAN was the most influential variable associated with HE classification, followed by DO and BW. When TAN concentrations were maintained below $0.14 \text{ mg-N}\cdot\text{L}^{-1}$, female lobsters with BW in the range of 819.5–895.6 g achieved HE values of at least 40.5%. In contrast, TAN levels exceeding $0.14 \text{ mg-N}\cdot\text{L}^{-1}$ were associated with reduced HE (<40.5%).

Table 2. Confusion matrix of decision tree model developed using body weight (BW) for classifying hatching efficiency (HE) in mud spiny lobster (*Panulirus polyphagus*) into low (<40.5%, Group 1) and high ($\geq$ 40.5%, Group 2) categories.

Actual / Predicted	Low HE (Group 1)	High HE (Group 2)
Low HE (Group 1)	42 (TN)	4 (FP)
High HE (Group 2)	23 (FN)	3 (TP)
Performance metric		
Precision	0.64	0.42
Recall	0.91	0.11
F1-score	0.76	0.18
Accuracy	62.50%	

Note: TN = true negative; FP = false positive; FN = false negative; TP = true positive.

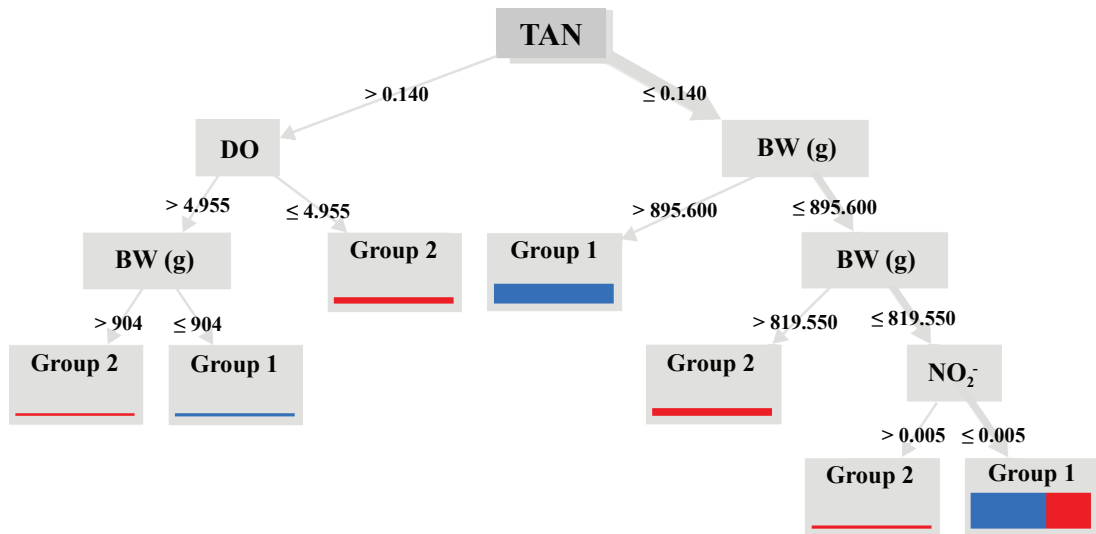


Figure 3. Decision tree -based prediction of hatching efficiency in mud spiny lobster (*Panulirus polyphagus*) as influenced by broodstock body weight (BW) and water quality parameters — dissolved oxygen (DO), total ammonia nitrogen (TAN) and nitrite (NO₂⁻). Hatching efficiency was classified into two groups: low (<40.5%, Group 1) and high (≥40.5%, Group 2).

Additionally, DO levels above 4.95 mg·L⁻¹ were associated with HE ≥40.5% for female broodstock weighing more than 904 g.

Overall, these findings highlighted the important roles of TAN, DO, and BW in HE classification and demonstrated the ability of the DT model to generate interpretable decision rules for classification.

DISCUSSION

In this study, decision tree (DT) modeling was used as the primary analytical approach to identify interpretable relationships between broodstock characteristics, environmental conditions, and hatching efficiency (HE), rather than to compare different modeling algorithms. The DT model provided an interpretable exploratory framework, with an overall cross-validated classification accuracy of 62.50%. However, classification performance differed between HE groups, with lower recall and F1-score for the high-HE class than for the low-HE class. Therefore, overall accuracy alone may not adequately reflect class-specific performance.

In this study, precision, recall, and F1-score indicated better classification performance for low HE than high HE. The high-HE class comprised 26 of 72 observations (36.1%), compared with 46 (63.9%) for low HE, which may have increased uncertainty in the performance estimates for high HE, particularly recall and F1-score. Thus, these metrics should be interpreted cautiously, as performance may also reflect the limited sample size and biological and environmental variability.

A key advantage of the DT model lies in its ability to generate transparent decision rules that directly link input variables to biological outcomes. In the current study, TAN, DO, and BW were identified as the most influential factors affecting hatching efficiency. The extracted rules indicated that maintaining the TAN concentration below 0.14 mg·N·L⁻¹ was critical for achieving high hatching success, whereas levels above this threshold were associated with reduced performance. This finding was consistent with other studies demonstrating the toxic effects of TAN on aquatic organisms, particularly during the early developmental stages, where elevated TAN can impair embryogenesis and reduce survival.

rates (Islam *et al.*, 2021; Azra *et al.*, 2022). DO also played a major role in determining hatching outcomes. The model indicated that DO levels above 4.95 mg·L⁻¹ were associated with improved HE, particularly in larger broodstock individuals. Adequate oxygen availability is essential for embryonic metabolism and energy production, with insufficient DO being reported widely to cause physiological stress and developmental abnormalities in aquatic species (Li *et al.*, 2020; Imran *et al.*, 2025). These findings highlighted the importance of maintaining optimal oxygen conditions in hatchery systems to support successful larval development. BW was another important factor influencing hatching efficiency, suggesting that larger females may have greater reproductive capacity and energy reserves, which contributed to improved egg quality and hatching success. This observation aligned with other research indicating that broodstock size was positively correlated with reproductive performance in crustaceans and other aquaculture species (Azra *et al.*, 2022).

Although both BW and CL showed poor predictive performance, BW had a less negative cross-validated R² than CL (-0.22 vs. -0.35). Because both models used HE as the same response variable, their MSE values were directly comparable. It should be emphasized that negative R² values for both variables indicate that neither BW nor CL alone provided an adequate linear predictor of HE, with both models performing worse than a mean-based baseline; the comparison between them was therefore relative rather than an indication that either variable was independently adequate. Although BW was not a reliable standalone predictor of HE, it showed relatively better explanatory performance and greater biological relevance as an indicator of broodstock condition. Therefore, BW was selected for subsequent decision tree modeling, on this relative and biological basis rather than on demonstrated standalone predictive adequacy. Furthermore, the observed interaction between BW and environmental conditions highlighted the importance of integrated management strategies that consider both biological and physicochemical factors.

From a practical perspective, the DT model provided actionable insights for hatchery management. The identified thresholds for TAN and DO, together with broodstock size, provide potentially useful decision rules for hatchery management. However, these thresholds should be regarded as exploratory decision rules rather than fixed management guidelines, given the limited sample size and absence of external validation. In particular, given the low recall (0.11) and F1-score (0.18) obtained for the high-HE group, the model's ability to positively identify broodstock or conditions likely to achieve high hatching efficiency remains limited; the identified thresholds are therefore more informative as indicators associated with low-HE avoidance than as reliable predictors of high-HE outcomes at this stage. Unlike more complex machine learning approaches, the DT model allows practitioners to easily interpret and apply these rules in real-world settings, making it particularly suitable for aquaculture applications where simplicity and transparency are essential (Molnar *et al.*, 2020; Alsakran *et al.*, 2025).

The application of ML in aquaculture has been recognized increasingly for its potential to enhance productivity, sustainability, and operational efficiency (Sun *et al.*, 2020; Gladju *et al.*, 2022; Zeng *et al.*, 2022; Imran *et al.*, 2025; Wu *et al.*, 2025). However, there has been only limited application in lobster aquaculture, particularly for hatchery management. The current study was one of the first attempts to apply an interpretable ML approach to predict hatching efficiency in mud spiny lobster, thereby contributing novel insights to the field. These findings should provide a foundation for developing decision-support tools, such as predictive applications or real-time monitoring systems, to optimize broodstock management and environmental control in hatchery operations.

The overall accuracy of 62.50% falls within the range reported in some previous aquaculture ML studies; however, direct comparisons should be interpreted cautiously because datasets, study conditions, variables, and validation procedures differ among studies (Kurniawan and Tiaharyadini,

2025; Saville *et al.*, 2026). Although deep learning models, including long short-term memory (LSTM) networks and convolutional neural networks (CNNs), can achieve higher predictive accuracy in some cases, they are often limited by their “black-box” nature, which reduces transparency and practical usability (Sun *et al.*, 2020; Wu *et al.*, 2025). In contrast, the DT model provided greater interpretability by generating explicit “if–then” decision rules, allowing users to more readily examine the relationships between input variables and outcomes. This transparency makes DT particularly suitable for real-world aquaculture management, where practical decision-making and ease of interpretation are essential (Huan *et al.*, 2020; Gkikas *et al.*, 2024; Alsakran *et al.*, 2025; Tullós *et al.*, 2025).

The present study has several limitations. The relatively small and imbalanced dataset may limit model generalizability, and no class-balancing or data augmentation techniques were applied. The DT model was evaluated using 10-fold cross-validation within a single dataset without external validation, while its relatively flexible settings may increase the risk of overfitting; therefore, the identified decision thresholds should be considered exploratory and may vary with larger or independent datasets. This study focused on DT as the primary analytical approach rather than comparison with alternative models. In addition, temperature, pH, and alkalinity did not appear as splitting variables in the final tree, and salinity was maintained at a constant 30‰ throughout the rearing period; consequently, their absence from the decision rules reflects the structure of this particular model and dataset and should not be interpreted as evidence that these parameters have no biological influence on hatching efficiency. Future studies should use larger and more diverse independent datasets, particularly additional high-HE cases, to validate model performance and threshold stability across production conditions and improve model robustness and generalizability (Qiu, 2024; Zhurakovskiy *et al.*, 2025).

CONCLUSIONS

The developed interpretable decision tree model provided an exploratory framework for understanding hatching efficiency in mud spiny lobster (*Panulirus polyphagus*) using broodstock characteristics and water quality parameters. Total ammonia nitrogen (TAN), dissolved oxygen (DO), and broodstock body weight were identified as the most influential variables, with threshold-based rules indicating that maintaining $\text{TAN} < 0.14 \text{ mg-N}\cdot\text{L}^{-1}$ and $\text{DO} > 4.95 \text{ mg}\cdot\text{L}^{-1}$ was associated with improved hatching performance. However, the model showed limited ability to identify the high-HE group, indicating that further model development and external validation are needed to assess and improve its generalizability and classification performance. Overall, the findings highlighted the potential of interpretable machine learning as an exploratory decision-support tool for informing broodstock selection and environmental management, thereby supporting sustainable aquaculture practices.

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