Journal of Agrocomplex and Engineering

e-ISSN 3109-9955 (online)

Volume 2, Issue 1 2026
Page 33-42

https://doi.org/xxxxxx

Application of Machine Learning for Early Stress Detection in Cultured Fish Based on Water Quality Fluctuation Patterns

Rahmat Saleh Mopangga[1]

[1]Aquaculture Technology Study Program, Muhammadiyah University of Gorontalo, Indonesia

ARTICLE INFO

Received: 19 December 2025
Revised: 13 January 2026
Accepted: 25 January 2026
Available online: 29 January 2026

Keywords:
Early Stress Detection
Machine Learning
Aquaculture
Water Quality
Random Forest

Corresponding Author:
Rahmat Saleh Mopangga

Email:
rahmatsalehmopangga@gmail.com

ABSTRACT

***Purpose**: This study aims to develop a machine learning–based approach for the early detection of stress in cultured fish by analyzing fluctuations in key water quality parameters. Early identification of stress conditions is essential for maintaining fish welfare, reducing mortality, and improving the productivity of intensive aquaculture systems.*

***Subjects and Methods:** This study employed a quantitative experimental approach to develop a machine learning–based model for the early detection of stress in cultured fish using water quality parameters. Water quality data, including dissolved oxygen, ammonia, pH, nitrite, and temperature, were continuously collected from an intensive aquaculture system using environmental sensors. Fish behavioral indicators were used to label stress and non-stress conditions. Three machine learning algorithms Random Forest, Support Vector Machine, and Artificial Neural Network were applied and evaluated using accuracy, precision, recall, F1-score, and AUC metrics.*

***Results:** The results indicated that dissolved oxygen and ammonia were the most significant predictors of fish stress, while pH and nitrite played supporting roles in influencing stress dynamics. Among the tested models, the Random Forest algorithm demonstrated the highest accuracy and stability in predicting stress conditions. The model effectively captured nonlinear relationships and temporal patterns within the dataset. Based on this model, an early warning system was developed to detect potential stress several hours before visible physiological or behavioral symptoms occurred.*

***Conclusions:** The integration of continuous water quality monitoring with machine learning techniques provides an effective predictive framework for aquaculture management, enabling proactive interventions, improving fish welfare, and supporting sustainable aquaculture practices.*

INTRODUCTION

Aquaculture is a rapidly growing food production sector and plays a crucial role in supporting global food security and regional economic growth (Telaumbanua & Zebua, 2026; Pradeepkiran, 2019; Gul et al., 2024). Increasing fish consumption has driven the adoption of intensive farming systems that emphasize production efficiency, high stocking densities, and input optimization. However, this intensification is often accompanied by increased environmental stress, particularly unstable water quality fluctuations. Unbalanced water conditions can trigger physiological stress in fish, reduce growth rates, increase susceptibility to disease, and cause significant economic losses for farmers (Rahantoknam et al., 2025; Wanja et al., 2020; Hossain et al., 2011). Therefore, developing an early detection system for fish stress is a strategic necessity for maintaining the sustainability and productivity of modern aquaculture.

Stress in fish is a complex biological response influenced by the interaction of various environmental, chemical, and biological factors. According to Menon et al. (2023); Bal et al. (2022), water quality parameters such as temperature, dissolved oxygen, pH, ammonia, nitrite, and salinity play a direct role in regulating the metabolic balance and homeostasis of aquatic organisms. Even small, sudden changes or long-term fluctuations can trigger chronic stress, impacting production performance. Conventional approaches to stress detection generally rely on visual observation, manual measurements of water quality, or laboratory analysis of physiological biomarkers (Muhammad et al., 2025; Wasilewski et al., 2024). These methods are relatively expensive, time-consuming, and reactive, making them less effective for early prevention.

Developments in environmental sensor technology and the Internet of Things (IoT) enable real-time and continuous water quality monitoring. These systems generate large-scale data that represent the temporal and spatial dynamics of water conditions (Cabecinha et al., 2009). However, the large data volume and non-linear relationships between parameters complicate analysis using conventional statistical approaches. Complex water quality fluctuation patterns often contain hidden information that is difficult to interpret manually (Mounce et al., 2015; Ahmed et al., 2020). Therefore, computational methods capable of extracting patterns, identifying anomalies, and generating accurate predictions are needed to support data-driven decision-making.

Machine learning offers an effective approach to analyzing complex and high-dimensional data. Kyriazos, T., & Poga (2024) said that, machine learning algorithms are able to learn patterns from historical data and build predictive models without relying on strict linearity assumptions. In aquaculture, this technology has been applied to predict water quality, classify fish diseases, optimize feeding, and estimate biomass production (Mandal & Ghosh, 2024; Alnemari et al., 2025; Aftab et al., 2024). Previous research has shown that machine learning can improve prediction accuracy and operational efficiency compared to traditional methods, potentially driving the transformation of aquaculture systems toward a more intelligent and adaptive approach.

Despite its significant potential, the application of machine learning for early detection of fish stress remains relatively limited. Most research focuses on predicting environmental parameters or diagnosing disease, without explicitly integrating water quality fluctuation patterns with fish's physiological stress responses (Mukherjee et al., 2017). Stress is an early indicator that often appears before disease or production failure. By modeling the temporal relationship between environmental variables and biological responses, machine learning-based systems can identify early warning signals that are not detected through conventional observations.

The development of machine learning-based early warning systems offers strategic benefits for aquaculture management. These systems enable farmers to proactively intervene, such as adjusting aeration, managing water changes, and adjusting stocking densities. Furthermore, automated monitoring reduces reliance on subjective operator judgment and improves decision-making consistency. Utilizing historical data also supports long-term performance evaluation and empirically evidence-based optimization of production strategies (Zega et al., 2025; Rahman, 2025; Vudugula et al., 2023).

The integration of machine learning with digital sensors aligns with the concept of smart aquaculture and the industry 4.0 paradigm, which emphasizes digitalization, automation, and resource efficiency (Hariyono et al., 2024). An early detection system for fish stress can be a key component of a smart aquaculture ecosystem by linking environmental monitoring with real-time biological responses. This approach not only increases productivity but also supports sustainable aquaculture practices through waste reduction, energy efficiency, and improved welfare of farmed organisms.

Based on this background, this study aims to apply machine learning to detect early stress in farmed fish based on water quality fluctuation patterns (Hridoy et al., 2025; Shreesha et al., 2023;

Baena-Navarro et al., 2025). This research is expected to produce a reliable predictive model, identify the environmental parameters most influential on fish stress, and provide a framework for implementing an intelligent monitoring system at an operational scale. This research contribution is expected to strengthen the adoption of digital technology in aquaculture and support the development of more resilient, efficient, and sustainable production systems. These findings are expected to serve as a scientific reference for policy development, technological innovation, and sustainability-oriented aquaculture management strategies at national and international levels for a sustainable global future.

METHODOLOGY

This study employed a quantitative experimental approach to develop a machine learning–based model for the early detection of stress in cultured fish using water quality parameters. The research was conducted in an intensive aquaculture system where environmental conditions were continuously monitored to capture fluctuations that may influence fish physiological stress. The primary water quality parameters observed in this study included dissolved oxygen, ammonia, pH, nitrite, and water temperature, as these variables are widely recognized as critical indicators affecting fish health and environmental stability in aquaculture systems. Water quality data were collected using environmental monitoring sensors installed in the culture ponds. The sensors recorded the parameters at regular intervals, generating a multivariate dataset that reflects dynamic changes in water quality conditions over time. In addition to environmental monitoring, fish behavioral and physiological indicators were observed to determine stress conditions. These indicators included changes in respiration rate, abnormal swimming activity, and reduced feeding behavior. Based on these observations, the dataset was labeled into stress and non-stress conditions to support the development of predictive models. Prior to model development, the dataset underwent a series of preprocessing procedures. These included data cleaning to remove incomplete or inconsistent records, normalization to standardize the scale of different variables, and feature selection to identify the most relevant parameters influencing fish stress. The processed dataset was then divided into training and testing subsets to ensure reliable model evaluation. Three machine learning algorithms were implemented and compared in this study, namely Random Forest, Support Vector Machine, and Artificial Neural Network. These algorithms were selected due to their capability to capture nonlinear relationships and complex interactions among environmental variables. The models were trained using the training dataset and subsequently evaluated using the testing dataset. Model performance was assessed using several classification metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve. These metrics were used to evaluate the predictive performance and stability of each algorithm in identifying stress conditions in cultured fish. Furthermore, feature importance analysis was conducted using the Random Forest model to determine the relative contribution of each water quality parameter to stress prediction. Based on the best-performing model, an early warning framework was developed to detect potential stress conditions in aquaculture environments before observable physiological or behavioral symptoms appear. This predictive system allows aquaculture managers to take timely management actions, such as adjusting aeration, water circulation, or feeding strategies, to maintain optimal environmental conditions and improve fish welfare and productivity.

RESULTS AND DISCUSSION

Analysis of Water Quality Fluctuation Patterns

Analysis of water quality fluctuation patterns indicates that physical and chemical water parameters interact in a complex manner and significantly influence the physiological state of farmed fish. Variations in parameters such as temperature, pH, dissolved oxygen (DO), and inorganic nitrogen levels have been shown to influence fish behavior and stress responses. Review studies indicate that changes in water quality can affect fish metabolism, internal organs, and sensory perception, which in turn modify behaviors such as swimming activity, feeding patterns, aggressiveness, and general stress responses (Sampaio & Freire, 2016; Dara et al., 2023). Water temperature is a physical factor that is highly sensitive to changes in the aquaculture environment. Sudden temperature fluctuations or those exceeding the species' tolerance limits can increase fish metabolic demands, accelerate respiration rates, and reduce oxygen solubility in the water. These conditions often trigger physiological stress, which occurs as an adaptive response of the fish's body to conditions that are less conducive to homeostasis (Agarwal et al., 2024). Temperature fluctuations are also associated with changes in other parameters such as dissolved oxygen and pH, thus affecting the energy density available for daily activities and growth.

Araújo-Luna et al. (2018) said that, dissolved oxygen is an important indicator of fish welfare because it plays a direct role in aerobic respiration. DO levels below the optimal threshold cause fish to experience hypoxia, accelerate the increase in stress, and inhibit growth efficiency and endurance (Anjarkasi et al., 2025). Decreased DO not only impacts respiration but also triggers adaptive behavioral changes such as surface breathing, reduced activity, and changes in feeding patterns, which indicate early signs of fish stress. Fluctuations in water pH have also been shown to contribute significantly to the stress response of farmed fish. A pH outside the optimal range can disrupt ion balance and enzyme function in the fish's body, as well as exacerbate the toxic effects of other parameters such as ammonia. A pH that is too low or too high not only inhibits physiological functions but also affects the fish's ability to regulate their osmotic pressure, impacting internal stress and long-term well-being.

Furthermore, inorganic nitrogen elements such as ammonia and nitrite exhibit fluctuation patterns that are closely related to metabolic processes and feed residues in the aquaculture system. Ammonia, which results from excretion and organic decomposition, is a toxin that can damage respiratory epithelial tissue and exacerbate stress responses at high concentrations (Parvathy et al., 2023). Nitrite, an intermediate product of the nitrogen cycle, can also impair the blood's ability to bind oxygen, which in turn accelerates physiological stress. Holistically, analysis of water quality fluctuation patterns indicates that fish stress responses are not the result of a single parameter, but rather the cumulative effect of multiple, dynamically interacting environmental factors. The temporal patterns of these parameters, both on a daily scale and across the culture cycle, reflect changing environmental conditions and require careful management. Helm et al. (2013) said that, a deep understanding of these patterns is crucial for designing machine learning-based prediction systems, where predictive models can detect anomalies in data and correlate them with potential stress conditions before symptoms of disease or fish mortality become apparent.

Machine Learning Algorithm Performance

This study evaluated the performance of several machine learning algorithms for early stress detection in farmed fish based on water quality fluctuation patterns. The algorithms tested included Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN). The evaluation was conducted using standard metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC), which were used to compare the predictive effectiveness of each model (Hatta & Irwansyah, 2025). Random Forest demonstrated superior performance in handling multivariate datasets with complex nonlinear relationships. This algorithm was able to consistently recognize water quality fluctuation patterns related to fish stress, with high precision and recall values, thus minimizing prediction errors, both false positives and false negatives (Saputra et al., 2024). RF also excels in assessing feature importance, allowing the model to highlight the water quality parameters most influential on fish stress.

Support Vector Machine demonstrated good ability to separate stressed and non-stressed classes, especially in relatively small datasets. SVM works by determining the optimal margin for classification, making it effective in data with high variability but limited quantity. However, SVM performance is strongly influenced by data scale and kernel selection, so proper preprocessing, such as data normalization, is necessary for optimal model performance. Jia et al. (2023) and Deng et al. (2024), Artificial Neural Networks offer flexibility in modeling highly complex nonlinear relationships and capturing subtle temporal patterns in data, including daily and seasonal fluctuations in water quality. ANNs require substantial data sets and computationally intensive training to prevent overfitting or underfitting. Furthermore, regularization techniques are often applied to improve the model's generalizability to new datasets (Nusrat & Jang, 2018). Evaluation results show significant performance differences between algorithms depending on data characteristics and the complexity of the relationships between parameters. Some algorithms excel at handling nonlinear patterns and large data sets, while others are better suited to limited datasets with high variability. These results provide a foundation for the development of machine learning-based monitoring systems applicable to fish farming with various environmental conditions and operational scales (Hossain et al., 2024).

Identify Key Parameters

Feature importance analysis was conducted to determine the water quality parameters that most influence stress in farmed fish. Using the Random Forest algorithm, the contribution of each feature was evaluated based on its influence on predicting fish stress conditions. The analysis results showed that dissolved oxygen (DO) and ammonia concentration (NH_3/NH_4^+) were the two main parameters that most influenced stress responses, consistent with previous findings emphasizing the importance of oxygen balance and the presence of inorganic nitrogen in supporting fish physiology. In addition to DO and ammonia, other parameters such as pH and nitrite also contribute to stress prediction, although their role is more modulatory. Sharp pH fluctuations can affect fish's ability to maintain ion balance and enzyme function, while high nitrite levels can disrupt the blood's ability to bind oxygen, which together trigger physiological stress. The combination of these parameters then forms a complex pattern that can be used to more accurately predict stress conditions. Feature importance analysis also revealed that interactions between parameters are often as important as individual parameter values. For example, an increase in ammonia levels followed by a decrease in dissolved oxygen had a greater impact on stress responses than changes in each parameter individually.

This finding aligns with research showing that fish stress results from the interaction of multiple environmental factors, rather than simply the effect of a single variable. Temporal data indicate that some parameters have a more dominant effect at certain times of the day or day. For example, a decrease in DO during the day due to increased water temperature tends to have a greater impact on stress than a decrease that occurs at night, because fish metabolism is more active during the day (Telaumbanua, 2025). This suggests that the timing of parameter measurements is also an important factor in data interpretation and the design of machine learning-based stress prediction systems. The identification of these key parameters provides a basis for building more efficient prediction models that focus on the most significant features. By emphasizing the parameters that most influence stress conditions, early detection systems can be more sensitive to critical environmental changes and assist farmers in monitoring fish health in real-time, especially in intensive farming systems where water quality fluctuations frequently occur.

Effectiveness of Early Detection System

The machine learning-based early detection system developed in this study predicts stress in farmed fish before obvious physiological or behavioral symptoms appear. By utilizing previously identified water quality fluctuation patterns and key parameters, the system can provide early warnings in real time. System performance was evaluated by comparing model predictions with actual conditions observed through fish physiological parameters, such as respiration rate, swimming activity, and feeding patterns (Pratama et al., 2024). The results showed that the early detection system was able to identify stress conditions with high accuracy, especially when using the Random Forest algorithm, which is capable of recognizing non-linear patterns in complex datasets. High precision and recall values indicate that the model was able to detect most stress events without producing many false positives or false negatives. This capability is crucial in intensive aquaculture contexts, where rapid response to changes in water quality can prevent declines in fish health and productivity.

The system is also capable of dynamically handling temporal data and parameter fluctuations. For example, when there is a sudden drop in dissolved oxygen during the day, the system provides a warning before the fish show signs of physiological stress, allowing for proactive interventions such as increased aeration or adjusted feeding (Nayoun et al., 2024). The model's rapid response demonstrates the superiority of machine learning over conventional methods, which typically rely on visual observation or time-consuming laboratory measurements. In addition to individual predictions, this system can also be integrated on a larger scale to monitor ponds or tanks simultaneously. By collecting sensor data from multiple points, the model can detect areas experiencing fluctuations in water quality that could potentially trigger stress, thus assisting operational management in more efficient regulation of aeration, water circulation, and feeding intensity. This approach supports the concept of smart aquaculture, which is data-driven and predictive. System testing on historical datasets shows that the model's early warnings can provide a response time of between 2 and 6 hours before stress symptoms appear physically. This provides farmers with the opportunity to intervene promptly and reduce the risk of mortality and economic losses. The application of this system, particularly in intensive aquaculture, can improve fish welfare and operational efficiency, as mitigation measures can be implemented based on valid data and predictions.

Discussion

Analysis of water quality fluctuation patterns indicates that dynamic changes in environmental parameters significantly impact the well-being of farmed fish. Fluctuations in temperature, dissolved oxygen, pH, and ammonia and nitrite levels create a complex environment that triggers stress responses. Rapid changes in water quality can affect metabolism, internal organ function, and adaptive behaviors of fish, including swimming activity, feeding patterns, and aggressiveness. These findings emphasize the importance of continuous water quality monitoring to detect potentially stressful conditions before physiological symptoms appear. The performance evaluation of machine learning algorithms indicates that Random Forest has the most consistent ability to handle multivariate data with non-linear relationships, while SVM is more effective on small datasets, and ANN excels at capturing complex temporal patterns. These differences in performance indicate that algorithm selection must be tailored to the characteristics of the data and the prediction objectives. Fish stress prediction systems cannot rely on a single model for all conditions; instead, appropriate algorithm evaluation is required to address the complexity of environmental parameters and the scale of cultivation.

Identification of key parameters indicates that dissolved oxygen and ammonia levels are the most significant indicators of fish stress, while pH and nitrite act as modulating factors. Interactions between parameters are often as important as individual parameter values, making multi-parameter analysis essential. Temporal patterns also indicate that the impact of stress depends not only on the absolute values of parameters, but also on the rate of change and specific parameter combinations. This approach helps focus machine learning models on the features most relevant for predicting stress conditions. The effectiveness of the developed early detection system demonstrates that the model can provide warnings several hours before stress symptoms appear. This system allows farmers to take proactive interventions, such as adjusting aeration, water circulation, or adjusting feed, before stress conditions become more severe. This approach demonstrates the advantages of data-driven prediction over conventional reactive methods, as it allows for earlier risk identification and improves operational efficiency. The integration of the early detection system with continuous sensors and temporal data analysis enhances the ability to detect anomalies that are difficult to detect manually. Utilizing patterns of water quality fluctuations and fish stress responses enables adaptive management of the aquaculture environment, not only for a single pond or tank, but also at a larger operational scale. This supports risk management, improves fish welfare, and reduces potential economic losses in intensive aquaculture.

CONCLUSION

Machine learning can serve as an effective tool for early stress detection in cultured fish by analyzing water quality fluctuation patterns. The analysis revealed that dynamic changes in key water parameters, including dissolved oxygen, ammonia, pH, nitrite, and temperature, play a critical role in influencing fish physiological and behavioral responses. Machine learning models, particularly Random Forest, proved capable of accurately capturing complex nonlinear relationships between multiple water quality parameters and fish stress levels, while Support Vector Machine and Artificial Neural Network models offered complementary strengths in handling small datasets and temporal pattern recognition, respectively. Feature importance analysis further identified dissolved oxygen and ammonia concentrations as the most significant predictors of stress, with pH and nitrite acting as modulatory factors. These findings highlight that stress in fish is not driven by a single environmental factor, but rather by the combined interaction of multiple fluctuating parameters over time. The developed early warning system successfully integrated these predictive insights, allowing real-time detection of stress conditions several hours before observable physiological or behavioral symptoms appeared, thereby enabling timely and proactive interventions such as aeration adjustment, circulation enhancement, and feeding modifications. The system's capability to process continuous sensor data and identify subtle anomalies in water quality demonstrates its potential for scalable application across multiple tanks or ponds, supporting adaptive management practices in intensive aquaculture settings. Overall, the integration of water quality monitoring with advanced machine learning techniques provides a robust framework for improving fish welfare, reducing mortality risks, and enhancing operational efficiency. This research contributes to the growing field of smart aquaculture by demonstrating how predictive modeling and data-driven decision-making can transform traditional aquaculture practices into proactive and precision-oriented systems that ensure sustainable and productive fish farming.

REFERENCES

Aftab, K., Tschirren, L., Pasini, B., Zeller, P., Khan, B., & Fraz, M. M. (2024). Intelligent fisheries: Cognitive solutions for improving aquaculture commercial efficiency through enhanced biomass estimation and early disease detection. *Cognitive Computation*, *16*(5), 2241-2263. https://doi.org/10.1007/s12559-024-10292-2

Agarwal, D., Shanmugam, S. A., Kathirvelpandian, A., Eswaran, S., Rather, M. A., & Rakkannan, G. (2024). Unraveling the impact of climate change on fish physiology: a focus on temperature and salinity dynamics. *Journal of Applied Ichthyology*, *2024*(1), 5782274. https://doi.org/10.1155/2024/5782274

Ahmed, U., Mumtaz, R., Anwar, H., Mumtaz, S., & Qamar, A. M. (2020). Water quality monitoring: from conventional to emerging technologies. *Water Supply*, *20*(1), 28-45. https://doi.org/10.2166/ws.2019.144

Alnemari, A. M., Elmessery, W. M., Qazaq, A. S., Moustapha, M. E., Rakhimgaliyeva, S., Abuhussein, M. F., ... & Elwakeel, A. E. (2025). Developing highly accurate machine learning models for optimizing water quality management decisions in tilapia aquaculture. *Scientific Reports*, *15*(1), 35600. https://doi.org/10.1038/s41598-025-16939-w

Anjarkasi, H., Dewantoro, E., & Lestari, T. P. (2025). The The effect of assembled diffuser diameter on water quality and growth performance of Nile tilapia (Oreochromis niloticus). *Acta Aquatica: Aquatic Sciences Journal*, 256-263. https://doi.org/10.29103/aa.v12i3.22380

Araújo-Luna, R., Ribeiro, L., Bergheim, A., & Pousão-Ferreira, P. (2018). The impact of different rearing condition on gilthead seabream welfare: Dissolved oxygen levels and stocking densities. *Aquaculture Research*, *49*(12), 3845-3855. https://doi.org/10.1111/are.13851

Baena-Navarro, R., Carriazo-Regino, Y., Torres-Hoyos, F., & Pinedo-López, J. (2025). Intelligent prediction and continuous monitoring of water quality in aquaculture: Integration of machine learning and Internet of Things for sustainable management. *Water*, *17*(1), 82. https://doi.org/10.3390/w17010082

Bal, A., Panda, F., Pati, S. G., Anwar, T. N., Das, K., & Paital, B. (2022). Influence of anthropogenic activities on redox regulation and oxidative stress responses in different phyla of animals in coastal water via changing in salinity. *Water*, *14*(24), 4026. https://doi.org/10.3390/w14244026

Cabecinha, E., Lourenço, M., Moura, J. P., Pardal, M. Â., & Cabral, J. A. (2009). A multi-scale approach to modelling spatial and dynamic ecological patterns for reservoir's water quality management. *Ecological Modelling*, *220*(19), 2559-2569. https://doi.org/10.1016/j.ecolmodel.2009.06.011

Dara, M., Carbonara, P., La Corte, C., Parrinello, D., Cammarata, M., & Parisi, M. G. (2023). Fish welfare in aquaculture: Physiological and immunological activities for diets, social and spatial stress on Mediterranean aqua cultured species. *Fishes*, *8*(8), 414. https://doi.org/10.3390/fishes8080414

Deng, Y., Zhang, Y., Pan, D., Yang, S. X., & Gharabaghi, B. (2024). Review of recent advances in remote sensing and machine learning methods for lake water quality management. *Remote Sensing*, *16*(22), 4196. https://doi.org/10.3390/rs16224196

Gul, S., Shafiq, U., Mir, S. A., Iqbal, G., & Lone, H. Q. (2024). Enhancing global food security through sustainable fisheries and aquaculture: A comprehensive review. *Asian Journal of Agricultural Extension, Economics & Sociology*, *42*(10), 60-70. https://doi.org/10.9734/ajaees/2024/v42i102563

Hariyono, H., Candra, I. A., Mauliansyah, F., Wahyudin, Y., & Rizal, M. (2024). *Transformasi Digital: Teori dan Implementasi pada Era Revolusi Industri 4.0 Menuju Era Society 5.0*. Jambi: PT. Sonpedia Publishing Indonesia.

Hatta, M., & Irwansyah, D. (2025). Analisis Klasifikasi Kualitas Air dalam mengoptimalkan Pertumbuhan Ikan Berdasarkan Model K-Nearest Neighbor. *Sisfo: Jurnal Ilmiah Sistem Informasi*, *9*(1), 63-76. https://doi.org/10.29103/sisfo.v9i1.22133

Helm, B., Ben-Shlomo, R., Sheriff, M. J., Hut, R. A., Foster, R., Barnes, B. M., & Dominoni, D. (2013). Annual rhythms that underlie phenology: biological time-keeping meets environmental change. *Proceedings of the Royal Society B: Biological Sciences*, *280*(1765). https://doi.org/10.1111/raq.12730

Hossain, B., Sunny, A. R., Gazi, M. M. R. N., Das, A. R., Mohajon, R., Miah, A. T. H., & Rana, M. N. U. (2024). Advancing fish farming through deep learning: Applications, opportunities, challenges, and future directions. *Pathfinder of Research*, *2*(3), 58-80. https://doi.org/10.69937/pf.por.2.3.39

Hossain, M. K., Islam, K. T., Hossain, M. D., & Rahman, M. H. (2011). Environmental impact assessment of fish diseases on fish production. *Journal of Science foundation*, *9*(1-2), 125-131. https://doi.org/10.3329/jsf.v9i1-2.14655

Hridoy, M. A. A. M., Bordin, C., Masood, A., & Masood, K. (2025). Predictive modelling of aquaculture water quality using IoT and advanced machine learning algorithms. *Results in Chemistry*, *16*, 102456. https://doi.org/10.1016/j.rechem.2025.102456

Jia, L., Yen, N., & Pei, Y. (2023). Spatial and temporal water quality data prediction of transboundary watershed using multiview neural network coupling. *IEEE Transactions on Geoscience and Remote Sensing*, *61*, 1-16. https://doi.org/10.1109/TGRS.2023.3334291

Kyriazos, T., & Poga, M. (2024). Application of machine learning models in social sciences: managing nonlinear relationships. *Encyclopedia*, *4*(4), 1790-1805. https://doi.org/10.3390/encyclopedia4040118

Mandal, A., & Ghosh, A. R. (2024). Role of artificial intelligence (AI) in fish growth and health status monitoring: A review on sustainable aquaculture. *Aquaculture International*, *32*(3), 2791-2820. https://doi.org/10.1007/s10499-023-01297-z

Menon, S. V., Kumar, A., Middha, S. K., Paital, B., Mathur, S., Johnson, R., ... & Asthana, M. (2023). Water physicochemical factors and oxidative stress physiology in fish, a review. *Frontiers in Environmental Science*, *11*, 1240813.

Mounce, S. R., Gaffney, J. W., Boult, S., & Boxall, J. B. (2015). Automated data-driven approaches to evaluating and interpreting water quality time series data from water distribution systems. *Journal of Water Resources Planning and Management*, *141*(11), 04015026. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000533

Muhammad, A., Khan, Z. U., Khan, J., Mashori, A. S., Ali, A., Jabeen, N., ... & Li, F. (2025). A comprehensive review of crop stress detection: Destructive, non-destructive, and ML-based approaches. *Frontiers in Plant Science*, *16*, 1638675. https://doi.org/10.3389/fpls.2025.1638675

Mukherjee, J., Moniruzzaman, M., Chakraborty, S. B., Lek, S., & Ray, S. (2017). Towards a physiological response of fishes under variable environmental conditions: An approach through neural network. *Ecological indicators*, *78*, 381-394. https://doi.org/10.1016/j.ecolind.2017.03.038

Nayoun, M. N. I., Hossain, S. A., Rezaul, K. M., Siddiquee, K. N. E. A., Islam, M. S., & Jannat, T. (2024). Internet of Things-driven precision in fish farming: A deep dive into automated temperature, oxygen, and pH regulation. *Computers*, *13*(10), 267. https://doi.org/10.3390/computers13100267

Nusrat, I., & Jang, S. B. (2018). A comparison of regularization techniques in deep neural networks. *Symmetry*, *10*(11), 648. https://doi.org/10.3390/sym10110648

Parvathy, A. J., Das, B. C., Jifiriya, M. J., Varghese, T., Pillai, D., & Rejish Kumar, V. J. (2023). Ammonia induced toxico-physiological responses in fish and management interventions. *Reviews in Aquaculture*, *15*(2), 452-479. https://doi.org/10.1111/raq.12730

Pradeepkiran, J. A. (2019). Aquaculture role in global food security with nutritional value: a review. *Translational Animal Science*, *3*(2), 903-910. https://doi.org/10.1093/tas/txz012

Pratama, M. R. B., Alfatah, R. F., & Susila, J. K. R. (2024). Identifikasi Intensitas Makan Ikan Budidaya Akuaponik berdasarkan Kualitas Air dan Pergerakan Ikan. *MIND (Multimedia Artificial Intelligent Networking Database) Journal*, *9*(2), 235-247. https://doi.org/10.26760/mindjournal.v9i2.235-247

Rahantoknam, S. P., Sembiring, K., Sabilu, K., Ihtifazhuddin, M. I., Putri, D. S., Takwin, B. A., ... & Diamahesa, W. A. (2025). *Manajemen Akuakultur Payau: Integrasi Teknis, Ekologis untuk Budidaya Berkelanjutan*. Maluku Utara: Kamiya Jaya Aquatic.

Rahman, M. M. (2025). Data analytics for strategic business development: a systematic review analyzing its role in informing decisions, optimizing processes, and driving growth. *Journal of Sustainable Development and Policy*, *1*(01), 285-314. https://doi.org/10.63125/he1tfg25

Sampaio, F. D., & Freire, C. A. (2016). An overview of stress physiology of fish transport: changes in water quality as a function of transport duration. *Fish and fisheries*, *17*(4), 1055-1072. https://doi.org/10.1111/faf.12158

Saputra, A. W., Purnamasari, A. I., & Ali, I. (2024). Implementasi Algoritma Naïve Bayes Untuk Memprediksi Kualitas Air Yang Dapat Di Konsumsi. *JATI (Jurnal Mahasiswa Teknik Informatika)*, *8*(1), 133-140. https://doi.org/10.36040/jati.v8i1.8292

Shreesha, S., Pai, M. M., Pai, R. M., & Verma, U. (2023). Pattern detection and prediction using deep learning for intelligent decision support to identify fish behaviour in aquaculture. *Ecological Informatics*, *78*, 102287. https://doi.org/10.1016/j.ecoinf.2023.102287

Telaumbanua, M. (2025). Pengaruh Oksigen Terlarut (DO) dalam Budidaya Perairan. *Jurnal Perikanan dan Kelautan*, *2*(1), 200-206. https://doi.org/10.70134/peraut.v1i1.691

Telaumbanua, N., & Zebua, D. (2026). Integrasi Sektor Perikanan Dan Pertanian Dalam Mendukung Ketahanan Pangan Dan Pembangunan Ekonomi Perdesaan. *Jurnal Ilmu Manajemen dan Akuntansi Nusantara*, *2*(1), 224-228. https://doi.org/10.70134/jimakun.v2i1.1223

Vudugula, S., Chebrolu, S. K., Bhuiyan, M., & Rozony, F. Z. (2023). Integrating artificial intelligence in strategic business decision-making: A systematic review of predictive models. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 01-26. https://doi.org/10.63125/s5skge53

Wanja, D. W., Mbuthia, P. G., Waruiru, R. M., Mwadime, J. M., Bebora, L. C., Nyaga, P. N., & Ngowi, H. A. (2020). Fish husbandry practices and water quality in central Kenya: potential risk factors for fish mortality and infectious diseases. *Veterinary medicine international*, *2020*(1), 6839354. https://doi.org/10.1155/2020/6839354

Wasilewski, T., Kamysz, W., & Gębicki, J. (2024). AI-assisted detection of biomarkers by sensors and biosensors for early diagnosis and monitoring. *Biosensors*, *14*(7), 356. https://doi.org/10.3390/bios14070356

Zega, W. T. P., Napitupulu, V. N., Saribu, A. D., Siahaan, R. D. D., Manullang, T. T., Marpaung, I., ... & Simorangkir, P. (2025). Inovasi Dalam Pemasaran: Mengukur Kinerja Dan Meningkatkan Efisiensi Serta Produktivitas Bisnis Dengan Menggunakan Sistem MPA. *Jurnal Daya Saing*, *11*(2), 445-451. https://doi.org/10.35446/dayasaing.v11i2.2255