Hindawi
Journal of Food Quality
Volume 2023, Article ID 3841882, 9 pages
https://doi.org/10.1155/2023/3841882

Research Article

Machine Learning Integrated Multivariate Water Quality Control Framework for Prawn Harvesting from Fresh Water Ponds

Gaganpreet Kaur,[1] M. Braveen,[2] Singamaneni Krishnapriya,[3] Surindar Gopalrao Wawale,[4] Jorge Castillo-Picon,[5] Dheeraj Malhotra,[6] and Jonathan Osei-Owusu [7]

[1]*Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India*
[2]*School of Computer Science and Engineering, Vellore Institute of Technology, Chennai Campus, Chennai, India*
[3]*Guru Nanak Institutions Technical Campus (An Autonomous Institution), Ibrahimpatnam, R.R. District, Hyderabad, India*
[4]*Agasti Arts, Commerce and Dadasaheb Rupwate Science College, Akole, India*
[5]*Universidad Nacional Santiago Antúnez de Mayolo, Huaraz, Peru*
[6]*Department of Information Technology, Vivekananda Institute of Professional Studies, Guru Gobind Singh Indraprastha University, Pitam Pura, New Delhi, Delhi, India*
[7]*Department of Biological, Physical and Mathematical Sciences, University of Environment and Sustainable Development, Somanya, Ghana*

Correspondence should be addressed to Jonathan Osei-Owusu; josei-owusu@uesd.edu.gh

Received 22 June 2022; Revised 14 August 2022; Accepted 24 November 2022; Published 23 January 2023

Academic Editor: Rijwan Khan

Water contamination, temperature imbalance, feed, space, and cost are key issues that traditional fish farming encounters. The aquaculture business still confronts obstacles such as the development of improved monitoring systems, the early detection of outbreaks, enormous mortality, and promoting sustainability, all of which are open problems that need to be solved. The goal of this study is to provide a machine learning (ML)-based aquaculture solution that boosts prawn growth and production in ponds. The study described a proposed framework that collects data using sensors, analyses it using a machine learning framework, and provides results like a preferred list of water quality (QOW) variables that affect prawn development and yield, as well as pond categorization into low, medium, and high prawn-producing ponds. In this study, we use eight distinct machine-learning classifiers to discover the driving elements that influence the development and yield of aquatic food products in ponds in terms of QOW variables, as well as three feature selection approaches to identify the aspects that have the largest impact on the pond's total harvest performance. To validate and obtain satisfying results, the suggested system was installed and tested. The average *F* score and accuracy when yield is employed as a harvest parameter are determined to be 0.85 and 0.78, respectively. The average merit ratings of temperature, dissolved oxygen, and salinity are significantly higher than those of the other QOW components. The temperature variations are greatest during the second, fourth, and seventh weeks. Temperature, salinity, and dissolved oxygen are the three QOW variables that have the largest influence on overall pond harvest performance, according to the data. Additionally, it has been discovered that a key QOW factor in separating high-yielding ponds from low-yielding ponds is the temperature change following stocking.

1. Introduction

Water quality monitoring is considered crucial for fish farming. Several studies have found that measuring dissolved oxygen is crucial to sidestep high values of water quality, which may result in serious harm to fish such as anoxia, hyperoxia, as well as hypoxia [1]. The term "water quality monitoring" refers to the process of collecting samples of water and analysing them. In order to assess if we are succeeding in cleaning up our waterways, it is crucial that we monitor the quality of the water. It indicates the condition and make-up of streams, rivers, and lakes both in the present and over the course of days, weeks, and years. The five parameters of dissolved oxygen, pH, temperature, salinity, and nutrients are used to gauge the quality of water. In aquaculture, it is unavoidable to be more intelligent in terms of 24×7 monitoring of water quality and precise feeding. However, the bacterial balance in the aquaculture environment may be disrupted as a result of 24×7 monitoring of water quality, thereby reducing the disease-resistant capabilities of fish [2]. Traditional aquaculture farming relied on experienced aquafarmers' observation and empirical judgement to identify and forecast farm health risks. Monitoring changes in water quality factors, namely dissolved oxygen, pH, temperature, and salinity, as well as others that are known to have a negative impact on the aquaculture environment is one element. For optimum fish farming, lakes and fisheries must maintain ideal amounts of dissolved oxygen. Fish producers should concentrate on steps to guarantee that sufficient amounts of dissolved oxygen are maintained in addition to feeds and fertilizer. Keep the pond free of undesirable things, sprinkle clean water from the upper reaches, and take other precautions. Until the condition improves, prevent feeding and using fertilisers. Use oxygen-boosting medications as directed by fishing specialists. The temperature and pH of the water pond must be measured to ensure the balance between hazardous and nontoxic nitrogen molecules such as ammonia and ammonium, thereby creating the need to monitor the temperature and pH of the water pond [3]. As a low-lying nation, natural disasters such as floods, cyclones, and other natural disasters have a substantial impact on aquaculture in both ponds and marine areas. Even little fluctuations in water quality parameter values above or below the typical, ideal range can cause physiological stress in aquatic life, affecting eating, breeding, and disease susceptibility [4]. Aquaculture and fishing are two of the most well-liked activities in coastal areas around the world. Additionally, given their vulnerability to climatic factors that endanger the economic stability of fishing communities that depend on fish for food security and money production, these activities are regarded as greater in the context of climate change. Recent research has shown proof of the harmful consequences of climate change on corals, including coral bleaching and changes to organism variety and composition, as well as on fish populations and aquaculture production [5–7].

In recent times, the use of AI in the fields of health, manufacturing, agriculture, and academia domain has grown in many folds [8–10]. The role of blockchain, IoT, and WSAN is well-known and popular among researchers due to their reasonably good advantages available at low cost [11–13]. Industry 4.0 and 5G/6G telecommunication have revolutionized the applications in the fields of health, manufacturing, agriculture, and academia. The domain of aquaculture has not remained untouched by the effects of the industry's 4.0/5.0 and 5G/6G revolutions [14]. Industry 4.0 is transforming how businesses produce, enhance, and sell their goods. The Internet of things (IoT), cloud computing, statistics, AI, and machine learning are among the cutting-edge technologies that companies are incorporating into their manufacturing processes. People will experience the effects of the 5G revolution as it spreads. 5G, which is planned to offer faster speeds, more capacity, and lower latency, is anticipated to be the driving force behind development in the future. Increased speeds, in particular, can provide new opportunities for commerce and community security. In the field of integrated AI and smart fish farming, especially ML and deep learning (DL), presents both new potential and obstacles for information and data processing [14]. Using the Internet of things (IoT), big data for data storage, cloud computing for remote processing, and artificial intelligence, as well as other current information technologies, aquaculture was able to make better use of resources and improve long-term sustainability [15]. Traditional freshwater fish farming practices are still use vast ponds with no water movement, no drainage, and no bottom silt treatment, which frequently create circumstances that encourage disease. The close quarters of millions of fish in their enclosed environment are the root of a lot of worries regarding fish farming. Solid wastes, such as feces, kitchen waste, and jellyfish, are dumped (often unprocessed) into the nearby waters, where they contribute to the water supply's pollution. It is now possible to collect real-time data, make quantitative decisions, use intelligent controls, make exact investments, and provide tailored service. For the development of water quality parameter prediction models, several types of ML approaches and methodologies have been investigated. In recent years, reliable ML models for estimating variables like nitrites and ammonia, as well as forecasting variables like dissolved oxygen, pond temperature, and pH, have been developed. The issues faced by different companies, including the agricultural sector, including harvesting of crops, irrigation, soil composition sensitivity, crop scouting, weeding, harvesting, and foundation, are managed by AI-based technology, which also helps to increase productivity across all sectors. On the fields, AI technology aids in the diagnosis of pests, illnesses, and malnutrition. AI sensors can also detect and identify weeds. The mythology that is used to classify diseases, segment the affected areas, and diagnose ailments.

The current study aims to determine the impact of 5 QOW factors in distinguishing high- and low-performance ponds (in terms of harvesting performance), as well as how fluctuations in QOW variables occur or are observed throughout the growing season, which influences final harvesting factors such as growth and yield. Neural networks (NN), support vector machines (SVM), k-nearest neighbours (kNN), logistic regression (LR), Gaussian Naive Bayes (NB), decision trees (DT), random forests (RF), as well as AdaBoost are some of the machine learning techniques used to categorise ponds [16]. By taking into account both linear and nonlinear correlations among QOW components together with the result of prawn production, QOW variables during the course of the prawn-growing season as well as their value for prawn production are examined. The five QOW variables are temperature, DO, salinity, pH, turbidity, and salinity. Mutual information feature selection approaches, interlinked-based attribute selection, and ReliefF have all been utilised to discover factors impacting water

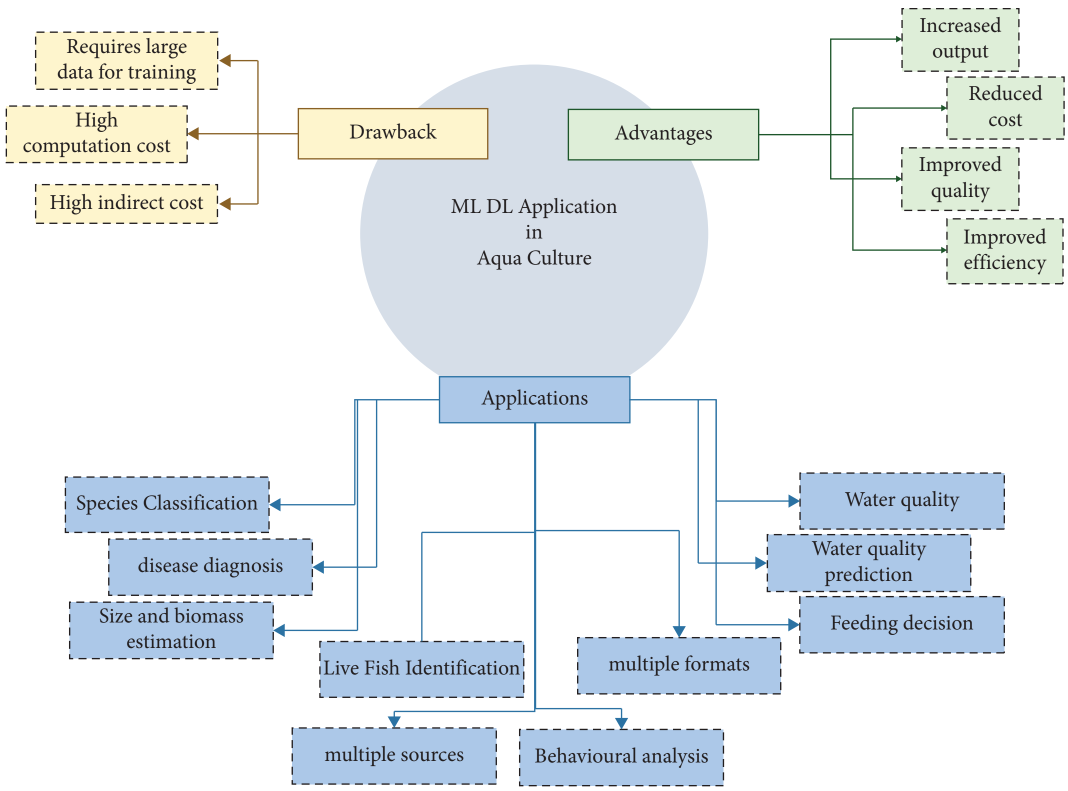

Figure 1: Application, advantage, and drawback of ML and DL in aquaculture practices.

quality for better animal development and productivity in ponds. Various applications, advantages, and drawbacks of machine learning and deep learning have been shown in Figure 1.

The body of the paper is organised as follows: Section 2 provides a quick review of the literature on machine learning applications in agricultural systems. The third section gives an overview of the dataset that has been used. The ML techniques we used are described in Section 4. The experimental framework has been presented and discussed in Section 5. Finally, Section 6 summarises the key findings and concludes the work with recommendations for further research.

2. Related Work

The toxicity levels of pond water are linked to nitrogen compounds, electric conductivity, and alkalinity. The occurrence of hazardous ions that affect the pH of the pond's water. Many studies have focused on predicting dissolved oxygen, one of the most essential factors in ensuring the minimal levels of QOW necessary in fish farming practices. For aquaculture forecasting of dissolved oxygen (DO), Huan et al. [17] recommend combining GBDT and LSTM. The computation time of the whole method is decreased by picking characteristics with highly correlated data for dissolved oxygen as input data. When compared to DL-based prediction models such as BP, GBDT-LSTM, ELM, and PSO-LSSVM, as well as single LSTM prediction models, the suggested model has demonstrated a greater prediction effect and accuracy.

Shi et al. [18] propose a new Clustering-based Softplus Extreme Learning Machine approach (CSELM) for the purpose of forecasting dissolved oxygen variation from time series data with high accuracy and efficiency. CSELM enhances efficiency despite having a high tolerance for some data loss and unclear outliers in sensor time series, demonstrating that CSELM outperforms PLS-ELM and ELM models in terms of high accuracy and better efficiency in predicting real-world dissolved oxygen content when compared to other models. Using the clustering technique, CSELM may endure sensor issues with data quality and still obtain good accuracy and effectiveness. Another benefit of CSELM is that the Softplus ELM has better-optimised network performance, which increases predictive performance. For aquaculture, which demands sophisticated supervision and operation, reliable and efficient dissolved oxygen prediction from time series data is essential. The current prediction techniques are, nevertheless, put to the test by nonlinear, continually generated data streams of dissolved oxygen [18]. Csábrági et al. [19] created a nonlinear ANN for forecasting and predicting dissolved oxygen content concentration in the Hungarian part of the Danube in another comparable study. It was also discovered that when evaluating dissolved oxygen levels, pH is the most critical element.

A precise forecast of dissolved oxygen can aid farmers in taking the required actions to sustain dissolved oxygen echelons suitable for healthy prawn growth, according to Rahman et al. [20] presents a novel strategy in which a set of predictors is created, each of which forecasts a certain time stamp in the future. On the other hand, Liu et al. [21] investigated the efficiency of attention-based recurrent neural networks (RNN) in predicting dissolved oxygen in the short and long term. The author also proposes two attention-based RNN architectures for capturing temporal correlations independently and learning spatiotemporal relationships concurrently that outperform state-of-the-art approaches. The findings of the proposed model reveal that attention-based RNNs can predict dissolved oxygen more accurately in both short- and long-term predictions.

In recirculating aquaculture, the level of dissolved oxygen is a vital indication of control; its content as well as dynamic fluctuations have been found to have a significant influence on the healthy growth of aquatic live feedstock. It is vital to forecast the levels of dissolved oxygen concentration in advance to ensure the safety of aquaculture operations. Ren et al. [22] suggested a forecasting model on the basis of deep belief networks to achieve dissolved oxygen content prediction. To analyse the original data space, a variational mode decomposition (VMD) data processing approach was used. The suggested model can predict DO concentration in temporal series rapidly as well as reliably, and its forecasting performance is equivalent to that of existing frameworks like AdaBoost, decision trees, CNN, and other similar models.

In fish farming, Zambrano et al. [23] introduced an ML model for manually observed water quality prediction. In cases where the number of measurements was restricted, the author used RF, MLR, and ANN to assess data from water quality indicators that are regularly recorded in fish growth and farming. The suggested model achieves the goals of predicting and estimating unseen factors based on observable data. When the water pond variables are examined only two times per day, the model employs random forests to anticipate DO, the temperature of the pond, pH, and ammonia, as well as ammonium. In contrast to earlier studies in the literature, we use machine learning to detect primary driving elements (for the measurement of QOW), which impact aquatic livestock development and productivity in commercial freshwater ponds. Grow-out period (in this study, the grow-out period was 190–210 days). The desire to reduce the cost of fish farming grows as the price of fish meal and inorganic fertilisers rises. This can be partially resolved by implementing a comprehensive farming system. To improve plant nutrient uptake, promote native fish development, and eventually boost fish production, fertilisers are added to fish ponds. The availability of natural food in pond water lowers the demand for synthetic feeds among fish, which in turn lowers productivity [24]. We use a series of filtering and attributes extraction methods to examine the effect of QOW variables throughout the growing season of prawns, as well as their value for prawn production, by taking into account both linear and nonlinear correlations among QOW factors along with the outcome of prawn production.

3. Data Collection and ML Framework

The data for this study was gathered during a grow-out season at a well-known prawn farm in Australia. The amount of time spent in culture (DoC) varied between 190 and 200 days. The water quality data has been taken from various ponds, each of which was set to a constant area of 10,000 square metres. DO, salinity, pH, and turbidity and temperature are among the five QOW variables that were measured twice a day. For 135 days, turbidity and salinity were monitored one time each day. Each QOW variable's weekly averages are considered over the last 135 days. For different ponds, growth (such as average prawn mass along with yield at harvesting time) was measured to categorise them into low-, medium-, and high-producing ponds. The classification process entails separating the ponds' performances based on all measured QOW characteristics. The ML technique used to solve this problem is depicted in Figure 2.

The pond's weekly averages of QOW variables have been taken as input, while the pond's performance considering the pond's class, growth, and yield have been used as output (target). Classifier models, which have been a series of complementary ML models exhibiting distinct patterns and treated as learning skills, employed the input and output data. Different models have been employed to increase variety in learning the linking attributes between QOW data and pond performance, with a focus on reducing over-fitting issues. Using 10-fold cross-validation, the classification performance of the various prediction models has been assessed.

Figure 2 depicts the attribute extraction and selection approach that has been used to assess the value of each QOW characteristic individually and to produce a relative rating for pond performance differentiation. Correlation-based Feature Selection (CFS), mutual Information (MI), and ReliefF (RLF) filtering feature selection techniques were used to refine and fine-tune time series data for every QOW variable of all ponds independently. Based on data fluctuations, these algorithms calculate the relevance of every QOW variable. The capacity of every QOW variable to predict and differentiate between high- and low-performing ponds is shown in merit scores. All QOW factors have been ranked according to their merit score. Overall harvest performance is linked to QOW factors at various points during the growing season. The dataset has been used to assess the impact of each QOW variable during each week of the prawn growth season. The QOW variable's time series data has been incorporated into MI, CFs, and RLF models. A 10-fold cross-validation approach was used to calculate the weekly influence. The aggregate merit score for each week aids in distinguishing between ponds that perform poorly and those that perform well. Characteristic features for QOW variables were defined as feature merit scores over 95 percentiles. This procedure was carried out independently for each QOW variable.

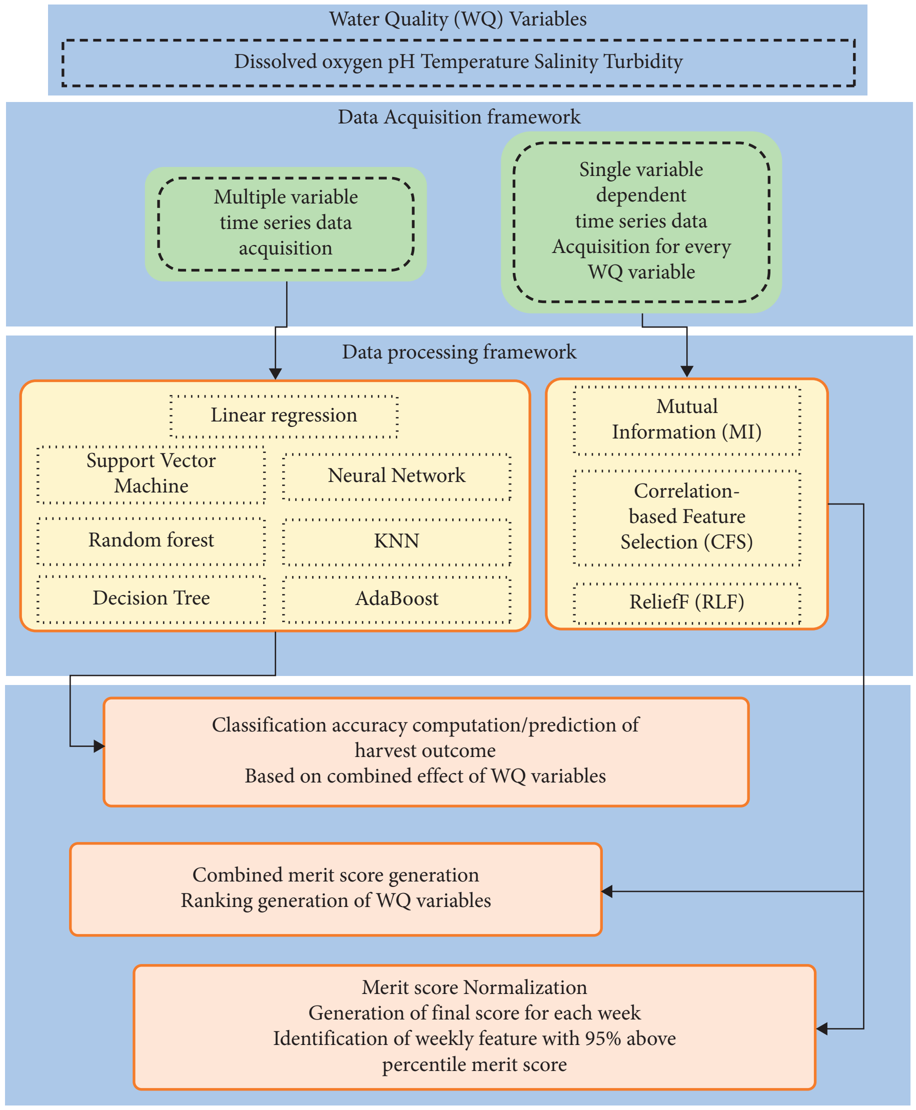

Figure 2: Schematic diagram of the proposed framework for pond classification, water quality ranking, and water quality parameter effect on prawn yield and growth.

4. Results

The experimental findings of identifying ponds as high- or low-performing as a function of the observed QOW factors are shown in Figure 3. A total of 5 runs of the tests have been completed for each model independently. *F* scores were used to assess the performance of many models along with accuracy metrics, with the main weighting given to the *F* score. When the yield is utilised as a performance indicator, NNs, SVMs, and NBs deliver the highest accurate forecast. Using growth as a performance indicator, high- and low-performing ponds have been identified. For growth metrics, a larger number of training data sets were employed, resulting in improved classification results. It may be inferred that all of the QOW factors have a significant impact on prawn production and that these QOW variables can be used to discriminate between ponds with high and poor production outcomes.

When growth is used as a harvest parameter, the average *F* score and accuracy found to be 0.86 and 0.84, respectively. When yield has been used as a harvest parameter, however, the average *F* score and accuracy have been found to be 0.85 and 0.78, respectively, as shown in Figure 4. Other algorithms are outperformed by DT, NNs, and SVM, which produce the most accurate forecast that is also independent of the harvest metric. The temporal series data for each QOW variable has been supplied independently into the attribute selection algorithms such as MI, CFS, and RLF in order to evaluate the significance of the harvest result for both prawn growth and yield. Figure 5 and Figure 6 depict the merit score of all QOW factors as well as their ranking based on both harvest measures. When growth is used as a harvest measure, the two most relevant QOW factors have been found to be temperature and salinity.

Temperature, dissolved oxygen, and salinity have much higher average merit scores than the other QOW factors,

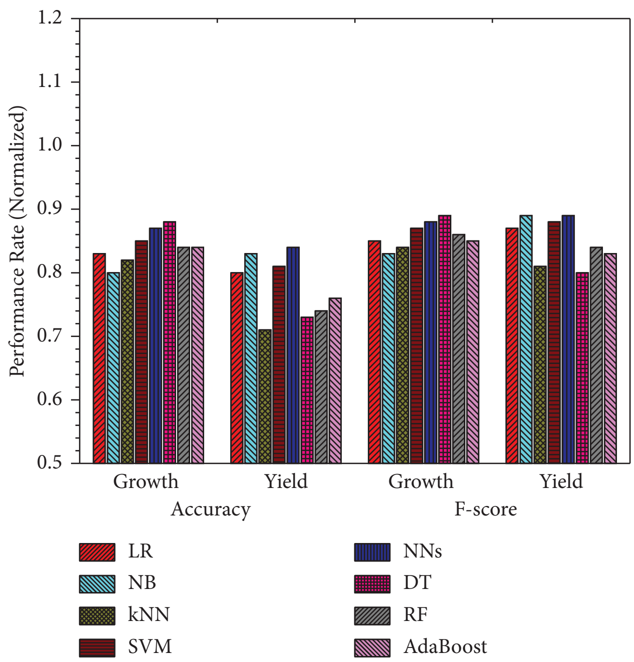

Figure 3: Comparison of the proposed model AdaBoost for classification performance in terms of accuracy and $F1$ score of various ML algorithms on the basis of growth and yield metrics, considering the combined effect of all water quality parameters.

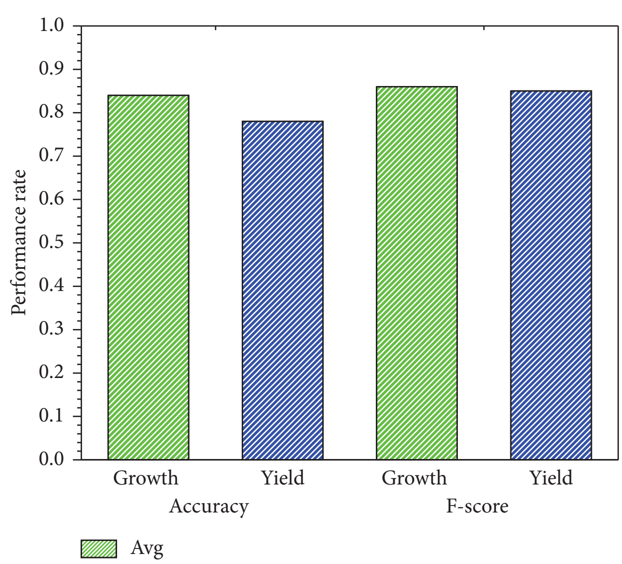

Figure 4: Average accuracy and $F1$ score of all the applied ML algorithms on the basis of growth and yield metrics.

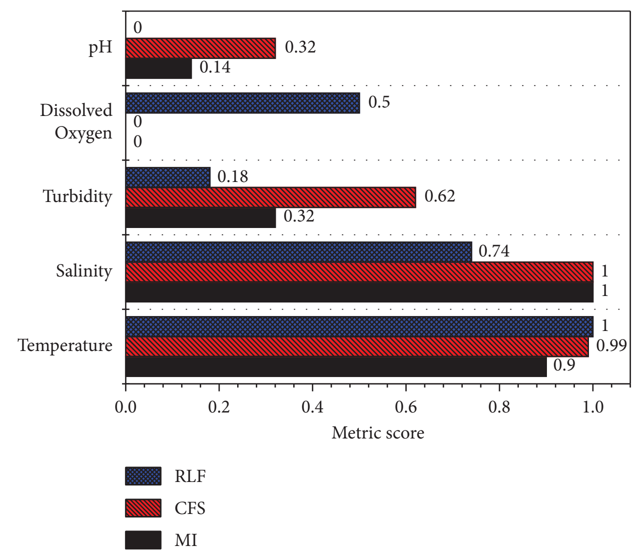

Figure 5: Influence of water quality variables on harvest outcome, considering growth as the main metric.

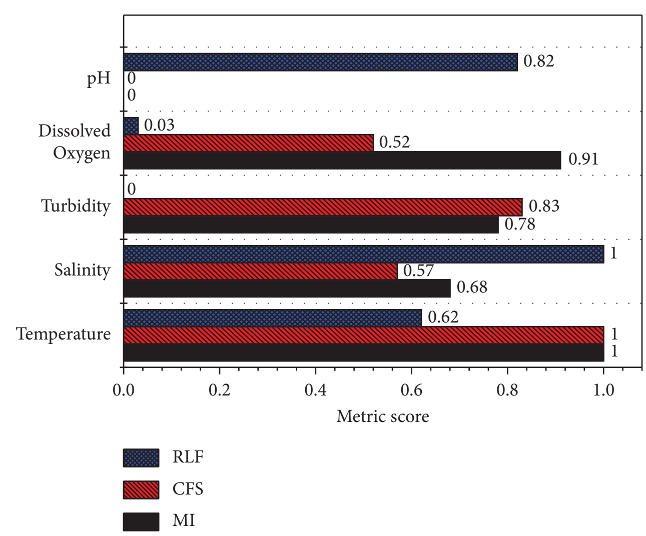

Figure 6: Influence of water quality variables on harvest outcome, considering yield as the main metric.

making them the most impactful QOW variables. When yield is used as the harvest parameter instead of growth, the most significant QOW factors are found to be temperature and salt. The three QOW factors revealed have a strong predictive capacity to distinguish between poor and high-performing ponds, which aids in keeping them within industry standard levels and so enhancing yield output. The influence of organism exposure on QOW factors has not been investigated in this study. Even though organisms' growth and survival may be affected by exposure, the focus is on the influence of QOW factors on growth and yield under ideal conditions.

The influence of each QOW variable at every point of the time series data during the prawn growth season, from stocking to harvesting time, has been evaluated individually and is indicated in Figure 7. As it is observed, the merit score has been found to be greater than 0.90 for temperature for the 2nd and 7th weeks, whereas salinity for the 19th and 20th weeks is considered as performance metrics. On the other hand, DO was found to have a higher metric score on the 17th week along with temperature on the 4th week when yield is accounted for as a performance parameter.

Figure 8 depicts the merit score for every week of the grow-out season, which has been reflecting the relevance of top-ranked QOW factors. The salinity difference between

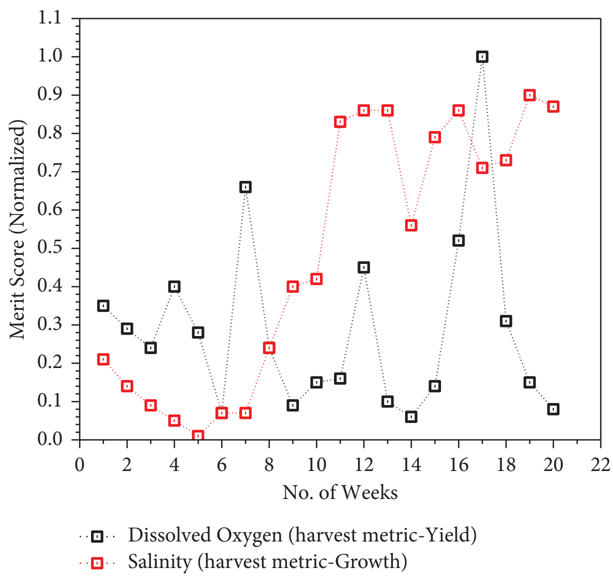

Figure 7: Impact of dissolved oxygen and salinity when harvest metrics are taken as yield and growth, respectively.

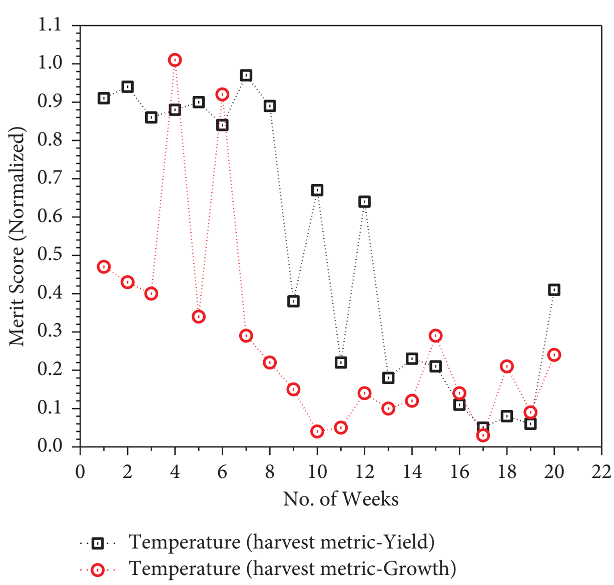

Figure 8: Impact of temperature variable at every point in time between stocking as well as harvesting date when harvest metric taken as yield and growth independently.

high- and low-performing ponds became increasingly noticeable towards the end of the season, thereby allowing high- and low-performing prawn-cultivating ponds to be distinguished. Temperature is related to metabolism in general, and higher levels indicate more development, as shown in Figure 8. The temperature variations are greatest during the 2nd, 4th, and 7th weeks; hence, they have been chosen via feature selection algorithms to contribute the most in distinguishing between high and low prawn cultivating performance ponds. The maximum temperature (harvest matric yield) has been observed during the 4th and 13th weeks, and the minimum temperature (harvest matric yield) has been detected in the 10th and 15th weeks. Whereas the maximum temperature (harvest matric growth) has been identified in the 7th week and the minimum maximum temperature (harvest matric growth) was experienced during the 15th week.

5. Discussion

Different QOW factors have a big impact on the development and survival of aquatic cattle. Despite the fact that earlier studies in the literature had not focused on defining the significant QOW factors or exploring how their fluctuations impact the development along with the survival of various aquatic livestock species, the machine learning algorithms provided here were tested on prawn development and yield, but they may readily be applied to other comparable biosystems. Changes in QOW characteristics and their impact on catfish, tilapia, and other livestock development and survival described in the present study on greenhouse ponds and the longer duration of a culture different species of prawn are distinguishable and novel from other reported work. Forecasting QOW is also a critical responsibility for aquaculture farm managers. The findings of the presented study may be combined with QOW predictions from other studies to help in establish an early warning system to aid farm managers in making better decisions.

Ponds that perform well and those that don't have been identified using growth as a performance measure. A conclusion that can be drawn is that all QOW variables have a significant impact on prawn output and can be utilised to distinguish between ponds with high and low production results. Temperature and salinity have been determined to be the two most important QOW parameters when growth is considered as a harvest indicator. The three QOW parameters can effectively discriminate between ponds that perform poorly and those that perform well, helping to keep them within acceptable ranges for the industry and so increasing yield production. The salinity difference between ponds with good and poor performances became more apparent as the season progressed.

6. Conclusion

We introduced a series of machine learning (ML) algorithms in this research to study how QOW factors influence the harvesting season outcome of aquatic livestock (prawn) in freshwater ponds. The proposed model outperforms other similar existing models in terms of pond classification accuracy, QOW variables ranking in terms of affecting yield, and growth of prawns in pond. A data set obtained from a prawn harvesting farm has been used to achieve experimental results. Using the provided data-driven ML technique, it is feasible to properly distinguish high- and low-performing ponds. DO and Salinity along with temperature, are determined to have the most impact on the performance of all the QOW factors during the harvesting season. Because optimum growth in the first few months might have a substantial impact on the final harvesting outcome, the temperature effect has been anticipated to directly affect the harvesting season. The most crucial component in differentiating high- and low-performance ponds is determined to be the difference in DO and salinity in the final third of the grow-out season. In conclusion, machine learning techniques showed great promise for producing decision support for aquaculture producers in order to stimulate scenarios that lead to higher-performing ponds and avoid the circumstances leading to low harvest results for the prawn cultivating sectors. Depending on the natural conditions, individual farms have distinct growth seasons, QOW requirements, customer requirements, and market concerns that influence management standards. The methods given in this presented work are data-oriented, and they can be used to run experiments and create findings using farm-specific data. For predicting changes in dissolved oxygen content from time series data, we will propose the prediction model CSELM, which combines two novel techniques: the k-method clustering based on DTW for efficiency and precision by sensibly grouping input data and utilizing their common trends, and the Softplus input vector based on PLS for enhancing ELM.

Data Availability

Data will be made available upon request to the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] R. S. S. Wu, K. S. Lam, D. W. MacKay, T. C. Lau, and V. Yam, "Impact of marine fish farming on water quality and bottom sediment: a case study in the sub-tropical environment," *Marine Environmental Research*, vol. 38, no. 2, pp. 115–145, 1994.

[2] M. Y. Ina-Salwany, N. Al-Saari, A. Mohamad et al., "Vibriosis in fish: a review on disease development and prevention," *Journal of Aquatic Animal Health*, vol. 31, no. 1, pp. 3–22, 2019.

[3] F. Budiman, M. Rivai, and M. A. Nugroho, "Monitoring and control system for ammonia and ph levels for fish cultivation implemented on raspberry pi 3B," in *Proceedings of the 2019 International Seminar on Intelligent Technology and Its Applications*, pp. 68–73, ISITIA), Surabaya, Indonesia, August 2019.

[4] M. Abdel-Tawwab, M. N. Monier, S. H. Hoseinifar, and C. Faggio, "Fish response to hypoxia stress: growth, physiological, and immunological biomarkers," *Fish Physiology and Biochemistry*, vol. 45, no. 3, pp. 997–1013, 2019.

[5] P. L. Munday, G. P. Jones, M. S. Pratchett, and A. J. Williams, "Climate change and the future for coral reef fishes," *Fish and Fisheries*, vol. 9, no. 3, pp. 261–285, 2008.

[6] M. S. Pratchett, P. L. Munday, S. K. Wilson et al., "Effects of climate-induced coral bleaching on coral-reef fishes 'äî ecological and economic consequences," *Oceanography and Marine Biology*, vol. 46, pp. 251–296, 2008.

[7] M. Ateweberhan, D. A. Feary, S. Keshavmurthy, A. Chen, M. H. Schleyer, and C. R. Sheppard, "Climate change impacts on coral reefs: synergies with local effects, possibilities for acclimation, and management implications," *Marine Pollution Bulletin*, vol. 74, no. 2, pp. 526–539, 2013.

[8] T. K. Lohani, M. T. Ayana, A. K. Mohammed, M. Shabaz, G. Dhiman, and V. Jagota, "A comprehensive approach of hydrological issues related to ground water using GIS in the Hindu holy city of Gaya, India," *World Journal of Engineering*, p. 6, 2021.

[9] J. Bhola, S. Soni, and J. Kakarla, "A scalable and energy-efficient MAC protocol for sensor and actor networks," *International Journal of Communication Systems*, vol. 32, no. 13, Article ID e4057, 2019.

[10] K. Phasinam, T. Kassanuk, and M. Shabaz, "Applicability of internet of things in smart farming," *Journal of Food Quality*, vol. 2022, Article ID 7692922, 7 pages, 2022.

[11] M. Yang, P. Kumar, J. Bhola, and M. Shabaz, "Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit," *International Journal of System Assurance Engineering and Management*, vol. 13, no. S1, pp. 322–330, 2021.

[12] A. Malik, G. Vaidya, V. Jagota et al., "Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach," *Journal of Food Quality*, vol. 2022, Article ID 9211700, 12 pages, 2022.

[13] A. Singh, G. Vaidya, V. Jagota et al., "Recent advancement in postharvest loss mitigation and quality management of fruits and vegetables using machine learning frameworks," *Journal of Food Quality*, vol. 2022, Article ID 6447282, 9 pages, 2022.

[14] S. García-Poza, A. Leandro, C. Cotas et al., "The evolution road of seaweed aquaculture: cultivation technologies and the industry 4.0," *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, p. 6528, 2020.

[15] X. Yang, S. Zhang, J. Liu, Q. Gao, S. Dong, and C. Zhou, "Deep learning for smart fish farming: applications, opportunities and challenges," *Reviews in Aquaculture*, vol. 13, no. 1, pp. 66–90, 2021.

[16] F. Wang, Z. Li, F. He, R. Wang, W. Yu, and F. Nie, "Feature learning viewpoint of adaboost and a new algorithm," *IEEE Access*, vol. 7, Article ID 149890, 2019.

[17] J. Huan, H. Li, M. Li, and B. Chen, "Prediction of dissolved oxygen in aquaculture based on gradient boosting decision tree and long short-term memory network: a study of Chang Zhou fishery demonstration base, China," *Computers and Electronics in Agriculture*, vol. 175, Article ID 105530, 2020.

[18] P. Shi, G. Li, Y. Yuan, G. Huang, and L. Kuang, "Prediction of dissolved oxygen content in aquaculture using clustering-based Softplus Extreme learning machine," *Computers and Electronics in Agriculture*, vol. 157, pp. 329–338, 2019.

[19] A. Csábrági, S. Molnár, P. Tanos, and J. Kovács, "Application of artificial neural networks to the forecasting of dissolved oxygen content in the Hungarian section of the river Danube," *Ecological Engineering*, vol. 100, pp. 63–72, 2017.

[20] A. Rahman, J. Dabrowski, and J. McCulloch, "Dissolved oxygen prediction in prawn ponds from a group of one step predictors," *Information Processing in Agriculture*, vol. 7, no. 2, pp. 307–317, 2020.

[21] Y. Liu, Q. Zhang, L. Song, and Y. Chen, "Attention-based recurrent neural networks for accurate short-term and long-term dissolved oxygen prediction," *Computers and Electronics in Agriculture*, vol. 165, Article ID 104964, 2019.

[22] Q. Ren, X. Wang, W. Li, Y. Wei, and D. An, "Research of dissolved oxygen prediction in recirculating aquaculture systems based on deep belief network," *Aquacultural Engineering*, vol. 90, Article ID 102085, 2020.

[23] A. F. Zambrano, L. F. Giraldo, J. Quimbayo, B. Medina, and E. Castillo, "Machine learning for manually-measured water

quality prediction in fish farming," *PLoS One*, vol. 16, no. 8, Article ID e0256380, 2021.
[24] I. M. Shaker, "Effect of using different types of organic manure (compost; chicken, Mycelium) and mineral fertilizer on water quality, plankton abundance and on growth performance of *Oreochromis niloticus* in earthen ponds," *AbbassaInt .Journal Aquarium*, pp. 203–226, 2008.