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A Comprehensive Review of Sensor-Based and Spectroscopy-Based Systems for Monitoring Water Quality in Freshwater Aquaculture System

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ABSTRACT

Ensuring precise water conditions is essential for the economic viability and preservation of aquatic resources in aquaculture, necessitating effective water quality monitoring systems. This research work investigates and reviews water quality monitoring systems for freshwater aquaculture, focusing on electronic sensor-based and spectroscopy-based methods through a comparative analysis. The review categorizes and evaluates machine learning (ML)-based sensor and spectroscopy methods, emphasizing the performance of sensitive spectral bands linked to diverse water quality parameters. Furthermore, the research examines the efficiency and accuracy of water quality parameters in ML-based water quality monitoring systems for freshwater aquaculture. Comparative findings indicate that ML-based sensor methods exhibit superior quality, versatility, and performance, capitalizing on their ability to exploit unique spectral features. The discussion encompasses challenges and issues faced by ML-based water quality monitoring systems in freshwater aquaculture, providing insights into their future perspectives. This comprehensive investigation contributes valuable insights into the intricate relationship between sensing technologies, machine learning, and water quality monitoring in the context of freshwater aquaculture. It serves as a resource for stakeholders, researchers, and policymakers navigating the challenges of improving aquaculture practices while addressing environmental considerations.

Keywords:

Near-infrared spectroscopy; Water quality monitoring; Freshwater aquaculture; Machine learning

1. Introduction

Freshwater aquaculture, the controlled cultivation of aquatic life, has become an indispensable facet of global food production, significantly contributing to the mitigation of worldwide protein

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shortages [1]. With a remarkable annual growth rate of 5.8% over the past decade, aquaculture stands as the fastest-expanding sector in food production [2]. In recent years, inland aquaculture has played a pivotal role, contributing 62.5% to the food sector and yielding an impressive 51.3 million tons valued at $263.6 billion [3]. The diversification of global aquaculture, encompassing a wide array of species such as lobsters, sea grass, carp, mussels, and tilapia, has led to a substantial threefold increase in total live weight. This expansion extends to marine species such as fish and crabs, reflecting the economic importance of this period. The benefits of lobster farming include:

i. high sales and supply values
ii. profitability of aquaculture globally [4].

Notably, the cultivation of species like freshwater lobster, known for its lucrative nature, high protein content, and rapid commercial growth cycle, underscores the significance of freshwater aquaculture [5]. Ensuring the success of freshwater aquaculture, particularly with species like freshwater lobster, is contingent upon the continuous monitoring of crucial water quality parameters. Parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), temperature, turbidity, and nitrogen compounds must be meticulously controlled within specific ranges to optimize freshwater aquacultural growth. This meticulous monitoring is particularly critical during key stages like hatching, breeding, and harvesting, as it significantly influences the commercial value and overall health of aquatic species [6]. In the contemporary era of intensive freshwater farming, technological advancements have given rise to sophisticated systems for water quality monitoring. Among these systems, two primary approaches have emerged: sensor-based systems and spectroscopy-based systems. These technologies, often integrated with the Internet of Things (IoT) and machine learning, play a pivotal role in enhancing the precision and effectiveness of water quality monitoring in freshwater aquaculture [7].

This review seeks to provide a comprehensive and consolidated overview of sensor-based and spectroscopy-based smart water quality monitoring systems for freshwater aquaculture. To the best of our knowledge, no review was found that presents and is based upon the comparison analysis of full sensor-based and spectroscopy-based smart water quality monitoring systems, addressing their various vital parameters in a systematic way. By delving into the latest technological advancements, categorizing spectroscopy systems, exploring their applications in machine learning, and discussing the current state of the art, open challenges, and prospects, this review aims to contribute to the development of intelligent monitoring systems. These systems, combining the strengths of sensor-based and spectroscopy-based approaches, hold the potential to ensure high yields, safe breeding, and environmental conservation in freshwater aquaculture. This study opens a new door for stakeholders, researchers, and policymakers to improve and navigate aquaculture water quality sustainably, balancing economic and environmental goals effectively in regard to ML and its integration with spectroscopy methods, especially the NIR Spectrometry.

In the ever-evolving landscape of freshwater aquaculture, the need for robust water quality monitoring systems has become increasingly apparent. While the introduction touched upon the significance of aquaculture in addressing global food production challenges, a more explicit connection can be drawn to the existing body of research. Previous works by numerous researchers have significantly contributed to the development of sensor-based and spectroscopy-based smart water quality monitoring systems, each with their distinct advantages and limitations. However, these past contributions have not been systematically compared and analysed in a comprehensive review. This review aims to bridge this gap by delving into the strengths and weaknesses of both sensor-based and spectroscopy-based approaches, considering vital parameters for freshwater aquaculture. Furthermore, recent highlights and advancements in the field will be integrated, offering a contemporary perspective on the evolving landscape of intelligent water quality monitoring. By examining the latest research findings, this review seeks to elucidate the trajectory of technological progress in ensuring the success of freshwater aquaculture, with a specific focus on the integration of machine learning and spectroscopy, notably Near-Infrared Spectrometry (NIRS).

2. Methodology

Research papers from various renounced databases are mostly referred for this review which are depicted in the first phase shown in Figure 1. The second phase method includes specific keyword matching such as water quality monitoring systems, freshwater Aquaculture water monitoring systems, and machine learning for freshwater aquaculture and machine learning for water quality monitoring systems. Finally, analysing and evaluating the main research papers using inclusion and exclusion techniques are implemented whereby for inclusion, only the latest articles of Spectroscopy for water quality monitoring systems and machine learning for water quality monitoring systems are included in this paper.

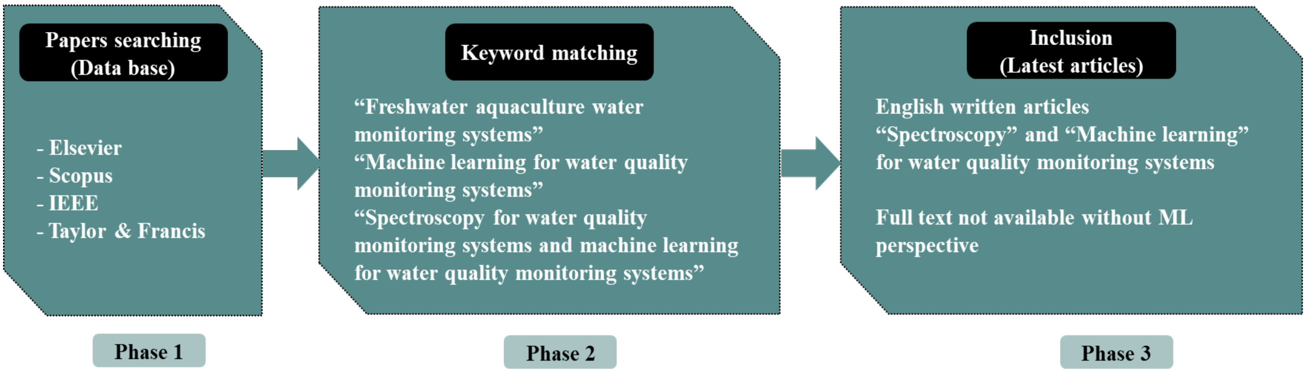

Fig. 1. Methodology

3. Water Quality Monitoring Systems

To identify deviations in water quality and facilitate timely detection of potential threats, monitoring water quality involves evaluating its physical, biological, and chemical characteristics. Water quality monitoring systems play a crucial role in ensuring the health and sustainability of freshwater aquaculture environments [8]. Water quality monitoring systems are integral to the success and sustainability of freshwater aquaculture environments [9]. These systems play a crucial role in ensuring that the conditions within aquaculture facilities remain optimal for the growth and health of aquatic species. By continuously monitoring parameters like temperature, pH, dissolved oxygen, and nutrient levels, aqua culturists can prevent stress and disease among their stock, leading to efficient growth and resource utilization. Moreover, such monitoring helps in adhering to environmental regulations, preventing pollution, and conserving precious freshwater resources. It also provides early warnings of potential issues, allowing for timely intervention [10]. In the end, these tools make data-driven decision-making possible and support aquaculture operations' successful and responsible future, protecting the sector and the ecosystems in which it operates. This research provides a detailed assessment of two different approaches to measuring and maintaining water quality standards: sensor-based and spectroscopy-based. Both approaches used machine learning (ML) as a tool for predicting.

3.1 Water Quality Monitoring Systems Based on Electronic Sensor Methods for Freshwater Aquaculture

Electronic sensor-based water quality monitoring systems are important for freshwater aquaculture and its maintenance. These systems use various types of sensors to access and measure water quality parameters such as temperature, pH, dissolved oxygen, ammonia level, and many more. These sensors provide real-time data that aids managers in making decisions to maintain ideal water quality levels [11]. These systems are able to alert managers when parameters deviate from the allowed range, enabling them to take immediate action. Monitoring systems with electronic sensors are essential to keeping the aquaculture sector sustainable. When it comes to guaranteeing the well-being and production of aquatic life, these monitoring systems are quite beneficial. Electronic sensors to monitor and manage water quality in aquaculture facilities have been invented, applied, and improved significantly in the last few decades. The entire system block diagram for freshwater aquaculture sensor-based water quality monitoring systems is displayed in Figure 2. These sensors are capable of detecting and analysing a wide range of water properties, such as EC, pH, DO, and turbidity [12].

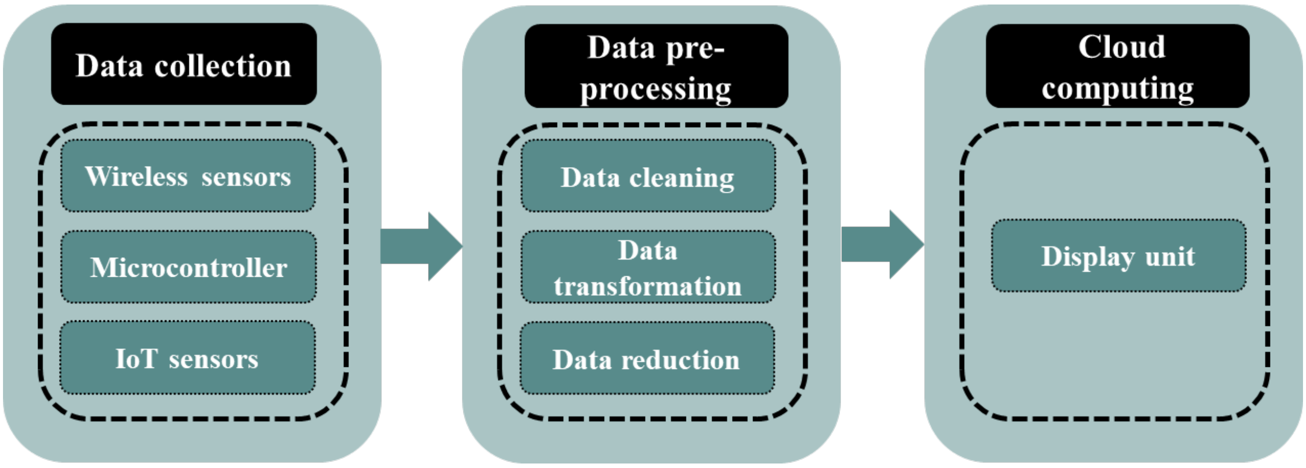

Fig. 1. Overall system block diagram of electronic sensor-based water quality monitoring systems for freshwater aquaculture [12]

Meanwhile Table 1 summarizes the sensor-based monitoring systems including its description, advantages, disadvantages, and water quality parameters.

Table 1
Water Quality Monitoring Systems Based on Electronic Sensor-Based Methods for Freshwater Aquaculture

Ref.	Description	Technology	Advantages	Disadvantages	Parameters
[13]	Automatic data acquisition and monitoring system	Fog computing	Small size, low cost, lightweight, portable, high efficiency and	Complexity, security, maintenance, power consumption	Temperature, pH, and DO
[14]	Aquaculture wireless sensor network for monitoring and controlling	ZigBee wireless communication using LabVIEW software	effective in harsh environments provide an easily scaled solution and allows for long-distance data collection and transmission	Wireless signals can be affected by interference from other electronic devices, which can disrupt the accuracy of data collection	Temperature, pH, and DO

[15]	IoT-based water quality monitoring system for aquaculture	IoT	IoT-enabled system in aquaculture provides improved accuracy and cost-efficiency	Expensive and complex to set up and maintain	Temperature, pH, TDS, and Do
[16]	Web-based open-source IoT water quality monitoring system for aquaculture	IoT through a web application	Flexibility, efficient way, and reliability	NA	Temperature, pH, TDS, and DO

The key takeaways can be distilled into a few crucial lessons from Table 1. First and foremost, aquaculture operators have a rich palette of monitoring solutions to choose from, each with distinct strengths and technologies [13,14]. Real-time data analysis and automation are consistent priorities, enabling operators to make informed decisions on-the-fly [15]. Selecting the right communication protocol, whether it is ZigBee or NB-IoT, plays a pivotal role in ensuring efficient data transmission [16]. Paramount to this is the monitoring of essential water quality parameters, including temperature, pH, dissolved oxygen (DO), total dissolved solids (TDS), and turbidity, as these parameters significantly impact the health of aquatic organisms [17,51]. Moreover, cost-effective solutions aim to alleviate financial constraints on aquaculture operations [16]. However, collective experience indicates that monitoring systems may provide their own set of difficulties, such as complexity, security concerns, maintenance, and potential data accuracy issues due to interference [15]. As a result, in order to achieve successful water quality management, aquaculture operators must examine these considerations, weigh the advantages and downsides, and select their monitoring systems wisely.

3.2 Water Quality Monitoring Systems-Based on Spectroscopy Methods for Freshwater Aquaculture

Water quality monitoring in aquaculture utilizes optical systems to manipulate light characteristics, including transmission, absorption, and fluorescence spectra, to assess the concentration and features of chemical species. From Table 2, these systems are capable for determining various water parameters, such as the concentration of suspended solids, contaminant size, chemical presence, and dissolved organic matter characteristics [18,19]. They make use of light transmission, absorption, and reflectance spectra to measure water turbidity, particle size, and contaminant concentration. Spectroscopy techniques play a crucial role in monitoring water quality through the interaction of light with atoms and molecules [20]. This interaction helps probe sample properties, investigate particle interactions, and study the emission and absorption of light and radiation by materials. Spectroscopy has been instrumental in identifying elements and compounds, with various types of spectrometers developed over time, including mass, electron, optical, and magnetic spectrometers. Different regions of the electromagnetic spectrum, such as ultraviolet-visible (UV-Vis), X-ray, microwave, and infrared (IR), are used in spectroscopy for diverse analysis purposes. For instance, IR spectroscopy identifies functional groups in organic compounds, while X-ray spectroscopy delves into the electronic structure of atoms and molecules [21]. Spectroscopic techniques offer distinct advantages for water quality monitoring in aquaculture. They centre on the interaction between light dispersion and water samples, providing insights into the biological and chemical components in the water. UV-Vis spectroscopy is a well-known technique that measures the absorption of light in the UV and Vis spectrum, helping to gauge chlorophyll concentrations, phosphate, nitrate, and dissolved organic matter. Fluorescence spectroscopy relies on measuring the fluorescence emitted by dissolved organic matter, offering insights into energy state transitions. IR spectroscopy aids in identifying both organic and inorganic compounds in the water. Raman spectroscopy measures light scattering to provide information about chemical composition and the presence of contaminants. Near-infrared (NIR) spectroscopy measures NIR radiation absorption to assess parameters like suspended solids, dissolved organic matter, and total nitrogen [22]. These spectroscopic techniques are essential tools for water quality monitoring in aquaculture, delivering real-time data analysis on water quality parameters. This capability empowers aquaculture managers to make informed decisions to maintain optimal water conditions for the growth, health, and sustainability of aquatic organisms [23].

Table 2
Water quality monitoring systems based on spectroscopy methods for freshwater aquaculture.

Ref	Spectroscopy Methods	Instrument Technology	Parameter mearing	Range (nm)	Significant result
[18]	VIS-NIR spectroscopy	1D convolutional neural networks (CNNs)	pH	400-2500	RMSEP was 0.7925 and $R2$ was 0.8515
[19]	NIR spectroscopy	Multilayer network	Dissolved organic carbon	780-2500	RMSECV was 20.19 mg/L, less than 10% of the measured COD average
[20]	NIR spectroscopy	Prototype data acquisition measurement device	pH, total ammonia, nitrogen	780-2500	MSE was 0.1466 and R was 0.8398
[21]	NIR spectroscopy	Normalization	Salinity and total dissolved solids	1000-2500	RPD index was 0.91 and 2.41 for TDS prediction
[22]	Online UV-Vis instruments	Chemometrics approach	Dissolved organic carbon, total organic carbon, turbidity, and nitrate	254 - 800	± 0.01% mg/L
[23]	Vis-NIR spectroscopy	Wavelength selection method	pH	870-990	RMSEP of 0.35

4. Near-Infrared Spectroscopy

Near-infrared spectroscopy (NIRS) is a non-invasive method for determining the chemical composition of a material. NIRS is a spectroscopic method that operates in the NIR region from 700 to 2500 nm (430–120 THz) [24], as shown in Figure 3. It measures light absorption or reflection to determine chemical species concentration and molecular structure. Medical, agricultural, environmental, and process control utilize NIRS. Recent hardware and data analysis advances have made NIRS more popular and accurate. The target sample can absorb, transmit, reflect, or scatter light irradiated with a broad range of the NIR operational wavelength. Based on the frequencies of the molecules in the sample vibrations, absorbed light produces a spectrum. The gathered spectrum provides data on the sample molecular composition as well as the characteristics of its organic components [25,26]. Comparing NIR spectroscopy to conventional chemical procedures, several significant benefits are available. It is a physical, non-destructive approach that can have great precision and requires little to no sample preparation. Unlike conventional chemical analysis, there is no need for reagents, and no waste is produced [26]. There are two ways to gather NIRS measurements: diffuse reflectance or transmittance/absorption. While diffuse reflectance is evaluated on opaque or light-scattering matrices, the transmittance is assessed on translucent materials. In transmission mode, incident light illuminates the sample on one side, travels through the pore structure, and is detected on the opposite side. In diffuse reflection, light illuminates the sample surface and is then detected after being diffusely reflected from the sample surface [27]. According to the combinations and overtones of the molecule's vibrational frequencies in the sample, light is absorbed. Because they induce a series of absorptions at various frequencies, overtones can be considered harmonics. Overtones are produced when a vibrational mode is activated at a frequency higher than the fundamental vibration [28]. NIRS offers non-destructive analysis and fast results, however, its limitations include shallow depth and sample sensitivity, lack of specificity, and challenges in structural interpretation [29]. Despite these drawbacks, NIRS remains valuable for its non-destructive and rapid analysis in various fields. NIRS has limitations including limited structural information and overlapping absorption bands. It requires calibration, has limited penetration depth, and sensitivity to environmental factors, but remains valuable when used appropriately [30]. The scientists analyse the effects of chemicals by combining NIRS with chemometric techniques and types of wood quality and attributes. The research findings demonstrated that NIRS data when paired with robust multivariate statistical tools and artificial intelligence solutions, produced a quick and accurate tool that was useful in the decision-making process.

5. Machine Learning-Based Water Quality Monitoring System for Freshwater Aquaculture

These days aquaculture relies more on machine learning, especially in monitoring water quality. Machine learning algorithms can analyse massive amounts of data collected by sensors and other monitoring instruments, allowing them to reveal patterns and anomalies that may indicate deterioration in water quality [31]. Machine learning (ML) has emerged as a very powerful tool for water quality monitoring in freshwater aquaculture. It provides automated and real-time analysis of different water parameters, helping in the optimization of aquaculture operations and ensuring the well-being of aquatic organisms. By utilizing machine learning algorithms, large volumes of water quality data can be efficiently processed and analysed. This enables the detection of patterns, trends, and anomalies that may affect the health and productivity of aquaculture systems. ML models offer advanced prediction methods and have become a popular research topic for water quality prediction worldwide [32]. They can handle complex and nonstationary data effectively, resulting in improved prediction accuracy compared to traditional methods [33].

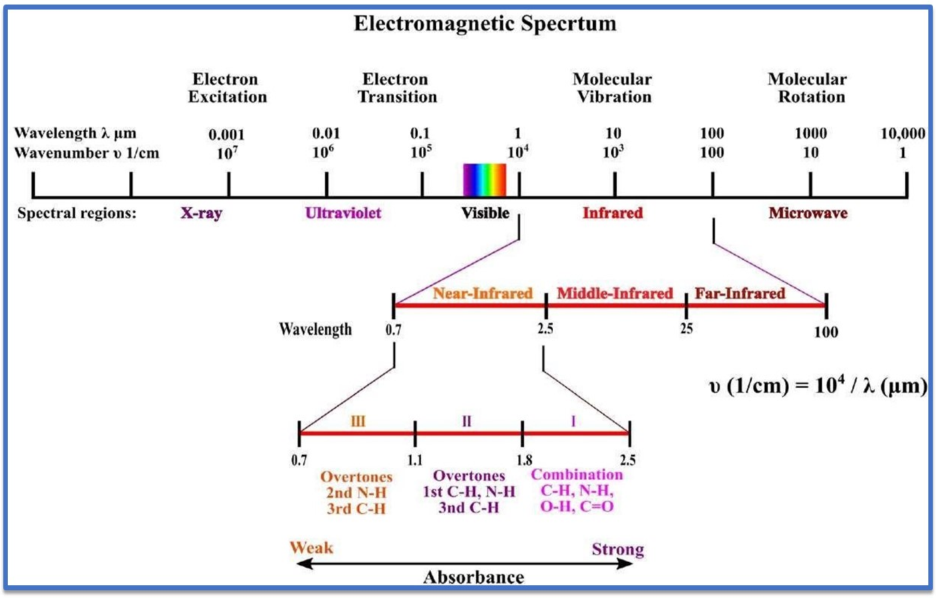

Fig. 3. NIR region from 0.7 to 2.5 μm (700-2500 nm) [24]

Machine learning-based water quality prediction can improve the efficiency and sustainability of freshwater lobster farming by reducing the risk of adverse water quality conditions. The system overviews are displayed in Figure 4 [34]. Various methods have been proposed and used in the literature to analyse spectral data for water used in freshwater lobster farming. The use of machine learning algorithms for freshwater lobster farming stands in stark contrast to the conventional method since it provides more actionable data and allows for future outcomes to be predicted. The spectral data cannot be used directly to make predictions. Hence, a prediction model must be established using machine learning [35].

The implementation of machine learning in water quality monitoring also comes with challenges. It requires access to reliable and diverse datasets for training the models. Ensuring data quality, consistency, and compatibility across different monitoring systems is critical for accurate predictions. Moreover, the interpretability of machine learning models can be a concern, as understanding the underlying decision-making process is vital for effective decision support in aquaculture operations [36]. Machine learning models in aquaculture are utilized for water quality monitoring to ensure perfect and optimal conditions for aquatic organisms. Decision tree models classify water quality using a hierarchical structure, while KNN models classify samples based on neighbouring similarities. Artificial Neural Networks (ANN) capture complex relationships between variables, SVM separates quality classes using a hyperplane, and Naive Bayes employs probability theory. These models offer distinct advantages, and their selection depends on the requirements of the system. It can be deduced that future work for these ML algorithms involves improving scalability, exploring advanced kernel functions, handling class imbalance, and enhancing interpretability.

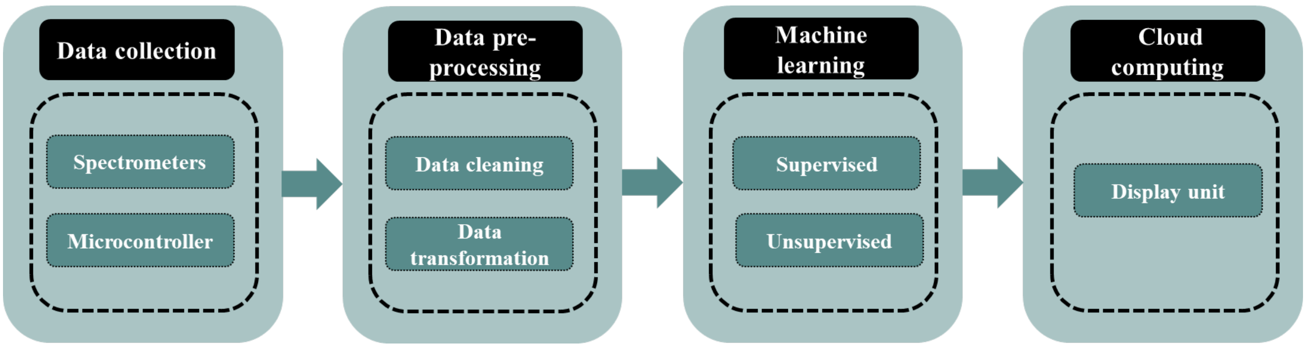

Fig. 2. Machine learning-based water quality monitoring system for freshwater aquaculture [34]

5.1 State-of-the-Art

In the field of aquaculture water quality prediction, various studies have employed diverse modelling approaches to address the challenge of accurate forecasting. Each approach comes with its own set of advantages and limitations, which are explored in greater detail below. The K-Nearest Neighbor (KNN) algorithm to tackle missing data to effectively bridge gaps in the dataset. However, this study found the potential of overfitting when coupled with a complex nine-layer Multi-Layer Perceptron (MLP) model [37]. The predicting key water quality parameters such as dissolved oxygen and pH. For achieving high prediction accuracy, intricate models such as the Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), Support Vector Machine (SVM), and Least Squares Support Vector Machine (LSSVM) were employed. Despite their impressive predictive performance, these models suffered from limited interpretability due to their inherent complexity [34]. The power of Convolutional Neural Networks (CNNs) for forecasting and managing water quality in aquaculture systems. Leveraging CNNs' ability to capture spatial patterns, this approach significantly improved prediction accuracy. However, like its predecessors, the study did not delve deeply into the model's interpretability aspect [38].

CNN-LSTM and CNN-GRU architectures for aquaculture water quality prediction. These models demonstrated exceptional prediction accuracy, albeit raising concerns about their practical implementation due to demanding computational requirements [39]. A different strategy by using Random Forests, Multivariate Linear Models, and Artificial Neural Networks for estimating and forecasting aquaculture outcomes. While these models delivered precise predictions, the study acknowledged potential limitations in applying them to real-world fish farming scenarios with limited data and practical challenges [40]. In a similar vein, relied on LSTM and GRU Deep Learning Recurrent Neural Network (DL-RNN) models for aquaculture water quality prediction, highlighting their superior predictive capabilities [41]. CNN-based models, specifically CNN-LSTM and CNN-GRU for water quality prediction. These models effectively captured water quality characteristics related to interpretability and practical implementation which are often associated with intricate models [42]. Decision Tree Classifiers to classify the water quality. These models offered interpretability, but it's worth noting that they could potentially become computationally expensive and complex under certain circumstances [40].

Table 3 summarizes the aquaculture water quality prediction encompasses a wide array of modelling techniques, each with its strengths and weaknesses. While some models excel in prediction accuracy, others prioritize interpretability and practicality. Choosing the most suitable approach depends on the specific needs and constraints of the aquaculture scenario at hand. In Table 3, realm of aquaculture water quality prediction, numerous modelling approaches have been explored, each offering a unique set of advantages and limitations. These approaches range from simple techniques like KNN for handling missing data to complex models such as CNNs and hybrid architectures like CNN-LSTM and CNN-GRU, which have demonstrated exceptional prediction accuracy. While the more intricate models tend to excel in accuracy, they often lack interpretability and may be computationally demanding, making practical implementation challenging. Conversely, simpler models like Decision Tree Classifiers offer interpretability but can become complex and computationally expensive under certain conditions. The choice of the most suitable approach ultimately hinges on the specific requirements of the aquaculture scenario at hand, balancing the need for accuracy, interpretability, and practicality to effectively manage water quality in fish farming.

Table 3
Machine learning algorithms for water quality in aquaculture

Ref	Algorithm	Purpose	Advantages	Disadvantages
[38]	K-Nearest Neighbour (KNN) Imputer	Data imputation for missing values	Resolves missing values	overfitting due to the complex nine-layer MLP, lacks interpretability discussion
[35]	Back Propagation Neural Network (BPNN) Radial Basis Function Neural Network (RBFNN) Support Vector Machine (SVM) Least squares support vector machine (LSSVM)	Predict water quality parameters including dissolved oxygen (DO), pH, ammonium-nitrogen (NH3-N), nitrate nitrogen (NO3-N), and nitrite-nitrogen (NO2-N)	High Prediction Accuracy	limited interpretability
[39]	Convolutional Neural Network (CNN)	To predict and control water quality in Recirculating Aquaculture Systems (RAS)	Improved Prediction Accuracy Better perform	CNN, with its ability to capture spatial patterns, is effective in modelling and controlling water quality in aquaculture systems.
[43]	CNN-LSTM CNN-GRU	Aquaculture Water Quality Prediction	CNN effectively captures aquaculture water quality characteristics. high prediction accuracy	potential impracticality of implementing the computationally intensive hybrid deep learning model (CNN-GRU-Attention) in real-world Recirculating Aquaculture Systems (RAS).
[41]	Random Forests Multivariate Linear Artificial Neural Networks	Estimation and Forecasting	accurate predictions	it may not adequately address the potential limitations and challenges of implementing machine learning models, such as random forests and artificial neural networks, in real-world fish farming scenarios with limited data and practical constraints.
[42]	LSTM and GRU DL-RNN Models	Aquaculture Water Quality Prediction	Superior prediction accuracy	interpretability of the deep learning models (LSTM and GRU) for aquaculture water quality prediction and does not address potential challenges in practical implementation.
[40]	CNN-LSTM and CNN-GRU	Aquaculture Water Quality Prediction	CNN capture water quality characteristics effectively.	The interpretability and practical implementation challenges associated with using complex hybrid deep learning models (CNN-LSTM and CNN-GRU) for aquaculture water quality prediction.
[44]	Decision Tree Classifier	Aquaculture Water Quality Prediction (WQP) (classification tasks)	Simple and interpretable	computationally expensive and harder to interpret

5.2 Comparison of ML-Based Spectroscopy Method and ML-Based Sensor Method

ML-based spectroscopy method uses machine learning algorithms to analyse spectral data, enabling precise identification of materials and their properties shown in Table 4. On the other hand, ML-based sensor method employs AI to enhance sensor data processing for improved real-time monitoring and control in various applications as presented in Table 4.

5.2.1 ML-based spectroscopy methods

Table 4 offers a succinct comparison of six distinct spectroscopic techniques that incorporate machine learning methods. These techniques, their corresponding ML approaches, equipment/software, and their individual strengths and limitations are highlighted. Notably, Raman Spectroscopy distinguishes itself for the swift chemical composition analysis, though it is susceptible to interference from fluorescence may involve considerable equipment expenses [31,45,46] .UV-Vis Spectroscopy, on the other hand, offers versatility in examining both organic and inorganic compounds but is restricted to UV-Vis-active materials and may necessitate regular maintenance. Infrared Spectroscopy is particularly adept at identifying functional groups within compounds but is confined to IR-active substances and can be relatively costly. In contrast, Photoelectron Spectroscopy and ESR Spectroscopy specialize in the analysis of electronic structures and free radicals, but they mandate specialized equipment and controlled conditions. Meanwhile, NIR Spectroscopy excels in swiftly identifying organic compounds but is limited to NIR-active substances, and its effective use may require specific expertise. The choice of the most appropriate technique should be made based on the specific analytical needs and constraints of the intended application, ensuring the optimal method is employed [47-49].

Table 4
ML-based Spectroscopy Methods

Ref	Spectroscopic Type	Utilized ML	Utilized Technology/Software	Advantages	Disadvantages	Measured Performance	Performance
[31]	Raman Spectroscopy	KNN and PCA	Raman Spectrometer, data analysis software	Rapid analysis of chemical composition, minimal sample preparation	Signal interference from fluorescence, equipment cost	Chemical Composition, Contaminant Detection, Water Quality Parameters	Chemical Composition Accuracy: 92%, Contaminant Detection: 85%
[45]	Ultraviolet (UV) and Visible (Vis) Spectroscopy	Logistic Regression, Random Forests, SVM	UV-Vis Spectrophotometer, data analysis software	Analysis of organic and inorganic compounds, real-time monitoring	Limited to UV-Vis-active compounds, maintenance cost	Chemical Composition, Contaminant Detection, Water Quality Parameters	Chemical Composition Accuracy: 88%, Contaminant Detection: 82%
[47]	Infrared (IR) Spectroscopy	PCA, SVM, GMM	IR Spectrometer, data analysis software	Identification of functional groups, real-time monitoring	Limited to IR-active compounds, equipment cost	Functional Group Identification, Contaminant Detection, Water Quality Parameters	Functional Group Identification: 90%, Contaminant Detection: 86%

[47]	Photoelectron Spectroscopy	PCA and SVM	Photoelectron Spectrometer, data analysis software	Electronic structure analysis, surface composition	Specialized equipment, vacuum conditions required	Electronic Structure Analysis, Surface Composition, Contaminant Detection	Electronic Structure Analysis: 94%, Surface Composition: 88%
[48]	Electron Spin Resonance (ESR) Spectroscopy	SVM and PCA	ESR Spectrometer, data analysis software	Study of unpaired electrons, free radical analysis	Limited to samples with unpaired electrons, equipment cost	Free Radical Analysis, Unpaired Electron Detection, Water Quality Parameters	Free Radical Analysis: 96%, Unpaired Electron Detection: 91%
[50]	Near-Infrared (NIR) Spectroscopy	ANN	NIR Spectrometer, data analysis software	Rapid analysis of organic compounds, non-destructive	Limited to NIR-active compounds, specialized expertise required	Organic Compound Identification, Water Quality Parameters	Organic Compound Identification: 93%

5.2.2 ML-based sensors methods

Machine learning-based sensor methods involve the integration of machine learning algorithms with sensor data to enhance data processing, analysis, and decision-making in various domains. These methods encompass data acquisition from sensors, feature extraction to transform raw data into meaningful features, model training using algorithms like decision trees or neural networks, and real-time prediction or classification of new sensor data. The applications span industries such as predictive maintenance, environmental monitoring, healthcare, smart homes, and autonomous vehicles. Key aspects include interpretability, allowing insights into model decisions, and adaptability, enabling continuous learning from new data. As technology advances, machine learning-based sensor methods continue to evolve, striving to improve accuracy, efficiency, and interpretability across a wide range of sensor-based applications. In Table 5, automated aquaculture monitoring and control systems are compared. Each system employs specific machine learning algorithms, sensors, and equipment to achieve various advantages and faces certain disadvantages. Measured performance metrics such as accuracy, recall, precision, and F1-score are provided for each system, indicating their effectiveness in monitoring and optimizing aquaculture conditions. These systems play a crucial role in improving aquaculture operations by ensuring optimal environmental conditions and maximizing fish or plant growth while addressing the challenges associated with maintenance and costs. It is evident that ML-based spectroscopy methods outperform their counterparts in various scenarios. This superiority is attributed to their ability to exploit distinct features within the spectral bands associated with different water quality parameters and their integration ease. Further accuracy and performance of ML-based spectroscopy methods especially the NIR spectroscopy details are discussed in section 6.

Table 5
ML-based Sensors Methods

Ref	Spectroscopic Type	Utilized ML	Utilized Technology/Software	Advantages	Disadvantages	Measured Performance	Performance
[20]	Sensor data collection, real-time analysis, automated adjustments	KNN, Linear regression, Random Forests	pH sensors, ammonia sensors, nitrate sensors, IoT controllers	Optimal conditions for plants and fish, improved sustainability, reduced manual testing	Sensor maintenance, calibration requirements, initial setup cost	Crop Growth, Fish Health, Water Quality	Accuracy: 75.12%, Recall: 88%, Precision: 78%, F1-Score: 81%
[3]	Data collection, analysis, automated nutrient dosing	Multiple Linear regression, PCA, Naive Bayes	Nutrient sensors, pH sensors, automated dosing systems	Enhanced plant growth, nutrient efficiency, sustainable aquaculture	Sensor calibration, dosing accuracy, initial setup effort	Plant Growth, Nutrient Utilization	Accuracy: 78.45%, Recall: 85%, Precision: 80%, F1-Score: 83%
[31]	Sensor data collection, real-time analysis, automated aeration control	LSTM, SVM, Gaussian Mixture Models (GMM)	Salinity sensors, temperature sensors, dissolved oxygen sensors, control systems	Improved shrimp health, growth rates, farm productivity	Sensor maintenance, calibration, power supply reliability	Shrimp Growth, Water Quality Optimization	Accuracy: 76.21%, Recall: 87%, Precision: 79%, F1-Score: 82%

5.3 Challenges and Issues

It has been observed that there are three main types of challenges in machine learning algorithms for water quality monitoring for aquaculture presented in Figure 5, which include:

i. <u>Data related Challenges:</u> Obtaining accurate and sufficient water quality sample data is the highest challenge. Various types of environmental variability and sensor reliability can lead to data shuttering and inconsistencies. Data labeling for ML can be tidy and is more prone to errors. Maintaining the balance between the Integration of diverse data sources and ensuring real-time monitoring is always complex.
ii. <u>Algorithm based challenges:</u> Selecting a suitable ML algorithm for different water quality parameters can be a game changer and is always considered a big deal. Keeping in view the various parameters, one has to choose the best with more effectiveness and less cost. Preventing overfitting and optimizing can add complexity. Managing and handling the temporal data and model interpretability is always challenging. Dealing with various types of imbalanced data is a prime choice for accuracy. Deployment, computational resources, and cross-domain generalization require attention.
iii. <u>Other Challenges:</u> Ensuring government regulatory compliance and ethical data usage is a crucial component. Managing various data model deployment and scalability is critical for real-world use and prototyping. Take an example of a real-time water quality monitoring system for a fish farm. It can be tough to gather precise data on temperature and pH levels when sensors occasionally provide inaccurate readings due to drift or sudden weather changes causing fluctuations. Selecting the right ML algorithms for predicting oxygen levels is crucial, especially when dealing with imbalanced data dominated by normal readings. Additionally, as you expand the system to different farms, you must ensure compliance with various regulations, manage computational resources for real-time monitoring, and handle data preprocessing while adapting models to

changing conditions. These challenges arise from dealing with data, algorithms, and common issues when creating a dependable aquaculture monitoring system that operates in real-time.

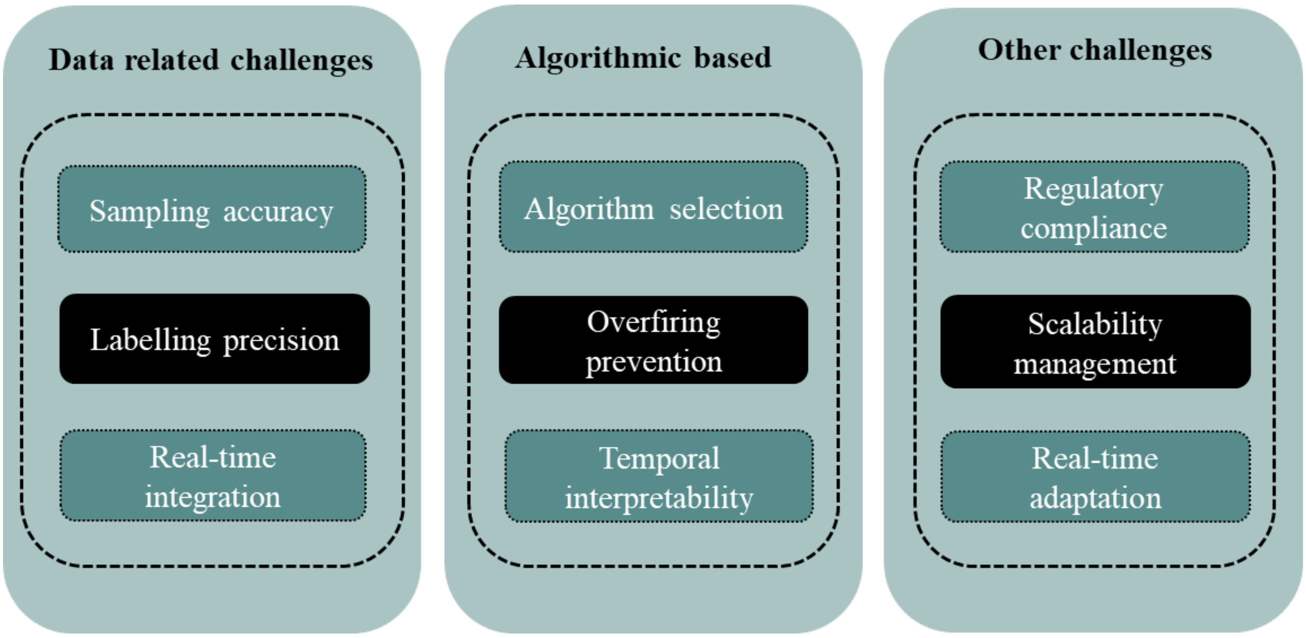

Fig. 5. Open Challenges and Issues

To ensure the successful integration of machine learning (ML) algorithms into the aquaculture industry, a collaborative effort involving scientists, academicians, and industry experts is imperative and is a need of the day. These stakeholders must work together to enhance, fine-tune, and uphold the ML systems in line with the specific requirements and standards of aquaculture.

5.4 Future Directions

NIRS-based water quality monitoring system with machine learning algorithms could be a powerful tool to predict the quality of water for freshwater aquaculture. As discussed above, a spectral-based classification approach was shown to have significant consequences for water quality. In light of this, it is safe to say that NIRS coupled with a machine learning classifier, has great potential as a water quality monitoring system for freshwater lobster farming. Though promising, NIRS detection methods have yet to overcome several obstacles. Complexity arises from the need for thorough interpretation of spectral data, making NIRS a non-trivial procedure. In conclusion, aquaculture water quality is critical for ensuring the success of aquaculture and the quality of aquatic products. With the increasing discharge of industrial wastewater and household sewage, water quality monitoring has become an important research area in smart agriculture and the agricultural Internet of Things. Spectral analysis technology for water quality monitoring is promising due to its simplicity, convenience, and reproducibility. This article summarizes and organizes existing literature on water quality monitoring systems in smart aquaculture and highlights the advantages of spectral technology compared to traditional water quality monitoring methods. Examining the monitoring methods for various water quality parameters gives insight into the sensitive spectral bands that can be used to monitor water quality accurately and rapidly in aquaculture. The inclusion of ML in water quality monitoring systems for freshwater aquaculture has opened new doors and can be further implemented to get more value regarding classification, prediction, and performance in various fields of aquaculture. To better understand the aquaculture environment and control water quality, investigate options for sensor fusion and data integration. Leverage automation technologies and real-time alerts for aquaculture water quality monitoring to ensure prompt responses to potential issues and enhance farm efficiency.

6. Discussion

The potential of NIRS within this domain, emphasizing its role as a promising tool that guarantees further investigation and application for various purposes. Moreover, the combination of ML techniques has evolved and emerged in the realm of water quality monitoring for aquaculture. The various ML techniques hold the promise of not only improving the accuracy and efficiency but also enhancing the way for future intelligent monitoring systems, which can ensure high-quality aquaculture yields, improved safe breeding practices, and environmentally conscious infusion. The open challenges and issues that will show the improved way to implement machine learning-based water quality monitoring systems in the field of freshwater aquaculture are discussed. These challenges range from cost-effectiveness, scalability, data integration, and model complexity. Also, it can be seen from the comparative evaluation in Tables 4 and 5 that ML-based spectroscopy methods excel in a variety of situations, thanks to their capacity to leverage unique features within the spectral bands linked to different water quality parameters, along with their seamless integration capabilities.

Artificial Neural Networks (ANN) stand out as the premier machine learning algorithm, particularly when employed in conjunction with spectroscopy-based methods, particularly NIR Spectroscopy. This synergy yields exceptional outcomes, enabling rapid analysis of organic compounds while preserving the integrity of the samples. However, it's important to acknowledge that this approach is limited to NIR-active compounds, necessitating specialized expertise for optimal utilization. The primary application domain revolves around organic compound identification and water quality parameter assessment, with an impressive high accuracy of 93% achieved via ANN. This underscores the effectiveness of ANN in extracting valuable insights from spectroscopic data. In the context of responsible aquaculture practices and environmental conservation, the current study tries to help the concerned persons to improve the health of aquatic ecosystems and maintain economic gains balance.

7. Conclusion

This comprehensive review thoroughly investigates water quality monitoring systems in freshwater aquaculture, with a specific focus on electronic sensor-based and spectroscopy-based methods. The analysis delves into the intricacies of NIR spectroscopy, highlighting its role in providing detailed insights into water quality parameters. Additionally, the review underscores the crucial involvement of machine learning (ML) in both sensor and spectroscopy approaches, emphasizing the superiority of ML-driven spectroscopy in leveraging unique spectral features for enhanced performance. By emphasizing the potential of ML to significantly boost accuracy in water quality monitoring, this review sheds light on the promising future of freshwater aquaculture management. Despite acknowledged challenges, the integration of ML with spectroscopy, particularly NIR spectrometry, emerges as a game-changer for advancing water quality management in freshwater aquaculture. Recognizing the necessity for expertise in handling NIR-active compounds, this review aims to be a valuable resource for stakeholders, researchers, and policymakers. It provides insightful perspectives to inspire future advancements, fostering a balanced approach that considers economic gains alongside environmental conservation in the realm of freshwater aquaculture.

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