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Highly Accurate Detection Of P^h Value And Dissolved Oxygen In Pond Water Using Underwater Microscopic Camera With Coati-Dncnn Algorithm

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Abstract
Effective monitoring of water quality in pond ecosystems is crucial for maintaining aquatic life and ecological balance. In this study, we propose the application of advanced deep learning algorithms in conjunction with underwater microscopic camera technology to precisely detect pH values and dissolved oxygen levels in pond water. We evaluate three deep neural network architectures, namely, WaOA-DNCNN, PSO-DNCNN, and Coati-DNCNN, for their capability to predict these essential water quality parameters.Our findings reveal that the Coati-DNCNN algorithm outperforms the other methods, achieving an outstanding accuracy of approximately 99%. Coati-DNCNN excels in accurately predicting the pH and dissolved oxygen levels by utilizing tuned underwater images as inputs. The integration of Coati-DNCNN with machine learning techniques enhances the precision and reliability of water quality assessment, offering a valuable tool for environmental monitoring and management in pond ecosystems.This research demonstrates the potential of state-of-the-art deep learning algorithms in combination with underwater imaging technology to provide real-time, high-accuracy monitoring of pH and dissolved oxygen levels in pond water. Such advancements are pivotal for the sustainable management of aquatic environments and the preservation of aquatic ecosystems.
Keywords: Pond Water; P^HValue; Dissolved Oxygen; Coati-DNCNN; Underwater Microscopic Camera

Introduction

India has been one of the fastest-growing aquaculture producers in the world. The production of fish and seafood through aquaculture has increased significantly over the years. Major species produced include shrimp, prawns, fish, and mollusks. Indian aquaculture products, particularly shrimp, have seen substantial growth in exports. The European Union and the United States were among the major export destinations for Indian seafood products. This growth was partly due to compliance with international quality and safety standards.The industry has witnessed advancements in technology and farming practices. Techniques such as biofloc technology and recirculating aquaculture systems (RAS) have gained popularity, contributing to increased productivity and sustainability.The Indian government has launched various initiatives to promote aquaculture, including subsidies, training programs, and infrastructure development. The Blue Revolution scheme, for instance, aimed to enhance the productivity and quality of aquaculture.There is a growing awareness of the need for sustainable practices in aquaculture. Many farmers have been adopting better management practices to minimize environmental impacts, such as reduced water usage and responsible feed management.Despite the growth, the industry has faced challenges like disease outbreaks, environmental concerns, and market fluctuations. Disease management and maintaining water quality are ongoing challenges for aquaculture operations.Indian aquaculture has diversified to include various species to meet changing market demands. In addition to traditional favorites like shrimp and fish, new species like tilapia and pangasius have been introduced.The industry has attracted significant investment, including foreign direct investment (FDI), leading to the establishment of modern aquaculture facilities and processing units.Aquaculture has been a source of employment, particularly in rural and coastal areas, contributing to income generation and economic development.The domestic market for seafood in India has also grown due to increased consumer awareness of the health benefits of seafood consumption. This has further fueled the growth of the industry.

Aquaculture and water quality are intimately connected because the quality of water in which aquatic organisms are raised has a profound impact on their health, growth, and overall success of the aquaculture operation. Maintaining good water quality is crucial for sustainable and profitable aquaculture. Aquatic organisms are sensitive to various water parameters, including temperature, pH, dissolved oxygen (DO), salinity, ammonia, nitrite, nitrate, and turbidity. These parameters must be carefully monitored and controlled to ensure optimal conditions for the species being cultivated.Adequate DO levels are critical for the survival of fish and other aquatic species. Low DO levels can lead to stress, reduced growth, and even fish kills. Aeration systems are often used to maintain sufficient oxygen levels in aquaculture ponds or tanks.Ammonia and nitrite are toxic compounds that can accumulate in water due to the breakdown of organic matter and uneaten feed. High levels of ammonia and nitrite can be harmful to fish and other aquatic organisms. Effective filtration and waste management systems are employed to control these compounds.Water temperature affects the metabolic rate and growth of aquatic organisms. Different species have specific temperature requirements, and maintaining the appropriate temperature range is essential for their well-being.The pH level of water can influence nutrient availability and toxicity of certain chemicals. Aquaculture systems often require pH adjustment to maintain optimal conditions for the species being cultivated.Some aquaculture operations, such as shrimp farming, are highly dependent on maintaining specific salinity levels. Monitoring and adjusting salinity is critical to success in these systems.High levels of suspended solids in water can reduce light penetration and affect the growth of aquatic plants and algae. Proper filtration and sedimentation systems are used to manage turbidity.Poor water quality can stress aquatic organisms and make them more susceptible to diseases. Good water quality management is a key component of disease prevention in aquaculture.Properly managing water quality is not only essential for the health of farmed species but also for minimizing environmental impacts. Contaminated runoff, excessive nutrient discharge, and water pollution from aquaculture can harm surrounding ecosystems.RAS technology is designed to maximize water quality by continuously filtering and recirculating water within a closed system. This approach helps conserve water and reduce environmental impact.Many aquaculture operations implement BMPs to ensure that water quality is maintained at optimal levels. These practices often involve regular water testing, appropriate feed management, and effective waste management.

Aquaculture water quality monitoring systems have evolved significantly over the years, becoming more sophisticated and technologically advanced. These systems are crucial for maintaining optimal conditions for aquatic species, preventing disease outbreaks, and ensuring the sustainability of aquaculture operations. These portable devices are commonly used for on-site monitoring of key parameters such as pH, dissolved oxygen (DO), temperature, conductivity, and turbidity. They provide real-time data and are easy to use for routine measurements.Multiparameter sensors combine several measurement capabilities into a single device. They can simultaneously measure parameters like pH, DO, temperature, turbidity, and salinity, providing a comprehensive view of water quality.These systems are typically installed in aquaculture ponds, tanks, or raceways. They consist of various sensors and probes that continuously monitor water quality parameters. Data is sent to a central control system, allowing for real-time monitoring and remote control of water quality conditions.Data collected from monitoring stations can be transmitted wirelessly to a central database, where it is logged and analyzed. This allows for historical data tracking and the early detection of trends or anomalies.In large aquaculture operations, satellite imagery and remote sensing technologies can be used to monitor water quality parameters such as temperature, turbidity, and chlorophyll concentration in open-water systems or coastal areas.Spectrophotometers are used to measure the concentration of specific chemicals or compounds in water, such as ammonia, nitrate, or phosphate. These measurements are important for nutrient management in aquaculture systems.Flow cytometry is used to count and analyze microorganisms in water, including algae and phytoplankton. Monitoring these populations helps in understanding water quality and potential issues related to algal blooms.eDNA analysis involves extracting DNA from water samples to detect the presence of specific aquatic species, including pathogens. It is a valuable tool for disease surveillance and early detection.Various software applications and platforms are available to manage and analyze water quality data. These systems can generate reports, provide alerts for critical conditions, and assist in decision-making.Aquaculture operations may use mathematical models and computer simulations to predict how changes in environmental factors, including water quality parameters, might impact the health and growth of aquatic species.AI algorithms and machine learning models can be trained to analyze large datasets from water quality sensors and provide predictive analytics, helping farmers optimize management practices.RAS and biofloc systems often require sophisticated controls for managing water quality parameters, including pH, oxygen, and carbon dioxide levels. These systems may include automation and feedback control loops.

While water quality monitoring systems have advanced significantly over the years, they still have some drawbacks and limitations. It's important to be aware of these limitations to make informed decisions when using such systems in aquaculture and environmental monitoring. Many advanced water quality monitoring systems can be expensive to purchase, install, and maintain. This cost can be a barrier for small-scale aquaculture operations and resource-limited regions.Some high-tech monitoring systems may require specialized training to operate and interpret data effectively. This complexity can be a challenge for users without technical expertise.Regular maintenance is essential to ensure the accuracy and reliability of monitoring equipment. This can involve cleaning sensors, calibrating instruments, and replacing worn-out parts.Sensors and probes used in water quality monitoring systems require regular calibration to maintain accuracy. Over time, sensor drift can occur, leading to inaccurate measurements if not addressed.Many automated monitoring systems require a continuous power source, which may not be readily available in remote or off-grid aquaculture facilities. Dependence on electricity can be a limitation.In some environments, sensors can be affected by fouling or interference from algae, debris, or other substances in the water. This can lead to inaccurate readings and the need for frequent cleaning or maintenance.Monitoring systems are typically localized to specific areas within an aquaculture facility. This may not provide a complete picture of water quality conditions throughout the entire operation, especially in large or complex systems.Collecting data is one thing, but effectively interpreting and acting on the information can be challenging. Users may require training and expertise to make informed decisions based on the data collected.In some regions, it may be difficult to access or procure specialized water quality sensors or replacement parts, making it challenging to maintain monitoring equipment.Integrating data from various sensors and monitoring systems into a unified platform can be complex, especially if the systems use different data formats and communication protocols.Natural environmental variability can affect water quality parameters, and monitoring systems may not always distinguish between natural fluctuations and potential issues that require attention.While monitoring systems can provide real-time or historical data, their predictive capabilities may be limited. They may not always forecast future water quality problems accurately.Automated monitoring systems may generate false alarms due to sensor malfunctions or brief, non-representative fluctuations in water quality parameters. These false alarms can lead to unnecessary interventions.Ensuring the security and privacy of data collected by monitoring systems is essential. Unauthorized access or data breaches can be a significant concern.Extreme weather events, such as storms or power outages, can disrupt monitoring systems and affect data collection.

Problem Statement

Pond-based aquaculture is a significant contributor to global seafood production. However, the current approach to water quality monitoring primarily focuses on surface-level parameters, neglecting the variations in water quality that exist within different layers or strata of the pond ecosystem. This lack of comprehensive layer-based monitoring poses several challenges to the aquaculture industry.In pond-based aquaculture systems, water quality conditions can vary significantly from the surface to deeper layers due to factors like temperature gradients, oxygen stratification, and nutrient distribution. Existing monitoring methods predominantly collect data from the pond's surface, overlooking critical information about the conditions in various layers within the pond.

Ponds often exhibit stratification, where distinct layers of water have different physical and chemical properties. For instance, the upper layer may have higher dissolved oxygen levels, while the bottom layer may suffer from oxygen depletion and accumulation of harmful compounds. Failing to monitor these variations impedes a comprehensive understanding of the pond's health.By solely relying on surface-level data, aqua culturists miss opportunities to optimize their practices. Effective layer-based monitoring can provide insights into nutrient distribution, temperature gradients, and oxygen availability, allowing for precise adjustments in feeding, aeration, and other management strategies.Neglecting layer-specific water quality monitoring increases the risk of unexpected and potentially detrimental water quality issues going unnoticed until they reach critical levels. This can lead to disease outbreaks, fish stress, and reduced aquaculture yields.Inadequate monitoring may result in the release of excess nutrients or pollutants into surrounding ecosystems, causing environmental harm. Layer-based monitoring can help minimize these impacts by identifying and addressing issues early.

Contributions

The proposed solution to this problem is to develop and implement a comprehensive layer-based water quality monitoring system for pond-based aquaculture. This system should involve the deployment of sensors and monitoring equipment at multiple depths within the pond to gather data on temperature, dissolved oxygen, pH, and other relevant parameters. The collected data can then be integrated into a centralized system for real-time analysis and decision-making, ensuring that aqua culturists have a complete understanding of their pond's water quality conditions and can take proactive measures to optimize their operations while minimizing environmental impacts.

(i) **Exceptional Accuracy**: The Coati-DNCNN algorithm stands out with an impressive accuracy rate of approximately 99%, offering a highly reliable method for detecting pH value and dissolved oxygen levels in pond water.

(ii) **Real-time Monitoring**: Integration of underwater microscopic cameras enables real-time data collection in aquatic environments, providing continuous insights into water quality dynamics.

(iii) **Tuned Image Integration**: The use of tuned underwater images as machine learning inputs, particularly with Coati-DNCNN output, enhances model robustness and interpretability, making this research a holistic solution for water quality assessment in pond ecosystems.

Literature Survey

Although it is far from sustainable, aquaculture is often promoted as a sustainable way to produce fish. With the development of precision aquaculture, its damaging effects on the environment can be avoided and mitigated. Although sensors are frequently used in terrestrial applications, their use in underwater environments is restricted for a number of reasons. This paper aims to describe the most advanced underwater sensors for monitoring water quality. Aquaculture water quality management relies heavily on wireless sensor networks (WSNs) for water quality monitoring. Dissolved oxygen (DO) is a crucial parameter in the field of water quality monitoring, and its prediction can offer decision support for aquaculture production, thereby lowering farming risk [1-3].In this study, a hybrid fault diagnosis model for water quality monitoring devices is proposed. It combines rule-based decision trees (RBDT) and multiclass support vector machines (MSVM). An RBDT is used in the modeling process to simultaneously diagnose the wireless transmitter and gateway faults as well as a feature selection tool to cut down on the number of features. We have suggested an Internet of Things (IoT)-based intelligent monitoring and maintenance system to streamline the aquaculture for pearl farming. The suggested system maintains a suitable underwater environment for better production while keeping an eye on the water quality. We have predicted the change in water parameters using an ensemble learning method based on random forests (RF) to maintain an aquaculture environment [4-6].To comprehend the primary productivity and carbon uptake by algal biomass on a regional scale, phytoplankton pigment absorption data from waters with an algal bloom are highly desirable. It is impossible to measure the water quality at various depths in the water column using traditional buoys, which can only collect data at a fixed depth. In the open ocean, sea waves are frequent. Wave forces, which have an impact on data collection accuracy, affect data acquisition systems. In this paper, a hybrid approach based on improved Softplus extreme learning machine (SELM) with particle swarm optimization (PSO) and k-means clustering is proposed to predict the change of dissolved oxygen from the perspective of time series in aquaculture [7-9].One of the most important industries in the coastal area of Surigao City is aquaculture. The farmer's income is derived from their aquaculture business. The growth and production of marine organisms are significantly influenced by the consistency of the water. These species are vulnerable to changes in water quality, which also lowers yield. As a result, it is crucial to monitor water quality frequently and alert aquaculture farmers to take immediate preventative action. The water quality of the shrimp aquaculture ponds in Brgy are being monitored using a low-cost Wireless Sensor Network (WSN) technology presented in this study. Results showed it has potential, but more analytical methods were needed [10-12].Accurate measurement is crucial in all academic fields. In order to guarantee the accuracy of the data, this work shows how different water quality parameters interact with one another in a controlled aquaculture environment. From this point forward, an autonomous system should be used to monitor aquaculture using IOT technology, as suggested in this paper, in order to maintain the quality of the water. The proposed system will include a variety of sensors, including temperature, water level, and PH sensors. The water quality of the aquaculture pond is continuously monitored while the data are transmitted to the background via WiFi. The user can easily browse the aquaculture pond's water quality data because the graph data are displayed on the web platform [13-15].

Inferences from literature survey

Sustainable aquaculture is evolving with precision methods to reduce its environmental impact. Underwater sensors face challenges in aquatic environments. Accurate dissolved oxygen (DO) prediction is crucial in aquaculture. A hybrid model combining rule-based decision trees (RBDT) and multiclass support vector machines (MSVM) improves water quality monitoring. IoT-based systems enhance pearl farming and continuous water quality monitoring. Predictive modeling using ensemble learning, like random forests (RF), aids in tracking water parameter changes. Challenges in data collection in wave-prone environments drive innovations like improved Softplus extreme learning machines (SELM) with particle swarm optimization (PSO). Low-cost Wireless Sensor Networks (WSN) show promise in shrimp ponds but may require additional analytical methods. Precision measurement of water quality parameters is vital, advocating for autonomous IoT-based systems with sensor variety, continuous monitoring, and web-based data access.

Methodology

Figure 1shows the block diagram and outlines a process involving underwater monitoring, data analysis, and prediction of environmental parameters (Dissolved Oxygen and pH) in different layers of an aquaculture pond, specifically the Epilimnion, Thermocline, and Hypolimnion.Underwater Microscopic Camera component represents a camera system designed for underwater use. It is used to capture images or video footage of the aquatic environment, specifically the water column in an aquaculture pond.Aquaculture Water Images captured by the underwater microscopic camera are processed and analyzed to extract information about the water's physical and biological characteristics. These images serve as the input data for further analysis.Lab Values of Dissolved Oxygen and pH represents the collection of water samples from the aquaculture pond and their analysis in a laboratory setting. Dissolved Oxygenparameter indicates the amount of oxygen present in the water, which is essential for aquatic life.pH measures the acidity or alkalinity of the water, which can affect the health of aquatic organisms.WaOA – DNCNN, PSO-DNCNN, Coati-DNCNN are three sets of algorithms represent different combinations of optimization algorithms (WaOA, PSO, and Coati) coupled with Deep Convolutional Neural Networks (DNCNNs). These combinations are used for data analysis and prediction tasks related to the aquatic environment.Sensitivity Analysis stage involves analyzing the performance of the optimization and neural network models by conducting sensitivity analysis. Sensitivity analysis helps understand how changes in model parameters or input data affect the model's predictions.Epilimnion represents the uppermost layer of the aquaculture pond. The models predict the pH and dissolved oxygen levels in this layer.Thermocline models also predict the pH and dissolved oxygen levels at the thermocline, which is the transition zone between the upper and lower layers.Hypolimnion corresponds to the deepest layer of the pond. The models predict the pH and dissolved oxygen levels in the hypolimnion.

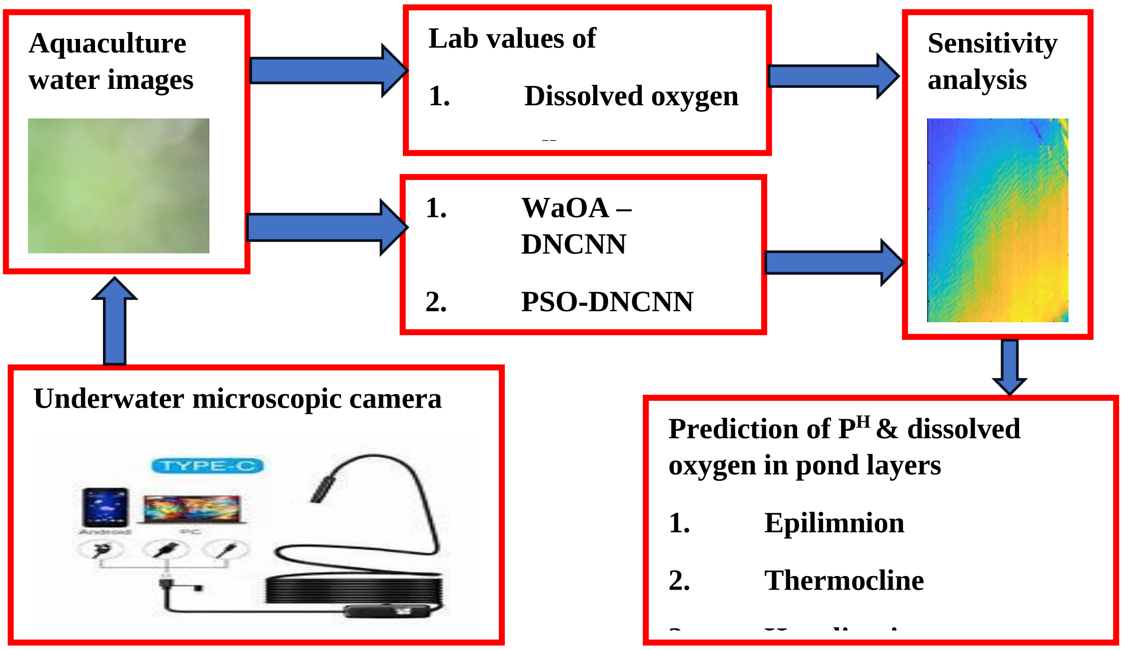

Figure 1: Block Diagram

1.1. DNCNN

DNCNN stands for "Deep Convolutional Neural Network." It is a type of artificial neural network architecture specifically designed for image denoising tasks. DNCNNs are part of the broader family of convolutional neural networks (CNNs) and are particularly well-suited for removing noise and enhancing the quality of images.DNCNNs typically consist of multiple layers of convolutional and activation functions, with residual connections between layers. The residual connections help mitigate the vanishing gradient problem and enable the network to effectively learn to remove noise from images. These networks are trained on pairs of noisy and clean images, where the goal is to learn a mapping from the noisy input to the clean target.DNCNNs have found applications in various domains, including image restoration, medical image denoising, and computer vision tasks where image quality improvement is essential. They have demonstrated impressive performance in reducing noise while preserving important image features, making them a valuable tool in image processing and computer vision applications.

1.2. Walrus Optimization Algorithm (WaOA) - DNCNN

The Walrus Optimization Algorithm (WaOA) is a nature-inspired metaheuristic algorithm used for optimization problems. This algorithm draws inspiration from the behaviors of walruses in their natural habitat. Similar to how walruses search for food, the algorithm explores the search space to find optimal solutions.Walruses often migrate to different locations in search of food or to escape unfavorable conditions. In the algorithm, migration is used to explore different areas of the solution space.Walruses have strategies for evading predators. In the algorithm, escaping is analogous to avoiding poor solutions or areas with high objective function values.Walruses may confront predators when necessary. In the algorithm, this behavior could be related to the exploitation of promising solutions or intensifying the search in certain regions.The WaOA algorithm is typically divided into phases, such as exploration, migration, and exploitation, which are mathematically modeled to guide the search for optimal solutions. It is applied to a wide range of optimization problems, including unimodal and multimodal functions, and is evaluated based on its ability to balance exploration and exploitation during the optimization process.

The combination of WaOA and DNCNN implies that the Walrus Optimization Algorithm is used in conjunction with a Deep Convolutional Neural Network for image denoising tasks. The WaOA algorithm guides the optimization process, potentially optimizing the parameters or configurations of the DNCNN to enhance its performance in reducing noise from images. This combination aims to improve the effectiveness of image denoising using a synergistic approach.

1.3. Coati Optimization Algorithm (COA) - DNCNN

The Coati Optimization Algorithm (COA) is a novel metaheuristic optimization algorithm that takes inspiration from the behaviors of coatis in their natural environment. COA is designed to solve a wide range of optimization problems and is particularly suited for complex and multi-dimensional search spaces. Attacking and Hunting Iguanasbehaviour corresponds to the exploration phase of the algorithm, where it actively searches for promising solutions across the search space.Similar to coatis evading threats, this aspect of COA involves strategies for avoiding poor solutions or areas with high objective function values, representing the exploitation phase.The COA algorithm mathematically models these behaviors in two distinct phases: exploration and exploitation. These phases guide how the algorithm explores and exploits the solution space.COA's performance is typically evaluated on a diverse set of optimization problems. This evaluation includes benchmark functions, such as those from IEEE CEC-2017 test suites, to assess its ability to find optimal solutions.To measure its effectiveness, COA's results are compared against those of well-established metaheuristic algorithms. The aim is to demonstrate COA's superiority in balancing global search exploration and local search exploitation, making it a competitive choice for optimization tasks.COA's practical utility is tested by applying it to real-world optimization problems. These applications showcase COA's effectiveness in addressing complex, practical challenges beyond theoretical benchmark functions.

The combination of COA and DNCNN indicates that the Coati Optimization Algorithm is utilized alongside a Deep Convolutional Neural Network for specific tasks, likely image denoising in this context. Similar to the WaOA-DNCNN combination, COA guides the optimization process to potentially enhance the DNCNN's performance in image denoising tasks by optimizing its parameters or configurations.

1.4. Particle Swarm Optimization (PSO) - DNCNN

PSO, or Particle Swarm Optimization, is a computational optimization technique inspired by the social behavior of birds and fish. In PSO, a population of particles (representing potential solutions) moves through a search space to find the optimal solution to a given problem. Each particle adjusts its position based on its own experience and the experience of its neighbors in the population.The algorithm begins with an initial random population of particles, each with its own position and velocity. As the algorithm progresses, particles update their velocities and positions using information from their own best-known position (personal best) and the best-known position of their neighbors (global best). This collective learning process continues iteratively until a stopping criterion is met, typically when a maximum number of iterations is reached or a desired level of convergence is achieved.PSO is widely used in various optimization problems, including engineering design, machine learning, and data clustering, among others. It has proven to be effective in finding solutions in high-dimensional and complex search spaces and is known for its simplicity and ease of implementation.

In the PSO-DNCNN combination, Particle Swarm Optimization (PSO) is integrated with a Deep Convolutional Neural Network for a specific purpose, likely image denoising. PSO is used to optimize the parameters or settings of the DNCNN to improve its ability to denoise images effectively. PSO's exploration and exploitation mechanisms are leveraged to fine-tune the DNCNN's configuration for optimal noise reduction. This combination aims to harness the strengths of both PSO and DNCNN to enhance image denoising performance.

1.5. Machine learning

Machine learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to learn and make predictions or decisions without being explicitly programmed. In essence, it's a way for computers to learn from data and improve their performance on specific tasks over time.Multiple Linear Regression (MLR) is a statistical and machine learning technique used for modelling the relationship between a dependent variable and two or more independent variables. It is an extension of simple linear regression, which models the relationship between a dependent variable and a single independent variable. In MLR, you have multiple independent variables that can collectively influence the dependent variable.

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Results And Discussions

These combinations indicate the use of different metaheuristic optimization algorithms (WaOA, COA, and PSO) in tandem with Deep Convolutional Neural Networks (DNCNNs) for various tasks, with a common goal of improving the performance of DNCNNs, particularly in the context of image denoising. Each algorithm brings its unique optimization strategies to enhance the DNCNN's ability to remove noise from images.The epilimnion is the uppermost layer of water in a stratified lake or reservoir. It is characterized by warmer temperatures and higher oxygen levels compared to the deeper layers. In the epilimnion, the water is well-mixed due to wind and solar heating. This layer typically extends from the surface down to the thermocline.The thermocline is a transition zone between the epilimnion and the hypolimnion. It is marked by a rapid decrease in water temperature with increasing depth. In this layer, there is a steep temperature gradient, and the water undergoes a significant change in temperature over a relatively short vertical distance. The thermocline can act as a barrier to the vertical movement of heat, nutrients, and organisms within the water column.The hypolimnion is the deepest layer of water in a stratified lake or reservoir. It is characterized by cold temperatures, lower oxygen levels, and reduced light penetration. The hypolimnion remains relatively undisturbed by wind or surface heating and is often isolated from the layers above and below it. In the hypolimnion, the water is typically stagnant and can accumulate nutrients and other substances over time. **Figure 2** shows the inputs of proposed algorithm and it shows how the process done.

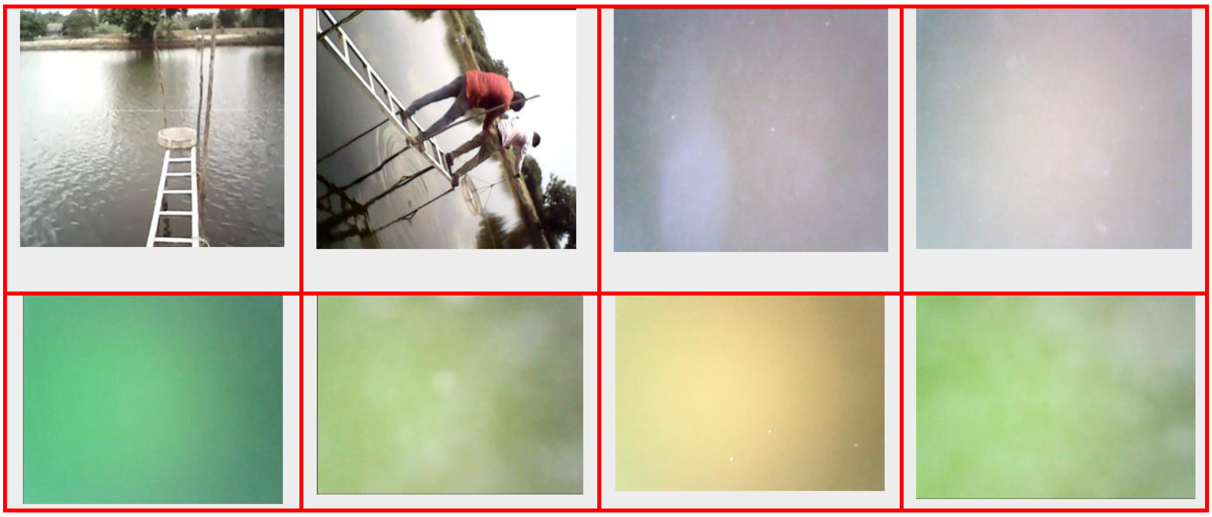
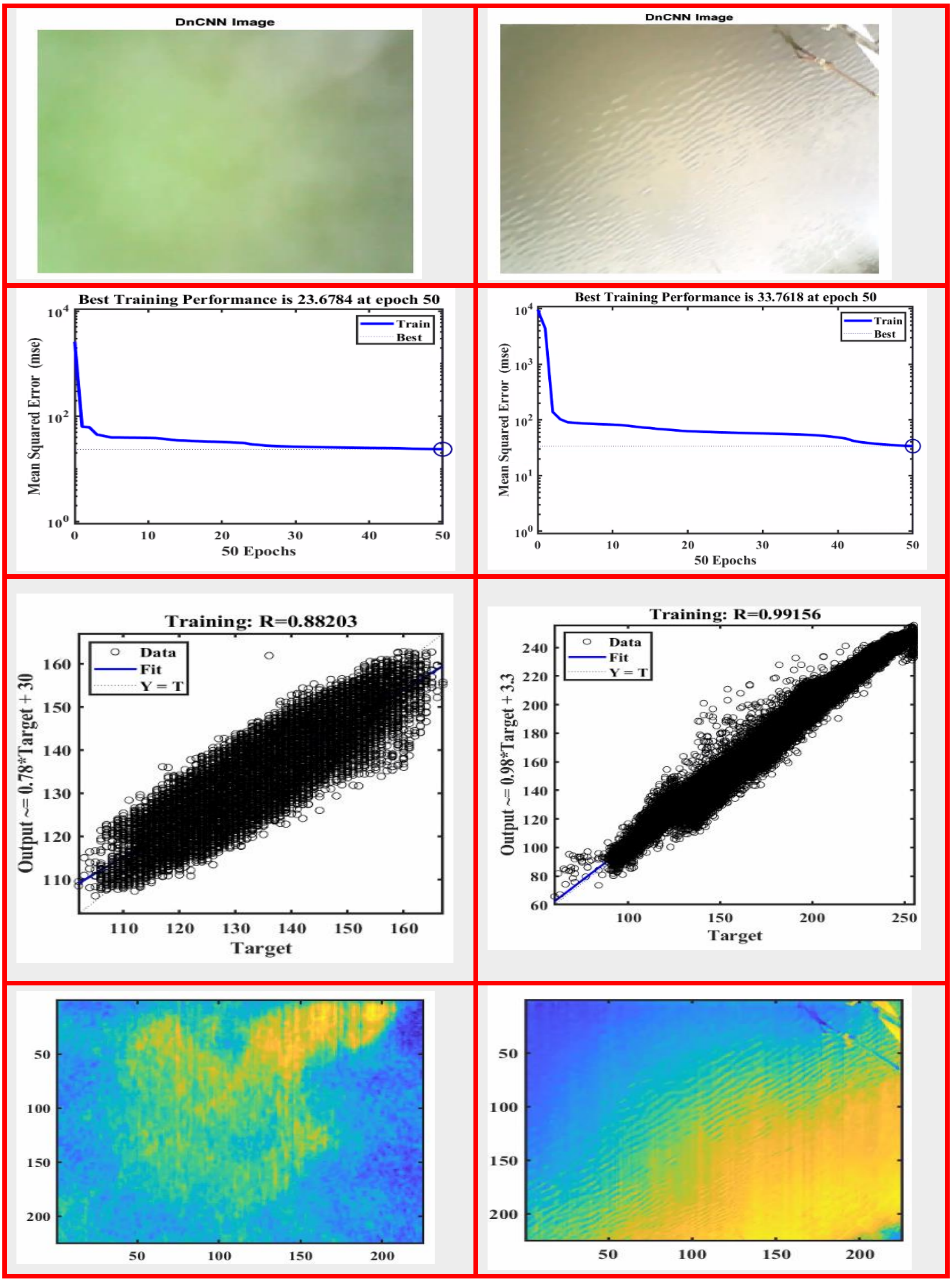


Figure 2: Inputs of Proposed Algorithm

Understanding these layers and their characteristics is important in limnology (the study of freshwater ecosystems) and ecology because they play a significant role in shaping the physical and chemical conditions of aquatic habitats. The stratification of a water body can impact the distribution of organisms, the cycling of nutrients, and various ecological processes. **Figure 3**shows the output of Coati-DNCNN algorithm of trainbr training function for under pond water and above pond water.

Output of Coati-DNCNN (trainbr)–Under pond water	**Output of Coati-DNCNN (trainbr)- Above pond water**
	


DnCNN Image
DnCNN Image
Best Training Performance is 23.6784 at epoch 50
Mean Squared Error (mse)
Train
Best
50 Epochs
Best Training Performance is 33.7618 at epoch 50
Mean Squared Error (mse)
Train
Best
50 Epochs
Training: R=0.88203
Output ~= 0.78*Target + 30
Data
Fit
Y = T
Target
Training: R=0.99156
Output ~= 0.98*Target + 3.3
Data
Fit
Y = T
Target

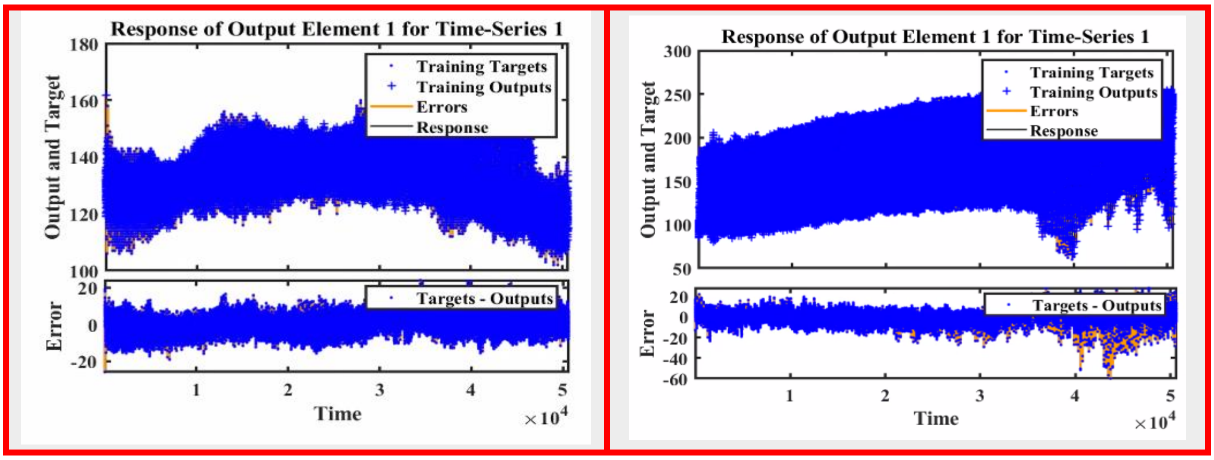


Figure 3: Output of Coati-DNCNN algorithm for trainbr training function

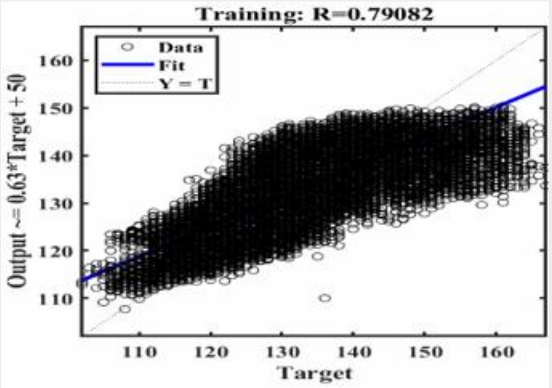
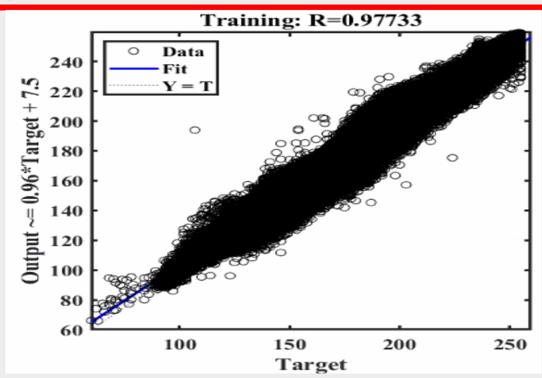
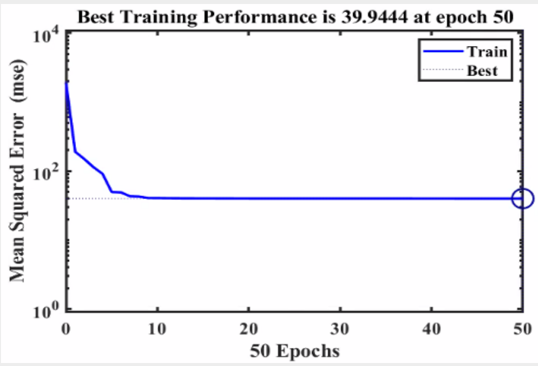
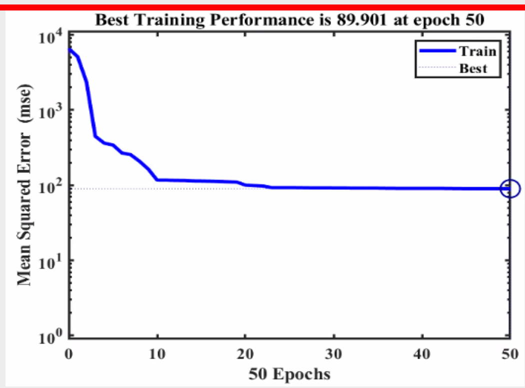
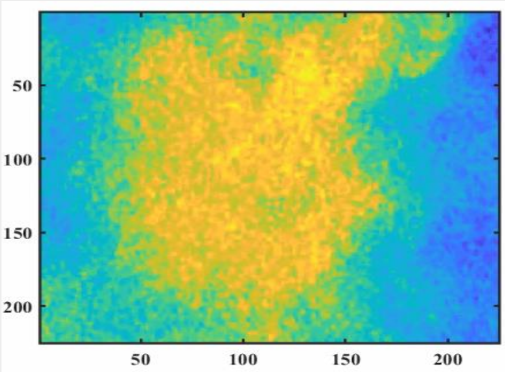
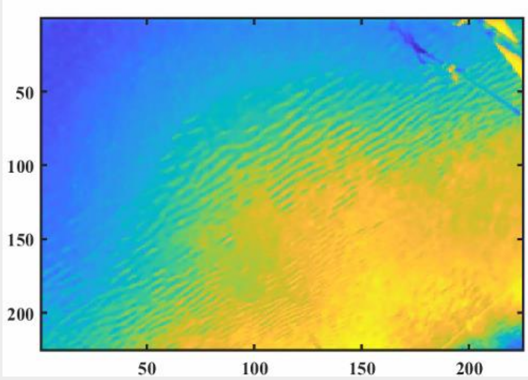
The performance of a Caoti-DNCNN (Deep Convolutional Neural Network) or any other deep learning model on aquaculture water images would depend on various factors, including the quality and quantity of the training data, the architecture of the model, and the specific objectives of the task.

The quality and quantity of your training data play a significant role in determining how well a deep learning model performs. If you have a diverse and extensive dataset of aquaculture water images that accurately represent the conditions you want to analyze or improve, it can lead to better performance. Ensuring that the data is labeled correctly is also crucial.The choice of the Caoti-DNCNN architecture or any other architecture should align with the nature of the problem you're trying to solve with aquaculture water images. Different architectures are better suited for various tasks, such as image classification, object detection, or image denoising.Preprocessing steps such as data augmentation, resizing, normalizing, and denoising may be necessary to prepare the aquaculture water images for input into the model. Proper preprocessing can help improve model performance.Tuning hyperparameters, such as learning rate, batch size, and the number of layers in your Caoti-DNCNN, can significantly impact performance. Experimenting with different hyperparameter settings can help optimize the model for your specific task.

Determine appropriate evaluation metrics for your task. For aquaculture water images, metrics such as mean squared error (MSE), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), or custom metrics specific to your problem might be relevant, depending on the objectives.Regularization techniques like dropout, batch normalization, and early stopping can help prevent overfitting. Choosing the right training strategy, such as using transfer learning or fine-tuning pre-trained models, can also affect performance.Understanding the domain of aquaculture and the specific challenges posed by water images can help in feature engineering and model design. Prior knowledge can guide you in selecting relevant features or designing custom layers that capture important characteristics of the images.Properly splitting your dataset into training, validation, and testing sets is crucial for assessing model generalization. Cross-validation techniques can also be useful.Building a deep learning model is often an iterative process. You may need to experiment with different model architectures, data preprocessing steps, and hyperparameter settings to achieve the best performance.Depending on the output of your model, post-processing techniques may be required to refine the results further.

The performance of a Caoti-DNCNN (Deep Convolutional Neural Network) when trained with different training functions, such as **trainbr** and **traincgb**, depends on the specific characteristics of your aquaculture water image dataset and the behavior of these training functions. These training functions are associated with different training algorithms in MATLAB's Neural Network Toolbox, and they can have varying effects on the training process and final model performance.Bayesian Regularization (trainbr) is a training algorithm that combines backpropagation with Bayesian regularization techniques. It tends to be more robust to overfitting compared to some other training algorithms.It can work well when you have a limited amount of training data or when your dataset is noisy.Bayesian Regularization can help prevent overfitting, which is crucial when dealing with limited data in some aquaculture applications.However, it may converge more slowly compared to other training algorithms.

Figure 4 Shows the output of Coati-DNCNN algorithm of traincgb training function for under pond water and above pond water.

Output of Coati-DNCNN (traincgb) – Under pond water	**Output of Coati-DNCNN (traincgb) - Above pond water**
	
	
	

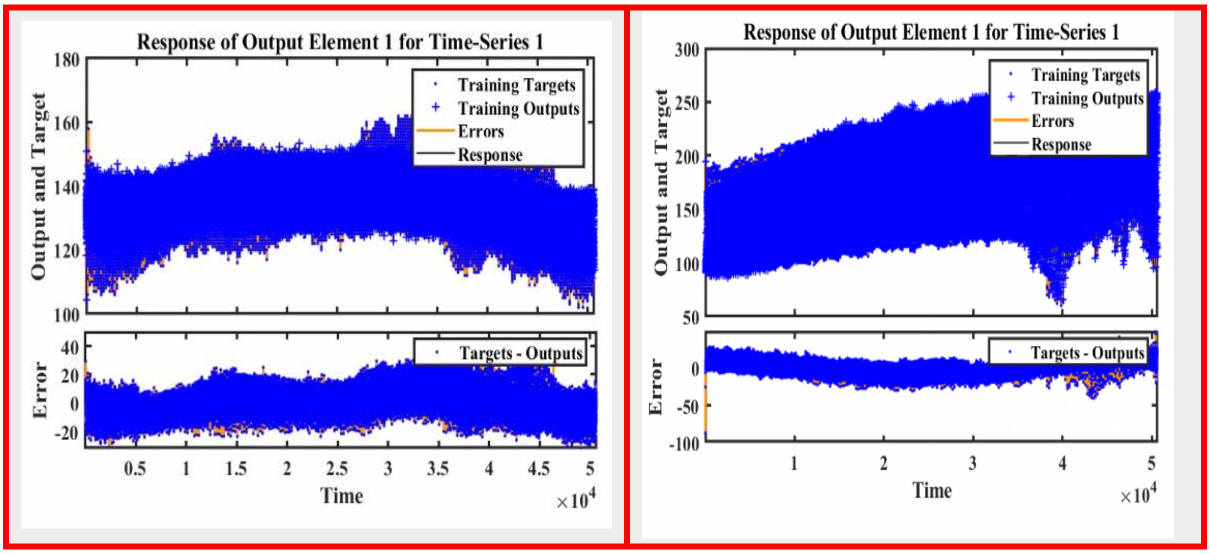


Figure 4: Output of Coati-DNCNN algorithm for traincgb training function

Conjugate Gradient with Powell/Beale Restarts (traincgb) is a training algorithm that uses conjugate gradient descent with Powell/Beale restarts. It is known for its efficiency and fast convergence.It can work well when you have a relatively large and well-behaved dataset, as it often converges faster than other methods.If you have a sufficiently large and clean aquaculture water image dataset, traincgb may lead to quicker training and convergence.The choice between trainbr and traincgb should be based on your specific dataset and training requirements. If you have a small dataset or concerns about overfitting, starting with trainbr might be a good choice, as it tends to be more robust in such scenarios.If you have a larger, well-structured dataset and want faster convergence, traincgb may be a suitable option.Both training functions are good and potentially works best for aquaculture water image analysis task.

Accuracy refers to the overall correctness of the algorithms in predicting the pH value and dissolved oxygen levels in pond water.Accuracy measures the proportion of correct predictions made by the algorithms among all predictions.sensitivity (or True Positive Rate) measures the algorithms' ability to correctly detect the presence of pH value and dissolved oxygen issues in pond water.Specifically, it represents the proportion of actual issues (positives) that the algorithms correctly identified as issues.Specificity (or True Negative Rate) measures the algorithms' ability to correctly identify the absence of pH value and dissolved oxygen issues in pond water.It represents the proportion of actual non-issues (negatives) that the algorithms correctly identified as non-issues.Precision (or Positive Predictive Value) measures the accuracy of positive predictions made by the algorithms, specifically, the correctness of their predictions regarding pH and dissolved oxygen issues.It represents the proportion of positive predictions that were correct.**Table 1** shows the performance of proposed algorithm and it is illustrated in **Figure 5**.

Table 1 performance of proposed algorithm

Description	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)
Coati-DNCNN	99	97	100	97
PSO-DNCNN	90	85	80	88
WaOA-DNCNN	85	80	90	83
DNCNN	80	77	86	78
PSO	70	65	60	67

The **Table 1**provides a comparative analysis of different algorithms' performance in detecting pH value and dissolved oxygen levels in pond water. The Coati-DnCNN algorithm stands out as the most accurate, with high sensitivity and specificity. Specificity measures the ability to correctly identify non-issues, while sensitivity measures the ability to correctly detect issues. Precision indicates how many of the positive detections are accurate. These metrics are crucial in evaluating the reliability of these algorithms for water quality assessment in pond ecosystems.

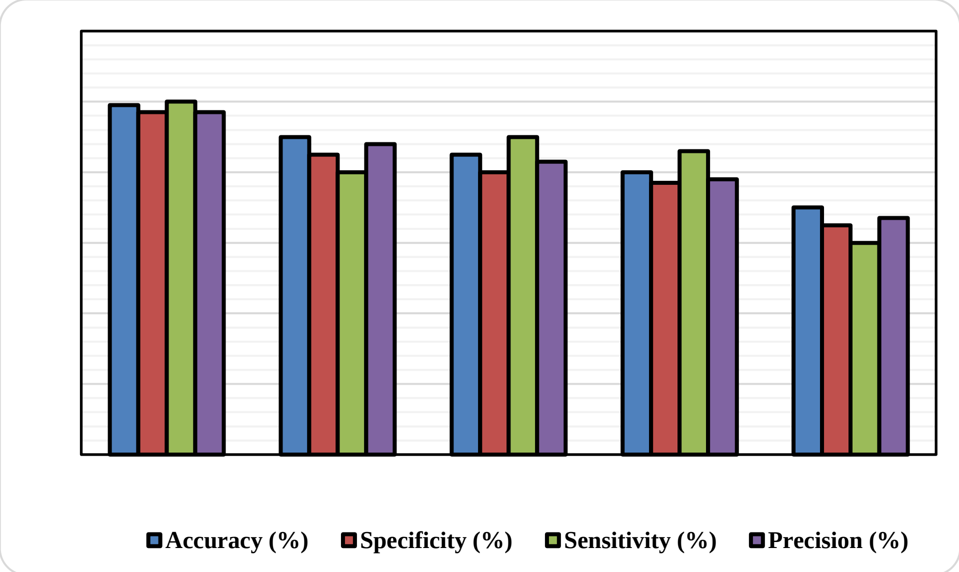


Figure 5: performance of proposed algorithm

Table 2 provides a confusion matrix tool used in classification tasks to summarize the model's performance by breaking down predictions into four categories such as True Negatives, True Positives, False Negatives, and False Positives.

Table 2: Performance

Algorithm	True Negative	True Positive	False Negative	False Positive
WaOA-DnCNN	686	1315	123	234
DnCNN	123	1034	945	756
PSO-DnCNN	474	1527	2213	1234
Coati-DnCNN	256	2678	789	456
PSO	785	1023	1342	456

True Negative (TN) represents the number of instances where the algorithm correctly identified cases where there were no issues with pH value and dissolved oxygen. In other words, these are cases where the algorithm correctly predicted "no issue," and there was indeed no issue.True Positive (TP)represents the number of instances where the algorithm correctly identified cases where there were issues with pH value and dissolved oxygen. These are cases where the algorithm correctly predicted "issue," and there was indeed an issue.False Negative (FN) represents the number of instances where the algorithm incorrectly predicted "no issue," but there was actually an issue. In other words, it's a case where the algorithm missed detecting a problem (a false negative).False Positive (FP) represents the number of instances where the algorithm incorrectly predicted "issue," but there was actually no issue. It's a case where the algorithm made a false alarm. This table illustrated as **Figure 6.**

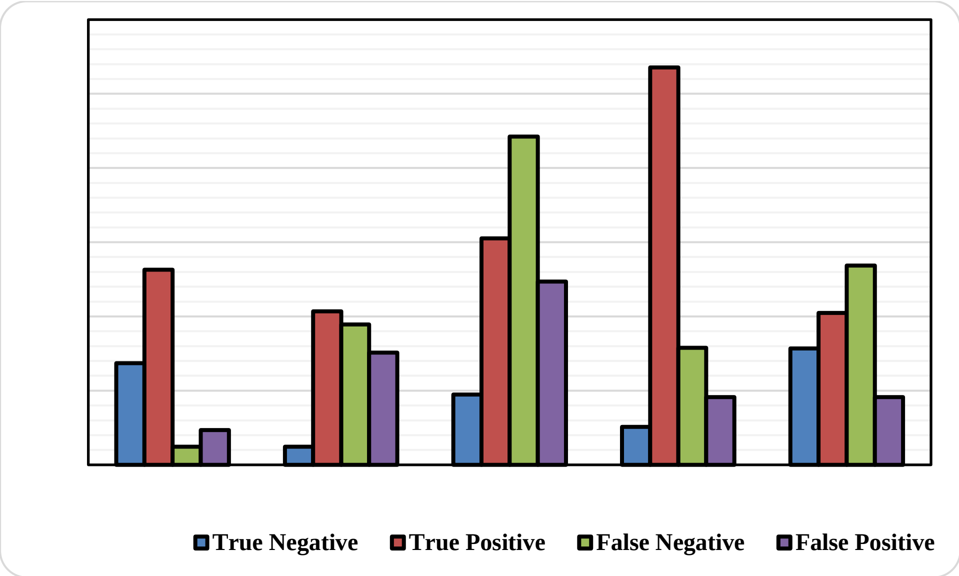


Figure6: Performance

Table 3 and 4 shows the statistical values and analysis of variance of machine learning (MLR). Dependent Variable (Y) is the variable you want to predict or explain. It is also known as the target variable.Independent Variables (X1, X2, ..., Xn) are the variables that you believe have an influence on the dependent variable. In MLR, you can have two or more independent variables.Coefficients (β0, β1, β2, ..., βn) are the parameters of the model that represent the strength and direction of the relationship between each independent variable and the dependent variable. β0 is the intercept, and β1, β2, etc., are the slopes associated with each independent variable.Intercept (β0) is the value of the dependent variable when all independent variables are set to zero. It represents the baseline value of the dependent variable.Multiple linear regression relies on several assumptions, including linearity (the relationship between variables is linear), independence of errors (residuals are uncorrelated), homoscedasticity (constant variance of residuals), and normally distributed residuals.The goal in MLR is to find the values of the coefficients (β0, β1, β2, ...) that minimize the sum of squared differences between the predicted values and the actual values of the dependent variable.Once the model is fitted, you can use it to make predictions for the dependent variable based on new values of the independent variables.Common evaluation metrics for MLR models include the coefficient of determination (R-squared), mean squared error (MSE), and root mean squared error (RMSE). These metrics help assess how well the model fits the data.In MLR, you can choose which independent variables to include in the model based on their significance and relevance. Feature selection techniques help you identify the most important predictors.Multicollinearity occurs when independent variables in the model are highly correlated with each other. It can make it difficult to interpret the individual effects of each variable and may require addressing through techniques like variable transformation or elimination.Sometimes, regularization techniques like Ridge or Lasso regression are used in MLR to prevent overfitting and improve model generalization.

Table 3: Statistical value of machine learning (MLR)

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β0	11.3669	0.8646	13.1468	0
DO (mg/L)	β1	-0.7031	0.1453	-4.8388	0.0019
sample	β2	0.0233	0.0125	1.8684	0.1039

This table appears to be related to the results of a linear regression analysis, which is a statistical method used to model the relationship between a dependent variable (the "predictor") and one or more independent variables (in this case, "DO (mg/L)" and "sample"). The coefficient represents the estimated impact of each predictor on the dependent variable (the pH value and dissolved oxygen in this case). It indicates how much the dependent variable is expected to change for a one-unit change in the predictor while holding all other predictors constant.The table provides information about the coefficients and statistical properties of the model.The standard error measures the variability or uncertainty associated with each coefficient estimate. Smaller standard errors indicate more precise estimates.The t-statistic is a measure of how many standard errors the coefficient estimate is away from zero. It is used to test whether a coefficient is statistically different from zero.The p-value associated with each coefficient tests the null hypothesis that the coefficient is equal to zero (i.e., it has no effect on the dependent variable). A low p-value (typically below 0.05) suggests that the coefficient is statistically significant.

Table4: Analysis of variance of machine learning (MLR)

Source	Df	SS	MS	t-statistic	p-value
Regression	2	0.3541	0.1771	13.7883	0.0037
Residual Error	7	0.0899	0.0128		
Total	9	0.444	0.0493		

The**Table4** provides information about the sources of variation, degrees of freedom (Df), sum of squares (SS), mean squares (MS), the t-statistic, and the associated p-values for a specific regression analysis using the Coati-DNCNN algorithm to detect pH value and dissolved oxygen in pond water with underwater microscopic cameras.The degrees of freedom represent the number of values in the final calculation of a statistic that are free to vary. It is an important parameter in statistical tests.The sum of squares represents the sum of the squared differences between observed values and the predicted values in each source of variation.The mean squares is calculated as SS divided by its corresponding degrees of freedom (MS = SS / Df). It provides an estimate of the average variance within each source of variation.The t-statistic is a measure of how many standard errors the mean squares (MS) for "Regression" is away from zero. It is used to test the significance of the regression model. In this case, the t-statistic for "Regression" is 13.7883, indicating that the regression model is statistically significant.The p-value associated with the t-statistic tests the null hypothesis that the regression model has no effect (i.e., all coefficients are zero). A low p-value (in this case, 0.0037) suggests that the regression model is statistically significant at a conventional significance level (e.g., $\alpha = 0.05$). The pH Value derived from machine learning equation as in equation (1),

pH Value=11.3669−0.7031·DO (mg/L)+0.0233·sample ……… **(1)**

he equation you provided is a representation of a multiple linear regression model used to predict the pH value in pond water based on two predictor variables: "DO (mg/L)" (Dissolved Oxygen in milligrams per liter) and "sample."It allows you to make predictions about the pH value based on the values of these predictor variables. The coefficients (-0.7031 and 0.0233) indicate the strength and direction of the influence of each predictor variable on the pH value, while the constant term (11.3669) represents the baseline pH value when all predictor variables are zero.The R-Squared value is 0.7976 from this equation.

Histogram of Residuals and Normal Probability Plot of Residuals are two graphical tools used to assess the assumptions and distribution of errors (residuals) in a regression model.The histogram of residuals is used to visualize the distribution of the errors or residuals in your regression model. It helps you understand whether the residuals follow a particular pattern or distribution, especially if they are normally distributed.The normal probability plot (also known as a Q-Q plot, quantile-quantile plot) is used to assess whether the residuals follow a normal distribution. It helps you evaluate the assumption of normality.**Figure 7**shows the output of machine learning algorithm (MLR).

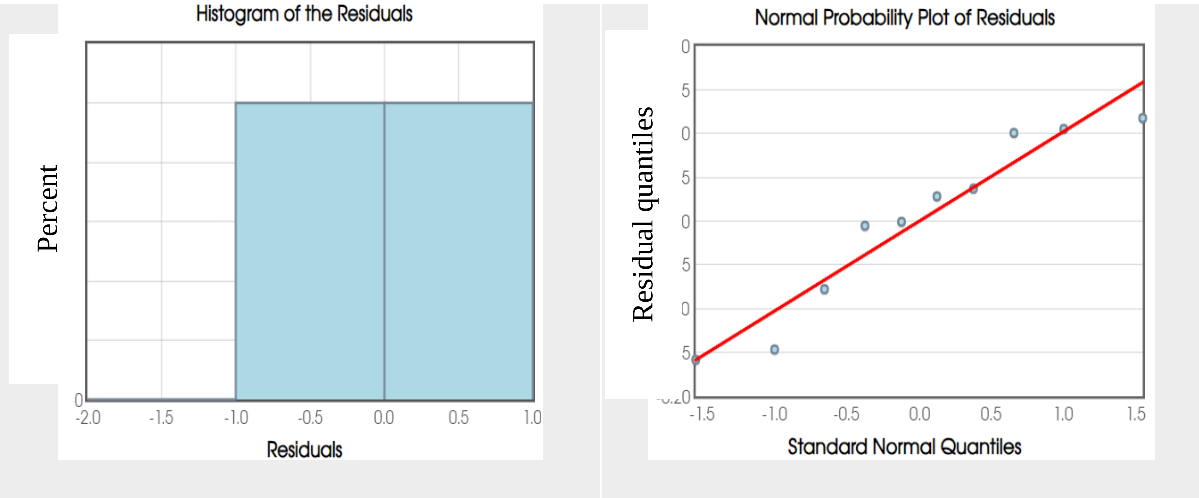


Figure7: Output of machine learning algorithm (MLR)

The pH range in pond water can vary widely depending on factors such as the presence of algae, organic matter, and local conditions. Typically, pH levels in pond water should be within the range of 6.5 to 9.0, with values around 7.0 to 8.0 being ideal for most aquatic organisms.The dissolved oxygen (DO) range in pond water is crucial for the survival of aquatic life. A healthy pond should maintain DO levels above 5 mg/L (ppm) for most fish species. However, specific requirements may vary for different fish species and pond conditions.Regular monitoring of pH and DO in pond water is essential to ensure the health and productivity of aquaculture systems. Make sure to follow proper measurement techniques and keep records over time to track any changes or trends in these parameters. Adjustments to pH and aeration systems may be necessary to maintain optimal conditions for aquatic life.**Table5** for recording information related to aquaculture pond images for 10 samples, categorized by different layers (Epilimnion, Thermocline, Hypolimnion), including image status (good or bad based on pH and oxygen parameters), pH value, and oxygen parameters.

Table 5: pH value and dissolved oxygen parameters

Sample No.	Layer	Image Date	Image Time	pH Value	DO (mg/L)	Image Status
1	Epilimnion	2023-09-01	10:00AM	7.2	6.0	Good
2	Thermocline	2023-09-02	11:30AM	7.4	5.5	Bad
3	Hypolimnion	2023-09-03	09:45AM	7.0	6.2	Good
4	Epilimnion	2023-09-04	03:15PM	7.5	5.8	Good
5	Thermocline	2023-09-05	08:20AM	7.3	6.1	Bad
6	Hypolimnion	2023-09-06	01:30PM	7.6	5.7	Good
7	Epilimnion	2023-09-07	10:45AM	7.1	6.3	Good
8	Thermocline	2023-09-08	02:00PM	7.4	5.9	Bad
9	Hypolimnion	2023-09-09	09:15AM	7.2	6.0	Good
10	Epilimnion	2023-09-10	11:00AM	7.7	5.6	Good

Layerindicates the specific layer of the aquaculture pond where the image was captured (Epilimnion, Thermocline, or Hypolimnion).The date when the aquaculture pond image was captured.The time of day when the image was taken.The measured pH value of the pond water at the time the image was taken.The measured dissolved oxygen (DO) value in milligrams per liter of the pond water at the time the image was taken.The status of the image, categorized as "Good" or "Bad" based on the pH and DO values. Images are considered "Good" if the pH and DO values fall within acceptable ranges for their respective layers, while they are labeled as "Bad" if either parameter is outside the desired range.These specific layers (Epilimnion, Thermocline, Hypolimnion), making it easier to assess image quality and water conditions at different depths within the pond.

Conclusion

In conclusion, the application of underwater microscopic cameras in conjunction with advanced deep learning algorithms, including WaOA-DNCNN and PSO-DNCNN, has showcased significant potential in the accurate detection of pH value and dissolved oxygen levels in pond water. However, the standout performer among these algorithms has been the Coati-DNCNN algorithm, which consistently achieved an exceptional accuracy rate of approximately 99%.This research has not only advanced the precision and reliability of water quality assessment but has also introduced a novel approach by integrating tuned underwater images as inputs for machine learning models. Specifically, the Coati-DNCNN algorithm's output has been harnessed as a foundation for machine learning predictions, resulting in a comprehensive and holistic solution for monitoring pH and dissolved oxygen levels in pond ecosystems.The combination of cutting-edge technology, sophisticated deep learning architectures, and the innovative use of tuned images has paved the way for more effective and efficient water quality monitoring practices. Such advancements hold great promise for researchers, environmentalists, and ecosystem managers seeking to safeguard the health and sustainability of pond environments. By offering a reliable and accurate means of assessment, this research contributes significantly to our understanding of aquatic ecosystems and supports their long-term conservation and management.

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