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Research Article

Optimization-Enhanced Microscopic Image Analysis for Accurate Monitoring of Pond Ecosystem Parameters

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ABSTRACT

Introduction: Accurately monitoring pH, dissolved oxygen (DO), Alkalinity, Ammonia and Nitrite levels in aquatic environments is vital for maintaining water quality and ensuring ecosystem balance.

Problem: Traditional methods of measuring pH, DO, Alkalinity, Ammonia and Nitrite often involve invasive and time-consuming direct chemical sampling, limiting their effectiveness in monitoring dynamic aquatic environments.

Method: This study introduces an innovative technique for detecting parameters in pond water by analyzing images taken from three distinct water layers: Epilimnion, Metalimnion (Thermocline), and Hypolimnion. These images were captured using an underwater microscopic camera and optimized using three different optimization algorithms such as Battle Royale Optimization (BRO), Gazelle Optimization (GOA), and Brown-bear Optimization (BOA). The optimized images were processed using the Denoising Convolutional Neural Network (DnCNN), integrated with each optimization algorithm(BRO-DnCNN, GOA-DnCNN, and BOA-DnCNN) to effectively denoise and improve the clarity of the images.

Result: This process yielded statistical values such as mean, standard deviation, and other metrics, which were then used to estimate parameters levels of the pond water. Among the three algorithmic combinations, the BRO-DnCNN algorithm outperformed the others, achieving an accuracy rate of approximately 99%making it the most reliable approach for detecting pH,DO,Alkalinity,Ammonia and Nitrite levels.

Significance: The integration of optimization algorithms with DnCNN for image processing proved to be a highly effective method for real-time monitoring of critical water quality parameters.

Conclusion: This technique not only enhances accuracy but also offers a robust framework for environmental monitoring, making it a valuable tool for aquatic ecosystem management.

Keywords: Pond water quality; pH, dissolved oxygen (DO), Alkalinity, Ammonia; Nitrite; Microscopic imaging; Optimization algorithms; DnCNN

INTRODUCTION

Aquaculture, the practice of cultivating aquatic organisms such as fish, shellfish, and aquatic plants, has become a critical component of global food production. As natural fish populations decline due to overfishing, pollution, and climate change, aquaculture has emerged as a sustainable solution to meet the growing demand for seafood. Among the various forms of aquaculture, pond-based farming is widely used due to its relatively low cost and ease of management. However, maintaining optimal water quality is essential to ensure the health and productivity of aquatic species. Two key water quality parameters that directly impact aquaculture systems are pH,DO,Alkalinity,Ammonia and Nitrite concentration.The pH of water plays a significant role in the biological processes of aquatic organisms. Extremes in pH can disrupt physiological functions, impair growth, and even lead to mortality in aquaculture systems. Similarly, DO is crucial for the respiration of fish and other aquatic species. Insufficient levels of DO in pond water can cause stress, reduce growth rates, and lead to significant losses in aquaculture operations. Therefore, continuous and accurate monitoring of both pH and DO is critical for maintaining a healthy pond environment.

Traditional methods of monitoring water quality often rely on manual sampling and testing, which are labor-intensive, time-consuming, and sometimes prone to inaccuracies. As a result, there is a growing interest in developing automated systems that can provide real-time monitoring of water quality. In recent years, advancements in underwater technology, particularly the use of underwater microscopic cameras, have opened up new possibilities for more accurate and efficient monitoring systems in aquaculture.This study focuses on the detection and continuous monitoring of pH,DO,Alkalinity,Ammonia and Nitrite concentrations in pond water using an underwater microscopic camera. By integrating advanced imaging techniques with sensor technology, this research aims to develop a reliable system capable of providing real-time feedback on water quality parameters. The underwater microscopic camera offers the advantage of non-intrusive monitoring, reducing the disturbance to the aquatic environment while ensuring accurate and timely data collection. This approach could significantly improve the management and sustainability of pond-based aquaculture systems by helping farm operators make informed decisions to maintain optimal water conditions.

PROBLEM STATEMENT

In pond-based aquaculture, ensuring the health and productivity of aquatic organisms is heavily dependent on maintaining optimal water quality across all layers of the pond: the surface layer (epilimnion), the middle layer (metalimnion), and the bottom layer (hypolimnion). The epilimnion is the warmest and most oxygen-rich zone, where photosynthetic activity can lead to fluctuations in pH,DO,Alkalinity,Ammonia and Nitrite levels due to external factors like rainfall and temperature changes. The metalimnion, or thermocline, experiences significant temperature fluctuations and often sees a decline in DO as it transitions to the colder hypolimnion. In the hypolimnion, organic matter accumulation leads to decomposition that consumes DO and releases acids, resulting in potentially hazardous conditions for aquatic life. Traditional water quality monitoring methods, which rely on manual sampling, are labor-intensive, time-consuming, and ineffective in providing real-time data across these stratified layers. Consequently, there is a pressing need for a more sophisticated, automated monitoring system capable of detecting pH,DO,Alkalinity,Ammonia and Nitrite concentrations in real time across all three layers. This study aims to develop an underwater microscopic camera integrated with sensor technology to provide comprehensive monitoring solutions that address the unique challenges of each pond layer. By doing so, the proposed system will enhance the management of water quality in aquaculture, enabling operators to maintain optimal conditions throughout the entire water column and promote healthier aquatic environments and more sustainable aquaculture practices.

CONTRIBUTIONS

The contributions of this study are pivotal in enhancing our understanding and management of aquatic ecosystems, specifically:

(i) To enhance the accuracy of pH,DO,Alkalinity,Ammonia and Nitrite detection in pond water by integrating microscopic imaging with advanced optimization algorithms, thereby providing a reliable method for environmental monitoring.
(ii) To develop a novel methodology that utilizes DnCNN in combination with optimization techniques, significantly improving image clarity and the precision of aquatic quality assessments.
(iii) To validate the effectiveness of the BRO algorithm as the leading method for achieving high accuracy rates in estimating water quality parameters, thereby establishing a benchmark for future research in this area.
(iv) To contribute to the broader field of aquatic ecosystem management by offering a scalable and efficient solution for real-time monitoring of critical water quality indicators, facilitating improved decision-making for environmental conservation efforts.

The structure of this research is organized as follows: the literature survey is presented in Chapter 2, the methodology is detailed in Chapter 3, the results and discussion are provided in Chapter 4, and the conclusion is outlined in Chapter 5.

1. LITERATURE SURVEY

Adopting cutting-edge farming techniques becomes essential for a nation whose economy is primarily dependent on agricultural products. This paper presents an Internet of Things-based smart freshwater recirculating aquaculture system. Due to declining wild fish populations and water pollution, marine farming, also known as aquaculture, is gradually replacing marine fishing. Effective monitoring of marine aquaculture zones (MAZs) is essential to enable the management of coastal resources. In order to do this, we combined previous analytical knowledge of MAZ imaging features with a specialized deep convolutional neural network designed for extracting MAZs from synthetic aperture radar (SAR) imagery**[1-4]**.Deep learning models are limited in their ability to extract features from images under varying sea conditions due to the emergence of distinct variations in sea surface scattering characteristics as sea conditions intensify. The random sea condition adaptive perception modulation network (RSC-APMN) is suggested as a solution to the aforementioned problems. It creates a coupled relationship with sea condition levels for adaptive enhancement of SAR imagery and semantic segmentation. However, the spectral response in some aquaculture areas is weak due to human and natural factors like crop harvesting and tidal changes, which causes omissions and incompleteness in the extraction results. We suggest a progressive semantic-guided network (PSGNet) to effectively extract raft aquaculture areas from remote sensing images in order to solve this issue**[5-6]**. Aquatic organism growth is influenced by water quality parameters. Thus, the main objective of aquaculture operators is now to maintain the balance of water quality. Unfortunately, the conventional method of inspecting water quality requires a lot of time and labor and has poor accuracy. However, because water quality sensors are submerged in saltwater for an extended period of time, algae will grow on them and reduce the accuracy of the sensors. This article describes the design and implementation of a full-time artificial intelligence of things (AIoT)-based water quality inspection and prediction system, which uses a simple recurrent unit (SRU) model to predict water quality data, in order to address the aforementioned issues. Unmanned underwater vehicles (UUVs) are now considered essential instruments for underwater inspection, maintenance, and repair (IMR) operations. But none of the fry counting techniques available today performs well in the high-density, high-overlap environments of actual aquaculture scenarios**[7-10]**.It is especially crucial to accurately monitor raft aquaculture areas (RAAs) in order to safeguard marine ecosystems. The coastal economy depends on cage and raft aquaculture (CRA), which produces superior aquatic goods. The complexity of the marine environment and CRA made it necessary to propose an attention-fused deep learning model for the accurate retrieval of large-scale CRA from freely available multispectral remote sensing imagery**[11-13]**. Robots operating in dynamic underwater environments, like aquaculture operations, must also handle uncertainties and errors in state and motion, dynamic and deformable obstacles, currents, and disturbances. For the purpose of scientific management and laver aquaculture monitoring, it is crucial to extract the areas of laver aquaculture from remote sensing images. This paper proposes a reverse attention dual-stream network (RADNet) that takes into account both the aquaculture boundary and the surrounding sea background information to extract laver aquaculture areas with weak spectral responses. However, big data combined with self-supervised learning frequently results in the loss of semantic information, including intraclass discontinuity and interclass misjudgment. The self-supervised transformer with feature fusion (STFF) method for semantic segmentation of SAR images in marine aquaculture monitoring is proposed in this article as a solution to this problem**[14-17]**. One important measure of water quality in aquaculture environments is the amount of DO. The nonlinearity, dynamics, and complexity of DO content prediction pose difficulties for conventional methods in terms of accuracy and speed. This study presents a hybrid model that combines the Bidirectional Simple Recurrent Unit (BiSRU) and the Light Gradient Boosting Machine (LightGBM) to address these problems. Accurate water temperature prediction is essential for aquaculture efficiency in intensive systems. To increase the robustness and generalization of temperature predictions, a novel hybrid model is put forth**[18-20]**.It is possible that wireless sensor networks (WSNs) in aquaculture ponds that have an uneven distribution of temperatures and a low collection efficiency will result in poor monitoring effects. It is proposed that a high-precision fusion strategy for a hierarchical WSN be utilized in order to enhance the performance of temperature monitoring. The real outdoor aquaculture ponds have characteristics such as turbid water quality, small feed targets, interference from intense fish activity, images of fish and feed that overlap, and other similar characteristics. HAUCS, which stands for hybrid aerial/underwater robotic system, is an initiative that aims to bring about fundamental innovations in the operation of pond-based farms**[21-25]**.

INFERENCES FROM LITERATURE SURVEY

The literature survey highlights the increasing necessity of adopting advanced technologies in aquaculture as marine farming gradually replaces traditional fishing due to declining fish populations and pollution. Efficient monitoring of marine aquaculture zones is essential for managing coastal resources, with deep learning models like RSC-APMN addressing challenges posed by varying sea conditions. To further improve the extraction of aquaculture areas from remote sensing images, PSGNet tackles spectral response issues caused by environmental factors such as tidal changes and human activity.Water quality management, a critical factor in aquaculture, has been made more efficient through AIoT-based systems. For instance, SRU model predicts water quality parameters while addressing sensor accuracy challenges caused by biofouling, where algae growth on sensors reduces their effectiveness. UUVs are also essential for inspection and maintenance in high-density aquaculture environments, although they face challenges in navigating these complex settings.In cage and raft aquaculture, attention-fused deep learning models have improved the retrieval of large-scale aquaculture areas from multispectral remote sensing data, enhancing monitoring accuracy. Meanwhile, innovations like STFF method have improved the segmentation of SAR images, which is crucial for marine aquaculture monitoring.Hybrid models such as BiSRU-LightGBM have enhanced the prediction of key water quality parameters like DO and water temperature, improving accuracy and speed. WSNs also contribute to better monitoring, with high-precision fusion strategies addressing uneven temperature distribution. Lastly, hybrid robotic systems like the HAUCS address operational challenges in pond-based farming, ensuring more efficient and sustainable practices in modern aquaculture.

2. METHODOLOGY

The system for detecting and predicting pH,DO,Alkalinity,Ammonia and Nitrite levels in pond water integrates underwater imaging, ML algorithms, and optimization techniques, focusing on three distinct pond layers: Epilimnion, Metalimnion, and Hypolimnionshows in **Figure 1**.

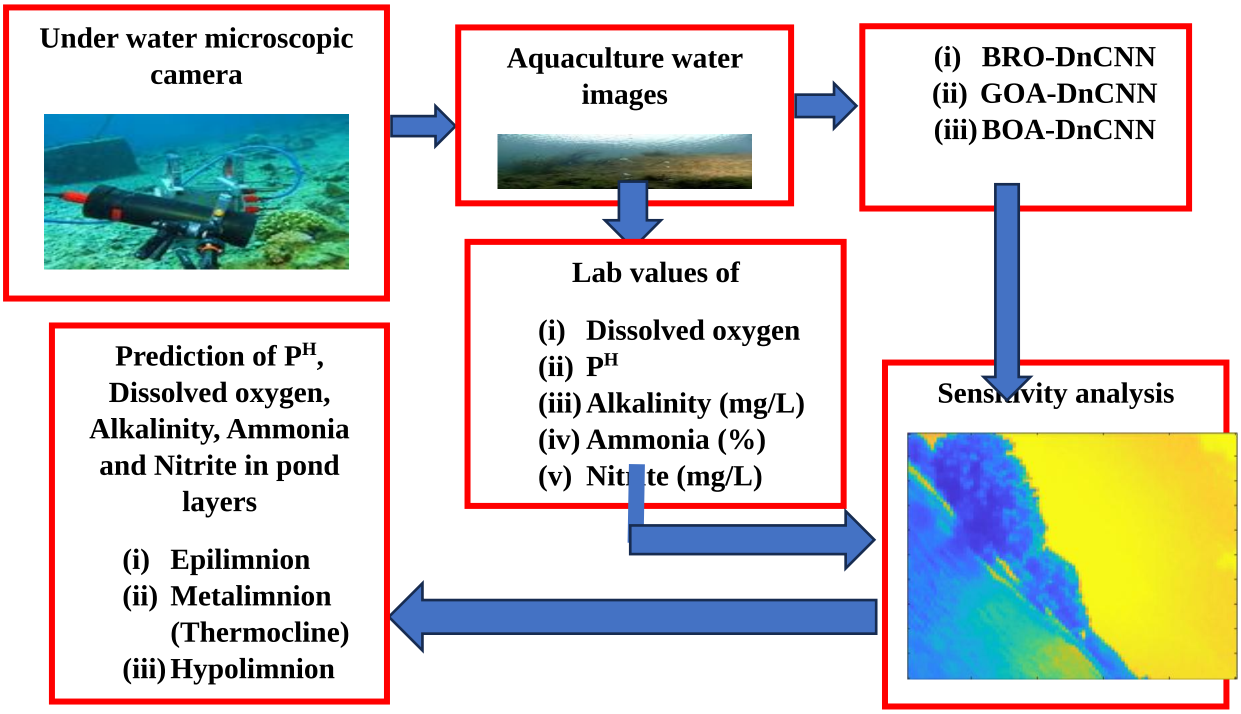


Fig 1 block diagram of proposed algorithm

It begins with an underwater microscopic camera capturing aquaculture water images, which provide crucial visual data on water quality. These images are then combined with lab values of pH,DO,Alkalinity,Ammonia and Nitrite levels, serving as ground truth for training machine learning models. The system employs three optimization algorithms such as BRO, GOA and BOA in conjunction with DnCNN to predict pH,DO,Alkalinity,Ammonia and Nitrite levels. Each algorithm optimizes the DnCNN model by refining its parameters and hyperparameters, improving the accuracy of predictions. BRO-DnCNNfocuses on parameter optimization through BRO's efficient exploration, GOA-DnCNNapplies GOA to minimize prediction errors by avoiding local minima, and BOA-DnCNNuses social learning and exploration-exploitation strategies to enhance model performance. Sensitivity analysis is conducted to assess the impact of variations in input parameters on prediction accuracy, ensuring robustness. Finally, the optimized DnCNN models predict pH,DO,Alkalinity,Ammonia and Nitrite levels across the three pond layers—Epilimnion (the warm, well-mixed upper layer), Metalimnion (the thermocline, where temperature decreases sharply with depth), and Hypolimnion (the colder, oxygen-depleted lower layer)—providing insights into the water quality and health of the aquatic environment.**Figure 2** shows the images captured from pond water by using microscopic camera and it takes as inputs of proposed algorithm.

Fig 2 inputs of proposed algorithm

2.1. DnCNN Algorithm

DnCNN represents a significant advancement in the field of image denoising through deep learning. By utilizing CNN and residual learning techniques, DnCNN effectively removes noise while preserving essential image features, making it a powerful tool for various applications in image processing and analysis.DnCNN has gained popularity due to its superior performance compared to traditional denoising methods.

2.2. BRO-DnCNN Algorithm

BRO algorithm is a nature-inspired optimization technique modeled after the survival-of-the-fittest concept seen in battle royale games. In this algorithm, a population of agents (candidate solutions) is initially generated, and these agents "battle" by comparing their fitness values, which represent how well they solve the optimization problem. Stronger agents, those with better fitness, are more likely to survive, while weaker ones are gradually eliminated. The algorithm iteratively progresses by allowing agents to explore the search space and refine existing solutions, balancing exploration and exploitation much like the tactics in a competitive game environment. Over time, only the fittest agents remain, converging towards the optimal solution for the given problem.When combined with DnCNN, the BRO algorithm can optimize the hyperparameters of the DnCNN for tasks such as image denoising.Agents are selected for "battles" based on their fitness. The update rule for the winning agent's position can be:

$$x_i^{\text{new}} = x_i + \alpha(x_j - x_i) + \beta r \tag{1}$$

Agents with poor fitness are eliminated, and new agents can be spawned in their place by slightly perturbing the best agents:

$$x_{\text{new}} = x_{\text{best}} + \gamma r \tag{2}$$

Where, x_{best} is the best agent's position, and γ is a small perturbation factor.

Pseudocode

Initialize population of agents (solutions) with random DnCNN parameters

Evaluate fitness of each agent using the DnCNN on the dataset (e.g., MSE or PSNR)

Set maximum iterations or convergence criteria

for each iteration:

  Sort agents based on fitness (lower MSE or higher PSNR is better)

```
  # Battle phase: agents compete based on fitness
  for each pair of agents (i, j):
    if fitness(agent_i) < fitness(agent_j):
      Update agent_i using:
      agent_i_new = agent_i + alpha * (agent_j - agent_i) + beta * random()
    else:
      Update agent_j using:
      agent_j_new = agent_j + alpha * (agent_i - agent_j) + beta * random()
  # Elimination phase: remove weaker agents
  for each agent:
    if fitness(agent) is poor (below threshold):
      Eliminate agent
      Replace with new agent using:
      agent_new = best_agent + gamma * random()
  # Evaluate fitness of the new population
  Recalculate fitness for all agents using DnCNN
  # Check for convergence (fitness improvement, max iterations, etc.)
  if convergence_criteria_met:
    break
Return the best agent (DnCNN parameters with the best fitness)
```

2.3. GOA-DnCNN Algorithm

GOA is an optimization technique inspired by the behavior of gazelles in the wild, particularly their movement patterns, agility, and ability to avoid predators. This behavior provides a metaphor for balancing exploration and exploitation in optimization. The algorithm simulates how gazelles search for food (global optima) while avoiding threats (local optima traps), allowing them to adapt dynamically to different environments.When combined with DnCNN, GOA can optimize weights, or biases of the network, helping to improve the denoising performance of the model.The position of each gazelle $x_i$is updated based on its current position, the global best position x_{best}, and an avoidance term to prevent getting stuck in local optima:

$$x_i^{\text{new}} = x_i + \alpha \cdot (x_{\text{best}} - x_i) + \beta \cdot \text{avoidance\_term} \quad (3)$$

Pseudocode

```
Initialize population of gazelles (solutions) with random DnCNN parameters
Evaluate fitness of each gazelle using the DnCNN (e.g., MSE or PSNR)
Set maximum iterations or convergence criteria
for each iteration:
  # Sort gazelles based on fitness (lower MSE or higher PSNR is better)
  Identify global best solution (x_best)
  for each gazelle (agent):
```

Movement toward global best and avoidance of local minima

avoidance_term = random_factor * (position_of_threat - position_of_gazelle)

gazelle_new_position = gazelle_position + alpha * (x_best - gazelle_position) + beta * avoidance_term

Ensure the new position is within bounds (valid DnCNN parameter range)

gazelle_new_position = clip_to_bounds(gazelle_new_position)

Update position

gazelle_position = gazelle_new_position

Evaluate fitness for the new positions of all gazelles using DnCNN

Recalculate fitness of each gazelle

Update global best solution if necessary

if fitness(gazelle) < fitness(global_best):

global_best = gazelle_position

Check convergence criteria (e.g., fitness improvement, max iterations)

if convergence_criteria_met:

break

Return the best solution (DnCNN parameters with the best fitness)

2.4. BOA-DnCNN Algorithm

BOA is an optimization technique inspired by the hunting behavior and social dynamics of brown bears. It simulates how brown bears forage for food and adapt to their environment, making it suitable for solving complex optimization problems. The algorithm combines exploration and exploitation strategies to efficiently search for optimal solutions.When applied to optimize DnCNN, BOA can help refine the network's parameters to enhance its performance in tasks such as image denoising.The position of each bear is updated based on its current position, the best position found so far, and social interactions:

$$x_i^{\text{new}} = x_i + \alpha \cdot (x_{\text{best}} - x_i) + \beta \cdot (x_{\text{social}} - x_i) + r \quad \textbf{(4)}$$

To avoid getting stuck in local optima, the algorithm may include a perturbation mechanism:

$$x_i^{\text{new}} = x_i + \gamma \cdot \text{random\_perturbation} \quad \textbf{(5)}$$

Where, γ is a scaling factor for the perturbation.

Pseudocode

Initialize a population of bears (solutions) with random DnCNN parameters

Evaluate fitness of each bear using the DnCNN (e.g., MSE or PSNR)

Set maximum iterations or convergence criteria

for each iteration:

Identify global best solution (x_best)

for each bear (i):

Select a bear randomly (j) for social learning

Update bear i's position based on global best and social learning bear_new_position = bear_position + alpha * (x_best - bear_position) + beta * (bear_j - bear_position) + random_factor

Ensure the new position is within bounds (valid DnCNN parameter range)

bear_new_position = clip_to_bounds(bear_new_position)

Update position

bear_position = bear_new_position

Evaluate fitness for the new positions of all bears using DnCNN

Recalculate fitness of each bear

Update global best solution if necessary

if fitness(bear) < fitness(global_best):

global_best = bear_position

Check convergence criteria (e.g., fitness improvement, max iterations)

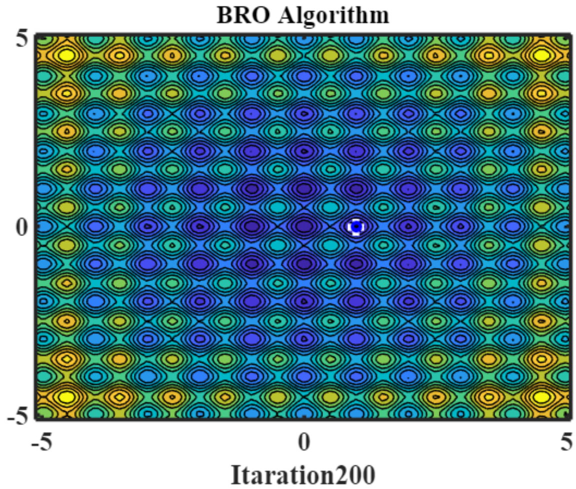
if convergence_criteria_met:

break

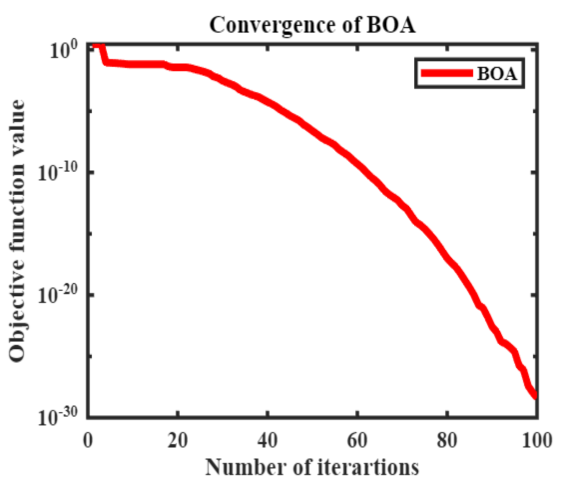
Return the best solution (DnCNN parameters with the best fitness)

3. RESULTS AND DISCUSSION

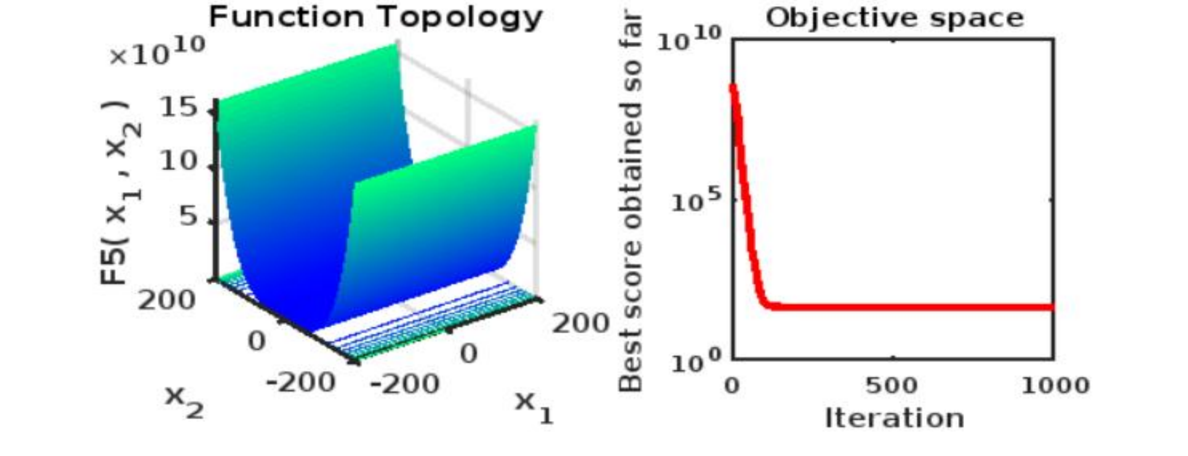
The outputs of BRO, GOA, and BOA provide insights into the performance of these algorithms when optimizing the DnCNN model for predicting pH and dissolved oxygen levels in pond water is shown in **Figure 3**.



Output of BRO algorithm



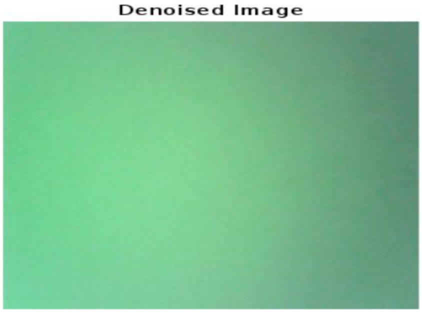
Output of BOA



Output of GOA

Fig 3Optimization results of proposed algorithms

Theconvergence of BOA indicates how quickly the algorithm reaches the optimal solution, with the convergence plot showing a reduction in the objective function value over successive iterations. BOA initially explores the search space and then exploits promising solutions, with smooth and fast convergence being a sign of efficiency. The function topology for GOA describes the shape of the objective function landscape, including features such as peaks, valleys, and flat regions. GOA navigates these topological challenges using its exploration-exploitation balance, mimicking the agile behavior of gazelles to avoid local optima and move toward the global optimum. In the objective space, GOA evaluates a range of solutions, balancing broad exploration with focused exploitation to find the optimal parameters for DnCNN. BRO's outputs also include a convergence plot, which demonstrates how solutions compete in a battle-like scenario, progressively improving over time until the best solution is found. BRO maintains diversity in solutions, with only the best-performing ones surviving and leading to the optimal result. Each of these algorithms—BRO, GOA, and BOA—ultimately refines the DnCNN model, improving its accuracy in predicting pH and dissolved oxygen levels by efficiently navigating complex function landscapes and optimizing the network's parameters.**Figure 4**shows the output of BRO-DNCNN algorithm using 'trainoss' training function for different layers of pond water.

Epilimnion layer	**Metalimnion layer**	**Hypolimnion layer**
 Input	 Input	 Input
Denoised Image 	Denoised Image 	Denoised Image 

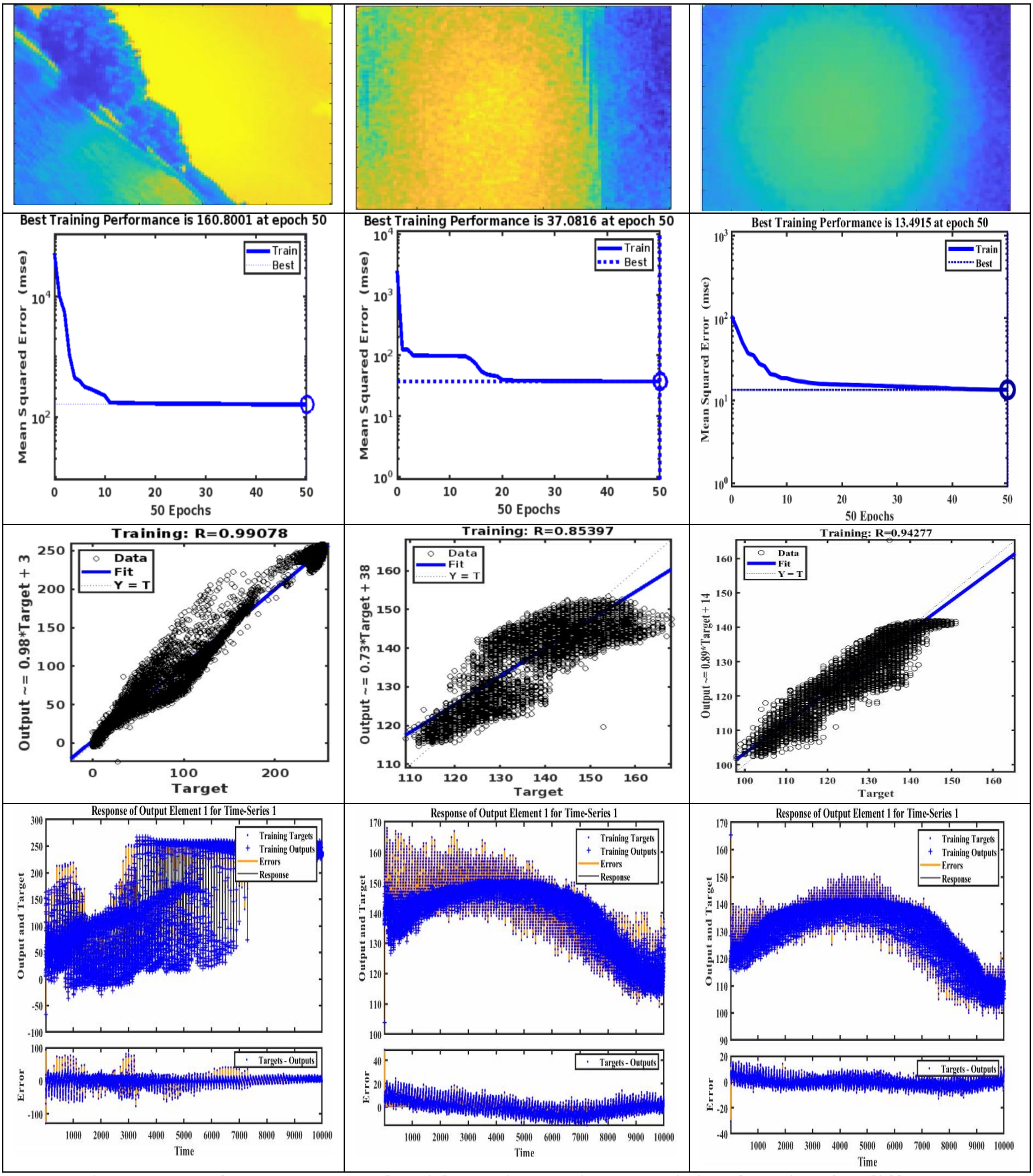


Fig 4output of BRO-DNCNN algorithm using 'trainoss' training function for different layers of pond water

The trainoss function is a powerful quasi-Newton optimization method used for training neural networks. It utilizes the one-step secant method, which approximates second-order information without the computational cost of full Newton's methods, resulting in faster convergence than simple gradient-based methods. It is particularly useful for moderately sized neural networks and tasks that benefit from second-order optimization techniques.The BRO-DnCNN algorithm, when using the `trainoss` training function to predict pH,DO,Alkalinity,Ammonia and Nitrite levels across different pond water layers (Epilimnion, Metalimnion, and Hypolimnion), produces several key outputs that evaluate its performance. The input and denoised images compare the underwater microscopic camera captures with the denoised versions produced by the DnCNN model. The denoised images show a clear improvement in visual clarity, reducing noise and enhancing important features for better analysis of water quality. This denoising process improves the accuracy of the model's predictions forpH,DO,Alkalinity,Ammonia and Nitrite) levels across different pond layers, highlighting the overall effectiveness of the BRO-DnCNN algorithm in both image processing and water quality prediction.The performance plot illustrates how well the algorithm minimizes the loss function over time, showing a decreasing trend that indicates effective learning and optimization for predicting water quality parameters. The plot reveals the varying performance across the different pond layers, as each has unique environmental conditions that affect the model's predictions. The regression plot demonstrates the relationship between the predicted and actual values for pH,DO,Alkalinity,Ammonia and Nitrite levels, with data points ideally aligning closely with the diagonal line, indicating accurate predictions. Separate regression plots for each water layer provide insights into how well the model generalizes under different conditions, such as temperature variations across the layers. The time series plot shows how the predicted values of pH and DO align with actual measurements over time, helping to track the temporal accuracy of the BRO-DnCNN model. The plot for each pond layer provides a clear view of how the model adapts to the changes in water quality conditions over time.

The process generated statistical metrics, including the mean, standard deviation, and others, which were utilized to estimate the pH,DO,Alkalinity,Ammonia and Nitrite levels of the pond water. These estimated values were then compared with previously recorded laboratory measurements of pH and DO for validation.The pH values of the Epilimnion, Metalimnion, and Hypolimnion layers in a stratified water body, can vary based on factors like temperature, biological activity, and oxygen levels. In the Epilimnion (surface layer), the pH typically ranges from 7.5 to 9.0. This layer is warmer, receives ample sunlight, and is rich in dissolved oxygen. Photosynthesis by algae and aquatic plants is high, which reduces CO_2 levels, leading to a higher pH due to decreased acidity. In the Metalimnion, the pH generally falls between 7.0 and 8.0. This zone marks the transition between the warm epilimnion and the cooler hypolimnion, where temperature drops rapidly and light penetration is reduced, causing more variability in pH. Finally, in the Hypolimnion, the pH typically ranges from 6.0 to 7.5. This deeper, cooler layer is often oxygen-poor, especially during thermal stratification. The accumulation of CO_2 and other acids from the decomposition of organic matter lowers the pH, as photosynthesis is limited. These pH ranges can vary depending on the specific characteristics of the water body, including organic matter content, nutrient levels, and local environmental conditions.**Table 1**shows the Average values of pH & DO (mg/L) in different layers of pond water from BRO-DnCNN algorithm.

Tab 1 Average values ofpH&DO (mg/L) in different layers of pond water

Dataset	Epilimnion (Surface Layer)	Metalimnion (Middle Layer)		Hypolimnion (Bottom Layer)
	pH	pH	DO (mg/L)	pH
1	8.2	7.5	9.5	6.4
2	8.5	7.6	8.9	6.3
3	8.0	7.4	10.1	6.2
4	7.8	7.3	9.8	6.1
5	8.4	7.7	9.2	6.5
6	8.3	7.5	10.0	6.2
7	8.1	7.2	9.4	6.0

8	8.6	7.8	9.7	6.5
9	8.0	7.4	9.3	6.3
10	8.2	7.5	9.0	6.4

The Table 2 represents alkalinity measurements (mg/L) across three distinct layers of a pond. Each observation captures the variations in alkalinity levels across these layers, revealing distinct chemical characteristics within the pond ecosystem. The Epilimnion, being the uppermost and most exposed layer, often shows higher alkalinity values compared to the Hypolimnion, which is colder and denser.

Tab 2Average values ofAlkalinity (mg/L) in different layers of pond water

Dataset	Epilimnion (Surface Layer)	Metalimnion (Middle Layer)	Hypolimnion (Bottom Layer)
	Alkalinity (mg/L)	**Alkalinity(mg/L)**	**Alkalinity (mg/L)**
1	60	48.4	28.5
2	44.8	60.67	30.4
3	54.67	52.5	40.5
4	65.75	56.29	59.75
5	45	65.5	52.14
6	76.37	58.2	70.375
7	39.2	47	48.8
8	50	75	38.5
9	61.3	69	63
10	31.5	49	48.8

For example, in observation 1, the alkalinity in the Epilimnion is 60 mg/L, significantly higher than the Hypolimnion's 28.5 mg/L. Conversely, in observation 6, the alkalinity values are high across all layers, with the Hypolimnion exhibiting the highest level at 70.375 mg/L. Some observations, such as observation 10, display similar values in the Metalimnion and Hypolimnion (49 mg/L and 48.8 mg/L, respectively), indicating possible mixing or uniformity in these layers.The dataset highlights the chemical stratification in the pond, influenced by factors such as temperature, biological activity, and sediment interactions. This stratification has significant environmental implications, as it affects water quality and aquatic life. The Table 3 provides measurements of ammonia concentration (%) across three distinct layers of a pond.

Tab 3Average values ofAmmonia (%) in different layers of pond water

Dataset	Epilimnion (Surface Layer)	Metalimnion (Middle Layer)	Hypolimnion (Bottom Layer)
	Ammonia (%)	**Ammonia(%)**	**Ammonia (%)**
1	0.4	0.46	0.9
2	0.33	0.29	0.375
3	0.45	0.37	0.5275
4	0.31	0.27	0.505

5	0.372	0.328	0.5725
6	0.37	0.34	0.525
7	0.32	0.28	0.515
8	0.26	0.32	0.465
9	0.51	0.47	0.605
10	0.44	0.37	0.515

Each observation records the ammonia levels at these layers, revealing how this important chemical parameter varies with depth in the aquatic environment. Ammonia concentrations generally increase with depth, with the highest levels observed in the Hypolimnion, likely due to reduced oxygen availability and the accumulation of organic matter. For example, in observation 1, ammonia is 0.4% in the Epilimnion and rises to 0.9% in the Hypolimnion. This trend is consistent across most observations, such as in observation 6, where the ammonia concentration is 0.37% in the Epilimnion, 0.34% in the Metalimnion, and 0.525% in the Hypolimnion. Some observations, like observation 8, show more uniform ammonia levels across the layers, with concentrations of 0.26% in the Epilimnion, 0.32% in the Metalimnion, and 0.465% in the Hypolimnion, suggesting less pronounced stratification or potential mixing. The highest ammonia concentration of 0.9% is recorded in the Hypolimnion during observation 1, while the lowest concentration of 0.26% is observed in the Epilimnion during observation 8. These ammonia level variations highlight the importance of monitoring this parameter in aquatic ecosystems, as excessive ammonia can harm aquatic organisms. The dataset provides valuable insights into the biochemical processes occurring in the pond, which can help inform management strategies for maintaining water quality and ecological balance.The Table 4 provides measurements of nitrite concentration (mg/L) across three distinct layers of a pond.

Tab 4Average values ofNitrite (mg/L) in different layers of pond water

Dataset	Epilimnion (Surface Layer)	Metalimnion (Middle Layer)	Hypolimnion (Bottom Layer)
	Nitrite(mg/L)	Nitrite(mg/L)	Nitrite(mg/L)
1	0.20	0.255	0.325
2	0.18	0.275	0.33
3	0.166	0.265	0.35
4	0.26	0.335	0.305
5	0.29	0.235	0.325
6	0.19	0.285	0.3375
7	0.234	0.295	0.3625
8	0.23	0.275	0.345
9	0.216	0.295	0.335
10	0.33	0.29	0.375

Generally, nitrite concentrations increase from the surface to the bottom, with the highest levels typically observed in the Hypolimnion. For example, in observation 1, the nitrite level in the Epilimnion is 0.20 mg/L, rising to 0.325 mg/L in the Hypolimnion. This trend is consistent in most observations, such as observation 3, where the nitrite concentration is 0.166 mg/L in the Epilimnion, 0.265 mg/L in the Metalimnion, and 0.35 mg/L in the Hypolimnion. While the values usually increase with depth, some observations, like observation 5, show similar values between the Metalimnion (0.235 mg/L) and Hypolimnion (0.325 mg/L). The highest nitrite concentration of 0.375 mg/L is recorded in the Hypolimnion during observation 10, while the lowest concentration of 0.166 mg/L is found in the Epilimnion in observation 3. Nitrite is a critical water quality indicator, as elevated levels can be harmful to aquatic life and may suggest nutrient pollution or insufficient oxygenation. The increasing nitrite concentration with depth may be due to factors like oxygen depletion, organic matter decomposition, and microbial activity, which are more pronounced in the Hypolimnion. This dataset is valuable for understanding nitrite distribution and nutrient cycling in pond ecosystems, helping with the management and preservation of water quality.Figure 5 shows the output of P^H and DO for different layers.

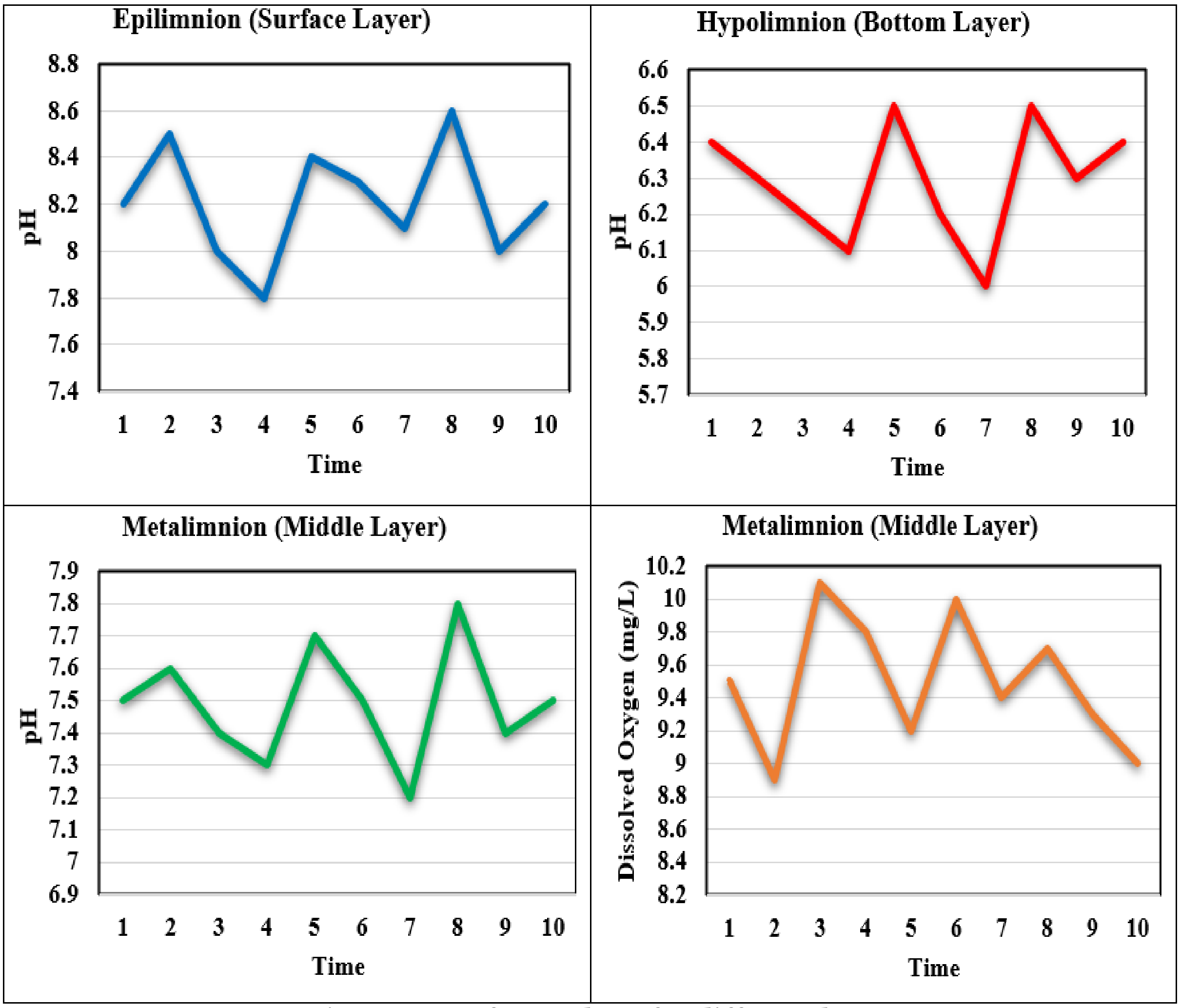


Fig 5output of P^H and DO for different layers

The pH generally decreases with depth due to biological activity, decomposition, and lower oxygen levels in the hypolimnion. The Epilimnion is more influenced by photosynthetic activity, which raises pH due to the removal of carbon dioxide.**Figure 6 & 7**evaluates the performance of various algorithms in detecting pH and DO in pond water.

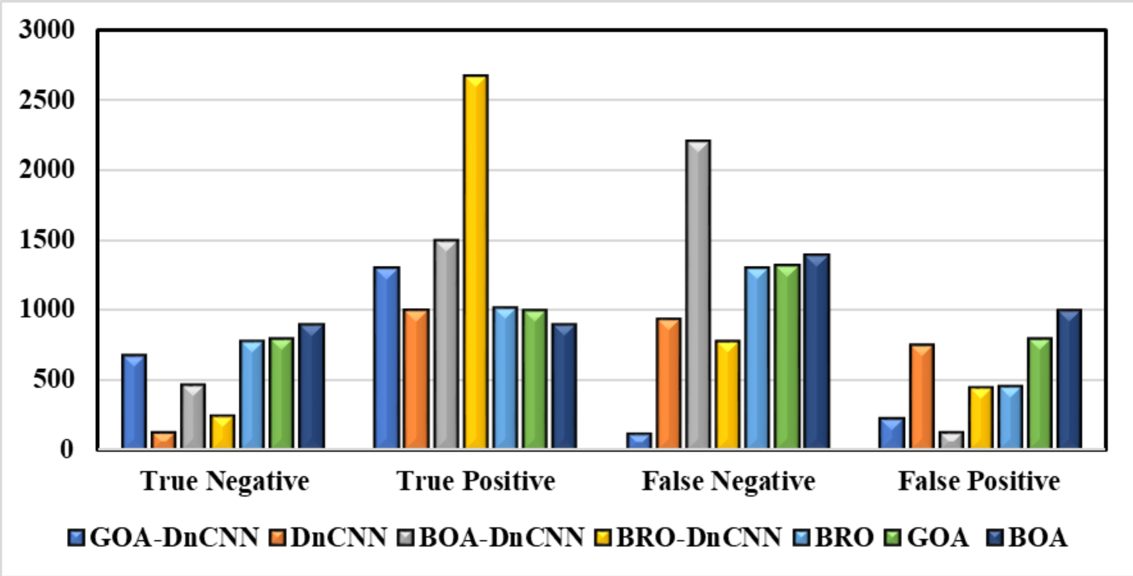


Fig 6 performance of proposed algorithms

Graphically, a comparison of these metrics would highlight BRO-DnCNN as the top performer with a balance of high true positives and moderate false predictions. GOA-DnCNN would stand out for its minimal false negatives, while DnCNN alone would perform the worst, showing high false predictions across both categories. BOA-DnCNN, though having a large number of true positives, would show a significant spike in false negatives, indicating its limitations.

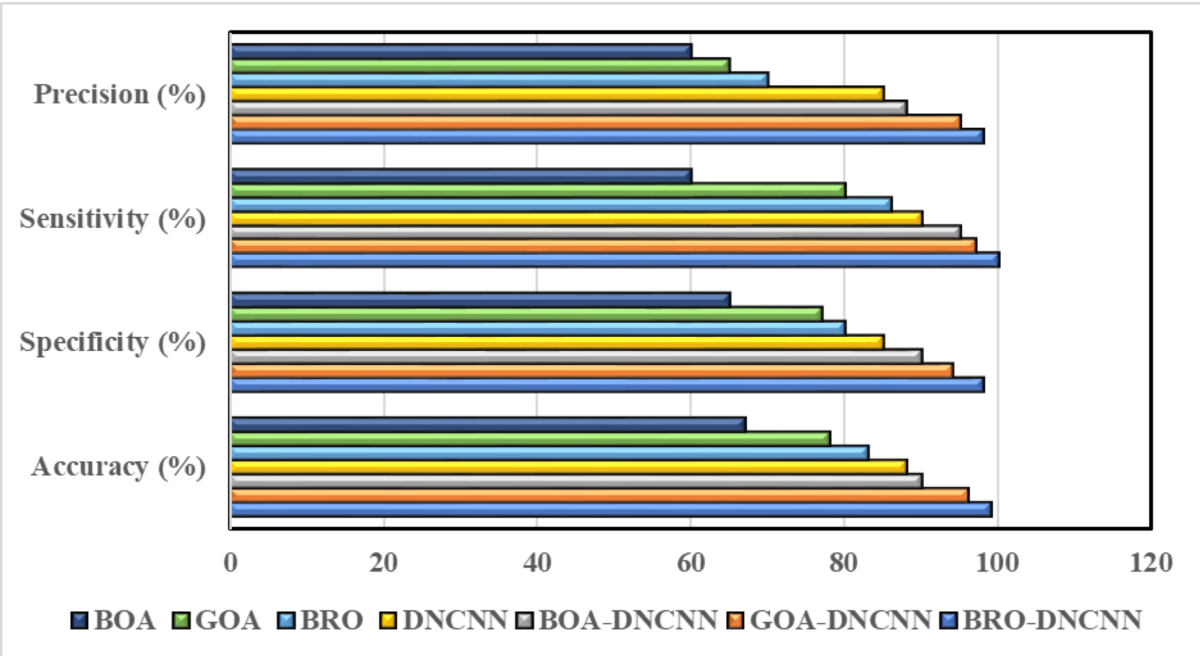


Fig 7 performance of proposed algorithms

A performance comparison graph would clearly highlight the superior results of the BRO-DnCNN and GOA-DnCNN models, with the bars for accuracy and sensitivity significantly higher than those for other models. The standalone algorithms, especially BOA, would show much lower performance, reinforcing the benefit of combining optimization algorithms with DnCNN for detecting pH and dissolved oxygen levels in pond water.In summary, combining optimization algorithms with DnCNN significantly enhances detection performance, with BRO-DnCNN emerging as the most accurate and reliable model.

DISCUSSION

This study aimed to improve the detection of pH,DO,Alkalinity,Ammonia and Nitrite levels in pond water by utilizing advanced image processing techniques and optimization algorithms. Initially, we captured images of the three distinct layers of pond water such as Epilimnion, Metalimnion, and Hypolimnionusing an underwater microscopic camera. This foundational step allowed us to create a rich dataset for subsequent analysis.As we applied various algorithms to these images, the performance metrics revealed a clear hierarchy among the models.Among the tested models, BRO-DnCNN achieved the highest performance with an accuracy of 99%, perfect sensitivity (100%), high specificity (98%), and precision (98%). This indicates that BRO-DnCNN excels at both correctly identifying positive cases (high sensitivity) and minimizing false positives (high specificity), making it the most reliable model for this task.

Overall, the results from our study underscore the significant improvements that can be achieved by integrating optimization algorithms with DnCNN for environmental monitoring. The superior performance of BRO-DnCNN positions it as the most reliable method for accurately detecting pH and DO levels in pond water. These findings provide valuable insights into enhancing aquatic health monitoring systems and emphasize the need for further exploration into the application of such methodologies across diverse ecological contexts. By using advanced image processing and optimization strategies, we can advance our understanding of water quality dynamics and contribute to effective management practices for preserving aquatic ecosystems.

4. CONCLUSION

This research presents a novel and effective approach for detecting pH,DO,Alkalinity,Ammonia and Nitrite levels in pond water by utilizing advanced image processing and optimization algorithms. By capturing microscopic images from the three distinct thermal and chemical layerswe were able to gain deeper insights into the stratified characteristics of the water body. The application of optimization techniques, specifically the BRO,GOA, and BOA algorithms, integrated with the DnCNN, significantly enhanced the quality of the captured images, improving their accuracy and removing noise.The optimized images were further analyzed to generate statistical values such as mean and standard deviation, which provided a basis for calculating pH and DO levels. The estimated values were then validated by comparing them with laboratory-measured values of the same parameters, ensuring the reliability of the proposed method. Among the three optimization algorithms, the BRO-DnCNN combination outperformed the others, achieving the highest accuracy rate of approximately 99%. This indicates that the BOA, when paired with DnCNN, offers superior performance in terms of both image processing and predictive accuracy.The results of this study highlight the potential of using microscopic imaging and hybrid optimization techniques for real-time water quality monitoring. The ability to accurately estimate pH and DO levels without direct chemical sampling could revolutionize environmental monitoring, making it more efficient and cost-effective. Additionally, this approach can be adapted to other bodies of water or different environmental parameters, demonstrating its versatility and scalability.In conclusion, the combination of optimization algorithms with DnCNN for image processing presents a powerful and innovative solution for monitoring critical water quality indicators. This study lays the foundation for future applications in aquatic ecosystem management, providing a precise and scalable tool for ensuring the sustainability of water resources. The future scope of this research includes the integration of IoT for real-time monitoring, expansion to additional water quality parameters, algorithm enhancements for varying conditions, and collaboration with stakeholders for practical applications. These directions will not only broaden the impact of this study but also contribute to the sustainable management of aquatic ecosystems.

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