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Research Article

An Optimized Bayesian Algorithm for Continuous Water Quality Monitoring at Different Locations in a Dam Reservoir Using Spatial and Temporal Pixels of Satellite Imagery

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ABSTRACT

Introduction: Water quality monitoring in different locations of a dam reservoir is a challenging task. Manual and laboratory methods of water quality estimation require more manpower and time. Dam water quality needs to be monitored to increase agricultural productivity and reduce biodiversity loss.

Objectives: In this paper, water quality in Nagi and Nagathi dam reservoirs located in Bihar, India are continuously monitored using spatial and temporal LandSat satellite image pixels.

Methods: Pixels are correlated with laboratory measured water quality parameters such as pH value and Dissolved oxygen. For accurate measurement of water quality, Landsat image pixels are perspectively projected using the proposed Transverse Dyadic Wavelet Transform (TDyWT) algorithms. The pixels are enhanced with the proposed three numbers of optimised residual Deep learning algorithms (DnCNN): (i) Particle Swarm Optimization-DnCNN (PSO-DnCNN) (ii) Red-Kite Optimization Algorithm-DnCNN (ROA-DnCNN), and (iii) Fuzzy-DnCNN. The statistical parameters of these enhanced water and moss pixels, such as contrast, entropy, band values, PSNR and SNR are correlated with the laboratory measure values of DO and pH using Bayesian optimised Multilevel Regression (BO-MR) approach.

Results: The BO-MR predicted water quality parameters in the different locations of the dam have an average accuracy of about 91% and 97%, when compared to ground truth verification.

Conclusions: Continuous water quality prediction in Nagi and Nagathi dams located in Bihar, India is performed using the spatial and temporal LandSat satellite image pixels. PH value and Dissolved oxygen values are predicted using Landsat image pixels using BO-MR. TDyWT algorithms and Particle Swarm Optimization-DnCNN (PSO-DnCNN) , Red-Kite Optimization Algorithm (ROA-DnCNN) and Fuzzy-DnCNN enhanced pixels are used for the prediction of the DO and pH values from pixels of water and moss, respectively. In the proposed algorithms, the combination of TDyWT and ROA-DnCNN have higher accuracy in DO and pH prediction such as 91% and 97%, respectively. when compared to ground truth verification. Problems in continuous monitoring is solved using the proposed method. Further, to obtain accurate and representative data, frequent sample collection is not required. However, sampling collection is often done in accessible locations only in the reservoir, and miss out on localized pollution or anomalies in traditional methods are avoided in the proposed method. Further, human errors in conducting analyses and recording the observations/data can affect the quality/accuracy of the results during traditional methods and this is avoided in the proposed ROA-DnCNN method of water quality measurement. Furthermore, other water quality measurements can be predicted.

Keywords: Water quality monitoring, deep learning, regression, wavelet transform ,vision transformer.

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INTRODUCTION

In dam reservoirs, quantity of water is preserved using various water conservation strategies such as Dam Linings, Control Evaporation and Efficient Spillway Design. The quality of the water is monitored frequently and not continuously due to huge cost and manpower. Maintaining good water quality is essential for the functioning of the dam (and the associated reservoir) and for supporting the aquatic ecosystems. The key factors affecting the quality of water are retention time of water in the reservoir, watershed characteristics and land use, quality of the inflowing water, stratification of the water column, biological processes within the reservoir, eutrophication due to excess nutrients, algal blooms, and sediment accumulation. The key water quality parameters in dams and reservoirs are physical, biological, biophysical and chemical in nature such as Turbidity, total suspended solids (TSS), pH, conductivity, temperature, chlorophyll concentration, Dissolved Oxygen (DO), nutrients (nitrogen and phosphorus), organic matter, heavy metals and other contaminants. It is essential that these parameters in a reservoir need to be maintained within the permissible limits, since impure water impacts both human and environmental health [1].

Measuring the concentrations of certain metal ions such as Pb, Zn, Mn in reservoir waters is a challenging task. Sedimentation drift, the process of sediment particles including heavy metals being transported and deposited by natural pathways into a dam reservoir, lead to excess heavy metals. The maximum allowable limits for the commonly encountered heavy metals in irrigation water are Pb: 0.1-0.5 mg/L, Zn: 2-5 mg/L, Mn: 0.2-1.0 mg/L. Excess of these can pose risks to agriculture and human health because they can be toxic to plants, animals, and humans, even at low concentrations [2]. Plants easily absorb these heavy metals, resulting in reduced growth, yield, and quality. Further, the consumption of water or crops containing such metals can lead to neurological damage, gastrointestinal problems, immunodeficiency, neurological damage, and reproductive issues in humans. Therefore, it is essential to monitor and manage heavy metal levels in reservoir waters to ensure safe and sustainable use for agriculture. Dams and reservoirs often face specific water quality challenges. Though measuring dam water quality is crucial for environmental monitoring, public health, and water resource management, the traditional methods and the remote sensing techniques have their own sets of challenges and limitations [3].

Problems in continuous monitoring of water quality using the traditional methods are requirement of considerable time, manpower and several specialized instruments for sample collection and laboratory analysis to estimate parameters such as TSS, pH, turbidity, nutrient levels, chlorophyll and contaminants. Further, to obtain accurate and representative data, frequent sample collection is necessary, which is manpower-intensive and expensive [4,5]. Ideally, sampling points should be evenly spread throughout the areal extent of the reservoir. However, sampling collection is often done in accessible locations only in the reservoir, and miss out on localized pollution or anomalies. As regards the error component, there is likely to be mistakes in sample collection, preservation, and transportation, which will result in inaccurate results. Further, human errors in conducting analyses and recording the observations/data can affect the quality/accuracy of the results.

Satellite remote sensing data suffer from issues related to spatial resolution, wherein the resolution of satellite imagery may not be sufficient to detect fine-scale water quality variations, particularly in smaller reservoirs. Another limitation is with regard to the satellite data analysis using various algorithms and models. Adegun et al (2023) [1] Mention that classification and analysis of high-resolution satellite images using conventional techniques are limited due to the complex characteristics of the imagery. The authors mention that these images are characterized by features such as spectral signatures, complex texture and shape, spatial relationships and temporal changes, which eventually make it difficult to obtain accurate results using conventional analysis. As a solution to this issue, and to achieve efficient classification of remote sensing satellite images, the authors carried out evaluation and analysis of deep learning approaches based on Convolutional Neural Networks and vision transformer. Kokalj et al (2023) [6] also support this statement and opine that among the various machine learning approaches, deep convolutional neural networks (CNNs) are the current state-of-the-art techniques. However, they add that DL approaches usually require a large number of already labelled samples for training; and inadequate or biased training data can lead to poor model performance. Thus, adequate and labelled datasets are crucial for developing and testing the DL methods, and inadequate training data can be seen as a limitation.

Measuring the concentration of metals and monitoring the quality at regular intervals in dam reservoirs it is a challenging task due to the following factors such as (i) The reservoir water can contain a variety of other substances, such as organic matter and other metals, that may interfere with the detection and quantification of the metallic ions. (ii) Certain metal ions (eg. Lead) in water may be present at very low concentrations. Hence, detecting such low levels require highly sensitive analytical techniques and equipment. (iii) During sample collection, storage, or analysis, there could be a possibility of contamination, which can affect the results. (iv) Metal ion concentrations in reservoir water can vary over time and between different locations within the reservoir. Thus, if the sample locations are far apart, and if sampling is not done frequency, we may obtain incomplete and erroneous results. (v) Lack of skilled personnel who are trained in handling sophisticated analytical instruments and interpreting the results accurately for metal ions is also a big limitation [7].

In a similar manner, dissolved oxygen (DO) and pH measurements can be erroneous because in certain reservoirs, water moss interferes with the measurement of these two parameters [8]. This is perhaps due to the following reasons: (i) Photosynthesis takes place in Water moss during daylight, to result in increased DO levels in the water, while during the night, the moss consumes oxygen by respiration, thus decreasing the DO levels. Hence, such a fluctuation makes it challenging to obtain consistent DO readings. (ii)When sensors are lowered in the reservoir to measure DO, the Water moss aids in the formation of biofilms on the surface of the sensors, thus affecting the accuracy of DO measurements.(iii) Decaying and decomposition of water moss in the reservoir consumes oxygen, leading to decreased DO levels and making the measurement difficult.(iv) As regards pH, during photosynthesis, water moss in the reservoirs takes up carbon dioxide (CO_2) from the dissolved carbonic acid. Such a removal of CO_2 causes the pH to fluctuate with the photosynthetic activity of the moss. (v) Organic acids are released into the water due from the decomposing water moss, which can lower the pH and affect the overall pH balance of the reservoir. (vi) As in the case of DO probes, pH sensors can also be affected by biofilm formed on their surfaces [8,9]. To summarize, while water moss can interfere with the measurement of DO and pH in reservoir water, we have to look for alternate methodologies to achieve accurate and reliable measurements. To overcome such challenges, this paper is concerned with the application of the Red-Kite Optimization Algorithm (ROA) and residual Deep CNN to the LANDSAT images of the Nagi and Nataki reservoirs in India, and predict the water quality with enhanced accuracy.

LITERATURE SURVEY

Since the research presented in this paper encompasses several disciplines of science and technology, it is pertinent to present a brief review of the various works carried out by other researchers[9,10]. Such a review, covering the several aspects of Dam reservoirs around the globe, namely traditional surveys and analysis of Dam water quality, multispectral and hyperspectral remote sensing-based works, satellite image processing techniques, algorithms and tools, ANN, DL and ML based approaches [11,12], and climate change related aspects are presented as follows:

Algal blooms occur in dam reservoirs due to a rapid increase in the population of algae, often leading to ecological imbalances and water quality issues[13]. A combined action of water temperature, residence time, and nutrients is key factor for this phenomenon to occur. As an effort for remediation, water quality simulation was carried out by Lee et al (2023) [14] in the Yeongju Dam in Naeseong-Cheon river, using a three-dimensional numerical model (EFDC - comprised of hydrodynamics, water quality, sediment transport and toxics) to analyze the variations in water quality due to the decrease of residence time according to the opening of the dam gates. The authors observed that the concentration of chlorophyll-a during summer 2021 exceeded the ‘algae warning’ compared to the previous algae warning system. While performing the simulation for the completely opened dam gates, the concentration of chlorophyll-a reduced below the ‘algae warning’ level, thus confirming that restoring the water flow and reducing the residence time will immediately reduce algae in the Dam.

Realising the need to evaluate the concentration of heavy metals, Pakusina et al (2018)[15]

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estimated the chemical and ecological characteristics of lakes in the Muraviovka Park, south of the city of Blagoveshchensk, the capital of the Amur Region, Russia. The reservoirs and lakes in the park serve as an important breeding ground for the White-naped (*Grus vipio*) and Red-crowned (*Grus japonensis*) Cranes, Oriental Stork (*Ciconia boyciana*), Yellow-breasted Bunting (*Emberiza aureola*), Swinhoe's Rail (*Coturnicops exquisitus*) and a number of other endangered/threatened bird species. High concentration of dissolved oxygen in the lake water indicates eutrophication. Further, birds living in the park have great amounts of iron, copper, lead and zinc in their feathers. The ecological state of lakes located in the Muraviovka Park necessitated this investigation to undertake appropriate actions and regulate economic activities.

In another study that evaluated heavy metal contamination in river water, Illham et al (2018) [16] analysed the change in water quality of rivers around Pomalaa nickel mining. The authors estimated TSS, Fe, Cr, Cd, Zn, Cu, Ni, Co and Pb in the river water during and post- mining activity, and categorized the total area into four classes as class A (very good and has met the standard for quality), class B (mildly polluted), class C (moderately polluted), and class D (severely polluted). The results showed that Huko-huko, Kumoro and Oko-oko rivers in Pomalaa area were mildly polluted during the mining activity.

In a study on the effect of heavy metals on the aquatic biota in waters of Pandaan creek, East Java, Indonesia, Hayati et al (2020) [17], examined the how Cadmium (Cd), produced from human activities and industry toxic material, has polluted the water and affected the reproductive health of Oreochromis niloticus, a large deep-bodied tilapia. The authors administered probiotics and Vitamin C in fishes and brought about significant recovery of sperm motility in freshwater fish exposed to Cd pollution.

When it comes to estimating the water quality parameters in a dam reservoir, sensor- based techniques are becoming popular, despite their limitations. Kim et al (2022) [18] demonstrated the application of prediction models on the senor-based data to estimate water quality parameters such as SS and turbidity in the Imha Dam reservoir, located in the range of Banbyeoncheon, a tributary of the Nakdong River. The inflow rivers are Banbyeoncheon, Yongjeoncheon, and Gilancheon in to this multipurpose dam reservoir built to provide water supply and prevent floods. The authors aimed to improve the accuracy of measuring the SS and turbidity which increase rise suddenly in the reservoir due to abnormal rainfall and extreme weather. Accordingly, they developed a relational expression to calculate the SS and used the AEM3D model to improve the accuracy of predicting turbidity through the turbidity- SS relationship developed by them. The authors conclude that by acquiring data on turbidity, TSS, particle size, and particle size fraction by sensor-based direct measurement, we can improve the accuracy of turbidity prediction in the future.

Use of Deep Learning and machine learning has been initiated a few years ago in many fields, including water quality studies in dam reservoirs. Kim et al (2021) [19] attempted to predict harmful algal blooms (HAB) in Bohyeonsan Dam and Yeongcheon Dam located in Yeongcheon-si, Gyeongsangbuk-do, South Korea, using random forest (RF) model, which is a Machine Learning model. Of the 14 water quality factors considered, water temperature was the most important in both the dams, followed by SS and T-N in Bohyeon Dam, and DO, Chl-a, and T-N in Yeongcheon Dam. After predicting the number of harmful blue-green algae cells using water temperature as an input factor through machine learning (ANN) and deep learning (RNN, LSTM, GRU) models, the overall increase/decrease pattern was well predicted. The authors also mention that, the coefficient of determination (R^2) was 0.98 for ANN, 0.46 for RNN, 0.38 for LSTM, and 0.41 for GRU, indicating that ANN performed the best.

The emerging climate change scenarios have compelled several researchers to use existing and new models to predict the quality of inflowing water. SWAT and CE-QUAL-W2 and two such models in series to climate change scenarios, that were used by Park et al (2017) [20]. The authors analyzed the impact of two climate change scenarios on flow rate and water quality of the Yongdam Dam and its basin in south Korea. While performing simulations for 2016 to 2095, it was observed that the number of rainfall days decreased and the rainfall intensities increased. Accordingly, waste load discharge from the basin decreased during the dry period and increased in the wet period. As a sequence to this study, the results of SWAT were used as boundary conditions of the CE-QUAL-W2 model to predict water level and water quality changes in the Dam. It was found that TSS and TP tend to increase during the summer when rainfall is higher, while TN has an opposite pattern because N has weak absorption to particulate materials. This study emphasizes the need to consider climate change scenarios while conducting Dam water quality studies.

Water quality of rivers can directly influence the Dam reservoirs. Discussing about drought and its impact on water quality in the rivers of Gamcheon mid-basin, south Korea [21].There is certainly a profound impact of rain-free days and accumulated precipitation on river water quality. This impact was quantitatively evaluated by the authors by developing the Load Duration Curve (LDC). It was observed that water quality changes in the rivers when there are more than 14 rainless days and the cumulative rainfall over 28 days is 32.1 mm or lesser. This observation forms the basis to quantify the impact of drought by developing a drought water quality index for rivers and other water systems [22].

Several works have been carried out with respect to using remote sensing for estimating the physical, biological, biophysical and chemical aspects of the water quality of a dam reservoir. Different analytical techniques have also been developed and demonstrated . A study for waterbody detection and estimation of water storage in agricultural reservoirs using remote sensing was carried out .Sentinel-1 SAR imagery for 3 years (2018-2020) of Edong, Gosam, and Giheung reservoirs in South Korea were subjected to threshold determination techniques such as fixed threshold, Otsu threshold and Kittler-Illingworth (KI) threshold. When the remote sensing-based findings were validated with field-based observations, it is noted that the most accurate results were from the KI threshold, and the water storage estimated by this method had a high agreement with (r = 0.9235). This study also gave us confidence in the use of Sentinel data for reservoir studies [23].

A different type of study was carried out using Sentinel-2 images of Hwanggang Dam. Since the dam reservoir is located in upstream of the Imjin River in North Korea, data sharing between the south and north Koreas is not made, and flood damage risk prevails due to heavy storm and discharge from the North Korean side into the south Korean side of the river. To overcome the difficulties in forecasting flood, a dam-inflow and reservoir water level change modelling system was generated by the authors using a lumped hydrological model and reservoir operation algorithm. The data on dam inflow was verified using water level derived from Sentinel-2 optical imagery and a 10m DEM. An acceptable R^2 value of 0.76 was obtained for water level from Jan. 2017 to Aug. 2020, thus demonstrating the usefulness of Sentinel-2 image data for reservoir studies [24].

A review of the available literature reveals that Landsat data have been widely used to monitor water quality parameters such as chlorophyll-a, turbidity, and surface temperature in reservoirs worldwide. For instance, González-Márquez et al. (2018)[25] used LANDSAT 8 images for depth and water quality assessment of El Guájaro reservoir, Colombia. Through multiple regression analysis between measured water quality parameters and the reflectance of the pixels corresponding to ground sampling stations, the authors demonstrated that it is possible to generate reliable models from Landsat 8 to estimate the spatial variation of turbidity, dissolved oxygen, pH and depth, as well the temporal variation of electrical conductivity. Kapalanga et al (2021) [26]examined Landsat 8 images of the Olushandja Dam in north-central Namibia, from November 2014 to June 2015, to develop regression analysis- based water quality retrieval algorithms. The medium to strong positive linear relationships between the Landsat-predicted and measured (in situ) data for turbidity (R^2=0.767); total nitrogen (R^2=0.798,); total phosphorus (R^2=0.907); total suspended solids (R^2=0.284,) and total algae count (R^2 =0.851), demonstrated the ability of remote sensing to provide rapid information on the spatio-temporal variability of surface water quality.

A study by Bielski and Tos (2022) [27] on Lake Dobczyce, a shallow dam reservoir in Myslenice Poviat, southern Poland, examined turbidity and chlorophyll-a content by analysing Sentinel-2 satellite imagery. The authors corrected the reflectance obtained from the satellite data with a bottom reflectance determined using the Lambert–Beer equation. The water quality estimation models helped to develop the maps of turbidity and chlorophyll-a content of the lake, thereby highlighting the potential of remote sensing in monitoring such biophysical parameters.An investigation by Fernando et al (2022) [28] used remote sensing to monitor water quality in estimating, understanding, and managing the impacts in sensitive dam reservoirs across Brazil, Colombia and Kenya, as part of the Water Funds portfolio. The authors focused on developing a remote sensing data processing approach to detect phytoplankton abundance and sediments in the

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dam reservoirs. They also performed cloud computing for rapid monitoring deployment and scalable coverage across numerous watersheds and geographies. The authors are of the view that additional insights may be revealed by integrating the water quality data sets of this work with other sources of information from local sensors, from water and sanitation utilities and from an analysis of the location conditions and their impacts.

An application of a recent satellite image processing technique, namely, multi-sensor image fusion was attempted to monitor the Edong and Cheontae Dam reservoirs in Korea. K- means clustering approach was applied to Compact Advanced Satellite 500(CAS500), Kompsat-3/3A, and Sentinel-2 derived Normalized Difference Water Index (NDWI), and

SAR backscattering coefficient from Sentinel-1 to delineate the boundaries of the two reservoirs. After that, the improvements in accuracies were attained by K-means clustering applied to the 2-D grid space of NDWI and SAR. The authors opine that with the development of high-resolution SAR satellites and image fusion techniques, better detection and delineation of water bodies can be done [29].

Of particular interest in water quality assessment in dam reservoirs is the use of hyperspectral imagery. These sensors are particularly useful for detecting and mapping Chlorophyll in reservoir waters. One such study is by Jang et al (2022) [30], wherein the authors estimated Chlorophyll-a concentration in the Baekjae Dam and Namyang lake, Korea. 17 hyperspectral images from aircraft and drone-based surveys carried out in 2016- 2017 (for Baekjae Dam) and in 2020 -2021 (for Namyang lake) were analyzed in conjunction with the simultaneous water quality data generated through sampling and analysis for dates that matched with each of the images. ANN applied to 30 chlorophyll bands resulted in a Chl- a estimation model. The learned model subsequently used to estimate Chl-a in the two water bodies showed that temperature change was the most important factor controlling the spatiotemporal distribution changes. This study in Korea has given us the appropriate inputs to design the methodology for our current work.

Similar studies by Binding et al. (2012) [31] have demonstrated the effectiveness of hyperspectral data in monitoring water quality in reservoirs and lakes. The authors have described how the hyperspectral sensors capture data in hundreds of narrow spectral bands, allowing for detailed analysis of water constituents. They add that such sensors provide high spectral resolution, enabling the identification of specific water quality parameters such as chlorophyll-a, dissolved organic matter (DOM), and suspended particulate matter (SPM). Hyperion on the EO-1 satellite is a prominent example.Wang and Yang (2019) conducted a quantitative and systematic review of the application of remote-sensing techniques for water quality assessment in China, with an aim to display the current research status and identify the existing challenges and future directions. Their review revealed that though the popularity of the application of remote sensing in water quality research is increasing in China, the findings related to water quality are often limited to qualitative description and the research is concentrated to a few regions only, thereby ignoring other regions of China. This has prompted us to apply remote sensing to study the quality of water in the reservoirs spread across the whole of India, and this research presented here, forms one such study.

Recent studies have used Machine Learning (ML) algorithms for continuous monitoring of water quality parameters in lakes and reservoirs. One such recent work is by Dehkordi et al (2024) [32], who applied machine learning (ML) models to Sentinel-2 imagery data to retrieve turbidity and specific conductance in Lake Houston, USA. A fuzzy similarity analysis (FSA) technique was proposed to enhance ML estimates of WQPs by using the prediction errors in effective training samples. The results showed that FSA significantly improved the accuracy of all ML predictions. Advanced technologies such as IoT, deep learning, and remote sensing improved real-time assessments and predictive accuracy in monitoring the water quality. Majnooni et al. (2024) [33] combine interpretable deep learning models with feature importance analysis to enhance decision-making in reservoir water quality monitoring, though the complexity of these models can limit interpretability and demand significant computational resources. Chen et al. (2024) [34] apply deep learning to predict water quality in the Huangyang Reservoir, emphasizing its ability to manage large datasets and provide real-time predictions, though they note challenges related to data availability and potential overfitting. Prasad et al. (2022) [35] integrate deep learning and auto deep learning techniques for robust water quality predictions, automating model selection and hyperparameter

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tuning. However, their method may overlook valuable insights from human expertise and requires high computational costs.

Khoi et al. (2022) [36] use machine learning algorithms to predict the water quality index (WQI) in the La Buong River, offering quicker insights with less computational demand, though these simpler models may struggle to capture complex patterns effectively. Tripathy & Mishra (2024) [37] provide a broad review of deep learning applications in hydrology, which fosters innovation but lacks empirical case studies or a focused methodology. Kulwant & Yadav (2024) [38] address challenges in water quality monitoring in India, with policy recommendations constrained by regional infrastructure and funding limitations. Meanwhile, Bidyabati & Nath (2023) [39] and Dahanga & Nath (2023) [40] use field measurements and water quality indices (WQI) for monitoring water quality in Indian rivers, though these methods may oversimplify complex issues and face temporal and resource constraints in capturing seasonal variations. Adhikari et al. (2023) [41] develop systems for real-time water quality monitoring using sensor technologies and data analytics, enabling immediate detection of issues, though challenges related to sensor reliability and setup costs remain. Similarly, Singh et al. (2022) [42] employ IoT devices for real-time monitoring along the River Ganga, which enhances public awareness but faces data privacy concerns and the need for continuous sensor maintenance.

Qian et al. (2022) [43] present a case study of the Qingcaosha Reservoir, integrating cruise monitoring technology, remote sensing, and deep learning to assess water quality with high accuracy. Their deep neural network (DNN) model outperforms traditional machine learning approaches, providing high-frequency, multidimensional analysis. Deng et al. (2024) [44] review how remote sensing and machine learning have advanced lake water quality management by enabling large-scale, accurate detection of key parameters like chlorophyll-a and turbidity, improving prediction precision. Luo et al. (2024) [45] propose a hybrid deep learning model for municipal water management, addressing traditional monitoring challenges and capturing complex data relationships for more reliable predictions. Rahu et al. (2023) [46] discuss frameworks combining IoT and machine learning for real-time water quality monitoring, enhancing response times. Zhang et al. (2024) [47] employ a multi-model ensemble approach to forecast dissolved oxygen levels in reservoirs, improving prediction accuracy by combining multiple models. Udeh et al. (2024) [48] demonstrate how machine learning and statistical analysis can enhance groundwater monitoring in Texas, providing better resource management insights. Finally, Mohd Zebaral Hoque et al. (2022) [49] show that regression learning models can significantly improve water quality index predictions, enhancing environmental monitoring accuracy.

A major limitation of the use of satellite imagery to estimate water quality parameters in a dam reservoir is that vegetation present in the reservoirs prohibits the satellite sensor to obtain spectral measurements of the water surface. The vegetation present in reservoirs not only limit the use of remote sensing for water quality estimation, but also affect the water quality of the Dam reservoir. A study on the effects of Salix subfragilis (Crack Willow) on the water quality in the Namang Dam reservoir in Korea was taken up by Jung (2017) [50]. The authors analyzed the phenological cycle of the Crack Willow colony in the Dam reservoir to know infer the effects on water quality. They observed that the water quality was deteriorating and resulted in death of the willow communities. Consequently, the fallen leaves, branches, and dead trees of willow affected the water quality of the Dam. This study gives us clue to analyse similar issues in the Nagi and Nakati Dams since we have Water Moss growing in these two reservoirs.

OBJECTIVES

In this paper, we propose:

(i) To collect water quality data such as pH, DO, NO3 etc. from the laboratory for different locations in the two water bodies (Nagi and Nakati reservoirs) and also from leaf samples of Water moss in the reservoir for estimation of lead content.

(ii) To propose the Red-Kite Optimization Algorithm (ROA) turned residual Deep CNN to enhance the pixels of the water, water moss and perspectively project the moss using the proposed Transverse Dyadic Wavelet transform in LANDSAT images.

(iii) To correlate the pixel features after processing with the proposed ROA-RCNN algorithm in LANDSAT image and the water quality parameters obtained from lab analysis of water and leaf samples.

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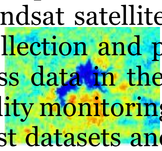
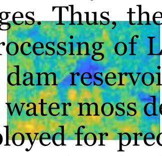
(iv) To predict the water quality of dam waters using the proposed Bayesian-optimized multi-regression algorithm, which can reduce overestimation and perform better for small data sets.

(v) To compare the predicted water quality parameters with the predictions of the existing algorithms.

METHODS

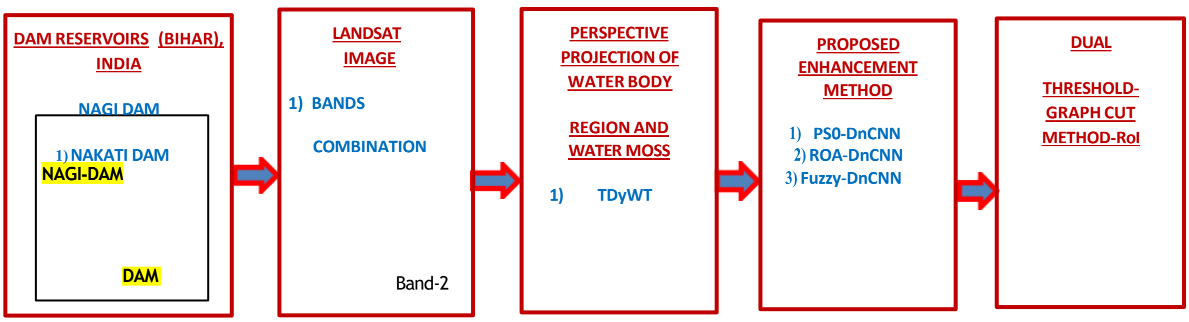
This study involves the use of satellite imagery, field-based sample collection, laboratory analysis of samples, image processing using optimized residual deep Convolutional Neural Networks (CNNs) and machine learning algorithms, and correlation- regression methods. We adopt a synergistic approach combining all these components to continuously monitor wa[illegible] and water moss in two dam reservoirs using Landsat satellite images. Thus, the metho[illegible]gy [illegible]lves multi-step processes, beginning with the collection and pre-processing of Landsat [illegible] the corresponding water quality and water moss data in the two dam reservoirs. The [illegible] pixel features are subsequently used for water quality monitoring and water moss detection. The optimized models are then validated using separate test datasets and deployed for predicting water quality in dam reservoirs. Prediction is attempted using the Bayesian-optimized multiple regression algorithm. Finally, the predicted water quality parameters are compared with the results obtained using the existing algorithms. This integrated approach leverages the strengths of both, CNN and machine learning algorithms and aids in efficient monitoring of water quality and water moss, enabling proactive management and decision-making for dam operators and water resource managers.





STUDY AREA

Nagi Dam and Nakati Dam are located in the south eastern part of Bihar state near the town of Jhajha, India. The dams are quite deep and are surrounded by rocky hillocks. These dams were built to supply water to the local farms. There are cultivable lands adjacent to both the dam reservoirs. Google Earth image and maps showing the location of Nagi and Nakati Dams considered for the present study in **Figure 1**. Nagi is an earthen dam, constructed in 1958 across the river Nagi, in the Nagi sub-basin of Ganga Basin. It has an area of 425 Ha, with a length of 1884 metres, and has a maximum height of 113.5m above its foundation. It has been designed to have a reservoir with a gross storage capacity of 108 MCM of water. There is a Nagi bird sanctuary on this reservoir. The reservoir is home to many species of fish, amphibians, birds, reptiles, etc. Nakati Dam was constructed in 1980 on Nakati river and has a full reservoir level area of 364 ha. Average water area the waterbody reduces to 75 ha in the month of April and May and again gain to 170 ha or more after monsoon. There is a Nakati Dam bird sanctuary on this reservoir. This sanctuary plays a crucial role in the conservation of bird species and their habitats in the region. However, this sanctuary faces challenges such as habitat degradation, pollution, and human encroachment, which can impact the bird population and overall ecosystem health.



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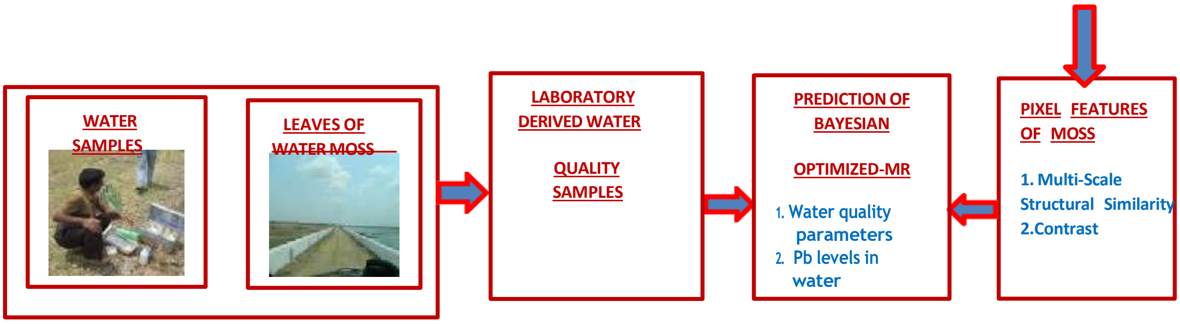

Figure 1: Flowchart of methodology employed for retrieval of water quality parameters in dam reservoirs using ROA-RCNN approach applied to LANDSAT image data.

LANDSAT BAND COMBINATIONS FOR DAM QUALITY MONITORING

Landsat band combinations are used for the monitoring and analysing the earth features such as land use, water regions, and coastal regions for identification of changes over a time period. Band combination enhances the water body region analysis. The combination helps to distinguish between moss in dam water and water region for monitoring the quality of dam water. In this paper, dam water quality is monitored using the band2, band3 and band4 combination due to reduced multi-collinearity, identifying the variation in moss and suppression of interference from water, which leads to accurately monitoring the water quality. The time series data of Landsat helps to monitor water quality of dam for changes in the period of time effectively. Comparing images at different times using consistent band combinations, significant changes in water quality is detected. The strategic selection of Landsat band combinations enhances water quality monitoring and management of dam water. Landsat imagery and Google Earth map images serve different purposes and have distinct advantages based on their characteristics. **Figure 2** shows the band combinations for LANDSAT images. Among the bands of LANDSAT images BAND-2, BAND-3 and BAND- 4 combinations are suitable for the water quality monitoring.

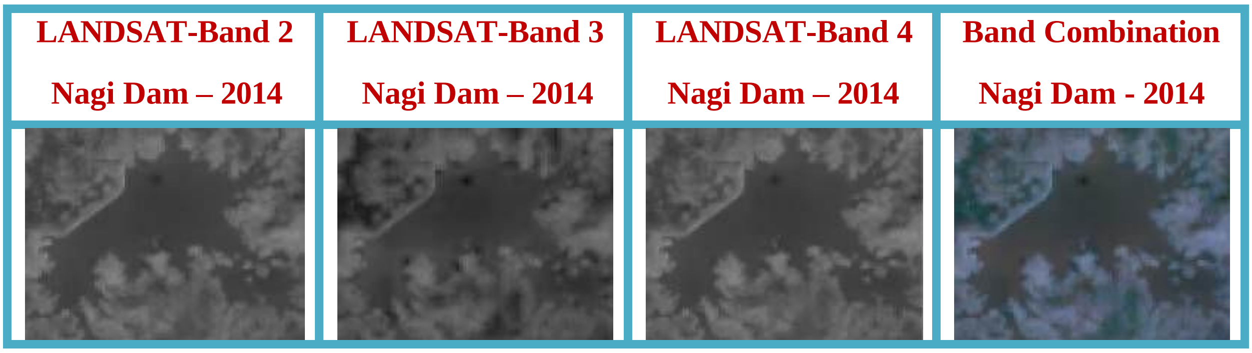

Figure 2. Landsat-band combinations for water quality monitoring

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Landsat images are characterised by higher temporal resolution, multi-spectral imaging capability and long-term data availability. These images have spatial resolution of 30 meters (15 meters for panchromatic), which is suitable for water quality analysis. In contrast, Google Earth image has different resolution depending on the location and source.

TDyWT FOR PERSPECTIVE PROJECTION OF MOSS IN DAM WATER

Transverse Dyadic Wavelet Transform (TDyWT) enhances image quality through preserving the edges and boundaries, reduces noise in the Landsat images. TDyWT decomposes an image into multiple frequency bands and lead to the separation of low- frequency (smooth regions) and high-frequency (edges and details) components and enhances the moss in the water body regions. Edge Preservation is performed by utilizing wavelet coefficients. TDyWT identifies and preserves edges in images and maintaining structural details, which is lost in that traditional DWT method, which often smooth out edges. As shown in **Figure 3**.

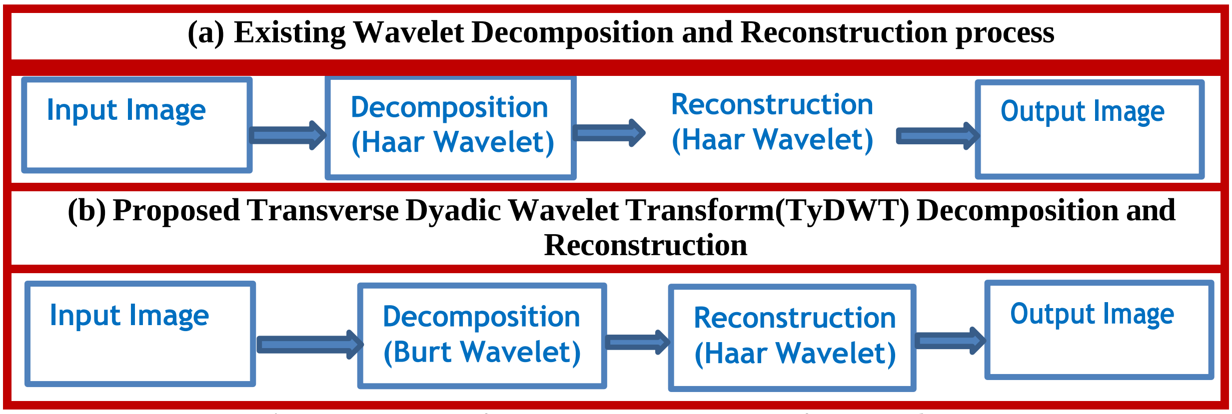

Figure 3. TyDWT for perspective projection of moss in dam water

1.1 ENHANCEMENT OF MOSS REGION IN DAM WATERS USING OPTIMISED- DNCNN

DnCNN (Denoising Convolutional Neural Network) is a deep learning architecture specifically designed for image enhancement. DnCNN consists of (i) Input Layer (ii) Convolutional Layers (iii) Batch Normalization Layers (iv) Residual Learning (v) Final Convolutional Layer (vi) Loss Function. **Table 1** summarizes the DnCNN architecture.

Table 1 Optimized - DnCNN Architecture

Layer Type	Description
Input Layer	Takes a noisy image as input
Convolutional Layers	Multiple layers for feature extraction
Activation Function	ReLU applied after each convolution
Batch Normalization	Normalizes activations for stability
Residual Learning	Skip connections for noise prediction
Final Convolutional Layer	Outputs estimated noise
Loss Function	Typically Mean Squared Error

DnCNN architecture combines multiple convolutional layers with residual learning and batch normalization for image enhancement. The Particle swarm optimization, Fuzzy optimization and ROA optimizes the DnCNN parameter such as (i) lrn_net = layrecnet(1,8);
(ii) lrn_net.train Param.show = 5; (iii) lrn_net.trainParam.epochs = 500 for enhancement of the dam

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water body regions.

ROA-DNCNN FOR MOSS REGION ENHANCEMENT IN THE DAM WATER

The Red-Kite Optimization Algorithm (ROA) mimics the hunting behaviour of red kites. Red kites hunt for prey and exhibit specific behaviours such as soaring, gliding, and diving to catch their prey. ROA algorithm translates these behaviours into mathematical operations for optimization. In ROA, potential solutions are represented as agents within a population. Each agent represents a candidate solution to the optimization problem. The ROA algorithm balances exploration (searching new areas of the solution space) and exploitation (refining known good solutions). This balance avoids local optima and enhances the likelihood of finding global optima. ROA Algorithm Steps are Initialization such as (i) Randomly initialize a population of agents within the defined search space. (ii) Define objective functions that need to be optimized. Then Fitness Evaluation, Evaluate the fitness of each agent based on the objective function(s). This determines how well each solution performs. Next is the Update Positions and mimics the hunting strategies of red kites such as
(i) Soaring: Agents explore new areas by making larger moves (ii) Gliding: Agents refine their current solutions by making smaller adjustments. (iii)Diving: Agents exploit promising regions by intensively searching around the best-known solutions. (iv) Selection: Select agents based on their fitness to create a new generation. The algorithm continues iterating through evaluation and updating until a termination criterion is met, such as a maximum number of iterations or convergence to a satisfactory solution.

ROA-DnCNN Algorithm

---

1. *Initialize parameters for ROA:*
   - *Set population size (N)*
   - *Set maximum number of iterations (max_iter)*
   - *Define bounds for DnCNN parameters (e.g., learning rate, number of layers, filter sizes)*
2. *Initialize population of particles:*

   For each particle in population:

   Initialize position (parameters of DnCNN) randomly within defined bounds Initialize velocity randomly

   Evaluate fitness (denoising performance) using a validation dataset Set personal best position and fitness
3. *Identify global best particle:*

   Find the particle with the best fitness in the population
4. *Main optimization loop:*

   For iter = 1 to max_iter:

   For each particle in population:

   *Update velocity using RKOA formula: velocity = inertia_weight * velocity*

   *+ cognitive_coeff * random() * (personal_best_position - current_position)*

   *+ social_coeff * random() * (global_best_position - current_position) Update position (DnCNN parameters):*

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current_position = current_position + velocity Ensure current_position is within bounds

Evaluate fitness with updated DnCNN parameters on validation dataset If fitness is better than personal best:

Update personal best position and fitness

Update global best position if any particle's personal best is better

5. *Train DnCNN with the optimal parameters found:*
   - *Use the global best position as the final parameters for DnCNN*
   - *Train DnCNN on the training dataset with these parameters*
6. *Evaluate performance of tuned DnCNN on test dataset:*
   - *Measure denoising quality using metrics like PSNR, SSIM, etc.*
7. *Return results:-Return the optimal DnCNN model and performance metrics*

Best Fitness Function plays a major role in optimization process. In RKOA, the fitness function typically reflects the goals of the specific application.

REGION OF INTEREST – GRAPH CUT METHOD FOR MOSS IN DAM RESERVOIRS

Dual-Threshold Graph Cut (DTGC) is an image segmentation method for Regions of Interest (ROI). Duar- Threshold Graph cut method is based on graph theory. In this method, image is converted into graph such as nodes and edges. Nodes represents the pixels or groups of pixels. Edges represent relationship among nodes, which is based on pixel intensity variations. Dual-Threshold Graph Cut method has foreground and background images and enhances the edges of object. The DTGC method of segmentation is based on energy function. Energy function is a mathematical framework used to quantify the quality of a segmentation. DTGC method optimizes the energy function for moss detection in dam water. Minimizing energy function defines new edge weights, and leads to precise moss locations within complex backgrounds, and improves the detection accuracy of moss compared to traditional methods. DTGC method has more Accuracy, Efficiency, and Flexibility. DTGC method enhances both accuracy and efficiency in identifying moss in water region of Landsat images. DTGC method enhances the moss in the water body. Moss enhancement is complex in water body with more turbidity. DTGC Method performs better due to Multiscale Feature Extraction, and Homogeneous Region Extraction. Moreover, DTGC method uses GMM method for differentiation of water and moss pixels for more accuracy. Fit the Gaussian distributions into two categories for deriving the dual thresholds for better visualization of water body and moss. Dual thresholds from GMM integrates with the graph cut model and redefines the weights of edges in the graph representation of the image. This adjustment enhances the graph's ability to separate water from moss more effectively. DTGC method integrated with optimizes DnCNN images and enhance background subtraction and improves moss detection accuracy during reflections on water surfaces.

PREDICTION OF WATER QUALITY IN NAKI AND NAKATHI DAM RESERVOIRS

The water quality parameters are analysed Ambient & Water temperature, pH, Conductivity, Turbidity, Total Dissolved Solids, Turbidity, Dissolved Oxygen, Free-Carbon dioxide, Carbonate & Bicarbonate Alkalinity, Chloride, Total Hardness, Phosphate- phosphorus, Nitrate-nitrogen, Biochemical Oxygen Demand, Chemical Oxygen. **Figure 4.** displays the photograph showing the Nagi and Nakathi Dam water regions.

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Nagi Dam	Nakati Dam
	

Figure 4. Photograph showing the Nagi and Nakathi Dam water regions

Table 2 shows the water quality measurement methods from the samples of water taken from different locations in the two dam regions. The laboratory method based water quality measurement on 25 May to 29 May 2023, and the latitude and longitude locations are shown in **Table 3.**

Table 2 . Water Quality Measurement Methods

Water quality parameter	Measurement methods
1) Temperature 2) Turbidity 3) pH 4) Conductivity and TDS 5) Dissolved oxygen	1) Centigrade mercury thermometer 2) Digital Nephelo-Turbidity Meter 3) Digital pH Meter 4) Conductivity-TDS Meter 5) Winkler's modified method

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Table 3. Laboratory Methods Based Water Quality Measurement On 25 May To 29 May 2023

	Nagi Dam			Nakti Dam		
Parameters	Site I	Site II	Site III	Site I	Site II	Site III
GPS position	*N 24°49.260 E 86°24.024'*	*N 24°48.789' E 86°24.315'*	*N 24°48.812' E 86°24.230'*	*N 24°51.208' E 86°26.340'*	*N 24°49.283' E 86°26.489'*	*N 24°50.894' E 86°26.694'*
Ambient Temp.(°C)	26	28	32	32	33	34.5
Water Temp. (°C)	26.3	27.3	28.5	30.8	31.9	33.5
Turbidity(NTU)	8.1	7.8	15.8	9.8	7.3	4.1
Conductivity(µs)	248	249	248	236	224	243
TDS	125	126	125	120	115	125
pH	7.5	7.5	7.5	7.5	8.9	9.5
DO	8.4	10.8	10.8	8.8	13.2	13.2
FCO_2	Abs.	24	Abs.	Abs.	Abs.	Abs.
$CO_3^{=}$	10	Abs.	10	10	10	15
HCO_3^{-}	28	28	26	30	26	30
TH	90	106	90	86	102	78
Cl^{-}	12.99	10.99	10.99	13.99	0.899	10.99
$PO_4 - P$	0.058	0.055	0.059	0.053	0.047	0.040
$NO_3 - N$	0.047	0.050	0.053	0.052	0.057	0.041
COD	86.2	-	-	86.2	-	-
BOD	1.3	0.09	2.8	1.2	1.3	1.1
As	Nil	0.02	0.02	0.02	0.01	0.025

PIXEL FEATURES OF MOSS AND WATER REGIONS

Image contrast is the difference in luminance or colour of object, which distinguishes the object from the background. Contrast plays a vital role in visual perception, as the human visual system is more sensitive to contrast than to absolute brightness levels. High contrast ratio is the significant difference between the lightest and darkest parts of an image. Water bodies have distinct spectral signatures compared to surrounding land surfaces. By enhancing contrast, the differences in luminance between water and land are obtained and delineation of water regions from moss are more accurate. In the context of image processing, entropy is a measure of the amount of information or uncertainty contained within an image. Higher entropy values indicate greater variability in pixel intensity, which differentiates water and moss. Water and moss have distinct spectral signatures that can be analyzed using entropy. For instance, water typically reflects different wavelengths compared to moss, and it allows for effective differentiation when entropy is applied to multispectral satellite data. This differentiation is crucial because both water and moss can appear similar in certain conditions. Peak Signal-to-Noise Ratio (PSNR) is a metric in image processing that quantifies the quality of a processed image by comparing an original reference image. PSNR measures the ratio between the maximum possible power of a image and the power of corrupting noise that affects

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quality. It is expressed in decibels (dB), where a higher PSNR value indicates better image quality and less distortion or noise in the processed image, compared to the original. PSNR values are used effectively to monitor the changes in water quality and respond to potential ecological issues. Signal-to-Noise Ratio (SNR) is used for detection of water and moss in satellite images. It quantifies the level of desired signal (reflectance from water or moss) relative to the background noise. SNR is used in image analysis for environmental monitoring.

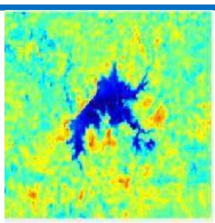
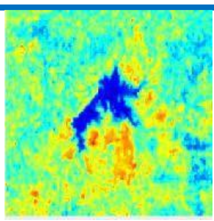
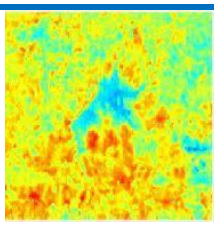
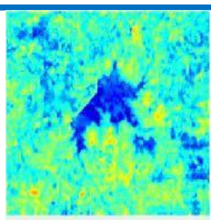
Bayesian optimized Multiple Regression (BO-MR) for prediction of water quality from LANDSAT Images

Bayesian optimization is used to tune the multiple regression hyperparameters for prediction of water quality in dam water using the pixels of Landsat images. Bayesian optimization is a sequential model-based method. Bayesian optimization allows for efficient exploration of the hyperparameter space to find optimal settings that enhance model performance. In multiple regression, the hyperparameters are: (i) Regularization Strength (Alpha); (ii)Learning Rate; and (iii) Number of Features.

RESULTS

The methodology involves collection and pre-processing of Landsat images, along with relevant water quality and water moss data from two dam reservoirs. The pixel features extracted from these images are then utilized for monitoring water quality and detecting water moss. Following this, the optimized models undergo validation using distinct test datasets before being deployed to predict water quality in the dam reservoirs. Predictions are made using a Bayesian-optimized multiple regression algorithm. Finally, the predicted water quality parameters are compared with results generated by existing algorithms to evaluate their accuracy and effectiveness. Input data is pre-processed using TyDWT. **Figure 3.** shows TyDWT for perspective projection of Moss in Dam Water. TDyWT corrects geometric distortions which occur during image acquisition. Aligning the pixels based on transformed coefficients, TDyWT ensures spatial relationships within the image, and preserves the object in the image with accurate edges and boundaries. The Transverse Dyadic Wavelet Transform improves the image quality through perspective projection using the multi-resolution analysis, edge preservation, noise reduction, and geometric distortion correction.

TDyWT adaptive thresholding methods during the reconstruction phase leads to dynamic adjustments based on local image characteristics, enhances the moss in water body region and minimizes artefacts as shown in **Figure 5.**

LANDSAT Image Nagi-Dam (2014)	**LANDSAT Image Nagi-Dam (2015)**	**LANDSAT Image Nagi-Dam (2016)**	**LANDSAT Image Nagi-Dam (2017)**
			
LANDSAT Image Nakati-Dam (2014)	**LANDSAT Image Nakati-Dam (2015)**	**LANDSAT Image Nakati-Dam (2016)**	**LANDSAT Image Nakati-Dam (2017)**

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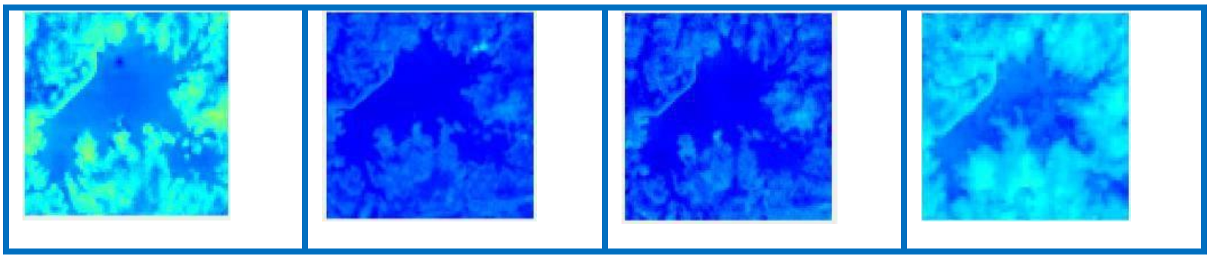


Figure 5. Proposed TyDWT algorithm-Spatial and temporal LANDSAT images of Nagi and Nakati Dam (2014-2017)- perspective projected pixels of water and moss.

Further, input image is enhanced using optimized DnCNN algorithm. **Figure 6** shows the Proposed ROA-DnCNN algorithm; Spatial and temporal Landsat images of Nagi and Nakati Dam (2014-2017); and the enhanced pixels of water and moss.

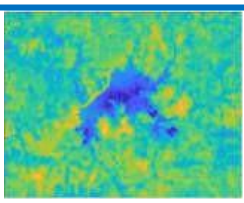
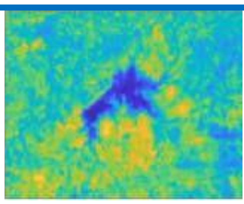
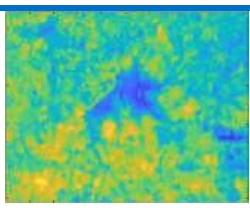
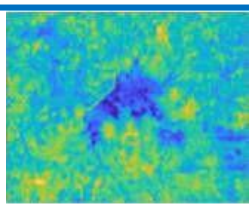
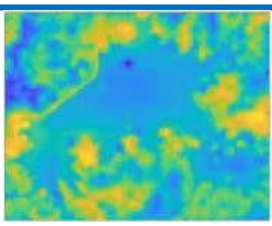
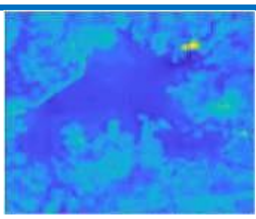
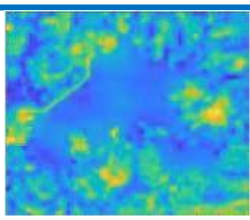
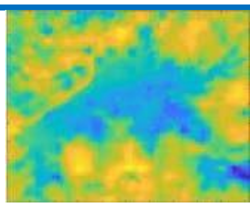
LANDSAT Image Nagi-Dam (2014)	LANDSAT Image Nagi-Dam (2015)	LANDSAT Image Nagi-Dam (2016)	LANDSAT Image Nagi-Dam (2017)
			
LANDSAT Image Nakati-Dam (2014)	LANDSAT Image Nakati-Dam (2015)	LANDSAT Image Nakati-Dam (2016)	LANDSAT Image Nakati-Dam (2017)
			

Figure 6. Proposed ROA-DnCNN algorithm; Spatial and temporal Landsat images of Nagi and Nakati Dam (2014-2017); and the enhanced pixels of water and moss.

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For image enhancement, the fitness function can be defined as (i) Minimize Power Loss: Fitness=Total Power Loss (ii) Minimize Voltage Deviation: Fitness=Voltage Deviation In multi-objective scenarios, a combined fitness function may be used, such as: (iii)Fitness=w1·(Power Loss)+w2·(Voltage Deviation) and (iv)Fitness=$w1$·(Power Loss)+$w2$
·(Voltage Deviation). where w1$w1$ and w2$w2$ are weights assigned to each objective based on their importance**.** Water and moss regions are segmented from the enhanced image using dual threshold graph cut method. The DTGC method employs the Gaussian Mixture Model (GMM) to differentiate between water and moss pixels, enhancing accuracy in the process. It fits Gaussian distributions into two categories to derive dual thresholds, which improve the visualization of both the water body and the moss. These dual thresholds, generated from the GMM, are integrated with a graph cut model, allowing for the redefinition of edge weights in the graph representation of the image. This adjustment significantly improves the model's ability to effectively separate water from moss. Additionally, the DTGC method is integrated with optimized DnCNN images, enhancing background subtraction and improving moss detection accuracy, even in the presence of reflections on water surfaces. **Figure 7** illustrates the output of dual threshold graph cut method.

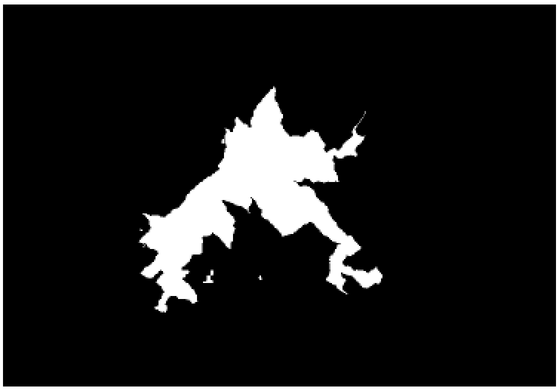
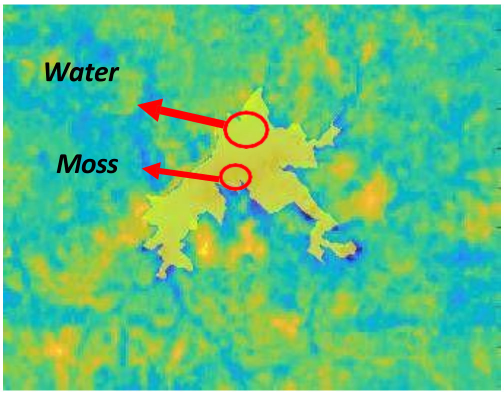
LANDSAT Image **Nagi-Dam (2023)**	**LANDSAT Image** **Nagi-Dam (2023)**
	

Figure 7. Segmentation of water and moss using the proposed Dual-Threshold Graph Cut (DTGC) algorithm.

The steps to apply Bayesian Optimization for prediction of water quality in the dam reservoir are as follows: (i) Define the Objective Function (ii) Choose a Surrogate Model (iii) Select an Acquisition Function (iv) Expected Improvement (EI) (v) Upper Confidence Bound (UCB).Regression analysis is performed with the noise in data. Bayesian optimization incorporates uncertainty into decision-making process. BO-MR handles continuous and discrete hyperparameters, make suitable for complex models especially for the water quality Monitoring. Bayesian optimization is an effective approach for tuning hyperparameters in multiple regression models. By using probabilistic modeling and strategic sampling based on past evaluations, it allows practitioners to optimize their models efficiently while managing computational resources effectively. This method is particularly valuable in scenarios where evaluations are costly or time-consuming, making it a preferred choice in many machine learning applications. From the statistical values of water region and moss region in the dam

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waters, pH and DO are measured for Naki and Nakati dam water regions from Landsat images. **Table 3** laboratory values are used in Bayesian regression. **Table 4 and Table 5** displays the statistical values of pixels at different location of Nagi and Nagathi dam resorvoirs.

Table 4 Statistical values of pixels of regions of pixel at different location of the Nagi Dam Reservoir (Sample Data)

dissolved oxygen	Ph	conductivity	total disolved solid	turbidity	Mean -water	entropy-water	psnr--water	snr-water	Mean -moss	entropy -moss	psnr-moss	snr-moss	WR	WG	WB	MR	MG	MB
8.93	7.5	239.33	123.59	7.09	132.52	5.95	21.87	17.67	139.3	4.49	22.35	18.4	42.14	148	240.8	52.69	42.51	163.7
8.84	7.76	228.12	115.48	5.27	134.67	6.23	22.04	18.41	139.7	4.44	23.64	19.5	41.12	148.5	239.5	52.47	42.97	163.5
9.61	7.6	228.81	118.44	7.33	136.68	6.07	20.74	17.59	139.3	4.42	23.5	18.7	42.75	154.6	237.3	58.18	39.91	166.7
8.51	7.66	232.57	121.32	7.07	131.21	6.24	22.41	18.38	140.4	5.19	24.01	18.9	39.78	152.1	243.3	52.82	39.85	168.4
9.43	7.5	226.03	116.46	6.3	131.86	5.51	22.12	17.06	137.7	6.32	22.13	19.1	43.19	145.7	244.2	53.31	40.38	169.1
9.09	7.63	239.75	117.13	5.03	135.02	6.26	22.14	18.62	140	3.65	22.3	19.5	42.41	144.3	245.5	62.9	42.43	165.7
10.19	7.5	237.95	119.02	5.14	134.11	6.19	22.39	16.75	141.4	5.33	22.98	19.6	40.17	152.3	246.4	59.42	41.53	166.9
9.55	7.67	230.74	124.65	5.29	133.78	5.88	22.57	17.81	138.4	5.05	23.18	19.9	41.5	155.9	252.9	56.04	40.77	167.5
9.96	7.61	235.68	116.46	7.4	132.76	6.08	22.19	16.78	139	5.4	22.62	19.1	44.99	144.7	240.1	52.42	41.49	166.3
10.09	7.69	234.84	119.91	8.26	135.86	5.62	22.2	17.31	141.3	6.24	23.46	18.5	42.02	151.1	245.6	51.69	40	168.7
8.44	7.57	240.38	123.81	9.42	139.48	5.6	21.71	17.29	137.8	6.51	22.89	18.9	39.54	149.4	249.7	59.49	40.12	163.8
10.35	7.95	226.16	117.46	7.39	136.54	6.29	21.49	18.44	140.3	6.63	22.61	18.8	41.72	149.8	237.8	49.32	40.9	165.7
8.88	7.57	225.2	123.45	8.3	138.69	5.91	21.41	18.69	140	5.56	23.24	19.1	43.49	152.6	245.8	62.04	40.78	170
9.73	8	234.19	118.75	6.72	133.59	6.23	22.45	17.42	141.5	6.9	24.07	18.3	43.24	154.1	244.4	48.54	39.7	168
10.03	7.7	228.41	119.44	9	137.47	5.66	21.35	16.45	137.8	6.52	22.78	18.6	36.65	152.9	249.1	55.55	42.61	167.1

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Table 5 Statistical values of pixels of regions of pixel at different location at the Nakati Dam Reservoir (Sample Data)

dissolved oxygen	ph	conductivity	total disolved solid	turbidity	Mean - water	entropy-water	psnr- - water	snr-water	Mean-moss	entropy-moss	psnr-moss	snr-moss	WR	WG	WB	MR	MG	MB
11.13	8.21	248.7	125.96	8.4	171.4	5.86	22.27	18.35	100.22	6.09	21.17	15.53	22.27	171.3	217.7	50.7	139.9	199.1
11.06	9.13	248.6	125.44	10.19	169.4	6.24	22.51	19.14	100.35	6.13	21.3	15.16	22.73	167	211	46.71	113.3	180
9.9	7.68	248.2	125.08	10.68	171.1	5.54	21.66	19.4	99.77	6.04	21.44	14.35	23.76	166.7	215	43.87	85.76	177.7
9.79	7.9	248.8	125.95	11.18	169	5.78	22.25	18.57	98.75	6.3	21.14	14.84	25.36	172.1	221.7	53.05	110.3	218.3
10.37	8.77	248.4	125.86	13.4	170.4	6.34	22.16	18.11	99.51	6.03	22.75	15.6	23.04	174.3	211.1	56.5	100.9	181.7
11.32	7.95	248.2	125.15	15.19	169.3	5.97	21.35	18.2	98.83	6.08	22.11	15.74	14.64	174.8	211.4	44.57	68.54	176.9
11.94	9.25	248.9	125.98	11.54	169	5.61	21.48	18.62	99.59	6.06	22.47	16.32	22.41	172.5	215.6	57.77	58.87	185.7
11.44	8.46	248.9	125.41	11.08	168.9	6.15	20.96	19.44	98.8	6.29	21.3	15.37	26.21	171.3	219.8	59.43	134.7	182.4
9.38	8.22	248.8	125.76	12.53	169.6	5.74	22.84	18.66	97.72	6.01	22.01	16.28	23.12	174.2	221.3	44.95	55.81	230
11.98	8.63	248.6	125.77	12	171.3	5.75	22.23	18.63	100.12	6.46	21.08	15.95	12.38	177.6	210.1	44.82	99.3	234.3
9.18	8.9	248.9	125.5	8.38	168.1	5.48	22.71	19.01	98.58	5.97	21.95	14.73	20.7	174	220	54.07	94.78	186.5
9.22	7.67	248.8	125.31	14.46	167.9	5.55	21.64	18.97	99.95	6.26	21.08	16.25	17.6	175.8	212.1	55.49	44.24	195
12.46	9.26	248.9	125.13	13.44	169.6	5.58	21.92	19.46	97.71	6.13	21.53	14.6	19.34	177.8	220	45.04	68.93	184.5
10.1	8.59	248.5	125	11.6	171.2	6.03	22.07	18.07	98.41	6.54	21.99	16.32	19.49	167	218	57.18	99.24	239.2
12.15	8.11	248.5	125.79	10.74	168.6	6.24	21.93	18.38	100.14	6.23	22.01	15.81	27.33	175.5	221.5	52.34	129.2	205.2

Figure 8 shows the prediction equation of water quality measurement from the Landsat image water pixels in Nagi Dam. **Figure 9** shows prediction equation of water quality measurement from the LANDSAT image moss pixels for DO measurement in Nakati Dam water. The data from **Table 4 and Table 5** are used for the prediction and shown in the **Figure 8 and Figure 9**, respectively. For analysing the data for prediction of PH and DO from water samples and moss of water region of dams such as Nagi and Nakati are performed using the online tool statsblue (https://stats.blue). Bayesian optimization for the Hyperparameter tuning is performed in the Matlab 2022b Version and tuned data is applied in statsblue online machine learning tool. The results from the tool is shown in the **Figure 8** and **Figure 9**.

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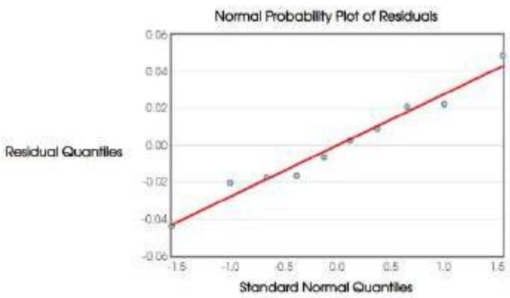
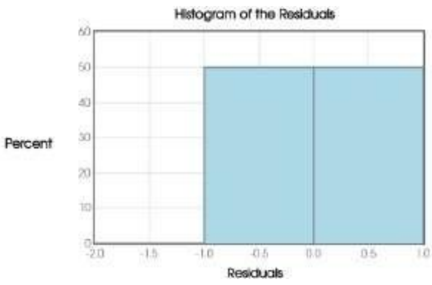


(a) Scatter plot for the BO-MR (pH prediction)



(b) Histogram plot of BO-MR (pH prediction)

(c) Prediction Equation for Nagi Dam pH value form water regions pixels

Model: $PH = -5.2107 + 0.0481 \cdot red + 0.021 \cdot green - 0.0217 \cdot blue + 0.0347 \cdot mean\_water + 0.2866 \cdot PSNR + 0.1123 \cdot entropy$

Summary of Overall Fit

R-Squared:	$r^2 = 0.9116$
Adjusted R-Squared:	$r^2_{adj} = 0.7348$
Residual Standard Error:	0.046 on 3 degrees of freedom.
Overall F-statistic:	5.1565 on 6 and 3 degrees of freedom.
Overall p-value:	0.1032

(d) Summary of overall fit BO-MR (pH prediction)

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	-5.2107	2.828	-1.8425	0.1626
red	β_1	0.0481	0.0177	2.7231	0.0724
green	β_2	0.021	0.0067	3.1098	0.0529
blue	β_3	-0.0217	0.0069	-3.129	0.0521
mean_water	β_4	0.0347	0.0115	3.0128	0.0571
PSNR	β_5	0.2866	0.0726	3.9493	0.029
entropy	β_6	0.1123	0.0277	4.0607	0.0269

(e) Prediction Coefficient (pH prediction)

Analysis of Variance Table

Source	df	SS	MS	F-statistic	p-value
Regression	6	0.0654	0.0109	5.1565	0.1032
Residual Error	3	0.0063	0.0021		
Total	9	0.0718	0.008		

(f) Analysis of Variance (pH-Prediction)

Five Number Summary of Residuals

Minimum:	Min$= -0.0437$
1st Quartile:	$Q_1 = -0.0173$
Median:	$M = -0.0018$
3rd Quartile:	$Q_3 = 0.021$
Maximum:	Max$= 0.0487$

(g) Five Number Summary (pH-Prediction)

Figure 8. Prediction equation of water quality measurement from the LANDSAT image water pixels in Nagi Dam

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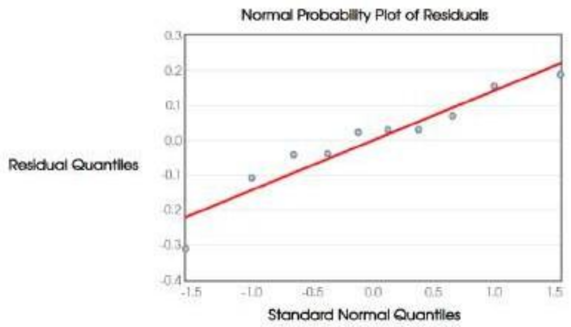
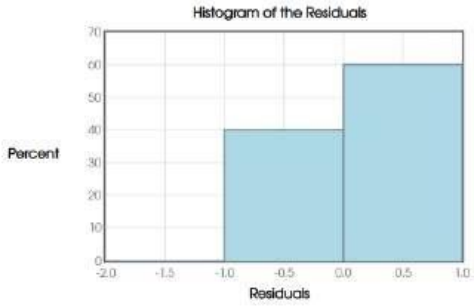


(a) Scatter plot for the BO-MR (DO- prediction)



(b) Histogram plot of BO-MR (DO- prediction)

(c) Prediction Equation for Nakati Dam Dissolved oxygen (DO) from Moss region pixels

Model: $\text{dissolved oxygen} = -56.9149 + 0.0122 \cdot \text{Moss-red} - 0.0075 \cdot \text{Moss-green} - 0.0341 \cdot \text{Moss-blue} + 0.4482 \cdot \text{moss\_Mean} - 0.6556 \cdot \text{Moss-PSNR} + 3.7839 \cdot \text{Moss-entropy} + 1.3511 \cdot \text{Moss-SNR}$

Summary of Overall Fit

R-Squared:	r^2 =0.9766
Adjusted R-Squared:	r^2_{adj} =0.8948
Residual Standard Error:	0.2974 on 2 degrees of freedom.
Overall F-statistic:	11.941 on 7 and 2 degrees of freedom.
Overall p-value:	0.0794

(d) Summary of overall fit BO-MR (DO-prediction)

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	-56.9149	17.8562	-3.1874	0.0859
Moss-red	β_1	0.0122	0.0268	0.4565	0.6928
Moss-green	β_2	-0.0075	0.0067	-1.1118	0.382
Moss-blue	β_3	-0.0341	0.0072	-4.7377	0.0418
moss_Mean	β_4	0.4482	0.1518	2.9528	0.0981
Moss-PSNR	β_5	-0.6556	0.3983	-1.6459	0.2415
Moss-entropy	β_6	3.7839	1.0891	3.4742	0.0738
Moss-SNR	β_7	1.3511	0.2408	5.611	0.0303

(e) Prediction Coefficient (DO- prediction)

Analysis of Variance Table

Source	df	SS	MS	F-statistic	p-value
Regression	7	7.3934	1.0562	11.941	0.0794
Residual Error	2	0.1769	0.0885		
Total	9	7.5703	0.8411		

(f) Analysis of Variance (DO--Prediction)

Five Number Summary of Residuals

Minimum:	Min$= -0.3091$
1st Quartile:	$Q_1 = -0.0412$
Median:	$M = 0.0265$
3rd Quartile:	$Q_3 = 0.0697$
Maximum:	Max$= 0.1882$

(g) Five Number Summary (DO--Prediction)

Figure 9. Prediction equation of water quality measurement from the Landsat image moss pixels for DO measurement in Nakati Dam water.

Figure 10 shows the pH- Prediction using water region pixels of Landsat Image. **Figure 11** shows the DO- Prediction using moss pixels of Landsat Image. **Figure 12** shows the comparison of proposed and existing algorithms in prediction of DO and pH.

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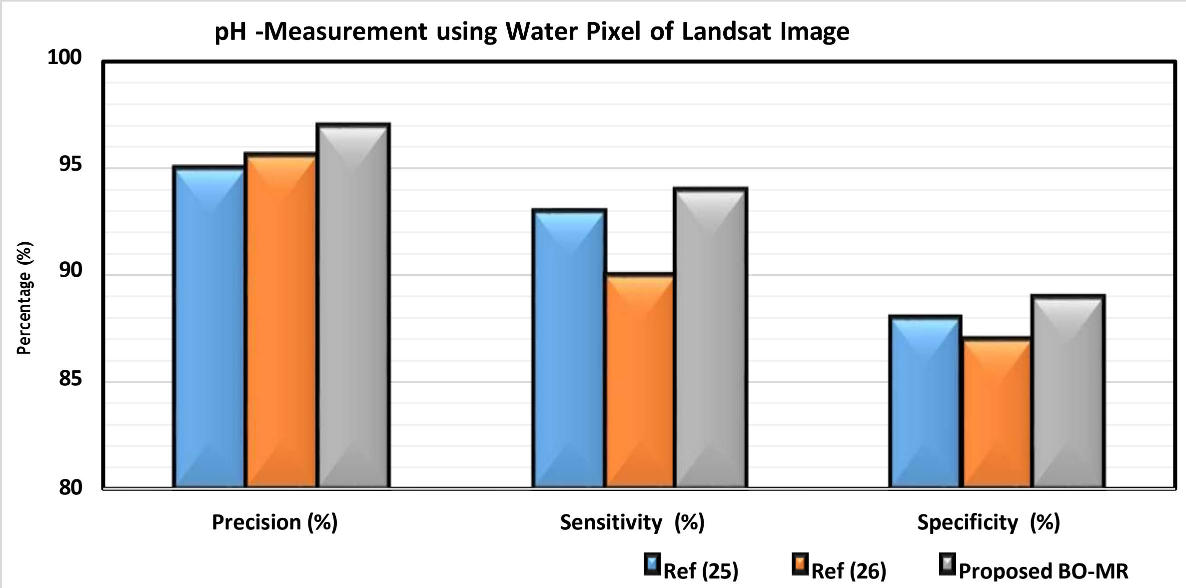

Figure 10 pH- Prediction using water region pixels of Landsat Image

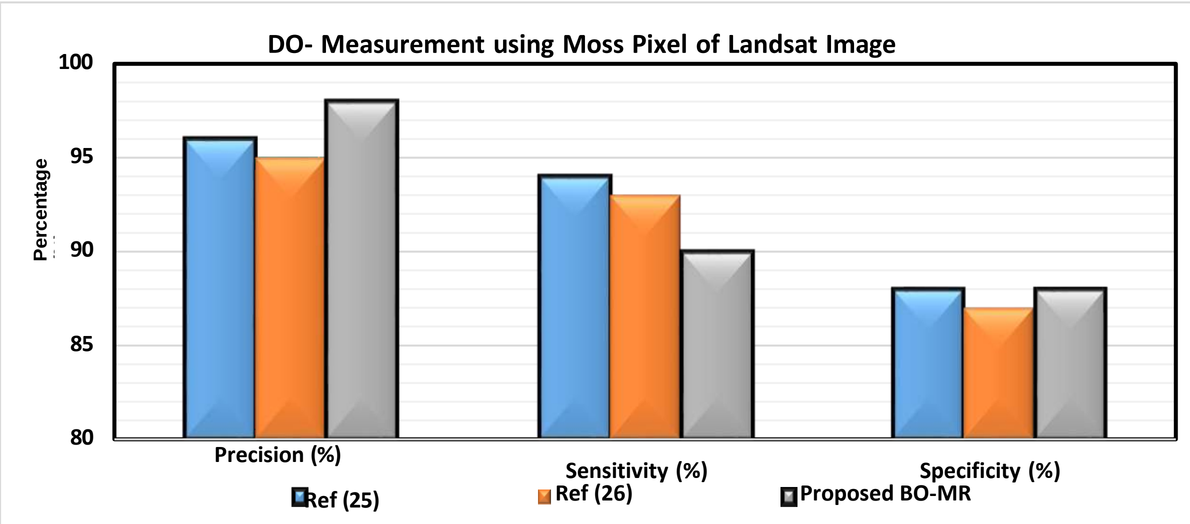

Figure 11 DO- Prediction using moss pixels of Landsat Image

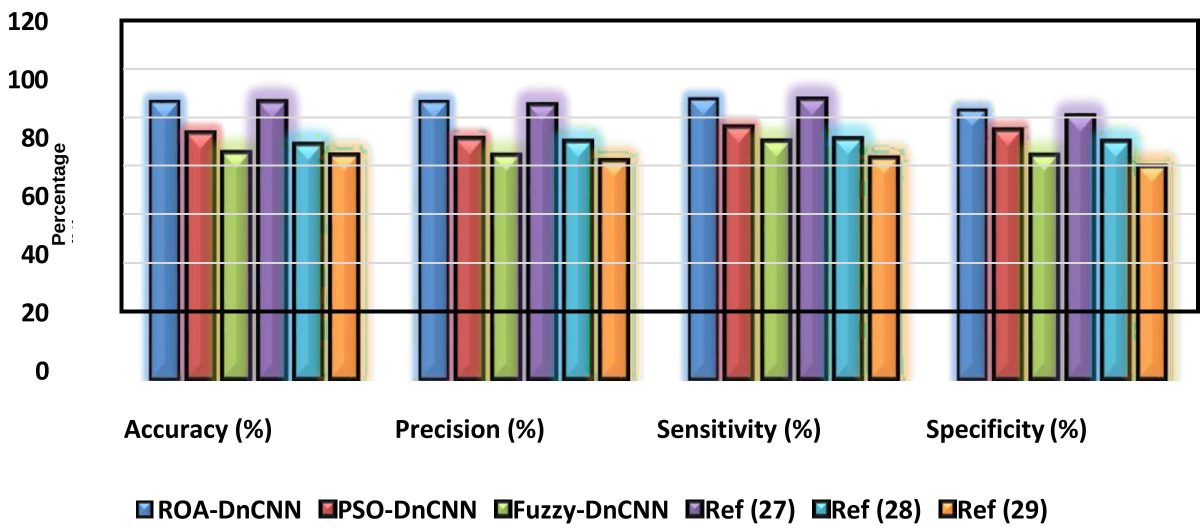

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Figure 12 Comparison of the proposed and existing algorithms in prediction of DO and pH

DISCUSSION

Water quality monitoring in dam is required for the ecological health management, unpolluted water for human use, and overall sustainability of aquatic environments. Continuous monitoring of the dam water quality is challenging in different seasons due to mosses and need more human resources. Sample collection from different location of dam region is more complicated and frequent boating for sample collection in different location is challenging. Moreover, water quality changes in different location of the dam regions. For continuous monitoring of the water quality is proposed in this paper. The Pixels of water region of dams in Landsat image are perspectively projected using Proposed Transverse dyadic wavelet transform (TDyWT). After the pixels are perspectively projected, the pixels are enhanced using proposed optimized deep learning algorithms such as (i) PSo-DnCNN (ii) ROA-DnCNN (iii) Fuzzy-DnCNN. The enhanced image is processed for region of interest using the proposed Dual-Threshold Graph Cut (DTGC) algorithm. Statistical values of water regions and moss are obtained to correlated with the laboratory values of water quality for prediction of pH level from water pixels and DO from Moss pixels using the BO-MR prediction equation.

TDyWT allows for the analysis of temporal Landsat images for water quality monitoring, as it can capture temporal variations in water quality parameters due to seasonal changes, pollution sources, and other factors that affect the water quality in reservoir. Further, the wavelet transform enables the extraction of features at various scales, which is essential for identifying subtle changes in water quality in a reservoir. Thus, the localized pollution sources are detected and we can have an understanding of their impacts on overall water quality of the reservoirs.

ROA-DnCNN provides superior results in water quality measurement in the two reservoirs while using Landsat satellite imagery mainly due to the fact that ROA-DnCNN is specifically designed to handle outliers and various types of noise effectively. Noise in satellite imagery may be due to atmospheric conditions, sensor inaccuracies, and other environmental factors. By identifying and mitigating the impact of outliers, ROA-DnCNN enhances the clarity of the images, leading to more accurate assessments of water quality parameters such as chlorophyll concentrations and turbidity. Further, the architecture of ROA-DnCNN leverages deep learning techniques to learn spatial features that are crucial for accurately interpreting water quality indicators. This capability is especially significant when the relationships between spectral bands and water quality metrics can be complex and nonlinear, as in the case of the Nagi and Nagati Dam Reservoirs. Since water quality can vary significantly across different regions of a reservoir due to polluting sources, sedimentation, and biological activity, it is pertinent that the design of the algorithm being suggested is robust. In the present context, the capability of ROA-DnCNN enables it to adapt to the spatial variations of water quality across the reservoirs, allowing for more localized and precise measurements. Thus, the model accurately reflects the true conditions of water quality across different areas of the two reservoirs.

Thus, by integrating TDyWT and ROA-DnCNN, the overall noise reduction process is improved. This dual approach helps in isolating relevant water quality signals from the noise, leading to clearer and more accurate data for analysis. Such an integration also enhances the model's robustness against environmental variability, such as fluctuations in pollution levels or sedimentation rates.

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