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Enhanced Water Quality Monitoring in Dam Reservoirs Using Optimized Vision Transformer and Bayesian-Optimized Support Vector Regression

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ABSTRACT

Introduction: Monitoring water quality at various locations in a dam reservoir is a complex task that requires significant time and manpower when using traditional manual and laboratory methods. Regular monitoring is essential for enhancing agricultural productivity and preventing biodiversity loss.

Objectives: This paper focuses on the continuous monitoring of water quality in the Nagi and Nagathi dam reservoirs in Bihar, India, utilizing spatial and temporal Landsat satellite image pixels.

Methods: To improve prediction accuracy, Landsat images are perspectively projected using the Transverse Dyadic Wavelet Transform (TDyWT) and enhanced with Particle Swarm Optimized Vision Transformer (PSOViT) and Adam Optimized Vision Transformer (AdamViT) algorithms. Statistical features such as mean, entropy, PSNR, and band values extracted from enhanced water and moss regions are correlated with laboratory-measured values using Bayesian Optimized Support Vector Regression (BO-SVR). The proposed methods, PSOViT-SVR and AdamViT-SVR, are employed to predict four water quality parameters namely pH, dissolved oxygen (DO), total dissolved solids (TDS), and Conductivity at different locations within the Nagi and Nagathi dams.

Results: Prediction accuracy of proposed method AdamViT-SVR followed by PSOViT-SVR is higher compared to existing methods.

Conclusions: Proposed methods achieved an average accuracy of 96% to predict pH, DO, TDS and Conductivity parameters when compared to ground truth verification.

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

INTRODUCTION

Water is essential for life, impacting human health, agriculture, and ecosystems. However, urbanization, industrial expansion, mass tourism, and climate change have significantly degraded water quality [1]. Contaminants like heavy metals, nutrients, pesticides, and pathogens pose serious risks to health and the environment, highlighting the need for effective water quality monitoring in lakes, rivers, and dams [2]. This work aims to develop a model for monitoring water quality in Nagi and Nagathi dams in Bihar, India. Recent technological advancements have improved monitoring methods through innovative sensor-based systems that enable real-time tracking of parameters such as turbidity, pH, conductivity, and temperature, ensuring safe drinking water and healthy aquatic ecosystems [3]. The primary water quality parameters in dams and reservoirs includes physical, biological, biophysical, and chemical aspects 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 [4,5]. It is essential to maintain these parameters within permissible limits, as impure water can adversely affect both human health and environmental integrity. Further, measuring the concentrations of certain metal ions, such as lead (Pb), zinc (Zn), and manganese (Mn), in reservoir waters presents significant challenges **[6,7]**. Sedimentation drift, the process by which sediment particles including heavy metals are transported and deposited naturally into a dam reservoir, can lead to elevated levels of these contaminants. The maximum allowable limits for commonly encountered heavy metals in irrigation water are as follows: Pb: 0.1-0.5 mg/L, Zn: 2-5 mg/L, and Mn: 0.2-1.0 mg/L. Exceeding these limits can pose serious risks to agriculture and human health, as even low concentrations can be toxic to plants, animals, and humans **[8]**. Plants readily absorb these heavy metals, which can result in reduced growth, yield, and quality. Additionally, the consumption of water or crops contaminated with these metals can lead to various health issues in humans, including neurological damage, gastrointestinal problems, immunodeficiency, and reproductive issues **[9,10]**.

Traditional methods of monitoring water quality through in situ measurements and laboratory analyses are often time-consuming and expensive, with limited geographical and temporal variability. In contrast, remote sensing offers a cost-effective and efficient alternative, providing unique spatial information and data continuity over large areas and inland water bodies **[11]**. This approach can be integrated with conventional methods to overcome the limitations associated with in situ monitoring. Remote sensing techniques and databases are particularly valuable for collecting data on ecological indicators in lakes, especially in areas that have not been extensively studied and have minimal in situ monitoring. With adequate validation from in situ data, remote sensing can deliver near-real-time insights into changes in lake conditions, such as algal blooms or droughts. Furthermore, interdisciplinary collaboration and validation efforts can enhance the accuracy and efficiency of remote sensing for evaluating and managing water bodies, while also reducing the time, effort, and costs involved **[12]**. The conventional approach to assessing water quality encompasses three primary categories: physical, chemical, and biological parameters. (i) Physical Parameters include metrics such as water temperature, transparency (measured by Secchi disk depth), salinity, turbidity, total suspended matter (TSM), colored dissolved organic matter (CDOM), odor, and electrical conductivity. These provide insights into the water's physical characteristics. (ii) Chemical Parameters involve indicators like pH, dissolved oxygen (DO), chemical oxygen demand (COD), biochemical oxygen demand (BOD), total nitrogen (TN), total phosphorus (TP), heavy metals, and non-metallic toxins, which are essential for understanding the chemical health of water bodies. (iii) Biological Parameters consist of metrics such as chlorophyll-a, total bacteria count, and total coliforms that assess biological activity and ecosystem health **[13]**. Remote sensing methods categorize parameters into those with active optical characteristics (e.g., chlorophyll-a) and those without defined optical properties (e.g., TN and TP), typically analyzed through correlations with optically active parameters **[14]**.

In summary, assessing the concentration and maintaining the quality of water in dam reservoirs presents considerable challenges due to environmental factors, technological limitations, and operational constraints **[15]**. The dynamics of water quality are complex, influenced by factors such as stratification, sedimentation, and nutrient cycling. Stratification leads to temperature-induced layering in the water column, which can prevent mixing and create low-oxygen conditions in deeper layers, affecting downstream water quality. Sedimentation further complicates assessments by trapping nutrients and pollutants, altering chemical compositions over time **[16]**. Traditional monitoring methods often rely on manual sampling, which is labour-intensive and may not provide real-time data; this approach can overlook spatial variability within the reservoir, resulting in incomplete assessments. Although advancements in sensor technology have improved monitoring efficiency, integrating these systems into existing infrastructure poses challenges due to high costs and complexity. Environmental changes, such as declining water levels from drought or increased evaporation, can magnify water quality issues by concentrating pollutants and promoting eutrophication **[17, 18]**. Additionally, the management and analysis of data collected from multiple sensors require robust frameworks to interpret trends accurately and facilitate timely decision-making. In overall, addressing these complicated challenges is essential for effective water quality management in dam reservoirs to safeguard human health and protect aquatic ecosystems **[19,20,21]**.

Research Gap

Despite advancements in water quality monitoring technologies, significant gaps remain in effectively assessing water quality in dam reservoirs. Current methods, such as manual sampling, are time-consuming and do not provide real-time data, leading to delays in addressing issues **[22,23]**. While sensor-based systems are emerging, there is insufficient integration between various sensor technologies and remote sensing methods, limiting comprehensive data collection across different depths and locations. Many predictive models rely on limited datasets and fail to consider the complex interactions among physical, chemical, and biological factors affecting water quality dynamics. There is a need for methods that utilize machine learning and deep learning techniques to improve prediction accuracy and enable real-time monitoring **[24,25,26]**. Addressing these gaps could lead to more effective water quality management strategies in dam reservoirs, ultimately protecting water resources and public health.

Problem Statement

Satellite images have low spatial resolution, making it difficult to detect small pollution areas or small water bodies. Additionally, the temporal resolution may not capture rapid changes in water quality. Weather conditions like clouds and haze can obstruct satellite images, leading to inaccurate results. Vegetation in reservoir areas complicates the measurement process. These challenges need to be explored in other reservoirs, such as Nagi and Nagathi dams, where water moss is present. To address these issues, the proposed method integrates both spatial and temporal pixels by combining Transverse Dyadic Transform with an optimized Vision Transformer to monitor the water quality effectively.

OBJECTIVES

Landsat images are perspectively projected using the Transverse Dyadic Wavelet Transform (TDyWT) and images are then enhanced with optimized Vision Transformers (ViTs), and moss regions are extracted using a dual-threshold graph cut method (DTGC). The statistical features derived from this process are correlated with laboratory values through Bayesian Optimized Support Vector Regression to predict water quality. The major contributions of the proposed work are:

(i) To collect water quality parameters from the laboratory for different locations in the two water bodies (Nagi and Nagathi reservoirs) and also from leaf samples of water moss in the reservoir for estimation of lead content.

(ii) To improve spatial representation and to highlight important structures, patterns within the image, Landsat images are perspectively projected using the Transverse Dyadic Wavelet Transform (TDyWT).

(iii) To enhance the pixels of water and moss using Particle Swarm Optimized Vision Transformer (PSOViT) and Adam Optimized Vision Transformer (AdamViT) for better analysis and monitoring of water quality in dam reservoirs.

(iv) To differentiate between water and moss regions using a dual threshold graph cut method and to correlate the extracted pixel features with laboratory values to predict water quality in dams using Bayesian Optimized Support Vector Regression (BOSVR).

(v) To validate the predicted water quality parameters by comparing them with the predictions of existing algorithms.

Recent research has focused on various methodologies for monitoring and assessing water quality across different regions, utilizing advanced technologies such as remote sensing, machine learning, and Internet of Things (IoT) systems as detailed**.** These studies highlight the effectiveness of these approaches in providing accurate and timely data for environmental management. Recent studies demonstrate a variety of methodologies and technologies employed for monitoring and assessing water quality across different geographical regions. Research from various studies highlights the effectiveness of remote sensing, machine learning, and IoT-based systems in monitoring water quality. In particular, satellite imagery for monitoring water quality has several significant limitations. The limited spatial resolution can hinder the detection of localized pollution and small water bodies, while the temporal resolution may not capture rapid water quality changes. Atmospheric conditions like clouds and haze can obscure images, leading to inaccurate assessments. Additionally, interpreting satellite spectral data into specific water quality parameters requires complex algorithms that may not account for local variations or contaminants. Vegetation in reservoir areas further complicates satellite measurements. For example, Kim (2021) **[18]** found that vegetation like Salix subfragilis in Korea's Namang Dam reservoir obstructed sensor readings and contributed to deteriorating water quality. This illustrates the necessity to investigate similar issues in other reservoirs, such as Nagi and Nagathi dams, where water moss is present. These challenges reduce the reliability of satellite-based monitoring compared to ground-based methods.

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METHODS

The proposed work employs a comprehensive methodology that combines satellite imagery, field sampling, laboratory analysis, image processing with optimized Vision Transformer (ViT) machine learning algorithms, and correlation-regression techniques to enable continuous monitoring of water quality and water moss in two dam reservoirs using Landsat satellite images as depicted in **Figure.1.** The methodology involves (i) Collection and pre-processing of Landsat images and relevant data on water quality and moss from the reservoirs. (ii) Feature extraction from the images aids in monitoring water quality and detecting water moss. (iii) Optimized models are validated using distinct test datasets to ensure accuracy in predicting water quality in the dam reservoirs. (iv) Predictions are made using a Bayesian-optimized support vector regression algorithm, and the predicted water quality parameters are compared with results from existing algorithms to assess performance. The proposed combined approach improves monitoring efficiency of water quality and water moss, enabling proactive management and decision-making for dam operators and water resource managers.

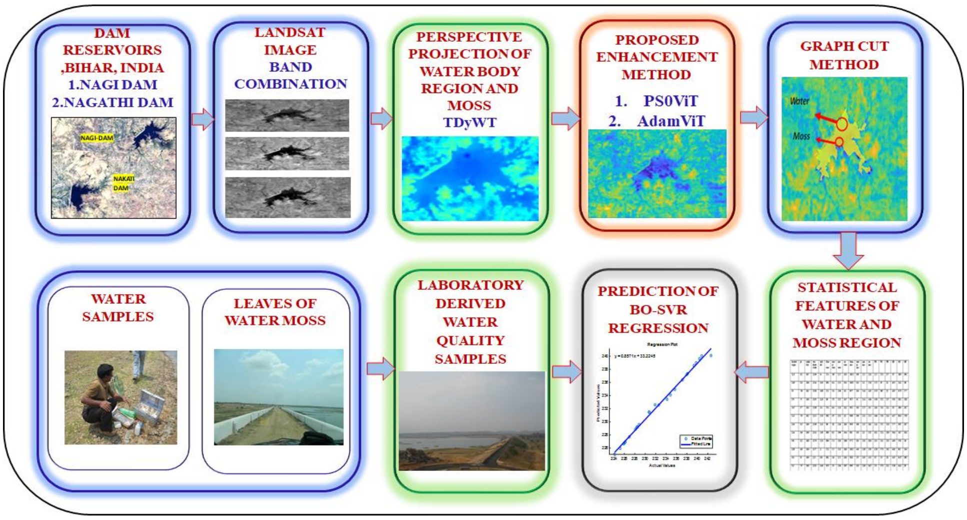

Figure.1 Water quality monitoring in Nagi and Nagathi dam reservoirs using optimized Vision Transformer and Bayesian optimized Support Vector Regression Algorithm.

STUDY AREA

Nagi Dam and Nagathi Dam are situated in the south-eastern region of Bihar, near the town of Jhajha, India. These deep dams are surrounded by rocky hillocks and were constructed to provide water for local agriculture. Adjacent to both reservoirs are cultivable lands. **Figure.2** shows the locations of Nagi and Nagathi Dams, which are the subjects of this study.

(a) Nagi Dam	(b) Nagathi Dam

Figure.2 Photograph of the water regions of Nagi and Nagathi Dams.

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Nagi Dam, an earthen structure completed in 1958, spans the Nagi River within the Ganga Basin's Nagi sub-basin. It covers an area of 425 hectares, stretches 1,884 meters in length, and reaches a maximum height of 113.5 meters above its foundation. The dam is designed to hold a gross storage capacity of 108 million cubic meters of water and features a bird sanctuary that supports a diverse array of wildlife, including fish, amphibians, birds, and reptiles.

Nagathi Dam constructed in 1980 on the Nagathi River, has a full reservoir area of 364 hectares. The average water area of the reservoir decreases to 75 hectares during April and May, then increases to 170 hectares or more in the following monsoon season. This reservoir also hosts a bird sanctuary that plays a vital role in conserving bird species and their habitats in the area. The sanctuary faces challenges like habitat degradation, pollution, and human disturbance, which threaten bird populations and the overall health of the ecosystem. Recently, both Nagi and Nagathi Bird Sanctuaries were recognized as wetlands of international importance under the Ramsar Convention, emphasizing their ecological significance.

LANDSAT BAND COMBINATIONS FOR DAM QUALITY MONITORING

Landsat images have several advantages such as high temporal resolution, multi-spectral imaging capabilities, and extensive long-term data availability. Their spatial resolution of 30 meters (or 15 meters for panchromatic images) makes them especially effective for water quality analysis. The use of band combinations from Landsat images is essential for monitoring water quality in dam reservoirs and analyzing various earth features, including land use, water bodies, and coastal regions. These combinations enable the effective detection of key water quality parameters, such as turbidity and chlorophyll-a levels. For example, the integration of near-infrared (NIR) and shortwave infrared (SWIR) bands aids to distinguish clear and turbid waters, which is crucial for accurate assessments. Specific combinations like NIR (Band 4), SWIR1 (Band 5), and Red (Band 3) enhance the definition of land-water boundaries, allowing for better identification of flooded areas and precise tracking of water level fluctuations that can significantly impact local ecosystems and agriculture.

Moreover, these band combinations are vital for monitoring temporal changes in water quality, particularly in response to environmental factors such as runoff or pollution, which is critical for proactive water resource management. The use of multiple bands also enables a thorough analysis of the surrounding environment, where changes in vegetation health indicate nutrient runoff and potential water quality issues. Ultimately, insights derived from optimized band combinations in Landsat imagery provide valuable data that support decision-making, particularly during ecological crisis or conservation initiatives. Using Landsat band combinations is important for accurately monitoring water quality in dam reservoirs, which helps improve environmental management and resource use. In this paper, dam water quality is monitored using a combination of Band 2, Band 3, and Band 4. This selection minimizes multi-collinearity, improving the identification of moss variations while reducing interference from water and thereby improves the accuracy of water quality assessments. The time series data from Landsat effectively tracks changes over time, allowing us to compare images taken at different intervals with consistent band combinations to detect significant shifts in water quality. **Figure.3** shows the band combination results to monitor quality of water.

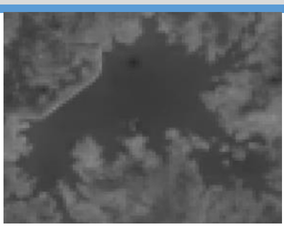
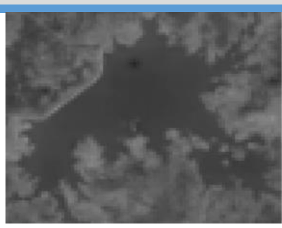
LANDSAT-Band 2 Nagi Dam – 2014	LANDSAT-Band 3 Nagi Dam – 2014	LANDSAT-Band 4 Nagi Dam – 2014	Band Combination Nagi Dam - 2014
			

Figure.3 Landsat-band combinations for water quality monitoring

PERSPECTIVE PROJECTION OF MOSS IN DAM WATER

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Moss indicates the nutrient levels and potential algal blooms that are crucial for understanding the dynamics of water quality. The clarity and precision of these assessments are improved by employing perspective projection techniques, which facilitate more accurate differentiation between moss and water surfaces. In the proposed work, Transverse dyadic wavelet transform is utilized for perspective projection, effectively capturing both fine details and broader growth patterns of moss with Butterworth in decomposition phase and Haar in reconstruction phase. Its multi-resolution analysis reduces noise and improves clarity, facilitating the distinction between moss and water even in the presence of environmental challenges. Wavelet transforms help track changes in moss coverage over time and results in information of the reaction of moss to nutrient runoff and pollution. Further, decomposition of signals aids in feature extraction and helps to identify critical indicators of aquatic ecosystem health, such as changes in moss growth and water quality. In comparison to traditional discrete wavelet transform (DWT), TDyWT has specific advantages such as (i) TDyWT correct geometric distortions caused by factors like satellite altitude and the curvature of the earth's surface. These distortions can significantly affect the accuracy of satellite imagery, leading to misinterpretation in land cover classification. TDyWT minimizes these distortions, resulting in clearer and more accurate representations of the earth's surface. (ii) TDyWT is also effective in handling mixed pixels areas where multiple land cover types coexist by improving the classification of different terrains. (iii) TDyWT improves image features like edges and curvatures, making it easier to identify land cover types such as vegetation and water bodies, and performs better than the traditional Discrete Wavelet Transform (DWT). In the proposed work, the use of adaptive thresholding in TDyWT method during the reconstruction phase adjust based on the specific characteristics of different areas in an image. For instance, in water body areas with moss, adaptive thresholding effectively highlights the moss by accurately distinguishing it from its surroundings, thereby enhancing its visibility. Additionally, this approach minimizes unwanted artifacts caused by variations in lighting or noise, resulting in a clearer and more detailed image. This dynamic methodology significantly improves the overall quality and accuracy of the image, particularly in complex areas of satellite imagery.

MOSS REGION ENHANCEMENT IN DAM WATERS using optimized Vision Transformer

Vision Transformer deep learning technique used to enhance water and moss pixels in the proposed methodology as it effectively captures complex patterns in images while maintaining high levels of accuracy and efficiency compared to traditional methods. **Table.1** summarizes the optimized Vision Transformer (ViT) architecture. The architecture typically includes layer normalization before each block to stabilize training and improve performance. Additionally, residual connections are employed after each block to facilitate information flow through the network without losing important features.

Table 1. Optimized ViT Architecture

Component	Description
Input	Landsat noisy Image
Image Patching	Image is divided into 16X16 non-overlapping patches for easy processing
Flatten and Embed Patches	Flatten each patch into format suitable for input to ViT model
Positional Encoding	Provide positional information of each patch within the image
Transformer Encoder	Consists of Multi-head Self attention layer (Enhances Feature Extraction) and Feed Forward network (transforms and processes the attention outputs to extract more complex features)
Last Multi-head self-attention layer	Specifically tuned using particle swarm and adam optimizer to enhance water and moss features.

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Classification Head	A final layer that predicts class labels based on features extracted by the transformer encoder.
Output Layer	Enhanced output

This architecture allows ViTs to learn complex patterns and hierarchical features effectively, making it well-suited for image enhancement. To improve the effectiveness and efficiency of image enhancement on ViT model, optimization technique during training phase, hyper-parameter tuning, fine tuning and optimizing self -attention mechanisms in ViT model can be done. The proposed work employs particle swarm optimization and adam optimization to enhance ViT model for enhancing water and moss regions in Landsat images.

Particle Swarm Optimized Vision Transformer (PSOViT)

The integration of ViT and Particle Swarm Optimization (PSO) allows for the identification of optimal configurations for critical hyper-parameters, including the number of layers, patch size, learning rate, and number of attention heads. Initial parameters such as size of input image, the number of particles, the maximum number of iterations and the bounds for hyper-parameters such as the number of layers, patch size, learning rate, and the number of attention heads are defined. Then each particle assigned a random position representing hyper-parameters within specified bounds. Each particle's velocity is also initialized, and both personal best and global best positions are set based on initial evaluations. In each iteration, ViT model is trained using the current hyper-parameters on the Landsat dataset, and its performance is evaluated using accuracy. If a particle's fitness exceeds its personal best, then that position is updated; similarly, if it surpasses the global best, the global best is updated. The velocity of each particle is then adjusted based on its previous velocity, its personal best position, and the global best position. The position is updated accordingly while ensuring it remains within defined bounds. After completing all iterations, the algorithm returns global best as the optimal hyper-parameters. Finally, the ViT model is trained using these optimal parameters on the entire Landsat dataset to enhance water and moss pixels, resulting in enhanced images for further analysis or application.

Adam optimized Vision Transformer (AdamViT)

Adam optimizer adjusts the learning rates for each parameter and makes the training phase more efficient compared to other optimization techniques. The optimizer's flexibility speeds up convergence and improves the performance of ViT model. As a result, the model can better detect and enhance specific pixel classes, such as water and moss in Landsat images. Initial hyper-parameters such as the number of layers, patch size, number of attention heads are defined. Then a specific layer is tuned based on the computation cross entropy loss to measure model's performance during training. The Adam optimizer is then initialized to facilitate dynamic learning rate adjustments throughout the training process. During each iteration, the model processes batches of images: it performs a forward pass to generate outputs, computes the loss against the true labels, and then updates the model parameters through back-propagation and updates weights using the adam optimizer. After training is complete, the model's performance is evaluated on a validation set to ensure it effectively enhances the targeted pixel classes. Finally, the trained model is applied to enhance specific pixel classes in the Landsat images, resulting in the desired output. In the proposed work, fine tuning of the last multi-head self-attention layer is done as it captures high-level features from the input data. Tuning this layer can significantly improve the model's ability to focus on relevant features, such as water and moss pixels.

SEGMEENTATION OF WATER AND MOSS REGION USING DUAL GRAPH CUT THRESHOLD

Dual-Threshold Graph Cut (DTGC) method is a segmentation technique used in the proposed methodology to identify Regions of Interest (ROI) in images which is particularly effective in applications such as water extraction from Landsat imagery. Initially, the input image is converted into a graph, where each pixel is represented as a node and edges indicate relationships based on intensity differences between neighbouring pixels. Segmentation accuracy is improved by using a dual-threshold approach derived from a Gaussian Mixture Model (GMM) to differentiate foreground and background elements, such as moss and water effectively in Landsat images. Dual-thresholding technique captures subtle variations in pixel intensity more effectively than traditional single-threshold methods.

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The method further optimizes the segmentation process through an energy minimization function, which refines edge weights within the graph. This optimization leads to more precise delineation of objects by minimizing the energy associated with misclassifications and promoting smooth transitions between segments. Additionally, DTGC incorporates multi-scale feature extraction techniques that capture important details at various scales, significantly improving performance compared to conventional methods. The method also emphasizes the identification of homogeneous regions within images, which further improves the accuracy in distinguishing different pixel types. In the proposed method, integrating optimised vision transformer with DTGC improves background subtraction and enhances moss detection accuracy even in the presence of reflections on water surfaces. Further, proposed integrated approach significantly improves the precision of moss detection in complex water environments.

PREDICTION OF WATER QUALITY IN DAM RESORVOIRS

Table.2 presents the water quality measurement methods for water samples collected from various locations in the two dam regions (Nagi and Nagathi).

Table 2. Water Quality Measurement Methods

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

Water quality parameters analyzed include ambient and water temperature, pH, conductivity, turbidity, total dissolved solids, dissolved oxygen, free carbon dioxide, carbonate and bicarbonate alkalinity, chloride, total hardness, phosphate-phosphorus, nitrate-nitrogen, biochemical oxygen demand, and chemical oxygen demand.

EXTRACTION OF STATISTICAL FEATURES FROM WATER AND MOSS REGIONS FOR PREDICTION

Statistical parameters such as mean, entropy, Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR) calculated to assess the quality and characteristics of water and moss regions. Mean value represents the average pixel intensity within a specified region, providing a basic measure of brightness Higher mean values may indicate brighter surfaces, such as clear water or healthy vegetation, while lower values might suggest darker, turbid waters or stressed moss. The second parameter Entropy is a measure of the amount of information or randomness in an image. It quantifies the distribution of pixel intensities, with higher entropy indicating more complexity and variability in the image. Also, entropy aids to assess the texture and patterns within water and moss regions. For example, areas with high entropy denote diverse aquatic environments or complex moss structures and low entropy indicate uniformity in pixel values. PSNR is a metric used to assess the quality of reconstructed images compared to original images. It is defined as the ratio between the maximum possible power of an image and the power of corrupting noise that affects its representation. A higher PSNR value indicates better quality and less distortion in the segmented regions. In Landsat imagery, PSNR can be used to evaluate how well the segmentation process preserves important features in water and moss regions.

PREDICTION OF WATER QUALITY IN DAM RESORVOIRS USING BAYESIAN OPTIMIZED SUPPORT VECTOR REGRESSION

Prediction of water quality in dam reservoirs using Bayesian Optimized Support Vector Regression (BO-SVR) proposed to improve the accuracy and reliability of predictions. Features such as red, green, and blue (RGB) pixel values, mean intensity, entropy, Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR) derived from water and moss regions are used for water quality prediction. The laboratory-based water quality measurements

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conducted from May 25 to May 29, 2023, with the corresponding latitude and longitude locations provided in **Table.3**.

Similarly, SNR measures the level of desired signal relative to background noise. SNR helps to determine the effectiveness of detecting features such as moss or water by assessing how much useful information is present compared to noise that could obscure these features. **Table.4** and **Table.5** displays the statistical values obtained from water and moss regions in Nagi and Nagathi dam resorvoirs.

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

Table. 4 Statistical values of pixels of regions 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

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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

Table. 5 Statistical values of pixels of regions of pixel at different location at the Nagathi 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

Extracted features are utilized as input variables and the water quality parameters are used as output variables. These features are collected as a dataset for training an SVR model. Hyper-parameter optimization conducted using Bayesian Optimization to find optimal values and to minimize prediction error. The SVR model is trained on the prepared feature set using these optimized hyper-parameters. The trained model is then used to predict water quality parameters, with its performance evaluated using metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). Each feature plays a significant role in predicting water quality. For example, RGB pixel values provide color characteristics for distinguishing land cover types, mean intensity indicates

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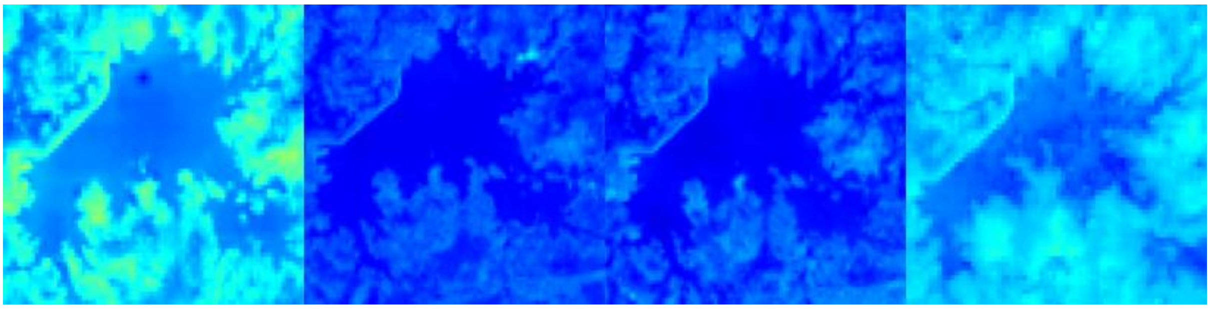
average brightness in water and moss regions, entropy reflects complexity in pixel distributions, PSNR assesses image quality preservation during segmentation, and SNR measures image clarity relative to noise. Proposed BO-SVR approach improves prediction accuracy and supports better water quality monitoring, aiding informed decision-making for environmental management.

RESULTS

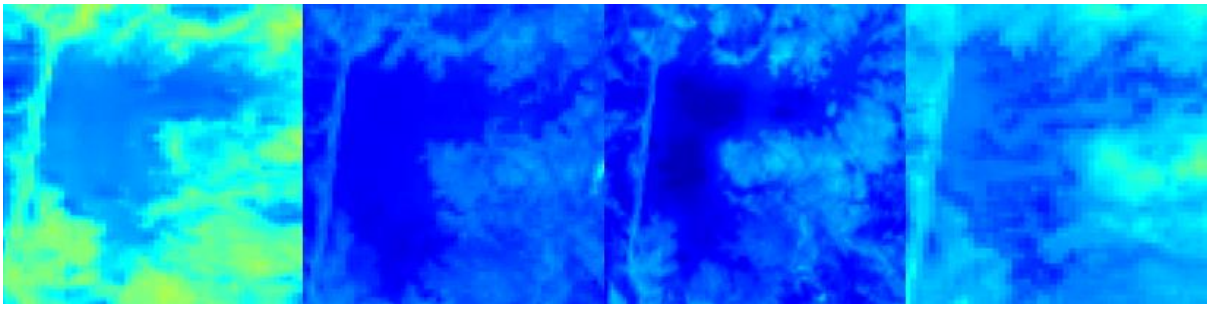
The proposed method combines deep learning and regression techniques to monitor four quality parameters such as pH, dissolved oxygen (DO), total dissolved solid (TDS) and conductivity in the Nagi and Nagathi dams in India. Initially, Landsat band images are acquired and processed using TDyWT for perspective projection, followed by enhancement through a Particle Swarm and Adam optimized Vision Transformer models (PSO ViT and Adam ViT). Subsequently, the method differentiates between water and moss regions using a dual threshold graph cut approach. Statistical features extracted from these regions and correlated with laboratory measurements to predict water quality using Bayesian optimized support vector regression (BOSVR). Two proposed methods named as PSOViT-SVR, AdamViT-SVR are implemented in MATLAB R 2023b to analyze and evaluate the results effectively.

As a first step, Landsat band combination images are acquired and perspectively projected using the Transverse Dyadic Wavelet Transform (TDyWT) to enhance visual quality by improving the contours, boundaries, and curvatures of land cover features. **Figure.4** and **Figure. 5** displays the TDyWT results for Nagi and Nakati dam respectively.



(a) Nagi 2014 (b) Nagi 2015 (c) Nagi 2016 (d) Nagi 2017

Figure.4 Perspectively projected water and moss pixels using TDyWT-Nagi dam



(a) Nagathi 2014 (b) Nagathi 2015 (c) Nagathi 2016 (d) Nagathi 2017

Figure.5 Perspectively projected water and moss pixels using TDyWT-Nagathi dam

The perspectively projected images are enhanced using particle swam optimized Vision Transformer (PSO ViT) and Adam optimized vision transformer (Adam ViT)

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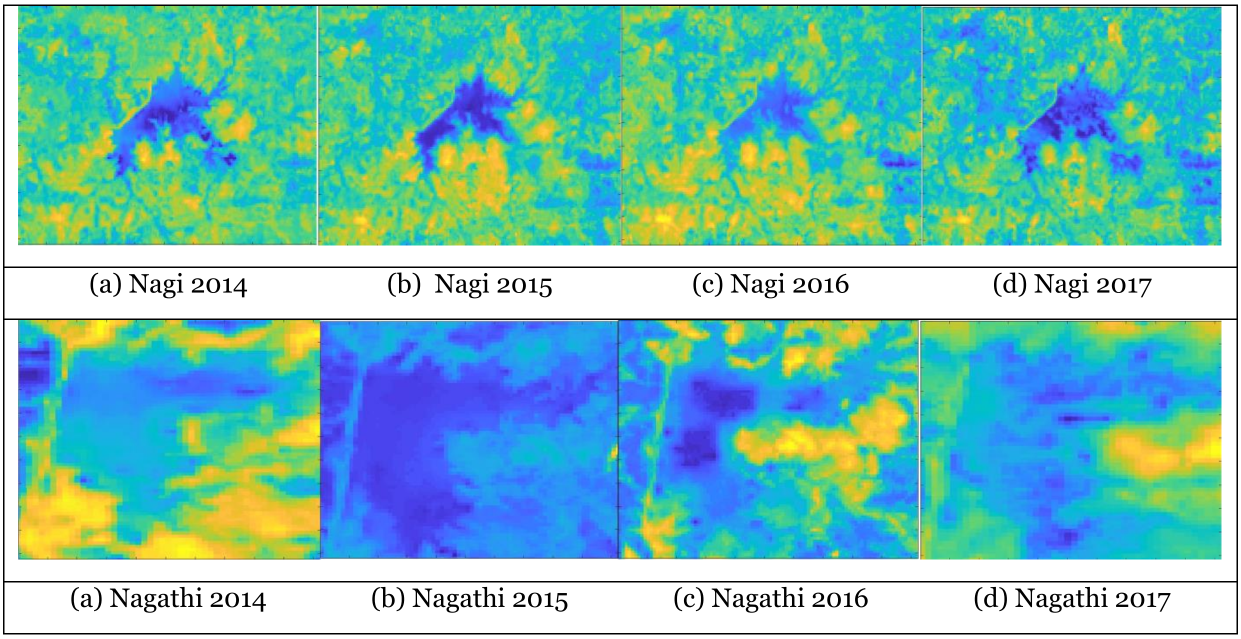

Figure.6 Proposed PSO ViT algorithm to enhance water and moss regions-Nagi and Nagathi dam reservoirs

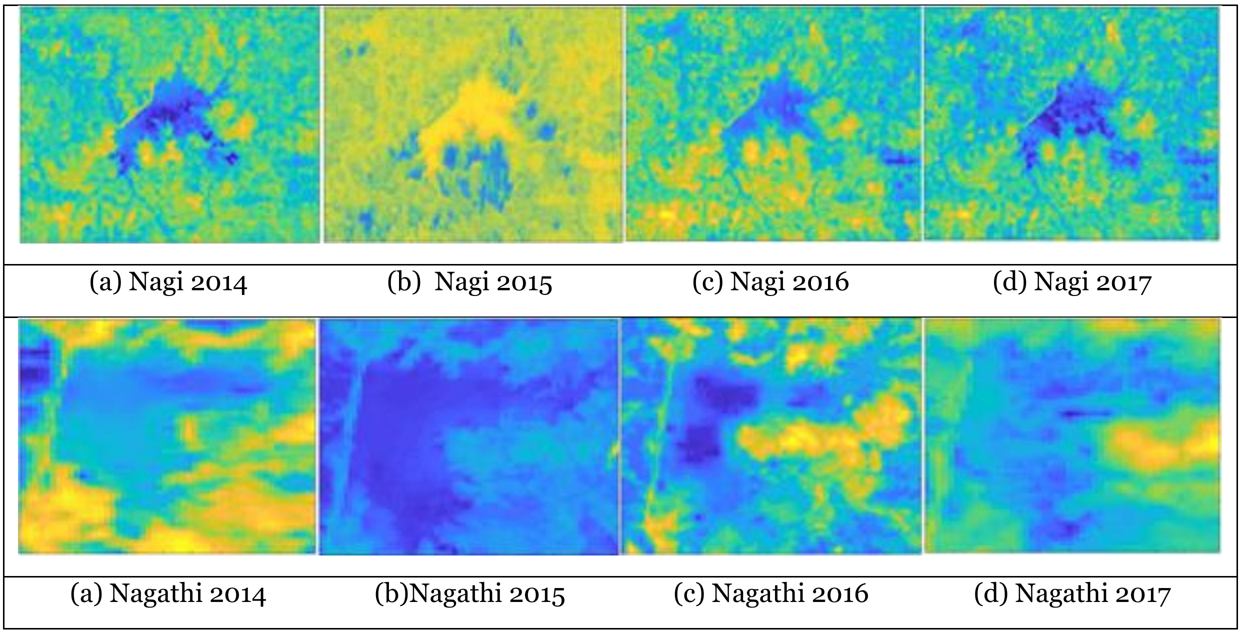

Figure.7 Proposed AdamViT algorithm to enhance water and moss regions-Nagi and Nakati dam reservoirs

Figure.6 and **Figure. 7** shows the spatial and temporal Landsat images of Nagi and Nagathi dam using optimized Vision Transformer. Adam optimization in Vision Transformer results is superior in enhancing water and moss regions compared to PSO ViT and is validated with the next step through Bayesian optimized Support vector Regression. The enhanced image used to differentiate water and moss regions using dual threshold graph cut method as shown in **Figure.8**.

Statistical features such as mean, entropy, PSNR, SNR, red pixel, green pixel and blue pixel are extracted from water and moss regions of DTGC output. Extracted features of pH, dissolved oxygen (DO), total dissolved solid (TDS) and Conductivity are correlated with their corresponding laboratory values measured with the use of Bayesian optimized Support Vector Regression.

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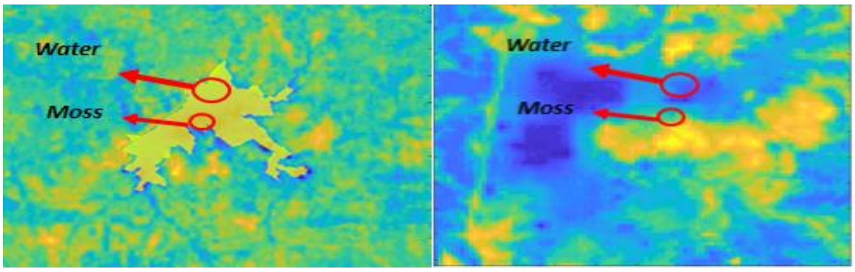
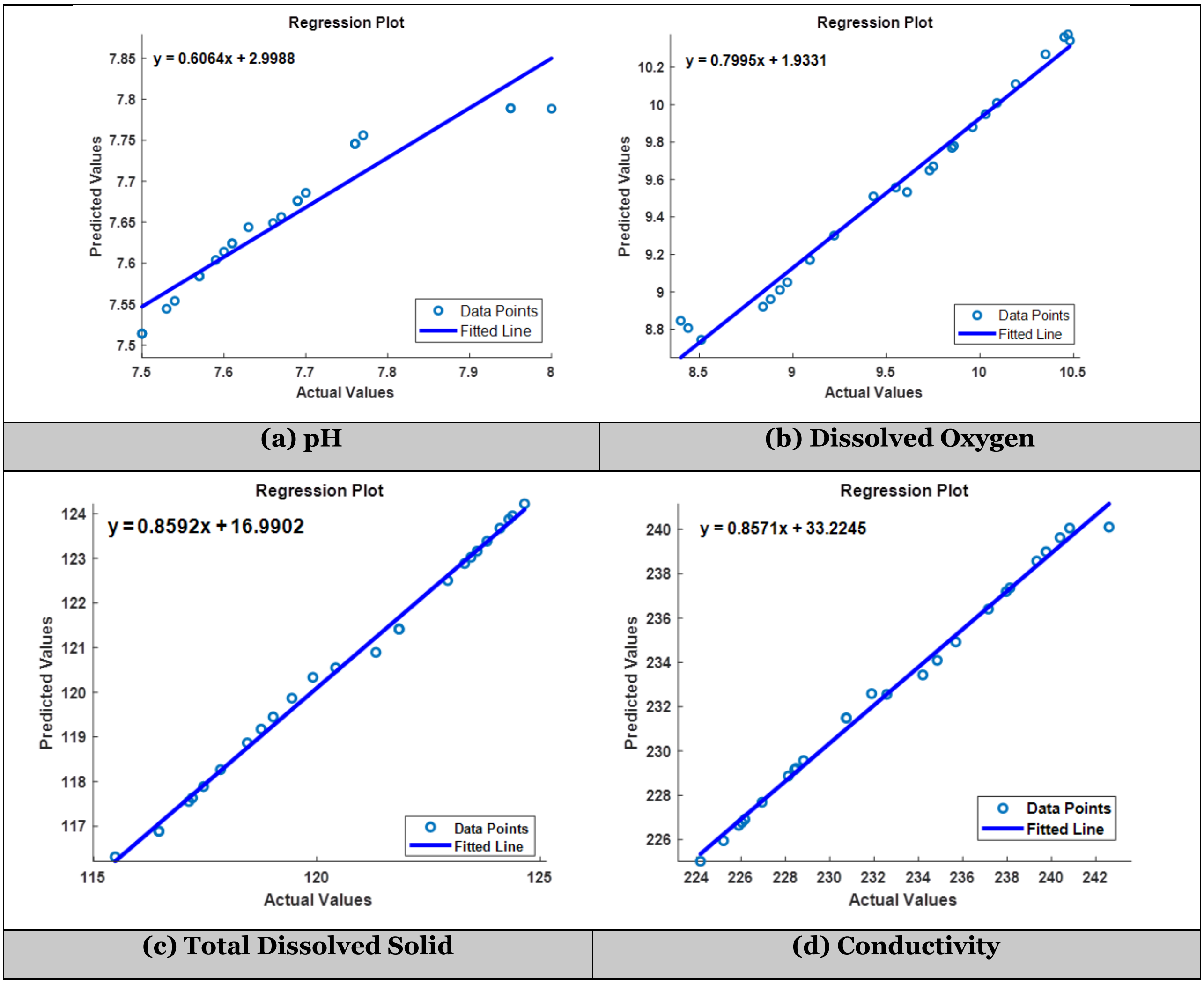


(a) Nagi Dam (b) Nagathi Dam

Figure.8 Results of Dual Threshold Graph Cut Method -Nagi and Nakati dam

Bayesian optimization improves the robustness of Support Vector Regression (SVR) in predicting water quality by optimizing hyper-parameters, incorporating uncertainty, efficiently exploring parameter space, reducing over-fitting risks, adapting to nonlinear relationships, and enabling statistical validation of predictions. The results of proposed methods PSOViT-SVR and AdamViT-SVR are analysed in terms of performance metrics such as mean square error, MAPE and R^2 metrics with existing methods. **Figure.9** and **Figure.10** shows regression and residual plots for pH, DO, TDS and Conductivity obtained for Adam optimized Vision Transformer with Bayesian optimized support vector regression (AdamViT-SVR) results.



(a) pH (b) Dissolved Oxygen

(c) Total Dissolved Solid (d) Conductivity

Figure.9 Regression plot results of proposed AdamVit-SVR for predicted water quality parameters pH, DO, TDS and Conductivity-Nagi dam

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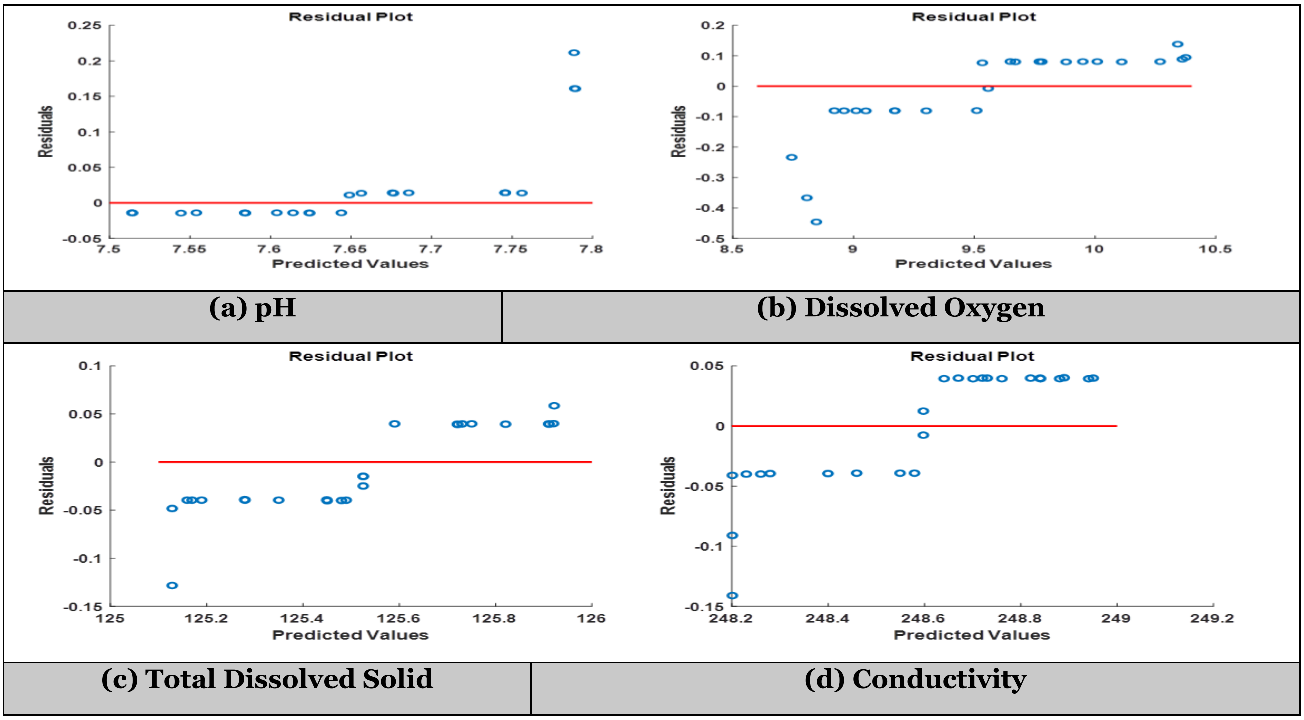

Figure.10 Residual plot results of proposed AdamVit-SVR for predicted water quality parameters pH, DO, TDS and Conductivity-Nagi dam

Similarly, the regression and residual results of Nagathi dam using AdamViT-SVR are shown in **Figure.11** and **Figure.12**.

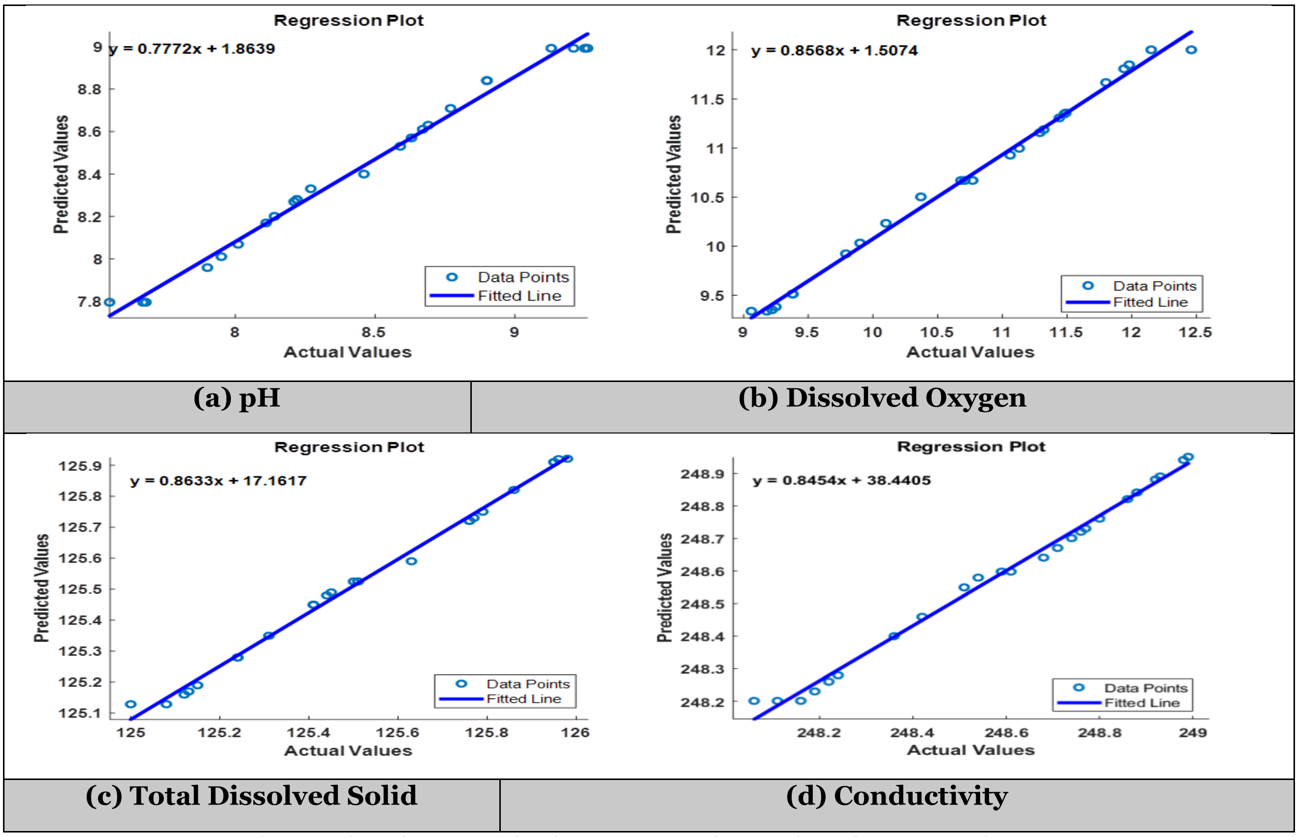

Figure.11 Regression plot results of proposed AdamViT-SVR for predicted water quality parameters pH, DO, TDS and Conductivity-Nagathi dam

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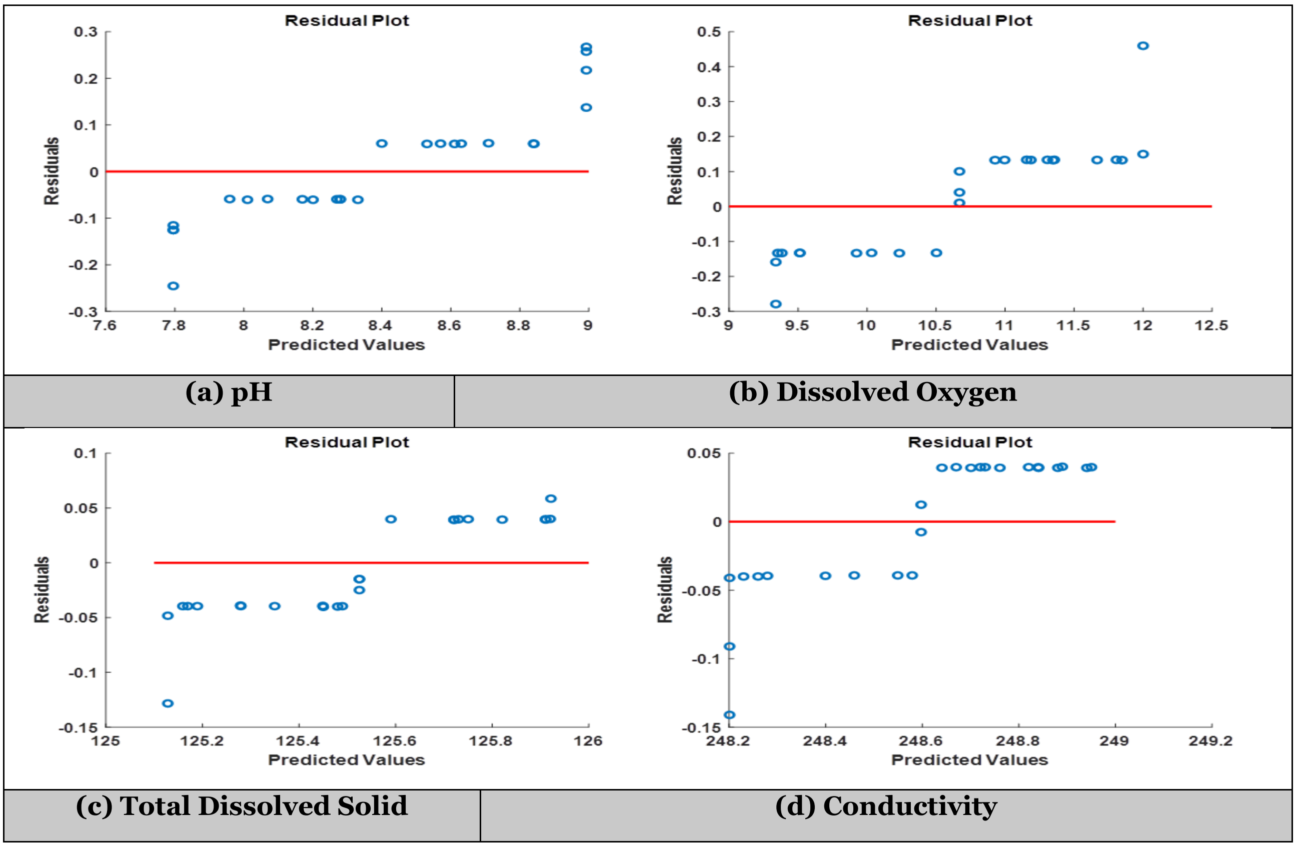

Figure.12 Residual plot results of proposed AdamViT-SVR for predicted water quality parameters pH, DO, TDS and Conductivity-Nagathi dam.

Performance metrics used to validate the proposed methods are R^2, Mean Square Error (MSE) and Mean Absolute Percentage error (MAPE). R^2 indicates the proportion of variance in the dependent variable explained by the independent variables in the model. MSE measures the average squared difference between predicted and actual values. MAPE represents prediction accuracy as a percentage, calculated by averaging the absolute percentage error between predicted and actual values.

Table.6 displays the performance metrics of Nagi dam. In terms of R^2, lower performance metrics of proposed PSOViT-SVR relative to AdamViT-SVR suggest that optimization techniques enhanced the predictive accuracy and resulted in a better water quality in compared to traditional existing methods. Further, in terms of MSE, and MAPE, AdamViT-SVR performance is superior compared to PSOViT-SVR and with other existing methods with lowest prediction error.

Table.6. Performance Metrics-Nagi Dam

R^2				
Methods	**pH**	**Dissolved Oxygen**	**Total Dissolved Solid**	**Conductivity**
Ref [27]	1.2014	1.3012	1.2034	1.0235
Ref [28]	1.0256	1.1106	1.1025	0.9826
Ref [29]	0.9566	0.9987	0.9974	0.9765
PSOViT-SVR	0.9011	0.9216	0.9602	0.9538
AdamViT-SVR	0.9177	0.9479	0.9772	0.9753

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MSE				
Methods	**pH**	**Dissolved Oxygen**	**Total Dissolved Solid**	**Conductivity**
Ref [27]	0.0965	0.0987	0.7298	1.1278
Ref [28]	0.0897	0.0814	0.6128	1.0025
Ref [29]	0.0568	0.0763	0.5214	0.9967
PSOViT-SVR	0.0341	0.0524	0.2453	0.8674
AdamViT-SVR	0.0140	0.0216	0.1954	0.7759
MAPE (%)				
Methods	**pH**	**Dissolved Oxygen**	**Total Dissolved Solid**	**Conductivity**
Ref [27]	0.9014	1.7124	0.9642	0.9356
Ref [28]	0.8127	1.5214	0.8678	0.8421
Ref [29]	0.7246	1.3547	0.7265	0.7968
PSOViT-SVR	0.5374	1.1127	0.5146	0.5127
AdamViT-SVR	0.4284	0.9941	0.3579	0.3416

Table.7 presents the performance metrics for the Nakati Dam. The lower R^2 values observed for the proposed PSOViT-SVR and AdamViT-SVR methods, indicating that optimization techniques have significantly enhanced predictive accuracy, resulting in better water quality assessments relative to traditional existing methods. Additionally, in terms of Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), the AdamViT-SVR method outperforms both PSOViT-SVR and other existing methods, demonstrating the lowest prediction errors overall. Further, the overall performance of proposed predictive methods validated with accuracy, precision, sensitivity and specificity for all the water quality parameters as shown in **Figure.13** and **Figure.14.** The results show that both PSOViT-SVR and AdamViT-SVR significantly outperform the reference methods in all metrics for both dams. For example, analysing the results for TDS: Accuracy represents how correct the model is, and AdamViT-SVR performs well with 96.00%, proving its effectiveness in water quality classification.

Table.7 Performance Metrics-Nagathi Dam

R^2				
Methods	**pH**	**Dissolved Oxygen**	**Total Dissolved Solid**	**Conductivity**
Ref [27]	0.8914	0.9018	0.9214	0.9291
Ref [28]	0.9051	0.9168	0.9368	0.9314
Ref [29]	0.9198	0.9387	0.9431	0.9421
PSOViT-SVR	0.9214	0.9611	0.9621	0.9598
AdamViT-SVR	0.9450	0.9754	0.9770	0.9712
MSE				

Methods	pH	Dissolved Oxygen	Total Dissolved Solid	Conductivity
Ref [27]	0.0784	0.0911	0.0532	0.0578
Ref [28]	0.0642	0.0832	0.0455	0.0412
Ref [29]	0.0571	0.0777	0.0388	0.0367
PSOViT-SVR	0.0421	0.0524	0.0125	0.0168
AdamViT-SVR	0.0148	0.0267	0.0021	0.0025
MAPE (%)				
Methods	pH	Dissolved Oxygen	Total Dissolved Solid	Conductivity
Ref [27]	3.8416	0.9567	0.0833	0.0698
Ref [28]	3.124	0.8112	0.0745	0.0522
Ref [29]	2.997	0.6173	0.0539	0.0491
PSOViT-SVR	2.1014	0.4897	0.0459	0.0245
AdamViT-SVR	1.1876	0.3499	0.0332	0.0175

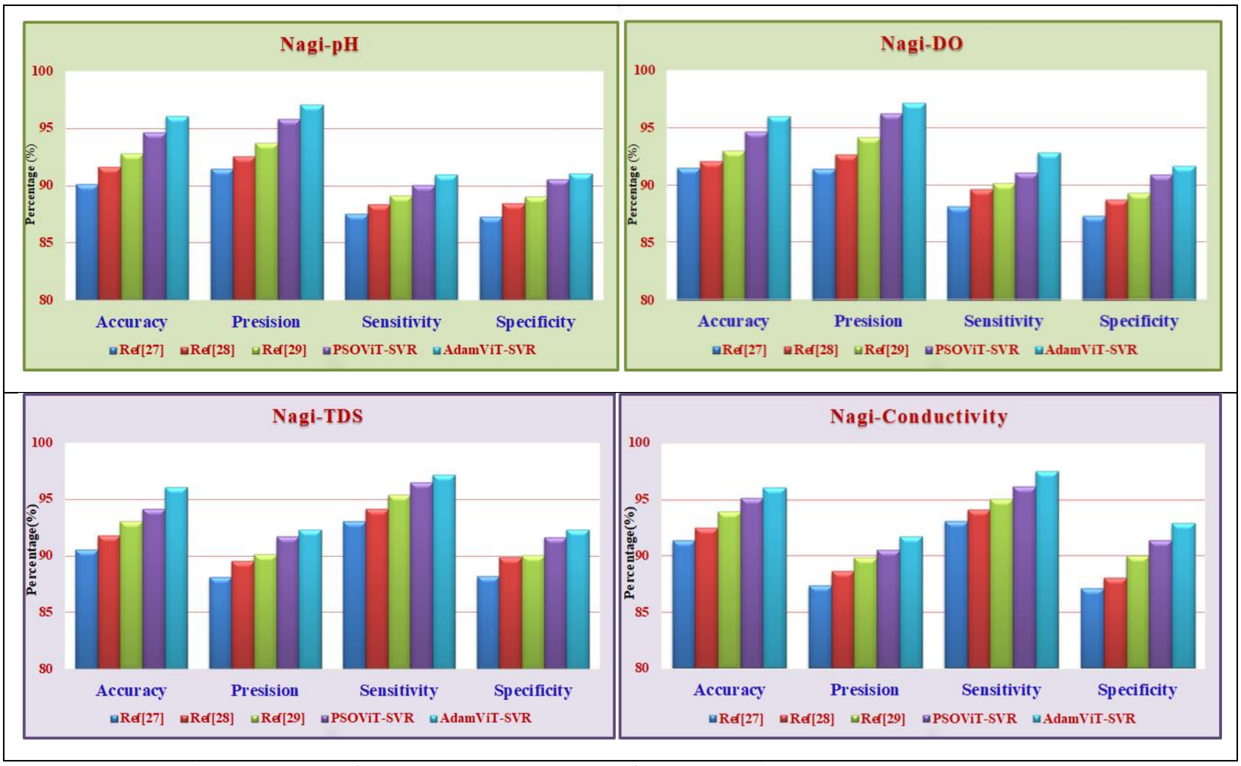

Figure.13 Performance comparison of water quality parameters-Nagi Dam

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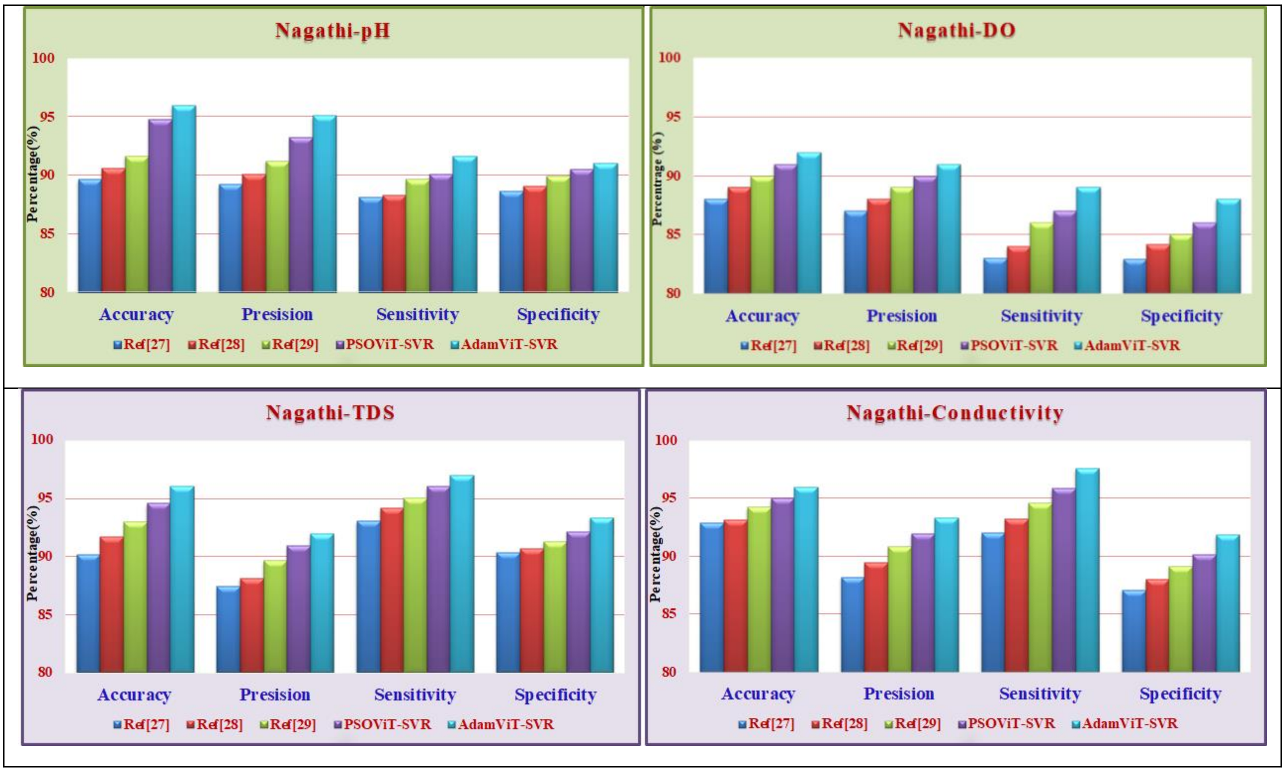

Figure.14 Performance comparison of water quality parameters-Nagathi Dam

In terms of Precision, which measures the true positive results among positive predictions, AdamViT-SVR is better with a score of 92.31%. Sensitivity, which checks how well the model identifies true positive cases, is important in environmental monitoring, and AdamViT-SVR leads with 97.14%, showing its strong ability to detect water quality issues. Specificity, which evaluates how well the model identifies true negatives, also shows AdamViT-SVR outperforming others with a score of 92.31%. These results show that optimization techniques improve the model's reliability in predicting water quality. Overall, AdamViT-SVR outperforms PSOViT-SVR and existing methods for all the four quality parameters pH, DO, TDS and Conductivity.

DISCUSSION

Monitoring water quality in dams is essential for managing ecological health, ensuring clean water for human use, and maintaining the sustainability of aquatic ecosystems. However, continuous monitoring throughout different seasons is challenging due to the presence of mosses and the need for extensive human resources. Collecting samples from various locations within the dam is also complex, with frequent boating required for sampling at different sites. Additionally, water quality can vary across different regions of the dam. To overcome this, an integrated approach is proposed using optimised Vision Transformer and Bayesian optimized support vector regression for continuous monitoring of water quality in dam reservoirs. Each component contributes significantly to improve data quality, enhancing predictive accuracy, and providing reliable assessments of water conditions. Perspective projection using the Transverse Dyadic Wavelet Transform (TDyWT) improves satellite images for water quality analysis. It corrects geometric distortions caused by variations in satellite altitude and the earth's curvature, ensuring accurate spatial relationships in the image. TDyWT also enhances the contours, boundaries, and curvatures of land cover features, making it easier to distinguish between elements like water bodies and vegetation. Additionally, TDyWT reduces noise in the images, ensuring high-quality data for accurate classification and prediction of water quality parameters. Image enhancement using Particle Swarm Optimized Vision Transformer (PSOViT) and Adam Optimized Vision Transformer (Adam-ViT) is a deep learning technique that extracts complex features. These models identify intricate patterns and relationships in the data, which is important for detecting subtle differences in water quality indicators. The optimization techniques fine-tune hyper-parameters, improving predictive accuracy and enabling more precise predictions of water quality parameters. Finally, predicting water quality parameters using Bayesian Optimized Support Vector Regression (SVR) enhances model performance. The Bayesian optimization fine-tunes hyper-parameters to improve prediction accuracy for parameters such as pH, dissolved oxygen, total dissolved solids, and conductivity. This increased accuracy is essential for effective water resource management. Additionally, the Bayesian approach incorporates uncertainty estimation, providing confidence intervals that help decision-makers assess the reliability of predictions. This is particularly important in environmental applications where risk assessment is crucial. SVR's ability to capture complex nonlinear relationships between input features from images and water quality parameters further strengthens its effectiveness under different environmental conditions.

ABLATION STUDY

Transverse Dyadic Wavelet Transform (TDyWT) plays a vital role in enhancing subsequent steps of the proposed method for predicting water quality in dam reservoirs. TDyWT improves the quality and utility of satellite imagery by providing precise delineation and accurate spatial measurements while effectively addressing common challenges associated with satellite data. This significance is demonstrated through the following ablation results: without the perspective projection of the original input data, the accuracy of predictions decreases because geometric corrections, multi-scale spatial representation for differentiating between water and moss, and noise reduction are not achieved. Consequently, when images are directly processed through the Vision Transformer and regression analysis without these enhancements, the overall predictive performance is low compared to perspectively projected TDyWT based proposed predictive method. Another important aspect is the optimization technique used in the Vision Transformer. The consistently higher scores across all metrics for the proposed AdamViT-SVR and PSOViT-SVR models demonstrate that the optimization methods applied to Support Vector Regression led to more reliable assessments. **Table. 8** shows the ablation study results for water quality monitoring in Nagi Dam. In overall, TDyWT improves data quality by correcting distortions and enhancing features. The use of optimization methods in PSOViT and AdamViT further boosts model performance, making them crucial for effective water quality assessment and management.

Table.8. Ablation Results-Nagi Dam Reservoir

Accuracy				
Methods	**pH**	**DO**	**TDS**	**Conductivity**
Without TDyWT	89.45	88.72	89.65	88.41
With TDyWT and Without Optimization in Vision Transformer	89.97	87.49	89.12	89.54
PSOViT-SVR	94.65	95.5	94.13	95.12
AdamViT-SVR	96.21	96	96.43	96.61

CONCLUSION

Continuous water quality prediction in Nagi and Nagathi dams, located in Bihar, India, is carried out using spatial and temporal pixels from Landsat satellite images. Water quality parameters pH, dissolved oxygen (DO), total dissolved solid (TDS) and Conductivity values are predicted from water and moss pixels to monitor the quality of water. Landsat images are perspectively projected using TDyWT and enhanced using optimised Vision transformer technique. Water and moss regions are separated with the use of dual threshold graph cut method and statistical features are extracted. Extracted features correlated with laboratory values for prediction with the use of Bayesian optimised Support Vector Regression. The proposed integrated approach yields higher average accuracy of 96% in predicting pH, DO, TDS and Conductivity in Nagi and Nagathi dam reservoirs when compared to ground truth verification. The proposed approach addresses the challenges of continuous monitoring by removing the need for frequent sample collection. It also minimizes human errors in analysis and data recording, thereby improving the accuracy of water quality measurements.

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