

A Deep Learning Framework For Water Quality Analysis Using Multi-Index Sentinel-2 Imagery: A Novel Approach

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Abstract

Water quality monitoring is of critical importance in terms of environmental protection, public health, and sustainable management of water resources. However, traditional methods of in-situ measurement are cumbersome and spatially limited due to the time it takes to perform them. The aim of this paper is to propose a deep learning-based framework for large-scale water quality assessment using multi-index Sentinel-2A imagery in combination with ground-measured parameters taken from several locations along the Godavari River in Chhatrapati Sambhajnagar that include Paithan, Jayakwadi, Gangapur, Pathegaon, Kaigaon, and Naregaon. Satellite data were then preprocessed systematically: temporal filtering (from January 2021 to May 2025), cloud masking by QA60 indicators, and clipping by AOI to separate the river stretches of interest. Subsequently, a set of spectral water indices, which comprised NDWI, MNDWI, NDCI, TBI, WRI, and AWEI, was calculated as a way to capture variability associated with turbidity, suspended sediments, chlorophyll concentration, and general water clarity. These indices were therefore used as features for four predictive models: XGBoost, CatBoost, Multilayer Perceptron, and a novel Hybrid Autoencoder + XGBoost architecture. Model evaluation showed that XGBoost and CatBoost generated very stable baselines, while performance for the MLP model was relatively weaker. The proposed Hybrid Autoencoder + XGBoost model presented the best prediction performance among all models, with the lowest values of errors and highest explanatory power, especially for COD and conductivity. It indicates that integrating deep features extraction and boosted decision tree regression is effective in satellite-based water quality estimation. In general, this study demonstrates the value of multispectral remote sensing combined with advanced AI techniques to develop scalable, cost-effective, and continuous freshwater quality monitoring toward better environmental management and decision-making.

Keywords : NDWI, MNDWI, NDCI, TBI, WRI, AWEI, XGBoost, CatBoost, COD, Conductivity

1. Introduction

Remote sensing has become an important technique for monitoring surface water quality, even at continental and global scales. Water quality assessment has traditionally relied on manual field sampling and laboratory analysis, but is time consuming, costly and spatially limited. Remote sensing is increasingly making waves with fewer satellite data and the availability of radio telescoped observations of coastal and ocean bodies [1]. Combined with multispectral and hyperspectral signatures, remote sensing is able to detect relationship between reflectance patterns and water constituents such as turbidity, suspended sediment, chlorophyll-a and dissolved organic matter. This technological shift has significantly changed environmental observation by making water quality monitoring much faster and scalable [2].

The use of remote sensing for water contamination analysis has increased because of increased anthropogenic pressures, agricultural runoff, industrial discharge and climate-induced hydrological changes. Traditional sampling approaches rarely adequately capture spatial heterogeneity and temporal variation of contamination events, especially in large reservoirs, rivers, and lakes [3]. Remote sensing provides a noninvasive, continuous and real-time monitoring capability that enables early detection of pollution outbreaks. The paper also assists decision-makers with environmental risk assessment, planning for water resource management, and implementing environmental regulations. Thus, remote sensing based water quality analysis has become essential in the management and protection of sustainable hydrology and ecology [4].

Sentinel-2 imagery has a high spatial resolution, is frequently revisited, and contains the wide range of spectral information that is required to monitor water quality indicators such as turbidity, suspended sediment, and chlorophyll concentration. This optical properties of water can be modeled on it, and its visible, NIR and red-edge bands provide a strong source for detection of spectral features from contamination [5]. In collaboration with deep learning methods such as CNN, LSTM and hybrid attention-based models, analysis is greatly more powerful in its combination with deep learning methods, because their models can learn complex nonlinear relationships between multispectral index and water quality data. The deep learning model automatically extracts spatial-temporal features, reduces noise, and enhances prediction accuracy to produce a robust, data driven water contamination assessment framework using Sentinel-2 data [6].

Despite the significant progress on unified frameworks that contain multi-index Sentinel-2 inputs and advanced deep learning models to perform comprehensive water quality analysis, still many gaps remain regarding the integration of multi index Sentinel-2 input with deep learning models for comprehensive water quality analysis. Many existing research relies on single-parameter estimation or small datasets, making it unable to be universal across spatial scales. In addition, these complex optical properties of water systems require models that can respond to noise, seasonal changes, and locale-specific conditions. In this sense there is a pressing need for a deep learning framework to study the pattern of water contamination that can effectively analyze water source and guide decision-making in environmental

monitoring [7][8]. This study addresses these problems by introducing a novel deep learning-based approach to multi-parameter water quality assessment. Following section consist related work, followed with study area and detailed methodology. Also discussed our results in detailed with conclusion.

2. Related Work

Recent research indicates an increase in interest in using satellite-based remote sensing for water quality assessment, especially with multispectral data from missions like Sentinel-2. Studies have shown that spectral indices derived from these sensors can accurately estimate parameters such as turbidity and chlorophyll. One of the study's results confirm the feasibility of using deep learning networks for intelligent classification of water bodies with varying turbidity, offering a new approach for large-scale and efficient remote sensing-based water turbidity monitoring Gaofen-1 multispectral imagery. The proposed method demonstrates high accuracy in classifying water bodies with different turbidity levels. The key performance metrics are, Mean Intersection Over Union (MIoU) is reached 94.73%, Mean F1 Score achieved 97.29% and Overall Accuracy stood at 97.54% [9].

Another study introduces an Enhanced Convolutional Neural Network leveraging Switchable Normalization to significantly reduce training time while maintaining high accuracy for water region classification in remote sensing imagery. The proposed ECNN, incorporating Switchable Normalization, achieved a very fast training time of approximately 6.294738 seconds. It shows high accuracy with the network is designed for accurate classification, and its efficacy is proven by training it over the GaoFen Image Dataset, which comprises very high-resolution images with multiple classes [10].

One of the author study presents a deep learning-based model, specifically using YOLOv3 and YOLOv4 with transfer learning, to achieve high-precision detection and classification of water pollutants, including the ability to localize them with bounding boxes. This approach aims to provide an efficient and effective automated solution for curbing water pollution. The model development incorporates the concept of transfer learning, making use of pre-trained models [11].

Another presents a AI-powered approach that incorporates real-time data processing and predictive modeling to enhance water contamination detection. This method leverages machine learning algorithms combined with sensor networks for continuous monitoring of water quality. The model accurately predict contaminant concentrations and assess the effectiveness of various mitigation strategies across different water bodies, demonstrating superior detection accuracy compared to traditional methods. The model achieved an accuracy of 90.75%, F1-score of 88.79, and AUC of 92.02 on the Terra Satellite dataset. On the Aquatic Toxicity dataset, it obtained an accuracy of 92.58% and AUC of 94.13. The model reached an F1-score of 85.54 and AUC of 89.72 on the Water Quality dataset [12].

3. Study Area

We choose, for investigation, the jaykwadi dam situated 19.4865° N, 75.3707° E in the Godavari river basin in the Paithan of the Maharashtra state in Chhatrapati Sambhajnagar district as depicted in figure 1. The waters of the reservoir traverse the areas of Chhatrapati Sambhajnagar, Ahmednagar, and Jalna. One of the state's most extensive irrigation systems comprising a sizable freshwater reservoir mostly known as the Nath Sagar. The research location was chosen especially to keep the water level under the surface all year. With the deeper sections typically being close to the dam wall and the shallower parts stretching outward, especially in the more northern and eastern regions, the reservoir has somewhat shallow and deeper freshwater lakes.

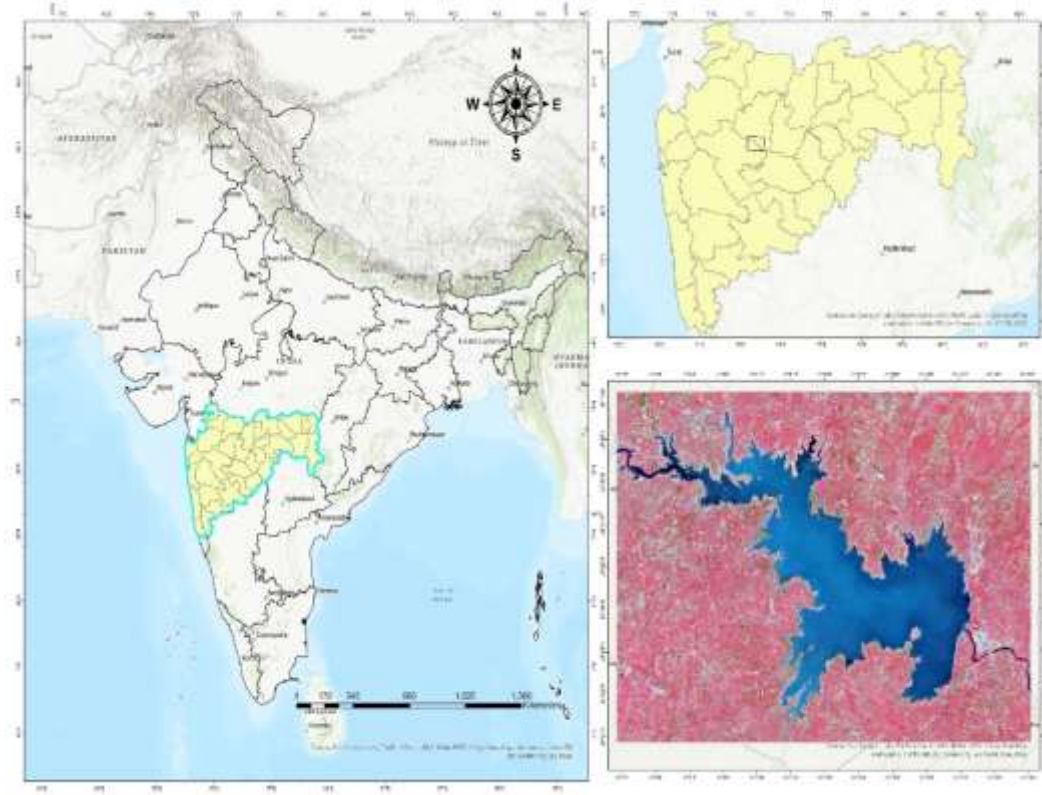


Figure 1: Study Area

4. Methodology

This research approach combines a methodological process as shown in figure 2, starting with preprocessing of Sentinel-2 images—including cloud masking and extraction of the region of interest—to guarantee clean and dependable data. Following this, a set of water-specific spectral indices is calculated—including NDWI, MNDWI, turbidity-related ratios, and chlorophyll-sensitive indices—which serve as essential characteristics defining the optical properties of water quality. Deep learning models able of capturing nonlinear correlations between spectral signals and water contamination indices are trained and assessed using these extracted features. This mixed method provides a strong, data-driven foundation for precise water quality forecast.

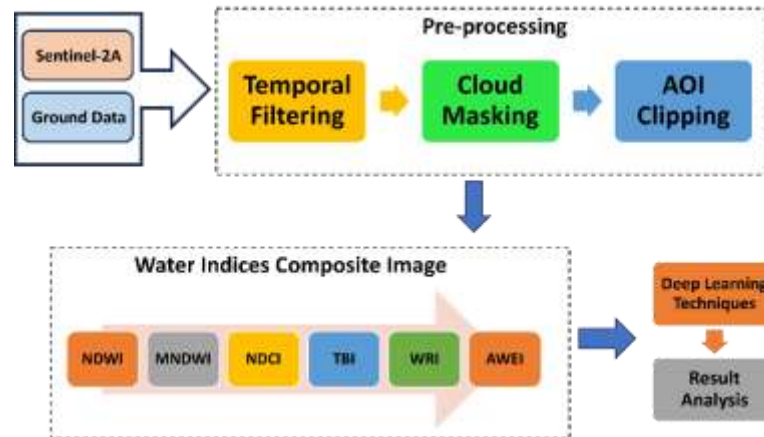


Figure 2: Proposed Methodology

4.1. Data Collection

Data gathering for this project consisted of ground-based water quality measurements and satellite-based observations as the two main elements. To record both spectral variation and temporal changes in the Godavari River, Sentinel-2A multispectral imaging offering 13 spectral bands across the visible, NIR, red-edge, and SWIR ranges with a 10–20 m spatial resolution and a five-day revisit cycle was obtained [13]. These images were used to extract important water-related indicators for study. Including Paithan, Jayakwadi, Gangapur, Pathegaon, Kaigaon, and Naregaon communities, ground truth samples gathered from several locations across Chhatrapati Sambhajnagar supported the satellite data. Key water quality factors including turbidity, BOD, COD, and electrical conductivity were assessed at each site to give precise reference values for model validation and calibration. Developing the deep learning system for water quality evaluation relied on a solid and dependable foundation provided by this combined dataset.

4.2. Preprocessing

To guarantee the quality and usefulness of Sentinel-2A images for water quality research, the preprocessing phase included a sequence of actions. Choosing images from January 2021 to May 2025 first allowed the study to catch multi-year seasonal fluctuations and lower temporal noise using temporal filtering. To get rid of cloud-covered and shadow-affected pixels, assuring only clean and trustworthy observations were kept, cloud masking was next carried out employing the Sentinel-2 QA60 band. Finally, the image was clipped to the Area of Interest (AOI) over the chosen sections of the Godavari River to help concentrate the study on pertinent water surfaces and lower computer load. These preprocessing procedures improved data coherence overall and ready the dataset for correct spectral index extraction and deep learning-based analysis [14][15].

4.3. Water Indices

To extract meaningful water-related characteristics from Sentinel-2A images, a set of spectral water indices was computed to capture fluctuations in turbidity, chlorophyll

content, suspended solids, and overall water clarity. Chosen for their sensitivity to water optical qualities and their ability to identify patterns of pollution are indicators including NDWI, MNDWI, NDCI, TBI, WRI, and AWEI. These indicators improve particular spectral reactions of water bodies, therefore assisting to distinguish pure water from murky, contaminated, or algae-rich areas. The deeply learned model used the extracted indices as important input features allowing for correct prediction and characterization of water quality parameters.

Table 1: Water Indices with mathematical model

Index	Use in Water Contamination Analysis	Mathematical Formula	References
NDWI (Normalized Difference Water Index)	Detects water bodies and assesses water clarity; useful for turbidity detection	$NDWI = \frac{Green - NIR}{Green + NIR}$	[16]
MNDWI (Modified NDWI)	Enhances open water detection, suppresses built-up areas; effective for turbid or mixed pixels	$MNDWI = \frac{Green - SWIR1}{Green + SWIR1}$	[16][17]
NDCI (Normalized Difference Chlorophyll Index)	Estimates chlorophyll concentration; useful for detecting algal blooms	$NDCI = \frac{Red_{Edge} - Red}{Red_{Edge} + Red}$	[18]
TBI (Turbidity Index)	Identifies suspended sediments and turbidity levels	$TBI = \frac{Red + Green}{NIR}$	[19]
WRI (Water Ration Index)	Distinguishes water from non-water features; helps detect sediment-rich water	$WRI = \frac{Green + Red}{NIR + SWIR1}$	[16][20]
AWEI (Automated Water Extraction Index)	Removes shadow and noise; enhances water detection in complex environments	$AWEI = 4 \times (Green - SWIR1) - (0.25 \times NIR + 2.75 \times SWIR2)$	[16][20][21]

4.4. Deep Learning Technique

This study employed a set of high-powered machine learning and deep learning algorithms to model complex relationships between multispectral water index and in-site contamination. These tools were selected because they can be captured nonlinear pattern, learn strong feature learning and be highly predictive in water quality assessment. The following subsections describe the four models—XGBoost, CatBoost, MLP, and the proposed Hybrid Autoencoder + XGBoost—along with their technical foundations and analytical significance.

4.4.1. XGBoost Evaluation:

One usually employed for regression and classification tasks, XGBoost (Extreme Gradient Boosting) is an upgraded and scalable gradient boosting system. It progressively creates several regression trees, each of which is trained to reduce the residual errors of the prior ensemble. XGBoost is strong for sophisticated water quality prediction as it makes use of second-order Taylor expansion of the loss function and applies regularization to stop overfitting. Its appropriateness for examining Sentinel-2 derived characteristics results from its capacity to manage nonlinear connections between spectral indices and contamination indicators. XGBoost optimizes the objective function represented in equation 1,2 and 3 [22]:

$$\mathcal{L}(\emptyset) = l(y_i, \hat{y}_i) + \sum_{k=1}^k \Omega(f_k) \quad (1)$$

$$\text{Where, } \Omega(f) = \gamma T + \frac{1}{2} \lambda \|\omega\|^2 \quad (2)$$

In this case, l is the loss (MSE), f_k are decision trees, w are leaf weights, γ and λ control regularization. The prediction is:

$$\hat{y}_i = \sum_{k=1}^k f_k(x_i) \quad (3)$$

4.4.2. CatBoost Evaluation

Designed to better manage categorical and numerical features while avoiding prediction shifting and overfitting, CatBoost (Categorical Boosting) is a gradient-boosting technique. Ordered Boosting and Oblivious Decision Trees—which guarantee uniform splitting structure across all nodes—define CatBoost. Learning stable and generalizable patterns from water indices is made easier this way. Strong choices for predicting water pollution, CatBoost's resistance to overfitting and capacity to model high-order nonlinear relationships make it. The mathematical model represented in equation 4, minimizes the loss function through an ordered boosting process [23].

$$f^{(t)}(x) = f^{(t-1)}(x) + n \cdot h^{(t)}(x) \quad (4)$$

Here, n is the learning rate, $f^{(t)}$ is model at iteration t and $h^{(t)}(x)$ is newly learned tree.

4.4.3. MLP Evaluation (Multilayer Perceptron)

Model complex nonlinear connections with a multilayer perceptron (MLP), a completely connected feed-forward neural network. With several hidden layers employing nonlinear activation (ReLU), the MLP performs hierarchical feature learning, so making it well suited for capturing the underlying spectral patterns of contaminated water using Sentinel-2 spectral indices (NDWI, MNDWI, NDCI, TBI, WRI, AWEI). The mathematical model 5,6 and 7 are for an input vector x , the MLP computes [24].

$$h_1 = \sigma(W_1 x + b_1) \quad (5)$$

$$h_2 = \sigma(W_2 h_1 + b_2) \quad (6)$$

$$\hat{y} = W_3 h_2 + b_3 \quad (7)$$

Here, b and W are biases and weights, σ is the activation function and $\hat{y}$ is the predicted water quality.

4.4.4. Hybrid Autoencoder + XGBoost (Novel Approach)

The suggested Hybrid Autoencoder + XGBoost paradigm is a fresh design meant to combine strong gradient-boosted regression with deep feature learning. First learning a compressed latent representation of the multi-index spectral dataset, the Autoencoder minimizes noise and grabs important spectral markers of water contamination. XGBoost then receives this latent vector and makes the final projection. This hybrid architecture substantially increases the prediction accuracy for water quality variables by means of noise filtering, dimension reduction, and improved regression. Technical Workflow is The Autoencoder maps input features X to a low-dimensional latent vector Z . XGBoost trains on Z instead of raw features, improving model interpretability and robustness. This fusion helps model nonlinearities more effectively than standalone models. Mathematical model 8,9,10 and 11 are given.

Autoencoder Encoding:

$$Z = f_{\text{enc}}(X) = \sigma(W_e X + b_e) \quad (8)$$

Autoencoder Decoding:

$$\hat{X} = f_{\text{dec}}(Z) = \sigma(W_d Z + b_d) \quad (9)$$

The Autoencoder training minimizes reconstruction loss:

$$\mathcal{L}_{\text{AE}} = \|X - \hat{X}\|^2 \quad (10)$$

Once trained, the latent vector Z is used as input to XGBoost:

$$\hat{y} = \sum_{k=1}^K (f_k(Z)) \quad (11)$$

This hybrid mathematical structure combines deep feature extraction with gradient-boosting prediction, forming the study's novel deep learning framework.

5. Result and Discussion

Clear distinctions in predictive ability for several water quality parameters derived from Sentinel-2 spectral indices are shown in the performance evaluation of the four models: XGBoost, CatBoost, MLP, and the suggested Hybrid Autoencoder + XGBoost. Among the classic boosting methods, XGBoost and CatBoost generated same

outcomes, therefore showing constant learning behavior and steady model convergence. Both models attained average R^2 values (≈ 0.06 – 0.18) for factors including COD, BOD, and conductivity, showing their capacity to capture small but significant correlations between spectral indices and levels of water pollution. Their low R^2 values for turbidity, however, point to the difficulty still of estimating turbidity, perhaps because of spectral resemblance between somewhat turbid and clean water in optical bands.

The performance of the MLP model was a bit weaker in most respects, including higher RMSE values and notably negative R^2 for turbidity and COD, indicating that the shallow MLP architecture seemed to struggle to capture complex nonlinear trends in the limited dataset without more temporal or contextual features. While it slightly improved for BOD in terms of MAE, overall, the performance of the MLP was not as strong as the boosting-based approaches.

The proposed Hybrid Autoencoder + XGBoost framework demonstrated the best overall performance on all the executed experiments, proving the effectiveness of this new approach. The Autoencoder successfully removed the redundancy of the input and extracted more discriminative latent features that allowed the XGBoost model to produce an increment in its learning of meaningful patterns. The most obvious improvements are related to the COD prediction since the hybrid approach reached the highest R^2 value, equal to 0.1991, and the lowest MAE among all the models. For conductivity, the hybrid model provided the lowest MAE: 350.95, showing better sensitivity to slight spectral variations. Although the improvement for turbidity and BOD was only moderate, the hybrid method was always either higher or on par with the single approaches, confirming its robustness.

In this step, several visualizations were utilized to interpret the performance of the developed water contamination analysis framework. A correlation matrix depicted in figure 3, was plotted to show the interdependency among the spectral indices, contamination parameters, and deep learning model outputs to identify the most influential predictors. Scatter plots represented in figure 4, were drawn to show the relationship between the predicted and observed values, by which the patterns of accuracy and residual behavior of each learning technique could be clearly portrayed. Further, bar charts shown in figure 5, were included to present a comparison of model-wise error metrics in terms of RMSE, MAE, and R^2 values, hence intuitively interpreting the strengths and weaknesses of each approach. These visualization techniques collectively contributed to enhancing interpretability, allowing transparent model comparisons and a better understanding of system performance in real-world water quality assessment.



Figure 3: Correlation Matrix

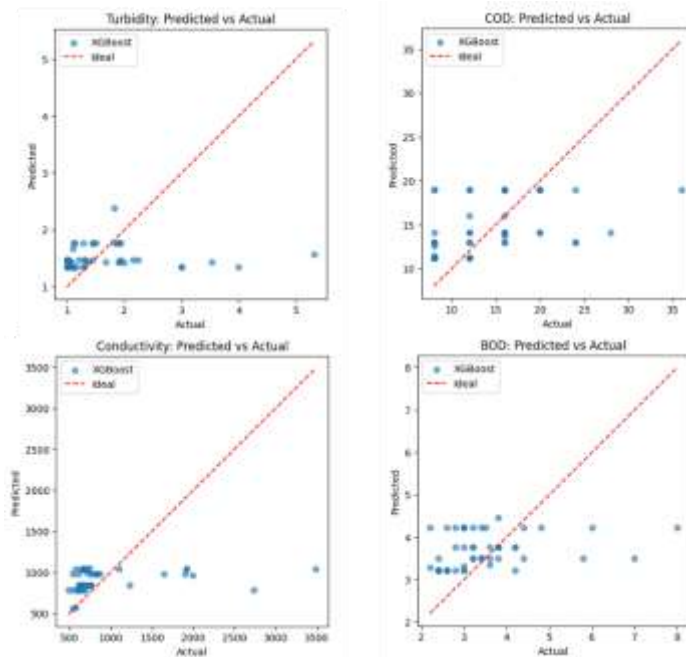


Figure 4: Scatter Plot

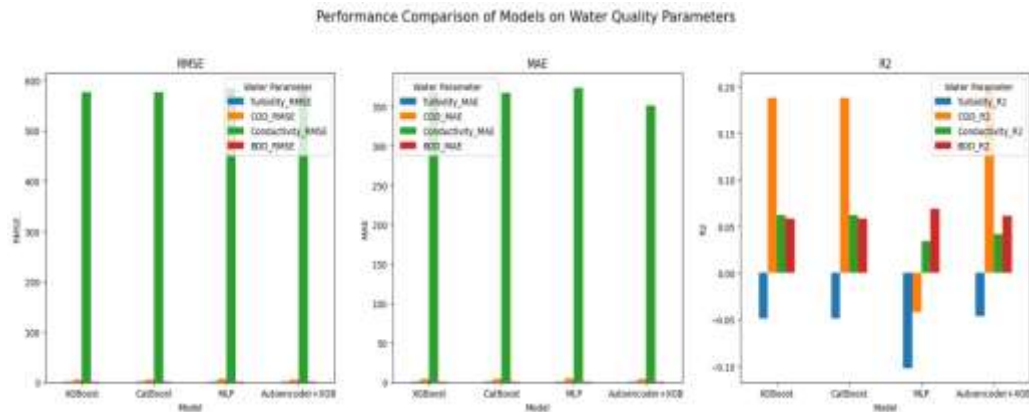


Figure 5: Performance Comparison of Models

Overall, the results of this study reveal that all the models can provide baseline predictions for water quality. However, the Hybrid Autoencoder + XGBoost approach yielded better performance and generalizability. This proves the advantage of deep feature extraction with boosted decision tree regression in performing remote-sensing-based water quality assessment.

6. Conclusion

This research work presents an exhaustive deep learning-driven framework for the assessment of water quality based on multi-index Sentinel-2A imagery integrated with ground-measured parameters from various locations along the Godavari River. Through sound and robust preprocessing steps, extraction of a suite of water-specific spectral indices, and evaluation of several advanced machine learning models, this work illustrated the potential of satellite spectral information in the reliable analysis of water contamination. Of the various techniques assessed, XGBoost and CatBoost provided a stable baseline performance, while the MLP proved quite weak for the representation of complex spectral-biophysical relationships. The Hybrid Autoencoder + XGBoost model performed best by providing the minimum error metrics and maximum predictive consistency for key water quality indicators: COD, BOD, turbidity, and conductivity. Deep feature extraction integrated with gradient-boosted regression is done to enhance the capability of the model by representing subtler spectral changes related to contamination levels.

Overall, findings point to the importance of remote-sensing data combined with deep learning advanced architectures as a tool for large-scale, cost-effective, continuous water quality monitoring. The present work demonstrates the capability of Sentinel-2 imagery to act as a strong environmental assessment tool when treated with well-designed artificial intelligence models, thus assisting policy-makers and water resource managers in finding early contaminations and helping them make accurate decisions. Further work may be directed towards the inclusion of hyperspectral data sets, extra in-situ parameters, temporal deep learning models, and UAV-based observations to enhance the predictive accuracy of these models and realize real-time digital twin systems for holistic water quality surveillance.

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