# A MACHINE LEARNING-DRIVEN COLLABORATIVE MODEL FOR WATER QUALITY EVALUATION IN INDIA

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*Abstract*— **Water quality is a big problem in India because pollution is rising, the climate is changing, and more people are moving to cities. It takes a long time and usually requires sampling by hand and lab analysis to check the quality of water around the world in the usual ways. The present methods have problems with size, reactivity, and adaptability. The study talks about a new way to do machine learning called Optimised Stacked Blending for Water Quality Index. An ensemble learning method is used by the system to guess missing water quality variables, and a resulting Water Quality Index (WQI) is used to give the water an overall score. This two-step method makes predictions more accurate and makes it easier to classify things. Tests that use real data from the Ganga River in Varanasi demonstrate good results, with a 95.81% accuracy rate for sorting tasks. The suggested model is better than older machine learning models like SVM, KNN, RF, and NN for both regression and classification. This model could be used for many things in India, such as checking on the environment, public health, and making policy decisions.**

*Keywords*—**Environmental Monitoring, Water Quality, Machine Learning, Stacked Blending, Classification, Regression, WQI.**

## I. INTRODUCTION

This Water is necessary for life since it supports ecosystems, farming, industry, and people's health. But the growing number of things people do has had a major impact on freshwater sources. There is only around 2.5% of the world's water that is freshwater, and only 1% of it is available for people to use. Industrial waste, agricultural runoff, and urban waste have all polluted water, which is now a major problem. This makes it very important to keep an eye on water quality.

The Ganga River, especially around Varanasi, is one of the dirtiest rivers in India. We need powerful tools for continuing and accurate water quality assessment because it is important for society and the economy. It takes a long time to analyse by hand, and it's easy to make mistakes.These problems have led researchers to look into employing artificial intelligence (AI) and machine learning (ML) to find data-driven solutions. Machine learning algorithms can automatically check the quality of water and give evaluations and projections that are almost real-time. These models can work with big datasets, guess at missing values, and sort water quality into different groups based on a number of factors shown in Fig. 1.

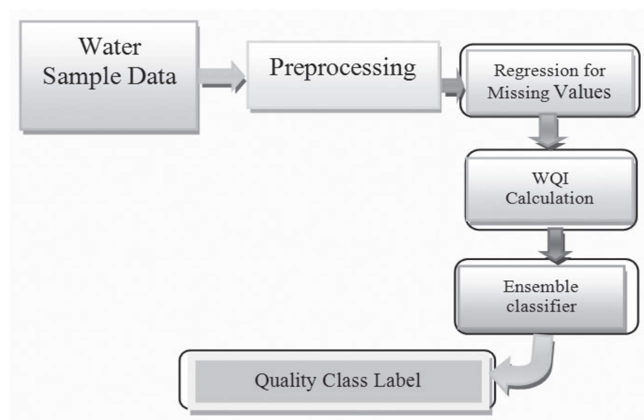


Fig.1. General Overview of the WQI model

Figure 1 provides a detailed depiction of the Water Quality Index (WQI) modeling pipeline established in this study for evaluating river water quality through machine learning methodologies. The procedure commences with the acquisition of water sample data from diverse sites, succeeded by preprocessing measures to address absent or inconsistent values. Regression models are subsequently utilized to predict absent water quality metrics based on inter-parameter correlations. The comprehensive datasets—consisting of both observed and projected values—are utilized to calculate the WQI, a composite metric indicative of overall water quality. This indicator is subsequently employed to classify water quality into established categories. The annotated dataset subsequently functions as input for an ensemble classification framework intended to automate the classification process. The ensemble consists of various base classifiers, including KNN, SVM, RF, and NN, whose outputs are aggregated through a meta-classifier to get final predictions. This comprehensive, phased methodology guarantees enhanced precision, resilience, and scalability in real-time water quality evaluation, specifically implemented for the Ganga River in the Varanasi area.

This paper details recent improvements in water quality evaluation through a thorough literature review, emphasizing the limitations and opportunities that informed the development of the suggested framework. The methodology section delineates the whole OSE-WQI model, encompassing data preparation, regression-based forecasting, WQI calculation, and the development of a stacked ensemble classifier. The following regression performance analysis and performance analysis section assesses the model's performance with empirical data from the Ganga River, examining both regression and classification findings. The practical application of the system for real-time environmental monitoring is examined, concluding with a summary of significant contributions and a delineation of future research directions to improve the model's scalability and adaptability.

## II. LITERATURE REVIEW

In the last several years, various methods to track water quality have evolved significantly, especially with the use of machine learning (ML). One of the most essential things these studies look at is the Water Quality Index (WQI). It helps you make in-depth evaluations based on a number of physicochemical factors, such as Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), pH, and Total Dissolved Solids (TDS). Even though people often employ standard WQI approaches, they usually have problems with weighting parameters in a way that isn't objective, dealing with missing or noisy data, and making generalisations across different geographic areas.

A lot of research has tried to solve these challenges by employing different ways. For example, P. Sudarshan et al. examined at TDS, DO, Nitrate, BOD, and hardness to see how good the water quality was in Hebbal Lake, India [1]. This study did show that some regions were dirty, but it couldn't be used in other places. In this paper[2], authors used a deep learning-based Bi-LSTM model to make an educated judgement about how clean the water in the Ganga River was. They proved that applying optimised loss functions made the predictions more accurate. In this autors sought to perform the same thing by combining ensemble classification with Relief feature selection [3]. This made the classification more accurate, but it also made the model harder to understand.

This paper built on this work by suggesting a fuzzy logic-based WQI method that uses triangular and trapezoidal membership functions to deal with uncertainty in water quality measures. On the other hand, the fuzzy method takes someone who understands a lot about the subject and could be hard to understand [4]. In this paper, authors built a system that employs artificial neural networks (ANN) to tell you what the water quality is like right now. This shows that it is feasible to watch the surroundings without people. But the ANN method needs a lot of processing power and depends a lot on how good the training data is [5].

In 2024, Kirui looked into how machine learning could assist us learn even more about the water's condition. With decision trees, XGBoost, and Bi-LSTM, they were able to guess the WQI with an accuracy of roughly 96%. This paper also used explainable AI (XAI) and ensemble models like Gradient Boosting, Random Forest, and XGBoost to make WQI predictions more accurate. The investigation showed that Gradient Boosting was the most accurate, with a 96% accuracy rate [6].

In this paper, autors looked at how outliers changed the Irish Environmental Water Quality Index (IEWQI) model to make sure the data was reliable. Their results showed that strong frameworks are needed that can operate with data that isn't flawless. This combined approach works, but you need to know a lot about both machine learning and fluid simulation in order to use it [7]. The dadatested a number of regression and classification methods, including Random Forest, XGBoost, AdaBoost, and Gradient Boosting, to find the optimum algorithm for predicting the Water Quality Index (WQI) and Water Quality Category (WQC). The top model got a score of 99.8% from $R^2$[8].

This paper describe a model that employs support vector machines and tree-based classifiers to check the quality of water in real time. They made it obvious that it could be used to help manage the environment. Even though it was hard to do the arithmetic, their investigation showed that ensemble techniques can aid with sifting water [9].

In this paper authors employed machine learning to study water samples from Ayodhya, India, and focused on contamination in groundwater. Their work focused on how ML may be used to find and fix groundwater pollution, however it was only done in a certain area[10]. Finally, the resercher came up with attention-based CNN-LSTM models that made multi-parameter water quality data more accurate by using spatial and temporal attention processes to focus on important factors [11].

These combined efforts show how water quality assessment systems are moving away from traditional WQI methodologies and towards data-driven, ML-enabled solutions. Even though these methods are different, they all have the same goals: to make predictions more accurate, to make them more reliable, to deal with missing or outlier data well, and to allow for real-time decision-making. This paper extends on these ideas by suggesting the WQI model, which is an optimised stacked ensemble classifier that combines KNN, SVM, Neural Networks, and Random Forest with a meta-classifier to make the final prediction. This method not only fixes problems found in previous studies, but it also establishes a new standard for classifying and predicting water quality, with over 95% accuracy in classification and better forecasting metrics like RMSE and MAPE for a variety of water parameters.

We find a number of research gaps in the current methods for assessing water quality. Traditional WQI models can't change easily and have trouble with data that is missing or partial, which makes predictions less accurate. Most of the research that came before this one don't use forecasting to figure out missing factors, which makes WQI less reliable. Also, integrated frameworks for classifying water have not made enough use of ensemble learning approaches. There aren't many region-specific models that use localised datasets, especially for contaminated rivers like India's Ganga.

## III. METHODOLOGY

The proposed framework for water quality assessment along the Ganga River is structured into four essential stages shown in Fig.2.

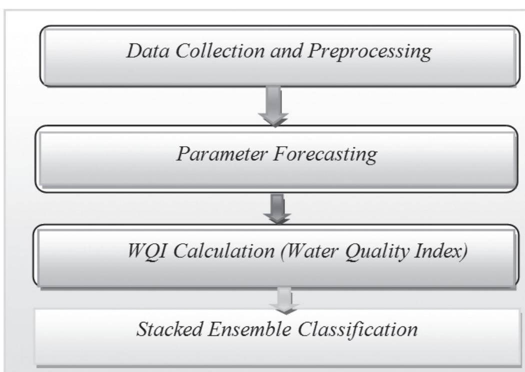


Fig. 2. Architecture of Proposed WQI Model

### *A. Data Collection and Preprocessing*

In this stage, first we collect the data from the Central Pollution Control Board (CPCB) in which we collect total 6598 samples from various monitoring stations. This data have physicochemical and biological attributes for example: Biochemical Oxygen Demand (BOD), pH, Dissolved Oxygen (DO), Conductivity (CND), coliforms and Total Dissolved Solids (TDS), and coliforms. The data preprocessing were applied to remove outliers, normalize parameter scales, handle missing values for data reliability and readiness as well as preparing the dataset for machine learning analysis.

### *B. Parameter Forecasting*

This stage addresses incomplete or missing values in the dataset. There are various regression algorithms were employed i.e. Random Forest (RF), K-Nearest Neighbors (KNN), Neural Networks (NN) and Support Vector Machine (SVM). This methology were used to evaluate unknown attrbutes values and increase the completeness of the dataset. Performance metrics used Root Mean Squared Error (RMSE), Accuracy, precision, recall, F-score to calculate the accuracy of the regression models. In subsequent computations, this step ensures that predictions are statistically usable and reliable.

### *C. WQI Calculation (Water Quality Index)*

In this phase, we calculate the Water Quality Index (WQI) that is a composite metric. It condenses complex multi-parameter WQD into a single numerical score. It facilitated easier and comparison interpretation across timeframes and locations.

The evaluation process started with converting each attributes into a **sub-index** using established quality rating curves which is derived from environmental standards i.e. or CPCB, WHO or BIS guidelines).

Every attribute was assigned a **weight (Wi)** based on its impact on aquatic life and public health. For example, **Dissolved Oxygen** and **BOD** were given higher weights due to their importance in calculating the biological integrity of water. The **quality rating (Qi)** for individual attributes was calculated and combined using a **weighted arithmetic formula**:

$$WQI = \frac{\sum_i^n W_i Q_i}{\sum_i^n W_i} \qquad (1)$$

### *D. Stacked Ensemble Classification*

In this phase, the overall water quality level is predicted using an ensemble learning methodology. First, we trained multiple base learners as SVM, RF, KNN, and NN independently on the dataset. To produce the final classification result, their outcomes were then fed into a meta-classifier, which synthesized the predictions. This stacked model leverages the significance of several models, enhancing overall robustness and accuracy. For environmental monitoring and policy decision-making, this model ensures that the final water quality label shows a consensus derived from various perspectives, making the system highly reliable.

## IV. REGRESSION PERFORMANCE ANALYSIS

Regression plays a key role in estimating missing water parameters, especially in scenarios where sensors fail or data is not recorded. The ensemble regression model performed best across all metrics:

- BOD RMSE: 0.5143
- COD RMSE: 0.6242
- R-value (BOD): 0.9887

Compared to standalone regressors, the ensemble model minimized error and improved generalization.

## V. PERFORMANCE EVALUATION

The Water Quality Index (WQI) values were divided into three different classes representing water quality levels to assess the effectiveness of the proposed framework is given below in Table I:

TABLE I. WQI Range for different classes

| Class | WQI Range | Water Quality Status |
|---|---|---|
| Class 1 | 24–49 | Good |
| Class 2 | 50–74 | Moderate |
| Class 3 | 75–100 | Poor |

To predict these classes, a **stacked ensemble classifier** was applied on the basis of water quality attributes and calculated WQI values. This model integrates multiple base learners (KNN, SVM, RF, and NN) and uses a meta-classifier for final predictions. The ensemble learning technique improved classification performance by leveraging the strengths of all individual classifiers.

*B. Performance Metricss*

The performance of the stacked model was evaluated using standard classification metrics is given below in Table II:

TABLE II. PERFORMANE VALUES of Proposed WQI Model

| Metric | Value |
|---|---|
| Accuracy | 95.83% |
| Precision | 91.66% |
| Recall | 92.31% |
| F1-Score | 92.05% |

These results represents that the stacked model gives **high predictive precision, recall accuracy** as well as overall **strong generalization**. When we compared this approach with individual classifiers (e.g., SVM, KNN), the stacked ensemble demonstrated best performance for all metrics, to confirm its reliability and robustness for environmental categorization tasks.

Confusion Matrix

This matrix gives deeper perception into the predictions of model by comparing real versus labels of predicted class. For the classification task, there are three hypothetical class of confusion matrix is given below in Table III:

TABLE III. confusion Matrix

| Actual\ Predicted | Class 1 (Good) | Class 2 (Moderate) | Class 3 (Poor) |
|---|---|---|---|
| **Class 1 (Good)** | 163 | 6 | 2 |
| **Class 2 (Moderate)** | 5 | 151 | 7 |
| **Class 3 (Poor)** | 3 | 8 | 152 |

- **Diagonal entries** demonstrates real predictions.
- **Off-diagonal entries** demonstrates misclassifications.
- The confusion matrix demonstrates **high classification accuracy** with minimal cross-class errors.

The stacked ensemble classifier was better than all the other models when it came to classifying, with an accuracy rate of 95.83%. It has a balanced precision (91.66%), recall (92.31%), and F1-score (92.05%), which show that it works well and consistently across all WQI-based water quality classes. This shows that the model may be used in real-world water quality monitoring systems, where making the right decisions and managing the environment depend on precise categorisation.

## VI. APPLICATIONS OF WQI

The optimised Score-Based Water Quality Index (OSB WQI) is a useful instrument that simplifies complicated water quality data by giving it a single score. People in authority, stakeholders, and decision-makers can easily see and fix problems with water quality because of this. We can utilise it in many different ways:

*A. Urban Planning*

The optimised Score-Based Water Quality Index (WQI) is very helpful for city planning since it tells municipal officials where water pollution is a problem. People can use this information to figure out how to deal with rubbish, build new roads and buildings, and set zoning rules. It helps planners use resources wisely and make sure that growth in cities doesn't put people's health and safety or the safety of water at risk.

*B. Agriculture*

WQI is highly useful in farming to stop people from using dirty water to water their crops. Bad water can damage crops, make the soil less healthy, and add harmful substances to the food supply. Farmers and agricultural officials can use the index to keep an eye on water resources and make sure that farming is done in a way that is healthy for the environment. This will help them save crops.

*C. Industrial monitoring*

When keeping an eye on industry, the indicator helps you locate companies and factories that are emitting pollutants in a way that isn't normal. Regulatory organisations can check on enterprises that contravene environmental rules and make sure they obey the rules of wastewater. It also helps find out where pollution comes from, which makes it easier to take specific enforcement actions.

*D. Public health*

From a public health point of view, WQI is an early warning method for discovering unsafe drinking water. Finding sources of contamination immediately limits the spread of diseases that cause watery stools, like cholera, dysentery, and typhoid. This information can help officials warn people, give them clean water, and do other things to keep people healthy

*E. To figure out Water Quality Index*

When you connect WQI to IoT devices, you can gather and watch data in real time, which makes it much more helpful. Sensors can communicate data on the quality of the water all the time, which makes it possible to set off warnings and do predictive analysis. This smart link helps managers of water resources make choices more quickly and effectively.

## VIII. CONCLUSION AND FUTURE DIRECTIONS

This paper describe WQI, which is a complete machine learning system that can check the quality of river water on its own. It is incredibly accurate and reliable since it uses regression to fill in missing data and a stacked ensemble classification method to grade quality. The Water Quality Index (WQI) is a good tool since it looks at both real and expected values. This means that datasets that don't have all the information can nevertheless be useful. When used in an optimised ensemble, classifiers such as KNN, SVM, RF, and Neural Networks can generalise and stay stable better than when used on their own. We tried the algorithm out on real data from the Ganga River in Varanasi and it got the accurate answer 95.83% of the time. These results demonstrate that it has a lot of potential for application in the real world to keep an eye on the environment and make judgements about policy. It might be better in the future if you add IoT devices to the model to get data in real time. It would be better if it could deal with larger datasets from more than one place. Adding new environmental elements like climate change, land use, or rainfall might make the evaluations more complete. Officials can also make decisions immediately away with mobile and cloud-based technologies. In the end, WQI could help manage water resources in a way that is good for the environment in many different climates and regions.

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