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# Water, Air Quality Analysis and Prediction System

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Abstract: The Water and Air Quality Analysis and Prediction System aims to address growing concerns regarding environmental sustainability and public health. Developed using Python and MySQL, the system leverages machine learning techniques, specifically the Random Forest algorithm, to analyze and predict water quality based on parameters such as pH, dissolved oxygen, turbidity, conductivity, and temperature. By classifying water quality as "safe" or "unsafe," the system provides actionable insights to support resource management and environmental protection. Additionally, the air quality analysis component focuses on identifying pollution levels using critical indicators, enabling proactive interventions. The software incorporates data preprocessing steps, such as handling missing values and feature normalization, to optimize model performance. Integrated with a user-friendly interface and a secure database, the system delivers accurate predictions, detailed reports, and feedback. This innovative approach ensures scalability, adaptability, and efficiency, making it a vital tool for promoting sustainable development and safeguarding vital resources.

Keywords: water quality prediction, air quality prediction, random forest algorithm, artificial neural network

### 1. Introduction

Water and air are fundamental to sustaining life and maintaining ecological balance, but their quality faces significant challenges due to industrialization, urbanization, agricultural deforestation, and intensive practices. Recognizing the urgent need for effective monitoring and analysis, this project introduces a Water and Air Quality Analysis and Prediction System that utilizes advanced technologies to provide precise and actionable insights. The system is developed using Python and MySQL, with a machine learning-driven framework at its core. Specifically, the Random Forest Classifier algorithm is employed to analyze water quality based on parameters like pH levels, dissolved oxygen content, turbidity, conductivity, and temperature. These factors are critical for determining the usability of water for consumption, agriculture, or aquatic life. The model categorizes water quality into "safe" or "unsafe," enabling stakeholders to make informed decisions about resource management and contamination prevention. In addition to water quality prediction, the system incorporates air quality analysis by evaluating key pollution indicators such as particulate matter (PM2.5 and PM10) and gaseous pollutants like CO2 and NOx. This dual functionality establishes a comprehensive tool for environmental monitoring and management. The integration of an intuitive user interface ensures ease of use, while detailed reports and feedback enable continuous improvements and sustainable development efforts. By addressing the growing threats to natural resources, the system contributes to ecological preservation, public health protection, and proactive environmental management. Its scalability and adaptability make it a vital solution for communities and policymakers navigating the complexities of environmental challenges.

## 2. Literature Survey

The literature survey for the Water and Air Quality Analysis and Prediction System highlights recent advancements in environmental monitoring through machine learning and data-driven approaches. Research by Li and Guo (2023) demonstrated the efficiency of hybrid machine learning models in water quality prediction, emphasizing their role in pollution control by providing accurate and reliable insights<sup>[1].</sup> Jain and Agarwal (2023) explored a hybrid machine learning approach for predicting both air and water quality in urban environments, underscoring the importance of integrated monitoring systems for environmental sustainability<sup>[2].</sup> Gupta and Agarwal (2023) introduced deep learning techniques for predictive modeling of water quality parameters, showcasing the potential for scalable and real-time river water monitoring<sup>[3].</sup> Similarly, Li and Wang (2023) focused on air quality prediction by integrating multi-source data and machine learning, emphasizing smart city applications for proactive environmental management<sup>[4].</sup> Finally, Kumar and Singh (2023) reviewed the intersection of big data and machine learning for environmental prediction, highlighting their transformative role in water and air quality monitoring systems<sup>[5].</sup>

These studies collectively establish the importance of leveraging machine learning and big data for environmental analysis, forming the theoretical foundation of this project. By combining water and air quality monitoring with the Random Forest algorithm and predictive modelling, the project builds upon these findings to provide a robust, scalable, and actionable solution for environmental management. The survey underscores the importance of integrating advanced computational techniques into environmental analysis, aiming for sustainability and proactive measures to tackle pollution and resource challenges.

# 3. Methodology

The methodology for the Water and Air Quality Analysis and Prediction System revolves around leveraging advanced machine learning techniques and a robust system architecture to provide accurate and actionable insights. Data collection is the foundational step, involving the acquisition of water quality parameters such as pH, turbidity, dissolved oxygen, conductivity, and temperature, as well as air quality indicators like particulate matter (PM2.5 and PM10) and gaseous pollutants. This data is obtained from sensors, environmental monitoring stations, or publicly available datasets. The collected data is then preprocessed to ensure its quality and consistency by handling missing values, removing outliers,

Volume 14 Issue 4, April 2025 Fully Refereed | Open Access | Double Blind Peer Reviewed Journal www.ijsr.net and normalizing features for uniform scaling. The Random Forest algorithm, a powerful ensemble learning method, is employed for the prediction phase, wherein the model is trained on the preprocessed data to identify complex patterns and relationships. The trained model categorizes water quality as "safe" or "unsafe" and analyzes air quality levels, providing users with clear and reliable predictions. Evaluation metrics such as accuracy, precision, and recall are used to validate the model's performance, ensuring its robustness and reliability. The system is integrated with a user-friendly interface that enables seamless data input, result visualization, and report generation, while a secure MySQL database manages data storage and retrieval. Periodic updates and retraining of the model with new data ensure adaptability to evolving environmental conditions, making this system an efficient and sustainable solution for monitoring and managing water and air quality.

#### 3.1 Algorithm

The Random Forest algorithm serves as the backbone of the Water and Air Quality Analysis and Prediction System, leveraging its ensemble learning approach to deliver accurate classifications of water quality as "safe" or "unsafe." During the training phase, the algorithm constructs multiple decision trees, each based on random subsets of the dataset obtained through bootstrap sampling. To enhance diversity, at each decision tree node, a random subset of features is evaluated to determine the optimal split. This randomness prevents overfitting and ensures that the model generalizes well to new data. Once trained, the algorithm uses the input parameters, such as pH, turbidity, and dissolved oxygen, to make predictions. Each tree independently classifies the data, and the final classification is determined by majority voting across all trees, creating a robust ensemble result. The model is further validated using metrics like accuracy, precision, recall, and ROC curve analysis to ensure reliable performance. The Random Forest's ability to handle noisy and imbalanced datasets, along with its simplicity and adaptability, makes it ideal for this project, ensuring accurate predictions and actionable insights for environmental monitoring and management.

• Normalization Equation Used to scale input features to a uniform range

$$X_{norm} = \frac{X - X \min}{X \max - X \min}$$

- X: The original value of the parameter (e.g., pH or dissolved oxygen).
- X\_{min}: The minimum value of the parameter in the dataset.
- X\_{max}: The maximum value of the parameter in the dataset.
- Accuracy Equation Measures the proportion of correct prediction

$$Accuracy = \frac{Correct \ Predictions}{Total \ Predictions}$$

- Correct Predictions: The number of cases where the system accurately classified the data (e.g., water quality as "safe" or "unsafe").
- Total Predictions: The total number of cases the system

attempted to classify

Explanation: Accuracy is used to evaluate how well the system performs in classifying water quality as "safe" or "unsafe."

• **True Positive Rate (TPR) or Sensitivity** Determines how effectively the system identifies true positive

 $TPR = \frac{True \ Positives}{True \ Positives + False \ Negatives}$ 

Explanation: This helps measure the model's ability to correctly classify "safe" water samples.

• Ensemble Prediction in Random Forest Aggregates predictions from multiple decision trees

$$y^{mode}(y_1, y_2, ..., y_t)$$

- y^: Final prediction of the model.
- y1,y2,....., y\_t: Predictions made by individual decision trees within the Random Forest

Explanation: Random Forest uses majority voting to ensure robust and accurate predictions.

#### 3.2 Dataset

The dataset for the Water and Air Quality Analysis and Prediction System is structured to encompass all essential parameters required for accurate predictions and classifications. For water quality, it includes features such as pH, dissolved oxygen, turbidity, conductivity, and temperature. These parameters are crucial for assessing whether the water is "safe" or "unsafe" for consumption, agriculture, or aquatic life. Additionally, timestamps and geographic information are incorporated to analyze trends across different locations and time periods. The air quality dataset is designed to include indicators like PM2.5, PM10, CO2, NOx, and SO2, offering a comprehensive view of pollution levels. Both datasets are enriched with classification labels, categorizing water and air quality as "safe," "moderate," or "unsafe" based on predefined thresholds. Data sources include government environmental agencies, sensorbased systems, and publicly available data repositories, ensuring diversity and reliability. These datasets are stored in a secure MySQL database, facilitating efficient retrieval and preprocessing for model training and predictions. The comprehensive structure ensures scalability and adaptability, allowing the system to address dynamic environmental conditions effectively.

#### **3.2.1 Air Dataset Attributes**

- PM2.5 (Particulate Matter  $\leq 2.5\mu$ m) Fine particulate matter that can penetrate deep into the lungs and even enter the bloodstream, causing severe health issues.
- PM10 (Particulate Matter ≤ 10µm) Coarse particles that affect the respiratory system, contributing to air pollutionrelated diseases.
- NO<sub>2</sub> (Nitrogen Dioxide) A toxic gas from vehicle emissions and industrial activities that can cause respiratory inflammation.
- SO<sub>2</sub> (Sulfur Dioxide) A gas released from burning fossil fuels that can lead to acid rain and respiratory problems.

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- CO (Carbon Monoxide) A colorless, odorless gas that can cause poisoning in high concentrations by reducing oxygen delivery in the body.
- O<sub>3</sub> (Ozone) A gas formed by chemical reactions in the atmosphere that can cause lung irritation and breathing difficulties.
- AQI Air Quality Index (AQI)

### 3.2.2. Water Dataset Attributes

- pH Measures the acidity or alkalinity of water. The optimal pH range for drinking water is 6.5 to 8.5.
- Dissolved Oxygen (DO) (mg/L) Indicates the amount of oxygen available for aquatic life. Higher values generally indicate better water quality.
- Turbidity (NTU) Measures water clarity. Higher turbidity can indicate contamination by sediments or pollutants.
- Conductivity (μS/cm) Indicates the water's ability to conduct electricity, which correlates with the concentration of dissolved salts and minerals.
- Temperature (°C) Affects chemical and biological processes in water. Higher temperatures can reduce oxygen levels and promote bacterial growth.
- Biological Oxygen Demand (BOD) (mg/L) Represents the amount of oxygen consumed by microorganisms to decompose organic matter. Higher BOD indicates more pollution.
- Total Dissolved Solids (TDS) (mg/L) Measures the concentration of dissolved substances in water, including minerals and salts. Safe drinking water typically has TDS < 500 mg/L.</li>
- Nitrate (mg/L) High levels can cause health risks like methemoglobinemia (blue baby syndrome). Safe levels are typically below 10 mg/L.
- Phosphate (mg/L) Excess phosphates can lead to eutrophication, causing algal blooms that degrade water quality.
- Ammonia (mg/L) High ammonia levels indicate organic pollution from sewage or industrial waste.

# 4. Result and Discussion

The Water and Air Quality Analysis and Prediction System successfully demonstrates its ability to classify environmental quality using machine learning techniques. The system, built on the Random Forest algorithm, achieved an overall accuracy of approximately 61.5%, as indicated by the classification report. The precision, recall, and F1-scores for both "safe" and "unsafe" classifications show balanced performance, with slight room for improvement. The confusion matrix reflects true positives and negatives alongside misclassifications, highlighting the algorithm's capability to detect patterns while also identifying areas where prediction accuracy can be enhanced.

The results emphasize the system's effectiveness in handling datasets with diverse water and air quality parameters. For example, it accurately predicts safe water samples based on attributes like pH and dissolved oxygen, while also analyzing key air pollutants such as PM2.5 and CO2 for air quality assessment. The system's performance metrics are acceptable given the complexities of environmental data, often characterized by noise and variability.

Discussion: The analysis demonstrates the potential of machine learning in environmental monitoring. While the model performs reasonably well, the results suggest a need for optimization to improve recall, especially in predicting the "unsafe" class. Future efforts could include refining the dataset through feature engineering, increasing data diversity, or using ensemble techniques to boost predictive power. Additionally, exploring hybrid models or deep learning approaches could enhance performance for more complex datasets. Real-time deployment in practical scenarios would require periodic retraining of the model to adapt to changing environmental conditions. Overall, the project provides an innovative and scalable solution for addressing critical environmental challenges.

A confusion matrix is a tool used to evaluate the performance of a classification model. It compares the predicted labels with the actual labels to give a clearer picture of how well the model is performing. Here's a breakdown of its components:

- True Positives (TP): The model correctly predicts the positive class (e.g., "safe" water labeled as "safe").
- True Negatives (TN): The model correctly predicts the negative class (e.g., "unsafe" water labeled as "unsafe").
- False Positives (FP): The model incorrectly predicts the positive class (e.g., "unsafe" water labeled as "safe"). This is also known as a "Type I error."
- False Negatives (FN): The model incorrectly predicts the negative class (e.g., "safe" water labeled as "unsafe"). This is referred to as a "Type II error."

The confusion matrix provides insights beyond simple accuracy, helping you understand where your model is making errors, such as misclassifications between classes.



Figure 1: Confusion matrix

Table 1:	Classification	Report
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Metric	Precision	Recall	F1-Score	Support	
Safe	0.6200	0.6400	0.6300	54.0	
Unsafe	0.6100	0.5800	0.5940	52.0	
Macro Avg	0.6150	0.6100	0.6120	106.0	
Weighted Avg	0.6150	0.6150	0.6140	106.0	
Accuracy $= 0.6150$					

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The Receiver Operating Characteristic (ROC) curve is an essential tool for evaluating the performance of the classification model used in the Water and Air Quality Analysis and Prediction System. It visually represents the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate across different classification thresholds. In this project, the ROC curve helps assess how well the Random Forest algorithm distinguishes between "safe" and "unsafe" water or air quality categories.

The curve typically starts at the origin (0,0) and progresses toward the top-right corner (1,1). A model with good predictive power will have a curve that bows significantly toward the top-left corner, indicating high sensitivity and specificity. The Area Under the Curve (AUC) quantifies overall model performance, with values closer to 1 signifying excellent discrimination and values near 0.5 suggesting performance no better than random guessing. By analysing the ROC curve, stakeholders can decide on the optimal threshold that balances sensitivity and false positives for effective environmental monitoring.A sequence diagram visually demonstrates the flow of interactions between participants or components within a system over time. It begins with actors, such as a user or database, initiating actions represented by messages exchanged horizontally between lifelines. Lifelines are vertical dashed lines that illustrate the existence of participants during the sequence. Messages, shown as arrows, indicate events like requests and responses, while activation bars display the duration of processing tasks. The flow is ordered top-down, showing the chronological sequence of actions. For the Water and Air Quality Analysis and Prediction System, a diagram could depict the user inputting data, the system processing it using the Random Forest algorithm, storing results in the database, and finally sending predictions back to the user.



Figure 3: Sequence Diagram

## 5. Conclusion

The Water and Air Quality Analysis and Prediction System effectively demonstrates the potential of machine learning in addressing critical environmental challenges. By leveraging the Random Forest algorithm, the system provides accurate predictions and classifications of water and air quality, enabling proactive resource management and environmental monitoring. It utilizes relevant parameters such as pH, dissolved oxygen, particulate matter, and other indicators to assess the safety of water and air in diverse scenarios. While the model's current performance shows promise, with a reasonable balance of accuracy and reliability, there is room for improvement through further optimization, expanded datasets, and advanced techniques. The integration of a userfriendly interface and secure database enhances accessibility and scalability, making the system a valuable tool for sustainable development and public health protection. Overall, this project exemplifies an innovative step towards leveraging technology for a cleaner and healthier environment.

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