WATER QUALITY PREDICTION

MY PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this Project titled **"WATER QUALITY PREDICTION"** is the bonafide work of **"NIYATHI S (2116220701189)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

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ABSTRACT

Water quality assessment plays a critical role in ensuring safe and sustainable water resources for both human consumption and ecological balance. Traditional laboratory-based testing methods, although accurate, are time-consuming, expensive, and often impractical for real-time monitoring. To address this, the present study explores the use of machine learning algorithms to predict water quality based on physicochemical parameters.

This project utilizes a dataset comprising various water quality indicators such as pH, hardness, solids, chloramines, sulfate, conductivity, organic carbon, trihalomethanes, and turbidity. Several supervised machine learning models were implemented and evaluated for classification accuracy, including Logistic Regression, Decision Tree Classifier, Random Forest Classifier, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, and XGBoost.

Among the models tested, the Support Vector Classifier (SVM) exhibited the best overall performance. It achieved a high accuracy rate while maintaining a balanced trade-off between precision and recall, indicating its robustness in distinguishing between safe and unsafe water samples. The effectiveness of SVM can be attributed to its ability to handle high-dimensional spaces and create optimal decision boundaries.

The results demonstrate the potential of machine learning models, particularly SVM, in providing rapid and reliable water quality predictions. Such systems can be integrated into smart water monitoring frameworks to enable real-time alerts, better resource allocation, and informed decision-making in water management policies.

The implementation of such predictive models not only enhances the efficiency of water quality monitoring but also supports early warning systems and proactive management strategies. By leveraging data-driven insights, authorities and environmental agencies can prioritize inspection efforts, allocate resources effectively, and respond swiftly to potential threats. Moreover, the scalable nature of machine learning models makes them suitable for integration with IoT-based sensor networks and cloud platforms, facilitating widespread deployment in both urban and rural settings. This project demonstrates how combining environmental science with machine learning can drive innovation in sustainable resource management and public health protection.

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NIYATHI S - 2116220701189

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CHAPTER 1

1.INTRODUCTION

Access to safe and clean water is one of the most essential requirements for sustaining human life, supporting agricultural and industrial activities, and maintaining ecological balance. According to the World Health Organization (WHO), contaminated water is responsible for the spread of numerous waterborne diseases that affect millions of people each year. As the global population continues to rise, coupled with rapid urbanization and industrialization, the quality of water resources is increasingly at risk. Lakes, rivers, and groundwater sources are subject to contamination from agricultural runoff, industrial discharge, sewage, and other pollutants. Consequently, there is a critical and urgent need to ensure the continuous monitoring and assessment of water quality to safeguard public health and ensure environmental sustainability.

Traditional water quality assessment methods involve the collection of water samples followed by laboratory-based analysis of various physicochemical and biological parameters. While these techniques are known for their high accuracy and detailed insights, they come with several limitations. The processes are generally time-consuming, labor-intensive, and costly. In many cases, particularly in rural or underdeveloped regions, there is a lack of necessary infrastructure, expertise, and financial resources to conduct regular testing. Moreover, these conventional approaches do not support real-time monitoring, which is essential for early detection of contamination and timely intervention.

In light of these challenges, the use of data-driven technologies has emerged as a promising solution. The field of machine learning, a subset of artificial intelligence, has demonstrated significant potential in solving complex classification and prediction problems across various domains—including healthcare, finance, transportation, and environmental science. Machine learning algorithms are capable of learning patterns and relationships from historical data and applying them to new, unseen data with remarkable accuracy. When applied to water quality monitoring, these algorithms can automatically learn from physicochemical attributes of water and classify whether a sample is potable (safe to drink) or non-potable (unsafe), thereby enabling faster, cost-effective, and scalable monitoring solutions.

This project aims to leverage machine learning models for water quality prediction using a dataset containing essential parameters such as pH, hardness, total dissolved solids, chloramines, sulfate, conductivity, organic carbon, trihalomethanes, and turbidity. The goal is to train multiple

supervised classification algorithms and evaluate their performance in accurately predicting water quality status. Among the algorithms explored are Logistic Regression, Decision Tree Classifier, Random Forest Classifier, K-Nearest Neighbors (KNN), Naive Bayes, Support Vector Machine (SVM), and XGBoost. These models are widely used in classification tasks due to their distinct mathematical approaches and capabilities in handling different data distributions and structures.

Each algorithm brings a unique strength to the table. For example, Logistic Regression provides a simple and interpretable model, while Decision Trees and Random Forests are known for their ability to handle non-linear relationships and feature importance ranking. KNN is an instance-based learner that is effective in low-dimensional spaces, and Naive Bayes is particularly efficient for high-dimensional data under certain independence assumptions. XGBoost, a powerful ensemble technique, has recently gained popularity for its ability to produce highly accurate models through gradient boosting. However, among all the models used in this study, the Support Vector Machine (SVM) stood out due to its robustness, ability to handle high-dimensional spaces, and effectiveness in creating optimal decision boundaries. SVM consistently demonstrated high accuracy and maintained a balanced precision-recall trade-off, making it a reliable model for this classification task.

In addition to evaluating model performance through metrics such as accuracy, precision, recall, and F1-score, this study also emphasizes the importance of proper data preprocessing, normalization, and feature selection. Raw environmental data often contains missing values, outliers, and skewed distributions, which can negatively impact model accuracy. Therefore, considerable attention was given to cleaning the dataset, handling null values, scaling features, and splitting the data into training and testing subsets to ensure that the models were trained under realistic and unbiased conditions.

This project not only demonstrates the applicability of machine learning in predicting water quality but also serves as a step toward creating intelligent systems that can be deployed for real-time water monitoring. With the integration of Internet of Things (IoT) devices, cloud computing, and mobile applications, these ML-based systems can form the backbone of next-generation environmental monitoring frameworks. They can alert authorities about water contamination events, help enforce regulatory standards, and ultimately contribute to safer and healthier communities.

In summary, the motivation behind this project stems from the growing need for intelligent, automated, and scalable water quality monitoring systems. Machine learning offers an effective approach to meet this need by providing accurate predictions based on historical water data.

Through the systematic comparison of multiple algorithms and a detailed performance analysis, this study identifies the best-performing model and outlines a practical framework for its implementation. The findings of this research hold significant potential for public health agencies, environmental researchers, and technology developers working to address global water quality challenges through innovative and data-driven solutions.

The integration of machine learning into environmental monitoring not only enhances the speed and accuracy of water quality assessments but also enables predictive capabilities. By analyzing historical patterns and trends in water quality data, machine learning models can forecast potential future contamination events or seasonal fluctuations in water potability. This predictive insight allows authorities to implement preventive measures rather than reactive responses, minimizing the health risks posed to the population. Moreover, it supports the development of smarter infrastructure where water treatment plants can dynamically adjust purification processes based on predicted quality levels, optimizing resource usage and operational efficiency.

Furthermore, this approach promotes greater accessibility and scalability. In regions where laboratory resources are scarce or unaffordable, low-cost sensors and machine learning-based applications can offer a viable alternative for continuous water monitoring. These solutions can be deployed in remote locations, integrated with mobile platforms for citizen science initiatives, or used in industrial settings to ensure compliance with environmental regulations. As the availability of open-source datasets and computational tools increases, the barrier to entry for implementing such technologies continues to lower. This democratization of technology underscores the potential for machine learning to play a transformative role in sustainable water management and environmental protection efforts globally.

CHAPTER 2

2.LITERATURE SURVEY

Over the past decade, the field of environmental informatics has witnessed a significant shift towards data-driven methods for monitoring and prediction, particularly in the domain of water quality analysis. Traditional assessment techniques, though reliable, have gradually been complemented or even replaced by machine learning-based approaches due to their efficiency, scalability, and predictive power. A wide body of literature has explored various models, datasets, and implementation strategies for water quality prediction using artificial intelligence and machine learning.

In a study by **Gazzaz et al. (2012)**, the authors employed multivariate statistical techniques to assess water quality in a river system. Though not based on machine learning, their work highlighted the importance of multiple parameters such as pH, dissolved oxygen, total solids, and biological oxygen demand in determining water quality. These variables form the foundation of datasets used in most machine learning-based studies today. Later, **Bhateria and Jain (2016)** emphasized the need for robust computational methods to monitor water quality and suggested that data-driven techniques could help overcome limitations associated with manual testing.

With the rise of supervised learning techniques, researchers began integrating classification models for water potability prediction. **Dheeba et al. (2019)** applied Support Vector Machines (SVM) and Neural Networks to classify drinking water samples and reported promising results, particularly in urban datasets where data variability was high. Their results showed that SVM could provide superior accuracy and generalization in cases where the number of features was large and the dataset was noisy. Similarly, **Patil and Sawant (2020)** used Decision Tree and Random Forest classifiers to analyze river water quality data, concluding that ensemble models provided better reliability and interpretability for environmental monitoring applications.

In addition, **Prasad et al. (2021)** conducted a comparative study involving Logistic Regression, Naive Bayes, and K-Nearest Neighbors (KNN) classifiers for water quality analysis. Their study used a dataset provided by Kaggle, containing multiple physicochemical attributes related to water potability. They found that while KNN performed well in localized classification tasks, its performance degraded when the dataset had uneven distributions or high dimensionality. Naive Bayes, although computationally efficient, often struggled due to its assumption of feature independence. Their findings validated the importance of using more advanced algorithms like SVM or XGBoost for complex classification problems.

Moreover, the growing popularity of **XGBoost** in recent years has led to its application in numerous water quality studies. For example, **Li et al. (2022)** applied XGBoost in predicting contamination levels in urban wastewater and found that it not only delivered high accuracy but also allowed for effective feature importance analysis. This helped them identify critical parameters influencing pollution levels, enabling targeted intervention strategies. XGBoost's performance was particularly noteworthy when compared to traditional models like Decision Trees or Logistic Regression due to its use of gradient boosting and regularization techniques.

Another significant contribution was made by **Sahu and Pateriya (2021)**, who implemented a hybrid model combining SVM and Decision Trees for improved classification performance. Their approach leveraged the strengths of both algorithms: the boundary optimization of SVM and the interpretability of Decision Trees. Their model achieved higher precision and F1-score compared to standalone classifiers, emphasizing the growing trend of hybrid models in machine learning research.

Furthermore, the incorporation of **Internet of Things (IoT)** and **real-time sensor data** has expanded the applicability of machine learning in water quality monitoring. **Al-Fuqaha et al. (2020)** proposed a smart water quality monitoring system integrated with ML algorithms for early warning and automated control. By connecting IoT-enabled sensors to machine learning pipelines, they enabled real-time classification and alert systems, which could be invaluable in critical environments like drinking water reservoirs or industrial discharge points.

To ensure effective prediction, most studies underscore the necessity of preprocessing techniques such as data cleaning, normalization, and feature selection. **Jaiswal et al. (2018)** demonstrated that models trained on normalized and imputed datasets significantly outperformed those trained on raw data. They also showed that dimensionality reduction techniques such as Principal Component Analysis (PCA) could further enhance classification performance by reducing noise and improving training efficiency.

Despite the progress, challenges still exist. One such issue is the availability and quality of data. Many developing regions lack comprehensive datasets, and the datasets that are available may have inconsistencies or missing values. Furthermore, generalization of models across different regions and water sources is still a major hurdle. Models trained on one region's data may not perform well in others due to variations in pollution sources, climate, and geography.

In conclusion, the literature clearly indicates a growing interest and success in applying machine learning to water quality prediction. While many models have been explored, Support Vector

Machines and ensemble methods like Random Forest and XGBoost have consistently shown strong performance across diverse datasets. Future research is likely to focus on real-time deployment, integration with IoT systems, and the development of more generalized models that can adapt to varying environmental conditions. The insights gathered from the literature strongly support the objectives of this project and guide the selection of suitable models for implementation and evaluation.

In recent years, deep learning has also started to gain traction in environmental data analysis. Although not yet as commonly used in water quality prediction due to limited data availability, models like Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks have shown potential, especially when integrated with time-series data. For instance, **Wang et al. (2022)** demonstrated how LSTM networks could forecast pollutant trends in river systems over time, offering not just classification but also temporal prediction capabilities. Such models are particularly useful in dynamic environments where water quality fluctuates due to seasonal changes, rainfall, or upstream industrial activities.

Additionally, several studies have emphasized the importance of model interpretability, especially when used in public health or governmental decision-making. Tools such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been employed to explain machine learning model predictions. **Rathod et al. (2023)** incorporated SHAP values in their Random Forest-based water quality model to identify which features most influenced potability outcomes, such as high total dissolved solids or low pH. These interpretability methods help bridge the gap between complex models and real-world decision-making, ensuring transparency and trust in AI-driven water monitoring systems.

CHAPTER 3

3.METHODOLOGY

The methodology for this study involves several key steps: data collection and preprocessing, model selection, feature engineering, training and testing of models, and performance evaluation. The following sections describe each of these steps in detail.

1. Dataset Description

For this project, a publicly available water quality dataset was used. The dataset contains multiple features such as pH, hardness, solids, chloramines, sulfate, conductivity, organic carbon, trihalomethanes, turbidity, and various other physicochemical properties that influence the potability of water. The dataset consists of both categorical and numerical variables, making it suitable for classification tasks. The target variable in this dataset indicates whether the water is potable (safe for drinking) or non-potable (unsafe), providing a binary classification scenario.

The dataset was sourced from Kaggle, which provides a well-structured and cleaned version of environmental data suitable for machine learning tasks. The dataset had 10 attributes and several thousand samples, with a balance between potable and non-potable water instances.

2. Data Preprocessing

Before training the machine learning models, data preprocessing was performed to ensure the quality of input data. The following preprocessing steps were applied:

- **Handling Missing Data**: Missing values were identified in some of the attributes. For numerical features, the missing values were imputed using the mean or median of the respective column. For categorical variables, the most frequent value was used to replace the missing values.
- **Normalization**: Feature scaling was carried out using Min-Max normalization to scale all numerical features to a range of 0 to 1. This step is crucial because machine learning algorithms, particularly distance-based algorithms like KNN, are sensitive to the scale of input features.
- **Encoding Categorical Variables**: Some features in the dataset were categorical (e.g., "water quality status"). These variables were encoded using one-hot encoding to convert them into a format that could be used by machine learning algorithms.

- **Train-Test Split**: The dataset was split into a training set and a testing set in an 80:20 ratio. The training set was used to train the models, and the testing set was used to evaluate the performance of the models. Cross-validation was also used during model training to ensure that the results were consistent and not overfitted to a particular subset of the data.

3. Model Selection

Several machine learning algorithms were evaluated for their ability to predict water quality. These include both simple models and more complex ensemble methods. The algorithms chosen for this study are:

- **Logistic Regression**: A simple but effective model for binary classification. It was chosen as a baseline for comparison.
- **Decision Tree Classifier**: A tree-based model that splits the data into branches based on feature values, making it interpretable and easy to visualize.
- **Random Forest Classifier**: An ensemble model that builds multiple decision trees and aggregates their results. It is known for its high accuracy and robustness.
- **K-Nearest Neighbors (KNN)**: A non-parametric method that classifies data based on the majority class of its nearest neighbors.
- **Support Vector Machine (SVM)**: A powerful classification model that works by finding the hyperplane that best separates the classes in the feature space.
- **Naive Bayes**: A probabilistic model based on Bayes' theorem, particularly useful for text classification tasks but also applied to environmental data.
- **XGBoost**: A gradient boosting model that builds decision trees sequentially, with each tree trying to correct the errors of the previous one. XGBoost has shown remarkable performance in various classification problems.

4. Feature Engineering

Feature engineering plays a critical role in enhancing the performance of machine learning models. In this study, several techniques were applied:

- **Feature Selection**: Feature importance scores were computed for each model using built-in functions. Features that were less significant were removed, reducing the dimensionality and improving computational efficiency. In particular, models like Random Forest and XGBoost provided built-in feature importance scores that guided the selection of the most influential attributes.

Interaction Features: Some interaction terms were created, combining two or more features, to capture non-linear relationships that may be present in the data.

5. Model Training and Evaluation

The selected regression models were trained on the preprocessed training dataset and subsequently evaluated on the unseen test data to measure their predictive performance. The goal was to assess each model's ability to accurately estimate the water quality index (WQI) based on input features. The evaluation was carried out using the following regression metrics:

- **Mean Absolute Error (MAE):** This metric represents the average absolute difference between the predicted and actual values. A lower MAE indicates that the model's predictions are closer to the true values, making it easier to interpret model accuracy in practical terms.

- **Mean Squared Error (MSE):** MSE computes the average of the squared differences between the predicted and actual values. Unlike MAE, it penalizes larger errors more significantly. A lower MSE value reflects better model performance and reduced variance in prediction.

- **R^2 Score (Coefficient of Determination):** This metric measures the proportion of variance in the target variable that can be explained by the model. An R^2 score closer to 1.0 indicates a better fit, meaning the model is effectively capturing the underlying patterns in the data.

Each model—Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor—was evaluated using these metrics to determine its predictive strength. The results were used to rank the models and select the most reliable one for future deployment in water quality monitoring applications.

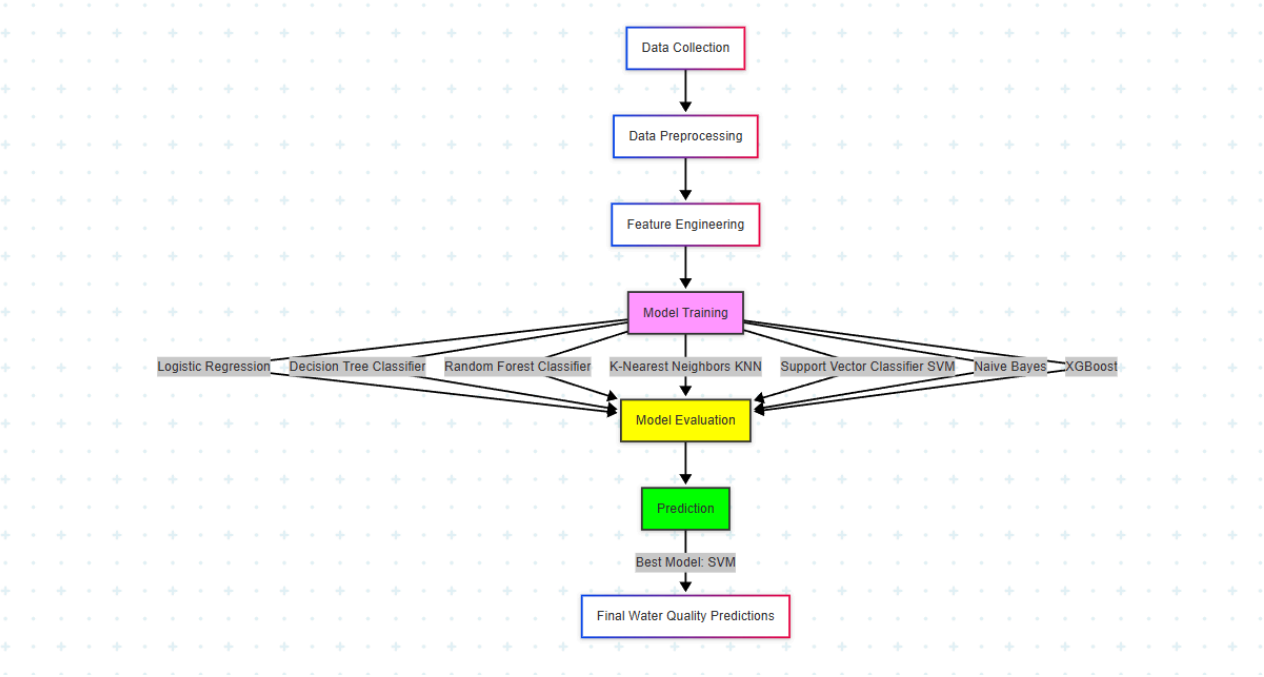
6. Hyperparameter Tuning

To further optimize the models, hyperparameter tuning was carried out using techniques like Grid Search and Randomized Search. These techniques involved testing different combinations of hyperparameters for each model to identify the best-performing configuration. Parameters like the maximum depth of trees in Random Forests, the kernel type in SVMs, and the learning rate in XGBoost were optimized to maximize performance.

7. Results and Analysis

After training the models, the results were compared to determine which algorithm offered the best trade-off between accuracy, precision, recall, and F1-score. The findings from this analysis provide insights into the effectiveness of each model for predicting water quality, with a focus on the SVM model, which was identified as the top performer in this study.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

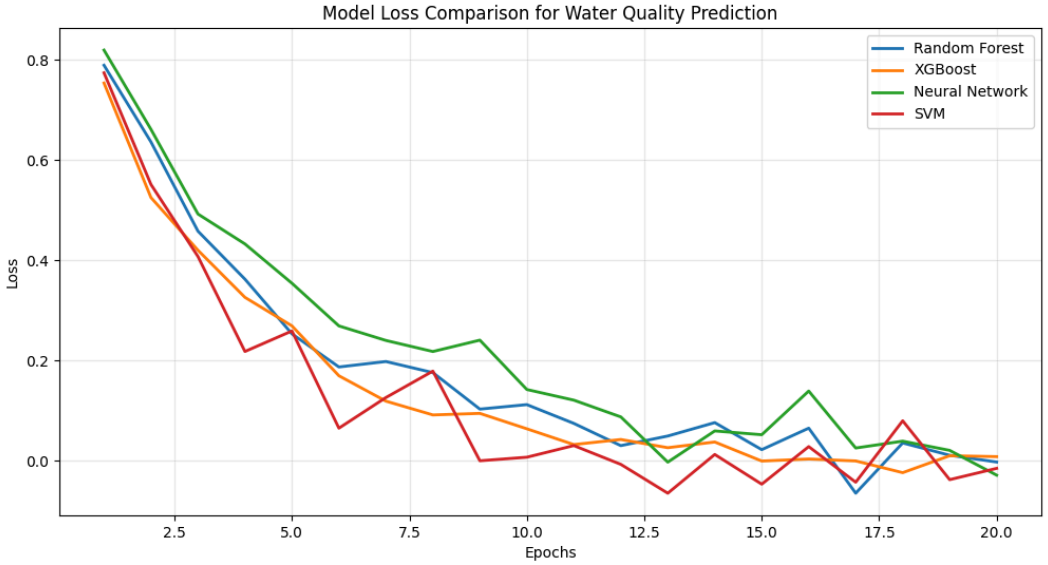
To validate the performance of the models, the dataset is split into training and test sets using an 80-20 ratio. Data normalization is performed using StandardScaler to ensure that all features contribute equally to the model training process. Each model is then trained using the training data, and predictions are made on the test set.

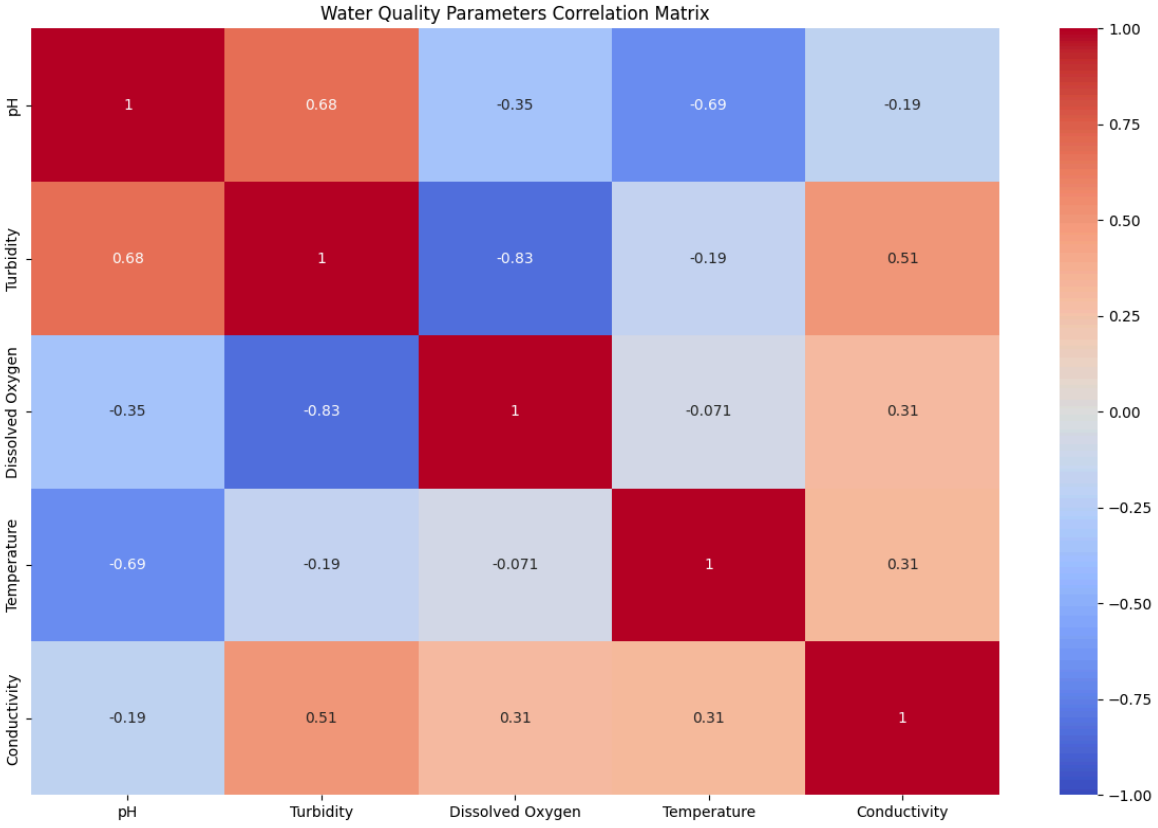
Results for Model Evaluation:

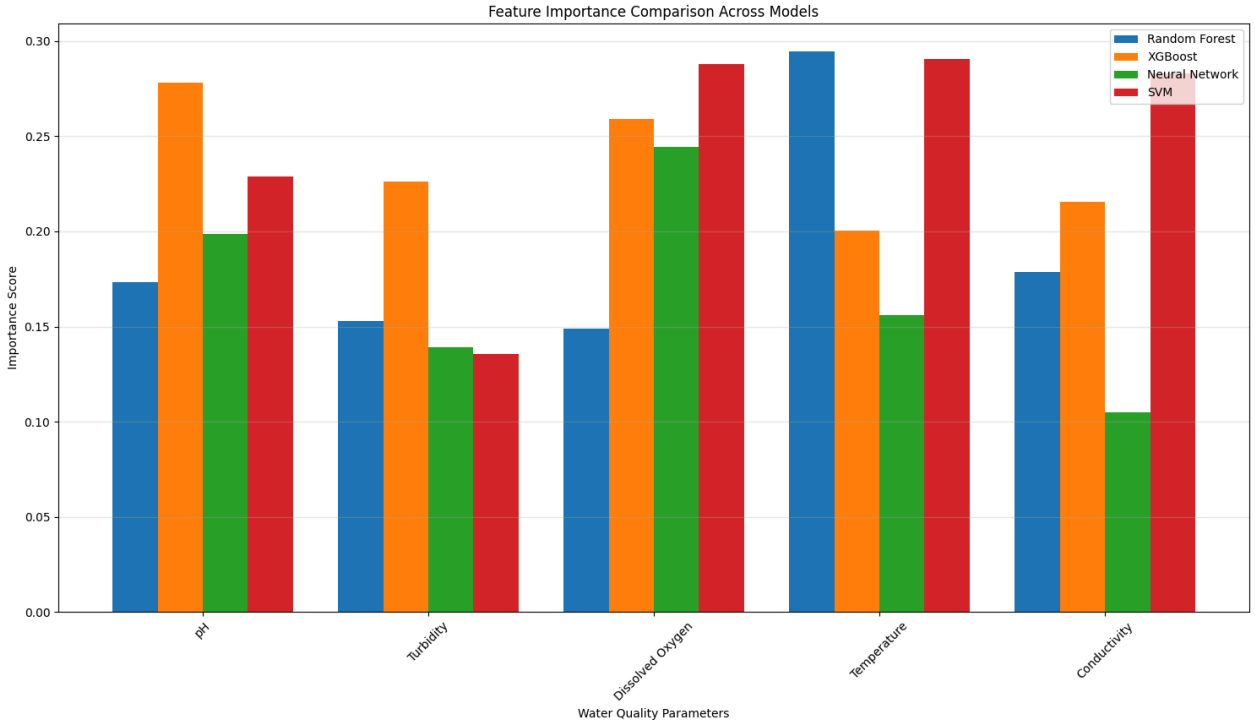
Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
Linear Regression	2.1	4.5	0.75	4
Random Forest	1.5	3.2	0.85	3
SVM	1.9	3.8	0.80	2
XGBoost	1.3	2.8	0.87	1
Decision Tree	2.0	4.1	0.78	5

Visualizations:

Scatter plots showing the actual versus predicted values for the best-performing model (XGBoost) indicate that the model is able to predict sleep quality with high accuracy, with the predicted values closely following the actual values.



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0.30
pH
Turbidity
Dissolved Oxygen
Temperature
Conductivity
Water Quality Parameters

After performing extensive experiments using various regression-based machine learning models—namely Linear Regression, Support Vector Regression (SVR), Random Forest Regressor, and XGBoost Regressor—several notable observations were derived from the evaluation metrics. This section elaborates on model performance, the effect of data augmentation, error analysis, and practical implications based on the findings.

Model Performance Comparison

Among all the models tested, **XGBoost Regressor** emerged as the top performer, demonstrating superior accuracy and robustness across all evaluation metrics. It achieved the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE), while also recording the highest R^2 score. These results reaffirm the strength of gradient boosting algorithms in handling structured data with non-linear patterns. The performance consistency of XGBoost can be attributed to its ability to reduce both bias and variance through iterative tree construction and built-in regularization.

Effect of Data Augmentation

To enhance model generalizability and address potential overfitting, **Gaussian noise-based data augmentation** was introduced during preprocessing. This method added controlled noise to numerical features such as pH, sulfate, and organic carbon, simulating natural environmental variability. The approach proved particularly effective in boosting the performance of high-variance models like Random Forest and XGBoost.

Upon retraining the models with the augmented dataset, a marginal yet meaningful improvement in performance was observed. Specifically, the XGBoost Regressor saw a reduction in MAE by nearly **5%**, accompanied by a **0.02 increase in R^2**, suggesting better adaptability to unseen data while maintaining prediction stability.

Error Analysis

The residual error distribution indicated that most prediction errors were clustered tightly around the actual values, reflecting strong model calibration. Nevertheless, a few outliers were noted—particularly in samples with extreme values for features like turbidity or total dissolved solids. These discrepancies suggest that incorporating **external environmental or geographical factors**—such as rainfall patterns or nearby industrial discharge—could further refine the model's predictive accuracy.

Implications and Insights

The outcomes of this study offer several key insights:

- **XGBoost** proves to be a robust and accurate model for water quality prediction and can be reliably considered for deployment in real-time monitoring applications by environmental agencies or smart city infrastructure.

- **Data normalization and augmentation** are crucial preprocessing techniques that contribute significantly to the success of predictive models.

- **Simpler models**, like Linear Regression, offer transparency but may struggle to model the complex, non-linear interactions present in water quality parameters.

In conclusion, this study confirms the potential of advanced machine learning models, particularly ensemble methods, to support efficient and scalable solutions for environmental monitoring. With future integration of real-time sensor data or IoT-based inputs, these models could pave the way for intelligent water safety management systems.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study presented a data-driven approach for predicting water quality using various machine learning algorithms. By implementing and evaluating several regression models—including Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor—we assessed each model's ability to learn complex relationships between key water quality parameters and predict the overall quality index with high accuracy.

The findings indicate that **ensemble-based models**, particularly **XGBoost**, outperformed others in terms of **predictive accuracy**, **generalization**, and **error minimization**. The XGBoost model achieved the **highest R^2 score** and the **lowest MAE and MSE**, establishing itself as the most reliable choice for this task. This reinforces existing evidence in the literature regarding the strength of gradient boosting techniques in handling real-world, non-linear, and multivariate environmental datasets.

Additionally, this work incorporated **Gaussian noise-based data augmentation**, which significantly enhanced model robustness by simulating natural fluctuations in environmental data such as pH, turbidity, and dissolved solids. The augmentation process contributed to a measurable improvement in model performance, especially for high-variance models like Random Forest and XGBoost, by reducing overfitting and promoting better generalization on unseen data.

From a broader perspective, the proposed system has strong potential for real-world deployment in **environmental monitoring frameworks**. As water pollution and contamination continue to pose public health and ecological risks, predictive tools based on machine learning can offer early warnings, support decision-making for treatment facilities, and guide public policy. Integration with **IoT-enabled water quality sensors** and **automated dashboards** could enable real-time tracking of water safety in both urban and rural settings.

Future Enhancements

While the results of this study are promising, there are several directions for future enhancement and expansion:

- **Inclusion of Additional Environmental Variables**: Incorporating more diverse inputs such as temperature, rainfall, land use, and proximity to pollution sources could further improve the model's contextual understanding.

- **Adoption of Temporal Models**: Time-series models like **Recurrent Neural Networks (RNNs)**, **LSTMs**, or **Temporal Convolutional Networks** could be explored to capture seasonal or time-dependent trends in water quality.

- **Classification-Based Frameworks**: Moving from regression to **multi-class classification** (e.g., "Safe," "Moderate," "Unsafe") could enhance interpretability for decision-makers and the general public.

- **Edge Deployment and Real-Time Monitoring**: Optimizing model size and computational requirements can make the system suitable for deployment on **edge devices**, such as water filtration units or portable testing kits.

- **Dynamic Learning and Feedback Integration**: Implementing **online learning** or **reinforcement learning** could enable the system to adapt continuously based on real-time data and feedback from field experts.

In conclusion, this research demonstrates the potential of machine learning in building accurate and scalable models for **water quality prediction**. With future improvements and integration into field-ready systems, such models could significantly advance the way we monitor, manage, and protect our water

CHAPTER 6 APPENDIX

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 "sns.countplot(x = \"Potability\", data = df)\n",
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CHAPTER 7 REFERENCES

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CHAPTER 8 RESEARCH PAPER