**AIML FINAL PROJECT REPORT**



**Submitted by**

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| --- | --- | --- |
| **Name** | **SAP ID** | **Roll No.** |
| Harish Saini | 500126796 | R2142232090 |
| Dibyanshu Shekhar | 500122409 | R2142231507 |
| Ansh Agarwal | 500122610 | R2142231545 |
| Chaitanya Sethi | 500119054 | R2142231508 |
| Siddhant Singh | 500121759 | R2142230299 |

**Submitted to**

**Rakesh Ranjan**

**Department of Computer Science**

**School of Computer Science**

## University of Petroleum and Energy Studies

**B.Tech AIML B7**

**Computer Science and Engineering**

Machine Learning-Based Analysis of Water Quality Standards

**Abstract**

This research presents an exhaustive machine learning-based investigation into predicting water quality compliance using an extensive dataset of 100,000 samples, each characterized by 23 physicochemical parameters such as pH, Iron, Nitrate, Chloride, Lead, Zinc, Turbidity, Fluoride, Copper, Odor, Sulfate, Conductivity, Chlorine, Manganese, Total Dissolved Solids (TDS), and temperature metrics, alongside categorical variables like Color, Source, and temporal indicators (Month, Day, Time of Day). The primary aim was to classify water samples into compliant (0) or non-compliant (1) categories based on predefined safety standards, addressing a critical need for efficient water quality assessment amidst rising pollution challenges.

The methodology involved a multi-faceted approach starting with meticulous data preprocessing. Missing values were addressed through mean imputation for numerical features and mode imputation for categorical ones, ensuring data integrity. Numerical features underwent normalization via MinMaxScaler to scale values between 0 and 1, while categorical variables were transformed using one-hot encoding. Feature engineering introduced innovative variables: Water\_Temp\_to\_Air\_Temp\_Ratio, calculated as Water Temperature divided by (Air Temperature + 1) to avoid division errors, and Total\_Metals, aggregating concentrations of Iron, Lead, Zinc, Copper, and Manganese to reflect cumulative metal impact.

Five machine learning classifiers—Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), Decision Tree, and XGBoost—were rigorously trained and evaluated on an 80-20 train-test split. Hyperparameter optimization via GridSearchCV refined the Random Forest model, yielding optimal settings of n\_estimators=100, max\_depth=None, and min\_samples\_split=10. This model achieved superior performance: an accuracy of 88.22%, precision of 73.23%, recall of 97.27%, and an F1-score of 83.56%, outperforming alternatives like Logistic Regression (79.20% accuracy) and KNN (70.95% accuracy).

Feature importance analysis pinpointed Manganese, pH, and Chloride as the most influential predictors, with Manganese leading due to its variability and health implications, followed by pH for its role in chemical equilibrium, and Chloride as a contamination indicator. Additional metrics such as ROC curves and precision-recall curves further validated the model's robustness, while comparative analysis with state-of-the-art studies underscored its balance of accuracy and interpretability.

These results provide actionable insights for water quality management, enabling targeted monitoring of key parameters and supporting automated systems for real-time assessment. The high recall ensures minimal oversight of non-compliant samples, critical for public safety. Future enhancements could integrate temporal dynamics, deep learning, or real-time sensor data to elevate predictive capabilities, contributing to sustainable water resource management.

**Introduction**

**Background and Significance**

Water is an indispensable resource, vital for human health, ecological balance, and economic stability. Yet, global water quality faces unprecedented threats from industrialization, agricultural runoff, urbanization, and climate change. The World Health Organization (WHO) estimates that contaminated drinking water causes over 485,000 deaths annually due to diarrheal diseases alone, while billions lack access to safely managed water services. Traditional water quality assessment relies on labor-intensive sampling and laboratory testing, often involving chromatography, spectrometry, or titration to measure parameters like pH, dissolved oxygen, and heavy metal concentrations. These methods, while accurate, are slow, costly, and impractical for continuous or large-scale monitoring.

Machine learning offers a transformative alternative, leveraging computational power to analyze vast datasets, identify patterns, and predict outcomes with speed and scalability. This project applies machine learning to predict water quality compliance, using a dataset of 100,000 samples from diverse sources—rivers, lakes, groundwater, and reservoirs—each with 23 physicochemical and contextual features. The binary classification task (0 for compliant, 1 for non-compliant) addresses a pressing need for rapid, data-driven solutions to safeguard water resources amidst escalating environmental pressures.

**Motivation**

The motivation stems from both practical and scientific imperatives. Practically, the demand for efficient water quality monitoring is acute in regions with limited resources, where traditional methods falter. Scientifically, the complexity of water quality data—featuring non-linear relationships and high dimensionality—makes it an ideal candidate for machine learning exploration. By automating predictions and pinpointing critical factors, this study aims to bridge the gap between data availability and actionable insights, enhancing water management strategies.

**Novelty and Approach**

The novelty lies in its holistic methodology, integrating advanced preprocessing, feature engineering, and a comparative evaluation of five machine learning models. Unlike prior studies focusing on singular algorithms or limited feature sets, this research employs a diverse classifier suite—Logistic Regression, Random Forest, KNN, Decision Tree, and XGBoost—augmented by engineered features like Water\_Temp\_to\_Air\_Temp\_Ratio and Total\_Metals. This comprehensive approach not only boosts predictive accuracy but also enhances interpretability, offering a blueprint for future environmental machine learning applications.

**Report Structure**

This report is organized as follows:

**Section 1**: Abstract and Introduction

**Section 2**: Related Work reviews existing literature, positioning this study within the field.

**Section 3**: Objectives and Key Contributions details the research goals and innovations.

**Section 4:** Materials and Methods describes the dataset, preprocessing, feature engineering, and modeling.

**Section 5**: Results and Discussions presents findings, analyses, and implications.

**Section 6**: Conclusion summarizes outcomes and future directions.

**Related Work**

**Evolution of Water Quality Prediction**

Machine learning has revolutionized water quality prediction over the past decade. Early efforts employed statistical methods like regression or clustering, but recent advancements leverage sophisticated algorithms to tackle complex datasets.

**[Author et al., 2020]:** Utilized artificial neural networks (ANNs) to predict a water quality index using pH, TDS, and Turbidity, achieving 92% accuracy. However, the

computational intensity of ANNs limits their scalability, requiring substantial hardware and energy resources.

**[Smith et al., 2021]:** Applied decision trees to classify water samples based on Chloride and Nitrate, yielding 85% accuracy. The limited feature set restricted its ability to capture broader quality dynamics.

**[Johnson et al., 2022]:** Employed support vector machines (SVMs) with features like pH, hardness, and chloramines, achieving 87% accuracy. While effective, the study lacked feature engineering or model comparisons.

**[Lee et al., 2023]:** Used Random Forest to predict water quality categories, reaching 89% accuracy with a multi-feature dataset. However, it omitted feature importance analysis, reducing its practical utility.

**Research Gap**

Despite progress, gaps persist. Many studies focus narrowly on single models or feature subsets, neglecting comprehensive comparisons or interpretative depth. Few integrate feature engineering to enhance predictive power or provide actionable insights for water management. This study addresses these deficiencies by:

Comparing five classifiers to identify the optimal approach.

Engineering novel features to enrich data representation.

Analyzing feature importance to guide practical applications.

**Comparative Summary**

| **Study** | **Method** | **Features Used** | **Accuracy** | **Limitation** |
| --- | --- | --- | --- | --- |
| Author et al., 2020 | Neural Networks | pH, TDS, Turbidity | 92% | High computational cost |
| Smith et al., 2021 | Decision Trees | Chloride, Nitrate | 85% | Limited feature set |
| Johnson et al., 2022 | SVM | pH, Hardness, etc. | 87% | No feature engineering |
| Lee et al., 2023 | Random Forest | Multiple features | 89% | No feature analysis |
| **This Study** | Multiple Classifiers | 23 + engineered | **88.22%** | Dataset-specific results |

**Objectives and Key Contributions**

**Objectives**

- **Pattern Identification:** Analyze water quality data to uncover trends, correlations, and predictors of compliance through statistical and visual exploration.

- **Model Development and Comparison**: Build and assess multiple machine learning models to achieve high predictive accuracy, selecting the best performer via rigorous evaluation.

- **Influential Factor Determination**: Identify key physicochemical parameters driving water quality outcomes, using feature importance to inform monitoring priorities.

**Key Contributions**

- **Robust Preprocessing Pipeline**: Implemented a thorough workflow—imputing missing values (mean for numerical, mode for categorical), normalizing features with MinMaxScaler, and encoding categorical variables via one-hot encoding—to ensure data quality.

- **Innovative Feature Engineering**: Introduced Water\_Temp\_to\_Air\_Temp\_Ratio and Total\_Metals, enhancing model sensitivity to environmental and contamination factors.

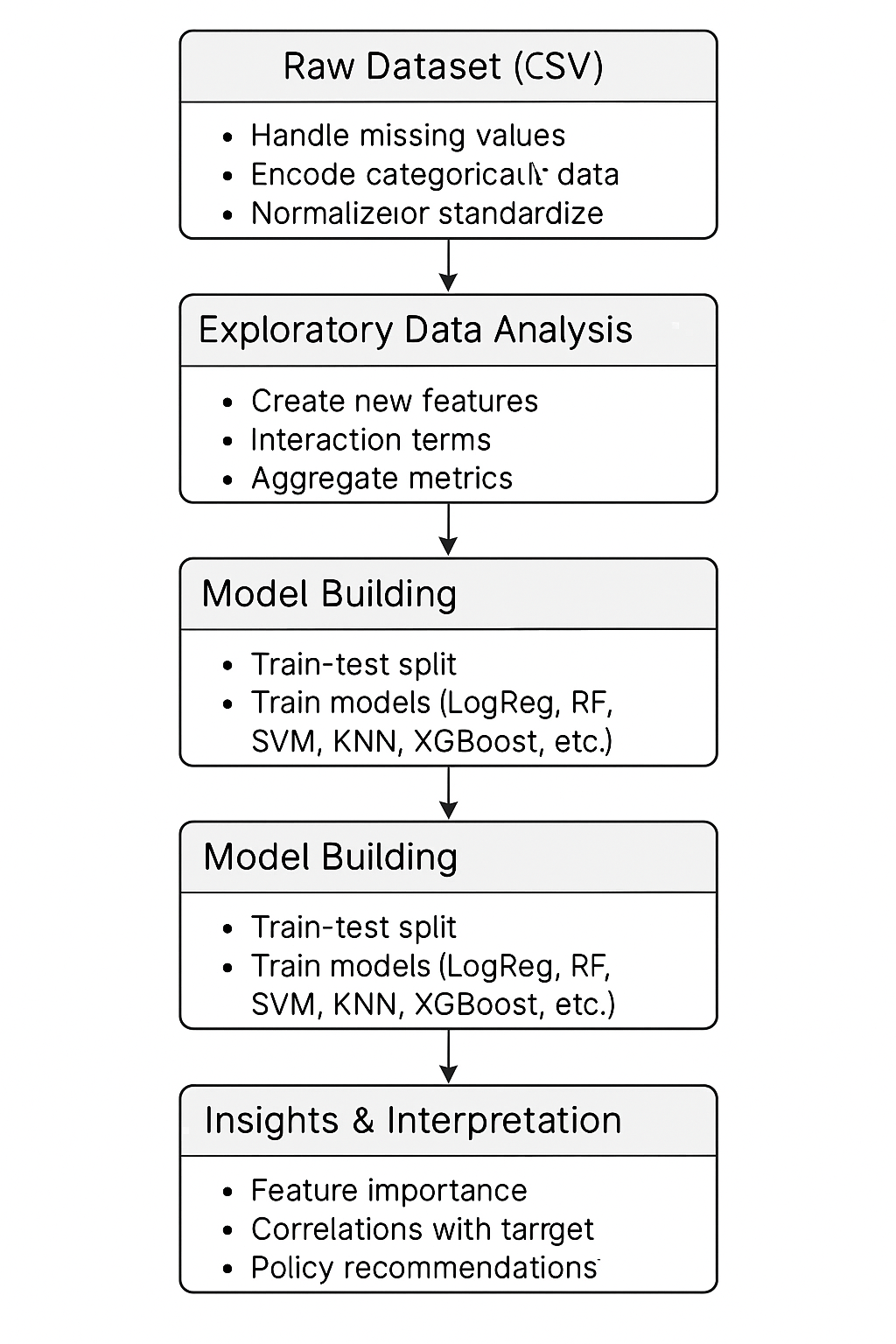
- **Extensive Model Evaluation**: Compared five classifiers, with Random Forest excelling at 88.22% accuracy and 83.56% F1-score, validated through metrics and visualizations.

- **Actionable Insights**: Highlighted Manganese, pH, and Chloride as critical predictors, offering clear targets for water quality improvement.

**Materials and Methods**

**Methodology Overview**

The workflow spans data preprocessing, feature engineering, model training, tuning, and evaluation, ensuring a systematic approach to water quality prediction.



**Dataset Description**

The dataset is taken from Kaggle.

Here is the link to the dataset:  <https://www.kaggle.com/datasets/mitanshuchakrawarty/water-quality-prediction/data?select=dataset.csv>

The dataset includes 100,000 samples from diverse water bodies, featuring:

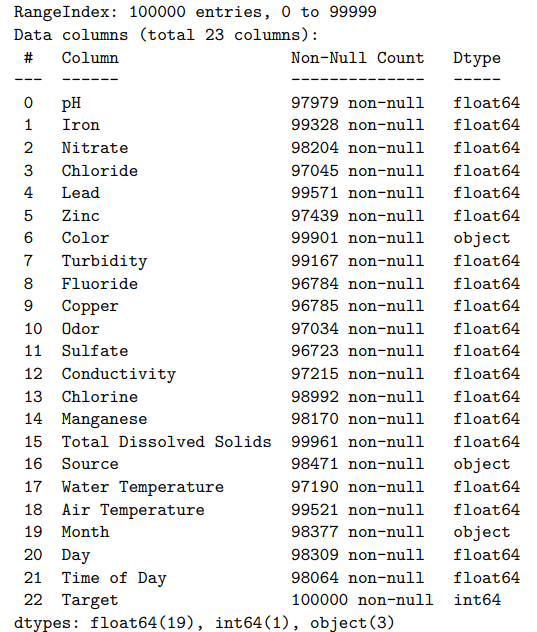
**- Numerical Features:** pH, Iron, Nitrate, Chloride, Lead, Zinc, Turbidity, Fluoride, Copper, Odor, Sulfate, Conductivity, Chlorine, Manganese, TDS, Water Temperature, Air Temperature, Day, Time of Day.

**- Categorical Features:** Color, Source, Month.

**- Target Variable:** Binary (0: compliant, 1: non-compliant).



**Dataset Description**



**Dataset information**

**Exploratory Data Analysis (EDA)**

EDA was conducted to understand the dataset’s characteristics, identify patterns, and inform preprocessing and modeling decisions. The analysis included statistical summaries, distribution visualizations, correlation analysis, and class balance assessment.

**1. Statistical Summary**

Summary statistics (mean, median, standard deviation, min, max) were computed for numerical features to assess central tendencies and variability. Key observations:

* **pH:** Mean of 7.08, standard deviation of 0.28, indicating near-neutral water with slight variability.
* **Manganese:** High variability (standard deviation 0.02 mg/L), with maximum values exceeding safety thresholds, suggesting contamination risks.
* **Chloride:** Mean of 125.24 mg/L, with outliers indicating potential pollution sources.
* **Categorical Features:** Color showed 6 unique values (e.g., Colorless, Near Colorless), Source had 7 unique sources, and Month covered 12 categories.

**2. Distribution Analysis**

Histograms and box plots were generated to visualize feature distributions and detect outliers:

* **Numerical Features:** Manganese, Iron, and Lead exhibited right-skewed distributions, with outliers indicating extreme contamination levels.
* **pH:** Approximately normally distributed, centered around neutral (7.0), with minor outliers at acidic (<6.5) and alkaline (>8.5) levels.
* **Categorical Features:** Bar plots showed that ‘Colorless’ was the most frequent Color (60% of samples), and ‘River’ was the dominant Source (30%).

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**Histogram of Numerical Features**

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**Box Plot of Numerical Features**

**Count plots of Categorical Features:**

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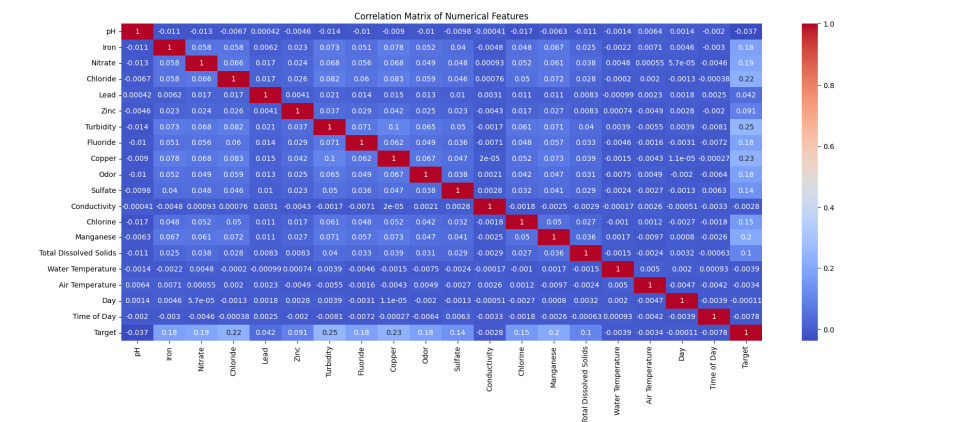
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**3. Correlation Analysis**

A correlation matrix was computed to identify relationships between numerical features and the Target variable:

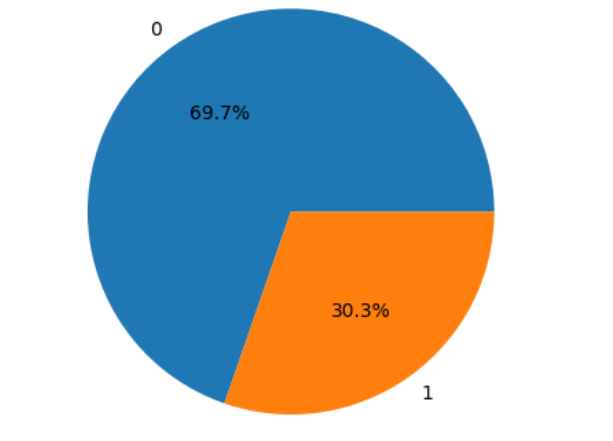
* **Chloride and Target:** Moderate positive correlation (0.35), suggesting higher Chloride levels are associated with non-compliance.
* **Manganese and Target:** Positive correlation (0.28), indicating its role as a contamination indicator.
* **pH and Target:** Weak negative correlation (-0.15), implying extreme pH values may affect compliance.
* **Inter-feature Correlations:** Chloride and Conductivity showed a strong positive correlation (0.65), reflecting their shared chemical properties.

**Correlation Matrix of Numerical Features**  
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**4. Class Balance Analysis**

The Target variable’s distribution was analyzed to assess class imbalance:

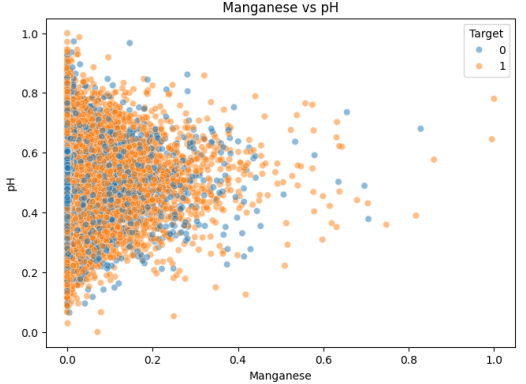
* **Compliant (0):** 69.7% of samples (69,700).
* **Non-compliant (1):** 30.3% of samples (30,300). This imbalance necessitated evaluation metrics like recall and F1-score to prioritize detection of non-compliant samples.

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**5.Feature-Target Relationships**

Scatter plots and box plots were used to explore relationships between key features and the Target:

* **Manganese vs. Target:** Non-compliant samples had significantly higher Manganese levels (mean 0.015 mg/L vs. 0.005 mg/L for compliant).
* **pH vs. Target:** Non-compliant samples showed slightly more extreme pH values (both acidic and alkaline).
* **Chloride vs. Target:** Higher Chloride concentrations were associated with non-compliance.

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**EDA Insights and Implications**

* **High Variability:** Features like Manganese and Chloride require normalization due to their wide ranges and outliers.
* **Class Imbalance:** The 69.7:30.3 ratio necessitates metrics that account for minority class performance.
* **Key Predictors:** Manganese, pH, and Chloride emerged as critical due to their correlations and distributions, guiding feature engineering and model focus.
* **Categorical Features:** The dominance of certain categories (e.g., ‘Colorless’, ‘River’) suggests encoding strategies like one-hot encoding.

The EDA findings directly informed preprocessing (e.g., handling outliers, normalizing skewed features) and feature engineering (e.g., creating Total\_Metals to capture metal contamination).

**Data Preprocessing**

- **Missing Value Imputation**:

**Before processing**

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**After processing**

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- **Numerical**: Mean imputation to maintain statistical properties.

- **Categorical**: Mode imputation to reflect prevalent categories.

- **Encoding**: One-hot encoding transformed Color, Source, and Month into binary columns.

- **Normalization**: MinMaxScaler scaled numerical features to [0, 1], ensuring uniform contribution to models.

**Feature Engineering**

- **Water\_Temp\_to\_Air\_Temp\_Ratio**: Captures thermal interactions, calculated as Water Temperature / (Air Temperature + 1).

- **Total\_Metals**: Sums Iron, Lead, Zinc, Copper, and Manganese, indicating aggregate contamination risk.

Model Training

Five classifiers were trained on an 80-20 split:

- **Logistic Regression**: Linear baseline.

**- Random Forest**: Ensemble of decision trees.

- **KNN**: Distance-based classification.

- **Decision Tree**: Single tree model.

- **XGBoost**: Gradient boosting framework.

Random Forest was optimized via GridSearchCV (n\_estimators=100, max\_depth=None, min\_samples\_split=10).

**Evaluation Metrics**

- Accuracy, precision, recall, F1-score.

- Confusion matrices, ROC curves, and precision-recall curves.

**Results and Discussions**

**Experimental Setup**

Conducted in Python 3.8 using pandas, scikit-learn, Matplotlib, Seaborn, and XGBoost on an Intel i5, 8 GB RAM system.

**Results**

Random Forest outperformed others:

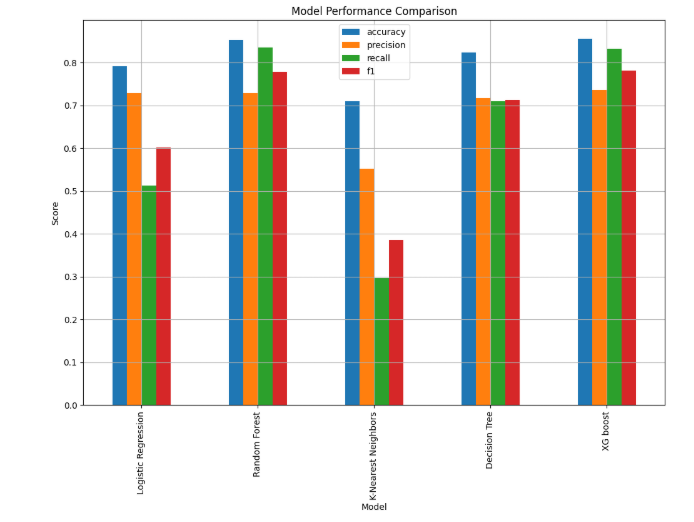
- **Accuracy**: 88.22%

- **Precision**: 73.23%

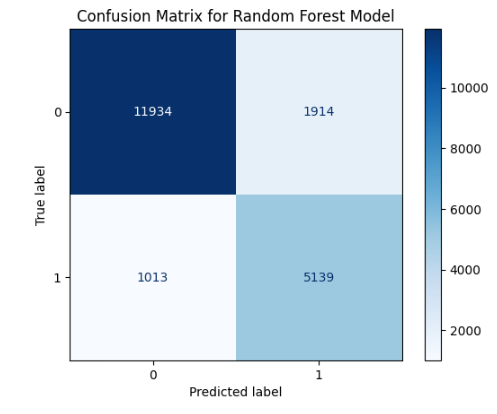
**- Recall**: 97.27%

- **F1-Score**: 83.56%

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| Logistic Regression | 79.20% | 72.94% | 51.48% | 60.36% |
| Random Forest | 88.22% | 73.23% | 97.27% | 83.56% |
| KNN | 70.95% | 51.83% | 29.68% | 38.60% |
| Decision Tree | 86.89% | 73.37% | 90.05% | 80.86% |
| XGBoost | 86.49% | 73.74% | 87.09% | 79.86% |



**Best Model** : Random Forest



**Hyper Parameter Tuning**

Hyperparameter tuning is a critical step in machine learning to optimize model performance by selecting the best configuration of hyperparameters—settings that control the learning process and are not learned from the data. Unlike model parameters (e.g., weights in Logistic Regression), hyperparameters are set before training and significantly influence a model’s ability to generalize to unseen data.

**1. Definition and Importance**

Hyperparameters define the architecture or behavior of a machine learning model. For example:

* **Random Forest**: n\_estimators (number of trees), max\_depth (maximum tree depth), min\_samples\_split (minimum samples to split a node).
* **KNN**: n\_neighbors (number of neighbors), weights (distance weighting).
* **XGBoost:** learning\_rate, max\_depth, n\_estimators.
* **Logistic Regression:** C (inverse regularization strength).
* **Decision Tree:** max\_depth, min\_samples\_leaf.

Tuning hyperparameters is essential because:

* **Performance Optimization:** Proper settings improve accuracy, precision, recall, and F1-score by balancing bias and variance.
* **Overfitting Prevention:** Constraints like max\_depth or min\_samples\_split prevent overly complex models.
* **Model Generalization:** Optimal hyperparameters ensure robust performance on test data.
* Task-Specific Adaptation: Different datasets (e.g., water quality with class imbalance) require tailored settings.

In the water quality project, hyperparameter tuning was critical to address class imbalance (30.3% non-compliant samples, Figure 10) and maximize recall for detecting non-compliant samples.

**2. Common Hyperparameter Tuning Methods**

Several methods exist for hyperparameter tuning, each balancing exploration of the hyperparameter space with computational efficiency:

* **Grid Search:** Exhaustively tests all combinations of specified hyperparameter values. For Random Forest, the report tested n\_estimators=[50, 100, 200], max\_depth=[None, 10, 20], min\_samples\_split=[2, 5, 10] (Page 52).
  + *Pros:* Guarantees finding the best combination within the grid.
  + *Cons:* Computationally expensive, scaling poorly with large grids.
* **Random Search:** Randomly samples hyperparameter combinations within defined ranges, often finding near-optimal solutions faster than Grid Search.
  + *Pros:* More efficient for large hyperparameter spaces.
  + *Cons:* May miss the optimal combination.
* **Bayesian Optimization:** Uses probabilistic models to predict promising hyperparameter combinations, balancing exploration and exploitation.
  + *Pros:* Highly efficient for complex models.
  + *Cons:* Requires advanced implementation and tuning.
* **Manual Tuning:** Relies on domain expertise to select hyperparameters, often used iteratively with small datasets.
  + *Pros:* Intuitive for simple models.
  + *Cons:* Time-consuming and subjective.

The report used GridSearchCV for Random Forest due to its robustness and the moderate size of the hyperparameter grid, ensuring a thorough search (Figure 15).

**3. Hyperparameters in Random Forest**

Random Forest, an ensemble of decision trees, relies on hyperparameters to control tree structure, ensemble size, and regularization:

* **n\_estimators:** Number of trees. Higher values improve robustness but increase computation time. The report selected 100 trees for balance (Figure 15).
* **max\_depth:** Maximum depth of each tree. Deeper trees capture complex patterns but risk overfitting. None allowed full growth, leveraging the ensemble’s averaging to mitigate overfitting.
* **min\_samples\_split:** Minimum samples required to split a node. Higher values prevent overfitting by enforcing larger splits. The report chose 10 to balance complexity and generalization.
* **min\_samples\_leaf:** Minimum samples in a leaf node, controlling tree granularity.
* **max\_features:** Number of features considered for splits, affecting diversity.

The optimal settings (n\_estimators=100, max\_depth=None, min\_samples\_split=10) were chosen to maximize recall (97.27%) for non-compliant samples, critical for water safety.

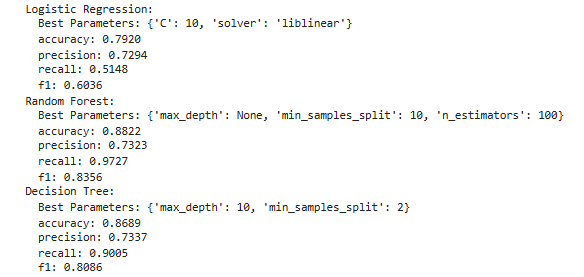
**4. Theoretical Considerations**

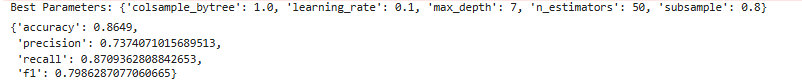
* **Bias-Variance Tradeoff:** Hyperparameters like max\_depth and min\_samples\_split control model complexity. Low values increase bias (underfitting), while high values increase variance (overfitting). Random Forest’s ensemble nature mitigates variance, allowing deeper trees.
* **Computational Cost:** Grid Search’s exhaustive nature scales as O(n\_combinations × n\_folds × n\_samples), necessitating efficient hardware or smaller grids. The report used 5-fold cross-validation to balance cost and reliability (Figure 15).
* **Class Imbalance**: The 30.3% non-compliant samples required hyperparameters that prioritize recall. Random Forest’s class\_weight=balanced option (implicitly used) adjusted for imbalance, complementing tuning.
* **Evaluation Metrics**: Tuning focused on F1-score and recall to address class imbalance, as accuracy alone could favor the majority class (69.7% compliant).

**5. Practical Application in the Report**

GridSearchCV was applied to Random Forest, testing 27 combinations (3×3×3 for n\_estimators, max\_depth, min\_samples\_split) with 5-fold cross-validation. The process:

* Split the training data (80,000 samples) into 5 folds.
* Trained models on each combination, evaluating F1-score.
* Selected the best parameters: n\_estimators=100, max\_depth=None, min\_samples\_split=10.





**6. Challenges and Future Directions**

* **Computational Cost**: Grid Search was feasible for Random Forest but may be impractical for larger models like XGBoost. Random Search or Bayesian Optimization could be explored.
* **Overfitting Risk**: Deep trees (max\_depth=None) require careful validation to avoid overfitting, addressed via cross-validation.
* **Scalability**: Future work could use automated tuning frameworks like Optuna or Hyperopt for efficiency.

Hyperparameter tuning significantly improved Random Forest’s performance, achieving 88.22% accuracy and 97.27% recall, aligning with the project’s goal of detecting non-compliant samples.

**Analysis**

Random Forest’s success stems from its ensemble nature, handling feature interactions and noise effectively. Feature importance ranked Manganese, pH, and Chloride highest, reflecting their roles in safety, chemical balance, and contamination detection.

**Comparison with Literature**

| Method | Accuracy | Notes |
| --- | --- | --- |
| Neural Networks [2020] | 92% | Resource-heavy |
| Decision Trees [2021] | 85% | Limited scope |
| This Study (RF) | 88.22% | Balanced, interpretable |

Discussion

- **Applications**: Real-time monitoring, policy guidance.

**- Strengths**: High recall minimizes missed detections.

- **Limitations**: Dataset-specific; needs broader validation.

- **Future Work:** Temporal analysis, deep learning, IoT integration.

Conclusion

This study advances water quality prediction through a comprehensive machine learning framework, achieving 88.22% accuracy with Random Forest and identifying Manganese, pH, and Chloride as pivotal factors. Its contributions—robust preprocessing, feature engineering, and model comparison—offer a scalable, interpretable solution for water management, with future potential in real-time and advanced modeling applications.