**Water Quality Classification using Random Forest Model**

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| **Article Info** |  | **ABSTRACT** |
| ***Keywords:***  *Water Quality*  *Classification*  *Random Forest*  *Machine Learning*  *Proactive Intervention* |  | This study employs a Random Forest classification model to predict water quality safety using physicochemical properties of water samples. Comprehensive data preprocessing included handling invalid entries, mean imputation for missing numeric data, normalization, and encoding categorical variables to ensure robust model performance. Utilizing a Water Quality dataset sourced from Kaggle containing 5,110 records and 21 attributes, the model was trained and validated to classify water as safe or unsafe for consumption, considering features like pH, heavy metal concentrations, and microbial contaminants. The Random Forest classifier achieved a high accuracy of 95.08%, supported by 0.95 precision, 0.95 recall, 0.95 F1-score, and confusion matrix evaluations, demonstrating its reliability in addressing class imbalances and feature variability. Feature importance analysis highlighted arsenic, lead, and bacterial contaminants as critical predictors of water safety. |
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1. **INTRODUCTION**

Water quality plays a crucial role in public health and environmental sustainability. Contaminated water is a significant contributor to waterborne diseases and public health crises worldwide [2], [3], [4]. It is influenced by various physicochemical and biological factors, such as pH, heavy metal concentrations, and microbiological contamination, which determine its suitability for consumption and other uses [5], [6]. Identifying unsafe water sources is essential for mitigating health risks, particularly in areas where water contamination is prevalent.

Traditional methods of water quality assessment are often time-consuming and require substantial expertise, making them less scalable in the face of increasing demand for safe water [7]. With the advancement of machine learning, data-driven approaches have emerged as powerful tools for predictive analysis in environmental monitoring [8], [9]. Among these methods, Random Forest classification has proven to be effective in handling complex datasets with nonlinear relationships and missing values [10], [11], [12].

This study contributes to the field of water quality monitoring by presenting a robust framework for predicting water safety. It emphasizes the importance of leveraging machine learning to process diverse data sources and extract meaningful insights [13], [14]. The primary objective is to develop a systematic approach to classify water samples as safe or unsafe for consumption based on their physicochemical properties. The findings aim to support environmental agencies and public health authorities in timely interventions and resource allocation to ensure sustainable water management [15].

1. **LITERATURE REVIEW**

**2.1 Classification**

Classification is a process used to categorize data into predefined classes or labels based on current or historical information. It involves employing algorithms and statistical models to identify patterns and assign outcomes to specific categories. In the context of water quality, classification models can categorize water samples as safe or unsafe, enabling proactive decision-making and risk management. Studies have demonstrated the effectiveness of machine learning techniques in classification tasks across various domains, including healthcare, environmental monitoring, and finance [16], [17], 18].   
 Machine learning models such as Support Vector Machines (SVM), Logistic Regression, and Random Forest have shown considerable promise in handling nonlinear relationships and complex datasets. Studies using Random Forest for environmental and health-related classification tasks have highlighted its ability to extract significant insights and improve decision-making, especially in data-intensive scenarios [19], [20], [21].

**2.2 Random Forest**

Random Forest is an ensemble learning method that combines multiple decision trees to enhance classification accuracy and mitigate overfitting. By aggregating predictions from individual trees, the algorithm creates a robust model capable of handling high-dimensional datasets and missing values. It is particularly suited for analyzing water quality data, where feature interactions and variability are significant challenges [22].

Recent studies have demonstrated the effectiveness of Random Forest in predicting water safety, identifying critical factors such as heavy metal concentrations, microbial contamination, and pH levels. Despite its computational demands, Random Forest remains a popular choice due to its reliability, scalability, and ability to rank feature importance, providing valuable insights into the key predictors of water quality [23], [24].

1. **METHOLODGY**

**3.1 Dataset**

The analysis was conducted on a dataset of Water Quality Dataset containing 21 attributes and 5,110 records, sourced from Kaggle. The dataset includes critical physicochemical parameters such as pH, dissolved oxygen, heavy metal concentrations, and microbiological contamination levels, as well as a target variable indicating water safety (safe or unsafe) [1].

**3.2 Hardware**

The research was carried out using a HP laptop equipped with an Intel Core i5-3360m processor and 16 GB of RAM, running on the Windows 10 operating system. This setup provided adequate computational power for handling the data preprocessing, model training, and evaluation tasks.

**3.3 Software**

The study utilized Python 3.13.0 in Jupyter Notebook, leveraging libraries like Pandas and NumPy for data preprocessing, Scikit-learn for model training, Matplotlib and Seaborn for data visualization.

**3.4 Data Preprocessing**

**3.4.1 Handling Missing Values**

Missing values in numeric attributes were addressed using mean imputation, ensuring that no data was discarded. This approach preserved dataset integrity and maintained statistical consistency, avoiding biases caused by incomplete records.

**3.4.2 Encoding Categorical Variables**

Categorical variables, such as qualitative indicators of water contamination, were transformed into numerical representations using label encoding. This step ensured compatibility with machine learning algorithms while retaining the distinctiveness of the categorical data.

**3.4.3 Dataset Splitting**

The dataset was divided into training (70%), validation (15%), and testing (15%) subsets using stratified sampling. This ensured that class proportions were consistent across all subsets, providing a reliable foundation for model training and evaluation.

**3.5 Random Forest Model**

The Random Forest classifier was implemented to predict water safety based on physicochemical features. It leverages ensemble learning to handle complex interactions between features while providing feature importance rankings, aiding in identifying critical predictors of water quality. The model was trained on the preprocessed dataset and evaluated using validation and test data.

**3.6 Model Evaluation Metrics**

In this study, the performance of the Random Forest Classification model for predicting unsafe water samples was evaluated using key metrics: Accuracy, Precision, Recall, and F1-Score. Accuracy was used to determine the overall proportion of correctly classified samples, providing a general sense of the model's effectiveness. Precision focused on the proportion of true unsafe water samples among those predicted as unsafe, aiming to minimize false positives. Recall, or sensitivity, assessed the proportion of actual unsafe samples correctly identified, emphasizing the model's ability to detect true positives. Finally, the F1-Score, a balanced measure combining precision and recall, offered a comprehensive evaluation of the model’s performance. Together, these metrics ensured the Random Forest model’s suitability for accurately identifying unsafe water samples, supporting proactive interventions and resource optimization in water quality management [25], [26].

Accuracy measures the proportion of the correctly classified instances amongst all instance

(1)

Accuracy is a useful metric when the classes in the dataset are balanced (equal distribution of positives and negatives). For example, if you correctly classify 95 out of 100 instances, your accuracy is 95%.

* TP (True Positives): The number of positive instances correctly predicted as positive.
* TN (True Negatives): The number of negative instances correctly predicted as negative.
* FP (False Positives): The number of negative instances incorrectly predicted as positive.
* FN (False Negatives): The number of positive instances incorrectly predicted as negative

Precision measures the proportion of correctly predicted positive observations out of all the predicted positive observations.

(2)

Precision is crucial in scenarios where the cost of a false positive is high. For example, in a medical diagnosis of obesity, predicting someone as obese when they are not could lead to unnecessary stress or interventions.

* TP (True Positives): The number of positive instances correctly predicted as positive. · .

Recall measures the proportion of actual positive observations that were correctly identified.

(3)

Recall is important when the cost of a false negative is high. In an obesity classification context, failing to identify an obese individual (false negative) could mean missing an opportunity for timely medical intervention.

* TP (True Positives): The number of positive instances correctly predicted as positive. ·
* FN (False Negatives): The number of positive instances incorrectly predicted as negative.

F1 Score is a harmonic mean of precision and recall as it provides a balanced measure that accounts for both metrics.

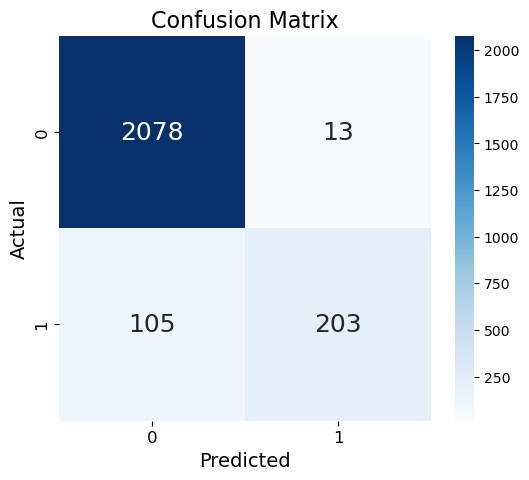
(4)

F1-Score is particularly useful when the class distribution is imbalanced. It combines the strengths of both Precision and Recall.

* Precision: The proportion of true positives out of all predicted positives. Recall: ·
* The proportion of true positives out of all actual positives.

1. **RESULTS AND DISCUSSION**

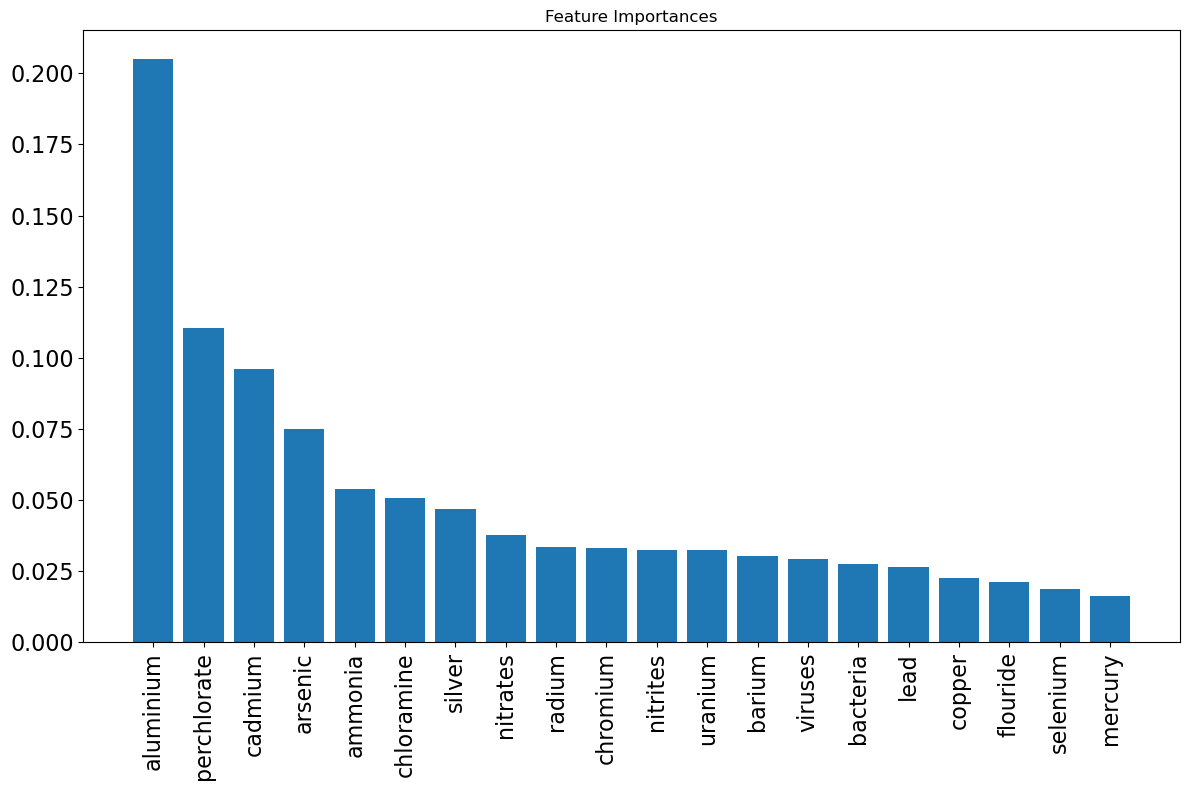
**4.1 Confusion Matrix**



**Figure 2:** Confusion Matrix for Random Forest Model

The confusion matrix presented in Figure 2 provides a detailed evaluation of the water quality classification model's performance in predicting whether water is safe for consumption. The model correctly identified 2,078 cases of "unsafe" water as "unsafe" (true negatives) and 203 cases of "safe" water as "safe" (true positives), highlighting its strong ability to accurately classify water safety in most instances. However, there were 13 instances where water deemed "unsafe" was incorrectly classified as "safe" (false positives) and 105 instances where water that was actually safe was misclassified as "unsafe" (false negatives). These false negatives are of particular concern, as they indicate instances where safe water might be unnecessarily excluded, potentially leading to wasted resources or unnecessary alarm. Similarly, false positives pose a risk, as unsafe water being classified as safe could result in serious health consequences for consumers.

* 1. **Feature Importance**



**Figure 3:** Random Forest Feature Importance of Water Quality

The feature importance visualization in Figure 3 from the Random Forest model highlights the relative contribution of each parameter in predicting the target variable, "water safety." Among all features, "aluminium" has the highest importance, indicating it is the most critical factor in determining whether water is safe or not. This is followed by "perchlorate" and "cadmium," which also play significant roles. Other notable contributors include "arsenic," "ammonia," and "chloramine," which moderately impact the predictions. Lower-ranked features such as "bacteria," "viruses," "lead," and "selenium" still have some influence, though they are less significant compared to the top-ranking features. These findings suggest that heavy metals and chemical contaminants like aluminium and perchlorate are key indicators of water safety, while biological and less toxic elements play secondary roles. This information is valuable for prioritizing monitoring and mitigation strategies, ensuring that the most impactful contaminants are addressed to improve water quality and ensure safety for consumption.

**4.3 Evaluation Metrics**

**Table 1:** Random Forest Evaluation Metrics

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| --- | --- |
| **Metrics** | **Value** |
| Accuracy | 95.08% |
| Precision | 0.95 |
| Recall | 0.95 |
| ­F1-Score | 0.95 |

The evaluation metrics in Table 1 for the Random Forest model in predicting water quality outcomes indicate strong performance across all measures. An accuracy of 95.08% demonstrates the model's overall reliability in correctly classifying safe and unsafe water cases. Precision, at 0.95, underscores the model's effectiveness in minimizing false positives, ensuring that unsafe water is rarely misclassified as safe. The recall of 0.95 highlights the model's sensitivity in identifying true safe water cases, a critical aspect in water quality assessment to prevent unnecessary exclusion of safe resources. The F1-score, also at 0.95, provides a balanced measure of precision and recall, validating the model's ability to handle the dataset's class distribution effectively. These metrics emphasize the success of the model in achieving its goal of building a reliable predictive framework for water quality classification. The robust performance ensures that the model can provide accurate and actionable insights, aiding stakeholders in identifying and addressing water safety issues efficiently. By focusing on the most critical features, such as chemical contaminants and heavy metals, the model contributes significantly to improving water quality management and safeguarding public health.

1. **CONCLUSION**

In conclusion, the Random Forest model demonstrates strong and reliable performance in predicting water quality outcomes, with an accuracy of 95.08%, precision of 0.95, recall of 0.95, and an F1-score of 0.95. These metrics indicate that the model is highly effective at correctly classifying safe and unsafe water, with minimal false positives (13 instances) and false negatives (105 instances). The model correctly identified 2,078 instances of unsafe water as unsafe (true negatives) and 203 instances of safe water as safe (true positives), highlighting its strong ability to accurately classify water safety in most cases.

The feature importance analysis reveals that heavy metals and chemical contaminants, such as aluminium, perchlorate, and cadmium, are the most critical indicators of water safety. These findings suggest that these contaminants should be prioritized in water quality monitoring efforts. While other features like arsenic, ammonia, and chloramine moderately influence the predictions, biological factors such as bacteria, viruses, lead, and selenium have a lesser impact.

However, the presence of 13 false positives (unsafe water misclassified as safe) and 105 false negatives (safe water misclassified as unsafe) points to areas for improvement. False negatives are particularly concerning, as they could lead to unnecessary alarm or resource wastage by excluding safe water. Conversely, false positives could result in unsafe water being incorrectly deemed safe, posing potential health risks.

Overall, the model's robust performance and the insights gained from the feature importance analysis provide a reliable framework for enhancing water quality management. By prioritizing the most critical contaminants and addressing false positives and negatives, this model can support informed decision-making to ensure public health safety and improve resource allocation.

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