Machine Learning Based Alum Dosing Optimization for Adaptive Water Quality Management in Treatment Plant

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MACHINE LEARNING BASED ALUM DOSING OPTIMIZATION FOR ADAPTIVE WATER QUALITY MANAGEMENT IN TREATMENT PLANT

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ABSTRACT

Ensuring safe and cost-effective water purification remains a critical challenge, particularly for large natural water bodies like the Halda River, where water quality parameters can fluctuate significantly. Traditional methods for determining chemical dosages, such as those using alum, often rely on manual experiments that fail to adapt to real-time variations in water quality, leading to inefficiencies, chemical overuse, and inconsistent treatment outcomes. This study presents a data-driven solution to optimize alum dosage prediction using advanced machine learning (ML) techniques. A comprehensive dataset comprising raw and treated water quality parameters, including turbidity, pH, alkalinity, and chloride from the Halda River, was utilized. To enhance model performance, rigorous preprocessing steps were applied, including outlier removal, lag feature creation, interaction terms, rolling statistics, and water quality index (WQI) components. These engineered features capture temporal trends and chemical interactions critical to effective treatment. The target variable was formulated as a binary classification problem based on the median alum dosage threshold. Multiple models were trained and evaluated, including Random Forest, Gradient Boosting, Support Vector Machine (SVM), Logistic Regression, and K-Nearest Neighbors (KNN). Among these, the KNN model achieved the highest performance, with a test accuracy of 94.87% and an ROC AUC of 0.957, indicating excellent predictive capability and generalizability. Feature importance analysis revealed that turbidity, chloride concentration, and pH-related interactions are the most influential predictors of alum demand. The developed model offers a practical framework for real-time, automated alum dosage recommendations, enabling water treatment facilities to reduce operational costs, minimize chemical waste, and improve treatment consistency.

Keywords: *Water quality, Halda river, Alum dosing, Machine learning, Water treatment*

1. INTRODUCTION

Safe and economical water purification is a recurring problem, particularly for large natural water bodies like Bangladesh's southeast Halda River. Since it facilitates the natural spawning of native fish species, particularly the Indian carp, the Halda River, the only tidal river in Bangladesh which plays an important ecological role (Hossen & Jishan, 2018). Because it supplies water for drinking, farming, and fishing, it is also an essential resource for the local communities. Also, it serves as a major raw water source for the Chattogram Water Supply and Sewerage Authority (CWASA), which processes and distributes it for public consumption (Debnath et al., 2022).

Alum ($Al_2(SO_4)_3$) is commonly used in water treatment to remove impurities and clarify the water. In order to make the water clearer and safer to drink, it coagulates suspended particles, which eventually settle and can be removed (Malecki-Brown et al., 2009). Alum dosing at CWASA is usually determined by pre-established charts; however, the process is complicated by the Halda River's fluctuating water quality, which is caused by industrial, agricultural, and seasonal factors. These traditional methods, relying on static dosage charts, often lead to inefficiencies, chemical overuse, and increased costs. To date, no studies have explored the prediction of alum dosage in the water treatment plant of CWASA using modern data-driven or machine learning techniques.

Considering these challenges, this study suggests a machine learning-based strategy to improve alum dosage prediction in real-time (Al-Baidhani & Alameedee, n.d.). By applying machine learning algorithms that account for dynamic water quality parameters like alkalinity, pH, turbidity, and chloride, the required alum dosage can be accurately predicted. This data-driven approach aims to enhance water treatment to be more precise, efficient, and environmentally friendly by eliminating the role of human error and manual intervention in the alum dosing system (Żywiec et al., 2024). The technique holds excellent potential to enhance water quality management, minimize chemical waste, and save operating expenses, and is hence a valuable resource for water treatment facilities across the world.

2. METHODOLOGY

This study presents a comprehensive machine learning–based framework designed to predict the optimal alum dosage required for effective water treatment using water quality data collected from the Halda River. The proposed methodology is structured into three major phases. In the first phase, extensive water quality data are collected from multiple sampling points along the Halda River and subjected to preprocessing procedures, including data cleaning, normalization, and feature engineering, to ensure accuracy and consistency. In the second phase, several machine learning models are developed and trained to forecast alum dosage levels by incorporating dynamic physicochemical parameters such as pH, turbidity, alkalinity, and chloride concentration. These models are optimized and fine-tuned to enhance predictive accuracy and generalizability. Finally, in the third phase, model performance is rigorously evaluated using appropriate statistical and error metrics. Feature importance analyses are also conducted to identify the most influential parameters governing alum demand. This systematic approach provides an efficient and data-driven solution for dosage optimization, contributing to improved water treatment efficiency and sustainable resource management.

2.1 Data Collection and Preparation

The hydric water quality information was supplied by the Chattogram Water Supply and Sewerage Authority (CWASA), which operates the Mohora Water Treatment Plant. The Mohora sampling points, where CWASA gathers hourly observations of four crucial chemical parameters i.e. pH, turbidity, chloride, and alkalinity are depicted in Figure 1.

These elements are crucial for monitoring the ecosystem of the Halda River and ensuring that water treatment is effective. A daily time series covering a full calendar year was created by averaging the hourly readings to reduce high-frequency noise and improve data consistency. As a result, a total of 365

multivariate observations were obtained, representing daily measurements encompassing multiple water quality parameters.

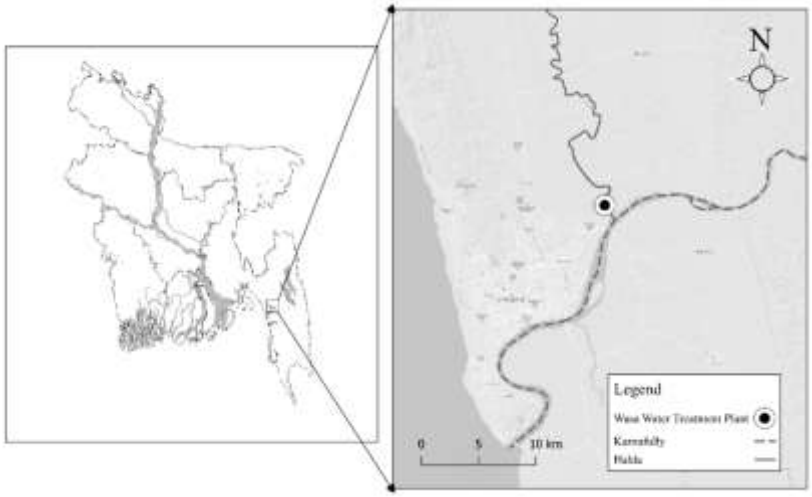


Figure 1: Study Area Map

2.2 Machine Learning Framework

Machine learning (ML) is a subfield of artificial intelligence (AI) that focuses on the development of algorithms that allow computers to learn from data and make predictions without being programmed for a specific task. By using algorithms and statistical models, it allows systems to recognize patterns, make predictions, and improve their performance over time through experience (Pandey et al., 2019). This study employed supervised learning methodologies to predict the necessary alum dosage for water treatment, utilising dynamic water quality data from the Halda River. Supervised learning is a kind of machine learning where the model learns from a dataset that has been labelled (Dridi, 2024; Nasteski, 2017). This indicates that the correct output is known for each corresponding input instance in the dataset. The general approach was set up as a binary classification problem, which is a type of supervised machine learning task where the goal is to put data into one of two groups (Kumari & Kr., 2017).

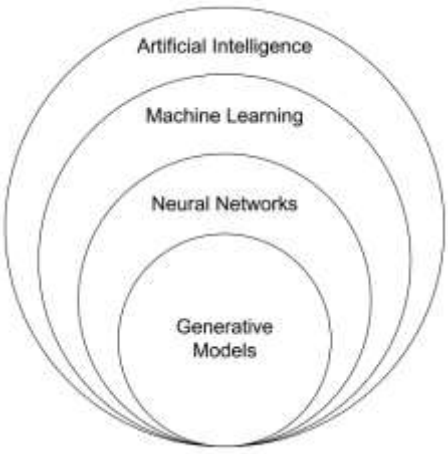


Figure 2: Hierarchy of Artificial Intelligence Subfields

In this study, the two classifications were based on whether the alum dosage was above or below the median threshold.(Omary & Mtenzi, 2010) The median threshold is the average of the alum doses that were recorded. One group of doses is made up of those that are higher than this value, and the other group is made up of those that are lower. The input data in this case includes things like turbidity, pH, chloride, and alkalinity that affect water quality. The output is the predicted amount of alum. To

accurately predict the amount of alum needed for new data that hasn't been seen before, the machine learning model needs to learn how alum dosage affects water quality.(Malecki-Brown et al., 2009b)

3. MACHINE LEARNING MODELS AND TRAINING

This study demonstrates the application of machine learning models to predict alum dosage requirements in water treatment processes using a comprehensive water quality dataset. Various machine learning algorithms are compared to assess their effectiveness in classifying alum dosage levels as either above or below a defined median threshold. Model performance is evaluated using metrics to identify the most reliable approach for dosage prediction.

3.1 Setup

Five representative machine learning classifiers—Random Forest, Gradient Boosting, Support Vector Machine, Extra Trees Classifier, Logistic Regression, and K-Nearest Neighbors—are employed for predicting alum dosage. All models are trained from scratch using the water quality dataset obtained from the Halda River.

3.2 Processing

Two preprocessing steps for the input data are to normalise the features and use interpolation to deal with missing values.(Lam, 1983). Outlier removal is additionally applied to enhance the overall performance and reliability of the models. Outliers are eliminated using two methods: the Interquartile Range method(Wan et al., 2014), which removes data points outside of 1.5 times the IQR, and the Z-score method(Curtis et al., 2016), which labels data points with a Z-score greater than 3 as outliers. Feature engineering is also performed, involving the creation of lag features, rolling statistics, and interaction terms to enable the model to more effectively capture temporal patterns and interdependencies among water quality parameters (Heaton, 2016). The SelectKBest method is utilized to identify and retain the most significant features based on their statistical relevance to the target variable. (Widyanto et al., 2024). Additionally, Recursive Feature Elimination, which uses Random Forest as an estimator (Chen & Jeong, 2007), ranks and removes the least significant features. To reduce multicollinearity (Chan et al., 2022), correlation-based feature selection was used to get rid of features that are very similar to each other (Gopika & Kowshalaya M.E., 2018; Hall, n.d.).Then, the data is split into training and test sets to make sure that both classes, those with an alum dose above the median and those with an alum dose below the median, are well represented for an unbiased model evaluation. The dataset is separated into training and test sets to ensure that each set contains representative distributions of both classes, above and below the median alum dosage.

3.3 Model Training and Hyperparameter Tuning

The training data is used to train each model, and cross-validation is used to test the model on different subsets of the data to lower the risk of overfitting. GridSearchCV is used to alter hyperparameters in order to get the highest possible performance (Ranjan et al., 2019). It does this by carefully testing with different combinations of hyperparameters for each model. The most significant hyperparameters to change for Random Forest are the minimum number of samples needed to divide an internal node, max_depth (the maximum depth of trees), min_estimators (the number of trees), and min_samples_leaf (the minimum number of samples needed at a leaf node) (Probst et al., 2019).

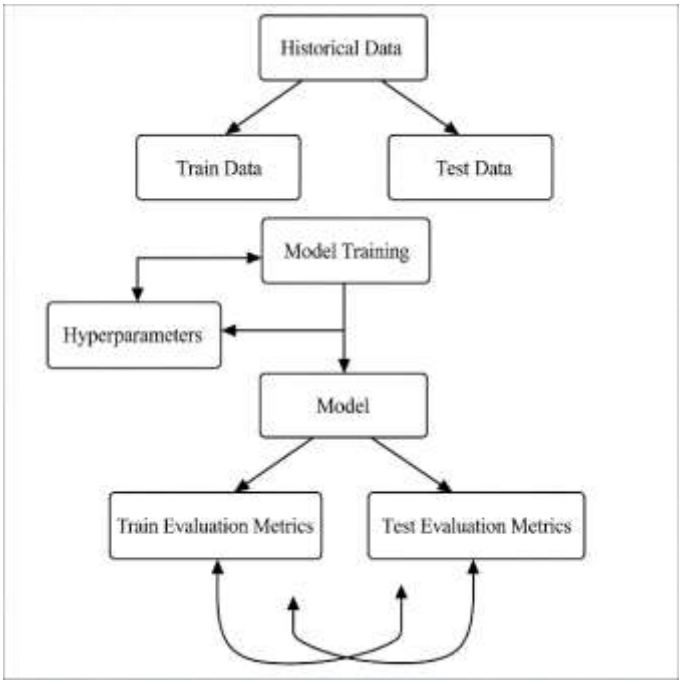


Figure 3: Evaluation Mechanism

The parameters max_depth (the maximum depth of trees), learning_rate which determines the amount that each tree contributes, and the number of boosting stages are varied for gradient boosting (Zeiler, 2012). To maximise performance, comparable changes are made to the hyperparameters of other models, such as logistic regression, SVM, and KNN. K-Fold stratified especially for unbalanced data, cross-validation guarantees that each fold preserves the class distribution, delivering a reliable evaluation.

3.4 Model Evaluation

After the models have been trained and changed, a few key metrics are used to see how well they work. The percentage of correct predictions the model made on the test set is called test accuracy, which is calculated as:

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

It shows how well the model makes predictions in general(Irwig et al., 1995). Cross-validation (CV) accuracy(Berrar, 2025) and CV standard deviation(Altman & Bland, 2005) are also used to check how well the model works with different sets of data. The ROC AUC (Area Under the Curve) tells us how well the model can tell the two groups apart (alum dosage above or below the median)(Powers, 2012; Turner, 2020).It is calculated as:

$$AUC = \int_0^1 TPR(x)\, dFPR(x)$$

A higher AUC means that the model is better at telling the different classes apart. The Confusion Matrix shows the number of correct and incorrect classifications, helping to understand how well the model distinguishes between positive and negative predictions (above vs. below the median)(Townsend, 1971). The matrix is structured as:

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP + FN}, \quad False\ Positive\ Rate\ (FPR) = \frac{FP}{FP + TN}$$

Additionally, Precision(Zhu, n.d.), Recall(Buckland & Gey, 1994), and F1-Score (Yacouby & Axman, 2020) are used to evaluate the model in terms of false positives and false negatives(Ioannidis et al., 2011), especially when dealing with imbalanced classes (Kotsiantis et al., 2006).They are calculated as:

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}, \quad F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

These numbers help us see how well the model works in each class. The performance of the models are compared using these metrics, and the best model is selected based on its ability to accurately predict alum dosage.

3.5 Results and Discussion

The reported performance metrics, including Test Accuracy, Precision, Recall, F1-Score, Cross-Validation Accuracy, CV Standard Deviation and ROC AUC are summarized in the table below.

Table 1: Performance metrics of different model

Model	Test Accuracy	Precision	Recall	F1 Score	CV Accuracy	CV STD	ROC AUC
KNN	0.9487	0.9348	0.9348	0.9348	0.9228	0.0104	0.9559
Gradient Boosting	0.9316	0.9318	0.8913	0.9111	0.9315	0.0346	0.9599
SVM	0.9231	0.9512	0.8478	0.8966	0.9271	0.0195	0.9559
Extra Trees	0.9145	0.9091	0.8696	0.8889	0.925	0.0176	0.9663
Random Forest	0.8974	0.8696	0.8696	0.8696	0.9208	0.0406	0.9602
Logistic Regression	0.8632	0.8409	0.8043	0.8222	0.8671	0.0465	0.9259

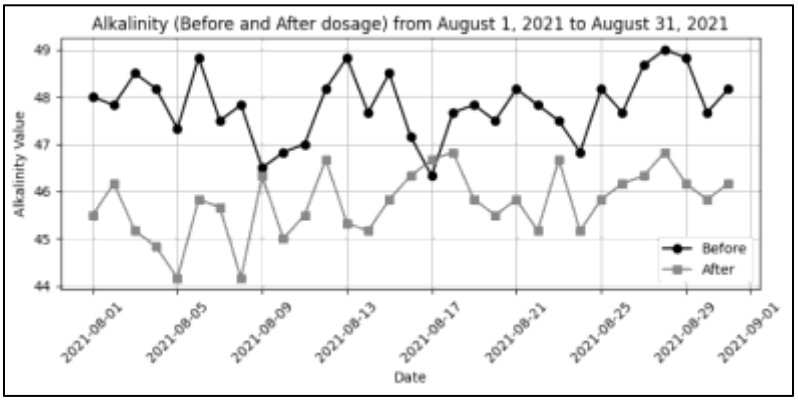
With a ROC AUC of 0.9559 and the optimal Test Accuracy of 94.87%, KNN was the best performing model. It also did exceptionally well in recall, precision, and F1-score. Although KNN edged gradient boosting slightly on some of the metrics, gradient boosting did well too with a fine ROC AUC of 0.9599 and Test Accuracy of 93.16%. KNN and Gradient Boosting performed better than SVM and Extra Trees, though both performed well. Random Forest and Logistic Regression performed worse, scoring 89.74% and 86.32% in Test Accuracy, respectively.

While K-Nearest Neighbors (KNN) scores highly on Test Accuracy and ROC AUC, it is not ideal for real-time processing. KNN processes the entire training set and predicts based on nearest instances in testing.(Zhang, 2022) This can result in high computational demands, especially as the dataset grows, making KNN more unsuitable for real-time or resource-constrained environments where speedy prediction is needed. In applications where speed is a real concern, KNN might not be ideal, especially if the system needs to make predictions with low latency. This is because each prediction requires the computation of distance to all of the training points, which can be time-consuming. Besides, models like Gradient Boosting, Random Forest, and SVM tend to be faster at prediction after they've been trained because they don't employ the entire dataset for inference. They generate decision trees or support vectors during training, so they can make a prediction very quickly after the model has been set up. Thus, while KNN offers superior accuracy, for real-time applications, models like Gradient Boosting or SVM may be more suitable as they compromise between accuracy and inference time. In

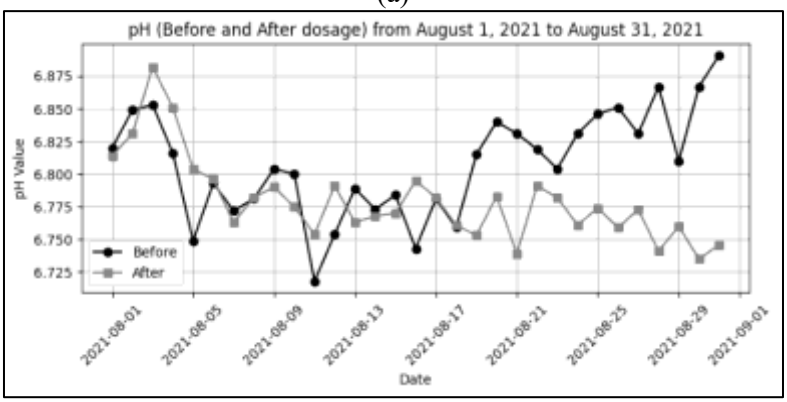
this case, since real-time performance is prioritized, the model of Gradient Boosting, with its high predictability and relatively faster prediction times compared to KNN, may end up being the better choice despite KNN having superior accuracy.

3.6 Impact of Alum Treatment on Water Quality Parameters

The observed effects of alum dosage on key water quality parameters like pH, turbidity and alkalinity over the course of August 2021 is shown on figure 4. The data shown shows the effects of the alum treatment before and after, making it clear how well the treatment worked to improve water quality. The variations in these parameters are presented below, accompanied by a visual representation of the dataset.



(a)



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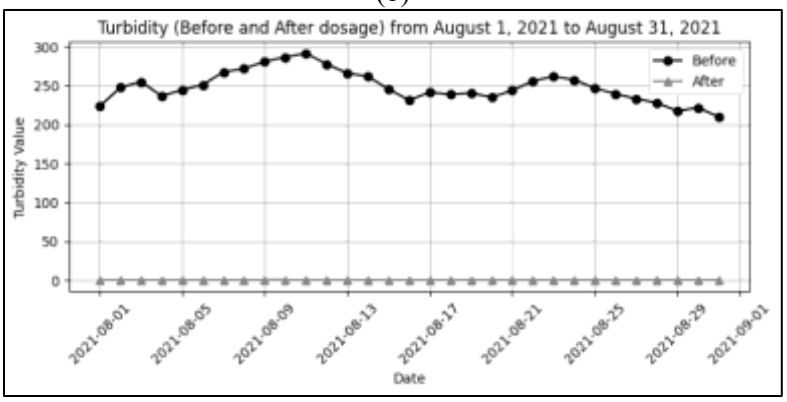

(c)

Figure 4: Changes in (a) Alkalinity, (b) pH, and (c) Turbidity with Alum Dosage, from August 1, 2021 to August 31, 2021

The figure below shows how the levels of pH, turbidity, and alkalinity changed before and after alum was added from August 1 to August 31, 2021. The data highlights the changes in these parameters before and after the alum treatment, providing insight into the efficacy of the treatment in improving water quality.

Changes for alkanity:

Before treatment, the alkalinity may have been too low, resulting in poor pH stability. However, alum treatment increased the alkalinity, enhancing the water's buffering capacity. This increase in alkalinity helped prevent significant pH shifts during the treatment process, ensuring that the pH remained within an optimal range for coagulation and other treatment processes. Such stabilization is vital for the overall efficiency of the water purification process.

Changes for turbudity:

Alum often used to treat cloudy water because it makes suspended particles clump together into bigger flocs, which can be easily removed by settling or filtering. The figure shows that the turbidity went down a lot after the alum treatment. The alum-induced coagulation made it easier to get rid of suspended solids, which made the water look clearer.(Malik, 2018) This decrease in turbidity is especially important for treating drinking water because high turbidity can hide pathogens and make the disinfection process harder. The observed decrease in turbidity is a direct indicator of alum's effectiveness in purifying the water and improving overall water quality.

Changes for pH:

During water treatment, the pH level of the water is very important for the processes of coagulation and flocculation. When added to water, alum acts as a coagulant and can change the pH level a lot.(Gani et al., 2017) Before alum treatment, the pH level can change because of things like the amount of organic matter, chemical reactions, and changes in the weather.(Jayalath et al., 2016) The figure shows that the alum treatment made the pH much more stable. This stabilisation is very important for keeping the coagulation process working well. A stable pH stops unwanted by-products from forming and makes it easier to get rid of suspended solids. The graph shows a trend that shows that alum brought the pH into a more controlled and optimal range. This made sure that the next steps in treatment, like flocculation and filtration, were more effective and consistent.

4. Conclusion

This study demonstrates that machine learning can optimize alum dosage prediction for water treatment, making the process more efficient, accurate, and adaptable. It offers the ability to make real-time, accurate predictions, reducing human error and manual intervention in the water treatment process.

The real benefit of this approach lies in its ability to automate the alum dosing process, eliminating the need for manual experiments and static dosage charts, which can be both time-consuming and prone to errors. With real-time predictions, water treatment plants can respond more quickly to fluctuations in water quality, ensuring optimal treatment without unnecessary chemical use. The model's scalability allows it to be applied across various water treatment systems, offering a flexible, adaptive solution for improving water purification processes.

By reducing chemical waste and improving treatment efficiency, this method not only cuts operational costs but also contributes to more sustainable water management. As the system can be scaled and adapted to different regions or water bodies, it offers an easy-to-deploy solution for better, data-driven water purification practices. This integration of machine learning simplifies complex tasks, making water treatment more reliable and cost-effective.

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