Predictive Multiple Machine Learning Models of Riverine Water Pollution Index: A Comprehensive Data-Driven Study

B.Sc. Engineering Thesis

By

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CERTIFICATION

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DECLERATION

The work contained in this thesis has not been previously submitted to meet the requirements for an award at this or any other higher education institution. To the best of our knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

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ABSTRACT

Water pollution of the Surma River is now a significant environmental problem with rapid accelerated urbanization, industrialization, and release of untreated wastewater. This study pioneers the integration of the Water Pollution Index (WPI) with cutting-edge machine learning algorithms to predict future water pollution levels in the Surma River. Unlike conventional approaches, our method achieves unprecedented accuracy by combining empirical water quality assessments with robust predictive analytics. A total of 648 surface water samples from three different sites were analyzed for 18 years (2007–2024) for eight physicochemical parameters, such as pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total dissolved solids (TDS), suspended solids (SS), electrical conductivity (EC), and temperature. Data analysis indicated that most of the samples were exceeded the World Health Organization (WHO) range: 9.26% of pH, 43.67% of DO, 26.85% of BOD, 87.04% of COD, 17.59% of TDS, 76.08% of SS, and 33.95% of EC values were outside desirable ranges. WPI values ranged from >1, indicating the majority of the samples as "**Highly polluted water,**" indicating high degradation at certain sites. Predictive modeling was conducted based on various machine learning algorithms among all **Linear Regression** gave the optimal accuracy with an R^2 = 0.999954, MSE = 0.000007, RMSE =0.002633, indicating exemplary predictive performance. To ensure the robustness of this result, k-fold cross-validation (e.g., 5-fold) was performed, confirming the model's generalizability and minimizing overfitting risks. The findings place in the limelight the likely increase in pollution levels, indicating the need for more stringent pollution control measures as well as efficient water resource management. The study provides valuable inputs for policymakers as well as environmental organizations to formulate effective strategies for maintaining the ecological balance of the Surma River.

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List of Abbreviations of Technical Symbols and Terms

Abbreviation	Full Form
WPI	Water Pollution Index
ML	Machine Learning
ANN	Artificial Neural Network
DO	Dissolved Oxygen
BOD	Biochemical Oxygen Demand
COD	Chemical Oxygen Demand
TDS	Total Dissolved Solids
SS	Suspended Solids
EC	Electrical Conductivity
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MSE	Mean Squared Error
R^2	Coefficient of Determination
K-Fold CV	K-Fold Cross-Validation
SHAP	SHapley Additive exPlanations
QGIS	Quantum Geographic Information System

CHAPTER 1

INTRODUCTION

1.1 Background

Water is a crucial asset that is essential to the survival of all living forms on Earth (Rahaman et al., 2024). It is an essential resource for industrial, agricultural, and residential uses (Masroor et al., 2021; Noori et al., 2020). Additionally, ecological health and biodiversity preservation depend on water. Nevertheless, despite its importance, it is constantly under danger because of the population's exponential growth, the speed at which cities are developing, and other developmental activities (Rahaman et al., 2022a; T. Xu et al., 2019).

In recent decades, the Surma River has experienced increasing pollution levels, largely driven by unregulated urban growth, industrial discharge, and agricultural runoff in and around Sylhet city. The absence of effective wastewater treatment and the discharge of untreated domestic and industrial effluents directly into the river have significantly deteriorated its water quality. This degradation not only affects aquatic life and ecosystem services but also poses serious health risks to local populations dependent on the river for daily activities. Monitoring such pollution and forecasting its progression are crucial for timely intervention and policy formulation. Conventional assessment methods are often limited by delayed reporting and insufficient spatial coverage. In contrast, integrating the Water Pollution Index (WPI) with machine learning models offers a data-driven approach for real-time analysis and future prediction, allowing for more responsive and evidence-based water management strategies.

1.2 Problem Statement

The amount and quality of water supplies have been impacted by climate change. The past several decades have seen an increase in the frequency of severe events, such as droughts and floods, as a result of anomalous rainfall and temperature patterns (Rahaman et al., 2022b; Rehman et al., 2022). Water shortage and decrease in water quality are the results of these catastrophes, which have also changed the natural cycle of water. The transportation and dilution of pollutants have also been impacted by changes in precipitation patterns, which has resulted in the pollution of water supplies (Brontowiyono et al., 2022; Zhu et al., 2022). A significant problem, severe water scarcity affects around 4 billion people worldwide for at least one month every year. Additionally, more than 2 billion people do not have access to a sufficient amount of water (Mekonnen & Hoekstra, 2016). Due to inadequate monitoring and evaluation at least 3 billion people are ignorant of the water quality they depend on (The Sustainable Development Goals Report, n.d.). In developing nations like Asia, Latin America, and Africa communities are less equipped to handle pollution and water scarcity (Water | OECD; 2025.). Approximately 80% of infections that harm people and sicken communities in underdeveloped countries are water-borne (S. F. Ahmed et al., 2022). While water pollution is a global crisis, developing nations like Bangladesh face severe contamination due to rapid industrialization and poor waste management at the same time (F. Ahmed et al., 2023; Islam et al., 2022; Matter et al., 2015).

Bangladesh is dealing with a severe water pollution issue, and environmental deterioration, particularly water pollution, has gotten frighteningly worse in recent years (Parvin et al., 2022). The primary causes of water pollution in Bangladesh include population growth, construction near water bodies, industrial effluent discharge, hospital and municipal waste, plastic waste, agricultural waste, pesticides, fertilizers, river grabbing, inefficient solid waste management, poverty, inadequate sanitation, and ignorance (Arifuzzaman et al., 2019). The freshwater and marine habitats may be threatened by a few of these, including plastic waste and industrial discharges, which can only be minimized (Budziak & Fyda, 2024; Mitrano et al., 2021; Sangkham et al., 2022). Research indicates that both natural and man-made sources can contaminate water (Google Books, 2025). However, due to urbanization, industrialization, and man-made issues, the majority of water sources, primarily surface water bodies, are contaminated (Pandey S, 2006). The Department of Environment (DoE), as the nation's top authority, closely monitors water quality through year-round programs, which have revealed a rising trend in pollution levels across rivers and other surface water sources over time(Department of Environment, Bangladesh; 2025)

The ecological health of the Surma River has significantly declined in recent decades due to unplanned and uncontrolled rapid urbanization, the discharge of untreated and partially treated wastewater, inadequate land-use planning, crowded bathing areas, and the disposal of solid waste in and near the river stretch. A wide number of research studies have categorized the Surma River's water quality status based on a comparison of specific water quality indicators to their regional and global standards (Howladar et al., 2021; M Sadequr Rahman Bhuyain et al., 2020; Sarkar et al., 2019; M. M. Uddin et al., n.d.). Researchers have conducted a great deal of study in support of the preservation and management of fresh surface water quality since water is essential to the sustainability of human civilization and the environment (Dooge, n.d.; M. G. Uddin et al., 2021) Consequently, a lot of research were carried out in the past two decades to investigate the water quality in order to grasp the general state of an ecosystem and the condition of the surface water (Drasovean & Murariu, 2019.). Effectively controlling water quality requires ongoing monitoring, which is also critical for protecting ecosystems, human health, sustainable water resource management, pollution prevention, and policy formation (Brack et al., 2017; Geissen et al., 2015). Assessment of possible hazards, health risk reduction, environmental preservation, and the guarantee of clean water supply for current and future generations can all be made possible by monitoring and evaluating water quality (Mokarram et al., 2020). But depending only on traditional monitoring techniques is insufficient. Instead, in order to avoid adverse effects on water quality, it is frequently necessary to use methods or models to identify such dangers in less time (Towfiqul Islam et al., 2021). According to these findings, a number of actions can be taken, such as starting treatments to remove pollutants, changing or diversifying water sources, promptly releasing public safety advisories, improving and modifying water treatment facilities, and putting emergency response plans in place that are suited to particular risks (Berglund et al., 2020; Feng et al., 2019). In recent years, artificial intelligence (AI) has emerged as a promising field for the development of sophisticated algorithms and prediction techniques that can be used to estimate the state of water quality by analyzing complex data. Water quality prediction is crucial for many socio-economic sectors that rely heavily on access to clean and safe water resources (A. A. Ahmed et al., 2024).

1.3 Research Objectives

The specific objectives of this research are as follows:

- Assess the Water Pollution Index (WPI) of the Surma River and analyze its regional variations.
- Develop and compare predictive AI models, including: Linear Regression, XGBoost Regressor, Random Forests Regressor, Bagging Regressor, AdaBoost Regressor, Gradient Boosting Regressor, Cat Boost Regressor and Artificial Neural Network.
- Determine significant independent parameters affecting WPI based on standardized regression coefficients.
- Address research gaps by applying machine learning in water quality assessment, offering new insights into sustainability and pollution control.

1.4 Scope and Limitations

This study aims to assess and predict the surface water quality of the Surma River using the Water Pollution Index (WPI) and advanced machine learning models. The assessment is based on 18 years of monthly data (2007–2024) collected from three key locations: Mendi-bag, Kean Bridge, and Sheikh Ghat. Eight major physicochemical parameters—pH, Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS), Suspended Solids (SS), Electrical Conductivity (EC), and temperature—were analyzed to calculate WPI and develop predictive models. Multiple machine learning algorithms were employed to forecast future pollution levels and evaluate parameter importance.

However, the scope is limited to surface water only and excludes groundwater quality. The study relies on secondary data provided by the Department of Environment (DoE), which may be subject to gaps or inconsistencies. Microbiological, heavy metal, and emerging contaminants are not included due to unavailability of data. Real-time monitoring was not possible, and therefore, temporal variations between sampling intervals may not be fully captured. Additionally, only three sites were selected, which may not reflect the full spatial variability of the Surma River system. Finally, although various models were tested, the selection of model hyperparameters was constrained by available computational resources, which may affect performance under different scenarios.

1.5 Significance of the Study

This study represents the first successful integration of the Water Pollution Index (WPI) with advanced machine learning techniques, specifically targeting the prediction of future water pollution levels in the Surma River. The proposed method enhances traditional WPI analysis by leveraging robust algorithms such as ANN and ensemble models, allowing for precise and dynamic prediction of pollution levels. This approach marks a significant advancement over conventional methods that rely solely on static empirical data. Ensemble learning methods like Random Forest, Gradient Boosting, and Adaptive Boosting are widely used in water quality assessment for their ability to model complex environmental data (Huan & Liu, 2024). Random Forest constructs several decision trees and takes average predictions, avoiding overfitting and increasing stability (Sun et al., 2024; Szomolányi & Clement, 2023). Gradient Boosting progressively optimizes weak learners, which capture complex patterns in water quality information effectively (Islam Khan et al., 2022) Adaptive Boosting dynamically adjusts model weights, increasing sensitivity to key pollution indicators. Ensemble methods avoid bias and variance and are thus stable for monitoring and forecasting water quality in varying aquatic ecosystems (Yan et al., 2023).

CHAPTER 2

LITERATURE REVIEW

2.1 Water Quality and Pollution Overview

The Surma River, flowing through Sylhet, Bangladesh, is facing serious environmental degradation due to unchecked urbanization, rapid industrial growth, and ineffective waste management. The Department of Environment (DoE) has reported increasing pollution trends in its surface water monitoring programs. Water quality assessments from 2007 to 2024, based on eight physicochemical parameters (pH, DO, BOD, COD, TDS, SS, EC, and temperature), reveal significant deviations from WHO and Bangladesh standards. Notably, 87.04% of COD, 76.08% of SS, and 43.67% of DO samples fall outside permissible limits. WPI values across the sampling stations ranged from 0.58 to 2.54, with a mean of 1.49, indicating a "highly polluted" classification for most samples. The root causes of this pollution include industrial effluents, hospital and municipal sewage, plastic and agricultural runoff, poor sanitation infrastructure, and illegal river encroachment. These pollutants not only degrade water quality but also disrupt aquatic ecosystems and pose direct threats to human health.

Water quality monitoring is essential but remains inadequate if reliant only on traditional assessment methods. The paper integrates Water Pollution Index (WPI) with machine learning models such as Random Forest, Gradient Boosting, and Artificial Neural Networks to enhance prediction accuracy and support proactive pollution management strategies.

2.2 Water Pollution Index (WPI) Concept

The Water Pollution Index (WPI) is a simplified yet powerful tool designed to assess surface water quality by aggregating pollution loads from multiple physicochemical parameters into a single numerical index. This approach allows for an objective, consistent, and interpretable assessment of pollution status across different locations and time periods. Unlike traditional water quality indices that often require subjective weighting of parameters or rely on ideal theoretical values, WPI uses a straightforward method that avoids these complexities, making it particularly suitable for data-driven studies and practical applications in environmental monitoring.

2.3 Machine Learning in Environmental Monitoring

Machine learning (ML) has emerged as an essential approach in environmental monitoring due to its capability to process large datasets, detect complex patterns, and improve predictive accuracy. Traditional methods often fail to capture non-linear relationships among variables or to provide timely forecasts for pollution events. In contrast, ML techniques offer faster, automated, and more accurate analysis for water quality monitoring and prediction (A. A. Ahmed et al., 2024; Huan & Liu, 2024).

Ensemble learning methods such as Random Forest, Gradient Boosting, and Adaptive Boosting have shown high reliability in environmental modeling by effectively managing data heterogeneity, minimizing bias and variance, and increasing robustness in variable aquatic systems (Yan et al., 2023). Random Forest builds multiple decision trees and aggregates predictions to enhance accuracy and avoid overfitting (Sun et al., 2024; Szomolányi & Clement, 2023). Gradient Boosting incrementally improves weak learners to model complex interactions among water quality indicators (Islam Khan et al., 2022). Adaptive Boosting dynamically adjusts model weights to increase sensitivity to key pollution parameters.

XGBoost, known for its speed and accuracy in handling structured data, has also been widely adopted for water pollution forecasting tasks (Abbas et al., 2024; Sidek et al., 2024). Bagging Regressor and CatBoost Regressor improve prediction stability and handle categorical variables effectively (Hassan et al., 2021; Li et al., 2024). Artificial Neural Networks (ANNs), due to their flexibility and ability to approximate complex nonlinear functions, are considered one of the most reliable tools in modern environmental data science (Nayak et al., 2023; Wu & Wang, 2022).

In this study, these ML models are applied to predict the Water Pollution Index (WPI) of the Surma River—marking the first known use of WPI as a target variable in predictive modeling. This approach combines the simplicity of WPI with the strength of ML to build a comprehensive, scalable, and interpretable framework for future pollution estimation, thereby offering a practical solution for improving water resource management in Bangladesh.

2.4 Related Works on Surma River Water Quality

Recent research has highlighted the effectiveness of several advanced machine learning algorithms in forecasting water contamination. Notably, models such as XGBoost is a powerful ensemble learning method that has been widely used for its fast and accurate handling of structured data and is very effective in water pollution forecasting (Abbas et al., 2024; Sidek et al., 2024). Similarly, Bagging Regressor enhances predictability by training ensemble members on random subsets of information and averaging predictions to reduce variance and enhance generalization (Hassan et al., 2021). Cat Boost Regressor, tailored to optimize categorical features, employs ordered boosting to minimize overfitting as well as maximize interpretability and is particularly suitable for environmental data sets (Li et al., 2024; Nasir et al., 2022). Linear Regression, a traditional statistical method, establishes a linear relationship between input features and water pollution levels that is easy to interpret and understand but less effective in the presence of non-linearity (Jafar et al., 2023; Palade et al., 2022). The ANN is a unique and flexible method that can handle a wide range of data kinds, as previous research has shown, it's importance in modern research is further supported by the fact that its intrinsic flexibility makes it a compelling and reliable choice for analyzing a variety of datasets (Nayak et al., 2023; Wu & Wang, 2022).

2.5 Research Gaps

Although numerous studies have assessed water quality in Bangladesh's rivers, including the Surma River, most have relied on conventional statistical analyses or single-parameter evaluations. These approaches often lack predictive capability and fail to capture the combined effect of multiple pollutants. While some studies have used machine learning for water quality prediction, they typically focus on individual parameters like BOD or DO rather than a comprehensive pollution index. No study has used the WPI as a target variable for machine learning-based prediction of future water pollution in any river in Bangladesh. This represents a key gap in the existing literature. WPI offers an integrated measure of water quality, but its use has been mostly limited to static assessments without any predictive modeling. This study addresses that gap by, for the first time, combining WPI with multiple machine learning models to forecast future pollution trends. This integration introduces a novel, interpretable, and scalable framework for assessing and predicting river water quality which provides a valuable decision-support tool for sustainable water resource management.

CHAPTER 3

METHODOLOGY

3.1 Study Area

Sylhet Surma River, located in the Sylhet Division of Bangladesh, is a hydrologically significant river flowing through the heart of Sylhet city. The river originates from the Barak River in India and plays a crucial role in the region's water resources, economy, and ecology. Covering a stretch within the urban and suburban areas of Sylhet, the Surma River is essential for agriculture, fisheries, and domestic water use. The geographical coordinates of the study sites range approximately between 24°55′N latitude and 91°52′E longitude. The river's altitude varies slightly but remains close to sea level, with seasonal fluctuations due to monsoon-driven changes in water levels. The Surma River exhibits varying water quality due to urban runoff, industrial discharge, and sediment transport from upstream areas. Geomorphological features along the river include floodplains, meandering channels, and deposition zones, which impact water flow and sedimentation patterns.

For this study, three sampling sites—Mendi-bag, Kean Bridge, and Sheikh Ghat were selected to assess the water quality variations and hydrological characteristics of the Surma River (Figure 1, facilitated by QGIS).

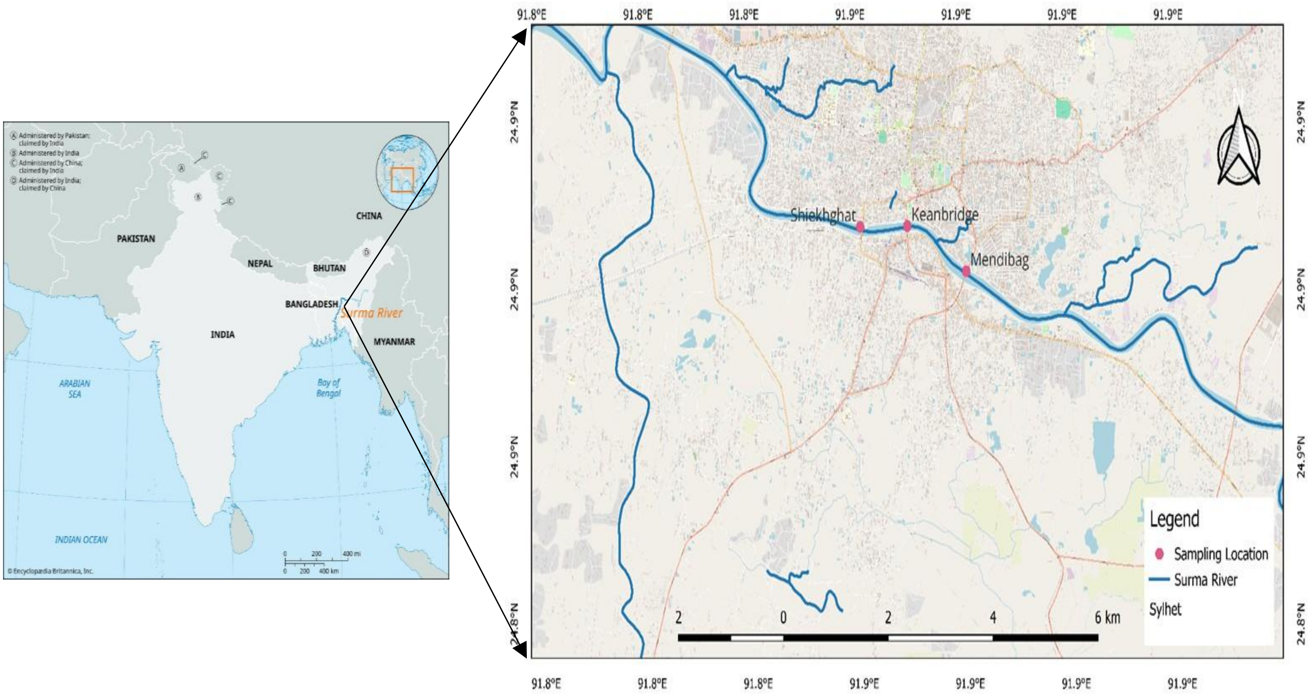


Figure 1. Study Area Map

3.2 Study framework

The proposed study framework systematically integrates conventional water quality assessment with advanced machine learning (ML) models to enhance the evaluation of surface water quality, as illustrated in Figure 2. The process begins with data collection and preprocessing, focusing on eight key physicochemical parameters to ensure reliable input data. The Water Pollution Index (WPI) method is then applied to quantify pollution levels, simplifying complex water quality data into a comprehensible format.

Subsequently, exploratory data analysis (EDA) and data preprocessing are performed using Standard Scaler normalization, ensuring consistency for ML model training. The dataset is divided using a 80:20 train-test split**,** with a validation set employed for hyperparameter tuning. A key advantage of this framework is its inclusion of multiple ML models—Linear Regression, Random Forest Regressor, XGBoost Regressor, Bagging Regressor, AdaBoost Regressor, Gradient Boosting Regressor, Cat Boost Regressor and Artificial Neural Network model enabling a comparative performance analysis based on evaluation metrics such as R^2, RMSE, and MAE**.**

However, the reliance on these models introduces challenges such as potential overfitting and computational complexity, particularly when dealing with large datasets or high-dimensional inputs. To assess model performance, radar plots and Taylor diagrams provide intuitive visual comparisons, though the selection of the optimal model could be further refined using cross-validation techniques to improve generalizability.

While the framework is well-structured and methodologically rigorous, its overall effectiveness heavily depends on data quality, model interpretability, and the trade-off between accuracy and computational efficiency—factors that are particularly crucial in resource-constrained environments like the Surma River region. The novelty of this study lies in the seamless integration of WPI with advanced machine learning models to improve predictive accuracy and reliability. By combining traditional water quality assessment with cutting-edge algorithms, this method significantly enhances the robustness and precision of water pollution forecasting.

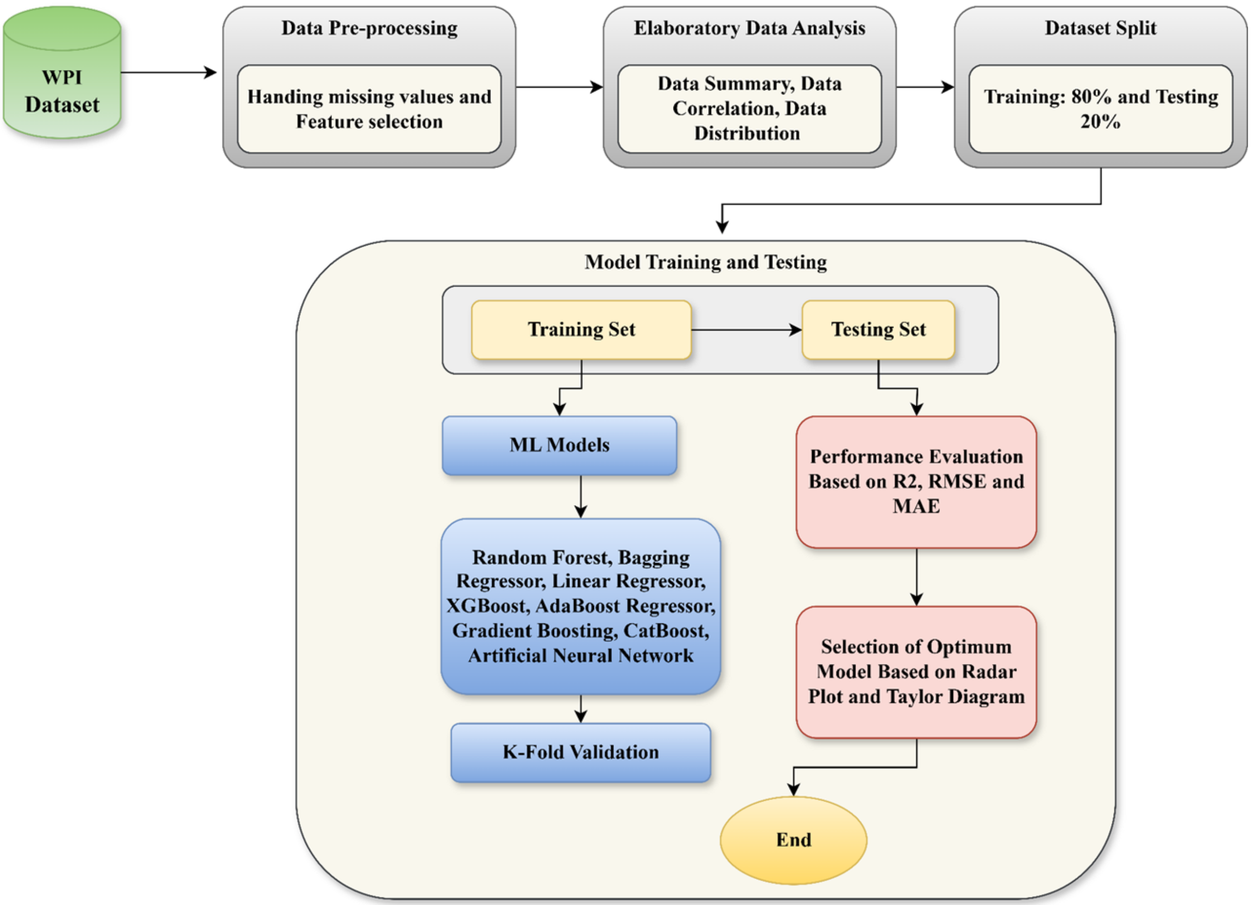


Figure 2. Framework of the Proposed Study

3.3 Data Collection

In this research, the monthly water quality data were analyzed, which were collected from three particular sampling stations on the mainstream of the Surma River. Data, from (2007-2024) 18 years dataset were obtained from the Department of Environment, Alampur, Sylhet, Bangladesh. Eight significant physicochemical parameters of water quality were analyzed and recorded: pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total dissolved solids (TDS), suspended solids (SS), water temperature (T), and electrical conductivity (EC).

3.4 Water Pollution Index (WPI) Calculation

Water Pollution Index (WPI) is a newly formulated method to rank water quality. For this purpose, total 8 water quality parameters pH, DO, BOD, COD, TDS, SS, Temp and EC were selected to estimate the pollution load of surface water by applying WPI, based on their standard permissible limits as defined by the Bangladesh Standard and WHO standard Table 2. However, WPI can accommodate more number of variables as it is flexible for n number of parameters.

In the first step the pollution load (PL_i) of i^{th} parameter was calculated using the following formula (Eq. (1));

$$\mathbf{PLi = 1 + \left(\frac{C_i - S_i}{S_i}\right)} \quad (1)$$

Where C_i is the actual value of the i^{th} parameter as measured, and S_i is the standard or acceptable maximum value of the related parameter. The quotient of C_i and S_i minus one is the relative increase or decrease in standardized value (PLi) of a particular parameter from its allowed limit (Si). For pH, 7 is neutral, but below 7 (< 7) or above 7 (> 7) is toxic. Based on this perspective, the following equations are proposed for different ranges of pH.

If, the pH is < 7, then (Eq. (2)); is recommended. Where, Si_a is minimum acceptable pH value i.e., 6.5

$$\mathbf{PLi = \left(\frac{C_i - 7}{Si_a - 7}\right)} \quad (2)$$

If, pH is > 7, then Si_b would be maximum acceptable pH value i.e., 8.5 and the suggested equation is mentioned below Eq. (3)

$$\mathbf{PLi} = \left(\frac{C_i - 7}{Si_b - 7}\right) \tag{3}$$

Ultimately, the pollution status of a water sample, as represented by the Water Pollution Index (WPI), can be determined by adding up the pollution load of all the measured parameters and then dividing by the total number of parameters (n) measured, as expressed in the following equation (Eq. 4). In exceptional cases where the concentration of a parameter measured is 0, it should be excluded from the total n for that sample.

$$\mathbf{WPI} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{PLi} \tag{4}$$

The WPI values can be classified into four groups based on the number of parameters (n) used, as in Table 1. The WPI provides a holistic approach by normalizing all the input parameters to a single value index to classify water quality. Any slight deviation in the concentration of an input parameter can alter the WPI classification of water quality. In addition, the WPI does not apply theoretical ideal values or varying weightages for parameters like some conventional indexing methods. The WPI is applicable to a wide range of datasets, even where variables are skewed or non-normally distributed **(Hossain & Patra, 2020)**. In addition, the use of several indices for different purposes in one study can be lengthy and time-consuming. WPI gives an overall impression of water quality status based given input parameters and can be specific to a specific application by applying the standard guideline values relevant to that particular purpose.

Table 1. Water classification method with respect to WPI score.

WPI Value	Category
<0.5	Excellent water
0.5 - 0.75	Good water
0.75 - 1	Moderately polluted water
>1	Highly polluted water

Table 2. Standards limits for parameters (Olayinka et al., 2014)

Serial No	Parameters	Bangladesh Standards	WHO Standards
1	pH	6.5-8.5	6.0-9.0
2	DO	6	5
3	BOD	6	2
4	COD	4	8
5	TDS	1000	500
6	SS	10	>10
7	EC	300	200
8	Temperature	20-30	-

3.5 Data Preprocessing

Machine learning depends on data preprocessing for creating structured data that ensures reliable results (Adhikari et al., 2024). Raw data needs systematic preparation in advance of training since it will boost the learning process and enhance predictive accuracy. The step remains essential because missing variables and data noise together with anomalies damage the model reliability which leads to poor prediction results.

One main goal during preprocessing is to enhance data quality by rectifying various errors as well as fixing missing data and resolving outliers that cause disruptions to learning patterns. The execution of data cleaning procedures enables preprocessing algorithms to prepare data models with meaningful and accurate information by taking care of missing values while shrinking noise effects and rectifying data inconsistencies.

Preprocessing techniques have a fundamental place in model efficiency because they help enhance data quality levels. Numerical value normalization combined with transformation and feature scaling techniques creates numbers with compatible ranges which helps algorithms reach faster convergence and higher accuracy rates. Standardization of data distributions supports bias prevention during learning while reducing computational difficulties that are common in high-dimensional analyses.

The systematic refinement of data representation through feature engineering continues after organizations perform basic data cleaning and scaling practices. The modifications and creation of new features in models help identify crucial patterns between data points better. The model's predictive capabilities increase when these techniques are used to transform and generate polynomial features from categorical variables which allows the extraction of useful insights for better accuracy.

Recent machine learning practitioners face the problem of overfitting which happens when training data memorization occurs instead of adopting new examples. Through preprocessing techniques, the data becomes easier to analyze because it decreases feature dimensions and removes unneeded data elements. Deep learning models and complex architectures need this measure most because high numbers of model parameters decrease generalization while making performance worse.

The preprocessing function becomes vital when dealing with datasets extracted from different sources to establish format consistency. Model reliability faces deterioration because measurement units differ as well as missing standards and structural discrepancies generate biases. The preprocessing process enables organizations to combine different datasets within one uniform framework which enhances their capacity to learn successfully from diverse information sources.

The preprocessing process makes computational operations more efficient through simplification of both data dimensions and sizes. This practice reduces resource requirements which shortens training duration and results in optimal system performance. Fast data processing becomes essential for big datasets together with real-time model deployment because it delivers both efficiency and speed requirements.

The final essential role of preprocessing involves enhancing the interpretability of models thus producing transparent results which can be effectively applied. The conversion of categorical variables to numerical forms creates better visibility into the role features play in model prediction assessments. The field of healthcare together with finance and policy analysis needs transparent processes to maintain decision-explanation and justification methods.

Machine learning begins with data preprocessing which serves as the essential structural base for all subsequent activities. Data preprocessing optimizes both model interpretability and execution speed besides maintaining data integrity while avoiding predictive errors known as overfitting. Advanced algorithms cannot ensure reliable results unless they process the data with enough rigor. Machine learning advances require robust preprocessing techniques because they ensure the development of accurate trustworthy models.

3.5.1 Cleaning, Missing Values

3.5.1.1 Duplicate Detection

To uphold the integrity of the dataset, an initial thorough examination was conducted to identify any duplicate records (Kumar et al., 2018). This meticulous process confirmed that no duplicate entries were present, thereby validating the uniqueness of each data point within the dataset. This step is crucial as duplicates can skew analysis and lead to erroneous conclusions.

3.5.1.2 Handling Missing Data

A comprehensive assessment of missing values was performed to pinpoint any incomplete data entries that could compromise the dataset's overall quality (Vinisha & Sujihelen, 2022). To address these gaps effectively, various imputation techniques were employed. Specifically, the median imputation method was utilized for the Chemical Oxygen Demand (COD) variable, which is characterized by a skewed distribution, ensuring that the central tendency is accurately represented without being influenced by outliers. Conversely, the mean imputation method was applied to other variables such as pH, Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Total Dissolved Solids (TDS), Suspended Solids (SS), Electrical Conductivity (EC), and Temperature. This approach was adopted to maintain consistency across the dataset and to uphold the integrity of the data representation.

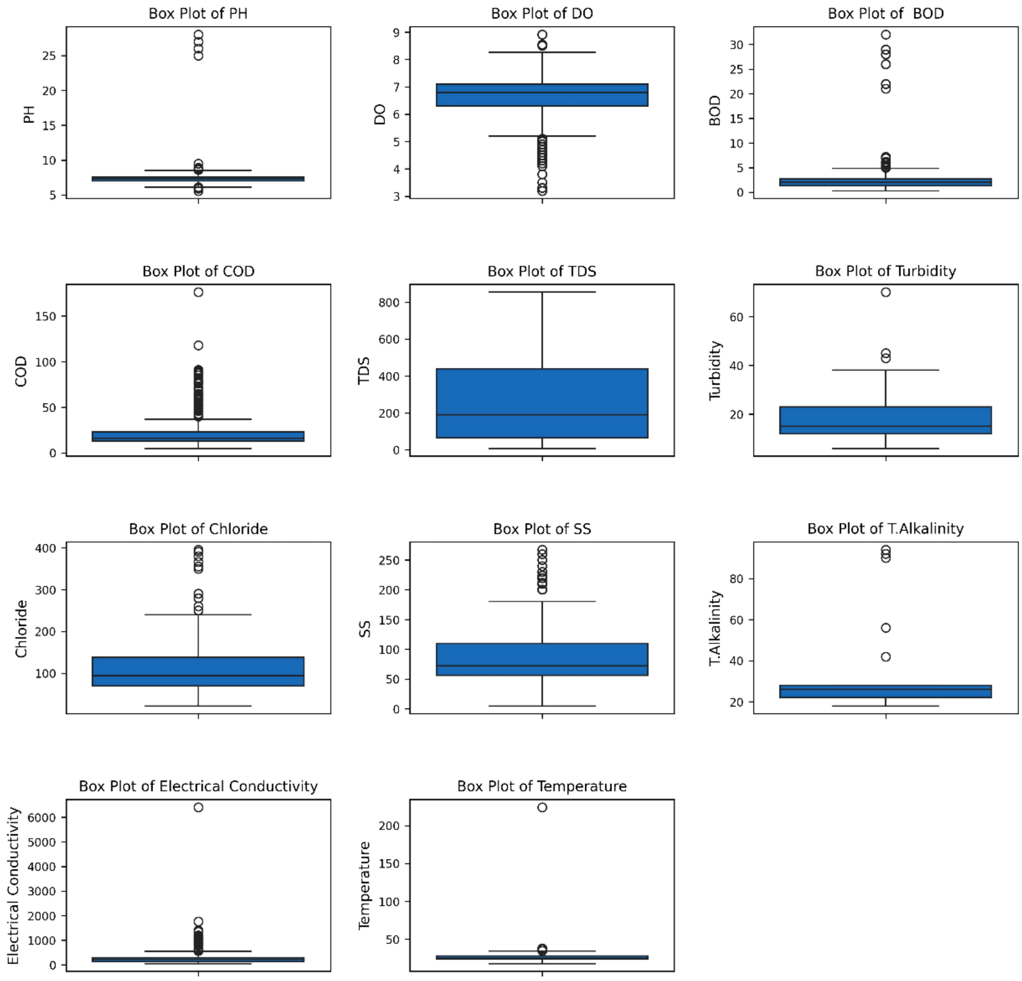
3.5.1.3 Data Type Conversion

During the data inspection phase, it was discovered that several numerical attributes were incorrectly stored as string values. To facilitate accurate computations and enhance the efficiency of modeling processes, these attributes were systematically converted into their appropriate numerical formats. This conversion is essential for ensuring that subsequent analyses and algorithms can process the data correctly without encountering type-related errors.

3.5.2 Outlier Detection and Treatment

Outlier detection was carried out using the Interquartile Range (IQR) method (Vinutha et al., 2018), a robust statistical technique that effectively identifies extreme deviations from the expected data distribution, as illustrated in Figure 3. Once identified, these outliers were addressed through appropriate capping and transformation techniques. This treatment not only mitigates the influence of these extreme values on the dataset but also enhances the overall stability and predictive performance of the models built upon this data.

$$\mathbf{IQR} = \mathbf{Q3} - \mathbf{Q1} \quad (5)$$



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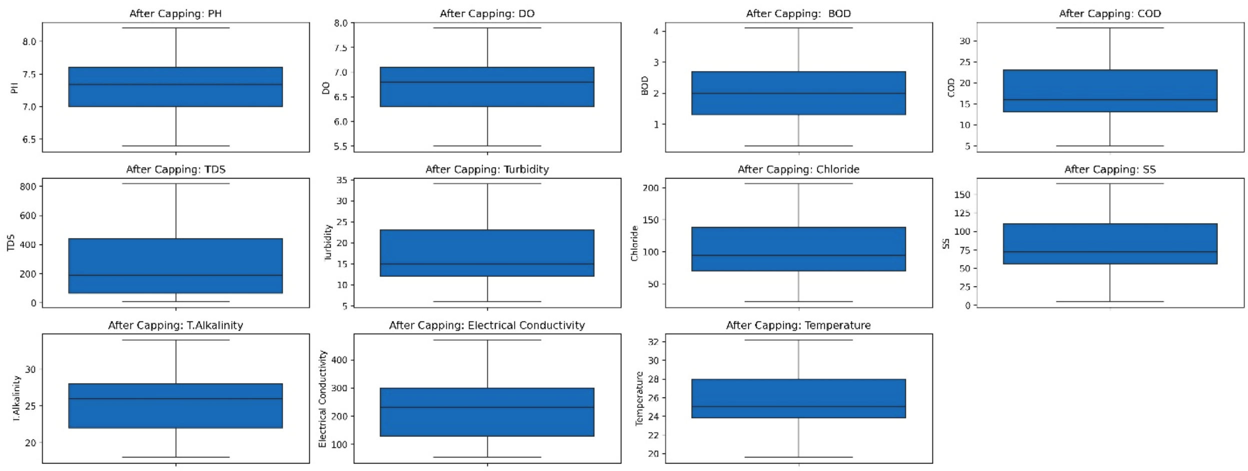


(b)

Figure 3. Outlier detection and treatment process in the dataset (a) before treatment (b) after treatment

3.5.2.1 Outlier Treatment

To mitigate the influence of extreme values, capping techniques were applied, ensuring model stability and predictive performance. The impact of outlier treatment on feature distributions is depicted in Figure 4. This method ensures that extreme outliers are capped while preserving the overall distribution of the dataset.

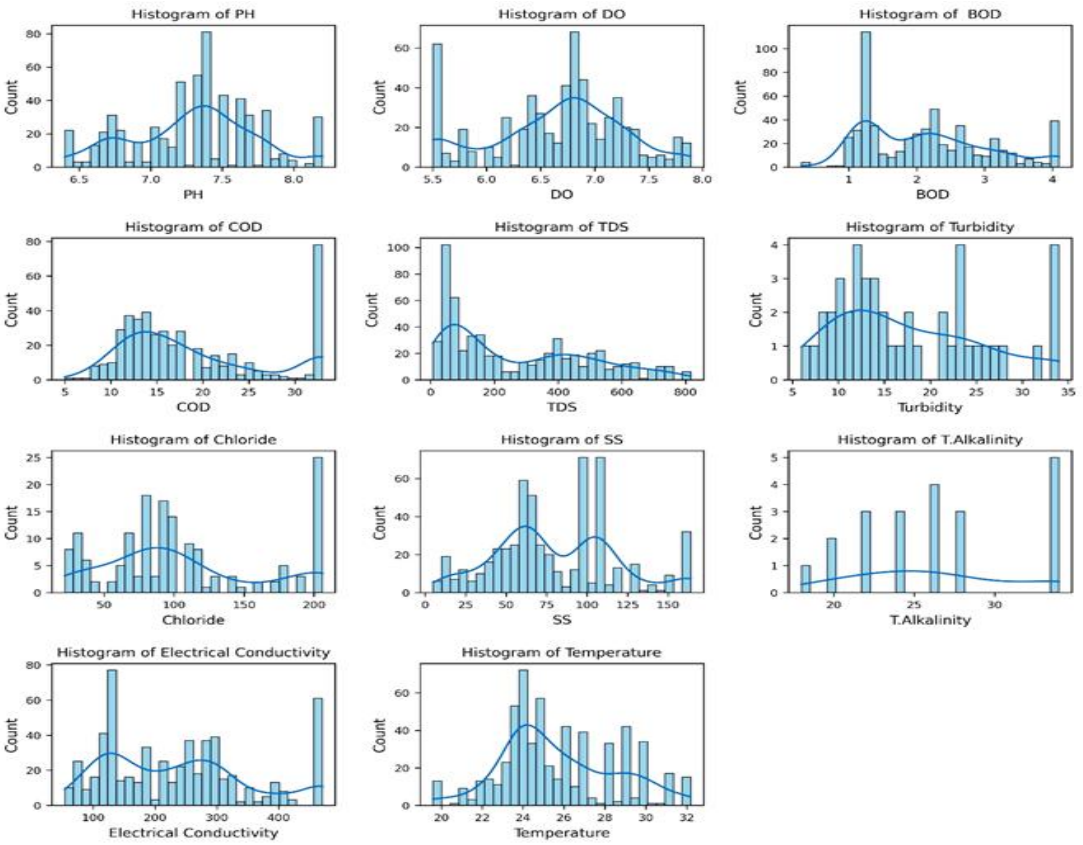


Figure 4. Histograms and Box plot after outlier handling

3.5.2.2 Normalization

To ensure uniformity and eliminate bias towards certain variables within the dataset, normalization techniques were applied. Depending on the distribution characteristics of the data, methods such as Min-Max scaling were employed. This step is vital in preparing the data for further analysis (Sola & Sevilla, 1997), as it ensures that all variables contribute equally to the results, thereby improving the reliability of any subsequent predictive modeling or statistical analysis.

$$\mathbf{X'} = \frac{\mathbf{X} - \mathbf{X_{min}}}{\mathbf{X_{max}} - \mathbf{X_{min}}} \quad (6)$$

3.6 Exploratory Data Analysis (EDA)

3.6.1 Visualizing Data Distributions

To gain insights into the underlying data structure, histograms, box plots, and density plots were employed in Figure 5 and Figure 6 to visualize the distribution of key water quality parameters, including pH, Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS), Turbidity, Chloride, Suspended Solids (SS), T-Alkalinity, Electrical Conductivity (EC), and Temperature. These visual tools facilitated a detailed assessment of skewness, normality, and variance within the dataset, ensuring a comprehensive understanding of each variable's statistical behavior and its potential impact on model performance.

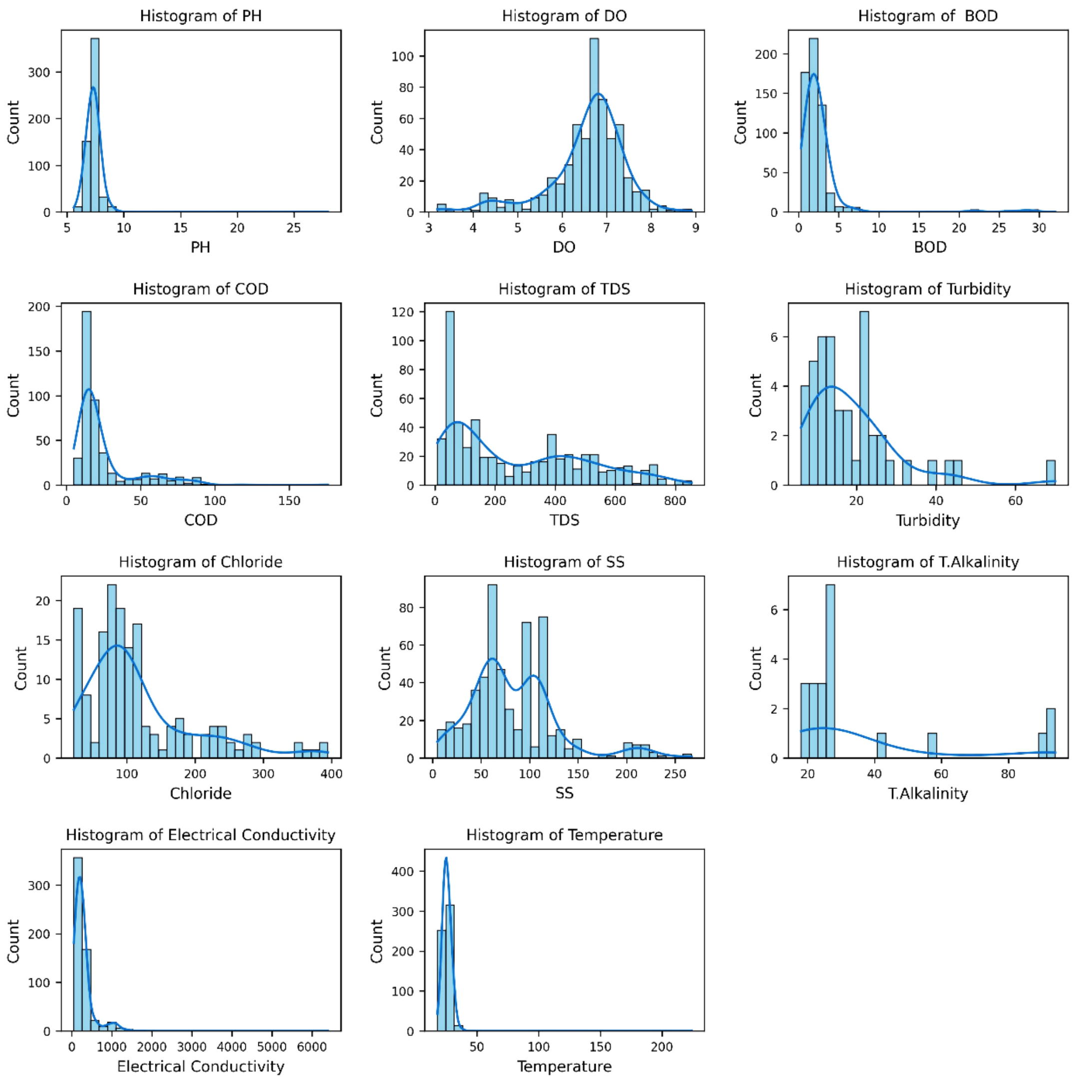


Figure 5. Histogram of Water Quality Parameters datasets

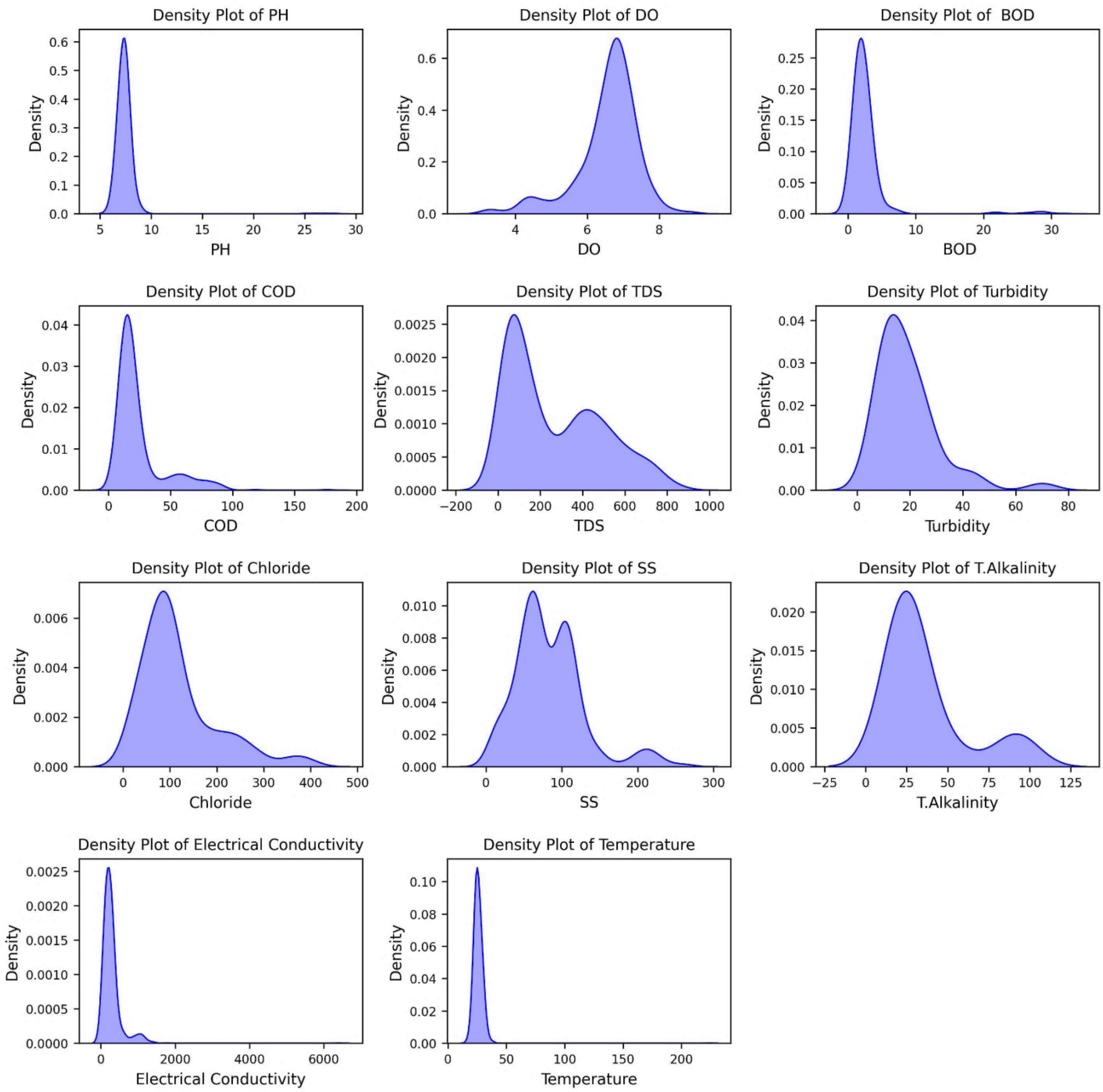


Figure 6. Density Plot of the Water Quality Parameters.

3.6.2 Feature Correlation Analysis

A Pearson correlation heatmap was employed in Figure 7 to evaluate the relationships between different water quality parameters and the target variable, Water Pollution Index (WPI). Features exhibiting weak correlations with WPI were deemed redundant and subsequently removed. These included Total Alkalinity, Chloride, Turbidity, Date, and Location, as they contributed minimal predictive value to the model. Following correlation analysis, only the most relevant features were retained to enhance model interpretability and efficiency. No additional feature engineering was deemed necessary, as the existing parameters sufficiently captured the predictive patterns required for WPI estimation.

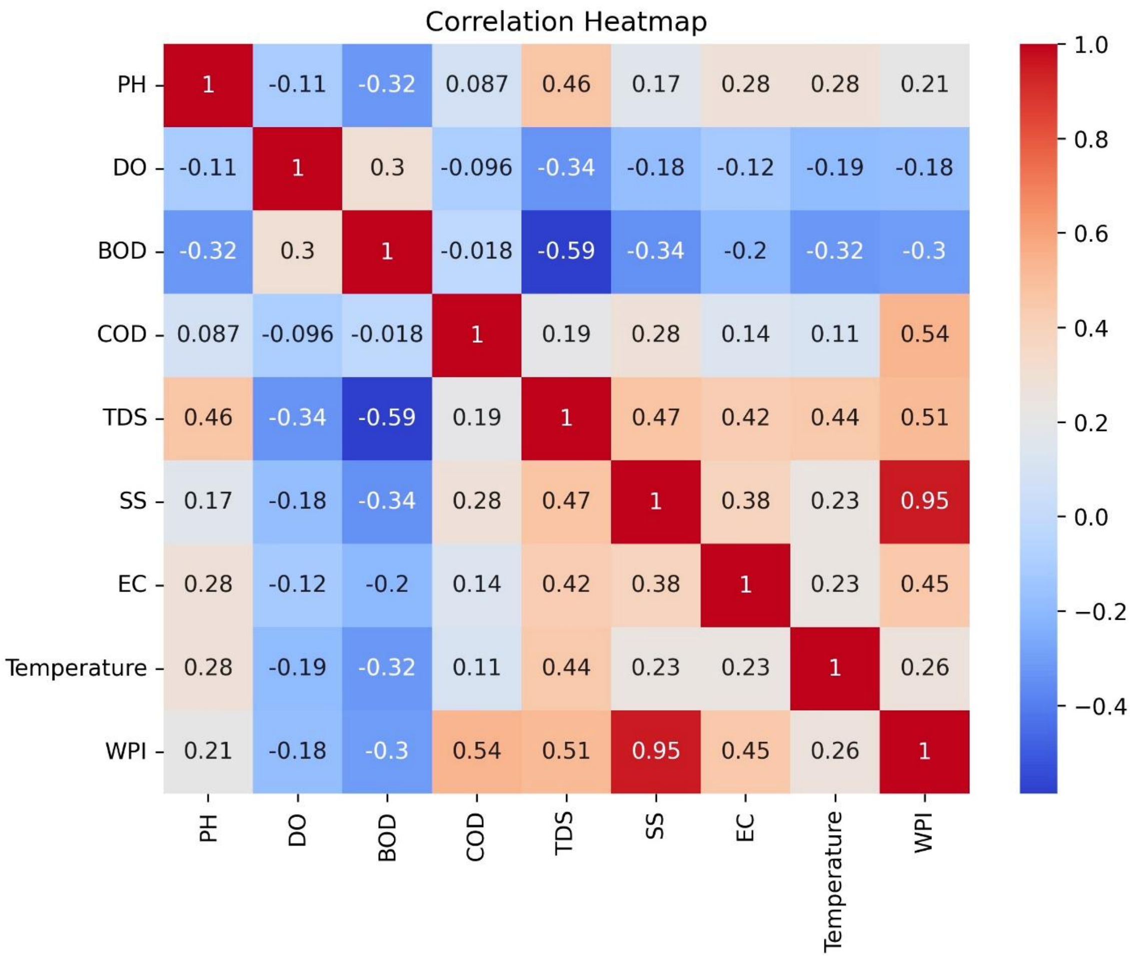


Figure 7. Heatmap plot representing the correlation matrix between numerical variables to be considered for the data model.

3.6.3 Data Splitting

To ensure an effective evaluation of model performance, the dataset was divided into training and testing sets using an 80/20 split. The training set (80%) was utilized to develop and fine-tune the models, while the test set (20%) served to evaluate the models' ability to generalize to unseen data. This approach mitigates the risk of overfitting (How to Split Machine Learning Datasets: Training, Validation, & Test Sets, n.d.)and provides a robust assessment of model performance on real-world scenarios.

3.7 Machine Learning Models

Eight machine learning models were deployed to predict the Water Pollution Index (WPI) through regression tasks with different parameter relationship detection abilities. The ML process involves dividing the dataset into two subsets: 80% for training, where the model learns from historical data, and 20% for testing, which evaluates the model's ability to generalize and predict outcomes for unseen data. The chosen models were Linear Regression, XGBoost Regressor, Random Forest Regressor, Bagging Regressor, AdaBoost Regressor, Gradient Boosting Regressor, Cat Boost Regressor, and Artificial Neural Network (ANN) serve as complete predictive measures to analyze all potential linear and non-linear variable relationships. The efficacy of each model was evaluated using critical statistical metrics: the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE), to determine the precision of the model's predictions in relation to the observed values.

3.7.1 Linear Regression

Linear regression is a foundational statistical approach that models the relationship between a dependent variable and one or more independent variables. In this study, it was used to establish a baseline for predicting the Water Pollution Index (WPI) based on key water quality parameters: pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total dissolved solids (TDS), suspended solids (SS), electrical conductivity (EC), and temperature.

The general form of the multiple linear regression model is:

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n} \tag{7}$$

Where:

- Y is the predicted WPI,
- B_0 is the intercept,
- B_1, β_2, ..., βn are the coefficients of the independent variables,
- X_1, X_2,..., Xn represent the water quality parameters (e.g., pH, DO, etc.),
- ε is the error term representing the difference between actual and predicted values.

Despite its simplicity, linear regression assumes a linear relationship among variables, independence of errors, homoscedasticity, and normality of residuals. These assumptions often limit its ability to capture non-linear interactions or higher-order dependencies among complex environmental parameters. Nevertheless, it provides a useful benchmark for evaluating the performance of more advanced machine learning models.

3.7.2 Random Forest Regressor

The predictive accuracy of the model needed improvement, so we added Random Forest Regressor, which used decision tree ensembles to expand the forecasting ability beyond linear regression capabilities(Liu, 2024). The model uses bootstrapping combined with multiple tree-based estimations to find non-linear patterns in features along with reducing model overfitting.

The model works by generating multiple decision trees using bootstrapped subsets of the training data. At each node in a tree, a random subset of features is considered to split the data, reducing correlation between trees. The final prediction is obtained by averaging the outputs of all individual trees:

$$\boldsymbol{\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} h_i(x)} \tag{8}$$

Where:

- $\hat{Y}$ is the predicted WPI,
- N is the number of trees in the forest,
- hi (x) is the prediction of the ith decision tree for input x.

This ensemble strategy helps reduce variance and overfitting common in single decision trees while capturing complex, non-linear patterns in the input variables (e.g., pH, DO, BOD, COD, TDS, SS, EC, temperature). It makes Random Forest particularly suitable for environmental modeling where variable interactions are often non-trivial.

3.7.3 XGBoost Regressor

XGBoost Regressor provided a perfect fit for complex high-dimensional datasets because it refines weak learners repeatedly in its gradated boosting approach. Even, XGBoost offers superior performance in handling complex datasets and non-linear relationships, often outperforming traditional models like linear regression. Additionally, XGBoost is highly efficient in managing large datasets and provides robust handling of missing values, making it a versatile choice for various predictive tasks (Hou et al., 2020; Suliman et al., 2024; Zolotareva,n.d.)
XGBoost Regressor Equation (Prediction),

$$\hat{\boldsymbol{Y}} = \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{K}} \boldsymbol{f}_{\boldsymbol{k}}(\boldsymbol{x}) \qquad (9)$$

Where:

- $\hat{Y}$ is the predicted output,
- K is the total number of trees,
- $f_{k(}x)$ is the k^{th} decision tree,

XGBoost Objective Function,

$$\textbf{Objective} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{10}$$

Where:

- $l(y_i, \hat{y}_i)$ is the loss function (e.g., squared error) between true and predicted values
- $\Omega(f_k)$ is the regularization term penalizing model complexity to prevent overfitting.

XGBoost handles missing values natively, is robust against multicollinearity, and performs well with high-dimensional data. These properties make it suitable for water quality prediction tasks where complex feature interactions and missing data are common.

3.7.4 Bagging Regressor

Bagging Regressor, short for *Bootstrap Aggregating*, is an ensemble technique designed to improve prediction stability and reduce variance, especially in datasets with high natural variability such as environmental and water quality data.

This method works by generating multiple subsets of the original training dataset through bootstrapping (sampling with replacement). A separate base model—typically a decision tree—is trained on each subset. The predictions from all models are then averaged to form the final output:

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^{N} \hat{Y}_i \tag{11}$$

Where:

- $\hat{Y}$ is the final predicted WPI,
- $\hat{Y}i$ is the prediction from the i^{th} model,
- N is the total number of models in the ensemble.

This strategy introduces randomness and independence among the models, which reduces overfitting and enhances model robustness. Unlike boosting methods that train models sequentially and correct previous errors, bagging trains all models in parallel, making it computationally efficient.

For water quality modeling, where measurement errors and seasonal fluctuations are common, bagging helps smooth out prediction inconsistencies and improves the model's ability to generalize across varying water conditions. Its performance is particularly effective when using high-variance base learners like decision trees.

3.7.5 AdaBoost Regressor

The selection of AdaBoost Regressor happened because it includes sequential learning capabilities to focus on misclassified cases, thereby enhancing predictive outcomes. Implementing this model requires careful preprocessing to prevent performance decline because it remains sensitive to outliers.

$$\hat{Y} = \sum_{m=1}^{M} \alpha_m h_m(x) \tag{12}$$

Where:

- $\hat{Y}$ is the final predicted output,
- $h_m(x)$ is the prediction from the m^{th} weak learner,
- α_m is the weight assigned based on the learner's accuracy,
- M is the total number of weak learners.

AdaBoost's sequential focus on harder-to-predict cases improves accuracy but also increases sensitivity to noise and outliers. Therefore, data preprocessing and outlier management are critical when using this model.

In the context of water pollution forecasting, AdaBoost helps refine predictions by incrementally improving on complex patterns not captured by earlier learners, making it useful when small predictive errors can lead to significant interpretation differences.

3.7.6 Gradient Boosting Regressor

Another technique of boosting, Gradient Boosting Regressor, was used in order to residual errors by gradient descent to model a highly complex model. However, this model works well but requires much fine-tuning of the hyperparameter so as to avoid overfitting.

Prediction:

$$\boldsymbol{\hat{Y} = \sum_{m=1}^{M} f_m(x)} \tag{13}$$

Here, $f_m(x)$ represents the m^{th} decision tree added in the sequence.

Objective Function:

$$\textbf{Objective} = \boldsymbol{\sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{m=1}^{M} \Omega(f_m)} \tag{14}$$

Where,

$l(y_i, \hat{y}_i)$ is the loss function (e.g., mean squared error)

$\Omega(f_m)$ is a regularization term controlling model complexity.

Gradient Descent Step:

$$\boldsymbol{g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i}} \tag{15}$$

This gradient g_i represents the direction in which the model should adjust to reduce prediction error.

Gradient Boosting offers high accuracy but is sensitive to overfitting if not properly tuned. Key hyperparameters include learning rate, tree depth, and number of estimators. In your water pollution prediction task, Gradient Boosting enables accurate modeling of the complex interdependencies among water quality parameters, provided that careful regularization and validation are applied.

3.7.7 Cat Boost Regressor

CatBoost Regressor was employed to further enhance model performance due to its advanced handling of categorical features and its robustness against overfitting. Unlike other boosting models, CatBoost does not require explicit encoding of categorical variables, as it applies a technique known as ordered boosting, which prevents data leakage by ensuring that future data points are not used in the encoding process of current samples. This feature made it particularly effective for our structured dataset, which included a mixture of numerical and categorical water quality indicators. Additionally, CatBoost incorporates several regularization mechanisms such as shrinkage (learning rate control) and L2 regularization, which help reduce model complexity and improve generalization. It also handles missing values internally and is optimized for fast computation, making it suitable for environmental datasets like ours with varied and sometimes incomplete entries. These characteristics justified its inclusion in our modeling framework, especially given its capacity to deliver high predictive accuracy with minimal preprocessing effort.

3.7.8 Proposed Model Architecture

The proposed artificial neural network (ANN) model shown in Figure 8 is designed to predict the Water Pollution Index (WPI) with high accuracy and robustness. The architecture comprises multiple fully connected layers, each optimized using advanced regularization techniques to enhance generalization and prevent overfitting.

$$\boldsymbol{f_l(z)} = \textbf{Dropout}\Big(\textbf{LeakyReLU}\big(\textbf{Batch Norm}(\boldsymbol{W_l z} + \boldsymbol{b_l})\big)\Big) \tag{16}$$

The input layer consists of 1024 neurons with L2 regularization ($\lambda = 0.0005$) to mitigate overfitting. Each hidden layer is followed by batch normalization to stabilize activations and LeakyReLU ($\alpha = 0.1$) to address the vanishing gradient issue. Dropout regularization (ranging from 0.1 to 0.3) is incorporated to enhance model robustness. The architecture employs a hierarchical structure with progressively decreasing neurons (512, 256, 128, 64, and 32), allowing for efficient feature extraction. The output layer comprises a single neuron without an activation function, as WPI prediction is a regression task.

For optimization, the model leverages the AdamW optimizer with weight decay (1e-5) to improve generalization. The learning rate is initialized at 0.01 and dynamically adjusted using a ReduceLROnPlateau scheduler, which reduces the learning rate by a factor of 0.5 when validation loss stagnates. To prevent overfitting, early stopping with a patience of 100 epochs is employed. The model is trained for 2000 epochs with a batch size of 64, ensuring stable updates and effective learning.

This optimized ANN architecture enables precise WPI prediction by integrating regularization techniques, adaptive learning rate scheduling, and an optimized training strategy, making it suitable for complex water quality assessment tasks.

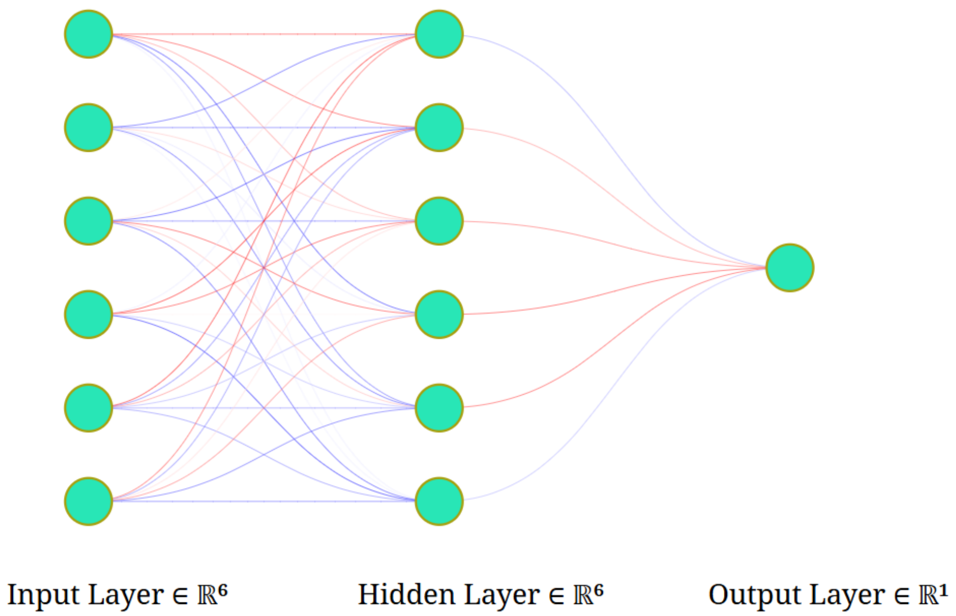


Figure 8. Architecture of Proposed Neural Network Model

3.7.9 Model Evaluation Metrics

This study incorporated an extensive array of statistical indicators and visualization methods to evaluate model performance and correctness. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) were employed as principal performance metrics, each providing distinct perspectives on the models' predictive efficacy. The performance of each trained model was assessed using three key evaluation metrics. Mean Squared Error (MSE) Quantifies the average squared difference between predicted and actual values, penalizing larger errors more heavily to emphasize overall prediction accuracy. Root Mean Squared Error (RMSE) Emphasizes larger errors by squaring residuals before averaging, offering insights into significant deviations in predictions. R-squared (R^2) evaluates how well the independent variables explain the variance in WPI, with values closer to 1 indicating superior model fit. Mathematically R^2 is expressed as:

$$\mathbf{R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}i)2}{\sum_{i=1}^{n}(yi - \bar{y}i)2}} \tag{17}$$

Where y_i = actual values, $\hat{y}_i$ = predicted values, and $\bar{y}$ = mean of actual values.

The formula for MAE is calculated by:

$$\mathbf{MAE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)} \tag{18}$$

Where N = number of observations, y_i = actual values, $\hat{y}_i$ = predicted values.

The formula for RMSE is given by:

$$\mathbf{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2}} \tag{19}$$

Where y_i = actual values, $\hat{y}_i$ = predicted values, N = number of observations.

The comparative analysis of R^2, MSE, RMSE and MAE across the models provided insights into their predictive reliability and generalizability.

3.8 K-Fold Cross Validation

To enhance model generalizability (Ellis & Mookim, 2013), 5-fold cross-validation was applied to Linear Regression, Random Forest, and XGBoost models. This technique systematically assessed model performance across multiple data splits, reducing variance and ensuring consistent evaluation. Performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 score, were used for comprehensive evaluation.

3.8.1 Rationale for Hyperparameter Choices

The selection of 900 estimators for ensemble models such as Random Forest, XGBoost, Bagging, AdaBoost, and Gradient Boosting was pivotal in reducing variance, improving model stability, and capturing intricate data patterns for enhanced predictive accuracy. L2 regularization in the ANN effectively controlled overfitting by penalizing large weight values, thereby enhancing generalization and robustness. The integration of dropout and batch normalization synergistically prevented overfitting and expedited convergence by normalizing activations and mitigating neuron co-dependence. Additionally, the implementation of early stopping with patience and learning rate scheduling prevented unnecessary training when performance plateaued and allowed for finer convergence by adapting learning rates, thus avoiding local minima and improving overall model performance.

3.9 SHAP Analysis for Feature Importance

To enhance the interpretability of machine learning models used in this study, SHAP (SHapley Additive exPlanations) analysis was conducted to quantify the contribution of each input parameter to the predicted Water Pollution Index (WPI). SHAP values are based on game theory and provide a unified measure of feature importance by computing the marginal contribution of each feature across all possible combinations of input variables. This method offers consistent and locally accurate interpretations for both linear and non-linear models.

The SHAP analysis revealed that **Suspended Solids (SS)** and **Chemical Oxygen Demand (COD)** were the most influential factors in predicting WPI, indicating their critical role in the overall pollution load of the Surma River. These two parameters consistently showed high SHAP values across multiple models, suggesting strong positive contributions to pollution levels. In contrast, parameters such as **Biochemical Oxygen Demand (BOD)** and **Dissolved Oxygen (DO)** had comparatively lower SHAP values, implying weaker influence on the model's output.

By identifying the most important predictors, SHAP analysis supports more targeted interventions and informs which parameters should be prioritized in future monitoring programs. Moreover, the use of SHAP adds transparency to the machine learning models, making the results more understandable to stakeholders and regulators involved in water quality management. This aligns with the study's broader goal of developing interpretable, data-driven tools for environmental decision-making.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 WPI and statistical analysis of parameters

Table 3 provides an overview of water quality parameters, which provides data regarding the water quality of the study area. The average pH of 7.28 reflects slightly alkaline conditions in acceptable limits and which represent stable geochemical conditions. pH could be influenced by seasonal variability and anthropogenic activity. Dissolved Oxygen (DO) is of average 6.74 mg/L and in the interval 5.2 to 8.26 mg/L, which corresponds to moderate concentrations of oxygen presence, appropriate for aquatic life. Biological Oxygen Demand (BOD) measurements (average: 2.02 mg/L, maximum: 4.8 mg/L) correspond to medium concentrations of organic contamination, caused either by wastewater discharges or by microbially produced activity. Chemical Oxygen Demand (COD) levels (mean: 15.77 mg/L, max: 37 mg/L) suggest moderate organic contamination, consistent with domestic or industrial wastewater influence. Total Dissolved Solids (TDS) values (mean: 270.49 mg/L, max: 854 mg/L) mostly remain within acceptable limits, but higher values suggest potential salinity or contamination from runoff or leaching. Suspended Solids (SS) (mean: 76.23 mg/L, max: 180 mg/L) are highly variable, likely due to intrusion of sediment or surface runoff. Electrical conductivity (mean: 213.70 µS/cm, max: 550 µS/cm) reflects moderate ion concentration and thus groundwater mineralization. The mean temperature of 25.64°C is within the range for surface water but could differ from seasonal to fluctuations from subsurface geothermal activity. Water Pollution Index (WPI) is between 0.58 and 2.54, mean value is 1.49, and corresponds to Highly pollution. The results show the probable problem of organic pollution, salinity, and suspended solids, which can be resolved by some management measures in a bid to improve water quality and maintain ecological balance.

Table 3. Descriptive statistics of water quality parameters in Surma river, Sylhet.

Parameter	p^H	DO	BOD	COD	TDS	SS	EC	Temperature	WPI
Count	648	648	648	648	648	648	648	648	648
Mean	7.27	6.74	2.02	15.76	270.48	76.22	213.70	25.63	1.48
Std	0.39	0.49	0.76	4.23	210.74	30.18	87.30	2.59	0.36
Min	6.12	5.20	0.30	5.00	8.00	5.00	54.00	18.00	0.57
25%	7.10	6.50	1.30	14.00	67.00	59.87	131.57	24.00	1.25
50%	7.28	6.74	2.02	15.00	255.00	76.22	213.70	25.50	1.46
75%	7.50	7.00	2.40	16.00	420.00	100.00	270.00	27.00	1.76
Max	8.50	8.26	4.80	37.00	854.00	180.00	550.00	34.20	2.53

4.2 Performance Evaluation of Models

To evaluate the predictive performance of the selected machine learning models for estimating the Water Pollution Index (WPI), several regression metrics were analyzed, including R-squared (R^2) Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The comparative performance of the models is summarized in Table 4.

The Linear Regression model achieved highest accuracy through its R^2 value of 0.999954 together with minimum MSE of 0.000007 and the best RMSE and MAE measurements of 0.002633 and 0.002030 respectively. The data alignment shows perfect model agreement indicating that independent variables have a very strong linear relationship with WPI. Such exceptional model performance should be evaluated through additional evaluations to eliminate overfitting issues and data leakage.

The XGBoost Regressor achieved the best performance from the ensemble models by generating an R^2 value of 0.982488 across with an MSE of 0.002644 and an RMSE of 0.051421. The error rates of XGBoost remain minimal while it extracts complex non-linear relationships from the data. The Random Forest Regressor and Bagging Regressor showed nearly identical results compared to each other and to XGBoost Regressor by producing R^2 values of 0.971894 and 0.971667 respectively. Again, in testing their RMSE measurements

(0.065143/0.065406) revealed slightly more errors than XGBoost but their data distribution agility remained strong.

Both Gradient Boosting Regressor and Cat Boost Regressor demonstrated better accuracy levels above all ensemble models included in testing. The R^2 score of Cat Boost reached 0.992235 to surpass GBR (R^2=0.990225 R^2= 0.990225) and simultaneously displayed a lower MSE measurement (0.001172 against 0.001475). Gradient boosting techniques succeed efficiently at model execution especially through Cat Boost which can process categorical data while requiring no special preprocessing.

The performance of AdaBoost Regressor was the least effective among all models because it achieved an R^2 value of 0.926761 and generated the highest error metrics with MSE = 0.011058 and RMSE = 0.105158 and MAE = 0.084907. The results indicate that AdaBoost failed to identify complex patterns in the dataset which might be attributed to its tendency to get affected by noise and outliers. The Artificial Neural Network (ANN) proved itself as the best ensemble model by delivering an R^2 of 0.993898 together with 0.000921 MSE and the lowest RMSE between ensemble models at 0.030354. This confirms ANN's capability in modeling complex non-linear dependencies, making it a strong contender for predictive modeling in water pollution assessment.

Table 4. Performance evaluation of ML models for surface water pollution prediction

Models	R^2	MAE	RMSE	MAE
Linear Regression	0.999954	0.000007	0.002633	0.002030
XGBoost Regressor	0.982488	0.002644	0.051421	0.029145
Random Forest Regressor	0.971894	0.004243	0.065143	0.035168
Bagging Regressor	0.971667	0.004277	0.065406	0.035129
AdaBoost Regressor	0.926761	0.011058	0.105158	0.084907
Gradient Boosting Regressor	0.990225	0.001475	0.038417	0.022203
Cat Boost Regressor	0.992235	0.001172	0.034239	0.022797
Artificial Neural Network (ANN)	0.993898	0.000921	0.030354	0.025421

4.3 Comparison and Visualization

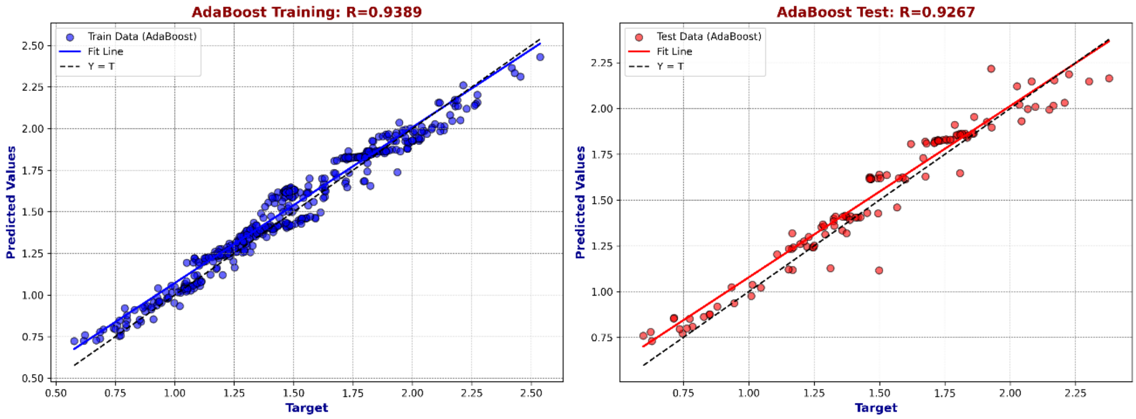
The performance evaluation of eight machine learning algorithms in predicting WPI, including accuracy and error metrics shows in Figure 9 Linear Regression shows the greatest degree of accurate prediction with nearly perfect fit between actual and predicted values, indicated through its extremely high R^2 value (0.999954) and minimal error metrics (MSE, RMSE, and MAE). This indicates a highly reliable predictability. Similarly, Artificial Neural Network (ANN) and Cat Boost Regressor show good predictability with R^2 values greater than 0.99 and very low error values, supporting their consistency in prediction. Gradient Boosting Regressor also shows strong performance with an R^2 value of 0.990225 and very low MAE, showing high accuracy. XGBoost, although not as accurate as Linear Regression and ANN, but shows good predictability with an R^2 value of 0.982488 and moderate error values. Yet, Random Forest and Bagging Regressor have slightly lower accuracy, indicated by R^2 scores of around 0.97 and higher values of RMSE and MAE, indicating some limitations in explaining variability. The lowest R^2 value of (0.926761) and highest values of error measures are illustrated by AdaBoost Regressor, showing lower predictive credibility. These plots visually affirm the statistical findings from

Table 3, highlighting Linear Regression's robustness and reliability in accurately predicting WPI in diverse conditions. To evaluate the performance and reliability of the proposed method, a comparison has been conducted with similar studies available in the literature. Table 5 presents the comparative analysis between the present study and existing literature. The Linear Regression model achieved an R^2 of 0.999954 in the present study, which is significantly higher than the R^2 of 0.65 reported in previous studies. Similarly, the XGBoost Regressor and Random Forest Regressor models obtained R^2 values of 0.982488 and 0.971894, respectively, both showing improved performance compared to literature values of 0.94 and 0.95. The CatBoost Regressor also demonstrated substantial improvement with an R^2 of 0.992235, whereas earlier studies reported a much lower R^2 of 0.71. For the AdaBoost Regressor, an R^2 of 0.926761 was obtained, slightly outperforming the literature value of 0.87. Finally, the Artificial Neural Network (ANN) model achieved an R^2 of 0.993898, which is notably higher than the R^2 of 0.80 reported in previous works.

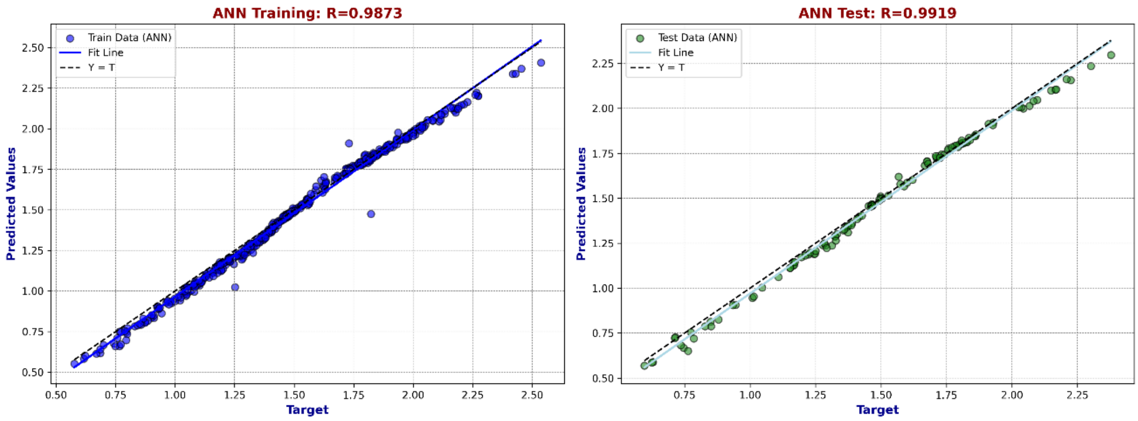
These findings indicate that the proposed models in the present study exhibit superior performance compared to existing literature, highlighting the robustness and reliability of the developed models for water quality prediction.

Table 5. Comparative analysis between the present study and previous works

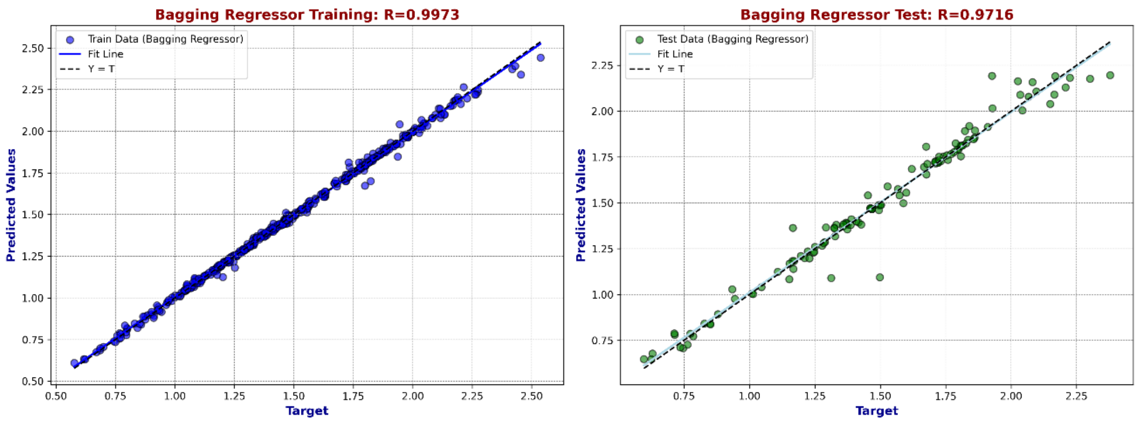
Models	Current study (R^2)	Literature (R^2)	Reference
Linear Regression	0.999954	0.65	(U. Ahmed et al., 2019)
XGBoost Regressor	0.982488	0.94	(Ma et al., 2025)
Random Forest Regressor	0.971894	0.95	(Karthick et al., 2024)
Cat Boost Regressor	0.992235	0.71	(Grbčić et al., 2021)
AdaBoost Regressor	0.926761	0.87	(Yousefi et al., 2024)
Artificial Neural Network (ANN)	0.993898	0.80	(Palani et al., 2008)



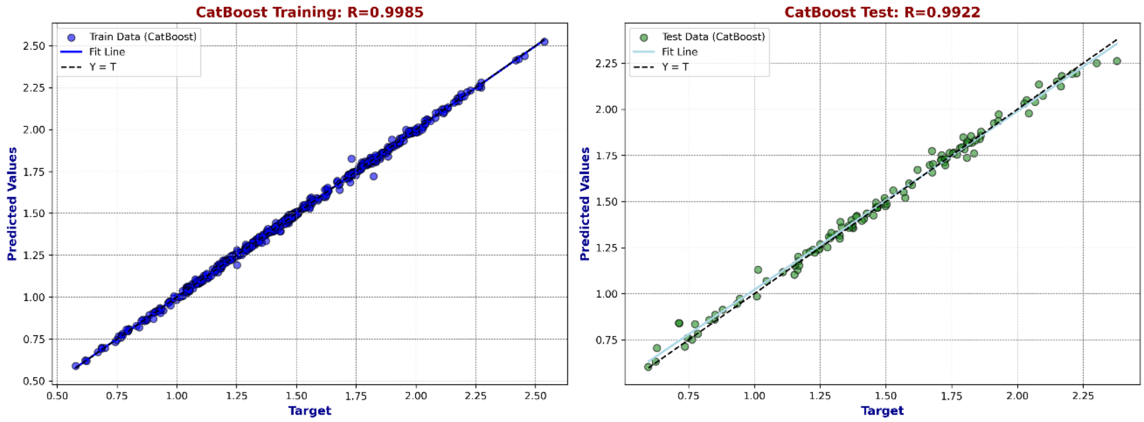
AdaBoost Regressor



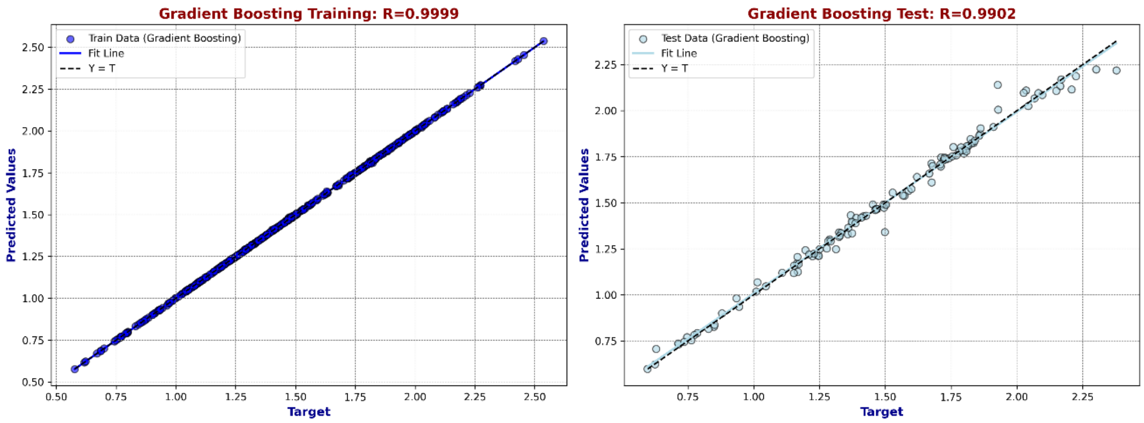
Artificial Neural Network



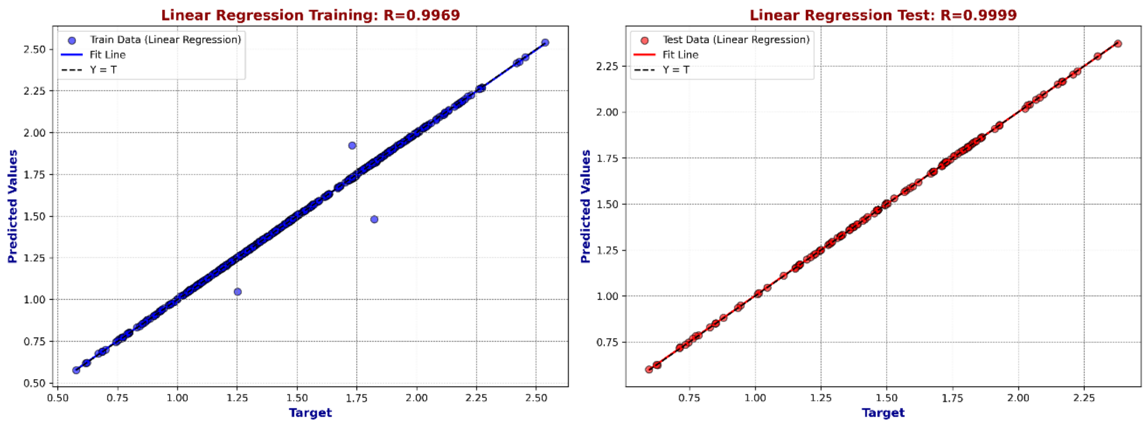
Bagging Regressor



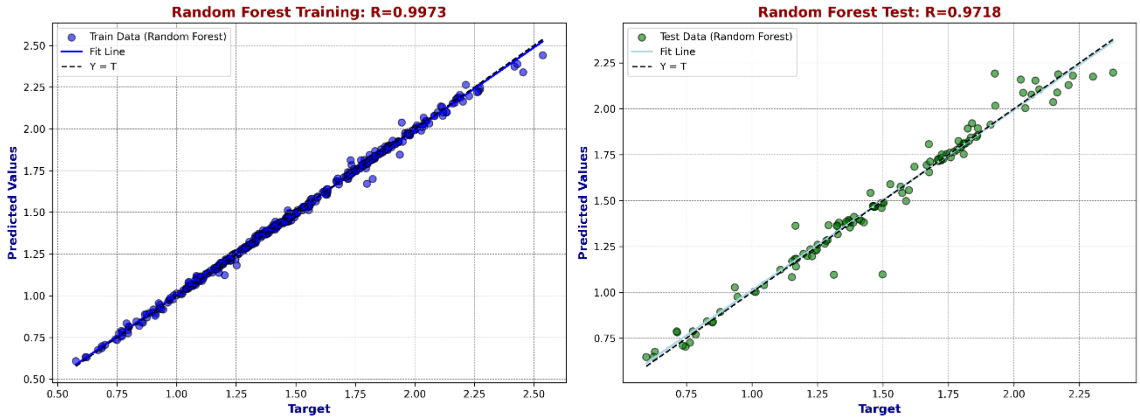
Cat Boost



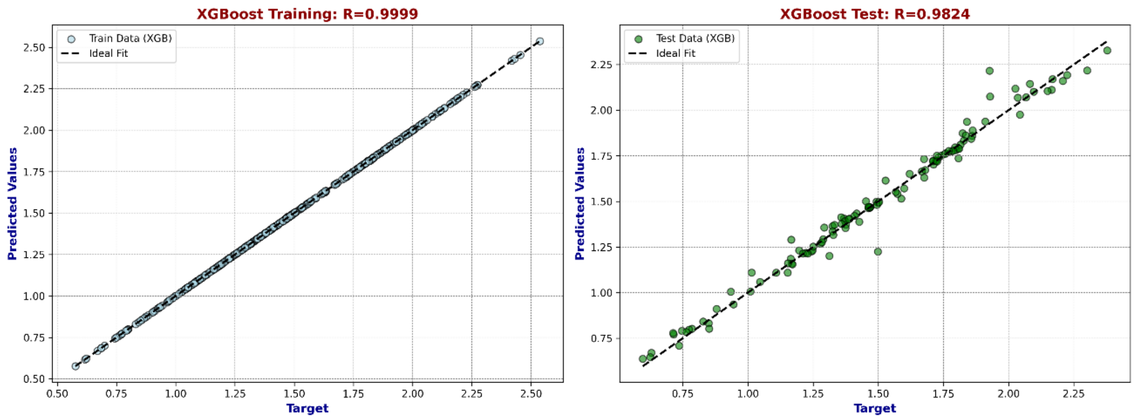
Gradient Boosting Regressor



Linear Regression



Random Forest



XG-Boost

Figure 9. Scatter plot between the observed WPI and predicted WPI using the ML models for training and testing phase. Dotted line represents the regression line.

4.4 Key Findings and Model Selection

From the comparative analysis, Linear Regression produced the best performance in terms of all regression metrics, suggesting that a linear relationship might dominate the dataset. However, given the potential risks of overfitting in near-perfect predictions, models such as ANN, Cat Boost, and XGBoost provide robust alternatives, demonstrating high accuracy while effectively handling non-linearity.

For practical deployment, ANN stands out due to its superior predictive capability, despite its higher computational complexity. Cat Boost and Gradient Boosting Regressor also emerge as strong candidates due to their balanced performance and efficiency in handling structured datasets. While Random Forest and Bagging Regressor offer stable predictions, they lag slightly behind boosting methods in accuracy.

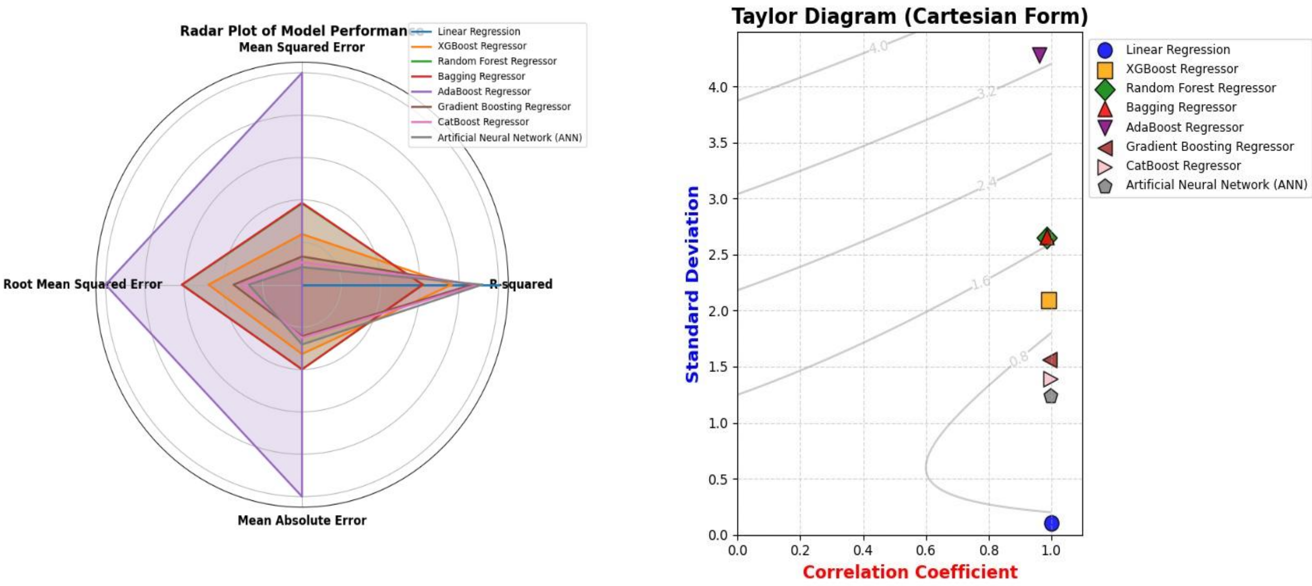
Overall, the results indicate that ANN, Cat Boost, and XGBoost are the most suitable models for predicting WPI, offering a balance between accuracy, error minimization, and generalizability. Further optimization through hyperparameter tuning and cross-validation can enhance their performance, ensuring reliable water pollution assessment and environmental decision-making.

4.4.1 Radar Plot

Figure 10 (a) Radar chart compares predictive performance of eight machine learning models on R-squared (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Artificial Neural Network (ANN) and Linear Regression have the highest R^2 and lowest error measures, indicating the best predictive stability and accuracy. Cat Boost and Gradient Boosting also exhibit good performance with high R^2 and mostly low errors. XGBoost and Bagging Regressors have middle-level performance with similar accuracy and error rates. Random Forest has a mildly higher error rate, reducing predictive reliability. AdaBoost is the worst model with the lowest R^2 and highest error values, reflecting lower predictability and more variability. The radar plot shows that models with the highest R^2 and lowest error values, like Linear Regression and ANN, are more appropriate for predictive WPI.

4.4.2 Taylor diagram

Figure 10 (b) Taylor diagram measures performance of different machine learning algorithms in relation to correlation coefficient, standard deviation, and centered root mean square error (plotted as contours). Nearest to ideal point (1, 0) on x-axis are most correlated and highest on predictability. Linear Regression is closest to ideal point and therefore reveals highest correlation and lowest error and hence maximum predictability. Artificial Neural Network (ANN) and CatBoost have high correlation but moderate standard deviation, indicating excellent performance. All of XGBoost, Random Forest, and Bagging Regressors follow average correlation and variation but large errors compared with ANN and Linear Regression. The worst predictability is indicated by AdaBoost which has lowest correlation and highest standard deviation. The plot is clear to portray the trade-offs among variability, error, and correlation by Linear Regression and ANN as the optimal model.



(a) **(b)**

Figure 10. (a) Radar plot and (b) Taylor diagram for evaluating the performance of ML models

4.5 K-Fold Cross-Validation Results

To ensure the robustness and generalizability of the selected machine learning models, K-Fold Cross-Validation (K-Fold CV) was applied, and the corresponding performance metrics are presented in Table 6. K-Fold CV is a crucial validation technique that mitigates the risk of overfitting by dividing the dataset into multiple subsets, systematically training and testing the model on different partitions. This approach provides a more reliable estimate of model performance compared to a simple train-test split, which may yield overly optimistic or pessimistic results depending on data partitioning.

After applying K-Fold CV, the Linear Regression model, which previously exhibited near-perfect predictions, experienced a slight decrease in performance, with an R^2 of 0.997094 and an MSE of 0.000398. While this is still a high accuracy score, it indicates that the initial model may have been slightly overfitted to a specific data partition. The increase in RMSE (0.016339) and MAE (0.003696) further supports this observation, reinforcing the necessity of cross-validation for ensuring model reliability.

For the XGBoost Regressor, the R^2 value dropped slightly to 0.979216, with an MSE of 0.002639 and RMSE of 0.050884. This indicates that while the model remains highly effective, it was previously benefiting from certain data patterns that did not generalize as well across different folds. Random Forest Regressor exhibited a similar trend, with an R2R^2 of 0.978921 and an MSE of 0.002726, demonstrating stable performance but confirming the importance of cross-validation in assessing true predictive capability.

4.6 Importance of K-Fold Cross-Validation

The necessity of K-Fold Cross-Validation in this study is evident from the observed changes in performance metrics. Without cross-validation, there is a risk of models being evaluated based on a single train-test split, leading to overestimated or underestimated accuracy. K-Fold CV ensures that every data point is used for both training and testing, providing a more robust, unbiased, and generalized performance evaluation.

Table 6. Performance evaluation of k-fold cross-validation

Models	R^2	MSE	RMSE	MAE
Linear Regression with K-Fold	0.997094	0.000398	0.016339	0.003696
XGBoost Regressor with K-Fold	0.979216	0.002639	0.050884	0.003696
Random Forest Regressor with K-Fold	0.978921	0.002726	0.050664	0.003696

Moreover, Table 6 shows the slight decline in performance metrics after applying K-Fold CV underscores that some models, particularly Linear Regression, were benefiting from data-specific biases in the initial split. By introducing multiple training-testing iterations, cross-validation confirms whether a model is genuinely learning the underlying patterns or merely memorizing a particular subset of data.

From these results, it is evident that K-Fold CV is not an arbitrary step but a necessary validation mechanism to ensure model reliability in real-world applications. By adopting this approach, we can confidently assert that the selected models, particularly XGBoost, Random Forest, and Linear Regression, maintain strong predictive performance even when exposed to different subsets of data. This reinforces their suitability for WPI prediction, ensuring that the models are well-equipped to handle unseen data in practical environmental assessments.

4.7 SHAP Analysis

The SHAP (Shapley Additive explanations) summary plot in the figure demonstrates an extensive evaluation of water quality parameter impacts on the model predictions. The horizontal SHAP value axis demonstrates feature inputs and y-axis displays the water quality measurements of Suspended Solids (SS), Chemical Oxygen Demand (COD), Electrical Conductivity (EC), Total Dissolved Solids (TDS), Temperature, pH, Biological Oxygen Demand (BOD), and Dissolved Oxygen (DO). A color gradient in the plot demonstrates the strength of each feature value through the use of red for high values and blue for low values. The plot contains distinct points representing each data instance where their x-axis placement shows the feature effects as positive or negative influences on output prediction.

The analysis shows SS and COD stand as dominant features because they produce SHAP value ranges which exceed those of the other examined parameters. These particular features produce significant effects on prediction results since their effects spread over positive and negative ranges. The output capacity of the model experiences major dual effects stemming from SS which demonstrates strong changes based on each feature value. The SHAP values for COD show an upward pattern when its value increases which indicates a positive direct connection between high COD measurements and rising model prediction outputs. Model output shows an inverse relationship with COD values when they decrease which leads to mainly negative SHAP values. The distribution of SHAP values for Temperature and pH is evenly spread around zero which demonstrates their moderate influence on model prediction results. Temperature and pH alterations do not substantially affect the model outcome because they contribute minimally to prediction results. The ranges of SHAP values indicate minimal importance to model outcomes for both BOD and DO parameters. The model's predictive process depends minimally on the input parameters thus demonstrating their low importance during the decision-making phase. Between them, EC and TDS present mixed SHAP values that lean towards negative contributions. SHAP values of these parameters demonstrate variable dependence because their impact on predictions alters based on feature values leading to a complex interaction between the features and target variable.

Overall, the SHAP summary plot shown in Figure 11 provides valuable insights into the relative importance and influence of different water quality parameters on model predictions. The findings emphasize the significant role of SS and COD while indicating the comparatively limited impact of BOD and DO. This interpretation is crucial for enhancing model interpretability and accuracy, as it allows researchers to prioritize the most influential features and make informed decisions regarding feature selection and model refinement.

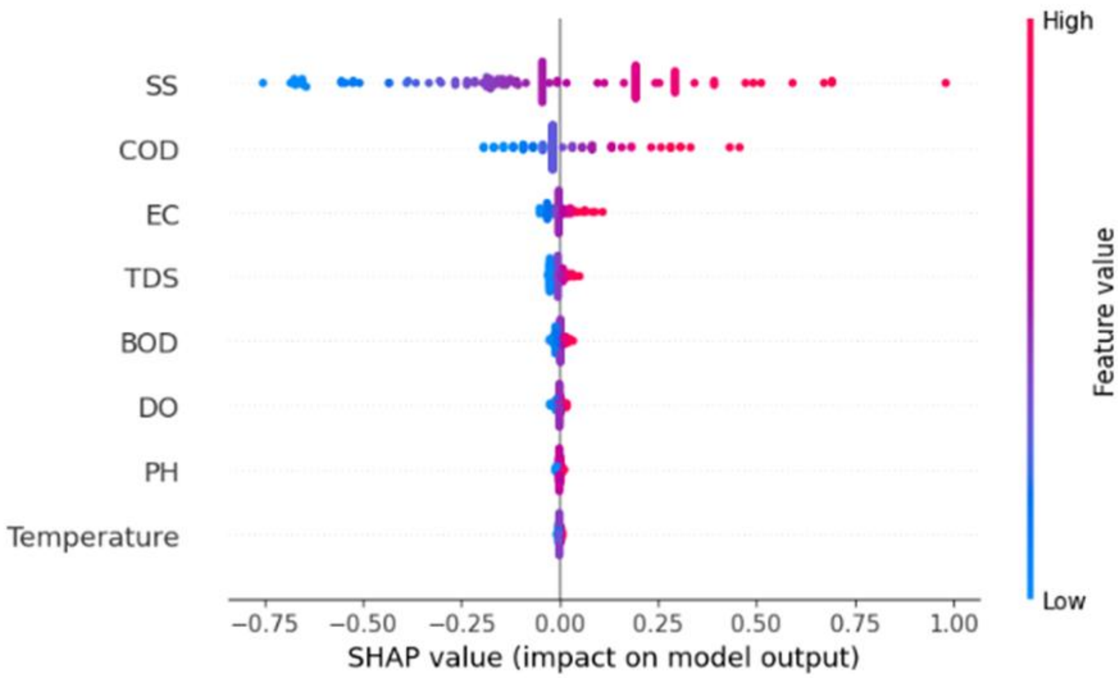


Figure 11. SHAP Summary Plot for Feature Importance in Model Output

4.8 Regression Analysis and Feature Significance using OLS

A multiple linear regression model was developed using the ordinary least squares (OLS) method to examine the relationship between various water quality parameters and the Water Pollution Index (WPI). The model demonstrated exceptional explanatory capacity, achieving an R-squared value of 0.998, which indicates that 99.8% of the variation in WPI was accounted for by the selected predictors. All input variables—including pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total dissolved solids (TDS), suspended solids (SS), electrical conductivity (EC), and temperature— were identified as statistically significant ($p < 0.05$), underscoring their strong influence on WPI. Notably, several predictors yielded p-values reported as 0.0000. These values do not represent true zeros but rather signify extremely high statistical significance, falling below the reporting threshold of the software. The relevance of these parameters was further reinforced through visual analysis shown in Figure 12, wherein the magnitude of the estimated coefficients aligned with their statistical significance, thereby confirming the critical role of all considered features in accurately predicting water pollution levels.

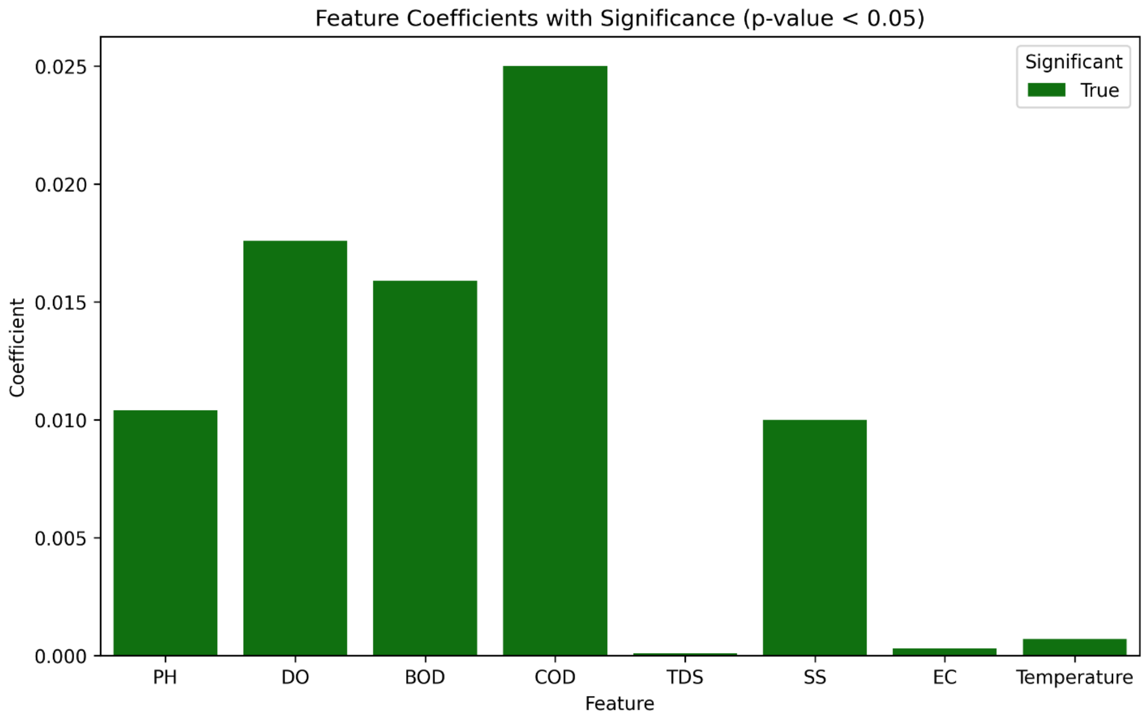


Figure 12. Feature Coefficients with Significance

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Summary of Findings

This research introduces a novel approach to water pollution prediction by integrating the Water Pollution Index (WPI) with advanced machine learning models. The method's high accuracy, particularly with the Linear Regression and ANN models, establishes a new benchmark for precision in environmental monitoring. This innovative methodology not only addresses the limitations of traditional WPI analysis but also offers a scalable framework for future applications in water resource management. Among the ML models utilized, Linear Regression provided the optimal result with $R^2 = 0.999954$ accuracy and the lowest error levels, thereby standing out as the most suitable model for predicting WPI. To ensure the robustness of this result, k-fold cross-validation (e.g., 5-fold) was performed, confirming the model's generalizability and minimizing overfitting risks. It was also determined that certain parameters like COD, TDS, SS, and EC were in excess of WHO guidelines, thereby demonstrating the unabated pollution woes witnessed in the Surma River.

5.2 Limitations

While this study demonstrates the potential of integrating ML techniques with WPI to enhance surface water pollution assessment, some limitations need to be highlighted. First, the dataset of this study comprises only 648 secondary samples obtained from the Department of Environment, which may cause bias or diminish generalizability. Second, the utilization of physicochemical parameters alone overlooks microbiological contaminants, which carry significance in comprehensive water pollution assessment. Third, only three geographically distant places of the Surma River have been taken into consideration in the study, and it is not possible to generalize the findings readily to locations having a different hydrogeological or socio-environmental setting. Moreover, computational demand and potential for overfitting were identified in some ML models, particularly the neural networks, which can cause scalability challenges in resource-poor areas.

5.3 Recommendations for Future Study

To overcome the limitations of the traditional water quality monitoring, the results of this work emphasize the importance of using advanced analytical techniques. Use of machine learning models is a foundation for improved water resource management decision-making. The future research should be aimed at expanding the data set size by collaborating at a regional level and enhancing predictive capacities of the models by combining real-time observing systems with the Internet of Things (IoT) technology. Prediction validation and result interpretation can also be improved by further combining ML models with geochemical and hydrologic approaches. The computational power would have to be optimized so that these methods could be implemented and executed at a mass capacity. The research in this work establishes a firm foundation for sustainable water quality management in the global quest for safe and clean water supplies.

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Annexure -A

Table A.1 Water quality parameter Datasets of Surma River from (2007 - 2024)

Location	Date	PH	DO	BOD	COD	TDS	EC	Temperature
Mendibag	1/1/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/2/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/3/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/4/2007	7.40	6.40	2.20	15.00	420.00	213.70	25.64
Mendibag	1/5/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/6/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/7/2007	7.50	6.74	1.50	15.00	650.00	213.70	34.00
Mendibag	1/8/2007	7.40	6.74	1.80	15.00	500.00	213.70	30.00
Mendibag	1/9/2007	7.50	5.60	1.30	15.00	700.00	213.70	30.00
Mendibag	1/10/2007	7.50	5.90	1.70	15.00	750.00	213.70	30.00
Mendibag	1/11/2007	7.50	5.90	1.20	15.00	500.00	213.70	30.00
Mendibag	1/12/2007	7.50	5.80	1.40	15.00	510.00	213.70	24.00
Mendibag	1/1/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/2/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/3/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/4/2008	7.30	6.20	1.30	15.00	720.00	213.70	25.64
Mendibag	1/5/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/6/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/7/2008	7.40	5.60	1.10	15.00	520.00	213.70	29.00
Mendibag	1/8/2008	7.60	5.70	1.30	15.00	550.00	213.70	28.00
Mendibag	1/9/2008	7.50	5.90	1.20	15.00	620.00	213.70	30.00
Mendibag	1/10/2008	7.90	5.80	1.20	15.00	740.00	213.70	30.00
Mendibag	1/11/2008	7.20	6.74	1.20	15.00	400.00	120.00	24.00
Mendibag	1/12/2008	7.20	6.74	1.30	15.00	450.00	140.00	23.00
Mendibag	1/1/2009	7.30	5.50	1.50	15.00	420.00	180.00	25.00
Mendibag	1/2/2009	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/3/2009	7.20	6.20	1.20	15.00	380.00	250.00	25.00
Mendibag	1/4/2009	7.00	7.70	1.20	15.00	370.00	280.00	31.00
Mendibag	1/5/2009	7.40	6.40	1.20	15.00	380.00	230.00	28.00
Mendibag	1/6/2009	7.60	6.80	1.30	15.00	370.00	220.00	29.00
Mendibag	1/7/2009	7.40	6.50	1.20	15.00	410.00	250.00	28.00
Mendibag	1/8/2009	7.50	6.80	1.20	15.00	340.00	230.00	29.00
Mendibag	1/9/2009	7.60	6.80	1.10	15.00	370.00	240.00	30.00
Mendibag	1/10/2009	7.80	6.80	1.10	15.00	380.00	260.00	28.00
Mendibag	1/11/2009	7.70	6.80	1.10	15.00	400.00	280.00	25.00
Mendibag	1/12/2009	7.40	6.40	1.20	15.00	440.00	290.00	20.00
Mendibag	1/1/2010	7.30	6.40	1.20	15.00	530.00	270.00	18.00
Mendibag	1/2/2010	7.40	6.00	1.20	15.00	400.00	280.00	20.00
Mendibag	1/3/2010	7.50	6.50	1.20	15.00	600.00	290.00	32.00
Mendibag	1/4/2010	7.70	6.40	1.20	15.00	640.00	300.00	30.00
Mendibag	1/5/2010	7.40	6.40	1.00	15.00	380.00	280.00	27.00
Mendibag	1/6/2010	7.60	6.10	1.10	15.00	400.00	300.00	28.00
Mendibag	1/7/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/8/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64

Mendibag	1/9/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/10/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/11/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/12/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/1/2011	7.50	6.80	1.10	15.00	500.00	220.00	28.00
Mendibag	1/2/2011	7.40	6.70	1.10	15.00	550.00	190.00	24.00
Mendibag	1/3/2011	7.50	6.80	1.20	15.00	600.00	200.00	22.00
Mendibag	1/4/2011	7.80	6.80	1.20	15.00	700.00	250.00	28.00
Mendibag	1/5/2011	7.70	6.80	1.20	15.00	750.00	290.00	27.00
Mendibag	1/6/2011	7.40	6.40	1.40	15.00	540.00	260.00	28.00
Mendibag	1/7/2011	7.80	7.80	1.10	15.00	500.00	280.00	30.00
Mendibag	1/8/2011	7.40	6.90	1.70	15.00	300.00	260.00	31.00
Mendibag	1/9/2011	7.90	7.80	1.00	15.00	400.00	300.00	31.00
Mendibag	1/10/2011	7.60	7.80	1.10	15.00	500.00	350.00	25.00
Mendibag	1/11/2011	7.60	7.80	1.20	15.00	500.00	410.00	25.00
Mendibag	1/12/2011	7.70	7.80	1.10	15.00	510.00	550.00	25.00
Mendibag	1/1/2012	7.80	6.80	1.20	15.00	700.00	300.00	32.00
Mendibag	1/2/2012	7.80	6.80	1.10	15.00	730.00	320.00	31.00
Mendibag	1/3/2012	7.70	6.40	1.30	15.00	700.00	320.00	32.00
Mendibag	1/4/2012	7.70	6.30	1.10	15.00	640.00	320.00	30.00
Mendibag	1/5/2012	7.40	6.20	1.00	15.00	370.00	300.00	31.00
Mendibag	1/6/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/7/2012	7.50	6.70	1.20	25.00	550.00	213.70	30.00
Mendibag	1/8/2012	7.20	6.74	1.90	15.00	190.00	280.00	30.00
Mendibag	1/9/2012	7.40	5.80	2.60	25.00	350.00	213.70	25.00
Mendibag	1/10/2012	7.50	6.40	1.20	29.00	53.40	213.70	27.00
Mendibag	1/11/2012	7.50	6.74	1.40	15.00	53.40	107.10	27.00
Mendibag	1/12/2012	7.65	6.74	1.80	23.00	97.60	213.70	22.00
Mendibag	1/1/2013	7.20	5.60	0.90	19.00	116.20	232.00	20.80
Mendibag	1/2/2013	6.90	7.20	1.70	15.00	118.80	238.00	22.70
Mendibag	1/3/2013	7.19	6.74	0.30	14.00	137.90	276.00	25.50
Mendibag	1/4/2013	7.80	6.74	0.40	16.00	546.00	358.00	26.50
Mendibag	1/5/2013	7.20	5.40	0.30	15.00	33.20	66.40	24.70
Mendibag	1/6/2013	6.20	7.30	1.40	15.00	38.10	76.20	26.20
Mendibag	1/7/2013	7.40	6.20	1.10	15.00	30.00	100.00	23.00
Mendibag	1/8/2013	6.70	6.90	0.80	15.00	38.75	77.50	24.10
Mendibag	1/9/2013	7.90	6.40	3.10	35.00	400.00	300.00	27.00
Mendibag	1/10/2013	6.30	6.20	0.30	15.00	33.20	66.40	26.20
Mendibag	1/11/2013	7.20	6.74	1.00	15.00	400.00	120.00	24.00
Mendibag	1/12/2013	7.20	6.80	1.30	15.00	450.00	140.00	23.00
Mendibag	1/1/2014	7.30	5.40	1.50	15.00	420.00	180.00	25.00
Mendibag	1/2/2014	7.80	5.80	2.40	15.00	700.00	300.00	24.00
Mendibag	1/3/2014	7.20	6.30	2.30	15.00	380.00	250.00	25.00
Mendibag	1/4/2014	7.80	6.20	1.90	22.00	700.00	250.00	26.00
Mendibag	1/5/2014	6.50	6.70	2.02	15.00	116.00	232.00	26.10
Mendibag	1/6/2014	7.80	6.30	1.10	33.00	400.00	300.00	25.64

Mendibag	1/7/2014	6.80	6.90	2.02	15.00	118.50	237.00	26.30
Mendibag	1/8/2014	7.10	6.74	2.02	15.00	85.80	171.70	26.00
Mendibag	1/9/2014	7.28	6.80	3.20	32.00	620.00	180.00	26.00
Mendibag	1/10/2014	7.28	6.50	1.10	15.00	380.00	260.00	28.00
Mendibag	1/11/2014	7.28	6.40	1.10	15.00	400.00	280.00	25.00
Mendibag	1/12/2014	7.10	6.74	2.02	15.00	86.00	172.00	24.30
Mendibag	1/1/2015	7.60	5.90	3.30	15.00	122.50	215.00	22.00
Mendibag	1/2/2015	6.80	6.00	1.60	15.00	147.90	220.00	23.00
Mendibag	1/3/2015	6.90	5.90	3.40	15.00	135.00	220.00	24.00
Mendibag	1/4/2015	6.40	5.90	1.60	15.00	135.00	330.00	25.00
Mendibag	1/5/2015	7.30	6.40	1.20	25.00	530.00	270.00	21.00
Mendibag	1/6/2015	7.60	6.80	1.30	15.00	370.00	220.00	25.00
Mendibag	1/7/2015	7.40	6.50	1.20	15.00	410.00	250.00	27.00
Mendibag	1/8/2015	7.40	6.90	1.70	15.00	300.00	260.00	24.00
Mendibag	1/9/2015	7.40	6.80	1.10	15.00	370.00	240.00	25.00
Mendibag	1/10/2015	7.60	7.80	1.10	15.00	500.00	350.00	25.00
Mendibag	1/11/2015	7.60	7.80	1.20	15.00	500.00	410.00	25.00
Mendibag	1/12/2015	7.60	6.40	1.20	15.00	440.00	290.00	26.00
Mendibag	1/1/2016	7.30	6.20	2.02	15.00	74.00	148.00	23.90
Mendibag	1/2/2016	7.30	6.20	2.10	27.00	190.00	270.00	25.00
Mendibag	1/3/2016	7.40	6.70	2.70	33.00	78.00	156.00	26.00
Mendibag	1/4/2016	7.30	6.30	2.02	15.00	144.00	288.00	28.30
Mendibag	1/5/2016	7.10	6.80	2.02	15.00	48.00	96.00	29.50
Mendibag	1/6/2016	7.20	6.30	2.02	15.00	58.00	112.00	28.60
Mendibag	1/7/2016	6.90	7.10	2.02	15.00	208.00	396.00	27.30
Mendibag	1/8/2016	7.28	6.70	2.02	24.00	340.00	220.00	27.00
Mendibag	1/9/2016	7.30	6.50	2.02	15.00	206.00	412.00	26.70
Mendibag	1/10/2016	7.00	6.80	2.02	15.00	209.00	418.00	25.30
Mendibag	1/11/2016	7.20	6.60	2.02	15.00	208.00	416.00	24.60
Mendibag	1/12/2016	7.20	5.60	2.02	15.00	106.00	212.00	23.20
Mendibag	1/1/2017	7.28	5.60	1.80	12.00	461.00	381.00	22.00
Mendibag	1/2/2017	7.81	6.90	2.70	11.00	133.00	266.00	24.00
Mendibag	1/3/2017	7.40	6.60	2.40	14.00	149.00	398.00	25.50
Mendibag	1/4/2017	7.40	6.60	2.70	18.00	160.00	402.00	26.80
Mendibag	1/5/2017	7.37	6.67	2.00	18.00	285.50	213.70	30.50
Mendibag	1/6/2017	7.31	6.72	2.10	12.00	208.00	412.00	30.60
Mendibag	1/7/2017	7.30	6.50	1.90	11.00	174.00	348.00	26.40
Mendibag	1/8/2017	7.30	6.85	2.80	11.00	198.00	396.00	27.30
Mendibag	1/9/2017	7.30	6.50	1.90	13.00	178.00	356.00	26.00
Mendibag	1/10/2017	7.30	6.80	1.90	13.00	178.00	356.00	26.90
Mendibag	1/11/2017	7.32	6.65	2.10	11.00	246.00	492.00	24.50
Mendibag	1/12/2017	7.32	6.70	2.10	11.00	246.00	492.00	25.64
Mendibag	1/1/2018	7.28	6.80	2.00	9.00	509.00	213.70	18.20
Mendibag	1/2/2018	7.40	6.80	2.00	9.00	561.00	213.70	23.70
Mendibag	1/3/2018	7.79	7.75	2.00	11.00	813.00	213.70	26.30
Mendibag	1/4/2018	8.50	7.80	2.00	9.00	438.00	213.70	29.50

Mendibag	1/5/2018	8.48	6.66	2.00	17.00	267.00	213.70	28.30
Mendibag	1/6/2018	7.70	6.62	1.90	15.00	263.00	213.70	26.30
Mendibag	1/7/2018	8.14	6.79	2.10	12.00	26.60	64.00	25.60
Mendibag	1/8/2018	7.79	6.62	1.90	9.00	813.00	167.70	26.30
Mendibag	1/9/2018	8.40	6.80	2.30	16.00	42.00	78.00	24.40
Mendibag	1/10/2018	8.00	6.60	2.10	16.00	49.00	108.00	26.20
Mendibag	1/11/2018	7.90	7.00	2.10	12.00	83.00	179.00	26.80
Mendibag	1/12/2018	7.50	7.10	2.10	10.00	79.00	158.00	22.30
Mendibag	1/1/2019	7.20	6.80	2.10	11.00	67.00	135.00	20.90
Mendibag	1/2/2019	7.80	6.74	2.80	11.00	141.00	287.00	25.30
Mendibag	1/3/2019	7.28	6.74	2.60	11.00	126.00	258.00	24.40
Mendibag	1/4/2019	8.40	7.50	1.60	8.00	142.00	313.00	26.50
Mendibag	1/5/2019	7.28	6.80	2.60	10.00	38.00	86.00	27.20
Mendibag	1/6/2019	7.20	6.60	2.02	12.00	27.00	56.00	24.00
Mendibag	1/7/2019	7.60	6.20	2.02	12.00	27.00	56.00	24.00
Mendibag	1/8/2019	7.60	6.70	2.02	13.00	53.00	106.00	25.30
Mendibag	1/9/2019	7.60	6.80	2.02	14.00	216.00	108.00	25.30
Mendibag	1/10/2019	7.40	6.90	2.02	14.00	215.00	107.00	24.90
Mendibag	1/11/2019	7.10	6.80	2.02	10.00	68.00	136.00	25.80
Mendibag	1/12/2019	7.20	7.90	4.00	11.00	60.00	141.40	24.20
Mendibag	1/1/2020	7.00	6.80	2.00	9.00	62.00	126.00	19.40
Mendibag	1/2/2020	7.20	7.00	2.00	9.00	60.00	124.00	22.30
Mendibag	1/3/2020	7.10	6.90	1.90	8.00	61.00	122.00	24.10
Mendibag	1/4/2020	7.28	6.86	1.50	6.00	74.00	301.00	23.60
Mendibag	1/5/2020	7.40	7.00	1.40	5.00	68.00	151.00	24.80
Mendibag	1/6/2020	6.73	7.19	1.90	13.00	32.10	76.20	24.40
Mendibag	1/7/2020	7.10	6.90	2.90	13.00	34.30	72.20	24.30
Mendibag	1/8/2020	7.20	7.10	2.30	12.00	35.20	70.90	25.10
Mendibag	1/9/2020	7.20	7.00	2.30	14.00	34.60	71.20	23.80
Mendibag	1/10/2020	7.28	6.74	1.80	14.00	60.50	119.20	22.90
Mendibag	1/11/2020	7.87	6.84	2.20	13.00	40.70	91.50	25.80
Mendibag	1/12/2020	7.20	6.80	2.30	14.00	34.60	71.20	23.80
Mendibag	1/1/2021	6.56	6.90	1.90	14.00	44.00	120.10	23.60
Mendibag	1/2/2021	6.57	6.80	2.30	18.00	48.00	122.30	26.40
Mendibag	1/3/2021	6.62	6.90	2.80	15.00	48.60	126.90	24.90
Mendibag	1/4/2021	6.61	6.80	2.60	17.00	49.70	128.90	25.90
Mendibag	1/5/2021	6.62	6.81	2.70	16.00	49.80	126.90	23.90
Mendibag	1/6/2021	6.69	6.88	3.30	17.00	49.00	127.80	23.60
Mendibag	1/7/2021	6.68	6.81	3.20	19.00	47.00	127.80	24.60
Mendibag	1/8/2021	6.69	6.83	3.30	23.00	49.00	127.20	24.30
Mendibag	1/9/2021	6.68	6.81	2.20	13.00	51.00	126.40	24.10
Mendibag	1/10/2021	6.79	6.89	2.40	14.00	52.00	128.10	23.50
Mendibag	1/11/2021	6.76	6.88	2.30	13.00	50.00	128.00	22.10
Mendibag	1/12/2021	6.88	6.74	2.90	16.00	68.40	127.70	23.20
Mendibag	1/1/2022	7.07	7.02	2.20	13.00	96.60	179.10	21.30
Mendibag	1/2/2022	7.17	6.91	2.30	12.00	92.40	176.00	22.80

Mendibag	1/3/2022	7.13	6.91	2.30	12.00	93.00	184.00	22.60
Mendibag	1/4/2022	6.68	7.06	3.00	12.00	56.00	116.00	23.80
Mendibag	1/5/2022	6.61	7.02	2.10	11.00	64.00	122.00	23.40
Mendibag	1/6/2022	6.67	7.00	2.20	12.00	61.00	126.00	23.60
Mendibag	1/7/2022	6.66	7.01	2.50	14.00	69.00	126.00	23.10
Mendibag	1/8/2022	6.75	7.12	2.60	13.00	68.00	127.00	23.50
Mendibag	1/9/2022	6.72	7.14	2.50	14.00	69.00	126.00	23.20
Mendibag	1/10/2022	6.69	7.11	2.40	16.00	62.00	118.00	22.00
Mendibag	1/11/2022	6.68	7.06	2.30	15.00	64.00	116.00	22.30
Mendibag	1/12/2022	6.73	6.86	2.10	13.00	52.00	126.00	22.20
Mendibag	1/1/2023	7.71	8.23	2.50	14.00	92.00	167.00	21.30
Mendibag	1/2/2023	7.31	7.21	2.40	14.00	142.00	292.00	24.70
Mendibag	1/3/2023	7.33	7.24	2.60	15.00	144.00	296.00	24.30
Mendibag	1/4/2023	7.39	7.34	2.80	18.00	142.00	294.00	24.30
Mendibag	1/5/2023	7.31	7.23	2.40	13.00	140.00	294.00	24.20
Mendibag	1/6/2023	7.36	7.21	2.40	14.00	143.00	253.00	24.10
Mendibag	1/7/2023	7.12	7.13	2.30	13.00	108.00	218.00	23.90
Mendibag	1/8/2023	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/9/2023	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Mendibag	1/10/2023	6.93	7.13	3.30	14.00	103.00	208.00	24.50
Mendibag	1/11/2023	6.82	6.93	3.70	12.00	107.00	215.00	24.50
Mendibag	1/12/2023	6.71	6.83	2.10	14.00	56.00	124.00	22.40
Mendibag	1/1/2024	6.73	6.80	2.20	15.00	60.00	128.00	22.60
Mendibag	1/2/2024	7.34	7.23	2.60	15.00	146.00	288.00	25.30
Mendibag	1/3/2024	7.32	7.26	2.80	16.00	140.00	282.00	24.60
Mendibag	1/4/2024	7.42	7.31	2.70	13.00	144.00	288.00	24.10
Mendibag	1/5/2024	7.42	7.31	2.80	14.00	62.00	128.00	24.10
Mendibag	1/6/2024	6.96	7.36	2.90	15.00	66.00	196.00	23.70
Mendibag	1/7/2024	7.03	7.17	3.20	14.00	62.00	187.00	23.90
Mendibag	1/8/2024	7.05	7.21	3.30	13.00	59.00	165.00	23.80
Mendibag	1/9/2024	7.12	7.19	3.60	15.00	68.00	184.00	26.30
Mendibag	1/10/2024	6.33	6.58	3.40	18.00	60.00	135.00	28.90
Mendibag	1/11/2024	6.37	6.53	3.40	17.00	58.00	123.00	25.30
Mendibag	1/12/2024	6.35	6.51	4.10	22.00	56.00	119.00	23.70
Kean Bridge	1/1/2007	7.10	6.10	1.90	15.00	287.00	74.00	25.00
Kean Bridge	1/2/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/3/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/4/2007	7.20	6.40	2.10	15.00	440.00	213.70	25.64
Kean Bridge	1/5/2007	7.40	6.40	1.30	15.00	520.00	550.00	25.64
Kean Bridge	1/6/2007	7.20	5.80	1.50	15.00	625.00	213.70	33.00
Kean Bridge	1/7/2007	7.60	6.74	1.00	15.00	720.00	213.70	34.20
Kean Bridge	1/8/2007	7.50	6.74	1.20	15.00	500.00	213.70	31.00
Kean Bridge	1/9/2007	7.30	6.74	1.30	15.00	730.00	213.70	29.00
Kean Bridge	1/10/2007	7.80	5.50	1.30	15.00	620.00	213.70	29.00
Kean Bridge	1/11/2007	7.50	5.80	1.20	15.00	550.00	213.70	29.00
Kean Bridge	1/12/2007	7.40	5.20	1.20	15.00	530.00	213.70	25.00

Kean Bridge	1/1/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/2/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/3/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/4/2008	7.30	6.40	1.20	15.00	720.00	213.70	25.64
Kean Bridge	1/5/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/6/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/7/2008	7.50	5.80	1.30	15.00	500.00	213.70	30.00
Kean Bridge	1/8/2008	7.40	5.80	1.20	15.00	600.00	213.70	29.00
Kean Bridge	1/9/2008	7.50	5.80	1.00	15.00	620.00	213.70	30.00
Kean Bridge	1/10/2008	7.70	5.40	1.30	15.00	740.00	213.70	29.00
Kean Bridge	1/11/2008	7.20	6.74	1.20	15.00	400.00	120.00	24.00
Kean Bridge	1/12/2008	7.20	6.74	1.30	15.00	450.00	140.00	23.00
Kean Bridge	1/1/2009	7.50	5.40	1.40	15.00	470.00	190.00	27.00
Kean Bridge	1/2/2009	7.70	5.80	1.30	15.00	480.00	215.00	25.00
Kean Bridge	1/3/2009	7.40	6.40	1.30	15.00	400.00	260.00	24.00
Kean Bridge	1/4/2009	7.10	7.60	1.40	15.00	380.00	290.00	31.00
Kean Bridge	1/5/2009	6.40	6.70	1.20	15.00	390.00	236.00	28.00
Kean Bridge	1/6/2009	7.20	6.70	1.10	15.00	410.00	230.00	30.00
Kean Bridge	1/7/2009	7.30	6.80	1.20	15.00	430.00	260.00	29.00
Kean Bridge	1/8/2009	7.40	6.20	1.30	15.00	340.00	235.00	30.00
Kean Bridge	1/9/2009	7.40	6.40	1.30	15.00	350.00	250.00	31.00
Kean Bridge	1/10/2009	7.70	6.50	1.00	15.00	400.00	270.00	28.00
Kean Bridge	1/11/2009	7.70	6.40	1.00	15.00	450.00	280.00	25.00
Kean Bridge	1/12/2009	7.40	6.40	1.20	15.00	450.00	295.00	20.00
Kean Bridge	1/1/2010	7.20	6.00	1.20	15.00	520.00	280.00	19.00
Kean Bridge	1/2/2010	7.40	6.20	1.30	15.00	500.00	290.00	20.00
Kean Bridge	1/3/2010	7.30	6.30	1.20	15.00	650.00	298.00	31.00
Kean Bridge	1/4/2010	7.40	6.20	1.00	15.00	630.00	320.00	29.00
Kean Bridge	1/5/2010	7.30	6.40	1.20	15.00	370.00	270.00	28.00
Kean Bridge	1/6/2010	7.40	6.30	1.10	15.00	400.00	350.00	27.00
Kean Bridge	1/7/2010	7.50	6.74	1.20	15.00	310.00	120.00	30.00
Kean Bridge	1/8/2010	7.40	6.90	1.40	15.00	340.00	160.00	29.00
Kean Bridge	1/9/2010	7.60	6.70	1.00	15.00	350.00	160.00	29.00
Kean Bridge	1/10/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/11/2010	7.40	6.90	1.40	15.00	340.00	160.00	29.00
Kean Bridge	1/12/2010	7.70	6.80	1.40	15.00	520.00	220.00	25.00
Kean Bridge	1/1/2011	7.80	6.80	1.20	15.00	540.00	230.00	29.00
Kean Bridge	1/2/2011	7.50	6.80	1.20	15.00	520.00	180.00	23.00
Kean Bridge	1/3/2011	7.80	6.70	1.10	15.00	650.00	220.00	23.00
Kean Bridge	1/4/2011	7.80	6.80	1.20	15.00	740.00	260.00	28.00
Kean Bridge	1/5/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/6/2011	7.50	6.60	1.10	15.00	620.00	250.00	29.00
Kean Bridge	1/7/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/8/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/9/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/10/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64

Kean Bridge	1/11/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/12/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/1/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/2/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/3/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/4/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/5/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/6/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/7/2012	7.50	5.80	2.30	15.00	500.00	260.00	28.00
Kean Bridge	1/8/2012	7.40	5.80	3.20	26.00	600.00	255.00	29.00
Kean Bridge	1/9/2012	7.50	5.80	2.00	19.00	620.00	310.00	27.00
Kean Bridge	1/10/2012	7.50	6.74	1.30	34.00	400.00	260.00	24.00
Kean Bridge	1/11/2012	7.50	6.74	1.20	28.00	705.00	310.00	27.00
Kean Bridge	1/12/2012	7.65	6.74	1.50	16.00	193.00	182.00	24.00
Kean Bridge	1/1/2013	7.20	6.00	1.20	16.00	520.00	280.00	24.00
Kean Bridge	1/2/2013	6.80	6.00	2.00	26.00	129.70	257.00	23.00
Kean Bridge	1/3/2013	7.70	6.30	1.10	10.00	640.00	320.00	22.00
Kean Bridge	1/4/2013	7.80	6.80	1.20	21.00	740.00	260.00	22.00
Kean Bridge	1/5/2013	7.30	6.40	1.20	25.00	370.00	270.00	28.00
Kean Bridge	1/6/2013	7.20	6.70	2.10	22.00	410.00	230.00	27.00
Kean Bridge	1/7/2013	7.40	6.20	1.00	29.00	630.00	320.00	26.00
Kean Bridge	1/8/2013	7.50	6.80	2.20	23.00	250.00	245.00	27.00
Kean Bridge	1/9/2013	7.40	6.40	3.30	22.00	350.00	250.00	28.00
Kean Bridge	1/10/2013	7.70	5.40	1.30	24.00	740.00	236.00	25.00
Kean Bridge	1/11/2013	7.30	6.74	1.40	17.00	470.00	124.00	29.00
Kean Bridge	1/12/2013	7.70	6.80	1.20	15.00	730.00	320.00	25.00
Kean Bridge	1/1/2014	7.50	5.40	1.40	27.00	270.49	190.00	27.00
Kean Bridge	1/2/2014	7.70	5.80	1.30	32.00	470.00	215.00	25.00
Kean Bridge	1/3/2014	7.30	6.30	1.20	23.00	650.00	298.00	26.00
Kean Bridge	1/4/2014	7.40	6.20	1.90	14.00	370.00	300.00	24.00
Kean Bridge	1/5/2014	7.20	6.50	3.30	21.00	285.00	265.00	25.00
Kean Bridge	1/6/2014	7.40	6.30	2.60	31.00	400.00	350.00	27.00
Kean Bridge	1/7/2014	7.50	6.74	2.20	25.00	310.00	120.00	27.00
Kean Bridge	1/8/2014	7.40	6.20	2.30	21.00	610.00	235.00	28.00
Kean Bridge	1/9/2014	7.60	6.80	1.20	20.00	400.00	320.00	28.00
Kean Bridge	1/10/2014	7.70	6.50	1.00	21.00	450.00	270.00	28.00
Kean Bridge	1/11/2014	7.70	6.40	1.00	14.00	450.00	280.00	25.00
Kean Bridge	1/12/2014	7.30	6.74	1.40	15.00	400.00	135.00	24.00
Kean Bridge	1/1/2015	7.40	5.70	3.90	15.00	128.50	212.00	21.00
Kean Bridge	1/2/2015	6.70	5.80	1.70	15.00	250.00	330.00	22.00
Kean Bridge	1/3/2015	7.60	6.50	2.40	17.00	312.00	255.00	28.00
Kean Bridge	1/4/2015	6.60	6.10	1.90	15.00	230.00	290.00	27.00
Kean Bridge	1/5/2015	6.80	6.20	1.40	15.00	166.30	240.00	26.00
Kean Bridge	1/6/2015	7.60	6.70	3.40	25.00	650.00	140.00	29.00
Kean Bridge	1/7/2015	7.30	6.80	1.20	28.00	280.00	264.00	27.00
Kean Bridge	1/8/2015	7.20	6.30	3.10	17.00	320.00	215.00	26.00

Kean Bridge	1/9/2015	7.30	6.60	1.50	23.00	280.00	190.00	27.00
Kean Bridge	1/10/2015	7.50	6.74	1.70	23.00	190.00	160.00	25.00
Kean Bridge	1/11/2015	7.40	6.90	1.40	17.00	340.00	295.00	29.00
Kean Bridge	1/12/2015	7.40	6.40	1.20	12.00	450.00	255.00	21.00
Kean Bridge	1/1/2016	7.60	5.90	4.20	17.00	180.00	255.00	24.00
Kean Bridge	1/2/2016	7.40	6.20	1.30	15.00	500.00	100.00	23.00
Kean Bridge	1/3/2016	7.80	6.70	1.10	19.00	650.00	220.00	25.00
Kean Bridge	1/4/2016	6.40	6.70	1.20	21.00	390.00	236.00	26.00
Kean Bridge	1/5/2016	7.20	6.60	2.30	23.00	322.00	275.00	25.00
Kean Bridge	1/6/2016	7.20	6.60	2.80	19.00	220.00	220.00	24.00
Kean Bridge	1/7/2016	7.30	6.80	3.10	18.00	430.00	260.00	29.00
Kean Bridge	1/8/2016	7.40	6.90	2.30	23.00	340.00	160.00	29.00
Kean Bridge	1/9/2016	7.60	6.70	1.00	20.00	350.00	160.00	26.00
Kean Bridge	1/10/2016	7.30	6.74	3.60	18.00	170.00	205.00	27.00
Kean Bridge	1/11/2016	7.20	6.70	2.80	19.00	330.00	240.00	24.00
Kean Bridge	1/12/2016	7.70	6.80	1.40	14.00	520.00	220.00	25.00
Kean Bridge	1/1/2017	7.40	5.60	2.10	15.00	120.00	227.00	23.00
Kean Bridge	1/2/2017	7.50	6.80	1.20	33.00	520.00	180.00	23.00
Kean Bridge	1/3/2017	7.40	6.40	1.40	25.00	540.00	260.00	26.00
Kean Bridge	1/4/2017	7.10	7.60	1.40	26.00	380.00	290.00	28.00
Kean Bridge	1/5/2017	7.40	6.30	2.10	27.00	270.00	240.00	27.00
Kean Bridge	1/6/2017	7.20	6.90	2.60	18.00	320.00	255.00	26.00
Kean Bridge	1/7/2017	7.60	6.50	3.30	15.00	355.00	296.00	28.00
Kean Bridge	1/8/2017	7.40	6.00	1.20	19.00	450.00	310.00	28.00
Kean Bridge	1/9/2017	7.20	6.50	1.60	19.00	310.00	185.00	28.00
Kean Bridge	1/10/2017	7.40	6.90	2.00	12.00	244.00	516.00	26.00
Kean Bridge	1/11/2017	7.20	6.90	2.10	13.00	222.00	469.00	25.00
Kean Bridge	1/12/2017	7.28	6.70	1.90	13.00	437.00	374.00	22.00
Kean Bridge	1/1/2018	7.28	6.90	1.90	10.00	481.00	86.20	29.50
Kean Bridge	1/2/2018	7.70	6.90	1.90	11.00	565.00	68.00	24.30
Kean Bridge	1/3/2018	7.14	7.20	2.20	13.00	48.33	163.04	27.63
Kean Bridge	1/4/2018	7.28	7.60	2.10	11.00	437.00	111.30	23.70
Kean Bridge	1/5/2018	7.28	6.62	1.90	18.00	262.00	85.90	18.90
Kean Bridge	1/6/2018	7.60	6.60	2.10	16.00	260.00	65.10	25.60
Kean Bridge	1/7/2018	8.10	6.72	2.00	14.00	27.20	213.70	26.30
Kean Bridge	1/8/2018	7.78	7.40	1.90	9.00	84.15	168.30	26.50
Kean Bridge	1/9/2018	8.20	6.70	2.40	16.00	36.00	213.70	28.80
Kean Bridge	1/10/2018	7.80	6.90	2.00	11.00	44.00	181.00	26.80
Kean Bridge	1/11/2018	7.80	6.90	2.00	11.00	84.00	73.80	21.70
Kean Bridge	1/12/2018	8.34	6.64	1.90	10.00	35.00	70.90	23.00
Kean Bridge	1/1/2019	7.10	7.30	1.90	12.00	66.00	132.00	26.50
Kean Bridge	1/2/2019	8.40	6.74	2.60	10.00	151.00	292.00	25.20
Kean Bridge	1/3/2019	6.90	6.60	2.90	10.00	141.00	288.00	24.00
Kean Bridge	1/4/2019	8.30	6.00	2.50	12.00	153.00	338.00	25.80
Kean Bridge	1/5/2019	7.28	7.40	2.90	12.00	37.00	82.00	20.90
Kean Bridge	1/6/2019	7.28	6.60	2.40	12.00	40.00	86.00	24.20

Kean Bridge	1/7/2019	7.40	6.60	2.02	14.00	26.00	55.00	31.00
Kean Bridge	1/8/2019	7.40	7.20	2.02	14.00	52.00	102.00	24.20
Kean Bridge	1/9/2019	7.20	6.90	2.02	13.00	206.00	103.00	27.20
Kean Bridge	1/10/2019	7.70	7.20	2.02	16.00	220.00	111.00	25.40
Kean Bridge	1/11/2019	7.30	6.90	2.02	12.00	69.00	138.00	25.00
Kean Bridge	1/12/2019	7.30	7.20	2.02	14.00	67.00	138.00	25.20
Kean Bridge	1/1/2020	6.90	6.70	3.00	8.00	64.00	112.00	22.30
Kean Bridge	1/2/2020	7.00	7.10	3.00	11.00	62.00	72.30	25.00
Kean Bridge	1/3/2020	7.40	7.00	2.00	8.00	62.00	124.40	22.60
Kean Bridge	1/4/2020	7.00	7.10	3.00	15.00	11.00	126.00	23.20
Kean Bridge	1/5/2020	6.90	6.70	3.00	15.00	8.00	130.00	19.20
Kean Bridge	1/6/2020	6.82	7.72	2.00	12.00	33.20	71.90	24.50
Kean Bridge	1/7/2020	6.90	7.00	2.00	10.00	33.90	78.00	24.30
Kean Bridge	1/8/2020	7.30	6.80	2.20	11.00	37.30	121.00	23.90
Kean Bridge	1/9/2020	7.00	6.80	2.40	16.00	36.20	102.00	23.60
Kean Bridge	1/10/2020	7.28	6.74	1.50	12.94	54.00	121.30	23.80
Kean Bridge	1/11/2020	7.85	6.84	2.40	15.00	56.00	92.30	25.60
Kean Bridge	1/12/2020	7.00	6.80	2.40	16.00	57.00	70.90	23.40
Kean Bridge	1/1/2021	6.61	7.00	1.70	12.00	47.00	129.78	23.62
Kean Bridge	1/2/2021	6.79	7.35	2.25	12.94	57.02	129.72	23.61
Kean Bridge	1/3/2021	6.79	8.00	2.20	14.05	61.65	128.92	23.61
Kean Bridge	1/4/2021	6.79	6.97	2.65	11.30	37.96	130.87	23.63
Kean Bridge	1/5/2021	6.61	7.00	1.70	12.00	57.00	122.60	23.90
Kean Bridge	1/6/2021	6.80	7.31	2.24	12.59	67.03	129.47	23.64
Kean Bridge	1/7/2021	6.80	7.27	2.31	12.31	63.80	129.04	23.62
Kean Bridge	1/8/2021	6.79	7.08	2.55	11.57	46.21	130.30	23.63
Kean Bridge	1/9/2021	6.80	7.21	2.47	12.08	59.46	129.28	23.61
Kean Bridge	1/10/2021	6.79	7.76	2.24	13.78	60.14	129.24	23.61
Kean Bridge	1/11/2021	6.79	7.58	2.26	13.50	59.06	129.46	23.61
Kean Bridge	1/12/2021	6.79	7.45	2.26	13.22	58.12	129.72	23.61
Kean Bridge	1/1/2022	6.62	7.02	2.00	11.00	62.00	120.00	23.62
Kean Bridge	1/2/2022	6.43	6.97	2.32	11.44	51.18	133.04	23.61
Kean Bridge	1/3/2022	6.42	6.89	2.30	11.15	50.37	133.36	23.61
Kean Bridge	1/4/2022	6.62	7.02	2.00	11.00	58.00	120.00	23.63
Kean Bridge	1/5/2022	6.68	6.92	2.30	13.00	66.00	118.00	23.90
Kean Bridge	1/6/2022	6.69	6.91	2.30	14.00	63.00	120.00	23.64
Kean Bridge	1/7/2022	6.65	6.90	2.40	13.00	64.00	124.00	23.62
Kean Bridge	1/8/2022	6.69	6.92	2.30	12.00	66.00	126.00	23.63
Kean Bridge	1/9/2022	6.66	6.94	2.20	11.00	67.00	128.00	23.61
Kean Bridge	1/10/2022	6.71	6.96	2.20	12.00	68.00	122.00	23.61
Kean Bridge	1/11/2022	6.69	6.94	2.10	13.00	65.00	120.00	23.61
Kean Bridge	1/12/2022	6.75	7.21	2.20	14.00	56.00	129.00	23.61
Kean Bridge	1/1/2023	7.85	8.22	2.30	13.00	94.00	172.00	22.60
Kean Bridge	1/2/2023	7.34	7.25	2.60	16.00	146.00	304.00	24.90
Kean Bridge	1/3/2023	7.36	7.27	3.10	18.00	151.00	302.00	24.60
Kean Bridge	1/4/2023	7.38	7.47	3.20	16.00	148.00	300.00	24.70

Kean Bridge	1/5/2023	7.34	7.23	3.30	19.00	153.00	304.00	24.40
Kean Bridge	1/6/2023	7.42	7.23	3.90	20.00	156.00	276.00	24.20
Kean Bridge	1/7/2023	7.17	7.19	3.40	18.00	113.00	222.00	24.00
Kean Bridge	1/8/2023	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Kean Bridge	1/9/2023	6.85	7.37	3.70	21.00	113.00	211.00	24.10
Kean Bridge	1/10/2023	6.89	7.32	3.90	23.00	106.00	210.00	24.30
Kean Bridge	1/11/2023	7.07	7.42	4.30	21.00	97.00	185.00	22.90
Kean Bridge	1/12/2023	6.73	7.23	2.30	16.00	58.00	127.00	22.30
Kean Bridge	1/1/2024	6.71	7.31	2.50	14.00	57.00	126.00	22.50
Kean Bridge	1/2/2024	7.39	7.28	2.80	17.00	146.00	301.00	25.20
Kean Bridge	1/3/2024	7.36	7.25	2.90	17.00	270.49	296.00	25.00
Kean Bridge	1/4/2024	7.34	7.42	3.20	17.00	146.00	296.00	24.70
Kean Bridge	1/5/2024	7.34	7.42	3.40	17.00	67.00	136.00	24.70
Kean Bridge	1/6/2024	7.01	7.39	3.10	16.00	68.00	189.00	23.90
Kean Bridge	1/7/2024	7.02	7.26	3.30	17.00	65.00	192.00	23.60
Kean Bridge	1/8/2024	6.95	7.26	3.20	16.00	67.00	187.00	23.50
Kean Bridge	1/9/2024	7.16	7.22	3.40	14.00	64.00	190.00	26.40
Kean Bridge	1/10/2024	6.29	6.84	3.30	15.00	60.00	134.00	28.90
Kean Bridge	1/11/2024	6.32	6.75	3.40	15.00	59.00	112.00	25.30
Kean Bridge	1/12/2024	6.38	6.72	3.80	18.00	58.00	110.00	23.70
Sheikh-ghat (Kazirbazar)	1/1/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/2/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/3/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/4/2007	7.30	6.30	2.40	15.00	430.00	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/5/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/6/2007	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/7/2007	7.50	6.74	1.40	15.00	580.00	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/8/2007	7.60	6.74	1.30	15.00	620.00	213.70	31.00
Sheikh-ghat (Kazirbazar)	1/9/2007	7.60	5.80	1.30	15.00	800.00	213.70	29.00
Sheikh-ghat (Kazirbazar)	1/10/2007	7.60	5.80	1.40	15.00	650.00	213.70	31.00
Sheikh-ghat (Kazirbazar)	1/11/2007	7.40	5.40	1.70	15.00	550.00	213.70	30.00
Sheikh-ghat (Kazirbazar)	1/12/2007	7.30	5.70	1.40	15.00	530.00	213.70	25.00
Sheikh-ghat (Kazirbazar)	1/1/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/2/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/3/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/4/2008	7.40	6.20	1.20	15.00	840.00	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/5/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/6/2008	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/7/2008	7.40	5.50	1.20	15.00	530.00	213.70	28.00
Sheikh-ghat (Kazirbazar)	1/8/2008	7.50	5.80	1.20	15.00	580.00	213.70	29.00
Sheikh-ghat (Kazirbazar)	1/9/2008	7.40	5.60	1.00	15.00	590.00	213.70	31.00

Sheikh-ghat (Kazirbazar)	1/10/2008	7.70	5.40	1.40	15.00	850.00	213.70	29.00
Sheikh-ghat (Kazirbazar)	1/11/2008	7.80	6.74	1.30	15.00	450.00	128.00	25.00
Sheikh-ghat (Kazirbazar)	1/12/2008	7.00	6.74	1.40	15.00	450.00	130.00	25.64
Sheikh-ghat (Kazirbazar)	1/1/2009	7.40	6.74	1.50	15.00	470.00	210.00	26.00
Sheikh-ghat (Kazirbazar)	1/2/2009	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/3/2009	7.50	6.40	1.40	15.00	360.00	270.00	24.00
Sheikh-ghat (Kazirbazar)	1/4/2009	7.00	7.20	1.40	15.00	400.00	300.00	30.00
Sheikh-ghat (Kazirbazar)	1/5/2009	6.60	6.90	1.00	15.00	395.00	240.00	30.00
Sheikh-ghat (Kazirbazar)	1/6/2009	7.50	6.90	1.40	15.00	430.00	245.00	30.00
Sheikh-ghat (Kazirbazar)	1/7/2009	7.40	6.20	1.00	15.00	460.00	162.00	30.00
Sheikh-ghat (Kazirbazar)	1/8/2009	7.30	6.40	1.40	15.00	410.00	240.00	29.00
Sheikh-ghat (Kazirbazar)	1/9/2009	7.60	6.40	1.30	15.00	390.00	260.00	30.00
Sheikh-ghat (Kazirbazar)	1/10/2009	7.60	6.50	1.00	15.00	380.00	280.00	29.00
Sheikh-ghat (Kazirbazar)	1/11/2009	7.60	6.40	1.20	15.00	430.00	290.00	24.00
Sheikh-ghat (Kazirbazar)	1/12/2009	7.50	6.70	1.30	15.00	500.00	300.00	18.00
Sheikh-ghat (Kazirbazar)	1/1/2010	7.20	6.30	1.30	15.00	500.00	290.00	18.00
Sheikh-ghat (Kazirbazar)	1/2/2010	7.40	6.30	1.00	15.00	400.00	300.00	21.00
Sheikh-ghat (Kazirbazar)	1/3/2010	7.20	6.50	1.20	15.00	700.00	310.00	32.00
Sheikh-ghat (Kazirbazar)	1/4/2010	7.60	6.00	1.20	15.00	610.00	300.00	30.00
Sheikh-ghat (Kazirbazar)	1/5/2010	7.30	6.20	1.00	15.00	280.00	300.00	29.00
Sheikh-ghat (Kazirbazar)	1/6/2010	7.60	6.40	1.20	15.00	680.00	360.00	28.00
Sheikh-ghat (Kazirbazar)	1/7/2010	7.28	6.20	1.00	15.00	430.00	160.00	30.00
Sheikh-ghat (Kazirbazar)	1/8/2010	7.50	6.70	1.20	15.00	290.00	165.00	29.00
Sheikh-ghat (Kazirbazar)	1/9/2010	7.40	6.74	1.20	15.00	340.00	185.00	30.00
Sheikh-ghat (Kazirbazar)	1/10/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/11/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/12/2010	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/1/2011	7.80	6.80	1.20	15.00	420.00	230.00	31.00
Sheikh-ghat (Kazirbazar)	1/2/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/3/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/4/2011	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/5/2011	7.80	7.80	1.30	15.00	730.00	290.00	28.00
Sheikh-ghat (Kazirbazar)	1/6/2011	7.70	6.90	1.30	15.00	710.00	280.00	29.00
Sheikh-ghat (Kazirbazar)	1/7/2011	7.70	7.50	1.30	15.00	580.00	320.00	29.00
Sheikh-ghat (Kazirbazar)	1/8/2011	7.40	6.70	1.20	15.00	540.00	340.00	30.00
Sheikh-ghat (Kazirbazar)	1/9/2011	7.60	7.80	1.30	15.00	580.00	420.00	31.00

Sheikh-ghat (Kazirbazar)	1/10/2011	7.70	7.50	1.10	15.00	530.00	358.00	23.00
Sheikh-ghat (Kazirbazar)	1/11/2011	7.80	7.70	1.10	15.00	470.00	390.00	24.00
Sheikh-ghat (Kazirbazar)	1/12/2011	7.70	7.50	1.20	15.00	540.00	213.70	27.00
Sheikh-ghat (Kazirbazar)	1/1/2012	7.70	6.70	1.20	15.00	750.00	330.00	31.00
Sheikh-ghat (Kazirbazar)	1/2/2012	7.70	6.70	1.20	15.00	740.00	330.00	32.00
Sheikh-ghat (Kazirbazar)	1/3/2012	7.80	6.60	1.20	15.00	710.00	300.00	30.00
Sheikh-ghat (Kazirbazar)	1/4/2012	7.50	6.70	1.10	15.00	630.00	320.00	31.00
Sheikh-ghat (Kazirbazar)	1/5/2012	7.20	6.10	1.10	15.00	450.00	310.00	32.00
Sheikh-ghat (Kazirbazar)	1/6/2012	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/7/2012	7.60	6.50	1.30	15.00	450.00	213.70	27.00
Sheikh-ghat (Kazirbazar)	1/8/2012	7.28	6.40	1.40	21.00	410.00	240.00	29.00
Sheikh-ghat (Kazirbazar)	1/9/2012	6.70	6.74	1.30	23.00	390.00	185.00	30.00
Sheikh-ghat (Kazirbazar)	1/10/2012	7.50	6.74	1.60	21.00	270.00	182.00	27.00
Sheikh-ghat (Kazirbazar)	1/11/2012	7.50	6.40	1.50	26.00	190.00	110.00	26.00
Sheikh-ghat (Kazirbazar)	1/12/2012	7.76	6.74	1.60	23.00	188.00	182.00	22.00
Sheikh-ghat (Kazirbazar)	1/1/2013	7.20	7.60	1.10	37.00	163.20	327.00	23.00
Sheikh-ghat (Kazirbazar)	1/2/2013	6.70	6.74	3.10	15.00	133.80	268.00	22.00
Sheikh-ghat (Kazirbazar)	1/3/2013	6.60	6.74	2.10	15.00	124.00	248.00	26.00
Sheikh-ghat (Kazirbazar)	1/4/2013	6.40	6.30	2.40	15.00	126.00	252.00	26.00
Sheikh-ghat (Kazirbazar)	1/5/2013	6.70	6.50	1.30	15.00	126.00	252.00	24.00
Sheikh-ghat (Kazirbazar)	1/6/2013	7.00	6.50	1.90	15.00	124.00	248.00	26.00
Sheikh-ghat (Kazirbazar)	1/7/2013	7.28	7.00	2.60	15.00	39.10	213.70	24.00
Sheikh-ghat (Kazirbazar)	1/8/2013	6.60	6.70	1.40	15.00	138.00	273.00	29.00
Sheikh-ghat (Kazirbazar)	1/9/2013	6.80	7.00	1.40	15.00	162.00	253.00	26.00
Sheikh-ghat (Kazirbazar)	1/10/2013	6.40	6.70	3.40	15.00	37.90	75.80	25.00
Sheikh-ghat (Kazirbazar)	1/11/2013	7.28	6.30	3.00	15.00	37.60	176.00	25.00
Sheikh-ghat (Kazirbazar)	1/12/2013	7.28	6.74	1.30	21.00	750.00	330.00	27.00
Sheikh-ghat (Kazirbazar)	1/1/2014	7.00	7.20	1.40	25.00	400.00	300.00	28.00
Sheikh-ghat (Kazirbazar)	1/2/2014	7.30	6.20	1.00	23.00	280.00	300.00	29.00
Sheikh-ghat (Kazirbazar)	1/3/2014	7.50	6.90	1.40	34.00	430.00	245.00	30.00
Sheikh-ghat (Kazirbazar)	1/4/2014	6.70	5.20	4.60	15.00	134.00	268.00	25.00
Sheikh-ghat (Kazirbazar)	1/5/2014	6.70	6.74	3.80	15.00	129.70	257.00	26.00
Sheikh-ghat (Kazirbazar)	1/6/2014	6.90	6.74	4.80	15.00	145.00	290.00	24.00
Sheikh-ghat (Kazirbazar)	1/7/2014	7.60	6.50	1.00	26.00	380.00	280.00	27.00
Sheikh-ghat (Kazirbazar)	1/8/2014	7.80	7.30	1.30	18.00	450.00	128.00	25.00
Sheikh-ghat (Kazirbazar)	1/9/2014	7.00	6.74	1.40	22.00	470.00	130.00	23.00

Sheikh-ghat (Kazirbazar)	1/10/2014	7.40	6.74	1.50	22.00	147.70	210.00	26.00
Sheikh-ghat (Kazirbazar)	1/11/2014	6.90	5.40	1.20	22.00	147.00	190.00	21.00
Sheikh-ghat (Kazirbazar)	1/12/2014	7.00	5.50	1.60	15.00	610.00	233.00	25.00
Sheikh-ghat (Kazirbazar)	1/1/2015	7.60	6.00	1.20	23.00	610.00	300.00	26.00
Sheikh-ghat (Kazirbazar)	1/2/2015	7.60	7.80	1.20	25.00	730.00	290.00	28.00
Sheikh-ghat (Kazirbazar)	1/3/2015	7.40	6.20	1.60	24.00	63.50	267.00	29.00
Sheikh-ghat (Kazirbazar)	1/4/2015	7.80	7.40	1.20	30.00	510.00	300.00	29.00
Sheikh-ghat (Kazirbazar)	1/5/2015	7.40	6.80	1.00	13.00	280.00	160.00	29.00
Sheikh-ghat (Kazirbazar)	1/6/2015	7.40	6.40	1.00	17.00	300.00	180.00	30.00
Sheikh-ghat (Kazirbazar)	1/7/2015	7.80	7.40	1.10	28.00	540.00	360.00	23.00
Sheikh-ghat (Kazirbazar)	1/8/2015	7.60	6.40	1.20	17.00	430.00	290.00	24.00
Sheikh-ghat (Kazirbazar)	1/9/2015	7.80	7.40	1.30	23.00	490.00	213.70	27.00
Sheikh-ghat (Kazirbazar)	1/10/2015	7.20	6.30	1.30	15.00	500.00	290.00	21.00
Sheikh-ghat (Kazirbazar)	1/11/2015	7.20	6.10	2.10	15.00	176.00	152.00	25.00
Sheikh-ghat (Kazirbazar)	1/12/2015	7.68	6.50	2.60	15.00	206.00	412.00	24.00
Sheikh-ghat (Kazirbazar)	1/1/2016	7.20	6.20	3.20	15.00	143.00	286.00	27.00
Sheikh-ghat (Kazirbazar)	1/2/2016	7.14	6.50	2.60	15.00	41.00	82.00	29.00
Sheikh-ghat (Kazirbazar)	1/3/2016	7.04	6.42	2.90	15.00	129.00	258.00	28.00
Sheikh-ghat (Kazirbazar)	1/4/2016	7.32	6.26	2.60	15.00	128.00	256.00	29.00
Sheikh-ghat (Kazirbazar)	1/5/2016	7.10	7.00	2.30	15.00	198.00	396.00	27.00
Sheikh-ghat (Kazirbazar)	1/6/2016	7.00	7.20	1.10	15.00	206.00	412.00	27.00
Sheikh-ghat (Kazirbazar)	1/7/2016	7.40	6.30	1.40	16.00	540.00	350.00	30.00
Sheikh-ghat (Kazirbazar)	1/8/2016	7.80	7.80	2.20	19.00	590.00	400.00	29.00
Sheikh-ghat (Kazirbazar)	1/9/2016	7.20	6.70	1.20	15.00	204.00	398.00	25.00
Sheikh-ghat (Kazirbazar)	1/10/2016	7.70	7.60	2.70	21.00	470.00	380.00	24.00
Sheikh-ghat (Kazirbazar)	1/11/2016	7.30	6.74	2.90	15.00	104.00	208.00	23.00
Sheikh-ghat (Kazirbazar)	1/12/2016	7.30	5.80	2.80	18.00	156.00	312.00	24.00
Sheikh-ghat (Kazirbazar)	1/1/2017	7.63	6.70	2.80	25.00	143.00	286.00	24.00
Sheikh-ghat (Kazirbazar)	1/2/2017	7.62	6.70	2.70	15.00	196.00	393.00	24.00
Sheikh-ghat (Kazirbazar)	1/3/2017	7.58	6.80	2.50	18.00	198.00	395.00	25.00
Sheikh-ghat (Kazirbazar)	1/4/2017	7.10	6.67	2.10	32.00	331.00	213.70	26.00
Sheikh-ghat (Kazirbazar)	1/5/2017	7.12	6.60	2.00	11.00	330.00	213.70	27.00
Sheikh-ghat (Kazirbazar)	1/6/2017	6.69	6.50	2.10	12.00	194.00	388.00	30.00
Sheikh-ghat (Kazirbazar)	1/7/2017	7.24	6.80	3.00	9.00	193.00	386.00	26.00
Sheikh-ghat (Kazirbazar)	1/8/2017	7.20	6.70	2.50	8.00	194.00	388.00	27.00
Sheikh-ghat (Kazirbazar)	1/9/2017	7.10	6.50	2.10	11.00	196.00	392.00	25.00

Sheikh-ghat (Kazirbazar)	1/10/2017	7.10	6.60	2.10	12.00	194.50	389.00	27.00
Sheikh-ghat (Kazirbazar)	1/11/2017	7.20	6.70	1.90	11.00	206.00	412.00	26.00
Sheikh-ghat (Kazirbazar)	1/12/2017	7.28	6.80	2.70	11.00	335.00	213.70	25.00
Sheikh-ghat (Kazirbazar)	1/1/2018	8.20	7.40	2.30	12.00	431.00	99.30	29.50
Sheikh-ghat (Kazirbazar)	1/2/2018	8.00	6.70	1.90	14.00	22.00	71.00	24.30
Sheikh-ghat (Kazirbazar)	1/3/2018	7.90	6.90	2.00	12.00	30.00	156.00	22.50
Sheikh-ghat (Kazirbazar)	1/4/2018	7.80	6.70	2.00	12.00	571.00	111.70	23.70
Sheikh-ghat (Kazirbazar)	1/5/2018	7.97	7.20	2.80	16.00	88.05	176.10	26.40
Sheikh-ghat (Kazirbazar)	1/6/2018	7.90	6.68	1.90	19.00	19.00	65.70	25.60
Sheikh-ghat (Kazirbazar)	1/7/2018	7.80	6.70	2.00	18.00	298.00	61.20	26.30
Sheikh-ghat (Kazirbazar)	1/8/2018	7.98	7.75	2.00	11.00	854.00	176.60	26.30
Sheikh-ghat (Kazirbazar)	1/9/2018	7.28	6.80	2.10	21.00	320.00	70.60	28.90
Sheikh-ghat (Kazirbazar)	1/10/2018	8.20	6.80	2.10	12.00	45.00	131.50	26.80
Sheikh-ghat (Kazirbazar)	1/11/2018	7.90	6.80	2.00	13.00	28.00	106.00	26.20
Sheikh-ghat (Kazirbazar)	1/12/2018	8.10	6.80	2.00	15.00	21.00	76.00	24.40
Sheikh-ghat (Kazirbazar)	1/1/2019	7.00	7.20	4.00	13.00	21.00	127.00	26.50
Sheikh-ghat (Kazirbazar)	1/2/2019	7.90	6.74	2.02	21.00	27.00	321.00	25.30
Sheikh-ghat (Kazirbazar)	1/3/2019	6.80	5.90	2.02	11.00	38.00	311.00	24.30
Sheikh-ghat (Kazirbazar)	1/4/2019	8.20	6.74	2.40	14.00	22.00	383.00	25.40
Sheikh-ghat (Kazirbazar)	1/5/2019	7.28	7.50	2.00	14.00	16.00	81.00	20.90
Sheikh-ghat (Kazirbazar)	1/6/2019	8.50	6.50	2.02	14.00	52.00	83.00	24.50
Sheikh-ghat (Kazirbazar)	1/7/2019	7.30	6.50	2.50	16.00	55.00	54.00	30.00
Sheikh-ghat (Kazirbazar)	1/8/2019	7.30	6.80	3.10	15.00	23.00	99.00	24.10
Sheikh-ghat (Kazirbazar)	1/9/2019	7.40	7.10	3.40	15.00	54.00	106.00	26.30
Sheikh-ghat (Kazirbazar)	1/10/2019	7.50	7.00	2.02	19.00	39.00	113.00	25.30
Sheikh-ghat (Kazirbazar)	1/11/2019	6.90	7.10	2.02	13.00	52.00	142.00	25.20
Sheikh-ghat (Kazirbazar)	1/12/2019	7.00	7.30	4.10	15.00	49.00	140.00	25.40
Sheikh-ghat (Kazirbazar)	1/1/2020	6.80	7.00	3.00	10.00	46.00	132.00	19.30
Sheikh-ghat (Kazirbazar)	1/2/2020	7.30	6.90	2.00	8.00	59.00	131.00	22.90
Sheikh-ghat (Kazirbazar)	1/3/2020	7.30	7.10	2.10	7.00	62.00	118.00	24.20
Sheikh-ghat (Kazirbazar)	1/4/2020	6.20	6.03	2.50	9.00	10.00	317.00	25.60
Sheikh-ghat (Kazirbazar)	1/5/2020	7.28	6.20	2.10	8.00	10.00	213.70	25.10
Sheikh-ghat (Kazirbazar)	1/6/2020	6.44	7.69	2.20	12.00	58.00	79.30	24.00
Sheikh-ghat (Kazirbazar)	1/7/2020	6.70	6.80	2.10	12.00	111.00	70.30	24.10
Sheikh-ghat (Kazirbazar)	1/8/2020	7.10	7.00	2.40	13.00	10.00	71.20	25.30
Sheikh-ghat (Kazirbazar)	1/9/2020	7.20	7.10	2.60	18.00	142.00	72.10	23.60

Sheikh-ghat (Kazirbazar)	1/10/2020	6.12	8.06	1.40	8.00	62.00	142.00	23.60
Sheikh-ghat (Kazirbazar)	1/11/2020	7.89	6.82	2.60	12.00	56.00	113.00	25.90
Sheikh-ghat (Kazirbazar)	1/12/2020	7.20	7.10	2.60	18.00	59.00	106.00	23.60
Sheikh-ghat (Kazirbazar)	1/1/2021	6.70	7.10	2.10	18.00	49.00	127.30	23.40
Sheikh-ghat (Kazirbazar)	1/2/2021	6.62	6.90	2.50	21.00	53.00	126.20	26.30
Sheikh-ghat (Kazirbazar)	1/3/2021	6.68	7.10	2.90	19.00	51.90	128.20	24.60
Sheikh-ghat (Kazirbazar)	1/4/2021	6.67	7.20	2.70	19.00	51.80	129.20	25.60
Sheikh-ghat (Kazirbazar)	1/5/2021	6.69	7.09	2.90	20.00	51.90	128.20	23.60
Sheikh-ghat (Kazirbazar)	1/6/2021	6.75	7.19	3.20	19.00	52.00	131.60	23.70
Sheikh-ghat (Kazirbazar)	1/7/2021	6.77	7.18	3.10	23.00	51.00	131.70	24.80
Sheikh-ghat (Kazirbazar)	1/8/2021	6.75	7.17	3.20	22.00	54.00	129.60	24.60
Sheikh-ghat (Kazirbazar)	1/9/2021	6.72	7.13	2.70	18.00	54.00	129.30	23.90
Sheikh-ghat (Kazirbazar)	1/10/2021	6.71	7.21	2.80	16.00	56.00	131.90	23.60
Sheikh-ghat (Kazirbazar)	1/11/2021	6.72	7.20	2.70	15.00	54.00	131.70	22.40
Sheikh-ghat (Kazirbazar)	1/12/2021	6.92	8.23	2.80	18.00	69.20	132.90	23.60
Sheikh-ghat (Kazirbazar)	1/1/2022	7.04	7.02	2.20	13.00	96.60	180.40	22.00
Sheikh-ghat (Kazirbazar)	1/2/2022	7.14	7.00	2.80	15.00	96.80	182.00	23.70
Sheikh-ghat (Kazirbazar)	1/3/2022	7.15	7.84	2.80	16.00	97.00	182.00	23.40
Sheikh-ghat (Kazirbazar)	1/4/2022	6.65	7.09	3.00	14.00	64.00	126.00	24.00
Sheikh-ghat (Kazirbazar)	1/5/2022	6.67	7.06	2.80	15.00	68.00	120.00	24.10
Sheikh-ghat (Kazirbazar)	1/6/2022	6.71	7.05	2.70	16.00	67.00	122.00	23.80
Sheikh-ghat (Kazirbazar)	1/7/2022	6.77	7.03	2.70	15.00	69.00	126.00	23.70
Sheikh-ghat (Kazirbazar)	1/8/2022	6.73	7.06	2.70	17.00	62.00	118.00	23.90
Sheikh-ghat (Kazirbazar)	1/9/2022	6.72	7.17	2.60	18.00	60.00	120.00	23.60
Sheikh-ghat (Kazirbazar)	1/10/2022	6.74	7.15	2.30	15.00	59.00	116.00	22.50
Sheikh-ghat (Kazirbazar)	1/11/2022	6.71	7.11	2.20	14.00	60.00	114.00	22.30
Sheikh-ghat (Kazirbazar)	1/12/2022	6.78	7.24	2.50	16.00	54.00	132.00	22.70
Sheikh-ghat (Kazirbazar)	1/1/2023	7.89	8.26	2.60	17.00	97.00	176.00	22.30
Sheikh-ghat (Kazirbazar)	1/2/2023	7.34	7.28	3.40	19.00	147.00	312.00	24.90
Sheikh-ghat (Kazirbazar)	1/3/2023	7.41	7.30	3.60	19.00	149.00	306.00	24.60
Sheikh-ghat (Kazirbazar)	1/4/2023	7.44	7.38	3.40	18.00	146.00	302.00	24.60
Sheikh-ghat (Kazirbazar)	1/5/2023	7.43	7.34	3.80	18.00	152.00	308.00	24.60
Sheikh-ghat (Kazirbazar)	1/6/2023	7.41	7.38	3.70	17.00	155.00	310.00	24.30
Sheikh-ghat (Kazirbazar)	1/7/2023	7.19	7.18	3.20	16.00	118.00	234.00	24.10
Sheikh-ghat (Kazirbazar)	1/8/2023	7.28	6.74	2.02	15.00	270.49	213.70	25.64
Sheikh-ghat (Kazirbazar)	1/9/2023	7.01	7.13	3.60	20.00	114.00	237.00	24.30

Sheikh-ghat (Kazirbazar)	1/10/2023	7.13	7.15	3.50	18.00	115.00	232.00	24.10
Sheikh-ghat (Kazirbazar)	1/11/2023	7.52	6.92	4.00	20.00	121.00	242.00	24.10
Sheikh-ghat (Kazirbazar)	1/12/2023	6.74	7.26	2.50	17.00	59.00	129.00	22.60
Sheikh-ghat (Kazirbazar)	1/1/2024	6.75	7.19	2.40	16.00	56.00	125.00	22.30
Sheikh-ghat (Kazirbazar)	1/2/2024	7.37	7.31	3.50	18.00	152.00	309.00	25.30
Sheikh-ghat (Kazirbazar)	1/3/2024	7.33	7.29	3.10	19.00	154.00	314.00	25.70
Sheikh-ghat (Kazirbazar)	1/4/2024	7.39	7.39	3.50	18.00	147.00	298.00	24.50
Sheikh-ghat (Kazirbazar)	1/5/2024	7.39	7.39	3.80	20.00	71.00	142.00	24.50
Sheikh-ghat (Kazirbazar)	1/6/2024	6.93	7.38	3.30	18.00	74.00	192.00	23.80
Sheikh-ghat (Kazirbazar)	1/7/2024	6.99	7.45	3.10	15.00	72.00	181.00	23.30
Sheikh-ghat (Kazirbazar)	1/8/2024	7.02	7.41	3.30	14.00	71.00	179.00	23.40
Sheikh-ghat (Kazirbazar)	1/9/2024	7.19	7.41	3.30	12.00	70.00	188.00	26.80
Sheikh-ghat (Kazirbazar)	1/10/2024	6.51	6.64	3.20	13.00	64.00	144.00	28.08
Sheikh-ghat (Kazirbazar)	1/11/2024	6.51	6.68	3.10	13.00	63.00	131.00	25.40
Sheikh-ghat (Kazirbazar)	1/12/2024	6.53	6.65	3.10	15.00	61.00	128.00	23.40