Seasonal Anomaly Detection in the Halda River Using a Multivariate Deep Learning Framework

AUTHORS

Md. Minaruzzaman Shovon [1]* **(Corresponding Author)**
Email: minar.svn@gmail.com

H A Hossain Tamjid [2]
Email: hossaint931@gmail.com

Md. Tamim [3]
Email: mtamim@cuet.ac.bd

[1,2,3] *Department of Water Resources Engineering, Chittagong University of Engineering & Technology (CUET), Chittagong, Bangladesh*

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Md. Minaruzzaman Shovon[1], H A Hossain Tamjid[2], Md. Tamim[3]

[1*]Department of Water Resources Engineering, CUET, Bangladesh (minar.svn@gmail.com)
[2]Department of Water Resources Engineering, CUET, Bangladesh (hossaint931@gmail.com)
[3]Department of Water Resources Engineering, CUET, Bangladesh (mtamim@cuet.ac.bd)

Abstract

Monitoring river water quality is essential to preserving ecological integrity, especially in ecologically significant rivers like the Halda, which is reportedly renowned for its natural freshwater carp spawning. CWASA greatly depends on the water from this river, treating and supplying it as potable water for the millions of individuals in the city. This study presents a deep learning-based approach using a deep autoencoder neural network for unsupervised anomaly detection in water quality data. Two-year time-series data for a detailed study, including daily measurements of the most important water quality indicators, i.e., pH, turbidity, alkalinity, and chloride concentration, was utilized. The autoencoder was chosen because of its ability to perform unsupervised learning on high-dimensional, unlabeled data, making it ideal for environmental monitoring scenarios in which anomalies are uncommon, diverse, and frequently undefined. The autoencoder learns compressed representations of normal water behavior and flags anomalies based on elevated reconstruction errors. To enhance interpretability, temporal features such as month- and climate-based seasons (Dry, Pre-Monsoon, Monsoon, and Post-Monsoon) were added. These seasonal labels provide environmental context when visualizing anomalies, making it easier to differentiate between expected and unusual events. The study revealed several important anomalies throughout the two years of observation and directly linked abrupt changes in water quality indicators, including pH, turbidity, alkalinity, and chloride concentration. The developed model not only enables early detection and diagnosis of abnormal shifts in water quality but also provides actionable insights for stakeholders and policymakers, facilitating timely and targeted environmental interventions.
Keywords: *Halda River; Anomaly Detection; Deep Autoencoder; Water Quality; Unsupervised Deep Learning*

1 Introduction

Anomaly detection is the process of identifying data instances that significantly deviate from expected patterns. These anomalies can be categorized as point anomalies, which are single data points that are abnormal; contextual anomalies, which are data points that are unusual only in a specific context (e.g., season); and collective anomalies, where a group of data points behaves unusually as a whole. Detecting these events in water quality data is a complex challenge due to the rare and heterogeneous nature of anomalies and the difficulty in distinguishing them from noise or faulty sensor readings (Ren et al., 2019).

The Halda River, located in southeastern Bangladesh, is a vital and ecologically significant tidal river system. (Hossen, 2018). The river also serves as a major source of water for Chittagong city's residents, who use its water for domestic, agricultural, and industrial purposes. However, the Halda River's ecosystem is continually threatened by pollution from various anthropogenic activities, including industrial waste disposal, municipal sewage, and agricultural runoff.

Numerous studies have documented the deteriorating water quality in the Halda River. Research has found that concentrations of several heavy metals in both water and sediment, including Al, Ni, Zn, and Mn, exceed the permissible limits set by international standards (Bhuyan & Bakar, 2017). These pollution events have been correlated with industrial effluents, municipal waste, and agricultural activities, with seasonal water flows playing a role in the mobility of pollutants. A Water Quality Index (WQI) assessment over a two-year period further classified the water in the downstream area of Modunaghat as "poor," making it unsuitable for direct drinking without treatment. Notably, some studies have shown that water quality can be worse during the monsoon season due to the flushing of pollutants, contradicting the general assumption of seasonal improvement (Hossen, 2018).

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While traditional machine learning methods such as K-Means and Local Outlier Factor (LOF) have shown success in some cases, they can struggle with the complex temporal and spatial relationships in real-time time-series data (El-Shafeiy et al., 2023). The challenges in timely monitoring form a strong justification for using real-time systems to detect anomalies in water quality, which is crucial for countering pollution, supplying safe water, and protecting aquatic ecosystems. This research uses a deep learning approach for the detection of anomalies in water quality data from the Halda River. Grounded in a deep autoencoder model framework, the system learns the normal state of water parameters—such as pH, turbidity, and alkalinity—and then tracks any major departure from these norms as an anomaly. The method is designed not only to detect point anomalies but also to identify subtle contextual and collective patterns that may arise from seasonal or environmental shifts. The proposed deep learning paradigm offers the necessary scalability, flexibility, and accuracy for continuous monitoring in a dynamic natural environment.

2 Methodology

This study uses a deep learning framework with an autoencoder to detect anomalies in water quality data from the Halda River. Our method includes three major steps: first, we gather and prepare the time-series data; next, we employ an autoencoder to model normal water quality behavior; finally, we use the model's output to identify significant deviations

2.1 Data Collection and Preparation

The hydric water quality data was sourced from the Mohora Water Treatment Plant, operated by the Chattogram Water Supply and Sewerage Authority (CWASA). CWASA collects high-frequency hourly observations of four important chemical parameters: pH, turbidity, chloride, and alkalinity from Mohora sampling points on Figure 1. These parameters are essential for monitoring the health of the Halda River's ecosystem and ensuring the efficacy of water treatment processes. To make the data more consistent and reduce high-frequency noise, the hourly readings were averaged to produce a daily time series covering a full calendar year, resulting in 365 multivariate observations.

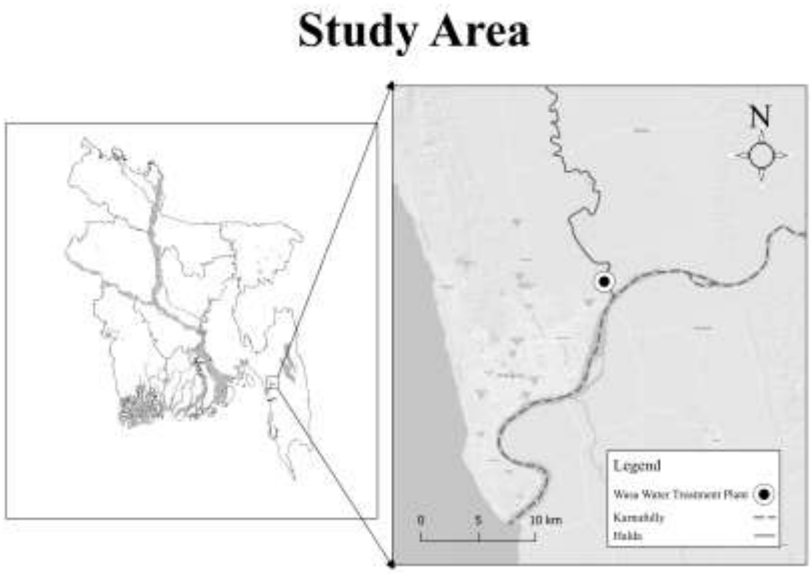


Figure 1: Study Area Map

To account for how regional climate changes affect water quality over time, a seasonal component was added to each data point. Bangladesh has four distinct seasons, which were used to analyze the temporal distribution of anomalies: the pre-monsoon (March to May), the monsoon (June to September), the post-monsoon (October to November), and the dry season (December to February).

2.2 Deep Learning Autoencoder Framework

Deep Learning is a subfield of machine learning that focuses on using artificial neural networks (ANNs) with multiple layers—hence "deep"—to learn complex patterns from data (Pang et al., 2022). This study utilized unsupervised autoencoder architecture to identify anomalous patterns in the Halda River's water quality data. Deep Learning, a branch of machine learning, uses multi-layered artificial neural networks (ANNs) to automatically learn hierarchical and nonlinear patterns. ANNs are brain-like models composed of interconnected neurons organized into hidden, and output layers, which transform inputs through weighted connections and activation functions to perform tasks like classification and feature extraction (Agatonovic-Kustrin & Beresford, 2000). The dense layer, where each neuron is connected to every other neuron in adjacent layers, is a vital part of the network, enabling the model to understand complex relationships between input features. An autoencoder is a specific type of ANN designed for unsupervised learning. It consists of two main parts: an encoder, which compresses input data into a low-dimensional latent representation, and a decoder, which attempts to reconstruct the original input from this compressed representation. Autoencoders are trained by minimizing the reconstruction error—the difference between the original input and the reconstructed output.(Tschannen et al., 2018)

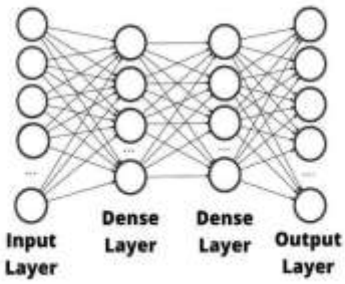


Figure 2: Artificial Neural Network

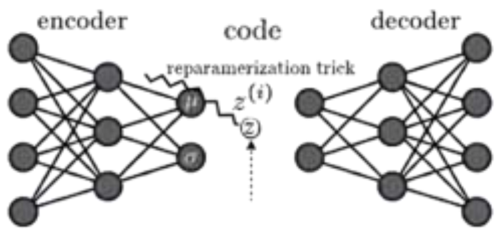


Figure 3: Encoder Decoder

By training the model on data representing normal conditions, it becomes proficient at reconstructing recognizable patterns. The model struggles to accurately reconstruct anomalous data, leading to a significantly higher reconstruction error. This principle forms the basis of our anomaly detection strategy (Abiodun et al., 2018).

2.3 Model Architecture and Training

A symmetrical deep autoencoder was developed using TensorFlow to analyze the normalized parameters of multivariate water quality (pH, turbidity, and alkalinity). The model's architecture comprised two principal components. The encoder processed the input data through a series of dense layers, systematically reducing the feature space dimensionality with layers of 64, 32, 16, and finally 8 neurons. This 8-neuron latent representation was then passed to the decoder, which expanded it back through successive dense layers of 16, 32, and 64 neurons. The final output layer used a sigmoid activation function to scale the data back to its original feature dimension.

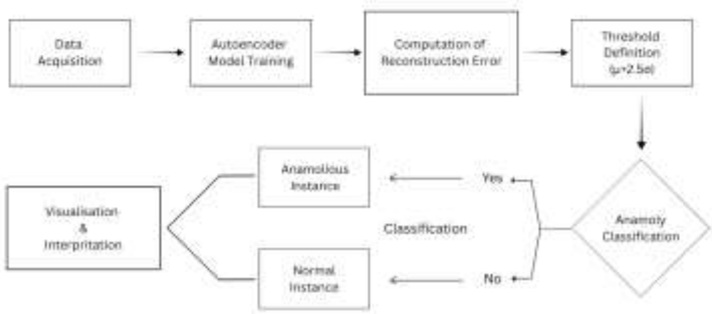


Figure 4: Model Architecture

All hidden layers employed the Rectified Linear Unit (ReLU) activation function to introduce non-linearity into the model. To improve generalization and mitigate overfitting, both dropout and L2 regularization techniques were incorporated into the model's architecture (Cortes et al., 2012).

2.4 Anomaly Detection

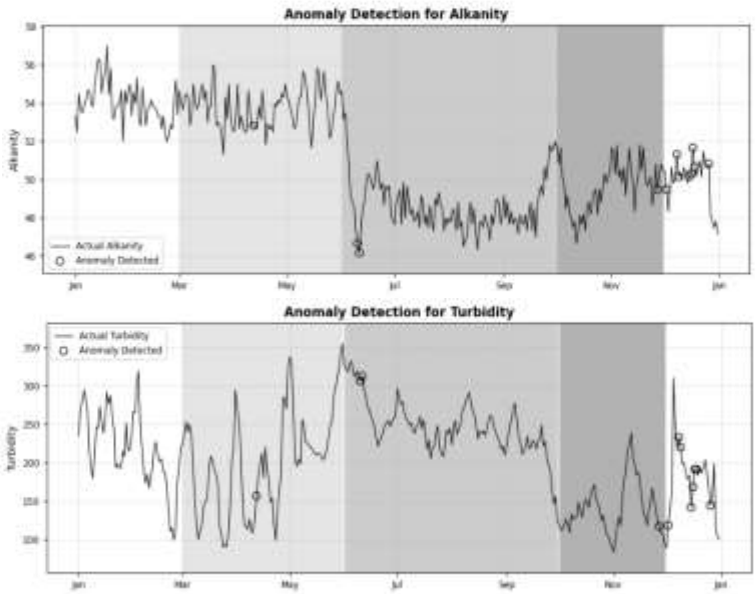
Anomalies were identified based on the model's reconstruction error, which was calculated for each input sample as the mean absolute difference between the original normalized feature values and the values reconstructed by the autoencoder. A dynamic threshold was implemented to flag potential anomalies; a data point was classified as anomalous if its reconstruction error exceeded the mean error of the training data by more than 2.5 standard deviations. This statistical approach allows the threshold to adapt to the model's performance and the inherent variability of the data. To reduce false positives, the analysis was supported by meticulous data preprocessing to handle missing values and noise, along with an evaluation of the seasonal context (Dhawas et al., 2024). This strategy proved effective in detecting significant deviations associated with known hydro-climatic events.

2.5 Seasonal Analysis and Visualization

To visualize the identified anomalies, the water quality data was plotted over time. The year was divided into seasonal periods based on the local hydroclimate to illustrate how anomalies relate to regular, natural variations. This technique clarified the occurrence of anomalies and their relationship to the river's natural cycles. By presenting the data within this seasonal context, researchers and decision-makers can gain a deeper understanding of the river's water quality dynamics.

3 Results and Discussion

The Deep Autoencoder model successfully detected nine anomalous days during the 2021 observation period in Figure 4. Days when the total water quality parameters diverged considerably from the baseline of typical river conditions are represented by these anomalies. Important information about the hydro-climatic factors causing the deterioration of water quality can be gleaned from the distribution of these nine anomalies. The dry season, which is marked by very little rainfall and very low upstream freshwater discharge, saw a remarkable concentration of anomalies. In contrast, we found no anomalies during the high-flow monsoon season. The seasonal distribution and important environmental factors are compiled in Table 1. Two main effects of low river flow are responsible for the high frequency of anomalies during the dry season. First, it significantly impairs the river's ability to dilute pollutants, making the effects of any discharge of industrial or municipal effluent much more noticeable and causing pH variations and turbidity spikes. Second, denser saltwater from the Bay of Bengal can enter farther upstream due to the substantial salinity intrusion made possible by the decreased freshwater pressure. (Hassan et al., 2023)



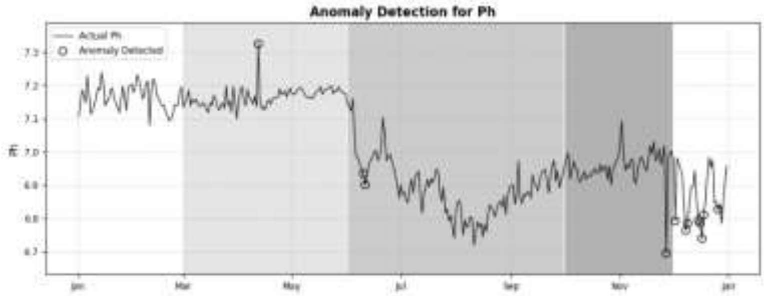


Figure 4: Anomaly Detected in Water

Table 1: Summary of Anomaly Distribution by Season.

Season	Number of Anomalies	Percentage of Total	Key Environmental Factors
Dry	7	78%	Low freshwater discharge, reduced pollutant dilution, increased salinity intrusion.
Pre-Monsoon	1	11%	Potential for early rainfall causing agricultural runoff.
Post-Monsoon	1	11%	Transitional period with decreasing river flow.
Monsoon	0	0%	High river discharge, strong flushing effect, high dilution capacity

Because of this intrusion, the river's basic chemistry is changed, impacting variables like alkalinity and producing circumstances that the model accurately recognizes as abnormal. On the other hand, the enormous rise in river discharge brought on by intense rains explains why there are no anomalies during the monsoon season. More stable and consistent water quality results from this strong flow's efficient flushing of the system, which removes pollutants and pushes the saline front back towards the sea. The results highlight the Halda River's increased susceptibility to salinity intrusion and low dilution capacity during the dry season. This implies that during this crucial time, monitoring and regulatory activities ought to be stepped up.

4 Conclusion

This study effectively illustrated how to use a deep autoencoder for unsupervised anomaly detection in water quality data from the Halda River. The model was successful in identifying notable deviations with high accuracy and learning the intricate, non-linear patterns of the river's typical state. To interpret these anomalies, seasonal analysis was essential. It was discovered that the river's ecosystem is most vulnerable during the dry season because of low freshwater discharge and the ensuing salinity intrusion.

This work's main contribution is a strong, data-driven framework that can be used as a pollution event early-warning system. Future work should concentrate on modifying the framework for real-time, hourly data streams to enable instant alerts, even though the current model works well for retrospective daily analysis. To more precisely identify the sources of pollution, future studies could also correlate the anomalies found with industrial or agricultural operations. In the end, this deep learning strategy is an important step toward the proactive, technologically driven preservation of the priceless ecosystem of the Halda River.

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