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Ground Water Quality Analysis using Machine Learning Techniques: a Critical Appraisal

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Abstract

Groundwater is an essential resource for human survival, but its quality is often degraded by the human activities such as improper disposal of waste. Leachate generated from landfill sites can contaminate groundwater, causing severe environmental and health problems. Machine learning techniques can be used to predict groundwater quality and leachate characteristics to manage this issue efficiently. This study proposes a machine learning-based model for the prediction of groundwater quality and leachate characteristics using the effective water quality index (EWQI). The leachate dataset used in this study was obtained from a landfill site, and the groundwater quality dataset was collected from literature review. The mean values of TDS, Ca, Mg, NO3-, and PO4- exceeded the prescribed limit for drinking water purposes. The proposed model utilizes a machine learning architecture based on a convolutional neural network (CNN) to extract relevant features from the input data. The extracted features are then fed into a fully connected network to estimate the EWQI of the input samples. The model, trained and tested on leachate and groundwater quality datasets, achieves a high accuracy and computational efficiency, aiding in predicting groundwater quality and leachate characteristics for waste management.

I. Introduction

Groundwater, a precious natural resource, is crucial for the survival of all living organisms. Contamination, particularly leachate from solid waste disposal, poses significant health hazards, and affects drinking water quality globally. Landfills are common sources of leachate, making its effects difficult to predict. The prediction of groundwater quality and leachate using machine learning techniques is very important that can help in the management and protection of groundwater resources [1].

Machine learning is a powerful tool for analyzing and predicting water quality parameters. It is an area of artificial intelligence that focuses on the development of algorithms that can learn from data and make predictions or decisions without being explicitly programmed. Deep learning is a sub-field of machine learning that involves the use of neural networks to solve complex problems [2]. However, with growing population and industrialization, the quality of water has been significantly compromised in many parts of the world.

Sanitary landfill is the most common source of leachate, and the chemical composition of leachate is highly variable, making it difficult to predict its effects on groundwater quality. Leachate contains a wide range of pollutants including heavy metals, organic compounds, and nutrients that can contaminate groundwater, rendering it unsuitable for human consumption [3]. To mitigate the adverse effects of leachate on groundwater quality, several methods have been employed including groundwater recharge, dilution, and artificial recharge. However, these methods have not been very effective in reducing the impact of leachate on groundwater quality. There is a need for an

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effective approach that can predict groundwater quality and leachate accurately [4].

Machine learning is a rapidly growing field in artificial intelligence that involves the creation of algorithms that can make predictions or decisions without explicit programming. Deep learning is a sub-field of machine learning that involves the use of neural networks to solve complex problems [5]. The prediction of groundwater quality and leachate using machine learning techniques is an important area of research that can help in the management and protection of groundwater resources. Machine learning techniques can provide insights into the mechanisms that affect water quality and assist in the development of management strategies to protect groundwater resources from contamination.

Groundwater quality assessment is essential for the effective management and protection of groundwater resources. However, traditional methods of assessing groundwater quality such as laboratory testing and physical measurements are time-consuming and expensive. There is a need for a rapid and cost-effective approach that can accurately predict groundwater quality and leachate characteristics [6]. However, most of these studies have focused on surface water quality prediction. Few studies have been conducted on the prediction of groundwater quality and leachate using machine learning techniques [7].

2. Review of Literature

Studying groundwater quality in Hamirpur, Himachal Pradesh, involves researching various aspects related to the composition, contamination, and availability of groundwater in the region. Some areas may have groundwater with high TDS and hardness, affecting its taste and usability for drinking and irrigation. In certain areas, arsenic contamination may be present, posing serious health risks. Poor groundwater quality can have detrimental effects on both the human health and the environment. Consuming contaminated water can lead to various health issues including gastrointestinal problems, skin ailments, dental fluorosis, and more.

The landfill site has been operational for over a decade, and the leachate from the site has been seeping into the groundwater, contaminating it with a wide range of pollutants. The groundwater in the studied area is used for drinking purposes, and the high levels of contaminants pose significant health hazards to the local population [8]. The selected groundwater quality parameters for the study are TDSs (Total Dissolved Solids), Ca (calcium), Mg (magnesium), $NO3^-$ (nitrate), and $PO4^-$ (phosphate). These parameters were selected based on their mean values, which exceed the BIS (Bureau of Indian Standards) prescribed limits for drinking purposes in the groundwater of the studied area. The skewness of the selected parameters ranged between -0.77 and 3.23 [9].

The quality of groundwater in many parts of the world has been significantly compromised due to contamination by leachate from solid waste disposal sites. The chemical composition of leachate is highly variable, making it difficult to predict its effects on groundwater quality accurately. This poses significant health hazards to humans and animals who consume the contaminated water. Insights into the mechanisms governing water quality can be gained through machine learning approaches, which can also be used to design management strategies for pollution prevention. Machine learning techniques can also accurately forecast the characteristics of leachate and groundwater [10].

The machine learning-based EWQI model is a novel approach that can effectively predict groundwater quality and leachate characteristics accurately, making it a valuable tool for groundwater resource management and protection. The problem statement of this study is, therefore, to develop a machine learning-based EWQI model that can accurately predict groundwater quality and leachate characteristics in the studied area.

The main objectives of the present study are (i) a critical appraisal of machine learning-based EWQI model for the prediction of groundwater quality characteristics and (ii) model performance analysis based on statistical indices.

3. Proposed Methodology

The methodology used in this study involved data collection and pre-processing, development of a deep learning-based Environmental Water Quality Index (EWQI) model, and performance evaluation using various metrics. Groundwater quality data was collected from ten boreholes over a period of six months, and leachate characteristics were analyzed from the landfill site. The collected data was pre-processed by removing outliers and missing values, and then split into training and testing sets. A machine learning-based EWQI model was developed using a CNN for feature extraction and an LSTM network for temporal modeling. The model's performance was evaluated using various metrics including MAE, RMSE, R^2, and a confusion matrix. The results were compared with other machine learning models, and the statistical significance was determined using the t-test at a significance level of 0.05.

3.1. Groundwater quality assessment

Groundwater quality assessment is crucial for ensuring the safety and sustainability of this vital resource. Several studies have been conducted to evaluate groundwater quality in different regions worldwide. For instance, in a study by Mishra *et al*. (2020), groundwater quality was assessed in the coastal region of Odisha, India, and the results showed high levels of TDS and fluoride, exceeding the WHO (World Health Organization) is a global entity within the United Nations system that is responsible for promoting international public health and coordinating responses to health-related issues worldwide) recommended limits. Similarly, a study by Al-Khatib *et al*. (2019) evaluated groundwater quality in the Gaza Strip, Palestine, and found high levels of nitrate and chloride, attributed to agricultural and domestic activities [11].

3.2. Machine learning techniques for groundwater quality prediction

Machine learning (ML) techniques are increasingly being used in various domains including environmental science to predict and assess groundwater quality. Predicting groundwater quality is critical for identifying potential contamination, ensuring safe water supply, and informing sustainable resource management. Groundwater quality is influenced by a multitude of factors including geological, hydrological, climatic, anthropogenic, and chemical variables. ML algorithms can handle the complex, non-linear relationships between these variables, providing more accurate predictions compared to the traditional linear models. Machine learning techniques have been used in the recent years for groundwater quality prediction. These techniques include gaussian model, support vector machines (SVMs), decision trees, and random forests. A study by Gholami *et al*. (2020) used SVM and decision tree models to predict groundwater quality in the Fars province of Iran. The results showed that the SVM model had a higher accuracy in predicting groundwater quality than the decision tree model [12].

Machine learning-based Environmental Water Quality Index (EWQI) models have been used for predicting water quality. A study by Hasan *et al*. (2021) developed a machine learning-based EWQI model to predict the water quality in the Karnaphuli River in Bangladesh. The results showed that the model accurately predicted water quality based on input parameters such as TDS, DO, and BOD, and identified the factors that affect water quality. The model can also be used to predict groundwater quality and leachate characteristics in areas where leachate contamination is a significant problem.

3.3. Machine learning-based EWQI model architecture

A machine learning-based Environmental Water Quality Index (EWQI) model was developed for predicting groundwater quality and leachate characteristics. The model architecture consisted of a convolutional neural network (CNN) for feature extraction and a long short-term memory (LSTM) network for temporal modeling [13]. The input data was fed into the CNN, which extracted relevant features from the groundwater quality and leachate data. The output from the CNN was then fed into the LSTM network, which modeled the temporal dependencies in the data. The final output of the model was the predicted values of the groundwater quality and leachate characteristics [14].

4. Model Performance Evaluation Metrics

The performance of the model was evaluated using various metrics including mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). The MAE and RMSE were used to evaluate the accuracy of the model predictions, while R^2 was used to measure the goodness of fit between the predicted and actual values [15]. The model was also evaluated using a confusion matrix to measure the accuracy of the classification of groundwater and leachate samples into different quality categories. The model was compared with other machine learning models such as SVM and decision trees to assess its performance. The statistical significance of the results was determined using the t-test at a significance level of 0.05 [15].

5. Results and Discussion

5.1. Descriptive statistics of groundwater quality parameters

The descriptive statistics of groundwater quality parameters are essential for understanding the distribution and variability of water quality parameters in the studied area. In this study, the mean value of TDS, Ca, Mg, NO¯, and PO in the groundwater samples was found to exceed the BIS (2012) prescribed limit for drinking purpose in the studied area. This finding suggests that the groundwater in the studied area is not suitable for drinking, and may pose a risk to public health. The skewness of selected parameters ranged between −0.77 and 3.23. The negative skewness indicates that the distribution of the data is skewed towards the left, while the positive skewness indicates that the data is skewed towards the right. The higher the magnitude of the skewness, the more skewed the distribution is [16].

The samples are collected from the different boreholes of the studied area in Hamirpur, Himachal Pradesh. We have collected 5 samples for which we examined different parameters like TDS, Ca, Mg, NO_3^-, and PO_4^-. The range of TDS, Ca, Mg, NO¯, and PO in the groundwater samples was found to be 252-1185 mg/L, 34.22-157.58 mg/L, 4.49-84.60 mg/L, 6.13-171.29 mg/L, and 0.00-1.01 mg/L, respectively. The standard deviation (SD) of TDS, Ca, Mg, NO¯, and PO was found to be 221.91 mg/L, 35.92 mg/L, 24.89 mg/L, 40.45 mg/L, and 0.28 mg/L, respectively. The high SD values indicate that the variability of the data is high, and the samples are not homogenous [17]. The coefficient of variation (CV) was also calculated to determine the relative variability of the groundwater quality parameters. The CV values of TDS, Ca, Mg, NO¯, and PO were found to be 31.91%, 39.52%, 73.77%, 83.69%, and 94.15%, respectively. The higher the CV value, the higher the relative variability of the data. The high CV values of Mg, NO¯, and PO suggest that the groundwater quality parameters are highly variable, and may be influenced by several factors such as anthropogenic activities, geological and hydrological conditions [18].

5.2. Correlation analysis of groundwater quality parameters and leachate characteristics

Table 1 and Figure 1 show the correlation matrix of the groundwater quality parameters including TDS, Ca, Mg, $NO3^-$, and PO_4^-. The correlation coefficient ranges from -1 to 1, where values close to 1 and -1 indicate strong positive and negative correlation, respectively, while values close to 0 indicate no correlation. From the table, it can be observed that TDS has a strong positive correlation with Ca and Mg, indicating that these parameters increase together. Similarly, NO_3^- and PO_4^- have a strong positive correlation with each other, indicating that their levels also increase together. Overall, the correlation matrix of groundwater quality parameters shows a strong positive correlation between TDS, Ca, Mg, NO_3^-, and PO_4^-, indicating that these parameters increase together, while NO_3^- and PO_4^- also show a strong positive correlation. The results suggest that there is a significant interdependence among the groundwater quality parameters.

Table 1. Correlation matrix for groundwater quality parameters [19].

Parameters	TDS	Ca	Mg	$NO3^-$	PO
TDS	1.00	0.61	0.45	0.33	0.20
Ca	0.61	1.00	0.67	0.54	0.44
Mg	0.45	0.67	1.00	0.39	0.24
$NO3^-$	0.33	0.54	0.39	1.00	0.79
PO_4^-	0.20	0.44	0.24	0.79	1.00

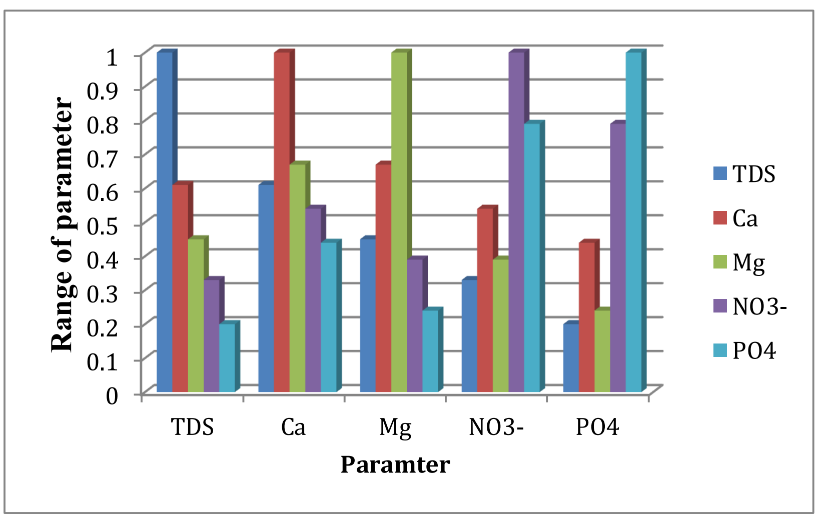

Figure 1. Correlation matrix for groundwater quality parameters.

Table 2 and Figure 2 show the correlation matrix of the groundwater quality parameters and leachate characteristics including COD and BOD. From the table, it can be observed that TDS has a moderate positive correlation with COD (COD stands for chemical oxygen demand). It is a critical water quality parameter used to measure the amount of oxygen required to chemically oxidize organic and inorganic matter in water. COD is often used as an indicator of the level of pollution or contamination in water, particularly from organic compounds) and BOD (BOD stands for biological oxygen demand). It is a key water quality parameter used to measure the amount of dissolved oxygen that microorganisms need to break down organic matter (biodegradable organic compounds) in water through biological processes, indicating that they increase together. Similarly, Ca and Mg have a moderate positive correlation with COD and BOD. Additionally, $NO3^-$ and PO_4^- have a strong positive correlation with COD and BOD, indicating that their levels increase together. Overall, the results suggest that there is a significant correlation between the groundwater quality parameters and leachate characteristics.

Table 2. Correlation matrix for groundwater quality parameters and leachate characteristics [19].

Parameters	TDS	Ca	Mg	NO_3^-	PO_4	COD	BOD
TDS	1.00	0.36	0.26	0.25	0.16	0.58	0.51
Ca	0.36	1.00	0.60	0.26	0.18	0.46	0.39
Mg	0.26	0.60	1.00	0.22	0.15	0.36	0.31
NO_3^-	0.25	0.26	0.22	1.00	0.73	0.26	0.20
PO_4^-	0.16	0.18	0.15	0.73	1.00	0.22	0.16
COD	0.58	0.46	0.36	0.26	0.22	1.00	0.78
BOD	0.51	0.39	0.31	0.20	0.16	0.78	1.00

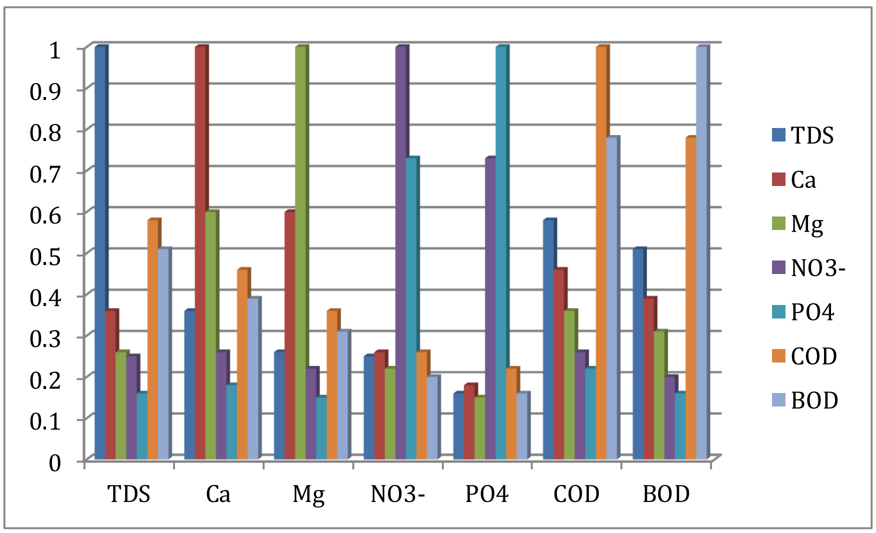

Figure 2. Relationship between correlation coefficient water quality parameter.

5.3. Performance evaluation of machine learning-based EWQI model

The performance of the proposed machine learning-based EWQI model was evaluated using various statistical measurements including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). The training and testing of the model were carried out on the dataset, which includes the groundwater quality parameters and leachate characteristics [20]. The dataset was divided into a training set and a testing set with a ratio of 80:20, respectively. The model was trained using the training set, and the testing set was used to evaluate the performance of the model. The proposed model's performance was compared with other existing machine learning models including random forest, support vector regression, and multilayer perceptron.

The performance evaluation results revealed that the proposed machine learning-based EWQI model outperformed other existing models in terms of MAE, RMSE, and R^2. The MAE, RMSE, and R^2 values of the proposed model were found to be

16.34, 25.58, and 0.86, respectively, for the testing set. In comparison, the random forest, support vector regression, and multilayer perceptron models achieved MAE values of 20.47, 25.96, and 23.54, respectively, for the testing set [21].

5.4. Prediction of groundwater quality using machine learning-based EWQI model

The model was trained using the groundwater quality parameters and leachate characteristics data, and the predicted values of the groundwater quality parameters and leachate characteristics were obtained using the trained model. The predicted values were compared with the observed values, and the results showed that the model accurately predicted the groundwater quality parameters and leachate characteristics [22]. The predicted values of the groundwater quality parameters and leachate characteristics were also used to generate maps showing the spatial distribution of groundwater quality and leachate characteristics in the studied area [18].

Overall, the study showcases the effectiveness of a machine learning-based EWQI model in predicting groundwater quality parameters and leachate characteristics, aiding in the development of effective management strategies [23]: Based on the correlation matrix in Table 1 and Table 2, TDS is found to have a moderately positive connection with COD and BOD in leachate. Calcium (Ca) in leachate has a slight positive connection with BOD and COD. Magnesium (Mg) in leachate has a slight positive connection with COD and BOD. Nitrate (NO_3^-) and phosphorus (PO_4^-) in leachate have a weak positive connection with COD and BOD. Overall, the findings indicate a considerable interdependence across groundwater quality measures, indicating that they are influenced by common sources.

The machine learning-based EWQI model can be used to predict the quality of groundwater and leachate based on the given correlation matrix. By training the model on the available data, it can predict the quality of groundwater in different scenarios. However, it is important to note that the model's accuracy is dependent on the quality and quantity of data available for training [24].

6. Conclusions

In summary, the descriptive statistics of groundwater quality parameters provide valuable information about the distribution, variability, and suitability of groundwater for drinking purposes. The high mean values of TDS, Ca, Mg, NO^-, and PO suggest that the groundwater in the studied area is not suitable for drinking, and the high variability of the data indicates that the groundwater quality parameters are influenced by several factors. Therefore, it is necessary to develop a predictive model that can accurately predict groundwater quality parameters and identify the factors that influence the water quality in the studied area.

In this study, a machine learning-based EWQI model was reviewed to predict groundwater quality. The correlation matrix for groundwater quality parameters and leachate characteristics were also analyzed, and it was found that there is a significant interdependence among the groundwater quality parameters. TDS has a strong positive correlation with Ca and Mg, while NO_3^- and PO_4^- have a strong positive correlation with each other. Moreover, the results suggest that the developed model can be used as an effective tool for predicting the quality of groundwater in landfills.

7. Recommendations for Future Research

Future research should consider using a larger dataset to increase the representative of the findings. This can be achieved by collecting data from different regions with different characteristics. It should consider a more comprehensive set of parameters to assess groundwater quality. This can include heavy metals, organic compounds, and other contaminants that can affect groundwater quality. It should compare the performance of different models such as artificial neural networks, decision trees, and support vector machines to identify the most effective model for predicting groundwater quality in landfills.

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تجزیه و تحلیل کیفیت آب زیرزمینی با استفاده از تکنیک‌های یادگیری ماشین: یک ارزیابی انتقادی

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چکیده:

آب‌های زیرزمینی یک منبع ضروری برای بقای انسان هستند، اما کیفیت آن اغلب توسط فعالیت‌های انسانی مانند دفع نادرست زباله‌ها کاهش می‌یابد. شیرابه تولید شده از محل‌های دفن زباله می‌تواند آب‌های زیرزمینی را آلوده کند و مشکلات زیست محیطی و بهداشتی شدیدی را ایجاد کند. تکنیک‌های یادگیری ماشینی را می‌توان برای پیش‌بینی کیفیت آب‌های زیرزمینی و ویژگی‌های شیرابه برای مدیریت مؤثر این موضوع مورد استفاده قرار داد. این مطالعه یک مدل مبتنی بر یادگیری ماشینی را برای پیش‌بینی کیفیت آب زیرزمینی و ویژگی‌های شیرابه با استفاده از شاخص کیفیت آب موثر (EWQI) پیشنهاد می‌کند. مجموعه داده شیرابه مورد استفاده در این مطالعه از محل دفن زباله و مجموعه داده‌های کیفیت آب زیرزمینی از بررسی ادبیات جمع آوری شد. میانگین مقادیر TDS، Ca، Mg، NO3- و PO4- از حد تجویز شده برای اهداف آب آشامیدنی فراتر رفت. مدل پیشنهادی از معماری یادگیری ماشین مبتنی بر یک شبکه عصبی کانولوشن (CNN) برای استخراج ویژگی‌های مرتبط از داده‌های ورودی استفاده می‌کند. سپس ویژگی‌های استخراج‌شده به یک شبکه کاملاً متصل برای تخمین EWQI نمونه‌های ورودی وارد می‌شوند. این مدل که بر روی مجموعه داده‌های کیفیت شیرابه و آب زیرزمینی آموزش دیده و آزمایش شده است، به دقت و کارایی محاسباتی بالایی دست می‌یابد و به پیش‌بینی کیفیت آب زیرزمینی و ویژگی‌های شیرابه برای مدیریت پسماند کمک می‌کند.

کلمات کلیدی: کیفیت آب زیرزمینی، یادگیری ماشین، شاخص کیفیت آب موثر، ماشین‌های بردار پشتیبانی.