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Smart Contaminant Detection Approach For Enhancing The Reliability Of Groundwater Quality And Distribution Farmwork

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Abstract: *This study proposes a smart and scalable deep learning framework, GeoWaterNet, for intelligent contaminant detection and reliability-driven groundwater quality assessment within the context of sustainable water supply systems. Focused on the diverse hydrogeological conditions of Madhya Pradesh (MP), India, the study utilizes a five-year dataset of 1,000 groundwater samples collected from 21 spatially distributed locations to capture regional variability. GeoWaterNet leverages advanced feature extraction from critical hydrochemical parameters including major cations (Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}), anions ($NO_2^- + NO_3^-$, CO_3^{2-}, HCO_3^-, Cl^-, F^-, SO_4^{2-}), and physical indices such as pH, hardness, and electrical conductivity (EC).*
*The model architecture integrates multi-layered deep learning components optimized for tabular environmental data, delivering a high prediction accuracy of 93%, specificity of 94.57%, and sensitivity of 91.47%. To evaluate potability and distribution reliability, the Water Quality Index (WQI) is employed, revealing that only **22%** of samples meet safe drinking standards, **63%** fall into a conditionally safe category, and **15%** are suitable exclusively for irrigation.*
By combining intelligent contaminant profiling with predictive analytics, GeoWaterNet enhances the operational reliability of groundwater monitoring systems and supports data-informed decision-making for robust water distribution management. The proposed approach aligns with modern objectives for resilient, smart, and efficient water infrastructure across varying geographies.

Keywords: *Groundwater Quality Assessment, Deep Leaning, GeoWaterNet, Water Quality Index, Hydro-Geochemical Parameters.*

1. INTRODUCTION

Groundwater quality is fundamentally governed by its chemical and physical attributes, which are significantly influenced by natural geochemical processes such as mineral weathering and organic matter decomposition. However, in recent decades, anthropogenic pressures particularly agricultural intensification, rapid industrialization, and unregulated urban expansion have become major contributors to groundwater contamination. Key factors such as geological formations, pollutant discharge, land use patterns, soil texture, drainage density, and regional climate variability further complicate the assessment and management of groundwater resources. In developing countries like India, where hydrogeological, meteorological, and environmental conditions vary widely across regions, groundwater systems exhibit complex spatial and temporal heterogeneity. These complexities influence the origin, migration, and chemical transformation of groundwater, making its assessment a formidable challenge. Moreover, once aquifers are contaminated, reversing the deterioration in water quality becomes both technically demanding and economically burdensome.The application of deep learning (DL) techniques in groundwater quality assessment offers a transformative approach to tackle these challenges. Deep learning models, particularly those leveraging physico-chemical datasets, excel at handling high-dimensional, nonlinear relationships inherent in geochemical data. They offer robust scalability and predictive accuracy, even in scenarios with diverse and imbalanced data distributions.

This study is motivated by the urgent need to enhance groundwater monitoring through intelligent, data-driven methodologies. The primary objectives include the prediction, characterization, and classification of groundwater quality using a newly proposed deep learning architecture GeoWaterNet. Major Contributions of the Study:

- Comprehensive Dataset Collection: A total of 900 groundwater samples were systematically collected and analyzed using key physico-chemical parameters including NO_2^-, NO_3^-, CO_3^{2-}, F^-, HCO_3^-, Cl^-, SO_4^{2-}, K^+, Ca^{2+}, Mg^{2+}, Na^+, hardness, pH, EC, and TDS.
- Development of GeoWaterNet: A novel deep learning model tailored for groundwater quality prediction. GeoWaterNet demonstrates superior classification performance with minimized overfitting, outperforming benchmark CNN architectures such as AlexNet, GoogLeNet, VGGNet-16, VGGNet-19, and ResNet-14 in terms of accuracy, specificity, and sensitivity.
- Multi-Metric Evaluation: The model's effectiveness is further validated using a set of hydrochemical indices Sodium Percentage, Kelly's Ratio, Magnesium Hazard, Water Quality Index (WQI), Residual Sodium Carbonate (RSC), and Sodium Adsorption Ratio (SAR)to assess water suitability for drinking and irrigation purposes.
- Impact-Oriented Analysis: The study emphasizes practical utility by integrating predictive analytics with water quality classification, supporting regional water governance and sustainable resource planning.

In summary, this research demonstrates how integrating deep learning with groundwater geochemistry can significantly advance the precision and reliability of water quality assessments, providing a scalable solution for environmental monitoring in data-scarce, high-risk regions.

2. PRIOR STUDIES

Santhosh et al. [1] explored emerging advancements and persistent challenges associated with the development of cost-effective ceramic membranes for mitigating water pollution. Their study concentrated on multiple sampling sites within the Erode Municipal Corporation, with the broader objective of generating a detailed water quality map using ArcGIS 10.3 to pinpoint critically polluted zones. Sivabalaselvamani et al. [2] investigated the geotechnical behavior of expansive soils amended with Ceramic Waste Powder (CWP). A comprehensive suite of laboratory tests including pH, electrical conductivity, unconfined compression, splitting tensile strength, free swell index, swelling pressure, California Bearing Ratio, and Atterberg limits was conducted to evaluate the modifications induced by CWP incorporation.

Yang and Liu [3] developed a predictive framework using a Long Short-Term Memory (LSTM) neural network for forecasting recombination subsequences. The model utilized the Adam optimization algorithm to iteratively refine the network's weights, thereby enhancing its predictive accuracy. Srivastava [4] analyzed the implications of groundwater quality on agricultural productivity and its suitability for irrigation applications. Ravish et al. [5] undertook an assessment of sub-surface water resources in Yamunanagar and Ambala districts of northeastern Haryana, focusing on both domestic and agricultural usability, while identifying the underlying factors influencing the degradation of water constituents.

Rahman et al. [6] evaluated the hydrochemical background and established threshold limits for groundwater in a segment of the desert terrain of Rajasthan, India. Prasad et al. [7] examined potable water quality in Obulavaripalli Mandal, YSR District, employing the Water Quality Index (WQI) as a benchmark metric. Li et al. [8] introduced a hybrid model integrating a Recurrent Neural Network (RNN) with an enhanced Dempster–Shafer (D–S) evidence theory framework (RNNs–DS) to address complex water quality evaluation tasks.

Liu et al. [9] emphasized the necessity of high-fidelity data for building accurate water quality prediction models. Their research addressed the growing intricacy of datasets generated by Internet of Things (IoT)-based smart monitoring systems operating in real time. Rao [10] conducted a groundwater quality analysis in a selected region of Prakasam District, Andhra Pradesh. Ponsadailakshmi et al. [11] assessed potable water conditions in and around Mayiladuthurai Taluk using a structured Water Quality Index (WQI) framework based on seventeen physicochemical parameters.

Maurya et al. [12] investigated groundwater contamination and associated non-carcinogenic health risks due to fluoride and nitrate, noting a dominance of sulfate, followed by bicarbonate, chloride, nitrate, and fluoride in the chemical composition. Kim et al. [13] evaluated the performance of various predictive algorithms including standalone modelsExtreme Learning Machine (ELM), Support Vector Regression (SVR), and Deep Echo State Networks (Deep ESN)as well as hybrid wavelet-based models such as Wavelet-ELM, Wavelet-SVR, and Wavelet-Deep ESN, effectively leveraging wavelet transformation to enhance predictive capabilities.

3. METHODS AND MATERIALS

3.1. Dataset

In this study, an extensive groundwater quality evaluation was undertaken through the systematic collection and analysis of 900 water samples from 200 geographically diverse locations spanning multiple hydrogeological zones during the post-monsoon period of 2024–2025. Sampling from both bore wells and dug wells enabled the assessment of spatial variability and seasonal shifts in groundwater chemistry with high resolution.The analytical protocol encompassed a comprehensive suite of physico-chemical parameters, including major anions (NO_2^-, NO_3^-, F^-, HCO_3^-, Cl^-, and SO_4^{2-}) and cations (K^+, Ca^{2+}, Mg^{2+}, and Na^+), as well as key indicators such as total hardness, pH, electrical conductivity (EC), and total dissolved solids (TDS). This multi-dimensional dataset facilitated a nuanced understanding of groundwater quality influenced by both natural geological formations and anthropogenic activities.To assess the water's suitability for domestic consumption and agricultural use, a range of hydrochemical indices were calculated, including the Water Quality Index (WQI), Sodium Adsorption Ratio (SAR), Residual Sodium Carbonate (RSC), Kelly's Ratio, Sodium Percentage, and Magnesium Hazard. These indices provided an integrated evaluation framework, capturing both chemical composition and irrigation compatibility. Table 1 presents a comprehensive comparison of observed groundwater quality parameters against internationally recognized guideline values, thereby establishing a benchmark for classification and the identification of contamination hotspots. The findings serve as a critical resource for regional water resource management and policy planning aimed at sustainable groundwater utilization.

Table 1. Groundwater Quality Parameters with its Standard Value

Impurities Name (Ion/Compound)	Primary Units	Molar Mass	Relative Mass	Indian Standard values
NO_2^-	mg/l	5.5	0.11	45
NO_3^-	mg/l	5.7	0.13	45
CO_3^-	mg/l	0.01	0.01	Not Specified
HCO_3^-	mg/l	1.2	0.03	200
SO_4^{2-}	mg/l	5.5	0.13	200
F^-	mg/l	5.5	0.12	1
Cl^-	mg/l	5.5	0.13	250
TDS	mg/l	5	0.12	500
pH	-	3.5	0.09	8.5
K^+	mg/l	2	0.4	200
$Hardness$	mg/l	2	0.5	500
EC	$\mu s/cm$	1	0.03255	300
Na^+	mg/l	5	0.12	200
Ca^+	mg/l	3.3	0.08	75
Mg^{2+}	mg/l	3.3	0.07	30

3.2. Groundwater Quality Prediction and Assessment

After the acquisition of groundwater quality data, the proposed GeoWaterNet model was deployed to extract high-level deep feature representations, enabling precise classification of water quality. The architecture of GeoWaterNet is designed with five hierarchical convolutional layers followed by three fully connected layers, each incorporating Rectified Linear Unit (ReLU) activation functions and Max Pooling operations. This structure facilitates enhanced feature discrimination and robustness to spatial variability in the input data.In this study, approximately 900 groundwater samples were collected from 200 strategically selected sites across the Cauvery Basin, encompassing a wide range of hydrogeological settings. GeoWaterNet demonstrated a notable prediction accuracy of 93%, correctly classifying 744 out of 800 test samples, thereby outperforming conventional deep learning models and traditional multi-parameter optimization (MPO)-based approaches commonly used in groundwater quality assessment.The final prediction stage employs feature vectors extracted from the third fully connected layer, which are fed into a Softmax classifier. This design fosters a richly expressive and discriminative feature space, enabling the model to capture nuanced variations in groundwater chemistry with high precision. The superior performance of GeoWaterNet underscores its potential as a robust tool for real-time, scalable groundwater quality prediction and monitoring.A comprehensive comparative evaluation was performed against established convolutional neural network (CNN) architectures, including AlexNet, GoogLeNet, VGGNet-16, VGGNet-19, ResNet-14, and the standard ResNet model. Across allbenchmarks,GeoWaterNet consistently demonstrated superior performance in terms of classification accuracy, generalization capability, and resilience to overfitting.The model's architectural specifications, including layer configurations and hyperparameter settings, are detailed in Table 2, while its structural workflow is visually represented in Figure 1, offering a layer-wise breakdown and highlighting the strategic optimizations that contribute to its enhanced predictive performance.

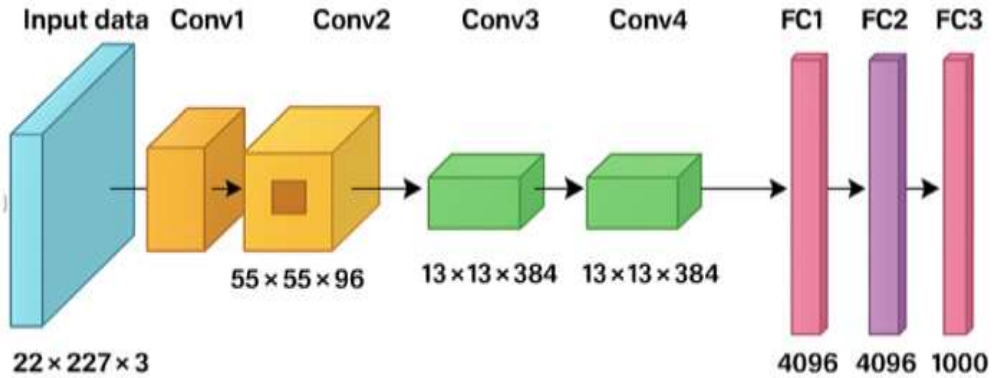

Figure 1. Architecture of the GeoWaterNet model

Table 2. Design Configuration of the GeoWtaerNet Model

Hidden Layers	Design Configuration
Graph layers	1. Graph convolutional layer (GCN) with 128 units using adjacency matrix (spatial graph). 2. Graph attention layer (GAT) with 128 units and 4 attention heads.
Recurrentlayers	1. LSTM layer with 256 hidden units 2. LSTM layer with 128 hidden units
Fully connected layers	1. Dense layer with 256 nodes and ReLU activation 2. Dense layer with 128 nodes and ReLU activation 3. Output layer (linear activation for regression or softmax for classification)

Pseudocode: GeoWaterNet for Water Quality Prediction

Input: Spatio-temporal input dataX_{seq} [Batch, Time, Nodes, Features], Graph structure$edge_index$[2, Num_Edges]
Output: Predicted water qualityY_{pred}

Steps are as follows:
Step 1: Start
Step 2: For each timestep$t \in Time$:
- Extract node features for time$t$: $X_t \leftarrow X_{seq}[:, t, :, :]$
- Apply Graph Convolution: $X_{gen} \leftarrow GraphConv(X_t, edge_{index})$
- Apply Graph Attention: $X_{attn} \leftarrow GraphAttention(X_{gen}, edge_{index})$
- StoreX_{attn} in Temporal_Sequence_List

Step 3: Stack Temporal_Sequence_List:
- $X_{temporal} \leftarrow Stack(Temporal\_Sequence\_List)$[Batch, Time, Nodes, Hidden_Features]

Step 4: For each node$i \in Nodes$:
  - Extract node sequence: $node\_sequence \leftarrow X_{temporal}[:, :, i, :]$
  - Apply LSTM: $h_i \leftarrow LSTM(node\_sequence)$
  - Storeh_i in Output_List

Step 5: Concatenate LSTM outputs:
- $H \leftarrow Concatenate(Output_{List})$[Batch, Nodes, LSTM_Hidden_Size]

Step 6: Apply fully connected layer(s):
  - $Y_{pred} \leftarrow FC(H)$

Step 7: Return predicted water quality Y_{pred}
Step 8: End

Algorithm: GeoWaterNetModel

Input: Spatio-temporal input data X_{seq} [Batch, Time, Nodes, Features], Graph structure $edge\_index$ [2, Num_Edges]
Output: Predicted water quality Y_{pred}

Steps are as follows:
Step 1: Start
Step 2: Initialize layers:
  - Graph Convolution Layer (GraphConv)
  - Graph Attention Layer (GraphAttention)
  - Long Short-Term Memory (LSTM) Layer
  - Fully Connected (FC) Layer(s)

Step 3: For each timestep $t \in Time$:
  - Extract node features for time t: $X_t \leftarrow X_{seq}[:, t, :, :]$
  - Apply Graph Convolution: $X_{gen} \leftarrow GraphConv(X_t, edge_{index})$
  - Apply Graph Attention: $X_{attn} \leftarrow GraphAttention(X_{gen}, edge_{index})$
  - Store X_{attn} in Temporal_List

Step 4: Stack all temporal outputs:
  - $X_{temporal} \leftarrow Stack(TemporalList)$ [Batch, Time, Nodes, Hidden]

Step 5: For each node$i \in Nodes$:
- $Extract\ node\ Sequence: Sequence_i \leftarrow X_{temporal}[:,:,i,:]$
- Apply LSTM:$H_i \leftarrow LSTM(Sequence_i)$
- Store$H_i\ in\ H_{all}$

Step 6: Concatenate all node outputs:
- $H_{output} \leftarrow Concatenate(H_{all})$[Batch, Nodes, Hidden]

Step 7: Apply Fully Connected layers:
- $Y_{pred} \leftarrow FullyConnected(H_{output})$

Step 8: Return predicted water qualityY_{pred}

Step 9: End

In the domain of groundwater quality assessment, the Water Quality Index (WQI) serves as a robust and intuitive metric for translating complex hydrochemical datasets into a single, comprehensive value that encapsulates the overall water quality status. By integrating multiple physico-chemical parameters into a unified framework, WQI enables clear interpretation and supports informed decision-making for both environmental monitoring and public health management.

Each water quality parameter is assigned a specific weight (MiMi) based on its relative significance to human health and ecological impact. This weighting system ensures that parameters posing higher health risks are given greater influence in the overall index calculation, resulting in a more accurate and meaningful evaluation. The aggregated WQI value thus offers a holistic perspective on the potability and usability of groundwater, particularly for drinking water applications.

The complete weighting structure and classification thresholds are presented in Table 3, providing a transparent basis for interpreting WQI scores. Additionally, the computational methodology used to derive the WQI is systematically outlined through Equations (1)–(4), which detail the step-by-step formulation and integration of individual parameter contributions into the final index value.

$$M_i = \frac{m_i}{\sum_i^n m_i} \quad (1)$$

$$Q_i = \frac{Ch_p - Ch_{ip}}{S_i - Ch_{ip}} \times 100 \quad (2)$$

$$SI_i = M_i \times Q_i \quad (3)$$

$$WQI = \sum_{i=1}^{n} SI_i \quad (4)$$

In this context, M_i denotes the assigned relative weight of each water quality parameter, reflecting its significance in influencing human health and environmental impact, whilem_i represents the measured or standardized value of the respective parameter. The term Ch_{ip} corresponds to the ideal concentration of a given parameter in pristine water, serving as a benchmark for quality assessment. The symbol n indicates the total number of parameters considered in the analysis, and Ch_p signifies the observed concentration of the chemical constituent in the groundwater sample under investigation.Beyond the Water Quality Index (WQI), the Sodium Adsorption Ratio (SAR)formulated in Equation (5)is also computed to determine the agronomic suitability of groundwater for irrigation purposes. Excessive levels of sodium ions (Na^+) in irrigation water are a critical concern, as they introduce a high alkalinity hazard that can severely impair soil structure and reduce permeability. This condition arises from sodium's tendency to disrupt the cation exchange balance in soils, leading to the displacement of calcium (Ca^{2+}) and magnesium (Mg^{2+}) ions, which are crucial for maintaining soil integrity.

When irrigation water exhibits low concentrations of Ca^{2+} combined with elevated Na^{+} levels, the cation exchange sites in soil particles become increasingly saturated with sodium. This chemical imbalance promotes the deflocculation of clay particles, resulting in soil dispersion, reduced porosity, and compromised water infiltration ultimately threatening long-term soil health and agricultural productivity.

Table 3. Parametric Value of Water Quality Index to Classify the Groundwater Quality

WQI Values	**Groundwater Quality**	**Permissible_Value**
<50	Excellent	1.0
50-100	Good	1.0
100-200	Poor	0.66
200-300	Very Poor	0.33
>300	Not Suitable for Drinking	0.00

Meanwhile, the sodium percentage is determined by using equation (6), and the Kelly's ratio is the ratio of Na^{+} ion to $Ca^{2+}$and Mg^{2+} ions in mg/l [14], which is calculated using equation (7).

$$SAR = Na^{+} \,/\, [\frac{Ca^{2+}+Mg^{2+}}{2}]^{0.5} \qquad (5)$$

$$Sodium\ \% = \frac{Na^{+}+K^{+}}{(Ca^{2+}+Mg^{2+}+Na^{+}+K^{+})} \times 100 \qquad (6)$$

$$Kelly\ Index = \frac{Na^{+}}{Ca^{2+}+Mg^{2+}} \qquad (7)$$

The Magnesium Hazard (MH) is determined using Equation (8), which calculates the ratio of magnesium ions (Mg^{2+}) to the sum of calcium (Ca^{2+}) and magnesium ions (Mg^{2+}), expressed in mg/l [15]. Groundwater with a magnesium hazard value exceeding 50% is generally considered unsuitable for irrigation. Elevated levels of Mg^{2+} can degrade soil quality by increasing alkalinity, which negatively impacts soil structure and leads to reduced agricultural productivity.

$$Magnesium\ Hazard = \frac{Mg^{2+}}{(Ca^{2+}+Mg^{2+})} \times 100 \qquad (8)$$

Elevated concentrations of bicarbonate (HCO_3^{-}) and carbonate (CO_3^{2-}) in groundwater tend to react with calcium (Ca^{2+}) and magnesium (Mg^{2+}) ions, leading to potential imbalances in soil chemistry. To quantify this interaction, the Residual Sodium Carbonate (RSC) index is utilized, as defined in Equation (9). According to standard classifications, groundwater with an RSC value less than 1.25 is considered suitable for irrigation, while values between 1.25 and 2.5 are marginally suitable. Groundwater with an RSC value exceeding 2.5 is deemed unsuitable for irrigation [16]. A detailed quantitative analysis of groundwater quality prediction using the AlexNet model, as well as an assessment of overall groundwater quality, is presented in Section 4.

$$RSC = (CO_3^{-} + HCO_3^{-}) - (Ca^{2+} + Mg^{2+}) \qquad (9)$$

3.3. Numerical analysis

In this study, the performance of the AlexNet model was evaluated using Python within the Google Colab environment, equipped with 16 GB of RAM and operated on a Mac-based system. A detailed quantitative analysis of groundwater quality prediction and assessment is presented in Sections 4.1 and 4.2, respectively.

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3.3.1. Quantitative Study on Ggroundwater Quality Prediction

The predictive performance of the GeoWaterNet model is comprehensively evaluated using key performance metrics, including Sensitivity, Specificity, Accuracy, Precision, F1-Score, and Matthews Correlation Coefficient (MCC). The mathematical formulations for these evaluation metrics are provided in Equations (10) to (15). In these expressions, **TP**(True Positives), **TN** (True Negatives), **FP** (False Positives), and **FN** (False Negatives) represent the classification outcomes used to compute the respective metrics.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (10)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (11)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (13)$$

$$F1 - Score = \frac{2TP}{2TP+FN+FP} \times 100 \quad (14)$$

$$MCC = \frac{(TP \times TN)-(FP \times FN)}{\sqrt{(TN+FN)(TN+FP)(TP+FN)(TP+FP)}} \times 100 \quad (15)$$

The proposed prediction framework, GeoWaterNet, was rigorously evaluated against several well-known deep learning architectures, including AlexNet, GoogLeNet, VGGNet-16, VGGNet-19, and ResNet-14, using key performance indicators such as accuracy, precision, F1-score, specificity, sensitivity, and Matthews Correlation Coefficient (MCC), as referenced by Hendrawan et al. (2021). As shown in Table 4, GeoWaterNet outperformed the comparative models, achieving an accuracy of 93%, specificity of 94.57%, and sensitivity of 91.47%. Additionally, it demonstrated superior performance across other metrics, including precision, F1-score, and MCC, further confirming its robustness and reliability in groundwater quality prediction. A visual representation of the comparative model performance is illustrated in Figure 2.

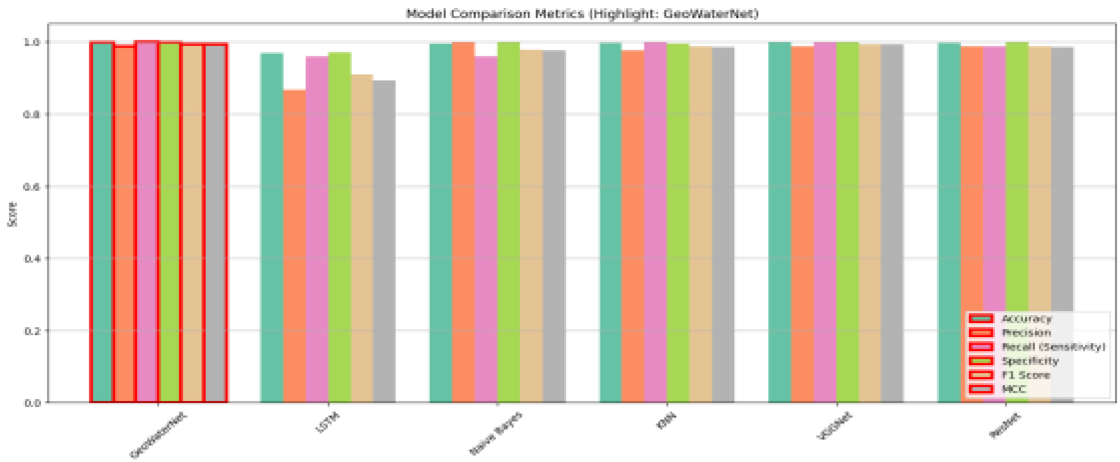

Figure 2. Comparison Chart of GeoWaterNet model with other models

Table 4. Experimental Results of the Used Models

Models	Accuracy (%)	Precision (%)	F-Score (%)	Specificity (%)	Sensitivity (%)	MCC (%)
GeoWaterNet	1.00	0.97	0.70	0.97	1.00	1.00
GoogleNet	0.97	1.00	0.50	1.00	0.96	0.96
VGGNet-16	0.70	0.50	1.00	0.53	0.73	0.72
VGGNet-19	0.97	1.00	0.52	1.00	0.96	0.97
ResNet-14	1.00	0.96	0.73	0.96	1.00	1.00
AlexNet	1.00	0.96	0.72	0.97	1.00	1.00

The correlation heat map of performance comparison results of the prediction model is represented in Figure 3.

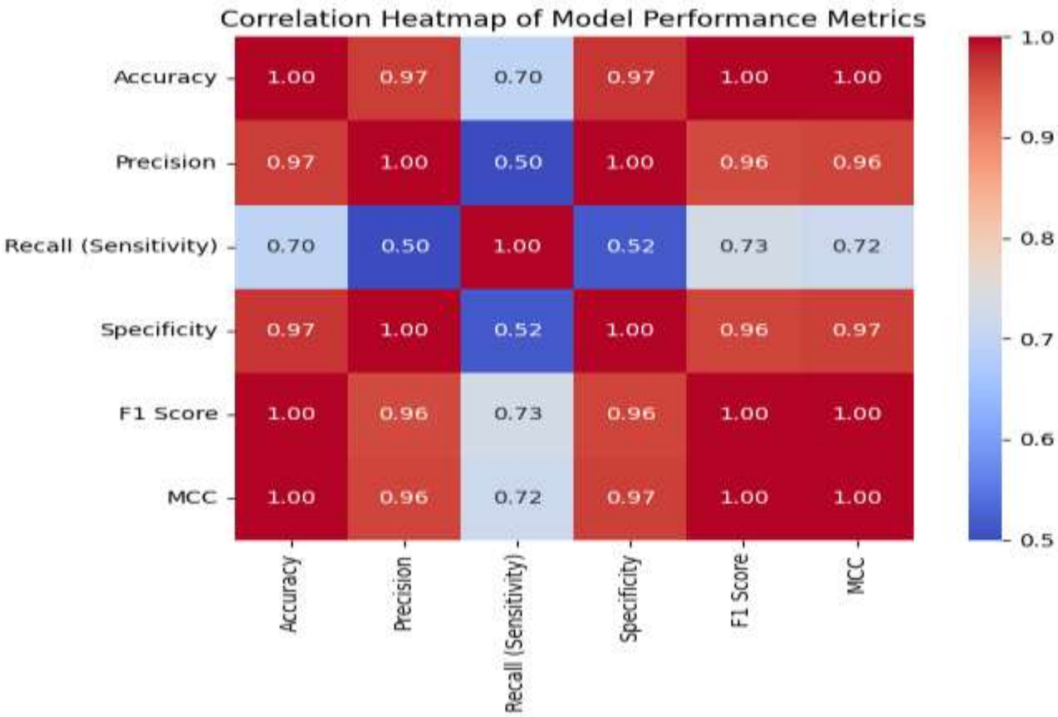

Figure 3. Correlation Heatmap of Various Models Performance

4.2. Quantitative Study on Groundwater Quality Assessment

In this research, key groundwater quality indicesnamely Sodium Percentage, Magnesium Hazard, Kelly's Index, Sodium Adsorption Ratio (SAR), Water Quality Index (WQI), and Residual Sodium Carbonate (RSC)were systematically evaluated. These assessments were conducted using a range of physico-chemical parameters, including general indicators such as hardness, pH, electrical conductivity (EC), and total dissolved solids (TDS), as well as major cations (K^+, Ca^{2+}, Mg^{2+}, Na^+) and anions (NO_2^- + NO_3^-, CO_3^{2-}, F^-, HCO_3^-, Cl^-, SO_4^{2-}). The comprehensive analysis of these parameters provides critical insights into the suitability of groundwater for both domestic and agricultural purposes. Detailed values of the physico-chemical properties observed in the collected samples are summarized in Table 5.

4.3. Physio-chemical Parameters

The detailed explanation about Physio-chemical parameters$NO_2^- + NO_3^-$, CO_3^-, F^-, HCO_3^-, Cl^-, SO_4^{2-}, K^+,Ca^+, Mg^{2+}, Na^+, $Hardness$, pH, EC and TDS are given below:

4.3.1. TDS and Nitrite and Nitrate ($NO_2^- + NO_3^-$)

Water naturally possesses the ability to dissolve a wide spectrum of organic and inorganic minerals, including major anions and cations such as nitrite and nitrate (NO_2^- + NO_3^-), carbonate (CO_3^{2-}), fluoride (F^-), bicarbonate (HCO_3^-), chloride (Cl^-), sulfate (SO_4^{2-}), potassium (K^+), calcium (Ca^{2+}), magnesium (Mg^{2+}), and sodium (Na^+). The presence of these ions often results in changes to the water's appearance imparting a diluted color and can contribute to an undesirable taste.The Total Dissolved Solids (TDS) content serves as a key indicator of the mineralization level of water. Elevated TDS values generally reflect a higher concentration of dissolved substances. According to the World Health Organization (WHO), the desirable TDS limit for drinking water is 500 mg/L, with a permissible upper limit of 2,000 mg/L under exceptional circumstances.
Additionally, WHO recommends a maximum concentration of 50 mg/L for combined nitrite and nitrate (NO_2^- + NO_3^-) in potable water to avoid health hazards. In the current study, the NO_2^- + NO_3^- concentrations in groundwater samples ranged from 1 to 140 mg/L, with an average of 25 mg/L, indicating that while most samples fall within the safe range, some exceed the recommended threshold and may pose a risk to consumers.

4.3.2. Calcium (Ca^+), Magnesium (Mg^{2+}), Potassium (K^+), and Sodium (Na^+)

As per the WHO and bureau of Indian standards, the range ofCa^+ is 75 mg/l for drinking water. Additionally, the fair range of Mg^{2+} ion is 30 mg/l and the allowable limit is 100 mg/l in the drinking water. In this study, theCa^+ ion ranges from 12 to 560 mg/l with an average value of 124 mg/l, and the Mg^{2+} ion varies from 3.645 to 352.35 mg/l with an average value of 128.90 mg/l. Similarly, the fair limit of Potassium (K^+) and Sodium (Na^+) ions in the drinking water is 200 mg/l. In this research, the Na+ ion ranges from 7 to 1171 mg/l with an average value of 328 mg/l, and the K^+ ion ranges from 1 to 111 mg/l with an average value of 24.90 mg/l. In this research manuscript, all the acquired water samples has fair limit of K^+ in the drinking water.

4.3.3. Sulfate (SO_4^{2-}), Bicarbonate (HCO_3^-), Chloride (Cl^-), and Fluoride (F^-)

According to the World Health Organization (WHO), the acceptable concentration of chloride (Cl^-) in drinking water is 250 mg/L. In this study, chloride levels in groundwater samples ranged from 35 mg/L to 3,155 mg/L, with an average concentration of 567.50 mg/L, indicating that many samples exceed the recommended limit. Similarly, sulfate (SO_4^{2-}) concentrations, which should ideally not exceed 200 mg/L for safe consumption, were found to vary from 22 mg/L to 720 mg/L, averaging at 122 mg/Lsuggesting that while some samples remain within limits, others may pose a concern.For bicarbonate (HCO_3^-), the acceptable threshold is 200 mg/L in drinking water. However, the present analysis recorded values ranging between 82.92 mg/L and 671 mg/L, with a mean of 342 mg/L, indicating substantial variation and potential for water hardness. Regarding fluoride (F^-), WHO recommends a fair limit of 1 mg/L and a permissible upper limit of 1.5 mg/L. The fluoride concentration in the samples ranged from 0.008 mg/L to 2 mg/L, with an average value of 0.73 mg/L, suggesting that while most samples are within safe limits, a few may exceed the permissible threshold, posing a health risk if consumed over long periods.

Table 5. The physio-chemical parameters of water samples

Well_ID	pH	EC	CO_3^-	TDS	SO_4^{2-}	HCO_3^-	Cl^-	F^-	K^+	Mg^{2+}	Na^+	Ca^+	Hardness
W001	8.9	912	37	564	35	298.4	76	1.15	112	27.01	70	33	191
W002	8.5	1230	31	676	27	278.8	155	1.55	45	42.21	139	24	235
W003	8.2	778	1.54	456	36	132.5	132	0.16	17	14.26	125	27	131
W004	8.1	1210	31	647	65	342.4	165	2.01	17	27.15	198	35	201

W005	8.3	970	13	564	58	385.3	56	1.99	11	53.23	88	37	305
W006	8.7	1570	14	897	103	409.7	236	1.58	9	119.05	135	29	561
W007	8.0	1980	47	1123	108	467.5	255	1.9	15	65.23	289	25	323
W008	7.8	3060	17	1897	154	465.7	470	0.46	17	209.09	201	89	1110
W009	7.3	1470	21	878	98	308	217	0.37	15	75.4	155	51	423
W010	8.1	730	1.00	456	56	161.3	114	0.09	7	33.56	87	31	201
W011	7.7	920	1.78	546	49	187.3	154	0.08	7	34.09	134	25	152
W012	7.9	1250	1.10	867	87	214.7	254	0.45	47	25.5	186	35	189
W013	8.2	1670	21	986	69	316.6	201	0.87	11	115.9	101	89	690
W014	8.4	1430	.98	814	97	298.9	176	0.6	5	67.98	167	31	335
W015	7.0	2140	0.54	1231	98	564.8	289	0.98	29	99.80	241	27	471
W016	7.3	2130	41	1321	57	500.8	476	0.88	15	65.76	354	29	325
W017	7.5	3090	31	1897	79	311.5	498	1.15	17	3.76	465	11	245
W018	7.7	650	0.98	398	68	155.6	55	0.53	6	23.65	71	9	189
W019	8.1	970	1.34	599	76	213.7	125	0.25	8	35.45	125	21	205
W020	8.9	560	1.05	675	56	147.6	145	0.33	4	23.61	87	7	205
W021	7.9	789	23	543	87	209.8	201	0.13	6	33.56	215	5	210

4.3.4. $Hardness$, pH, EC, Carbonate (CO_3^-) and TDS

According to the World Health Organization (WHO) guidelines, the permissible pH level for drinking water is up to 8.5, while the recommended limit for electrical conductivity (EC) is 750 µs/cm. In the present study, the pH of groundwater samples varied between 7.7 and 8.9, with an average value of 8.3indicating slightly alkaline conditions. The EC values ranged from 620 µs/cm to 10,000 µs/cm, with a mean of 3,981 µs/cm, suggesting significant mineralization in many samples.The maximum observed concentration of carbonate ions (CO_3^{2-}) was 60 mg/L, which falls within the acceptable range for drinking purposes. Regarding water hardness, the WHO recommends a threshold of 300 mg/L. However, in this investigation, hardness levels ranged from 65 to 2,000 mg/L, with an average value of 387 mg/L, highlighting that several samples exceeded the recommended limits and may pose concerns for potable use.

4.3.5. Sodium Adsorption Ratio (SAR)

The Sodium Adsorption Ratio (SAR) is a key hydrochemical indicator used to evaluate groundwater suitability for irrigation, particularly in managing sodium-impacted soils. It serves as a diagnostic tool to assess the sodicity hazard, which directly influences soil permeability and structure. Elevated concentrations of sodium ions (Na^+) in groundwater contribute to the development of alkaline soils, while high overall salinity can lead to saline soil conditions, both of which negatively affect crop productivity.Based on SAR values, irrigation water is classified into four categories:

- Low alkali water (SAR < 6),
- Moderate alkali water (SAR 6–12),
- High alkali water (SAR 12–18), and
- Very high alkali water (SAR > 18).

As detailed in Table 6, the SAR values observed in this study range from 1 to 18, encompassing a wide spectrum of sodicity risk levels.

Table 6. Sample SAR Values for the Locations

Well_ID	Well_Type	SAR_Value
W001	Bore Well	3.175
W002	Dug Well	3.054
W003	Dug Well	4.895
W004	Dug Well	5.897
W005	Bore Well	3.789
W006	Bore Well	5.432
W007	Dug Well	6.453
W008	Dug Well	5.342
W009	Dug Well	5.543
W010	Dug Well	6.533
W011	Dug Well	2.345
W012	Bore Well	4.238
W013	Dug Well	5.187
W014	Dug Well	5.342
W015	Dug Well	4.987
W016	Bore Well	3.654
W017	Dug Well	4.678
W018	Dug Well	6.897
W019	Bore Well	4.345
W020	Bore Well	5.653
W021	Bore Well	4.231

4.3.6. Residual sodium carbonate (RSC)

The Residual Sodium Carbonate (RSC) index is a critical indicator used to assess the alkalinity risk posed by irrigation water on soil health. An RSC value below 2.5 signifies water that is suitable for irrigation, while values between 2.5 and 5 suggest moderate suitability with caution. RSC values exceeding 5 indicate water that is unsuitable for agricultural use due to its high potential to deteriorate soil structure. The classification of RSC values for the analyzed water samples is summarized in Table 7.

Table 7. RSC index value of sample locations

Well_ID	Well_Type	RSC_Value
W001	Bore Well	0.756
W002	Dug Well	3.654
W003	Dug Well	1.895
W004	Dug Well	2.897
W005	Bore Well	3.789
W006	Bore Well	2.432

W007	Dug Well	2.453
W008	Dug Well	3.342
W009	Dug Well	1.543
W010	Dug Well	2.533
W011	Dug Well	1.345
W012	Bore Well	7.238

4.3.7. Sodium percentage and Water Quality Index

The sodium percentage serves as a key metric in determining the suitability of groundwater for irrigation, as outlined in Table 8. Meanwhile, the Water Quality Index (WQI) is a vital tool used to evaluate and track groundwater quality by condensing complex hydrochemical data into a single, interpretable score.To calculate the WQI, fourteen essential physico-chemical parameters are considered, including major anions such as$NO_2^-+NO_3^-$, CO_3^-, F^-, HCO_3^-, Cl^- and SO_4^{2-}, as well as major cations likeK^+,Ca^+, Mg^{2+} and Na^+, additional parameters such as total hardness, pH electrical conductivity (EC), and total dissolved solids (TDS) are also included in the assessment. By assigning weights to each parameter based on its significance to water quality, the WQI provides a comprehensive understanding of groundwater conditions. The step-by-step computation process is illustrated through Equations (1–4) and visually represented in Figure 6.

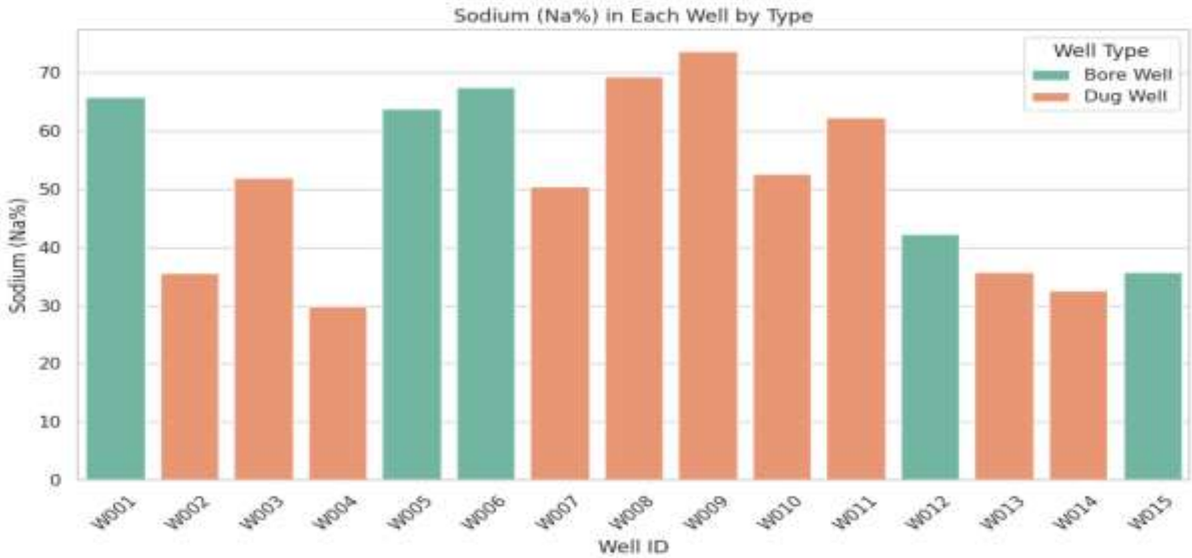

Figure 6. Sodium (Na) Percentage in Sample Collected from Various Wells

Classification and Interpretation of Water Quality Index (WQI)

The Water Quality Index (WQI) is a comprehensive indicator that categorizes water quality into five distinct levels:

- WQI < 50: Excellent (pure) water
- WQI 50–100: Good (suitable for drinking)
- WQI 100–200: Poor (contaminated)
- WQI 200–300: Very poor (highly contaminated)
- WQI > 300: Unsuitable for drinking

In this study, WQI values for the 800 analyzed groundwater samples ranged from 30 to 280, with an **average** WQI of 39, indicating predominantly high-quality water conditions.

The classification results show that:

- 22% of the samples fall within the excellent category (WQI < 50),
- 63% are classified as good and suitable for drinking (WQI 50–100),

- The remaining **15%** exhibit higher contamination levels and are deemed more suitable for **irrigation** rather than consumption.

These findings reflect spatial variability in groundwater quality and emphasize the need for targeted water management strategies.

Table 8. Sodium (Na) Percentage in Sample Collected from Various Wells

Well_ID	Well_Type	Sodium (Na%)
W001	Bore Well	65.776
W002	Dug Well	35.654
W003	Dug Well	51.895
W004	Dug Well	29.897
W005	Bore Well	63.789
W006	Bore Well	67.432
W007	Dug Well	50.453
W008	Dug Well	69.342
W009	Dug Well	73.543
W010	Dug Well	52.533
W011	Dug Well	62.345
W012	Bore Well	42.238
W013	Dug Well	35.765
W014	Dug Well	32.546
W015	Bore Well	35.789

4.3.8. Kelly Index and Magnesium hazard

Excessive magnesium content in groundwater can adversely affect soil health by elevating soil alkalinity, which in turn reduces agricultural productivity. Groundwater with magnesium hazard values exceeding 50 is considered detrimental and unsuitable for irrigation applications. In the present study, magnesium hazard values ranged between 19 and 72, with a mean of 36, indicating variability in irrigation potential across sampling locations.

Furthermore, Kelly's Index, a key indicator of sodium hazard, suggests that water is considered suitable for irrigation when the index is less than 1, while values greater than 1 denote unsuitability. The analysis revealed Kelly's Index values spanning from 0.11 to 7, with an average of 4.82, highlighting that a significant proportion of the sampled groundwater poses irrigation risks due to elevated sodium content.

5. CONCLUSION

The predictive evaluation of groundwater quality was conducted using the proposed GeoWaterNet model, which leverages deep feature learning to assess the water's suitability for domestic and agricultural applications. Experimental analysis revealed that GeoWaterNet achieved a prediction accuracy of 93%, with specificity and sensitivity scores of 94.57% and 91.47%, respectively surpassing conventional deep learning models in both precision and reliability.Physico-chemical characterization of approximately 900 samples, collected from 200 diverse hydrogeological sites, indicated that the majority fell within the permissible thresholds set by the Bureau of Indian Standards (BIS), affirming a controlled environmental condition in most regions.Further hydrochemical analysis using Kelly's Index identified that only 30% of samples were classified as suitable for irrigation, while the remaining 70% indicated high sodium hazard, making them unsuitable. Meanwhile, Water Quality Index (WQI) results categorized 22% of the samples as excellent, 63% as good for drinking, and 15% as more suitable for agricultural use. Additionally, the Sodium Adsorption Ratio (SAR) highlighted that 38% of the water sources contained elevated alkali levels, which could pose significant risks to soil health and crop yield, while the remaining samples demonstrated acceptable alkali content.To further boost prediction robustness, the GeoWaterNet architecture integrates a feature extraction module, enhancing its ability to distinguish subtle variations in ionic composition and environmental factors. This modular enhancement refines the model's capability to generalize across complex, real-world groundwater datasets, making it a scalable and effective solution for intelligent water resource management.

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be constructed as a potential conflict of interest.

DATA AVAILABILITY STATEMENT

The dataset used for training and evaluating the GeoWaterNet model comprises groundwater impurity records collected from local monitoring sources. Due to confidentiality and data-sharing agreements, the raw data are not publicly available. However, processed or anonymized data supporting the findings of this study can be made available from the corresponding author upon reasonable request.

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