Global NEST Journal, Vol 26, No X, pp 1-9

Effective deep learning based prediction model for groundwater quality assessment using physio-chemical parameters

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Received: 28/10/2023, Accepted: 26/02/2024, Available online: 02/03/2024
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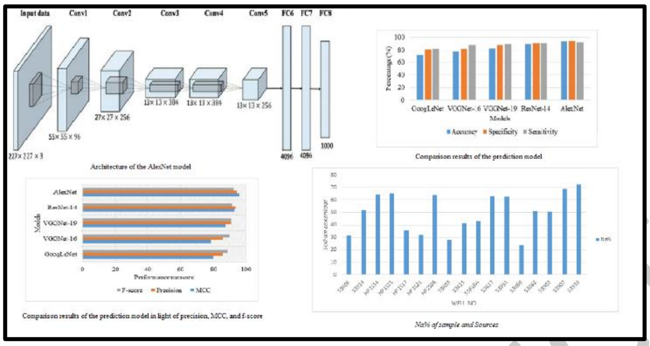
https://doi.org/10.30955/gnj.005474

Graphical abstract



Abstract

The purpose of this study is to anticipate and investigate the groundwater quality in the regions of the Cauvery basin. In the post-monsoon season of 2020, 800 samples were collected from 200 different places for this paper. The AlexNet model is used in this book to forecast the water quality. In order to examine the groundwater quality, the anticipated groundwater samples are analyzed using main cations (K+, Mg2+, Ca2+, and Na+), major anions (NO2-+NO3-, CO3-, F-, HCO3-, Cl-, and SO42-), hardness, pH, and Electrical Conductivity (EC). The accuracy, specificity, and sensitivity of the AlexNet model are used in this publication to validate its efficacy. Validating the following metrics determines if water is suitable for drinking and irrigation: sodium percentage, magnesium ratio, Kelly's ratio, sodium adsorption ratio, water quality index (WQI), and residual sodium carbonate (RSC). According to the research, the AlexNet model predicted water quality with 93%, 94.57%, and 91.47% accuracy, specificity, and sensitivity, respectively. According to the experimental results, the WQI value shows that 22% of the collected samples are acceptable for drinking, 63% are suitable for drinking, and the other 15% are only fit for irrigation and should not be consumed.

Keywords: AlexNet, environmental science, groundwater quality assessment, geochemistry, Hydro-geochemical parameters, water quality index.

1. Introduction

The groundwater quality is the function of its chemical and physical parameters, which depends on the soluble products of decomposition and weathering (Srinivasamoorthy *et al.* 2011). The groundwater is polluted, due to the external contaminants like agricultural practices and industrial urban, and it is majorly influenced by the factors like industrial growth, geology, emission of pollutants, sewage disposal, weathering, soil nature, and other environmental conditions (Adimalla and Taloor 2020; Adimalla 2020; Maurya *et al.* 2021). In the groundwater quality assessment, the chemical composition is crucial in finding the quality of water for numerous utility purpose like industrial, agricultural, and domestic (Rahman *et al.* 2020; Srivastava 2019). As per WHO and bureau of Indian standards, around 80% of the human diseases are occurred by consuming polluted-water. Most of the population in India depends on the groundwater for drinking (Barik and Pattanayak 2019). As per central-pollution-control-board, around 30,000 million liter per day of wastewater is produced from the class II towns and class I cities in that 45% of the wastewater is produced from 35 metro-cities (Rao 2018). The developing nations like India have wide spectral differences in hydrological, geological, meteorological, and environmental conditions, where the groundwater origin, occurrence, and migrations depends on the elements like lineament density, drainage density, geomorphology, land use, slope, and geology (Jain and Vaid 2018; Chaurasia *et al.* 2018). Once the groundwater is polluted, it is hard in recovering the water quality in the nations such as India. The advantages of using deep learning technique in Groundwater Quality Assessment using Physio-chemical Parameters is to handle large datasets and solve intricate nonlinear issues are two advantages of AI techniques (Santhosh Kumaar *et al.* 2022; Shanmugasundaram and Shanmugam 2023). Because computing capabilities are always improving, researchers may now use a wide range of AI models. Numerous researchers have successfully used techniques like artificial neural networks (ANN) to forecast the quality of water around the globe (Sivabalaselvamani *et al.* 2022). The major objectives of this manuscript are in predicting, investigating, and characterizing the groundwater quality. The contributions of this manuscript are listed as follows:

- Totally, 800 samples are acquired and analyzed with the physio-chemical parameters: NO_2- +NO_3-, CO_3-, F^-, HCO_3-, Cl-, SO_4^{2-}, K^+, Mg^{2+}, Ca^{2+}, Na^+, hardness, pH, EC, and TDS for investigating the groundwater quality.
- The groundwater quality prediction is performed by utilizing deep learning model named AlexNet. The AlexNet has limited classification error without overfitting problem related to the comparative models: GoogLeNet, VGGNet-16, VGGNet-19 and ResNet-14 by means of accuracy, specificity, and sensitivity.
- In the experimental segment, the performance measures such as sodium percentage, Kelly's index, magnesium hazard, WQI, RSC, and SAR are employed for investigating the water suitability for both irrigation and drinking. Similarly, the performance measures: accuracy, specificity, and sensitivity are utilized for analyzing the efficacy of the prediction model.

Recent manuscripts related to "groundwater quality assessment" are surveyed in Section 2. Sections 3 represents the materials and methods of the present research work. Numerical examination of this manuscript is given in Section 4. At last, the conclusion of this manuscript is mentioned in Section 5.

2. Related works

Arulbalaji and Gurugnanam (2017) done groundwater quality assessment for Salem district. In this literature study, 59 water samples were acquired and investigated with EC, pH, TDS, alkalinity, hardness, CO_3^-, NO_2^- +NO_3^-, F^-, Cl^-, SO_4^{2-}, HCO_3^-, K^+, Mg^{2+}, Ca^{2+} and Na^+. The groundwater suitability was assessed for irrigation and drinking purposes based on the analytical results: WQI, SAR, Kelly index, magnesium hazard, RSC, and sodium percentage. This literature study revealed that the groundwater samples acquired from the Lokkur, Tholasampatti, Marakottai, Tharamangalam, Elampillai, and Manathal villages were not-suitable for irrigation and drinking, because the acquired samples have higher magnesium concentration, salinity, and hardness.

Adimalla *et al.* (2020) acquired 105 groundwater samples from semi-arid region of Telangana for investigating the suitability of water for both irrigation and drinking. The experimental outcomes revealed that majority of the water samples were suitable for drinking purpose based on EC, TDS, pH, hardness, Mg^{2+}, Ca^{2+}, Na^+, K^+, Cl^-, and SO_4^{2-}. Around 60% and 36% of the acquired samples were excellent and good for drinking according to WQI value. In addition, the Wilcox diagram revealed that around 90% of the acquired samples were excellent for agricultural purpose, and the residual water samples were considerably good for agricultural purpose.

Khatri *et al.* (2020) done groundwater quality assessment for Satlasana Taluk in Gujarat state, India. In this literature study, 50 groundwater samples were acquired from nine villages for investigating the groundwater quality. The physico-chemicals like turbidity, dissolved oxygen, pH, TDS, total alkalinity, total hardness and chloride were investigated in the groundwater sources for 6 months. The Canadian council ministers of environment's WQI revealed that 54% of the water samples were considerably suitable, and the weighted arithmetic WQI showed that 46% of the acquired water samples were excellent for drinking purpose.

Divahar *et al.* (2020) investigated the water quality for Kalingarayan Canal, Erode, Tamil Nadu, India. In this literature, nine water samples were acquired between January 2014 to December 2016 for investigating the groundwater quality. The physio-chemicals: pH, TDS, EC, total hardness, sulphates, chlorides, magnesium, nitrates, sodium, and calcium were examined for observing the status of water quality by means of WQI. The experimental result revealed that the acquired water samples has high magnesium and calcium content, so it cannot be utilized for drinking as well as irrigation purposes. Ravish *et al.* (2020) monitored the water quality in Yamunanagar and Ambala districts, Haryana, India for both irrigation and domestic purposes. From the acquired data, the experimental result revealed that the groundwater of Yamunanagar and Ambala districts were appropriate only for industrial purpose.

Adimalla and Qian (2019) has analyzed the water quality of Nanganur region for drinking purpose by means of WQI. The overall observation revealed that the acquired water samples were alkaline in nature. The mean ionic dominance pattern was in the order of nitrate < chloride < sulphate < bicarbonate < potassium < magnesium < calcium < sodium for anions and cations, respectively. The nitrate concentration was 3.96 times greater than the acceptable limit in the acquired water samples, which was considered to be unfit for domestic purpose. The experimental results confirmed that the 86% of the acquired samples were inappropriate for drinking according to WQI value.

Prasad *et al.* (2019) analyzed the water quality of Obulavaripalli Mandal, YSR district, Andhra Pradesh, India for drinking purpose. In order to analyze WQI in the study area, 20 water samples were acquired and analyzed with the physico-chemicals like EC, pH, TDS, fluoride, sulphate, chloride, magnesium, calcium, and total alkalinity. The WQI value revealed that the 30% of the samples were under poor-category, 40% of the samples were under good-category, and the residual 30% of the water samples were under excellent-category for drinking purpose. The experimental outcomes revealed that the acquired groundwater samples were not fit for drinking purpose.

Ponsadailakshmi *et al.* (2018) evaluated the groundwater quality of Mayiladuthurai taluk, Nagapattinam district, Tamil Nadu, India. In this literature study, 17 water quality parameters and 20 water samples were acquired for investigating the quality of groundwater. In the experimental phase, drinking WQI demonstrated that the acquired samples were excellent for drinking.

Acharya *et al.* (2018) analyzed the groundwater quality of southwest Delhi, India. In order to investigate the water quality, 50 groundwater samples and the parameters such as EC, TDS, pH, total hardness, salinity, nitrates, sulfates, fluoride, chloride, total alkalinity, potassium, sodium, magnesium, and calcium were determined. The WQI value showed that 66% of the acquired water samples were inappropriate, and the residual 34% of the samples were excellent for both irrigation and drinking. Additionally, Ahmed *et al.* (2019) utilized supervised machine learning techniques such as random forest, decision tree, and Naïve Bayes classifier for an effective water quality prediction.

Kadam *et al.* (2019) integrated multiple linear regression modelling approach and Artificial Neural Network (ANN) for water quality prediction in the shivganga river basin, India. Liu *et al.* (2019) presented Long Short-Term Memory (LSTM) to analyze and predict the water quality. Li *et al.* (2019) has combined improved evidence theory and Recurrent Neural Network (RNN) model for an effective water quality prediction. The machine learning techniques has obtained reasonable prediction accuracy by utilizing minimum number of the parameters for validating the possible water use in quality detection system. The manual intervention is more in the machine learning techniques Ahmed *et al.* (2019). The deep learning models: ANN and LSTM network attained significant performance in the groundwater quality prediction, especially for drinking purpose Kadam *et al.* (2019). The irrigation includes the drawbacks of vanishing gradient and over-fitting problems Liu *et al.* (2019). RNN effectively predicts the ground water quality in the Qiantang River, China. RNN is computationally expensive, while processing more number of data Li *et al.* (2019).

Kaish and Khan (2010) investigated water contamination in the Aligarh metropolitan region. Water samples were obtained from three different locations and examined for twelve different water quality indicators in this study. TDS 642.62 mg/L, pH 8.68, temperature 26.11 C, hardness 263.19 mg/L, and chloride 148.66 mg/L were recorded as the maximum concentrations of water quality indicators. The study's findings revealed that the concentrations of water quality measures exceeded the specified limits. The analysis indicated that Aligarh's water quality was compromised.

Tiwari *et al.* (2015) assessed the groundwater quality in the Hamirpur area of Uttar Pradesh, India. pH, total dissolved solids, sulfate, nitrate, chloride, fluoride, hardness, alkalinity, and heavy metals were all measured in groundwater samples obtained by hand pumps. The results of these parameters were compared to the BIS drinking water quality requirements (IS: 10500:2012). The high total dissolved solids, hardness, and alkalinity levels indicate that the water was unfit for direct drinking use without filtering.

3. Methodology

This section details about the data collection, groundwater quality prediction and groundwater quality assessment.

3.1. Data collection

In the environmental science application, 800 groundwater samples (bore and dug wells) are acquired from the 200 different regions, during post monsoon season of 2020. In this research study, the acquired water samples are analyzed with the major anions (NO_2^- +NO_3^-, CO_3^-, F^-, HCO_3^-, Cl^- and SO_4^{2-}), major cations (K^+, Mg^{2+}, Ca^{2+} and Na^+), hardness, EC, TDS and pH. Based on the analytical results, WQI, SAR, RSC, Kelly index, sodium percentage and magnesium hazard are calculated to evaluate the groundwater quality. Groundwater quality parameters with its standard value is represented in Table 1.

Table 1. Groundwater quality parameters with its standard value

Parameters	Units	Relative weights	Weights	Standard value based on Indian Standard
Fluoride (F^-)	mg/l	0.11	5	1
Sodium (Na^+)	mg/l	0.11	5	200
Calcium (Ca^{2+})	mg/l	0.07	3	75
Magnesium (Mg^{2+})	mg/l	0.07	3	30
Nitrite and nitrate (NO_2^- +NO_3^-)	mg/l	0.11	5	45
Sulfate (SO_4^{2+})	mg/l	0.11	5	200
Bicarbonate (HCO_3^-)	mg/l	0.02	1	200
Chloride (Cl^-)	mg/l	0.11	5	250
TDS	mg/l	0.11	5	500
pH	-	0.09	4	8.5
Potassium (K^+)	mg/l	0.04	2	200
Hardness	mg/l	0.04	2	500
EC	µs/cm	0.03125	1	300

3.2. Groundwater quality prediction and assessment

After data collection, the AlexNet model is employed for extracting the deep feature vectors that are fed to the input layer. The AlexNet model consists of five convolutional layers, and three fully connected layer, where every layer is followed by Max Pooling Operation (MPO) and Rectifier Linear Unit (ReLU) activation function for groundwater quality prediction. In this paper, the deep feature values are extracted from 3rd fully connected layer with the softmax classifier. The hyper-parameters utilized in the AlexNet model are determined as follows: L2 regularization is 1.000e-04, maximum epoch is 10, learning rate is 0.15, momentum is 0.6, validation frequency is 30 and training algorithm is stochastic gradient descent algorithm.

As specified earlier, around 800 groundwater samples are acquired from 200 locations near Cauvery basin regions. Among 800 samples, the implemented deep learning model: AlexNet accurately predicts the groundwater quality of 744 samples with accuracy of 93%. The prediction accuracy is better related to other deep learning models like GoogLeNet, VGGNet-16, VGGNet-19, and ResNet-14. The design configuration of the AlexNet model is stated in Table 2 and the architecture of AlexNet is given in Figure 1.

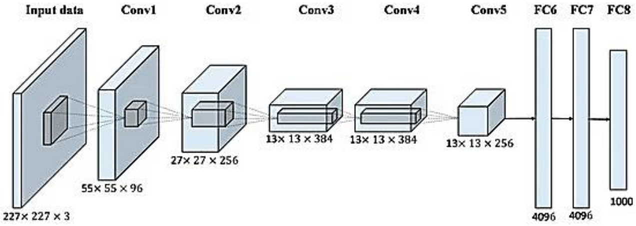


Figure 1. Architecture of the AlexNet model

Table 2. Design configuration of the AlexNet model

Hidden layers		Design configuration
Convolutional layers	1	850 filters in size 7 × 7 with the MPO
	2	850 filters in size 5 × 5 with the MPO
	3	680 filters in size 5 × 5 with the MPO
	4	680 filters in size 5 × 5 with the MPO
	5	450 filters in size 2 × 2 with the MPO
Fully connected layers	1	2096 nodes with the ReLU activation function
	2	2096 nodes with the ReLU activation function
	3	400 nodes with the ReLU activation function

In the groundwater quality assessment, the WQI is an effective tool for appraising the water quality. The WQI reduces the acquired data into an individual value, so it is easy to understand the water quality information. In WQI, weight value W_i is allocated to every groundwater quality parameters, based on its related importance, the overall quality of groundwater is determined for drinking (Adimalla *et al.* 2018; Khan and Jhariya 2017), which is indicated in Table 3. Equations (1-4) shows the WQI determination.

$$W_i = \frac{w_i}{\sum_i^n w_i} \tag{1}$$

$$Q_i = \frac{C_i - C_{ip}}{S_i - C_{ip}} \times 100 \tag{2}$$

$$SI_i = W_i \times Q_i \tag{3}$$

$$WQI = \sum_{i=1}^{n} SI_i \tag{4}$$

Where, W_i states relative-weight value, w_i denotes weight of every water quality parameter, C_{ip}states ideal value of the parameters in pure water, *n* indicates numer of water quality parameters, and C_i denotes chemical parameter's concentration in the water samples. In addition, the SAR value of acquired water sample is calculated by utilizing equation (5). Generally, higher concentration of Na^+ results in alkali hazard and the pre-dominance concentration of Mg^{2+} and Ca^{2+} results in less alkali hazard. The cation exchange complex gets saturated with Na^+, while the irrigation water has lower Ca^{2+} and higher Na^+ concentration. Due to clay particles dispersion, the structure of the soil gets destroyed (Klopp and Daigh 2020).

Table 3. Parametric value of Water Quality Index to classify the groundwater quality

WQI value	Groundwater quality
>300	Water is unsuitable for drinking
200-300	Very poor water
100-200	Poor water
50-100	Good water
<50	Excellent

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 (Hossain *et al.* 2020), which is calculated using equation (7).

$$SAR = Na^+ / [\frac{Ca^{2+} + Mg^{2+}}{2}]^{0.5} \tag{5}$$

$$Sodium\ percentage = (Na^+ + K^+) / (Ca^{2+} + Mg^{2+} + Na^+ + K^+) \times 100 \tag{6}$$

$$Kelly\, index = Na^+ / (Ca^{2+} + Mg^{2+}) \tag{7}$$

Magnesium hazard is calculated by using equation (8), which is the ratio of Mg^{2+} ion to Ca^{2+} and Mg^{2+} ions in mg/l (Chebet *et al.* 2020). If the ratio of magnesium is higher than 50%, and then the groundwater is suitable for irrigation. Further, the higher concentration of Mg^{2+} ion adversely affects the quality of soil by increasing the soil alkalinity that results in less crop yield.

$$Magnesium\, hazard = Mg^{2+} / (Ca^{2+} + Mg^{2+}) \times 100 \tag{8}$$

The high concentration of HCO_3^- and CO_3^- in groundwater forms propensity with the ions Ca^{2+} and Mg^{2+}. A term RSC is developed in order to quantify this effect, which is mathematically represented in equation (9). As per RSC value, the groundwater with < 1.25 value is appropriate for irrigation purpose, and the samples with 2.5 RSC value is marginally appropriate for irrigation purpose. Additionally, the RSC value with > 2.5 is inappropriate for irrigation purpose (Aher and Gaikwad 2017). Then, the quantitative study on groundwater quality prediction by using AlexNet and the quantitative study on groundwater quality assessment are given in the section 4.

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

4. Numerical analysis

Here, the AlexNet model's efficacy is analyzed by MATLAB 2020 tool with 16 GB RAM and Linux operating system. Hence, the quantitative study on the groundwater quality prediction, and the quantitative study on groundwater quality assessment are given in the sections 4.1 and 4.2.

4.1. Quantitative study on groundwater quality prediction

The prediction performance of the AlexNet model is investigated by means of sensitivity, Mathew's Correlation Coefficient (MCC), accuracy, precision, specificity and f-score. The mathematical presentation of the undertaken performance metrics is given in the equations (10-15). Where, FP, FN, TP, and TN are indicated as False Positives, False Negatives, True Positives, and True Negatives values.

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

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

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

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

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

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

The prediction model named AlexNet performance is compared with a few deep learning models such as GoogLeNet, Visual Geometry Group (VGG) Net-16, VGGNet-19, and ResNet-14 by means of sensitivity, accuracy, and specificity Hendrawan *et al.* (2021). By viewing Table 4, the AlexNet model obtained higher prediction performance with accuracy of 93%, specificity of 94.57%, and sensitivity of 91.47%, which are superior related to the comparative models like GoogLeNet, VGGNet-16, VGGNet-19 and ResNet-14. The comparison results of the prediction model: AlexNet is represented in Figure 2.

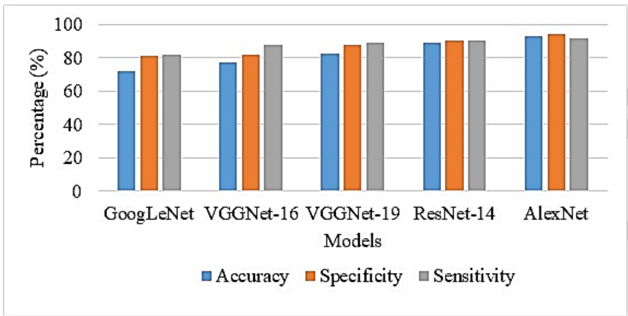


Figure 2. Comparison results of the prediction model

Table 4. Experimental results of the prediction model

Models	Accuracy (%)	Specificity (%)	Sensitivity (%)
GoogLeNet	71.80	80.98	82.09
VGGNet-16	77.48	81.84	87.65
VGGNet-19	82.64	87.78	88.88
ResNet-14	88.90	90.39	90.35
AlexNet	**93**	**94.57**	**91.47**

Table 5. Experimental results of the prediction model in light of MCC, precision, and f-score

Models	MCC (%)	Precision (%)	F-score (%)
GoogLeNet	79.80	85.90	88.90
VGGNet-16	78.40	85.80	89.65
VGGNet-19	87.44	90.78	90.86
ResNet-14	92.90	93.39	91.30
AlexNet	**95.80**	**94.50**	**92.48**

Similarly, the proposed AlexNet model's effectiveness is validated using different evaluation measures. By viewing Table 5, the AlexNet model has attained superior prediction performance with MCC of 95.80%, precision of 94.50%, and f-score of 92.48%, which are high related to the comparative models like GoogLeNet, VGGNet-16, VGGNet-19, and ResNet-14. The comparison results of the prediction model in light of MCC, precision, and f-score is represented in Figure 3.

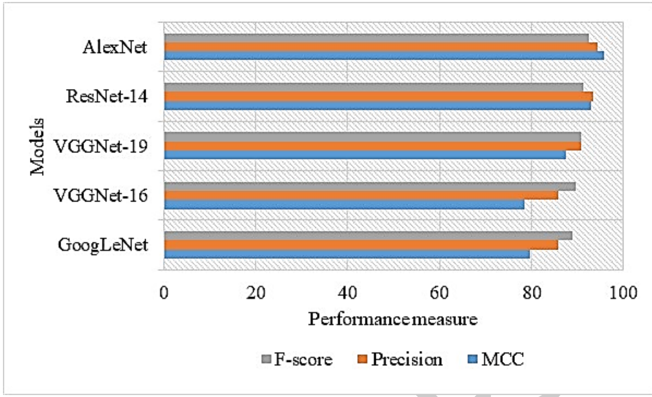


Figure 3. Comparison results of the prediction model in light of precision, MCC, and f-score

4.2. Quantitative study on groundwater quality assessment

In this research study, the sodium percentage, magnesium hazard, Kelly's index, SAR, WQI, and RSC are analyzed by using the physico-chemicals like TDS, pH, hardness, EC, major cations (Mg^{2+}, K^+, Ca^{2+} and Na^+) and major anions (F^-, NO_2^-+NO_3^-, CO_3^-, HCO_3^-, Cl^- and SO_4^{2-}) for investigating the groundwater quality (Kim *et al.* 2022; Yang & Liu 2021; Cabello *et al.* 2022). The physio-chemical parameters of water samples are presented in Table 6.

4.3. Physio-chemical parameters

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

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

Usually, water has the ability to dissolve an extensive range of organic and in-organic minerals like Mg^{2+}, F^-, K^+, Ca^{2+}, Na^+, CO_3^-, HCO_3^-, NO_2^- +NO_3^-, Cl^-, SO_4^2, etc. These anions and cations results in diluted color in appearance, and un-wanted taste of water. Higher TDS value represents that the water is highly mineralized. Based on World Health Organization (WHO), TDS has the fair limit of 500 mg/l and the permissible limit of 2000 mg/l for drinking purpose. Further, the fair limit of Nitrite and nitrate (NO_2^-+NO_3^-) concentration in groundwater is 50 mg/l. In this study, the NO_2^-+NO_3^- ion ranges from 1 to 140 mg/l with mean of 25 mg/l.

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

As per the WHO and bureau of Indian standards, the range of Ca^{2+} 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, the Ca^{2+} 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 ($HCO3^-$), Chloride (Cl^-), and Fluoride (F^-)

According to the WHO, the fair range of Chloride (Cl^-) ion is 250 mg/l in the drinking water. In this research study, the Cl^- ion ranges from 35 to 3155 mg/l with an average value of 567.50 mg/l. Further, acceptable range of Sulfate (SO_4^{2+}) ion is 200 mg/l in the drinking water. In this study, the SO_4^{2+} ranges from 22 to 720 mg/l with an average value of 122 mg/l. In addition, the range of Bicarbonate (HCO_3^-) ion is 200 mg/l in the drinking water. In this study, the HCO_3^- ion varies from 82.9166 to 671 mg/l with an average value of 342 mg/l. Further, the fair range of Fluoride (F^-) ion is 1 mg/l and the permissible range is 1.5 mg/l in the drinking water. In addition, the F^- ion varies from 0.008 to 2 mg/l with an average value of 0.73 mg/l.

Table 6. Physico-chemical characteristics of water samples

Well No	TDS	NO_2^- $+NO_3^-$	Ca^{2+}	Mg^{2+}	Na^+	K^+	Cl^-	SO_4^{2-}	HCO_3^-	F^-	pH	EC	CO_3^-	Hardness
53606	561	7	32	26.73	69	111	74	35	292.8	1.05	8.7	910	36	190
53914	656	6	22	41.31	138	41	177	36	286.7	1.47	8.6	1140	30	225
HP1S14	460	14	26	13.36	115	15	128	22	128.41	0.14	8.1	770	1.51	120
HP1S15	686	4	34	26.73	184	15	156	62	323.3	2	8.7	1210	30	195
HP1S17	519	8	34	52.24	78	10	46	58	384.3	1.96	8.4	950	12	300
HP1S21	897	15	28	119.07	124	8	234	101	408.7	1.52	8.3	1670	12	560
HP2S04	1019	2	24	63.18	276	14	248	104	463.6	1.8	8.8	1810	48	320
53603	1758	84	88	208.98	196	16	469	149	463.6	0.42	8	3060	16	1080
53615	848	25	48	72.9	140	13	213	96	305	0.36	8	1470	19	420
53616A	397	1	28	31.59	71	5	106	53	159.22	0.09	7.7	710	0.75	200
53617	475	2	22	23.08	124	5	135	48	178.27	0.09	8	820	1.67	150
53851	719	8	32	24.3	175	37	223	86	213.5	0.35	7.9	1200	0.98	180
53860	986	56	86	112.99	99	10	199	67	317.2	0.76	7.9	1760	19	680
53862	801	35	28	61.96	159	4	156	91	292.8	0.5	7.8	1320	0.87	325
53902	1151	26	24	99.63	239	27	277	95	542.9	0.83	8	2040	0.35	470
53907	1200	9	20	65.61	340	13	418	53	500.2	1.12	8	2120	39	320
53910	1766	8	130	3.64	435	16	496	69	311.1	0.43	7.7	3080	29	340
HP2S10	381	17	34	24.3	60	4	35	58	149.08	0.15	7.8	620	0.88	185
HP2S13	499	5	24	34.02	110	6	113	62	208.73	0.13	7.8	900	1.23	200

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

According to WHO, the pH limit of groundwater is 8.5 and the EC limit is 750 $\mu s/cm$ for drinking purpose. In this study, pH value ranges from 7.7 to 8.9 with an average pH value of 8.3. EC ranges from 620 $\mu s/cm$ to 10000 $\mu s/cm$ with an average value of 3981 $\mu s/cm$. In this research study, the maximum CO_3^- range is 60 mg/l, which is acceptable for drinking purpose. On the other hand, the acceptable range of hardness is 300 mg/l for drinking purpose. In this study, the hardness varies from 65 to 2000 mg/l with an average value of 387 mg/l.

4.3.5. Sodium Adsorption Ratio (SAR)

SAR index is an effective groundwater quality parameter, which is utilized in the management of sodium-affected soil. The SAR index is an indicator utilized for analyzing the suitability of water for irrigation purpose and it is a diagnostic parameter to find the sodicity hazard of a soil. A higher concentration of Na^+ in water leads to the formation of alkaline soil and the higher salt concentration in groundwater leads to the formation of saline soil. On the basis of SAR value, the water samples are categorized into 4 types such as very high alkali waters (SAR>18), high alkali waters (SAR ranges 12-18), medium alkali waters (SAR ranges 6-12), and lower alkali water (SAR<6). As mentioned in Table 7, SAR index value ranges from 1 to 18.

Table 7. SAR value of sample locations

Well No	Well Type	Latitude	Longitude	SAR
53606	Dug Well	11°14'40"	78°14'00"	2.178394
53616A	Dug Well	11°05'18"	78°04'35"	2.097258
53617	Dug Well	11°06'35"	78°00'40"	3.593767
53851	Dug Well	11°35'20"	77°26'48"	4.951956
53862	Dug Well	11°30'42"	78°05'45"	2.873303
53902	Dug Well	11°07'15"	78°07'40"	4.948967
53907	Dug Well	11°29'10"	78°02'05"	6.537004
53914	Dug Well	11°15'50"	77°50'05"	4.003014
HP1S14	Bore Well	11°21'00"	78°06'35"	4.568943
HP1S15	Bore Well	11°14'15"	78°09'05"	5.734164
HP1S17	Bore Well	11°14'40"	78°14'00"	1.95951
HP1S21	Bore Well	11°19'45"	78°18'25"	2.279728
HP2S04	Bore Well	11°25'00"	78°00'20"	6.712935
53603	Dug Well	11°24'20"	78°15'40"	2.594947

4.3.6. Residual sodium carbonate (RSC)

The RSC index value of soil water or irrigation water is utilized to represent the alkalinity hazard of soil. The water samples with <2.5 RSC is appropriate for irrigation, >2.5 RSC is considerably appropriate for agriculture and the RSC with >5 is inappropriate for irrigation. As indicated in Table 8, the RSC index value ranges from 0.5 to 8 with an average index value of 2.1 (Figures 4 and 5).

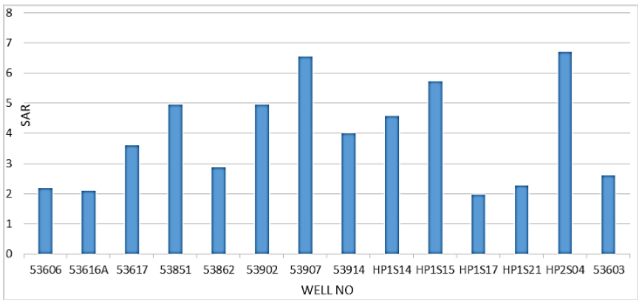


Figure 4. SAR value of sample and Sources

Table 8. RSC index value of sample locations

Well No	Well Type	RSC
53606	Dug Well	2.202857
53912AY	Bore Well	0.5048379
53914	Dug Well	1.202169
HP1S15	Bore Well	2.402981
HP1S17	Bore Well	0.7032822
HP2S04	Bore Well	2.802349
53901	Bore Well	1.301326
53907	Dug Well	1.801932
MWSN09	Bore Well	8.000062

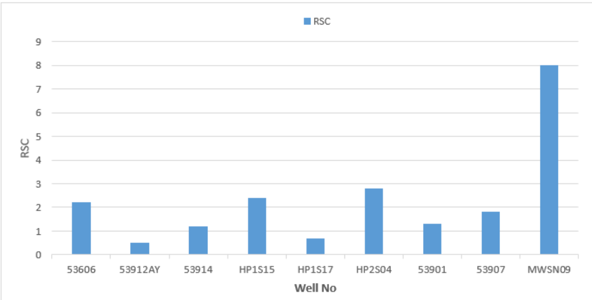


Figure 5. RSC index value of sample and Sources

4.3.7. Sodium percentage and Water Quality Index

For irrigation purpose, the sodium percentage is used to validate the suitability of groundwater, which is denoted in Table 9. The WQI value is used to monitor and assess the quality of groundwater to understand the issues by integrating the complex data. In order to compute the WQI value, fourteen Physio-chemical parameters like major anions (NO_2^- +NO_3^-, CO_3^-, F^-, HCO_3^-, Cl^- and SO_4^{2-}), major cations (K^+, Mg^{2+}, Ca^{2+} and Na^+), hardness, EC, TDS and pH are utilized. Based on the relative importance of the Physio-chemical parameters, the overall groundwater quality is determined by using the equations (1-4) (Figure 6).

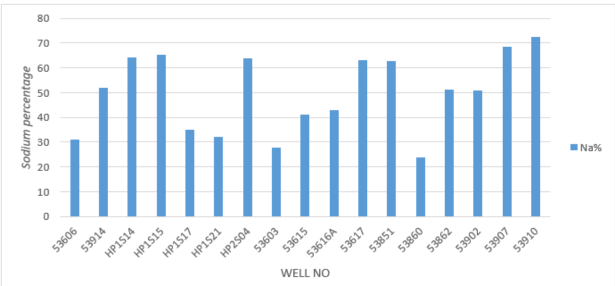


Figure 6. Na% of sample and Sources

WQI value is classified into 5 types like <50 value (pure water), 50-100 value (appropriate water), 100-200 value (contaminated water), 200-300 value (highly contaminated water) and >300 value (inappropriate) for drinking. In this research, the WQI usually ranges between 30 to 280 with an average value of 39. From the acquired 800 samples, 22% of the acquired samples are appropriate for drinking, 63% of the acquired samples are better for drinking, and then the residual 15% of the acquired samples are majorly suitable for irrigation purpose.

Table 9. Na% of sample locations

Well No	Well Type	Latitude	Longitude	Na%
53606	Dug Well	11°14'40"	78°14'00"	31.14434
53914	Dug Well	11°15'50"	77°50'05"	51.97778
HP1S14	Bore Well	11°21'00"	78°06'35"	64.26964
HP1S15	Bore Well	11°14'15"	78°09'05"	65.1568
HP1S17	Bore Well	11°14'40"	78°14'00"	35.17882
HP1S21	Bore Well	11°19'45"	78°18'25"	32.1175
HP2S04	Bore Well	11°25'00"	78°00'20"	63.99409
53603	Dug Well	11°24'20"	78°15'40"	27.93159
53615	Dug Well	11°14'35"	78°05'55"	41.10088
53616A	Dug Well	11°05'18"	78°04'35"	42.816
53617	Dug Well	11°06'35"	78°00'40"	63.31297
53851	Dug Well	11°35'20"	77°26'48"	62.62524
53860	Dug Well	11°30'30"	78°08'45"	23.72338
53862	Dug Well	11°30'42"	78°05'45"	51.17468
53902	Dug Well	11°07'15"	78°07'40"	50.75506
53907	Dug Well	11°29'10"	78°02'05"	68.72719
53910	Dug Well	11°20'10"	77°58'00"	72.44521

4.3.8. Kelly Index and Magnesium hazard

In groundwater, the higher concentration of magnesium affects the soil quality by increasing the alkalinity of soil that leads to limited crop yield. Groundwater with <50 magnesium is harmful and inappropriate for irrigation purpose. In this study, the magnesium hazard value varies from 19 to 72 with a mean of 36. Additionally, the Kelly's index with <1 is appropriate for irrigation purpose and >1 is not suitable for irrigation. In this study, the Kelly's index value varies from 0.11 to 7 with a mean of 4.82.

5. Conclusion

- The groundwater quality is predicted by utilizing AlexNet model for investigating its suitability. The experimental investigation showed that the

AlexNet model has obtained 93%, 94.57%, and 91.47% of accuracy, specificity and sensitivity in the water quality prediction, which are better compared to other deep learning models.

- The majority of the water samples collected fall within the permitted limits specified by the Bureau of Indian Standards, which successfully regulates the environmental conditions, according to the experimental results of the physico-chemical examination of the samples.
- According to Kelly's index, 30% of the samples collected during the experimental phase are ideal for irrigation, whereas 70% of the samples collected are improper. WQI results show that 22% of collected samples are excellent, 63% of collected samples are good for consumption, and 15% of collected samples are primarily suited for irrigation.
- Furthermore, SAR indicates that 38% of the collected samples have higher alkali water content, whereas the remaining samples have lower alkali water content. As the feature extension, a feature extraction module is included in the AlexNet model for further improving the performance of groundwater quality prediction.

References

Acharya, S., Sharma, S. K., & Khandegar, V. (Jun. 2018). Assessment of groundwater quality by water quality indices for irrigation and drinking in South West Delhi, India. Data in Brief, 18, 2019-2028. https://doi.org/10.1016/j.dib.2018.04.120

Adimalla, N. (Feb. 2020). Spatial distribution, exposure, and potential health risk assessment from nitrate in drinking water from semi-arid region of South India. Human and Ecological Risk Assessment: An International Journal, 26(2), 310-334. https://doi.org/10.1080/10807039.2018.1508329

Adimalla, N., & Qian, H. (Jul. 2019). Groundwater quality evaluation using water quality index (WQI) for drinking purposes and human health risk (HHR) assessment in an agricultural region of Nanganur, south India. Ecotoxicology and environmental safety, 176, 153-161. https://doi.org/10.1016/j.ecoenv.2019.03.066.

Adimalla, N., & Taloor, A. K. (Apr. 2020). Hydrogeochemical investigation of groundwater quality in the hard rock terrain of South India using Geographic Information System (GIS) and groundwater quality index (GWQI) techniques. Groundwater for Sustainable Development, 10, 100288. https://doi.org/10.1016/j.gsd.2019.100288

Adimalla, N., Dhakate, R., Kasarla, A., & Taloor, A. K. (Apr. 2020). Appraisal of groundwater quality for drinking and irrigation purposes in Central Telangana, India. Groundwater for Sustainable Development, 10, 100334. https://doi.org/10.1016/j.gsd.2020.100334

Adimalla, N., Li, P., & Venkatayogi, S. (Jun. 2018). Hydrogeochemical evaluation of groundwater quality for drinking and irrigation purposes and integrated interpretation with water quality index studies. Environmental Processes, 5(2), 363-383. https://doi.org/10.1007/s40710-018-0297-4

Aher, K. R., & Gaikwad, S. G. (2017). Irrigation groundwater quality based on hydrochemical analysis of Nandgaon block, Nashik district in Maharashtra. International Journal of Advanced Geosciences, 5(1), 1-5. https://doi.org/10.14419/ijag.v5i1.7116

Ahmed, U., Mumtaz, R., Anwar, H., Shah, A. A., Irfan, R., & García-Nieto, J. (Oct. 2019). Efficient water quality prediction using supervised machine learning. Water, 11(11), 2210. https://doi.org/10.3390/w11112210

Arulbalaji, P., & Gurugnanam, B. (Oct. 2017). Groundwater quality assessment using geospatial and statistical tools in Salem District, Tamil Nadu, India. Applied Water Science, 7(6), 2737-2751. DOI:10.1007/s13201-016-0501-5

Barik, R., & Pattanayak, S. K. (Apr. 2019). Assessment of groundwater quality for irrigation of green spaces in the Rourkela city of Odisha, India. Groundwater for Sustainable Development, 8, 428-438. https://doi.org/10.1016/j.gsd.2019.01.005

Cabello, C. A., Canini, N. D., & Lluisma, B. C. (Aug. 2022). Water quality assessment of Dodiongan Falls in Bonbonon, Iligan City, Philippines. AIMS Environmental Science, 9(4), 526-537. https://doi.org/10.3934/environsci.2022031

Chaurasia, A. K., Pandey, H. K., Tiwari, S. K., Prakash, R., Pandey, P., & Ram, A. (Jul. 2018). Groundwater quality assessment using water quality index (WQI) in parts of Varanasi district, Uttar Pradesh, India. Journal of the Geological Society of India, 92(1), 76-82. https://doi.org/10.1007/s12594-018-0955-1

Chebet, E. B., Kibet, J. K., & Mbui, D. (Apr. 2020). The assessment of water quality in river Molo water basin, Kenya. Applied Water Science, 10(4), 92. https://doi.org/10.1007/s13201-020-1173-8

Divahar, R., Raj, P. A., Sangeetha, S. P., Mohanakavitha, T., & Meenambal, T. (Oct. 2020). Dataset on the assessment of water quality of ground water in Kalingarayan Canal, Erode district, Tamil Nadu, India. Data in Brief, 32, 106112. https://doi.org/10.1016/j.dib.2020.106112

Hossain, M., Patra, P. K., Begum, S. N., & Rahaman, C. H. (Dec. 2020). Spatial and sensitivity analysis of integrated groundwater quality index towards irrigational suitability investigation. Applied Geochemistry, 123, 104782. https://doi.org/10.1016/j.apgeochem.2020.104782

Jain, C. K., & Vaid, U. (Mar. 2018). Assessment of groundwater quality for drinking and irrigation purposes using hydrochemical studies in Nalbari district of Assam, India. Environmental earth sciences, 77(6), 254. https://doi.org/10.1007/s12665-018-7422-6

Kadam, A. K., Wagh, V. M., Muley, A. A., Umrikar, B. N., & Sankhua, R. N. (Sep. 2019). Prediction of water quality index using artificial neural network and multiple linear regression modelling approach in Shivganga River basin, India. Modeling Earth Systems and Environment, 5(3), 951-962. https://doi.org/10.1007/s40808-019-00581-3

Khan, R., & Jhariya, D. C. (Jul. 2017). Groundwater quality assessment for drinking purpose in Raipur city, Chhattisgarh using water quality index and geographic information system. Journal of the Geological Society of India, 90(1), 69-76. https://doi.org/10.1007/s12594-017-0665-0

Khatri, N., Tyagi, S., Rawtani, D., Tharmavaram, M., & Kamboj, R. D. (Apr. 2020). Analysis and assessment of ground water quality in Satlasana Taluka, Mehsana district, Gujarat, India through application of water quality indices. Groundwater for

Sustainable Development, 10, 100321. https://doi.org/10.1016/j.gsd.2019.100321

Kim, S., Alizamir, M., Seo, Y., Heddam, S., Chung, I.-M., Kim, Y.-O., Kisi, O., & Singh, V. P. (Sep. 2022). Estimating the incubated river water quality indicator based on machine learning and deep learning paradigms: BOD5 Prediction. Mathematical Biosciences and Engineering, 19(12), 12744-12773. https://doi.org/10.3934/mbe.2022595

Klopp, H. W., & Daigh, A. L. M. (Jul. 2020). Measured saline and sodic solutions effects on soil saturated hydraulic conductivity, electrical conductivity and sodium adsorption ratio. Arid Land Research and Management, 34(3), 264-286. https://doi.org/10.1080/15324982.2019.1672221

Li, L., Jiang, P., Xu, H., Lin, G., Guo, D., & Wu, H. (Jul. 2019). Water quality prediction based on recurrent neural network and improved evidence theory: a case study of Qiantang River, China. Environmental Science and Pollution Research, 26(19), 19879-19896. https://doi.org/10.1007/s11356-019-05116-y

Liu, P., Wang, J., Sangaiah, A. K., Xie, Y., & Yin, X. (Apr. 2019). Analysis and prediction of water quality using LSTM deep neural networks in IoT environment. Sustainability, 11(7), 2058. https://doi.org/10.3390/su11072058

Maurya, J., Pradhan, S. N., Seema, & Ghosh, A. K. (2021). Evaluation of ground water quality and health risk assessment due to nitrate and fluoride in the Middle Indo-Gangetic plains of India. Human and Ecological Risk Assessment: An International Journal, 27(5), 1349-1365. https://doi.org/10.1080/10807039.2020.1844559

Ponsadailakshmi, S., Sankari, S. G., Prasanna, S. M., & Madhurambal, G. (Mar. 2018). Evaluation of water quality suitability for drinking using drinking water quality index in Nagapattinam district, Tamil Nadu in Southern India. Groundwater for Sustainable Development, 6, 43-49. https://doi.org/10.1016/j.gsd.2017.10.005

Prasad, M., Sunitha, V., Reddy, Y. S., Suvarna, B., Reddy, B. M., & Reddy, M. R. (Jun. 2019). Data on water quality index development for groundwater quality assessment from Obulavaripalli Mandal, YSR district, AP India. Data in Brief, 24, 103846. https://doi.org/10.1016/j.dib.2019.103846

Rahman, A., Tiwari, K. K., & Mondal, N. C. (Nov. 2020). Assessment of hydrochemical backgrounds and threshold values of groundwater in a part of desert area, Rajasthan, India. Environmental Pollution, 266(Part 3), 115150. https://doi.org/10.1016/j.envpol.2020.115150

Rao, N. S. (Mar. 2018). Groundwater quality from a part of Prakasam district, Andhra Pradesh, India. Applied Water Science, 8(1), 30. https://doi.org/10.1007/s13201-018-0665-2

Ravish, S., Setia, B., & Deswal, S. (Nov. 2020). Groundwater quality and geochemical signatures in the northeastern Haryana, India. Arabian Journal of Geosciences, 13(21), 1145. https://doi.org/10.1007/s12517-020-06094-z.

Srinivasamoorthy, K., Nanthakumar, C., Vasanthavigar, M., Vijayaraghavan, K., Rajivgandhi, R., Chidambaram, S., Anandhan, P., Manivannan, R., & Vasudevan, S. (Feb. 2011). Groundwater quality assessment from a hard rock terrain, Salem district of Tamilnadu, India. Arabian Journal of Geosciences, 4(1-2), 91-102. DOI:10.1007/s12517-009-0076-7

Srivastava, S. K. (May 2019). Assessment of groundwater quality for the suitability of irrigation and its impacts on crop yields in the Guna district, India. Agricultural water management, 216, 224-241. https://doi.org/10.1016/j.agwat.2019.02.005

Yang, H., & Liu, S. (Sep. 2021). A prediction model of aquaculture water quality based on multiscale decomposition. Mathematical Biosciences and Engineering, 18(6), 7561-7579. https://doi.org/10.3934/mbe.2021374

Santhosh Kumaar K., Muralimohan N., Kulanthaivel P. and Sathiskumar S. "Spatial Analysis of Ground water and their treatment with Low-Cost Ceramic membrane" 2022; 23(6): 892-901.

Sivabalaselvamani D., Kulanthaivel P., Yogapriya J. and Inderjit Singh Dhanoa "Study on engineering strength properties of ceramic waste powder stabilized expansive soil using machine learning algorithms" 2022; 23(6): 902-911.

Shanmugasundaram V and Shanmugam B. Application of cement treated magnesite mine tailings as subgrade. Construction and Building Materials. 2023 Feb 15;365:130064.https://doi.org/10.1016/j.conbuildmat.2022.130064.

Hendrawan Y., Rohmatulloh B, Ilmi F.I., Fauzy M.R., Damayanti R., Al Riza D.F., Hermanto M.B. and Sandra, AlexNet convolutional neural network to classify the types of Indonesian coffee beans, IOP Conf. Series: Earth and Environmental Science 905 (2021) 012059, doi:10.1088/1755-1315/905/1/012059

Kaish M, Khan MA. Evaluation of water quality of some small water bodies of Aligarh, Uttar Pradesh. Proceedings of International Conference on Emerging Technologies for Sustainable Environment A.M.U. Aligarh, India. 2010; Oct: 176-180.

Tiwari M, Shukla NK, Kumar V, Sharma GD, Gupta MK, Singh A, Toppo P, Tiwari MK. Assessment of groundwater quality of Hamirpur district, Uttar Pradesh, India. Int J of current microbiology and applied Sci. 2015; 4(1):597- 603.