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Application of Artificial Intelligence in addressing Land degradation: A case study of Jumar watershed, Ranchi, Jharkhand

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ABSTRACT

Land degradation is a globally recognized problem, causing a whooping damage of billions for both developed and developing countries. The purpose of the study is to understand the role and potential of AI-based models in analysing water quality which is one of the crucial indicators of land degradation. Through the literature analysis, it has been found that models like Artificial neural network (ANN), Support Vector Mechanism (SVM), Classification and Regression trees (CART), random forest (RF), XGBoost (XGB) etc., are widely used and exhibit higher accuracy in regression, modelling, and prediction of water quality data. For the understanding of the application of a few of these models, a case study of the Jumar watershed of Ranchi is chosen to predict the Water Quality Index (WQI) using the seasonal physiochemical data of water quality parameters for the years 2021 and 2022. 29 surface water sampling sites were selected for laboratory analysis based on APHA and IS 10500:2012. The results have been analysed using standards provided by WHO, BIS, and ICMR, and crucial parameters were extracted using Principal component analysis (PCA). The data indicated poor water quality throughout the year for both 2021 and 2022. The WQI has been determined using the Weighted water quality index (WWQI) and predicted using SVM, ANN and CART models. The results show that ANN (R2 =0.29) has comparatively poor performance while the SVM (R2 = 0.82) and CART (R2 = 0.90) models were found to be best in water quality prediction for the Jumar watershed. The data was validated using RSME which was found to be less for SVM and CART compared to ANN. It could be concluded that the CART model was best for predicting the surface water quality index of the Jumar watershed among the applied machine learning algorithms.

KEYWORDS

Artificial intelligence; Artificial neural network; CART; SDG; soil quality; Support Vector Mechanism; water quality; Weighted water quality index.

ABBREVIATIONS

APHA- American Public Health Association
BIS- Bureau of Indian Standards
CART- Classification and Regression tree
ICMR- Indian Council of Medical Research
PCA- principal component analysis
RF- Random Forest
RSME- Root Mean Square Error
SDG- sustainable development goals
SVM -Support Vector Mechanism
UN- United Nations
WHO-World health organisation
WQI- Water Quality Index
XGB-XG Boost

1. INTRODUCTION

Addressing land degradation stands as a significant challenge within the framework of the United Nations formulated 'sustainable development goal 15: life on land' aimed to be achieved by 2030. Problems of land degradation are more prominent in Asian (US$84 billion) and African (US$65 billion) countries, although no country is free of this ever-looming issue [1]. Out of 80 substantially identified countries under land degradation, 36 lie under Africa. Identification, control, and management of the Land degradation process is an arduous task. There is a severe lack of data, monitoring, and future predictions regarding the problem [2]. Most countries do not have proper resources and plans to address and monitor the ecological issues. Practically, the environmental components do not function alone, they all have synergistic effects on land processes [3]. Every country has its own topography, climate, resource distribution, population, socio-culture, and economic constraints making it nearly impossible to identify the exact cause of land degradation. Hence without the complete picture, it is hard to make conservation management and plans [4].

The common land degradation issues acclaimed globally such as desertification, soil erosion and fatigue, land pollution, deterioration in quality water and soil resources, and loss of crop productivity, all of which result in socio-economic losses [5]. Among these factors water stress and water quality have been considered quite important as water being a natural solvent can show early signs of contamination compared to soil resources which have higher resilience towards pollutants. Urbanisation, climate mitigation, exponentially growing population, industrialisation, mining, overuse of Agro-chemicals, overgrazing, and change in Land use land cover have been known to be the main drivers of land degradation [6]. The cities catering to most of the world's population are all suffering from water scarcity and stress. Countries like Pakistan, Lebanon, Syria, Nepal, Afghanistan, Turkey, etc. are ranked as the most water-stressed areas by the International Monetary Fund and UN-Water reports of 2022.

To solve these issues, an advancing technique of Artificial intelligence (AI) has been gaining popularity, globally. AI was introduced in 1950, as a branch of computer science that would help develop machine models based on human intelligence [7]. AI collects information like a human brain, analyses, processes, predicts, and solves problems mimicking Human intelligence or the human brain [8]. Some common examples of the application of AI were seen during the COVID-19 period when AI-based

Apps like AarogyaSetu helped in collecting data on patients, warning against possible contamination zones, diagnosis of disease etc. In times of COVID-19, the role of AI in the prediction of problems was seen prominently in different fields of environment and related fields. The impact of climate and urbanization on COVID cases was studied using the MLR model by Pirouz et al., (2020) [9]. AI-based models like deep learning, machine learning, Artificial neural networks, and Bayesian networks [10], have been known to address problems related to agriculture, soil erosion, water stress and scarcity etc.

In this study, the purpose was to (1) determine the physio-chemical factors that affect the surface water quality in watersheds using PCA. (2) Then using the extracted factors calculate WQI on overall data (3) Apply AI-based models such as SVM, CART and ANN for predicting the surface water quality index of the Jumar watershed. This study will provide a glimpse of the potential of AI in monitoring and predicting the indicators of land degradation [11].

2. MATERIAL AND METHODOLOGY

2.1 Study area

For the study, the Jumar River watershed lying in Ranchi district, Jharkhand, covering an area of 289 sq. km. was selected (Figure 1). The watershed is agrarian and has a rainfed agriculture with a prominent monocropping of paddy in monsoon. The watershed has a sub-humid climate with a rolling undulated surface. The geology of the area consists of pre-Cambrian rock [12].

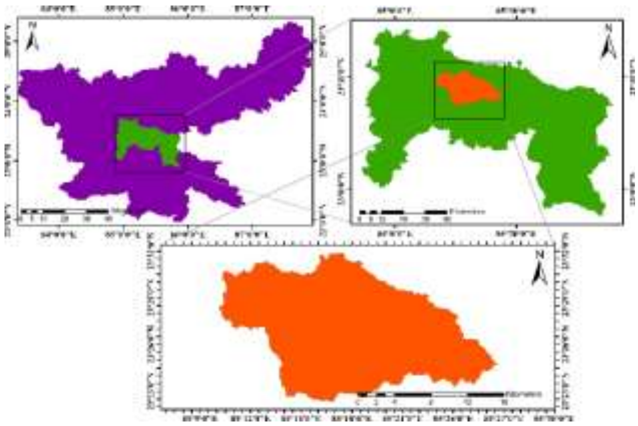

Fig. 1 Map of Jumar watershed in Ranchi, Jharkhand

The soil series dystric Nitosols and lithosols are found prominently in the region. The average rainfall varies between 1200-1400 mm annually. The locals utilize the water from surface resources like ponds and rivers through pumps for agriculture and daily use. Through seasonal site investigation it has been found that the area suffers from water stress in summers and winters [13], [14].

2.2 Mechanism of AI

AI is the modern tool of the 21st century and can be used for identification and solving any problem requiring human intelligence [15]. Currently, AI-based models are being used for functions of future predictions, pattern recognition, evaluation problem solving etc. Some major advantages of AI-based models are they can easily handle missing and non-linear values and data while post-training, it is easier to predict the data at high speed and accuracy.

Among various types of AI-based tools, machine learning (ML) is one in most demand and usually trains data through supervised, unsupervised and reinforcement training [16]. Supervised learning consists of regression and prediction models, in which the model is trained by dividing the data into 70:30 ratio or 80:20 ratio, ('i.e., 70 % of data is used for training while 30% is used for testing'). It is mostly based on ANN [17]

Using boosted regression tree (BRT), alternative decision tree (ADT), random forest (RF) etc., the erosion factors were analysed prioritized and validated using Receiver operating characteristics (ROC) and the models i.e., BRT, ADT, and RF show notable accurateness with ROC values [18]. AI-based models can be easily used for climate trend analysis. Global climate models (MIROC5, EC-EARTH, CNRM-CM5, etc.,) were studied for rainfall projection in the Himalayan region by Iqbal et al., (2020) using 'Support Vector Machine Recursive Feature Elimination' (SVM-RFE) algorithm [19]. Relation in climate, human activities and vegetation using the Normalized difference vegetation index (NDVI) in China was done by Shi et al., (2020) [20] Similarly, Urban water resource management was studied by Xiang et al., (2021) as AI models have the influential capacity to logically examine, model, be flexible, and predict the water demand and capacity. Hence, the Application of AI-based models has been successfully utilized in addressing the indicators and factors of Land degradation.

2.3 Water quality analysis

Water is a universal solvent and its contamination can indicate environmental and land degradation easily [21]. The trend in water quality parameters helps in understanding change in contamination level, change in water quality etc. Turbidity, Hardness, Dissolved Oxygen (DO), Biological Oxygen Demand (BOD), Total dissolved solids (TDS), pH, Electrical conductivity (EC), Sodium (Na^+), Potassium (K^+), Magnesium (Mg^{2+}), Calcium (Ca^{2+}) and Nitrate (NO_3^-) were analysed for the winter (November), summer (April) and monsoon (July) seasons of 2021 and 2022. The samples were taken from J1 to J29 at different sites of the major water bodies including River Jumar, present in the watershed (Figure 2). The permissible limit and method of analysis are provided in Table 1. The results were analysed based on the APHA, WHO and BIS 10500 standards [22]

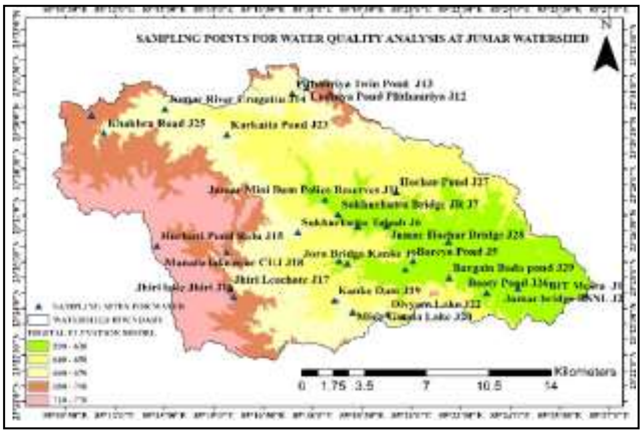

Fig. 2 Surface water sampling sites for monitoring water quality at Jumar watershed

Table. 1 Parameters selected using PCA for WQI prediction based on IS, WHO, and ICMR standard

Parameters	Standard	APHA and IS 10500:2012 based Analytical Methods
pH	6.5-8.5 (IS 10500)	pH- meter
Dissolved Oxygen (DO)	5 (ICMR)	DO kit
Biochemical Oxygen Demand (BOD)	5 (ICMR)	Winkler Azide method
Hardness	200 (IS 10500)	Titrimetric
Calcium (Ca^{2+})	75 (IS 10500)	ICP-OES
Chloride (Cl^{-})	250 (IS 10500)	Titrimetric
Magnesium (Mg^{2+})	30 (IS 10500)	ICP-OES
Alkalinity	200 (IS 10500)	Titrimetric
Electrical conductivity (EC)	500 (WHO)	Gravimetric
Total Dissolved Solid (TDS)	500 (IS 10500)	Gravimetric
Potassium (K^{+})	12 (IS 10500)	ICP-OES
Sodium (Na^{+})	30 (IS 10500)	ICP-OES
Nitrate (NO_3^{-})	45 (IS 10500)	Spectrophotometry
Turbidity	10 (NTU) (IS 10500)	Turbidity meter

2.4 Water Quality Index (WQI)

The weighted water quality index was developed by Brown et al. in 1970 and has since been widely used, especially for region-specific studies [23]-[24]. This method has a broader approach and can accommodate multiple parameters. This index converts the values of multiple parameters into a single unitless number, ranging between 0-100, with the quality defined between very poor to excellent [25]. Depending on the natural and anthropogenic factors the quality of water may vary [26].

$$\mathrm{WQI} = \frac{(\Sigma\, \mathrm{Qn\, Wn})}{\Sigma\, \mathrm{Wn}} \qquad (1)$$

Q_n= Quality rating of nth water quality parameters; W_n= The unit weight of nth water quality parameters. The quality rating of nth water quality parameters will be calculated using Equation 2

$$\mathrm{Qn} = 100\, \frac{(\mathrm{Vn}-\mathrm{Vi})}{(\mathrm{Vs}-\mathrm{Vi})} \qquad (2)$$

V_n= Actual value which has come after the analysis of that parameter; V_s= Standard value of that parameter; V_i= Ideal value of that parameter (V_i will be 0 of all parameters except pH =7 and DO = 14.6 mg/l); W_n = Unit weight, which will be calculated using the formula

$$W_n = \frac{k}{\mathrm{Vs}} \qquad (3)$$

Where k is the constant proportionality which can be calculated by Equation 4

$$k = [\frac{1}{\Sigma[\frac{1}{\mathrm{Vs}}]} = 1,2,3 \ldots \ldots n] \qquad (4)$$

Then, the obtained index value matched with the quality status range and hence the quality of water is found.

2.5 Principal component analysis

Factor analysis, using principal component analysis (PCA) and Varimax rotation, is a statistical technique that identifies dormant factors in a data set and improves interpretation [27]. Initially, PCA is used to extract items by finding linear combinations of variables that capture the most variance. Varimax rotation is then used to increase the interpretability by optimizing the variation of the squared weights and reducing the cross-weights [28]. This process simplifies object organization and facilitates the interpretation of relationships between variables and objects. It reveals the underlying structure of a dataset and identifies important hidden factors that explain observed variable relationships. The PCA was done using IBM SPSS statistics 26.

2.6 Support Vector Mechanism (SVM)

SVM is one of the most popular supervised learning algorithms in machine learning used for both regression and classification. SVM is used to produce the best hyperplane that can divide n-D space into categories so that new data can be inserted into the correct category in future analysis [29]. This best decision line is known as Hyperplane, which is created by choosing points or vectors hence its algorithm is known as SVM. The first stage of the model is developed by preparing a data set, which is divided into training and testing. The testing data is used post-training for calibration and validation purposes [30]. Function fitting using SVM aims to diminish the variation between observed values and output model Using Eq. 5. In comparison to ANN, SVM's have high human interpretability as they are equidistant to classes while ANN's can be arbitrarily close to classes in learning [11]. SVM was performed using MATLAB R2023a.

$$R_{svm}(\omega, \xi^{*}) = \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^{*}) \qquad (5)$$

Where, ω= normal vector;

$\frac{1}{2}||\omega||^2$ = regularization factor;

C= penalty factor for error

B = bias

ξ = error function

Radial Basis Function RBF Kernel function

It is a commonly used kernel in machine learning used with SVM for finding the non-linear classifier and regression (Using Eq. 6).

$$K(x_i, x_j) = \exp\,(-\gamma\, ||x_i - x_j||)^2 \qquad (6)$$

x_i, x_j = inputs

γ = regularization parameter

2.7 Artificial neural network (ANN)

Artificial neural networks are computational models inspired by the structure and function of biological neural networks in human brains. ANN has interconnected artificial neurons organised into three layers input, hidden and output layers. Each connection has a weight that determines its strength and each neuron exerts different activating functions in the outputs [31]. Figure 3 shows Components of AI and Functioning of ANN models.

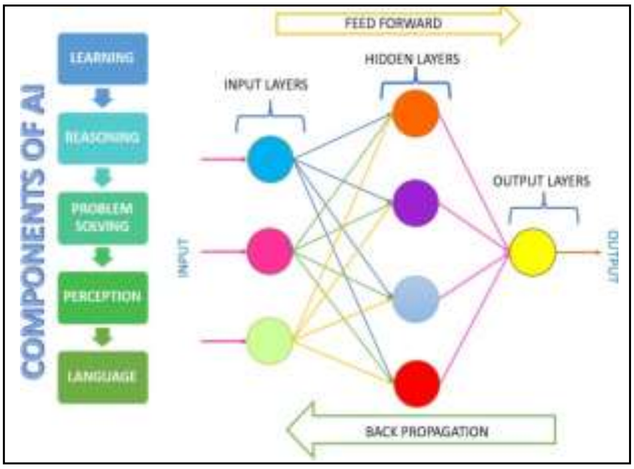

Fig. 3 Components of AI and Functioning of ANN models

Their ability to capture complex, nonlinear relationships in data makes ANNs a powerful tool in machine learning and artificial intelligence, enabling functions such as image classification, language translation and autonomous driving [32]. Although ANN has a lot of advantages such as the size of the network and the number of layers can be a constraint and fast prediction post-training, it also comes with certain drawbacks [33]. For example, it takes longer training time, and the convergence of neural networks is not guaranteed, In a real-world problem the degree of complexity is higher but with constraints on the size of data may not make a good prediction for unseen data. ANN was performed using MATLAB R2023a

2.8 Classification and Regression Trees (CART)

The Classification and Regression Trees (CART) model is a powerful and flexible machine learning tool that has gained prominence for prediction and decision-making tasks [34]. It excels at identifying crucial features within datasets by analysing their tree structure, helping in feature selection dimensionality reduction and anomaly detection. This model helps in the prediction of both categorical and continuous numerical values while maintaining high interpretability, prioritizing transparency, and accountability. It can also capture intricate non-linear relationships in data, accommodating interactions between variables that linear models may struggle to capture, which is an advantage over linear regression models. They handle missing data gracefully, making decisions based on available information for each observation.

3. RESULT AND DISCUSSION

3.1 Physiochemical and WQI analysis

In this study, the mean seasonal value of the water quality parameters was determined. In the present investigation, average turbidity was found to be higher in the monsoon season (98.12 ± 4.11 NTU) for both the years 2021 and 2022 compared to the permissible limit of 10 NTU at all sites. However, the massive increase in turbidity was attributed mostly to surface erosion and high-intensity runoff carried from non-point sources (agricultural lands) in the watershed [35].

Similarly, the results of TDS and EC show a higher increase in the pre-monsoon and winter season as in the Summer and post-monsoon season the water table lowers and the concentration of salts, metals and impurities increase in the water bodies [36]. The parameters such as DO, BOD, chlorine, and nitrate are within permissible limits (Table 1). Alkalinity and Hardness were on the higher side for both the summer season and winter season. It is due to the presence of salts of magnesium and calcium leached in the water through runoff and geogenic sources [37]. The amount of sodium and potassium was also on the higher side in monsoon months, mostly due to surface erosion and sedimentation of the soil rich in these metals. The pH was within the permissible limit but indicated slight alkalinity [38].

The major cause of high metal and salts are due to geogenic causes accelerated by human activities like intensive farming and urbanisation [39]. Additionally, the soil type of the watershed is clayey silty loam and is mainly classified as dystric Nitosols and lithosols that have a rich composition of metals such as calcium, potassium, Magnesium, and Sodium. These types of soil are dispersive and due to a lack of vegetation cover which provides adequate strength against surface erosion, the topsoil gets eroded with intense rainfall [40]. Also, the commercial farmlands are usually mono-cropped and left unsown in post-harvest, due lack of irrigation water. The factor analysis based on PCA was done to extract significant factors from the overall dataset. KMO and Bartlett's sphericity test results are 0.630 and 8404.339 (df =666, p < 0.001), respectively, indicating that factor analysis (FA) using Principal component analysis is effective in reducing the dimensionality of the dataset. In the current study, the FA with varimax rotation yields 13 factors [28](presented in Table 2) with eigenvalues >1 and accounted for about 75.564% of the total variance.

Table. 2 Seasonal average of the surface water quality parameters

Parameters	**Seasonal Average**		
	Pre-Monsoon	Monsoon	Post monsoon
pH	7.87	7.56	7.81
DO (mg/l)	5.49	5.64	5.51
BOD (mg/l)	2.56	2.89	2.56
Hardness (mg/l)	104	99.28	100.07
Ca^{2+} (mg/l)	52.46	54.25	55.27
Cl^- (mg/l)	6.410	9.85	6.6
Mg^{2+} (mg/l)	17.8633	17.1163	17.3971
Alkalinity (mg/l)	138.6453	85.8844	117.826
EC (μS/cm)	522.63	460.25	499.72
TDS (mg/l)	256.53	225.35	246.21
K^+ (mg/l)	25.46	32.45	12.48
Na^+ (mg/l)	23.45	27.48	38.12
NO_3^- (mg/l)	21.6532	10.0904	11.4300

Turbidity (NTU)	6	79	9
WQI	68.145 (Poor)	73.486 (Very Poor)	69.45 (Poor)

Applying the significant parameters, in the water quality index (Equation (1-4)) the WQI was determined. The seasonal WQI indicated 'poor' water quality in all seasons, and 'very poor' in monsoon season. the increased salts, pH alkalinity, hardness, and metal concentration in summer while, increased turbidity and nitrate in monsoon make the water unfit for human consumption [41]. The decreasing trend observed in the water quality index shows that with time the water quality will further deteriorate. This could be because of increased urbanisation, climate change and agro-chemical-based intensive farming. Hence, it is crucial to monitor and predict water quality so that both human health and agricultural productivity are not badly affected [42].

Table. 3 Performance of AI Algorithms in water quality prediction

WQI output	**R^2**		**RMSE**	
	Training	Testing	Training	Testing
SVM (70:30)	0.79	0.77	0.069	0.072
SVM (80:20)	0.82	0.79	0.077	0.08
ANN (70:30)	0.49	0.29	0.35	0.48
CART	0.92	0.90	0.078	0.087

3.2 Prediction using SVM

To predict the WQI of the Jumar watershed, the SVM has been performed using the Radial basis function (RBF) on the dataset by dividing the data first into 70:30 ratio, that is 70 % training and 30 % testing [30]. The training accuracy or goodness of fit, R^2 was found to be around 79%, while the testing accuracy was about 77%. The root mean square error was lower during training about 6.9% while 7.2% was found during testing (Table 3).

To enhance the training accuracy the dataset was again divided into an 80:20 ratio and a slight improvement in the prediction model was observed [11]. The training accuracy R^2 was found to be around 82%, while the testing accuracy was about 79%. The root mean square error (RMSE) during training was about 7.7 % while an RMSE of 8 % was found during testing (Figure 4).

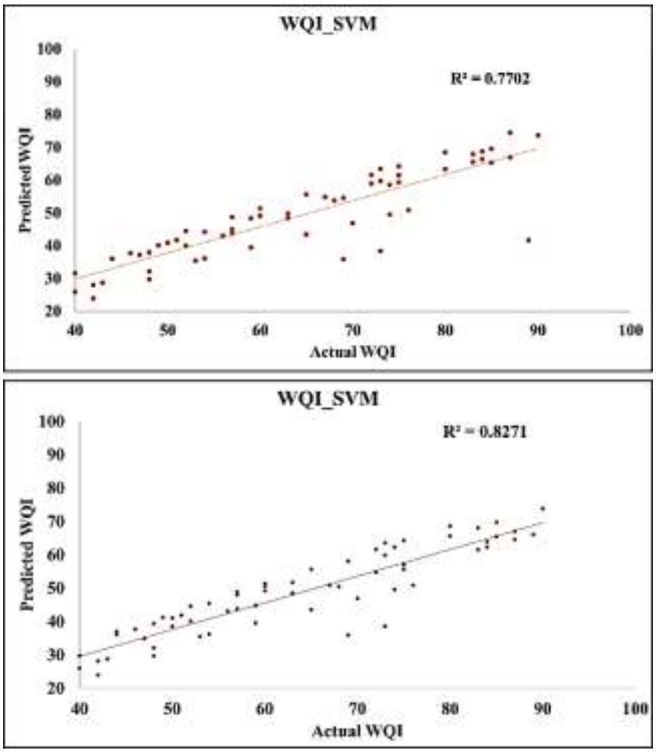

Fig. 4 Scatter plots displaying relationships between measured and estimated values of the water quality index (WQI) (A) 70:30 data training to testing ratio (B) 80:20 data training to testing ratio

3.3 Prediction using ANN

The WQI model prediction was also done using an Artificial neural network (ANN) with a dataset divided into 70% training and 30 testing. The testing data was further divided into 15% validation and 15 % testing with 10 hidden layers [43].

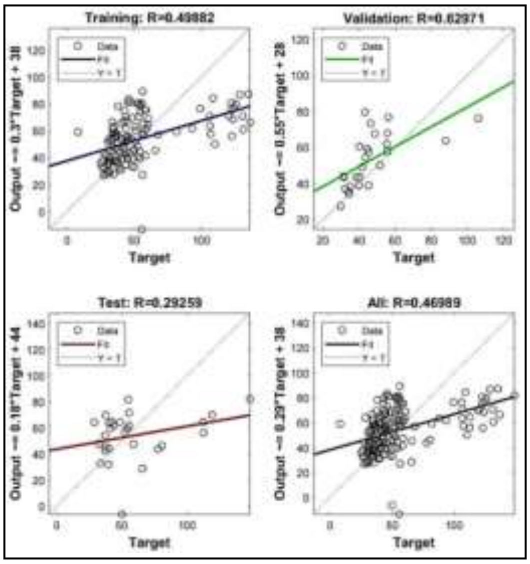

Fig. 5 Scatter plots displaying relationships between measured and estimated values of the water quality index

The ANN performed poorly compared to other AL-based algorithms in predicting WQI. The training accuracy R^2 was found to be around 49%, the validation accuracy was about 62%, and the testing accuracy was about 29%. The root mean square error (RMSE) during training was about 35 %

while RMSE of 48 % was found during testing (Figure 5). Further changes in the testing ratio of the dataset made no significant changes. Literature suggests that the application and accuracy of ML algorithms are data dependent and hence may not apply to all kinds of data efficiently [17], [44].

3.4 Prediction using CART

Using the Classification and regression tree (CART) algorithm the WQI was predicted for the surface water quality of the Jumar watershed [45]. The training accuracy R^2 was found to be around 92%, while the testing accuracy was about 90%. The root mean square error (RMSE) during training was about 7.8 % while RMSE of 8.7 % was found during testing (Figure 6). The CART model performed best among the three ML algorithms used for prediction analysis.

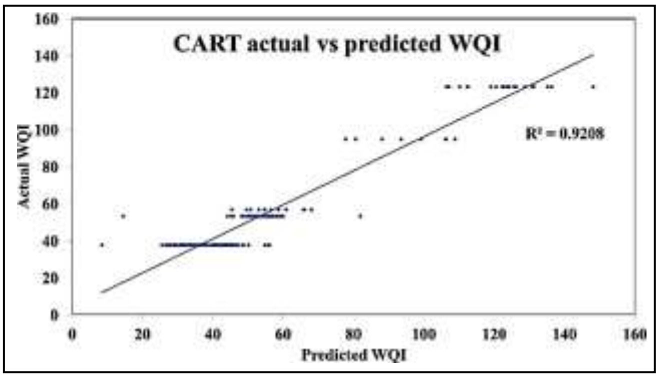

Fig. 6 Scatter plots displaying relationships between measured and estimated values of the water quality index

The interpretability of CART models facilitated a deeper understanding of the factors influencing WQI. The most relative variable was found to be Turbidity, TDS, EC and K^+ with relative importance in percentages higher than 5% [18]. While other parameters had lower (≤ 5%) importance. The optimal tree obtained based on the 13 input parameters is presented below in (Figure 7).

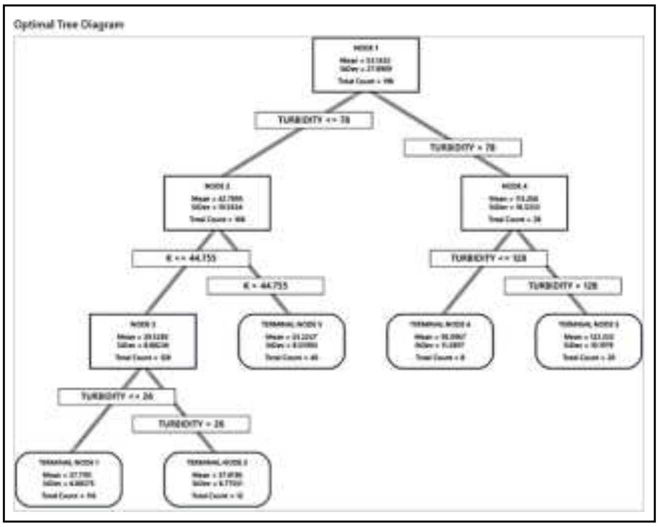

Fig. 7 Optimal tree diagram obtained for WQI prediction.

4. CONCLUSION

In conclusion, the research highlights the critical issue of land degradation and deals with the monitoring and prediction of water quality index, which acts as a crucial indicator. The land degradation issue and its impact on water quality has far-reaching consequences for both developed and developing countries. The study showed the significant potential of AI-based models in analysing and predicting water quality index through the case study of the Jumar watershed of Ranchi district. Through the analysis, it was evident that ML models such as SVM and CART outperformed ANN in predicting water quality for datasets generated based on seasonal analysis of the surface water bodies. The result suggested that SVM and CART models are robust tools for assessing WQI as presented by their R^2 values and lower RMSE values. These findings underscore the importance of using advanced data-driven technologies to address environmental challenges and promote effective land and water management. Further research and application of AI-based models can contribute significantly to mitigating the detrimental effect of land degradation on water quality and other factors of the ecosystem.

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