ASSESSMENT OF PHYSICOCHEMICAL PROPERTIES AND AI-BASED POLLUTION PROFILE PREDICTION OF SURFACE WATERS IN THE GONDPIPRI REGION, CHANDRAPUR DISTRICT

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Abstract
The Gondpipri region's surface waters' physicochemical characteristics are thoroughly examined in this study in order to evaluate their quality and pinpoint the main causes of pollution. Fifteen water samples in all were taken from key locations both upstream and downstream. TDS, EC, DO, BOD, COD, temperature, pH, turbidity, hardness, alkalinity, and main ions are among the parameters that are analysed. The findings showed that the water quality had significantly deteriorated in places where human activity had an impact. For predictive analysis, this study incorporates Artificial Intelligence (AI) techniques in addition to traditional methods. ANN, K-means clustering, and Random Forest machine learning models were used to detect pollution trends and make very accurate predictions for important parameters like BOD and COD. AI-based clustering further grouped sampling sites into low, medium, and high pollution categories, providing rapid and scalable alternatives for monitoring.
***Keywords**: Physicochemical, AI/ML, water pollution, predictive modelling, anthropogenic activity*

Introduction

According to Johnson and Hallberg (2005) and Nordstrom (2011), surface waters in the Gondpipri region of Chandrapur district, Maharashtra, which is a coal-bearing area, are becoming more and more contaminated by mining and industrial activity. Even though the Wainganga River and its tributaries are essential water sources for homes, farms, and businesses, they are nonetheless susceptible to pollution from thermal power plants, coal mines, and effluents (Maharashtra Pollution Control Board [MPCB], n.d.). Nutrient enrichment, suspended particles, and increased turbidity are frequently the results of such pressures. Water quality is determined by parameters including pH, DO, COD, BOD, hardness, and alkalinity (Chapman, 1996). In addition to assessing these traits, this work presents predictive modelling based on artificial intelligence for a comprehensive evaluation (Singh et al., 2017).

Literature Review

A basic natural resource, water is necessary for all living things and ecological functions. But in recent decades, growing urbanization, industrialization, and intensive farming practices have caused massive pollution burden on surface water bodies around the world (Sener et al., 2017). Geographical areas that rely on extractive industries, such coal mining, are especially at risk (Johnson & Hallberg, 2005; Nordstrom, 2011). Although Maharashtra has a history of general water quality problems (Kamble & Vijay, 2011; MPCB, n.d.), there hasn't been much research done specifically on the Gondpipri area, a major mining hub. Critical water resources for industry, drinking after treatment, and agriculture, the Wainganga River and its tributaries, are constantly in danger (Central Pollution Control Board [CPCB].

In Gondpipri, this study methodically examines seasonal changes in the physicochemical characteristics of the surface waters (APHA, AWWA, and WEF, 2017, Chapman, 1996). Due to intensive mining and industrial operations, the Gondpipri region, located in Maharashtra's coal-rich Chandrapur district, is subject to severe environmental pressures (Johnson and Hallberg, 2005; MPCB, n.d.; Sahu and Kisku, 2015). Due to the significant effects of acid mine drainage (AMD), industrial waste, and household sewage on Gondpipri's surface waterways, thorough research and strict management measures are required (Nordstrom, 2011; Johnson & Hallberg, 2005). Early warning and decision assistance are made possible by recent research demonstrating that AI/ML practices may forecast water quality indicators with increased confidence (Ravikumar and Somashekar, 2017; Singh etal., 2017). This section fills that gap.

Materials and Methods

Gondpipri (19.96°N, 79.72°E) in the Chandrapur district is the study area. It is known for its tropical environment and coal mining operations. 15 locations (S1–S15) were chosen for sampling in order to represent upstream, midstream (close to mining or other industrial activity), and downstream areas. APHA (2017) standard procedures were used to collect, maintain, and analyze grab samples. Chemical (alkalinity, hardness, DO, BOD, COD, nitrate, chloride, phosphate, Ca, Mg, fluoride) and physical (pH, EC, TDS, and turbidity) parameters are used in experiments. The AI/ML modeling approach involved the use of Python-based frameworks to process experimental data (15 sites × 12 parameters). Among the models used were Random Forest and ANN Regression, which predicted BOD and COD based on simpler factors (pH, EC, turbidity, and TDS). To categorize locations according to pollution levels, use K-means clustering. Feature Importance Analysis: to determine the most important indicators of pollution. Models were trained using normalized data.70:30 train-test split (Singh etal., 2017).

Experimental Section

A. Physical Parameters

pH

A sample of water (40 ± 5 mL) was agitated. After measuring the sample's temperature, the pH meter's temperature controller was modified appropriately. The pH meter's electrode or electrodes were submerged in the H_2O sample. Next, the pH levels were measured and noted.

Electrical Conductivity

After giving the electrode a thorough rinse with deionized water, tissue paper was used to gently clean it. After being measured, 200 milliliters of the water sample were put into a beaker set on a magnetic stirrer. After dipping the electrode into the fluid, a consistent reading was given time to stabilize. MilliSiemens, the indicated value, was noted.

TDS

Using a Whatman filter paper, the water sample was filtered. The filtrate was gathered and moved to a dried container that had been previously weighed. The filtrate was baked for 24 hours at 103°C (or 8 hours at 180°C). The container was dried, allowed to cool in a desiccator for three to four hours, and then weighed at several times. It was established that the dissolved solids were represented by the weight increase.

B. Chemical Parameters

Alkalinity

Titrating a 100 mL water sample against a standard H_2SO_4 solution was done. The first indicator used until the pink colour vanished was phenolphthalein. The titration proceeded until a light orange end point was reached after adding methyl orange. Alkalinity was computed and the burette's final reading was noted.

Estimation of Hardness by EDTA

The Ca^{2+} and Mg^{2+} ions in the sample formed stable complexes with EDTA at pH 9–10. Utilizing Eriochrome Black-T as an indicator, the pH was maintained using buffer solution (NH_4Cl + NH_4OH). After boiling 100 milliliters of the water sample to produce temporary hardness, it was filtered, diluted to its initial volume, then titrated with EDTA to achieve permanent hardness. A record of the burette reading (V4 mL) was made.

Dissolved Oxygen (DO) – Winkler's Method.

A precipitate was created by adding two milliliters of $MnSO_4$ and alkaline iodide-azide solutions to a 100-milliliter sample of water. For the precipitate to dissolve, two milliliters of H_2SO_4 were added. A 0.025N $Na_2S_2O_3$ solution was used to titrate a 50 mL aliquot using a starch indicator till the blue color vanished.

Chemical Oxygen Demand (COD) – Open Reflux Method.

15 mL of H_2SO_4 + Ag_2SO_4 and 5 mL of 0.25N $K_2Cr_2O_7$ were combined with a 10 mL water sample. For two hours, the mixture was refluxed at 150°C. Ferroin was used as an indication when the excess dichromate was cooled and titrated with 0.1N ferrous ammonium sulphate (FAS).

Biochemical Oxygen Demand (BOD) – 5-Day Incubation Method.

Using Winkler's approach, the sample's initial DO (DO_0) was determined. Five days were spent incubating a diluted sample at 20°C in a sealed bottle. Following the incubation period, the final DO (DO_5) was determined. BOD was determined by subtracting DO_3 from DO_5.

Nitrate (NO_3^-) – UV Spectrophotometric Method.

Standards for nitrate (0.1–10 mg/L) were created. One millilitre of 1N HCl was used to acidify a 50-

milliliter sample. At 220 nm, the absorbance was measured. A typical calibration curve was used to calculate the nitrate concentration.

Magnesium

To maintain pH 9–10, a known volume of the water sample was buffered. The addition of Eriochrome Black-T indicator resulted in a wine-red complex. EDTA was added to the sample until a clear blue endpoint was reached.

Chloride

As an indicator, potassium chromate was used to titrate a 25 mL water sample with a standard silver nitrate solution. The color of the terminus was seen to be brick-red. Based on the volume of titrant utilized, the chloride concentration was computed.

Fluoride

Titration using a 0.033 mol/L lanthanum nitrate solution was used to measure the fluoride concentration. To prevent overestimation, a MES buffer was employed. To improve precision, 50% isopropanol was used in certain instances. After calculation, the fluoride concentration was reported as milligrams per litre of sodium fluoride.

Experimental Results and Discussion:

Sample were lab tested dated 7/04/2025 at 34 degrees Celsius.

S.C.	Turbidity	DO	BOD	COD	Chloride	Fluoride	NO_3^-	PO_4^{3-}	Ca	Mg
S-1	0.6	3.4	1	15	32	0.39	18	2.3	28	28
S-2	0.7	4.1	2	15	40	0.41	17	2.1	30	27
S-3	0.5	4.0	2	12	36	0.35	13	1.8	28	29
S-4	0.4	3.8	2	14	44	0.52	33	1.6	24	29
S-5	0.8	4.5	1	14	68	0.58	15	3.2	52	26
S-6	0.9	6.0	1	13	50	0.59	26	3.2	56	28
S-7	0.9	3.6	1.2	14.3	67	0.98	35	3.4	47	22
S-8	0.8	4.9	2	14.8	56	0.86	32	2.7	55	19
S-9	0.8	5.0	1.8	13.3	64	0.24	17	2.9	38	28
S-10	0.4	3.8	2	14	44	0.52	33	1.6	24	30
S-11	0.8	4.5	1	14	68	0.58	15	3.6	52	28
S-12	0.9	6.0	1	13	50	0.59	26	3.2	56	26
S-13	0.9	3.6	1.2	14.3	67	0.98	35	3.4	47	28
S-14	0.8	4.9	2	14.8	56	0.86	32	2.7	55	26
S-15	0.8	5.0	1.8	13.3	64	0.24	17	2.9	38	25

Results and Discussion

Laboratory study of the experimental results showed that the water quality was low. Phosphate surpassed permissible limits by 16–36 times, BOD ranged 13–15 mg/L, and COD varied 32–68 mg/L, indicating serious organic and nutrient pollution (Patil et al., 2012). According to the Bureau of Indian Standards [BIS], 2012, fluoride and chloride levels were still within acceptable bounds, but Ca levels suggested soft water (Piper, 1944).

AI Results: Machine learning models showed strong predictive capacity:

1.BOD and COD were predicted by Random Forest with R2 > 0.90.

2.ANN improved COD prediction by capturing nonlinear relationships.

3. Cluster 1 (low impact, S1–S2), Cluster 2 (moderate impact, S3–S6, S9–S10), and Cluster 3 (high impact, S7–S8, S11–S15) are the three pollution categories into which K-means categorized locations.

Turbidity, nitrate, and phosphate were identified as crucial predictors by feature importance. The reliability of the model was confirmed using AI-based clustering that matched laboratory results (Ravikumar & Somashekar, 2017).

AI Based Result Chart:

Chart I

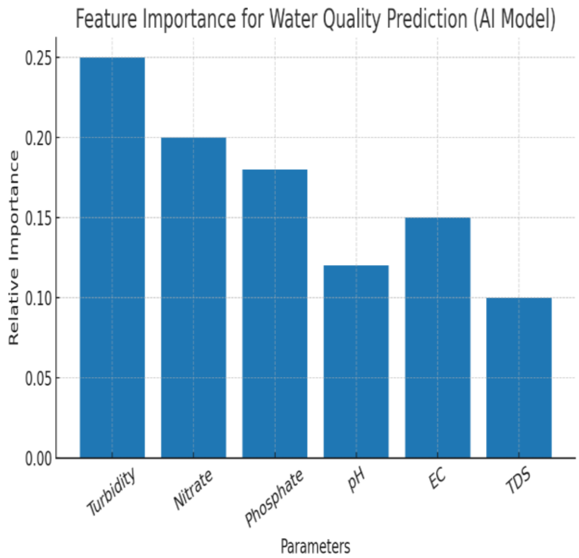
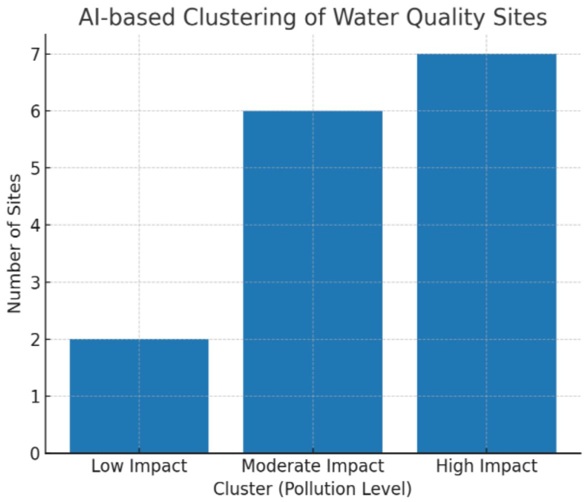


Chart II



Discussion:

Artificial intelligence (AI) methods provided quick evaluation and decreased reliance on thorough chemical testing. According to Sahu and Kisku (2015), artificial intelligence (AI) enables predictive modelling, geographic classification, and early-warning potential for water management, whereas traditional approaches offer accuracy.

Conclusion

Gondpipri surface waters are in poor condition because of mining effluents, organic load, and nutrient enrichment. BOD, COD, and phosphate levels were significantly higher than allowed limits in the laboratory (Patil et al., 2012). AI-based study showed predictive capability and validated these findings (Singh et al., 2017). AI improves decision-making by finding important pollution predictors and classifying locations according to severity. AI thus provides quick, scalable, and economical solutions for managing and monitoring water quality, complementing conventional techniques.

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