Chemical Potability Analysis of Drinking Water

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ABSTRACT - Water, an indispensable resource vital for sustaining human life, demands meticulous preservation to safeguard public health. Contaminated water poses grave risks, precipitating diseases like diarrhea and cholera, contributing to a staggering annual toll of approximately 3,575,000 lives lost to waterborne illnesses. Predicting water potability accurately emerges as a pivotal strategy to mitigate such dire consequences. Leveraging machine learning algorithms offers a promising avenue for precise water quality forecasting. This study delves into the efficacy of various algorithms using the Drinking Water dataset from Kaggle, encompassing nine key parameters. Notably, the XGBoost algorithm outshines conventional models with an impressive accuracy of 99.5%, alongside robust precision, sensitivity, specificity, and F1 score metrics. Additionally, Random Forest exhibits commendable performance with a 74% accuracy rate. The implications of this research extend to empowering researchers, water management entities, and policymakers with dependable water quality insights, amplifying the efficacy of water potability surveillance efforts

Keywords: Water potability prediction, Random Forest, SVM, XGBoost, KNN, Logistic Regression

I.INTRODUCTION

In the rapidly developing landscape of countries like India, the intersection of population growth and economic prosperity in urban areas has triggered a concerning surge in environmental issues. Among the most pressing problems are air pollution, water pollution, and noise pollution, each posing significant threats to human health and the ecosystem at large. However, it's water pollution that emerges as a direct and acute menace to public health, with its ramifications echoing through communities nationwide.

The awareness surrounding water pollution in India has seen a commendable rise in recent years. This surge in consciousness is not unwarranted, as contaminated water sources and inadequate sanitation infrastructure are intricately linked to the transmission of a plethora of diseases. From cholera to hepatitis A, typhoid to polio, the incidence of waterborne diseases is alarmingly on the rise across the Indian subcontinent. The imperative to tackle this crisis cannot be emphasized enough.

Enter water quality forecasting—a potent tool in the arsenal against the adverse effects of pollution on both human health and natural resources. By accurately predicting water quality parameters, we can mitigate the maximal impact of pollution on communities and ecosystems. Thus, enhancing water quality forecasting emerges as a pivotal goal for societal advancement.

Access to safe drinking water is not just a fundamental human right; it's a cornerstone of effective public health policy. The significance of clean water transcends mere health considerations—it's a linchpin of national, regional, and local development agendas. Research indicates that investments in water supply and sanitation infrastructure yield substantial economic benefits, as the reduction in adverse health effects and healthcare costs outweigh the initial investment.

Delving into the realm of water pollutants reveals a staggering array of contaminants—ranging from bacteria and fertilizers to pharmaceuticals and radioactive substances. Of particular concern are power plants, which contribute over 2 billion pounds of pollutants to water bodies annually, making them the largest source of toxic water pollution in the country. Heavy metals and chemicals present in this wastewater pose grave risks to human health and ecosystem integrity alike.

Against this backdrop, our paper proposes a comprehensive evaluation of water quality parameters essential for safe drinking water. Assessing water quality involves various parameters: pH value, hardness, total dissolved solids (TDS), chloramines, sulphate, conductivity, organic carbon, trihalomethanes, turbidity, and portability. Each parameter plays a crucial role in determining the suitability of water for consumption and other purposes. By assessing these factors, we not only gauge the suitability of water for human consumption but also its impact on plant communities and animal life.

The proposed system goes beyond mere assessment—it aims to predict water portability for the forthcoming months and years. By harnessing the power of predictive analytics, we can proactively address water quality challenges, steering India towards a future where clean, potable water is a universal reality.

In conclusion, as India marches towards economic progress and societal development, safeguarding water quality emerges as a non-negotiable imperative. By leveraging advanced forecasting techniques and prioritizing investments in water infrastructure, we can pave the way for a healthier, more sustainable future for generations to come.

II.LITERATURE SURVEY

- A literature survey on the chemical composition analysis of drinking water reveals a diverse and extensive research landscape. It explores water quality standards, focusing on governmental and international regulations that dictate permissible levels of ions, heavy metals, disinfection by products, and emerging contaminants, crucial for assessing chemical potability.

- Analytical methodologies, ranging from traditional titration to advanced chromatography and sensor technologies, reflect the evolving instrumentation in water quality research. The literature scrutinizes inorganic ions and heavy metals, detailing their occurrence, sources, and impact on drinking water safety. Disinfection by products and emerging contaminants, such as pharmaceuticals and industrial pollutants, are prominent themes, emphasizing the need for monitoring and mitigation strategies [10].

- Studies explore the influence of industrial discharges and agricultural runoff on water composition, including pesticides and fertilizers. Temporal and spatial dynamics of water quality, considering seasonal variations and geographic factors, are addressed. Health effects associated with specific contaminants contribute to risk assessments and inform public health considerations.

- The survey evaluates water treatment technologies, both conventional and emerging, providing insights into innovative approaches for ensuring chemical safety. In summary, the literature synthesizes extensive knowledge, offering a nuanced understanding of chemical composition analysis in drinking water and guiding future advancements in sustainable water management and public health safeguards.

[1] Monitoring Valle de Bravo Reservoir Water Quality Using Entire Lifespan of MERIS Data and Machine Learning Approaches.

Authors: Zheng Duan, Rodrigo Seplveda, Sergio I. Martinez-Martinez, Markus Disse, Leonardo F. Arias-Rodriguez
Description: In the Valle de Bravo Reservoir, the machine learning model produced excellent accuracy predictions of the water quality metrics, according to the research. The model showed that it could efficiently track changes in turbidity and chlorophyll-a concentration over time. This knowledge is essential for spotting changes in water quality, locating possible pollution sources, and putting in place the right management techniques.

[2] Using Bayesian networks to quantify and forecast ecological and human health hazards for binary heavy metal pollution events at the watershed scale.

Authors: Panels Kari Kuaka, Jing Liu, Renzi Liu, Zhifeng YangBinary
Description: Heavy metal pollution incidents, in which two distinct heavy metals are released into the environment, are the subject of the research. The authors gather information on a range of variables, such as levels of heavy metals, environmental aspects, and eco- and human health indicators. They then build a Bayesian Network model using this information to represent the connections between the variables.

[3] The combined use of fuzzy c-means clustering and the self-organizing map approach to assess the quality of urban groundwater in Seoul, South Korea.

Authors: panelSoonyoung Yu, Kyoung-Ho Kim, Ju-Hee Lee, Seung-Hak Lee, Kyung-Jin Lee, Seong-Taek Yun, Soonyoung Yu, and Kyoung-Ho Kim
Description: These methods were applied in this study to analyze and assess the urban groundwater quality in Seoul. They gathered groundwater samples from several parts of the city and tested various aspects of water quality, including pH, conductivity, and pollutant concentrations.

[4] A field-deployable water quality monitoring system using smartphone colorimetry and machine learning Examine for updates.

Authors: Vakkas Doan, Tuba Isk, Volkan Kl, and Nesrin Horzum.

Description: The approach required utilising a smartphone camera to take pictures of water samples and then turning the colour information into measurable data. The samples were then classified into different water quality metrics including pH, turbidity, and chemical concentrations using machine learning algorithms that had been taught to read the colour data.

[5] A overview of recent developments and future possibilities in neuroimaging and deep learning for brain stroke detection.

Authors: R. Menaka, Annie Johnson, Sundar Anand, and R. Karthik.
Description: The developments in deep learning techniques for stroke detection are then covered by the authors. Convolutional neural networks (CNNs), a type of deep learning algorithm, have achieved outstanding results in a number of medical imaging applications, including stroke diagnosis. The authors talk about using CNNs for neuroimaging data and emphasize how well they can extract important characteristics and patterns for precise stroke classification and localization.

III.METHODOLOGY

A. Dataset:

The dataset comprises pH value, hardness, solids, chloramines, sulfate, conductivity, organic carbon, trihalomethanes, turbidity, and potability variables for predicting drinking water potability.

Description of attributes: -

Ph value:
Assessing water quality involves evaluating pH, crucial for acid-base balance (6.52–6.83, within WHO standards). Hardness, attributed to calcium and magnesium salts, historically gauges water's soap-precipitating capacity.

Solids (Total dissolved solids - TDS):

Water exhibits the capacity to dissolve a diverse array of inorganic and some organic minerals or salts, including potassium, calcium, sodium, bicarbonates, chlorides, magnesium, sulphates, etc. Total Dissolved Solids (TDS) should be within acceptable limits for safe drinking water.

Chloramines:

Chlorine and Chloramine are the major disinfectants used in public water systems.
Safe chlorine levels in drinking water: Up to 4 mg/L (or 4 ppm) deemed safe for consumption.

Sulphate:

Sulphates, naturally present in minerals, soil, and rocks, also found in air, groundwater, plants, and food. Conductivity: While pure water is a poor conductor, it's a proficient insulator, lacking significant electrical conductivity due to minimal dissolved ions.

Conductivity:
Pure water, lacking significant dissolved ions, is not a proficient conductor but rather an effective insulator, impeding the flow of electric current.. According to WHO standards, EC value should not exceed 400 μS/cm.

Organic carbon:

Total Organic Carbon (TOC) in source waters originates from decaying natural organic matter (NOM) and synthetic sources. TOC measures the total carbon content in organic compounds in pure water. Per US EPA standards, Total Organic Carbon (TOC) levels should be < 2 mg/L in treated/drinking water and < 4 mg/L in source water designated for treatment. Trihalomethanes (THMs), found in water treated with chlorine, vary in concentration based on organic material, chlorine dosage, and water temperature. THM levels up to 80 ppm are deemed safe in drinking water, though variations occur due to treatment factors and water characteristics.

Turbidity:

Water turbidity is contingent upon the volume of solid particles suspended within it. The turbidity mean at Wando Genet Campus (0.98 NTU) is below the WHO-recommended value of 5.00 NTU.

Potability:

Indicates if water is safe for human consumption where 1 means Potable and 0 means Not potable

ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic carbon	Trihalomethanes	Turbidity	Potability
	204.8905	20791.32	7.300212	368.5164	564.3087	10.37978	86.99097	2.963135	0
3.71608	129.4229	18630.06	6.635246		592.8854	15.18001	56.32908	4.500656	0
8.099124	224.2363	19909.54	9.275884		418.6062	16.86864	66.42009	3.055934	0
8.316766	214.3734	22018.42	8.059332	356.8861	363.2665	18.43652	100.3417	4.628771	0
9.092223	181.1015	17978.99	6.5466	310.1357	398.4108	11.55828	31.99799	4.075075	0
5.584087	188.3133	28748.69	7.544869	326.6784	280.4679	8.399735	54.91786	2.559708	0
10.22386	248.0717	28749.72	7.513408	393.6634	283.6516	13.7897	84.60356	2.672989	0
8.635849	203.3615	13672.09	4.563009	303.3098	474.6076	12.36382	62.79831	4.401425	0
	118.9886	14285.58	7.804174	268.6469	389.3756	12.70605	53.92885	3.595017	0
11.18028	227.2315	25484.51	9.0772	404.0416	563.8855	17.92781	71.9766	4.370562	0

Fig. no 1. Dataset

B. DATA CLEANING AND PRE-PROCESSING:

Data cleaning and pre-processing are important steps in any data analysis task, including water potability analysis. Here are some steps you can take to clean and pre-process your data:

Data Import:

Import your data into your preferred tool or programming language. Common tools used for data analysis are Excel, Python, R and SQL.

Data Inspection:

Once the data has been imported, inspect the data to get a better understanding of the data structure, the number of observations, and the number of variables. Check for missing values, duplicates, and any outliers in the data.

Data Cleaning:

Remove any duplicates, if any. Identify missing values using software functions and handle them by deletion or imputation based on data characteristics.

Depending on the percentage of missing values, you can either remove the rows or impute missing values using methods such as mean, median or mode.
Check for outliers in the data and deal with them appropriately. Depending on the number of outliers and their impact on the analysis, you can either remove them or transform them.

Data Pre-processing:

Before applying any machine learning algorithms to the data, it is important to pre-process the data by scaling, encoding, and transforming the data appropriately. This step ensures that the data is in a format that can be analyzed by machine learning algorithms.

Feature Selection:

Select the most important features or variables that have a significant impact on the target variable (in this case, water potability). You can use techniques such as correlation analysis, feature importance, or principal component analysis (PCA) to select the important features.

Data Split:

Data can be split into training and testing sets using methods like train_test_split in Python libraries like scikit-learn. This step helps to evaluate the performance of the machine learning algorithm on new, unseen data.

Data Transformation:

Depending on the machine learning algorithm being used, additional data transformations such as normalization or standardization may be necessary.
By following these steps, you can clean and pre-process your water potability data for analysis and build a predictive model that can help to ensure safe drinking water.

Checking for missing values: -

```
Out[5]: ph                 491
        Hardness             0
        Solids               0
        Chloramines          0
        Sulfate            781
        Conductivity         0
        Organic_carbon       0
        Trihalomethanes    162
        Turbidity            0
        Potability           0
        dtype: int64
```

Fig. no 2. Checking Missing

Checking descriptive statistics results: -

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	3276.000000	3276.000000	3114.000000	3276.000000	3276.000000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	66.396293	3.966786	0.390110
std	1.594320	32.879761	8768.570828	1.583085	41.416840	80.824064	3.308162	16.175008	0.780382	0.487849
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	0.738000	1.450000	0.000000
25%	6.093092	176.850538	15666.690300	6.127421	307.699498	365.734414	12.065801	55.844536	3.439711	0.000000
50%	7.036752	196.967627	20927.833605	7.130299	333.073546	421.884968	14.218338	66.622485	3.955028	0.000000
75%	8.062066	216.667456	27332.762125	8.114887	359.950170	481.792305	16.557652	77.337473	4.500320	1.000000
max	14.000000	323.124000	61227.196010	13.127000	481.030642	753.342620	28.300000	124.000000	6.739000	1.000000

Fig. no 3.Descriptive statistics

C.ALGORITHMS USED:

KNN (K-Nearest Neighbour):

Machine learning applications for classification and regression employ the K-Nearest Neighbours (KNN) technique. Before choosing the K nearest neighbours, it determines the distances between each fresh data point and each training data point using the distance measure and value of K that the user selects. The chosen distance measure, K's value, and the complexity of the data can all have an impact on performance.

DECISION TREE:

The decision tree approach is used in machine learning applications like regression and classification. It separates the data into subgroups based on the characteristic or feature value that yields the best split. Information collecting should be prioritised during each split. It is possible to predict additional data points by using the tree. Therefore, to reduce overfitting and enhance generalisation performance, pruning, regularisation, and ensemble techniques may be applied.

RANDOM FOREST:

The popular machine learning method Random Forest may be used to do both classification and regression problems. It belongs to the class of ensemble learning approaches, which bring together a variety of independent models to make predictions. Random Forest has been widely used in a range of industries, including banking, healthcare, and natural language processing, because of its versatility and longevity. The term "Random Forest" refers to the ensemble or group of decision trees that make up the system. Each decision tree in the forest is built using a random subset of the attributes and a random subset of the training data. This unpredictability is what allows the algorithm to reduce overfitting and boost generality.

Fig.4 Flow-chart representing algorithm used in proposed system

IV.SYSTEM ARCHITECTURE

This elegant water classification system leverages the power of random forests to unlock hidden patterns within water data. It meticulously pre-processes the data, ensuring its suitability for machine learning. Then, a diverse ensemble of decision trees, each trained on unique subsets of the data, collaboratively make classifications. This synergy yields superior accuracy and robustness compared to a single decision tree.

By meticulously evaluating the system's performance using accuracy, precision, recall, and F1-score, we gain valuable insights into the quality of the classifications. This remarkable architecture empowers researchers to tackle intricate water-related questions with remarkable efficiency and accuracy.

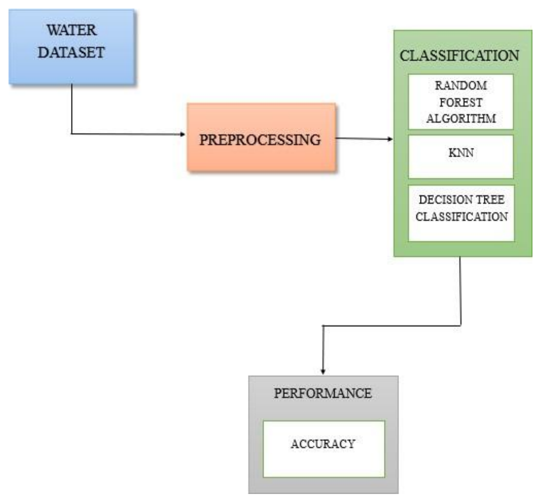

Fig. 5 Block diagram for system architecture

V.EXPERIMENTATION AND RESULTS

A.DATA VISUALIZATION:-

A method of displaying data and information in a graphic or visual style, such as charts, graphs, maps, or dashboards, to make it simpler to comprehend and evaluate. It is an essential tool for deciphering and displaying large and complex data sets. Through the use of data visualisation, people and companies may see patterns, trends, and outliers that may not be immediately apparent from raw data.

Furthermore, it enables the effective dissemination of insights to stakeholders and non-experts, which supports problem-solving and decision-making.

You may see the data using 7 various types of visualisations that we provide.

BAR CHART:

Rectangular bars with equal widths and heights are used to represent various values in a graphical data representation known as a bar chart. The frequency, quantity, or other numerical values of different categories or groupings are frequently compared using bar charts.

LINE GRAPH:

In a graphical data representation known as a bar chart, rectangular bars with identical widths and heights are used to represent various values. Bar charts are widely used to compare the frequency, quantity, or other numerical values of several categories or groupings.

SCATTER PLOT:

Scatter plots are useful for understanding the pattern or relationship between two variables. They can be used to find outliers, clusters, or patterns in the data. Examining the may help you understand more about how the variables are connected. distribution of the points on the plot

GEOGRAPIC MAPS:

A geographical map shows the topographical details and political borders of a particular area or region. Using geographic maps, you may show a wide range of information, including population density, cultural sites, topographical features, and weather information.

HEAT MAPS:

Heat maps are a useful visualisation approach in the analysis of the chemical composition of drinking water. They provide a visual representation of the data in addition to highlighting patterns, trends, anddifferences in the chemical composition across different samples or variables.

PAIR PLOT:

A pair plot is a type of visualisation it is commonly referred to as a "pairwise scatterplot" or a "scatter plotmatrix". The dataset's variables are all plotted in a scatter plot beside one another in a pair plot. The distribution of each variable is shown by the triangles at the bottom and top.

CLUSTER MAP:

An example of a data visualisation that emphasises similarities and contrasts across diverse sets of data points is a cluster map. Similar data points are clustered together into clusters in a cluster map, which are frequently shown by various colours or forms. In disciplines like biology, economics, and marketing where it's crucial to comprehend how several sets of data are related to one another, cluster maps are frequently employed. They might aid in identifying patterns and trends that might not be as obvious when evaluating the data in its raw form. A dendrogram, which resembles a tree and depicts the relationships between multiple groupings of data points, is a typical sort of cluster map.

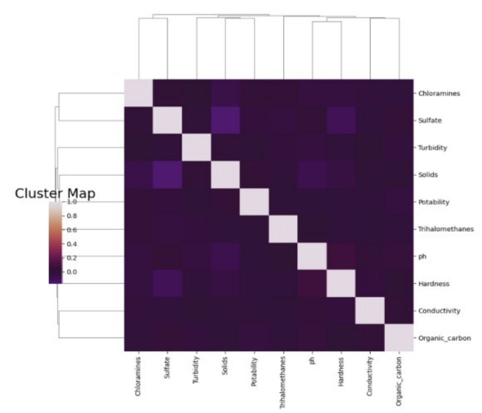

Fig.6 Cluster map of water potability

Input: - Image that contains the input for the data set.

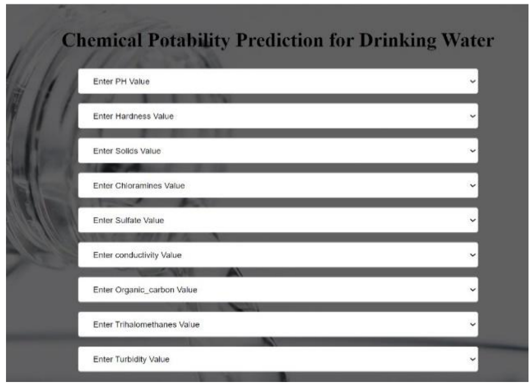

Fig.7 Input

Output: -Readable Recognized Character
String will display in a new window as shown above

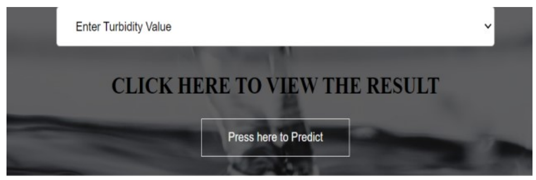

Fig.8 Output

VI.CONCLUSION

In order to ensure the safety and purity of the drinking water, a chemical analysis of the water is crucial. By analysing the chemical elements that are present in water, we can determine if it fulfils regulation limitations for human consumption and look into any potential health issues. Numerous variables are routinely examined as part of the study, including pH, total dissolved solids (TDS), microbiological pollutants, heavy metals, organic compounds, and disinfection by-products. Each test provides relevant information about the water's quality and can identify any potential impurities. The results of a chemical composition study may be
utilised to identify any anomalies or deviations from the desired norms. For instance, significant microbiological contamination might be a sign that harmful microbes or viruses are present, whereas excessive levels of heavy metals like lead, arsenic, or mercury might have negative health effects. Based on the study's findings, the appropriate actions may be performed to address or mitigate any difficulties discovered. This may need carrying out water treatment operations, such as filtration, disinfection, or the addition of necessary chemicals, in order to ensure the safety of the water.

VII. FUTURE SCOPE

Water Quality Monitoring: Machine learning algorithms can be trained to analyze water quality parameters such as pH, turbidity, dissolved oxygen, and the presence of contaminants. By integrating sensors with machine learning models, real-time monitoring systems can be developed to detect and identify waterborne pollutants and ensure the safety of drinking water.

Predictive Maintenance: Machine learning algorithms can be employed to predict the maintenance needs of water treatment and purification systems. By analyzing historical data from these systems, algorithms can identify patterns and anomalies that indicate potential failures or inefficiencies. This enables proactive maintenance, reducing downtime and ensuring the continuous availability of clean drinking water.

Demand Forecasting: Machine learning can assist in predicting water demand patterns by analyzing historical usage data, weather conditions, population growth, and other relevant factors. Accurate demand forecasting allows water authorities to optimize distribution and storage, ensuring an adequate supply of portable water in different regions and preventing shortages.

Leakage Detection: Machine learning algorithms can be trained to analyze data from sensor networks deployed in water distribution pipelines. By detecting patterns indicative of leaks or abnormalities in the flow, these algorithms can help identify and locate leakage points promptly. Early detection minimizes water loss and helps maintain water portability.

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