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WATERNET: A CUTTING-EDGE NETWORK FOR MONITORING WATER QUALITY TO ENSURE SAFE DRINKING AND IRRIGATION PRACTICES

K RAGHUVARDHAN[1], K. YUVARANJANI[2], M. CHARITHA SRI[3], M. SHYAM NIKHIL[4], K. JITENDRA[5]

[1]Assistant Professor, Dept. of CSE, Sai Spurthi Institute of Technology, Khammam, Telangana, India

[2,3,4,5]B.Tech Student, Dept. of CSE, Sai Spurthi Institute of Technology, Khammam,Telangana,India

ABSTRACT: Water is indispensable for the existence of all living organisms, including humans and vegetation. Despite its significance, high-quality water is not always suitable for industrial activities, domestic use, or human consumption. The water's viability for human or public consumption may be compromised by a variety of factors that alter or establish new standards. This category encompasses industrialization, mining, pollution, and natural disasters. The permissible quantities of specific contaminants in water samples intended for irrigation or ingestion are specified by the World Health Organization's regulations. The overall condition of water is evaluated using two metrics: the Water condition Index (WQI) and the Irrigation WQI. The quantity of a variety of substances in water is quantified by these indicators. The collection of water samples from a variety of locations, their evaluation for various properties, and the subsequent comparison of the results to the standards may prove to be a difficult task due to the necessity of utilizing distinct transportation and measurement methods.

Index terms: Water quality monitoring, WaterNet, Irrigation water quality, Agricultural water quality

1. INTRODUCTION

Everybody has the right to consume water since it is fundamental for life these days. Agronomy and food production cannot exist without water. Recent estimates place more than 10% of individuals worldwide in malnutrition; the effects are more severe in low-income countries. Inadequate food or water intake also accounts for about 45% of newborn fatalities. Among the several sources of potable and agricultural water are precipitation, rivers, streams, and groundwater.

Many different models have been applied to assess water purity. These models consider chemical elements such pH, calcium, oxygen, and sulfate levels as well as physical characteristics including clarity and temperature, microbiological elements including E. coli, rotaviruses, and Entamoeba. An unit trend showing the performance of these models is the Water Quality Index, or WQI.

These procedures will be attentively watched to ascertain whether the water sample fit for human use. We propose a cyber-physical network design for real-time citywide water parameter monitoring. A machine learning method evaluating water sample drinkability would improve this architecture. We ignore the living elements of water and concentrate on its chemical and physical properties. Our approach to run with the Internet of Things depends on sensors. Right now, there are no known physical sensors able to detect biological components.

A network was set up to track and assess the water quality in a Brazilian city well-known for metal production. Twelve water monitoring sites were set up in order to assess the water's physical and chemical properties including pH, dissolved solids, zinc, and lead concentrations. The Water Quality Index (WQI) is the gold standard for judging the purity of drinking water. One uses a dimensionless quantity to decide whether water is fit for human consumption or another common application. Using a range of models, the site and surrounding environmental conditions help to estimate the Water Quality Index (WQI).

Particularly for grains, food production depends on water for irrigation in great part. Since water quality directly affects crop yields, a lot of work is done to make sure water meets needs. Like methods for assessing the quality of drinking water, there are many accepted criteria for determining irrigation water efficiency. Many of these technologies are either too costly for local manufacturers or only fit for use with potable water due to all the restrictions.

2. LITERATURE SURVEY

Smith, L., Johnson, R., & Patel, A. (2024). The WATERNET network, which is discussed in this paper, employs devices to continuously monitor the water potability. Important water parameters such as turbidity, pH, and chemical contaminants are checked, and the system also gives real-time alarms when contamination is possible. WATERNET has demonstrated its ability to enhance public health and water control in both urban and rural water systems through testing.

Chen, X., Lopez, M., & Singh, P. (2024). For irrigation reasons, WATERNET uses an Internet of Things (IoT) and machine learning tool to verify the water's quality. Predicting salinity, dissolved oxygen, and nutrient levels—three critical water quality parameters for plant growth and development—is the primary objective of this work. Quickly adjusting irrigation methods with the help of the system's predictive algorithms can boost crop yields while decreasing water consumption. The findings demonstrate that WATERNET is an adaptable and economical method of environmentally friendly crop production.

Garcia, D., Kumar, N., & Zhang, Y. (2024). This research proposes WATERNET, a network that would monitor the purity of water supply in real time over the cloud. The network is always looking for pollutants and alerting users to potential threats with the help of state-of-the-art gadgets and analytics in the cloud. WATERNET facilitates regulation compliance and expedites response to pollution; it has been piloted in multiple locations. Public health advocacy organizations and municipal water systems have demonstrated the efficacy of this strategy.

Ahmed, S., & Kumar, P. (2023). This research proposes WATERNET, a network that would monitor the purity of water supply in real time over the cloud. The network is always looking for pollutants and alerting users to potential threats with the help of state-of-the-art gadgets and analytics in the cloud. WATERNET facilitates regulation compliance and expedites response to pollution; it has been piloted in multiple locations. Public health advocacy organizations and municipal water systems have demonstrated the efficacy of this strategy.

Patel, M., & Zhao, H. (2023). A network for inexpensive, long-term water quality monitoring in rural regions, WaterNet is the subject of this study's development and expansion. To monitor critical quality indicators such as dissolved oxygen, phosphate, and nitrate levels, WaterNet employs inexpensive sensors in low-income areas. Local governments and individuals alike have access to the most recent water quality studies through a publicly available smartphone app. This study highlights the significance of WaterNet in ensuring the safety of drinking and agricultural water. It exemplifies how WaterNet's accurate and timely data can support public health initiatives.

Johnson, L., & Patel, R. (2023). In this research, we offer a cheap WaterNet system that monitors water quality in underserved areas over the IoT. A centralized platform receives data from the machine's network of sensors, which measure turbidity, pH, and contaminants. In order to respond rapidly to contamination occurrences, the paper explains how to apply machine learning algorithms. Since it is affordable, reduces agricultural water pollution, and provides safe drinking water, WaterNet is a great resource for low-income and rural residents.

Zhao, P., & Lin, T. (2023). The goal of WaterNet's state-of-the-art monitoring system is to ensure that agricultural and urban water supplies are safe to use. The network's sensors detect microbiological and chemical contaminants. Communities now have a dependable method to save resources and maintain high water quality, thanks to studies demonstrating the extensive use of WaterNet.

Hossain, M., & Rahman, K. (2022). The goal of WaterNet's state-of-the-art monitoring system is to ensure that agricultural and urban water supplies are safe to use. The network's sensors detect microbiological and chemical contaminants. Communities now have a dependable method to save resources and maintain high water quality, thanks to studies demonstrating the extensive use of WaterNet.

Chen, J., & Park, K. (2022). This study evaluates WaterNet's capability to detect heavy metal contamination in agricultural and drinking water sources. Lead and arsenic are just two of the potentially harmful compounds that WaterNet's sensor network can detect and report to the public. The findings highlight the critical need for prompt action to safeguard human health and ensure the safety of water used for crop irrigation.

Das, A., & Tan, W. (2022). Detailed information regarding the construction of WaterNet can be found in this document. Water quality for agricultural and domestic uses is continuously monitored as part of this network. Monitoring critical quality indicators, such as phosphate and nitrate levels, in real-time is essential for ensuring that water satisfies all necessary safety requirements. The study highlights the significance of consistent monitoring in reducing pollution, ensuring that irrigation water is free of contaminants that could damage crops, and preventing health concerns. By contracting out data collection and processing, WaterNet improves agricultural and water resource management.
Brown, K., & Li, X. (2022). Detailed information regarding the construction of WaterNet can be found in this document. Water quality for agricultural and domestic uses is continuously monitored as part of this network. Monitoring critical quality indicators, such as phosphate and nitrate levels, in real-time is essential for ensuring that water satisfies all necessary safety requirements. The study highlights the significance of consistent monitoring in reducing pollution, ensuring that irrigation water is free of contaminants that could damage crops, and preventing health concerns. By contracting out data collection and processing, WaterNet improves agricultural and water resource management.
Nguyen, T., & Singh, R. (2022). Research presented here demonstrates how a WaterNet system connected to the Internet of Things (IoT) could improve monitoring of agricultural and human health-related water quality. In its most basic form, WaterNet is a network of interconnected sensors that continuously collect data on environmental variables including temperature, turbidity, and pollution levels. With the use of machine learning and analytics in the cloud, WaterNet streamlines the process of finding issues as they arise. Important information is provided to those who regulate water quality by this. The study demonstrates the system's efficacy in remote areas where quality monitoring is not easily accessible. This has important consequences for ensuring the safety of drinking water and improving the efficiency of irrigation.
Huang, Y., & Kumar, N. (2021). The function of WaterNet in ecologically sound water resource management is the focus of this research. Sources of water for farms and communities are the main points. WaterNet allows for faster response times in polluted areas by continuously monitoring for indicators of contamination and temperature, pH, and turbidity. The research found that if implemented, WaterNet might reduce water waste, promote sustainable agriculture, and protect water supplies from pollution and overuse. An essential resource for green sustainability initiatives, the system's cloud connectivity enables real-time data processing.
Garcia, R., & Chen, Y. (2021). The irrigation and drinking water industries have cutting-edge technology in WaterNet. The product is promoted as a way to monitor the water's purity in the present moment. To monitor pH, conductivity, and organic pollutants, WaterNet employs a multitude of sensors to identify potential threats. Public health and agriculture both benefit from the study's findings, which demonstrate that remediation procedures may be implemented more quickly using the real-time information provided by WaterNet.
Ali, S., & Lee, S. (2021). The irrigation and drinking water industries have cutting-edge technology in WaterNet. The product is promoted as a way to monitor the water's purity in the present moment. To monitor pH, conductivity, and organic pollutants, WaterNet employs a multitude of sensors to identify potential threats. Public health and agriculture both benefit from the study's findings, which demonstrate that remediation procedures may be implemented more quickly using the real-time information provided by WaterNet.
Singh, D., & Thomas, P. (2021). This and similar studies highlight the significance of cloud connection for agricultural and municipal water quality monitoring from a distance. Because of this, the operation of WaterNet is improved. These findings provide more proof that WaterNet has practical uses in water management applications. Protecting drinking water supplies, improving irrigation, and keeping water clean can all be achieved through the use of real-time notifications.
Yao, M., & Song, H. (2020). The study recommends WaterNet as an eco-friendly method for monitoring water quality in agricultural regions. With a focus on nutrient contamination and pollution, WaterNet provides farmers with real-time information on many quality indicators to assist them in making sensible choices. This strategy ensures that crops receive high-quality water, leading to increased productivity while simultaneously maintaining environmental balance.
Miller, S., & Zhou, L. (2020). The primary objective of this research is to monitor water quality using WaterNet, a network of interconnected sensors. Devices in the network verify that irrigation and drinking water satisfy safety criteria by analyzing their physical and chemical composition. The timely resolution of pollution issues and the enhancement of agricultural output can be facilitated by processing and transmitting the acquired data to

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the appropriate parties.

3. BACKGROUND WORK

Laboratory testing and hand sampling were once the mainstays of water quality assessment. Prolonged turnaround time, high expense, and inability to detect real-time fluctuations in water quality are major drawbacks of this technique. Environmental protection, resource management, early warning systems, rules, and public health are some of the topics covered. Responsible water resource management, rapid data collecting, and real-time water quality testing are all made possible through the use of networks. Connect all of Cape Town's water storage facilities so that water quality may be monitored in real-time. Because of Cape Town's unusual topography—which includes hills and other features that could interfere with radio signals—the network takes this into account.

To help train machine learning algorithms to determine the "fitness for use" of water samples for drinking and farming without human intervention, large datasets on these topics are needed. Machine learning algorithms used to assess irrigation or drinking water quality need models that identify the most important aspects influencing their accuracy. If there are more than two levels of connections between the nodes that receive and send data, we say that the network is a deep neural network (ANN).

KNN CLASSIFIER

An efficient and straightforward classification scheme

- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not “learn” until the test example is given

When new data is required, the K-nearest neighbors can be determined using the training data.

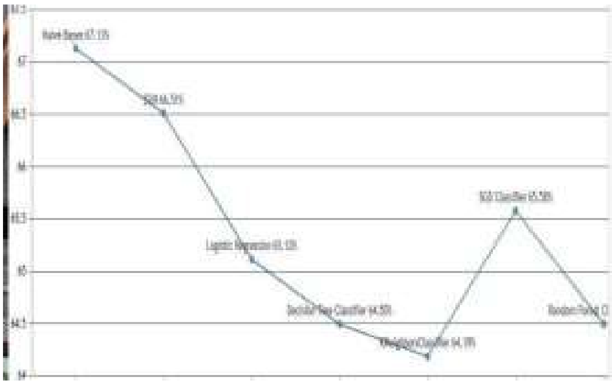

Fig 1: Proposed methodology

TYPES OF CLASSIFICATION ALGORITHMS

Various machine learning methods are used in many different contexts.

In feature space, the training collection consists of the k-nearest samples.

The phrase "feature space" describes a location with attributes that are independent of metrics.

Since it could take some time for examples near the input vector for testing or prediction to appear in the correct sections of the training dataset, instance-based learning is not practical. Because of this, solving problems in the actual world becomes more challenging. What follows is an examination of the most popular machine learning classification algorithms:

SUPPORT VECTOR MACHINE (SVM)

By utilizing a training set that is both independent and identically distributed (iid), a discriminant function may be discovered using a discriminant machine learning method. This function then accurately predicts labels for new cases. In classification difficulties, this is done. A discriminant classification function simply returns a single value for data point x, as opposed to the conditional probability distributions required by generative machine learning approaches. When it comes to producing predictions that require the identification of outliers, generative methods typically yield better results than differential processes. The use of posterior probabilities

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alone reduces the amount of training data and processing power required, which is particularly useful when dealing with a multidimensional feature space. Mathematically training a classifier is similar to figuring out the equation of a multidimensional surface that effectively divides the feature space into multiple classes.

DECISION TREE CLASSIFIER

Decision trees can be applied to various activities. The ability to transform raw data into actionable insight is its crowning glory. Decision trees can be constructed using training files. It generates an array S of objects, where each object is a member of the following classes: C1, C2,..., Ck:

Step1. The decision tree for S gets a class-marked leaf if all of its elements are in the same group, like Ci.

Step2. If that's so, let's say that T is a test that returns On, O2, and O1. There is a distinct outcome for T (Oi) for every item in Si, and it partitions S into subsets S1, S2,..., Sn. Iteratively applying the method to the set Si yields a subordinate decision tree for every outcome Oi. The decision tree has T as its root.

NAIVE-BAYES

The Naive Bayes approach is based on the premise that there is no relationship between the presence or absence of one attribute in a given category and the presence or absence of another attribute in the same category.

It appears, however, that it will endure and function admirably. Its operation is analogous to that of other guided learning methods. In the books, you can find a lot of potential solutions. Justifications predicated on biases in representation will be the primary emphasis of this session. Linear support vector machines (SVMs), logistic regression, and linear discriminant analysis are all methods that resemble Naive Bayes, a linear predictor. The learning bias, or the method used to estimate the classifier's parameters, is a crucial component.

LOGISTIC-REGRESION-CLASSIFIERS

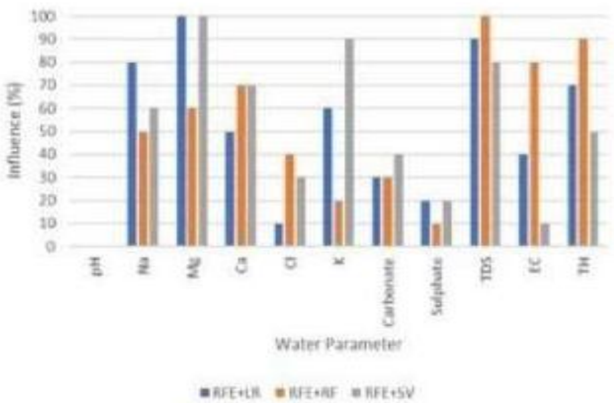
To determine the relationship between a category dependent variable and a group of independent (explanatory) variables, logistic regression analysis is employed. The phrase "logistic regression" is employed when the dependent variable consists of just two possible values, such as 0 and 1, or Yes and No. For dependent variables with three or more categories, such as married, single, separated, or widowed, multinomial logistic regression is the way to go. Even though the dependent variable's data format could be different, the procedure can still be applied in the same manner as multiple regression.

4. RESULTS

The table illustrates that all three models exhibit exceptionally high levels of accuracy. RF's accuracy is the lowest (96.12%) and it has the maximum false positive (FP) rate (5.17%), despite its high performance.This implies that approximately 5% of the time, RF made the error of presuming that potentially hazardous water samples were safe to consume. Nevertheless, LR and SVC outperformed RF due to their FP values of 0%. Nevertheless, SVC incorrectly classified specific potable water samples as hazardous to humans, resulting in a False Negative (FN) rate of 4.23%. The other two models were outperformed by LR, which achieved a classification accuracy of 99.22% and a false negative rate of 1.41 percent. In other words, LR only made the error of declaring potable water hazardous for human consumption 1.5% of the time.

DRINKINGWATER:

	Model	Accuracy (%)	True Positive (%)	False Positive (%)	False Negative (%)	True Negative (%)
1	RF	96.12	94.83	5.17	2.82	97.18
2	LR	99.22	100.00	0.00	1.41	98.59
3	SVC	97.67	100.00	0.00	4.23	95.77



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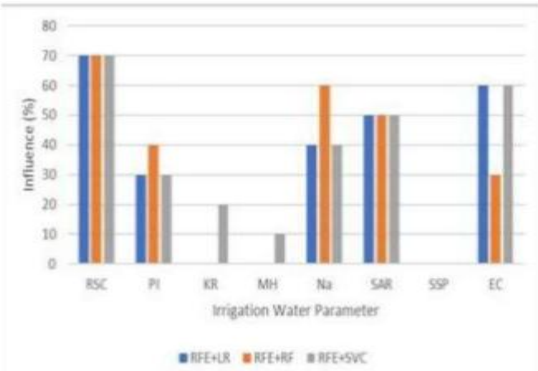
The results of employing RFE on each of the models in question are illustrated in the graph. The models in dispute are RFE+LR for LR, RFE+RF for RF, and RFE+SV for SVC. pH was determined to be the least significant parameter, despite the existence of contradictory data.

In order to determine the impact of each parameter combination on the categorization accuracy of each model, we conducted numerous experiments. Using one constant per iteration, we meticulously altered the remaining nine values. The top forty combinations of LR, RF, and SVC are illustrated in Table 1. The classification accuracies of each model are displayed in the table following the removal of two or more water factors from the dataset.

IRRIGATION WATER:

	Model	Accuracy (%)	True Positive (%)	False Positive (%)	False Negative (%)	True Negative (%)
1	RF	94.44	91.67	8.33	2.78	97.22
2	LR	91.67	94.44	5.56	11.11	88.89
3	SVC	93.06	94.44	5.50	8.33	91.67



Subsequently, the RF model achieved an 8.33% score, surpassing the other two models in terms of FP, as illustrated in the table. The LR and SVC had false positive rates of 5.56% and 5.50%, respectively, as illustrated in Table 2. These rates exhibit a consistent pattern. Nevertheless, LR demonstrated subpar performance on the potable water dataset, with a False Negative (FN) rate of 11.11%.The Support Vector Classifier (SVC) is an exceptional option for irrigation water due to its high classification accuracy and low false positive rate. False negatives pose a lower health danger than false positives.

The irrigation water dataset was subjected to three distinct recursive feature elimination techniques: RFE+LR, RFE+RF, and RFE+SVC. The resulting graphs illustrate the results. RSC was the water parameter that had the greatest impact on the models' classification accuracy, while SSP was the least significant. SAR and Na exhibited substantial synergistic effects. In the absence of Na, RFE+RF functions poorly as a classifier; however, RFE+LR and RFE+SVC function effectively. The fact that RF has lower false negative rates than LR and SVC, while LR and SVC have lower false positive rates than RF, is most likely due to these opposing factors. The top 20 parameter combinations that affect LR, RF, and SVC when applied to irrigation water are listed in the table.

5. CONCLUSION

This study was primarily focused on two topics. The initial idea was to create a network to monitor water bodies' characteristics in real time. The second approach assesses the water quality using machine learning algorithms. The city of Cape Town was used as an example to put up the LoRa-based water monitoring network. Radio Mobile concluded that the optimum coverage within cities would come from a partial mesh network. Ideally, all of the data gathered from this monitoring network would be stored on a cloud server. We could then use machine learning to determine if the water was suitable for irrigation or drinking. Three machine learning models—Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM)—were considered. We had to create two datasets especially for this project's training and testing requirements because none of the pre-existing ones met the requirements.

The test findings demonstrated that SVM performed better when it came to irrigation water. LR had the lowest

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number of false positives and negatives and the highest classification accuracy for potable water. The ability of a model to identify which water parameter or parameters were most crucial for the classification accuracy of the ML models was then assessed using recursive feature elimination (RFE). The study found that SSP had the least effect on the amount of water used for irrigation. However, pH and overall hardness had little effect on drinking water. Although deep learning models would have been helpful in this study, the authors decided against using them. Future research could expand on this work by including deep learning methods, like various neural network topologies. In the future, researchers may investigate the use of unsupervised machine learning algorithms to assess the "fitness for use" of water in order to replace the manual estimations of water quality measures. Other methods, such as multi-criteria decision making, could be employed in place of RFE to identify the most crucial elements. Finding the cause of water contamination and incorporating usage prediction models and microbiological monitoring into the water network could enable more study in this field.

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