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WaterNet A Network for Monitoring and Assessing Water Quality for Drinking and Irrigation Purposes

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ABSTRACT

Water is a fundamental requirement for human, animal, and plant survival. Despite its importance, quality water is not always available for drinking, domestic and/or industrial use. Numerous factors such as industrialization, mining, pollution, and natural occurrences impact the quality of water, as they introduce or alter various parameters present therein, thus, affecting its suitability for human consumption or general use. The World Health Organization has guidelines which stipulate the threshold levels of various parameters present in water samples intended for consumption or irrigation. The Water Quality Index (WQI) and Irrigation WQI (IWQI) are metrics used to express the level of these parameters to determine the overall water quality. Collecting water samples from different sources, measuring the various parameters present, and bench-marking these measurements against pre-set standards, while adhering to various guidelines during transportation and measurement can be extremely daunting. To this end this study proposes a network architecture to collect data on water parameters in real-time and use Machine Learning (ML) tools to automatically determine suitability of water

samples for drinking and irrigation purposes. The developed monitoring network is based on LoRa and takes the land topology into consideration. Results of simulations done in Radio Mobile revealed a partial mesh network topology as the most adequate. Due to the absence of large and open datasets on drinking and irrigation water, datasets usable for training ML models were developed. Three ML models - Random Forest (RF), Logistic Regression (LR) and Support Vector Machine (SVM) were considered for the water classification process and results obtained showed that LR performed best for drinking water, while SVM was better suited for irrigation water. Recursive feature elimination was then combined with the three ML models to reveal which of the water parameters had the greatest influence on the classification accuracies of the respective model

1.INTRODUCTION

Nowadays, everyone has the right to drink clean water since it is essential to human survival. One of the seventeen Sustainable Development Goals (SDG) established by the

UN in 2015 to provide a brighter future for everyone is the availability of safe drinking water. For example, there should be universal access to clean water and sanitation by 2030, according to the sixth objective [2]. Thirdly, we want everyone to be healthy and well-adjusted, and clean water is a key component to that [3]. In developing countries across Asia and Africa, water-borne diseases like cholera, typhoid, and diarrhoea are a leading cause of death, particularly among children. Producing food and agricultural goods also needs water. Starvation is responsible for around 45% of newborn mortality, and recent estimates reveal that 10% of the global population is malnourished [5]. Developing nations are particularly impacted by this problem. As a result, guaranteeing food security on a worldwide scale is crucial. One of the Sustainable Development Goals (SDG) is food security, which is a prerequisite for achieving the other goals (goal 2), which aim to eradicate hunger via the promotion of sustainable agriculture and the improvement of food distribution. Water is essential for irrigation and animal consumption, which in turn makes it essential for food production and agriculture as a whole. As a result, it is critical to guarantee access to water for farming and to manage it sustainably.

You may get water for drinking and irrigation from a variety of places, such as rivers, streams, rain, and groundwater (which can be reached by boreholes and wells). Beyond natural factors, chemical wastes from human activities, such as mining, crude oil extraction, and industrial wastes, often end up in streams, rivers, and other sources of water, changing the nature and properties of these waters. The constituents of water samples obtained from these sources are often influenced by the source's nature and characteristics. Domestic uses, drinking, and feeding aquatic life are some of the ways these waters get up in homes and fields.

used to hydrate crops or cattle. This water is very dangerous and may even be fatal if consumed. Consequently, it is essential to establish an appropriate procedure to guarantee continuous monitoring of the water from its point of origin to its final destination. Water quality, or "fitness for use," for human and animal food, irrigation, and residential or industrial purposes may be evaluated by collecting samples of water at each monitoring site.

2.LITERATURE SURVEY

We go over a few books and articles that have been written on similar topics in this part. The three primary sections of this part are as follows: first, the uses of wireless networks for water parameter monitoring. Next, criteria for determining potable water quality, and finally, studies that investigate how to determine if water is appropriate for irrigation.

1) Water Monitoring using Wireless Communication Networks:

A network was established in a Brazilian city that produces metals to measure and monitor water parameters [12]. An assortment of physicochemical water parameters, such as pH, dissolved solids, zinc, lead, and others, were measured at twelve separate monitoring sites. Our last step was to apply principal component analysis to the collected data. The Limpopo River Basin in Mozambique was also the subject of a similar water quality monitoring system [13], which included the installation of 23 monitoring stations to collect data on a variety of physiochemical and microbiological parameters. Using a genetic algorithm in conjunction with a one-dimensional water quality simulation, the authors of [14] created a financially feasible model to solve the problems associated with

designing water monitoring systems, such as the best locations for gauges and sample frequencies. The authors solved the NP-hard issue of optimally situating monitoring stations, even though the work was simply simulated using a genetic algorithm.

2. Determine the Potability of Water:

Up until recently, the Water Quality Index (WQI) was the gold standard for determining how safe a water supply was for human use. This numerical number, which does not have a unit, is used to determine if water is fit for human consumption or other purposes. There are a number of methods available for determining WQI, and their applicability varies with respect to both geographical and environmental factors. There are approximately 35 water quality index (WQI) models in use worldwide, according to a recent study by Uddin et al. [23]. However, the authors believe that the following are the most important: the Horton Index, the National Sanitation Foundation WQI, the CCME WQI in Canada, the SRDD index in Scotland, the Bascaron index (BWQI), the Fuzzy Interface system (FIS), and the MWQI in Malaysia. The research compared the models according to their structure, parameters, indexing and weighting criteria,

regions of application, and limits. A WQI score of fifty or above was deemed satisfactory for the majority of these models. Also, in a similar vein, [6] examined many WQI models, focusing on the significance of the parameters. Using a combination of analytical hierarchical process (AHP) and assessing attractiveness by a categorically based evaluation method (MACBETH), this study assigned weights to water characteristics and chose the most significant ones based on their use in the literature.

3. Evaluation of Irrigation Water Quality

A crucial component of food production, particularly in crop cultivation, is irrigation water. There has to be a coordinated effort to guarantee adequate water quality standards since water quality may influence agricultural productivity [25]. Irrigation water quality index (IWQI) is one of numerous traditional methods for determining water quality, similar to water quality for drinking [26]. However, most of these methods are either only applicable to water for drinking or are too expensive for local farmers to be practical. Researchers have suggested alternative ML-based

methods, some of which are included in this section.

3. EXISTING SYSTEM

A network was established in a Brazilian city that produces metals to measure and monitor water parameters [12]. The pH, dissolved solids, zinc, lead, and other physico-chemical water parameters were measured at twelve separate monitoring sites. The data was then subjected to principal component analysis for further examination. Similarly, by establishing 23 monitoring stations to measure physico-chemical and microbiological characteristics, the authors of [13] were able to analyze the water quality in Mozambique's Limpopo River Basin. Using a genetic algorithm in conjunction with a one-dimensional water quality simulation, the authors of [14] created a financially feasible model to solve the problems associated with designing water monitoring systems, such as the best locations for gauges and sample frequencies. The authors solved the NP-hard issue of optimally situating monitoring stations, even though the work was simply simulated using a genetic algorithm. Sampling a body of water at regular intervals to collect relevant metrics is

a common practice for water parameter monitoring. Potential hydrogen (pH), temperature, salt levels, and other physico-chemical and microbiological parameters could be part of these metrics. The transmission of measured parameters to a base station allows for the required decision(s) to be made in a water monitoring network. The sparseness of the sent data makes water monitoring networks need lightweight communication methods that can send tiny data over vast distances. Research indicates that LPWAN (Low Power Wide Area Network) technologies are the most popular choice for these kinds of uses. In [19], the topic of LPWAN technology was thoroughly covered. Sig-Fox, Lora, Ingenui, and Telensa were among the sub-GHz options assessed in this study, along with their range, transmission rate, and channel count. After Sig Fox with 10 km in cities and 50 km in rural areas, Ingenu came in at 15 km in urban settings, LoRa at 5 km in urban areas, and Sig Fox at 15 km in rural regions. Software simulations vs real-world testing has been a long-drawn dispute about the evaluation of communication technologies. The outcomes of simulations are often comparable to those of real-world testing, according to a number of academics,

however this argument is far from over. For example, in [20], the authors contrasted the outcomes of simulations with those of real-world tests for intervehicle communication utilizing LoRa. For the simulation, they used NS3, and for the real-world testing, they utilized an Arduino UNO C Dragino LoRa module. The benchmark metrics used were Propagation loss, coverage Packet Inter-reception (PIR), Packet Delivery Ratio (PDR), and Received Signal Strength Indicator (RSSI). They came to the conclusion that the simulator's findings matched those of the actual testing. Similarly, in a related study, they evaluated the performance of LoRa as a Wi-Fi bridge in a radio mobile simulator with that in real-world experiments utilizing micro controllers C LoRa modules. Although it found that the simulator worked effectively, [21] did not compare the simulated and real-world outcomes side by side for each statistic that was studied, in contrast to [20]. In order to test the communication performance utilizing the 800/900MHz and 2.4GHz frequencies, seven pairs of XBee modules were set up [22]. Results from both the Radio Mobile simulator and the actual testing were found to be consistent, they concluded.

3.1 PROPOSED SYSTEM:

This study proposes a water monitoring network that would be installed in the city of Cape Town, Western Cape, South Africa. The goal of the network is to track various water parameters in the city's various water treatment facilities and storage dams. To ascertain if the data collected by the network is fit for human consumption or irrigation, it is subjected to Machine Learning (ML) algorithms.

1) Construct a system to gather and track water quality data in real-time from all of Cape Town's storage dams. This system accounts for Cape Town's specific topography, which includes hills and other factors that might block radio waves from reaching their destinations.

2) Collect large datasets on irrigation and drinking water so that machine learning models may be trained and tested to automatically decide whether water is "fit for use" for irrigation or drinking.

3) Construct models to analyze water for irrigation or drinking purposes, and identify the most important elements that affect the accuracy of machine learning models.

FEASIBILITY STUDY

In this stage, we assess the project's viability and provide a business proposal outlining the project's broad strokes and rough budget. Conducting a feasibility assessment of the proposed system is an essential part of system analysis. Making sure the suggested solution won't be a financial strain on the business is our first priority. A basic familiarity with the system's primary needs is necessary for conducting a feasibility study.

The feasibility study takes three main factors into account:

- **ECONOMICAL FEASIBILITY**
- **TECHNICAL FEASIBILITY**
- **SOCIAL FEASIBILITY**

Economical Feasibility

The purpose of this research is to examine the system's potential monetary effect on the company. The corporation has a finite amount of money to invest on the system's R&D. All costs must have a rationale. As a result, the built system was able to stay under budget, and the majority of the technologies used are publicly accessible. It was necessary to buy just the personalized items.

Technical Feasibility:

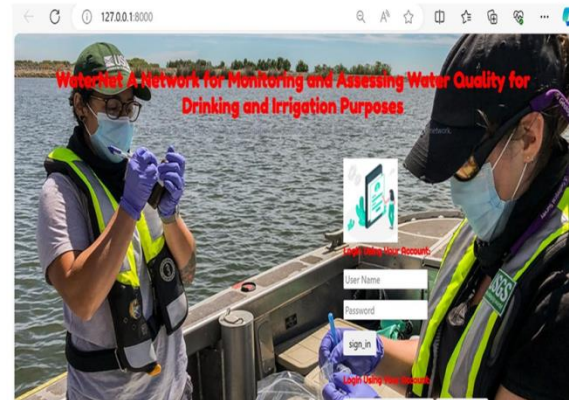
The technical requirements, or viability, of the system are the focus of this research. The existing technological resources should not be overly taxed by any system that is created. The current technological resources will be put to heavy use as a result of this. Because of this, the customer will face a great deal of pressure. Since no or very little adjustments are needed to deploy the designed system, its need must be low.

Social Feasibility:

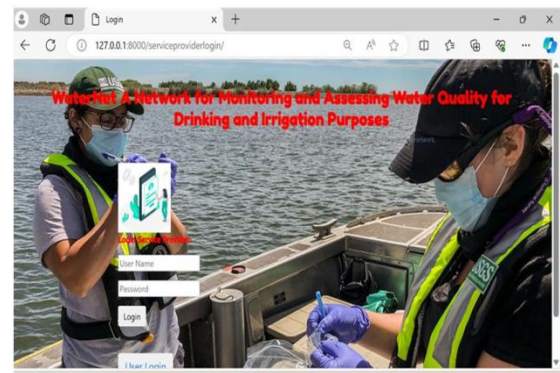
The study's focus is on gauging the user's degree of satisfaction with the system. This entails teaching the user how to make the most of the technology. Instead of seeing the system as an enemy, users should see it as an essential tool. The techniques used to familiarize the user with the system and educate him about it are the only factors that determine the degree of acceptance by the users. As the system's end user, he needs to feel more comfortable providing feedback in the form of constructive criticism.

4. OUTPUT SCREENS

AdminLoginPage:



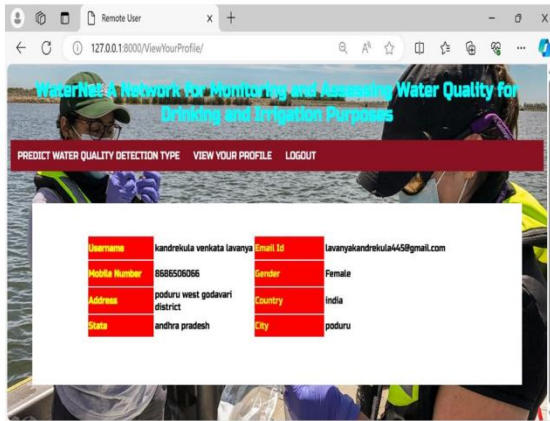
Login Page:



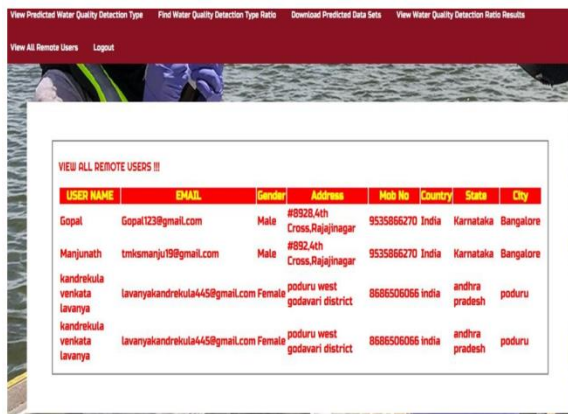
RegistrationPage:



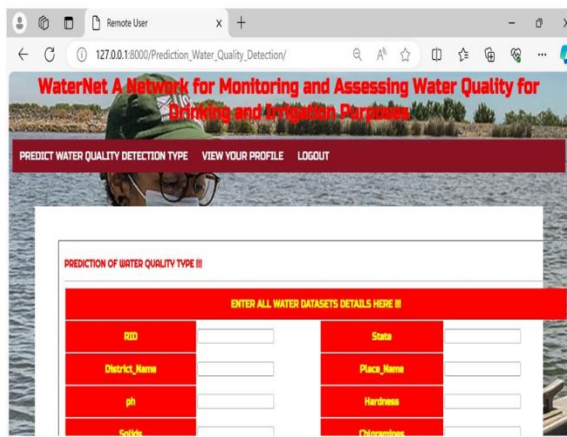
User Profile:



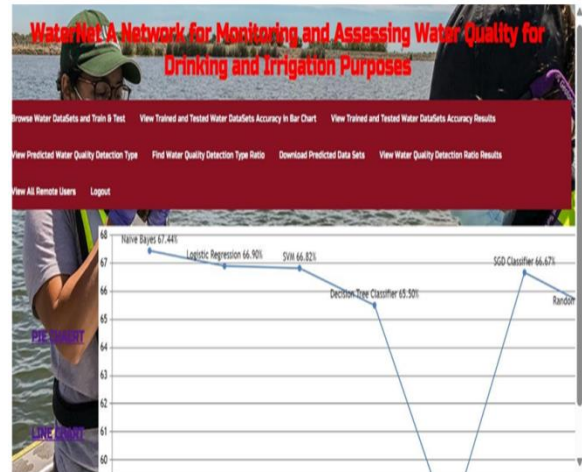
All Remote Users:



Water Quality Prediction:



Water Quality statisticalData:



Visualizing the Accuracy:



5. CONCLUSION

One of the primary goals of this study was to propose a network that could monitor water bodies in real time and record information about various water characteristics. Next, we have the use of ML models to determine the water quality. Lo Ra is a low power long range data transmission protocol; the City of

Cape Town served as a case study for the development of the water monitoring network. According to Radio Mobile's simulation results, the best network architecture to cover the metropolis is a partial mesh network. In a perfect world, a cloud server would compile all of the data collected by this network of sensors, and then machine learning algorithms could be deployed to determine if the water was appropriate for human consumption or agricultural use. This study trained and tested three machine learning models—Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM)—using two appropriate datasets that were created in response to the lack of relevant datasets. The test results showed that SVM was more appropriate for irrigation water, whereas LR was superior for drinking water due to its lower false positive and negative values and greatest classification accuracy.

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