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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 fit 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.

INDEX TERMS Cyber physical system, LoRa, drinking water, irrigation water, machine learning, water quality index, water monitoring network.

I. INTRODUCTION

Access to water is a critical component of human lives and is now considered a basic human right. Access to clean water is also one of the 17 Sustainable Development Goals (SDG) set up by the United Nations in 2015 to achieve a better future for all [1]. Specifically, the sixth goal, which is to ensure and sustain the availability of water and sanitation to all [2]. Potable water can also be linked to the third SDG goal – good health and well-being, as contaminated water can be a transmission medium for diseases such as cholera, typhoid, and diarrhoea, which are jointly the highest cause of mortality (especially children) in developing nations of Africa and Asia [3]. Water is also important in agriculture and food production. Recent statistics shows that about 10% of the world population is malnourished, with developing countries being hit the hardest, with starvation resulting in about 45% of infant mortality [5]. Ensuring global food security is thus

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of utmost importance. Food security has been recognized as a critical requirement, hence its inclusion as one of the SDG (goal 2), with specific focus on ending hunger, by promoting sustainable agriculture and improving food distribution. Food production and agriculture in general rely heavily on water, both for irrigation and for animal consumption. It is thus pertinent to ensure the availability and sustainable management of water fit for agricultural use.

There are several sources of water for both drinking and irrigation use, including rivers, streams, rain, and groundwater (accessed through wells and boreholes). The nature and characteristics of a source of water are often critical factors that influence the constituents of water samples obtained therein. Beyond natural factors, chemical wastes from human activities such as mining, crude oil extraction, and industrial wastes, most often end up in streams, rivers, and other sources of water, changing the nature and properties of these waters. These waters then end up in homes or farms, where they are used for domestic purposes, drank, fed to livestock, or used to water crops. Consuming this type of water can have dire health consequences or result in death. It is therefore paramount that a proper process be put in place to ensure end-to-end monitoring of the water right from the source to its last point of use. At each monitoring point, samples of water need to be collected to assess the quality or ‘‘fitness for use’’ for human (and animal) consumption, irrigation and domestic (or industrial) uses.

Several models have been developed to assess water quality, all of which consider various parameters, including chemical (such as hydrogen potential (pH), calcium, oxygen, sulphate levels etc.), microbial (such as E. coli, rotaviruses, Entamoeba etc.), and physical (temperature and clarity). These models produce a unit metric, known as the Water Quality Index (WQI), as output. Globally, different guidelines have been adapted for calculating WQI. For instance, in parts of Europe, the British Columbia Water Quality Index (BCWQI) and the Scottish Research Development Department (SRDD) are used, while in North America, the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI) and National Sanitation Foundation Water Quality Index (NSFWQI) are predominant. In Asia, specifically India, the Bureau of Indian Standards (BIS) is prominent, while in Africa, notable standards include the South African National Standard for drinking water (SANS 241-1) and the Kenya Bureau of Standards (KEBS). A number of these models have been reviewed in [6]. It is important to note that many of these national standards are mostly local adaptations of the standards defined by the World Health Organization (WHO) [7]. This work is based on the South African and WHO standards.

Indeed, measuring water parameters for diverse water samples can be a laborious and daunting task, as it often involves adhering to a stringent set of rules in collecting the water samples, maintaining set conditions during transportation to the test laboratories, following standard methodologies in analysing the samples, and generally ensuring quality control. Some of these processes (and corresponding guidelines) are given in [8], [9]. The output of these processes indicates if the water sample is potable or non-potable. In this work, we propose a Cyber-physical network architecture for real-time monitoring of water parameters across a city and an alternative model based on machine learning to determine potability of water samples. Like [10]–[13] [14], our work also only focuses on the physical and chemical parameters of water, while ignoring the biological. This is because our model is meant to be sensor based (in the context of the Internet of Things), and to our knowledge, there are no physical sensors for measuring biological parameters, such as the presence of E. coli in water. We do not trivialize the importance of microbial water parameters, and our proposed model can indeed be adapted to consider these parameters by simply incorporating suitable physical sensors (if available) or virtual / soft sensors, such as the one proposed in [15] into our model.

Figure 1 gives a high-level depiction of our proposed architecture which is built upon 4 layers. The constituent components of this architecture are described as follows:

1) **Sensing Layer:** As depicted in the figure, the sensing layer interacts directly with the water samples in a river, stream, dam etc. to measure water parameters. It is built into a vertical pole tagged ‘‘sensor probe’’ and consists of numerous sensors bundled together. These sensors might include pH, conductivity, turbidity, temperature, residual chlorine etc., similar to those offered by Libelium [16]. All telemetry data measured by these sensors are sent to the Fog Nodes (FNs), wired or wirelessly, via the sending unit. In scenarios where installing sensors in water source(s) is extremely difficult or when the required sensors are not readily available, water parameter readings can be collected from the associated water treatment plants.
2) **Edge Layer:** This layer consists of low-end processing devices (edge modules), such as single board computers (e.g., Raspberry Pi or Nvidia Jetson), or microcontrollers (e.g. Arduino, ESP32). These devices act as i.) data pre-processing units, responsible for the collection, aggregation, filtration, and shaping of data received from the sensing layer; ii) network gateway to ‘‘ferry’’ telemetry data to the FNs, through 3G/4G/5G cellular or other low powered long-range network solutions.
3) **Fog / Cloud Layer:**
   - Fog Nodes (FNs): these are small sized distributed cloud computing nodes that bring computing and storage closer to the data source, thus reducing latency resulting from transmission delay to/from the remote Cloud [17]. The FN is responsible for classification of water samples using machine learning models such as the ones proposed in this work. Due to the limited computing power at the Fog (compared to the Cloud), only the most influential parameters need to be considered when

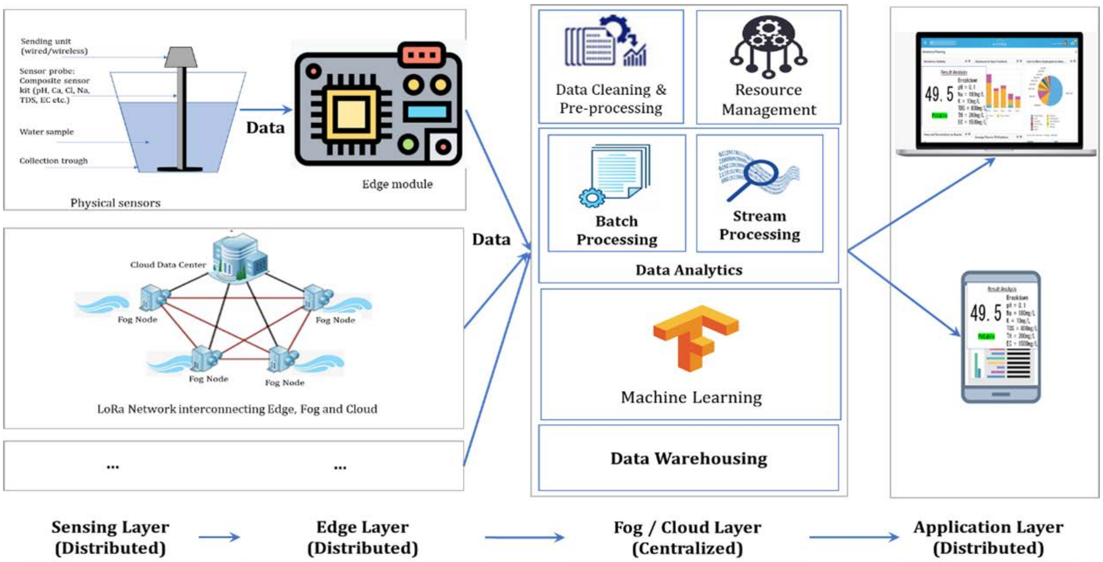

FIGURE 1. Conceptual framework for Water Quality Monitoring.

classifying water samples. This can be beneficial as less sensors would be required (since not all parameters are being measured) and by extension lower computing resources would be needed for the classification process. Furthermore, resource management, scheduling etc. can also be carried out on FNs. When long term storage and/or advanced computations are required, which are beyond the Fog's capacity, data are forwarded to the Cloud data centre.

- Cloud Data Centre: The Cloud is a remote high performance computing infrastructure, which provides computing on demand [18]. In our system, the Cloud serves as a data warehouse as well as a platform for performing advanced data analytics, dashboarding, and hosting for relevant services and software.

4) **Application Layer:** serves as an interface between users (water management authorities, end users / customers, other stakeholders) and software / services running in the Cloud. Relevant software for water parameter monitoring are hosted at this layer and made available to users through mobile and web platforms.

The water monitoring network proposed in this work is to be deployed in the City of Cape Town in Western Cape, South Africa, with the intention of monitoring water parameters in water storage dams and/or water treatment plants across the city. Data gathered by the monitoring network are then passed through Machine Learning (ML) models to determine their suitability for consumption or irrigation purposes. The specific contributions of this work can be summarized as follows:

1) Build a network for real-time collection and monitoring of water quality across water storage dams in the city of Cape Town. This network takes into consideration the unique geographical features of Cape Town, such as mountains and elevations that might obstruct radio frequency propagation.
2) Curate ample sized datasets on drinking and irrigation water that can be used to train (and test) machine learning models to automatically determine the "fitness for use" of a sample of water for drinking and/or irrigation purposes.
3) Build models that determine the most critical parameters that influence the accuracy of machine learning models in analysing water for drinking or irrigation.

Regarding the order of this paper, following this introductory section, is a review of related works in section II. Section III discusses our methodology for building the city-wide water monitoring network, while section IV presents the datasets curation process and machine learning models considered for determining quality of water samples. Implementation processes and obtained results from our experiments are discussed in sections V and VI respectively. Section VII discusses the economic viability of our proposed solution, while section VIII concludes the paper and gives insights into future directions.

II. REVIEW OF LITERATURE

In this section, we review some existing works in literature on related subject matters. This section is divided into three main categories; first, the applications of wireless networks in monitoring water parameters. Second, yard-sticks for assessment drinkable water, and lastly, research works that focus on assessing suitability of water for irrigation purposes.

1) WIRELESS COMMUNICATION NETWORKS FOR WATER MONITORING

In [12], a network for measuring and monitoring water parameters in a metal producing city in Brazil was developed.

Twelve water monitoring stations were setup to measure several physico-chemical water parameters, including pH, dissolved solids, Zinc, Lead etc. Finally, obtained results were analysed using principal component analysis. In a similar manner, [13] developed a system to monitor water quality in Limpopo River Basin in Mozambique and set up 23 monitoring stations to measure physico-chemical and microbiological parameters, and ultimately assess the quality of water in the river basin. To address the challenges of optimal placement of gauges and sampling frequencies, which are often faced when developing water monitoring systems, the authors in [14] developed an economically viable model that combined genetic algorithm with 1-D water quality simulation. Though the work was only simulated by using genetic algorithm, the authors were able to solve the NP hard problem of optimally placing monitoring stations.

Monitoring water parameters often entails periodically sampling a body of water to capture relevant metrics. These metrics might include physico-chemical and microbiological measurements, such as potential of hydrogen (pH), temperature, sodium levels etc. In a water monitoring network, measured parameters need to be transferred to a base station where relevant decision(s) would be taken. Due to the sparse nature of transmitted data, light weight communication protocols capable of transmitting relatively small data over long distance are required for water monitoring networks. From literature, Low Power Wide Area Network (LPWAN) technologies have been favoured for such applications. An extensive discussion on LPWAN technologies was done in [19]. The work compared a few sub-GHz solutions including SigFox, LoRa, Ingenu and Telensa, with respect to their range, transmission rate, and channel count. Ingenu was reported to have the longest range in city settings at 15 km, followed by SigFox at 10 km (in cities) and 50 km (in rural areas); then LoRa at 5 km (in cities), and 15 km in rural settings.

Regarding the assessment of communication technologies, there has been a long-drawn debate over the efficacy of software simulations versus real-world testing. Though this debate still rages, several researchers have shown that simulation results are often at par with real-world tests. For instance, using LoRa, the authors in [20] compared simulation results with real world test for intervehicle communication. They used NS3 as a simulation platform and an Arduino UNO + Dragino LoRa module for the real-world tests, while Propagation loss, coverage Packet Inter-reception (PIR), Packet Delivery Ratio (PDR) and Received Signal Strength Indicator (RSSI) level were used as benchmark metrics. They concluded that the results of the simulator were consistent with those of the real-world tests. In a similar work, Hassan [21] also compared the efficacy of simulation results (from Radio Mobile simulator) with real-world tests (using micro controllers + LoRa modules) when using LoRa as a bridge for Wi-Fi. Unlike [20], [21] did not give a side-by-side comparison of simulated vs. real-world results for each metric considered but concluded that the simulator performed well. [22] set up seven pairs of XBee modules and compared communication performance using both the 800/900MHz and 2.4GHz frequencies. They concluded that simulation results from the Radio Mobile simulator corroborated with those of real-world tests.

2) ASSESSING WATER POTABILITY

When assessing the quality of drinking water, the Water Quality Index (WQI) has been the de facto metric. It is a unitless numeric value that gauges the suitability of water for human consumption or general usage. As stated earlier, several models exist for calculating WQI depending on the location and environmental conditions in such locations. In a recent study by Uddin *et al.* [23], it was noted that there are about 35 WQI models in use globally; however, in their opinion, the major ones are the Horton Index, National Sanitation Foundation WQI, the Canadian Council of Ministers of the Environment (CCME) WQI, Scottish Research development Department (SRDD) index, Bascaron index (BWQI), Fuzzy Interface system (FIS), and the Malaysian water quality index (MWQI). The study compared these models in terms of structural composition, parameters considered, indexing and weighting criteria, application areas and inherent limitations. For most of these models, a WQI value of at least 50 was considered acceptable. In a related work [6] also reviewed several WQI models but with emphasis on parameter importance. The work selected the most common parameters used in literature and applied analytical hierarchical process (AHP) and measuring attractiveness by a categorically based evaluation technique (MACBETH) to assign weights to water parameters and select the most relevant ones.

In [10] the authors sought to assess the impact of mining activities on water quality in certain areas of Bangladesh. Twelve parameters were considered, including pH, electrical conductivity (EC), turbidity, hardness, salinity etc. These were then benchmarked against the WHO standards to determine WQI. In another work, [11] applied WQI to urban water resource management. The work follows up on an earlier study in [12], where a water monitoring network was set up to give information about water, by including information about the quality of water across the twelve monitoring points using WQI. Two models were used to calculate the WQI, namely CCME WQI and Cetesb WQI. CCME classified all samples as poor, while Cetesb resulted in a mix of Good, Fair and Poor.

A major shortcoming of WQI is its site specificity, which implies that WQI is often calculated for a specific body of water or region, using the parameters therein. It therefore cannot be automatically applied to a different water body except when the two share similar attributes and parameter ranges. Moreover, WQI are developed to target specific use case(s), hence, bounded by the constraints set for that use case(s). In a bid to tackle this and make WQI water sample agnostic, [24] proposed a universal WQI model that is applicable to all water bodies in South Africa. The authors applied 13 parameters selected from literature and experts. To obtain a universal WQI, the authors created a custom aggregation function, which treats the WQI inputs from different water sources as a system of linear equations. Their unified model was able to classify water samples from the different sources effectively.

3) ASSESSING WATER QUALITY FOR IRRIGATION

Irrigation water is a vital part of food production, especially crop farming. The quality of water can affect crop yield, hence concerted efforts need to be made to ensure proper water quality standards [25]. Like with drinking water, several classical techniques exist for ascertaining the quality of irrigation water (or irrigation water quality index – IWQI), however most are either tailored to drinking water alone or not economically viable for local farmers as they require many parameters [26]. Alternate techniques which rely on ML have been proposed by researchers, a few of which are discussed in this subsection.

The authors in [27] aimed to predict the levels of Exchangeable Sodium Percentage (ESP), Magnesium Adsorption Ratio (MAR), Potential Salinity (PS), Residual Sodium Carbonate (RSC), Sodium Adsorption Ratio (SAR), and Total Dissolved Solid (TDS) in irrigation water using ML models. Their work showed that Adaboost and Random Forest (RF) were good predictors, but Artificial Neural Network (ANN) and Support Vector Machine (SVM) were less sensitive to input variables. In [26] the authors also proposed a model for determining the quality of water for irrigation purposes using three parameters - sodium, chloride, and EC. The work started off with five water parameters – sodium, chloride, EC, bicarbonate, and SAR, which were then reduced to the final three using correlation models. They then compared the classification performance of various machine learning models on these three parameters and obtained results that showed that Random Forest performed the best, when compared to Decision Trees, Naïve Bayes, Gradient Boosting, SVM and ANN. In a similar work, IWQI was calculated in [28] using a model proposed in [29] with sodium, chloride, EC, bicarbonate, and SAR as parameters. Singh *et al.* [30] also considered the SAR, Sodium level, Kelly's Index (KI) and permeability index (PI) to determine IWQI using regression and ANN models. The regression models were used to determine the correlation between water parameters, while ANN models were used for the prediction.

A commonality among works on irrigation water is the term irrigation water quality index (IWQI), which is an index used to measure the quality of water for crop irrigation. It takes into consideration the individual contribution and relative weight of each water parameter when classifying water samples for irrigation [29]. There are various approaches to calculating IWQI, notable among which are the WQI approach proposed by WHO (as used in [10], [24], [31]) and that of Meireles *et al.* [29]. For this work, we stick to WHO's approach, which we also use for assessing the quality of drinking water. However, for completeness purposes, we summarize the steps of Meireles *et al.*'s approach in Algorithm 2.

It is important to note that though WQI and IWQI are widely used in literature, they have their limitations. An obvious disadvantage of combining water index for irrigation is that the specific effect of each water parameter is somewhat masked. For instance, sodium is known to affect soil dispersion as it reduces infiltration by increasing SAR. It is also toxic if sprayed on leaves through irrigation sprinkler. On the other hand, NO_3 and PO_4, may be beneficial for irrigation as they are nutrients required by plants. These causes and effects of individual constituents are masked off when WQI/IWQI are used.

From the reviewed literature two major inferences can be drawn, which are:

1) In many of the works that proposed a ''network'' for water monitoring, the actual network architecture was not shown. Most authors simply stated that a certain number of monitoring stations were setup to measure water parameters. This is probably because, the actual analyses were carried out in laboratories and not on site. Furthermore, details about the communication technologies, communication media and protocols used were not discussed. This work seeks to fill this research gap.
2) Most of these studies split water parameters into physical (temperature, cloudiness, etc.), chemical (pH, carbonate, nitrate levels, etc.), biological (presence of bacteria, virus, etc.), heavy metals (lead, cobalt, etc.) and others; and applied one or two WQI (or IWQI) models to determine water quality. The application of machine learning models, which are economically viable options for interpreting water sample analyses, is still in its infancy, especially in the context of developing nations. This is another interesting research gap which this study attempts to fill.

III. THE WATER MONITORING NETWORK

As earlier stated, one of the objectives of this work is to develop a realistic network for monitoring water parameters in real-time. This network which we term ''WaterNet'' is based on a LPWAN technology and is intended to support a Cyber-Physical System for Water (CPS-W). CPS-W, like most CPS [32] combines an IoT-based sensing and actuation subsystem with Fog/Cloud computing [17]. This combination has been used in numerous applications, such as in health [33], transportation [34], [35], and environmental monitoring [36]. The nodes in WaterNet would be wirelessly interconnected by a two-layer LoRa network. LoRa (Long Range) is a type of LPWAN that emphasizes power conservation over data transmission rate [19]. It has been shown that by using LoRa, data can be transmitted up to a range of 300 km in ideal situations (clear line of sight, good antenna height, antenna gain, transmission power and transmission frequency) but at the cost of data bandwidth [37]. Due to the small size of telemetry data being exchanged across WaterNet nodes, only minimal bandwidth is required, hence, LoRa is suitable for our application.

A. CAPE TOWN WATER SYSTEM

WaterNet is being proposed for monitoring water parameters in Cape Town, a city in the Western Cape province of South Africa. There are fifteen major water storage dams that supply water to the City of Cape Town (CCT) and its immediate environs. Eleven of these dams are owned by the CCT, while the other four are owned by the Department of Water and Sanitation [38]. Figure 2 shows a high-level depiction of the locations of the dams across the city. This work focuses on the 11 dams owned by CCT and develops a network model for monitoring water quality parameters for drinking and irrigation purposes. It is important to note that, beyond monitoring ‘‘fitness for use’’ for drinking and irrigation, this system can also be used to monitor water levels as well as usage and refill rates of the dams. Though a few of these dams have monitoring systems in place, most are either manually operated or are stand-alone systems. Our objective is thus, to develop a city-wide water quality monitoring network that interconnects all the dams and enables real-time online monitoring of water parameters across them.

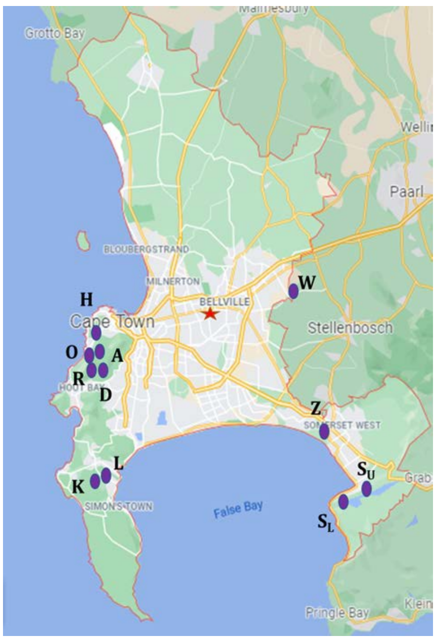

FIGURE 2. **Locations of CCT-owned dams across the City of Cape Town, South Africa. Where A = Alexandra Resv. Dam; D = DeVilliers Dam; H = Hely-Hutchinson Resv. Dam; K = Kleinplaas Dam; L = Lewis Gay Dam; O = Woodhead Dam; SL = Steenbras Dam – Lower; SU = Steenbras Dam – Upper; R = Victoria Dam; W = Wemmershoek Dam; Z = Land-en-Zeezicht Dam.**

B. WATERNET

The 11 dams considered are connected to 7 Water Treatment Plants (WTP) across the city. Figure 3 gives a visual illustration of our proposed solution, with the dams labelled with alphabets (A, K, L,...), while the WTPs are labelled FN1, FN2...FN7. To monitor water parameters, sensors are installed in each dam to relay telemetry data through edge gateways (GW) to the WTP for processing. The WTPs are considered as Fog Nodes (FN) that can handle some degree of computationally intensive processing, including data aggregation, filtration, basic analysis, and storage. The WTPs (FNs) are in turn connected to a central location, in our case the ILLIFU Cloud computing research facility, located at the University of the Western Cape (UWC), where advanced computing activities and data warehousing take place [39].

IV. ASSESSING WATER QUALITY

The purpose of WaterNet is to gather data on water parameters from dams across the city. These parameters are then used to assess the quality of water with regards ‘‘fitness for use’’ for drinking and irrigation purposes. In this work, rather than relying on instrumental and physico-chemical analysis carried out in laboratories to assess water parameters, we propose the use of machine learning (ML) models, which take the numerous water parameters into consideration and automatically determine if a sample of water is potable or fit for agricultural use. The motivation is to reduce the cost and complexities involved in collecting, testing, and analysing water samples to determine their status. By using ML and transfer learning, a pre-trained ML model from one site can be transferred to another location and results would be obtained in minutes.

Figure 4 is a flow chart depicting the methodology adopted, with each of the phases discussed as follows.

A. DATA CURATION

Like most research on ML a dataset is required. However, due to the absence of large, dedicated, and open access datasets of drinking and irrigation water, especially in Africa, we created our own. To create our datasets, we aggregated several ‘‘small’’ datasets of water for drinking and irrigation (or agriculture) primarily from Elsevier’s Data in Brief (DiB). DiB is an open access journal dedicated to publishing details on research data [40]. We used the following search phrases ‘‘irrigation water,’’ ‘‘potable water,’’ ‘‘groundwater,’’ and ‘‘drinking water,’’ then filtered out unrelated articles. We ended up with 11 publications (mostly from Asia), 7 of which also had data on irrigation water. The datasets were scraped, combined, and saved into two csv files, for drinking and irrigation respectively, using Microsoft Excel.

For our work, the primary requirement was to have data that could be used to train (and test) our ML models to classify water samples. Ideally, a water monitoring network would have been the source of these data on water parameter, however, since to our knowledge, no such data aggregation network exists, we had to improvise. At this stage we are less concerned about the source of the data, as this work is simply a proof of concept, instead we concerned ourselves with ensuring that the respective datasets contained relatively similar feature sets (water parameters). This is similar to what was done in [24]. Tables 1 and 2 show a comparison of features (water parameters) across the different publications considered.

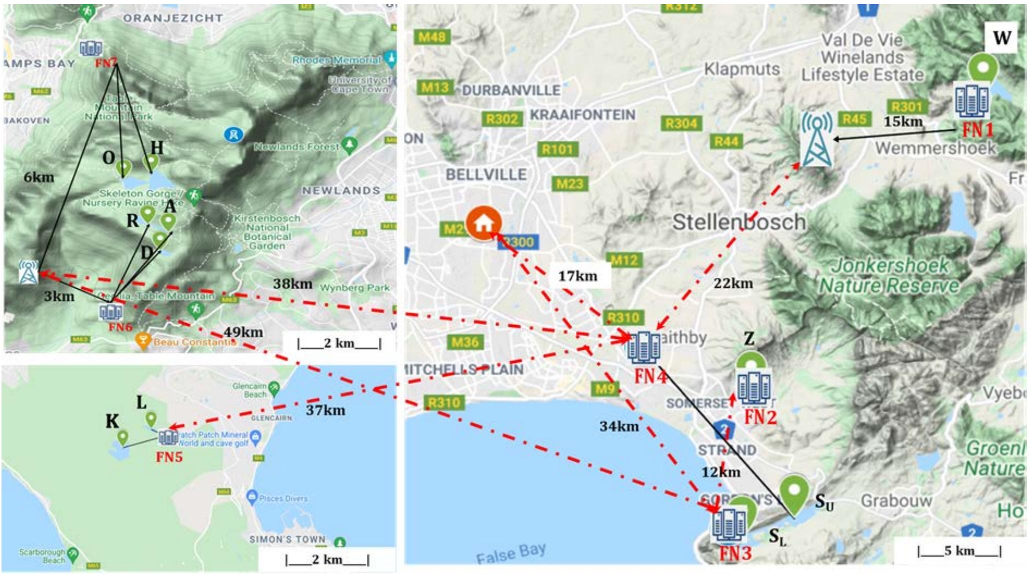

FIGURE 3. Proposed dam monitoring network for the City of Cape Town - WaterNet. Where FN1 = Wemmershoek WTP; FN2 = Helderberg WTP; FN3 = Steenbras WTP; FN4 = Faure WTP; FN5 = Brooklands WTP; FN6 = Constantia Nek WTP; FN7 = Kloof Nek WTP.

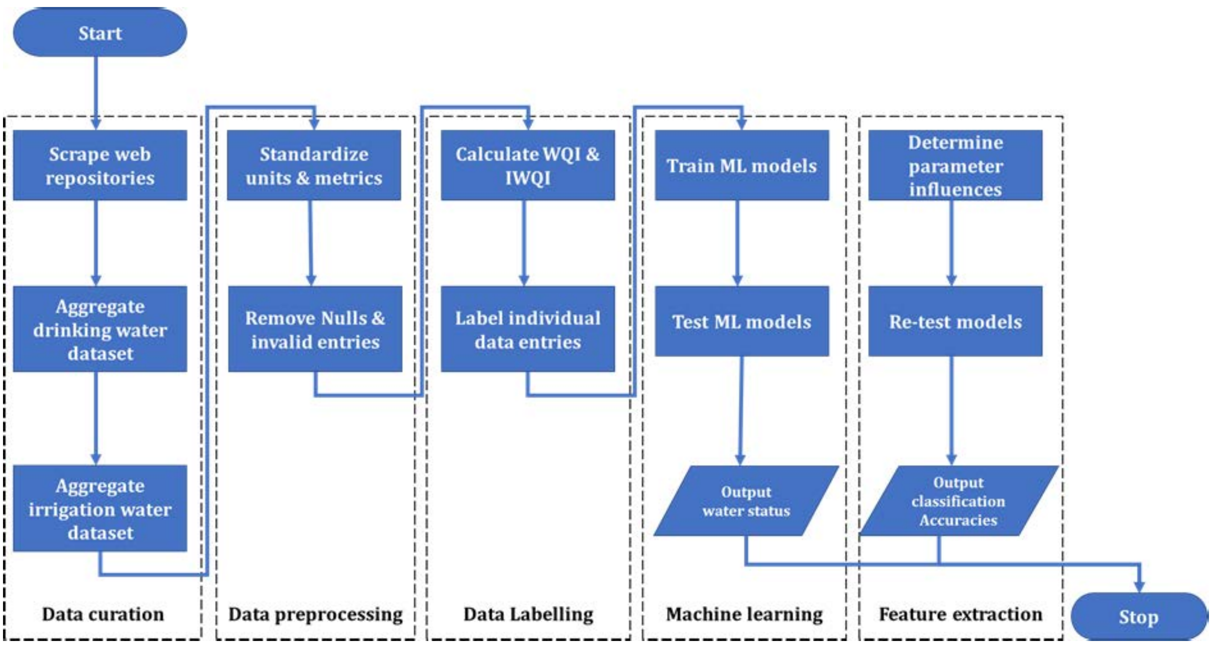

FIGURE 4. Process flow for Water Quality Assessment using ML.

Table 1 only shows the most common features across the datasets considered. Some of the datasets contained additional parameters such as nitrate, fluorine in [41]; nitrate, Florine, Salinity in [42]; Total Prec. Potential, Turbidity, Colour, Total coliform, E. coli, organic carbon, chlorophyll, nitrites, ammonium, phosphate, and iron in [43]; and Colour, nitrite, ammonia, zinc, barium, boron, copper, iron, lead, mercury etc. in [44]. These parameters were excluded from Table 1 because we only found at most 2 papers that had them in common.

In Table 2, the features marked "XX" were not included in the original dataset but were calculated by us using the constituent parameters and formula on Table 3. Table 3 also shows the definition of the acronyms used in Tables 1 and 2, and the unit of each feature. After aggregation we ended up with two datasets containing approximately

TABLE 1. Feature comparison for potable water.

Ref.	pH	Na	Mg	Ca	Cl	K	CO3	HCO3	SO4	F	Turbidity	TDS	EC	TH	Label
[31]	X		X	X	X	X			X			X	X	X	
[41]	X	X	X	X	X	X		X	X	X		X	X	X	X
[42]		X	X	X	X	X		X	X	X					
[43]	X	X	X		X	X	X		X		X		X	X	
[44]	X	X			X				X	X	X	X	X		
[45]	X	X	X	X	X				X			X	X	X	
[46]	X	X	X	X			X				X	X			
[47]	X	X	X	X	X	X		X	X			X	X	X	X
[48]	X	X	X	X	X		X	X	X			X	X	X	
[49]	X	X	X	X	X	X	X	X	X			X	X	X	
[50]	X										X		X		

TABLE 2. Feature comparison for irrigation water.

Ref.	RSC	PI	KR	MH	Na%	SAR	SSP	Label
[31]		X	X	X	X	X	X	
[41]	X	X	X	X	X	X	XX	
[42]	X	X	X	X	X	X	X	
[46]		XX	XX	XX	X	X	XX	X
[47]	X	X	X	X	X	X	X	
[48]	X	X	X	X	X	X	X	
[49]	X	X	X	X	X	X	X	

700 and 360 unique entries for drinking water and irrigation water respectively.

B. DATA PRE-PROCESSING & LABELLING

Of the entire aggregated drinking water dataset, only about 16% were pre-labelled (i.e., the status of the water sample was included in the dataset). We then wrote a Python script to calculate the WQI (and IWQI) for the unlabelled data. From literature, researchers often assign different weights to the individual water parameters to counter the masking effect of WQI. However, because we are building a generic model, we assigned equal weights to all parameters in our Python script to avoid introducing any form of bias. For the drinking water dataset, we cross-referenced the calculated WQI value with those defined in [7] and [44]. If the calculated WQI < 50, the data entry was labelled 1 (i.e. potable) or 0 (non-potable) if otherwise. For the irrigation water dataset, we also set the threshold to 50, as such IWQI values $>= 50$ were considered permissible for irrigation. Hence, we labelled data entries with IWQI < 50 as not suitable for irrigation (0) and values $>= 50$ as usable (1).

Kindly note that the threshold value of 50 was only used as a general guide for assessing fitness of use. This value (i.e. 50) has also been used in several literature [42], [45]–[47] to indicate water of good (or excellent) quality. Indeed, the overall WQI may indicate that a sample of water is fit for use, but there may be some constituents beyond this threshold levels which are not captured, e.g., toxicity. Table 3 summarizes the acceptable value range for each parameter as used in our labelling script, while the process of calculating WQI and IWQI are discussed in the next subsections.

1) CALCULATING WQI FOR DRINKING WATER

Water Quality Index (WQI) is a simple dimensionless index for assessing the quality of water based on various parameters [6]. There are numerous ways of determining the WQI based on different models as discussed in the introductory section. In this work we apply the method proposed by Horton [51] which is summarized in Algorithm 1

All the steps in Algorithm 1 are relatively straightforward except step 1. Feature selection has been a long-battled

TABLE 3. Acceptable range for various water parameters [7], [44].

Parameter	Definition	Unit/Formula	Accepted Range
pH	Potential of Hydrogen		5 – 9.7
Na	Sodium	mg/L	<= 200
Mg	Magnesium	mg/L	< 50*
Ca	Calcium	mg/L	< 75*
Cl	Chloride	mg/L	<=300
K	Potassium	mg/L	< 12*
SO4	Sulphate	mg/L	<= 500
HCO3	Bicarbonate	mg/L	120-200*
CO3	Carbonate	mg/L	1% of HCO3*
Turbidity	Cloudiness	NTU	<= 5
TDS	Total Dissolved Solids	mg/L	<= 1200
EC	Electrical Conductivity	mS/m	<= 170
TH	Total Hardness	mg/L	100 – 300*
RSC	Residual Sodium Carbonate	$(\mathrm{HCO}_3 + CO_3) - (Ca + Mg)$	<1.25*
PI	Permeability Index	$\frac{Na + \sqrt{(HCO_3)}}{(Ca + Mg + Na)} 100$	>70*
KR	Kelly's Ratio	$\frac{Na}{(Ca + Mg)}$	<1.5*
MH	Magnesium Hazard	$[Mg/(Ca + Mg)]$ $\times 100$	<50*
Na%	Sodium Percentage	$\frac{(Na + K)}{(Ca + Mg + Na + K)}$ $\times 100$	<40*
SAR	Sodium Adsorption Ratio	$\frac{Na}{\sqrt{(Ca + Mg)/2}}$	0-10
SSP	Soluble Sodium Percentage	$\frac{Na}{(Ca + Mg + Na)} x100$	<50*

Algorithm 1 Calculating WQI for Drinking Water.

1. Select relevant parameters

$$(P = [P_1, P_2, P_3 \ldots P_n]).$$

2. Assign weights to each parameter (w_p), $1 < p < n$
3. Calculate relative weight

$$W_p = \frac{w_p}{\sum_{p=1}^{n} w_p}$$

4. Calculate quality index

$$q_p = \frac{C_p}{S_p * 100}$$

5. Obtain

$$WQI = \sum_{p=1}^{n} W_p * q_p$$

where P = parameter selected, w_p = weight of parameter p, n = number of parameters, C_p = concentration of p, S_p = standard value for parameter p as stipulated by WHO [7].

challenge due to various viewpoints on which parameters are most important, especially across different geographical domains. For instance, a certain parameter that might be considered critical in one country, because it is naturally present in their water bodies, might not be relevant in another country, where such elemental parameter is absent. To this end, various countries have developed their own models for measuring WQI. Common among these include the Canadian CCMEWQI, India's BIS, the U.S. Environmental Protection Agency (EPA), the South African SANS 241-1, and the global model by the World Health Organization (WHO).

2) CALCULATING IWQI FOR IRRIGATION WATER

As stated earlier, there are two common approaches for calculating IWQI. The first one, which is used in this study, is based on WQI (Algorithm 1), while the second, proposed in [29], is summarized in Algorithm 2.

Algorithm 2 Calculating WQI for Irrigation Water [29].

1. Identify prominent parameters in the sample, i.e. EC, sodium, chloride, bicarbonate, SAR.
2. Determine weights for each parameter.

2a. Calculate quality measurement value

$$q_i = q_m ax - \frac{(X_{ij} - X_{inf}) * q_{iamp}}{X_{amp}}$$

2b. Calculate aggregate weight

$$w_i = \frac{\sum_{j=1}^{k} F_j * A_{ij}}{\sum_{j=1}^{k} \sum_{i=1}^{n} F_j * A_{ij}}$$

3. Obtain

$$IWQI = \sum_{i=1}^{n} q_i * w_i$$

where q_{max} = max value of q_i in its class; X_{ij} is the value of parameter i; X_{inf} is the lowest value in the class to which X_{ij} falls; q_{iamp} = class amplitude; X_{amp} = amplitude of X_{ij}'s class; w_i = parameter weight; F = autovalue of the first component; A_{ij} = explainability of parameter i by j; j = factor count. Details about each variable can be found in [29].

C. MACHINE LEARNING MODELS FOR DETERMINING QUALITY OF WATER

As earlier stated, the second objective of this work is to use ML models to automatically classify water samples. We selected the 11 most common water parameters from the dataset sources to run the ML on. These were pH, sodium, magnesium, calcium, chloride, potassium, sulphate, carbonate, TDS, EC, and TH. Three ML classification models were considered, namely Random Forest (RF), Logistic Regression (LR) and Support Vector Classifier (SVC).

RF is the amalgamation of a multitude of decision trees [52]. It can be used for both regression and classification problems. When used as a classifier it outputs the ''majority vote'' from all the individual trees. Unlike decision trees (DT), RF generally does not suffer from over-fit on training data. It also uses bagging and random feature selection to overcome the high variance problem of DT [53]. LR models the probability that an event would occur, called the dependent variable based on one or more independent variable(s). LR is well suited to finding binary output probabilities, i.e., True or False (1 or 0) and it does not require a linear relationship between the dependent and independent variables. In applying it to this work, the 11 features were considered the independent variables, while the potability (1 or 0) was the dependent variable. SVC is a form of Support Vector Machine, which is a nonlinear solver for classification and regression problems [54]. A unique advantage of SVM over models such as Neural Network is its ability to perform well with smaller datasets, hence our decision to use it. Given a set of data points, SVM seeks to draw a line (hyperplane) that separates the data point into unique classes. Typically, the hyperplane must maximise the distance from support vectors of each class with the smallest possible data separation error. For this work we used a linear kernel with our SVC model.

For this work, water assessment is considered a classification problem, with the primary objective of classifying water samples into ''fit for use'' or not. LR was used because it is well suited for binary classification problems using the sigmoid function, though it is susceptible to outliers. On the other hand, SVC was considered because, like LR, it is also well suited for two-class problems but less affected by outliers. It also works well with smaller datasets, which is the case with this work. RF was considered because it can work with datasets of different sizes and with mixed feature sets. It is also generally faster than SVC. Finally, these 3 ML models were chosen because they represent 3 different types of ML models, viz. LR is based on statistic (regression analysis), SVC is based on data geometry, while RF is a type of ensemble learning ML model.

D. DETERMINING PARAMETER INFLUENCE

Here the goal is to dig deeper into the classification problem to determine which features (water parameters) are the most influential in determining water potability (or irrigation suitability) when using ML models. We utilized the recursive feature elimination (RFE) method to achieve this, similar to the approach used in [55].

RFE is a backward feature selection method that searches for the best performing features by first utilizing the entire feature set to train a given model. It then scores each feature based on its contribution to the overall performance of the model, after which it iteratively removes poor performing features and retrains the model, until further removal of features does not improve the model's performance [56]. In this work we used accuracy as the scoring factor and criteria for eliminating features.

V. IMPLEMENTATION

Our implementation process was split into two phases – A and B. Phase A focused on WaterNet – the water monitoring network, while Phase B focused on assessing the quality of water based on water parameters received from WaterNet.

A. PHASE A - SIMULATING WATERNET

To simulate this city-wide water monitoring network (WaterNet) a combination of Google maps, Topographic-map.com and Radio Mobile software [57] was used. Google maps is a web-based mapping and real-time location sharing service by Google [58], while Topographic-map.com is a free online tool which provides details about the geographical landscape of an area including hills, mountains, and valleys [59]. Radio Mobile is a network planning tool for simulating radio frequency propagation [57]. It uses an irregular terrain propagation model to simulate coverage and point-to-point transmissions of radio signals. This terrain propagation feature makes Radio Mobile ideal for our application because Cape Town is a city with many undulating plains, with several lowlands sandwiched between mountains and hills. This uneven geography of the city makes direct line of sight radio propagation difficult, and creates an interesting networking challenge, as most communication frequencies do not propagate through rocks and/or mountains. Radio Mobile is therefore ideal for testing reachability, signal strengths and line of sights of radio propagations in WaterNet.

We began by creating a custom map in Google map with all relevant points of interest marked. This was then imported into Radio Mobile as a KML file, with all coordinates embedded. In Radio Mobile, a 2-layer hierarchical network model was created. At the lower level the dams were connected to their respective WTPs (FNs) using LoRa network configured with frequency range of 863-870 MHz, transmission power of 14 dBm, receiver threshold of −80 dBm, and 10m high antennas. At the higher level, the FNs were connected to ILLIFU Cloud data centre using a 2.4 GHz LoRa network [60] configured with frequency ranging between 2.41-2.46 GHz, transmission power of 22 dBm, receiver threshold of −75 dBm, antenna gain of 21 dBi and height of 30 m. Figure 5 shows the 2-layer Cyber Physical hierarchical network of WaterNet, where X-GW are the gateways (edge devices) at each dam and FN1…FN7 are the WTPs hosting the Fog Nodes. To get more range we used a high spreading factor of 12. Ideally, higher spreading factor results in lower data rates [19] but this is acceptable in our use case, as we would only be sending small sized telemetry data at pre-set intervals.

B. PHASE B - ASSESSING WATER QUALITY

With the WaterNet established and telemetry data on water parameters being sent to the Fog and Cloud respectively, data analysis and ML can be used to gain useful insights or assess the quality of water at each dam. For this work, we curated data from different sources to simulate parameters received from WaterNet. Simulations presented in this section thus focus on the use of ML to assess quality of water for drinking or irrigation purposes.

Experimental simulations were carried out on Google Colab, with a Python 3 Google Compute module, configured with 12 GB of RAM, and 2.3 GHz 2 Core Intel Xeon CPU. Sci-Kit learn was used for the ML models, Pandas and NumPy for data manipulation, while matplotlib was used for data visualization. Finally, the dataset was split into 84% training and 16% test data.

Three 3 ML models were considered and contrasted against each other using five metrics, namely accuracy, true positive (TP), false positive (FP), false negative (FN) and true negative (TN). Of these five metrics, accuracy, FP, and FN were the most critical to us. Accuracy is a measure of a model's classification performance, i.e., the percentage of water samples that were correctly classified. False positive is the percentage of impure water samples that were misclassified as potable. This is important because misclassifying non-potable water as drinkable can be hazardous with severe consequences to the health if consumed. False negative on the other hand is a measure of the percentage of potable traffic that were wrongly classified as not safe for consumption.

VI. RESULTS & DISCUSSIONS

In line with the previous section on implementation, our results are also presented in two phases, the first focuses on the results of the water monitoring network (WaterNet), while the second focuses on assessing water quality for drinking and irrigation purposes using ML.

A. WATER MONITORING NETWORK

Table 4 summarizes the results and observations from simulating the network on Radio Mobile. It can be observed that not all FNs can directly (1 hop) reach ILLIFU, in fact, only 2 (FN3 and FN4) are able to. Thus, a point-to-point star network

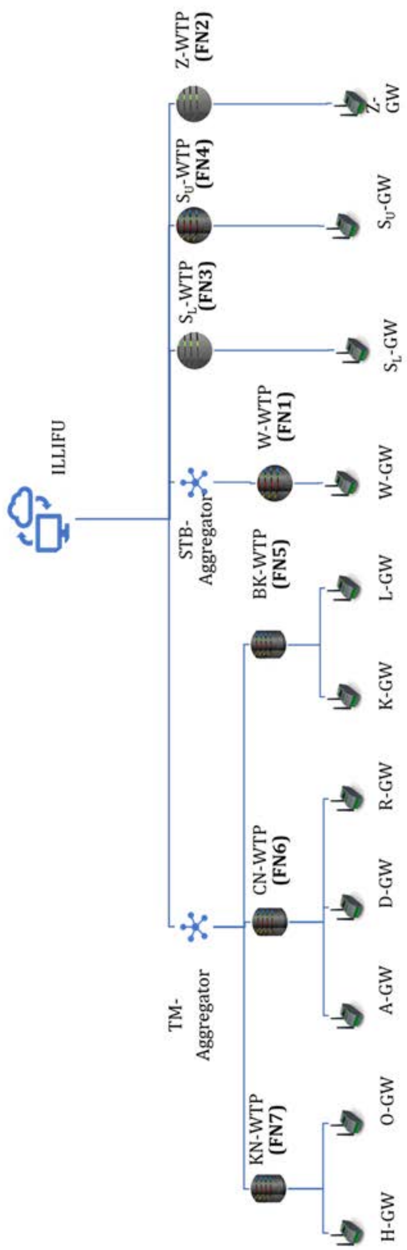

FIGURE 5. **Hierarchical Cyber Physical Network for WaterNet.**

topology cannot be used, instead a partial mesh with node rebroadcast is considered. FN1 is located close to the ground level and almost fully surrounded by high grounds, hence the need for a repeater (STA) mounted on a 1136 m high hilltop at Stellenbosch farms (-33.90989, 18.74262). Despite this repeater, FN1 (via the repeater) is still unable to directly reach ILLIFU but has FN4 in its line of sight. FN1 can therefore reach ILLIFU by hopping through STA and FN4.

Like FN1, FN2's LOS to ILLIFU is obstructed by a hill and has to be rebroadcasted via FN3. FN5 requires an antenna of about 40-50 m height to reach FN4, from where its signal is rebroadcasted to ILLIFU. FN6 and FN7 are somewhat isolated and unreachable by all FNs, because they are located behind Table Mountain. To allow reachability to both sites, a repeater (TMA) is placed on a hill around Hout Bay in Cape Town.

Figure 6 is a snapshot of the partial mesh network extracted from Radio Mobile. The figure reveals that most traffic traverse through FN3 and FN4, hence were the most critical nodes in the network. A reasonable explanation for this is that both FN3 and FN4 have clear line of sight to ILLIFU, as there are no high rise geographical structure on their paths.

1) LINK COSTS

Though IEEE 802.15.4 standard stipulates an ''Rx sensitivity'' value of -85dBm for both the 868/915 MHz and 2.4 GHz networks [61], commercially values of up to -100 dBm are acceptable. W.r.t signal voltage, the stipulation is 12.6 uV (calculated using Eq. 3), which implies that radio frequency signals that arrive at a receiver with a root mean square voltage of at least 12.6 uV can be detected with about 99% accuracy (less than 1% data error) [62]. From Table 5, almost all paths have a sensitivity value greater than -85dBm and a signal voltage greater than 12.6 uV. This implies reachability and less than 1% data error rate. The only exceptions are FN1-SMA, FN6-TMA and FN7-TMA with values sensitivity values lower than -85 dBm.

Table 5 summarizes the obtained link cost results from Radio Mobile. On the table, ''Tx height'' and ''Rx height'' respectively mean the antenna heights of the transmitter and receiver from ground level. Path loss (or path attenuation) means the reduction in power of the radio waves as they propagate through free space, resulting from reflection, refraction, absorption, etc. It is calculated using (1). Finally, ''Rx Sensitivity'' and ''Signal Voltage'' are indicators of the sensitivity of a receiver on a network path. Receiver sensitivity is the minimum input signal required to overcome noise and produce an acceptable output signal with less than 1% packet error rate at the receiver [62]. Receiver sensitivity and signal voltage are calculated using (2) and (3).

$$PathLoss = 20 * log(d) + 20 * log(f) + 20 * log(\frac{4 * \pi}{c}) - G_T - G_R \qquad (1)$$

where d = distance between both transmitter and receiver antennas, f = signal frequency, c = speed of light, G_T and G_R are the gains of the transmitter and receiver antennas respectively.

$$ReceiverSensitivity(S_r) = \frac{S}{N_{min}} * K * T * B * \frac{NF}{G} \qquad (2)$$

$$SignalVoltage(uV) = \sqrt{R * 10^{\frac{S_r - 30}{10}}} \qquad (3)$$

where S_r = receiver sensitivity, S/N_{min} = Minimum signal-to-noise ratio required to detect a signal, K = Boltzmann's Constant ($1.38 * 10^{-23} Joule^o K$), T = absolute temperature of receiver in Kelvin ($290^o K$), B = Receiver Bandwidth (Hz), G = antenna gain of receiver, and R = Resistance of the antenna.

TABLE 4. Observations from simulating waternet on radio mobile.

Node	Location	Dam(s) /Node(s)	Nodes in Line of Sight	Direct link to ILLIFU	Route to ILLIFU	Hops to ILLIFU	Comment
FN1	-33.83471,19.07271	W-GW	None	No	Via STA and FN4	3	Obstructed by hills around stellenbosch
FN2	-34.06278,18.87325	Z-GW	FN3	No	Via FN3	2	Obstruction by hills around Somerset West
FN3	-34.17483,18.84976	SL-GW	FN2, FN4, ILLIFU, TM-Aggregator (TMA)	Yes	Yes	1	
FN4	-34.03109,18.77176	SU-GW	FN1, FN3, FN5, ILLIFU, STA, TMA	Yes	Yes	1	SU-GW could be sent to FN3 or via fibre optic cables to FN4.
FN5	-34.16912,18.39958	L-GW, K-GW	FN4	No	Via FN4	2	Using at least a 45m antenna
FN6	-34.00554,18.39972	A-GW, D-GW, R-GW	None	No	Via TMA FN4	3	
FN7	-33.94782,18.39513	H-GW, O-GW	None	No	Via TMA FN4	3	
STA	-33.88553,18.92877	FN1, W-GN	FN1, FN4	No	Via FN4	2	Co-ordinates: -33.88553, 18.92877
TMA	-33.99611,18.36361	FN6, FN7	FN3, FN4 FN6, FN7	No	Via FN3 or FN4	2	Co-ordinates: -33.99611, 18.36361
ILLIFU	-33.93352,18.62795	-	FN3, FN4	-	-	0	

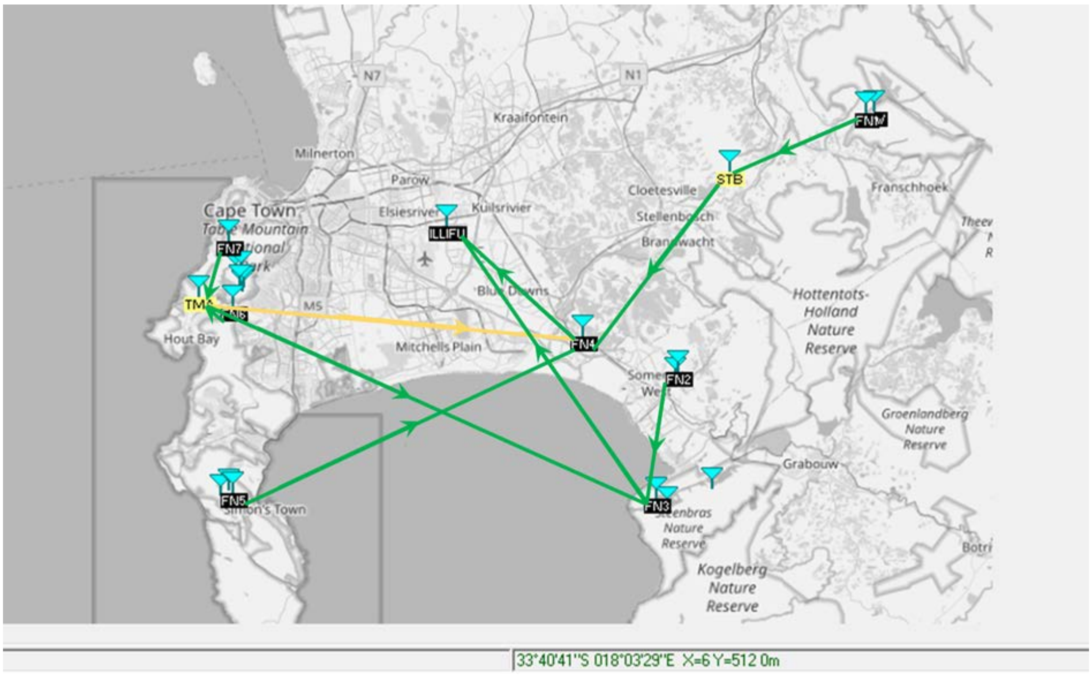

FIGURE 6. Snapshot of the partial mesh network topology from Radio Mobile simulator.

We considered two options to interconnect FN1 and SMA. The first is based on 863-870 MHz network, which was used for the lower-level connection as shown in Figure 5. The 863-870 MHz yielded sensitivity values lower than the IEEE stipulations at just 0.1 uV, hence not suitable. As an alternative, we used the 2.4 GHz network instead and obtained a much better signal voltage of 375.9 uV. The links between FN6, FN7 and TMA are sub-GHz and a sensitivity value of up to -100 dBm is acceptable for these kinds of frequency range. Though there is an increased probability of higher error rates, this is acceptable in our use case as telemetry messages being transmitted are very small and occasional re-transmissions would not overwhelm the network.

2) OTHER OBSERVATIONS

Figure 5 shows the two-layer network, wherein the dams are connected to their respective fog nodes via an 863-870 MHz LoRa network. It is important to note that this wireless connection might not always be feasible as many of the dams are either located below sea level and obstructed by mountains and hills or at higher altitudes than their respective WTPs. Figure 7 shows four instances of

TABLE 5. Inter-nodal link costs.

	Tx Site	Rx Site	Distance (Km)	Tx Height (m)	Rx Height (m)	Path Loss (dB)	Rx Sensitivity (dBm)	Signal Voltage (uV)
1a	FN1	SMA	15.3	281.7	1136.6	144.2	-127.2	0.1
1b	FN1	SMA	15.3	281.7	1136.6	122.5	-55.5	375.92
2	FN2	FN3	12.64	137.9	326.8	125.8	-58.8	257.58
3	FN3	ILLIFU	33.72	326.8	63.3	131.5	-64.5	132.61
4	FN4	ILLIFU	17.13	115.3	63.3	127.8	-60.8	204.05
5	FN5	FN4	37.32	189.2	115.3	141.9	-74.9	40.07
6	FN6	TMA	3.49	267.6	722.9	108.9	-91.9	5.66
7	FN7	TMA	6.10	345.3	722.9	112.2	-95.2	3.90
8	TMA	FN3	49.03	722.9	326.8	136.9	-69.9	72.01
9	TMA	FN4	37.83	722.9	115.3	141.1	-74.1	44.28
10	SMA	FN4	21.71	1136.6	115.3	131.7	-64.7	130.15

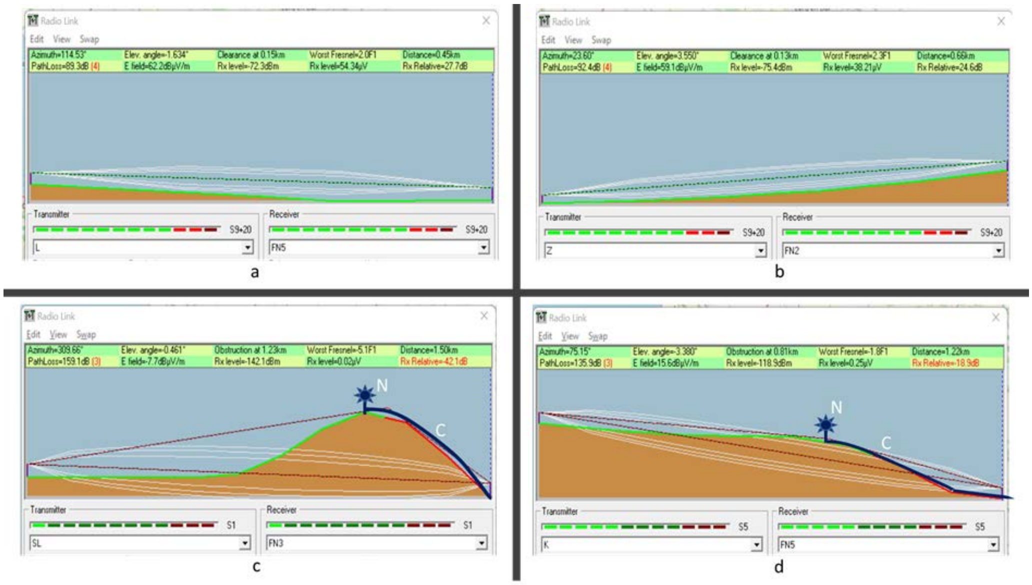

FIGURE 7. Snapshot of land structure between FNs and Dams from Radio Mobile simulator.

network connections between (water parameter sensors in) the dams and their corresponding WTP (FN). In the figures the brown coloured structure represents earth/ground, while the blue colour represents free space. The green and red lines represent reachability, while the white lines represent electromagnetic Fresnel zone.

Figures 7a and 7b show a clear line of sight between the dams and FNs. In such situations simple point-to-point network with antennas of height 10-30 m can be set up to connect both entities. Figures 7c and 7d on the other hand are more complicated scenarios, as there is no clear line of sight between the entities. For such cases, we proffer two solutions. In the first, the LoRa node can be placed on an elevated surface (where a line of sight to the FN can be established) and cable(s) used to connect the sensors in the dam to the LoRa node. This is as shown in Figures 7c and 7d, with the LoRa node and cable respectively labelled N and C. The second solution would be to take the parameter readings from the water treatment plant (FN) rather than the dam. Here it is assumed that pre-existing channels are in place to allow water flows directly from the dam to the treatment plant for processing.

B. CREATING THE DATASET

It is expected that WaterNet would provide data about water parameters, however, for this work and as discussed earlier, we used hypothetical datasets curated data from existing datasets on the Internet. This subsection presents the result of the data curation process.

Using Algorithm 1, we were able to calculate water quality index (WQI) and irrigation water quality index (IWQI) for all data entries. WQI values range from 0 to 100 and were mapped to fitness of use for drinking or irrigation. Figures 8 and 9 show snippets of the final labelled datasets, with the penultimate column in both figures, representing the calculated WQI values, while the last column depicts the fitness of use, as described in section VI-B.

Figures 10 and 11 show the histogram depiction of each parameter in the drinking and irrigation water datasets. For the drinking water dataset, most of the parameters had relatively similar distribution shapes except pH, WQI and potability. The potability curve shows a slight imbalance between potable (300) and non-potable data (400), however, the numbers are close enough not to skew the results. Figures 12(a) and 12(b) show that pH and especially WQI have a normal distribution curve (using Gaussian kernel), which is indicative of a relatively balanced drinking water dataset. Relatively balanced sample classes were also observed for parameters in the irrigation water dataset, with 175 samples considered suitable for irrigation and 185 considered as not suitable. Figure 12(c) also reveals a normal distribution curve for the calculated IWQI for the irrigation water dataset.

After labelling all data points that were originally unlabelled in the datasets, we used the pre-labelled data as test data, against which we benchmarked our labelled data using several machine learning models (ML). Furthermore, to determine the most influential water parameters, we ran experiments using RFE with cross validation to select the optimal number of features. These features (water parameters) were then ranked in descending order of their influence on the classification accuracy of each model. Finally, we reran the three ML models (RF, LR and SVC) with different combinations of excluded features to determine the change in their accuracies (if any). The ML models and corresponding results are discussed in the next subsection for both drinking and irrigation water.

C. DRINKING WATER

1) DETERMINING POTABILITY OF DRINKING WATER

Table 6 shows that all 3 models performed well w.r.t accuracy scores. RF had the least accuracy at 96.12% and, though impressive, had the highest False Negative (FP) rate at 5.17%. This implies that RF misclassified hazardous water samples as safe for drinking about 5% of the time. LR and SVC on the other hand resulted in FP values of 0% and are thus better alternatives for RF. However, SVC had a False Negative (FN) rate of 4.23%, implying that it misclassified some potable water samples as not drinkable. LR gave the best results of the 3 models with 99.22% classification accuracy and 1.41% FN. In essence, LR only misclassified safe drinking water as non-potable about 1.5% of the time.

TABLE 6. Result of model comparison using all features on drinking water dataset.

	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

2) DETERMINING PARAMETER INFLUENCE ON DRINKING WATER

Figure 13 shows a graphical depiction of the result of carrying out RFE on each of the models considered, that is, RFE on LR (RFE+LR), RFE on RF (RFE+RF), and RFE on SVC (RFE+SV). The result, though non-uniform, revealed that pH was the least influential parameter across board.

The graph shows that pH has zero influence on the overall classification accuracy, and this is expected as Figure 12(a)

```
1 X.head(10)
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	id	pH	Sodium	Magnesium	Calcium	Chloride	Potassium	Carbonate	Sulphate	TDS	EC	TH	WQI	Potability
0	L1	7.3	77.5	32.6	81.4	63.6	2.0	419.7	68.2	640.0	1045.0	338.0	70.597120	0.0
1	L2	7.5	36.1	31.1	42.4	19.5	1.6	273.3	57.1	400.0	645.0	234.0	48.298251	1.0
2	L3	7.7	119.4	19.0	58.2	60.7	1.2	195.2	220.8	640.0	998.0	224.0	55.761878	0.0
3	L4	6.0	117.1	29.7	145.4	37.3	2.7	580.7	190.1	950.0	1516.0	486.0	97.028982	0.0
4	L5	7.0	45.1	23.4	49.6	23.4	1.2	248.9	74.9	410.0	658.0	220.0	46.462197	1.0
5	L6	7.0	73.4	33.0	50.4	35.2	2.3	346.5	83.0	540.0	875.0	262.0	58.783534	0.0
6	L7	7.2	121.9	29.7	67.8	47.2	1.2	195.2	310.1	740.0	1153.0	292.0	63.377606	0.0
7	L8	7.3	54.1	16.6	56.6	24.5	1.2	297.7	45.1	420.0	676.0	210.0	48.343252	1.0
8	L9	7.3	55.2	25.3	68.6	45.1	2.0	307.4	74.9	510.0	817.0	276.0	57.078475	0.0
9	L10	7.2	59.8	32.6	57.4	31.2	3.1	341.6	80.2	530.0	848.0	278.0	59.604469	0.0

FIGURE 8. Snippet of labelled drinking water dataset showing calculated WQI and potability values for the first 10 data points. Refer to units in Table 3.

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1 A.head(10)
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	id	RSC	PI	KR	MH	Na	SAR	SSP	EC	IWQI	USABLE
0	1	0.12	59.2	0.5	39.8	33.6	1.8	33.3	1045	63.379762	1.0
1	2	-0.21	58.9	0.3	54.8	25.6	1.0	25.1	645	50.337302	1.0
2	3	-1.28	72.2	1.2	35.0	53.8	3.5	53.7	998	68.144246	1.0
3	4	-0.20	55.2	0.5	25.2	34.7	2.3	34.4	1516	64.631448	1.0
4	5	-0.33	62.5	0.4	43.8	31.1	1.3	30.8	658	51.432242	1.0
5	6	0.43	66.0	0.6	52.0	38.2	2.0	37.8	875	71.445437	1.0
6	7	-2.64	63.6	0.9	42.0	47.7	3.1	47.6	1153	51.132837	1.0
7	8	0.68	69.6	0.6	32.6	36.2	1.6	35.9	676	65.043849	1.0
8	9	-0.48	58.7	0.4	37.9	30.7	1.4	30.3	817	50.248115	1.0
9	10	0.04	60.9	0.5	48.4	32.5	1.6	31.9	848	60.917361	1.0

FIGURE 9. Snippet of labelled irrigation water dataset showing calculated IWQI and usability values for the first 10 data points. Refer to units in Table 3.

and Table 3 allude to this. From Table 3, pH values ranging between 5 and 9.7 are considered safe for consumption and since almost all pH values in our dataset fall within this range (as shown in Figure 12(a)), pH would therefore have minimal effect on the classification accuracy. A similar explanation holds true for sulphate (SO_4) with most of the values in our dataset being within the safe limit (<= 500mg/L). These are in sharp contrast to magnesium (Mg) for instance, which according to Table 3, should have a value of less than 50mg/L, but our drinking water dataset has numerous entries with values ranging between 100 – 750mg/L, hence the heavy influence of Mg.

To further examine the influence of different combinations of parameters on the classification accuracies of each model, we ran iterative experiments using all possible combinations of parameters. For each iteration we held one parameter constant and cycled through the other 10. Table 7 summarizes the results of the top 40 combinations for LR, RF and SVC respectively. For each model, the table shows the resulting classification accuracies when at least two water parameters are removed from the dataset.

Table 7 and Figure 14 further buttress our results in Figure 13, that pH had the least effect on the classification accuracies of all 3 models, while magnesium (and EC) were the most influential parameter for drinking water.

D. IRRIGATION WATER

1) DETERMINING USABILITY OF IRRIGATION WATER

Similar to the results on Table 6, Table 8 also shows that RF performed the worst of all three models w.r.t. to FP with a

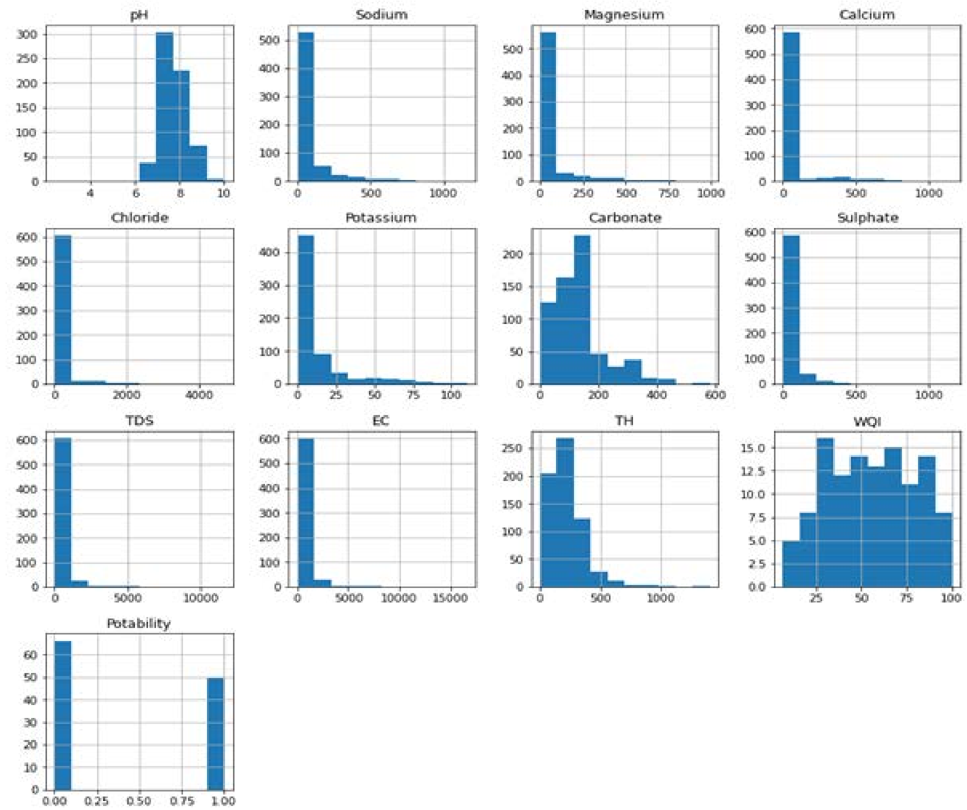


FIGURE 10. **Histogram plot (count vs. value) of water parameters in the drinking water dataset.**

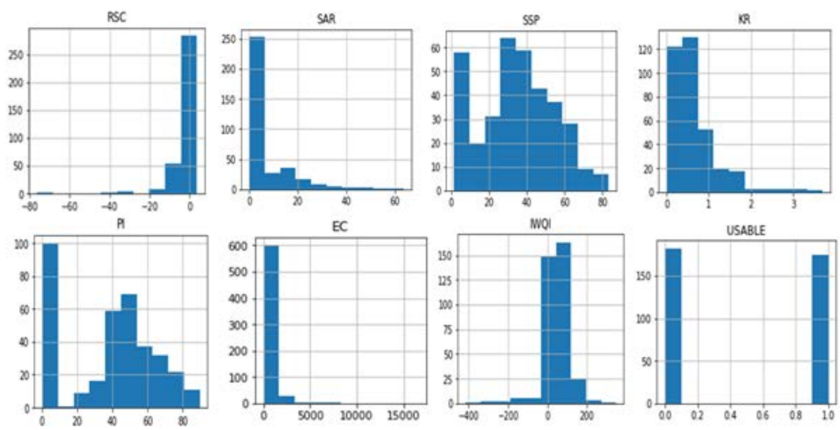
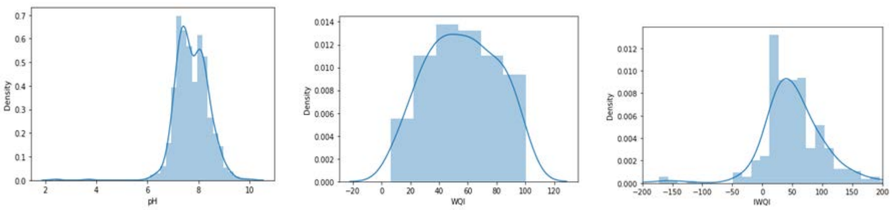


FIGURE 11. **Histogram plot (count vs. value) of water parameters in the irrigation water dataset.**

score of 8.33%. The same trend as in Table 6 is also observed for LR and SVC, with both having the lower FP rates of 5.56% and 5.50% respectively. However, in contrast to the results of the drinking water dataset, LR performed the worst w.r.t False Negative (FN) at 11.11%. The effect of FN are not as adverse on health as FP, hence, SVC would be considered the best option for irrigation water, as it gave acceptably high classification accuracy and the lowest False Positive value.

2) DETERMINING PARAMETER INFLUENCE IN IRRIGATION WATER

Figure 15 shows a graphical depiction of the results of recursive feature elimination (RFE+LR, RFE+RF, and RFE+SVC) on the irrigation water dataset. It reveals that SSP had the least influence on the classification accuracies of the models, while RSC was the most influential feature (water parameter). SAR and Na were also relatively influential across board. EC is seen to be very influential with



(a) Distribution of pH values in drinking water dataset (b) Distribution of calculated WQI values in drinking water dataset (c) Distribution of calculated IWQI values in irrigation water dataset

FIGURE 12. Density distribution curves for select water parameters.

TABLE 7. Parameter influence on classification accuracies of ML models for drinking water.

Excluded Parameters	LR Accuracies (%)	RF Accuracies (%)	SVC Accuracies (%)
pH & TH	99.22	98.45	97.67
Carbonate & Na	96.90	98.45	96.90
Mg & Na	96.12	98.45	96.90
Chloride & Ca	96.12	94.57	95.35
Carbonate & Ca	96.12	94.57	95.35
Carbonate & Chloride	96.12	94.57	94.57
TDS & Na	96.12	98.45	97.67
TDS & Ca	96.12	93.80	94.57
pH & Mg	95.35	96.12	94.57
Chloride & SO4	95.35	95.35	95.35
pH & Ca	94.57	95.35	93.80
pH & Chloride	94.57	95.35	94.57
pH & SO4	94.57	96.12	96.12
Chloride & Na	94.57	94.57	94.57
Chloride & Mg	94.57	96.12	94.57
pH & Carbonate	93.80	96.12	96.12
Mg & K	93.02	93.80	93.02
Carbonate & K	93.02	92.25	93.02
TDS & K	93.02	92.25	93.02
TH & Na	93.02	98.45	93.80
TH & Mg	93.02	96.12	93.02
pH & K	92.25	95.35	94.57
TH & Ca	92.25	93.80	93.02
TH & Chloride	92.25	93.02	93.02
TH & K	92.25	93.02	93.02
Chloride & TDS	91.47	94.57	92.25
Chloride & EC	90.70	93.80	90.70
TH & Carbonate	90.70	93.80	90.70
pH & TDS	89.92	94.57	91.47
pH & EC	89.92	93.80	90.70
Mg & Carbonate	89.15	93.80	89.15
Mg & SO4	89.15	93.80	89.92
TDS & SO4	89.15	89.92	89.92
TH & SO4	89.15	92.25	88.37
Carbonate & TDS	88.37	92.25	89.15
Mg & TDS	87.60	90.70	89.15
Carbonate & EC	85.27	90.70	86.05
TH & TDS	85.27	89.15	85.27
Mg & EC	84.50	84.50	83.72
TH & EC	83.72	86.05	83.72

TABLE 8. Result of model comparison using all features on irrigation water dataset.

	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

RFE+LR and RFE+SVC but not with RFE+RF, yet the reverse is the case with Na. These contrasting influences are most likely responsible for the lower false positive values observed with LR and SVC compared to RF, and the lower false negative values of RF compared to LR and SVC on Table 8. Table 9 summarizes the results of the top 20 combinations of parameters influencing LR, RF and SVC when used on irrigation water.

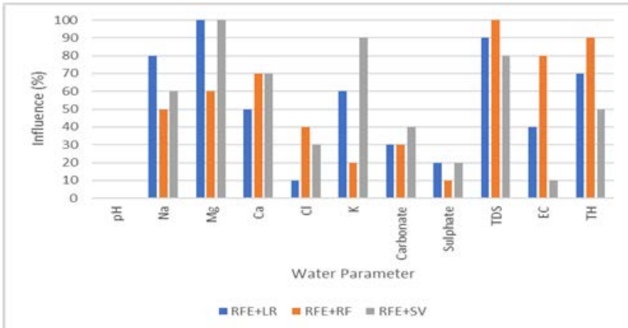


FIGURE 13. Parameters influencing the classification accuracy of drinking water.

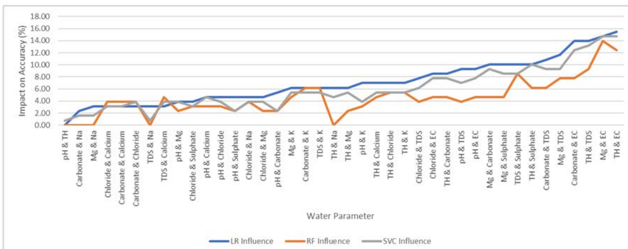


FIGURE 14. Impact of various parameters on classification accuracies of drinking water.

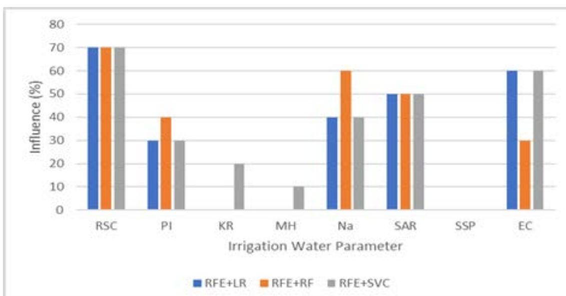


FIGURE 15. Parameter influencing the classification accuracy of irrigation water.

TABLE 9. **Parameter influence on classification accuracies of ML models for irrigation water.**

Excluded Parameters	LR Accuracies (%)	RF Accuracies (%)	SVC Accuracies (%)
SSP & SAR	93.06	93.06	95.83
SSP & PI	90.28	91.67	91.67
SSP & KR	90.28	93.06	93.06
SSP & MH	90.28	93.06	93.06
SSP & Na	88.89	93.06	93.06
KR & RSC	83.33	90.28	79.17
KR & PI	83.33	90.28	79.17
RSC & KR	81.94	90.28	86.11
RSC & MH	81.94	90.28	84.72
Na & RSC	81.94	90.28	86.11
Na & PI	81.94	88.89	80.56
Na & KR	81.94	88.89	80.56
Na & MH	81.94	87.50	81.94
RSC & Na	79.17	91.67	79.17
KR & Na	76.39	87.50	76.39
Na & SSP	76.39	95.83	93.06
RSC & SAR	73.61	87.50	66.67
RSC & SSP	68.06	90.28	84.72
KR & SAR	58.33	77.78	68.06
KR & SSP	58.33	91.67	90.28

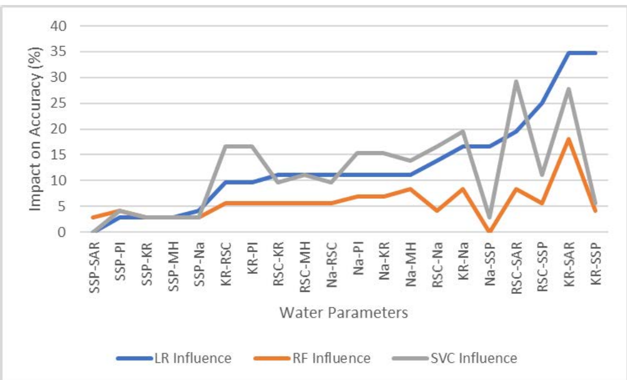


FIGURE 16. **Impact of various parameters on classification accuracies of irrigation water.**

The results in Figure 15 are further confirmed by those on Table 9 and Figure 16. Thus, it can be inferred that SSP has the least effect on the classification accuracy of the three ML models considered, while KR and RSC are the most influential parameters in irrigation water.

VII. ECONOMIC VIABILITY

In this section, we discuss some basic financial considerations to highlight the advantage of our proposed LoRa-based WaterNet over pre-existing solutions such as cellular networks.

A. INFRASTRUCTURE COST

Table 10 is a high-level hypothetical bill of materials (BOM), showing the main components required for WaterNet and their approximate costs in US Dollars (USD). The cost reported are based on prices obtained from various online retailers and were correct as at the time of writing. Though certain components such as cables, power adapters, connection jacks, software were not included, the BOM reveals that the solution is achievable with an estimated budget of about US$ 100,000. In essence, with this budget, a water monitoring network covering 11 widely dispersed (and sometimes remote) locations can be deployed in a matter of days. In comparison, setting up a single standard base transceiver station (cellular tower) in a remote location without cellular coverage, costs between US$ 100,000 – US$ 150,000. This cost is exclusive of foundation and concrete works, fencing and brick works, the air-conditioned control room, electrification and wiring, antennas, and backup power generator(s), all of which could raise the cost of the tower to about US$ 250,000. Beyond the cost, erecting cellular towers require extensive site surveys and environmental impact assessment prior to approvals from regulatory authorities, both of which can take several months to complete.

To put this in context, setting up WaterNet to monitor water parameters using cellular networks would cost at least double the cost of using LoRa and would take significantly longer time. This is based on the assumption that only one cellular tower needs to be erected. In situations where all the locations to be monitored are in remote locations with no cellular coverage, the time and cost would grow astronomically. An argument can be made for situations where cellular coverage already exists. In such scenarios, WaterNet could piggyback on the existing infrastructure, thus, the cost

TABLE 10. **High-level bill of material for waternet.**

Item	Description	Qty	Approx. Unit Price (USD)	Total Price (USD)	Comment
Sensors	Composite sensor module (such as Libelium Smart Water Ions [63])	11	7000	77000	A cheaper option could be to purchase the individual sensors and connected them to the Edge nodes
Edge Nodes	Single board computer (such as Raspberry Pi)	12	40	480	
	Micro-controller with Analog to Digital Converter (such as Arduino Mega)	12	30	360	Interface between analog sensors and the Edge module
LoRa Modules	800/900 MHz LoRa module (such as Semtech SX1272)	14	50	700	Interconnects the FNs and ILLIFU
	2.4 GHz LoRa module (such as Semtech SX1280)	18	75	1350	Interconnects the GWs and FNs
LoRa Antennas	Outdoor antennas for the LoRa modules	32	100	3200	Boosts LoRa's range
Fog Nodes	High end computer e.g., Core i7 Gen 11, 16GB RAM, 1TB HDD, RTX3070	7	1500	10500	
TOTAL				93,590	

TABLE 11. SWOT analysis of waternet.

Strengths	Weaknesses
• LoRa is significantly cheaper compared to other technologies. • Operates on open / license-free radio frequencies. • Coverage in remote areas. • Easy to deploy. • No recurrent subscription bills. • Secure and dedicated network • Can run autonomously with little human intervention	• Susceptible to obstructions from mountains, buildings, trees etc. • 2.4GHz might be susceptible to interference from Wi-Fi, Microwave ovens and other 2.4GHz RF waves emitters. • Requires erecting long antennas.
Opportunities	**Threats**
• Modular and highly scalable. • Other functionalities such as usage prediction and microbial monitoring can be incorporated. • Can be expanded to other locations and provinces. • Output of data analysis at the Fog and Cloud nodes can give useful insights to help stakeholders make development plans.	• Competition from cellular carriers e.g., 3G and 4G LTE. • Permits might be required to mount antennas. • Can be hindered by Government policies.

of the LoRa modules and antennas (US$ 5,250) would be excluded from the BOM. A close examination of Table 10 shows that the LoRa modules and accessories only account for about 5% of the total cost, hence their exclusion leaves about 95% of the original total cost (US$ 88,340). Moreover, by using cellular networks, other cost elements would be introduced, including cost of cellular gateways, SIM cards, recurrent data subscription fees, etc.; all of which would raise the price above the US$ 100,000 estimated budget. These show that our proposed LoRa-based WaterNet solution is a more economically viable option.

B. SWOT ANALYSIS

The SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis is often used to identify potential opportunities, advantages, potential weaknesses, and threats to proposed solutions. Table 11 summaries the SWOT analysis for the water monitoring network.

VIII. CONCLUSION

This work focused on two major concept, firstly, the proposal of a real-time water monitoring network for gathering data on water parameters from water bodies. Secondly, the application of machine learning (ML) models as means of assessing water quality. The developed water monitoring network is based on LoRa, a low power long range protocol for data transmission, and was developed using the City of Cape Town as case study. Results of the simulation done in Radio Mobile, revealed a partial mesh network topology as the most adequate network to cover the city. Data gathered from this monitoring network would ideally be aggregated on a Cloud server, where ML models can then be applied to assess the water's fitness of use for drinking or irrigation purposes. Due to the absence of relevant datasets, two suitable datasets were built in this work and used to training and testing three ML models considered, which are Random Forest (RF), Logistic Regression (LR) and Support Vector Machine (SVM). Results of the test showed that LR performed best for drinking water, as it gave the highest classification accuracy and lowest false positive and negative values, while SVM was better suited for irrigation water. Finally, a model for identifying the most influential water parameter(s) w.r.t classification accuracies of the ML models was then explored using recursive feature elimination (RFE). Obtained results showed that pH, and total hardness were the least influential parameters in drinking water, while SSP was the least for irrigation water.

Though the authors acknowledge the possible application of deep learning models, these were not used in this work. In future works, deep learning models such as the various variants of neural networks could be considered as expansion to this work. Furthermore, water quality indices were manually calculated and used to assess the "fitness for use" of water, future works could explore the application of unsupervised ML models as alternatives to manually calculated water quality indices. In the same vein, rather than using RFE, other approaches such as multi criteria decision making could also be considered to identify influential parameters. Finally, incorporating usage prediction models and microbial monitoring into the water network as well as tracking sources of water contaminates could also be avenues to further this work.

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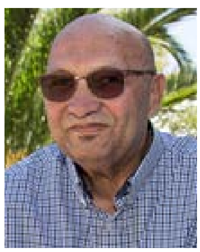

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