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WATERNET A NETWORK FOR MANAGING AND ACCESSING WATER

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ABSTRACT

WaterNet is an innovative network designed for the continuous monitoring and evaluation of water quality that will be used for potable as well as agricultural purposes. The system is to be a combination of several sensors and real-time data analytics for monitoring critical water quality indicators such as pH levels, turbidity, chemical pollutants, and microbial activity in a wide variety of water sources. Through provision of timely and accurate information in concert with notifications on the status of water, WaterNet improves the implementation of decision-making strategies pertaining to public health as well as agriculture management. From its site, there exists the availability of up-to-date data meant for all stakeholders within this aspect-water utility firms, farmers, among other district local governing bodies - ensuring the drinking water's quality plus irrigation safety. More than that, WaterNet is capable of predicting potential water quality threats through the integration of climate, weather, and land-use information, thereby encouraging proactive strategies for water treatment and resource conservation. The system enhances good water management practices, early identification of contamination, and sustainable utilization of water resources to ensure public health protection and enhanced agricultural productivity.

Keywords-Water quality monitoring, drinking water, irrigation water, real-time data, sensor network, water contaminants, water quality parameters**.**

I. INTRODUCTION

Access to safe drinking water is a basic human right and is essential for the health and well-being of individuals, communities and ecosystems. It is also a key element of the United Nations Sustainable Development Goals (SDGs), in particular Goal 6, which aims to ensure the availability and sustainable management of water and sanitation for all. In addition, clean water is essential in achieving Goal 3, which focuses on good health and well-being. Contaminated water is a major cause of diseases such as cholera, typhoid, and diarrhea, particularly in developing countries, where it remains a leading cause of mortality, especially among children. Besides being a significant source for the health of human beings, it is an essential tool used in agricultural activities, and all these are linked directly to food security and nutrition. In many countries facing water scarcity and pollution,

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adequate management of water sources means ensuring public health and improving agricultural productivity. The origins of drinking water and water for irrigation include rivers, lakes, reservoirs and groundwater. However, through industrial processes, mining, and agriculture, these water sources become contaminated with pollutants and chemical contaminants that may degrade water quality significantly. Water contaminated in this manner may cause adverse health effects and negatively impact agricultural productivity if not addressed. Therefore, there is a strong need for the comprehensive and real-time monitoring of water quality to ensure that water is safe for human consumption and agricultural use. A number of models have been developed to assess water quality, considering parameters such as pH, turbidity, chemical composition, and microbial contamination. The Water Quality Index is one such method that presents a standardized way of measuring and reporting water quality. Such methodologies, however, have issues when it comes to real-time measurements over large regions due to labor-intensive processes and having to adhere to strict protocol which may not be feasible at present times. To address this concern, we propose a cyber-physical network architecture for a real-time water quality monitor in Cape Town, South Africa. This network harnesses IoT sensors, the application of machine learning, and cloud-based data analytics to effectively assess water quality. With the monitoring of water quality at different points, the proposed system is capable of providing timely information about water safety, and contamination events can be addressed immediately.

The architecture includes sensing, edge, fog, and cloud layers that are all critical for the efficient collection, processing, and analysis of data. The final goal of this project is the development of a scalable and adaptive system that offers safe water for drinking water and irrigation purposes, thereby providing contributions to public health and food security.

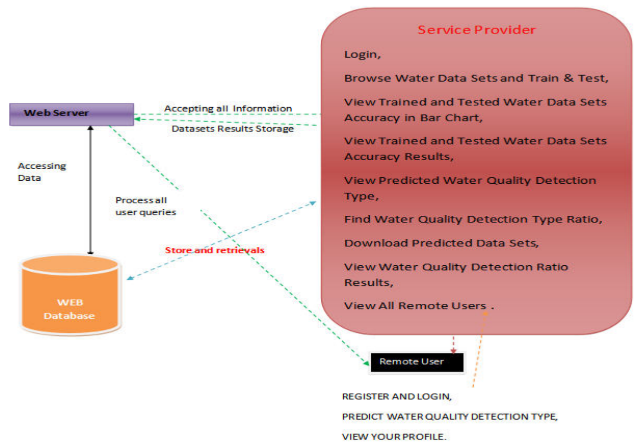

Fig 1: System Architecture

II. RELATED WORK

"Transforming our world: Implementing the 2030 agenda through sustainable development goal indicators"

Author: B. X. Lee et al., 2016

It explains the paper that outlines the implementation of the 2030 Agenda for Sustainable Development and indicators in achieving the SDGs. It focused on how the indicators on SDGs could be adopted in all sectors to determine the progress around the globe. The authors emphasize the importance of data collection and analysis to ensure that goals such as clean water and sanitation (SDG

6) are met by 2030. This work underscores the role of public health policy in implementing the SDGs.

"Integrated Approaches for Sustainable Development Goals Planning: The Case of Goal 6 on Water and Sanitation"

Author: U. ESCAP, 2017

This report by the United Nations Economic and Social Commission for Asia and the Pacific is a source of information for integrated planning approaches toward SDG 6, with a focus on water and sanitation. Challenges, solutions, and strategies can be adapted at the national and regional levels toward addressing water scarcity, improvement in sanitation, and promotion of sustainable water management practices.

"Water: Protection of the Human Environment" by World Health Organization (WHO), 2022

This WHO online resource underscores the critical role clean water plays in both human health and environmental protection. The paper explains in detail how unsafe water harms human health by spreading various waterborne diseases and also emphasizes the prevention of those diseases through safe drinking water. It is a part of the WHO's broader endeavor to enhance access to worldwide water and sanitation standards with special attention towards vulnerable areas.

"Water research in support of the sustainable development goal 6: A case study in Belgium"

Author: L. Ho et al., 2020

This paper is a case study from Belgium that discusses how water research can be of help in achieving SDG 6. The authors explore the role of scientific research in supporting policies to improve the quality and availability of water. The case study offers lessons and strategies that can be adapted to other countries and regions facing similar water-related challenges.

"Global Nutrition Report 2016: From Promise to Impact: Ending Malnutrition by 2030" International Food Policy Research Institute, 2016

This report gauges the global progress on the eradication of malnutrition, especially in developing countries. It points out the areas where water quality and availability intersect with nutrition, particularly in regions where poor water quality contributes to malnutrition and disease. The report underscores the need for integrated approaches to achieve food security, improve nutrition, and enhance water quality at the same time.

"Modification of the water quality index (WQI) process for simple calculation using the multicriteria decision-making (MCDM) method: A review"

Author: N. Akhtar et al., 2021

This is a review article focusing on the Water Quality Index (WQI), which is a tool to assess water quality based on various physical, chemical, and biological parameters. Authors also consider the addition of modifications in the WQI conventional process. It makes it easier and increases the accuracy of computation for assessing the quality of water using Multicriteria Decision-Making methods. The paper would discuss the application of

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MCDM that helps water management decision-makers with an easier and more reliable means to evaluate the quality of water.

III. IMPLEMENTATION

The implementation of the real-time water monitoring network and machine learning models for water quality assessment involves several key elements. First, a water monitoring network was designed using LoRa (Long Range) technology, which is ideal for low-power and large-scale networks. This allowed water quality data to be collected from multiple stations spread over a large area, such as the city of Cape Town. The results of the simulation of Radio Mobile showed that mesh network topology provides more efficient coverage and reliable data transfer. The collected data, comprising parameters such as pH, turbidity, dissolved oxygen and total hardness, were sent to a cloud server for analysis. Then, machine learning models such as Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM) were used to classify the water based on its potential for drinking or irrigation purposes. Two datasets were made for training and testing these models. The models were assessed by their classification accuracy, with logistic regression being the best performing for drinking water and SVM for irrigation water. Recursive feature elimination (RFE) was employed to determine the most significant parameters of water affecting classification. The results indicate that pH and total hardness are less significant factors for drinking water, but SSP is less significant for irrigation water. Although the models based on deep learning were not involved in this research, future studies could expand more into this problem by examining neural networks and unsupervised machine learning approaches. Integrating multi-criteria decision-making methods along with microbial monitoring will also improve the accuracy and scope of the monitoring system. In that regard, the system would set up a solid base for real-time data-driven water quality monitoring and assessment for contributing more sustainably managed water resources..

IV. ALGORITHM

The decision tree algorithm

The decision tree algorithm is a recursive process that divides the data set into subgroups based on a series of tests, with the aim of maximizing the purity of the class in each sub. It starts with the data set and evaluates a test on the data, selecting the function that best divides the data into homogeneous groups. The process is reiterated recursively for each subset, forming tree structure. The leaves for the tree represent the predicted class labels, and decision texts represent the branches for the tree. If each object in a subset all belongs to the same class, the process stops and such a subset is marked as a leaf node with the corresponding class label. Otherwise, the data set is further divided based on more tests and the process is repeated until all data points are classified.

Gradient Boost Algorithm

Gradient Boost Algorithm is an iterative machine learning algorithm in which models are built in stages. Initially, a simple model usually a weak learner, such as a decision tree is trained on the data. At each step, it computes residual errors from the model so far and builds another new model that aims at the correction of errors, puts it into a model pool, and so forth. Each new model works with the errors of previous ones; thus, the overall ensemble is enhanced step by step. The final prediction is obtained by combining the predictions of all the models in general, often by weighted averaging.

K-Nearest Neighbors (KNN) Algorithm

K-Nearest Neighbors (KNN) works to classify a new data point based on the class of the majority of its nearest neighbors in the feature space. To classify a new instance, the algorithm calculates the distance (usually the Euclidean distance) between the new data point and all other points in the training data set. The algorithm selects the K closest points and assigns the most common class label among these K neighbors. The number of neighbors to consider is defined by the parameter K, which is a hyperparameter. If K is 1, then the new data point is sorted by the nearest neighbor, while higher values of K can help smooth out noise in the data.

Logistic regression algorithm

The logistic regression models the relationship between a dependent variable that can have two or more possible outcomes and independent variables by estimating the probabilities that the dependent variable belongs to a special class. It maps linear combinations of input functions into probabilities using the logistic function. The algorithm employs techniques such as maximum likelihood estimation to estimate the coefficients of the model, with iterative adjustments to minimize the difference between the predicted probability values and the actual outcomes. The output for binary classification is the probability value between 0 and 1, assigned with a class label of 0 or 1.

Naive Bayes Algorithm

The Naive Bayes algorithm is based on Bayes' theorem, which gives the probability of a class given the features of an instance. It assumes independence of features conditional on the class, which simplifies the calculation of class probabilities. It will calculate the probability of the new instance belonging to each class based on the features. The class with the highest probability is selected. Parameters (probability) For each given feature, classes are estimated from the training data, and the final classification is carried out by comparing the posterior probabilities over all possible classes.

Random Forest Algorithm

Random Forest is the ensemble learning method which constructs various decision trees using random subsets of features as well as data points. For every tree, the algorithm picks a random sample from the data set and a random subset of features so that all trees are different. Once the trees are built, the algorithm combines its predictions. If the problem is classification, then the majority vote is used. In regression tasks, averaging is used. This way, the overfitting problem that typically plagues single decision trees is minimized, and generalization performance improves. Random forests are more accurate in general than individual decision trees because of their nature.

Support Vector Machine (SVM) Algorithm

Support Vector Machine is a supervised learning algorithm that tries to identify the best hyperplane that separates different classes of data points. This algorithm identifies the hyperplane maximizing the difference between each class's nearest points or the support vectors. SVM can handle both linear and nonlinear classification by applying kernel functions to transform the data into higher dimensional spaces where a linear hyperplane can be used. Once the optimal hyperplane is found, the classifier can predict the class of new data points based on which side of the hyperplane they lie. The goal of SVM is to find the hyperplane that minimizes the classification error while maximizing the margin.

RESULT

Fig 1: User Login

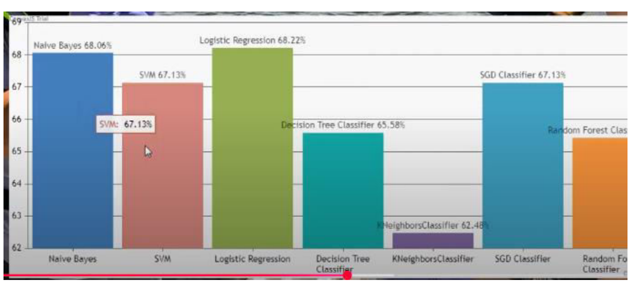

Fig:2, Accuracy Bar Chart

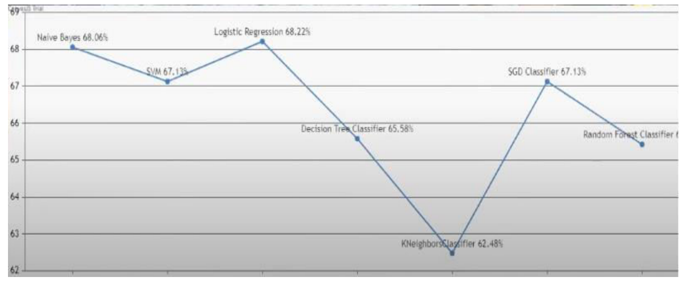

Fig:3, Tested &Trained Results

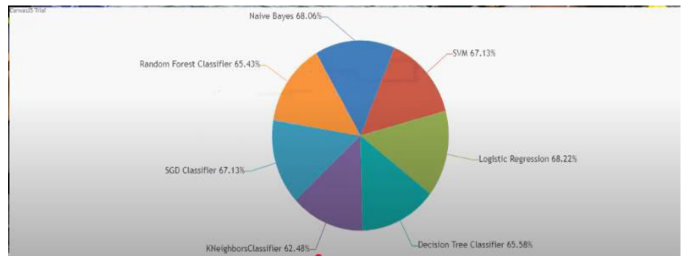

Fig:4:Pie Chart Results

CONCLUSION

This study has involved the design of a real-time water monitoring network, as well as applying machine learning (ML) models in the analysis of water quality. The monitoring system designed was based on the LoRa (Long Range) protocol, using Cape Town as the case study. Results from simulations indicate that the partial mesh network topology would be effective in covering an entire city. All collected data through this network will be transferred to a cloud server, on which the ML model is implemented in order to evaluate if water sources can be used for either consumption or irrigation purposes. For the study, two datasets were created to train and test three ML models, including Random Forest (RF), Logistic Regression (LR) and Supporting Vector Machine (SVM). Classification of quality of drinking water. The results show that in quality analysis for drinking water, it revealed a significant classification accuracy by means of a small number of false positive and negatives. In contrast to SVM, logistic regression provided good results for the testing with irrigation water. Moreover, using recursive feature elimination (RFE), it was established that certain water parameters, like pH and total hardness, were less effective in determining the classification accuracy of drinking water, whereas SSP had less effect on irrigation water. As this work is related to the supervised learning models, there can be further research work in terms of deep learning models, like neural networks, which can make the water quality assessment. Furthermore, future studies may include the application of unsupervised machine learning models as an alternative to the water quality indices that are manually calculated. This research also allows in the direction of further developing understanding of the influential parameters of water quality classification under the MCDM approach. To be brief, this study concludes the possibility that has been realized with the utilization of real-time water monitoring networks and machine learning models together to build a water-quality assessment system more reliable and efficient. Future developments may improve upon this work by integrating more sophisticated models, microbial surveillance, and water pollutant monitoring strategies toward more sustainable water resource management.

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