SALINITY IN DRINKING WATER IS ANALYZED BY A PHOTONIC SENSOR AND MACHINE LEARNING

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ABSTRACT

Traditional techniques for determining water salinity, or TDS, can be time-consuming and call for specialised equipment. By using developments in machine learning, we create a smart analysis system that makes use of a photonic sensor to collect real-time data and machine learning algorithms for precise and effective evaluation of water quality. The suggested system seeks to deliver fast information on portable water, enabling quick steps to guarantee the security and quality of drinking water. To prove the system's efficacy and dependability, we provide experimental findings and performance assessments. The results of this study provide a viable method for improving water quality monitoring and enhancing community well-being by enabling real-time evaluation and management of drinking water supplies.

Keyword: - *TDS, Photonic Sensor.*

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1. INTRODUCTION

The ability to get clean, drinkable water is essential for maintaining human wellbeing. For the sake of preserving public health, drinking water quality must be monitored and guaranteed. Salinity, also known as Total Dissolved Solids (TDS), is a crucial characteristic for determining how portable water is. Traditional methods for measuring salinity or TDS sometimes require laborious laboratory analysis or the use of specialized apparatus, which limits their application in real-time. Technology advancements, particularly the blending of machine learning methods with photonic sensors, have created new opportunities for the real-time assessment of salinity, or TDS, in drinking water. Accurate and fast evaluations of water portability may be made by utilizing the power of machine learning algorithms, enabling proactive actions to be taken when abnormalities or departures from permissible levels are found. The combination of machine learning with photonic sensors offers a potential strategy for getting beyond the drawbacks of conventional approaches and enabling accurate, quick, and affordable evaluation of water quality. It is now feasible to continually monitor salinity or TDS levels and offer real-time warnings or notifications when water quality criteria are violated by using a smart analytical system that makes use of the capabilities of machine learning algorithms. It will go into the concepts and methods underlying photonic sensors and examine if they are appropriate for gathering salinity or TDS data. Additionally, the study will investigate several machine learning methods that may be used for reliable and accurate sensor data interpretation, such as feature extraction, data preprocessing, and supervised learning algorithms.

2. RELATED WORKS

Water is necessary for the life and flourishing of every living thing on earth. Human activities and natural processes damage the 3% of the planet's total water supply that is suitable for drinking [1, 2]. Therefore, ongoing monitoring of the water quality is unquestionably important for human health, particularly in light of the developing world's population expansion, resource scarcity, and industrialization [3, 4]. Nearly 20% of the population of the globe lacks access to safe drinking water [5]. Different particles that might degrade water's quality can be dissolved by water [6–7]. The concepts of chemical, physical, and electrical factors are connected to water quality. Water evaporation, rainfall, and subterranean water collection in wells and springs are all hydrological elements that affect water quality [8, 9]. Heavy metals, minerals, and hazardous organic and inorganic compounds are among the physical and chemical elements that make up the majority of suspended particles in water. Additionally, biological substances like bacteria and viruses can impair underground water resources and ultimately affect human well-being [10]. However, water of superior quality can shield people from illness and improve their health [11]. Any metals and mineral salts dissolved in water that can flow through a 2-m filter or smaller are regarded as having a TDS [4]. TDS is an accepted measure of the quality of water. The three main factors used to evaluate the water quality are electrical conductivity (EC), temperature, and pH [5, 12, 13]. The conductivity measure, or TDS, is directly correlated with the water's EC and temperature [14–15]. As a result, measuring the EC of water may be used to compute TDS. Additionally, considering the influence that temperature has on the water during the TDS testing is essential to avoiding errors in the findings. In order to follow the purity of water in a variety of settings, include drinking water, medical labs, cleanliness for the manufacture of electronic devices, usage in agriculture, hydroponic greenhouse nutrition systems, and seafood [16–18], TDS assessment of water is a valuable approach. TDS concentrations between 100 and 500 ppm are permitted for use in drinking water and agricultural; concentrations over this point can be dangerous [19–21]. The traditional TDS measurement process involved taking a sample of the water and shipping it to a lab for analysis. This method had many drawbacks, notably an extended turnaround period and greater cost [5, 17]. However, measuring may be made considerably easier by utilising a compact, miniature TDS sensor. TDS analysis is frequently performed using optical and electrical techniques. The electrical approach, however, is less time-consuming and more affordable [22]. Coil- and electrode-based techniques make up the electrical approach. Two coils are protected by the insulator in the coil-based approach, which is also known as the inductive or toroidal inductors method. The first coil enters an electrical current into the water, and the second coil detects that current, which is directly related to the electrical conductivity (EC) of the water. However, this technology has significant drawbacks, including pricey structures, intricate read-out circuitry, and electromagnetic radiation from the surroundings [20]. On the other hand, the technique yields reduced limits because it directly measures the EC of the water. The approach uses two, three, or four electrodes, depending on the instrument design. Capacitive and frequency approaches are two more divisions of the electrode-based approach [24, 25]. The rusting of electrodes, which causes measurement inaccuracies and necessitates further calibration, is one of the most frequent problems with electrode-based TDS sensors [23, 26]. Consideration and resolution of this topic might improve the sensor's efficiency and lessen measurement issues.

3. METHODOLOGY

The generated simulated data as well as ready-to-use training data are fed into the MATLAB programme. Using a Raspberry Pi, the results are shown on an LCD display.

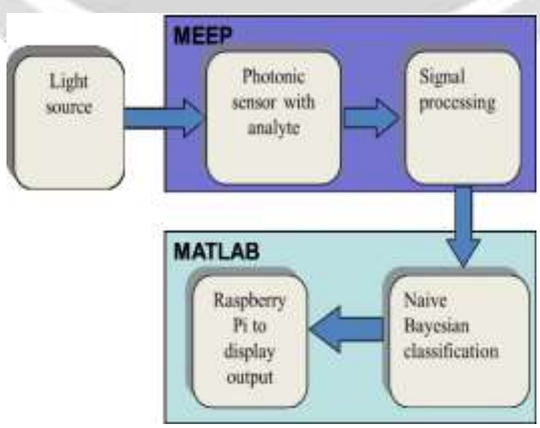

Fig -1: Salinity/TDS

4. SENSOR

An internal transmission channel is referred to as a two-dimensional Photonic Crystal (PhC) line defect. Periodic dielectric formations called photonic crystals have a photonic bandgap that prevents the transmission of specific wavelengths or frequencies. It is possible to direct light through the PhC structure by adding a line problem, which is a location where the periodicity of the crystal is disturbed.

It is important to note that the output gearbox power and frequency have changed. Figure 2 depicts the development of a PhC-based sensor as well as the movement of light.

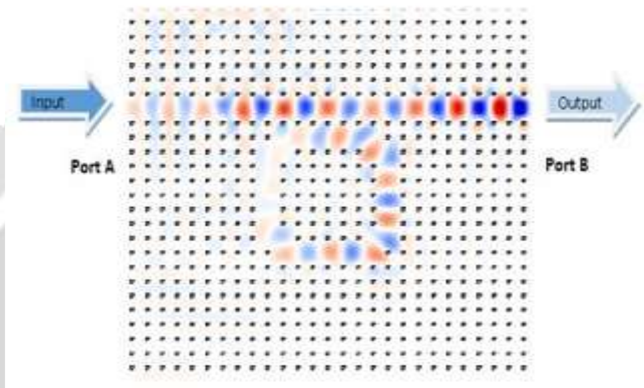

Fig -2 : Two-dimensional PhC line defect design

5. ALGORITHM FOR MACHINE LEARNING

Machine learning is an automated method that uses historical data to inform future progress. Making learning algorithms that carry out learning automatically and with the least amount of human participation is crucial to this. The "Naive" in its name refers to the fact that the Naive Bayes classifier is a straightforward Bayesian machine learning method that relies on the Bayes theorem and the presumption of data independence.

P (c|x) is equal to P (x 1 |c) * P (x 2 |c) *P (x n |c) x*P (c).

The post hoc probability of a class (c, target), given the predictor (x, characteristics), is represented by the expression P (c|x). A class's prior probability is P (c). The symbol P (x|c) stands for the likelihood, or probability, of a class given by a predictor (x).

6. RESULT

The data obtained from the computerised outcomes from the PhC-based sensors were detected, assessed, and categorised using the created MATLAB-based code, which was then utilised to determine the ppm level of salinity in drinking water. Using the test data, the process selects the class with the highest posterior probability. By comparing the class assigned to the test data with the actual class of the test data, it is possible to evaluate the algorithm's correctness. The ratio of accurate classifications to total classifications serves as a gauge for the classifier's accuracy.

The training data from the chosen USB discs and the salinity/TDS simulation results are used by the built-in programme (Figure 4a). The observed result is shown on the Raspberry Pi's display based on the findings of the pH check. The display reads "High Salinity" when the result is greater than or equal to 2000 ppm (Fig. 4b) and if the amount is 1000 ppm or below, it is considered "low salinity" (Fig. 4c).

a)

b)

c)

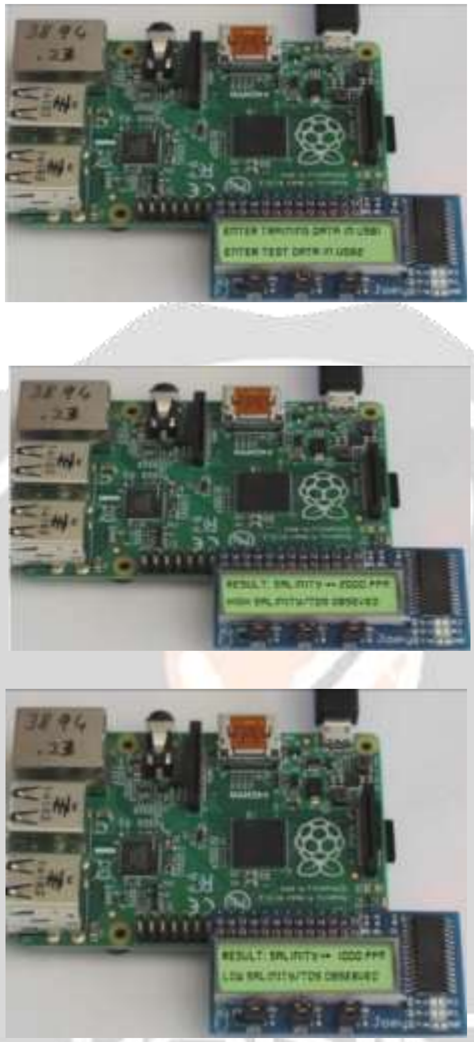

Fig -4: (a)integrated device display using a Raspberry Pi, and (b) shows the results of a 2000 ppm TDS test. (c) Water salinity result of 1000 ppm.

7. CONCLUSIONS

This study proposes the design and implementation of a real-time wireless water quality monitoring system for drinking water. The designed system has been put to the test in the real world to evaluate water quality indicators. It is an inexpensive, lightweight, and power-efficient solution. The technology may also send large amounts of data to distant sites. The fuzzy regulations and impurity detection algorithm assist in identifying the categorise the water according to the level of pollution in the pipeline. The public, local office authorities, and water users may access comprehensive data through this implementation. The safety of drinking water is guaranteed by the mobile app and SMS warning. In the future, we intend to examine how well the system we built performs in the presence of different types of pollutants, such as lead and nitrates.

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