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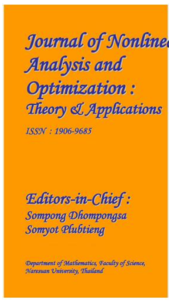

Next-Gen IoT and Machine Learning model for water quality assessment and tracking system

Melam Jagadeeswari
Student MTech(Embedded Systems)
Aditya College of Engineering
melamjagadeeswari3@gmail.com

Y Sugandhi Naidu
Associate Professor
Aditya College of Engineering
sugandhi_ece@acoe.edu.in

ABSTRACT: Organisms depend on water for survival, yet only about 1% of Earth's water is fresh and usable. With global population growth increasing water demands, agriculture consumes over 70% of freshwater, often inefficiently and wastefully. Effective water management, critical for agriculture, is addressing the impending freshwater scarcity. Advanced technologies like IoT and cloud systems optimize water use by integrating climate and water quality data. The research study examines a smart irrigation system using IoT to measure water quality, applying Machine Language (ML) to enhance crop yields and efficiency by advising farmers on water thresholds. Various ML algorithms are assessed for their effectiveness in classifying data.

Keywords: Smart irrigation, IoT, Machine Learning.

I. INTRODUCTION

Food is a basic necessity for everyone, making agriculture vital to any country's economy. Throughout American history, agriculture has played a pivotal role, signifying social and economic prosperity when there is a robust farming community. Agriculture is the primary sector providing employment in many nations, often requiring assistance with planting and animal care on large, populous farms. These farms can leverage nearby processing facilities to enhance their agricultural operations. The role of agriculture in human civilization has evolved significantly, allowing for more efficient resource use and reduced labor. However, achieving a balance between supply and demand has been challenging due to high population densities [1].

By 2050, the global population is projected to reach 9.8 billion, with much of the growth expected in developing countries. Urbanization is also on the rise, with urban populations expected to increase from 49% to 70% by 2050 [2]. Rising incomes in these developing nations will likely increase demand for food, prompting greater attention to nutritional quality. This shift may lead consumers to favor proteins like beans and meat over grains and cereals. Despite being scarce, water remains a crucial natural resource for irrigation in agricultural areas. Irrigation consumes a significant amount of water in rural areas, impacting crop yields, influenced by various environmental factors such as soil conditions, temperature, moisture levels, and humidity. Farmers heavily rely on expertise and guidance during crop cultivation to ensure sustainable water management in agricultural fields. Water scarcity is a critical global issue expected to deteriorate. "Smart farming," merging agriculture with technology, is increasingly adopted to monitor and improve crop health efficiently. It focuses on optimizing resource use and reducing costs while maintaining high output quality, moving away from uniform pesticide and fertilizer application methods. Freshwater, vital for ecosystems, is scarce globally, comprising just 2.53% of total water. The World Resources Institute warns of imminent water shortages across nations [4]. Excessive freshwater use by industries and agriculture profoundly affects downstream ecosystems. Sustainable management is essential to ensure water availability for future generations. Various soil types like clay, saline, and sandy soils influence water retention and nutrient accessibility for plants [5]. The rise of Internet of Things (IoT) technology has revolutionized smart farming by enabling real-time data collection and storage. Smart sensor networks in irrigation systems gather field data to optimize plant watering schedules. Machine learning (ML) plays a crucial role in precision agriculture, enhancing efficiency and prediction accuracy across diverse sectors like healthcare, manufacturing, and logistics, though it raises concerns about data security and privacy [6]. Global studies predict a worsening water crisis by 2025 due to extensive industrial and agricultural freshwater use, highlighting the urgency of sustainable water management. In Pakistan, most freshwater—81%—is used for irrigation, with significant implications for future water availability and the necessity for effective conservation strategies [7].

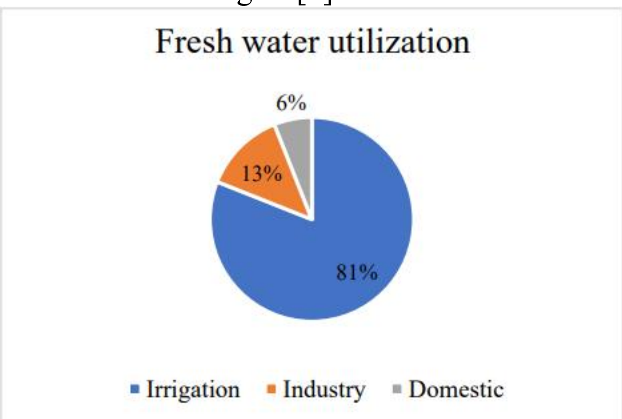

Fig1: Fresh water Utilization

Global population growth and rising demands are rapidly depleting natural resources. Irrigation, which consumes over 75% of the world's freshwater, plays a crucial role in agriculture but faces significant challenges regarding water quality. Improving irrigation practices is essential due to inefficiencies despite being the largest water consumer globally. Effective management requires farmers to monitor soil type, climate conditions, available water resources, soil moisture, nutrients, and pH levels to address agricultural complexities. To tackle these challenges, integrating data-driven technologies and advanced approaches is paramount. This study explores current IoT-enabled technologies aimed at enhancing agricultural water quality and improving irrigation management [8]. It highlights the evolution of irrigation and IoT technologies, underscores the importance of optimizing irrigation practices, and discusses potential benefits from reducing water wastage through dynamic optimization strategies. The study examines IoT deployments, including models, controllers, sensors, cloud platforms, water prediction techniques, and ML models tailored for irrigation management. Developing more efficient irrigation management software hinges on accessing real-time data such as water quality, weather patterns, plant health, and soil conditions. While advocating for adopting an Internet of Things approach in agriculture, the study emphasizes the critical need to address privacy and security concerns within IoT applications.

Methodologically, the study employs feature engineering methods like principal component analysis and utilizes ML algorithms such as Support Vector Machines (SVM), logitic regression, Random Forests (RF), Decision Trees (DT), and Naive Bayes to classify pre-processed datasets. Evaluation metrics such as accuracyre are used to gauge the performance of these ML systems [9].

II. PROBLEM STATEMENT

Monitoring water quality is vital to ensure safe water resource management. Traditional methods are expensive, time-consuming, often inaccurate, and lack real-time data availability. In recent years, IoT [10, 39, 43] and ML [40] have emerged as effective technologies to improve water quality monitoring. IoT employs networked sensors to automate data collection and transmission to digital platforms, offering remote access to real-time data. This approach reduces costs and time compared to conventional methods while enhancing ML system accuracy and efficiency. ML algorithms can analyze IoT sensor data [11] to detect patterns indicating changes in water quality and forecast future conditions using historical and current data. This predictive capability helps preempt potential water quality issues before they escalate. A comprehensive IoT and ML framework is essential to effectively address these challenges, including developing reliable sensors, robust data processing methods, and accurate ML algorithms for precise water quality forecasting. Ultimately, leveraging IoT and ML for water quality monitoring could transform how we manage water resources. These technologies provide real-time data and predictive insights crucial for ensuring safe and sustainable water supplies for future generations.

III. OBJECTIVES

To ensure the safety and efficacy of irrigation water for crops and soil health, specific objectives for irrigation water quality include:

1. Ensuring irrigation water is free from harmful chemicals and impurities that could adversely affect crops.
2. Monitoring Total Dissolved Solids (TDS) levels in irrigation water to prevent damage to crops and depletion of soil nutrients. TDS levels can vary significantly based on soil type, fertilizer use, and other factors, complicating the establishment of a baseline level. According to the United Nations (UN) [38], "Monitoring TDS is crucial to maintain irrigation water within safe limits and avoid negative impacts on crop yields."

IV. RELATED WORK

The focus is on IoT applications for monitoring water quality in agriculture, crucial for ensuring safe water use in crop production. Recent studies highlight IoT's capability for real-time monitoring and efficient data collection in various agricultural settings. For instance, studies have shown IoT systems integrating pH, dissolved oxygen, temperature, and other sensors to monitor water quality parameters in precision agriculture and greenhouse tomato production. Additionally, IoT technology has been successfully applied in monitoring water quality in Chinese rice paddy fields, demonstrating its effectiveness in providing accurate and timely data.

Monitoring water quality in agriculture is crucial for sustainable practices and environmental protection. The integration of ML techniques has significantly improved the accuracy and efficiency of this monitoring. Recent studies have applied ML algorithms extensively in this area. For instance, research has used ML to predict water quality indicators in Chinese water bodies [15], demonstrating enhanced forecasting capabilities. Deep learning methods have been effective in forecasting groundwater nitrate levels, outperforming traditional models [16]. ML has also been pivotal in classifying water quality data based on key indicators [17] and detecting anomalies in water quality datasets, as shown in research on Pakistani river data [18]. Overall, these findings underscore ML's potential to improve the cost-effectiveness, precision, and sustainability of agricultural water quality monitoring.

V. METHODOLOGY

This section introduces the framework of a smart irrigation system designed for IoT networks in agricultural fields, depicted in Figure 2. Key components of the framework include real-time datasets, TDS sensors, Arduino devices, centralized data collection, ML techniques, and various applications.

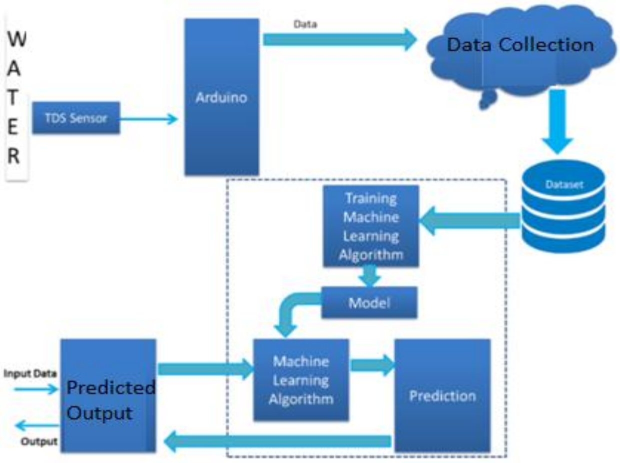

Fig2: Framework for waterquality

A. Main Components of Proposed Framework

Arduino UNO

Arduino Uno stands out as a highly popular microcontroller board centered around the ATmega328P processor. It is equipped with both digital and analog input/output pins that facilitate seamless interaction with a diverse array of sensors and actuators. This board boasts 14 digital pins, 6 analog inputs, a USB interface for both programming and power supply, an ICSP header, and a reset button. Renowned for its user-friendly nature and adaptability, Arduino Uno finds extensive application in prototyping and do-it-yourself (DIY) electronics endeavors. Programming the Arduino Uno is facilitated through the Arduino Software (IDE), streamlining the processes of code composition and upload to the board. Operating at 5V DC, the board is compatible with a broad spectrum of shields and modules, rendering it suitable for a wide range of uses, spanning from robotics and automation to IoT applications and interactive artistic installations.

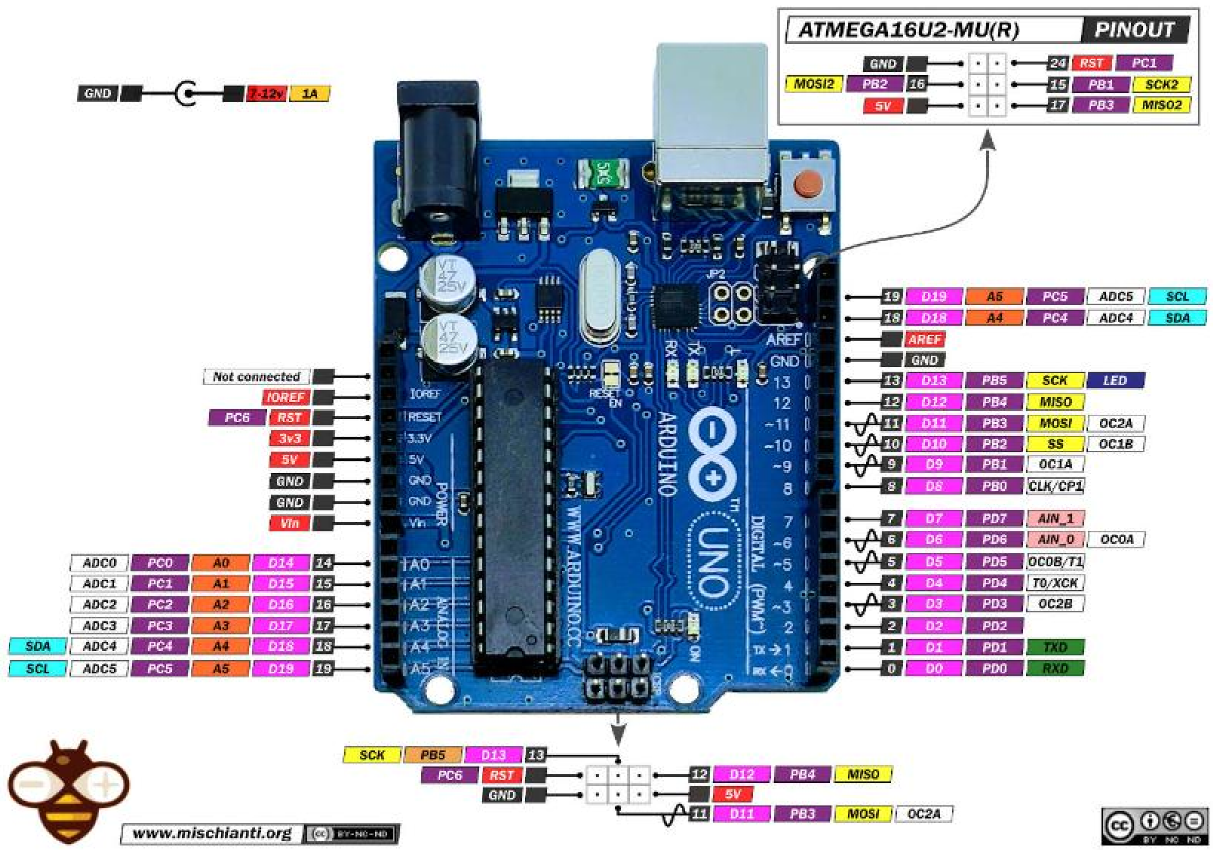

Fig3: Arduino Uno Pinout

B. Machine Learning Algorithms

i) Support Vector Machine (SVM) classifiers are a family of learning algorithms that employ regression and classification methods to categorize data patterns. Their primary aim is to classify new data points by determining their position relative to a defined gap. In the context of this study, SVM models are utilized to accurately classify the quality of water used in efficient irrigation into distinct categories [34].

ii) Random Forests Random Forest (RF) is a highly effective ensemble learning technique commonly applied in classification tasks. It operates by aggregating predictions from numerous decision trees (DTs) generated during training. The final output of the forest is determined based on the mode of predictions from these individual DTs. RF constructs DTs using random subsets of the training data, which helps reduce variance in the model, enhances overall performance, and mitigates issues related to overfitting [35].

iii) Logistic Regression Logistic regression is a statistical method used to establish the relationship between a dependent variable and one or more independent variables. In some contexts, the terms response and predictors are interchangeably used for dependent and independent variables, respectively. Variables such as temperature variations, humidity, soil moisture, and pH levels are examples of factors not directly related to predicting plant type. The formula describing logistic regression is presented below [35]:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta kXk + \varepsilon \quad (1)$$

Where:

Y = Response variable (predicted variable)
Xi = Independent variables
β0 = Y-intercept (constant)
βi = Coefficient for each independent variable
ε = Error term (residual)

iv) Naive Bayes Naive Bayes algorithms are a group of supervised learning techniques that employ Bayes' theorem for probabilistic classification. These methods operate under the assumption that features are independent of each other. Each feature is presumed to contribute independently to the probability that an observation belongs to a specific class. Despite being among the simplest Bayesian network models, Naive Bayes algorithms can achieve high accuracy levels, especially when combined with kernel density approximation. They excel in both binary and multiclass classification scenarios, particularly when dealing with clearly defined input variables, including numerical inputs. Naive Bayes is particularly valuable for predictive analytics and leveraging historical data to make forecasts [35].

v) Decision Trees (DT) are non-parametric supervised learning methods utilized in both regression and classification tasks. They are hierarchical structures composed of a root node, branches, internal nodes, and leaf nodes. DTs provide a systematic way to evaluate various possibilities and make informed decisions. They serve as effective tools for aiding decision-making by presenting different courses of action and exploring their potential outcomes. The tree-like structure of decision trees allows for a clear representation of decisions and their associated outcomes, events, probabilities, utilities, and resources.

VI. RESULTS

For the hardware setup of pin A0 on an Arduino with a PCB (Printed Circuit Board) for the project "Machine Learning-Driven TDS Monitoring on IoT Development Platforms," follow these steps:

1. Design PCB Layout: Design a PCB layout that includes provisions for connecting the Arduino and other components. Place headers or terminal blocks for easy connection of wires and components.
2. Connect A0 Pin : Use a wire to connect the A0 pin on the Arduino header to the corresponding connection point on the PCB. This can be done by soldering a wire between the Arduino pin and the pad or terminal block designated for A0 on the PCB.
3. Sensor Connection: Connect the TDS sensor to data pin A0 and also connect vcc,gnd on the Arduino via the PCB. Depending on the sensor interface , ensure appropriate wiring and signal conditioning, if necessary.
4. Communication Module(com): Incorporate a communication module to transmit TDS

sensor data to the cloud for storage and analysis.

5. Power Supply:Provide power to the Arduino and PCB setup using a suitable power source. This could be a USB power adapter, batteries, or an external power supply, depending on the project requirements.
6. Testing: Before deployment, thoroughly test the hardware setup to ensure proper functionality. Verify sensor readings, communication with the Arduino, and any other functionalities required for TDS monitoring.

By following these steps, we can create a hardware setup for pin A0 on an Arduino with a PCB, enabling TDS monitoring as part of the IoT development platform project.

Algorithms Accuracy for Output

S.No.	Algorithm	Accuracy
1	Random Forest Classifier	100
2	Decision Tree Classifier	100
3	K-Nearest Neighbor	93.9
4	Support Vector Machine	100
5	Logistic Regression	97.7

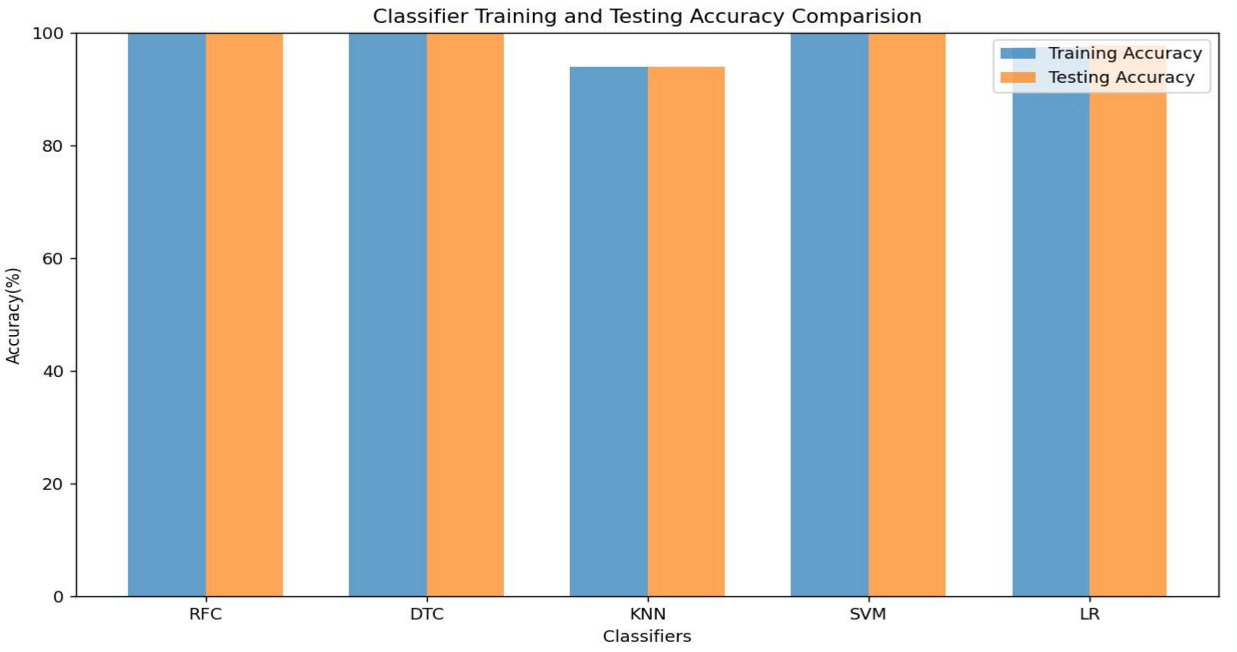

Fig4: Machine learning accuracy graphs

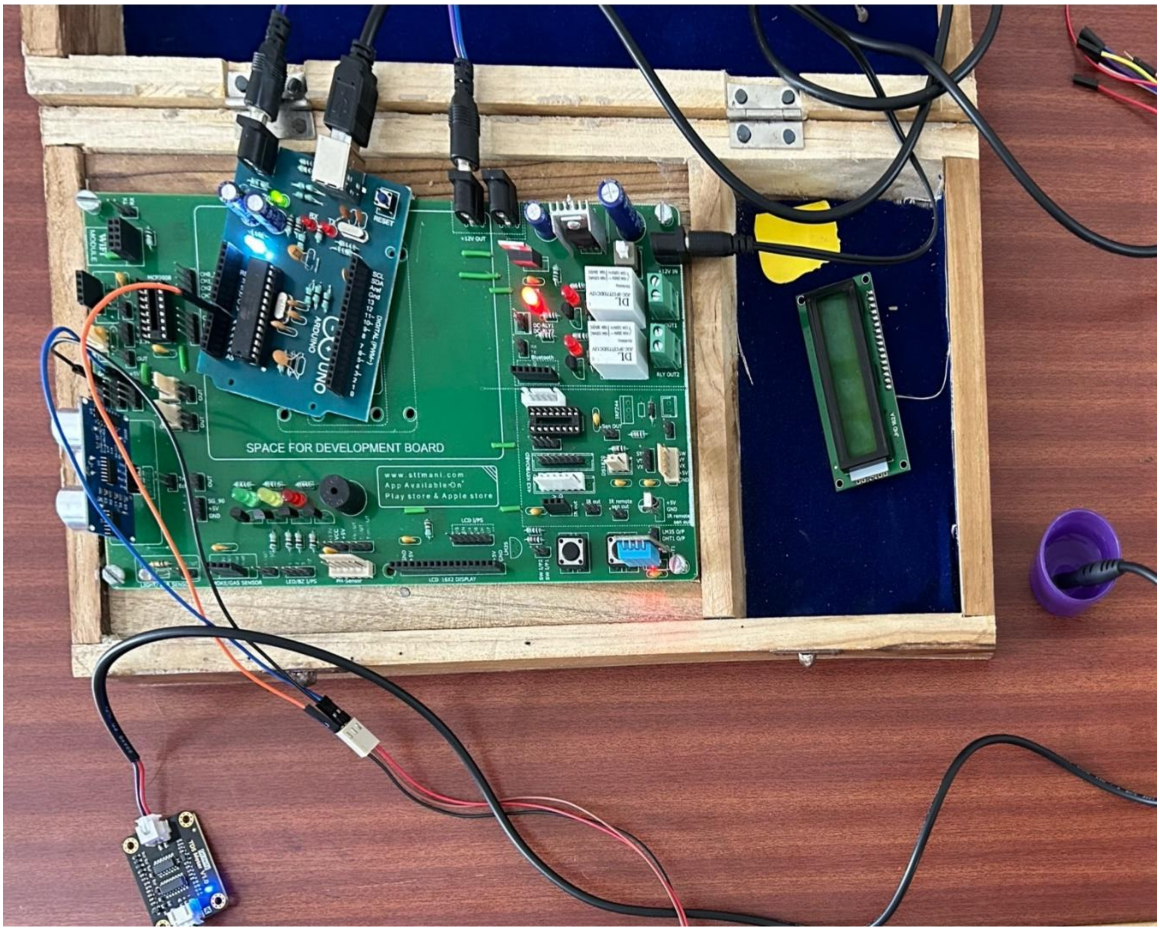

Fig 5: Implementation of Project

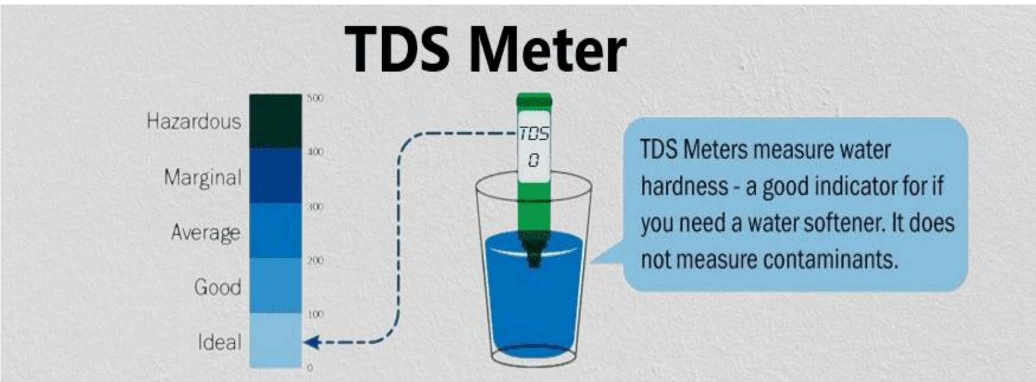

Fig6: TDS Sensor

VII. CONCLUSION

Integrating Machine Learning (ML) with IoT platforms dedicated to Total Dissolved Solids (TDS) monitoring marks a significant advancement in intelligent water management. This combination enables continuous monitoring, detection of anomalies, and predictive abilities, facilitating proactive measures to ensure water quality. Harnessing ML's capabilities empowers stakeholders to secure a sustainable and safe water supply for everyone involved.

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