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A Smart IoT-Based System for Real-Time RO Water Quality Monitoring

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Abstract: - Water is an essential resource for life, and the health of all living things, including humans, is directly impacted by its quality. Effective water quality monitoring is essential when pollution levels rise because manual testing is frequently impractical for daily use. Using the Internet of Things (IoT) in conjunction with machine learning to provide real-time water-quality analysis and prediction is a promising strategy. This study suggests developing an IoT sensor-driven water quality monitoring system specifically for RO water purifiers. Providing clean and safe drinking water is the system's main goal, especially in high-use environments like houses and schools. It sends timely messages to users when filters need to be replaced, automating the monitoring process. This method improves health outcomes and promotes environmental sustainability by increasing user awareness and decreasing the risks associated with postponed maintenance.

Keywords: Water Quality, RO Purifier, IOT, Machine Learning, LSTM.

I. INTRODUCTION

Water is one of the most important resources for life, and its quality directly affects both human and environmental health. Access to clean and safe drinking water has grown more crucial as pollution levels rise. Real-time monitoring of water quality parameters is critical for pollution reduction, water resource conservation, and sustainable management. To evaluate the suitability of water for human consumption and ecological balance, physical, chemical, and biological parameters are usually analyzed. Monitoring key indicators allows for the prompt detection of changes in water conditions as well as early alerts of potential contaminants or risks [1,2]. Traditional water quality testing methods, however, are frequently labor-intensive, time-consuming, and inappropriate for continuous or large-scale monitoring, particularly in dynamic or resource-constrained contexts.

The usage of Internet of Things (IoT) technology in water quality monitoring has grown fast because to its efficiency, scalability, and adaptability to a variety of environmental and analytical needs. Kamaruidzaman et al. [3] conducted a comprehensive survey, highlighting the importance of IoT and accessible tools in successful water quality monitoring. Dimas Adiputra et al. [4] created a real-time monitoring system that tracks important water quality metrics using IoT. While Lakshmikantha et al. [5] emphasized the significance of early detection utilizing smart IoT systems to minimize contamination and maintain ecological balance, Chowdhury et al. [6] suggested a sensor-based IoT system for ongoing river water quality monitoring. Budiarti et al. [7] employed Raspberry Pi in their IoT-based system to track water quality in real time and automate it, thereby supporting sustainable water resource management. Das and Jain [8] developed a low-cost, real-time monitoring system that employs pH, conductivity, and temperature sensors and transmits data via ZigBee and GSM. Gupta et al. [9] developed a smart water management system in residential settings that uses ultrasonic and turbidity sensors to monitor water level and quality.

With continuous technological development, machine learning (ML) and IoT have become a potent combination for predictive analysis and real-time water quality monitoring. This combination makes it easier to gather and process vast amounts of sensor data, which results in more precise evaluations. For improved analysis and water quality prediction, Ashwini et al. [10] used machine learning techniques including Random Forest (RF) and K-Nearest Neighbors (KNN). K-means clustering was used by Angel Vergina et al. [11] to improve prediction accuracy in an intelligent IoT system that included conductivity, turbidity, and pH sensors. In order to further enhance early contamination identification, Ashwini et al. [12] used neural networks and cloud-based data collecting with NodeMCU, combining factors such as color, conductivity, turbidity, pH, and dissolved oxygen.

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Soundarya et al. [13] used a Raspberry Pi 3 and Arduino Uno to create a low-cost prototype with pH and TDS sensors and K-means for predicting water quality. Mohammad et al. [14] utilized Artificial Neural Networks (ANN) with real-time sensor data (pH, temperature, ORP, turbidity, conductivity) to classify water into hazardous, cautionary, or safe categories. Sagan et al. [15] demonstrated the potential of machine learning in enhancing large-scale water quality monitoring by integrating sensor data with satellite imagery.

Unlike existing studies that primarily target large-scale water sources, this work addresses the underexplored area of domestic Reverse Osmosis (RO) systems, where water quality degradation often goes undetected due to the absence of integrated monitoring and predictive tools. The novelty of this study lies in the real-time integration of IoT with machine learning for condition-based monitoring and predictive maintenance in household RO systems. In this domain, limited or no prior work has been reported. Specifically, the system not only tracks critical water quality parameters but also leverages historical sensor data to predict filter health and generate timely replacement alerts, thereby extending device life and ensuring consistent water safety. To the best of our knowledge, this is one of the first implementations combining low-cost hardware, cloud-based analytics, and intelligent decision-making for end-to-end RO system management at the domestic level. The paper is organized as follows: The proposed methodology is described in Section 2. The results and analysis are elaborated in Section 3. Finally, Section 4 provides a conclusion.

II. PROPOSED METHODOLOGY

This work proposes a real-time water quality monitoring system for RO filters by measuring key parameters such as temperature, pH, turbidity, and Total Dissolved Solids (TDS). These parameters are captured using dedicated sensors connected to an Arduino microcontroller. The real-time data is transmitted via the ESP8266 Wi-Fi module to a machine learning model that evaluates the water quality. Based on the model's predictions, the system determines whether the water is safe for consumption and provides alerts when the RO filter requires replacement. This enables timely maintenance and ensures sustained filtration efficiency. The overall system architecture is illustrated in Fig. 1.

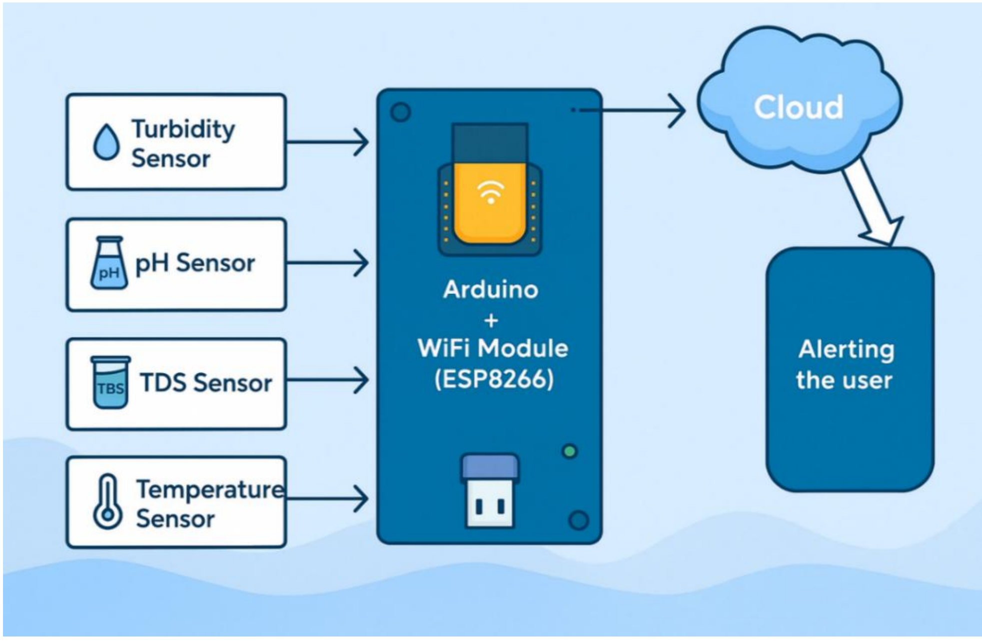

Fig.1. Block Diagram of Proposed Work

An Arduino microcontroller and an ESP8266 NodeMCU module were integrated in the Intelligent IoT-Based Water Quality Monitoring System to enable data transmission via the internet. The system included sensors for pH, TDS, turbidity, and temperature that were immersed in water to continuously monitor essential water quality parameters. When the sensors were operational, they captured data in real time. The Arduino processed the data and transmitted it to a cloud platform via the ESP8266 module. This design made it simple to use a mobile app to obtain information about the quality of the water from any location. The system was able to consistently identify parameter changes and promptly notify users of circumstances that required action, such as the need to replace a filter or the possibility of contamination.

A. Components of the Desig

1) Turbidity Sensor

The Arduino-compatible turbidity sensor operates based on the principles of light transmittance and scattering to measure the cloudiness (turbidity) of water, which increases with higher concentrations of Total Suspended Solids. The sensor emits a light beam into the water, and suspended particles scatter the light. A photodetector, positioned at a 90° angle to the light source, measures the intensity of the scattered light. Since the light intensity is inversely proportional to particle concentration, lower levels of scattered light indicate higher turbidity. These sensors are widely used in laboratory research, sediment transport studies, wastewater treatment, and river water monitoring. For RO-purified water, turbidity should typically be less than 1 NTU. The connection between the turbidity sensor and the Arduino board is illustrated in Fig. 2.

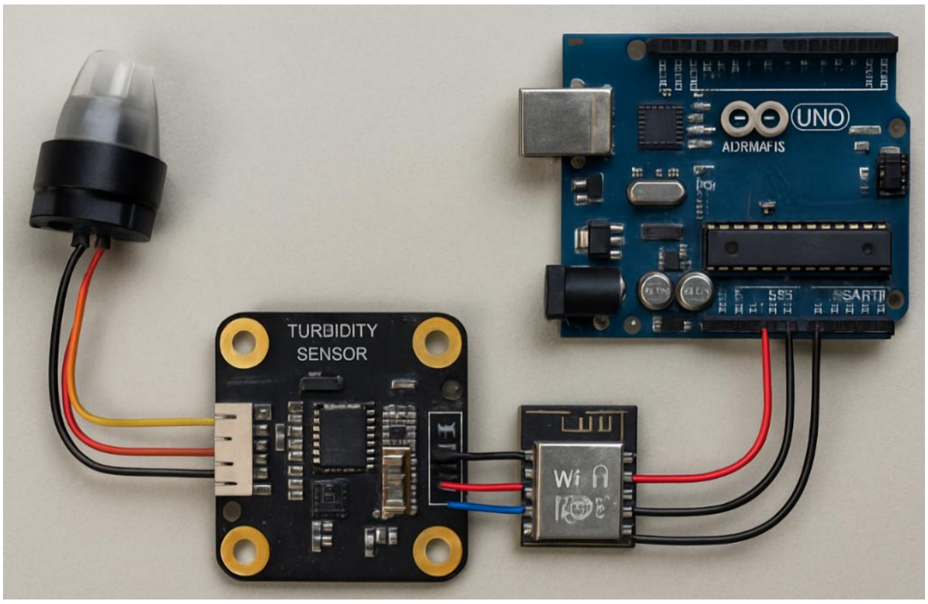

Fig. 2. Turbidity sensor's connection to the Arduino board

2) pH Sensor

pH indicates the concentration of hydrogen ions in water, helping determine whether the water is acidic or alkaline. A typical pH sensor consists of a glass electrode, made of a silver wire immersed in potassium chloride within a special glass bulb, and a reference electrode with a similar setup. Accurate measurement requires calibration using buffer solutions of known pH values. As per Government of India standards, the pH of RO-purified water should range between 6.5 and 8.5. Testing revealed that most RO filters maintained a stable pH around 7. The connection between the pH sensor and the Arduino board is shown in Fig. 3.

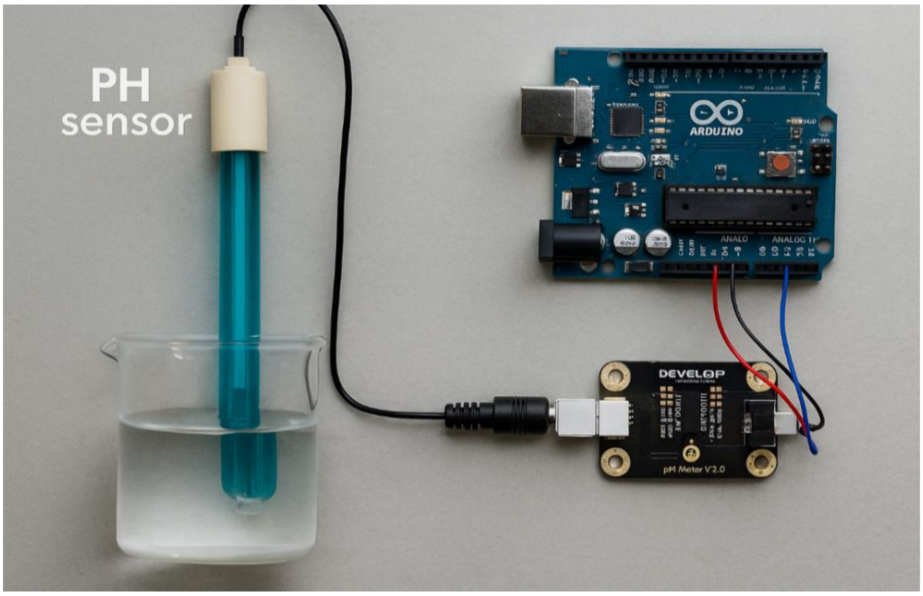

Fig. 3. pH sensor's connection to the Arduino board

3) TDS Sensor

TDS represents the concentration of dissolved organic and inorganic substances in water, typically expressed in parts per million (ppm) or mg/L. Lower TDS values indicate higher water purity. RO-purified water generally falls within 0 to 10 ppm, while tap water can range from 20 to 300 ppm, depending on the source. This study employs the KS0429 Keyestudio TDS Meter V1.0, an analog sensor compatible with Arduino, widely used in hydroponics and household applications. Operating with 3.3–5.5V input and generating 0–2.3V analog output, it suits both 3.3V and 5V systems. The use of an AC excitation signal prevents probe polarization, enhancing both accuracy and durability. Its waterproof design allows for continuous submersion and long-term monitoring. The connection between the TDS sensor and Arduino board is illustrated in Fig. 4.

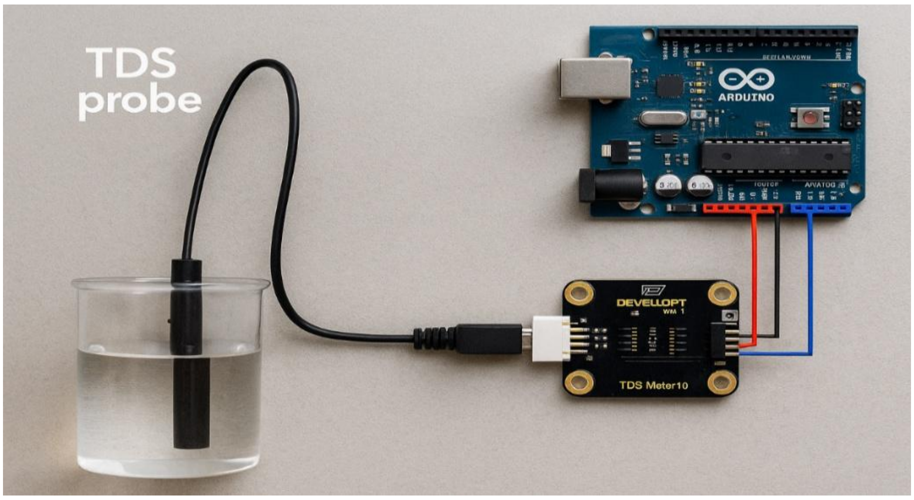

Fig. 4. TDS sensor's connection to the Arduino board

4) Waterproof Temperature Sensor

The DS18B20 is a rugged, waterproof digital temperature sensor developed in Dallas, Texas, USA. It accurately measures temperatures ranging from -55°C to 125°C with a precision of ±0.5°C and supports a resolution of 9 to 12 bits. The sensor features an alert function with user-programmable high and low thresholds stored in non-volatile memory. It operates via a simple 1-Wire communication protocol and supports parasitic power. Owing to its robustness, it is ideal for direct contact temperature sensing in real-world applications. During testing, all RO purifiers consistently maintained an optimal water temperature of 25°C, demonstrating the DS18B20's effectiveness in real-time monitoring. The wiring diagram connecting the DS18B20 to the Arduino board is shown in Fig. 5.

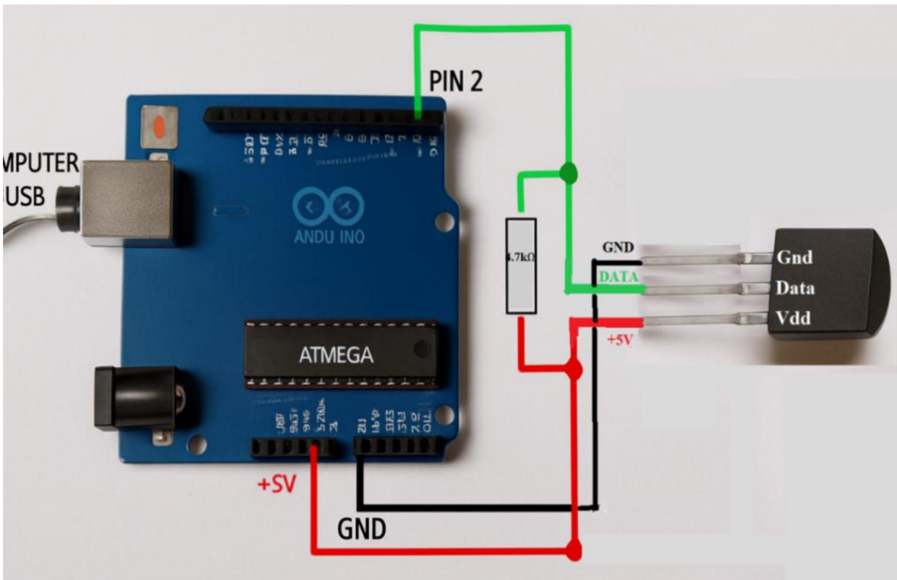

Fig. 5. Temperature sensor's connection to the Arduino board

5) Node MCU

The NodeMCU is used to transmit the sensor data to the cloud. It is an open-source development board based on the ESP8266 Wi-Fi module, programmed using the Espressif NON-OS SDK and the SPIFFS file system. The firmware is written in C and enables seamless network connectivity. In this system, the NodeMCU is configured to connect to a Wi-Fi network named "project1" and transmit real-time sensor data to the Adafruit cloud platform for monitoring and storage. The pin configuration of the NodeMCU is shown in Fig. 6.

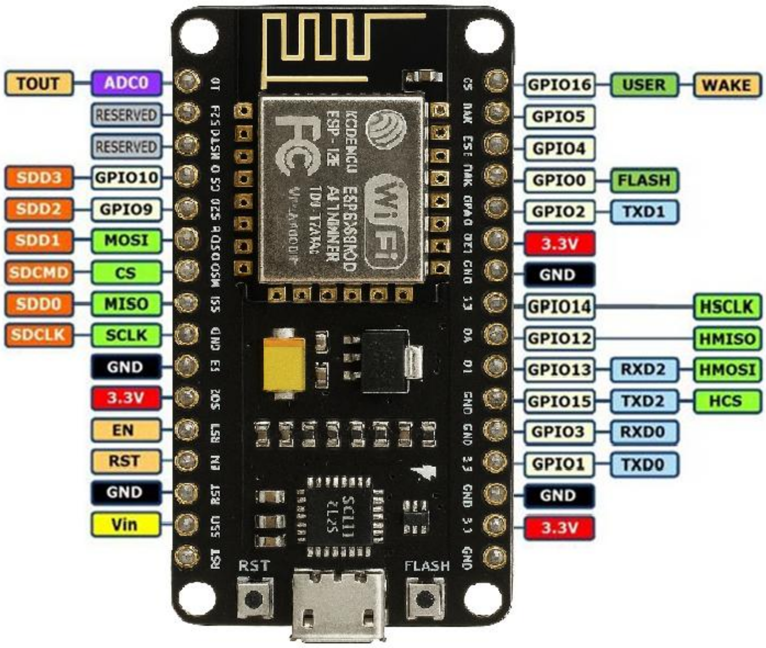

Fig. 6. Node MCU

B. Hardware Implementation of the Proposed Methodology

The Arduino Uno provided a +5V supply and ground reference, connected to the respective power and ground rails of the PCB. Analog sensors were interfaced by connecting their VCC, GND, and output lines to the PCB. The turbidity, pH, and TDS sensors were connected to analog input pins A1, A0, and A2, respectively. A digital temperature sensor was connected to digital pin D2. For wireless communication, the NodeMCU's Rx pin was linked to the Arduino's D1 (Tx) pin, with its ground connected to the common PCB ground. After completing all connections, the components were enclosed in a protective casing. The Arduino was powered and configured via a USB connection to a PC.

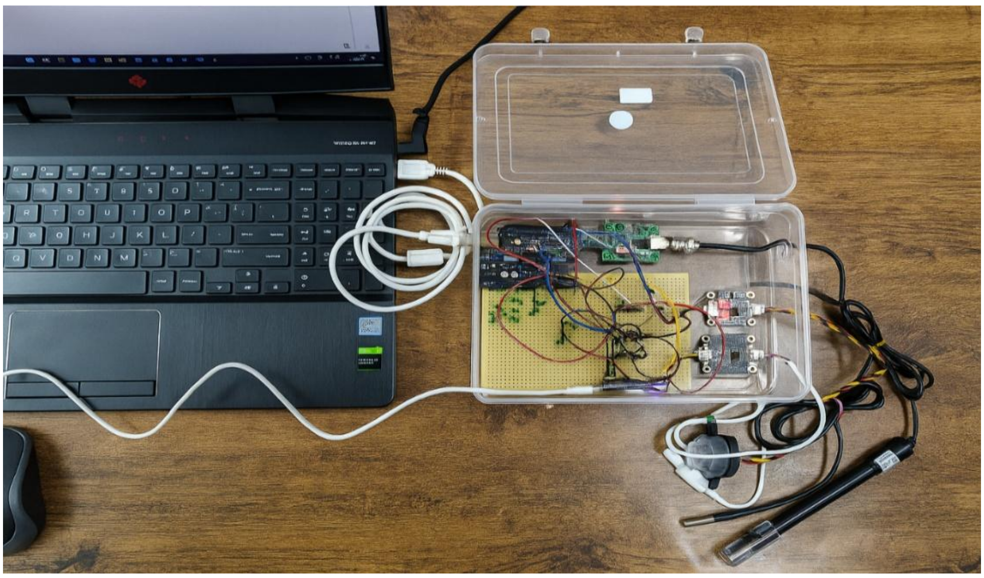

Fig. 7. Hardware Implementation

III. RESULTS AND DISCUSSION

After the proposed system was constructed and powered on, the sensors were activated, allowing for real-time measurement and analysis of temperature, TDS, pH, and turbidity. The real-time readings of temperature, TDS, pH, and turbidity are displayed via the serial monitor and shown in Fig.8.

```
20:30:23.092 → Temperature: 27°C, pH: 7.0, Turbidity: 5.00 NTU, TDS: 956 ppm
20:30:33.212 → Temperature: 27°C, pH: 7.0, Turbidity: 5.00 NTU, TDS: 956 ppm
20:30:43.293 → Temperature: 27°C, pH: 7.0, Turbidity: 5.00 NTU, TDS: 956 ppm
20:30:53.420 → Temperature: 27°C, pH: 7.0, Turbidity: 8.00 NTU, TDS: 956 ppm
20:31:03.532 → Temperature: 27°C, pH: 7.0, Turbidity: 9.00 NTU, TDS: 956 ppm
20:31:13.613 → Temperature: 27°C, pH: 6.0, Turbidity: 9.00 NTU, TDS: 956 ppm
20:31:23.724 → Temperature: 27°C, pH: 6.0, Turbidity: 9.00 NTU, TDS: 957 ppm
20:31:33.848 → Temperature: 27°C, pH: 6.0, Turbidity: 9.00 NTU, TDS: 956 ppm
20:31:43.923 → Temperature: 27°C, pH: 6.0, Turbidity: 10.00 NTU, TDS: 957 ppm
20:31:54.048 → Temperature: 27°C, pH: 7.0, Turbidity: 10.00 NTU, TDS: 957 ppm
20:32:04.166 → Temperature: 27°C, pH: 7.0, Turbidity: 5.00 NTU, TDS: 956 ppm
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Fig. 8. Serial Monitor's Output

In addition to local serial monitoring, the system is linked to Adafruit IO, a powerful and user-friendly cloud service optimized for IoT applications. The Adafruit IO cloud dashboard effectively displayed the real-time data gathered from the water quality sensors utilizing gauge-style widgets for clear visualization, as seen in Fig. 9. The dashboard included separate panels for each critical parameter—TDS, pH, turbidity, and temperature—allowing users to check water quality at a glance. Through the facilitation of ongoing data tracking, trend analysis, and timely decision-making for efficient water quality management, this cloud-based interface improves the system's functionality.

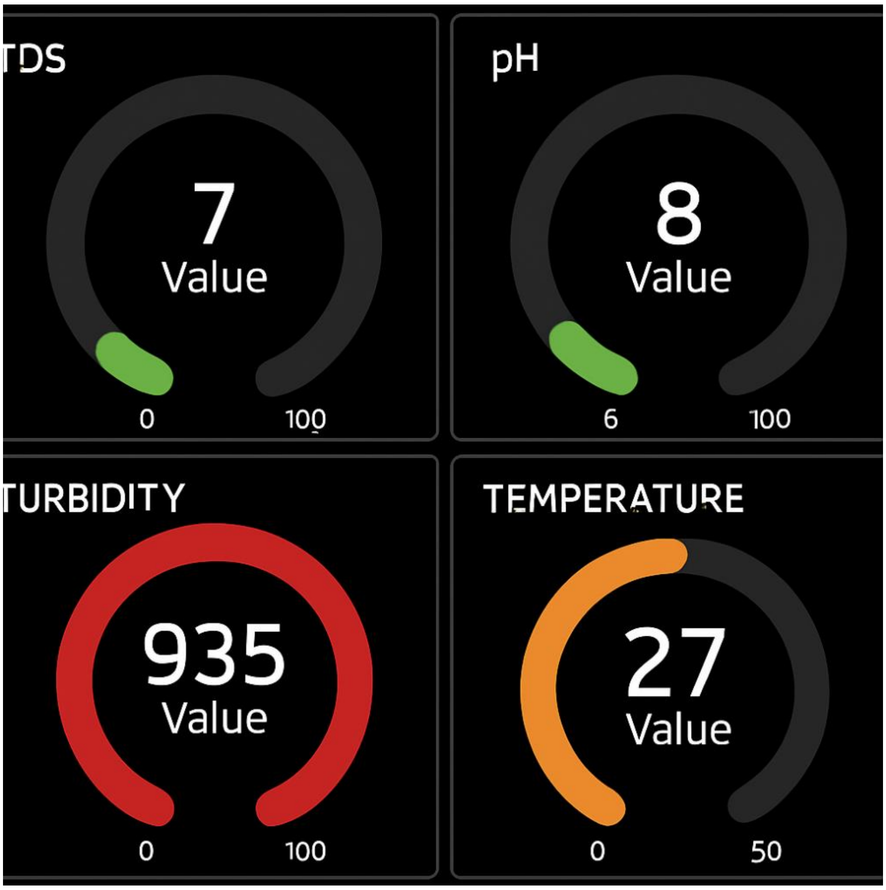

Fig. 9. Adafruit's Output

The dataset was gathered manually over 130 days, from January 1, 2025, to May 10, 2025, and water quality metrics such as TDS, pH, turbidity, and temperature were recorded to ensure consistency.

The TDS values slowly rose from 20 ppm at the beginning of January 2025 to 26 ppm by the end of the month. The highest TDS level during this time was 27 ppm. Other factors, like pH, turbidity, and temperature, stayed mostly the same and didn't change much. The TDS level started at 27 ppm in February 2025 and slowly rose to 29 ppm. During this month, the lowest TDS level was 23 ppm. As in January, there were no big changes in the other water quality indicators. In March 2025, the range of TDS levels was a little wider, going from 24 ppm to 33 ppm. Even though there were some changes, pH, turbidity, and temperature stayed the same, which means that there were no major problems with the environment or the system. Between April and May of 2025, there was a noticeable rise in TDS levels. The value increased from 44 ppm at the minimum to 54 ppm at the highest. This large increase raises the possibility that the RO filter is degrading and needs to be replaced or maintained right away. Notably, temperature, turbidity, and pH held steady without experiencing significant changes, even with this abrupt increase in TDS.

According to established water quality standards and practitioner input, a slow rise in TDS readings during the first three months (January to March) is considered to be normal filtration system functioning. However, at the beginning of the fourth month (April), a sharp rise in TDS levels usually signifies the beginning of RO membrane degradation caused by filter saturation. To avoid the RO membrane and related components deteriorating more quickly, it is advised that filters be changed at this point. TDS levels may rise sharply if this isn't done, highlighting the significance of ongoing monitoring and prompt filter replacement in RO systems. It was also mentioned that if the TDS level exceeds 100 ppm, the water is deemed unsafe for consumption.

Time series decomposition was used to better understand the temporal behavior of the TDS data. To gain a better understanding of the underlying patterns in the dataset, the resulting trend, seasonality, and residual components were examined and are displayed in Fig. 10. The trend plot supports the observation of membrane degradation over time by highlighting the general upward trajectory in TDS levels. Recurring fluctuations that might be related to changes in environmental conditions or water usage are revealed by the seasonal component. Lastly, irregularities are captured by the residual component, which may reveal abrupt anomalies or outside disturbances. This breakdown makes it easier to diagnose system behavior and predict maintenance requirements.

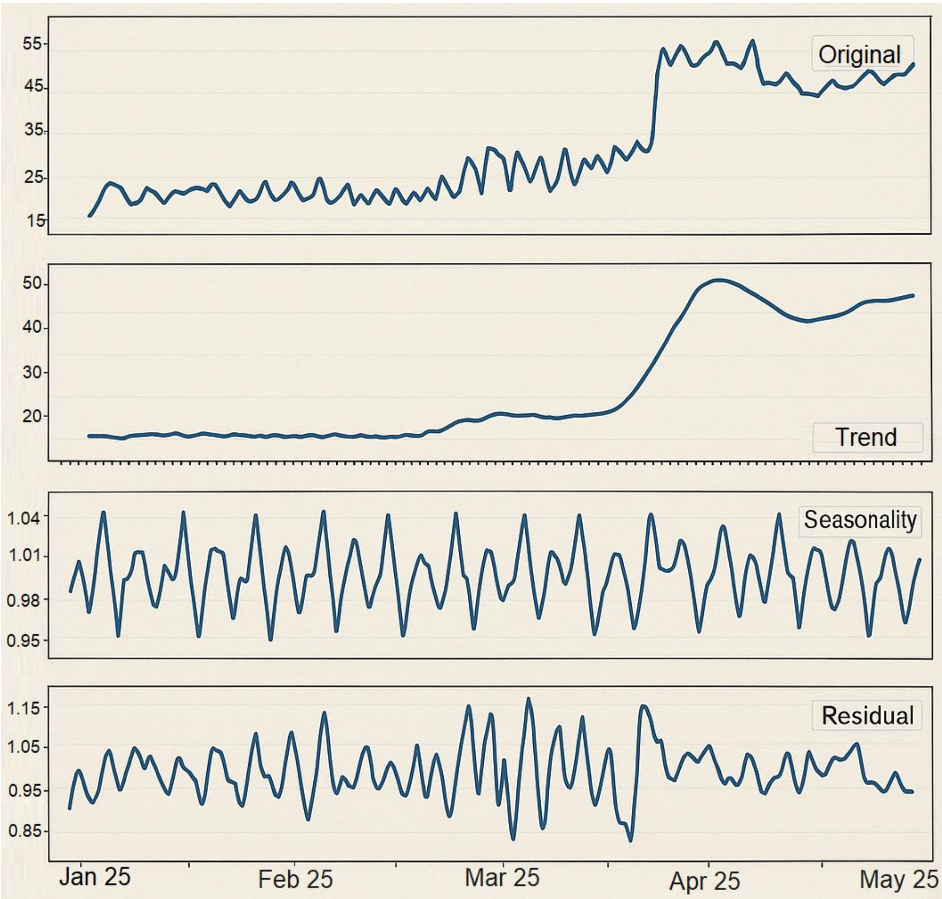

Fig. 10. Trend, seasonality, and residual plots

In recent years, machine learning has emerged as a strong tool for predictive modeling and data-driven decision-making in a variety of fields, including water quality monitoring. ML algorithms can recognize complicated, non-linear trends in historical data, making them extremely useful for forecasting critical parameters and detecting abnormalities.

ML techniques were used in this study to create an effective model and evaluate its efficacy in predicting TDS levels. Eighty percent of the dataset was utilized for training, which allowed the models to discover underlying patterns and optimize hyperparameters, while the remaining twenty percent was used for testing, which assessed the models' capacity for generalization and prediction accuracy. Python was used to carry out the implementation under the Anaconda environment. NumPy and Pandas were used for data management and preprocessing, Scikit-learn for applying and assessing machine learning techniques, and Matplotlib's Pyplot for visualizing findings [16]. A methodical and effective approach to predictive modeling using actual water quality data was guaranteed by this methodology. Among the various algorithms explored, the Long Short-Term Memory (LSTM) model demonstrated strong potential for time-series prediction of TDS values. Fig.11 presents a comparison between the actual TDS measurements of the RO purifier and the predicted TDS values generated using the LSTM model.

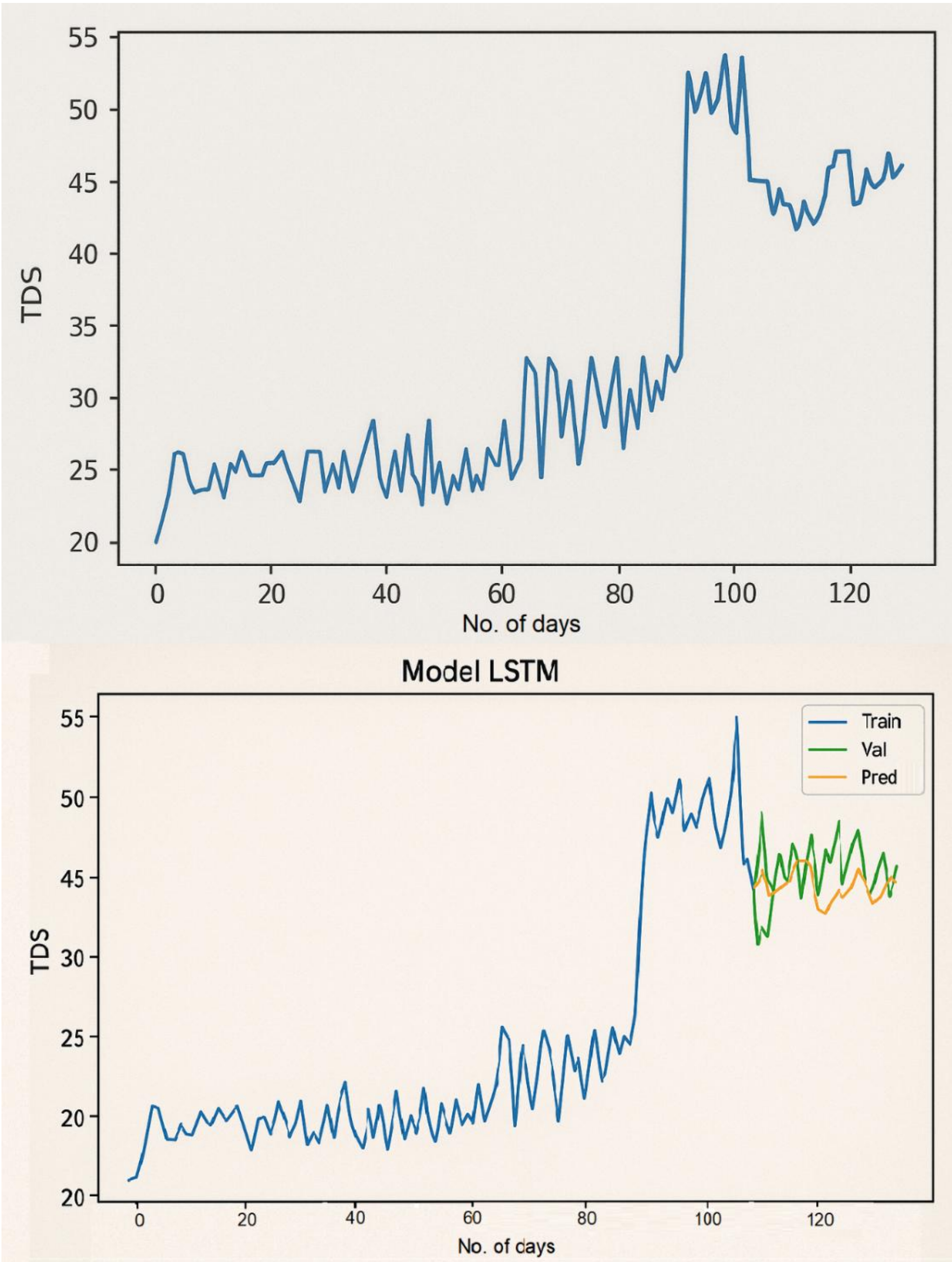

Fig. 11. TDS plot

From Fig. 11, it is evident that the LSTM model effectively captured the overall trend and seasonal fluctuations in TDS values, particularly the sustained elevation following the sharp rise observed around day 95. While minor deviations were noted between predicted and actual values during the validation phase, the high degree of alignment demonstrates the model's robust generalization capability for short-term forecasting of TDS levels.

A web-based interface created with the Flask framework was incorporated with the trained LSTM model to convert this ability to predict into a useful tool for end users. Ten consecutive TDS readings can be entered into this interface, and the system will then produce projections for the future. In order to analyze the water quality and ascertain the RO filter's working status, an automated alarm mechanism compares these predictions to predetermined threshold values. The program includes a decision-support mechanism that interprets anticipated TDS levels to determine both water quality and the RO filter's operational status. Water is deemed safe for drinking, and no filter replacement is necessary if the TDS result is 40 ppm or less. Although the water is safe for levels between 41 and 70 ppm, it is advised to replace the filter to preserve the effectiveness of purification. The water is deemed hazardous and requires an immediate filter change when the TDS reading surpasses 70 ppm. Fig. 12 illustrates the alert interface in action. The water was classified as safe with a filter change advice because the expected TDS value was 52 ppm.

Fig. 12. Predicted TDS-Based Decision

This example demonstrates the system's ability to reliably estimate water quality indicators and then translate these forecasts into actionable maintenance suggestions, allowing for proactive management of water purification systems.

IV. CONCLUSION

Access to clean and safe drinking water is vital for maintaining public health. This work addresses the need by providing an effective solution for real-time water quality monitoring and prediction, with a focus on the performance of RO purification systems. Key parameters such as Total Dissolved Solids, pH, turbidity, and temperature are continuously monitored using dedicated sensors. These sensors are interfaced with an Arduino UNO microcontroller, while data transmission to the Adafruit cloud server is facilitated by the ESP8266 NodeMCU, enabling seamless remote monitoring. To enable predictive analysis, machine learning techniques were employed—specifically, an LSTM model was developed to forecast future TDS values. A web-based interface, built using the Flask framework, allows users to input ten consecutive TDS readings, based on which the system generates predictions. The interface also incorporates an automated alert mechanism that provides clear recommendations regarding the condition of the RO filter based on the predicted values. Overall, this system demonstrates a practical and intelligent approach to water quality management by integrating IoT technologies with machine learning, thereby supporting timely maintenance and ensuring safe water consumption.

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