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DESIGN AND DEVELOPMENT OF A LOW-COST IOT-ENABLED REMOTE SENSING DEVICE FOR WATER QUALITY MONITORING IN DEVELOPING COUNTRIES

[1]Ariagbofo, B.O., [2]Imakpokpomwan, G.O., [3]Aghedo, O.M., and [4]Osse, E.
[1,2,3,4]Electrical/Electronics Engineering University Of Benin, Benin City, Nigeria
Corresponding Author's Email address: bariagbofo@gmail.com

Abstract
This study evaluates the effectiveness of an IoT-enabled remote sensing device for real-time water quality monitoring, tailored to the unique challenges of developing countries like Nigeria. Utilizing a NodeMCU ESP8266 microcontroller, temperature, TDS, and turbidity sensors, and Firebase Realtime Database for data storage, the system provides accurate and timely insights into water quality parameters. Tested in a controlled aquaculture pond, the device demonstrated its efficiency in gathering and transmitting data, supporting both environmental monitoring and aquaculture optimization. The system's low-cost, energy-efficient design makes it accessible for resource-constrained settings, addressing the historical underutilization of IoT technologies in developing nations. This innovation holds potential for broad applications, from sustainability research and guiding government policies to enable real-time monitoring of natural water bodies, promoting better water resource management and environmental stewardship.
Keywords: IoT, Monitoring, Remote sensing, Water quality, Nigeria

1. INTRODUCTION

Water quality management is a critical issue that directly aligns with the United Nations Sustainable Development Goals (SDGs), particularly Goal 6, which aims to ensure the availability and sustainable management of clean water and sanitation for all. Access to safe drinking water is foundational to achieving broader global objectives related to health, food security, and sustainable economic development. Yet, Nigeria faces a critical water quality crisis, exacerbated by rapid urbanization, industrialization, and agricultural practices. These dynamics have led to widespread pollution of surface and groundwater, posing substantial risks to public health, aquatic ecosystems, and socioeconomic activities (Omokaro *et al*., 2024).

Approximately 66.3 million Nigerians lack access to safe drinking water, highlighting the severity of the challenge (Ighalo & Adeniyi, 2020). Surface water quality in Nigeria is generally poor, with groundwater contamination arising from diverse sources, including landfill leachate, industrial effluents, and oil exploration (Ighalo & Adeniyi, 2020). In the Niger Delta region alone, over 13 million barrels of oil have been spilled, significantly degrading coastal wetlands and agricultural lands (Omokaro *et al*., 2024). Urban groundwater quality is shaped by local geology, urbanization patterns, industrial activity, and inadequate waste management practices (Ocheri, 2014). However, weak environmental policies and limited coordination between federal and state governments exacerbate these challenges, leading to insufficient interventions (Omokaro *et al*., 2024).

Globally, water pollution continues to jeopardize water security, with over 25% of the world's population unable to access safe drinking water in 2022 (World Health Organization & United Nations International Children's Emergency Fund [WHO & UNICEF], 2023). Achieving environmental sustainability necessitates effective monitoring and intervention strategies. Emerging technologies, particularly the Internet of Things (IoT), have been identified as transformative tools for real-time water quality assessment (Ighalo & Adeniyi, 2020; Tyagi *et al*., 2024). IoT finds a wide usage in data acquisition, processing and interpretation in many fields of interest, and Remote Sensing is one of them, being an important area of signal processing research and studies (United Nations Environment Programme, 2019). IoT-enabled systems integrate smart sensors to measure critical parameters, including pH, turbidity, temperature, and total dissolved solids (TDS), transmitting data to cloud servers for real-time analysis and visualization (Pasika & Gandla, 2020; Sanya *et al*., 2022). Despite their proven potential, the integration of IoT remote sensing technologies for environmental monitoring remains limited in certain regions like Africa (Rodríguez-Andrés, Montaño-Ruiz, & Valdivia, 2023). Research on smart sensors in these contexts is sparse, highlighting the need for localized innovations that leverage IoT capabilities. IoT-based systems equipped with robust sensors can enable cost-effective and scalable solutions for water quality monitoring, particularly in resource-constrained settings (Tyagi *et al*., 2024; Ulo & Sinha, 2021).

The integration of remote sensing with IoT offers additional benefits for agricultural productivity, aligning with SDG 2, which aims to end hunger and promote sustainable agriculture. Precision aquaculture, driven by these technologies, will allow fish farmers to optimize resource use, enhance yields, and minimize environmental impacts.

The focus of this research is on evaluating the potential effectiveness of a cost-effective, scalable IoT device for real-time water quality monitoring in Nigeria's aquatic habitats. Tailored for resource-constrained settings, the device aims to support aquaculture and environmental sustainability while aiding pollution control efforts (Ulo, E., & Sinha, S. (2021); United Nations Environment Programme. (2019)). By integrating IoT and machine learning, the system provides valuable data for government policy, predictive modeling, fostering sustainability research, and targeted interventions, ultimately contributing to SDGs 6, 1 (No Poverty), and 2 (Zero Hunger). This device's scalability allows for deployment across various aquatic environments in Nigeria, ensuring both environmental conservation and support for local farmers. By fostering collaboration among researchers, policymakers, and communities, this research aims to create resilient systems that promote sustainable water management, economic development, and social equity, positioning Nigeria and other developing countries to meet their sustainability goals.

2. MATERIALS AND METHOD

This study focuses on evaluating the effectiveness of an IoT-based water quality monitoring device that integrates three key sensors: the DS18B20 waterproof temperature sensor, TDS Meter V1.0, and a turbidity sensor. These sensors work in unison with the NodeMCU ESP8266 microcontroller to collect real-time data on water temperature, total dissolved solids (TDS), and turbidity. The System's block diagram is presented in figure 1. Data collection was conducted using the AquaSense device deployed in a 15×15×4 ft tarpaulin fish pond in Benin City, Nigeria. The device sampled temperature every second and TDS and turbidity every five seconds and logged into an excel sheet. The collected data is analyzed using a machine learning model built with Python, which classifies water quality into three pollution levels: low, medium, and high.

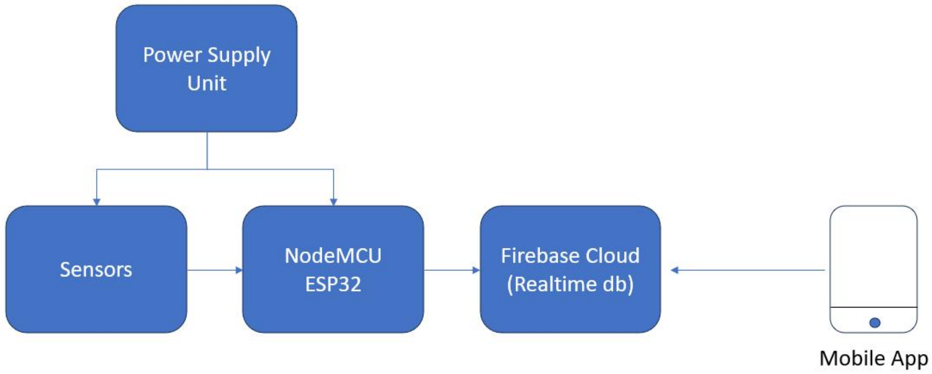

Figure 1: System Block Diagram

A. Sensor Classification

The Sensors involve three main components: DS18B20 waterproof temperature sensor, TDS Meter V1.0 and lastly turbidity sensor. The DS18B20 waterproof temperature sensor is designed for accurate and reliable water temperature measurement, especially in aquatic environments like fish ponds. It operates within a broad temperature range from -55°C to +125°C and provides a high level of accuracy, maintaining a precision of ±0.5°C between -10°C and +85°C. The sensor communicates digitally, reducing the risk of errors and ensuring precise temperature data transmission to the connected microcontroller or processing system. The TDS Meter V1.0 measures total dissolved solids (TDS) in water, which indicates the concentration of substances like salts, minerals, and organic matter. These measurements are critical for assessing water quality. The sensor can measure TDS in parts per million (ppm), with a typical range of 0 to 1000 ppm, although advanced models can measure up to 5000 ppm. It offers an accuracy of ±10% of the measured value, providing reliable data for monitoring water purity. The sensor can output either an analog or digital signal, making it suitable for integration into various water quality monitoring systems. The turbidity sensor is designed to assess the clarity of water by measuring the level of suspended particles, with the results expressed in Nephelometric Turbidity Units (NTU). The typical range for most applications is 0 to 1000 NTU, though advanced versions may extend the range. The sensor's accuracy is ±2% of the measured value or ±0.5 NTU, whichever is greater. It outputs either an analog or digital signal proportional to the degree of light scattering caused by the particles in the water, ensuring accurate water quality and clarity analysis.

B. Device Architecture

The system architecture as shown in figure 2 incorporates three main components: sensors for data acquisition, a microcontroller for processing and transmitting the data, and a mobile application that serves as a user interface for accessing the data. Sensor integration involved precise wiring configurations, ensuring that the DS18B20 used a single-wire communication protocol, while the TDS and turbidity sensors utilized their respective analog and digital interfaces. Data acquisition was programmed at predefined intervals, with temperature readings captured every second and TDS and turbidity readings taken every five seconds.

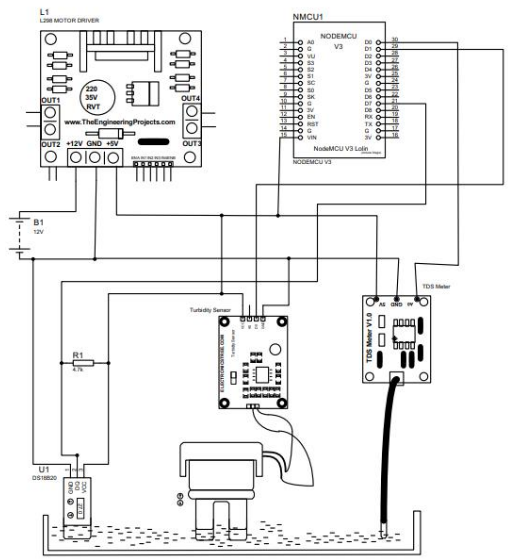

Figure 2: Device architecture showing sensors and microcontroller

C. Data Collection

Data collection was carried out using the AquaSense device deployed in a controlled aquaculture setting specifically, a 15×15×4 ft tarpaulin fish pond located in an urban area of Benin City, Nigeria. This environment was deliberately selected over natural water bodies for two primary reasons: it offered a higher degree of experimental control, and it was more readily accessible for sustained monitoring. Natural water bodies in urban settings introduce unpredictable variables such as runoff events, human interference, and fluctuating seasonal conditions that could compromise the consistency of initial data collection. The tarpaulin pond, by contrast, allowed conditions to remain stable enough to establish a reliable baseline dataset reflective of typical Nigerian aquaculture environments. The device continuously sampled three water quality parameters at predefined intervals. Temperature readings were captured every second using the DS18B20 waterproof sensor, while TDS and turbidity readings were recorded every five seconds via the TDS Meter V1.0 and turbidity sensor respectively. These intervals were chosen to balance data granularity with the processing capacity of the

NodeMCU ESP8266 microcontroller. Observed values fell within the ranges of 20–30°C for temperature, 100–400 ppm for TDS, and 5–50 NTU for turbidity: ranges consistent with water quality conditions commonly reported in Nigerian fish pond studies. Upon acquisition, sensor readings were transmitted wirelessly over Wi-Fi from the NodeMCU to a Firebase Realtime Database via HTTP requests using the Firebase REST API. Data was stored in a structured format such as /sensors/temperature, /sensors/tds, and /sensors/turbidity., enabling organized retrieval for subsequent preprocessing and model training. The collection period spanned multiple sessions to ensure sufficient data volume and variability across the three pollution classification categories: low, medium, and high; used in the machine learning model. To address class imbalance across the three pollution classification categories: low, medium, and high. Oversampling techniques were applied to the minority classes during preprocessing. Approximately 40% of the final training dataset was synthetically generated, ensuring a more balanced class distribution and reducing the risk of model bias toward the dominant class.

c. Data Preprocessing To enhance the reliability of the dataset, data was generated from tests conducted in a 15x15x4 ft tarpaulin fish pond. This choice of testing environment was due to its accessibility and the level of control it provided over experimental conditions. Unlike natural water bodies, which are less readily accessible in urban settings and introduce an element of unpredictability, the tarpaulin fish pond allowed for consistent and controlled data collection. The dataset captured typical water quality conditions observed in Nigerian fish ponds, including values for temperature (20–30°C), TDS (100–400 ppm), and turbidity (5–50 NTU). Data preprocessing involved several critical steps to ensure accuracy and utility. Outliers and erroneous readings were identified and removed during the cleaning process, while normalization was applied to harmonize the scales of different features. Feature engineering was also performed to derive additional insights from the data, such as moving averages and peak values, providing a richer dataset for analysis. This controlled approach to data collection and preprocessing ensured that the dataset was both reliable and reflective of real-world conditions in Nigerian aquaculture environments. Plate 1 shows the device prototype.

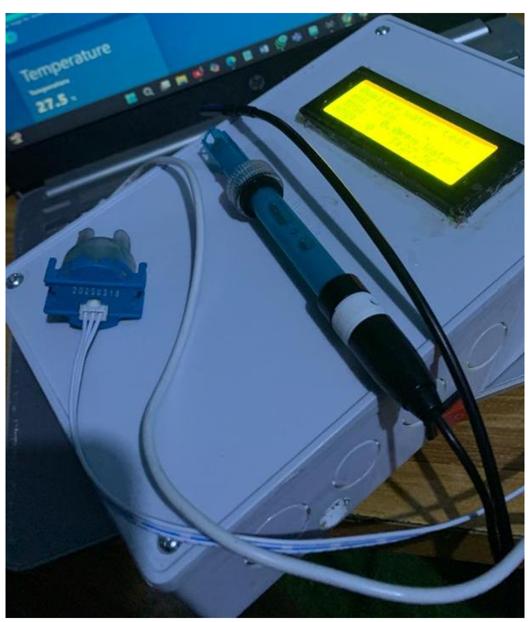

Plate 1: Device Prototype

d. Data Analysis

To visually assess the relationships between each parameter and pollution levels, box plots were created. These visualizations (See figure 4,5 & 6) revealed how variations in water temperature, TDS, and turbidity aligned with different pollution levels (low, medium, and high). For instance, it was observed that higher turbidity levels were more frequently associated with higher pollution classes, while deviations in temperature and TDS also showed discernible patterns correlating with pollution. These box plots provided an initial understanding of the distribution and variability of the parameters, as well as potential outliers in the data.

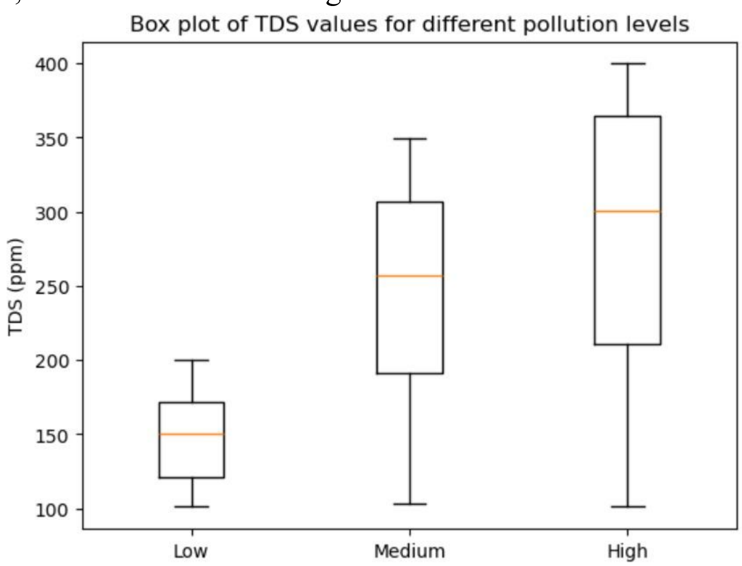

Figure 4: TDS box plot for different pollution levels

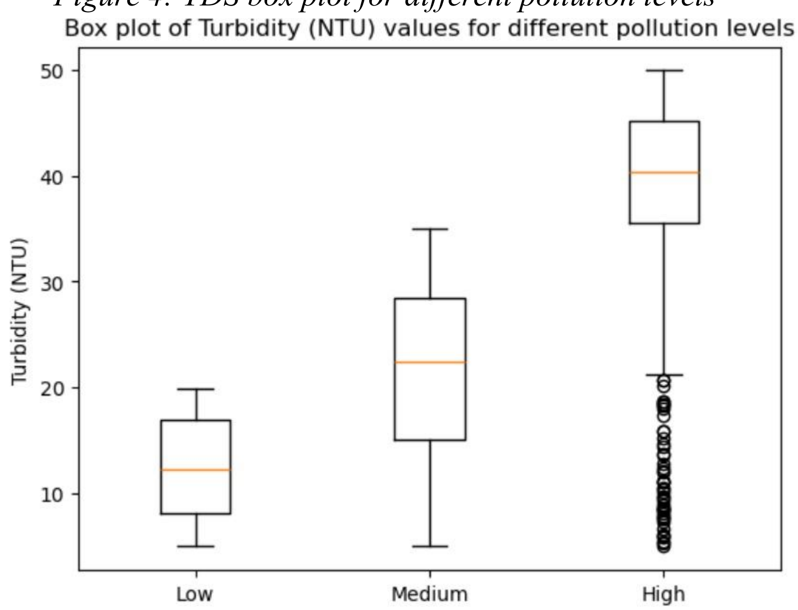

Figure 5: Turbidity box plot for different pollution levels

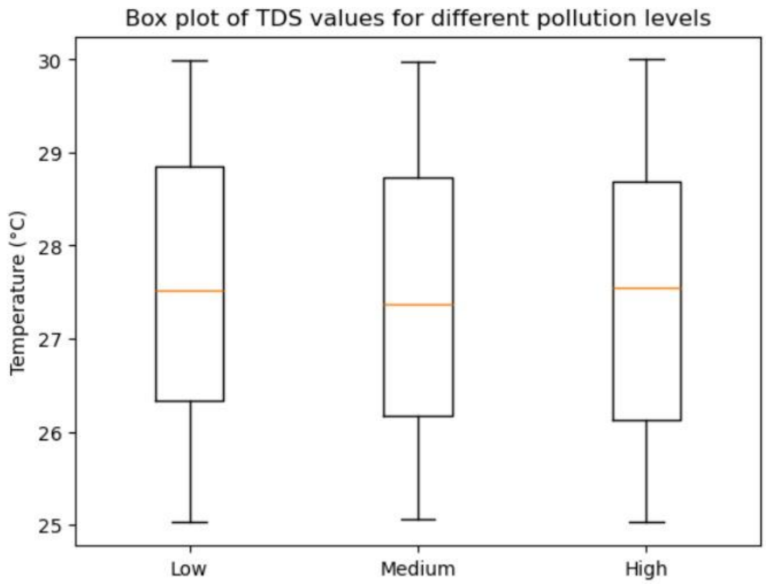

Figure 6: Temperature box plot for different pollution levels

To further quantify the relationships between these variables, a correlation matrix was generated and visualized as a heat map. This matrix displayed the pairwise correlation coefficients between temperature, TDS, turbidity, and pollution levels. The analysis revealed significant correlations, particularly between turbidity and pollution levels, highlighting turbidity as a strong predictor for water quality classification. While temperature and TDS exhibited weaker correlations individually, their combined impact on pollution classification was explored further during the model training phase.

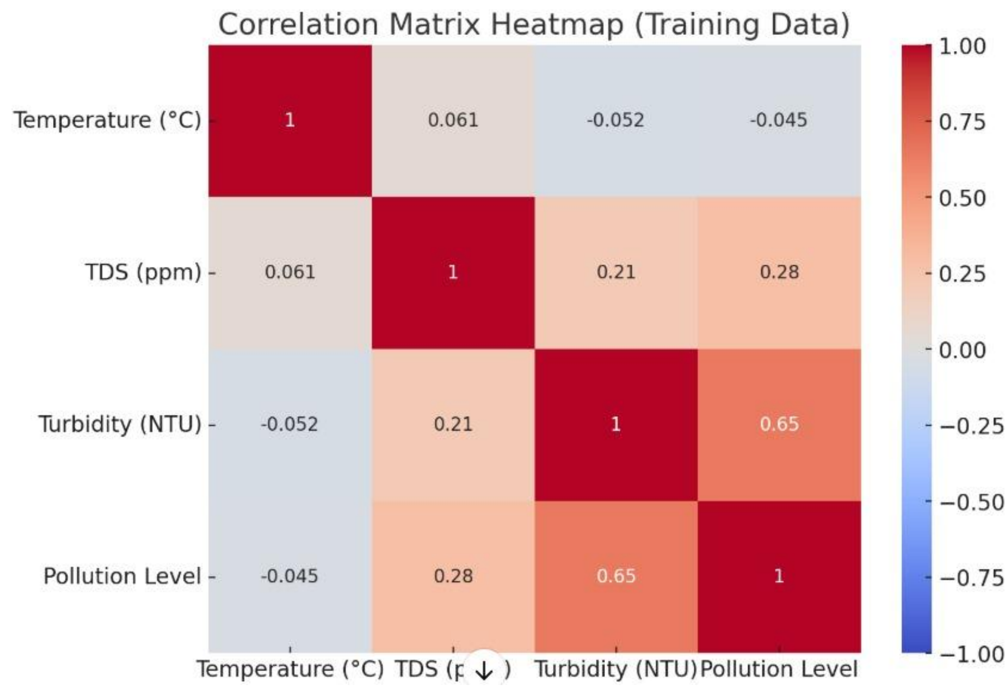

Figure 7: Correlation Matrix Heat map (Training Data)

e. Machine Learning Model Training

The machine learning model employed Random Forest, which outperformed other algorithms such as Support Vector Machines and Decision Trees during the evaluation phase. Training was conducted using historical data from the sensors. The final model achieved high classification accuracy and was deployed for real-time use.

```
Accuracy: 0.65625

F1 Scores:
Macro F1-Score: 0.60
Weighted F1-Score: 0.64

Classification Report:
              precision    recall  f1-score   support

           1       0.59      0.35      0.44        37
           2       0.66      0.81      0.73        90
           3       0.68      0.58      0.62        33

    accuracy                           0.66       160
   macro avg       0.64      0.58      0.60       160
weighted avg       0.65      0.66      0.64       160
```

Figure 8: Training Data Results

Deployment involved integrating the device in aquaculture ponds, where it transmitted data wirelessly to a real-time database. The real-time data was then displayed on a mobile application that featured a user-friendly dashboard and historical data visualizations.

3. RESULTS

The implemented system effectively classifies water quality and monitors pollution in real-time. The machine learning model achieved over 65% accuracy in categorizing water samples into low, medium, and high pollution levels, demonstrating reliable performance in providing actionable insights. Evaluation metrics such as accuracy, precision, recall, and F1-score confirmed the model's efficacy.

```
Accuracy Score:
65.50%

F1 Scores:
Macro F1-Score: 0.54
Weighted F1-Score: 0.62

Classification Report:
              precision    recall  f1-score   support

           1       0.67      0.21      0.31        39
           2       0.65      0.88      0.75       116
           3       0.68      0.47      0.55        45

    accuracy                           0.66       200
   macro avg       0.66      0.52      0.54       200
weighted avg       0.66      0.66      0.62       200
```

Figure 9: Testing Data Results

Real-time monitoring capabilities were tested and found to be highly responsive, generating timely alerts when pollution levels exceed thresholds, allowing for rapid intervention to mitigate risks to ecosystems and human health. A mobile application was developed to enhance usability, featuring a user dashboard displaying real-time sensor data and classification results. The app also includes an alerts system to notify users of water quality deviations, enabling quick responses to issues. Additionally, data visualization tools in the app provide historical trends of water quality, aiding decision-making and long-term planning.

A. Energy Consumption Analysis

This section evaluates the energy requirements of the system, providing a detailed breakdown of energy consumption for each component. The analysis was based on standard operating conditions and typical durations, calculated using the formula:

Energy Consumption (J) = Voltage (V) × Current (A) × Time (s)

The following components were assessed individually for their energy consumption over a 24-hour period (86,400 seconds):

Table 1: Component Specifications and Energy Consumption

Components	Operating Voltage (V)	Current Consumption (mA)	Energy Consumption (J)
NodeMCU ESP8266	3.3	70	20,020.8
Turbidity Sensor	5.0	30	12,960.0
DS18B20 Temperature Sensor	5.0	1.5	648.0
TDS Sensor	5.0	10	4320.0
L298N Motor Driver(voltage Regulator)	7-35 (input)	50	25,574.4

The energy consumption analysis shows that the system consumes approximately 63,523.2 J over a 24-hour period, translating to an average power consumption of 0.735 W.

B. NodeMCU, Firebase, and Flutter App Integration

The integration of NodeMCU, Firebase, and a Flutter app enables real-time monitoring of sensor data. The NodeMCU, a Wi-Fi-enabled microcontroller, collects data from temperature, TDS, and turbidity sensors at set intervals (e.g., every five seconds). This data is then sent to Firebase Realtime Database via HTTP requests using the Firebase REST API, where it is stored in an organized format under paths like /sensors/temperature, /sensors/tds, and /sensors/turbidity.

Firebase's real-time synchronization feature ensures that updates are instantly reflected across all connected clients. The Flutter app connects to Firebase using its SDK, setting up listeners for the specific sensor paths to receive updates in real time. This allows the app to display the most current sensor readings, such as temperature, TDS, and turbidity, without the need for manual polling. The app provides an intuitive user interface where users can view and track real-time sensor data, enabling efficient monitoring and management of water quality on mobile devices.

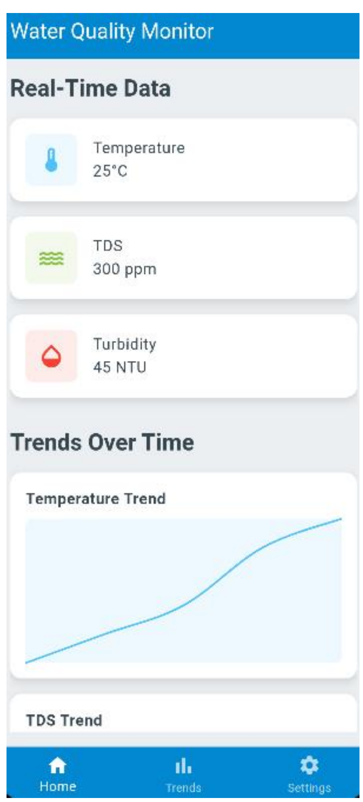

Figure 10: Mobile app interface

4. CONCLUSION

This research highlights the potential of IoT-enabled remote sensing systems for real-time water quality monitoring, with a specific focus on developing nations like Nigeria, where access to consistent and actionable environmental data is often limited. The system integrates cost-effective, energy-efficient components such as the NodeMCU ESP8266 microcontroller along with temperature, TDS, and turbidity sensors, offering a scalable and efficient solution for monitoring essential water quality parameters. By utilizing Firebase Realtime Database and a Flutter-based mobile application, the system ensures seamless data synchronization and easy accessibility, providing decision-makers, researchers, and stakeholders with reliable, up-to-date information to inform their actions. While the system was tested in an aquaculture pond to ensure a controllable environment for data collection, its broader application extends to monitoring water bodies such as rivers, lakes, and reservoirs. This capability can play a vital role in sustainability research, offering insights into long-term water quality trends and aiding in the assessment of pollution levels. By identifying critical changes in water conditions early, the system can help guide government response efforts, inform environmental policies, and support initiatives aimed at preserving natural water resources.

Additionally, the system holds significant promise for aquaculture management as a secondary benefit, providing farmers with the tools to optimize water quality and improve productivity. The energy consumption analysis demonstrates the feasibility of deploying the system in resource-constrained settings, further reinforcing its applicability in underserved areas. This study lays the groundwork for leveraging IoT and remote sensing technologies in regions that have been slower to adopt such advancements, empowering communities to take proactive steps toward sustainable water resource management. Future research can focus on expanding sensor integration for more comprehensive monitoring, enhancing predictive analytics through machine learning, and deploying the system across diverse geographical and environmental contexts. By doing so, this innovation can serve as a critical tool for sustainable development, empowering communities, and advancing environmental stewardship in developing nations.

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