

IOT-Based Water Pollution Detection Boat with Real-Time Monitoring

Dr. Pushparani M K¹, Sharavari M S², Nayana S M ³, Likhith L⁴, Manoj M ⁵

¹Senior Assistant Professor, Dept. of CSD, Alva's Institute of Engineering and Technology, Moodabidiri, Karnataka, India.

^{2,3,4,5}UG Student, Dept. of CSD, Alva's Institute of Engineering and Technology, Moodabidiri, Karnataka, India.

Emails: $drpushparani@aiet.org.in^1$, $4al21cg049sharvari@gmail.com^2$, $4al21cg040@gmail.com^3$, $4al21cg035@gmail.com^4$, $4al21cg036@gmail.com^5$

Abstract

Sustainable development, public health, and aquatic ecosystems are all seriously threatened by water pollution. Conventional monitoring techniques are frequently time-consuming, sedentary, and unable to offer real-time data from inaccessible or remote locations. The creation of an affordable, remote-controlled water pollution detecting boat with necessary sensors and a live data transmission system is shown in this study. The boat can sail on its own or with a remote control, gathering data on temperature, turbidity, and pH in real time [3], [15]. A web-based interface receives the gathered data, allowing for remote monitoring and analysis. For environmental organizations, researchers, and conservationists, the system offers a scalable, independent solution that makes water quality testing more effective and approachable. By automating data collection and enabling real-time access to water quality parameters, this project addresses critical environmental challenges related to pollution detection and resource management.

Keywords: Water pollution monitoring, IoT-based water quality assessment, real-time data transmission, *Blynk, environmental conservation.*

1. Introduction

Water pollution monitoring is critical for protecting the safety of aquatic life and human populations who rely on clean water sources. Industrial discharge, agricultural runoff, and home garbage have all contributed to a major increase in global water pollution levels [9]. Traditional approaches, such as stationary monitoring stations and manual sampling, are limited in terms of cost, accessibility, and efficiency [2], [5]. These solutions are frequently site-specific, necessitating significant human effort and restricting real-time intervention possibilities. The goal of this research is to create a remotecontrolled water pollution detection boat capable of navigating across bodies of water, collecting realtime data, and transmitting it to a web-based interface for remote monitoring [1], [7]. This project aims to create an efficient navigation system, integrate water quality sensors, and perform real-time data transfer to provide accurate and continuous monitoring of water bodies. The boat offers a novel solution for real-time environmental monitoring through the use of IoT technologies and autonomous navigation [13]. The

system can operate in a variety of water habitats, including lakes, rivers, and reservoirs, making it an effective tool for environmental preservation and study. Furthermore, the incorporation of GPS enables for the mapping of pollution sources and the tracking of water quality changes over time, increasing its usefulness in long-term environmental research [18]. **2. Literature Review**

2.1.Machine Learning Techniques for Predicting Water Pollution Trends (2021)

Tan investigated the use of machine learning techniques to anticipate pollution trends using previous water quality data. The study emphasized the use of data-driven methodologies to spot patterns in environmental changes, allowing for earlier warnings and better pollution control decisions. Using huge datasets from multiple water bodies, the model successfully recognized pollution patterns based on pH, turbidity, and temperature. However, one of the most significant issues identified was the need for large datasets to increase predictive accuracy. The study revealed that, while machine



learning models generate useful insights, their efficacy is contingent on the availability of highquality, continuous data streams [1].

2.2.Deployment of Autonomous Surface Vehicles (ASVs) for Automated Water Sampling (2021)

Roberts looked at the use of autonomous surface vehicles (ASVs) for continuous water sampling. The study revealed how autonomous surface vehicles (ASVs) can collect real-time data from different places within a body of water. These robotic devices were outfitted with a variety of sensors to monitor characteristics such as dissolved oxygen, turbidity, and pH. The findings revealed that ASVs outperform standard monitoring approaches in terms of efficiency, scalability, and labor intensity. However, issues like as high initial investment prices, maintenance requirements, and low operational efficiency in stormy water conditions have been identified impediments as to widespread implementation. Despite these limitations, ASVs have emerged as a viable tool for automated and long-term environmental monitoring [2].

2.3.Cloud-Based IoT System for Water Quality Data Analytics (2021)

Rao and Gupta introduced a cloud-integrated IoT system that collects, processes, and analyzes water quality data in real time. This system utilized wireless sensor networks (WSNs) to gather data on various water parameters and transmit it to a centralized cloud platform. The research highlighted the benefits of cloud computing, including remote accessibility, real-time alerts, and data visualization for better environmental management. The study also addressed concerns about data security, network reliability, and potential loss of connectivity in remote areas. The researchers suggested that improving network infrastructure and data encryption techniques could help mitigate these challenges. Overall, the study demonstrated the viability of cloud-based IoT solutions in modernizing water pollution monitoring and enhancing data-driven decision-making [3].

2.4.Multi-Parameter Water Probes for Reservoir Monitoring (2022)

Patel worked on installing multi-parameter water

probes in reservoirs to monitor water quality indicators such as pH, dissolved oxygen, and turbidity. The study underscored the value of longterm, automated data gathering in detecting modest changes in water quality over time. Unlike handheld devices that require manual sampling, these multiparameter probes collected continuous real-time data while submerged in water. While the technique was excellent in collecting reliable data, its stationary nature limited coverage to specific spots within a reservoir. The study proposed integrating these probes with mobility platforms like self-driving boats to improve coverage and data collecting efficiency [4].

3. System Analysis 3.1.Introduction

The Water Pollution Detection Boat is an IoT-based project that monitors water quality metrics like pH, turbidity, and temperature in real time. This system uses a remote-controlled boat outfitted with sensors and wireless communication capabilities to give an effective and mobile option for water quality assessment. The collected data is uploaded to a cloudbased platform called Blynk for easy access and analysis. This project seeks to overcome the limits of existing water monitoring methods by providing realtime information, improved mobility, and increased accessibility.

3.2.Existing Systems

Water pollution monitoring has traditionally relied on stationary monitoring stations, manual sampling methods, and laboratory-based analysis. Recent advancements introduced IoT-based sensor networks to automate data collection and transmission. The following are some notable existing systems:

- Stationary Sensor Networks: Fixed sensors are put at predefined areas to measure water quality parameters. These networks provide consistent monitoring in specified areas but are limited to predefined places, making them less effective for bigger or remote water bodies. [6].
- Handheld Testing Devices: Portable devices requiring manual sampling and testing. These devices are simple to use and provide fast results, but they rely substantially on personal



effort and are not appropriate for continuous monitoring. [7].

- IoT-Based Monitoring Stations: Systems that use wireless sensor networks to monitor data in real time. These systems use IoT technology to deliver real-time data to centralized platforms, resulting in improved accessibility. However, they frequently demand large infrastructure expenditures and maintenance. [8].
- Autonomous Surface Vehicles (ASVs): Robotic boats are designed to check water quality without human interaction. ASVs can cover huge regions and collect data automatically, but they are typically expensive and hard to run, limiting their utility in smaller projects. [9].

3.3.Limitations of older versions

Despite advancements in water quality monitoring, existing systems present several challenges:

- Lack of Mobility: Most systems are fixed and have limited spatial coverage. Stationary monitoring stations, while useful for monitoring specific sites, cannot cover larger or more dynamic water basins. This constraint restricts their ability to track pollution sources that travel with water currents. Tan and Li (2021) found that fixed monitoring stations are unable to respond to spatial fluctuations in water quality. [10].
- Manual Intervention: Manual sampling using handheld devices is time-consuming. Manual methods are labor-intensive, prone to human error, and do not provide continuous monitoring capabilities. According to Rao and Gupta (2021), manual testing equipment are still commonly employed in developing regions due to cost considerations. However, they cannot give the real-time insights essential for successful pollution management. [11]
- High Costs: IoT-based stations and ASVs may require large initial investments. Deploying and maintaining complex IoT infrastructure takes significant financial resources, making it less accessible to small-

scale or community-driven projects. Patel and Desai (2022) underline the economic limitations associated with IoT-enabled water quality monitoring systems, particularly when expanding the sensor network to provide better coverage. [12].

- Delayed Data Access: Traditional monitoring techniques have a time lag between data collection and analysis. Data obtained manually must be carried to laboratories for analysis, which causes delays that prevent rapid decision-making. Jones and Allen (2021) observe that delayed data access can result in missing contamination incidents, particularly in sensitive ecosystems. [13].
- Limited Parameter Tracking: Some systems just monitor basic parameters and have limited customization options. Many present devices are designed to monitor specific contaminants or water quality indicators, limiting their adaptability. Smith and Taylor (2023) noticed that most commercial water monitoring devices do not provide modular sensor setups, limiting their usefulness in varied situations. [6].

3.4.Proposed System

The proposed Water Pollution Detection Boat introduces a cost-effective, mobile, and real-time water monitoring solution. Unlike stationary systems, this boat can traverse water bodies, capturing data from various locations. Key features include:

- Mobility: The suggested boat is outfitted with motors and a remote-control system, allowing it to travel between various areas of interest in a water body. This mobility guarantees that samples are not limited to set places, delivering more thorough water quality data. [14].
- Real-Time Monitoring: Real-time monitoring capabilities enable consumers to access water quality data quickly via the Blynk app. Sensor measurements for pH, turbidity, and temperature are constantly updated, allowing prompt detection of pollution occurrences. [15].
- IoT Integration: The system makes use of an



ESP32 microcontroller with Wi-Fi built-in, which allows for wireless data transmission. This integration lowers the requirement for physical infrastructure and ensures that sensor data may be accessed remotely [16].

- User-Friendly Interface: The Blynk dashboard provides a simple interface for visualizing water quality parameters. The application is available via cellphones or laptops, allowing end users to monitor conditions in real-time without technical skills. [17].
- Cost-Effective Design: To keep costs down, the project favors the usage of low-cost offthe-shelf components. The use of ESP32, basic sensors, and easily available materials keeps the system accessible for educational and small-scale research applications. [18]. Figure 1 shows The graph compares the performance of different water quality monitoring systems based on mobility, realtime monitoring, cost-effectiveness, and ease of use, highlighting the advantages of the water pollution detection boat.

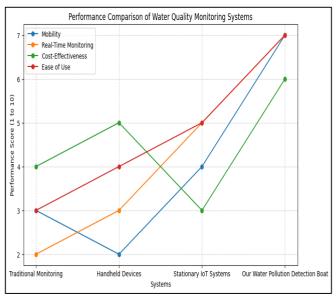


Figure 1 The graph compares the performance of different water quality monitoring systems based on mobility, real-time monitoring, cost-effectiveness, and ease of use, highlighting the advantages of the water pollution detection boat.

4. Methodology 4.1.Software

4.1.1. IoT Platform Integration and Connectivity

The Blynk IoT platform is being used for remote monitoring and control of water quality indicators. The ESP32 microcontroller interfaces with the Blynk platform via a secure connection enabled by the Blynk authentication token. This token connects the system to a predetermined Blynk project that is configured with the template ID and name. The Blynk platform allows customers to monitor water quality measures such as turbidity, temperature, and pH from anywhere in the world using the Blynk mobile or web app. To enable this connectivity, the ESP32 is configured with Wi-Fi credentials, such as the network SSID and password. Upon starting, the ESP32 automatically connects to the specified Wi-Fi network and commences communication with the Blynk server. This connection allows real-time transmission of sensor data to the cloud, ensuring continuous updates without manual intervention. The use of the Blynk platform simplifies the overall system architecture, as it provides a user-friendly interface for monitoring data and managing device settings [19].

4.1.2. Sensor Data Processing and Mapping

The software collects and processes data from three key sensors—turbidity, pH, and temperature using the analog-to-digital conversion (ADC) functionality of the ESP32. The sensor readings are captured as raw values, which are then mapped to interpretable ranges that represent actual water quality parameters. For instance:

- The turbidity sensor generates an analog signal on a scale of 0 to 100, with 0 representing pure water and 100 indicating severely turbid (filthy) water. This mapped value enables simpler understanding and study of water purity [20].
- The pH sensor output is an analog signal that is converted to a voltage and then used to calculate the pH value. The pH is an important indication of water quality since it represents the acidity or alkalinity of the water [3].



• The temperature sensor (DS18B20) uses a digital communication protocol to provide temperature data in degrees Celsius, essential for analyzing environmental conditions [8].

Each sensor reading is analyzed and delivered to the Blynk cloud via virtual pins. The virtual pin assignments enable specific sensor data to be delivered to the associated widgets in the Blynk app (for example, V0 for turbidity, V1 for temperature, and V2 for pH). This data is continuously updated in the cloud, allowing for real-time visibility into water conditions.

4.1.3. Timers and Real-Time Data Updates

To ensure that data is captured and transferred at regular intervals, the software employs a Blynk Timer object. This timer regularly calls the transmit Sensor function, which reads sensor data and updates the Blynk cloud. The system is designed to capture sensor data every 100 milliseconds, allowing for near-instantaneous updates on water quality. This high frequency of data gathering is required for real-time monitoring, allowing users to respond quickly to changes in water conditions such as increased turbidity or pH swings. The inclusion of a timer guarantees that the system runs autonomously, eliminating the need for manual intervention. The timer starts the data collection procedure at regular intervals, allowing for continuous monitoring and real-time feedback to stakeholders such as environmental agencies or researchers.

4.1.4. Control Logic and Water Quality Classification

It The software also incorporates control logic for classifying water quality based on sensor readings. For example, the system uses specific thresholds to categorize water clarity:

- Clear: Turbidity values below 20 indicate clear water, and a green LED is activated to signal this condition.
- Cloudy: Turbidity values between 20 and 50 indicate moderately cloudy water, triggering a yellow LED.
- Dirty: Turbidity values above 50 indicate highly turbid (dirty) water, and a red LED is

activated.

4.2.Hardware

4.2.1. Microcontroller (ESP32)

The ESP32 microcontroller is the system's central processing unit. It was chosen for its low power consumption, dual-core processing capabilities, and built-in Wi-Fi module, which allow for seamless interaction with the Blynk platform for IoT monitoring and control. The ESP32 receives sensor data, processes it, and sends it to the cloud platform for remote monitoring. In the circuit schematic (Figure IV-1), the ESP32 is connected to three critical sensors: a pH sensor, a Dallas Temperature Sensor, and a turbidity sensor. The pH sensor is linked to the ESP32's analog input pin and monitors the acidity or alkalinity of water. The Dallas Temperature Sensor is a digital sensor that uses the One Wire protocol to measure water temperature. The turbidity sensor, which is attached to another analog input pin, monitors the turbidity of the water and detects the presence of suspended particles. The sensors are powered by the ESP32's VCC and GND pins. The sensor data is processed in real time and sent to the cloud platform, where remote users can monitor water quality metrics using the Blynk interface. Figure 2 shows Circuit Diagram of ESP32 Interfaced with pH Sensor, Dallas Temperature Sensor, and **Turbidity Sensor**



Figure 2 Circuit Diagram of ESP32 Interfaced with pH Sensor, Dallas Temperature Sensor, and Turbidity Sensor

4.2.2. Arduino UNO and Motor Control for Boat Navigation

The Arduino UNO is the fundamental controller for the boat's navigation system, managing the boat's movement using two DC motors. The L298N motor



driver interfaces the Arduino with the motors. This motor driver is critical because it enables the Arduino to regulate the motors' speed and direction by regulating the voltage and current sent to each motor. The motor driver operates via an H-Bridge circuit, which can control two motors individually, allowing for forward and reverse movement. The technology achieves differential drive by regulating each motor separately, allowing the boat to spin by adjusting the engines' speed or direction. For example, to turn the boat to the left, one motor may rotate forward while the other rotates backward. This capacity ensures smooth and effective navigation on the water, allowing the boat to monitor diverse locations while remaining stable. The system also incorporates an HC-05 Bluetooth module, which allows wireless communication between the boat and a mobile device or PC. This Bluetooth module connects to the Arduino's TX (Transmit) and RX (Receive) pins, allowing users to submit commands remotely from their smartphone or computer. The orders are sent to the Arduino, which then processes them and adjusts the motor speeds and directions accordingly. The Bluetooth module increases flexibility by allowing the boat to be controlled without requiring human interaction, making it perfect for usage in remote or difficult-to-access water bodies. The complete navigation system is powered by a rechargeable battery, allowing the boat to operate independently in a variety of environments without requiring a steady power supply. Figure IV-2 shows how the Arduino UNO connects to the L298N motor driver. DC motors, and HC-05 Bluetooth module. The motor driver controls the direction and speed of the two motors, while the Bluetooth module allows for wireless communication with a remote device. The diagram depicts the power connections from the battery and the signal connections between the Arduino and the other components. Figure 3 shows Circuit Diagram of Arduino allowing for nearinstantaneous updates on water quality. This high frequency of data gathering is required for real-time monitoring, allowing users to respond quickly to changes in water conditions such real time and sent to the UNO with Motor Driver, Bluetooth Module, and DC Motors

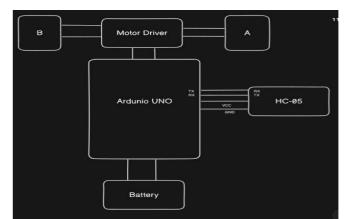


Figure 3 Circuit Diagram of Arduino UNO with Motor Driver, Bluetooth Module, and DC Motors

4.2.3. Key Hardware Components

- ESP32 Microcontroller: The main microcontroller for processing sensor data and communicating with the cloud.
- Arduino UNO: Responsible for controlling the boat's motors and receiving Bluetooth commands.
- Motor Driver: Used to control the power supplied to the motors to move the boat in different directions.
- Bluetooth Module (HC-05): Facilitates wireless communication between the boat and the user's smartphone.
- pH Sensor: Measures the pH level of the water.
- Turbidity Sensor: Measures the clarity of the water.
- Dallas Temperature Sensor: Measures the water temperature.
- Battery: Powers the entire system, including the Arduino UNO and the motors.

4.2.4. System Operation

The total system works by merging the water quality monitoring and boat navigation systems. The ESP32 analyzes water parameters such as pH, turbidity, and temperature in real time and sends the data to the Blynk platform, which the user can examine remotely. The Arduino UNO simultaneously controls the boat's movement using motor drivers and receives commands from a smartphone via the HC-05 Bluetooth module. This hardware combination



provides both environmental monitoring and control over the boat's movement, making it a complete solution for remote water quality analysis and vessel operation.

5. Results

The boat's navigation and data collecting capabilities were tested in controlled situations to ensure accuracy, dependability, and stability. The system successfully demonstrated its ability to monitor water contamination in real time, with accurate sensor readings and flawless remote data transmission. Figure 4 shows Readings from The Sensors Displayed On Dashboard

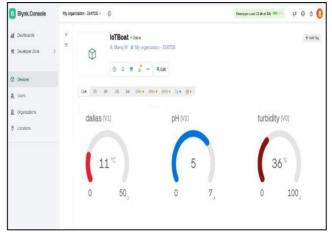


Figure 4 Readings from The Sensors Displayed On Dashboard

The image shows a hand handling a small, remotecontrolled water pollution detection boat. The boat is outfitted with a variety of sensors and technological components that allow for real-time water quality monitoring. A visible power source (a 9V battery), sensor cabling, and an associated microcontroller, most likely used for data processing and communication, are all key elements. The boat is equipped with revolving paddles or flaps that aid in moving over the water. The adjacent laptop screen shows a dashboard with live data being relayed from the boat, including sensor readings for characteristics such as turbidity and temperature. Figure 5 Shows Compact Water Pollution Detection Boat Equipped with Sensors for Real-Time Water Quality Monitoring, Showcasing Live Data Transmission on a Blynk Dashboard

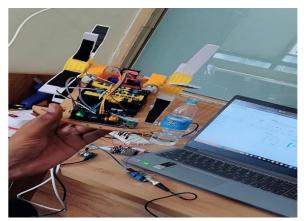


Figure 5 Compact Water Pollution Detection Boat Equipped with Sensors for Real-Time Water Quality Monitoring, Showcasing Live Data Transmission on a Blynk Dashboard

The image shows a water quality monitoring system with pH, turbidity, and temperature sensors connected to a microcontroller via a breadboard for real-time data collection. The pH sensor (blue probe) evaluates water acidity or alkalinity, the turbidity sensor (black probe) determines water clarity by detecting suspended particles, and the temperature sensor ensures precise thermal readings, which are critical for water quality analysis. Signal conditioning modules process sensor outputs before sending them to a computer or cloud system for additional analysis, which is consistent with the study aims outlined in the journal publication. Figure 6 shows Experimental Setup for Real-Time Water Quality Monitoring Using pH, Turbidity, And Temperature Sensors

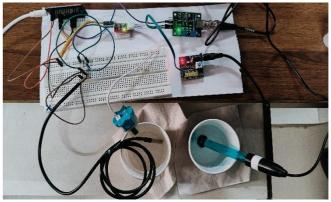


Figure 6 Experimental Setup for Real-Time Water Quality Monitoring Using pH, Turbidity, And Temperature Sensors



The images illustrate a terminal interface for a microcontroller-based motor control system that communicates via Bluetooth utilizing the HC-05 module. The system logs show a successful connection to the HC-05, followed by commands like "r" and "f", which most likely control motor activities. The log messages validate motor actions, with the phrases "Motors started." and "Motors stopped." signifying state changes. The interface also has several preset command buttons (M1-M10) for user input, allowing remote motor control via a Bluetooth-enabled smartphone. Figure 7 shows Bluetooth-Based Motor Control Interface Using the HC-05 Module

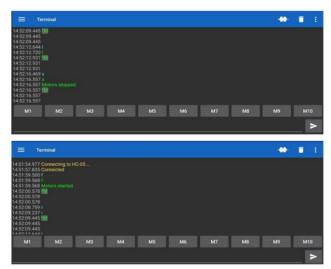


Figure 7 Bluetooth-Based Motor Control Interface Using the HC-05 Module

Conclusion and Future Scope

The creation of a remote-controlled water pollution detecting boat has successfully addressed the difficulties connected with real-time monitoring of water quality in aquatic environments. This project, which combines IoT technology, sensor systems, and autonomous navigation [6], offers a scalable and efficient solution for monitoring important parameters such as pH, turbidity, and temperature [11]. The capacity to remotely control the boat and retrieve real-time data from various locations makes it more useful in environmental research, water resource management, and pollution control. The system's capacity to communicate live data to a webbased platform enables stakeholders such as environmental agencies, researchers, and policymakers to continuously monitor water quality, resulting in better informed decision-making. Furthermore, the integration of GPS tracking enables precise mapping of pollution sources, making it easier to track environmental changes over time. The results illustrate the boat's ability to collect and transmit data while maintaining stable navigation in regulated situations. Its wireless connectivity, paired

regulated situations. Its wireless connectivity, paired with excellent power management, gives it a more affordable alternative to standard water monitoring systems. This research marks a big step forward in environmental monitoring technology, offering a clever, adaptive, and user-friendly solution for analysing water quality in a variety of water bodies [12]. Moving forward, various enhancements can be made to increase the system's functionality and scalability. Future deployments could include using AI-driven analytics to forecast pollution trends [7] and detect water quality anomalies. Expanding the system's sensor capabilities to detect a wider spectrum of pollutants, such as dissolved oxygen or salt, would broaden its application in a variety of sectors and ecosystems. Furthermore, the boat's navigation might be automated using machine learning techniques, allowing it to optimise routes for more efficient data collection. These additions would position the system as a comprehensive environmental monitoring tool capable of adapting to the changing issues of water pollution and resource management [14].

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