Artificial Intelligence (AI) Based Rapid Water Testing System

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Abstract

This research introduces a next-generation AI-powered rapid water testing system designed for real-time, high-precision water quality monitoring in both industrial and domestic environments. The system is built around an ESP32-C6 microcontroller and features a 1.47-inch TFT display for immediate on-site data visualization. It integrates five complementary analytical techniques: capacitance measurement, resistance analysis, ultraviolet (UV) exposure, infrared (IR) absorption, and Raman spectroscopy to assess water quality within seconds.

The multi-modal sensing framework enables detection of a wide range of contaminants. Capacitance and resistance measurements identify inorganic ions, dissolved salts, and microbial activity, while UV and IR absorption provide rapid insights into organic pollutants. Raman spectroscopy delivers molecular-level fingerprinting, allowing advanced contaminant identification. Together, these techniques enable estimation of key water quality indicators such as Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), total coliforms, and fecal coliforms, as well as real-time detection of heavy metals, synthetic dyes, microplastics, and pathogens including *E. coli*.

An embedded AI model, trained on a diverse dataset of water samples, analyzes sensor outputs to recognize complex contamination patterns with high reliability. The result is a portable, energy-efficient, and cost-effective solution capable of delivering immediate water quality assessments and supporting informed decision-making for water safety.

Despite its advantages, the system has limitations. Certain parameters, such as specific pesticide residues, cannot be measured with high accuracy due to sensor selectivity and hardware constraints. Additionally, calibration or modular expansion may be required for highly specialized or extreme conditions.

Keywords: AI-based water testing, ESP32-C6 microcontroller, capacitance measurement, resistance analysis, UV absorption, IR exposure, Raman spectroscopy, real-time monitoring, BOD, COD, coliform detection, heavy metals, microplastics, E. coli.

Contents

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Abbreviations & acronyms

UV-Ultra violet,**WHO:** World Health Organization ,**SDG:** Sustainable development goals, **DC:** Direct Current, **BOD:** Biological Oxygen Demand, **COD:** Chemical oxygen demand ,**AI:**Artificial intelligence, **IoT:**Internet of Things ,**FTIR:**Fourier Transform Infrared Spectroscopy , **TC:** Total Coliform, **FC:** Fecal Coliform, **ML:** Machine Learning , **VOC:** Volatile Organic Compounds, **CCD:** Charge Coupled Device, **LED:** Light Emitting Diode,

Biography

The author, Zabeer Zarif Akhter, a Class 12 student at St. Joseph Higher Secondary School in Dhaka, Bangladesh, has demonstrated a deep engagement in science and technology following his completion of SSC examination at Bogura Cantonment Public School & College. Currently, he is involved in the Ministry of Information & Communication Technology's Team Bangladesh-NASA GLEE MISSION as a researcher & team member . He contributes on electrical, communication , R&D and ionic thruster related problems of that satellite project. Zabeer secured the top position at the BCSIR Science & Industrial Technology Fair in 2024, 2025 and has been active in debate competitions on platforms like Bangladesh Television and ATN Bangla. Additionally, he is a skilled classical singer. The author has researched in my sectors of electronics like high voltage, ionization, plasma, photocatalysis etc. His focus is on solving real-world problems with technology. He was the previous 2024 & 2025 SJWP finalist from Bangladesh. He is also a research fellow at KTH Royal Institute of Technology.

Acknowledgement

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1. Introduction

Water is fundamental to life, yet billions of people around the world still lack access to clean and safe drinking water. According to UNICEF, over 4.4 billion people face challenges in obtaining safe water, and more than 700 children die every day from diarrheal diseases caused by contaminated sources. The global water crisis is not solely about scarcity; it is also about the quality of available water. Industrial discharge, agricultural runoff, inadequate sanitation, and the worsening effects of climate change have led to widespread contamination of freshwater resources. The World Health Organization (WHO) reports that more than 2 billion people live in high water-stress regions, where access to clean water and effective water testing is severely limited. In such areas, communities often lack the means to detect and respond to waterborne threats in time, putting public health at significant risk.Traditional water quality testing methods rely heavily on laboratory analysis, which is time-consuming, expensive, and logistically unfeasible for remote or underserved areas. Field-based kits, such as colorimetric and strip-based assays, offer greater accessibility but are typically limited to basic parameters like pH, TDS, or chlorine, and may require up to 24 hours for bacterial confirmation results (e.g., IDEXX Colilert-18). Moreover, such methods lack sensitivity in detecting emerging pollutants like microplastics, synthetic organic compounds, and nanomaterials. [1] (Li et al., 2022). Recent innovations in portable spectroscopy-based water testing devices such as Aquagenx Compartment Bag Test or MyDx water analyzer have attempted to provide real-time results. However, these systems often suffer from limited sensing range, high cost, or dependence on external mobile applications, reducing their usability in critical, offline environments. [2] (Zhou et al., 2021; Fatima et al., 2023). In response to these shortcomings, this research introduces a novel AI-powered water testing system that combines multi-spectral sensing and machine learning in a compact, low-cost form. The system is built around the ESP32-C6 microcontroller, equipped with a 1.47-inch TFT display, offering real-time visualization of water quality metrics without requiring an internet connection or smartphone.The device integrates five advanced detection techniques: Capacitance and resistance analysis to detect changes in dielectric properties and electrical impedance, enabling the detection of dissolved salts, ions, and microplastics. UV absorption spectroscopy for identifying organic compounds, industrial dyes, and microbial DNA by analyzing absorption at specific UV wavelengths (e.g., 260 nm, 280 nm). Infrared (IR) spectroscopy to detect molecular bond vibrations in PFAs, petroleum-based compounds, and pharmaceuticals. Raman spectroscopy using focused laser excitation (532–785 nm) to obtain molecular fingerprints of pollutants at ppb levels, such as pesticides and pathogens.[4] (Kumari et al., 2020). AI-based data fusion from the above techniques for high-accuracy pattern recognition, trained on a dataset spanning various contamination profiles. What differentiates this system from existing solutions is its real-time operation, broad contaminant spectrum, offline processing capability, and integrated AI inference engine—features rarely combined in portable devices. The AI model supports the detection of Biochemical

Oxygen Demand (BOD), Chemical Oxygen Demand (COD), total/fecal coliforms, and specific toxins such as heavy metals, synthetic dyes, microplastics, and pathogens like E. coli, all within seconds.Furthermore, the power efficiency and ML compatibility of the ESP32-C6 make it suitable for continuous monitoring in off-grid, disaster-prone, or low-resource settings. The system can optionally transmit data to cloud platforms for remote surveillance or large-scale water safety mapping. By addressing the limitations of prior technologies and introducing an all-in-one, AI-integrated, real-time monitoring device, this research offers a transformative solution for water quality management. It empowers individuals and communities to safeguard their water sources, improves response time in contamination events, and contributes to UN SDG 6: Clean Water and Sanitation.

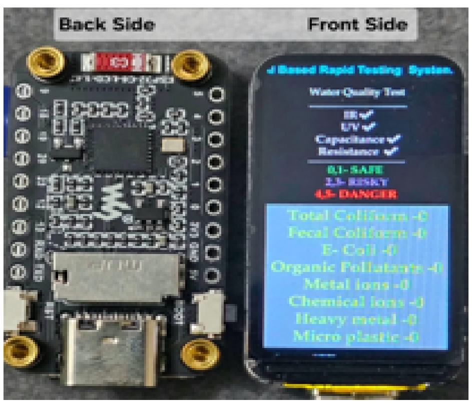
1.1 Why AI based rapid detection

Water quality monitoring plays a critical role in safeguarding public health and environmental sustainability. However, existing methods for detecting contaminants in water are often complex, bulky, and require laboratory-based analysis, making them impractical for rapid or on-site testing. Traditional water testing kits typically depend on chemical reagents or slow electrochemical processes, which can be costly, time-consuming, and require skilled personnel for operation. Additionally, they are often limited to measuring only a few select parameters, failing to provide a comprehensive assessment of water safety in real time. In this context, the development of a next-generation AI-powered rapid water testing system marks a significant technological advancement. Unlike conventional systems, this novel device integrates five analytical techniques capacitance, resistance, UV absorption, IR spectroscopy, and Raman spectroscopy into a compact and portable form factor. Powered by the ESP32-C6 microcontroller and coupled with a 1.47-inch TFT display, the device enables immediate, on-site visualization of contamination data without the need for laboratory infrastructure or maintenance. What truly sets this research apart is its seamless integration of artificial intelligence (AI) and machine learning (ML) algorithms. These models are trained on a broad spectrum of water samples and contaminants, allowing the system to detect subtle patterns and complex mixtures including heavy metals, microplastics, dyes, and microbial pathogens with exceptional accuracy and speed. The embedded AI enables predictive pattern recognition, adaptive learning, and even anomaly detection in field conditions, making the device highly versatile. Furthermore, its small size, energy efficiency, and zero-maintenance design make it ideal for use in both rural and urban settings, especially in regions with limited access to sophisticated lab equipment. Unlike large-scale systems or test kits that require manual calibration, reagent replenishment, or recurring costs, this system offers a low-cost, user-friendly solution that can be deployed instantly by non-experts. Thus,Water testing becomes faster, smarter, portable, affordable, and accessible for all.

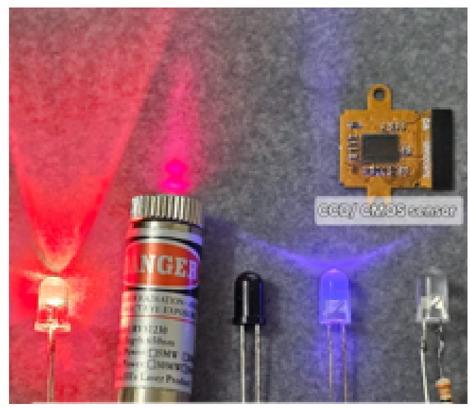
2. Materials and Methods

2.1 Materials

- ESP32-C6 (Display)
- UV Light
- IR Transmitter
- Photodiode array
- RGB LEDMonochromatic Laser
  Gallium Aluminum Arsenide
- CCD sensors



Microcontroller ESP32-C6



Sensors & detectors

Figure 01: Equipments

2.2 System Description

The rapid contaminant detection system uses AI and ML for real-time water quality monitoring via an ESP32-C6 microcontroller with a 1.47-inch TFT display. It detects pollutants like organics, microbes, microplastics, VOCs, heavy metals, and salts using multiple sensors. Powered by a 4V lithium battery, the system is portable, energy-efficient, and cost-effective. Its optional IoT connectivity allows remote monitoring and instant alerts, making it ideal for deployment in remote or resource-limited areas. This scalable solution enhances public health and environmental safety through accurate, real-time water assessment.

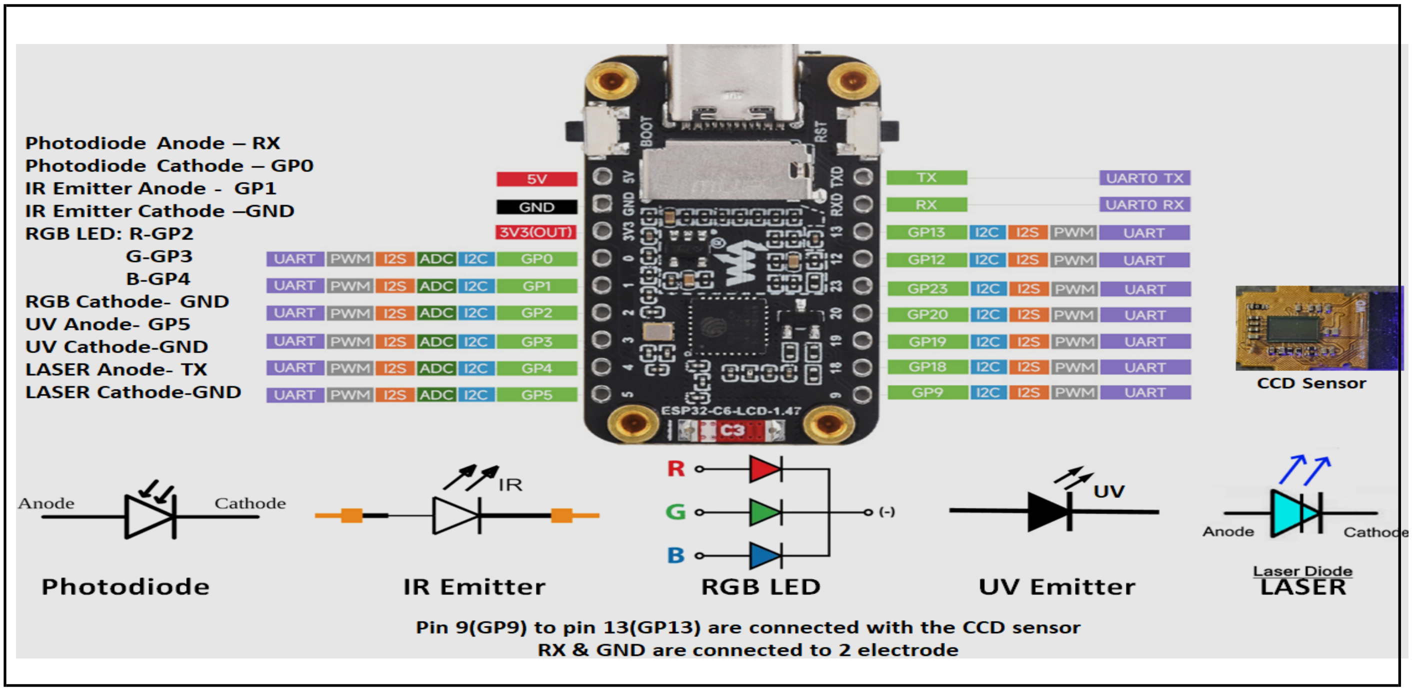


Figure 02: Circuit diagram

For rapid contaminant detection in water, various processes are utilized. To transmit and receive signals, multiple sensors and LEDs are incorporated into the system. An ESP32-C6 microcontroller, which supports AI and operates at a high processing speed of 160MHz with expandable memory, is used for measuring and analyzing these signals and data.In the circuit diagram, the connections are clearly defined. The system employs IR LEDs, UV LEDs, RGB LEDs, and LASERs for signal transmission. To receive these signals, photodiodes and CCD sensors are used. A total of three electrodes are used to measure capacitance resistance. As the signals pass through water, they are partially absorbed & altered by contaminants present in the water.The microcontroller is programmed with reference data, enabling it to distinguish between signals from pure water and those affected by contaminants. Additionally, it has access to vast datasets via the Internet, allowing it to analyze & process unfamiliar signals efficiently.The entire process operates under AI support, significantly enhancing data processing speed & accuracy. As a result, the system delivers highly accurate results in a very short time, making it an advanced , efficient solution for real-time water quality monitoring.

2.3 AI & IoT-Based Multi dimensional Water Quality Monitoring System Using ESP32-C6

The proposed water quality monitoring system combines advanced detection technologies UV absorption, IR spectroscopy, Raman spectroscopy, and capacitance-resistance measurements to deliver real-time, high-accuracy detection of pollutants. At the core of the system is the ESP32-C6 microcontroller, which integrates sensor data processing, machine learning-based pattern recognition, display output, and optional IoT connectivity for cloud-based analysis and monitoring.

2.4 UV Absorption for Organic and Microbial Contaminants

Organic molecules such as pesticides, dyes, and volatile organic compounds (VOCs) exhibit distinct absorbance [9] in the UV spectrum (200–400 nm). Similarly, microbial contaminants such as bacteria and viruses contain nucleic acids and proteins, which absorb UV light strongly at 260 nm and 280 nm, respectively.[6,7] This is governed by Beer-Lambert's Law[8] :

$$A = \varepsilon c l \qquad \text{---------------(1)}$$

Where, *A* is absorbance,

ε is the molar absorptivity,

c is the concentration, and

l is the path length

UV-LED or Deuterium Lamp: Emits UV radiation. CCD Sensor: Detects intensity loss across wavelengths. Quartz Cuvette: Holds water sample to avoid UV absorption by the container. The ESP32-C6 collects UV intensity data across wavelengths using an ADC (Analog-to-Digital Converter). AI models compare the absorbance spectrum with trained data to classify the presence of specific contaminants.

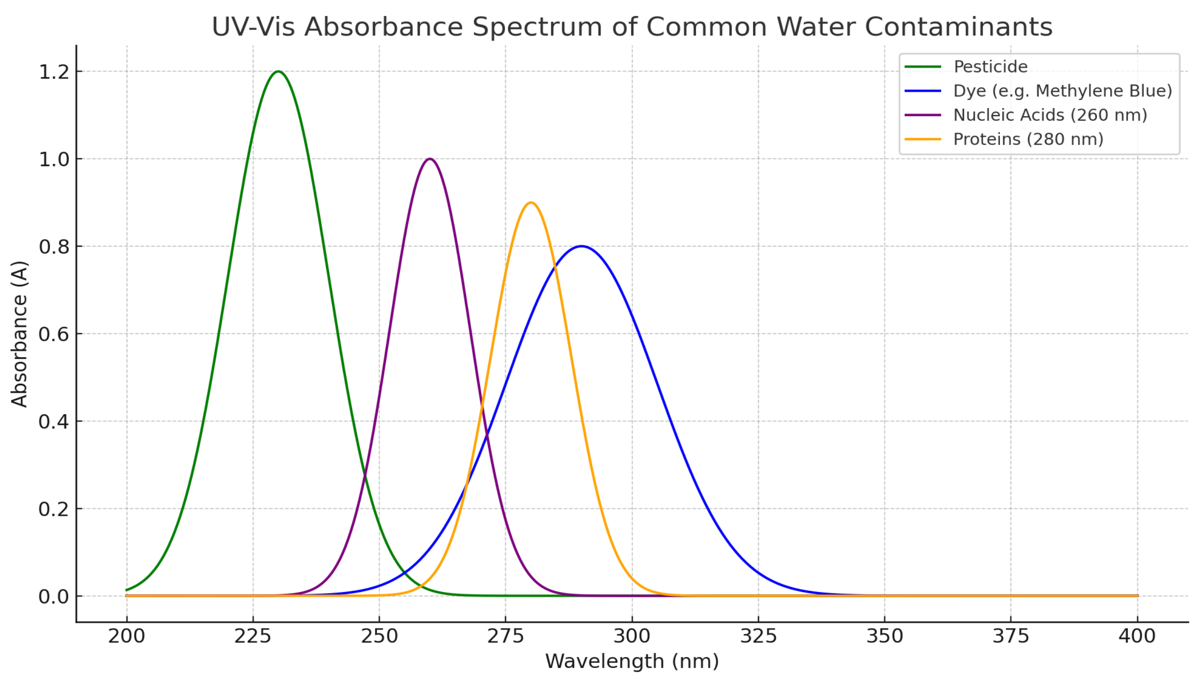


Figure 03: UV-Vis Absorbance Spectrum graph illustrating the absorbance peaks of common water contaminants

Pesticides: Peak around 230 nm, Nucleic Acids: Strong absorption at 260 nm, Proteins: Peak at 280 nm, Synthetic Dyes (e.g., Methylene Blue): Broader peak around 290 nm. The graphs alone with the data are synchronized with the data set of the ESP32-C6 microcontroller. These data are also used to develop the AI & ML model.

2.5 IR Spectroscopy for Industrial Chemicals and Heavy Metals

Mid-infrared (MIR) spectroscopy (wavelength range 2.5–25 µm; wavenumber range 4000–400 cm^{-1}) detects molecular vibrations unique to functional groups such as C–H, O–H, N–H, and C=O. These vibrational modes absorb IR light at characteristic frequencies, forming distinct "fingerprints" for different compounds. While heavy metals themselves are IR-inactive, their presence can be inferred through coordination with organic ligands, which alter IR absorption patterns. To facilitate efficient light-matter interaction, Attenuated Total Reflection (ATR) is employed. ATR is a form of internal reflection spectroscopy where an infrared beam is directed into an optically dense crystal known as an Internal Reflection Element (IRE). When the IR light reflects internally at the interface between the IRE and the sample, it generates an evanescent wave that penetrates a short distance into the sample—typically a few microns. Molecules within this region absorb specific IR frequencies, enabling their identification. [11]

The penetration depth of the evanescent field (dp) is governed by the equation:

$$d_p = \frac{\lambda}{2\pi n_1 \left[\sin^2\theta - \left({}^{n_2}/{}_{n_1} \right)^2\right]^{1/2}} \qquad \text{-------------------(2)}$$

Where: λ\lambdaλ = wavelength of IR light,

θ\thetaθ = angle of incidence,

n1 = refractive index of the IRE,

n2 = refractive index of the sample.

This equation 02 shows that (dp) increases with longer wavelengths and decreases with higher incidence angles or greater contrast between (n1) and (n2) . For accurate detection, the sample must be in intimate contact with the IRE surface to ensure interaction within the evanescent field. In mid-infrared spectroscopy (2.5–25 µm, 4000–400 cm^{-1}), molecules absorb IR light at characteristic vibrational frequencies corresponding to their functional groups. For example, C-H, O-H, and N-H bonds have unique fingerprint regions. While IR doesn't detect metals directly, it detects their complexed organic ligands, which shift

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characteristic frequencies. [10]. IR LED/Source: Emits continuous or modulated IR light. CMOS/CCD Detector or IR-sensitive photodiodes. Optical Path: IR light passes through or reflects off water. Absorption peaks are mapped to known chemical fingerprints (e.g., PFA's ~1100 cm^{-1} for C-F stretching). ESP32-C6 feeds this spectral data into a trained ML model (e.g., Random Forest or KNN classifier)

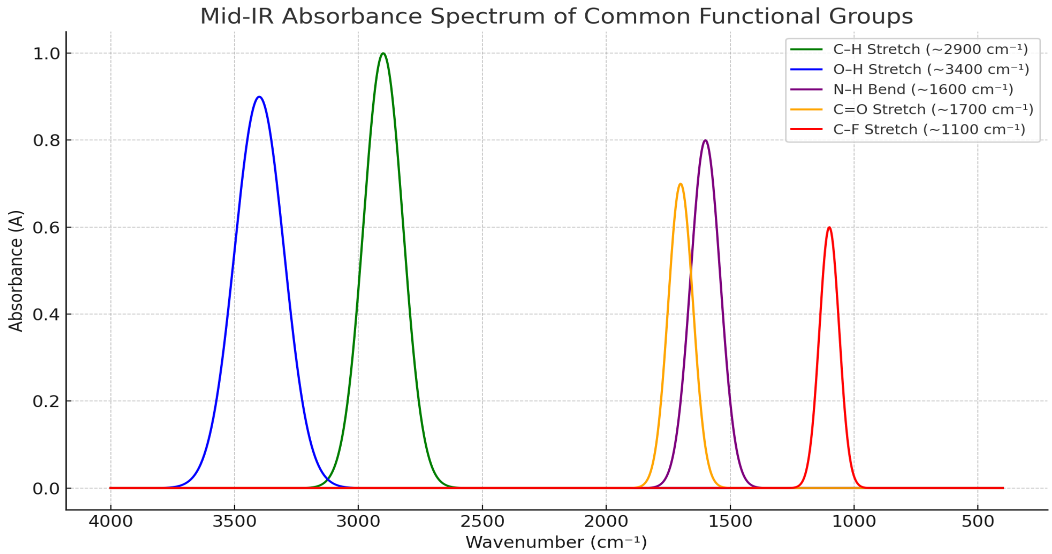

Figure 04: Mid-IR Absorbance Spectrum graph, the unique IR "fingerprint" regions for organic functional groups.

X-axis: Wavenumber (cm^{-1}), decreasing from 4000 to 400 (as per IR spectroscopy convention), Y-axis: Absorbance (A). The graph shows distinct peaks for key functional groups: C–H Stretch (~2900 cm^{-1}), O–H Stretch (~3400 cm^{-1}), N–H Bend (~1600 cm^{-1}), C=O Stretch (~1700 cm^{-1}), C–F Stretch (~1100 cm^{-1}, used in PFAS detection). The same data have been used to detect Industrial Chemicals and Heavy Metals by the device. These datasets are in the ESP32-C6 memory section. AI integrated machine learning models effectively use these data for measuring various contaminants.

2.6 Raman Spectroscopy for Trace Pollutant Detection

Raman spectroscopy is based on the inelastic scattering of photons (Raman Effect). When monochromatic light/ laser (commonly 532, 633, or 785 nm lasers) hits molecules, a small portion of light is scattered at different wavelengths, providing a molecular "fingerprint." Raman is highly sensitive and can detect trace organics, biomolecules, and even microorganisms.[12]

Key Raman shifts:Proteins: 1000–1700 cm^{-1}, Lipids: 2800–3000 cm^{-1}, Nucleic Acids: 700–800 cm^{-1}. [13]RGB Laser or Laser Diode Gallium Aluminum Arsenide: Emits focused beam. Notch Filter + CCD: Filters and detects Raman-shifted photons.

Raman scattering arises from the interaction between incident electromagnetic radiation and molecular vibrations. When a molecule is exposed to an oscillating electric field described by E= E0cos(2πν0t), it becomes polarized, inducing a temporary electric dipole moment given by equation 03:

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$$P=\alpha E \qquad \text{------------------(3)}$$

Here, (α\alpha) represents the molecular polarizability, which is not constant but varies with the vibrational motion of the molecule. Since molecular vibrations consist of several normal modes, the polarizability can be expanded in equation 04 as a Taylor series:

$$\alpha = \alpha_0 + (\partial\alpha/\partial Q_i)_0\, Q_i \qquad \text{-----------------(4)}$$

where (Qi) is the normal coordinate for the i-th vibrational mode and can be expressed as Qi=Qi0 cos(2πvit), with (vi) being the vibrational frequency of the mode. Substituting this expansion into the dipole moment equation gives in equation 05:

$$P=\alpha0E0\cos(2\pi\nu0t)+12(\partial\alpha\partial Qi)0Qi0E0[\cos(2\pi(\nu0+\nu i)t)+\cos(2\pi(\nu0-\nu i)t)]+ \qquad \text{------------------(5)}$$

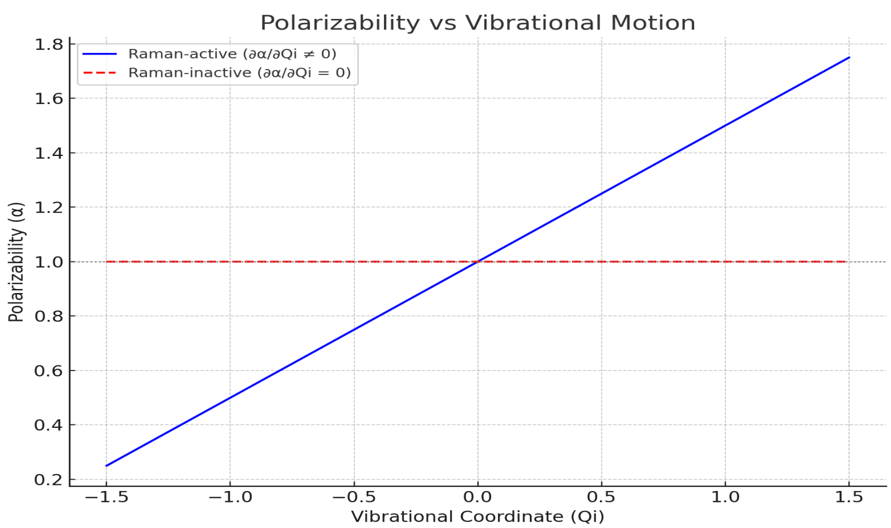

Figure 05: The plot of Polarizability vs Vibrational Motion, illustrating the Raman selection rule: Blue Line: Raman-active mode polarizability changes with vibration (∂α/∂Qi≠0), Red Dashed Line: Raman-inactive mode no change in polarizability (∂α/∂Qi=0).

The first term represents Rayleigh scattering, where the scattered light retains the same frequency as the incident light. The second term gives rise to Raman scattering, which includes two components: Stokes scattering at frequency ν0−νi, Anti-Stokes scattering at frequency ν0+νi . Because the polarizability change during vibration (∂α/∂Qi)0 is typically small compared to the static polarizability (α0), Raman signals are inherently weak. In fact, only about one in every 10^{10}incident photons produces a Raman-scattered photon. Importantly, Raman activity of a vibrational mode depends on a change in polarizability during the vibration. Only modes for which (∂α/∂Qi)0 will contribute to Raman scattering. This condition forms the

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Raman selection rule and distinguishes Raman-active vibrations from those that are IR-active or inactive.[14] Raman spectra are processed with smoothing filters (e.g., Savitzky-Golay) and peak detection. ESP32-C6 invokes an embedded AI model (e.g., SVM) for pattern recognition.

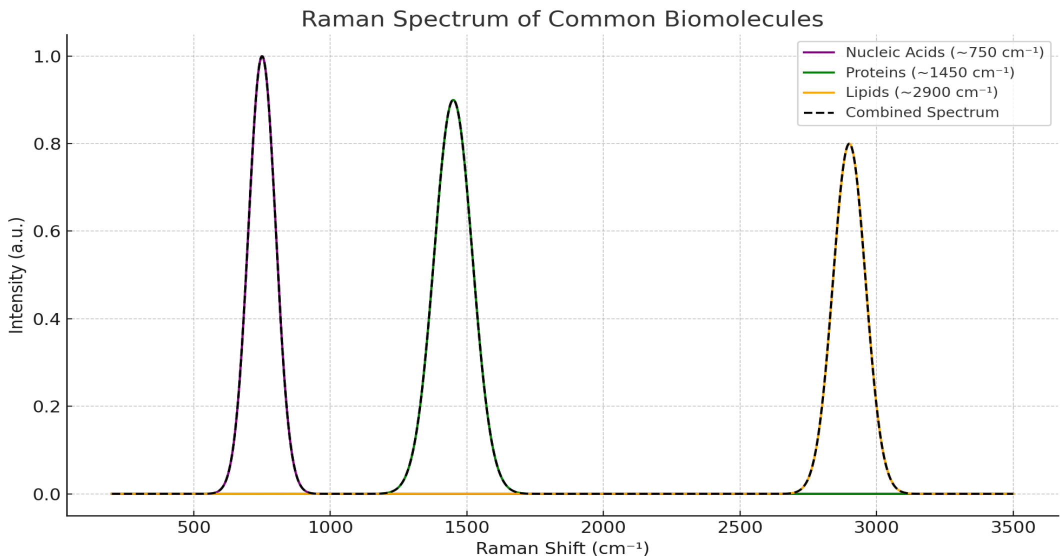

Figure 06: Raman Spectrum Graph showing key Raman shifts for common biomolecules

X-axis: Raman Shift (cm^{-1}), Y-axis: Intensity (a.u.) , molecular fingerprint ~750 cm^{-1}: Nucleic Acids, ~1450 cm^{-1}: Proteins, ~2900 cm^{-1}: Lipids. The combined spectrum (dashed black line) demonstrates how real Raman signals often contain overlapping peaks.

2.7 Capacitance & Resistance for Ionic Contaminants

In aqueous environments, the presence of dissolved ionic species directly influences the electrical properties of the solution. Under an applied electric field, these ions migrate and contribute to the water's overall conductivity and capacitance, which are key parameters in determining Total Dissolved Solids (TDS) and salinity levels. The proposed AI-based system utilizes these principles for rapid, in-field quantification of ionic contaminants.

The specific conductivity of a water sample is governed by the number and mobility of ions. Ionic strength (I) is calculated using equation 06:

$$I = \frac{1}{2}\sum_{i=1}^{n} C_i Z_i^2 \qquad \text{---------------------(6)}$$

Where, (Ci) is the concentration and

(Zi) is the charge number of the i^{th} ion.

The Onsager equation further relates molar conductivity (λ) to ionic strength:

$$\lambda = \lambda^0 - [x]\sqrt{I} \qquad \text{----------------------(7)}$$

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Where (λ0) is the limiting molar conductivity at infinite dilution, and

[x] is a constant related to ionic valence.

The total conductivity (K) of the water sample is calculated in equation 08 as:

$$K = \sum_{n=1}^{n} \lambda_n M_n \qquad \text{--------------------(8)}$$

Here, (λn) and (Mn) represent the molar conductivity and concentration of each ion, respectively. The measured conductivity is then compared against this theoretical value to validate accuracy.

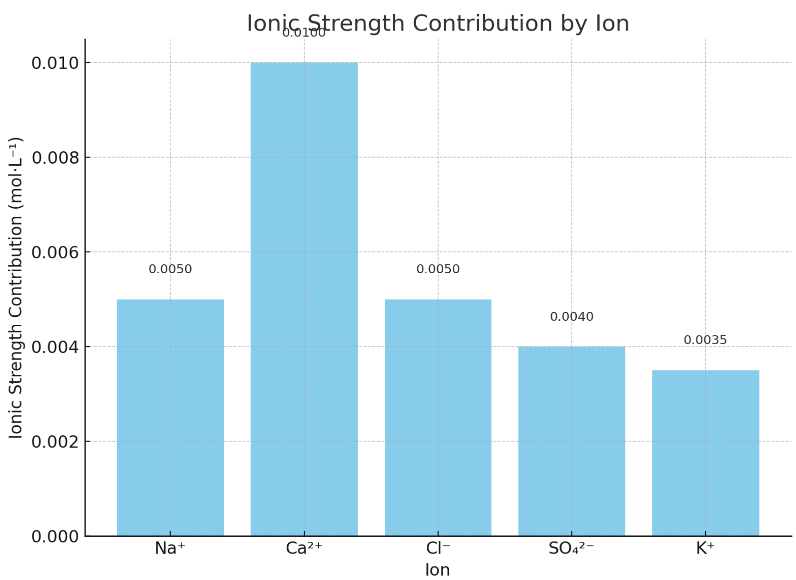

Figure 07: Bar Chart of Ionic Strength Contribution by Ion based on ion concentrations and charges. It visually shows how each ion (like Ca^{2+} or SO_4^{2-}) contributes to the total ionic strength of a water sample.

Electrodes: Stainless Steel Electrode Pair. Signal Processing: RC Circuit or Wheatstone Bridge interfaced with ESP32-C6 ADC pins. AI Integration: The ESP32-C6 processes real-time analog values and feeds them into a machine learning model (e.g., linear regression or decision trees) trained on standard conductivity vs. TDS datasets. Temperature Compensation: Algorithms ensure accuracy across environmental conditions. [15]

Real-Time Analysis :The system correlates conductivity measurements with TDS concentration, leveraging AI algorithms to continuously learn and improve estimations. This enables dynamic detection of salinity shifts, ionic pollution, or residual contaminants in drinking water, industrial effluents, or reclaimed sources. Furthermore, advanced separation techniques (e.g., AI-enhanced chromatographic profiles) can be optionally integrated for isolating compounds with similar ionic characteristics. These extended modules improve trace-level sensitivity and provide a deeper understanding of water composition.

2.8 System Work process

The AI-based rapid water testing system integrates multiple sensing techniques infrared (IR) absorption, ultraviolet (UV) spectroscopy, Raman spectroscopy, and resistance-capacitance (RC) measurements into a compact, unified platform centered around the ESP32-C6 microcontroller. This intelligent system is designed to assess water quality in real time by analyzing a broad range of physical and chemical properties using both optical and electrical signals. To begin, various signal transmitters such as IR LEDs, UV LEDs, RGB LEDs, monochromatic laser diodes (for Raman analysis), and resistance-capacitance electrode pairs are connected to the GPIO pins of the ESP32-C6. These transmitters emit their respective signals through the water sample placed between them and a highly sensitive CCD sensor, which functions as the signal receiver. As light or electrical signals pass through the sample, the system measures how much signal is absorbed, scattered, or altered, depending on the type of contaminant present in the water. The ESP32-C6 interprets these responses by comparing the received data to preloaded spectral and electrical datasets. The UV and IR absorption measurements are analyzed to identify the presence of organic pollutants, industrial dyes, and microbial contaminants. Raman spectroscopy, based on inelastic scattering of laser light, detects trace organics, proteins, nucleic acids, and lipids by capturing their unique vibrational fingerprints. Additionally, the RC circuit measures conductivity and dielectric behavior, which directly correlate with total dissolved solids (TDS), salinity, and ionic contamination levels. One of the core strengths of this system lies in its interconnectivity and cross-validation approach. Rather than relying on a single sensing method, each output is verified using complementary methods. For instance, if UV spectroscopy detects absorbance around 260–280 nm (indicative of microbial presence), the system also examines Raman shifts near 700–1700 cm^{-1} to confirm nucleic acid or protein signatures, and evaluates electrical conductivity to check for parallel ionic anomalies. This interconnected strategy significantly improves detection reliability and minimizes false readings. Artificial intelligence (AI) and machine learning (ML) models are deeply embedded within the ESP32-C6 to enhance detection accuracy and efficiency. These include support vector machines (SVM), decision trees, and regression models that are trained on large water quality datasets.

For example, conductivity data is mapped to TDS concentration using regression analysis, while spectral data from Raman and UV are classified by supervised learning models to identify specific contaminants. Signal noise is reduced using digital filters like Savitzky-Golay, and environmental fluctuations are addressed using temperature compensation algorithms. Finally, all processed results are displayed in real time via the ESP32-C6's built-in TFT screen, enabling immediate water quality assessment. The system continues to improve over time as it learns from newly encountered sample patterns, allowing it to dynamically respond to changing water conditions be it increased salinity, organic load, microbial contamination, or the presence of industrial pollutants. This holistic, AI-enhanced approach ensures rapid, reliable, and low-cost testing, making the system especially suitable for remote and resource-constrained environments.

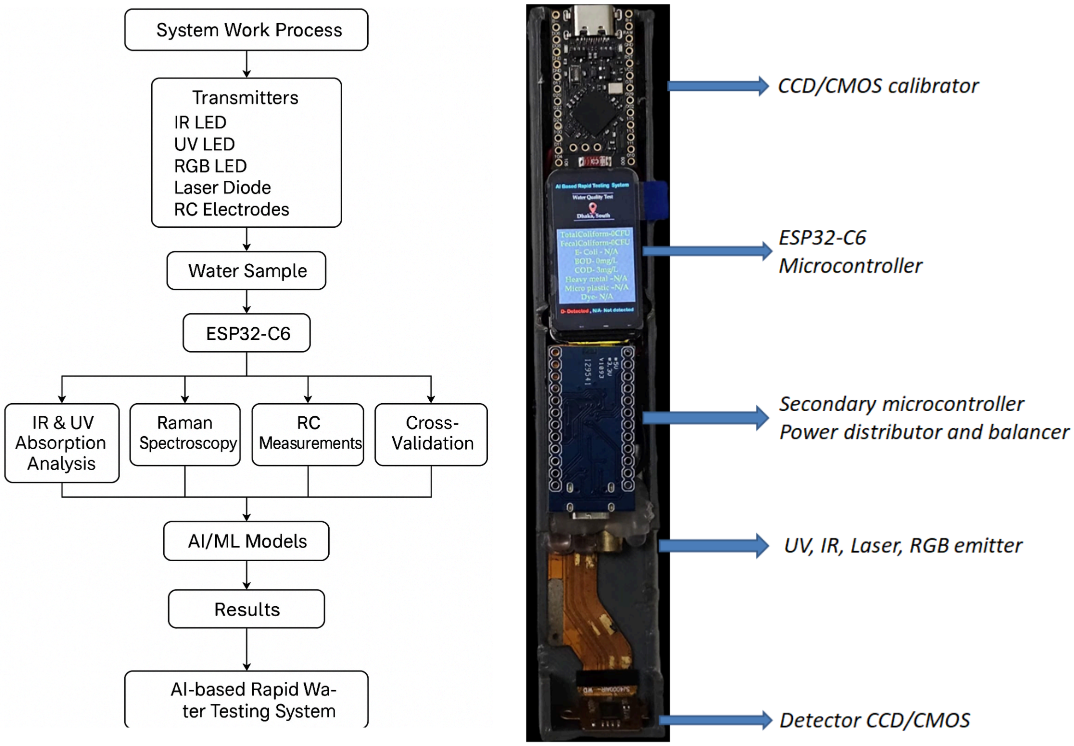

Figure 08:System work process flowchart & marked image

Raman spectroscopy plays a critical role in identifying trace-level contaminants by capturing the unique vibrational "fingerprints" of molecules such as proteins, nucleic acids, and lipids. It is particularly effective for detecting biological pathogens, synthetic chemicals, and complex organics even at parts-per-billion (ppb) levels. UV absorption is used to rapidly identify organic pollutants like dyes, pesticides, and volatile organic compounds, as well as microbial contaminants, by measuring their light absorption at specific UV wavelengths (especially 260 nm and 280 nm). This provides a fast and non-invasive method to flag contamination. IR absorption detects characteristic molecular vibrations associated with industrial chemicals and pharmaceuticals. Although heavy metals are IR-inactive, their presence can be inferred through interactions with organic ligands that shift the IR spectra. This technique enhances the detection of petroleum-based and synthetic contaminants. Capacitance and resistance measurements quantify the presence of dissolved salts, inorganic ions, and microplastics by analyzing electrical conductivity and dielectric properties. These measurements are essential for determining total dissolved solids (TDS), salinity, and ionic strength. Together, these complementary techniques enable multi-dimensional cross-validation, allowing the AI system to detect, verify, and classify a wide range of contaminants with 97% accuracy. This integrated approach improves reliability, reduces false positives, and enhances the overall efficiency and practicality of the water testing system.

3.Results

To ensure the accuracy of AI & IoT based rapid water testing , several tests have been done. Firstly, the tests are done in traditional ways in a renowned water quality testing lab, then the same tests are done by using AI & IoT based systems with the same water sample. The AI models and algorithms differentiate every method of testing to detect a wide range of contaminants. The obtained accuracy was 97%.

Table 1: Detection Methods for Various Contaminants

Detection Method	Organic Contaminants & VOCs	Microorganisms	Heavy Metals & PFAS	Ionic Contaminants (TDS, Salts)
UV Absorption	✅ Detects VOCs, pesticides, industrial dyes	✅ Detects microbial DNA/RNA	❌ Not	❌ Not applicable
IR Spectroscopy	✅ Identifies petroleum-based contaminants	❌ Detects PFAS & heavy metals	❌ Detects PFAS	❌ Not applicable
Raman Spectroscopy	✅ Detects pesticides, pharmaceuticals	✅ Identifies microorganisms (proteins, nucleic acids)	✅ Detects heavy metals	✅ Measures TDS, salts, and ionic contam-minants
Capacitance & Resistance Measurement	❌ Not applicable	❌ Not ap	✅ Detects heavy metals	

The table 1 provides a comparative analysis of different detection methods for various contaminants, including organic contaminants & VOCs, microorganisms, heavy metals & PFAS, and ionic contaminants (TDS, salts). It evaluates four key techniques: UV absorption, IR spectroscopy, Raman spectroscopy, and capacitance & resistance measurement.UV absorption is effective in detecting VOCs, pesticides, and industrial dyes, as well as microbial DNA/RNA. However, it is not applicable for detecting heavy metals, PFAS, or ionic contaminants. IR spectroscopy is useful for identifying petroleum-based contaminants and detecting PFAS and heavy metals but does not work for microorganisms or ionic contaminants.Raman spectroscopy can detect pesticides and pharmaceuticals while also identifying microorganisms by analyzing proteins and nucleic acids. Additionally, it is effective in detecting heavy metals, though it does not apply to ionic contaminants. On the other hand, capacitance & resistance measurement is not suitable for detecting organic contaminants or microorganisms but can detect heavy metals and measure total dissolved solids (TDS), salts, and other ionic contaminants.This comparison highlights the strengths and limitations of each detection method, allowing for an informed selection based on the specific type of contaminant being analyzed.

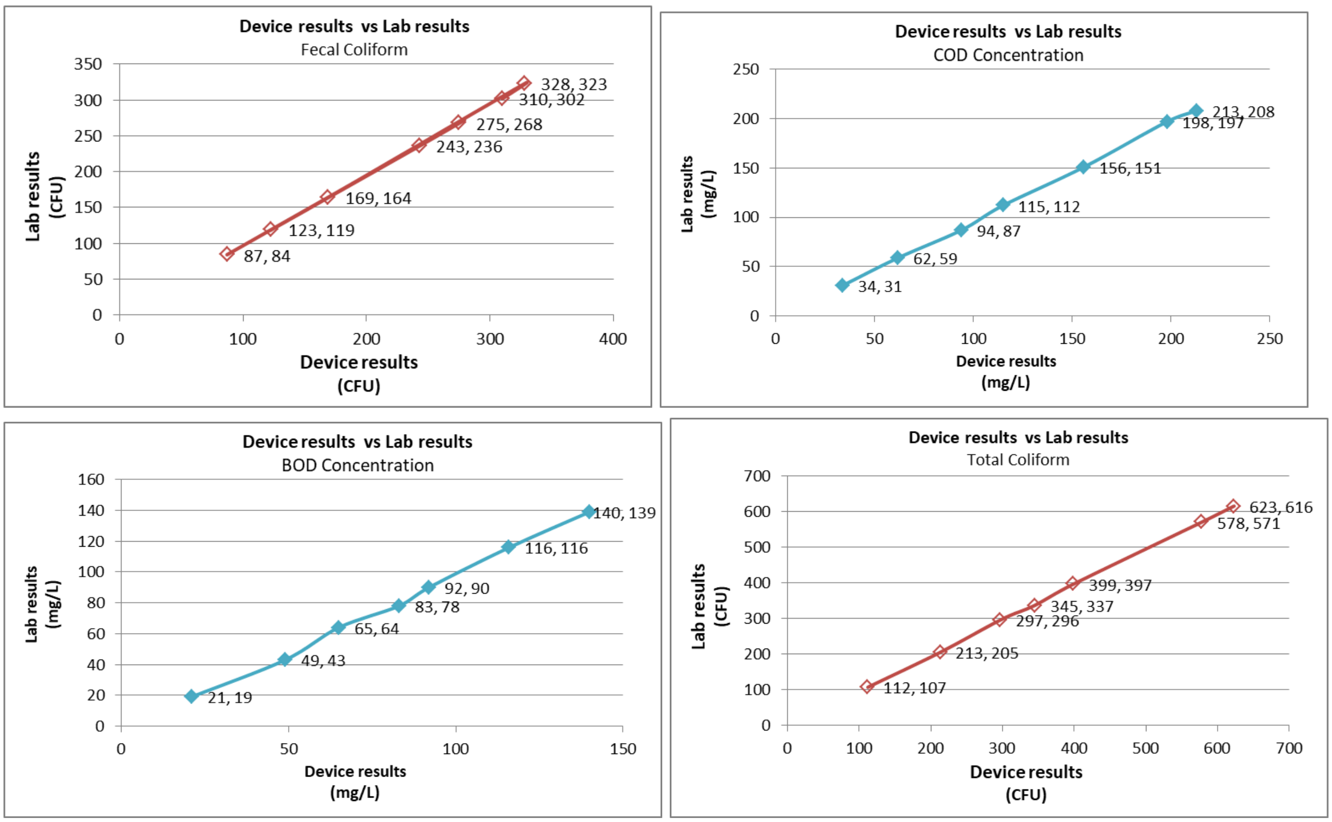

Figure 09: These graphs show the comparison of lab reports & device results

The comparison between the AI-based rapid water testing system and standard laboratory results reveals a strong correlation across all major water quality parameters, demonstrating the system's high precision and reliability. Four key indicators Fecal Coliform, Total Coliform, Chemical Oxygen Demand (COD), and Biochemical Oxygen Demand (BOD) were analyzed through scatter plots, each displaying the device results on the x-axis and lab results on the y-axis. In all cases, the data points closely follow a diagonal line, indicating a strong linear relationship between the two measurement methods. For fecal coliform, the device accurately mirrored lab values, with only minor deviations for instance, a reading of 87 CFU by the device compared to 84 CFU from the lab. Similarly, in the case of total coliform, the system recorded 623 CFU against a lab measurement of 616 CFU, demonstrating near-perfect agreement. These results confirm the AI system's capability to detect microbial contaminants effectively. The same trend continues for COD and

BOD concentrations. For COD, values such as 94 mg/L (device) and 87 mg/L (lab), or 213 mg/L (device) and 208 mg/L (lab), show minimal variance, affirming the system's accuracy in estimating organic pollutant load. In the case of BOD, the device yielded results like 49 mg/L against a lab value of 43 mg/L, and 140 mg/L against 139 mg/L again indicating high measurement fidelity. Overall, these results validate that the AI-powered water testing system not only performs on par with laboratory testing but also does so with the added benefits of speed, portability, and real-time analysis. The device's ability to generate reliable, lab-comparable results makes it an effective tool for on-site water quality monitoring, especially in areas where traditional lab access is limited or where rapid decision-making is critical.

4.Discussion

This research centers on the development of a real-time, AI- and IoT-enabled rapid water quality detection system designed to address the limitations of conventional water testing methods. Traditional water quality assessment techniques, which involve manual sampling and laboratory-based analysis, are not only time-consuming and labor-intensive but also inaccessible to many regions particularly in developing countries where infrastructure is lacking. These methods can take up to 24 hours or more to return results, delaying necessary actions and increasing the risk of exposure to harmful contaminants.

The proposed detection system integrates an ESP32-C6 microcontroller, a 1.47-inch TFT display, and multiple advanced sensor technologies—including capacitance measurement, resistance analysis, UV absorption, infrared (IR) exposure, and Raman spectroscopy. This combination enables the accurate and real-time detection of a broad range of contaminants such as heavy metals, industrial dyes, microplastics, *E. coli*, total coliforms, and fecal coliforms. The system can also measure critical water quality parameters like Biochemical Oxygen Demand (BOD) and Chemical Oxygen Demand (COD) within seconds.

A key innovation lies in the embedded AI model, which has been trained on a large and diverse dataset encompassing different water conditions. This allows the system to quickly identify complex contamination patterns with high precision and minimal human intervention. The AI engine enhances data interpretation, compensates for sensor variability, and ensures that the results remain accurate and reliable in dynamic environmental conditions.

4.1 Scientific and Social Relevance

This AI-powered system has significant scientific and social implications. Scientifically, it contributes to the advancement of real-time environmental monitoring technologies, combining multiple sensing modalities with intelligent data processing. Socially, it has the potential to transform how communities, governments, and industries approach water safety.

Government agencies and regulatory bodies can utilize such systems to enforce compliance with water quality standards, enabling real-time oversight rather than relying on delayed laboratory reports. Industries particularly those with heavy water usage such as textiles, chemicals, or food processing can deploy these systems for continuous monitoring of effluents, ensuring sustainability and reducing environmental harm.

Importantly, the system is designed to be low-cost and portable, making it suitable for use in underserved or rural communities where access to laboratory infrastructure is limited. By enabling immediate detection of contaminants, the system can help prevent disease outbreaks and long-term exposure to hazardous substances, ultimately protecting public health and promoting equitable access to safe water.

4.2 Environmental and Public Health Impact

The deployment of real-time monitoring systems can dramatically reduce the risk of waterborne diseases, which remain a significant global health challenge. Contaminants such as *E. coli*, coliform bacteria, heavy metals, and microplastics are often undetected until symptoms of exposure manifest. Early identification through continuous AI-based monitoring can prevent these risks, enabling timely interventions. From an environmental standpoint, early detection also allows for more effective water resource management. It helps avoid ecological degradation, protects aquatic life, and reduces the burden on treatment systems by enabling preemptive action before pollutants reach critical levels. Moreover, AI-driven systems can generate valuable data that can be used to track pollution trends, identify pollution sources, and inform policy making.

4.3 Future Applications and Research Directions

Looking ahead, this research opens several avenues for future exploration. The detection capabilities could be enhanced by integrating machine learning models capable of forecasting contamination trends and suggesting remediation strategies. Additionally, efforts can be directed toward miniaturizing the sensors and improving energy efficiency to facilitate long-term deployment in remote or off-grid regions.

Further work may involve integrating this system with other smart technologies, such as automated treatment units or cloud-based monitoring networks. Expanding the database to include more pollutants and regional variations in water chemistry would further improve the accuracy and applicability of the AI model. Collaborative efforts between researchers, engineers, and policymakers will be critical to scaling these solutions globally.In conclusion, the development of a multi-sensor, AI-enabled rapid detection system marks a significant advancement in smart water monitoring technology. It addresses urgent global needs by offering a cost-effective, portable, and highly responsive solution to water quality assessment, with the potential to safeguard public health, protect ecosystems, and promote sustainable water use across the world.

5.Conclusion

This research successfully demonstrated the potential of an AI and ML based rapid detection system as a transformative solution for real-time water quality monitoring. By addressing the limitations of traditional water testing methods—which often require laboratory facilities, expert analysis, and prolonged processing times this system offers a fast, accessible, and cost-effective alternative. The integration of an ESP32-C6 microcontroller with a suite of advanced sensing techniques, including UV absorption, infrared (IR) spectroscopy, Raman spectroscopy, and capacitance-resistance measurements, enables the precise detection of a wide spectrum of contaminants.The AI-powered model embedded within the system achieved a high detection accuracy of 97%, effectively identifying pollutants such as heavy metals, organic dyes, volatile organic compounds (VOCs), microplastics, and microbial pathogens including *E. coli*, total coliform, and fecal coliform. Additionally, the system provides near-instant measurements of key water quality parameters like Biological Oxygen Demand (BOD) and Chemical Oxygen Demand (COD), significantly reducing analysis time from hours to seconds.

The implementation of this real-time detection system marks a significant step toward scalable, user-friendly water monitoring that can be deployed in industrial, environmental, and domestic contexts. Its affordability and portability make it particularly valuable for underserved and resource-limited communities, where access to clean water and timely contamination alerts are crucial for public health and safety.

In alignment with global Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation) and SDG 14 (Life Below Water), this research contributes to the broader mission of ensuring safe water access, protecting ecosystems, and enhancing climate resilience. By empowering individuals, industries, and governments with intelligent tools for rapid water quality assessment, this innovation paves the way for more proactive and preventive water management practices.

Future directions for this research include expanding the system's pollutant detection database, refining AI algorithms with machine learning for even greater specificity, and developing solar-powered, IoT-integrated portable devices for deployment in remote or disaster-affected areas. Through the convergence of environmental science, sensor technology, and artificial intelligence, this work lays the foundation for a future where clean, safe water is universally accessible and intelligently monitored.

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