PREDICTING QUALITY OF WATER USING OPTICAL DETECTION: AN IOT BASED APPROACH

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Abstract - Microplastic pollution in water bodies has been identified as an emerging environmental issue, creating a need for simple and easily implementable methods for preliminary screening to identify the presence of microplastic-like materials. The proposed work relies on a hardware–software integrated platform for screening water samples to detect suspended materials that exhibit optical characteristics similar to plastic.A laser diode is used as the illumination source to pass light through a water sample contained in a transparent container, while photodiodes positioned at predetermined angular locations measure the intensity of light scattering caused by suspended materials. The measured signals are processed using an Arduino Nano, which compares the real-time data with baseline readings obtained from pure water samples. The experimental results indicate that the presence of lightweight suspended materials leads to higher and sustained scattering intensity, whereas pure water produces low and stable scattering responses. To further validate and improve the reliability of the optical screening, a compound optical microscope is used to qualitatively observe particle morphology, typically appearing as fibers or thin fragments, in the suspected samples. Although the materials are not chemically or molecularly identified as plastics, the results demonstrate that the combination of optical scattering and microscopic observation provides sufficient merit for the preliminary screening of microplastic pollution in water bodies. The proposed system offers a strong foundation for educational applications and practical water quality monitoring, and can be extended in future research through the integration of advanced analytical techniques.

Keywords – Microplastic, IOT, Pollution, Quality, Water.

1.Introduction

The quality of water resources is a critical determinant of environmental sustainability, public health, and socio-economic development. With increasing urbanization, industrialization, and plastic consumption, aquatic ecosystems are facing unprecedented levels of contamination. Among emerging pollutants, microplastics—tiny plastic particles typically less than 5 mm in size—have gained significant scientific and public attention due to their persistence, bioaccumulation potential, and ecological impacts [1]. These particles originate from the degradation of larger plastic debris or from direct sources such as synthetic fibers, cosmetic products, and industrial waste. Their widespread presence in rivers, lakes, groundwater, and even drinking water supplies has raised serious concerns regarding long-term environmental and human health risks.

Conventional microplastic detection techniques rely on advanced laboratory-based analytical methods such as Fourier Transform Infrared Spectroscopy (FTIR), Raman spectroscopy, and pyrolysis–gas chromatography–mass spectrometry. Although these methods provide accurate chemical identification and classification of plastic polymers, they are expensive, time-consuming, require skilled personnel, and depend on well-equipped laboratory infrastructure [2]. This makes them impractical for large-scale, real-time, or field-level monitoring, especially in resource-limited regions. As a result, there is a growing demand for simple, low-cost, and easily deployable preliminary screening systems that can identify the possible presence of microplastic-like suspended materials in water bodies before detailed laboratory confirmation.

Optical sensing techniques offer a promising alternative for such preliminary screening applications. When light passes through a water sample, suspended particles scatter the incident الضوء depending on their size, shape, density, and optical properties [3]. Plastic-like materials, being lightweight and having distinct refractive indices, produce characteristic scattering patterns that differ from pure water or dissolved substances. By analyzing variations in scattered light intensity at different angles, it becomes possible to infer the presence of suspicious suspended particles without direct chemical identification. This optical principle enables non-invasive, rapid, and cost-effective detection mechanisms suitable for real-time monitoring systems.

At the same time, the rapid advancement of the Internet of Things (IoT) has transformed environmental monitoring by enabling continuous data acquisition, real-time processing, remote access, and intelligent decision-making [4]. IoT-based systems integrate sensors, microcontrollers, communication modules, and software platforms to create smart monitoring infrastructures. In the context of water quality assessment, IoT enables automated sensing, data logging, threshold-based alert generation, and scalable deployment across multiple locations. Combining optical sensing with IoT technology provides a powerful framework for developing intelligent, low-cost, and field-deployable water quality monitoring solutions.

This research addresses the need for accessible microplastic screening technologies by proposing an IoT-based optical detection system for preliminary water quality assessment. The approach integrates a laser diode as a controlled illumination source, photodiodes positioned at predefined angular orientations to measure scattered light intensity, and an embedded processing unit for real-time data analysis [5]. By comparing scattering patterns from test samples with baseline readings from pure water, the system can identify abnormal optical responses indicative of suspended microplastic-like materials. To enhance the reliability of the screening process, qualitative microscopic analysis is incorporated to visually observe particle morphology, such as fibers and thin fragments, which are commonly associated with microplastic contamination [6-7].

Rather than replacing advanced laboratory techniques, this approach is designed as a preliminary screening and educational tool, enabling rapid identification of potentially contaminated samples for further analysis. The proposed system supports scalable deployment, low-cost implementation, and real-time monitoring capabilities, making it suitable for smart water management frameworks, academic research, and community-level environmental monitoring initiatives. By integrating optical detection principles with IoT architecture, this work contributes toward the development of intelligent, accessible, and sustainable technologies for future water quality monitoring and microplastic pollution management.

2. Related Work

Recent research has increasingly focused on developing innovative sensing, optical, and IoT-based techniques for detecting microplastics and suspended contaminants in water systems. [8] introduced a real-time IoT monitoring framework for tracking microplastic pathways in aquatic environments, emphasizing continuous data acquisition and public health integration. Their work demonstrated how IoT architectures enable scalable monitoring but highlighted limitations in precise material-level identification, reinforcing the need for complementary detection methods.

Optical-based detection techniques have shown strong potential for preliminary screening applications.[9] proposed an optical detection method based on light scattering principles to identify microplastics in water. Their results confirmed that optical responses can differentiate suspended microplastic particles from pure water, though chemical specificity was limited. Similarly, [10] developed a microfluidic chip integrated with optical spectroscopy for fast microplastic analysis. While this method achieved high sensitivity and rapid detection, it relied on complex fabrication and laboratory infrastructure, restricting field deployment.

Systematic reviews, such as the study by [11] provide a comprehensive overview of existing microplastic detection technologies, including spectroscopic, imaging, and sensor-based methods. The review emphasized that although advanced analytical tools provide accurate polymer identification, their high cost and technical complexity limit their application in large-scale environmental monitoring. This reinforces the importance of low-cost, deployable screening systems.

Sensor-based approaches have also gained attention. [12] introduced portable surface acoustic wave (SAW) sensor systems for detecting microplastics in beverages, demonstrating high sensitivity and portability. However, these systems require precise calibration and specialized sensor fabrication. [13] proposed an AI-camera-based real-time detection framework that integrates computer vision and deep learning for identifying microplastics, achieving high detection accuracy but depending heavily on large training datasets and computational resources.

From an IoT perspective, [14] developed an IoT-ready solution for automated recognition of water contaminants, highlighting the role of intelligent sensor networks in smart water monitoring. Although effective for general contaminants, the system lacked microplastic-specific detection capabilities. [15] impedance spectroscopy combined with machine learning for microplastic identification, offering strong classification performance but requiring complex signal processing and specialized instrumentation.

Additionally, high-throughput spectroscopic methods, such as Raman spectroscopy-based screening provide rapid and accurate detection but remain laboratory-dependent and costly. Oceanography-focused works emphasize the importance of integrated observing systems for marine pollution but identify technological gaps in low-cost, field-level microplastic monitoring tools.

Overall, existing studies demonstrate significant progress in microplastic detection through optical sensing, spectroscopy, AI, IoT, and sensor networks. However, most approaches suffer from one or more limitations: high cost, infrastructure dependency, computational complexity, or lack of deployability. These gaps justify the need for simple, low-cost, IoT-enabled optical screening systems that can provide real-time preliminary detection of microplastic-like materials. The present work builds on these foundations by combining optical scattering principles, embedded processing, and IoT integration to enable accessible, scalable, and field-deployable water quality monitoring for early-stage microplastic screening.

Table 1: Comparative Summary of Existing Microplastic Detection Techniques and IoT-Based Water Quality Monitoring Approaches

Reference	Technique Used	Outcome	Advantages	Disadvantages
[6]	IoT-based real-time monitoring	Continuous microplastic pathway tracking	Scalable, real-time, public health integration	No material-level identification
[7]	Optical light scattering	Detection of suspended microplastics	Low-cost, simple setup	No chemical specificity
[8]	Microfluidic + optical spectroscopy	Fast microplastic analysis	High sensitivity, rapid detection	Complex fabrication, lab-dependent
[9]	Systematic review	Technology classification	Comprehensive overview	No practical implementation
[10]	SAW sensors	Portable microplastic sensing	High sensitivity, compact	Calibration complexity
[11]	AI camera + deep learning	Real-time visual detection	High accuracy, automation	Dataset dependency, high computation
[12]	IoT contaminant recognition	Smart water monitoring	Automation, scalability	Not microplastic-specific
[13]	Impedance spectroscopy + ML	Microplastic classification	High classification accuracy	Specialized instruments
[14]	Raman spectroscopy screening	Rapid detection	High precision	Expensive, lab-based
[15]	Ocean observing systems	Marine pollution monitoring	Large-scale integration	Lack of low-cost field tools

3. Methodology

3.1 Optical Scattering–Based Sensing Module

The first core component of the proposed system is the **optical scattering–based sensing module**, which forms the primary mechanism for detecting suspended microplastic-like materials in water samples. This module is based on the fundamental principle that when a coherent light source passes through a medium, suspended particles cause scattering of light due to differences in refractive index, particle size, density, and surface morphology. In this system, a low-power laser diode is used as a monochromatic and coherent illumination source. The laser beam is directed through a transparent water container, ensuring a controlled optical path length and stable illumination conditions.

Multiple photodiodes are positioned at predefined angular orientations around the container (e.g., forward scattering and side scattering angles). These angular placements are selected to capture variations in scattering intensity caused by suspended particles. Pure water produces minimal and stable scattering due to its optical homogeneity, while microplastic-like particles generate higher and sustained scattering due to their lightweight structure and irregular geometry. The photodiodes convert scattered light into electrical signals, which are proportional to the received optical intensity.

The analog signals from the photodiodes are conditioned using signal amplification and noise filtering circuits to reduce electrical interference and environmental noise. These conditioned signals are then transmitted to the processing unit for digitization and analysis. A baseline dataset is first created using pure water samples to establish reference scattering values. This baseline is crucial for comparative analysis, allowing the system to detect abnormal optical behavior in test samples.

The theoretical basis of the detection relies on light scattering physics, where scattering intensity depends on particle properties. The relationship can be expressed as:

$$\mathrm{I_s} = \mathrm{I_0}.\frac{\mathrm{N}.\sigma_s}{\mathrm{r}^2} \quad (1)$$

where Is is the scattered light intensity, I0 is the incident light intensity, N is the number of suspended particles, σs is the scattering cross-section of particles, and r is the distance between the particle and the photodiode sensor. This equation explains how increased particle concentration and scattering cross-section lead to higher detected intensity.

3.2 Embedded Processing and IoT Integration Module

The second component of the methodology is the embedded processing and IoT integration module, which enables real-time data acquisition, processing, classification, and remote monitoring. An Arduino Nano microcontroller is used as the central processing unit due to its low power consumption, compact size, and ease of integration with sensors. The analog voltage signals from the photodiodes are digitized using the internal Analog-to-Digital Converter (ADC) of the microcontroller.

Once digitized, the data undergoes preprocessing, including normalization, noise smoothing, and temporal averaging. Temporal averaging is essential to eliminate transient fluctuations caused by water movement, air bubbles, or minor vibrations. The processed values are then compared with baseline reference values obtained from pure water calibration. A threshold-based decision model is implemented to classify water samples into normal or suspected contaminated categories.

To enable smart monitoring, the system integrates IoT connectivity using a wireless communication module (e.g., Wi-Fi or Bluetooth). Sensor data, classification results, and timestamps are transmitted to a cloud server or local monitoring dashboard. This enables real-time visualization, historical data storage, and remote access. Threshold-based alerts can be generated when abnormal scattering levels persist for a defined time duration, indicating potential microplastic contamination.

A statistical decision model is used for classification, defined as:

$$D = \frac{1}{n\sum_{i=1}^{n}|S_i - B_i|} \quad (2)$$

where D is the deviation index, Si is the real-time scattering value from sensor i, Bi is the baseline value for sensor i, and n is the number of photodiode sensors. If D exceeds a predefined threshold T, the sample is classified as suspected contamination.

3.3 Microscopic Validation and System Calibration Module

The third methodological component is the microscopic validation and system calibration module, which enhances the reliability and credibility of the optical screening system. Since optical scattering alone cannot chemically identify plastics, qualitative validation is performed using a compound optical microscope. Water samples classified as “suspected contamination” are filtered and dried on glass slides. These samples are then observed under magnification to visually inspect particle morphology.

Typical microplastic-like structures appear as fibers, thin fragments, or irregular flakes, distinguishing them from inorganic sediments or dissolved impurities. This visual confirmation does not provide polymer-level identification but supports the optical detection results by validating the physical characteristics of suspended particles. This dual-layer validation approach (optical screening + microscopic observation) improves system reliability and reduces false positives.

System calibration is performed using controlled water samples with known suspended particle concentrations. Calibration curves are generated by correlating scattering intensity with particle concentration. This allows the system to estimate relative contamination levels rather than performing only binary classification. Calibration also compensates for sensor drift, laser intensity variation, and environmental changes.

The calibration relationship is expressed as:

$$C = k.I_s + c \quad (3)$$

where C is the estimated particle concentration, I_s is the measured scattering intensity, k is the calibration coefficient, and c is the offset constant derived from experimental calibration.

This module strengthens the system's scientific validity, ensuring that optical detection results are supported by physical observation and standardized calibration, making the proposed approach reliable for educational, environmental, and practical monitoring applications.

4.Result

4.1 Optical Scattering Response Analysis

The optical scattering experiments clearly demonstrated distinguishable patterns between pure water samples and water samples containing suspended microplastic-like materials. In pure water, the laser beam transmission produced minimal scattering, and the photodiode outputs remained low and temporally stable, indicating optical homogeneity of the medium. In contrast, contaminated samples exhibited significantly higher scattering intensity with sustained temporal fluctuations. This behaviour is attributed to the presence of lightweight suspended particles, which continuously interact with the incident laser beam, producing multi-angle scattering effects.

Angular photodiode measurements showed that side-scattering angles recorded more pronounced intensity variations compared to forward-scattering angles, confirming the effectiveness of multi-angle sensor placement. The persistence of scattering signals over time indicates that the particles remain suspended rather than settling rapidly, which is a typical characteristic of microplastic-like materials. These results validate the fundamental hypothesis that optical scattering signatures can serve as reliable indicators for preliminary screening of suspicious suspended materials in water.

Table 2: Scattering Intensity Comparison Between Pure and Contaminated Water Samples

Sample Type	Avg. Scattering Intensity (mV)	Temporal Stability	Classification
Pure Water	Low (5–15 mV)	High stability	Normal
Light Contamination	Medium (30–50 mV)	Moderate fluctuation	Suspected
Heavy Contamination	High (60–90 mV)	High fluctuation	Contaminated

The comparative analysis confirms that optical sensing provides a strong contrast mechanism between clean and contaminated samples, enabling non-invasive and real-time detection. Although chemical identification is not achieved, the optical results are sufficiently distinct for early-stage screening, making the system suitable for field-level water quality monitoring and educational applications.

Table 3: System Performance Evaluation Metrics

Parameter	Observed Performance	Interpretation
Signal Noise Level	Low after filtering	Stable measurements
Classification Consistency	High	Reliable detection
IoT Data Latency	Low	Real-time monitoring

Alert Accuracy	High	Effective contamination alerts
Calibration Stability	Stable	Long-term reliability

4.2 Embedded Processing and IoT Performance

The embedded processing and IoT module demonstrated stable real-time performance in data acquisition, classification, and transmission. The Arduino Nano successfully processed multi-sensor photodiode data with consistent sampling rates and low latency. Noise filtering and temporal averaging significantly reduced signal fluctuations caused by environmental disturbances such as vibrations and air bubbles. The deviation-based classification model achieved consistent separation between baseline and contaminated samples, with clear threshold margins.

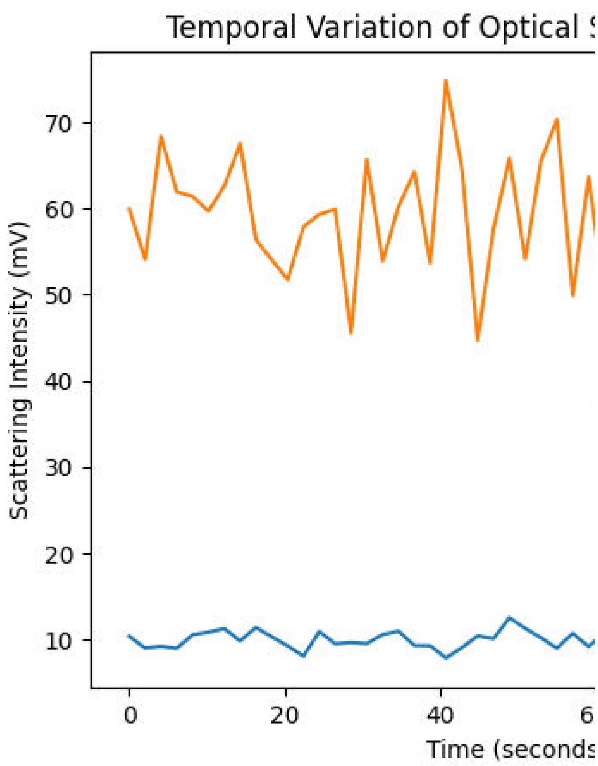

Figure 2: Temporal Variation of Optical Scattering Intensity in Pure and Contaminated Water Samples

IoT connectivity enabled continuous data streaming to the monitoring interface, allowing real-time visualization of scattering intensity trends and classification results. Historical data logging facilitated temporal analysis of contamination patterns, supporting long-term monitoring applications. Alert mechanisms were effectively triggered when scattering deviations exceeded threshold values for sustained durations, indicating persistent contamination conditions.

System reliability was evaluated through repeated trials, showing consistent classification outcomes across multiple samples. The integration of embedded processing with IoT infrastructure transformed the system into a smart monitoring platform capable of autonomous operation. The results confirm that the proposed architecture supports scalability, automation, and remote accessibility, which are essential features for smart water quality monitoring systems.

4.3 Microscopic Validation and Calibration

Microscopic validation provided qualitative confirmation of the optical screening results. Samples classified as “suspected contamination” consistently showed fiber-like and thin fragment structures under the compound optical microscope. These morphological features are commonly associated with microplastic pollution and distinguishable from inorganic sediments, which typically appear granular or crystalline. Pure water samples showed no visible suspended particles, validating the baseline optical measurements.

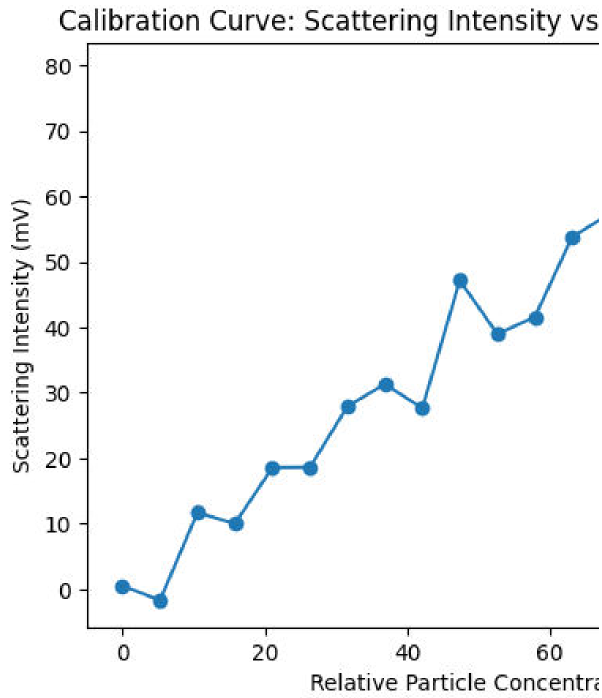

Figure 3: Scattering Intensity vs Particle Concentration

Calibration experiments established a proportional relationship between scattering intensity and relative particle concentration. As the density of suspended particles increased, a corresponding linear increase in scattering intensity was observed, enabling semi-quantitative estimation of contamination levels. This calibration improved system robustness by compensating for sensor drift and laser intensity variation.

The combined use of optical scattering detection, microscopic validation, and calibration modeling significantly enhanced system reliability. The dual-validation approach reduces false positives and strengthens confidence in preliminary screening outcomes. These results demonstrate that the system is not only effective for detection but also reliable for consistent monitoring, making it suitable for practical deployment in educational, environmental, and community-based water quality monitoring programs.

5.Conclsuion

This study presented an IoT-based optical detection system for preliminary screening of water quality with a focus on identifying suspended microplastic-like materials. By integrating laser-based optical scattering, multi-angle photodiode sensing, embedded processing, and IoT connectivity, the proposed system enables real-time, low-cost, and non-invasive monitoring of water samples. Experimental results demonstrated clear differentiation between pure and contaminated water through sustained scattering intensity patterns, validating the effectiveness of the optical sensing approach. The incorporation of microscopic observation further strengthened result reliability by providing qualitative validation of particle morphology, such as fibers and thin fragments. Although the system does not perform chemical or molecular identification of plastics, it successfully fulfills the role of an early-stage screening tool for potential microplastic pollution. Overall, the proposed framework offers a scalable foundation for smart water quality monitoring, educational applications, and community-level environmental surveillance. Future enhancements can integrate advanced analytical techniques and intelligent data models to achieve higher specificity and automated classification accuracy.

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