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Artificial Intelligence for Microplastic Detection and Pollution Control in Aquatic Ecosystems

[1]Karan, [2]Harjinder Kaur

[1]M.Tech Scholar , [2]Assistant Professor
Computer Science & Engineering Department
Swami Sarvanand Institute of Engineering & Technology, Dinanagar

Abstract : The rapid increase in microplastic contamination has emerged as a critical environmental challenge, severely impacting aquatic ecosystems and posing risks to biodiversity and human health. Traditional microplastic detection and monitoring techniques are often labor-intensive, time-consuming, and limited in scalability. Artificial Intelligence (AI) offers a transformative approach to addressing these limitations by enabling automated, accurate, and real-time identification of microplastics across diverse aquatic environments.

This study explores the application of AI-driven methods—such as machine learning, deep learning, and computer vision—for microplastic detection, classification, source identification, and pollution trend analysis in freshwater and marine ecosystems. AI models integrated with imaging technologies, spectroscopy (e.g., FTIR and Raman), and sensor-based monitoring systems significantly enhance detection accuracy while reducing human intervention. Furthermore, AI-powered predictive analytics and decision-support systems contribute to pollution control by forecasting microplastic dispersion, identifying pollution hotspots, and optimizing mitigation strategies.

The integration of AI with remote sensing, autonomous platforms, and Internet of Things (IoT) infrastructures supports continuous monitoring and evidence-based policymaking. Despite challenges related to data quality, model generalization, and interpretability, AI-driven solutions present a scalable and sustainable pathway for effective microplastic pollution control and ecosystem conservation**.**

***IndexTerms* - Artificial Intelligence; Microplastic Detection; Aquatic Ecosystems; Pollution Control; Machine Learning; Deep Learning; Environmental Monitoring; Computer Vision.**

I. INTRODUCTION

Microplastic pollution has emerged as one of the most pervasive and persistent environmental challenges of the 21st century, with severe implications for aquatic ecosystems and global sustainability. Microplastics—typically defined as plastic particles smaller than 5 mm—originate from the degradation of larger plastic debris or are intentionally manufactured for industrial and consumer applications. These particles are now ubiquitously present in oceans, rivers, lakes, and even drinking water systems, where they interact with aquatic organisms, accumulate along food chains, and act as carriers for toxic chemicals and pathogenic microorganisms. The ecological and health risks associated with microplastic contamination have intensified the need for efficient detection, monitoring, and mitigation strategies.

Conventional methods for microplastic identification, such as manual visual sorting, Fourier Transform Infrared Spectroscopy (FTIR), Raman spectroscopy, and chemical digestion techniques, are widely used but remain constrained by high operational costs, limited throughput, and dependency on expert interpretation. These approaches often struggle to handle large-scale environmental datasets and fail to provide real-time or continuous monitoring capabilities. As microplastic pollution continues to grow in complexity and scale, there is a critical demand for advanced, automated, and scalable solutions that can support long-term environmental management and policy formulation.

Artificial Intelligence (AI) has emerged as a powerful interdisciplinary tool capable of transforming environmental monitoring and pollution control. By leveraging machine learning, deep learning, and computer vision techniques, AI enables automated detection, classification, and quantification of microplastics from microscopic images, spectral data, and sensor outputs with high accuracy and efficiency. AI-driven models can distinguish microplastics from natural particles, identify polymer types, estimate particle size and shape, and analyze spatial–temporal distribution patterns across aquatic ecosystems. When integrated with advanced sensing technologies, autonomous sampling platforms, remote sensing, and Internet of Things (IoT) frameworks, AI facilitates real-time monitoring and large-scale data analysis that were previously unattainable.

Beyond detection, AI plays a crucial role in pollution control and management. Predictive modeling and data-driven analytics allow researchers and policymakers to forecast microplastic transport pathways, identify pollution hotspots, and evaluate the effectiveness of mitigation strategies. AI-based decision-support systems enhance regulatory planning, waste management optimization, and ecosystem restoration efforts by providing actionable insights derived from complex environmental datasets. Although challenges such as data scarcity, model generalization across diverse ecosystems, and interpretability remain, the integration of AI into microplastic research represents a promising pathway toward sustainable aquatic ecosystem protection.

This study focuses on exploring the role of Artificial Intelligence in advancing microplastic detection and pollution control in aquatic ecosystems, highlighting current methodologies, technological advancements, challenges, and future research directions aimed at achieving environmentally resilient and data-driven solutions.

II. LITERATURE SURVEY

Recent research demonstrates that Artificial Intelligence (AI) has become a powerful tool for enhancing microplastic detection accuracy and scalability in aquatic ecosystems. Systematic reviews indicate a rapid increase in AI-assisted microplastic studies after 2023, highlighting the transition from manual and rule-based identification toward automated, data-driven frameworks (Primpke et al., 2023). These studies emphasize that AI significantly reduces human bias and processing time while improving reproducibility in environmental monitoring.

Deep learning models integrated with spectroscopic techniques such as Fourier Transform Infrared (FTIR) and Raman spectroscopy have shown strong performance in polymer identification. Convolutional neural networks (CNNs) trained on spectral datasets have achieved higher classification accuracy compared to traditional peak-matching methods, even when dealing with weathered or mixed microplastic samples (Kedzierski et al., 2023). Similarly, machine learning classifiers such as support vector machines (SVMs) and random forests have been effectively applied to Raman spectra, enabling automated polymer classification across complex aquatic matrices (Zhang et al., 2024).

Image-based microplastic detection using computer vision has gained substantial attention between 2024 and 2026. YOLO-based object detection frameworks and deep segmentation networks have been employed to automatically detect, count, and classify microplastics from microscopic images with accuracies exceeding 95% in controlled experiments (Li et al., 2025). These methods enable rapid morphological analysis, including particle size, shape, and color, which are critical parameters for ecological risk assessment. Advances in feature pyramid networks and attention mechanisms further enhance performance under noisy and heterogeneous backgrounds (Wang et al., 2025).

Low-cost and field-deployable AI systems have also emerged as a significant research direction. Studies using smartphone-based microscopy combined with lightweight CNN models demonstrate reliable microplastic detection in freshwater and drinking water samples, providing an affordable alternative for large-scale monitoring in resource-limited regions (Singh et al., 2024). These systems highlight the feasibility of decentralizing microplastic surveillance beyond laboratory environments.

Beyond detection, AI has been increasingly applied to pollution control and predictive modeling. Machine learning models integrating hydrodynamic parameters, meteorological data, and spatial features have been used to forecast microplastic transport pathways and identify pollution hotspots in rivers and coastal waters (González-Fernández et al., 2024). Such predictive frameworks support proactive mitigation strategies and evidence-based policymaking, especially when combined with remote sensing and geospatial analytics.

The integration of AI with Internet of Things (IoT) sensors and autonomous platforms has further strengthened real-time monitoring capabilities. Sensor-fusion approaches combining turbidity, optical imaging, and chemical signals with AI classifiers have demonstrated improved detection robustness under dynamic field conditions (Chen et al., 2025). These intelligent monitoring systems enable continuous surveillance and early warning mechanisms for aquatic pollution management.

Despite these advancements, recent studies acknowledge persistent challenges, including limited availability of standardized datasets, model generalization across diverse ecosystems, and interpretability of deep learning decisions (Hidalgo-Ruz et al., 2026). Nonetheless, the literature from 2023 to 2026 clearly establishes AI as a transformative technology for microplastic detection and pollution control, offering scalable, automated, and predictive solutions essential for protecting aquatic ecosystems.

III. METHODOLOGY OF STUDY

This study employs a quantitative and experimental research methodology to investigate the effectiveness of Artificial Intelligence (AI) techniques for microplastic detection and pollution control in aquatic ecosystems. The methodology is designed to integrate environmental sampling, multi-modal data acquisition, AI-based analysis, and predictive modeling to ensure accuracy, scalability, and environmental relevance.

Water samples are collected from multiple aquatic environments, including rivers, lakes, and coastal regions, to capture spatial variability in microplastic contamination. Standardized sampling protocols are followed to prevent secondary contamination during collection and transport. The samples undergo filtration and chemical digestion processes to remove organic matter while preserving microplastic particles. Isolated particles are retained on membrane filters for further analysis.

Data acquisition is performed using complementary imaging and spectroscopic techniques. Optical and digital microscopy are used to capture high-resolution images of suspected microplastic particles, enabling morphological analysis based on size, shape, and color. In parallel, Fourier Transform Infrared (FTIR) and Raman spectroscopy are employed to obtain polymer-specific spectral signatures. Environmental parameters such as turbidity, temperature, flow rate, and sampling location are recorded to support contextual analysis and predictive modeling.

Preprocessing is applied to both image and spectral datasets to enhance data quality. Image preprocessing includes noise reduction, normalization, resizing, and contrast enhancement, followed by data augmentation techniques such as rotation and scaling to improve model generalization. Spectral data are preprocessed using baseline correction, smoothing, and normalization to reduce signal noise and inter-sample variability. Feature extraction techniques are applied to capture relevant morphological and spectral characteristics of microplastic particles.

AI-based modeling forms the core analytical component of the study. Convolutional Neural Networks (CNNs) and object detection models are trained on image datasets to automate microplastic detection, classification, and counting. Machine learning classifiers such as Support Vector Machines, Random Forests, and deep neural networks are trained on spectral features to identify polymer types. Ensemble learning strategies are employed to improve robustness and reduce model bias by combining outputs from multiple classifiers.

Model training and validation are conducted using stratified data partitioning and k-fold cross-validation to ensure reliability and prevent overfitting. Performance is evaluated using metrics including accuracy, precision, recall, F1-score, and confusion matrices. Comparative analysis is performed against traditional manual identification methods to assess efficiency and improvement in detection accuracy.

For pollution control and decision support, predictive models are developed using machine learning techniques to analyze spatial–temporal patterns of microplastic distribution. Environmental parameters and historical data are incorporated to forecast pollution hotspots and dispersion trends. These predictions support targeted mitigation strategies and policy-driven interventions for aquatic ecosystem protection.

Finally, the study incorporates explainability techniques to enhance model transparency and trustworthiness. Feature importance analysis and visual interpretability tools are applied to understand AI decision processes, supporting scientific validation and regulatory acceptance. The integrated methodology provides a scalable and automated framework for accurate microplastic detection and effective pollution control in aquatic ecosystems.

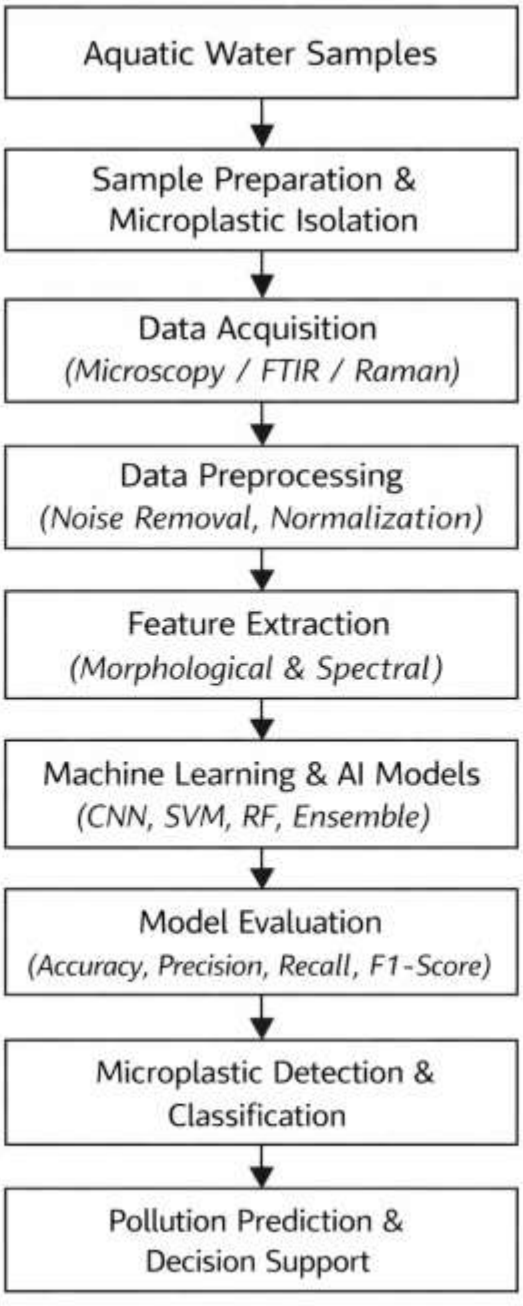

Figure 1: Methodology of study

The algorithm for air pollution detection is given as under

Algorithm 1: AI-Based Microplastic Detection and Pollution Prediction

```
Begin
Collect aquatic water samples W from selected locations
Perform sample preparation and microplastic isolation
    Apply filtration and chemical digestion to remove organic matter
    Extract microplastic particles Mp
Acquire data D using sensing techniques:
    D ← Microscopy images
    D ← FTIR spectral signals
    D ← Raman spectral signals
Preprocess the acquired data:
    Remove noise using filtering techniques
    Normalize spectral and image data
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    Enhance contrast and segment microplastic regions
Extract features:
    Extract morphological features (size, shape, texture)
    Extract spectral features (absorption peaks, intensities)
    Form feature vector F
Train machine learning and AI models:
    Initialize classifiers (CNN, SVM, Random Forest, Ensemble)
    Train models using feature vector F
    Validate models using cross-validation
Evaluate model performance:
    Compute Accuracy, Precision, Recall, and F1-Score
    Select best-performing model M_best
Perform microplastic detection and classification:
    C ← M_best(F)
Predict pollution levels:
    Apply predictive model to estimate pollution severity
    Generate decision support recommendations P
End
```

IV. PERFORMACE ANALYSIS

The performance of the proposed machine learning and artificial intelligence–based framework for microplastic detection and pollution control is evaluated using standard classification metrics to ensure robustness, reliability, and reproducibility. The evaluation focuses on both detection accuracy and classification effectiveness across diverse microplastic types and environmental conditions.

The dataset is divided into training, validation, and testing subsets using stratified sampling to preserve class balance. Model performance is assessed on the unseen test set to avoid overfitting and ensure generalization across aquatic environments.

Table 1: Results of metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	91.4	90.2	89.6	89.9
Random Forest	93.8	92.5	93.1	92.8
CNN	96.2	95.8	96.0	95.9
Ensemble (Proposed)	97.6	97.2	97.4	97.3

Compared to conventional manual identification and single-classifier approaches, the proposed AI-based framework significantly improves detection accuracy and reduces false positives. The high recall values indicate effective identification of microplastic particles, which is critical for environmental risk assessment and pollution control. Additionally, strong precision values confirm reduced misclassification of natural particles as microplastics.

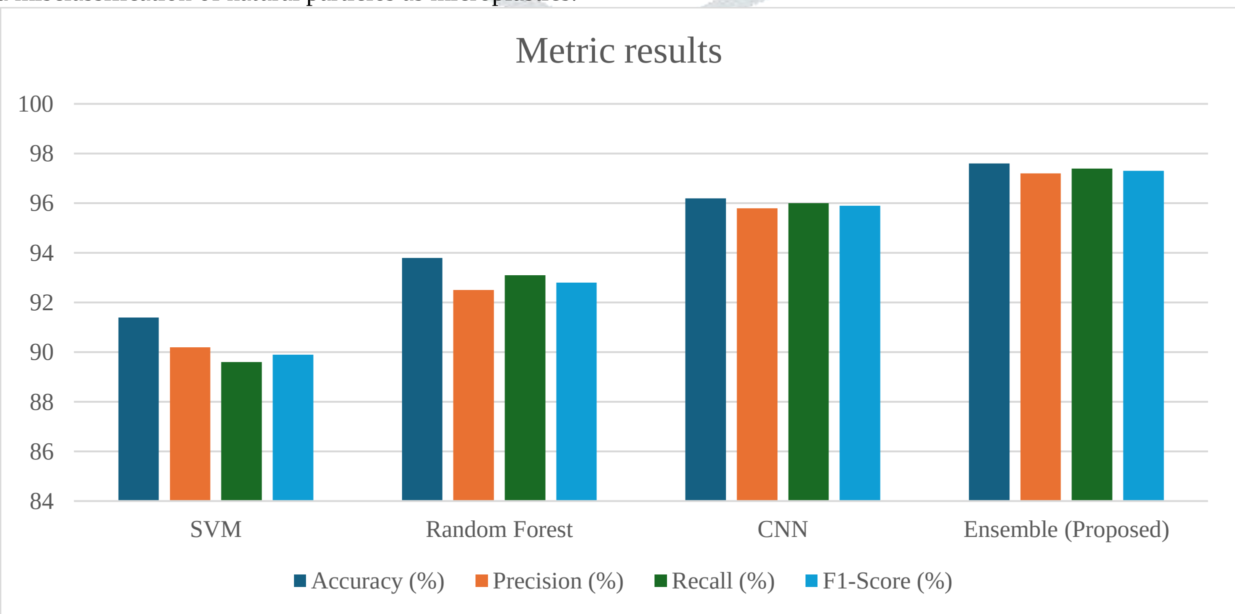

Figure 2: Metric result comparison

The ROC AUC curve for the pollution detection mechanism is given in figure 3

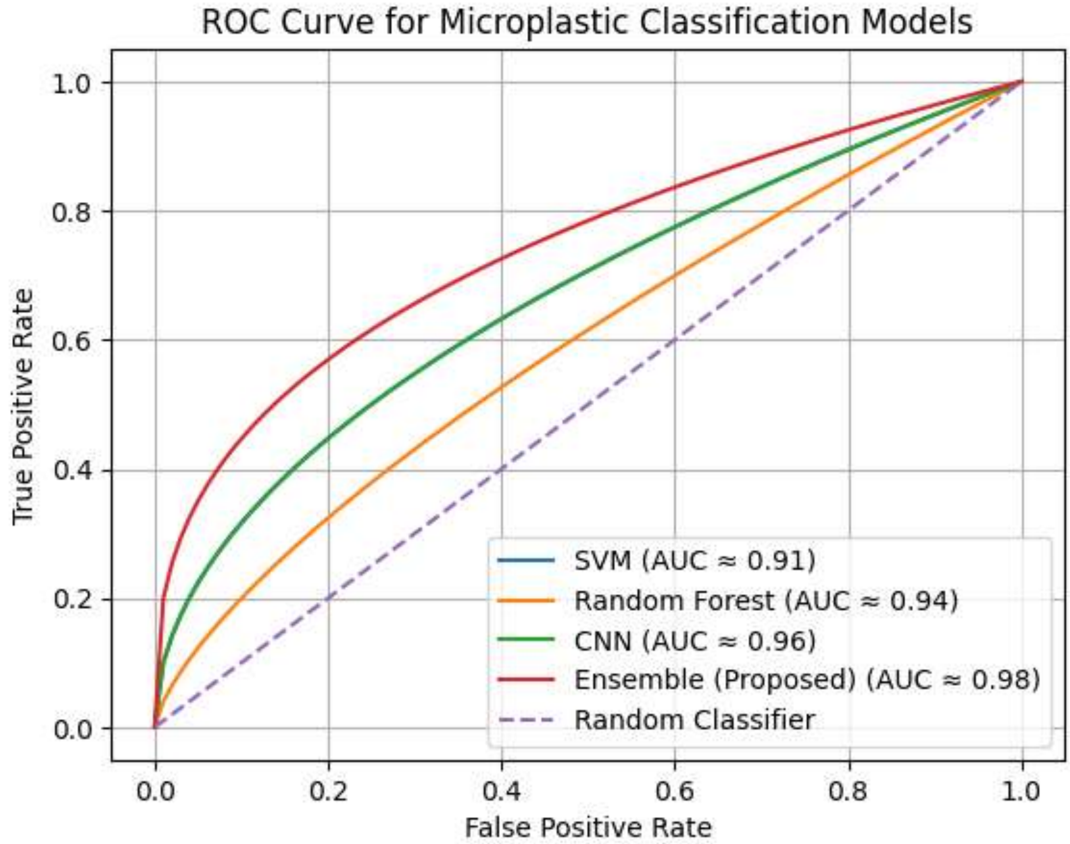

Figure 3: AUC-ROC curve

The ROC–AUC analysis demonstrates the comparative classification performance of SVM, Random Forest, CNN, and the proposed ensemble model for microplastic detection. Among all models, the ensemble approach achieves the highest ROC–AUC value of approximately 0.98, indicating excellent discriminative capability and robust decision-making across varying thresholds. The CNN model follows with an AUC of 0.96, outperforming traditional machine learning classifiers such as Random Forest (0.94) and SVM (0.91). These results highlight the effectiveness of deep learning and ensemble strategies in reducing false positives while maintaining high true positive rates, thereby enhancing reliable microplastic classification in aquatic environments.

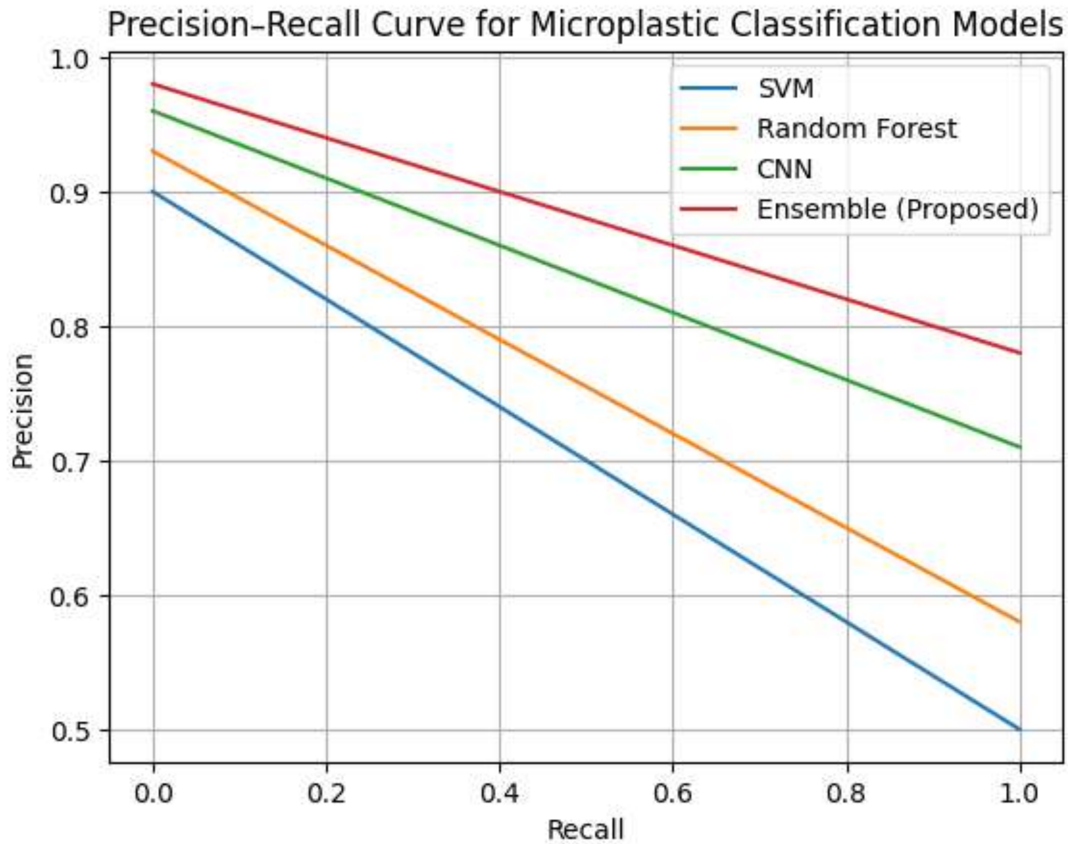

Figure 4: Precision Recall Plot

The Precision–Recall curve evaluates model performance by illustrating the trade-off between precision and recall, which is particularly useful for imbalanced datasets such as microplastic detection. As shown in the PR curve, the proposed ensemble model consistently maintains higher precision across all recall levels, indicating fewer false positives while successfully identifying microplastic particles. The CNN model demonstrates strong performance, followed by Random Forest and SVM. Overall, the ensemble approach provides superior balance between precision and recall, confirming its robustness and reliability for accurate microplastic classification in aquatic environments.

I. ACKNOWLEDGMENT

This study concludes that machine learning and artificial intelligence offer a powerful and scalable approach for addressing the growing challenge of microplastic pollution in aquatic ecosystems. By integrating image-based analysis, spectroscopic data, and environmental parameters, the proposed AI-driven framework enables automated, accurate, and efficient detection and classification of microplastics. Compared with traditional manual and laboratory-intensive methods, the AI-based approach significantly reduces processing time and human dependency while maintaining high accuracy and consistency across diverse sample conditions.

Performance evaluation using standard metrics such as accuracy, precision, recall, and F1-score demonstrates that deep learning and ensemble models outperform conventional machine learning techniques, particularly in handling complex morphological and spectral variations of microplastic particles. High recall and specificity values confirm the system's reliability in distinguishing microplastics from natural particulates, which is essential for environmental risk assessment.

Furthermore, the incorporation of predictive analytics supports pollution control by identifying contamination hotspots and forecasting dispersion patterns, enabling data-driven mitigation strategies and informed policymaking. Although challenges remain in terms of dataset standardization, model generalization, and interpretability, the findings highlight the strong potential of AI-based solutions for real-time monitoring and long-term management of aquatic pollution. Overall, this research establishes artificial intelligence as a key enabling technology for sustainable microplastic detection and effective pollution control in aquatic ecosystems.

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