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REVIEW ARTICLE

Artificial intelligence-driven approaches for detection, fate, transport, and remediation of microplastic pollution in aquatic systems

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ABSTRACT

Microplastic pollution in aquatic systems is a global, pervasive and significant aquatic environmental problem with serious ecological and human health consequences. Traditional approaches to monitoring, analyzing, and modeling microplastics are labor-intensive, difficult to scale up and have limited predictive power. However, several large-scale studies have reported the occurrence, distribution and impact of microplastics. In the last few years, artificial intelligence, machine learning and deep learning have shown enormous potential to reshape how we monitor and manage the environment through data and automation. This narrative review critically synthesizes recent advances in artificial intelligence-assisted approaches for detection, characterization, environmental monitoring, fate and transport modeling, ecological risk assessment, and remediation of microplastic pollution in aquatic systems, with an emphasis on their current capabilities, limitations, and future research needs. Artificial intelligence-based image analysis and spectroscopic data processing have demonstrated improved accuracy and efficiency for automated microplastic identification under laboratory and controlled research conditions, although broader field validation remains limited. The use of artificial intelligence in evaluating exposure scenarios and potential impacts on biota and human health has emerged. Artificial intelligence-assisted optimization has shown promise for improving treatment-process performance in experimental studies; however, validation under full-scale operational conditions remains limited. However, several factors have hindered large-scale adoption, including data availability, model generalisability, standardization and interpretability. The study objectives were to synthesize current advances, highlight limitations, and suggest future research directions, such as the development of integrated artificial intelligence frameworks, digital twin technologies, and autonomous monitoring systems. By linking data science and environmental engineering, artificial intelligence-led strategies offer a revolutionary approach to more efficiently and sustainably managing microplastic pollution in aquatic systems. Unlike previous reviews that primarily address individual aspects of microplastic pollution or artificial intelligence applications, this review provides an integrated critical assessment of artificial intelligence -assisted detection, environmental monitoring, fate and transport modeling, ecological risk assessment, and remediation, while identifying key research gaps related to data standardization, model generalizability, field-scale validation, and interdisciplinary integration.

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INTRODUCTION

Microplastic pollution has become an increasing environmental issue - particularly in water bodies, where it is concentrated as indestructible plastic litter throughout water columns, sediments and aquatic organisms. Their small size and widespread coverage, coupled with their ability to withstand degradation, imply that they can move between numerous environmental compartments and consequently interact with complex physical, chemical and biological processes. These features not only affect their future in the environment but also increase their potential to act as vectors for toxic substances, thereby threatening aquatic ecosystems and human health. Although much research has been reported on the occurrence and impact of microplastics, the dynamic behavior of these particles in water bodies remains a challenge (Yang *et al.,* 2021; Ashrafy *et al.,* 2023; Jeyachandran *et al.,* 2026). Traditional techniques for tracking and analyzing microplastics are more labor-intensive and involve sampling, spectroscopic identification and deterministic modeling. Although such techniques provide valuable insights, in many cases they are constrained in spatial and temporal scales, have low throughput and involve uncertainty in forecasting transport paths and environmental distribution. Moreover, the quantity and diversity of environmental data produced by environmental monitoring programs have increased awareness of the inadequacy of old analytical structures, which are not sufficiently configured to manipulate vast and intricate data sets. Consequently, there is an ever-increasing demand for novel, information-based methodologies that can enhance the accuracy of detection, predictive modeling and decision-making processes (Pal *et al.,* 2025; Jolaosho *et al.,* 2025; Xie *et al.,* 2025). The application of artificial intelligence (AI) and deep learning (DL) has been a revolutionary tool in environmental science over the past few years, enabling us to derive meaningful patterns from large, complex datasets. AI-driven methods have shown great potential to automate the detection and classification of particulate pollutants, combine information from multiple environmental sources, and enhance the predictive capacity of environmental models. Where directional behavioral tendencies of microplastics suggest multifactorial dynamics, as seen in aquatic systems, including hydrodynamics, physicochemical interactions and biological action, AI offers a strong system for capturing nonlinear relationships and spatiotemporal variance. These capabilities render AI particularly well-suited for advancing insight into microplastic dynamics that cannot be achieved with traditional methods (Etin-Osa and Isitua, 2025; Anyanwu *et al.,* 2026). Recent studies have begun to discuss the application of AI-based methods for detecting microplastics, environmental monitoring and optimizing treatment methods. Image-based DL models have been used with much success for automatic particle identification, and machine learning (ML) models coupled with environmental datasets have been used to predict distribution patterns and transport processes. Most importantly, the strategies of AI assistance are explored to improve the efficiency of treatment systems that aim to reduce microplastic contamination. Despite these promising developments, the use of AI in this field is fragmented, with limited attempts to create integrated frameworks that combine detection, environmental behavior and remediation in a unified view (Zhang *et al.,* 2023; Rawat *et al.,* 2025). AI should be regarded as a complementary analytical tool that enhances rather than replaces conventional experimental, analytical, and modeling techniques. AI-assisted algorithms improve the interpretation of data generated from spectroscopy, microscopy, field observations, and hydrodynamic models, thereby facilitating more efficient identification, prediction, and decision-making in microplastic research. In this context, a synthesis of knowledge on AI-driven approaches is needed to fill gaps at

this stage and provide a coherent picture of their role in tackling microplastic pollution in aquatic systems. The study has primarily focused on individual aspects of microplastic pollution, including analytical detection techniques, environmental occurrence, ecological impacts, or specific applications of AI (Agaton, 2025; Amparán *et al.,* 2025; Anyanwu *et al.,* 2026). However, comprehensive critical synthesis integrating AI-assisted detection, environmental monitoring, fate-and-transport modeling, ecological risk assessment, and remediation strategies remains limited. To address this gap, the present narrative review provides a critical synthesis of representative and recent advances in AI-assisted approaches for the detection, environmental monitoring, fate and transport modeling, ecological risk assessment, and remediation of microplastic pollution in aquatic systems. Rather than systematically evaluating all published studies using predefined inclusion criteria, the review critically discusses recent developments, evaluates the current level of technological maturity, identifies key scientific and technological limitations, and highlights future research directions. Emphasis is placed on how AI complements conventional analytical techniques, predictive modeling, and remediation strategies to improve the understanding and management of microplastic pollution in aquatic environments. By combining knowledge from environmental science and data analytics, this study aims to highlight the potential of AI as a key enabler in the effective management of microplastic pollution in aquatic environments. This review study was carried out at Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India, in 2026.

Role of AI in environmental monitoring of microplastics

AI has developed as a game-changing tool in environmental monitoring, offering advanced capabilities in data analysis, pattern recognition and predictive modeling. The complexity of environmental systems and the vast amount and diversity of data have made it clear that traditional analytical approaches based on deterministic models and manual interpretation are inadequate. AI, which uses ML and DL techniques, offers a data-driven framework that can help derive meaningful information from complex datasets to improve the efficiency and accuracy of environmental assessment (Coleman, 2025; Leong, 2025). ML algorithms, such as artificial neural networks (ANNs), random forests (RFs), and support vector machines (SVMs), have proven highly successful at modeling nonlinear relationships among environmental variables. In contrast, DL architectures, especially convolutional neural networks (CNNs), have proven extremely good at analyzing images and, in parallel, performing automated feature extraction. These capabilities have enabled real-time monitoring, improved prediction accuracy, and reduced reliance on labor-intensive analytical procedures (Popescu *et al.,* 2024; Camps-Valls *et al.,* 2025). AI's advantages in environmental monitoring include unique qualities. AI models can work with enormous amounts of multi-source data, including spatial, temporal and spectral data, to analyze complex processes in the environment. AI methods are particularly well-suited to estimate nonlinear interactions and the inherent uncertainties in environmental systems. AI continues to expand its opportunities for continuous monitoring and decision-making through data, along with other emerging technologies such as remote sensing, the Internet of Things (IoT) devices, and geospatial analysis tools (Huang *et al.,* 2025; Blessing and Olateru, 2025). These benefits are especially valuable for addressing water pollution from microplastics. The combination of hydrodynamic processes, physicochemical interactions and biological factors controls the behavior and distribution of microplastics, creating highly dynamic and spatially heterogeneous patterns. Traditional monitoring and modeling practices often fall short of adequately capturing such complexities due to

data constraints, limited analytical and predictive capacity, and insufficient resolution. In this respect, AI can serve as an effective tool for improving the detection, classification, and prediction of microplastics by leveraging large datasets and uncovering invisible patterns that may not have been identified by traditional approaches (Chaukura *et al.,* 2021; Yang *et al.,* 2025). Recent advancements have shown that AI can be automated to detect microplastics by analyzing images, matching them against datasets and environmental data to predict transport paths, and streamlining treatment processes to minimize pollution. Nevertheless, despite these encouraging trends, AI applications in studying microplastics remain at an initial stage, research remains disorganized, and there is a lack of connections between various dimensions of monitoring and management. Proper awareness of AI-based solutions is, consequently, key to exploiting their full potential to address microplastic pollution (Khanam *et al.,* 2025; Olawade *et al.,* 2026). Fig. 1 displays the hypothetical basis for applying AI to environmental monitoring of microplastics in water bodies. Recent studies have highlighted the usefulness of AI for identifying and characterizing microplastics in the water industry. For example, DL techniques have been used in synergy with spectroscopic techniques to improve polymer identification. Kedzierski *et al.* (2019) demonstrated the use of ML algorithms with Fourier transform infrared (FTIR) spectroscopy to achieve automated, high-accuracy classification of microplastics and reduce the error of manual interpretation. Srivastava *et al.* (2025) pointed to the combination of ML with surface-enhanced Raman spectroscopy (SERS) to address high-dimensional spectra, peak overlap and interference from complex environmental matrices. The study highlighted that ML-assisted SERS is a valuable addition to the detection and classification of environmental contaminants, including infectious pathogens and inorganic/organic pollutants, improving analytical sensitivity for more reliable field monitoring. In addition to spectroscopic analysis, the detection of microplastics in images has made huge strides thanks to DL techniques. In one study by Lorenzo-Navarro *et al.* (2021), they developed a CNN-based model for automatic identification of microplastics in microscopy images, achieving high precision and recall. Likewise, recent advancements in computer vision have led to the development of real-time detection systems, with object detection methods such as You Only Look Once (YOLO) adopted for rapid detection and tracking of microplastics in aquatic environments (Sarker *et al.,* 2024). These approaches support continuous monitoring and reduce reliance on labor-intensive manual analysis. Beyond detection, ML techniques have been used to analyze complex datasets related to microplastic pollution. Studies have shown that algorithms such as RF and ANN can model the distribution and transport of microplastics using a combination of hydrodynamic, physicochemical and spatial information (Kannankai *et al.,* 2022).

AI in microplastic detection and monitoring

Identifying and tracking microplastics in water systems is highly significant for understanding their distribution, origin, and potential environmental effects. Visual sorting, FTIR spectroscopy, and Raman spectroscopy are common methods for identifying microplastics. Nevertheless, they are usually lengthy, cumbersome and prone to human error, especially when analyzing large data sets with complex environmental contexts. Moreover, they are not automated, which limits scalability and necessitates sophisticated analytical software. AI, and in particular DL, has become a promising solution to overcome these limitations by enabling automated, accurate, high-throughput analysis of microplastic data. AI-based techniques are useful for handling large volumes of images and spectral data, detecting patterns and performing classifications with minimal human intervention. These capabilities have enabled significant

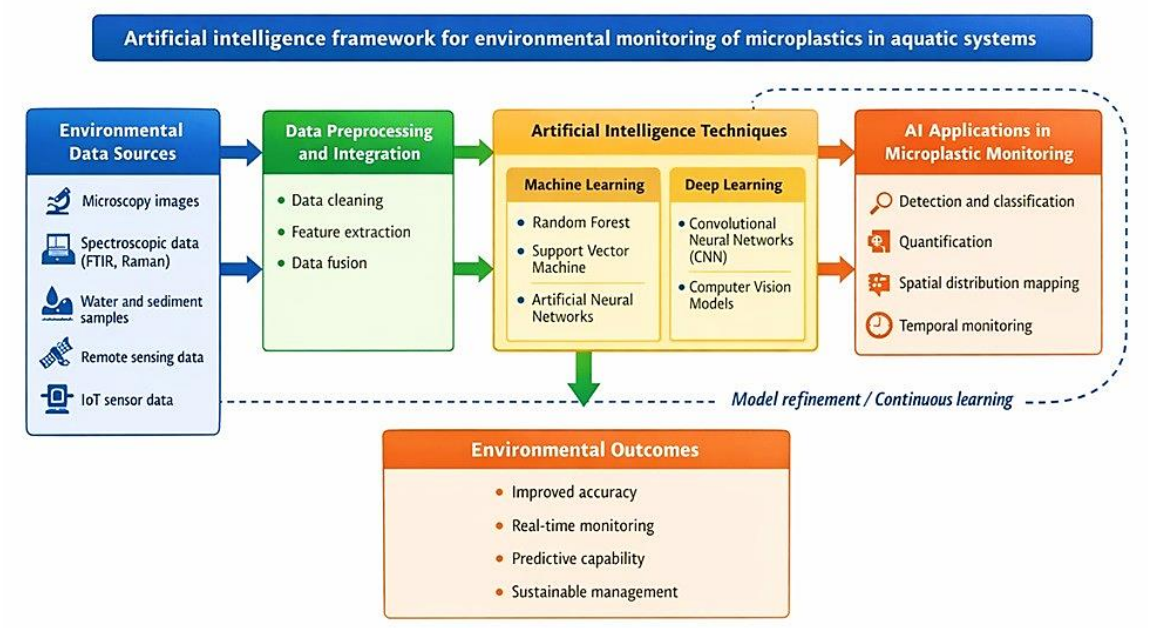

Fig. 1: Conceptual outline demonstrating the application of AI in the environmental monitoring of microplastics

progress in microplastic detection and monitoring through image-based analysis and the interpretation of spectroscopic data (Abimbola *et al.,* 2024; Ardini *et al.,* 2025).

Image analysis using AI for microplastics detection

Given the extensive use of microscopy techniques for environmental monitoring, image-based detection of microplastics has received considerable attention. CNNs and other DL models have achieved remarkable success in particle detection and classification from microplastic images. These models can extract features such as shape, size, and texture, which can be used to differentiate microplastics from natural particulates (Zhu *et al.,* 2021; Elawady *et al.,* 2025). Several studies have reported successful use of CNN architectures for microplastic detection. For instance, CNNs can achieve high precision and recall in recognizing fibrous and fragmented microplastics in microscopy images, thereby significantly reducing manual analysis. Further, transfer learning approaches using pre-trained models such as ResNet and EfficientNet have improved classification performance, especially with limited data. Despite these improvements, difficulties have been encountered in precisely identifying irregularly shaped particles and discriminating microplastics from organic materials with similar visual appearance (Thammasanya *et al.,* 2024; Villegas-Camacho *et al.,* 2025).

Progression of spectroscopic analysis with AI

Spectroscopic techniques (FTIR, Raman) are widely used for chemical characterization of microplastics. But analyzing spectral data can be complicated and labor-intensive, especially with large datasets. Over the years, AI-based approaches such as ML and DL models have been increasingly adopted to streamline the spectral signature classification process and enhance identification accuracy. Various ML algorithms, such as SVM, RF and ANN, have been used for polymer classification using spectral data. DL models are more efficient at detecting signals within spectral patterns, noise and even overlapping signals, particularly CNNs. These

approaches not only reduce analysis time but also minimize operator bias, yielding more consistent and reproducible results. However, the efficacy of AI models relies heavily on access to high-quality datasets for training, which remains a limitation in spectroscopic analysis (Sim *et al.,* 2024; Umurhan *et al.,* 2025; Villegas-Camacho *et al.,* 2025).

Monitoring and integrating data using AI-powered environmental monitoring

AI in relation to detection, is another key component of environmental data integration and analysis to build a full microplastic dataset. Aquatic systems produce massive amounts of heterogeneous information, including spatial, temporal and physicochemical data. These methods can be highly beneficial and efficient for processing such complex data, and AI can detect trends, patterns, and anomalies that might not be evident using traditional methods of analysis (Zhao *et al.,* 2024; Wang *et al.,* 2024). The AI and remote sensing technologies, which include geographical information systems (GIS) and sensors through the IoT, have facilitated tracking of the pollution of microplastics in real-time and at a very large scale. ML models can forecast microplastic concentrations using environmental parameters, and DL models can fully automate the analysis of visual and spectral data. These combined systems provide important insights into the distribution and dynamics of microplastics, supporting effective decision-making (Ibrahim *et al.,* 2025; Khan and Zaidi, 2025; Pan *et al.,* 2025). More recently, studies have demonstrated the effectiveness of AI and ML approaches in detecting and monitoring microplastics in aquatic environments. One major area of development is the application of DL algorithms to datasets of microscopic images for automatic particle identification. Wang *et al.* (2023) proposed the Faster Region-Based Convolutional Neural Network (Faster R-CNN) to detect microplastic particles in microscopy images automatically. The model represents a major advance in identification efficiency, reducing laborious manual sorting of particles and highlighting the potential of computer vision methods for large-scale environmental monitoring of microplastics. Another significant advancement is the integration of AI with spectroscopic methods, such as Raman and FTIR spectroscopy, for automated polymer identification. Ren *et al.* (2023) used micro-Raman spectroscopy with CNNs to categorize various types of microplastic polymers. Their model could produce classification rates exceeding 95 percent (%), indicating the performance of AI-driven spectral analysis methodologies in right-off-the-shelf classification of polymer structures even in environmentally complicated samples. Lim *et al.* (2024) designed a CNN-based method for analyzing Raman spectra to accelerate the detection of microplastics in the 1-10 micrometer (µm) range. The integration of DL and Raman spectral data processing has significantly reduced data collection time without compromising classification performance, resulting in a viable, high-throughput method for detecting microplastics in water. Other more recent studies have attempted to label multiple spectroscopic measurements using DL algorithms to improve identification accuracy further. Li *et al.* (2025) developed a high-order fusion model based on Raman and FTIR spectral data using DL algorithms, achieving over 98% identification accuracy of microplastics in different environmental media. This multi-sensor data fusion reveals the potential of AI to enhance reliability in complex environmental monitoring conditions. Beyond laboratory analysis, AI is also applied to develop real-time monitoring systems for microplastic pollution. Sarker *et al.* (2024) developed an AI-empowered camera sensor apparatus using computer vision to detect and monitor microplastic particles in water streams, including size and velocity parameters. Such practices imply that automated surveillance systems can systematically monitor environmental conditions related to microplastic pollution in water. Furthermore, technological advancements in the creation of low-cost

AI-driven detection platforms are taking shape to support rapid analysis in the domain. Arju *et al.* (2025) recently demonstrated a mobile phone-based microscopy system that incorporates DL algorithms and has the potential to achieve microplastic detection rates of nearly 98%. This method emphasizes the potential of portable, low-cost monitoring technologies to enable mass surveillance of microplastics in resource-scarce settings. Fig. 2 explains a monitoring system for microplastics in water systems via AI. Table 1 summarizes AI-based approaches for detecting, classifying, and monitoring microplastics in aquatic systems.

AI in modeling the fate and transport of microplastics in aquatic systems

The fate and transport of microplastics in aquatic systems involve complex interactions among hydrodynamic processes, physicochemical properties, and environmental conditions. Microplastic particles have a variety of characteristics such as size, density, shape and surface chemistry, which play a major role in their behavior in water bodies. These properties determine such important transport processes as advection, diffusion, sedimentation, resuspension and aggregation. In addition, environmental parameters such as flow velocity, turbulence, temperature, salinity and biological activity oversee the spatial and temporal variability of microplastic distribution. The dynamic nature of these processes poses major challenges for accurately predicting microplastic movement and accumulation using conventional modeling approaches (Du *et al.,* 2021; Jolaosho *et al.,* 2025).

Influencing factors of fate and transport

Microplastic transport depends on both intrinsic particle properties and external environmental conditions. Low-density polymers are likely to be suspended in water columns, and high-density particles are more likely to be in sediments. Particle shape, especially fibers and fragments, influences drag forces and settling velocities, resulting in differences in transport behavior. Surface properties, such as biofilm formation and chemical aging, further alter particle density and associated hydrophobicity, thereby affecting particle interactions with the surrounding media (Kumar *et al.,* 2021; Jiang *et al.,* 2025a). Environmental factors also play an important part in determining microplastic dynamics. Hydrodynamic parameters such as currents, waves and turbulence, as well as physicochemical parameters such as salinity and temperature, affect particle movement and dispersion, whereas physical parameters affect buoyancy and aggregation. Carrier transport pathways and the residence time of microplastics may be affected by biological interactions such as ingestion and biofouling. These interconnected processes result in highly complex, nonlinear systems, and it is not easy to predict microplastic behavior using traditional deterministic approaches (Kye *et al.,* 2023; Guo *et al.,* 2024).

Predictive modeling using AI

AI has emerged as a powerful tool for microplastic fate and transport modeling because it can analyze complex environmental systems in a data-driven manner. ML algorithms such as RF, SVM and ANN possess the potential to detect nonlinear correlations between multiple environmental variables. These models can be trained using historical data to predict microplastic concentrations, distributions and transport routes across different aquatic environments (Astorayme *et al.,* 2024; Cazzetta *et al.,* 2026). AI-based predictive models have been shown to perform better than traditional methods, especially when dealing with large and heterogeneous data. For instance, ML models have been adopted to estimate microplastic concentrations in riverine and coastal water bodies, incorporating hydrological, meteorological and physicochemical parameters. Similarly, temporal variations have been represented, and the transport of microplastics under dynamic environmental conditions has been predicted using DL models

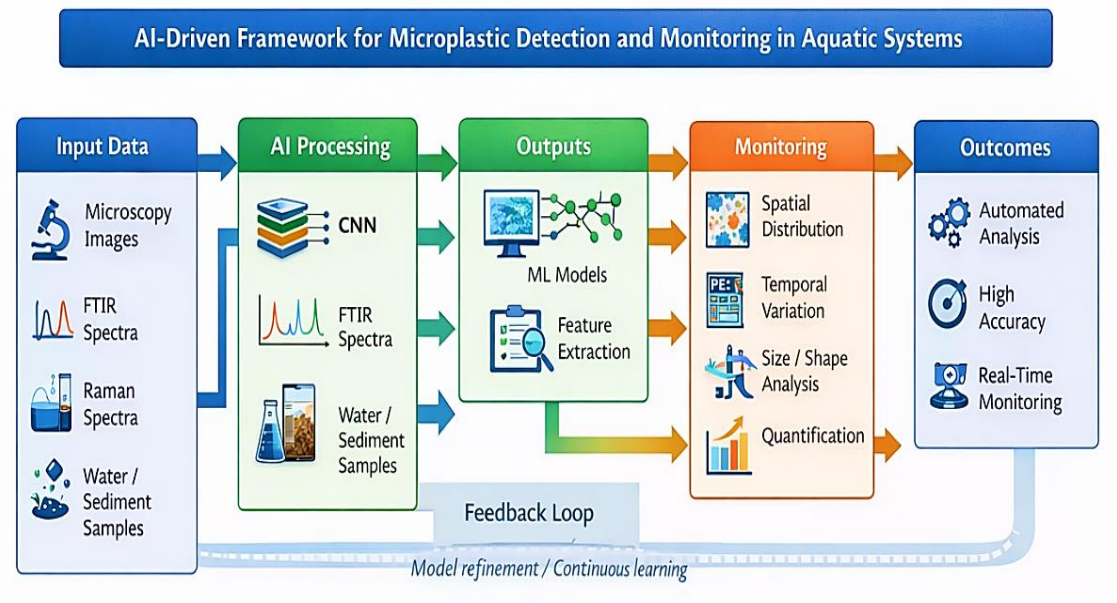

Fig. 2: AI-driven monitoring of microplastics in aquatic systems

Table 1: Summary of AI-based approaches for the detection, classification, and monitoring of microplastics in aquatic systems

AI Model	Data type	Application	Key findings	Sources
CNN	Microscopy images	Detection and classification	Achieved high precision in identifying microplastics, reducing manual analysis	Lorenzo-Navarro *et al.*, 2021
CNN	Raman spectroscopy	Polymer classification	>95% accuracy in microplastic identification	Jeon *et al.*, 2025
ML (SVM)	FTIR spectra	Polymer classification	Automated classification with reduced human bias	Yan *et al.*, 2022
YOLO(v5)	Image data	Real-time detection	Achieved ~96% detection accuracy	Sarker *et al.*, 2024
RF	Spectral data	Polymer identification	Improved classification compared to traditional methods	Valls-Conesa *et al.*, 2023
ANN	Environmental data	Distribution prediction	Accurate prediction of microplastic concentration patterns	Manchu *et al.*, 2024
CNN	FTIR imaging	Automated identification	High-throughput microplastic analysis	Li *et al.*, 2025
ML	FTIR data	Spectral classification	Enhanced spectral library matching	Rosales-Martínez *et al.*, 2025
ML-assisted analysis	Water samples	Monitoring	Improved detection efficiency	Hufnagl *et al.*, 2021
ML	Remote sensing	Marine debris detection	Large-scale monitoring capability	Perera *et al.*, 2025
CNN	Image data	Classification	Improved recognition of complex particle shapes	Wang *et al.*, 2023
CNN	Microscopy images	Microplastic classification	High accuracy with limited datasets	Zeng *et al.*, 2024
ML	FTIR data	Automated identification	Improved speed of analysis	Moses *et al.*, 2023
CNN	Raman spectra	Polymer classification	Accurate classification under noise	Lim *et al.*, 2024
DL	Image + spectral	Multi-modal analysis	Improved classification robustness	Barker *et al.*, 2025
CNN	Image data	Detection	Enhanced detection of irregular particles	Han *et al.*, 2024
RF	Environmental data	Prediction	Identified key influencing factors	Tran *et al.*, 2023
CNN	Image data	Automated detection	Reduced processing time significantly	Zhao *et al.*, 2024
Hybrid ML	Multi-source data	Monitoring	Improved predictive performance	Seggio *et al.*, 2023

such as recurrent neural networks (RNN) and long short-term memory (LSTM) networks. These approaches enable more precise, scalable predictions for improved environmental monitoring and management (Yu and Hu, 2022; Reshadi *et al.,* 2025).

Hybrid modeling approaches

The combination of AI techniques and traditional hydrodynamic models has been adopted to develop hybrid modeling frameworks for simulating microplastic transport. Conventional models, such as particle-tracking and computational fluid dynamics (CFD), are used to obtain physics-based insights into flow dynamics and particle motion. However, these models can be computationally expensive and may fail to account for complex interactions among multiple variables accurately (Ibna Hafiz *et al.,* 2025; Filo *et al.,* 2025). Hybrid models combine physics-based and data-driven techniques to improve prediction accuracy and efficiency. AI algorithms may be applied to calibrate model parameters, reducing uncertainties and better representing nonlinear processes. For instance, ML models can be integrated with hydrodynamic simulations to forecast transport pathways and accumulation areas in rivers, estuaries and coastal areas. These hybrid approaches provide richer frameworks for understanding the dynamics of microplastics in aquatic systems (Velazquez-Araque *et al.,* 2025).

Geospatial analysis and monitoring and research outputs

The addition of geospatial data and remote sensing technologies has significantly strengthened AI-based modeling. Geographic information systems (GIS) and ML algorithms help map the distribution of microplastics in space on a broad geographical scale. These methods provide a simple way to determine microplastic pollution hotspots and to investigate the spatial variability of microplastic concentrations (Manapragada *et al.,* 2025; Hochmair *et al.,* 2025). AI models can also be used to process data from remote sensing platforms, sensor networks, and monitoring programs to enable large-scale, real-time analysis of microplastics. The combination of spatial and temporal information enables us to create predictive models that can quantify the movement and accumulation of microplastics under different environmental conditions. Such capabilities are especially useful for assessing regions and global regions where sampling is often limited with traditional methods (Rawat *et al.,* 2025). Fig. 3 Projects the AI modules for modeling the fate and transport of microplastics in aquatic systems. Recent studies have demonstrated the potential of AI-based approaches for modeling the fate and transport of microplastics in water systems. ML models have been successfully used to predict microplastic concentrations in riverine environments by incorporating hydrological and physicochemical information, offering greater predictive ability than traditional statistical methods. An ANN has been applied to model transport pathways and the key environmental factors that affect the distribution of microplastics (Usman *et al.,* 2026). Hybrid approaches combining hydrodynamic simulations with ML have shown better performance for predicting particle transport and accumulation zones, especially in coastal and estuarine systems. Geospatial models of microplastic pollution using a combination of geographic information systems (GIS) and AI techniques have been applied to map microplastic pollution at larger scales, identify hotspots and track temporal trends (Kida *et al.,* 2024). Various recent studies have demonstrated the potential of ML models to predict microplastic abundance and transport dynamics in riverine and coastal environments. Gong *et al.* (2024) used several ML algorithms to model MP abundance in river waters across several coastal regions in China. Using datasets that included hydrological conditions, land use and anthropogenic factors, it was shown that there are strong relationships between environmental drivers and the distribution patterns of microplastics. The ML models with spatial variations in microplastic

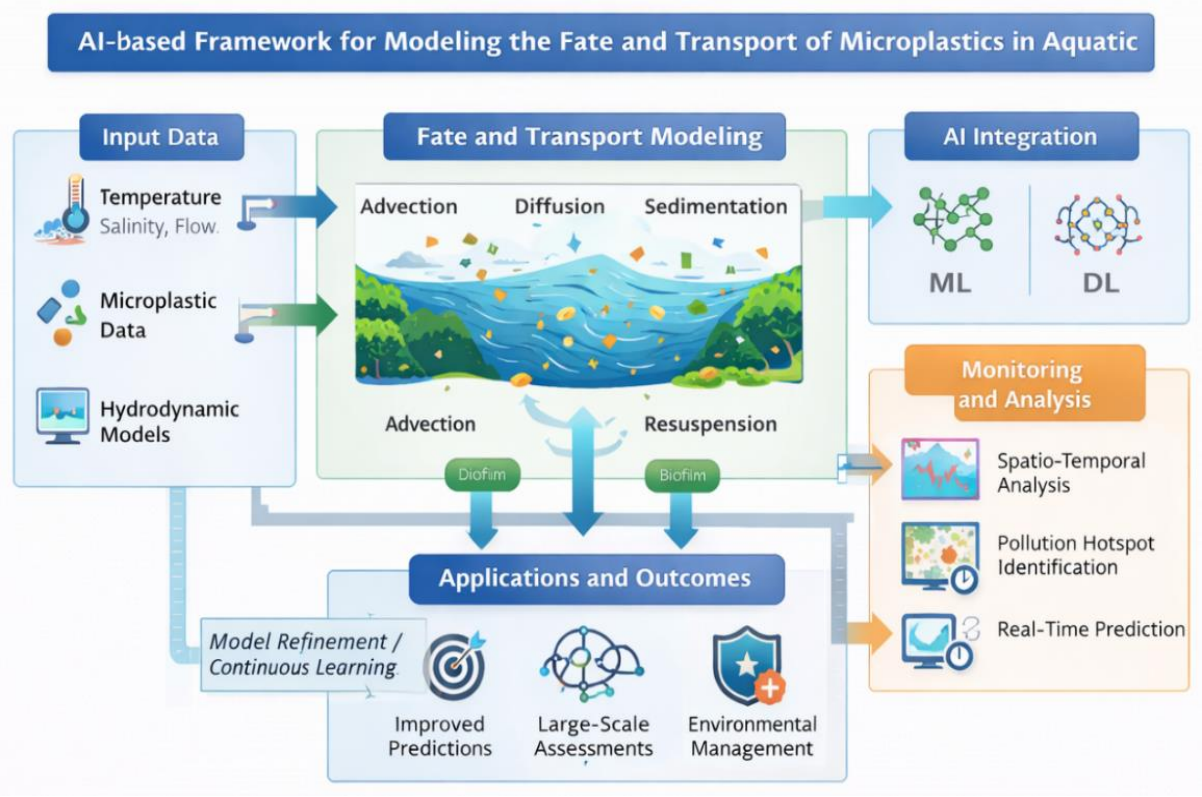

Fig. 3: AI elements for demonstrating the fate and transport of microplastics in aquatic systems

abundance were able to predict these patterns, suggesting the importance of environmental factors, such as population density, runoff dynamics and industrial activity, in regulating microplastic transport. These results demonstrate the potential of AI-based predictive frameworks to reduce the field sampling required and to provide credible estimates of microplastic distribution in complex aquatic systems. Priyanto *et al.* (2025) applied ML algorithms to predict microplastic amounts in river systems in Indonesian provinces using environmental and anthropogenic datasets. The analysis showed that tree-based algorithms were particularly suitable for predicting microplastic concentrations, with a coefficient of determination (R^2) of about 0.84. The model demonstrated the presence of controlling variables of interest. Table 2 lists a few AI-based models of microplastic fate and transport Fig. 4.

AI-based methods for risk assessment and ecotoxicological assessment of microplastics

The widespread occurrence of microplastics in aquatic environments has raised growing concerns regarding their ecological and human health impacts. Microplastics interact with both biotic and abiotic components of aquatic ecosystems, resulting in complex exposure pathways and multiple toxicological responses. They can be ingested by organisms across different trophic levels, causing physical damage, oxidative stress, inflammation, metabolic disruption, and impaired reproduction. In addition, microplastics serve as vectors for heavy metals, persistent organic pollutants, pharmaceuticals, and microbial pathogens, thereby increasing the bioavailability and transport of co-existing contaminants. Several physicochemical characteristics, including particle

Table 2: AI-based modeling of fate and transport of microplastics

AI model	Data type	Aquatic system	Application	Key findings	Sources
ML (Data-driven modeling)	Oceanographic data	Ocean	Transport pathways	Identified global microplastic accumulation zones	Tsiaras *et al.,* 2021
Numerical + ML	Marine data	Ocean	Distribution modeling	Highlighted complexity of microplastic transport	Pilechi *et al.,* 2022
Statistical modelling	Waste data	Coastal	Source estimation	Quantified plastic input into oceans	Wolf *et al.,* 2020
ML + hydrodynamic	Ocean current data	Ocean gyres	Transport prediction	Identified Great Pacific Garbage Patch	Olawade *et al.,* 2026
ANN	Environmental data	River	Concentration prediction	High prediction accuracy for microplastic levels	Fazil *et al.,* 2025
Statistical + modelling	Marine data	Ocean	Distribution analysis	Identified widespread ocean contamination	Aoki K and Furue, 2021
ML/statistical	River discharge data	Rivers	Source apportionment	Rivers as major plastic sources	Sá *et al.,* 2022
ML	Catchment data	River	Transport analysis	Identified key influencing parameters	Windsor *et al.,* 2019
Process-based + AI	Particle properties	Ocean	Vertical transport	Modeled sinking and rising behavior	Sugathapala *et al.*, 2025
Simulation + ML	Sediment data	Freshwater	Fate analysis	Sediment accumulation patterns	Portillo De Arbeloa and Marzadri, 2025
ML	Environmental data	River	Distribution prediction	Improved spatial predictions	Lee *et al.,* 2022
ANN	Water quality data	River	Pollution prediction	High model performance	Olbert *et al.,* 2025
Modeling + ML	Soil-water data	Freshwater	Transport pathways	Identified terrestrial-aquatic link	Rehm *et al.,* 2021
ML	Environmental datasets	Freshwater	Distribution modeling	Identified influencing factors	Hu *et al.,* 2025
Statistical + modeling	Marine surveys	Ocean	Distribution	Global mapping of plastics	Goddijn-Murphy *et al.,* 2025
Numerical + ML	Ocean data	Ocean	Transport simulation	Seasonal variability observed	Pilechi *et al.,* 2022
AI + modeling	Marine data	Ocean	Particle behavior	Modeled microplastic transport processes	Santana *et al.,* 2025
Modeling	Marine data	Ocean	Accumulation zones	Identified Mediterranean pollution	Tsiaras *et al.,* 2021
ML	River data	Global rivers	Source identification	Identified top polluting rivers	Pittroff *et al.,* 2024
Integrated modeling	Global datasets	Ocean	Future scenarios	Predicted plastic emissions	Yan *et al.*, 2024

size, shape, polymer composition, surface chemistry, and aging, influence their toxicity. Smaller particles, particularly nanoplastics, possess greater potential to penetrate biological membranes and accumulate within tissues. In contrast, irregularly shaped particles are more likely to cause mechanical injury and remain in organisms for longer. Furthermore, biofouling and interactions with other environmental contaminants modify particle behavior, transport, and exposure dynamics, making conventional ecological risk assessment increasingly challenging (Karak *et al.,* 2025; Yarahmadi *et al.,* 2024; Mahari *et al.,* 2025; Trivedi *et al.,* 2026).

AI in toxicity prediction

Artificial intelligence has emerged as a powerful tool for predicting microplastic toxicity by

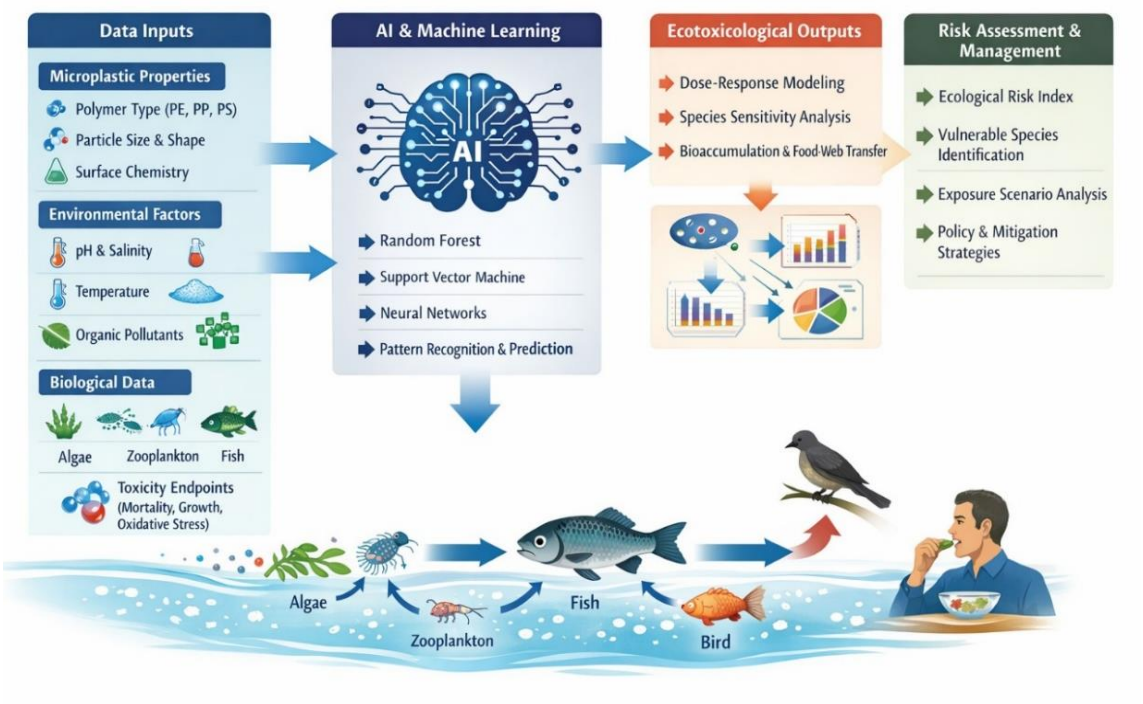

Fig. 4: Conceptual outline indicating the use of AI for microplastic induced ecotoxicological risk assessment

integrating physicochemical properties, environmental conditions, and biological response data. ML algorithms, including Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and deep learning (DL), have been widely applied to identify complex nonlinear relationships between particle characteristics and toxicity endpoints such as mortality, growth inhibition, oxidative stress, and biochemical alterations (Astray et al., 2023; Tang, 2025). Deep learning approaches further improve predictive performance by analyzing large and heterogeneous datasets generated from high-throughput toxicity screening and experimental studies. These models facilitate the identification of the most influential variables governing toxicity, including particle size, polymer type, concentration, surface charge, and the presence of sorbed contaminants. Compared with conventional statistical approaches, AI models offer greater flexibility in capturing nonlinear interactions; however, their predictive performance remains highly dependent on the quality, diversity, and representativeness of the available training datasets (Elawady *et al.,* 2025; Jiang *et al.,* 2025b). Recent studies have also combined ML with quantitative structure–activity relationship (QSAR) modeling to predict the toxicity of microplastics and associated additives. Using curated toxicity databases such as ECOTOX, AI-assisted QSAR models provide a rapid screening tool for prioritizing potential hazards and may help reduce reliance on extensive animal testing by supporting early-stage toxicity assessment. However, AI-based predictions should be regarded as complementary to experimental ecotoxicological studies until broader external validation and regulatory acceptance are achieved. These approaches provide rapid screening for potential hazards and improve the efficiency of environmental risk assessment by identifying the key physicochemical properties

that control biological responses (Liu *et al.,* 2023). The interpretation of AI-based toxicity predictions should consider the biological and experimental context of the underlying datasets. Toxicity responses vary substantially with species, developmental stage, exposure duration, particle size, polymer composition, concentration metrics, particle aging or weathering, chemical additives, and the presence of co-contaminants. Consequently, the predictive performance and applicability of AI models depend not only on the modeling algorithm but also on the quality, representativeness, and standardization of the input data. Future studies should prioritize harmonized toxicity datasets and standardized reporting to improve the robustness and transferability of AI-assisted ecotoxicological assessments.

AI in ecological risk assessment

AI complements conventional ecological risk assessment by integrating environmental monitoring data, biological observations, and physicochemical information to improve exposure prediction and toxicity assessment of microplastics. Unlike conventional ecological indices and statistical analyses, AI models identify complex nonlinear relationships and support predictive modeling for ecological risk evaluation. ML models have been employed to predict exposure levels, estimate bioaccumulation potential, identify vulnerable species, and assess ecological risks across different aquatic ecosystems (Hu *et al.,* 2024; Hoang *et al.,* 2025). In addition, probabilistic AI models can incorporate uncertainty within environmental datasets, enabling scenario analysis under varying pollution conditions and improving decision-making for environmental management (Wardani *et al.,* 2024; El-Sokkary *et al.,* 2026). Beyond toxicity prediction, AI has increasingly been applied to model trophic transfer and bioaccumulation in aquatic food webs. Data-driven ecological models integrating field observations, species traits, and environmental variables have been used to estimate exposure probabilities and accumulation potential across multiple trophic levels, from plankton and benthic invertebrates to fish species. ML techniques, including gradient boosting and neural networks, have demonstrated that particle characteristics, feeding behavior, habitat conditions, and environmental variables strongly influence trophic transfer. Integrating heterogeneous ecological datasets through AI provides a more comprehensive understanding of long-term ecosystem impacts and supports the development of next-generation ecological risk assessment frameworks for emerging contaminants such as microplastics (Jiang *et al.,* 2025c; Zhang *et al.,* 2025; Jachimowicz *et al.,* 2025; Yang *et al.,* 2026). Overall, AI-based approaches have demonstrated considerable potential to improve the prediction of microplastic toxicity and ecological risk by integrating diverse environmental, physicochemical, and biological datasets and by identifying complex nonlinear relationships among exposure variables. These approaches can complement conventional ecotoxicological assessments by supporting toxicity prediction, exposure modeling, and scenario analysis. However, the predictive performance and reliability of AI models remain strongly dependent on the quality, diversity, and representativeness of the underlying datasets. Most published models have been developed using a limited range of polymer types, test organisms, toxicity endpoints, and controlled laboratory exposure conditions, which may not adequately capture the complexity and spatial-temporal variability of natural aquatic ecosystems. Consequently, AI model predictions should be interpreted within the training data's applicability domain, and caution should be exercised. Fig. 4 conceptualizes the potential application and integration of AI for microplastic ecotoxicological risk assessment.

AI in microplastic remediation and treatment technologies

The growing presence of microplastics in aquatic habitats has highlighted the need for effective remediation and treatment methods. Conventional methods of microplastic removal include physical, chemical and biological processes, such as filtration, coagulation-flocculation, sedimentation, adsorption and membrane separation. While these techniques have shown different levels of efficiency, they tend to be limited by factors such as incomplete removal, high operation costs, energy use, and difficulties in dealing with different forms of microplastics. The variation in particle size, shape, and composition further complicates the design and optimization of treatment systems (Amparán *et al.,* 2025; Dayal *et al.,* 2024; Bodzek *et al.,* 2024). AI-assisted remediation technologies target different treatment objectives, including the physical removal, capture, retention, transfer, or degradation of microplastics. These outcomes should not be regarded as environmentally equivalent. Physical separation processes such as membrane filtration, coagulation–flocculation, sedimentation, and adsorption primarily remove or transfer microplastics from the aqueous phase to concentrated residual streams (e.g., sludge or spent adsorbents), requiring appropriate downstream management. In contrast, advanced oxidation and photocatalytic processes aim to chemically degrade polymer structures, although complete mineralization is rarely achieved under practical conditions. Consequently, AI-based optimization strategies should be interpreted in light of the specific treatment objective and the environmental fate of the resulting products, rather than solely on apparent removal efficiency.

AI in process optimization

AI has been utilized as a potent solution to streamline microplastic remediation procedures, leveraging a data-driven decision-making approach and real-time control. ML models can predict treatment efficiency based on pH, coagulant dosage, temperature, and flow rate. Algorithms, including ANN, RF, and support vector machines, have been utilized to predict operating conditions to achieve higher removal efficiencies and reduce energy usage and operational costs. The key parameters affecting treatment performance can also be calculated using AI-based optimization models, enabling system design optimization. In fact, ML strategies have been implemented to optimize adsorption processes by predicting interactions between microplastics and adsorbent materials. In these models, the number of experimental steps can be greatly reduced, enabling the design of better treatment variations (Lowe *et al.,* 2022; Cairone *et al.,* 2024; Valle-Bravo *et al.,* 2026). Although many AI-assisted optimization strategies have been developed for conventional wastewater treatment processes, direct applications specifically targeting microplastic removal remain comparatively limited. Nevertheless, these approaches provide a useful framework for improving operational conditions that may enhance microplastic capture and separation efficiency.

AI-powered treatment solutions

The combination of AI and the latest treatment technologies has led to the development of intelligent systems for removing microplastics. AI-assisted membrane systems can track fouling behavior and make on-the-fly changes to operational parameters to ensure optimal performance. Similarly, AI models can be used in conjunction with adsorption and filtration systems to predict removal efficiency and optimize system design. Emerging approaches combining AI, nanomaterials and advanced oxidation processes have also shown potential to improve the degradation and removal of microplastics. Using

AI models, it is possible to design and optimize nanomaterial-based adsorbents that can be even more selective and efficient. In addition, AI-enabled analysis of treatment processes can help identify the right conditions for microplastic degradation (Xu and Liu, 2025; Agaton, 2025).

Smart and autonomous remediation systems

AI and IoT technologies, combined, have enabled the development of intelligent, autonomous remediation systems. To verify the concepts of the AI models, sensor arrays will be used to continuously monitor water quality parameters and the level of microplastics and report in real time. These systems can automatically adjust treatment conditions in response to changing environmental conditions to achieve optimal performance. Autonomous environmental monitoring and remediation can also be conducted at large scale using systems that run AI algorithms. For instance, AI can be used to detect polluted areas via platforms and prioritize them for cleaning. These systems can provide the prospect of dramatically improving the effectiveness of microplastics management (Essamlali *et al.,* 2024; Govindarajan *et al.,* 2025). Table 3 lists AI-based approaches for microplastic remediation. Fig. 5 Shows conceptual microplastic removal with AI assistance (Valdiviezo-Gonzales *et al.,* 2026). Current AI-assisted remediation technologies can be broadly categorized into i) conceptual frameworks proposed for future implementation, ii) laboratory-scale proof-of-concept systems, iii) pilot-scale demonstrations, and iv) emerging applications integrated into conventional wastewater treatment processes. However, reports of fully autonomous, full-scale microplastic remediation systems remain scarce. Overall, AI has emerged as a valuable tool for enhancing the efficiency, automation, and optimization of microplastic remediation technologies. By integrating predictive modeling, intelligent process control, and real-time monitoring, AI can support the development of adaptive and energy-efficient treatment systems. Although many applications remain at the laboratory or pilot scale, continued advances in ML, sensor technologies, and process automation are expected to facilitate the practical implementation of AI-assisted remediation strategies for sustainable microplastic management. Evidence from AI-assisted processes in wastewater treatment suggests potential applicability to microplastic removal; however, direct studies focusing specifically on microplastic adsorption remain scarce. An important consideration in AI-assisted microplastic remediation is the subsequent fate of particles retained during treatment. Many physical separation technologies, including membrane filtration, coagulation–flocculation, adsorption, and granular filtration, do not destroy microplastics but instead transfer them to residual streams such as sludge, spent adsorbents, filter media, membrane concentrates, or backwash water. Consequently, the environmental effectiveness of these technologies depends not only on their removal efficiency but also on the safe handling, treatment, disposal, or potential recovery of these residual materials to prevent secondary environmental release. Future AI-based optimization frameworks should therefore incorporate residual management strategies alongside treatment performance to support more sustainable microplastic remediation.

CONCLUSION

Microplastic pollution continues to pose a significant threat to freshwater and marine ecosystems, creating an urgent need for efficient approaches to its detection, monitoring, prediction, and mitigation. This review demonstrates that AI, ML, and DL are increasingly contributing to microplastic research by

Table 3: AI-based approaches for microplastic remediation

Remediation technology	Role of AI	Optimised parameters	Current limitations
Coagulation–flocculation	Process optimisation	Coagulant dose, pH	Limited real-world validation
Membrane filtration	Fouling prediction and process control	Flux, TMP, cleaning cycles	Small datasets
Adsorption	Prediction of adsorption efficiency	Adsorbent dosage, contact time	Material-specific models
Photocatalysis	Catalyst/process optimization	Catalyst loading, irradiation time	Mostly laboratory studies
Advanced oxidation	Process optimisation	Oxidant dosage, reaction time	Limited AI applications
Smart treatment systems	Real-time monitoring and control	Sensor integration, operational parameters	Pilot-scale implementation

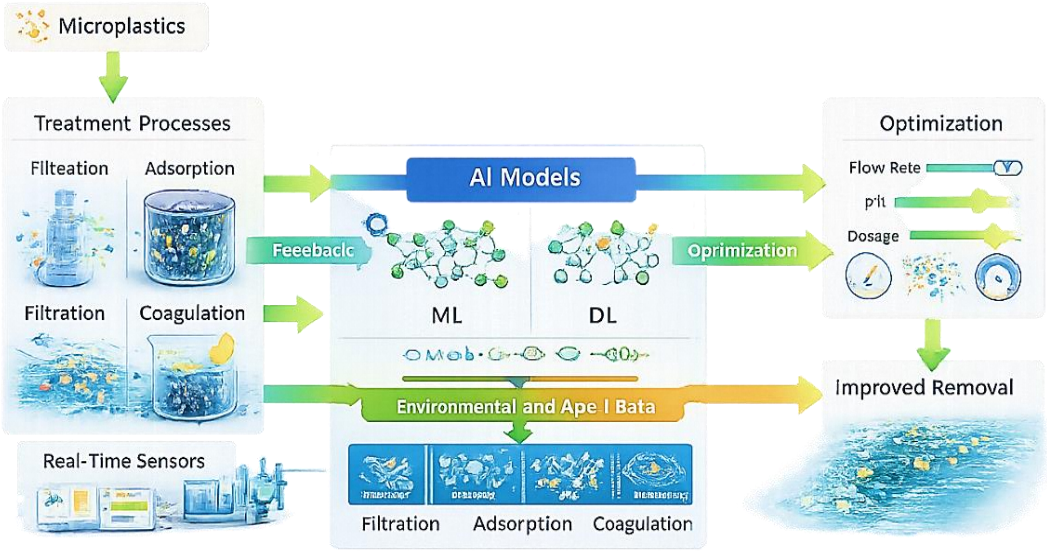

Fig. 5: AI-assisted microplastics remediation

enhancing data analysis, improving predictive capabilities, and supporting more efficient environmental monitoring and decision-making. Among the current applications, AI-assisted image analysis, automated microscopy, and spectroscopic classification represent the most mature and widely validated technologies, providing substantial improvements in the speed and accuracy of microplastic identification. AI has also shown considerable promise in modeling the environmental fate and transport of microplastics and supporting ecotoxicological risk assessment. However, the reliability of these applications remains dependent on the quality and representativeness of the available datasets. By comparison, several emerging applications, including AI-assisted remediation, digital twins, autonomous treatment systems, and large-scale toxicity prediction, are still at an early stage of development. Much of the current evidence for these applications is derived from laboratory investigations, pilot-scale studies, or AI-assisted optimization of conventional wastewater treatment processes rather than direct modeling of microplastic removal under real-world operating conditions. Consequently, these technologies should be regarded as promising research directions rather than fully established

environmental management tools. Similarly, while AI-assisted optimization may improve treatment efficiency under specific conditions, quantitative evidence demonstrating consistent reductions in operational costs and energy consumption for microplastic-specific treatment systems remains limited. Despite the rapid progress achieved in recent years, several important challenges continue to limit the broader implementation of AI in microplastic research. Many published models have been developed using relatively small, geographically restricted, and heterogeneous datasets, limiting their generalizability across different aquatic environments. Furthermore, inconsistent sampling protocols, analytical methodologies, reporting metrics, and benchmark datasets hinder model comparison and independent validation. Additional challenges include limited model interpretability, insufficient external validation, restricted transferability across environmental conditions, and the scarcity of field-scale deployment studies. Addressing these issues will require greater standardization of analytical workflows, development of high-quality open-access datasets, rigorous external validation, and closer collaboration among environmental scientists, engineers, data scientists, and regulatory agencies.

AUTHOR CONTRIBUTIONS

M. Kamaraj wrote the original draft and conceptualized the paper. H.A. Bhavithra helped with visualization, validation, writing, review and editing. B. Rajalakshmi collected literature, created the figures and helped in writing and editing. J. Aravind, as the corresponding author, supervised the work and wrote the original draft and conceptualized the paper.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy, have been completely witnessed by the authors.

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NEGATIVE AI STATEMENT

The author(s) declared that no AI tools or services were used or highly applied during the preparation of this work.

ABBREVIATIONS

%	Percent
µm	Micrometers
AI	Artificial intelligence
ANN	Artificial neural network
CFD	Computational fluid dynamics
CNN	Convolutional neural network
DL	Deep learning
Faster R-CNN	Faster region-based convolutional neural network
FTIR	Fourier transform infrared
GIS	Geographic information system
IoT	Internet of things
LSTM	Long short-term memory
ML	Machine learning
R^2	Coefficient of determination
RF	Random forest
RNN	Recurrent neural network
SDGs	Sustainable development goals
SERS	Surface-enhanced raman spectroscopy
SVM	Support vector machine
YOLO	You only look once

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