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Advancing environmental sustainability through emerging AI-based monitoring and mitigation strategies for microplastic pollution in aquatic ecosystems

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Abstract

Microplastics have become a significant pollutant in aquatic ecosystems, with serious implications for biodiversity, food safety, and environmental sustainability. This paper reviews the nature and sources of microplastic pollution, alongside its ecological and human health impacts. Recognizing the limitations of traditional monitoring and removal methods, the study explores emerging artificial intelligence (AI)-based strategies as innovative tools for improving environmental monitoring and pollution mitigation. The manuscript discusses how AI techniques such as machine learning, computer vision, and remote sensing can enhance the detection, classification, and prediction of microplastic distribution in water bodies. It also highlights the potential of AI-driven robotic systems in supporting targeted mitigation efforts. While these technologies show promise, further interdisciplinary research and development are necessary to fully realize their application in real-world environmental management. The integration of AI offers a proactive path toward achieving cleaner aquatic ecosystems and supporting global sustainability goals.

Keywords: Microplastic Pollution; Aquatic Ecosystems; Artificial Intelligence; Environmental Monitoring; Machine Learning; Computer Vision; Sustainability

1. Introduction

Microplastic pollution in aquatic ecosystems is a critical environmental issue that has gained increasing attention over the past few decades. Defined as synthetic solid particles or polymeric materials measuring less than 5 millimeters in diameter, microplastics can be categorized into primary and secondary types [1]. Primary microplastics are intentionally manufactured for use in products such as cosmetics, cleaning products, and industrial abrasives. In contrast, secondary microplastics result from the breakdown of larger plastic debris through processes like photodegradation, mechanical wear, and chemical degradation. These particles are often too small to be efficiently filtered by water treatment plants, leading to their widespread distribution in marine and freshwater environments. The sources of microplastic pollution are extensive, ranging from synthetic fibers shed from clothing and textiles during washing, to plastic waste that degrades into smaller pieces over time. The persistence of these particles in aquatic

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ecosystems, combined with their ability to accumulate and persist in the environment, presents significant challenges for both environmental sustainability and ecosystem health.

The global environmental and ecological impact of microplastic pollution is profound and widespread. Aquatic organisms across various trophic levels are vulnerable to the ingestion of microplastics, which can lead to a range of harmful effects. For instance, smaller marine organisms, such as plankton, can mistake microplastic particles for food, which then enter the food chain. Studies have shown that microplastics can cause physical damage to the gastrointestinal systems of marine species, leading to internal abrasions, blockages, and reduced feeding efficiency [2]. Furthermore, the ingestion of microplastics can impair growth and reproduction in various aquatic organisms, threatening biodiversity and ecosystem services. In addition to these direct impacts, microplastics also act as vectors for persistent organic pollutants (POPs), which include chemicals such as pesticides and industrial compounds that adhere to the surface of plastic particles. These chemicals are then transported across the aquatic environment, potentially entering the food web and reaching human populations. The effects of microplastics are not confined to marine ecosystems alone; freshwater systems such as rivers and lakes are also increasingly contaminated, further exacerbating the scope of the problem [3].

This issue of microplastic pollution is intricately linked to the United Nations Sustainable Development Goals (SDGs), particularly Goal 14, which focuses on conserving and sustainably using the oceans, seas, and marine resources for sustainable development. Microplastic pollution directly threatens marine life by disrupting ecosystems, harming aquatic species, and compromising the health of marine environments. According to Jambeck et al. [4], the widespread presence of plastic waste in the oceans, which includes microplastics, has severe consequences for marine biodiversity and the livelihoods of coastal communities dependent on marine resources. Moreover, microplastic pollution also intersects with SDG 12, which calls for responsible consumption and production. The increasing prevalence of plastic products and their subsequent degradation into microplastics highlight the need for sustainable practices in plastic production, consumption, and disposal. Therefore, addressing microplastic pollution is crucial for achieving these SDGs and advancing global environmental sustainability efforts. Efforts to mitigate the impacts of microplastics align with the broader goals of protecting biodiversity, promoting the sustainable use of marine resources, and ensuring environmental health [2,3].

The role of Artificial Intelligence (AI) in addressing environmental challenges has been growing rapidly in recent years, offering new avenues for monitoring, analyzing, and mitigating pollution. AI technologies, such as machine learning, image recognition, and data analytics, are being increasingly applied in environmental science to enhance the efficiency and accuracy of pollution detection and management [5,6]. In the context of microplastic pollution, AI has demonstrated significant potential in revolutionizing environmental monitoring techniques. For instance, AI-powered image recognition systems can analyze large datasets of images from remote sensors and underwater cameras to identify microplastic particles, reducing the need for manual inspection and increasing the speed of data processing [7]. Machine learning algorithms can also be used to predict the movement and distribution of microplastics in aquatic ecosystems, helping to identify hotspots for targeted interventions. Furthermore, AI has the capacity to optimize waste management processes, by predicting and detecting microplastic sources and facilitating the development of mitigation strategies tailored to specific environments. The integration of AI in environmental science thus represents a transformative approach that can improve the effectiveness of monitoring systems and inform data-driven decision-making processes aimed at reducing microplastic pollution [6,7].

The purpose of this review is to explore the emerging role of AI-based monitoring and mitigation strategies in the fight against microplastic pollution in aquatic ecosystems, with a focus on advancing environmental sustainability. By synthesizing recent research, this review aims to provide a comprehensive overview of how AI technologies are being applied to monitor and manage microplastic pollution. This review will address the various sources of microplastics, their environmental impacts, and the innovative AI tools and techniques being utilized to address these challenges. Through this analysis, the review seeks to underscore the importance of interdisciplinary approaches, combining environmental science and AI, to effectively tackle the microplastic crisis and promote a more sustainable future. The scope of this review is to highlight the potential of AI in enhancing environmental sustainability through improved pollution monitoring, predictive modeling, and targeted mitigation efforts.

2. Microplastic Pollution in Aquatic Ecosystems: Current Landscape

2.1. Types and Classifications of Microplastics

Microplastics, defined as plastic particles smaller than 5 mm in size, are classified into two major categories: primary and secondary microplastics. Primary microplastics are deliberately manufactured at microscopic sizes for specific industrial applications [8]. These include microbeads, which are commonly used in cosmetics, personal care products, and cleaning agents, as well as microfibers shed from synthetic textiles such as polyester and nylon. They also encompass plastic pellets or "nurdles" used as raw material in the production of larger plastic items. The manufacturing process of these materials results in microplastics directly entering aquatic systems, contributing to their pervasive spread in the environment [8].

On the other hand, secondary microplastics result from the physical degradation and fragmentation of larger plastic debris over time. This fragmentation occurs through mechanical processes, photodegradation, and chemical weathering, which break down plastics into smaller and smaller particles [9]. Items such as plastic bottles, packaging, and fishing nets are common sources of secondary microplastics. These microplastics are more ubiquitous in the environment due to the sheer volume of plastic waste present in aquatic ecosystems. They can persist for decades or even centuries, causing long-term contamination of water bodies [10].

Both primary and secondary microplastics can have significant impacts on aquatic ecosystems due to their small size and diverse physical and chemical properties. The classification of microplastics based on their origin helps to understand their pathways and fate in the environment and aids in identifying effective mitigation strategies [9-11]. To further illustrate the distinctions between primary and secondary microplastics, their sources, and environmental behavior, Table 1 presents a detailed classification and characterization matrix that highlights key attributes relevant to their environmental fate.

Table 1 Classification and Characteristics of Microplastics

Type (Primary / Secondary)	**Example Source**	**Size Range**	**Shape / Morphology**	**Common Polymer Composition**	**Typical Environmental Behavior**
Primary	Cosmetics (microbeads), industrial abrasives, plastic pellets (nurdles)	<5 mm	Spherical, granular, fibrous	Polyethylene (PE), Polypropylene (PP), Polystyrene (PS)	Often suspended in water, widely dispersed
Primary	Synthetic fibers from textiles (e.g., polyester)	<5 mm	Fibrous	Polyester, Nylon	Remain suspended or settle depending on density
Secondary	Plastic bottles, fishing nets, packaging	Variable, <5 mm after degradation	Irregular, fragmented	Varies—PE, PP, PET, etc.	Accumulates in sediments, bioavailable to fauna

2.2. Behavior, Transport, and Fate in Marine and Freshwater Systems

Microplastics exhibit complex behavior in aquatic environments, and their movement and persistence are influenced by factors such as size, density, and surface characteristics. The behavior of microplastics varies greatly depending on their physical properties [12]. For instance, smaller microplastics tend to remain suspended in the water column, while larger particles may sink to the sediments. The buoyancy of microplastics is also influenced by the chemical composition of the polymer, with some types being more likely to float on the surface or aggregate with other particles [12-15].

Understanding the movement of microplastics through various environmental compartments is crucial for assessing their ecological impact. After their release into the environment through domestic, industrial, and agricultural activities, microplastics are subject to complex transport dynamics involving wind dispersal, runoff, river transport, and tidal deposition. These pathways determine their distribution across soils, freshwater, and marine environments, influencing their persistence and interactions with biota. The schematic below provides a comprehensive overview of the major pathways and processes involved in the environmental transport and fate of microplastics across terrestrial and aquatic systems (Figure 1).

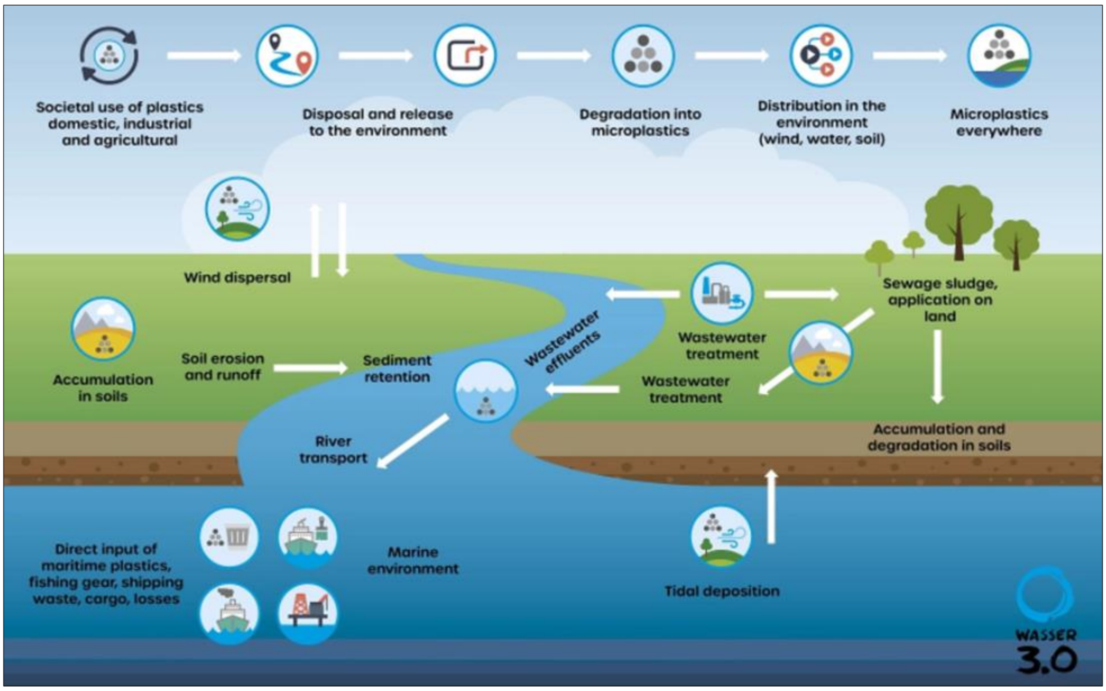

Figure 1 Pathways and Fate of Microplastics in Terrestrial and Aquatic Ecosystems. Reproduced with permission from ref. [13]

Once introduced into the aquatic environment, microplastics can be transported over long distances by ocean currents, rivers, and wind [16]. Studies have shown that microplastics are found in remote regions of the ocean, far from their source of origin. They can be carried from urban areas to the open sea, highlighting the widespread nature of the contamination. In freshwater systems, microplastics are similarly transported by rivers and streams, accumulating in areas such as riverbeds, wetlands, and lakes [16-18].

The fate of microplastics in marine and freshwater systems depends on their interaction with environmental processes and biota. Over time, microplastics may accumulate in the sediments or be ingested by marine organisms. In some cases, these particles can enter the food chain, leading to bioaccumulation and biomagnification. The persistence of microplastics in the environment is concerning, as they resist natural degradation processes, and their presence in ecosystems can last for hundreds of years [19-20].

Recent studies have provided important insights into the behavior and transport of microplastics in aquatic systems. For instance, according to research by Coyle et al. [21], microplastics have been found to accumulate in marine sediments and riverbeds, where they pose a threat to benthic organisms. In addition, microplastics' ability to adsorb toxic substances, such as persistent organic pollutants (POPs), increases their ecological risk, as these chemicals may be released into organisms when ingested, leading to toxic effects [21].

2.3. Ecological and Health Risks to Organisms and Humans

Microplastic pollution in aquatic ecosystems presents significant ecological and health risks to both organisms and humans. For aquatic organisms, the ingestion of microplastics is a major concern. Many marine and freshwater species, including fish, shellfish, and invertebrates, mistake microplastics for food, leading to internal injuries, digestive blockages, and impaired feeding [22]. The ingestion of microplastics can also affect growth, reproduction, and survival, as evidenced by studies on fish populations that have shown reduced growth rates and reproductive success following microplastic exposure [22,23].

The ingestion of microplastics can also result in the bioaccumulation of toxic chemicals present on the plastic's surface. These chemicals, which may include heavy metals, pesticides, and other pollutants, can leach into the organisms' tissues, leading to adverse health effects [24]. This is of particular concern in marine ecosystems, where microplastics can enter the food chain and accumulate in higher trophic levels. In the case of apex predators, such as marine mammals, the effects of microplastic ingestion may have severe consequences for species health and population sustainability [25].

For humans, the primary route of exposure to microplastics is through the consumption of contaminated seafood, particularly fish and shellfish [26]. In recent years, studies have shown that microplastics are present in commercially important seafood species, raising concerns about human health risks [26-28]. In addition to ingestion, humans can be exposed to microplastics through drinking water, where microplastic particles have been detected in both bottled and tap water globally. Some researchers have even suggested that inhalation of airborne microplastic fibers could pose a health risk, especially in areas with high levels of industrial plastic processing or waste incineration [29-31].

The potential health risks to humans from microplastic exposure are still under investigation, but early studies suggest that microplastics may cause inflammation, oxidative stress, and immune system dysfunction. According to a study by Akbari & Jaafari [20], the ingestion of microplastics has been linked to inflammation in laboratory animals, suggesting that chronic exposure may lead to more serious health conditions. Moreover, the presence of toxic chemicals adsorbed onto microplastics could contribute to long-term health risks, including endocrine disruption, reproductive toxicity, and cancer.

2.4. Gaps in Traditional Monitoring and Control Strategies

Monitoring and controlling microplastic pollution in aquatic ecosystems has proven to be a challenging task due to several limitations in traditional methods [32]. One major challenge is the lack of standardized monitoring protocols for microplastics, which makes it difficult to compare results across studies. The diversity in size, shape, and polymer type of microplastics requires the use of specialized detection methods, many of which are still in the developmental stage. Traditional sampling methods, such as trawling nets and surface water collection, are often insufficient for capturing smaller microplastics or those that are buried in sediments [33-35].

Furthermore, the global scale of microplastic pollution presents significant logistical challenges for monitoring efforts. Microplastics are widely distributed across marine and freshwater systems, often in remote or difficult-to-reach areas. Effective monitoring requires a large-scale and coordinated approach, with regular sampling in both high-traffic and remote regions. However, the cost and complexity of such monitoring programs are substantial, limiting their feasibility [34,36].

In terms of control strategies, traditional efforts have largely focused on reducing plastic waste inputs into the environment, such as banning single-use plastics and improving waste management systems. While these efforts are important, they have been insufficient to address the already existing pollution in aquatic ecosystems. The lack of effective removal technologies, particularly for microplastics in wastewater, remains a significant obstacle [37,38]. Advances in filtration and treatment technologies, such as the development of microplastic capture systems in wastewater treatment plants, are needed to reduce microplastic contamination at its source [38].

A study by Choudhury et al. [18] emphasized the need for more comprehensive and effective mitigation measures, suggesting that both prevention and active removal strategies are necessary to address microplastic pollution. The development of novel techniques, including the use of artificial intelligence (AI) for monitoring and predicting microplastic distribution, represents a promising area of research. These technologies could provide more efficient, cost-effective, and widespread solutions to microplastic pollution control [18].

3. Role of Artificial Intelligence in Environmental Monitoring

Artificial intelligence (AI) has brought transformative changes to environmental monitoring, particularly in the detection and analysis of microplastic pollution in aquatic ecosystems. AI technologies, including machine learning (ML), deep learning (DL), and computer vision, are revolutionizing the way researchers and environmental scientists study and address microplastic pollution [39,40]. These technologies enhance data processing, enable real-time monitoring, and allow for the efficient classification and tracking of microplastic contamination across large geographical areas. Additionally, AI-driven systems are able to process vast amounts of data from various sources, including remote sensing, drones, underwater imaging, and sensor networks, providing researchers with valuable insights that would be difficult or impossible to obtain using traditional methods [41,42].

3.1. AI Subfields Relevant to Microplastics

AI subfields, such as machine learning (ML), deep learning (DL), and computer vision, have been crucial in the development of more effective systems for monitoring and detecting microplastics in aquatic environments [43]. Machine learning encompasses a wide range of algorithms that can be trained to detect patterns and make predictions from data. This capability is particularly useful for classifying microplastics from other environmental debris. ML algorithms, such as decision trees, random forests, and support vector machines, have been applied to environmental data to differentiate microplastics based on specific features such as size, shape, and texture [31]. These machine learning algorithms are especially beneficial in automating the analysis of large datasets, reducing human error and the time required for data processing.

Deep learning, a subset of machine learning, utilizes neural networks with multiple layers to learn complex patterns in data. Convolutional neural networks (CNNs) are especially prominent in deep learning applications for microplastic detection. These networks are trained on large datasets of images to detect microplastics in various environmental contexts, such as satellite imagery, underwater photos, and drone footage. DL models, particularly CNNs, have demonstrated high accuracy in identifying microplastic particles, even in challenging environments where microplastics are visually similar to other materials like organic debris [39]. The use of deep learning in microplastic detection has the potential to revolutionize how large-scale environmental monitoring efforts are carried out, by providing high-speed, automated solutions for continuous data analysis.

Computer vision, another critical AI subfield, is designed to enable machines to interpret and understand visual information from the world around them. In the context of microplastic pollution, computer vision algorithms are applied to interpret visual data obtained from underwater cameras, drones, or satellites. These systems analyze images to detect microplastic debris, classifying them according to various characteristics such as shape, size, and texture. By automating the image analysis process, computer vision significantly reduces the need for manual intervention, enabling continuous, real-time monitoring of aquatic ecosystems [40]. This application of computer vision plays a crucial role in detecting microplastics that may not be easily identified through traditional monitoring methods. Table 2 summarizes the major artificial intelligence techniques applied in microplastic monitoring, mapping each to their specific applications, data requirements, strengths, and case study examples drawn from recent literature.

Table 2 AI Techniques and Their Application to Microplastic Monitoring

AI Technique	Application	Data Type Used	Strengths	Limitations	Case Study Reference
Machine Learning (SVM, Random Forest)	Classification of microplastics vs non-plastics	Imaging, spectral data	High accuracy, interpretable models	Requires feature engineering, sensitive to noisy data	[48]
Deep Learning (CNN)	Image-based detection of microplastics	Drone/underwater/satellite imagery	Automated feature learning, high accuracy	Data-intensive, opaque decision-making	[39]
Computer Vision	Visual identification and classification	Camera/drone footage	Real-time processing, scalable	Limited by image quality, lighting	[47]
Predictive Modeling (ML/DL)	Forecasting microplastic movement and distribution	Historical pollution data, environmental variables	Supports preventive action	Requires continuous data input	[49]

3.2. Data Sources: Remote Sensing, Drones, Underwater Imaging, Sensor Networks

AI applications for microplastic detection depend heavily on the integration of diverse data sources. Remote sensing, a key technology in environmental monitoring, allows for the collection of large-scale data from satellite and aerial imagery. Satellite-based remote sensing provides high-resolution images that are essential for identifying microplastic particles on the ocean surface or in large freshwater bodies. AI-powered image classification models are used to analyze these images, providing insights into the concentration and distribution of microplastics across vast regions [44]. Remote sensing enables the monitoring of large aquatic ecosystems that may otherwise be inaccessible, offering an efficient and cost-effective solution for global-scale microplastic surveillance.

Drones have become increasingly popular for collecting environmental data in both marine and freshwater ecosystems. Equipped with high-resolution cameras and sensors, drones capture detailed images and videos of water bodies, which are then analyzed using machine learning and computer vision algorithms. Drones are particularly valuable in hard-to-reach areas where traditional monitoring techniques may be limited. Their mobility and ability to gather real-time data make them an indispensable tool for monitoring microplastic pollution [45,46]. Additionally, drones provide researchers with the ability to collect high-quality data across a range of geographic locations, offering a broader scope for monitoring microplastic pollution in diverse ecosystems.

Underwater imaging technologies, such as sonar systems and underwater robots, are crucial for detecting microplastics that are not visible from the surface. These technologies allow for the collection of detailed data on submerged microplastics that may be suspended in the water column or embedded in the sediments. AI algorithms can process this data to identify microplastic particles based on their size, shape, and other physical characteristics [47,48]. Furthermore, sensor networks deployed in aquatic environments provide real-time data on environmental conditions, such as temperature, water quality, and particle concentrations. When combined with AI-based systems, these sensor networks improve the accuracy and efficiency of microplastic detection by providing continuous, high-frequency data [49]. A concise overview of the various AI-integrated data sources used in microplastic detection is provided in Table 3, detailing the tools, application environments, and technological limitations associated with each method.

Table 3 Summary of AI-Integrated Data Sources for Microplastic Detection

Data Source	Example Device/Tool	Resolution / Sensitivity	Application Environment	Role in AI-Based Analysis	Limitations
Remote Sensing	PRISMA Satellite, Sentinel-2	Up to 30m (optical), spectral bands	Marine	Broad spatial monitoring, used in CNNs for classification	Limited to surface plastics, cloud interference
Drones	DJI Phantom with multispectral sensors	High-resolution images (cm level)	Freshwater & Coastal	Used for real-time microplastic spotting via image processing	Battery limits, small area coverage
Underwater Imaging	ROVs with optical cameras	High resolution (mm scale)	Deep sea & lake beds	Detailed close-up classification with AI	Limited by visibility, costly
Sensor Networks	In-situ turbidity/fluorescence sensors	Real-time particulate matter	Rivers, treatment plants	Feeds ML models for trend analysis	Non-specific signal, maintenance needs

3.3. Application to Microplastic Detection

AI technologies have found widespread application in the detection of microplastics, particularly in areas such as image recognition, hyperspectral and multispectral data classification, and predictive modeling.

Image recognition, facilitated by deep learning algorithms like CNNs, is one of the most powerful applications of AI in microplastic detection. In recent studies, CNNs have been successfully applied to classify and detect microplastic particles in images obtained from drones, satellites, and underwater cameras. By training CNN models on large datasets of labeled images, these algorithms can identify microplastics with high accuracy, even when they are mixed with other types of marine debris [39]. This application allows for the automation of image processing, reducing the need for manual inspections and speeding up the analysis process.

Hyperspectral and multispectral data classification techniques are becoming increasingly important for microplastic detection, particularly in marine environments. These imaging techniques capture data across multiple wavelengths of light, allowing for the identification of materials based on their unique spectral signatures. When combined with AI algorithms, hyperspectral and multispectral data can be analyzed to differentiate microplastics from natural particles or sediments. These AI models are particularly useful in detecting microplastics that are invisible to the naked eye or that may be submerged beneath the surface of the water [44]. The ability to analyze multispectral and hyperspectral data through AI-powered systems enables more accurate and comprehensive monitoring of microplastic pollution.

Predictive modeling and pattern recognition, powered by machine learning and deep learning, have also become essential tools in the study of microplastics. AI models can be trained to recognize patterns in historical environmental data, allowing for predictions about the movement and accumulation of microplastics in aquatic ecosystems. By combining predictive models with real-time sensor data, researchers can better understand microplastic distribution dynamics and predict where future contamination may occur [49]. These models are particularly useful for long-term monitoring efforts, providing valuable insights into the effectiveness of mitigation strategies and helping policymakers make informed decisions about managing microplastic pollution.

3.4. Case Studies/Examples from Recent Literature

Recent case studies illustrate the significant impact AI has had in advancing microplastic detection. Studies by Hamzah et al. [45] and Maharjan et al. [50] demonstrated the use of drones equipped with machine learning models to detect microplastics in freshwater environments. By analyzing images captured by the drones, the machine learning algorithms were able to detect microplastic particles with high precision. This study highlights the potential of drone-based AI systems in detecting microplastics in hard-to-reach areas and offers a practical solution for real-time environmental monitoring.

Another notable example comes from Hu et al. [39], who utilized deep learning algorithms to analyze satellite imagery for large-scale monitoring of oceanic microplastics. Their study showed how AI-powered image recognition could be applied to satellite data to track microplastic pollution across the world's oceans. This approach allowed for the identification of areas with high concentrations of microplastics, providing critical information for marine conservation efforts and policy-making.

In a study conducted by Taggio et al. [47], hyperspectral imaging and machine learning algorithms were used to detect microplastics in marine environments. By analyzing hyperspectral images, the researchers were able to identify microplastic particles that were not visible using traditional methods. This study demonstrated the power of AI and hyperspectral technology in overcoming the limitations of visual detection and improving the accuracy of microplastic monitoring.

4. AI-Driven Mitigation Strategies and Sustainable Interventions

Artificial intelligence offers transformative potential in developing mitigation strategies for microplastic pollution, enabling targeted, efficient, and scalable interventions. AI-driven solutions are revolutionizing the monitoring, prediction, and management of microplastics, with applications ranging from optimizing waste management processes to advancing recycling technologies [51,52]. Through predictive modeling, AI enhances the ability to foresee areas with high contamination risks, allowing for preemptive actions that minimize environmental damage. Additionally, AI facilitates the design of sustainable interventions by streamlining waste collection and treatment processes and supporting circular economy initiatives that aim to reduce plastic production and consumption. These AI-based strategies align with broader environmental sustainability goals and demonstrate the promising role of technology in mitigating the pervasive issue of microplastic pollution [4,53].

4.1. Autonomous Robotics and Underwater Vehicles for Cleanup

The integration of autonomous robotics and underwater vehicles in microplastic cleanup efforts presents a groundbreaking approach to combating pollution in aquatic ecosystems. These robotic systems, equipped with AI technologies, enable precise detection, collection, and removal of microplastics from both freshwater and marine environments [54]. The development of these systems has been driven by the need for scalable, efficient, and sustainable solutions capable of operating in challenging aquatic environments where traditional methods are ineffective. Autonomous underwater vehicles (AUVs) equipped with advanced sensors, such as optical and infrared imaging systems, facilitate real-time monitoring of pollution levels, identifying microplastic concentrations with high accuracy [55,56]. These technologies can also be designed to perform cleanup tasks autonomously, reducing the need for human intervention in dangerous or remote locations.

AI plays a central role in optimizing the efficiency of these robots, using machine learning algorithms to process data from sensors and adapt to varying environmental conditions. These systems are capable of distinguishing between microplastics and other organic or inorganic materials, ensuring that only harmful pollutants are targeted for removal. Additionally, the deployment of autonomous vehicles reduces operational costs and labor intensity, enabling continuous and large-scale cleaning operations. The combination of AI and robotics in underwater cleanup is also fostering the development of intelligent navigation systems that can autonomously map and chart polluted areas, adjusting their cleaning routes to maximize efficiency [54].

Robotic cleanup technologies are being tested in a variety of aquatic environments, with several pilot projects successfully employing AI-driven solutions for the removal of microplastics from rivers, lakes, and oceans. These AI-integrated robots not only provide a significant reduction in pollution but also promote the sustainability of aquatic ecosystems by preventing the accumulation of plastics in sensitive areas. The capability of these robots to collect plastic debris at a high rate and in difficult-to-reach locations offers a novel solution that aligns with long-term environmental conservation efforts [57,58].

4.2. AI-Optimized Bioremediation and Filtration Systems

AI-optimized bioremediation and filtration systems present an innovative approach to tackling microplastic pollution by enhancing natural processes and improving the efficiency of filtration technologies. Machine learning models are increasingly utilized to analyze large datasets, which help identify the most effective microbial strains capable of breaking down microplastics. Through AI, the environmental conditions required for optimal microbial activity can be precisely controlled, resulting in more efficient degradation of microplastics in aquatic ecosystems. These AI-driven systems can also monitor real-time data from sensors embedded in water bodies to assess the degradation process, predict future outcomes, and adjust conditions accordingly, thereby maximizing the effectiveness of bioremediation efforts [59,60].

In parallel, AI plays a crucial role in enhancing filtration systems designed to capture microplastics from water sources. Advanced filtration techniques, such as membrane-based filtration and electrostatic separation, can be optimized through AI algorithms that analyze water flow, pressure, and particle size distribution in real-time. These AI systems can dynamically adjust filter parameters, improving the capture rates of microplastics while minimizing energy consumption and operational costs [59]. By combining AI with filtration technologies, the overall efficiency of microplastic removal is significantly improved, making it possible to scale these systems for widespread use in water treatment facilities.

The integration of AI into both bioremediation and filtration not only enhances the effectiveness of these systems but also contributes to the sustainability of aquatic ecosystems. AI algorithms assist in the identification of areas most affected by microplastic pollution, enabling targeted interventions. Furthermore, the combination of bioremediation with filtration systems ensures that microplastics are not only broken down but also physically removed from the environment. This multi-layered approach provides a promising pathway for mitigating microplastic contamination in aquatic environments while contributing to long-term environmental sustainability goals [61].

4.3. Wastewater Treatment Plant (WWTP) Monitoring and Process Optimization

AI plays a significant role in optimizing the operations of wastewater treatment plants (WWTPs), crucial for reducing microplastic contamination in aquatic ecosystems. Machine learning algorithms can be employed to enhance the detection of microplastics in wastewater by integrating sensor data with real-time analysis, improving the efficiency and effectiveness of filtration systems. Advanced AI-driven models analyze large datasets from sensors placed throughout the treatment process, identifying patterns in microplastic presence and behavior. These insights enable the fine-tuning of operational parameters, such as flow rates, chemical dosing, and filtration methods, to ensure higher removal efficiency of microplastics from wastewater before discharge into water bodies [39,62].

The application of AI in process optimization extends beyond monitoring; predictive models can anticipate variations in influent water quality, allowing for adjustments in treatment protocols. For instance, AI can predict fluctuations in the concentrations of microplastics based on historical data and environmental factors, enabling operators to adapt treatment schedules accordingly. This proactive approach not only enhances the removal efficiency but also minimizes energy consumption, thereby contributing to the overall sustainability of the WWTP. Studies have highlighted the integration of AI models in monitoring and controlling biological and chemical processes within WWTPs, leading to significant improvements in both cost-effectiveness and performance [61,63].

AI-powered optimization techniques also foster the development of closed-loop systems in WWTPs, where waste byproducts are reused or repurposed, contributing to circular economy goals. By improving the overall efficiency of these plants, AI reduces the operational costs and environmental footprint of wastewater treatment processes, while simultaneously curbing the release of microplastics into the ecosystem. Furthermore, these AI tools can be integrated with real-time environmental monitoring systems, which, in turn, helps in ensuring compliance with water quality regulations and contributes to overall environmental sustainability [64].

4.4. Role of AI in Lifecycle Analysis and Circular Economy Strategies

Artificial intelligence plays a crucial role in supporting lifecycle analysis (LCA) and advancing circular economy strategies aimed at mitigating microplastic pollution. By employing machine learning algorithms, AI can track the entire lifecycle of plastics from production and usage to disposal and recycling. This data-driven approach enables more accurate assessments of the environmental impact of various plastic materials, including their breakdown into microplastics. AI-powered models can analyze large datasets, identifying critical points where interventions can reduce waste generation or improve recycling efficiency [65]. Additionally, AI facilitates the integration of waste management systems with circular economy principles by optimizing recycling processes, making them more efficient, and reducing reliance on virgin plastic production.

AI-driven technologies can also improve the design of sustainable materials, promoting the creation of products that are easier to recycle and have lower environmental impacts throughout their lifecycle. AI algorithms assess material properties, consumer usage patterns, and recycling capabilities to identify innovative materials that reduce the generation of microplastics [66,67]. These solutions can support circular economy goals by ensuring a closed-loop system where plastics are continuously reused, recycled, or upcycled, minimizing environmental harm. Furthermore, AI supports circular economy business models by providing predictive analytics that guide resource recovery processes and streamline the flow of materials across the production and consumption stages [68,69]. These strategies align with sustainable development goals and contribute to the reduction of plastic waste entering aquatic ecosystems. To compare the emerging AI-driven mitigation approaches, Table 4 outlines the key strategies, their technological maturity, AI functions, and the corresponding environmental and operational benefits and limitations.

Table 4 Comparative Assessment of AI-Driven Mitigation Strategies

Strategy Type	Description	AI Role	Technological Readiness Level (TRL)	Benefits	Challenges / Limitations
Autonomous Robotics	Underwater or surface robots to collect microplastics	Navigation, object detection & mapping	TRL 6–7 (pilot stage)	Continuous, non-human intervention	Costly, energy-demanding
AI-Optimized Bioremediation	Microbial degradation of plastics	Optimize microbial activity using ML	TRL 4–5 (experimental)	Eco-friendly, scalable	Slow, needs ideal conditions
Filtration Systems	Advanced physical removal (e.g., membranes)	AI regulates flow & efficiency	TRL 7–8	High capture rate	Maintenance intensive
WWTP Process Optimization	Enhanced treatment processes	Predict influent variation, optimize settings	TRL 8–9	Boosts removal rates, reduces cost	Requires sensor network
Lifecycle/Circular Economy Models	Tracking plastic from production to disposal	AI for pattern detection and system modeling	TRL 5–6	Supports recycling innovation	Needs robust data, regulatory alignment

5. Challenges, Limitations, and Ethical Considerations

The application of artificial intelligence (AI) in addressing microplastic pollution is not without challenges and limitations. While AI offers promising solutions, the integration of these technologies into environmental science and management requires careful consideration of data, costs, ethics, and regulatory frameworks. This section explores the key challenges that accompany the use of AI in the monitoring and mitigation of microplastic pollution.

5.1. Data Scarcity and Model Generalization Across Ecosystems

The scarcity of high-quality, comprehensive datasets presents a significant barrier to the application of AI for microplastic detection and mitigation. Microplastic pollution is highly context-dependent, varying significantly across different ecosystems, such as marine, freshwater, and terrestrial environments. AI models trained on limited or biased datasets may struggle to generalize across diverse geographical regions and environmental conditions [70]. In many cases, there is a lack of comprehensive monitoring data from remote or under-studied areas, which limits the robustness and applicability of AI models.

Moreover, the diverse nature of microplastics in terms of size, shape, composition, and sources complicates the development of AI models that can accurately identify and quantify pollution in different ecosystems [39]. The absence of a standardized and universally accepted classification system for microplastics further complicates model training. Researchers like Zarfl [71] highlight that without an exhaustive and consistent dataset, AI models risk overfitting to certain environments or types of microplastic pollution, resulting in reduced model accuracy and real-world applicability.

Lastly, data scarcity also extends to environmental monitoring technologies, such as sensors and drones, which may not provide consistent data across all regions. AI models trained with data from high-resource regions may struggle to function effectively in areas with limited technological infrastructure. This challenge demands increased investment in data collection and a more coordinated approach to data-sharing among researchers and policymakers [72,73].

5.2. High Cost and Technical Complexity of AI Solutions

The high cost and technical complexity of implementing AI-driven solutions for microplastic pollution mitigation represent significant barriers to widespread adoption. AI systems require considerable investments in hardware, software, and specialized expertise. The development of deep learning models, in particular, demands large computational resources, which can be costly and inaccessible to many environmental agencies and smaller research institutions [17,74-78]. The cost of acquiring high-resolution imagery, remote sensing data, and deploying drones or underwater robots further exacerbates these financial challenges.

Additionally, the technical complexity involved in deploying AI models in real-world environments can hinder scalability. For example, machine learning models need continuous updates to adapt to new data, requiring ongoing monitoring and maintenance. This long-term commitment to technical support and the need for specialized personnel can place a strain on institutions and organizations with limited funding. AI models also require extensive training datasets, which, as mentioned earlier, are not always available for every ecosystem, increasing both the development time and cost of AI solutions [79].

Furthermore, integrating AI technologies into existing environmental monitoring frameworks can be a complex task that requires overcoming technical challenges related to data interoperability, system integration, and automation. To address these barriers, there needs to be concerted effort in streamlining AI technologies and making them more accessible for large-scale implementation [80]. This would require not only significant financial investments but also changes in the infrastructure of environmental management systems.

5.3. Risk of Algorithmic Bias and Lack of Transparency in Decision-Making

AI models, while capable of processing vast amounts of data, are vulnerable to biases that can affect their accuracy and fairness. The risk of algorithmic bias is particularly concerning when AI is used in environmental science, where biased decision-making could lead to ineffective policies or even exacerbate environmental issues. Bias in AI models can stem from various sources, including the data used to train the models, the selection of features, and the underlying assumptions built into the algorithms [76].

In the context of microplastic pollution, biased models might prioritize pollution mitigation in areas that are already heavily studied while neglecting regions that are under-researched or that exhibit different pollution patterns. Additionally, the lack of transparency in AI decision-making processes—often referred to as the "black-box" nature of AI—further complicates efforts to ensure fairness and accountability. Decision-makers may not fully understand how AI models arrive at conclusions, making it difficult to assess their accuracy or identify potential issues [81]. Transparency in AI models is critical, particularly in environmental applications, where decisions can have significant long-term consequences on ecosystems and public health.

To address these concerns, researchers like Soundariya et al. [74] suggest the development of explainable AI (XAI), which aims to provide clearer insights into how models reach their conclusions. Ensuring transparency and reducing bias in AI algorithms is an essential step in promoting trust and accountability in AI-driven environmental strategies.

5.4. Environmental and Ethical Footprint of AI Infrastructures

The environmental impact of AI infrastructures is another critical consideration. While AI technologies offer significant benefits in environmental sustainability, the development and deployment of AI systems can have substantial environmental footprints. The training of AI models, especially those based on deep learning, requires immense computational resources that contribute to high energy consumption [82,83]. These processes, if powered by non-renewable energy sources, can exacerbate the environmental issues that AI is meant to address, creating a paradox where AI solutions might indirectly contribute to environmental degradation.

Moreover, the extraction of rare minerals and metals used in AI hardware, such as GPUs and other high-performance computing equipment, also poses environmental and ethical challenges. The mining and disposal of electronic waste can lead to additional environmental harms, including soil and water contamination [84]. These ethical considerations must be taken into account when evaluating the overall sustainability of AI solutions for microplastic pollution mitigation. The future of AI in environmental science should, therefore, focus not only on mitigating pollution but also on minimizing the ecological footprint of AI technologies themselves.

5.5. Need for Regulatory Standards and Open Datasets

As AI continues to be integrated into environmental monitoring and microplastic pollution management, the establishment of regulatory standards and the availability of open datasets become crucial. Currently, the lack of standardized practices in AI applications within environmental science leads to fragmented and inconsistent approaches. The absence of universal standards for data collection, processing, and analysis in microplastic monitoring complicates the development of global strategies to combat pollution [75].

Moreover, open access to datasets is essential for fostering collaboration and ensuring that AI models are built on diverse and representative data. Many researchers and organizations are hindered by limited access to high-quality datasets, which can impede the development of accurate and generalizable AI models. Initiatives to promote open data-sharing platforms and standardized data formats are necessary to facilitate research and innovation in AI-driven environmental solutions [77].

Regulatory frameworks must also be put in place to ensure that AI applications in environmental monitoring are safe, equitable, and aligned with sustainability goals. These regulations should address issues such as data privacy, ethical AI use, and the minimization of environmental impact from AI infrastructures [85]. By establishing clear guidelines and fostering open access to data, governments and research institutions can ensure that AI technologies are leveraged effectively and responsibly for environmental sustainability.

6. Future Research Directions

The continuous advancement of artificial intelligence (AI) technologies has opened numerous avenues for future research in mitigating microplastic pollution. The potential integration of AI with other emerging technologies, including the Internet of Things (IoT), edge computing, citizen science, and policy-driven frameworks, promises to enhance real-time monitoring, data collection, and the effectiveness of mitigation strategies. This section explores some critical future directions that will likely play a pivotal role in advancing the understanding and management of microplastic pollution in aquatic ecosystems.

6.1. Integration of AI with IoT and Edge Computing in Real-Time Monitoring

The integration of AI with IoT and edge computing holds great potential for revolutionizing the real-time monitoring of microplastic pollution. IoT devices can collect vast amounts of environmental data from various sources, including water quality sensors, remote drones, and underwater robots. These devices generate continuous streams of data, which, when coupled with AI, can provide near-instantaneous analysis, helping to detect microplastics in real-time. AI algorithms, particularly machine learning models, can analyze this data on-site through edge computing, thus reducing the dependency on cloud computing and enabling faster decision-making [86].

AI-powered IoT systems can improve monitoring networks by autonomously identifying hotspots of microplastic accumulation, pinpointing sources of contamination, and providing actionable insights. The synergy between these technologies allows for more granular and timely monitoring, which is essential for understanding the dynamics of microplastic pollution in different environments. Additionally, AI-driven predictive models can forecast future pollution trends, enabling proactive measures to reduce plastic waste before it reaches critical levels [87]. The continuous interaction between AI, IoT, and edge computing will undoubtedly shape the future landscape of microplastic detection and management, allowing for more effective and efficient mitigation strategies.

6.2. Fusion of AI with Citizen Science and Participatory Sensing

Citizen science and participatory sensing are powerful approaches for enhancing environmental monitoring. By integrating AI with these methods, it becomes possible to engage the public in large-scale data collection efforts while leveraging their collective knowledge for more accurate and inclusive environmental monitoring. Citizen scientists, equipped with mobile apps, sensors, and AI-powered tools, can report sightings of microplastics, track their own consumption patterns, and even assist in data analysis. This democratization of scientific inquiry fosters widespread awareness and action towards combating microplastic pollution [88].

AI can help organize, process, and analyze the data collected through citizen science, improving the quality of the information gathered. With advanced machine learning techniques, AI systems can correct errors, identify patterns in citizen-generated data, and provide real-time feedback to participants, thereby enhancing the reliability of the monitoring efforts. The fusion of AI with citizen science can also lead to the development of more localized and context-specific data, which is critical in understanding the regional variation in microplastic pollution [89]. By bridging the gap between technology and community participation, AI-powered citizen science initiatives will significantly contribute to the larger environmental sustainability movement and help track the effectiveness of mitigation strategies.

6.3. Multimodal Systems: Combining Imaging, Spectroscopy, and Machine Learning

Future research should focus on combining multiple data collection methods such as imaging, spectroscopy, and machine learning to create multimodal systems capable of providing highly accurate, comprehensive, and scalable microplastic detection solutions. Imaging technologies, such as optical and electron microscopy, allow for high-resolution identification of microplastic particles, while spectroscopy methods, including Raman and FTIR spectroscopy, can identify the chemical composition of these particles [90]. The integration of these techniques with machine learning models enhances their detection capabilities by enabling the automation of image and spectral data analysis, facilitating the classification of microplastics from other materials in complex aquatic environments.

Multimodal systems powered by AI have the potential to significantly improve the sensitivity and specificity of microplastic detection. By combining multiple data sources, AI can generate a more robust understanding of microplastic contamination, helping to identify particles of various sizes, shapes, and compositions. Moreover, these systems can be used in real-time, allowing for quicker responses to microplastic pollution and more effective tracking of contamination over time. The fusion of imaging, spectroscopy, and AI will provide researchers and policymakers with the necessary tools to devise precise, data-driven strategies for managing microplastic pollution at both local and global scales [91].

6.4. Transdisciplinary Collaboration (Environmental Science, Computer Science, Policy)

Transdisciplinary collaboration is essential for addressing the complex, multifaceted challenges of microplastic pollution. The integration of environmental science, computer science, and policy development will create synergies that can drive innovative solutions. Environmental scientists bring deep knowledge of ecosystems, pollutants, and their impacts on marine and freshwater environments, while computer scientists can develop the necessary AI algorithms and systems to monitor, detect, and model microplastic pollution. Policymakers play a crucial role in translating scientific findings into actionable laws, regulations, and strategies that can reduce plastic waste and mitigate its environmental effects [92].

Collaboration across these disciplines allows for the development of AI-powered tools that are both scientifically sound and aligned with regulatory requirements. A concerted effort from these sectors can lead to the creation of global databases, integrated monitoring platforms, and policy frameworks that are informed by cutting-edge AI technologies. Transdisciplinary research will help identify practical solutions for scaling microplastic mitigation strategies and ensuring they are incorporated into national and international policies on waste management and environmental sustainability [4,93,94]. Moving forward, fostering a culture of collaboration among experts from diverse fields will be pivotal in addressing the growing threat of microplastic pollution.

6.5. Policy-Driven AI Frameworks for Microplastic Governance

The development of AI frameworks tailored to microplastic governance is a crucial aspect of future research. These frameworks will guide the implementation of AI-based technologies in environmental policy, helping to create standardized, transparent, and accountable systems for monitoring and mitigating microplastic pollution. Governments and international organizations must integrate AI into existing regulatory frameworks, ensuring that its applications are consistent with international environmental agreements, such as the United Nations Sustainable Development Goals (SDGs) [95]. AI-based policy frameworks can support decision-making by providing real-time data, predictive insights, and transparent reporting on microplastic pollution levels.

Furthermore, AI can be utilized to enhance compliance with existing regulations by enabling more efficient monitoring of waste disposal and recycling practices. Machine learning models can identify patterns of non-compliance or inefficiencies in waste management systems, thus facilitating more effective enforcement of policies. These AI-driven policy frameworks could also incorporate adaptive learning, where policies evolve based on new data and insights gained from ongoing monitoring. By embedding AI in microplastic governance, policymakers will be able to respond more rapidly and effectively to the increasing environmental threat posed by microplastics [4]. As AI-driven frameworks gain traction, they will support a more data-driven, proactive approach to managing plastic pollution at local, national, and global levels.

7. Conclusion

The mounting challenge of microplastic pollution in aquatic ecosystems demands innovative and multidisciplinary approaches to mitigate its pervasive impact. This review has explored the significant role of artificial intelligence (AI) in enhancing the detection, monitoring, and management of microplastics, shedding light on its potential to transform environmental science. By integrating AI technologies such as machine learning, deep learning, and computer vision with data sources like remote sensing, drones, and underwater imaging, it becomes possible to create more efficient, accurate, and real-time monitoring systems. These AI-driven solutions hold promise not only for detecting microplastics in diverse environments but also for driving predictive modeling and improving decision-making in mitigation strategies.

Furthermore, the role of AI in sustainable interventions, such as lifecycle analysis and circular economy strategies, is pivotal in reshaping waste management practices and fostering a more sustainable relationship with our natural resources. By leveraging AI's capabilities in environmental monitoring, researchers and policymakers can develop adaptive, data-driven frameworks that facilitate informed decisions and promote environmental sustainability.

While considerable progress has been made, several challenges remain, particularly in bridging the gaps in traditional monitoring techniques and fostering collaboration across disciplines. Future research should focus on advancing the integration of AI with IoT and edge computing, enhancing citizen science, and developing multimodal systems that combine diverse data sources for comprehensive microplastic monitoring. Additionally, the establishment of policy-driven AI frameworks will be critical to governing microplastic pollution and ensuring that mitigation efforts are both effective and equitable.

As AI continues to evolve, its potential in addressing microplastic pollution will only grow, offering promising avenues for sustainable interventions and effective governance. Collaboration among environmental scientists, computer scientists, policymakers, and the public will be crucial in realizing the full potential of AI to safeguard aquatic ecosystems and achieve long-term environmental sustainability. Ultimately, AI represents a transformative tool in the global effort to combat microplastic pollution, providing the technological foundation for more resilient and sustainable ecosystems in the future.

Compliance with ethical standards

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The authors declare that they have no conflict of interest to be disclosed.

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