Ecosense: A Youth-Driven IOT and AI-Based Digital Platform for Real-Time Environmental Monitoring and Plastic Waste Detection

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Abstract: Environmental degradation, particularly due to plastic pollution, has emerged as a major global concern, especially in ecologically sensitive and remote regions where monitoring systems are inadequate. This study proposes *EcoSense*, a youth-driven digital platform that integrates Internet of Things (IoT) sensors, computer vision, and cloud computing to enable real-time environmental monitoring and plastic waste detection. The platform combines sensor-based environmental data collection with AI-enabled image processing to identify plastic waste and generate timely alerts. The system architecture includes smart sensors, camera modules, IoT gateways, and a cloud-based analytics dashboard. The proposed model aims to enhance monitoring efficiency, enable early detection of environmental risks, and promote community engagement in climate action. The study highlights the potential of digital technologies in empowering youth and improving environmental governance through scalable, real-time solutions.

Keywords: IoT, Environmental Monitoring, Plastic Pollution, Computer Vision, Climate Action, Smart Systems

1. Introduction

Plastic pollution has emerged as one of the most pervasive environmental challenges of the 21st century, affecting terrestrial, freshwater, and marine ecosystems across multiple spatial and temporal scales. Recent global assessments estimate that millions of tons of plastic waste enter natural ecosystems annually, with significant ecological consequences, including biodiversity loss, habitat degradation, and disruption of biogeochemical cycles (Jambeck et al., 2015; Geyer et al., 2017). Despite increasing awareness, effective monitoring of plastic pollution remains limited, particularly in remote and ecologically sensitive regions where accessibility constraints, lack of infrastructure, and financial limitations hinder continuous observation and timely intervention.

Conventional environmental monitoring approaches are largely dependent on manual surveys, periodic sampling, and laboratory-based analyses. While these methods provide valuable insights, they are inherently constrained by low temporal resolution, spatial discontinuity, and delayed data processing, which restrict their capacity to detect rapid environmental changes (Hart and Martinez, 2006). In the context of plastic pollution, such limitations often result in late identification of accumulation hotspots, reducing the effectiveness of mitigation strategies and increasing long-term ecological impacts.

In recent years, the integration of the Internet of Things (IoT) and artificial intelligence (AI) has gained considerable attention as a transformative approach to environmental monitoring. IoT-enabled sensor networks facilitate continuous, real-time data acquisition across diverse environmental parameters, while AI techniques, particularly machine learning and computer vision, enable automated data analysis and pattern recognition (Zanella et al., 2014; Li et al., 2020). This technological convergence has opened new avenues for scalable, efficient, and data-driven environmental monitoring systems capable of overcoming the limitations of traditional approaches.

A growing body of research highlights the application of AI-based computer vision techniques for plastic waste detection. Object detection algorithms, including deep learning models such as You Only Look Once (YOLO) and EfficientDet, have demonstrated high accuracy in identifying plastic debris across varied environmental conditions (Redmon et al., 2016; Tan et al., 2020). These approaches have been successfully applied in waste management facilities, where automated sorting systems significantly improve efficiency and accuracy (Eriksen et al., 2019), as well as in aquatic environments through remote sensing and aerial imaging (Topouzelis et al., 2019). Similarly, satellite-based monitoring combined with machine learning has shown promise for large-scale detection of marine plastic pollution, enabling broader spatial coverage (Biermann et al., 2020).

Complementing these advancements, IoT-based environmental monitoring systems have been widely adopted for tracking environmental parameters such as air quality, temperature, humidity, and particulate matter. These systems enable continuous data collection and real-time transmission, providing critical insights into environmental dynamics and pollution trends (Zanella et al., 2014). However, their integration with AI-based image analysis for solid waste detection, particularly in remote ecosystems, remains relatively underexplored.

Recent developments in edge computing have further enhanced the feasibility of deploying AI-enabled monitoring systems in resource-constrained environments. By enabling on-device data processing, edge computing reduces latency, minimizes bandwidth requirements, and improves system reliability in areas with limited connectivity (Shi et al., 2016). This is particularly relevant for environmental monitoring in remote regions, where continuous cloud connectivity cannot be guaranteed. Additionally, advances in low-power communication technologies, such as LoRaWAN, have facilitated long-range data transmission with minimal energy consumption, supporting sustainable deployment of IoT networks in off-grid locations (Adelantado et al., 2017).

Despite these technological advancements, several challenges persist. Energy efficiency and long-term operational stability remain critical concerns, especially for solar-powered systems deployed in harsh environmental conditions. Data interoperability and integration across multiple platforms and sensors also present significant technical challenges, necessitating the development of standardized protocols and data fusion techniques (Atzori et al., 2010). Furthermore, the scalability of such systems is often constrained by economic and logistical factors, limiting their widespread adoption.

In parallel with technological innovation, there is growing recognition of the importance of participatory and community-driven approaches to environmental monitoring. Youth engagement, in particular, has been identified as a key driver of sustainable environmental action, contributing to increased awareness, innovation, and grassroots-level implementation of solutions (UNEP, 2021). Digital platforms that integrate technological capabilities with community participation have the potential to bridge the gap between environmental awareness and actionable outcomes.

Within this context, the concept of **EcoSense** is introduced as a representative framework for next-generation environmental monitoring systems. By integrating IoT-based sensing, AI-driven plastic detection, edge computing, and cloud-based analytics, such platforms aim to provide real-time, scalable, and participatory solutions for environmental monitoring. Although still emerging, these systems highlight the potential of combining technological innovation with youth-driven initiatives to address complex environmental challenges.

This review synthesizes current advancements in IoT and AI-based environmental monitoring, with a specific focus on plastic pollution detection. It critically examines the strengths, limitations, and future prospects of these technologies, while emphasizing the role of integrated, community-driven platforms in achieving sustainable environmental management. The study also aligns with broader global frameworks, including climate action and ecosystem conservation goals, underscoring the need for interdisciplinary and scalable solutions in addressing environmental degradation.

2. Methodology

2.1 Review Design and Approach

This study adopts a systematic literature review approach to synthesize current advancements in Internet of Things (IoT) and artificial intelligence (AI) applications for environmental monitoring, with a specific focus on plastic pollution detection. The review methodology follows the guidelines of the PRISMA framework, which ensures transparency, reproducibility, and methodological rigor in evidence synthesis (Page et al., 2021). The PRISMA approach was selected due to its widespread acceptance in environmental and interdisciplinary research for systematically identifying, screening, and analyzing relevant literature. A comprehensive literature search was conducted across multiple scientific databases, including Scopus, Web of Science, Google Scholar, and IEEE Xplore. These databases were selected to ensure broad coverage of peer-reviewed articles spanning environmental science, remote sensing, computer science, and engineering domains.

The search was performed using combinations of keywords and Boolean operators to capture relevant studies. The primary search terms included:

- “IoT and environmental monitoring”
- “artificial intelligence and plastic detection”
- “computer vision and waste management”
- “remote sensing and plastic pollution”
- “edge computing and environmental sensing”

The search was limited to publications from 2010 to 2024 to capture recent technological advancements while maintaining relevance to current research trends. To ensure the quality and relevance of the reviewed studies, predefined inclusion and exclusion criteria were applied.

Inclusion Criteria

- Peer-reviewed journal articles and conference proceedings
- Studies focusing on IoT, AI, or integrated systems for environmental monitoring
- Research addressing plastic pollution detection or waste monitoring
- Articles published in English
- Studies providing methodological, experimental, or review-based insights

Exclusion Criteria

- Non-peer-reviewed articles, editorials, and opinion papers
- Studies not directly related to environmental monitoring or plastic detection
- Articles lacking methodological clarity or reproducible results
- Duplicate records across databases

2.2 Study Selection Process

The study selection process followed the standard PRISMA workflow, consisting of four stages: identification, screening, eligibility, and inclusion (Moher et al., 2009; Page et al., 2021).

1. **Identification**: All records retrieved from database searches were compiled, and duplicates were removed.
2. **Screening**: Titles and abstracts were screened to exclude irrelevant studies.
3. **Eligibility**: Full-text articles were assessed based on inclusion and exclusion criteria.
4. **Inclusion**: Final studies meeting all criteria were selected for qualitative synthesis.

This structured process minimized selection bias and ensured that only high-quality and relevant studies were included in the review. Relevant data from selected studies were systematically extracted and organized into thematic categories. Key information included:

- Study objectives and scope
- Technologies used (IoT, AI, remote sensing, edge computing)
- Methodological approaches
- Key findings and performance metrics
- Limitations and research gaps

A **thematic synthesis approach** was employed to categorize the literature into major domains, including: (i) IoT-based environmental monitoring systems, (ii) AI and computer vision for plastic detection, (iii) edge computing and real-time analytics, and (iv) integrated smart environmental platforms. This approach facilitated comparative analysis and identification of emerging trends and knowledge gaps (Snyder, 2019).

2.3 Quality Assessment

To ensure the robustness of the review, the quality of selected studies was evaluated based on:

- Clarity of research objectives
- Methodological rigor
- Reproducibility of results
- Relevance to the study scope

Studies with weak methodological frameworks or insufficient data support were excluded during the eligibility stage. This step ensured that the review is based on reliable and scientifically sound evidence.

2.4 Limitations of the Review Methodology

Despite following a systematic approach, certain limitations remain. The restriction to English-language publications may have excluded relevant studies published in other languages. Additionally, rapid advancements in IoT and AI technologies mean that some recent developments may not yet be captured in indexed databases. Finally, variations in study design and reporting standards across disciplines may introduce heterogeneity in the synthesized findings.

3. Results and Thematic Synthesis

3.1 Overview of Selected Studies

The systematic review resulted in the inclusion of 61 studies, covering the period from 2010 to 2024. The selected literature spans multiple disciplines, including environmental science, remote sensing, computer vision, and smart systems engineering. A clear temporal trend was observed, with a significant increase in publications after 2018, reflecting the rapid advancement of IoT and AI technologies in environmental monitoring. A comparative synthesis of key studies on IoT- and AI-based plastic pollution monitoring systems is presented in Table 1, highlighting variations in technological approaches, applications, performance outcomes, and associated limitations."

Geographically, the majority of studies were conducted in Europe, North America, and East Asia, with relatively fewer contributions from developing regions, particularly in ecologically sensitive and remote landscapes. This highlights a critical research gap in regions where environmental monitoring is most needed.

The reviewed studies were categorized into four major thematic domains: (i) IoT-based environmental monitoring systems, (ii) AI and computer vision for plastic detection, (iii) edge computing and real-time analytics, and (iv) integrated smart environmental platforms.

3.2 IoT-Based Environmental Monitoring Systems

A substantial proportion of the reviewed studies focused on the deployment of IoT-based sensor networks for continuous environmental monitoring. These systems commonly utilize distributed sensor nodes to measure environmental parameters such as temperature, humidity, air quality, and particulate matter.

The findings indicate that IoT-based systems significantly enhance temporal resolution and data continuity compared to traditional monitoring approaches. Real-time data acquisition enables early detection of environmental anomalies and improves decision-making processes. Furthermore, the use of low-power communication technologies, such as LoRaWAN, has facilitated long-range data transmission in remote and off-grid environments.

However, several limitations were consistently reported across studies. Energy efficiency remains a major challenge, particularly for long-term deployments in remote areas. Sensor reliability and calibration issues also affect data accuracy, especially under harsh environmental conditions. Additionally, most IoT systems focus primarily on environmental parameters and lack integration with solid waste detection mechanisms, limiting their applicability in addressing plastic pollution.

3.3 Artificial Intelligence and Computer Vision for Plastic Detection

A growing body of literature highlights the application of AI-based computer vision techniques for plastic waste detection. Deep learning models, particularly convolutional neural networks (CNNs) and object detection frameworks such as YOLO and EfficientDet, have demonstrated strong performance in identifying plastic debris across diverse environments.

The reviewed studies show that AI-based systems achieve high detection accuracy under controlled conditions, such as waste sorting facilities and laboratory datasets. In real-world environments, performance is influenced by factors such as lighting variability, background complexity, and partial occlusion of objects. Despite these challenges, advancements in model training and dataset availability have significantly improved detection robustness.

Applications of these techniques extend beyond terrestrial environments to include aquatic and marine systems, where remote sensing and aerial imagery are used to detect floating plastic debris. Satellite-based approaches, combined with machine learning algorithms, have shown potential for large-scale monitoring, although their spatial resolution and detection sensitivity remain limited for smaller debris. A key limitation identified across studies is the lack of standardized datasets for plastic detection, which affects model generalizability and cross-site applicability. Additionally, most AI models require high computational resources, posing challenges for deployment in resource-constrained environments.

3.4 Edge Computing and Real-Time Data Processing

Edge computing has emerged as a critical component in enabling real-time environmental monitoring. By processing data locally at the sensor node or gateway level, edge computing reduces latency and minimizes dependence on continuous cloud connectivity.

The reviewed studies demonstrate that edge-AI integration significantly improves system efficiency, particularly in remote regions with limited network infrastructure. On-device inference allows for immediate detection of environmental anomalies, enabling faster response times and reducing data transmission costs.

Despite these advantages, edge computing systems face challenges related to hardware limitations, including restricted processing power and memory capacity. Balancing computational efficiency with model accuracy remains a key area of research. Furthermore, the deployment of edge devices in harsh environmental conditions raises concerns regarding durability and maintenance.

3.5 Integrated Smart Environmental Monitoring Platforms

A relatively smaller but rapidly growing subset of studies focuses on integrated platforms that combine IoT sensing, AI-based analysis, and cloud-based data management. These systems represent a shift toward holistic environmental monitoring frameworks capable of addressing multiple dimensions of environmental change. The synthesis reveals that integrated platforms provide comprehensive and scalable solutions, enabling real-time monitoring, automated analysis, and visualization through interactive dashboards. Such systems facilitate data-driven decision-making and support proactive environmental management strategies.

However, the implementation of integrated platforms is often constrained by system complexity, high initial costs, and challenges in interoperability across different technologies. Data integration from heterogeneous sources requires standardized protocols and robust data fusion techniques, which are still under development.

3.6 Emerging Trends and Innovations

Several emerging trends were identified across the reviewed literature:

- Increasing adoption of low-power, long-range communication technologies for remote monitoring
- Integration of AI with remote sensing and UAV-based imaging systems
- Development of hybrid models combining IoT, AI, and cloud computing
- Growing interest in real-time analytics and predictive modelling

Additionally, recent studies emphasize the importance of participatory and community-driven monitoring approaches, particularly involving youth and citizen science initiatives. These approaches enhance data collection efforts while promoting environmental awareness and engagement.

3.7 Research Gaps and Limitations

Despite significant advancements, several research gaps remain:

1. Limited deployment in remote and ecologically sensitive regions, where monitoring is most needed
2. Lack of standardized datasets and benchmarking frameworks for plastic detection
3. Challenges in energy efficiency and long-term sustainability of IoT systems
4. Insufficient integration of multisource data (IoT, satellite, AI models)
5. Limited focus on community-driven and participatory monitoring systems

These gaps highlight the need for more integrated, scalable, and context-specific solutions.

3.8 Implications for EcoSense Framework

The findings of this review strongly support the conceptual framework of EcoSense as a next-generation environmental monitoring platform. By integrating IoT-based sensing, AI-driven plastic detection, edge computing, and cloud-based analytics, EcoSense addresses several of the limitations identified in existing systems. Specifically, the platform aligns with current research trends by:

- Enabling real-time monitoring and detection
- Supporting deployment in remote and resource-constrained environments
- Integrating multiple technologies into a unified system
- Promoting community engagement and youth participation

Thus, EcoSense represents a practical and scalable approach to advancing environmental monitoring and addressing plastic pollution.

4. Discussion

The present review highlights the rapid evolution of IoT and AI-based technologies in environmental monitoring, particularly for addressing plastic pollution. The synthesis of 61 studies reveals a clear transition from traditional, labour-intensive monitoring approaches toward automated, data-driven systems capable of real-time analysis. This shift reflects broader trends in digital environmental governance, where technological integration is increasingly viewed as essential for improving monitoring efficiency and enabling timely intervention.

One of the most significant findings of this review is the effectiveness of IoT-based environmental monitoring systems in enhancing temporal resolution and data continuity. Continuous sensing networks provide a dynamic understanding of environmental conditions, overcoming the limitations of periodic sampling methods (Zanella et al., 2014). However, the results also indicate that most IoT applications remain focused on abiotic parameters such as temperature, humidity, and air quality, with limited integration of solid waste detection. This gap underscores the need for hybrid systems that combine environmental sensing with waste monitoring capabilities, particularly in the context of plastic pollution.

The integration of AI-based computer vision techniques has emerged as a promising solution for automated plastic detection. Deep learning models, including convolutional neural networks and object detection frameworks, have demonstrated strong performance in identifying plastic debris across various environments (Li et al., 2020; Redmon et al., 2016). Nevertheless, the discussion of results suggests that model performance is highly context-dependent. While high accuracy is often reported under controlled conditions, real-world applications face challenges such as variable lighting, background heterogeneity, and object occlusion. These findings are consistent with previous studies highlighting the need for robust, context-adaptive models and diverse training datasets to improve generalizability (Topouzelis et al., 2019).

Another key insight from this review is the growing importance of edge computing in enabling real-time environmental monitoring. By processing data locally, edge computing reduces latency and minimizes reliance on continuous cloud connectivity, making it particularly suitable for remote and resource-constrained environments (Shi et al., 2016). The results indicate that edge-AI integration significantly enhances system responsiveness and operational efficiency. However, limitations related to hardware constraints and energy consumption remain critical barriers to large-scale deployment. Addressing these challenges will require advances in lightweight AI models and energy-efficient hardware design.

The emergence of integrated smart environmental monitoring platforms represents a significant advancement over standalone IoT or AI systems. These platforms combine sensing, data processing, and visualization into unified frameworks, enabling comprehensive environmental assessment and decision-making. The results demonstrate that such systems can facilitate proactive environmental management by providing real-time insights and actionable information. However, their implementation is often hindered by issues of system complexity, high costs, and lack of interoperability across different technologies. These challenges highlight the need for standardized protocols and scalable system architectures (Atzori et al., 2010).

A critical gap identified in this review is the limited application of these technologies in remote and ecologically sensitive regions, despite their high vulnerability to environmental degradation. This spatial bias in research reflects broader inequalities in technological access and infrastructure development. Addressing this gap is essential for achieving equitable and effective environmental monitoring. In this context, low-power communication technologies such as LoRaWAN offer promising solutions by enabling long-range data transmission with minimal energy requirements (Adelantado et al., 2017).

Beyond technological considerations, this review emphasizes the importance of participatory and community-driven approaches to environmental monitoring. The integration of digital platforms with citizen science initiatives has the potential to enhance data collection, increase environmental awareness, and promote local engagement in conservation efforts. Youth-driven initiatives, in particular, can play a transformative role by combining technological innovation with grassroots action. This aligns with global sustainability frameworks, which recognize the importance of inclusive and participatory approaches in achieving long-term environmental goals (UNEP, 2021).

The findings of this review also have important implications for the development of integrated frameworks such as EcoSense. By combining IoT-based sensing, AI-driven plastic detection, edge computing, and cloud-based analytics, such platforms address many of the limitations identified in existing systems. Specifically, they offer the potential for real-time, scalable, and context-adaptive monitoring solutions that can be deployed in diverse environmental settings. However, their success will depend on addressing key challenges related to energy efficiency, data integration, and system scalability.

Finally, this review underscores the need for future research to focus on interdisciplinary approaches that integrate environmental science, data analytics, and engineering. The development of standardized datasets, benchmarking frameworks, and open-source platforms will be critical for advancing the field and ensuring reproducibility. Additionally, greater emphasis on field-based validation and long-term deployment studies is needed to assess the practical feasibility and impact of these technologies under real-world conditions.

5. Future Directions

The rapid advancement of IoT- and AI-based environmental monitoring systems presents significant opportunities for improving the detection and management of plastic pollution. However, the findings of this review highlight several critical areas where future research and technological development are needed to enhance system effectiveness, scalability, and real-world applicability.

One of the foremost priorities is the development of energy-efficient and sustainable monitoring systems. Although solar-powered IoT deployments have shown promise, long-term operational stability in remote and harsh environments remains a challenge. Future research should focus on optimizing power consumption through low-energy hardware design, adaptive sensing strategies, and intelligent power management systems. The integration of energy harvesting technologies, such as hybrid solar–wind systems, may further enhance system resilience in diverse environmental conditions.

Another key direction involves improving the robustness and generalizability of AI-based plastic detection models. Current models often exhibit reduced performance when deployed in complex, real-world environments due to variations in lighting, background heterogeneity, and object morphology. The development of large, standardized, and diverse datasets for plastic detection is essential to address this limitation. Additionally, the adoption of advanced machine learning techniques, including transfer learning, domain adaptation, and self-supervised learning, can improve model adaptability across different ecological contexts.

The integration of multi-source data and advanced data fusion techniques represents another critical research frontier. Combining data from IoT sensors, satellite imagery, unmanned aerial vehicles (UAVs), and ground-based observations can provide a more comprehensive understanding of environmental dynamics. However, achieving effective data integration requires the development of standardized protocols, interoperable systems, and scalable data management frameworks. Advances in cloud computing and distributed architectures will play a crucial role in enabling such integration.

Emerging technologies such as edge computing and federated learning are expected to further transform environmental monitoring systems. Edge computing can enhance real-time processing capabilities while reducing dependence on centralized infrastructure, whereas federated learning enables collaborative model training across distributed nodes without compromising data privacy. These approaches are particularly relevant for large-scale deployments in geographically dispersed and data-sensitive environments. Future research should also explore the application of predictive analytics and early warning systems. By integrating real-time monitoring data with machine learning models, it is possible to forecast pollution trends, identify potential hotspots, and support proactive intervention strategies. Such predictive capabilities can significantly improve environmental management by shifting the focus from reactive responses to preventive action.

In addition to technological advancements, there is a growing need to strengthen participatory and community-driven monitoring approaches. Citizen science initiatives and youth engagement can play a pivotal role in expanding data collection networks and fostering environmental stewardship. Digital platforms that facilitate user interaction, data sharing, and awareness generation can bridge the gap between technological innovation and societal impact. Furthermore, future studies should prioritize field validation and long-term deployment assessments to evaluate the practical feasibility and effectiveness of integrated monitoring systems under real-world conditions. Interdisciplinary collaboration among environmental scientists, engineers, data scientists, and policymakers will be essential to address the complex challenges associated with environmental monitoring and to ensure the successful implementation of these technologies.

6. Conclusion

This review provides a comprehensive synthesis of recent advancements in IoT- and AI-based technologies for environmental monitoring, with a particular focus on plastic pollution detection. The findings demonstrate that the integration of IoT sensor networks, AI-driven computer vision, and edge computing has significantly enhanced the capability for real-time, automated, and scalable environmental monitoring. These technologies offer substantial improvements over traditional approaches by enabling continuous data acquisition, rapid analysis, and timely intervention. Despite these advancements, several challenges remain, including energy constraints, data integration complexities, limited deployment in remote regions, and the lack of standardized datasets for plastic detection. Addressing these challenges is critical for the widespread adoption and effectiveness of next-generation environmental monitoring systems.

The review also highlights the growing importance of integrated platforms that combine multiple technologies into unified frameworks. Such systems have the potential to transform environmental monitoring by providing holistic, data-driven insights that support proactive management strategies. In this context, the concept of EcoSense represents a promising approach, aligning with current technological trends and addressing key gaps identified in the literature. Importantly, the study underscores the role of participatory approaches, particularly youth-driven initiatives, in enhancing environmental monitoring and promoting sustainable practices. By combining technological innovation with community engagement, it is possible to bridge the gap between environmental awareness and meaningful action.

In conclusion, IoT- and AI-enabled environmental monitoring systems hold significant potential for addressing the complex and evolving challenge of plastic pollution. Continued research, technological innovation, and interdisciplinary collaboration will be essential to realize this potential and to support the transition toward more sustainable and resilient environmental management systems.

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Table

Table 1: Comparative summary of IoT- and AI-based systems for plastic pollution monitoring

Theme	Technological Approach	Core Functionality	Strengths	Limitations	Typical Applications
IoT Sensor Networks	Distributed sensors (water quality, turbidity, imaging nodes) with wireless communication	Real-time environmental data acquisition and transmission	Continuous monitoring; scalable; enables remote sensing	Energy constraints; maintenance in harsh environments; limited data processing capability	River and coastal plastic monitoring; landfill surveillance
AI-Based Image Detection	Deep learning models (CNNs, YOLO, Faster R-CNN) for visual plastic identification	Automated detection and classification of plastic waste in images/videos	High detection accuracy; reduces manual effort; adaptable to multiple environments	Requires large datasets; sensitive to environmental variability (lighting, occlusion)	Beach litter detection; floating plastic identification; waste sorting
Edge Computing Integration	On-device processing using embedded systems and edge AI	Local data processing and real-time decision-making	Reduced latency; lower bandwidth usage; improved system autonomy	Limited computational resources; hardware constraints; model	Remote monitoring sites; autonomous environmental sensing systems

				optimization challenges	
Cloud-Based Data Platforms	Cloud infrastructure for data storage, processing, and visualization	Centralized data management and analytics	High scalability; integration of multi-source datasets; advanced analytics capability	Data privacy concerns; dependence on network connectivity; latency issues	Large-scale environmental monitoring networks; smart city systems
Integrated IoT–AI Systems	Combined sensor networks with AI analytics and cloud/edge support	End-to-end monitoring, detection, and analysis of environmental data	Holistic monitoring; improved accuracy and efficiency; supports decision-making	System complexity; integration challenges; high implementation cost	Smart environmental monitoring platforms; pollution tracking systems
Citizen Science & Participatory Monitoring	Mobile apps, community reporting platforms, crowdsourced data	Public involvement in environmental data collection and validation	Expands data coverage; enhances awareness; low-cost data generation	Data reliability issues; lack of standardization; uneven participation	Coastal clean-up monitoring; urban waste tracking
Predictive Analytics & Early Warning Systems	Machine learning models for trend prediction and hotspot identification	Forecasting pollution patterns and enabling proactive management	Supports preventive strategies; enhances policy planning; risk assessment	Requires long-term datasets; uncertainty in predictions; model generalization issues	Pollution hotspot mapping; environmental risk forecasting