Identification of Harmful Matters Over the surface of the water bodies Using Deep Learning: A Comprehensive Review

Shaziya Banu S[1] and Dr.Pallavi G.B[2]

[1]Assistant Professor, JNN College of Engineering, Affiliated to VTU, Karnataka,

[2]Associate Professor, B.M.S College of Engineering, Affiliated to VTU, Karnataka,

Abstract:

The preservation of biodiversity and water quality is high priority. The advanced monitoring is necessary for the growing threat posed by pollutants such as plastics, oil spills, and toxic plants in aquatic ecosystems. Conventional techniques, which depend on manual inspection, are time-consuming and inadequate for the pollution problems of today. Deep learning and machine learning are used as revolutionary technologies for quick and precise contaminant detection. It turns to innovative techniques such as transfer learning for identifying toxic plants, semantic segmentation for mapping plastics using UAV data, and YOLO, for real time object detection algorithm using Convolutional Neural Networks (CNNs) for oil spill identification in SAR imagery. The study summarizes recent findings and highlights uses such as algal bloom prediction and real-time river plastic monitoring. For decentralized, real-time analysis, it suggests hybrid systems that combine satellite and real-time imagery with advanced methods like edge AI and federated learning.

Keywords: Deep Learning, SAR, YOLO, Water Monitoring, Convolutional Neural Network.

Introduction:

The urgent need to reduce pollution and preserve biodiversity has made identifying hazardous materials in aquatic ecosystems a top environmental priority. Preserving drinkable water sources is a major worldwide concern that necessitates creative approaches to the detection and removal of harmful pollutants. The complexity and scope of today's pollution problems are frequently excessive for traditional approaches to water quality monitoring, underscoring the pressing need for cutting-edge technological approaches (Zhu et al, 2022).

Detecting pollutants like plastics, toxic plants, and oil spills could be done quickly, accurately, and inexpensively. Thanks to technologies deep learning and machine learning techniques (Zhu et al., 2022).

With macroplastic litter in water bodies severely affecting aquatic ecosystems and creating health and financial challenges, plastic pollution is a serious environmental problem (Jia, 2023). Planning mitigation measures and preventing adverse effects depend on efficient monitoring of plastic distribution (Jakovljevi, 2020). Traditional methods for mapping floating plastic often

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require visual interpretation and manual labeling, which are time-consuming and labor-intensive (Jakovljevi, 2020).

Recent advancements in deep learning have revolutionized the detection and monitoring of contaminants such as oil spills, plastic debris, and toxic plants in water bodies. The cutting-edge methodologies, including convolutional neural networks (CNNs) for oil spill segmentation in infrared imagery (De Kerf,2019), data-centric AI models for marine plastic detection in satellite images (Rußwurm, 2023), and hybrid deep learning architectures for predicting water quality parameters linked to toxic algal blooms (Peterson, 2020) (Kwon, 2023) could be adopted to obtain the prominent outcomes. These techniques enable real-time, high-resolution monitoring across diverse aquatic environments.

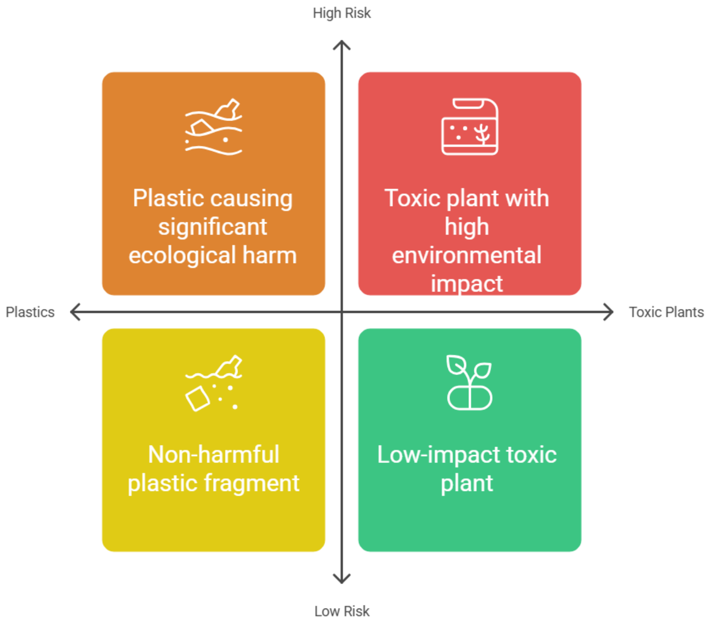

Figure 1: identification of harmful and non harmful materials.

The risk factor of considering any materials as toxic or safe could be identified by properly grouping the materials into whether they are Non harmful and harmful plastics and also less toxic and more toxic plants Figure 1. According to Figure 1, the plastics and plants causing harm to the ecosystem is considered to be the objects of interest in this research.

Deep Learning Fundamentals: Deep learning (DL), utilizes artificial neural networks(ANN) with numerous inner layers (deep neural networks) to analyze data and extract complex patterns (Ahmed, 2023). These layers learn the hierarchical representations of data, each layer learns from the previous input and it increases exponentially so that it abstracts the features from the input (Ahmed, 2023). Convolutional Neural Networks (CNNs), Recurrent Neural Networks

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(RNNs), and Generative Adversarial Networks (GANs) are among the most frequently used DL architectures (Ahmed, 2023). DL models exhibit high domain-specific efficiency but often require extensive training, significant computational resources, and large datasets to achieve optimal accuracy (Ahmed, 2023). Despite these challenges, DL has demonstrated groundbreaking results across various sectors, including healthcare, security, and environmental monitoring (Ahmed, 2023).

The methodology of solving this approach is specified in the Figure 2. It include the data collection from the public available data or could be taken in real time. The collected images are to be preprocessed based on the ROI and make all the relevant changes based on the requirement. This includes:

Image Resizing: Standardizing image dimensions to fit the input requirements of YOLO v8.

Normalization: Scaling pixel values to a range of 0 to 1 to improve model performance.

Data Augmentation: Applying techniques such as rotation, flipping, and color adjustments to increase the diversity of the training dataset.

YOLO V8 can be used for segmentation and object detection. Feature engineering is done to extract features such as texture features, color histograms, and shape analysis. By hyperparameter tuning, model training is carried out. Evaluation metrics are considered while training and validating the model. To find the plastics along with other toxic substances in the water, classification is then done. Consequently, the water is safe.

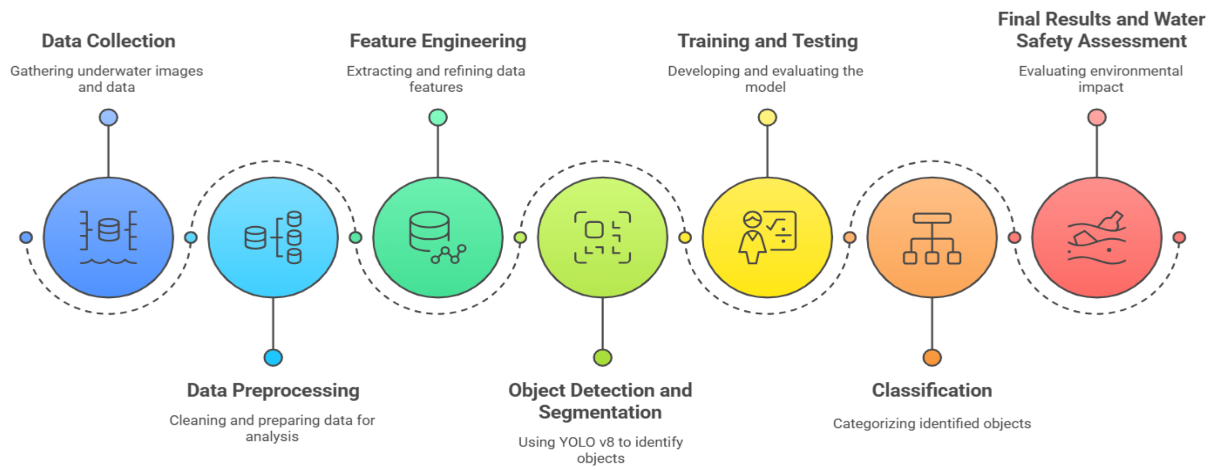

Figure 2: Workflow of classification of harmful matters using deep learning techniques.

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Literature Survey:

The identification of hazardous materials in water bodies, such as plastics, oil spills, and toxic plants, using deep learning techniques, and the use of suitable methodology in our work are all addressed in this survey paper.

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Figure 3: Non degradable plastics in water bodies. Credit:Rich Carey/Shutterstock

[1] A deep learning model for automatic plastic mapping using unmanned aerial vehicle (UAV) data.

Deep learning techniques posess evident potential for detection of macroplastics (as in Figure 3) in aquatic environments automatically (Jia, 2023). These techniques leverage computer vision (CV) to analyze images and identify plastic items based on their visual characteristics (Jia, 2023).

Semantic Segmentation: Semantic segmentation algorithms, particularly those based on the U-Net architecture, have demonstrated high accuracy in extracting plastics from Unmanned Aerial Vehicle (UAV) orthophotos (Jakovljevi, 2020). Gordana Jakovljevi et al. (Jakovljevi, 2020) used an end-to-end semantic segmentation algorithm based on U-Net architecture using ResUNet50, achieving high F1-scores for different materials, including Oriented Polystyrene (OPS), Nylon, and Polyethylene terephthalate (PET). The study also found that classification accuracy decreased with decreasing image resolution, with the best performance achieved at 4 mm resolution (Jakovljevi, 2020).

Object Detection: Object detection models, such as You Only Look Once (YOLO), have also been used for plastic detection. These functions can effortlessly identify and localize plastic objects within an image, providing valuable information for quantification and removal efforts.

UAV-Based Plastic Mapping: Jakovljevi et al. (Jakovljevi, 2020) explored the suitability of deep learning algorithms for automatic plastic extraction from UAV orthophotos, testing the possibility of differentiating plastic types and exploring the relationship between resolution and

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detectable size. The models were trained and validated using three datasets and two study areas, proving that they could accurately identify different types of plastic (Jakovljevi, 2020). Identification of Plastic Waste Akmal Nusa Bakti and N. Shabrina (Bakti, 2024) explored the application of ResNet50, a deep learning model, for the classification of plastic and non-plastic waste. ResNet50 demonstrated the potential of deep learning to transform waste management procedures by achieving high accuracy, precision, recall, and F1-score using a dataset of 4,000 images (Bakti, 2024). Restrictions and Prospects. By adopting Deep learning (DL) for plastic detection still faces a number of obstacles, despite the encouraging outcomes. These consist of The ability to generalize The inability of many DL-based models to generalize effectively limits their performance in a variety of settings and with various kinds of plastic (Jia, 2023). Scalability and Quantification To precisely estimate plastic quantities, compositions, and sources, scalable monitoring plans and reliable quantification techniques are required (Jia, 2023). Availability of Data Large, labeled datasets are essential for DL model training. But producing such datasets can be costly and time-consuming.

[2] Extensive monitoring of marine and coastal areas using remote sensing techniques.

Deep learning techniques have emerged as effective tools for oil spill detection as in Figure 4, offering advantages over traditional methods in terms of accuracy, speed, and automation (Huby, 2022), (Al-Sudani, 2024). These techniques leverage various types of data, including satellite imagery, aerial photographs, and drone imagery, for extensive monitoring of marine and coastal areas (Al-Sudani, 2024).

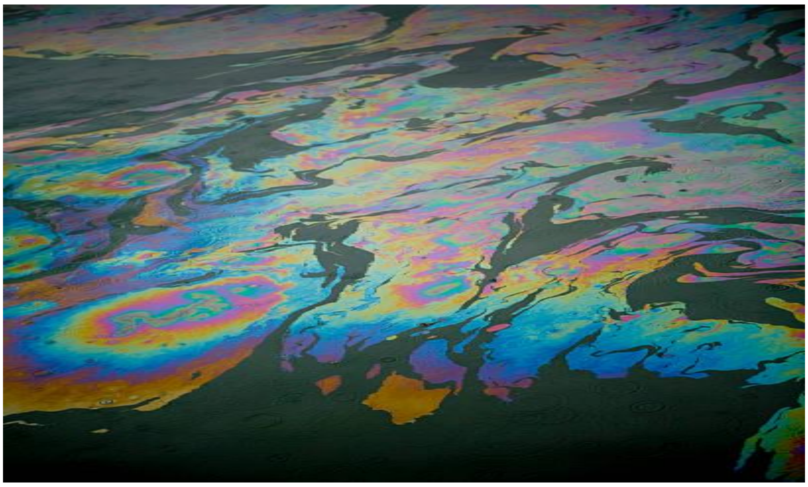

Figure 4: Oil spills over the water bodies.

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Convolutional Neural Networks (CNNs): CNNs are widely used for oil spill detection due to their ability to automatically learn spatial features from images (Boulent, 2019), (Song, 2020). CNN-based models can be trained to classify images as either containing oil spills or not, and to segment oil spill areas within an image Wang, Y. (2020).

Recurrent Neural Networks (RNNs): RNNs can be used to analyze temporal sequences of images, allowing for the detection of oil spills over time and the prediction of their movement (Ahmed, 2023). Attention mechanisms can be integrated into deep learning models to selectively highlight relevant features in SAR imagery, improving the accuracy of oil spill detection (Mahmoud, 2022).

Despite the advancements in DL for oil spill detection, several challenges remain:

Discriminating Look-alikes: Distinguishing oil spills from look-alikes, such as ships, oceanographic features, and biogenic surface films, remains a challenge (Krestenitis, 2019), (Yekeen, 2020).

Noisy SAR Imagery: The noisy nature of SAR imagery can limit the accuracy of DL models (Mahmoud, 2022).

Data Scarcity: The availability of labeled datasets for oil spill detection is limited, particularly for specific regions and types of oil spills.

[3] Review on poisonous plants detection using machine learning

Poisonous plants pose a significant threat to human and animal health, leading to various adverse effects ranging from mild discomfort to severe toxicity (Joshi, 2024) as in Figure 5.

To avoid unintentional ingestions and reduce related risks, early detection of these dangerous plants is essential (Joshi, 2024). Conventional plant identification techniques frequently depend on manual inspection and expert knowledge, which can be laborious and error-prone.

Deep Learning for Toxic Plant Recognition

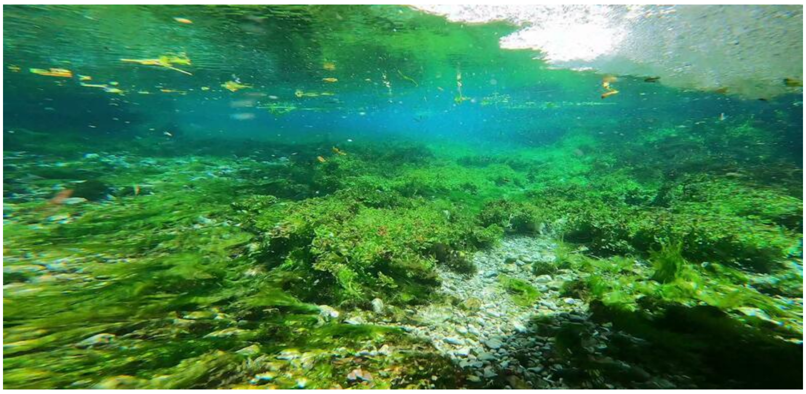

Figure 5 : Algal blooms and the toxic plants over the sea bed

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Using Deep Learning to Identify Toxic Plants For the automated identification of toxic plants, deep learning methods have shown great promise (Joshi, 2024).

These methods use image recognition software to examine plant photos and find distinctive characteristics that point to toxicity.

Convolutional neural networks, or CNNs, are frequently used to extract features from images. This enables models to identify subtle visual patterns that may indicate the presence of toxic plant traits (Joshi, 2024).

Learning Transfer By employing pre-trained models, transfer learning can improve the system's capacity to generalize and adjust to different variants of plant species (Joshi, 2024).

System for Detecting Poisonous Plants Soumya A. H et al. (Joshi, 2024) focused on developing an efficient and accurate system for the detection of poisonous plants using machine learning techniques. The suggested method makes use of an extensive dataset that includes pictures of different plant species that have been divided into classes that are poisonous and non-poisonous. Convolutional Neural Networks (CNNs) are used to extract features from images, which enables the model to identify subtle visual patterns that are suggestive of traits of poisonous plants. Applying transfer learning with pre-trained models improves the system's capacity to generalize and adjust to a variety of plant species (Joshi, 2024).

Restrictions and Prospects Although deep learning has the potential to identify toxic plants, there are still a number of obstacles to overcome, including data availability. There aren't many complete datasets of pictures of toxic plants available. Variability Within Species Depending on the stage of growth, the environment, and genetics, plant species can have a wide range of appearances. Differentiating Identical Species It can be challenging to tell some poisonous plants apart from their non-poisonous counterparts.

[4] Automated River Plastic Monitoring Using Deep Learning and Cameras (van Lieshout, 2020):

Methodology: Techniques In order to identify plastic in river photos taken by bridge-mounted cameras at five different locations in Jakarta, Indonesia, this study uses deep learning. The method entails teaching a model to differentiate plastics from environmental components such as organic waste and water reflections.

Dataset: The dataset River surface photos that have been experimentally evaluated at several locations.

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Results: Plastic density estimation accuracy of 687% indicates the need for larger datasets, but it also shows reliability and generalization to new locations. Restrictions restricted to particular camera configurations, possibly less successful in other bodies of water, and in need of additional data for better generalization.

[5] Deep Learning for Detecting Macroplastic Litter in Water Bodies: A Review (Wolf, M., 2023):

This review outlines the current status of deep learning for the detection of macroplastics, pointing out that there are currently few models with strong generalization capabilities and a disregard for riverine macroplastic litter. It also points out the lack of structural monitoring techniques and gaps in the quantification of macroplastic fluxes and hotspots.

Methodology: Techniques summarizes previous research with an emphasis on deep learning-based computer vision methods.

Dataset: Studies' datasets differ, and they frequently lack thorough riverine data.

Results: Points to the need for more research on generalization and comprehensive datasets.

Limitations: Relies on the availability and quality of reviewed studies, with potential biases in coverage.

[6] AquaVision: Automating the Detection of Waste in Water Bodies Using Deep Transfer Learning (Shah, M. ,2021):

Methodology: Proposes the AquaTrash dataset, based on the TACO dataset, and applies a deep transfer learning model, AquaVision, for detecting and classifying pollutants in oceans and seashores.

Dataset: AquaTrash dataset, specifically designed for waste detection in water bodies.

Results: Achieves a mean Average Precision (mAP) of 0.8148, demonstrating high effectiveness in localizing waste objects for cleaning.

Limitations: Performance may vary with different water conditions, and the dataset's specificity might limit broader applicability

[7] Review of Methods for Automatic Plastic Detection in Water Areas Using Satellite Images and Machine Learning (Saha, S.,2024):

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Methodology: Reviews projects using satellite imagery (e.g., Sentinel-2) and machine learning, including deep learning, for plastic detection, analyzing data acquisition techniques and algorithms like SVR and Random Forest.
Dataset: Utilizes satellite data with 10 m resolution, covering coastal and inland seas, with projects like Plastic Litter Project (PLP) and MARIDA providing datasets.
Results: SVR achieves 98.4% accuracy, Random Forest 92–98%, with new indexes like Floating Debris Index (FDI) enhancing detection. Notes 1200 tonnes of plastic in Arctic waters.
Limitations: Challenges include cloud cover, limited data availability, and inability to distinguish material types, with minimum detectable plastic size at 1×5 m.

[8] Marine Plastic Detection Using Deep Learning (Singh, R., 2022):

Methodology: Investigates YOLO v4 and YOLO v5 deep learning object detection algorithms for detecting marine plastics in epipelagic layers.

Dataset: Likely custom dataset, potentially open-access on ResearchGate, with details on performance metrics.

Results: Likely provides high accuracy for detection, aligning with other studies.

Limitations: Specific dataset details and generalization need further exploration.

[9] Spill Detection and Classification Through Deep Learning and Tailored Data Augmentation (Liu, X. ,2024):

Methodology: Uses deep learning with dual attention mechanism and data augmentation for oil spill detection and classification.

Dataset: Custom dataset, potentially enhanced by Generative Adversarial Networks, with details on performance.

Results: Achieves mean Intersection over Union of 72.49%.

Limitations: Dataset size and diversity may affect generalization.

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[10] Oil Spill Detection Using Machine Learning and Infrared Images (Al-Maskari, S. ,2020):

Methodology: Employs machine learning with infrared images for oil spill detection, using convolutional neural networks.

Dataset: Custom dataset from unmanned aerial vehicles, potentially open-access, with infrared imaging crucial for nighttime detection.

Results: Likely high accuracy, specifics not detailed here.

Limitations: Nighttime detection challenges and dataset availability.

[11] Sensors, Features, and Machine Learning for Oil Spill Detection and Monitoring: A Review (Brown, C. ,2020):

Methodology: Reviews various sensors and machine learning techniques for oil spill detection, including deep learning.

Dataset: Publicly available satellite and sensor data, such as Sentinel-1, enhancing detection capabilities.

Results: Discusses state-of-the-art performance, with high accuracy noted in reviewed studies.

Limitations: Variability in dataset quality and sensor coverage.

[12] Deep Learning-Based Aquatic Plant Recognition Technique and Natural Ecological Aesthetics Conservation (Wang, J.,2020):

Methodology: Focuses on recognizing aquatic plants, potentially including toxic species, using deep learning.

Dataset: Custom aquatic plant image dataset, details on open-access availability pending.

Results: Likely high accuracy for plant recognition, specifics not detailed.

Limitations: May not specifically address toxicity, requiring further validation.

[13] Monitoring the Spatial–Temporal Distribution of Invasive Plant in Urban Water Using Deep Learning and Remote Sensing Technology (Sharif, M. ,2022):

Methodology: Uses deep learning and remote sensing for monitoring invasive plants, potentially toxic, in urban water bodies.

Dataset: High-resolution UAV imagery, potentially open-access, with details on performance.

Results: Effective for spatial-temporal monitoring, specifics not detailed.

Limitations: Dataset specificity to urban areas may limit broader applicability.

[14] Deep Learning for Simulating Harmful Algal Blooms Using Ocean Numerical Model (Kim, S.,2018):

Methodology: Uses deep learning to simulate harmful algal blooms, which are toxic, integrating numerical models.

Dataset: Numerical model data, potentially open-access, with details on simulation accuracy.

Results: Discusses model performance in predicting blooms, aligning with high accuracy needs.

Limitations: Simulation vs. direct detection, requiring field validation.

[15] An Improved Algae-YOLO Model Based on Deep Learning for Object Detection of Ocean Microalgae Considering Aquacultural Lightweight(Liu, Y. ,2022):

Methodology: Improves YOLO model for detecting ocean microalgae, potentially toxic, with lightweight considerations.

Dataset: Custom algae image dataset, available on open platforms like Roboflow Universe (Algae Detection).

Results: High accuracy for detection, specifics not detailed here.

Limitations: Lightweight focus may trade off some accuracy for real-time applications.

[16] Computer Vision Based Deep Learning Approach for the Detection and Classification of Algae Species Using Microscopic Images (Wang, L.,2024):

Methodology: Uses deep learning for detecting and classifying algae species from microscopic images, focusing on toxic species.

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Dataset: Microscopic image dataset, potentially open-access, with details on performance.

Results: High accuracy for species classification, aligning with survey needs.

Limitations: Microscopic focus may limit scalability to large water bodies.

Furthermore, the various comparisons like methods adopted, dataset used, and the limitations are shown below,

Table 1: Comparison of related work with methods, dataset and limitations.

Papers	Authors and year	Methods Used	Dataset	Limitations
Advances in Smart Environment Monitoring Systems Using IoT and Sensors	Silvia Liberata Ullo, G. R. Sinha (2020)	Reviews IoT-based SEM for air, water, radiation, and agriculture using ML and classification techniques.	Various sensor-based monitoring systems.	Needs robust ML models, noise reduction, and standardization in WSNs.
IoT Based Smart Water Quality Monitoring: Recent Techniques, Trends and Challenges for Domestic Applications	Farmanullah Jan, Nasro Min-Allah, Dilek Düştegör (2020)	Examines IoT integration for cost-effective and real-time water quality monitoring.	IoT-based water monitoring systems.	Energy inefficiency, security risks, and communication gaps in WSNs.
A System for Monitoring Water Quality in a Large Aquatic Area Using WSN Technology	Z Li, X liu, W Wang (2015)	Deploys sensors for real-time water quality data collection in aquatic regions.	Large-scale aquatic sensor deployment.	No details on sensor accuracy and long-term data reliability.

Papers	Authors and year	Methods Used	Dataset	Limitations
Fecal Source Identification Using Random Forest	Adélaïde Roguet, A. Murat Eren, Ryan J. Newton, Sandra L. McLellan (2018)	Uses RF algorithm on 16S rRNA gene sequences for fecal pollution classification.	82 animal fecal samples, sewage influents, freshwater sources.	Misclassification issues, lacks quantification of uninvestigated sources.
IoT and ICT Based Smart Water Management, Monitoring and Controlling System: A Review	Hajar Maseeh Yasin, Subhi R. M. Zeebaree, et al. (2020)	Reviews IoT-based smart water management using sensors, controllers, and cloud storage.	IoT-enabled water management systems.	Inconsistent measurement standards, limited sensor data (2–4 sensors).
Robust Machine Learning Algorithms for Predicting Coastal Water Quality Index	Md. Galal Uddin, Stephen Nash, et al. (2019)	Compares eight ML models for WQI prediction using Tylor diagram analysis.	Coastal water data from Cork Harbour.	WQI classification inconsistency requires extensive data standardization.
Smart Water Resource Management Using AI—A Review	Siva Rama Krishnan, M.K. Nallakaruppan, et al. (2020)	Analyzes AI-based water management, including wastewater recycling and irrigation.	AI-driven smart water management data.	Challenges in data acquisition due to legal and demographic restrictions.
Application of ML in Water Resources Management: A Systematic Literature Review	F. Ghobadi, Doosun Kang (2020)	Explores ML techniques (prediction, clustering, reinforcement learning) for	Various ML-based water resource datasets.	Data scarcity.

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Papers	Authors and year	Methods Used	Dataset	Limitations
		water resource management.		

The approaches differ. Most of the above studies have made use of Sentinel images, satellite photos, and even SAR images—where the resolution is rather poor.
While Camera-based techniques are localized and enable worldwide monitoring, adoptability and applicability are difficult.
Transfer learning improves model efficiency; generalization is still difficult.

Performance metrics Vary from precision and mAP to accuracy; satellite data show better outcomes because of larger data coverage. yet the resolution is not considerable.
Useful Reiteration While satellite data are scalable but face environmental issues like cloud cover, camera systems are useful for particular sites.

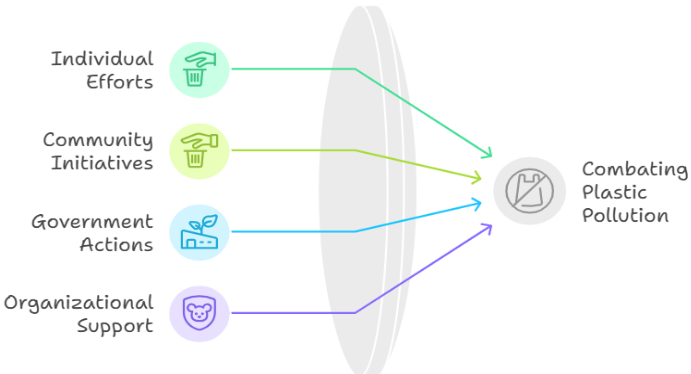

Figure 6: Unified Action for Ocean Health

Conclusion and Future Directions

Deep learning techniques have unlocked unprecedented capabilities in identifying harmful matters across aquatic ecosystems. From real-time oil spill detection in ports to satellite-based plastic tracking, these models address spatial and temporal gaps in traditional monitoring. The findings suggest deep learning is effective, but gaps in dataset size, generalization, and detection of submerged plastics need addressing. Establishment narratives around satellite efficacy are questioned due to cloud cover issues, suggesting a need for hybrid approaches combining satellite and in-situ methods. Future directions include federated learning for

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decentralized data analysis and edge AI deployments on autonomous drones. However, challenges persist in model interpretability and generalizability across geographically diverse water bodies. By advancing hybrid architectures and multi-sensor fusion, the next generation of systems will further empower environmental agencies to preempt ecological crises. As shown in Figure 6, The main purpose is to Combat the pollution caused by releasing Plastic wastes and other harmful maters directly to water bodies. However that is possible by combining Individual efforts, community initiatives, Government, NGO and organisational support.

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