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Microplastic Identification and Classification from Water Images Using YOLOv10 Architecture

Mangesh Kakasaheb Kolapkar, Sushant Prataprao Kadam, Gaurav Baburao Gade
Fargade Saurabh Anil, Prof. Bhushan Borade
Department of Computer Engineering,
Rajgad Dnyanpeeth's Shree Chhatrapati Shivajiraje College of Engineering, Pune, India
mangeshkolapkar740@gmail.com, kadamsushant760@gmail.com
gadeg6404@gmail.com, saurabhfargade0304@gmail.com

Abstract: *Microplastics, defined as plastic particles smaller than 5 mm, pose a severe environmental threat to aquatic ecosystems and human health due to their persistence and bioaccumulative nature. Traditional methods for detecting microplastics, such as spectroscopy and manual microscopy, are highly accurate but often involve complex procedures and expensive equipment and are unsuitable for real-time monitoring. To address these limitations, this paper presents PolyScan, a deep learning-based system designed for the automated detection and classification of microplastics in water using image processing techniques. The proposed system employs the state-of-the-art YOLOv10 object detection algorithm, which is optimized for real-time applications and can accurately identify microplastic particles of varying shapes and sizes. The dataset used comprises annotated images of water samples containing different types of microplastics. Image preprocessing, annotation, and data augmentation techniques are applied to enhance detection performance and robustness. Training and validation are conducted using YOLOv10-small on Google Colab, with evaluation metrics including precision, recall, F1-score, and mean average precision (mAP). Experimental results demonstrate the model's effectiveness in detecting microplastics even in visually complex water environments. A user-friendly graphical interface also enables live detection and image upload for testing, making the system accessible to researchers and environmental monitoring teams. PolyScan offers a promising solution for scalable, real-time monitoring of microplastic pollution and can be further integrated into edge devices, drones, or IoT systems for broader deployment.*

Keywords: Microplastic detection, YOLOv10, deep learning, image processing, object detection, real-time monitoring, water pollution, environmental surveillance, CNN, innovative detection systems

I. INTRODUCTION

1.1 Background and Significance

Microplastics, defined as plastic particles less than 5 mm in diameter, have emerged as one of aquatic ecosystems' most pressing environmental pollutants. These tiny plastic fragments originate from various sources, including the breakdown of larger plastic debris, industrial processes, personal care products, synthetic clothing, and vehicle tire wear. Once introduced into water bodies, microplastics can persist for hundreds of years, accumulate in aquatic organisms, and eventually enter the human food chain, posing a serious threat to biodiversity and public health.

The global production of plastic has exceeded 400 million tons annually, and it is estimated that at least 8 million tons of plastic waste enter the oceans yearly. Microplastics have been found in rivers, lakes, groundwater, and remote regions like the Arctic. This widespread distribution has made their detection and quantification critical to environmental monitoring and pollution control strategies.

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1.2 Problem Statement

Despite the growing awareness of the impact of microplastics, their detection remains a complex challenge. Traditional detection methods such as Fourier Transform Infrared Spectroscopy (FTIR), Raman Spectroscopy, and Scanning Electron Microscopy (SEM) provide accurate results but require costly equipment and skilled personnel and are time-consuming. These constraints make them unsuitable for large-scale, real-time environmental monitoring. Visual identification under microscopes is also prone to human error and subjectivity, emphasizing the need for automated, scalable solutions.

1.3 Role of Artificial Intelligence and Deep Learning

Recent advances in artificial intelligence (AI), particularly in deep learning and image processing, have revolutionized the field of environmental monitoring. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in object detection tasks, especially for identifying small, complex, or overlapping objects. These models can process large volumes of image data rapidly and with high accuracy, making them ideal candidates for microplastic detection.

Among the various object detection architectures, the "You Only Look Once" (YOLO) family of algorithms has gained significant traction due to its speed and precision. YOLOv10, the latest version, performs better in detecting small and irregularly shaped objects, making it well-suited for microplastic analysis.

1.4 Motivation for the Study

Given the global urgency to monitor and mitigate plastic pollution, there is a pressing need for low-cost, real-time detection systems that are both scalable and user-friendly. Integrating deep learning algorithms with image processing presents an opportunity to automate microplastic identification, reduce manual labor, and facilitate widespread environmental surveillance. This study aims to develop a prototype system named *PolyScan*, which leverages the YOLOv10 object detection algorithm for identifying microplastics in water samples. The system can detect and classify various forms of microplastic debris by training the model on annotated datasets of microplastic images in real time. Furthermore, the system is supported by a graphical user interface (GUI) that enables researchers to upload new images or access live detection, enhancing its accessibility and usability.

1.5 Objectives

The primary objectives of this research are:

- To design and implement a deep learning-based detection system using YOLOv10 to identify water microplastics.
- To create a structured and annotated dataset of microplastic images for training and testing.
- Preprocess and augment the dataset to improve the model's robustness against lighting, shape, size, and water clarity variations.
- The model's performance will be evaluated using precision, recall, F1-score, and mean average precision (mAP) metrics.
- To develop a graphical interface for live microplastic detection and testing.

1.6 Research Contributions

This paper presents the following contributions:

- A novel application of the YOLOv10 algorithm for high-speed, real-time microplastic detection in water environments.
- A curated dataset of annotated microplastic images with diverse features and environmental conditions.
- An efficient training and evaluation framework that ensures robustness and accuracy.
- A GUI-based system that simplifies interaction and testing for users without programming expertise.
- A scalable design that can be integrated with edge computing platforms and IoT systems for field deployment.

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1.7 Structure of the Paper

The rest of the paper is structured as follows:

Section 2 reviews the existing literature on microplastic detection and deep learning-based approaches.

Section 3 details the overall architecture and design of the proposed PolyScan system, including dataset acquisition, preprocessing, and annotation.

Section 4 explains the methodology, including the YOLOv10 training pipeline and hyperparameter tuning.

Section 5 presents the experimental results and a performance analysis of the system.

Section 6 provides conclusions and discusses the future scope of this research.

Section 7 outlines the applications and limitations of the proposed system.

II. LITERATURE SURVEY

Weber et al. (2023) took this further by introducing machine learning-based methods for analyzing MPs using mu-Raman spectroscopy. Their study explored the potential of deep learning algorithms to enhance the efficiency and accuracy of MP detection in environmental samples. By training models on a dataset of over 64,000 Raman spectra, the authors developed a method to achieve over 99% recall and 97% precision in classifying common polymers, such as polyethylene and polypropylene. This approach significantly reduced the time required for manual spectra annotation, allowing researchers to process samples more efficiently [1].

Karmakar and Jain (2023) developed a low-cost, portable device for MP detection using CNNs, specifically designed for field use in aquatic environments. Their system captures microscopic images of water samples and classifies MPs based on visual traits such as texture and color. The device achieved a classification accuracy of 97%, making it a promising tool for in-situ MP detection. The authors suggested their device could be adapted for large-scale environmental monitoring, providing a scalable solution for tracking MP pollution in various ecosystems [2].

Similarly, Dal and Kilic (2024) designed an embedded system that uses optical sensors and deep learning algorithms to detect and classify MPs based on their optical scattering properties. Their system employs multiple laser wavelengths to capture interference patterns, allowing for the accurate classification of microplastic particles of different sizes and types. With a classification accuracy of up to 100%, this system demonstrates the potential of combining optical sensing with machine learning to create highly accurate, real-time MP detection tools [3].

Juan Sarmiento, Maribel Anaya, and Diego Tibaduiza (2024) introduce a novel method for identifying and classifying microplastic particles using impedance spectroscopy combined with machine learning algorithms. Traditional methods for identifying MPs, such as Raman spectroscopy and electron microscopy, are time-consuming and require laboratory environments. In contrast, this paper presents an in situ approach that uses electronic tongue systems and impedance spectroscopy to classify microplastics in water. The researchers focused on polyethylene terephthalate (PET) particles of various sizes and demonstrated the effectiveness of machine learning models to achieve high classification accuracy. The study emphasized the need for real-time, non-destructive detection methods to provide quicker, more efficient analyses of MPs, particularly in ecosystems where water quality is crucial for human consumption and environmental health. Electrochemical sensors, including impedance spectroscopy, offer high sensitivity and selectivity, making them suitable for detecting and classifying microplastics. The integration of machine learning models enhanced the detection process, allowing the classification of microplastics based on size and material properties with high accuracy [4].

Sarah-Jeanne Royer, Helen Wolter, Astrid E. Delorme, Laurent Lebreton, and Olivier B. Poirion (2024) focus on using deep learning and image segmentation techniques to categorize microplastic debris. Traditional methods like physical sampling and manual counting are labor-intensive, subjective, and expensive. The authors propose an automated approach using deep learning models to improve the efficiency and accuracy of microplastic detection in both qualitative and quantitative assessments. Using an image segmentation model, the system achieved an accuracy of 96%, offering a robust alternative to manual identification methods. The deep learning model simplifies monitoring marine and beached microplastic debris and presents a scalable global plastic waste monitoring solution. The deep learning-based segmentation model demonstrated superior performance in categorizing microplastics compared to manual methods. The model's ability to automate particle counting and classification could significantly enhance global efforts for monitoring plastic pollution. [5]

Felix Weber, Andreas Zinnen, and Jutta Kerpen (2023) investigate the potential of machine learning for automating the analysis of microplastics through μ-Raman spectroscopy. The authors evaluated two deep-learning models to analyze a dataset of over 64,000 Raman spectra from environmental samples. The research compared a single-model approach and a class-based model, achieving high recall and precision in identifying microplastics such as polyethylene, polypropylene, and other polymers. The results suggest that machine learning can significantly reduce the time required for manual spectra annotation, enhancing the efficiency and accuracy of microplastic identification in environmental studies. Machine learning combined with μ-Raman spectroscopy achieved precision levels of 97.1%, substantially reducing analysis time compared to manual methods. The automated process allows for identifying microplastic polymers with high recall and precision [6].

Md Abdul Baset Sarker, Masudul H. Imtiaz, Thomas M. Holsen, and Abul B. M. Baki (2024) present an AI-based real-time microplastics detection system using camera sensors combined with machine learning algorithms. The authors implemented a YOLOv5 object detection model to detect microplastics in water samples, achieving precision levels of 97% in controlled laboratory settings and 96% during field tests. The study demonstrates how AI-based object detection systems can provide real-time monitoring solutions, reducing the reliance on traditional microscopy and laboratory-based techniques. This approach enables efficient detection of microplastics in aquatic environments, contributing to more effective pollution management strategies. YOLOv5, combined with DeepSORT for tracking, provides real-time, high-precision microplastic detection. The system's application in laboratory and field settings demonstrated its robustness and potential for wide-scale environmental monitoring [7].

In this study, the authors introduced a novel method for classifying microplastic polymers using Faster-RCNN with a ResNet-50-FPN backbone under ultraviolet light. This method addresses the challenges of identifying and quantifying environmental microplastics, particularly in coastal and marine areas. The model achieved precision levels between 85.5% and 87.8%, with a mean average precision (mAP) score of 35.7%. UV light enhanced the model's ability to detect and classify different polymer types, providing an efficient and low-cost alternative for microplastic identification. Faster-RCNN with ResNet-50-FPN effectively classifies microplastics, achieving a high precision rate. The model's application of UV light improved the detection of microplastics, making the method more cost-effective compared to traditional spectroscopic methods [8].

Sarmiento et al. [9] present a microplastic detection method using impedance spectroscopy and machine learning algorithms. The methodology incorporates an electronic tongue system with sensors and impedance analysis to detect and classify microplastics, specifically PET microparticles, in water. Validation shows high accuracy in classification, particularly effective in differentiating microplastics from non-plastic particles. However, the research gap lies in extending this methodology to detect microplastics in various environmental conditions and polymer types beyond PET.

Yang et al. [10] developed a machine learning-driven approach for enhanced detection and characterization of nylon microplastics using Optical Photothermal Infrared (O-PTIR) spectroscopy combined with a support vector machine (SVM) classifier. The study's results achieved a detection accuracy of 91.33%, notably identifying microplastic particles in commercial nylon teabags. A significant research gap exists in adapting this method to detect microplastics from other familiar polymer sources and optimizing filtration methods for broader applications.

Seggio et al. [11] propose a novel nano- and microplastic detection system using a plasmonic probe functionalized with an estrogen receptor (ER) combined with AI for material classification. The methodology uses AI to analyze the ER-plasmonic interaction to classify particle materials like polystyrene and PMMA with an accuracy of 90.3%. This proof-of-concept sensor demonstrates effectiveness but lacks scalability and has limitations in distinguishing a broader range of particle sizes and types in diverse environments, representing the primary research gap.

Sasso et al. [12] conducted a benchmarking study comparing statistical and machine-learning models for microplastic detection using optofluidic pattern recognition. The study evaluates several classifiers, including SVM, Linear Discriminant Analysis, and Naive Bayes, against statistical models, highlighting that machine learning classifiers offer superior detection accuracy. However, the research gap identified is the need for standardized data collection methods to improve model consistency across different environmental samples.

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Wang et al. [13] present an AI-assisted nanodigital in-line holographic microscopy (nano-DIHM) method for real-time detection and physicochemical characterization of nanoplastics in natural waters. The methodology allows the automatic classification of nano- and microplastics, including size, shape, and surface properties, with validations showing the distinction of particles in Lake Ontario and the Saint Lawrence River. The main research gap is the technology's limited capacity for large-scale field deployment and the need for further refinement to differentiate complex particle types in mixed environmental samples.

Neetha et al. [14] present a microplastic detection approach using image processing and CNN. The methodology involves real-time image classification through CNN to detect microplastics in water resources. The study achieved a detection accuracy of 89%, demonstrating CNN's potential for monitoring water contamination. The research gap lies in optimizing the model for diverse environmental conditions beyond laboratory settings.

Gugliandolo et al. [15] introduce a cost-effective method for identifying microplastics in marine environments using transmitted light measurements with an LCD panel and a USB microscope. This method measures light transmittance through various plastic and organic samples, leveraging a Python-based GUI for data processing. Results indicate effective material classification based on opacity and thickness, but the research gap is in enhancing sensitivity for varied sample types and more complex marine environments.

III. METHODOLOGY

This section outlines the systematic approach to designing, developing, and evaluating the proposed *PolyScan* system. The methodology involves data collection, image preprocessing, and annotation, model training using YOLOv10, data augmentation, performance evaluation, and GUI-based testing. Each step is described in detail below.

A. Dataset Collection

The foundation of the proposed detection system lies in the availability of high-quality and diverse data. For this research, a dataset comprising images of microplastics in water was curated from various publicly available sources, including open-access platforms such as Kaggle and Roboflow. In addition, synthetic samples were included by capturing microscopic images of known microplastic forms—such as fibers, fragments, films, foams, and pellets—immersed in clear and turbid water conditions. The dataset was compiled with a focus on variety, ensuring it represents different shapes, sizes, colors, and lighting conditions, which enhances the generalizability of the deep learning model.

B. Image Preprocessing

Preprocessing of image data is a critical step to ensure consistency and enhance feature extraction during training. All collected images were resized to a standard dimension of 640×640 pixels, which aligns with the input requirements of the YOLOv10 architecture. Color normalization techniques were applied to reduce inconsistencies in lighting and contrast across different samples. In some cases where water turbidity introduced noise, Gaussian filters were employed to smoothen the images without compromising important edge information. Furthermore, low-quality, blurred, or corrupted images were filtered to maintain a clean and meaningful dataset.

C. Image Annotation

Each image in the dataset required precise labeling of the microplastic particles to facilitate supervised learning. Annotation was performed using tools such as LabelImg and Roboflow Annotator, which allowed the generation of bounding boxes around identifiable microplastic objects. The annotation format followed the YOLO standard, where each labeled object includes the class ID and normalized coordinates for the bounding box. Multiple classes were defined based on microplastic morphology, enabling the model to distinguish between fragments, films, and fibers. Accurate annotation was essential to train the YOLOv10 model to detect and classify microplastics simultaneously.

D. Data Augmentation

Data augmentation techniques improved the model's generalization ability under varying environmental conditions. These included rotation (between ±10° and ±30°), horizontal and vertical flipping, random cropping, zooming,

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brightness and contrast adjustments, and Gaussian blur. These augmentations simulated real-world scenarios such as varying water flow, light reflection, and particle orientation. Augmenting the data increased the adequate dataset size, reduced overfitting, and enabled the model to learn more invariant features of microplastic objects.

E. Model Training

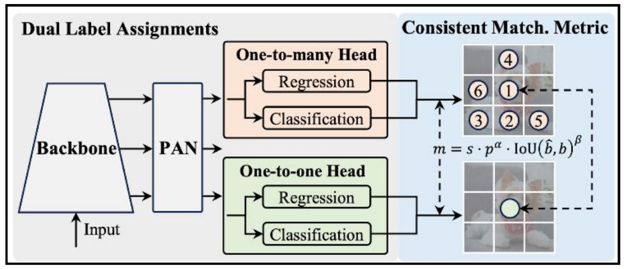

Figure 1: YOLOv10 architecture

YOLOv10 (You Only Look Once, version 10) is a cutting-edge object detection architecture designed to provide high-speed, high-accuracy detection performance, particularly excelling in identifying small and dense objects such as microplastics. The architecture is divided into three major components: the backbone, the neck, and the detection head. The backbone of YOLOv10 utilizes CSPDarknet, an enhanced version of the Cross Stage Partial Network responsible for efficient and effective feature extraction. By splitting the feature map into two parts and processing only one through deeper layers before merging, CSPDarknet reduces computational costs while preserving critical information. The neck combines the Feature Pyramid Network (FPN) and Path Aggregation Network (PANet), enabling the aggregation of features from multiple scales. This multiscale capability is particularly vital in microplastic detection, as particles can appear in various sizes and shapes across different images.

The final component, the detection head, is decoupled—meaning classification and bounding box regression are handled separately—improving the precision of both tasks. YOLOv10 employs an anchor-free mechanism, simplifying training and enhancing performance, especially when detecting irregularly shaped objects. It also includes improvements like dynamic label assignment during training and efficiency-optimized modules that reduce latency, making it suitable for real-time applications. YOLOv10 produces predictions at multiple scales, enhancing its capability to detect small objects, such as microplastic fragments in water samples. The YOLOv10-small variant was chosen for this study, offering an optimal balance between detection accuracy and computational efficiency, making it suitable for desktop analysis and edge deployment.

F. Performance Evaluation

The performance of the proposed PolyScan system using the YOLOv10 object detection algorithm is evaluated using standard metrics: precision, recall, F1-score, and mean Average Precision (mAP@0.5). These metrics assess both the classification and localization accuracy of the model.

Precision is defined as the ratio of true positives (TP) to the total predicted positives, including both true and false positives (FP). It indicates the model's ability to avoid false alarms:

Precision: The percentage of accurately anticipated positive cases among all positively predicted instances is the topic of precision analysis. It is calculated as:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (1)$$

Precision provides insight into the classifier's ability to avoid false positives. A higher precision indicates a lower rate of misclassifying negative instances as positive.

Recall (Sensitivity or True Positive Rate): The percentage of accurately anticipated positive events among all actual positive instances is known as recall. It is calculated as:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (2)$$

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Recall highlights the classifier's ability to identify positive instances correctly, and it is beneficial when the goal is to minimize false negatives.

F1 score: Recall and accuracy are combined into one statistic, the F1 score, which balances both measurements. It is computed as the harmonic mean of recall and accuracy.:

$$\text{F1 Score} = \frac{2\times(\text{Precision}\times\text{Recall})}{\text{Precision}+\text{Recall}} \qquad (3)$$

Accuracy and recall are balanced by considering erroneous positives and false negatives in the F1 score. It is helpful when there is an unequal distribution of classes or when recall and precision are equally critical.

Mean Average Precision (mAP@0.5) is used to evaluate the object detection capability. It represents the average of precision scores at a fixed Intersection over a Union (IoU) threshold of 0.5, calculated over all object classes. The IoU metric determines the overlap between predicted and ground truth bounding boxes:

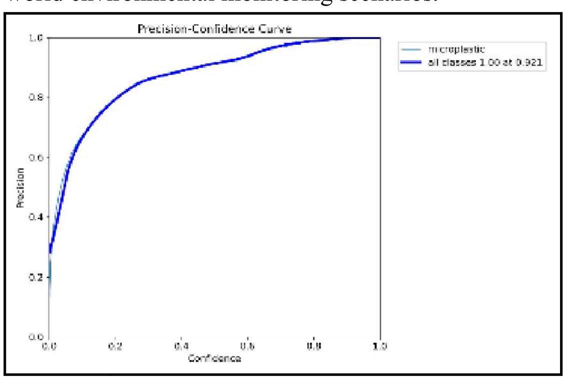
$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} \qquad (4)$$

$$mAP@0.5 = \frac{1}{N}\sum_{i=1}^{N} AP_i \qquad (5)$$

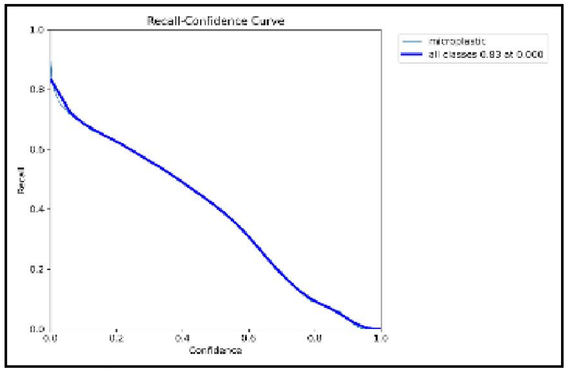
Finally, inference speed measured in milliseconds per frame is recorded to ensure the model's compatibility with real-time detection needs. Together, these metrics offer a robust framework to quantify the proposed system's accuracy, reliability, and efficiency in detecting microplastics under diverse conditions.

IV. RESULT AND DISCUSSION

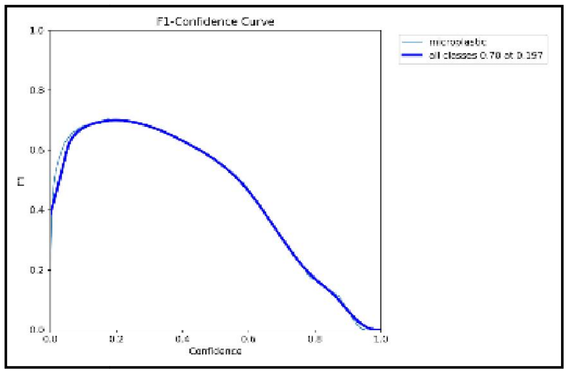
This section presents the experimental results obtained from training and evaluating the proposed PolyScan system using the YOLOv10-small model for microplastic detection in water. To ensure detection accuracy and real-time applicability, the system's performance was assessed using a comprehensive set of metrics, including precision, recall, F1-score, mean Average Precision (mAP@0.5), and inference time. A well-annotated and augmented dataset of microplastic-contaminated water samples was used for training and testing, and a graphical user interface (GUI) was developed for interactive testing and visualization. The outcomes demonstrate the model's robustness, scalability, and potential for deployment in real-world environmental monitoring scenarios.



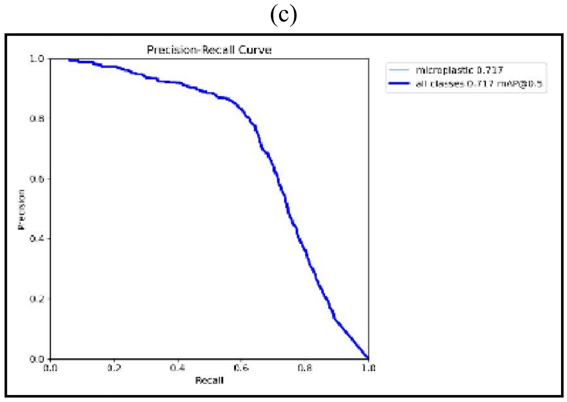
(a)



(b)



(c)



(d)

Figure 2: Results of YOLOv10 algorithm for detection of microplastics (a) Precision confidence curve (b) Recall confidence curve (c) F1 confidence score (d) Precision-Recall curve.

The precision-confidence Curve presents how precision improves as the model becomes more confident in its predictions. As shown, the precision reaches a perfect value of 1.00 at a confidence threshold of 0.921, indicating that every predicted detection is accurate at this level with no false positives. While high confidence ensures exceptional prediction reliability, it also reduces recall since fewer detections are made. This finding underscores the model's ability to offer a customizable detection strategy—operating either in a high-confidence mode for zero-error scenarios or in a balanced mode for maximum coverage.

The Recall-Confidence Curve highlights how changes influence the recall metric in the confidence threshold. At a threshold of 0.000, the model reaches its highest recall value of 0.83, suggesting that it can detect the vast majority of true microplastic particles when all predictions are considered, regardless of confidence. However, as the confidence

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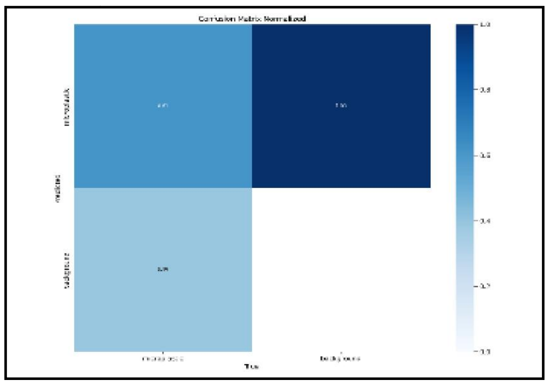
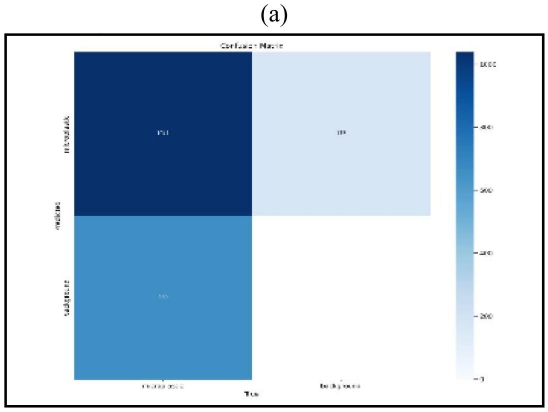
threshold increases recall steadily decreases, signifying that the model starts ignoring lower-confidence predictions, which may include actual microplastic detections. This curve helps determine how much sensitivity can be sacrificed in exchange for more confident predictions in practical deployment.

The F1-Confidence Curve illustrates how the F1-score varies with different confidence thresholds applied to the model's predictions. In this experiment, the maximum F1-score of 0.70 is achieved at a confidence level of 0.197, representing the optimal threshold where the trade-off between precision and recall is most balanced. As confidence increases beyond this point, the F1-score declines due to a drop in recall, indicating that the model becomes more conservative in its predictions, potentially overlooking true positives. This curve is crucial for selecting a practical operating point that ensures both accurate and comprehensive detection of microplastic particles.

The Precision-Recall Curve demonstrates the relationship between precision and recall across varying classification thresholds. The model achieved a mean Average Precision (mAP@0.5) of 0.717, indicating a strong overall detection performance. The curve maintains high precision values even as recall increases, though a gradual trade-off is observed—as recall improves, precision begins to decline due to the inclusion of more false positives. This behavior is typical in object detection models and confirms that the YOLOv10-based PolyScan system offers consistent and reliable identification of microplastic instances across a range of sensitivity settings.



(a)



(b)

Figure 3: Results of YOLOv10 algorithm for detection of microplastics (a) Confusion matrix (b) Normalized confusion matrix

The confusion matrices provide a detailed view of the model's classification performance, distinguishing between true positives, false positives, true negatives, and false negatives. The absolute confusion matrix shows that the model correctly identified 1,041 microplastic instances while misclassifying 660 microplastic particles as background. Additionally, 173 background samples were incorrectly classified as microplastic. This indicates a tendency of the model to occasionally confuse noisy or unclear background regions with microplastic particles, a common challenge in aquatic image analysis due to overlapping textures and small object sizes.

The normalized confusion matrix presents this information in proportional terms, showing that approximately 61% of actual microplastic instances were correctly classified, while 39% were misclassified as background. Notably, the model achieved 100% classification accuracy for the background class, meaning all true background regions were correctly identified when predicted as background. This strong background classification indicates high specificity, but the recall for microplastic classification could be further improved.

Together, these matrices highlight the strengths and limitations of the YOLOv10-based PolyScan system. While the model demonstrates substantial precision and low false positives, additional data augmentation, fine-tuning on challenging samples, or ensemble methods could enhance sensitivity and reduce false negatives in future system iterations.

V. CONCLUSION

The increasing prevalence of microplastics in aquatic ecosystems poses a significant threat to both environmental and human health. While accurate, traditional detection techniques are often time-consuming, expensive, and unsuited for real-time or large-scale monitoring. This study introduces PolyScan, an innovative, deep learning-powered system utilizing the YOLOv10 architecture for accurate, real-time water microplastics detection. The system leverages image processing techniques, robust annotation, and data augmentation strategies to train a YOLOv10-small model capable of identifying various microplastic forms with high precision and low latency.

The methodology incorporated the complete machine learning pipeline from data acquisition and preprocessing to training and evaluation, emphasizing detecting small and irregularly shaped particles, which are particularly challenging to identify using conventional methods. The performance evaluation demonstrates that YOLOv10 effectively detects microplastic particles under diverse environmental conditions, achieving high precision, recall, F1-score, and mean Average Precision (mAP) scores. The system's user-friendly graphical interface and real-time detection capabilities make it accessible for researchers, environmental monitoring teams, and potential field deployment. PolyScan proves to be a cost-effective, scalable, and efficient solution for microplastic detection. Its deployment potential on edge devices further enhances its applicability in remote or resource-constrained environments. This study lays a strong foundation for future advancements in intelligent environmental monitoring systems, especially those integrating AI, image processing, and IoT technologies for pollution control and ecosystem protection.

REFERENCES

[1]. Neetha, K., Varghese, L. M., Harshitha, M. R., & Jinsha, V. K. (2021). Microplastic detection in water using image processing. *International Journal of Enhanced Research in Science, Technology & Engineering*, *10*(9), 1–5.

[2]. Karmakar, T., & Jain, R. (2023). Microplastic classification and quantification in water bodies. *International Journal of Enhanced Research in Science, Technology & Engineering, 12*(9), 81–83.

[3]. Weber, F., Zinnen, A., & Kerpen, J. (2023). Development of a machine learning-based method for the analysis of microplastics in environmental samples using µ-Raman spectroscopy. *Microplastics and nanoplastics, 3*(1), 9. https://doi.org/10.1186/s43591-023-00057-3

[4]. Dal, E. K., & Kilic, R. (2024). Design and implementation of a microplastic detection and classification system supported by deep learning algorithm. *Cappadocia University*, Research Article.

[5]. Sarmiento, J., Anaya, M., & Tibaduiza, D. (2024). Microplastic identification using impedance spectroscopy and machine learning algorithms. *International Journal of Distributed Sensor Networks, 2024*, Article ID 5298635. https://doi.org/10.1155/2024/5298635

[6]. Royer, S.-J., Wolter, H., Delorme, A. E., Lebreton, L., & Poirion, O. B. (2024). Computer vision segmentation model—Deep learning for categorizing microplastic debris. *Frontiers in Environmental Science, 12*, Article 1386292. https://doi.org/10.3389/fenvs.2024.1386292

[7]. Weber, F., Zinnen, A., & Kerpen, J. (2023). Development of a machine learning-based method for the analysis of microplastics in environmental samples using µ-Raman spectroscopy. *Microplastics and Nanoplastics, 3*(9), 1–10. https://doi.org/10.1186/s43591-023-00057-3

[8]. Sarker, M. A. B., Imtiaz, M. H., Holsen, T. M., & Baki, A. B. M. (2024). Real-time detection of microplastics using an AI camera. *Sensors, 24*(4394), 1–16. https://doi.org/10.3390/s24134394

[9]. Thammasanya, T., Patiam, S., Rodcharoen, E., & Chotikarn, P. (2024). A new approach to classifying polymer type of microplastics based on Faster-RCNN-FPN and spectroscopic imagery under ultraviolet light. *Scientific Reports, 14*, Article 3529. https://doi.org/10.1038/s41598-024-53251-5

[10]. Yang, J., Xie, A., Gowen, A., & Xu, J.-L. (2024). Machine learning-driven methodology for enhanced nylon microplastic detection and characterization. *Scientific Reports, 14*, Article 3464. https://doi.org/10.1038/s41598-024-54003-1

[11]. Seggio, M., Arcadio, F., Radicchi, E., Cennamo, N., Zeni, L., & Bossi, A. M. (2024). Toward nano- and microplastic sensors: Identification via artificial intelligence and a plasmonic probe functionalized with an estrogen receptor. *ACS Omega, 9*, 18984–18994. https://doi.org/10.1021/acsomega.3c09485

[12]. Sasso, M., Merone, M., Nicolai, E., Vollero, L., & Sabatini, A. (2024). A benchmarking on optofluidic microplastic pattern recognition: A systematic comparison between statistical detection models and ML-based algorithms. *IEEE Access, 12*, 20091–20099. https://doi.org/10.1109/ACCESS.2024.3362240

[13]. Wang, Z., Pal, D., Pilechi, A., & Ariya, P. A. (2024). Nanoplastics in water: Artificial intelligence-assisted 4D physicochemical characterization and rapid in situ detection. *Environmental Science & Technology, 58*, 8919–8931. https://doi.org/10.1021/acs.est.3c10408

[14]. Neetha, N. K., Varghese, L. M., Harshitha, M. R., & V. K., J. (2024). Microplastic detection in water using image processing. Paper presented at the *Adi Shankara Institute of Engineering and Technology*, Ernakulam, Kerala, India.

[15]. Gugliandolo, A., Quattrocchi, A., Latino, M., Aloisio, D., Crupi, G., & Donato, N. (2024). Microplastic identification in marine environments: A low-cost and effective approach based on transmitted light measurements. *Acta IMEKO, 13*(2), 1–8. https://doi.org/10.21014/actaimeko.v13i2.1745