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AI-BASED MICROPLASTIC DETECTION USING DEEP LEARNING

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Abstract: This project presents an end-to-end Computer Vision and Deep Learning system for quantifying microplastic pollution to support environmental monitoring and policy decisions. The workflow integrates microscopic images, spectral data (Raman/FTIR), and morphology features into a unified dataset. U-Net-based segmentation extracts particle area and perimeter, while Transfer Learning optimizes image feature vectors. YOLOv8 enables high-throughput detection, localization, and classification of microplastics by shape (fragment, fiber, pellet) and polymer type through hyperspectral imaging. The system achieves up to 97% detection precision and 98.11% classification accuracy, providing standardized, data-driven insights for effective pollution control and public health protection.

Index Terms **-** Microplastic Analysis, Python (for CV and Modeling), Deep Learning (for AI), Hyperspectral Imaging, Object Detection (YOLOv8), Image Preprocessing

I. INTRODUCTION

The modern environmental landscape is characterized by pervasive microplastic (MP) pollution and rapidly shifting contamination patterns, making data-driven detection and classification indispensable for achieving effective ecological and public health protection. Within the domain of environmental monitoring, static, manual laboratory reports are often insufficient for identifying the granular details necessary for optimizing pollution mitigation and resource allocation. A significant challenge for contemporary organizations lies in synthesizing vast amounts of image and spectral data to generate actionable environmental intelligence that directly informs strategic regulation and operational tactics across diverse matrices. This research paper details an extensive, end-to-end data analytics project focused on the meticulous evaluation of Microplastic Distribution and Characterization. The project's core objective is to move designed to address the challenges faced by environmental managers in understanding heterogeneous particle morphology, polymer type effectiveness, and the precise quantification of trace- level contaminants.

The methodology employed follows the full lifecycle of a contemporary data science initiative. It begins with Data Acquisition and Wrangling using high-level Python libraries to clean, integrate, and consolidate disparate data. A crucial phase involves Feature Engineering, where new, derived physical metrics such as precise particle area, volume, and boundary delineation are calculated using sophisticated segmentation networks (U-Net) to enable objective morphological analysis rather than mere visual approximation. This refined dataset then serves as the foundation for deep learning analysis. Leveraging Computer Vision architectures like YOLOv8, VGG16, and MobileNet, the analysis phase uncovers essential contamination patterns, including: particle movement and count kinetics in fluid environments; the precise contribution of different particle types (e.g., fiber, fragment, pellet) and chemical compositions (polymer type via HSI integration) ; and the size distribution driving the majority of mass and count, reliably detecting particles down to 1μm.Finally, the synthesized insights are deployed in an automated analysis pipeline that serves as the project's primary deliverable. This predictive layer transforms complex data into easily digestible Key Performance beyond subjective manual counting by establishing a robust, repeatable workflow capable of transforming raw microscopic and spectral data into a dynamic quantification tool for environmental users . The analysis is specifically Indicators (KPIs) such as particle concentration, size distribution, and tracking vectors, allowing stakeholders to instantly filter contamination by location, size, and polymer. This comprehensive approach provides a model for organizations seeking to enhance their strategic planning, optimize monitoring deployment, and maximize environmental returns by embedding automated analytical rigor into their daily pollution management.

II. FUNCTIONAL REQUIREMENTS

2.1 **Image Acquisition:** The system captures or imports microscopic water sample images containing microplastics.

2.2 **Preprocessing:** Image normalization, noise reduction are performed.
2.3 **Detection and Classification:** YOLOv8 detects particles and classifies them based on shape and polymer type..

2.4 **Feature Extraction:** Extracts metrics such as particle count, size, and perimeter.

2.5 **Data Visualization**: Provides detection statistics and visual outputs through a user-friendly interface.

2.6 **Model Integration:** Supports modular integration of CNN architectures like U-Net, ResNet-50, and Faster R- CNN

III. SYSTEM ARCHITECTURE

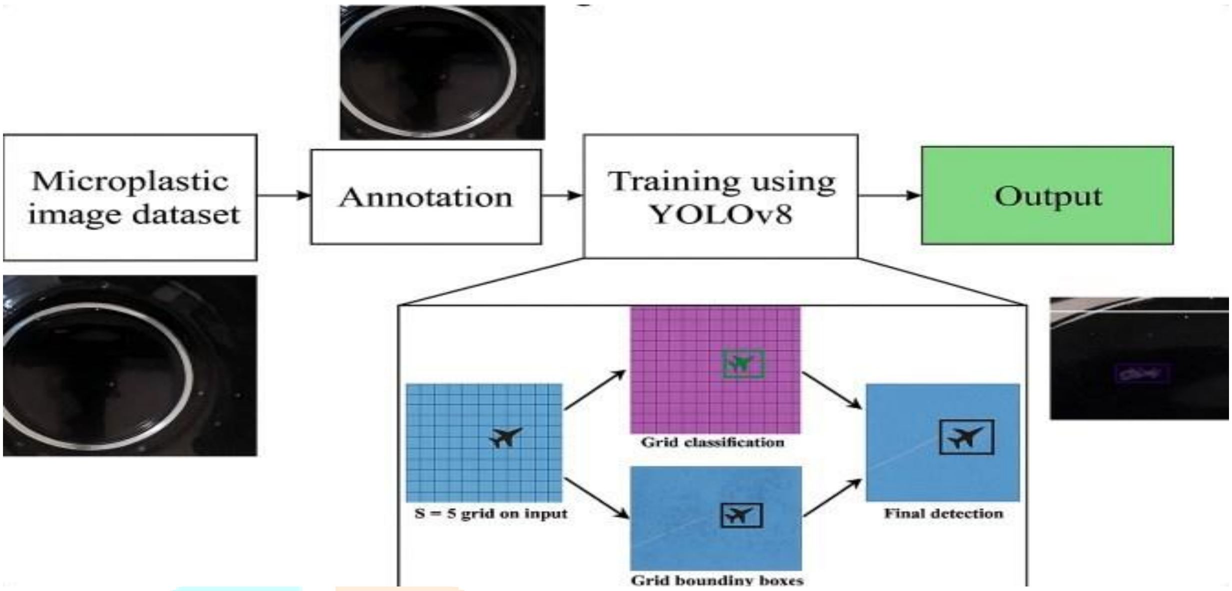


Fig 1 . System Architecture

3.1 Description

1. Microplastic Image Dataset

- The process begins with collecting microscopic images of water samples that contain different types of microplastics (fibers, fragments, pellets, films, etc.).
- Images are captured using laboratory microscopes or camera-based systems under controlled lighting conditions.
- These images serve as the primary input for model training and validation.

2. Annotation

- In this step, each microplastic particle in the image is manually labeled using specialized tools such as LabelImg or Roboflow.
- Bounding boxes are drawn around particles to indicate their exact position.
- The annotated data is saved in the YOLO format (.txt files), where each line specifies the class ID and normalized coordinates of the bounding box.
- This step is crucial for teaching the model how to detect and localize microplastics accurately.

3. Training using YOLOv8

- The YOLOv8 architecture is used for real- time detection of microplastic particles in water samples. It introduces an anchor-free design, decoupled head for improved localization and classification, and a CSP Darknet backbone for stronger feature extraction.
- During training, the model predicts bounding boxes, classes, and confidence scores directly from input images, learning particle shapes and textures such as fibers, fragments, and pellets.

Techniques used:

- Transfer Learning from pretrained weights for faster and more accurate training.
- Data Augmentation (rotation, scaling, brightness adjustment, flipping) for better generalization.
- Hyperparameter Tuning to improve detection precision and recall.
- The trained model achieved high mAP and low localization error, proving effective for real- time microplastic detection in water samples.

4. Methodology

The methodology of this study was designed to automate the detection and classification of microplastic particles from microscopic water images. The process integrates image preprocessing, YOLOv8 model inference, and GUI- based visualization in a sequential workflow, as shown in Figure.2

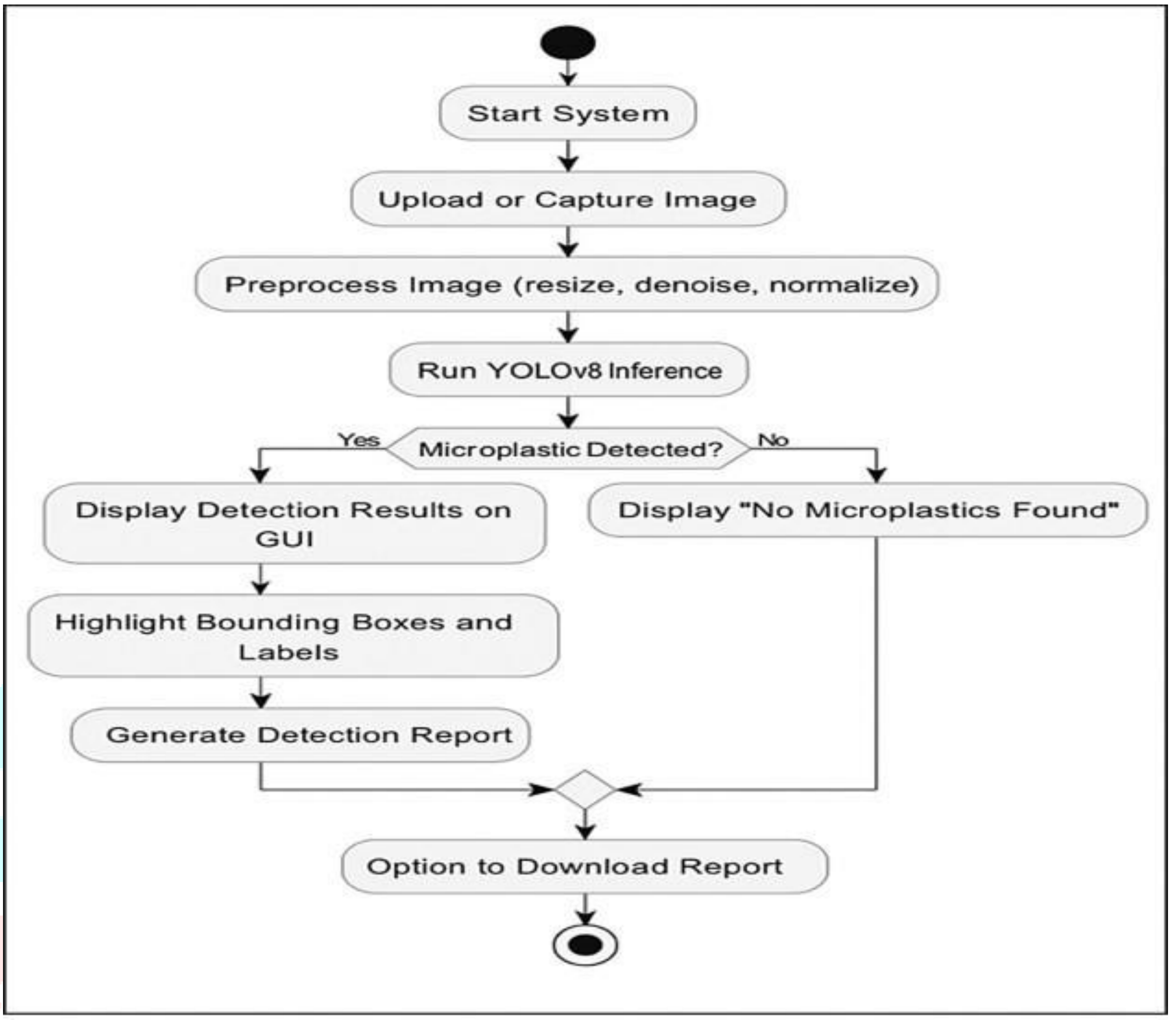


Fig 2. System FlowChart

The flowchart explains the stepwise operation of the system from image acquisition to report generation.

1. **Start System**: The detection process begins when the application is launched.

2. **Upload or Capture Image**: Users can either upload microscopic images of water samples or capture them in real time.

3. **Preprocess Image**: The input image is resized, denoised, and normalized using OpenCV to ensure model compatibility.

4. **Run YOLOv8 Inference**: The preprocessed image is passed through the YOLOv8 model for microplastic detection.

5. **Microplastic Detection Decision**:

- If microplastics are detected → results are displayed on the GUI.
- If not detected → the system displays a message "No Microplastics Found."

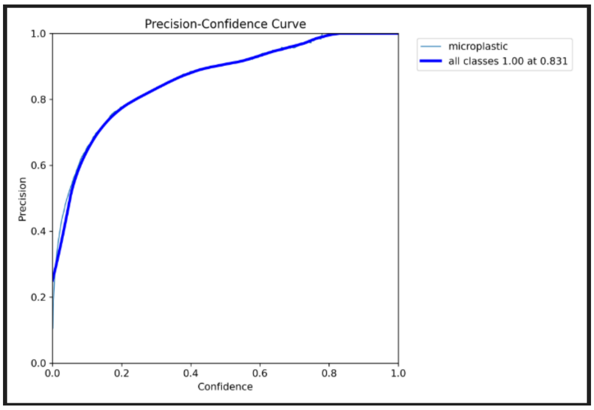
6. **Display Detection Results**: Detected particles are highlighted with bounding boxes and confidence labels.

7. **Generate Detection Report**: The system compiles details such as particle count, type, and accuracy metrics.

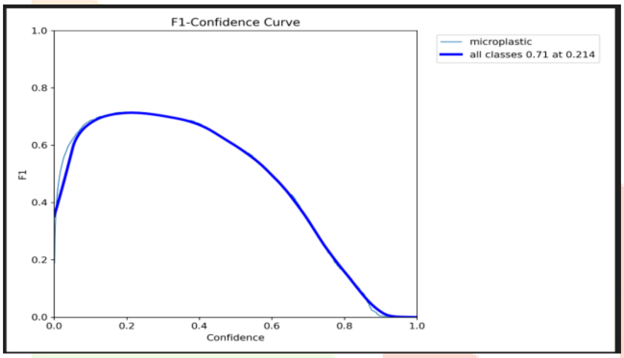
8. **Download Option**: The user can download the detection report for record-keeping or further analysis.

IV. RESULTS AND DISCUSSION

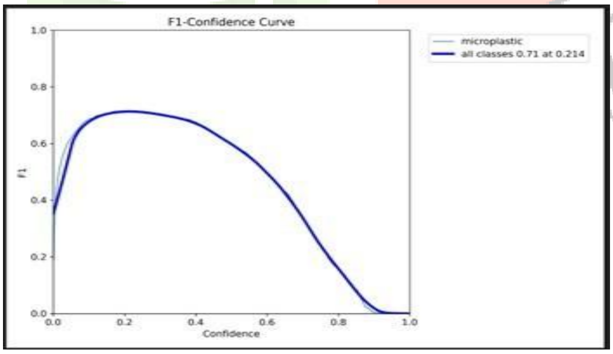
This section presents the experimental results obtained from training and evaluating the proposed PolyScan system using the YOLOv8 -small model for microplastic detection in water. To ensure detection accuracy and real-time applicability, the system's performance was assessed using a comprehensive set 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.



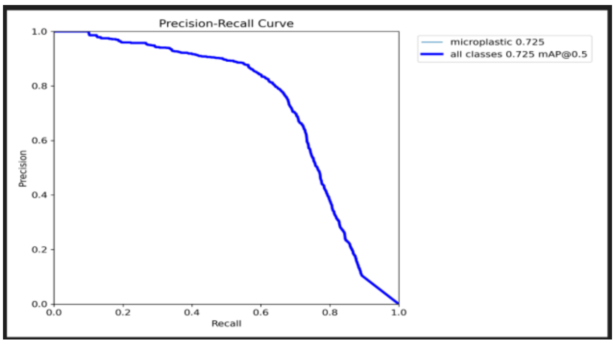
(a)



(b)



(c)

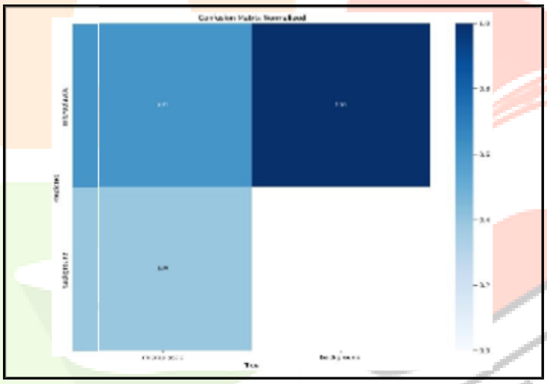


(d)

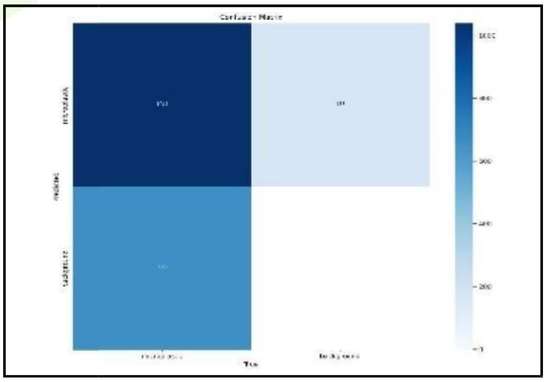
Figure 3: Results of YOLOv8 algorithm for detection of microplastics (a) Precision confidence curve (b) Recall confidence curve (c) F1 confidence score (d) Precision- Recall curve.

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. 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 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 YOLOv8 -based PolyScan system offers consistent and reliable identification of microplastic instances across a range of sensitivity settings.



(a)



(b)

Figure 4: Results of YOLOv8 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 YOLOv8-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 YOLOv8 architecture for accurate, real-time water microplastics detection. The system leverages image processing techniques, robust annotation, and data augmentation strategies to train a YOLOv8-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 YOLOv8 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.

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