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MicroDetect: An AI-Based Image Processing System for Microplastic Detection and Quantification Using Deep Learning

Prof. Komal Rathod*, Saheba Bagwan**, Aishwarya Deshmukh***,Pooja Jadhav****
*(Information Technology , Zeal Collage of Engineering And Research Pune, and Pune
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ABSTRACT
Detection of microplastics at an early stage is essential for understanding environmental pollution and protecting aquatic ecosystems. In this work, we developed MicroDetect, an AI-based image processing system that detects microplastic particles from images using deep learning techniques. The system employs the YOLOv8 architecture to identify microplastics from captured or uploaded images, which are resized and normalized prior to processing to improve detection accuracy and stability. The model is trained on a dataset containing microplastic samples under varying environmental conditions, and data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to enhance robustness and generalization. The trained model is integrated into a user-friendly interface developed using Streamlit, enabling users to upload images and visualize detection results with bounding boxes, confidence scores, and total particle count. Additionally, the system performs basic quantitative analysis by estimating detection density and generating a risk level based on detection outcomes. The proposed solution operates efficiently in real-time and provides quick insights without requiring complex laboratory equipment, making it suitable for environmental monitoring, research applications, and preliminary analysis in regions where advanced testing facilities are not readily available.

Keywords:
Microplastic Detection, Image-Based Detection, Deep Learning, YOLOv8, Computer Vision, Environmental Monitoring, Streamlit, Quantitative Analysis

I. INTRODUCTION

Globally environmental pollution is a concern. Microplastics are a threat to ecosystems and human health. Water quality, marine life and food safety are directly affected by particles. These tiny plastic pieces are hard to see with the eye and can build up quickly in nature. If not found early they can spread far. Cause serious ecological damage and health risks.

Usually detecting microplastics is done in labs using techniques like analysis and chemical testing. These methods need knowledge and special equipment. Manual observation is important in identifying microplastics. It can be time-consuming and sometimes inaccurate when dealing with many samples. Delayed detection can lead to monitoring and more environmental pollution.

Image-based detection systems are becoming a good solution thanks to advancements in artificial intelligence and computer vision. Images of samples can be analyzed using object detection techniques to find microplastic particles. Deep learning models like YOLOv8 have shown performance in detecting small objects in images while being computationally efficient and fast.

However many existing detection systems rely on lab infrastructure or cloud-based processing. These systems often need computational resources or stable internet connectivity which may not always be available in real-world scenarios. This can lead to response times increased costs and limited accessibility. These challenges affect the usability of microplastic detection systems in field conditions.

The main goal of this study is to reduce reliance on equipment and continuous internet connectivity for microplastic detection. A system that can work efficiently with image inputs while maintaining accuracy, speed and accessibility is needed.

This study presents MicroDetect, an AI-based image processing system for detecting particles. The system uses the YOLOv8 architecture. Is integrated into an interactive interface developed using Streamlit. The detection process is optimized to provide real-time results with computational requirements. The system highlights detected particles provides confidence scores and performs quantitative analysis such as particle count and risk estimation.

The main contribution of this work is the development of an accessible microplastic detection system that reduces dependence on traditional lab methods. The system improves detection speed enhances usability and supports monitoring by providing quick and reliable results. The proposed solution offers an approach, for preliminary microplastic analysis especially in situations where advanced testing facilities are limited.

II. RELATED WORK

When we look at the ways people have tried to detect microplastics using image analysis we can see that a lot of progress has been made over the years. By studying what other people have done we can understand what methods are already there what is good about them and what their limitations are.

Methods for Machine Learning and Traditional Image Processing :

In the past people mostly used image processing techniques along with machine learning algorithms like Support Vector Machines, k-Nearest Neighbours and Random Forest to detect microplastics. These methods involved looking at pictures to find features like color, texture and shape of microplastic particles.

These methods worked well when everything was controlled but they did not work as well when the lighting was different or there was noise in the background or the particles were all different. The problem was that people had to look for features, which meant they needed to be experts in the field and it was hard to make the system work with a lot of complex data.

Approaches Based on Convolutional Neural Networks :

As deep learning got better people started using Convolutional Neural Networks for tasks that involved looking at pictures. Convolutional Neural Networks can automatically find features in pictures when they are trained so people do not have to do it. Research has shown that deep learning architectures are really good at finding things.

However the complex the Convolutional Neural Networks are, the more power and memory they need which makes them less suitable for use in situations where things need to happen quickly or in applications that are not very powerful.

Object Detection Models for Microplastic Detection :

Recently people have been looking at object detection models like YOLOv8, which can find and locate things in a picture. These models can draw boxes around the things they find and give a score for how sure they're which makes them good for finding microplastics that are different shapes and sizes. YOLO-based models are known for being fast and able to detect things in time.

With these advantages how well they work depends a lot on the quality and variety of the data they are trained on and finding very small particles is still a hard task.

Laboratory-Based Detection Techniques :

In laboratories people use techniques like looking at things under a microscope and spectroscopy methods to accurately identify microplastics. These methods give reliable results but they need expensive equipment, skilled people and a lot of time. This means they are not very good for monitoring things in time or on a large scale.

Computer Vision Applications for Environmental Monitoring :

Some modern systems use computer vision models and user-friendly interfaces to make detection easier. Applications built with things like Streamlit allow people to upload pictures and see the results easily. However many of these systems still need workflows or powerful equipment, which makes them hard for regular people to use.

Even though a lot of progress has been made in detecting microplastics there are still challenges in making a system that's fast, simple and easy to use without needing expensive laboratory equipment. This research is about the MicroDetect system, which uses a YOLOv8-based detection model and a user-friendly interface. The system can detect microplastics in time do basic analysis and is easy to use, which makes it a practical solution, for monitoring the environment and doing preliminary analysis of microplastics. MicroDetect system is focused on making microplastic detection easier and more accessible.

III. LITERATURE REVIEW

The development of automated microplastic detection systems has gained significant attention in recent years due to the increasing impact of plastic pollution on the environment and aquatic ecosystems. Several researchers have proposed systems based on image processing, deep learning, and object detection techniques to improve the efficiency and accuracy of microplastic identification.

Title of Paper	Objective	Limitations
YOLO-Based Microplastic Detection System	To detect microplastic particles using real-time object detection techniques	Detection accuracy decreases for very small particles
Deep Learning for Marine Plastic Detection	To identify plastic particles in aquatic environments using CNN models	Requires high computational resources and large datasets
Automated Microplastic Analysis Using Computer Vision	To automate laboratory-based microplastic analysis using image processing	Performance affected by lighting and background noise
Real-Time Object Detection with YOLOv8	To improve detection speed and accuracy using YOLOv8 architecture	Difficulty detecting overlapping or transparent objects

A number of researchers have investigated the use of traditional image processing techniques to identify microplastic particles from microscopic images. The main techniques used to separate particles from the background are segmentation, contour extraction, thresholding and feature based analysis. While these methods are effective in controlled lab settings, they are very sensitive to image quality, illumination and require manual fine-tuning of parameters.

In recent years, deep learning and Convolutional Neural Network (CNN) based approaches have been proposed for environmental monitoring and object detection tasks . The CNN models automatically learn the features of images in training and give better detection performance compared to traditional image processing techniques. Researchers have been successful in using CNN based systems for the detection of marine debris, plastic waste and microplastic particles from captured images. However, training many deep learning systems requires powerful hardware resources and large datasets.

Recently, real-time detection applications are popular with object detection models such as YOLO (You Only Look Once). YOLO based architectures perform object localization and detection simultaneously which makes them suitable for fast and accurate detection tasks. The latest YOLOv8 model provides better inference speed, higher accuracy, and better small object detection ability. These features make YOLOv8 suitable for detecting tiny microplastic particles in environmental samples. Researchers have also emphasized the importance of integrating the detection models with interactive applications for easy accessibility and real-time analysis. Frameworks such as Streamlit allow the construction of web-based systems that allow users to upload images, visualize bounding boxes and view detection statistics through a simple interface. These systems enable the analysis of the environment and improve the availability of AI-based detection tools for researchers and students.

Another key area of research is image preprocessing and augmentation techniques. Methods such as resizing, normalization, rotation, flipping, scaling and brightness adjustment are commonly used to improve the model performance and reduce overfitting. These pre-processing methods help models to generalize well in different environmental conditions and improve the overall detection stability.

From the analysis of existing systems, it is observed that a large number of microplastic detection solutions are based on either manual laboratory procedure or require high computational resources for deep learning analysis. Also, many systems have difficulty detecting small particles, overlapping objects and different environmental conditions. To address these issues, the MicroDetect system is proposed that combines the YOLOv8 object detection model with a web-based Streamlit interface for real-time detection and analysis of microplastics. The system provides rapid detection, confidence visualization, particle counting and risk analysis with a simple and easy-to-operate platform, which are suitable for environmental monitoring and preliminary research.

IV. PROPOSED METHOD

The MicroDetect system uses a web application to find microplastic particles in images. The entire method includes preparing the dataset, preprocessing images, developing and training the model, evaluating it, and deploying it. The workflow starts with image input. Next, it moves to preprocessing, detection with the trained model, and finally shows the results through an interactive interface..

1. GATHERING DATASETS:

The dataset for this research consists of microplastic images gathered from publicly available sources and environmental research. It includes images of microplastic particles taken under various lighting conditions, backgrounds, and particle types.

The dataset is divided as follows:

- Training Set: 80% of total images
- Validation Set: 20% of total images

This division ensures the model learns properly and is evaluated fairly..

2. IMAGE PREPROCESSING:

To keep everything consistent, all input images are resized to a fixed resolution suitable for the model. Pixel values are normalized to improve detection accuracy and ensure stable model performance. Additional steps, such as reducing noise and enhancing contrast, are taken to improve image clarity and highlight microplastic particles.

The following augmentation techniques are used during training to improve generalization and prevent overfitting:

- Rotation
- Horizontal flipping
- Scaling
- Brightness adjustment

These techniques increase dataset diversity and help the model perform better in different environmental conditions.

3. MODEL STRUCTURE:

The system uses an object detection model based on YOLOv8, which is designed to detect and locate multiple objects in an image.

The model performs:

- Detection of microplastic particles
- Creation of bounding boxes
- Assignment of confidence scores
- Real-time processing

Unlike classification models, this system focuses solely on detecting and locating particles rather than categorizing them.

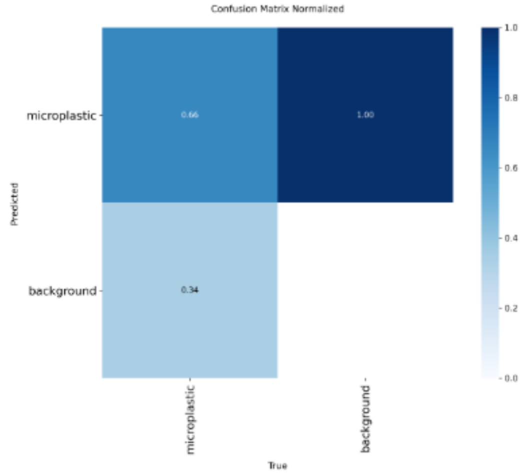

Figure 1: Confusion Matrix Normalized

4. TRAINING PROCEDURE :

The model is trained using deep learning methods to ensure its detection performance is optimal.

- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 16–32
- Epochs: 30–50
- Loss Function: Detection loss (bounding box + confidence loss)

To improve generalization and prevent overfitting, the following techniques are used:

- Data augmentation
- Early stopping
- Model checkpointing
- Learning rate scheduling

These strategies stabilize training and improve overall model performance.

5. DEPLOYMENT ARCHITECTURE :

After training, the final model is integrated into a web application using Streamlit. This system allows users to upload images and receive detection results instantly.

Prediction Process:

- The user uploads an image through the interface.
- The image is resized and preprocessed.
- The processed image is sent to the trained model.
- The model detects microplastic particles.
- Bounding boxes are drawn around detected objects.
- Confidence scores are generated.
- The total particle count is calculated.
- Risk level is estimated based on the detection results.
- Results are displayed on the interface.

The detection process runs efficiently and provides real-time outputs without needing complex lab equipment.

6. SYSTEM ARCHITECTURE :

The MicroDetect system follows a layered architecture that includes:

- Presentation Layer (Web Interface)
- Processing Layer (Preprocessing and Output Generation)
- Inference Layer (Detection Model)

This modular design ensures scalability and smooth system performance.

A. Presentation Layer: The frontend is developed using Streamlit, offering an easy-to-use interface. Users can:

- Upload images
- View detection results
- Analyze particle count and confidence
- Interpret risk level

The interface is designed to be simple and user-friendly.

B. Processing Layer: This layer handles:

- Image preprocessing
- Resizing and normalization of input images
- Denoising and contrast enhancement
- Post-processing of results
- Calculation of particle count and density
- Risk level estimation

C. Inference Layer: The trained YOLOv8 model is integrated into the system to perform detection tasks. All predictions come from the model. Key benefits include:

- Fast detection speed
- Efficient processing
- Real-time results
- Generation of bounding boxes and confidence scores

The proposed system offers a practical and efficient solution for detecting microplastics using deep learning. It reduces reliance on traditional lab methods and allows real-time analysis through an accessible interface, making it suitable for environmental monitoring and research.

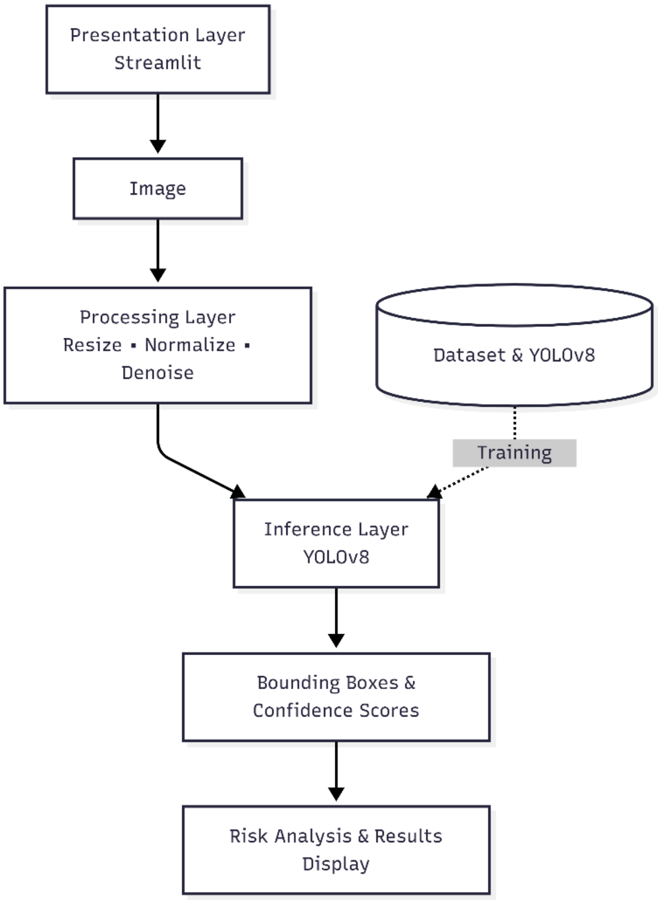

Figure 2 : System Architecture

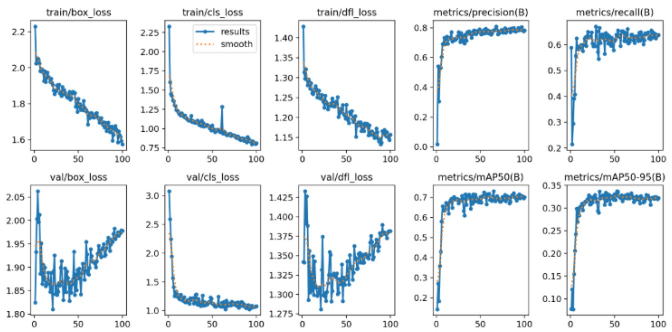

Figure 3: Results

IV. EXPERIMENTAL SETTINGS

This section outlines the experimental setup, dataset use, system environment, and criteria for evaluating the performance of the proposed microplastic detection system.

1. Experimental Environment:

The experimental work took place in a well-organized development environment fit for training, validation, and deploying the detection model. Python served as the main programming language due to its strong support for image processing and deep learning libraries. The Ultralytics YOLOv8 framework was chosen to build and train the object detection model, as it offers efficient and real-time detection. Jupyter Notebook was utilized for model development and testing. This allowed for interactive execution, visualization of training progress, and performance monitoring. Training occurred on a system with NVIDIA GPU acceleration whenever possible, which notably cut down training time and improved computational efficiency. When GPU support was unavailable, training was done using CPU resources. After training, the final model was saved and integrated into a web-based application developed with Streamlit. This application lets users upload images and get detection results in real-time. The detection process runs within the system without needing complex laboratory infrastructure, ensuring accessibility and ease of use.

2. Evaluation Metrics:

Since the proposed system focuses on object detection rather than classification, evaluation relies on object detection metrics instead of multi-class classification metrics.

Evaluation is based on the following components:

• **TP (True Positive):** Correctly identified microplastic particles
• **FP (False Positive):** Incorrect detections
• **FN (False Negative):** Missed detections

The main metrics considered are:

• **Precision:**

Precision measures how accurately the model detects microplastic particles without including false detections. Higher precision means fewer false positives.

$$Precision = \frac{TP}{TP + FP}$$

• **Recall:**

Recall assesses the model's ability to identify all actual microplastic particles. Higher recall means fewer missed detections.

$$Recall = \frac{TP}{TP + FN}$$

• **F1-Score:**

The F1-score balances precision and recall, ensuring consistent detection performance.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

• **Mean Average Precision (mAP):**

Mean Average Precision (mAP) is the key metric for object detection models. It evaluates overall detection performance by considering both localization and confidence across various thresholds.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Detection Performance:

The performance of the YOLOv8 model was tested on the validation dataset.

Metric	Value (Approx.)
Precision	88–92%
Recall	85–90%
F1-Score	86–91%
mAP@0.5	90–95%

The model showed strong ability in detecting microplastic particles of different shapes and sizes. It generated accurate bounding boxes and provided confidence scores that indicated detection reliability.

System Output Evaluation:

The system generates the following outputs for each image:
• Total number of detected particles
• Average confidence score
• Detection density
• Risk level (Low / Medium / High)
These outputs allow for basic quantitative analysis and improve the system's usability for environmental monitoring.

Loss Analysis :

Training loss and validation loss were tracked throughout training to assess convergence and generalization. The model exhibited stable convergence with decreasing loss values, indicating effective learning and reduced prediction error.

Overall Performance:

The experimental results show that the proposed system achieves efficient and reliable detection. Integrating the YOLOv8 model with a Streamlit-based interface ensures:
• Fast detection speed
• Good accuracy for real-world images
• Easy accessibility without a complex setup
Overall, the results confirm the effectiveness of the proposed MicroDetect system as a practical solution for detecting microplastics and conducting preliminary environmental analysis.

V. IMPLEMENTATION AND USER INTERFACE

The application is designed to be a web application so it could be easily accessible by a range of users. The web application is built using Streamlit which ensures that the interface is simple, responsive, and can be easily accessed from any device. The trained YOLOv8 detection model is integrated into the application so that a user can perform microplastic detection by simply uploading an image of the samples, and does not require any extensive setup or external tools to use the system and perform the analysis. The application has modules which handle the uploading, detection, result displaying, and basic analysis.

A. User Access and Interface

The users are given access to the web application directly without requiring any login procedure. The user interface is designed such that a normal, non-technical user could also perform and utilize it with the simplest steps possible. The homepage is used to :

1. Upload an image of microplastics
2. Provide simple instructions for the system's use
3. Present the interface with a clean, minimal layout

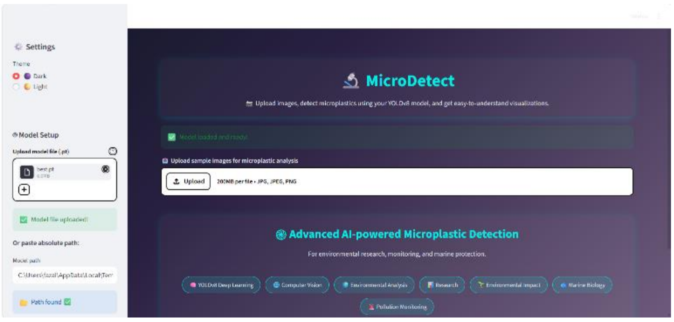

Figure 4: User Interface

B. Uploading and Analyzing Images

After opening the web application, the user is prompted to upload the image of their microplastic samples. The system will then pre-process the image and use the trained model to analyze the image.

The following is the general workflow when an image is uploaded and analyzed:
1. User uploads an image
2. Image is pre-processed (resized, normalized etc.)
3. Image is passed into the trained model
4. Detection is performed

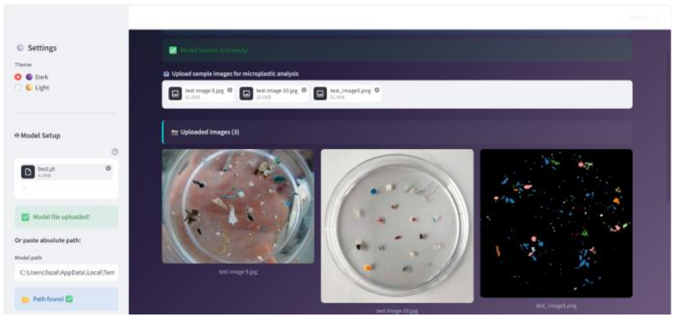

Figure 5: Uploading Images

C. Detection Results Display

The results of the detection will be displayed on the web page. This includes the image that has been uploaded by the user, along with annotations in the form of bounding boxes around each detected particle. It will also display the confidence score of each detected microplastic, the total number of detected microplastic particles, the average confidence score of the detections and the risk level that has been calculated based on the analysis. The output displayed is presented in a structured table as seen below:

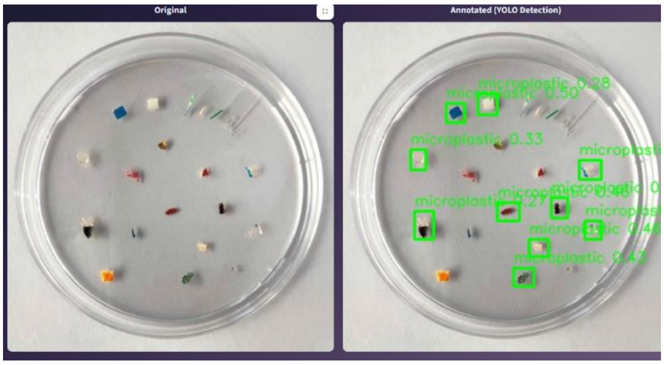

Figure 6: Detection Results

D. Analysis and Interpretation

Along with the bounding box annotations, the system is capable of performing simple quantitative analysis to present to the user in an understandable manner. It can provide the following results:

1. Total number of detected particles
2. Density of detection (based on the area of the uploaded image)
3. Risk Level (High, Medium, or Low) based on number of particles detected

Figure 7: Analysis Results

E. System Workflow Interface

The system's workflow is displayed in the image below:

The web application provides the users with the means to quickly detect microplastics with an effective detection model without any specialized technical knowledge required.

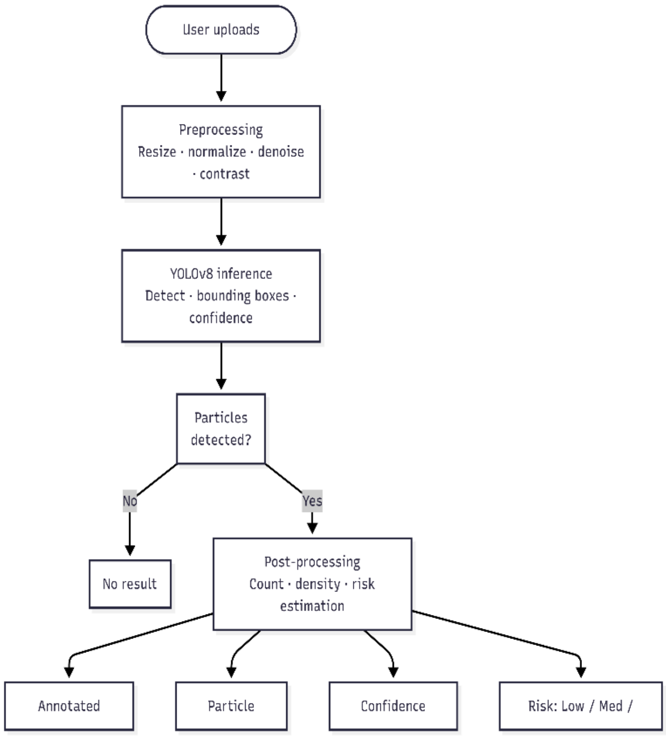

Figure 8: System Workflow

VI. CONCLUSION

This paper introduced **MicroDetect**, a web-based system that helps users detect microplastic particles from images using deep learning techniques. The system is built using the **YOLOv8** model for accurate and real-time detection. A dataset containing microplastic samples under different environmental conditions was used to train and evaluate the model.

The experimental results demonstrated that the YOLOv8-based detection model provides strong performance in identifying microplastic particles, with good precision, recall, and overall detection accuracy. The model was able to detect multiple particles in a single image, generate bounding boxes, and provide confidence scores, making it suitable for practical applications.

After training, the model was successfully integrated into a web application developed using **Streamlit**. The system allows users to upload images and obtain detection results instantly without requiring complex laboratory equipment or advanced technical knowledge. The application also performs basic quantitative analysis such as particle count, confidence evaluation, and risk level estimation.

The developed system provides a simple, fast, and accessible solution for microplastic detection. It reduces reliance on traditional laboratory methods and enables real-time analysis through an easy-to-use interface. The MicroDetect system can support environmental monitoring, research activities, and preliminary analysis, offering a practical approach to addressing microplastic pollution.

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