International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4,2025
https://theaspd.com/index.php

Plastiview: Deep Learning Based Microplastic Detection In Water

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Abstract
Microplastics are emerging as a serious threat to both aquatic ecosystems and human health. While conventional detection methods such as FTIR and Raman spectroscopy offer high accuracy, they are often expensive, time-consuming, and unsuitable for use in field settings. To address these limitations, this paper introduces Plastiview, a low-cost, real-time microplastic detection system that combines a Raspberry Pi 4B, a USB digital microscope, and the YOLOv5s deep learning model. Using OpenCV, the system processes microscope-captured images and displays the detected microplastic count on a compact LCD screen. Trained and tested on publicly available datasets, the model achieved a precision of 0.825, a recall of 0.696, and a mean Average Precision (mAP@50) of 0.748. Designed for portability and standalone use, Plastiview offers a practical solution for environmental monitoring without the need for complex lab setups. With its modular architecture, the system also opens doors for future enhancements such as cloud-based data storage, remote access, and integration of additional sensors, making it a scalable tool for real-world applications in microplastic detection.

INTRODUCTION

The growing presence of microplastics in aquatic ecosystems has emerged as a significant global concern. These tiny plastic fragments, originating from the degradation of larger plastics and various consumer products, infiltrate water, soil, and air, ultimately entering the food chain. Microplastics have been detected in drinking water, seafood, and even human tissues, raising serious public health concerns [1][2][4]. Traditional detection methods, such as FTIR and Raman spectroscopy, though accurate, are expensive, time-consuming, and impractical for large-scale field applications. Furthermore, manual identification is prone to errors, especially in distinguishing microplastics from similarly sized organic particles [18][16]. To address these challenges, Plastiview presents a cost-effective, real-time detection system that integrates a Raspberry Pi 4B, a TOBO digital microscope, and the YOLOv5s object detection model. The system captures and processes high-resolution images of water samples, detects microplastics based on size and texture, and displays results on an LCD screen. The model is trained using publicly available microplastic datasets and validated with strong performance metrics, including a precision of 0.825 and a recall of 0.696. This approach eliminates the need for complex laboratory setups, offering a portable and scalable solution for environmental monitoring and industrial applications.The Plastiview system is designed to be modular and adaptable, supporting future enhancements such as remote data monitoring, cloud integration, and the inclusion of additional sensors for comprehensive water quality analysis. By combining embedded systems and deep learning, it provides a compact, efficient alternative to traditional detection methods, paving the way for more accessible and effective environmental conservation efforts. Its open-source foundation and low-cost implementation make it ideal for academic research, industry compliance, and grassroots initiatives aimed at tackling the global microplastic pollution crisis.

LITERATURE SURVEY

Microplastics have increasingly drawn global attention due to their widespread environmental and health impacts. Boucher and Friot [1] explored the global footprint of primary microplastics, estimatingthat up to 31% of ocean plastic pollution comes from sources like synthetic textile abrasion and tire wear. Their findings emphasized the urgent need for effective detection and mitigation strategies.

To tackle this, researchers have proposed various innovative methods. For instance, Nair et al. [2] developed an IoT-enabled spectrometer capable of detecting microplastics in food with 96% accuracy, offering a portable and real-time solution for food safety. Similarly, Weber et al. [3] combined machine learning with μ-Raman spectroscopy to improve polymer classification efficiency, minimizing the time and effort required for human annotation. Iri et al. [4] introduced a cost-effective Raman spectrometer integrated with IoT features, which could identify microplastics in water at concentrations as low as 0.015% w/v. Meanwhile, N. K. et al. [5] reviewed the use of convolutional neural networks (CNNs) for detecting microplastics in water, highlighting their potential for real-time, automated analysis compared to conventional lab-based methods. Some researchers explored alternative sensing approaches. Malyuskin [6], for example, proposed the use of resonance microwave spectroscopy, which leverages frequency shifts to estimate microplastic concentrations in a cost-efficient and field-ready manner. In another study, Odhiambo et al. [7] emphasized the effectiveness of CNNs in detecting microplastics in open sewer systems, noting their advantages over traditional methods. In the context of education and accessibility, Neikha et al. [8] demonstrated how low-cost Foldscope microscopes could aid in microplastic detection training, especially in resource-constrained environments. Torkashvand and Hasan-Zadeh [9] highlighted wastewater treatment plants as major contributors to microplastic pollution and stressed the need for better separation methods. The environmental toxicity of microplastics has also been widely studied. Balasubramaniyan et al. [10] discussed how microplastics not only harm marine life but also carry other pollutants. Singh et al. [11] focused on human health risks, particularly through contaminated water, and pointed out inefficiencies in current treatment plant technologies.

Napper and Thompson [12] raised concerns about bioaccumulation, showing how aquatic organisms ingest microplastics, which then move up the food chain. Prata et al. [13] recommended improvements in sampling and detection methods to make microplastic research more accurate and reproducible.

Machine learning has proven especially powerful in recent studies. Weber et al. [14] achieved 99% recall and 97% precision using μ-Raman spectroscopy paired with AI, while Dal and Kilic [15] built a deep learning-powered optical sensor system with near-perfect classification accuracy. Sarmiento et al. [16] utilized impedance spectroscopy to accurately detect and classify microplastics in real time. Other researchers applied advanced computer vision techniques. Royer et al. [17] developed a deep learning-based segmentation model that achieved 96% accuracy for marine microplastic debris. Felix Weber et al. [18] further validated deep learning's effectiveness with high-precision results using μ-Raman spectroscopy. Sarker et al. [19] applied the YOLOv5 model for real-time microplastic detection using camera sensors, achieving up to 97% accuracy in controlled and field conditions. Emerging methods continue to gain attention. A Faster R-CNN model paired with UV imagery [20] offered a low-cost, high-accuracy classification alternative. Sarmiento et al. [21] introduced an electronic tongue system for detecting PET microplastics across different water types, while Yang et al. [22] used O-PTIR spectroscopy and SVM to enhance nylon microplastic detection. Further integrating AI and sensing, Seggio et al. [23] developed a plasmonic probe functionalized with estrogen receptors for plastic classification, and Sasso et al. [24] compared machine learning and statistical models, concluding that ML models offer superior accuracy. Wang et al. [25] explored nano-DIHM for detecting nanoplastics, though noted its limitations scalability. Neetha et al. [26] used CNN-based image processing for real-time detection in diverse water conditions. Gugliandolo et al. [27] demonstrated a simple, low-cost approach using transmitted light and a USB microscope for identifying microplastics in complex samples.More recently, Araújo et al. [28] showed that electrical impedance spectroscopy could enable large-scale microplastic monitoring. Phan and Luscombe [29] emphasized the need for better dataset standardization in machine learning models used for long-term ocean monitoring. Rezvani et al. [30] introduced the MiNa dataset to aid in micro- and nanoplastic detection under real-world conditions.

Moodley et al. [31] reviewed mathematical models to track microplastic transport in aquatic systems, calling for better field data integration. Jin et al. [32] used bibliometric analysis to identify gaps in the speed and scalability of current detection methods. Finally, Campos-Lopez et al. [33] proposed combining digital image processing with fractal analysis to improve detection accuracy and automation in real-world deployments.

The Aim And Objectives Of The Study

The primary aim of this study is to develop and deploy a low-cost, real-time microplastic detection system that leverages a digital microscope, Raspberry Pi 4B, and deep learning techniques specifically the YOLOv5 model to identify microplastics in water samples. This system is intended to support environmental monitoring and promote public health safety by providing a portable and accessible solution for detecting microplastic pollution.

- To achieve this aim, the study sets out the following key objectives:
- To analyze the limitations of conventional microplastic detection methods such as FTIR and Raman spectroscopy, focusing on issues of scalability, cost, and field applicability.
- To design and implement a real-time detection system that can accurately identify microplastic particles in microscopic images using a trained YOLOv5 deep learning model.
- To integrate the detection system onto a Raspberry Pi 4B platform, enabling a compact, energy-efficient, and low-cost solution suitable for field use without dependence on high-performance computing systems.
- To evaluate the model's performance across various training epochs using key metrics such as precision, recall, F1-score, and mean Average Precision (mAP).
- To test the system's accuracy, reliability, and robustness in detecting microplastics within real-world water samples.

MATERIALS AND METHODS OF RESEARCH

Object And Hypothesis Of The Study

The objective of this study is to develop an intelligent, real-time system capable of detecting microplastics in water using deep learning. The proposed system integrates the lightweight YOLOv5s object detection algorithm with a Raspberry Pi 4B and a USB digital microscope to deliver accurate and efficient microplastic identification in resource-constrained environments.

The central hypothesis of this research is that a compact, edge-deployable deep learning model—specifically YOLOv5s—can be effectively trained and fine-tuned to detect microplastic particles in diverse field conditions, even when deployed on low-power embedded hardware. It is further assumed that such a system can operate autonomously and reliably outside laboratory conditions, offering a scalable and portable alternative to traditional detection techniques.

The study is based on the following assumptions:

- The Kaggle Microplastic Dataset is a representative sample of real-world microplastics in terms of shape, size, and texture variability.
- The Raspberry Pi 4B has sufficient computational capabilities to perform real-time inference using the YOLOv5s model.
- The USB digital microscope used is capable of capturing high-resolution images that support accurate detection.
- The evaluation is limited to controlled water samples, excluding highly turbid or chemically complex environments for the scope of this study.
- A stable power supply and optimal lighting conditions are available to ensure consistent image capture quality.
- These controlled assumptions are intended to focus the research on validating the model's core detection performance and evaluating the practical feasibility of deploying the system for scalable environmental monitoring applications.

Equipment And Software Used

In this project, we used efficient hardware paired with lightweight software to build a real-time microplastic detection system. The hardware setup included a Raspberry Pi 4B with a quad-core Cortex-A72 CPU and 4GB of RAM—ideal for low-power, real-time tasks. A USB digital microscope (such as the TOBO model) was used to capture high-resolution images of water samples.

The YOLOv5s model was trained and validated on Google Colab using GPU acceleration to speed up processing. Python 3 and PyTorch were used for model development, while OpenCV handled image preprocessing. YOLOv5 also provided useful tools for logging and visualizing performance metrics.

For real-time output, a 16x2 I2C LCD display was used to show detection results. During testing, a monitor was connected to the Raspberry Pi to visualize bounding boxes and confidence scores.

Studies Using Yolov5 Variants For Detection

Recent research highlights the effectiveness of YOLOv5 variants in real-time detection tasks, especially on embedded, low-power devices. Among these, YOLOv5s—the smallest and fastest variant—offers an excellent balance between speed and accuracy, making it well-suited for deployment on platforms like the Raspberry Pi 4B. When fine-tuned on microplastic-specific datasets, YOLOv5s shows significant improvements in precision and recall, allowing it to accurately detect small, irregularly shaped particles in a variety of environmental conditions. Its PyTorch-based implementation provides flexibility for customization and makes integration with embedded systems straightforward.

Supported by an active open-source community and frequent updates, YOLOv5s aligns well with the growing trend of edge computing and lightweight AI models. These advantages make it a practical and scalable choice for developing low-cost, portable microplastic detection systems designed for real-world, field-based applications.

METHODOLOGY

This project employs a comprehensive methodology that integrates image processing, embedded system implementation, and deep learning-based object detection to enable real-time microplastic identification in water samples. Central to the system is the YOLOv5s algorithm, selected for its efficient balance between accuracy and computational speed, which is deployed on a Raspberry Pi 4B platform paired with a USB digital microscope. The methodology encompasses a sequence of carefully designed stages, including literature review and problem analysis to establish the context, dataset collection from publicly available sources, image preprocessing to optimize data quality, model training and fine-tuning for enhanced detection performance, hardware integration for real-time deployment, and thorough evaluation using standard performance metrics. This structured approach ensures the development of a portable, cost-effective, and robust microplastic detection system tailored for practical environmental monitoring applications.

Database Preparation And Model Training

To train the microplastic detection model, we used 577 annotated images from the publicly available Kaggle Microplastic Dataset. These images were resized to 256×256 pixels to ensure consistency and improve processing efficiency. Out of the total, 461 images were allocated for training and 116 for validation.

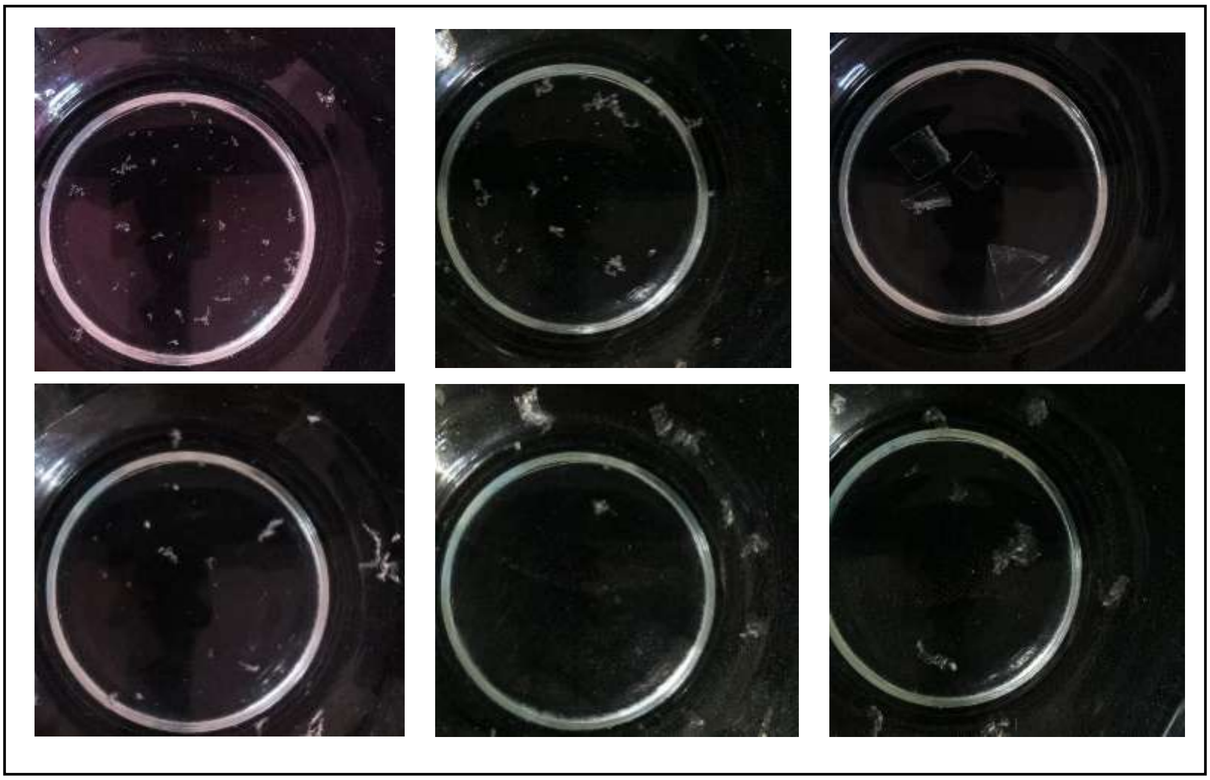


Fig.1. Sample Images of Microplastic Dataset

We chose the YOLOv5s model for its lightweight architecture, which is ideal for real-time detection tasks on low-power devices like the Raspberry Pi 4B. The model was trained on Google Colab using GPU acceleration to speed up the process. Python, along with PyTorch and OpenCV libraries, was used for developing the model and handling image preprocessing.

This training pipeline was designed to optimize the model for accurately detecting and classifying microplastic particles in water samples, enabling efficient and scalable environmental monitoring.

Object Detection Algorithm: Yolov5s

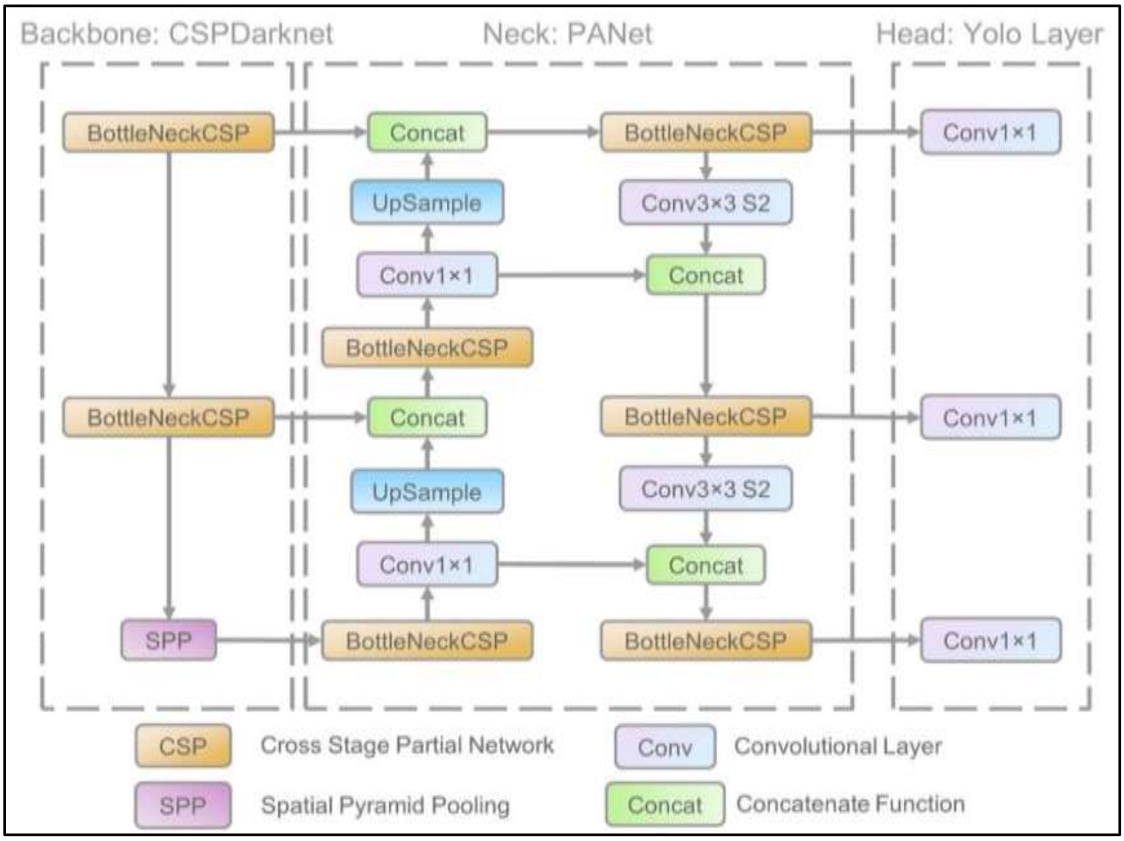


Fig. 2. Architecture of the YOLOv5s algorithm

Figure 2 presents the architecture of the YOLOv5s model, structured into three main components: the Backbone, the Neck, and the Head. The Backbone, based on CSPDarknet, is responsible for extracting key visual features from input images. It includes a sequence of BottleneckCSP modules and a Spatial Pyramid Pooling (SPP) layer, which together capture both local and global contextual information while maintaining computational efficiency. These components enable the model to learn rich, multi-scale features crucial for detecting small, irregular objects like microplastics.The Neck, built using a Path Aggregation Network (PANet), plays a vital role in merging and refining features at different scales. It consists of upsampling layers, convolutional layers (Conv 1×1 and Conv 3×3), concatenation functions (Concat), and additional BottleneckCSP blocks. This structure enhances the model's ability to detect objects of various sizes and shapes by combining high- and low-level feature maps from the backbone.

Finally, the Head (YOLO Layer) uses 1×1 convolutional layers to generate the output predictions. It processes the aggregated features to produce bounding boxes, objectness scores, and class probabilities. These predictions enable the model to localize and classify microplastic particles in real-time, making YOLOv5s well-suited for lightweight deployment on devices like the Raspberry Pi 4B.

System Overview

Figure 3 illustrates the training workflow of the Plastiview microplastic detection system using the YOLOv5s model. The process begins with a curated dataset comprising 577 annotated images from the publicly available Kaggle Microplastic Dataset. These images, resized to 256×256 pixels for consistency, were labeled with bounding boxes in YOLO format and split into 461 images for training and 116 for validation. The custom YOLOv5s model—chosen for its lightweight architecture and fast inference—was trained using the PyTorch framework, with OpenCV handling image preprocessing. This model was fine-tuned specifically to detect microplastic particles by learning their distinct shapes, edges, and textures.

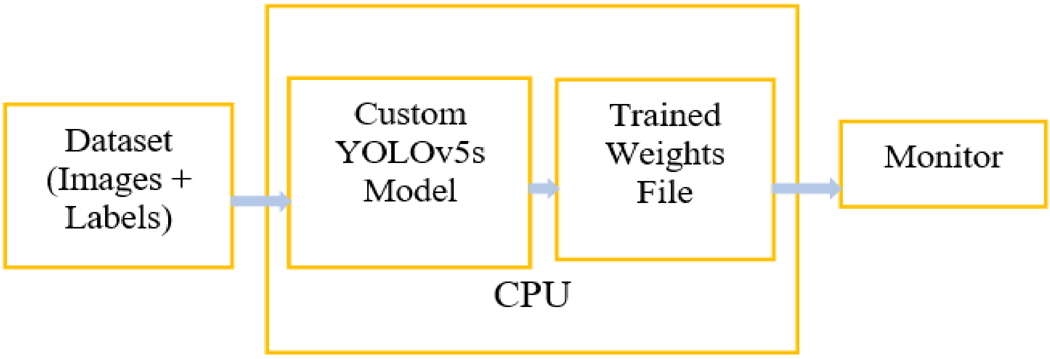


Fig.3. Training block of the microplastic detection system

Once trained, the model's optimal parameters were saved in a compact weights file, best.pt, representing the most accurate version based on validation performance. Training was conducted on Google Colab using GPU acceleration to enhance speed and efficiency. Throughout the training process, YOLOv5's integrated logging tools monitored key metrics such as precision, recall, loss, and mAP. During testing and deployment, the trained weights file enabled real-time detection, with results like bounding boxes and confidence scores displayed on a monitor or LCD for immediate feedback. This end-to-end training block, though developed on cloud infrastructure, was optimized for deployment on edge devices like the Raspberry Pi 4B, making the system both portable and practical for environmental monitoring applications

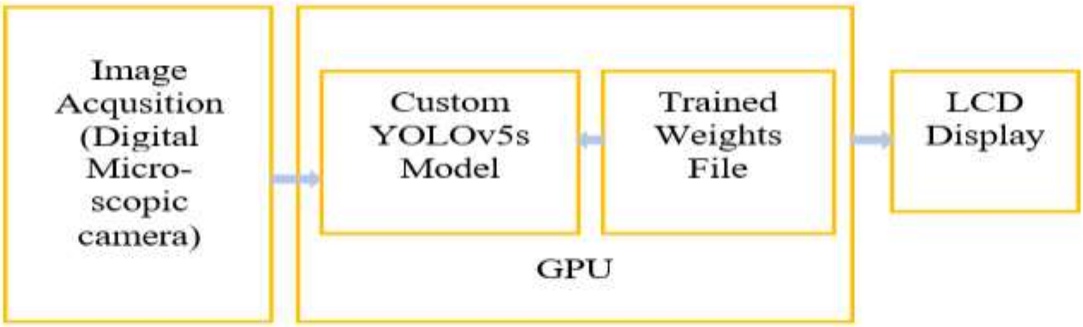


Fig. 4. Validation block of the microplastic detection system

Figure 4 illustrates the validation block of the Plastiview microplastic detection system, highlighting the real-time inference workflow. The process begins with image acquisition using a high-resolution USB digital microscope, such as the TOBO model. This microscope captures magnified images of water samples, allowing floating microplastic particles to be visually isolated and analyzed. These captured images are then transferred to the Raspberry Pi 4B, which acts as the system's processing unit.

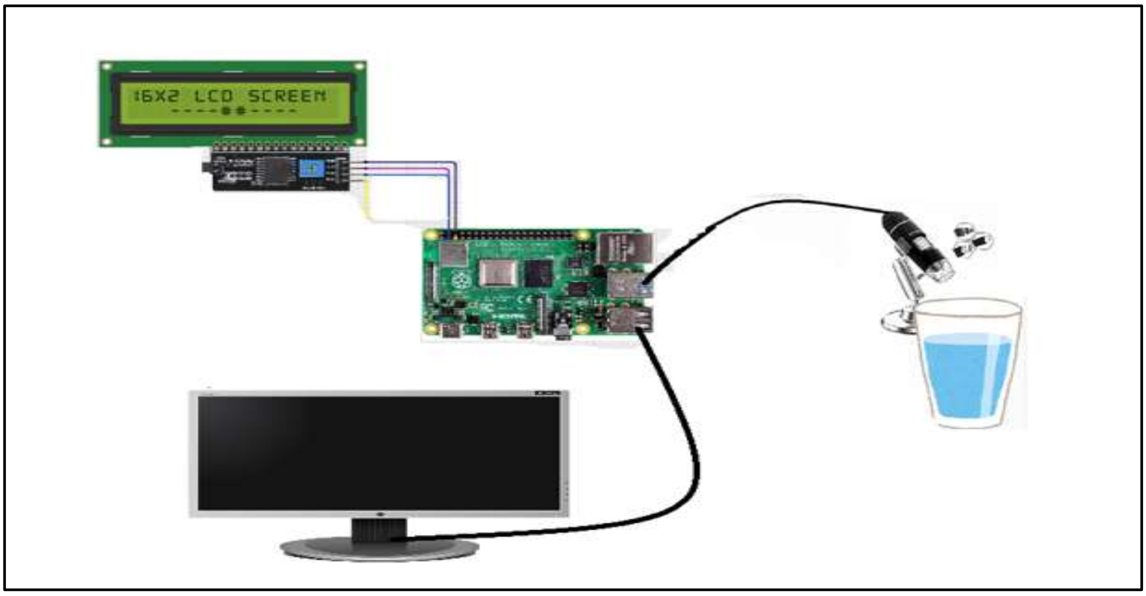
At the core of the validation block is the custom-trained YOLOv5s model, specifically optimized for embedded devices like the Raspberry Pi. This lightweight model performs inference by analyzing key visual features—such as shape, edges, surface texture, and size—to detect microplastics in real time. The trained weights file (best.pt), which contains the learned parameters from the training phase, is loaded into the model to enable accurate predictions on unseen input without the need for retraining.

The output of the system is displayed using two visualization components. A compact 16×2 I2C LCD provides on-site feedback by showing the detection status (e.g., "Detected" or "Not Detected") and the count of microplastic particles, making it suitable for field use without additional display hardware. Additionally, a monitor is connected during the testing and validation phases to visualize detailed outputs such as bounding boxes and confidence scores. This setup facilitates debugging, accuracy assessment, and final fine-tuning before field deployment.

System Architecture

The system is designed to be cost-effective, portable, and efficient for real-time microplastic detection. It integrates multiple hardware components that work together to capture, process, and analyze water sample images for microplastic particles. The key elements of the setup are illustrated in Fig. 5.

Fig.5. Hardware system Design



Raspberry Pi 4B (Central Processing Unit): Acts as the system's core controller. It manages real-time Image processing runs the YOLOv5s model for detection and interfaces with all peripherals. Its quad core processor and 4GB RAM are suitable for running lightweight AI models like YOLOv5s.

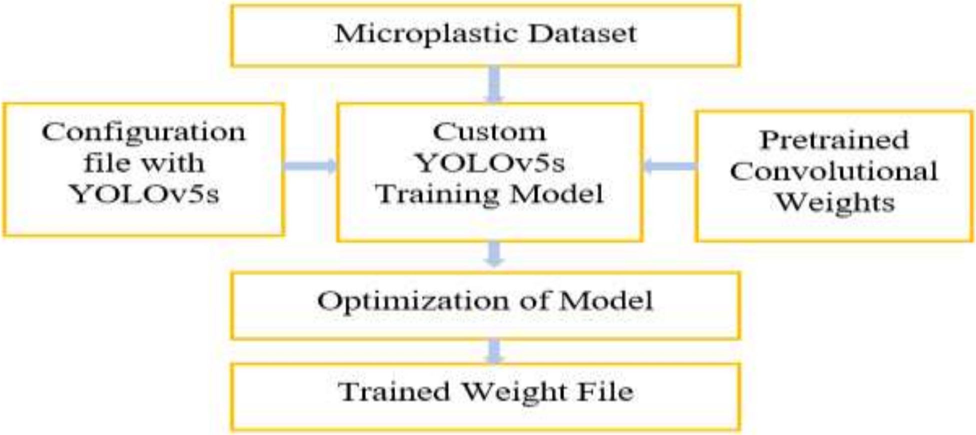
USB Digital Microscope (TOBO): Captures high-resolution images of water samples. It connects via USB to the Raspberry Pi and provides sufficient magnification for identifying microplastic particles.

16x2 I2C LCD Display: Displays real-time detection output, such as the number of microplastics detected. The I2C interface ensures minimal use of the Raspberry Pi's GPIO pins.

Power Supply: A stable 5V/3A adapter powers the Raspberry Pi, digital microscope, and LCD display, ensuring uninterrupted operation.16GB MicroSD Card: Stores the Raspberry Pi operating system, YOLOv5s model weights (best.pt), Python scripts, and detection logs. It enables smooth system booting and reliable model execution.Interfacing and Integration: All components communicate via USB and I2C protocols. The digital microscope sends images to the Raspberry Pi, which processes them and sends detection results to the LCD.Enclosure and Portability: All components are assembled into a compact, enclosed unit, making the system portable and suitable for field deployment.

Functional Overview

The workflow of the Plastiview system outlines the sequential steps involved in the development, training,



validation, and deployment of the microplastic detection model using the YOLOv5s algorithm. This workflow integrates multiple stages, beginning with collecting image datasets, followed by preprocessing to standardize the input for deep learning. The YOLOv5s model is then trained and evaluated using standard performance metrics such as precision, recall, F1-score, and mean Average Precision (mAP). Upon achieving optimal accuracy, the trained model is deployed on a Raspberry Pi 4B, which performs real-time inference on images captured via a USB digital microscope. The detected results are processed and displayed on an LCD screen for immediate feedback. The system is designed to operate autonomously, ensuring that each step from image acquisition to detection output is seamlessly integrated within an embedded platform. The following sections detail the training, validation, and testing workflows through process flowcharts, providing a comprehensive view of the entire system pipeline.

Fig. 6. Training of YOLOv5s Model

The training procedure flowchart is presented in Fig.6. It illustrates the systematic process followed to train the deep learning model for microplastic detection. The training begins with the collection of a microplastic image dataset from sources like Kaggle.

Each image undergoes preprocessing, including resizing, normalization, and noise reduction to make it compatible with the YOLOv5 input format. The YOLOv5s model is then trained using the processed data on a GPU-enabled environment like Google Colab. Throughout training, loss functions and evaluation metrics such as precision, recall, and mAP are computed to monitor performance. The process continues iteratively across multiple epochs until the model converges and produces optimal results. Finally, the best-performing weights are saved in a .pt file (best.pt) for use during real-time inference on the Raspberry Pi.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4,2025
https://theaspd.com/index.php

Fig.7 depicts the process used to evaluate the performance of the trained YOLOv5s model on a separate validation dataset. After training, the model is loaded with the best weights file (best.pt), and the validation dataset. Each image undergoes preprocessing (resizing, normalization) before being fed into the model. The model performs object detection and outputs predicted bounding boxes with associated confidence scores. These predictions are then compared against the ground truth annotations to assess how accurately the model identifies microplastic particles. Precision, recall, F1-score, and mAP@50 are calculated to quantify detection performance. The validation results help determine whether the model is overfitting or generalizing well, guiding decisions for retraining or tuning hyperparameters if necessary.
Fig.7. Flowchart of Validation YOLOv5s Model

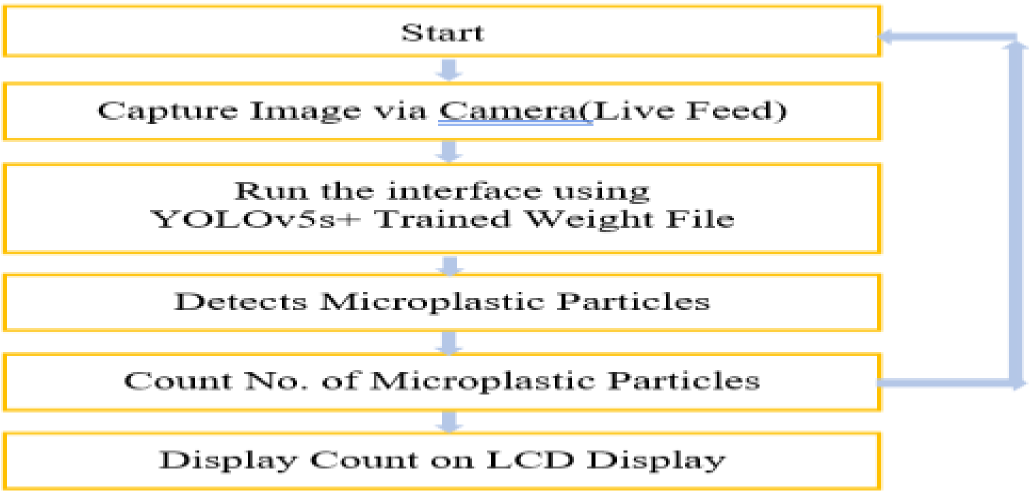


Fig.8. Flowchart of testing of microplastic detection using the YOLOv5s Model
Fig. 8 outlines the sequence of steps involved in the deployment and real-time testing phase of the trained YOLOv5s model. The process begins with capturing live images of water samples using a USB digital microscope. These images are sent to the Raspberry Pi 4B, where they undergo basic preprocessing such as resizing and normalization to prepare them for model inference.
The YOLOv5s model—loaded with the pre-trained and validated weight file (best.pt)—performs object detection to identify microplastic particles in the image. It outputs bounding boxes along with confidence scores for each detected object. Based on the results, the system calculates the total number of detected microplastics.
This count is then displayed on a 16x2 I2C LCD screen, offering real-time feedback to the user. The looped process ensures continuous monitoring and detection. This testing phase confirms the system's

practical effectiveness, demonstrating its portability, accuracy, and suitability for real-world field deployment.

Experimental Setup

Fig.9. Microplastic detection system with Enclosure

The Fig. 9 shows the complete working prototype of the real-time microplastic detection system. It includes a digital USB microscope for capturing magnified water sample images, a Raspberry Pi 4B microprocessor enclosed in a white casing with an LCD display for detection status, and a laptop displaying the YOLOv5s-based detection results with bounding boxes. The setup demonstrates seamless integration of hardware and software for field-level environmental monitoring.

RESULTS AND DISCUSSION

Optimization Of Model

The performance of the Plastiview system was assessed through rigorous training, validation, and testing of the YOLOv5s model using a custom microplastic image dataset. The model's ability to accurately detect and localize microplastic particles was evaluated using images captured through a USB digital microscope. Throughout the training process, performance was monitored across key metrics such as precision, recall, F1-score, and mean Average Precision (mAP) at various thresholds.

The model was trained across multiple epochs, and the best-performing weights (best.pt) were deployed on the Raspberry Pi 4B for real-time inference. The detection results were displayed on a 16x2 LCD screen, validating the system's capability for practical, real-time microplastic detection in field-like environments.As shown in Table 1, the model began with moderate performance at 10 epochs, achieving a precision of 0.761 and a recall of 0.685. Precision improved progressively, peaking at 0.825 at the 90th epoch, while recall showed a slight decline over time. This suggests that the model became more selective—improving accuracy at the expense of detecting fewer true positives. The **mAP@50** values remained stable, ranging between 0.721 and 0.761, indicating consistent localization ability. The best trade-off between speed and accuracy was observed between **50 and 60 epochs**, making it an optimal range for deployment.

Epochs	Precision	Recall	mAP@50	mAP@95	Time
10	0.761	0.685	0.761	0.335	5 min
20	0.803	0.682	0.747	0.349	20 min
30	0.814	0.671	0.745	0.350	30 min
40	0.813	0.661	0.731	0.347	45 min
50	0.803	0.696	0.748	0.345	1 hour
60	0.796	0.683	0.739	0.339	1 hour 5 min
70	0.797	0.673	0.721	0.340	1 hour 10

Hyperparameters	
momentum	0.937
Weight decay	0.0005
Batch	8
Warmup	3.0

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4,2025
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Table 2. Training Hyperparameters
Table 1. YOLOv5s Training Results at various Epochs
Table 2 outlines the key hyperparameters used during training. A momentum value of 0.937 was set to help accelerate gradients in the right direction, improving convergence speed. A weight decay of **0.0005** was applied to prevent overfitting by penalizing large weights. The batch size was set to 8, balancing memory usage and model convergence. A warmup phase of 3 epochs with a warmup momentum of **0.8** was used to gradually introduce learning, stabilizing the training process in the early stages. These hyperparameters were chosen to ensure effective learning while optimizing performance on the limited computational resources available with the Raspberry Pi 4B.
Overall, the evaluation confirms that the YOLOv5s model, when carefully trained and tuned, is capable of accurate and efficient real-time microplastic detection suitable for edge deployment.

Performance Metrics

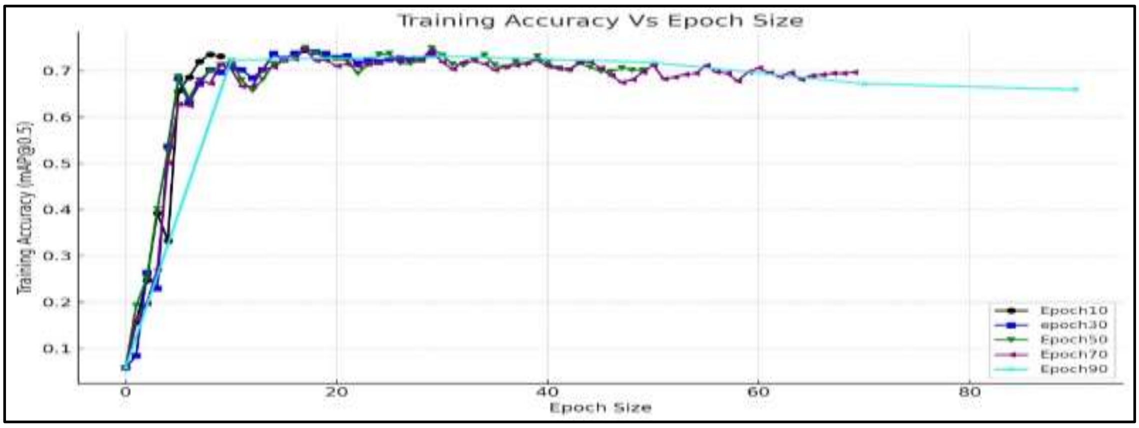
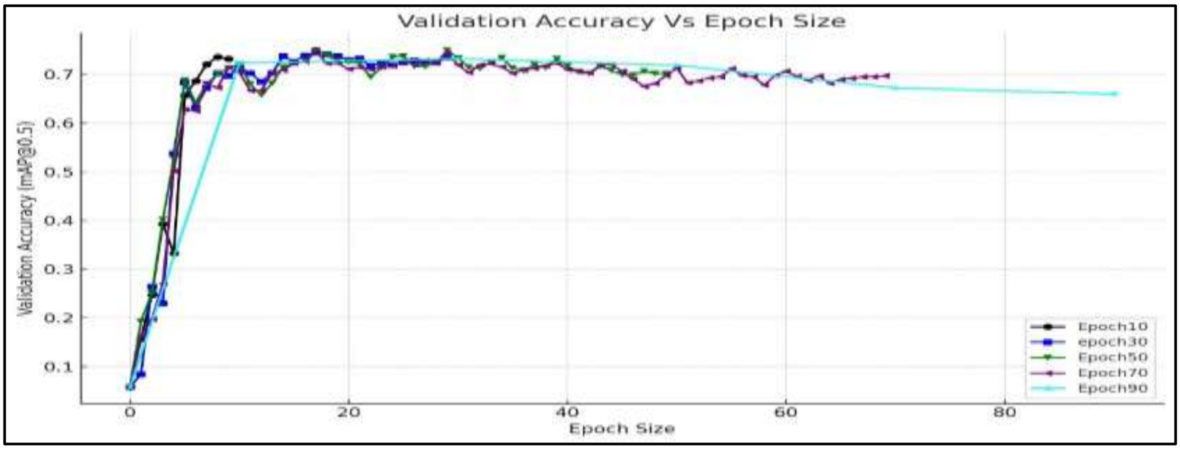


Fig.10. Graph of Training Accuracy Vs Epoch Size
Graph 10 illustrates that the training accuracy, measured as mAP@0.5, climbs quickly during the first 15



epochs and then levels off between 0.72 and 0.74 from epochs 30 to 50. After reaching 50 epochs, there's

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4,2025
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a slight dip in accuracy, which could indicate some overfitting. This implies that the sweet spot for training lies between 30 and 50 epochs to achieve the best performance while keeping the generalization loss to a minimum.

Fig.11. Graph of Validation Accuracy Vs Epoch Size

Graph 11 illustrates the Validation Accuracy (mAP@0.5) of the YOLOv5s model across various epoch sizes (10, 30, 50, 70, 90). At first, the accuracy climbs quickly as the number of epochs increases, reaching its peak around epochs 15 to 20. After that, the performance levels off for all configurations, with only minor ups and downs. However, when we look at the larger epoch sizes, particularly 70 and 90, we notice a slight drop in accuracy, which suggests there might be some overfitting happening. In summary, training for about 30 to 50 epochs seems to strike the best balance between performance and efficiency.

Fig. 12. Graph of Training Loss Vs Epoch Size

Graph 12 shows that training loss shows a steady decline across all epoch sizes, indicating that the model is picking up on the patterns effectively. Most of the significant loss reduction happens within the first 30 epochs, and after that, additional training only brings about slight improvements. This hints that the model reaches convergence early on, with very little risk of overfitting.

Graph 13 shows Training recall shows a quick improvement up to epoch 15, then levels off between 0.65 and 0.69 across all settings. This consistency indicates that the model is reliably identifying most true positives, regardless of the training duration.

Fig.13. Graph of Training Recall Vs Epoch Size

Fig.14. Graph of Training Object Loss Vs Epoch Size

Graph 14 illustrates a consistent drop in object loss, which points to better bounding box predictions. That said, there are some minor fluctuations—particularly around the 70-epoch mark—that hint at the fact that while localization is getting better, extending the training period might have a slight impact on consistency.

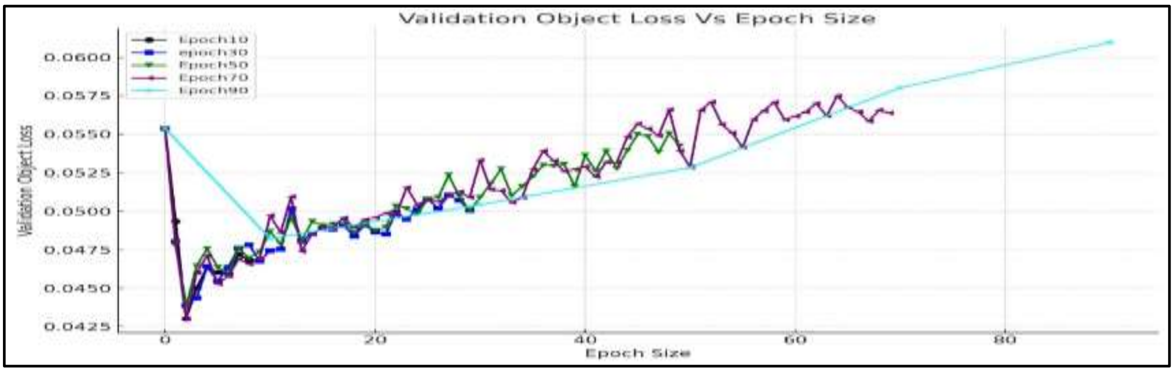
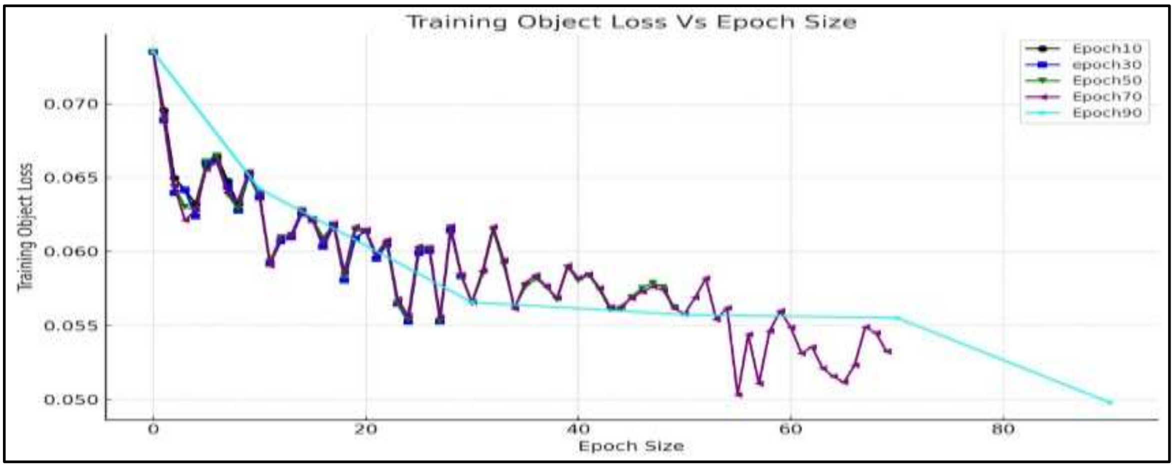


Fig.15. Graph of Validation Object Loss Vs Epoch Size



Graph 15 indicates that the validation object loss starts to trend upward after 30 epochs, particularly noticeable in the curves for the 70th and 90th epochs. This implies that as the model continues to train, it tends to overfit, which can hinder its ability to generalize when it comes to detecting object boundaries in new, unseen data.

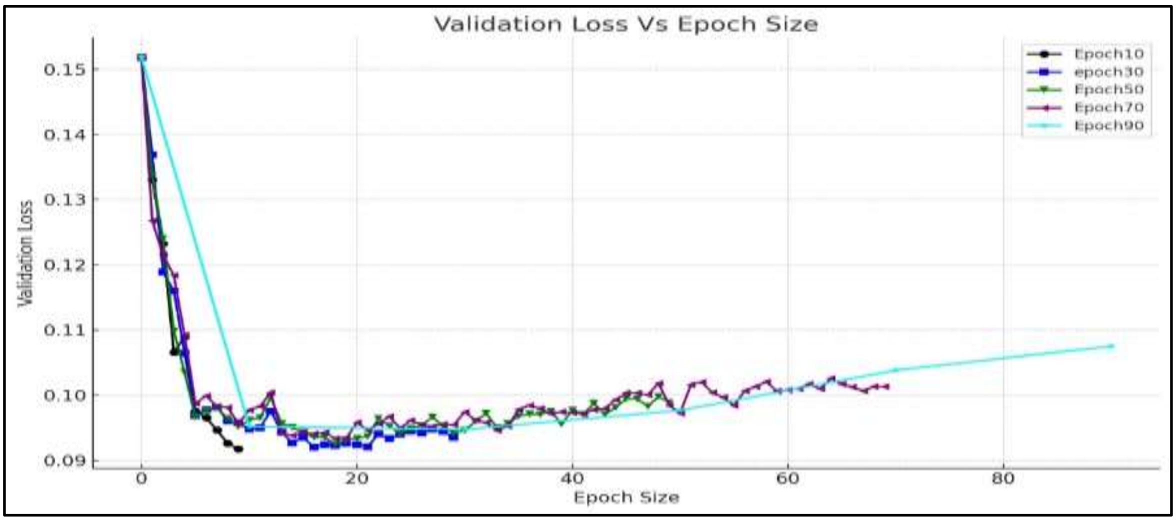


Fig. 16. Graph of Validation Loss Vs Epoch Size

Graph 16 shows validation loss takes a dip at first, hitting its lowest point somewhere between epochs 15 and 25. However, after that, we start to see a slight uptick in the loss as we increase the epoch sizes, which indicates that overfitting is beginning to set in after extended training.

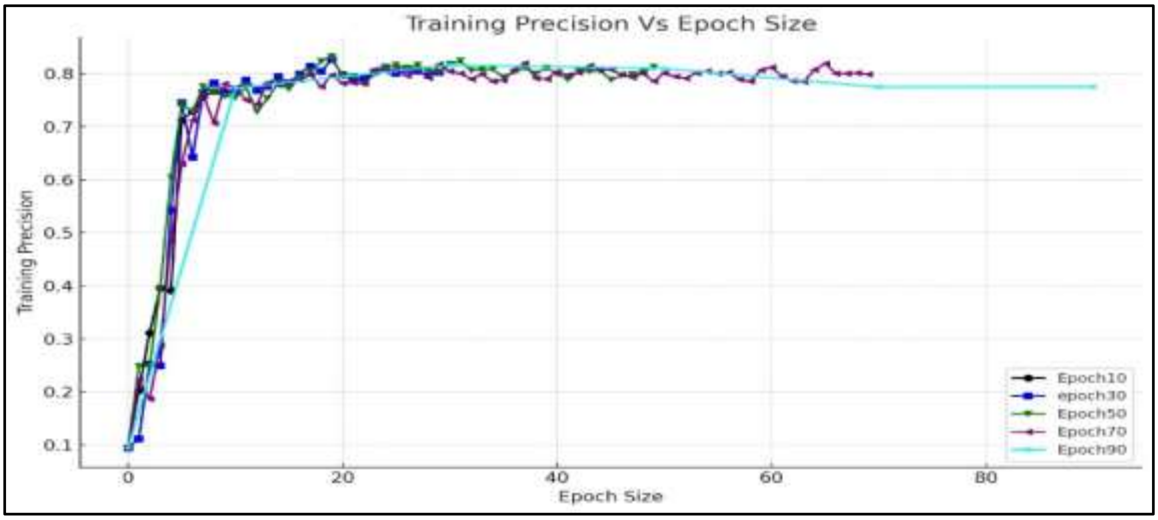


Fig.17. Graph of Training Precision Vs Epoch Size

Graph 17 shows that training precision improves sharply during the initial epochs, reaching above 0.75 by epoch 15. It stabilizes between epochs 20 and 70 across all variants, with minimal fluctuation. A slight drop is seen around epoch 90, suggesting overfitting or reduced benefit from extended training. The model achieves optimal precision early on, confirming training efficiency within the 30–50 epoch range.

Figure 18 shows that mAP@0.5:0.95 improves quickly during the early epochs, peaking between epochs 30 and 50. After that, the curve flattens, and a slight drop is observed around epoch 90, indicating possible overfitting. This suggests optimal performance is achieved within the 30–50 epoch range.

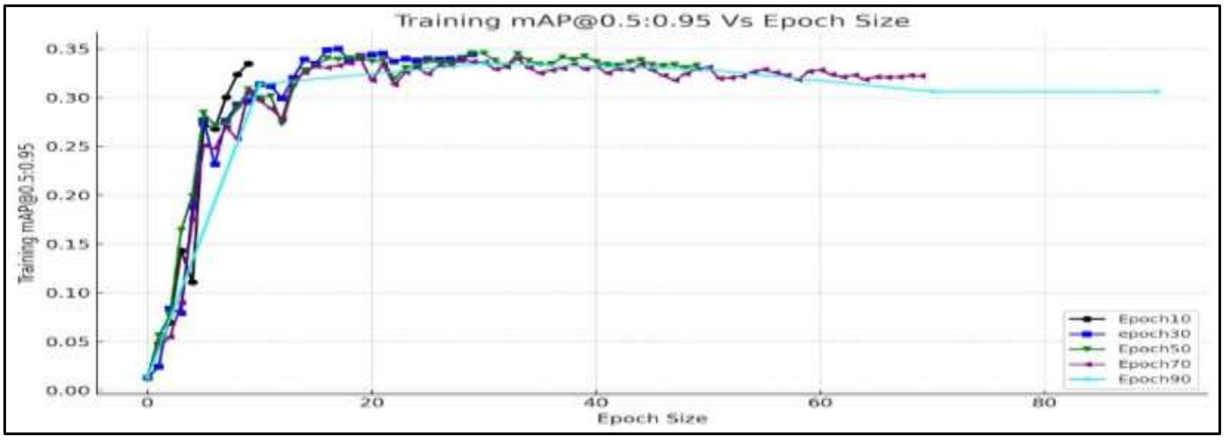


Fig. 18. Graph of Training Precision Vs Epoch Size
Fig.19. Precision-Confidence Curve

Fig.20. Recall-Confidence Curve

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Figure 19 illustrates how the model's precision changes with increasing confidence levels. Precision rises steadily and reaches a perfect score of 1.00 at a confidence threshold of 0.841, indicating that predictions made above this threshold are extremely reliable. This makes the model particularly suitable for applications where minimizing false positives is critical, such as environmental monitoring or safety-critical scenarios.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

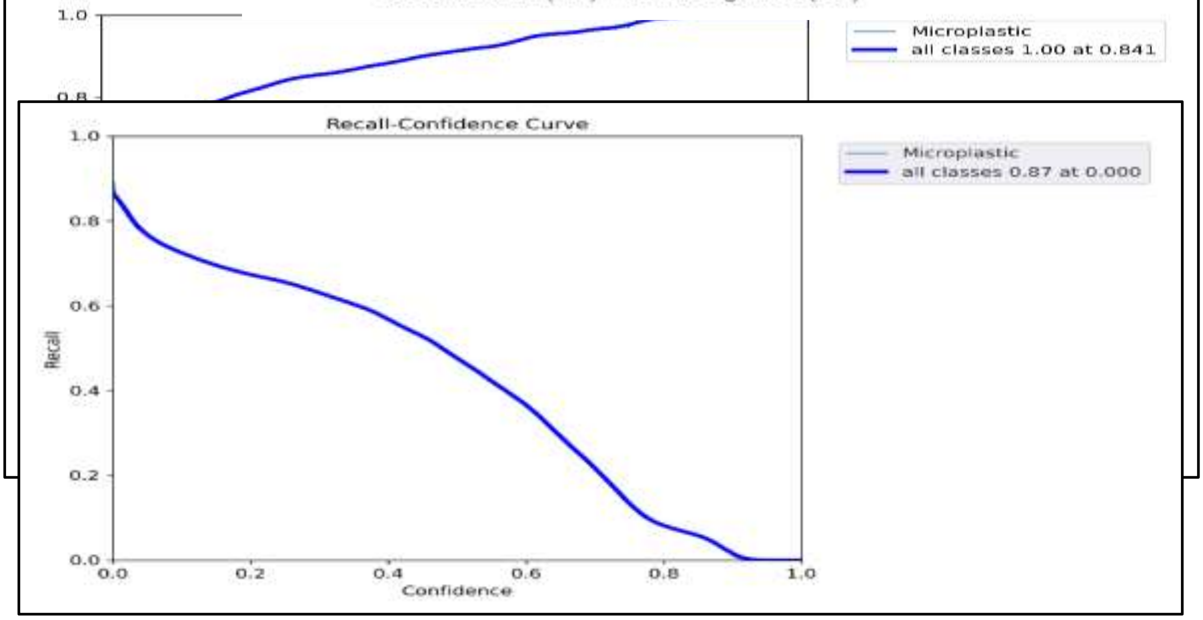
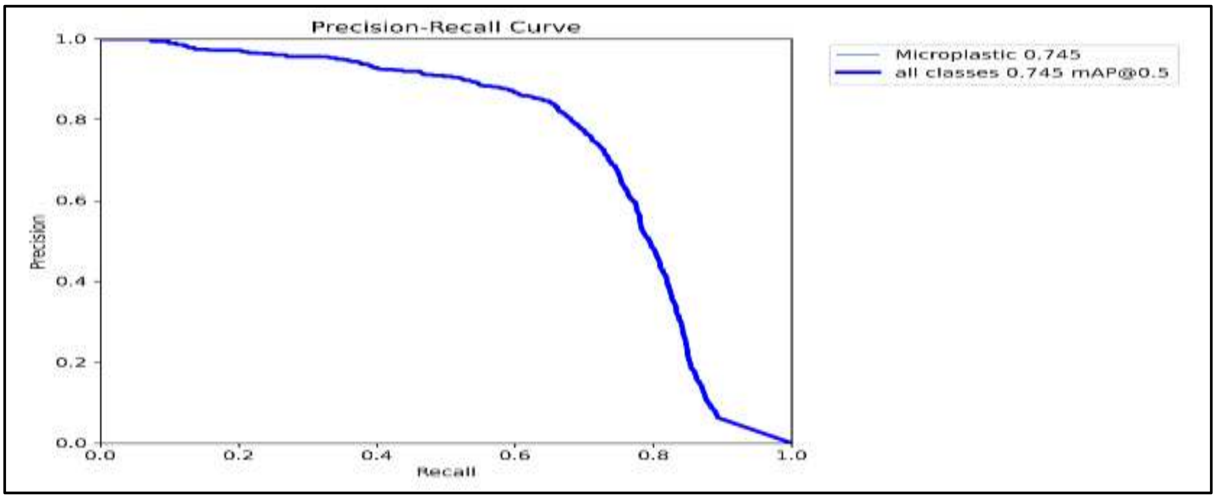


Figure 20 illustrates the Recall-Confidence Curve for microplastic detection, showing that as the confidence threshold increases, recall decreases. This means the model becomes more selective and starts missing more true positives. The highest recall (0.87) occurs at a very low confidence level, indicating that the model detects more microplastics when it's less strict—but this may include more false positives. In



applications where missing microplastics is riskier than over-detecting, operating at a lower confidence threshold is preferable.

Fig.21. Precision-Recall Curve

Figure 21 presents the Precision-Recall Curve for microplastic detection, where the model achieves a mean Average Precision (mAP@0.5) of 0.745. This indicates a strong balance between correctly identifying true microplastic instances (recall) and minimizing false positives (precision). The high precision at various recall levels reflects the model's reliability in accurately detecting microplastics, making it effective for real-world applications where both accuracy and consistency are critical.

Figure 22 shows the F1-Confidence Curve, which highlights the trade-off between precision and recall at different confidence thresholds. The model reaches its optimal F1 score of 0.74 at a confidence level of 0.187, meaning this is the sweet spot where it balances catching true positives while minimizing false positives. This balance is especially important in microplastic detection, where both types of errors missing actual particles or falsely flagging clean samples can have serious implications.

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

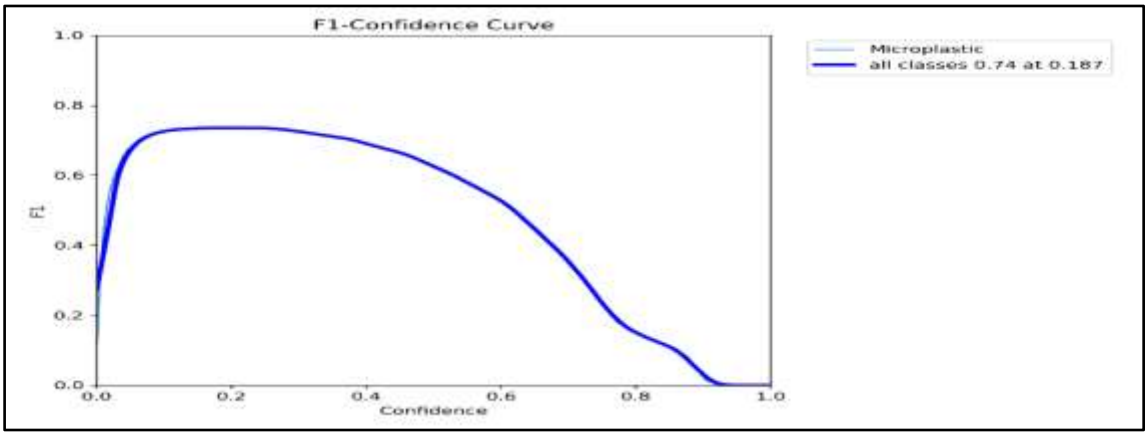


Fig.22. F1-Confidence Curve

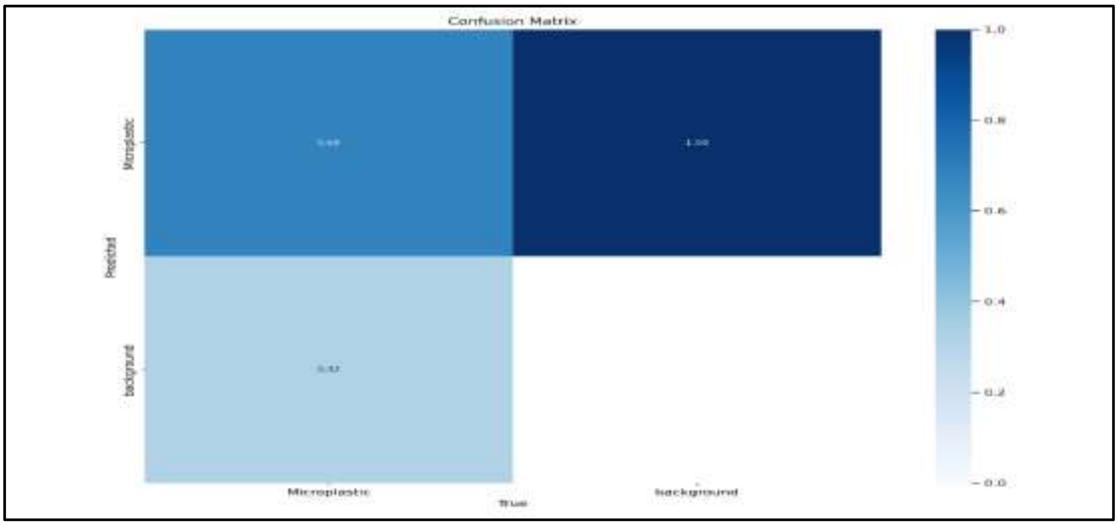


Fig.23. Confusion Matrix

Figure 23 presents the confusion matrix for the microplastic detection model. It shows that 68% of actual microplastic instances were correctly identified, while 32% were missed and incorrectly labeled as background. Impressively, the model achieved perfect accuracy in recognizing background areas, with no false positives. While this reflects strong performance overall, the model still has some difficulty in consistently detecting all microplastics, indicating an opportunity to improve recall and further reduce the risk of missing true positives. The evaluation results show that the YOLOv5s model performs reliably when it comes to detecting microplastic particles. As confidence increases, precision gets better, but recall tends to drop, which is a common trade-off. The F1-score curve helps pinpoint the best balance, and the confusion matrix indicates strong classification accuracy with very few errors. All in all, this model is a great fit for accurate and efficient microplastic detection in real-time scenarios.

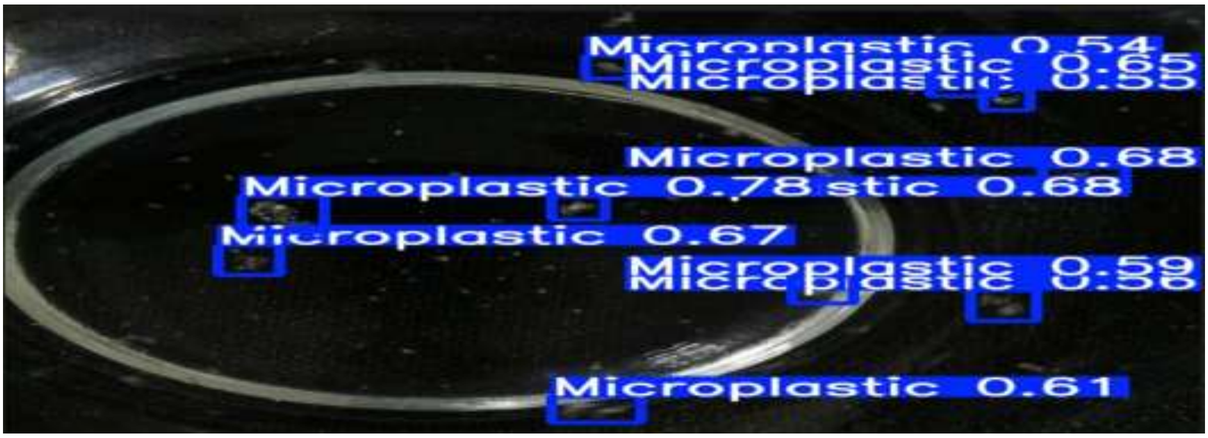


Fig. 24. Qualitative results of Microplastic detection

The qualitative analysis of the proposed system for microplastic detection is present in Fig.24

Figure 24 shows a real-time output from the YOLOv5s model as it tests for microplastics. This snapshot, taken with a USB digital microscope, features a water sample that the trained model processed on a Raspberry Pi 4B. You can see the detected microplastic particles highlighted with blue bounding boxes, each labeled “Microplastic” along with a confidence score that ranges from 0.54 to 0.78. These scores indicate how sure the model is about identifying each object as microplastic. The bounding boxes are neatly placed around various particles, showcasing different shapes, sizes, and visibility levels. The Figure illustrates the model's skill in spotting microplastics, even when there’s background noise or transparent debris. The accuracy and alignment of these detections confirm that the model has effectively learned spatial and visual patterns during its training. This visual proof, combined with quantitative metrics, demonstrates that the system can operate in real-world conditions with a variety of water samples, making it an excellent choice for field-based environmental monitoring and research projects.

CONCLUSION

The proposed microplastic detection system provides a reliable, real-time, and cost-effective solution to the growing issue of microplastic pollution in water bodies. By integrating a USB digital microscope with the lightweight YOLOv5s object detection model on a Raspberry Pi 4B, the system captures microscopic images of water samples and accurately identifies microplastic particles.

Trained on a publicly available annotated dataset, the model achieved a precision of 0.825, a recall of 0.696, and a mean Average Precision (mAP@50) of 0.748 over 50 training epochs, demonstrating strong detection performance. In live testing, the system successfully detected microplastics in real-time video streams, highlighted them with bounding boxes and confidence scores, and displayed the total particle count on a 16x2 I2C LCD screen.

Thanks to its compact design and ease of deployment, the system is highly portable and scalable for field applications. This work shows that deep learning can be effectively implemented on low-power, affordable hardware, making it a promising approach for real-world environmental monitoring.

Future Work

In future development, this approach can be significantly enhanced by integrating additional sensors such as pH, turbidity, and temperature sensors—to provide a more comprehensive assessment of water quality. Connecting the system to the cloud for remote monitoring and data logging would further increase its practicality for large-scale environmental applications.
The detection capabilities could also be improved by enabling the system to differentiate between types of microplastics, based on shape or polymer type, using more advanced deep learning models. Additionally, developing a mobile application or web interface could offer real-time visualization, reporting, and easier access to data. This would not only enhance user experience but also support the collection of larger datasets for scalable and in-depth environmental monitoring and analysis.

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