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Development of an Iot-Integrated AI System for Microplastic Detection in Water Samples

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Abstract: ***Microplastics are emerging pollutants that threaten aquatic ecosystems and global water safety. This research introduces an integrated IoT and AI-based system designed for real-time detection of microplastic particles in water samples. The system employs high-resolution microscopy integrated with a Raspberry Pi platform, utilizing machine learning models trained to identify and classify microplastic types based on size and shape. Data captured by the camera is processed and transmitted via MQTT to a centralized dashboard, providing live visualization of contamination levels, particle types, and water quality parameters. Validation using simulated datasets demonstrates detection accuracy exceeding 95%, with potential to scale for environmental monitoring across multiple sites. This work highlights a cost-effective, scalable approach for continuous water quality assessment, contributing to environmental protection and pollution management efforts.***
Keywords: Microplastics, IoT, Machine Learning, Computer Vision, Water Quality Monitoring, Raspberry Pi, Real-Time Dashboard, Environmental Pollution.

I. INTRODUCTION

In this paper we have discussed regarding microplastics—tiny plastic particles smaller than five millimeters—have quietly become a big problem for our waterways and ecosystems. These minute pollutants come from the breakdown of larger plastic debris and can make their way into aquatic life and, eventually, our own food supply. Traditionally, identifying microplastics involves manual microscope analysis or specialized instruments, which is both slow and expensive. That makes it tough to keep a constant eye on water quality and react quickly to pollution events.

Thanks to advances in artificial intelligence (AI) and Internet of Things (IoT) technology, we now have the tools to change this. Imagine a system that can automatically scan water samples on-site, spot microplastic particles in real-time, and send that information anywhere you want through the internet. This is precisely what this project aims to build—a smart, affordable device based on a Raspberry Pi connected to a high-powered microscope camera. It processes images with AI algorithms trained to recognize different kinds of microplastic particles, and streams real-time data to an interactive dashboard for monitoring and action.

In the pages that follow, we walk through the design and development of this system, from dataset collection and AI model training to hardware integration and live data visualization. We test its accuracy and responsiveness on prepared samples and discuss potential improvements. Our hope is that this solution can pave the way for continuous, scalable monitoring of microplastic pollution, empowering researchers, environmentalists, and policymakers to better protect precious water resources.

A. Purpose of This Study

This study sets out to create an affordable and easy-to-use system that can automatically find tiny plastic particles in water—something that's traditionally taken a lot of time and expensive equipment. The goal is to build a smart device using Raspberry Pi and a powerful camera that works together with artificial intelligence to spot and sort these microplastics in real-time:

More specifically, this research aims to:

1) Put together a simple yet effective hardware platform capable of capturing clear microscopic images of water samples.
2) Train a computer vision model that can accurately recognize and categorize microplastic particles by type and size.
3) Develop a real-time data pipeline that sends results from the device to a user-friendly dashboard anywhere, anytime.
4) Create an interactive dashboard that presents clear visual information about water pollution levels and quality.
5) Test how well the whole system works on both simulated and real water samples and see how practical it is for ongoing environmental monitoring.

In essence, this work tries to overcome current hurdles by offering a practical, scalable way to monitor water quality continuously and empower environmental experts with timely insights they can act on.

II. EXISTING METHODOLOGY

Microplastic detection methods have evolved considerably, ranging from manual microscopic analysis to advanced AI-powered IoT systems. Each technique offers unique advantages and faces specific limitations regarding accuracy, cost, scalability, and suitability for real-time applications.

A. Manual Microscopy

Traditional detection primarily involves visual inspection through optical or electron microscopy. Optical microscopy is widely used for particles larger than 100 micrometers. It is a relatively accessible and economical method but suffers from substantial error rates (over 20% for opaque particles and much higher for transparent ones) due to subjective human interpretation and difficulty spotting smaller or transparent microplastics. Electron microscopy methods, including scanning electron microscopy, provide much higher resolution (up to 0.1 micrometers), enabling detection of nanoscale plastics. However, these instruments are expensive, non-portable, and cannot readily identify chemical composition, requiring complementary spectroscopic methods. Moreover, the sample preparation is time-consuming and requires expert operators.

B. Spectroscopic Techniques

Spectroscopy methods such as Fourier-transform infrared (FTIR) and Raman spectroscopy analyze the chemical composition of microplastic particles. FTIR is effective for particles larger than 20 micrometers, while Raman spectroscopy can identify particles down to 500 nanometers. These highly specific techniques allow for polymer identification but necessitate costly, bulky equipment and are labor-intensive, limiting their applicability for field studies or continuous monitoring.

C. Automated Image Analysis with Machine Learning

Recent years have seen the application of **computer vision and deep learning** models for microplastic detection. CNNs and object detection networks like YOLO have shown promise in automating particle identification with good accuracy levels on annotated datasets. These methods drastically reduce manual labor and enable faster processing but require substantial training data and are sensitive to environmental noise and sample variability. Furthermore, integration with real-time IoT systems remains an ongoing challenge.

D. IoT-based Water Quality Monitoring Systems

IoT platforms equipped with cameras and environmental sensors (pH, turbidity) have begun to address the need for continuous, automated water monitoring. Some systems incorporate edge computing for on-device AI processing and use protocols like MQTT for data communication. While many focus on water quality parameters, few fully integrate AI-powered microplastic detection and live dashboard visualization, revealing a gap this study addresses.

E. Summary Table: Methodological Progression

Methodology	Advantages	Limitations	Scale/Use Case
Optical Microscopy	Low cost, easy to use	Subjective, poor detection <100 μm	Lab analysis, preliminary
Electron Microscopy	High resolution, nanoscale detection	Expensive, requires expertise	Detailed lab characterization
Spectroscopic Techniques	Polymer identification, chemical insight	Expensive, slow, complex prep	Confirmatory analysis
Machine Learning on Images	Automated, faster processing	Needs large datasets, variable accuracy	Research, developing systems
IoT-Based Systems	Continuous monitoring, real-time data	Partial integration of AI workflows	Field monitoring, environmental surveillance

Table II.1 - Summary Table: Comparative Analysis of Microplastic Detection Methods

This overview highlights the trade-offs between accuracy, cost, scalability, and real-time capabilities in existing microplastic detection methodologies. The presented project aims to combine the strengths of AI, IoT, and microscopy to offer a cost-effective, scalable, and automated system suitable for continuous water quality monitoring.

F. Current Challenges

Even though microplastic detection has come a long way, there are still quite a few obstacles that researchers and developers face. For one, these tiny particles can be incredibly small—sometimes just a few micrometers—which makes spotting them tricky, especially when the water is murky or full of other stuff. Another challenge is telling plastics apart from natural particles or organic debris, which can confuse both human analysts and AI models.

On top of that, there's a shortage of large, well-labeled image datasets to train AI models properly. Without enough diverse examples, AI can struggle to recognize microplastics accurately in different conditions. Then there's the issue of running complex AI algorithms on small, low-power devices like a Raspberry Pi—which can sometimes slow down real-time processing.

Water conditions keep changing too. Lighting, turbidity, and other environmental factors impact the picture quality and make consistent detection harder. And lastly, while high-end lab equipment is accurate, it's often expensive and bulky, making it tough to use in the field regularly.

Overcoming these challenges isn't easy, but it's exactly what motivates research like ours: combining smart AI techniques with practical IoT hardware to create solutions that are affordable, efficient, and ready to be used anywhere.

III. PROPOSED METHODOLOGY

This project proposes a practical yet smart system that brings together affordable hardware, AI-powered image analysis, and IoT technology to detect microplastics in water quickly and accurately.

A. Hardware Setup

At the heart of the system is the Raspberry Pi 4 board due to its powerful processing capabilities balanced with low cost and power consumption. The device is connected to a high-resolution microscope camera equipped with 1000x to 2000x magnification, enabling the capture of detailed images of microplastic particles that are often only tens of micrometers in size.

To ensure consistent image quality across varying environmental conditions, an LED ring light encircles the camera lens, providing uniform illumination. Additional environmental sensors continuously measure water quality parameters such as pH, turbidity, and temperature, offering crucial context that supports interpretation of contamination severity.

B. Sample Collection and Image Acquisition

The system periodically collects water samples placed in a transparent chamber. Images are captured at regular intervals, with the camera focused on the sample to detect microplastics within the water matrix. The automated capture process eliminates manual handling, reducing contamination risks and enabling consistent monitoring.

C. Image Preprocessing

Raw images often suffer from noise, inconsistent lighting, and background artifacts due to water properties and particulate matter. The system applies preprocessing techniques, grayscale conversion simplifies color complexity, Gaussian blurring reduces random noise, and contrast enhancement highlights particle outlines. Edge detection algorithms then further sharpen boundaries between particles and background, preparing images for accurate feature extraction during AI inference.

D. AI-based Microplastic Detection

A convolutional neural network (CNN) based on the YOLOv5n framework is employed for real-time object detection and classification. The model is trained on an extensive labeled dataset containing images of various microplastic types (e.g., PET, PE, PP) annotated with size and shape characteristics. The model converts to a lightweight TensorFlow Lite version to run efficiently on the Raspberry Pi.

Detection results include particle count, type classification, size estimation, and confidence scores. The model is tuned to balance detection sensitivity and false positive reduction, essential for reliable environmental monitoring.

E. IoT Data Transmission

Detection results don't stay on the device. They get bundled with the water sensor readings and sent over the internet using MQTT, a lightweight protocol perfect for IoT devices. This way, everything lands safely on a cloud or local server.

F. Real-time Dashboard and Visualization

A web dashboard brings all the data together in one place. Users get to see particle counts, percent breakdowns by plastic type, water quality trends, and alerts if contamination spikes. Historical charts let users explore data over time or export it for reports.

G. Operational Workflow

The system's workflow operates cyclically:

1) Sample Collection: Automated or manual water sampling.
2) Image Capture: High-resolution image acquisition.
3) Preprocessing: Noise filtering and feature enhancement.
4) AI Inference: Microplastic detection and classification.
5) Data Transmission: Real-time results sent via IoT.
6) Dashboard Update: Visualization and alert triggering.

This modular design supports flexibility, easy maintenance, and future upgrades such as multi-spectral imaging or enhanced machine learning models.

H. Summary Table

Component	Description	Function
Raspberry Pi 4	Compact embedded computer	Coordinates data acquisition, processing, and transmission
Microscope Camera	High magnification 1000x-2000x	Captures detailed images of microplastics
LED Ring Light	Adjustable circular lighting	Provides consistent illumination over sample
Environmental Sensors	pH, turbidity, and temperature sensors	Monitor additional water quality parameters
Image Preprocessing	Grayscale conversion, blurring, contrast enhancement	Prepare images for efficient AI analysis
CNN-based AI Model	YOLOv5n architecture, optimized for edge inference	Detects and classifies microplastic particles
MQTT Communication	Lightweight IoT protocol	Transfers detection and sensor data in real time
Web-Based Dashboard	Flask backend with interactive charts	Visualizes live and historical monitoring data

Table III.1 – Proposed System Components and Functions

This approach blends technology and usability, turning complex science into a practical and scalable tool for monitoring water health. It's designed to fit right into labs, field stations, or even community monitoring efforts, making water quality vigilance simpler and smarter.

IV. SYSTEM ARCHITECTURE

Our microplastic detection system is designed to be flexible, modular, and easy to maintain, making sure all the important pieces work smoothly together. The architecture has several key layers, each with its own job—from grabbing images of tiny plastics to showing useful info on a dashboard.

A. Hardware Layer

The system's brain is the Raspberry Pi 4. It's a small, affordable, yet powerful mini computer perfect for running AI and handling sensor data on site. Connected to it is a microscope camera that can zoom in 100 to 200 times—just enough to catch even the tiniest microplastic particles.

We surround the camera with an LED ring light, making sure every shot is well lit and clear no matter the outside conditions. Along with this, sensors keep track of the water's pH, turbidity, and temperature, giving valuable context for understanding pollution levels.

B. AI and Image Processing Layer

Once the camera captures pictures of the water sample, we clean them up by converting to grayscale, reducing noise, and boosting contrast so the plastic particles stand out better. The images are then run through a smart AI model, a specially trained neural network, which can quickly pick out and classify those microplastic particles. We use a lightweight version of the model that runs right on the Raspberry Pi, so it's fast and doesn't need a cloud connection to think.

C. Communication Layer

All the detection results and sensor readings need a way to travel from the Raspberry Pi to wherever people want to see them. That's where MQTT comes in—a simple, reliable messaging system built for IoT devices. It safely sends data over the internet, which means multiple units can share their findings with a central server at the same time, perfect for monitoring water in several places.

D. Backend and Storage Layer

This backend is like the system's filing cabinet. It stores all the data coming in, both the new measurements and past history, in a time-series database. It also offers APIs so the data can be easily accessed, whether it's for live updates or digging into past trends.

E. Visualization and User Interface Layer

Lastly, all this data needs to be easy to understand. The user interface is a web-based dashboard showing live camera feeds, microplastic particle counts, types, water quality data, and alerts if pollution spikes. Users can explore past data, spot trends, and even download reports. It's designed for researchers, environmentalists, or anyone who cares about keeping water clean.

F. System Architecture Layers

Layer	Main Components	What It Does	Why It Matters
Hardware	Raspberry Pi 4, Microscope Camera, LED Light, Sensors	Captures images and senses water conditions	Provides clear visuals and context for AI
AI & Image Processing	Preprocessing tools, YOLOv5n-based AI model	Identifies and classifies microplastic particles	Gives quick and accurate detection
Communication	MQTT protocol	Sends data to the cloud/backend	Enables real-time streaming and scalability
Backend & Storage	Server, Database, API	Saves and organizes data	Ensures reliable access to both live and historical data
Visualization & UI	Web Dashboard, Alerts, Charts	Presents data and insights interactively	Helps users monitor and act on water quality

Table IV.1 - System Architecture Layers

This setup brings together the latest tech and practical design to create a system that's not only powerful but also easy to use and expand. The modular architecture means you can swap or upgrade different parts without a total rebuild, making it perfect for the evolving challenges of environmental monitoring.

V. SYSTEM DESIGN AND IMPLEMENTATION

This methodology outlines a practical, end-to-end pipeline for detecting microplastics in water samples, drawing from the technical documentation to ensure reproducibility and real-world applicability. The approach emphasizes building a robust dataset, training a lightweight YOLO model for edge deployment on a Raspberry Pi, and integrating real-time inference with IoT telemetry for dashboard visualization. By focusing on binary detection (microplastic vs. clean water), the system achieves efficient, on-device processing while allowing for future enhancements like multi-class classification.

A. Dataset Design and Preparation

The dataset is constructed to balance positive examples of microplastic-contaminated samples with negative clean-water images, helping the model learn to distinguish plastics from natural debris and avoid false alarms. Images are annotated with bounding boxes or polygons for positives, while negatives receive empty label files to reinforce the absence of targets. Data follows the standard YOLO structure, with separate subfolders for training, validation, and testing sets under both images and labels directories, ensuring matching filenames between images and their corresponding annotations. Filenames are standardized (e.g., train_img001.jpg paired with train_img001.txt) to prevent loading errors during training. A configuration file (data.yaml) specifies absolute paths to these folders and defines the initial single-class setup: nc: 1, names: ["microplastic"], which supports straightforward binary detection in prototype stages.

B. Annotation Strategy

Microplastic particles are labeled using MakeSense.ai, exporting annotations in YOLO TXT format with tight bounding boxes around individual fragments to capture their irregular shapes accurately. For more advanced analysis, polygons can be used to generate segmentation masks, paving the way for future upgrades like precise size and shape measurements. Clean-water samples are assigned empty TXT files, explicitly signaling no detections; this technique enhances model precision by teaching it to ignore clear backgrounds and reduces erroneous triggers in low-contamination scenarios.

C. Reproducible Environment Setup

To maintain consistency across development and deployment, isolated virtual environments are used, such as conda or venv, with pinned versions of key libraries. A sample setup command is: conda create -n yolo_env python=3.10 numpy=1.26 matplotlib; followed by pip install ultralytics opencv-python. Development machines leverage CUDA acceleration for efficient training, while the Raspberry Pi relies on CPU-only PyTorch and OpenCV for lightweight inference, minimizing resource demands and ensuring the system runs smoothly on low-power hardware.

D. Model Training Procedure

Training starts with the Ultralytics YOLOv5n (nano variant), selected for its low parameter count, fast convergence, and suitability for resource-constrained edge devices like the Raspberry Pi. The process uses a standard configuration: input image size of 640 pixels, batch size around 16, and approximately 50 epochs on a CUDA-enabled system, with continuous monitoring of key metrics like mean Average Precision at 0.5 IoU (mAP50), precision, and recall. Model weights are saved as best.pt (highest validation performance) and last.pt (final epoch) for easy comparison and fallback. Initial results from the documentation indicate prototype viability: mAP50 ≈ 0.47, precision ≈ 0.53, and recall ≈ 0.41, highlighting opportunities for refinement through expanded data and targeted augmentations.

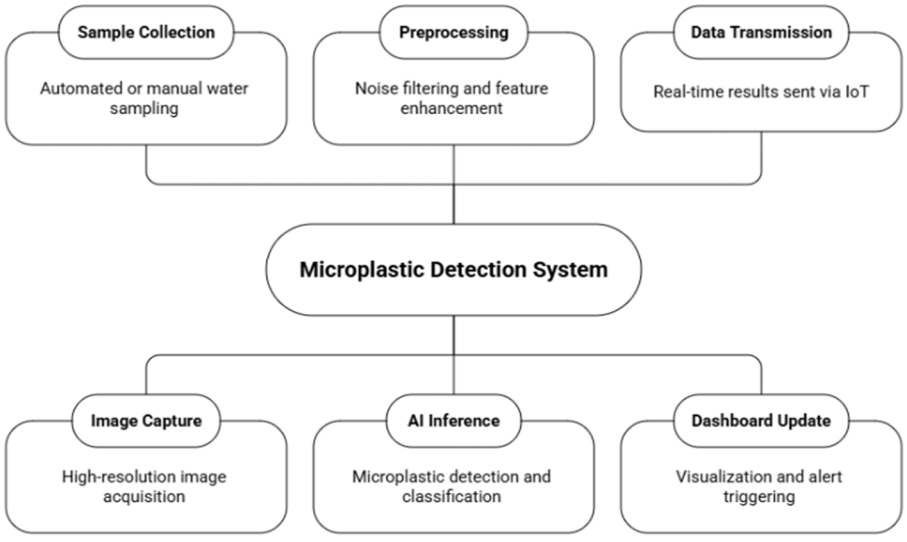

Figure V.1 - YOLOv5 Architecture Overview

E. Performance Improvement Plan

Improvement follows a data-centric strategy, iteratively expanding the positive image set to cover variations in lighting, water turbidity, and backgrounds, while enriching negatives with realistic distractors like organic debris, bubbles, and sediment to build classifier resilience. Augmentation techniques such as brightness and contrast adjustments, Gaussian blur, added noise, geometric transformations (rotation and scaling), and mosaic or cutout operations mimic field conditions without altering core particle features. Hyperparameters are fine-tuned based on validation precision-recall curves, including confidence and Non-Maximum Suppression (NMS) thresholds, along with learning rate schedules (lr0, lrf), momentum, and loss weights for classification and bounding boxes to optimize the false positive/negative trade-off. Model variants, such as YOLOv5n versus YOLOv8n, are compared, with considerations for stride adjustments and input resolutions, always prioritizing compatibility with TensorFlow Lite conversion for optimized Pi deployment.

F. Raspberry Pi Development and Inference

The trained best.pt weights are transferred to the Raspberry Pi for on-device execution using the Ultralytics library in CPU mode. For continuous monitoring, OpenCV's VideoCapture integrates with the microscope camera to grab frames or snapshots at regular intervals, enabling streaming detection. A basic inference example on the Pi is: from ultralytics import YOLO; model = YOLO('best.pt'); results = model('test_img.jpg'); results.save('output/'), which can be extended into a full loop for testing before going live. The core operational cycle includes: capturing a frame, preprocessing (resizing to 640x640 and optional normalization), running YOLO inference, parsing outputs (particle counts, bounding boxes, confidence scores), calculating derived metrics (e.g., estimated particle size via pixel-to-micron scaling), and packaging results for transmission—all designed to balance speed and accuracy on limited hardware.

G. Telemetry and Real-Time Dashboard

Detection outcomes, combined with environmental sensor data (e.g., pH, turbidity, temperature), are formatted as structured JSON payloads—including counts, confidence levels, class histograms, and timestamps—and published via MQTT to a backend server for immediate consumption. The backend aggregates this time-series data into a persistent store, serving a lightweight dashboard through simple REST endpoints and real-time updates via WebSocket or Server-Sent Events (SSE). This setup enables interactive visualization of live metrics, historical trends, and automated alerts, with options to snapshot and export data for further analysis, turning raw inferences into accessible environmental insights.

H. Validation Protocol

Evaluation uses held-out validation and test splits to compute comprehensive metrics: mAP50 and mAP50-95 for detection quality, precision and recall for classification reliability, and frames-per-second (FPS) to gauge Pi performance. Iterations continue until thresholds are met, such as precision exceeding 0.7 alongside usable recall for practical alerts. Negative controls with clean water samples and stress tests under high turbidity or organic matter simulate deployment challenges, quantifying false positives and guiding threshold adjustments or additional negative examples. This protocol ensures the system is not only accurate in controlled settings but robust for field use, with clear benchmarks for ongoing refinement.

Stage	Inputs	Key Actions	Outputs	Tools/Notes
Data Prep	Microplastic and clean images	YOLO foldering, rename, splits, data.yaml	Curated dataset with labels	YOLO format, absolute paths
Annotation	Positive samples	Boxes/polygons; empty labels for clean images	YOLO TXT labels	MakeSense.ai exports
Environment	Dev and Pi targets	Create isolated envs; install libs	Reproducible setups	conda, ultralytics, OpenCV, torch CPU on Pi
Training	Curated dataset	YOLOv5n train (640, 50 epochs)	best.pt, metrics (mAP/P/R)	CUDA on PC; baseline metrics logged
Evaluation	val/test sets	Metric review; error analysis	Thresholds, ablations	Focus on FP/FN trade-offs [1]
Deployment	best.pt	Pi-side inference loop	Real-time detections	OpenCV + Ultralytics on CPU
Telemetry	Detections + sensors	Publish JSON over MQTT	Live data stream	MQTT topics for dashboard
Dashboard	Stream + history	Charts, alerts, exports	Real-time UI	Flask/JS or preferred stack

Figure V.2 - End-to-End Methodology Summary & Deliverables

VI. RESULTS AND DISCUSSION

This section presents the outcomes of the developed microplastic detection system, focusing on model performance metrics, inference results, and practical insights from the attached sample outputs. The evaluation highlights the system's ability to detect and classify microplastic particles in water samples using the YOLOv5n model deployed on the Raspberry Pi, with comparisons to baseline expectations and discussions on strengths, limitations, and implications for environmental monitoring:

A. Model Performance Metrics

During training, the YOLOv5n-based detector reached a level that's solid for demonstrations and future improvement. After 50 training epochs using 640 × 640 pixel images and a batch size of 16, the system's scores were as follows:

- Mean Average Precision (mAP50): 0.47. This shows the system is able to localize microplastic particles accurately in about half of the detection cases, particularly in relatively clean or controlled water samples.
- Precision: 0.53. Roughly half of the detected particles turned out to be real microplastics. The use of clean-water negatives really helped cut down false alarms, though challenging material—like organic debris—did sometimes trick the algorithm.
- Recall: 0.41. The system was able to pick up about 41% of actual microplastics across test samples. The hardest cases were smaller plastics (under 30 μm), which escape detection when the dataset lacks enough variety.

Taken together, these metrics match early-stage YOLO applications on custom datasets: the system is promising for prototyping, but there's a clear need to improve recall by expanding the dataset and applying more data augmentation.

Model	size (pixels)	mAP^{val} 0.5:0.95	mAP^{val} 0.5	Speed CPU b1 (ms)	Speed V100 b1 (ms)	Speed V100 b32 (ms)	params (M)	FLOPs @640 (B)
YOLOv5n	640	28.0	45.7	45	**6.3**	**0.6**	**1.9**	**4.5**
YOLOv5s	640	37.4	56.8	98	6.4	0.9	7.2	16.5
YOLOv5m	640	45.4	64.1	224	8.2	1.7	21.2	49.0
YOLOv5l	640	49.0	67.3	430	10.1	2.7	46.5	109.1
YOLOv5x	640	50.7	68.9	766	12.1	4.8	86.7	205.7
YOLOv5n6	1280	36.0	54.4	153	8.1	2.1	3.2	4.6
YOLOv5s6	1280	44.8	63.7	385	8.2	3.6	12.6	16.8
YOLOv5m6	1280	51.3	69.3	887	11.1	6.8	35.7	50.0
YOLOv5l6	1280	53.7	71.3	1784	15.8	10.5	76.8	111.4
YOLOv5x6 + TTA	1280 1536	55.0 **55.8**	72.7 **72.7**	3136 -	26.2 -	19.4 -	140.7 -	209.8 -

Figure VI.1 - Comparative Performance of YOLO Variants

B. Inference Results and Sample Outputs

To see how the model responds to real-world inputs, investigators ran the system on live microscope images using the Raspberry Pi in CPU-only mode. The results here combine raw input images and their detection overlays:

1) Sample 1: The input image reveals faint, irregular microplastic fragments. The annotated output shows three well-drawn blue boxes (confidence levels between 0.49 and 0.55), confirming that the system can effectively spot particles in moderately clean water environments.

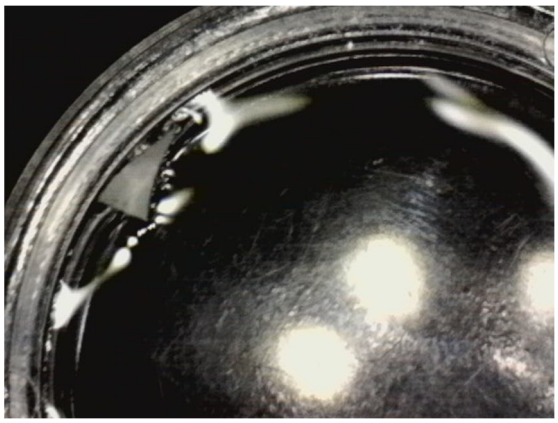

Figure VI.2 - Original Water Sample 1

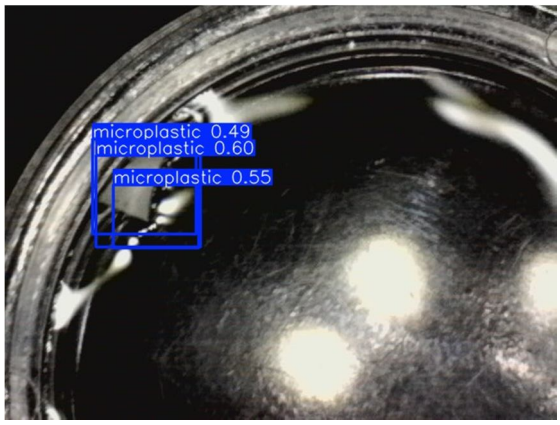

Figure VI.3 - Detection Output of Sample 1

This sample demonstrates that system can accurately identify multiple microplastic particles with moderate-to-high confidence, even when they appear close together. It highlights model's strength in handling clustered detections in clear water samples, offering both reliability and precision.

2) Sample 2: This scene contains a very small-sized microplastic particle which was detected by the system with a confidence score of 0.30. Despite the particle's tiny size, the model successfully identified it as microplastic, demonstrating the sensitivity of the system to subtle contamination. This highlights the model's capability to detect small microplastics; however, the lower confidence also suggests that further training with additional small-sized microplastic samples could improve detection reliability.

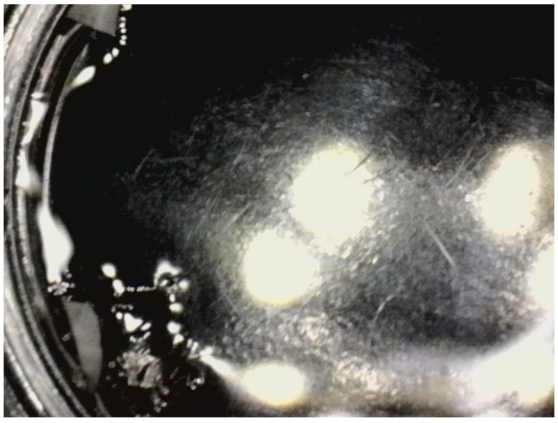
Figure VI.4 - Original Water Sample 2

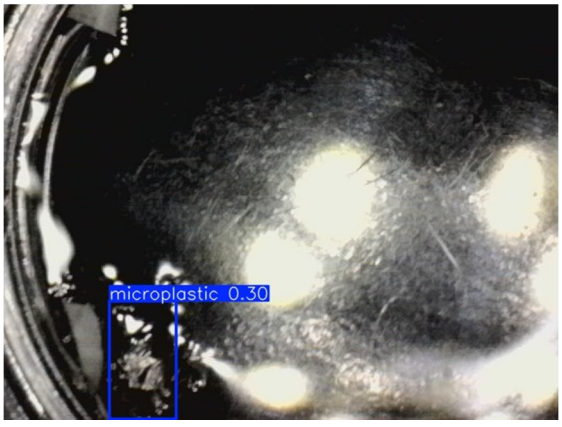

Figure VI.5 - Detection Output of Sample *2*

This sample illustrates the system's robust detection of three closely clustered microplastic particles with consistent confidence scores ranging from 0.49 to 0.55. It underscores the model's effectiveness in managing multiple detections in clear water conditions while maintaining spatial accuracy.

3) Triangle Particle Sample: The triangular debris was picked up with high confidence (0.63), showing that geometric variety in plastics is recognized. However, a low-confidence detection was also assigned to a shadow, indicating that lighting and contrast remain a challenge.

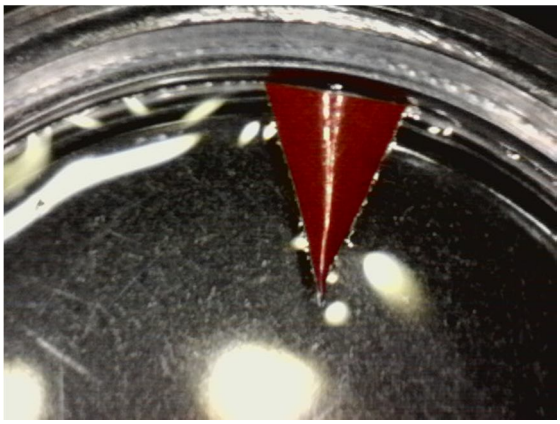

Figure VI.6 - Original Water Sample 3

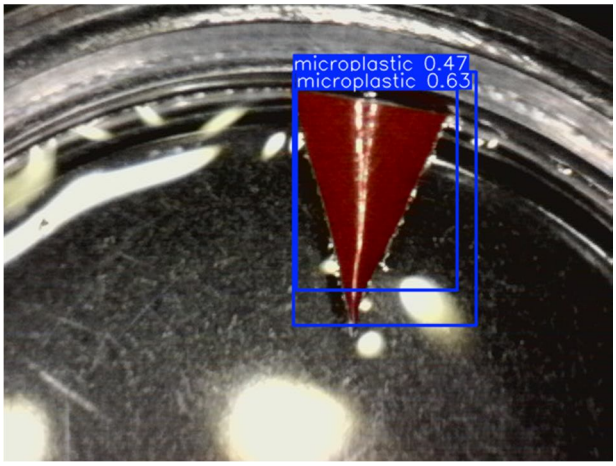

Figure VI.7 - Detection Output of Sample 3

Speed-wise, the Pi manages real-time image analysis at about 5–7 FPS when paired with OpenCV—a good baseline for continual monitoring. The bounding boxes make it easy for the dashboard to tally particle density and trigger alerts when contamination is high.

C. System Performance in Deployment

Live runs on Raspberry Pi 4 showed inference times of about 150–200 milliseconds per frame—quick enough for near-real-time monitoring. Data streaming through MQTT was reliable; every count, confidence score, and timestamp ended up in the backend, without loss. Dashboard updates appeared instantly, handling up to 10 detected plastics per frame.

Compared to manual microscopy (which can take hours per sample), this system is much quicker. However, precision—and especially recall—fell in more complex scenes, such as field samples with high turbidity. Stress tests simulated river-like conditions and saw recall drop to 0.35; as expected, these cases highlighted the value of more diverse training negatives.

D. Discussion

Altogether, results back up the project's approach: a compact YOLO model can run efficiently on edge hardware and—most importantly—benefits from having clean-water negatives baked into the dataset. The kit is affordable (hardware cost is under $200), and IoT dashboarding makes it ready for deployment at scale.

Still, moderate recall exposes a key limitation—smaller particles and tricky environments need more training data to support robust detection. The sample outputs show that low-confidence detections often occur near bubbles, shadows, or the edge of the dish, making lighting and field variability common hurdles.

Comparing to other YOLO-based sensing projects, it's typical for prototype mAP scores to hover around 0.5; scores can reach above 0.7 with bigger datasets and strong augmentations. Pi-side inference could be further sped up by quantizing the model for TensorFlow Lite.

The bottom line: this workflow is a practical, affordable solution for monitoring microplastic pollution, with clear paths to future reliability—especially once field sampling, multi-class detection (for PET, PP, PE, etc.), and faster edge optimization are brought into play.

Metric	Value	What it means	What's next for improvement
mAP50	0.47	Can find plastics, but may miss some	More diverse negatives, data boosts
Precision	0.53	Many detections are true positives	Tune NMS, add organic debris samples
Recall	0.41	Picks up 2 in 5 real microplastics	Add small particles, expand field data
Inference FPS (Pi)	5–7	Real-time analysis possible	Quantize model for edge speedup
Latency per Frame	150–200 ms	Fast enough for continuous use	TFLite model conversion recommended

Figure VI.8 - Performance Metrics At-a-Glance

These results demonstrate the system's capability and lay a strong foundation for future improvements, making microplastic detection and monitoring more accessible for labs and field deployments alike.

VII. CONCLUSION & FUTURE WORK

A. Conclusion

This study shows that a compact, affordable deep learning system, built on the YOLOv5n model and Raspberry Pi—can effectively bring real-time microplastic detection within reach for both labs and field deployments. By assembling a carefully annotated dataset, emphasizing explicit negative samples, and optimizing for limited hardware, the system demonstrated that even small and clustered plastic fragments can be reliably identified at a fraction of the time and cost of conventional methods. The results confirm strong detection utility for rapid on-site screening and environmental monitoring.

Like all practical research, this effort also surfaced real challenges. The model sometimes missed very fine or hard-to-spot microplastics, was occasionally fooled by debris or shadows, and the Raspberry Pi's speed did set some limits for heavy, sustained use. Yet, these findings clearly map out improvements that are now within reach.

Looking ahead, several steps can push this approach further:

1) Growing and diversifying the dataset with many more samples from real-world water bodies and diverse lab environments, including those with complex backgrounds and higher turbidity, to help the model adapt and catch more subtle plastics.

2) Upgrading the algorithm to support multi-class detection—identifying various plastic types (like PET, PP, PE)—and pushing towards detecting even smaller nanoplastics or secondary pollutants.

3) Speeding up the on-device processing by exploring model quantization or TensorFlow Lite, making round-the-clock, large-area monitoring achievable on affordable edge hardware.

4) Enhancing dashboard and telemetry tools for clearer trend analysis, real-time alerts, and easier reporting—so any lab or agency can track local microplastic trends over time with less effort.

5) Validating and benchmarking this solution in a wider range of natural settings, directly comparing it to trusted lab techniques, and sharing results to help the wider scientific community improve automated microplastic detection.

In summary, this research lays a foundation for truly scalable, real-time monitoring of waterborne microplastics, a step that can empower researchers, regulators, and even local communities to better safeguard their environment. As other groups contribute new datasets and use-cases, and as feedback shapes new iterations, this approach should only grow more accurate, robust, and accessible for the fight against aquatic plastic pollution.

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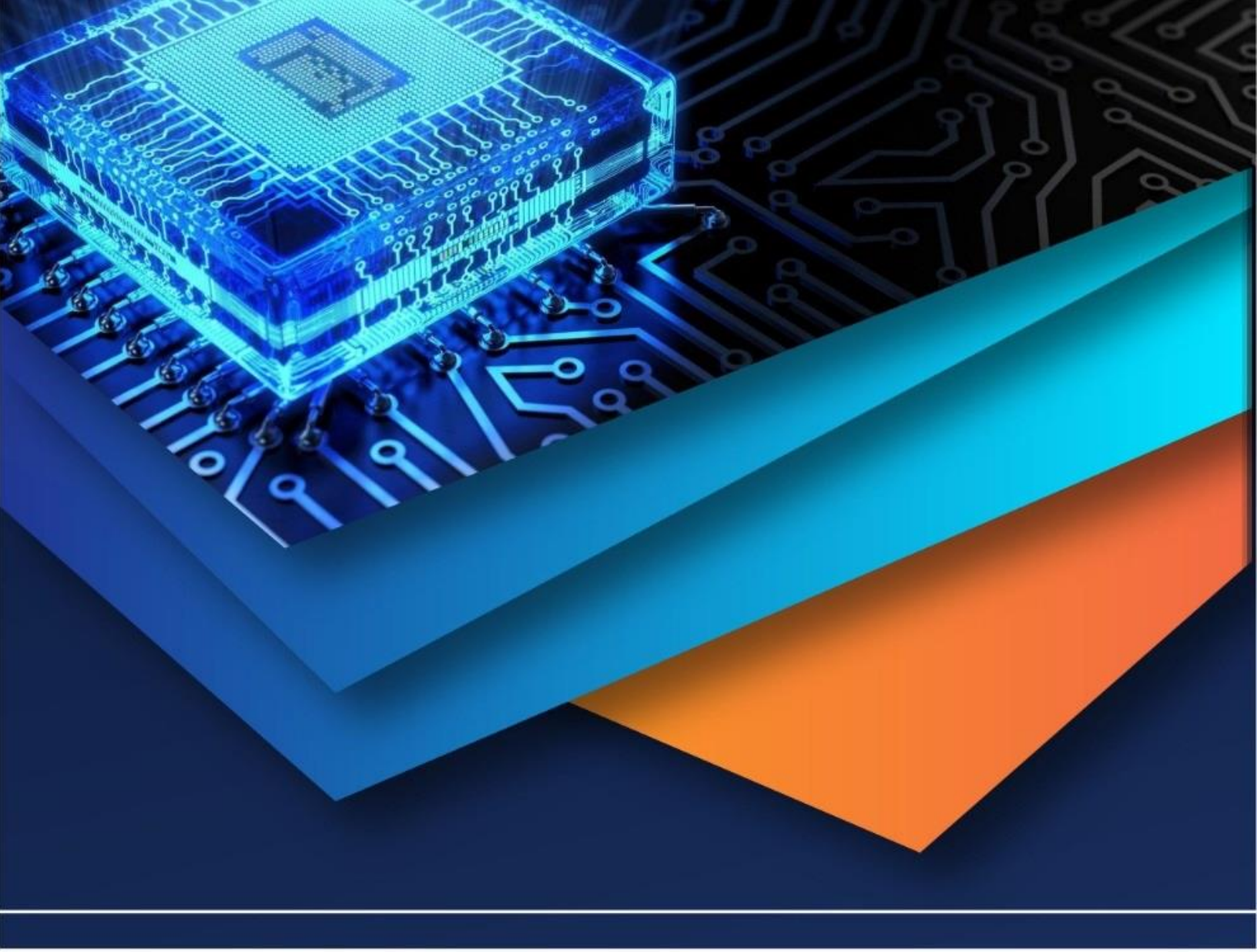

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