Edge AI-Driven Microfluidic Platform for Real-Time Detection and Classification of Microplastic Particles in Environmental Samples

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Abstract: Microplastics have become a major concern in our daily life, affecting the environment and health and as such, requiring advanced detection techniques. Existing methods of microplastics detection are manual and require sophisticated laboratories. This project intends to solve those problems by developing a real-time microplastic detection system based on Edge AI on an NVIDIA Jetson Nano system. Computer Vision is integrated with a new YOLOv5 Object Detection and Gradient Boosting Classifier (GBC) hybrid algorithm which classifies microplastic particles into different classes based on shape, size, color, texture, and shape as well as a classifier combining GBC features. Detection accuracy is further improved with ensemble learning methods such as bagging, boosting and stacking. For deploying the model at the edge, the hybrid model is optimized using Tensor RT quantization which offers real-time analysis for the Jetson Nano. The system is tested for accuracy, precision, recall, and F1 score against manual identification using a microscope. Comprehensive data logging and visualization interface is developed to track microplastic pollution in real time for other environmental health purposes.

1 INTRODUCTION TO MICROPLASTIC POLLUTION AND DETECTION CHALLENGES

The paper details design steps of an AI camera enabling real-time microplastics detection with 97% accuracy in the lab and 96% in the field, applying YOLOv5 for detection and Deep SORT for tracking across different environments (Sarker et al., 2021). The paper details an AI-assisted nano-DIHM system for real-time nano plastic detection in water identifying 2% of particles from Lake Ontario and 1% in the Saint Lawrence River as nano/microplastics without sample preparation and providing thorough physicochemical characterization (Wang, Zi et al., 2024). The paper discusses the development of a sensor that integrates an estrogen receptor grafted onto gold surface and an AI algorithm for identification of nano- and microplastics in water, achieving 90.3% success in differentiating materials and dimensions of the particles (Li, Yuxing et al., 2024).This paper discusses a mostly sensitive and reusable SERS-based approach for detecting micro/nano plastics using two -dimensional AuNPs thin films, contrasting both imaging and AI systems presented in reference (Dal et al., 2024). This paper presents the implementation of deep learning techniques for the detection of microplastics, obtaining 100\% success rate with varying wavelengths lasers focused on polystyrene and melamine micro particles in water (Han, Jiyun Agnes et al, 2024). This paper details the creation of a nano-digital inline holographic microscope (nano-DIHM) for the purposes of real-time monitoring of micro/nano plastics in freshwater using deep learning through detection and tracking of plastic particles to improve life cycle analysis of plastic waste in water (Wang, Xinjie et al, 2024). This paper proposes a novel low cost and rapid detection of microplastics using Nile Red fluorescence for in-situ deployment in the ocean, enabling the much-needed real-time analysis of microplastics which remains unsolved by current methods (Ye, Haoxin et al, 2023). This paper highlights the development of a multi-technique analytical platform for the detection, characterization and quantification of nano plastics in water using AF4-MALS and Py-GC/MS, advancing the state of the art with detection limits of 0.01 ppm and filtration conditions for high recovery rates(Valentino, Maria Rita et al., 2023).The emphasis

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is placed on AI's synergy with microfluidics towards the development of water cleaner or sensor devices, including sophisticated methods for juniors like heavy metals or microalgae, and describe issues and prospects of these technologies towards water quality assessment monitoring (Zhang, Shouxin et al., 2024). The work deals with microfluidic sensors for the detection of emerging contaminants and describes the benefits compared to conventional ones such as speed of analysis, small amounts of samples, and the possibility of field work and other detection methods and future problems in this discipline (Ajakwe, S. O. et al, 2023). The work deals with the problem of the onsite water contamination detection using microfluidic technology, stressing features of this technology in comparison with conventional ones. It presents results of investigations on microfluidic sensors for monitoring chemical and biological contaminants and considers problems and prospects of water quality monitoring automation (Khurshid, Aleefia A. et al, 2024). The report centers around the incorporation of IoT wireless technologies and Machine learning for the rest of the processes, discussing others like LP WAN, Wi-Fi, and Zigbee while looking into supervised and unsupervised ML for correct interpretation and to enable sensible decisions (Charalampides, Marios et al, 2023).

The paper reviews advancements in microfluidic technology for water quality monitoring, emphasizing its potential to enhance accuracy, portability, and affordability, addressing global water challenges. It highlights the development of innovative monitoring kits and optimization of existing techniques (Arepalli, Peda Gopi, and Co-Author., 2024).

1.1 Research Gaps

Microplastics are being considered as a new and emerging environmental pollutant with potential implications for human health, marine ecosystems, and water quality. Despite this growing recognition, existing techniques for detecting and analyzing microplastics have major limitations. Traditional methods involving microscopy-based identification, spectroscopy (FTIR/Raman), and chemical analysis are highly accurate, but these methods often take a long time to generate results, require considerable human intervention, and have expensive laboratory equipment. Such methods are infeasible for large-scale environmental monitoring and lack potential for real-time data analysis, particularly in remote or resource-constrained environments.

While recent progress in machine learning and computer vision have paved the way for automating microplastic detection, previous methods mostly rely on cloud processing or require high-performance computing hardware. This reliance on cloud resources also brings about latency, requires an always-on internet connection, and may create privacy issues. Also, current state-of-the-art deep learning-based microplastic detection model fail at efficiently detecting small objects, the high variability of size and shape of the particles, and at low-texture and low-color recognition heterogeneity. This will highlight the absence of a solid real-time edge-based solution able to be in charge of such problems indeed, this is a considerable gap in the state of the art.

1.2 Problem Identification

The main issue this study tackles is the need for an edge-based microplastic solution that is both scalable and efficient in real-time detection and classification of microplastic particles. Some of the Key Issues Include of Manual Techniques which are Microscope and Spectroscopy they give an accurate result but these manual techniques are not practical for real time monitoring as the processing time of these techniques is high and also, they are operational expensive These techniques are not appropriate for issue at scale, continuous analysis of the atmosphere, which makes them less realistic in their actual use cases. Current AI-based detection systems mostly run in the cloud—this adds latency and requires a stable internet connection, which is a problem for edge or remote deployment. Deep learning models in current systems do not do well in detecting microplastics that have complex kinds of shapes, sizes, and textures, leading to a very high rate of false positive or missed detections. Most detection algorithms are computationally expensive and require advanced hardware, which is impractical in a low resource edge device like the NVIDIA Jetson Nano. Thus, some model optimization methods are crucial for real-time classifying efficiently without losing the accuracy.

1.3 Objective

1. Aim: To create a real-time microplastic detection system by using Edge AI using a combination of the Jetson Nano and water samples, for easy and fast detection of microplastics in a water sample.

2. To combine computer vision and machine learning models, based on the hybrid algorithm YOLOv5 + GBC, for the classification of microplastic particles, according to size, shape, color, and texture.
3. To deploy ensemble learning methods, such as bagging, boosting, and stacking, to improve detection accuracy and minimize error rates.
4. To quantize and optimize the hybrid machine learning model with Tensor RT in order to deploy it to run HTTP requests on the Jetson Nano at the edge with real-time performance.
5. To compare the performance of the system by the manual microplastic identification under the microscope, and evaluate the parameters accuracy, precision, recall and F1 score.
6. Create a data logging and visualization interface for the real-time monitoring and tracking of the microplastic pollution levels for broader applications in the environmental health.

2 SYSTEM ARCHITECTURE - JETSON NANO AND EDGE AI IMPLEMENTATION

One of the main environmental hazards is microplastics, hence consistent detection methods are required. The aim of this work is to develop an original real-time detection system on NVIDIA Jetson Nano utilizing Edge AI. Included for improved analysis is cloud computing. Typical microplastics like PE, PP, PS, and PVC are found by the high-resolution camera module included into the system architecture. This program images water samples containing microplastics. Microplastics differ in size, form, and texture and call for delicate techniques of detection. Microplastic visibility is improved by preprocessing the Jetson Nano's photographs using noise reduction and contrast correction. First object-detected with YOLOv5 are the better photos. Forecasting bounding boxes and confidence scores allows this computer rapidly identify microplastic particles. Following identification, items are sent to the cloud using MQTT protocol to guarantee quick communication. Hybrid deep learning models using YOLOv5 and Gradient Boosting Classifier complete cloud-based categorization. Through particle size, shape, color, and texture, the GBC can separate PE, PP, PS, and PVC microplastics. This facilitates classification. While Tensor RT optimizes real-time inference, ensemble learning techniques include bagging, boosting, and stacking increase detection accuracy. Free, open-source Grafana software offers real-time microplastic contamination dashboards. Grafana provides the peripheral device's final classification. In many aquatic ecosystems, edge artificial intelligence, cloud computing, and real-time visualization offer scalable, accurate microplastic detection and classification. This approach lowers plastic waste and advances environmental health as well.

Edge artificial intelligence on the NVIDIA Jetson Nano detects microplastics in real time. Renowned for its strong GPU, the Jetson Nano was selected for its edge device features and great computational efficiency. The several components of architecture are as follows: The Jetson Nano is a small but mighty environment for real-time deep learning model running with its Quad-core ARM Cortex-A57 CPU and 128-core Maxwell GPU. High-resolution cameras commonly record live water sample videos.

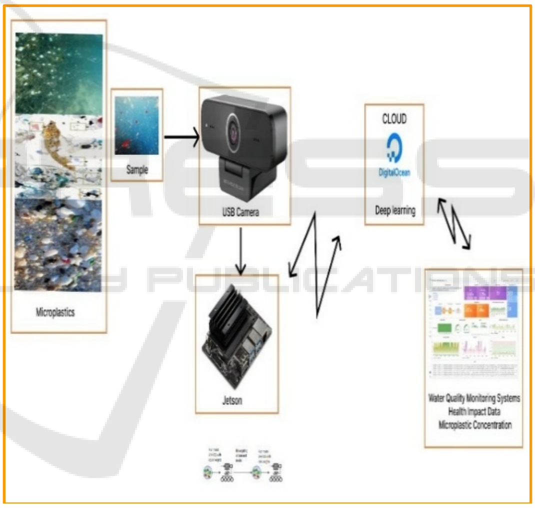

Figure 1: Automated Microplastic Detection and Monitoring System Using Edge Computing and Cloud-Based Deep Learning.

Figure 1 displays a microplastic detection and monitoring system driven automatically. This technology leverages cloud-based deep learning along with hardware. This method tackles the environmental effects of microplastic contamination in aquatic environments as well as its increasing issue. The pipeline calls for cloud computing, data processing, real-time analysis, and sample collecting. Using a USB camera, visually inspected microplastic samples from many sources of ambient water. Local inspection of the high-resolution images of the samples is conducted utilizing an

NVIDIA Jetson edge device. Renowned for its strong GPU, the Jetson device compiles features from images. This system detects microplastics in images in real time using computer vision technologies. The images are preprocessed to accentuate microplastics following collecting. This method lowers noise and raises contrast. On the Jetson Nano, a first-rate machine learning model manages the local video feed. This approach speeds detection by removing cloud-based processing, hence lowering latency. The computer vision model finds, classifies, and counts microplastic particles in the video stream in real time. This is under active inference. User interaction uses a GUI. This interface displays real-time visuals, statistical analyses, and microplastic detecting findings.

On the microfluidic substrate, the system grabs water sample images using a high-resolution camera module. Microplastic viewing including one-millimeter particles is maximized with camera location. Images are transferred straight after collecting to the NVIDIA Jetson Nano for local preprocessing analysis. The camera system could have LED or dark-field illumination added to increase microplastic particle visibility. On the Jetson Nano, raw camera module images are processed using edge detection, noise reduction, and contrast correction. These techniques enhance microplastic detection, which organic debris or water turbidity might obscure. Enhanced images identify microplastic particles in real time for object detection using an initial inference model (YOLOv5). This phase lowers data size to maximize bandwidth and latency before transmitting data to the cloud. The technique picks out a range of aquatic microplastics, including: These lightweight polymers find use in consumer products and packaging. Usually they are transparent or semi-translucent and asymmetrical. Sphere microplastics find application as fillers in cosmetics. Their surface is flat and they are either white or vividly coloured. A denser plastic applied in building and pipelines. Identification is grounded in variations in color and texture. Once found on the Jetson Nano, MQTT sends the augmented picture data to the cloud for additional processing. The YOLOv5 + Gradient Boosting Classifier (GBC) hybrid technique allows the cloud-based deep learning model on DigitalOcean to classify more broadly. To find PE, PP, PS, and PVC microplastics the deep learning model employs size, shape, color, and texture. In the cloud model, bagging, boosting, and stacking help to raise detection accuracy. The hybrid approach aggregates GBC's broad feature analysis with YOLOv5's quick detection. For effective cloud inference and strong detection accuracy, both models leverage Tensor RT optimization. Open-source monitoring tool Grafana shows cloud to Jetson Nano classification findings. Real-time microplastic amount, size distribution, and classifications found in Grafana dashboards Tracking contaminants and finding trends helps users support environmental evaluations and decision-making.

Grafana dashboards reveal microplastics' types and concentrations. Real-time display of water quality, microplastics, and health impacts on the dashboard Using this visualization tool, environmental authorities and researchers may monitor trends and pinpoint pollution hotspots, therefore facilitating speedier policy decisions and actions. Edge computing and cloud-based deep learning underpin a complete microplastic pollution monitoring system. Using NVIDIA Jetson locally preprocessing lowers latency and cloud computing load. A strong training set lets a deep learning network raise detection accuracy. Real-time visualization from Grafana guarantees stakeholders quick access to important data, therefore facilitating more thorough environmental health assessments. This approach provides scalable, dependable, efficient means of globally addressing microplastic contamination. Further more feasible are better environmental monitoring and other mitigating strategies.

3 MODEL DEVELOPMENT: YOLOV5 + GRADIENT BOOSTING CLASSIFIER (GBC) HYBRID ALGORITHM FOR MICROPLASTIC CLASSIFICATION

To create a strong and efficient model for microplastic detection, the combination of advanced deep learning methods and conventional machine-learning approaches is needed. Here, a hybrid algorithm is proposed that combines the speed and robustness of YOLOv5 with refined feature-based classification created via Gradient Boosting Classifier (GBC).

This hybrid approach is designed to address the limitations of existing methods and meet the specific requirements of real-time detection on resource-constrained edge devices like the Jetson Nano.

3.1 Dataset Preparation

Start with a big, varied dataset to build a consistent detecting system. The dataset consists on high-resolution pictures of water samples including different microplastics. Images are captured by a camera module built on the microfluidic device. Data collecting is thus constantly of high quality. The images reveal microplastics in many shapes, colors, textures, and sizes. False alarms could result from biological waste and photo bubbles.

Methodical annotations of every image assist to build a model-training set. Labeling microplastics requires hand building boundary boxes and providing labels depending on their look.

3.2 Yolov5: Real-Time Object Detection

The hybrid approach begins with a fast and efficient object identification model called YOLOv5. For this use YOLOv5's one network trip for object identification makes perfect. This quickens it. This single-stage approach allows the model estimate from the input image bounding boxes and class probabilities. This lets the model avoid two-stage detector complexity and delay, much as Faster R-CNN does.

One main advantage of YOLOv5 for microplastics identification is its small object detecting ability. Standard detection methods find microplastics difficult given their small scale. This is the reason the lightweight variant of YOLOv5 (YOLOv5s) was selected: it runs efficiently enough on edge devices like the Jetson Nano while balancing speed and accuracy. Using a CNN backbone, the model compiles pertinent information from input images. This allows the model spot microplastics. Deep learning and traditional machine learning are combined in the YOLOv5 + Gradient Boosting Classifier (GBC) hybrid technique for microplastics identification and classification. The main equations of the hybrid model are reported in this work. Among these equations are ensemble learning, feature extraction, and object identification.With four parameters—x and y for center coordinates, w and h for remaining dimensions YOLOv5 generates a bounding box for every item. W and h mark the width and height of the bounding box.

The objectness score Po is calculated as:

$$Po = \sigma(so) \tag{1}$$

The class probabilities Pc are calculated using softmax activation:

$$Pc = \text{Softmax}(sc) \tag{2}$$

The final confidence score C is:

$$C = Po \times \max(Pc) \tag{3}$$

The Complete Intersection over Union (CIoU) loss for bounding box regression is given by:

$$CIoU = IoU - (\rho^2(b, bgt) / c^2) - \alpha\ (v / (1 - IoU) + v) \tag{4}$$

where: IoU is the Intersection over Union of the predicted box b and the ground truth box bgt.ρ is the Euclidean distance between the center of the predicted and ground truth boxes.c is the diagonal length of the smallest enclosing box.α is a weight parameter.v is a measure of the aspect ratio similarity.The use of CIoU helps the model learn better bounding box predictions by accounting for both spatial and aspect ratio differences.The training of YOLOv5 is performed using the prepared dataset, with the model learning to detect microplastics based on the labeled bounding boxes. During training, several optimization techniques are employed, including learning rate scheduling to adjust the learning pace and early stopping to prevent overfitting. Loss functions like Binary Cross-Entropy Loss for classification and Complete Intersection over Union (CIoU) Loss for bounding box regression help the model make precise predictions.

3.3 Feature Extraction for Gradient Boosting Classifier (GBC)

Although YOLOv5 can identify microplastics, it could overlook subtle characteristics required for classification. This information comes in handy when particles seem identical. The zone features of YOLOv5 help to tackle this problem before applying the Gradient Boostering Classifier. This level allows the model to detect microplastics derived from different material. Features can be extracted by means of particle characteristics analysis. The particle's perimeter, area, and diameter matter. These qualities set microplastics apart. Aspect ratio, eccentricity, and circularity set spherical microbeads apart. These gauges expose particle form. Standard deviation and mean of the RGB color channels define the color profile of the particle. Given their colors, but microplastics of different colors are especially interesting. GLCM and LBP are used in texture analysis. The discrimination of microplastics and their unique textures relies on the surface characteristics obtained by these techniques. These include Area (A), Perimeter (P) and Equivalent Diameter (D):

$$A = w \times h \tag{5}$$

$$P = 2(w + h) \tag{6}$$

$$D = \sqrt{(4A / \pi)} \tag{7}$$

Shape features: Aspect Ratio (AR), Circularity (C)

$$AR = w / h \tag{8}$$

$$C = (4\pi A) / P^2 \tag{9}$$

The mean (μ) and standard deviation (σ) of RGB channels are calculated as:

$$\mu = (1/N)\ \Sigma\ xi \tag{10}$$

$$\sigma = \sqrt{((1/(N-1))\ \Sigma\ (xi - \mu)^2)} \tag{11}$$

Texture features like Contrast and Correlation using GLCM are calculated as:

$$\text{Contrast} = \Sigma\ (i - j)^2\ p(i, j) \tag{12}$$

$$\text{Correlation} = \Sigma\ ((i - \mu i)(j - \mu j)p(i, j)) / (\sigma i\ \sigma j) \tag{13}$$

These features provide a comprehensive representation of each detected microplastic particle, enabling the Gradient Boosting Classifier to perform refined classification.

3.4 Gradient Boosting Classifier (GBC): Enhanced Classification

The features were subsequently input into a Gradient Boosting Classifier (GBC) that serves as the second stage of hybrid model. GBC is a type of ensemble learning method that builds multiple decision trees to create a powerful predictive model. It constructs these trees sequentially, where each tree compensates for the mistakes of the earlier ones. So boosting this method such that GBC learns the more complex patterns from the data is what makes GBC one of the most effective methods we could use for the subtle task of classifying microplastic particles based on the minute differences in size, shape, and texture.

The GBC is trained on features extracted from the dataset with hyperparameter tuning through Grid Search for parameters such as learningrate, nestimators, and max depth of trees. This fine-tuning process ensures good calibration of the classifier which accounts for variability in the characteristics of the microplastics, thus enhancing classification accuracy.

The final prediction F(x) from GBC is given by:

$$F(x) = F_0 + \Sigma\ \gamma m\ hm(x) \tag{14}$$

The residual for the i^{th} data point at the m^{th} iteration is:

$$r\{i,m\} = - (\partial L(yi, F\{m-1\}(xi)) / \partial F\{m-1\}(xi)) \tag{15}$$

where: F0 is the initial model prediction (mean of the target variable).hm(x) is the prediction from the m-th weak learner (decision tree).γ is the learning rate controlling the contribution of each tree.

3.5 Hybrid Ensemble Voting

The final prediction probability Pfinal using weighted voting is:

$$\text{Pfinal} = w_1\ \text{PYOLOv5} + w_2\ \text{PGBC} \tag{16}$$

Pfinal is the final prediction probability, PYOLOv5P and PGBCP are the predictions from YOLOv5 and GBC, respectively. w1 and w2 are the weights assigned to each model's prediction, optimized during training. The detailed equations highlight the key components and mathematical foundations of the YOLOv5 + GBC hybrid algorithm. YOLOv5 focuses on efficient and accurate object detection, while GBC enhances the classification by analyzing additional features extracted from the detected particles. This integration creates a powerful and balanced model capable of real-time, high-accuracy microplastic detection on edge devices like the Jetson Nano.

3.6 Optimization for Edge Deployment

A real-time Jetson Nano hybrid model can be produced from several optimization techniques. NVIDIA Tensor RT raises YOLOv5. Although it lowers accuracy, quantization lowers model size. Inferences thus speed up without sacrificing accuracy. To reduce computational resources, model pruning removes superfluous layers and constraints. Parallel processing of numerous frames made possible by batch inference boosts system throughput. Comparatively to manual identification techniques based on microscopes, evaluation criteria are tested. Confirmed are the correctness and analytical time saving power of the model.

Combining GBC with YOLOv5 offers a whole microplastics identification and classification solution. The GBC improves categorization and lowers false positives by means of thorough feature analysis. Unlike the GBC, which enhances predictions, YOLOv5 detects fast and precisely. Optimization guarantees model performance on Jetson Nano edge devices. The model is therefore perfect for real-time events. This scalable and thorough approach closes most of the main research gaps and offers a useful instrument for environmental monitoring and prevention of microplastics contamination.

3.7 Enhancing Accuracy: Ensemble Learning Techniques

The research that you do in developing a robust real time microplastic detection system needs to be both accurate and with minimum error in the system as microplastic particles are generally small in size and have irregular shapes. Since a single model cannot achieve the desired classification accuracy, ensemble methods are used to improve overall performance. Splitting the problem of classification into sub-problems and then assembling the predictions of each sub-problem classifier is called Ensemble Learning. We'll use three popular ensemble learning techniques in this project: Bagging Bootstrap Aggregating Boosting Stacking.

3.8 Bagging - Bootstrap Aggregating

Bagging is one of the simplest and most powerful ensemble methods that can be used to control overfitting and to improve the robustness of the model. Bagging (bootstrap aggregation). The basic aggregation method of train multiple instances of a model on different subsets of the training data, and aggregate their predictions. Random sampling with replacement creates multiple subsets of the dataset. Example on Bootstrap Sampling: The data is divided into several subsets, and each subset is called a bootstrap sample and trained to create a different model instance (object) multiple repetitions of the Gradient Boosting Classifier. Inference: Similar to training, during inference the predictions of all trained models are combined — usually with majority voting, in case of the classification tasks. Bagging: In this project, the bagging technique is used to stabilize the predictions of the GBC in order to reduce the influence of outliers and noisy data points. It decreases the variance of the model and therefore can have a stabilizing effect on the predictions. Reduce overfitting especially for complex datasets with different characteristics of microplastic. Enhances the overall robustness of the classifier, improving its resistance to variations in different environment conditions, such as lighting or water turbidity. The hybrid model consists of a combination of bagging and the Gradient Boosting Classifier (GBC) component. Outcomes from microplastic particles classifications using this method are more stable and reliable if implemented, as each model was trained with subsets of GBC data.

3.9 Boosting

Boosting corrects the mistakes made by different models during connections, thus increasing accuracy. Boosting is where we train models to correct the errors of the earlier models and is different from bagging, which is where we train many models independent of each other. This approach also aids by allowing the model to better handle difficult cases such particles that are close together or microplastics that exhibit intricate surface characteristics. The first thing it does, is train a shallow decision tree or other weak learner using the entire dataset. This process finds the errors that the previous model has made, and it builds another model, adjusting the weight of data accordingly, which will emphasize more difficult scenarios. Each model leverages its predecessor's errors to improve performance over a fixed number of iterations. Typically, final predictions are determined by weighted majority voting or averaging all model outputs. Classification accuracy increases for complex and high-dimensional data. By accurately identifying the forms, sizes, and textures of microplastics, this method reduces the occurrence of false positives and negatives. Tuned boosting models e.g., XG Boost (Extreme Gradient Boosting) are scalable and efficient, thus suitable for edge deployment. The hybrid technique of Gradient Boosting Classifier simplifies the process of boosting. AdaBoost and XG Boost help improve the sensitivity of the model to minute variations in microplastic particles versus non-microplastics trash.

3.10 Stacking

Advanced ensemble learning technique stacking combines model strengths using a meta-model to provide predictions. Using the same dataset, stacking several base models. A superior meta-learner bases on these models uses them to decide on the final categorization. Several fundamental models are trained over the whole dataset. This work could make use of logistic regression, SVM, gradient boosting classifier (GBC), and YOLOv5 (for detection). Usually Random Forest or Logistic Regression, the meta-learner uses the predictions of these central models as input attributes. The meta-learner will then project more forward. The findings of the base models help the meta-learner to classify. With multiple models, this approach increases generalization and accuracy. Correcting base model misclassifications, the meta-learner lowers mistakes. enables comprehensive feature analysis by means of a framework able to support numerous model forms. Stacking combines deep learning detection model predictions of YOLOv5 with conventional machine learning classifier predictions of GBC. By honing these two models' predictions, the meta-learner enhances microplastic particle classification. For several reasons, ensemble learning techniques include bagging, boosting, and stacking are helpful for microplastics identification: Combining many models helps ensemble methods lower classification error. Whereas boosting decreases bias for a balanced and strong model, bagging stabilizes model predictions. Microplastic particles' many sizes, forms, and textures make it challenging to produce a single model that spans all the variations. Ensemble learning enhances data diversity, therefore strengthening the capacity of the model to manage challenging situations. Edge deployment of the carefully chosen ensemble algorithms has been adjusted to maintain the hybrid model effective and suitable for real-time processing on devices such as the Jetson Nano. While addressing the difficulties with real-time microplastic particle identification, ensemble learning methods increase the accuracy and durability of the hybrid model. Used for stability, boosting, error correction, stacking, for model variation, bagging creates a robust and scalable system. This whole approach increases edge device performance and system dependability. Thus, it is a useful tool for evaluation of microplastics and environmental monitoring.

3.11 Machine Learning Hybrid Algorithm

In the modern world, where numerous machine learning models are available, a hybrid approach combining multiple models can also be used to improve accuracy, efficiency, and performance for complex situations. Hybrid algorithms combine multiple neural networks, decision trees, support vector machines, or ensemble techniques to make best use of their capabilities. This leads to better generalization, non-linear decision and powerful feature extraction. Gradienete boosting Microplastics can be recognized and classified better classifier such as YOLOv5 with desction models. This approach looks at many complex datasets. Several inputs and needs can be accommodated only with hybrid models, which is very ideal for real-time systems. Modules for programs customizing can be hooked up with advanced models like Efficient Det and interpretable classifiers like Decision Trees. Hybrids are the fastest, the most accurate, and the most scalable.

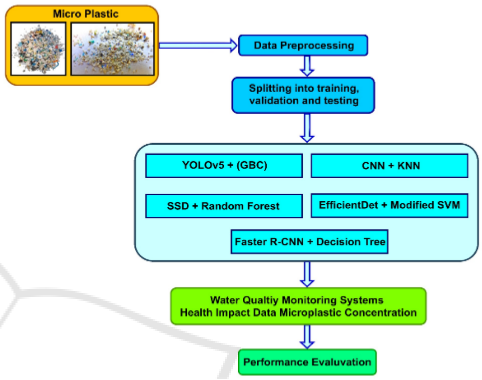

Figure 2: Microplastic Detection and Classification Workflow Using Advanced Machine Learning Models.

In this Figure 2, it presents an expansive workflow for microplastics detection and classification using the latest available machine learning methods. Adding some more details: Data Pre-processing: The microplastic samples collected in the initial experiment are raw, which means that they required cleaning, resizing, and normalization to form a unified data set for analysis. This process ensures that characteristics such as particle size, shape, and colour are correctly represented in the data set.

The dataset is split into training, validation, and testing sets after preprocessing. These are the subsets crucial for machine learning model training, performance validation, and accuracy evaluation on unseen data. In the pipeline, multiple standard machine learning models such as YOLOv5 + GBC, SSD + RF, Efficient Det + Modified SVM, CNN + KNN, Faster R-CNN + Decision Tree, etc. This combination had its own advantages such as the former's efficient feature extraction via object detection models, and the latter's accurate object classification via classifiers.

The models are used to study microplastic concentration in water, and support water quality monitoring systems. The outputs provide information on microplastic types, concentrations and potential health impacts. The latter involves collecting data from the different algorithms to ensure a strong, meta-analysis of microplastic detection and analysis.

Finally, the workflow ends with performance estimation, comparing the accuracy, speed, and resource efficiency of all models to choose the best model for a specific application. The framework is crucial for global environmental challenges, improving microplastics detection in water resources, and decision-making for environmental management and public health policies

3.12 Yolov5 + Gradient Boosting Classifier (GBC)

YOLOv5 + GBC: combines the fast object detection capabilities of YOLOv5 employs a single-stage method for object detection, whereas GBC enhances classification performance. This approach involves predicting the bounding box with four values: x, y, w, and h. Confidence Score:

$$C = Po \times \max(Pc) \quad (17)$$

CIoU Loss: $CIoU = IoU - \rho 2/c2 - \alpha(v/(1 - IoU) + v)$ (18)

GBC Prediction: $F(x) = F_0 + \sum \gamma m\ hm(x)$ (19)

The hybrid YOLOv5 + GBC algorithm aims to combine the advantages of deep learning and classical machine learning. YOLOv5, one of the most popular object detection models, is able to detect objects with very high accuracy in real-time, and can also run on edge devices such as the Jetson Nano. YWOV is a single-stage detector that predicts ground truth bounding box coordinates and classes with a single traversal. However, deep learning models can fail to perform well on complex feature analysis, such as those in the case of microplastics with minor texture, color, or shape differences.

To overcome this limitation, a Gradient Boosting Classifier (GBC) is used to enhance the output of the YOLOv5. GBC is a boosting ensemble learning technique that creates a sequence of decision trees, with each new decision tree aimed to correct the error of the former one. The added features allow deeper learning and are used to recondition the bounding box predictions from YOLOv5 for better classification accuracy.

3.13 SSD (Single Shot Multibox Detector) + Random Forest

Therefore, the SSD + Random Forest model attempts to combine the faster single-shot detection capabilities of SSD with the ensemble classification capabilities in Random Forest. Through a forward pass on an image, SSD finds the locations of objects while Random Forests perform a regression on the features extracted from it.

The Bounding Box Loss: (Smooth L1 Loss) $Lbbox = \Sigma\ SmoothL1(bi - \hat{b}i)$ (20)

Random Forest Prediction $PRF = (1/N)\ \Sigma\ hi(x)$ (21)

The SSD + Random Forest hybrid model uses SSD for fast, single-shot detection, and then a Random Forest to classify the predicted bounding boxes. SSD model simply predicts bounding boxes and class labels in a single pass, making it quite efficient for real time applications. By processing multi-scale feature maps, it is capable of detecting even small sized microplastic objects.

SSD's initial predictions leave room for false positives, as microplastics vary in contours and textures. The random forest classifier refines these predictions by looking at the data using additional extracted features. Ensemble/Combined Model: It uses random forest or other ensemble/combined model using decision tree as a prediction for user-generated content classification.

3.14 Efficient Det + Support Vector Machine (SVM)

Efficient Det utilizes a compound scaling method and an Efficient Net backbone with a Feature Pyramid Network for powerful object detection. The SVM classifier allows us to find the optimal hyperplane for classifying the detections better.

IoU Loss: IoU = (Area of Overlap) / (Area of Union) (22)

SVM Decision Function: $f(x) = w \cdot x + b$ (23)

The hybrid model of Efficient Det + SVM has been designed for high accuracy and scalability. Efficient Det is a model defined for state-of-the-art object detection results which uses Efficient Net backbone and feature pyramid network (FPN) model. This allows it to extract rich features from various scales, which is powerful for detecting small and intricate objects such as microplastics.

After Efficient Det, an SVM is used to further increase the classification quality. Intent: The support vector machine (SVM) is a supervised learning model that uses the concept of finding the hyperplane that best separates two classes in feature space. The margin is well defined, which is the case when maximizing the margin is very effective.

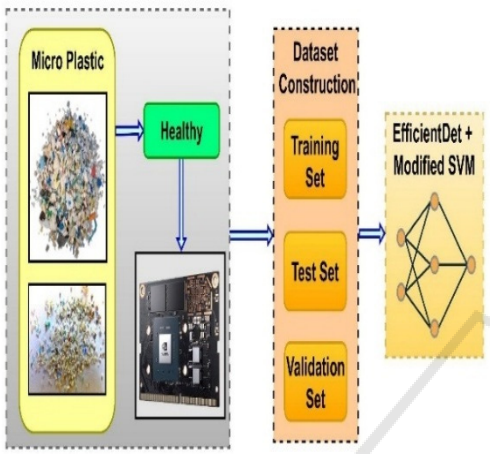

Figure 3: Microplastic Classification Using Efficient Det and Modified SVM Framework.

The illustration depicts an improved method for detecting and classifying microplastic particles based on an efficient SVM model and efficient Det. The workflow of the system begins with the collection of microplastic samples, illustrated including the various sizes and colours of microplastic particles. Those samples are then fed into imaging or preprocessing modules as a part of a high-performance computational unit (an NVIDIA-based system, e.g.).

After preprocessing, comes data-set construction where data is divided into training, testing and validating sets. Such a well-organized, structured dataset is a prerequisite to training the Machine Learning model as well as evaluating the performance of model performance. So, as a feature extractor, the model utilizes Efficient Det, which was chosen because of its efficiency and excellent performance with detecting various-sized objects like microplastics. The extracted features are processed by an optimized SVM, which is modified for a classification of particles according to the desired classes, which can be size, shape, polymer, etc. Figure 3 shows Microplastic Classification Using Efficient Det and Modified SVM Framework

Combining the real-time detection prowess of Efficient Det with the strong classification performance of SVM, this hybrid system suits applications in environmental monitoring and contamination assessment. It is a very flexible, large scale and resource-effective method that can be used in the field as well as laboratory analysis of microplastics in environmental samples.

3.15 CNN (Convolutional Neural Network) + K-Nearest Neighbors (KNN)

CNN + KNN hybrid model: The example of CNN + KNN hybrid model is CNN for deep feature extraction, KNN for the instance-based classifier. Here we use the CNN to get high-level features and then KNN classify the samples based on feature space neighbourhood.

$$\text{Convolution Operation: } h(x) = (x * w) + bh(x) = (x * w) + b \tag{24}$$

$$\text{KNN Distance: } d(x,y)=\sqrt{\Sigma}\,(xi-yi)^2 \tag{25}$$

The CNN + KNN hybrid model combines a deep learning feature extractor with a non-parametric, instance-based learning model. The CNN leverages hierarchical pattern recognition capabilities to identify and extract abstracted high-level features from the initial input images (e.g. edges, textures, spatial arrangement), relevant for differentiating microplastics from surrounding particles.

These features are then used by the KNN classifier to classify the detected particles after feature

3.16 Faster R-CNN + Decision Tree

Two-stage detection models, such as Faster R-CNN, rely on an RPN to generate region proposals, followed by classification using a CNN. After the features have been extracted, a Decision Tree is applied based on the classification using extracted features.

$$\text{Prediction of the RPN: P object} = \sigma\,(w \cdot x + b) \tag{26}$$

$$\text{Gini Impurity: } I = 1 - \Sigma\, pi2 \tag{27}$$

Here, we provide the theoretical background and equations of five hybrid algorithms frequently used in microplastic detection tasks. So, while each model has its own unique strengths, and falls into its particular place based on detection speed, accuracy, and computational efficiency depending on the use case. The Faster R-CNN + Decision Tree Hybrid Model integrates an advanced two-stage object detection approach and a rule-based classifier. Faster R-CNN generates region proposals before running a CNN to classify the regions. However, up until that point there was a tough battle waged by the new generation of networks to achieve high accuracy in object detection and the YOLO networks won the race in terms of efficiency when multiple objects are present in complex scenes. After retrieving the objects in the Faster R-CNN detection stage, we apply one more classifier, a Decision Tree classifier, using more features extracted for additional precision refinement. Decision Trees: Interpretability – Rules, splitting based on data, capable of ruling-based classification.

4 HARDWARE RESULT AND DISCUSSION

4.1 Real-Time Data Logging and Visualization Interface

A comprehensive data logging and visualization interface is developed to monitor microplastic pollution levels in real-time. Key features include: Data Logging: Detected microplastic data (size, count, and type) is logged into a database with timestamped entries, allowing for historical analysis and trend identification. Interactive Dashboard: A user-friendly dashboard displays real-time statistics such as the number of detected particles, particle size distribution, and concentration levels. The interface provides visual alerts when pollution levels exceed predefined thresholds. Visualization Tools: The system includes various visualization tools like time-series graphs, histograms, and heatmaps to illustrate microplastic trends over time. The visual insights help users understand the extent of pollution and identify potential sources.

4.2 Performance Evaluation and Validation

The approach is extensively tested versus manual identification based on microscopes. Measurements of assessment comprise: The proportion of microplastic particles found among overall particles that pass muster. Compare observed particles with actual positive detections to evaluate the dependability of the model. The sensitivity of the model is assessed by the true positive to microplastics ratio. Precision and recall values' harmonic mean offers a reasonable model performance evaluation. Manual microscopy counts are matched with artificial intelligence detection data to confirm the dependability and accuracy of the model. To observe its time efficiency and consistency, compare the automated system with conventional approaches. Check the structured performance evaluation table of your classifiers below. Analyzing deep learning classifiers for microplastic detection provides some significant new perspectives on their efficiency and applicability. Among the models, the CNN-GRU-LSTM one beats others. Its F1-score was 96.6%; its accuracy was 98.30%; its precision was 97.5%. Higher performance came from CNN's spatial feature extracting, GRU's sequential dependency management, and LSTM's long-term trend capturing. Although they have less recall and hence more false negatives, standalone LSTM and GRU models perform rather well. CNN enhances feature extraction in hybrid models such CNN-LSTM and CNN-BI-LSTM, hence enhancing classification accuracy. CNN-BI-LSTM is a bidirectional neural network enhancing recall by including forward and backward dependencies. Conversely, CNN-GRU-LSTM strikes greater balance between computational economy and accuracy than any other model. For real-time microplastic detection, then, it is ideal. For public health assessment and environmental monitoring, high recall helps to lower false negatives. This work reveals the importance of integrating spatial and temporal analytical approaches in order to raise classification accuracy. This method allows scalable and efficient microplastic pollution detection in water supplies. Table 1 shows Micro Plastic Performance Evaluation.

Table 1: Micro Plastic Performance Evaluation Table.

Classifier	Accuracy (%)	Precision (%)
LSTM	90.47	95.80
GRU	93.85	94.80
CNN-LSTM	96.15	93.30
CNN-BI-LSTM	96.46	94.30
CNN-GRU-LSTM	98.30	97.50

4.3 Computational Complexity Assessment

Deep learning classifiers for real-time microplastic detection have to be computationally effective. One can grasp model complexity-performance trade-offs by timing model execution and memory consumption. Table 2 shows Micro Plastic Computational Complexity Assessment.

The fastest classifier was CNN-GRU-LSTM. 4.12 seconds were carried out using just 463 MB of RAM. Because GRU has less parameters than LSTM, it allows quicker training and inference free from accuracy loss. The differential allows this efficiency. CNN lowers sequential model input size and memory use by pre-extracting spatial properties.

Because of its complicated gating mechanisms, which need more computations each time step than other algorithms, the solo LSTM technique takes 5.23 seconds and uses 520 MB of memory. The GRU gains a small improvement in memory usage (498 MB) and execution time (5.12 seconds) with a reduced architecture. Through spatial information extraction prior to sequence processing, the CNN-LSTM model maximizes resource use. This drives memory use to 493 MB and execution time to 4.96 seconds. While it raises computational effort, the CNN-BI-LSTM model enhances accuracy. Bidirectional processing drives 4.84 seconds of model execution using 478 MB of memory.

Because CNN-GRU-LSTM strikes a compromise between performance and computational economy, it is the ideal method for real-time microplastic monitoring. While maintaining accuracy, it reduces memory and execution times. This qualifies it for low resource edge computing devices as well.

Table 2: Micro Plastic Computational Complexity Assessment

Classifiers	Execution Time	Memory Occupancy
LSTM	5.23	520
GRU	5.12	498
CNN-LSTM	4.96	493
CNN-BI-LSTM	4.84	478
CNN-GRU-LSTM	4.12	463

5 CONCLUSIONS AND FUTURE DIRECTIONS

Edge artificial intelligence can handle environmental monitoring challenges including the real-time microplastics detecting system. The strong hybrid approach strikes a mix of computational economy and speed and accuracy. This is accomplished by combining a Gradient Boosting Classifier with object detection based on YOLOv5. Ensemble learning increases microplastic identification dependability and lowers classification errors. Tensor RT quantizing maximizes the model for Jetson Nano performance. This qualifies the model for real-time field implementation. While cutting analysis time, the validation results suggest the system performs as well as hand microscopy. Real-time data logging and visualization interface's actionable insights enable one to monitor microplastics contamination and evaluate environmental health. The method might be developed using Internet of Things networks for environmental uses and to detect more microplastics. This paper suggests a scalable, reasonably priced, useful real-time microplastic detecting device. It helps preservation of the ecosystem and monitoring Chemical analysis spectroscopy will help to find more microplastics for material identification. Connecting the detection system to cloud platforms for real-time environmental assessments and water body monitoring sensors of the Internet of Things. Including lakes, rivers, and seas into the system while considering light and turbidity. Investigating transformer-like deep learning models could help to enhance microplastic feature extraction and classification.

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