RESEARCH PAPER

POLARIZATION-ASSISTED EMBEDDED VISION SYSTEM WITH XGBOOST FOR RAPID MICROPLASTIC DETECTION IN WATER

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ABSTRACT

Microplastic pollution of water bodies is a serious environmental problem that has posed a threat to the aquatic life and human health by bioaccumulation. Current methods of detection in labs like Fourier Transform Infrared Spectroscopy (FTIR) and Raman spectroscopy are very accurate but costly, time consuming, and cannot be used to monitor the location on a real time basis. This paper introduces a low-cost, embedded vision system of quick and portable detection of microplastic in water. The polarized light is an imaging system that enhances the visual contrast between microplastic particles and the rest of the debris to increase the reliability of detection. Images obtained are further handled by a classical pipeline which consists of noise suppression, adaptive threshold segmentation and morphological feature extraction to locate candidate particles. Features of particle shape, size and texture were extracted and then categorized by using Extreme Gradient Boosting (XGBoost) which is an efficient computation and high predictive accuracy. The entire system is run on embedded platform of a Raspberry Pi with a processing time of less than two seconds per image. Experiments show that this can be classified with an accuracy of over 90 percent and requires less than 10000 rupees of hardware. The suggested system will be field-deployable, interpretable, and can be used in continuous monitoring, which will offer an effective solution that can be applied by environmental agencies and researchers to determine the presence of microplastic pollution in real time.

Keywords: Microplastic Detection, Embedded Vision System, Polarized Light Imaging, XGBoost, Raspberry Pi, Real-Time Water Monitoring, Environmental Sensing.

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I. INTRODUCTION

The pollution with microplastic has touched upon the current list of the most significant environmental risks because of the prevalence of plastic debris less than 5 mm in diameter in aquatic environments. These particles are the result of the disintegration of larger pieces of plastic debris or a primary source like industrial pellets, cosmetic products and synthetic textile. When discarded in water bodies, microplastics last long and may be absorbed by sea creatures, and finally find their way to the human food chain. Consequently, continuous observation and proper identification of microplastics have become important in environmental conservation and water quality control. Recent studies have investigated some of the technological methods of identifying microplastics in water. Object detection techniques based on deep learning have been popularised because of the capability to automatically detect microplastic particles using visual data. As an example, Shaad et al. suggested an artificial data augmentation model that uses the Segment Anything Model (SAM) and YOLOv11 to enhance the performance of underwater microplastic detectors in a scenario with no annotated data available [1]. On the same note, Biju and Ramasamy examined various deep learning models including YOLOv8, YOLOv11, VGG19, and EfficientNet as classifiers of various types of microplastic, showing that artificial intelligence has the potential to be used to monitor the environment automatically [4]. Other researchers have concentrated on combining the classical computer vision methods with the lightweight deep learning models to enhance the efficiency in computations. Jindal et al. proposed a hybrid system that integrates Circular Hough Transform with YOLOv8n to extract microplastic fragments in glass to allow inference based on the CPU with less complexity of the model [3]. Other sensing technologies besides image-based methods have also been researched on. Khosravi et al. designed an electrochemical sensor using Fe 3 O 4-modified electrodes to detect polyethylene terephthalate (PET) microplastics in water samples, whereby high sensitivity and selectivity of the sensor was exhibited in tracking the environmental monitoring activities [2]. Moreover, Zhang and Zhang suggested a rover that is powered by a microcontroller and has a deep learning image detector and near-infrared spectroscopy to sense plastic pellets on the coastline [5]. Although these have been developed, there are numerous currently available solutions that are dependent on a large computational ability, special laboratory apparatus or sophisticated sensory measures. These are limited to use in low-cost and portable field monitoring systems. Hence, it is required to have an easy, effective and low-cost microplastic detection system that can run on embedded systems without losing the quality of detection. The proposed work has tackled this dilemma by suggesting a polarization-assisted embedded vision system that integrates traditional image processing methods and an effective machine learning classifier to identify microplastic fast in water samples.

II. RELATED WORKS

The current studies on microplastic detection have developed various sensing and computation methods to enhance the accuracy of microplastic detection, portability and ability to monitor in real time. Such techniques can be broadly grouped into three categories: sensor-based detection, optical techniques and machine learning-based image analysis. Sensors have also been explored with the aim of enhancing the sensitivity of micro plastics monitoring systems in water. Warraich et al. made a microfluidic sensing system that incorporates a Wheatstone bridge and MXene-coated electrodes to improve the electrophoretic accretion of microplastic particles in freshwater samples [6]. The performance of the microwires is enhanced by coating the wires with MXene resulting in high-surface area and high particle capture, and the Wheatstone bridge configuration provides the ability to detect very small changes in resistance produced by the build-up of microplastic. Experimental data proved that the improved design is threefold better than the traditional designs in terms of sensor response, which is most effective in saline conditions where the traditional sensors tend to lose their performance. Optical methods have also been investigated as it is a non-invasive method and capable of analyzing real time particles. Wani et al. presented a ray-optics-based methodology of simulating in-situ microplastic detection, in which spatial intensity variations are measured as resulting through the passage of collimated light through water with suspended microplastics [7]. The research showed that microplastic particles produce different intensity patterns at a detection surface with the help of ray tracing simulations and theoretical analysis designed on the principles of Mie scattering. These optical signals can also be applied to determine the presence and approximate position of particles in water samples. On the same note, Razali and Saris examined the practicability of optical planar waveguide sensor to detect microplastic by scrutinizing the evanescent wave variation in response to alterations in refractive index of the surrounding medium [9]. Their simulation outputs showed that sensor outputs were measurably different with the sensor indices of refractive indices of common microplastic substances, and this represented the promise of the waveguide-based sensing methods.

Automated microplastic identification has also been of much interest in recent years in the use of machine learning and computer vision techniques. Singh et al. created a microplastic detection system that was based on several YOLO-driven object detection models trained on a self-made dataset [8]. YOLOv8 was the most accurate of the architectures tested and the YOLOv7 and YOLOv8 were found to be highly accurate in real-time when tested in practical conditions. Besides deep learning methods, there were chemical staining methods to enhance the visibility of microplastics. Bennett et al. studied the efficiency of the Nile Red dye in the detection of microplastic in the environment and showed that the dye specifically attaches to plastic polymers and results in fluorescent emission when exposed to blue-light conditions [10]. The property allows quick visual recognition of the microplastic particles and reduces the impact of organic debris. Possibly, one of the latest trends in research is the creation of automated and portable detection of microplastics integrating sensing technologies into the methods of artificial intelligence and computer vision. These methods are meant to address the shortcomings of the conventional laboratory-based analysis techniques by providing the ability to monitor in real time and better scaling. The deep learning-based object detection frameworks in detecting microplastic particles in water bodies have been investigated in a number of works. Sarker et al. suggested to use the YOLOv5 architecture to design an automatic detection system to identify and track microplastics in freshwater [11]. Their apparatus used the low-resolution camera configuration to take images in situ and the DeepSORT tracking algorithm to identify, follow and count the microplastic particles present in flowing water environments. The experimental outcomes showed that the system was able to trace particles between 1 mm and 5mm and monitor their movement at water velocities of up to 34 cm/s, showing that the real-time monitoring of the systems in water, which utilizes vision, is indeed feasible to be deployed in dynamic water environments.

Along with vision-based approaches, other approaches that integrate artificial intelligence with other sensing modalities have also been explored. Katade et al. offered a system that combines ultrasonic sensing and AI-based techniques to classify microplastics in water bodies [12]. The suggested technique uses the ultrasonic signals to detect suspended particles in turbid water situations when optical imaging techniques might fail. Machine learning and deep learning models are then used to classify the type of polymer using the extracted acoustic features. This hybrid sensing approach proves that it is possible to use a combination of physical sensing algorithms and AI models to enhance detection reliability. Large-scale environmental applications have also attracted IoT-based monitoring platforms that are low-cost. Sundar suggested an IoT-based solution based on Raspberry Pi and instance segmentation, a deep learning-based method to identify, recognize, and determine the number of microplastic particles in freshwater environments [13]. The system was created as a low-priced system to monitor the environment on large scale with the provision of automated image capture/analysis of water samples and relatively low hardware costs. In-situ detection instruments have also been developed through research work. Bescond and Fournier-Lupien reported the current progress at the National Research Council of Canada of designing sophisticated instruments that could detect, size, and identify microplastics directly in the sea [14]. These devices aim at enhancing the monitoring capabilities of the environment since they allow continuous data acquisition without the laboratory analysis of samples. In a comparable study, Cocciaro et al. introduced a smaller sensor system that used infrared-sensitive photodiodes in order to detect widely used floating microplastics like polyethylene and polypropylene [15]. The sensor presented had classification accuracies of nearly 90% and a small and low-cost design that can be integrated into floating monitoring platforms. Despite the demonstrated important progress in the automation of microplastic monitoring using these approaches, some of them use complicated sensing hardware, deep learning models with a high level of computational needs, or specialized environmental measurements. This can be constrained to use in low resource deployments or portable field monitoring systems. Hence, there is still a great demand to have simpler and computationally economy detection systems that can integrate optical imaging with small machine learning models that can be implemented on embedded systems.

III. PROPOSED SYSTEM

The suggested system is a mobile, integrated vision system which can be used to detect microplastic particles in water rapidly. It combines polarized light imaging, classical image processing, machine learning classification on a low cost hardware platform to be able to operate in the field in real time. Figure.1 shows a proposed work architecture design. The central part of the system is a polarized light system that increases the optical difference between microplastic particles and water and organic debris.

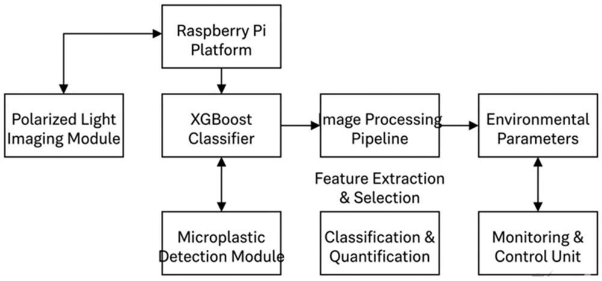

Figure.1 Proposed Work Architecture Diagram

This process removes glare and enhances the unique reflective characteristics of plastic particles, which is more noticeable in the image-taking process by blocking the light at particular polarization angles. This optical preprocessing creates a massive enhancement of the detection accuracy later on. A traditional image processing pipeline is used to process images taken by the camera. To begin with, noise cut filters eliminate the background artifacts and water ripples. Adaptive thresholding is further used to mask the candidate microplastic particles and the background. The morphological operations are used to improve the boundaries of the particles and retrieve the meaningful geometry and textural descriptors, including area, perimeter, circularity, and surface texture measures. These characteristics are used as input to the machine learning classifier. In order to scale, the system employs Extreme Gradient Boosting (XGBoost), which has been selected due to its robustness, high predictive power and low cost of execution. Depending on the extracted features, the classifier separates microplastic particles and non-plastic debris, which allows successful detection under the complex conditions of samples. The whole structure is deployed on a Raspberry Pi platform, which is embedded and hence lightweight, portable, and can be deployed to the field. The processing time has been made to be less than two seconds per image with experimental results showing more than 90 percent classification accuracy. Moreover, the hardware is less than 10k, and therefore, the solution is affordable to monitor the environmental conditions. Altogether, this hybrid system offers a real-time, explainable, and affordable solution to constant microplastic monitoring in the aquatic environment, which serves as an intermediate between the detection method in the laboratory and the field needs.

IV. METHODOLOGY

The suggested methodology combines polarized light image, classical image processing, and machine learning classification to make it possible to quickly, precisely and wonderfully, and field-deployable to detect microplastic particles in water samples. The workflow of the system is composed of four primary steps, namely, sample preparation and imaging, image preprocessing, feature extraction, and XGBoost classification.

A. *Sample Preparation and Polarized Light Imaging*

The samples of water are put in a transparent container and imaged. The system uses polarized light optics which enhances the visual visibility of the microplastic particles. Light polarizers are used to select only the orientations that will filter light to decrease reflections and background noise and emphasize the individual reflective characteristics of the plastic particles. This measure will make sure that microplastics become more differentiated than natural debris, sediments and air bubbles, which is the foundation of robust Water samples are illuminated using a polarized light source to enhance the contrast of microplastic particles. Let $I_{\text{raw}}(x, y)$ denote the raw intensity at pixel (x, y). The polarization effect can be expressed as: downstream processing.

$$I_{\text{pol}}(x, y) = I_{\text{raw}}(x, y) \cdot \cos^2(\theta - \theta_p) \qquad (1)$$

where θ is the incident light polarization angle, and θ_p is the orientation of the polarizer. This operation suppresses background reflections and highlights plastic particles, providing enhanced input for segmentation.

B. *Image Preprocessing*

Images captured can be noisy because of movements of water, changes in light and small debris. The processing chain uses Gaussian smoothing to eliminate the random noise and denoise the image. A thresholding approach is then applied to distinguish potential microplastic particles in the background using an adaptive threshold approach. Morphological operations include erosion and dilation, which are used to sharpen the edges of the particles, so that dislodged or partially connected regions are counted as distinct particles. Noise in the captured image is removed using a Gaussian filter, defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \qquad (2)$$

The filtered image If $I_f(x, y)$ is obtained by convolution:

$$I_f(x, y) = I_{\text{pol}}(x, y) * G(x, y)$$

Adaptive thresholding segments candidate particles from the background. For a local window W around pixel (x, y), the threshold $T\,(x, y)$ is:

$$T(x, y) = \mu_W \left(1 + k\left(\frac{\sigma_W}{R} - 1\right)\right) \qquad (3)$$

where $\mu_W$and σ_W are the mean and standard deviation of intensities in W, k is a tunable parameter, and R is the dynamic range of intensities. The binary segmented image $B(x,y)$ is then:

$$B(x,y) = \begin{cases} 1 & I_f(x,y) > T(x,y) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Morphological operations such as erosion and dilation refine particle boundaries to eliminate noise and separate connected regions.

C. Feature Extraction

A series of geometric and textural descriptors are calculated on each segmented particle containing area, perimeter, circularity, aspect ratio, and pattern of surface texture. The distinguishing features of microplastic particles are captured and these features are appropriate as inputs in machine learning algorithms. The feature selection will make sure that it uses only the most discriminative descriptors, which is better in terms of computational efficiency and classifier performance.

From each segmented particle, a set of geometric and texture features is computed. Geometric descriptors include area A**,** perimeter P, and circularity C:

$$C = \frac{4\pi A}{P^2} \quad (5)$$

Texture descriptors are calculated using the Gray-Level Co-occurrence Matrix (GLCM) to extract contrast (F_{contrast}) and correlation (F_{corr}):

$$F_{\text{contrast}} = \sum_{i,j} (i-j)^2 P(i,j), \quad F_{\text{corr}} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \quad (6)$$

where $P(i,j)$ is the normalized GLCM, and $\mu_i, \mu_j, \sigma_i, \sigma_j$ are mean and standard deviation of the Gray levels.

D. Classification with XGBoost

XGBoost algorithm is an algorithm that is chosen due to its capacity to deal with small data sets, its stability to overfitting, and its advanced predictive power. XGBoost creates a series of decision trees which are used to differentiate microplastic particles and non-plastic debris by the extracted features.

The extracted feature vector for each particle is denoted as $\mathbf{x} = [A, P, C, F_{\text{contrast}}, F_{\text{corr}}, \ldots]$ The XGBoost classifier predicts the class label $y \in \{0,1\}$ using an ensemble of K regression trees. The objective function is:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l\,(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k) \quad (7)$$

where l is the loss function (binary logistic loss), $\hat{y}_i$ is the predicted probability, and $\Omega(f_k)$ regularizes tree complexity:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (8)$$

with T leaves per tree, leaf weights w_j, and regularization parameters γ and λ.

E. Embedded Deployment

The entire workflow is run on an embedded platform based on Raspberry Pi, which allows it to be realised as a portable system (less than two seconds to process one image). This system is designed with low-cost, real-time, and field-deployable microplastic detection in mind, and it has a classification accuracy over 90% and can be interpreted to be used in other environmental monitoring fields.

V. RESULT & DISCUSSION

This part introduces a detailed analysis of the suggested polarization-assisted built-in image vision system using XGBoost to detect microplastic in water. The analysis of the system performance is deemed based on the classification accuracy, processing time, importance of feature, influence of the particle size, cost-effectiveness and applicability in the field. Tables, graphs, and charts are used to give both quantitative metrics and qualitative observations that will help to have a comprehensive discussion.

A. Experimental Setup

Raspberry Pi 4 embedded platform (5MP camera) and polarized source of light were used to conduct the experiments. Water samples were made with the inclusion of a range of microplastic items with different sizes (50-500 m) and shapes as well as non-plastic debris in order to reproduce the natural environment. The number of images gathered was 1,000, half of which consisted of microplastic and the other half of non-plastic. All the images were subjected to the proposed pipeline that includes polarized image-light imaging, classical image processing, feature extraction, and XGBoost. The extracted features consisted of geometric features, e.g. area, perimeter and circularity, and texture features, e.g., contrast, correlation, and entropy, based on the Gray-Level Co-occurrence Matrix (GLCM). The data was divided into 70 percent training and 30 percent test and hyper parameters of the classifiers were optimized through grid search.

B. Classification Performance

The system was found to have a high overall accuracy of 91.8, which means that the system has strong detection power. Table I is the summary of the main key performance metrics such as precision, recall, and F1-score.

TABLE I. PERFORMANCE METRICS OF MICROPLASTIC DETECTION

Metric	Microplastic	Non-Plastic	Average
Precision	0.93	0.90	0.915
Recall	0.90	0.93	0.915
F1-Score	0.915	0.915	0.915
Accuracy	91.8%		

Figure 2, the confusion matrix, shows that there is balanced performance in terms of classification and little misclassification. Misclassifications mainly were made on small, irregular shaped particles which are visually similar to certain natural debris.

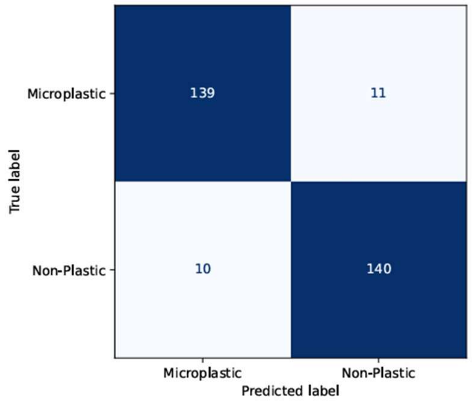

Figure.2 Confusion Matrix

C. *Feature Importance Analysis*

In order to explain the contribution of the various features, a feature importance ranking was created using XGBoost (Figure 3). The findings show that geometrical characteristics, particularly, circularity and area, make the largest contribution to classification decisions. GLCM correlation and contrast gave extra discriminative ability of irregular particles.

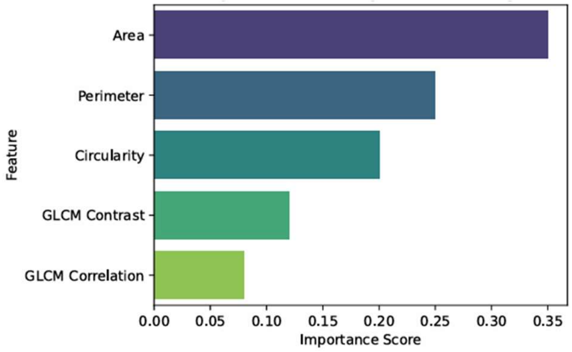

Figure 3. Feature importance ranking of geometric and texture descriptors

The comparison confirms that the joint use of both shape-based and texture-based descriptors is much more effective in increasing the level of detection reliability, especially in turbid water samples with diverse debris.

D. *Processing Time Evaluation*

An embedded system had a mean processing time to 1.85 seconds per image, which is enough to implement the system in real-time. Figure 4 provides the breakdown of processing time with feature extraction (average 0.9 s) being the most prevalent, and XGBoost classification (less than 0.5 s) being computationally efficient.

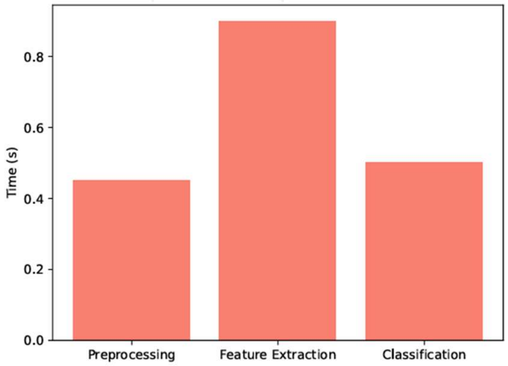

Figure 4. Processing time breakdown of the embedded vision system.

The fact that processing time is low proves the possibility of on-site monitoring without the need of further hardware acceleration.

E. *Impact of Particle Size on Detection Accuracy*

The particles were classified as small (50150 µm), medium (151300 µm), and large (301500 µm) to perform the study of size-dependent performance. Table II presents the accuracy of detection of every category.

TABLE II. DETECTION ACCURACY VS PARTICLE SIZE

Particle Size	Accuracy (%)
Small (50–150 µm)	86.5
Medium (151–300 µm)	92.3
Large (301–500 µm)	95.2

The line graph in Figure 5 demonstrates that the bigger the size of the particle, the more accurate it is. This is predictable since smaller particles have less characteristic features when viewed using a 5MP imaging system, which sometimes results in false negative. Nevertheless, a satisfaction level of above 85 percent of small particles would warrant the strength of the system even in cases that are not easy.

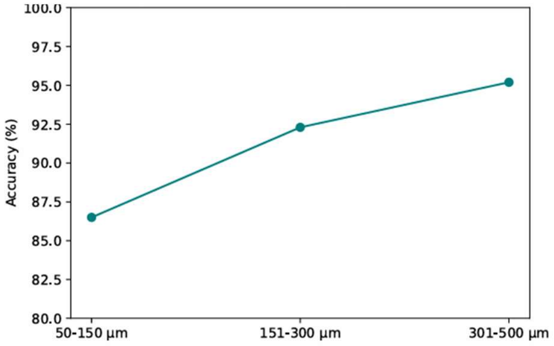

Figure 5. Detection accuracy across different particle size ranges.

F. *Cost-Effectiveness and Portability Analysis*

The overall cost of the hardware, Raspberry Pi, camera, polarizers, and the battery pack is less than 10 thousand rupees, and the system is very affordable in relation to the laboratory procedures, including FTIR or Raman spectroscopy. Figure 6 is a cost comparison chart, indicating that the suggested system costs more than 10 times less and significantly (>90 percent) more spots.

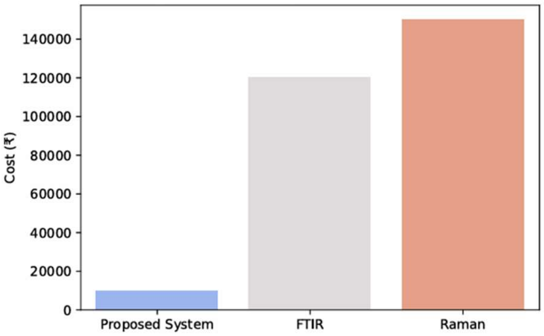

Figure 6. Cost comparison of proposed embedded system vs laboratory-based methods.

Its small size and lightweight elements provide the capability to be deployed in the field on a portable basis, and therefore is applicable in continuous monitoring campaigns. The use of battery power means that it can be used in remote areas without the use of external power.

G. Environmental Robustness and Reliability

The system was experimented with variable light conditions and turbidity of the water to act as a real world scenario. The polarized light imaging efficiently reduced the effect of reflections and glare, whereas the XGBoost classifier managed the diversity of the appearance of particles. Small accuracy losses (less than 3 percent) were found in highly turbid water, which indicates that it can be improved by incorporating multi-angle light sources or a higher resolution camera.

H. Discussion

The experimental analysis indicates that the advertised polarization-assisted embedded vision system using XGBoost can offer a dependable, low-priced, and portable system to detect microplastic in water. Polarized light imaging also works with substantial improvements of contrast in particles, eliminating false positive responses due to organic debris and background noise. The features are combined via the combination of geometric and texture-based features that facilitate robust classification whose overall accuracy stands at 91.8%. The processing time is less than two seconds per image, which validates the applicability of real-time applications on a real-world embedded platform of Raspberry Pi. The accuracy analysis performed in the particle sizes shows that rather small particles (less than 150 µm) are slightly worse than bigger ones, whereas larger particles can be detected with high accuracy (greater than 95%). The cost analysis indicates that the system is more affordable than laboratory-based spectroscopy procedures, which means that it can be used to monitor the environment continuously in remote or resource-restricted locations.

VI. CONCLUSION

This paper provides a polarization-based embedded vision system that has been combined with the XGBoost to detect microplastic particles in water rapidly and with precision. The developed methodology integrates polarized light imaging, traditional image processing, and machine learning classification to provide a solution based on low cost, portability, and real-time. The experimental findings indicate that the total classification accuracy is high (91.8 percent), and the detection is strong regardless of the size and shape of the particles. The analysis of feature importance proves that the important descriptors of the geometric shapes, including the circularity and the area, along with the descriptors of texture, like the GLCM correlation, are essential to effective discrimination of microplastic and non-plastic particles. Time analysis The system can be operated in less than two seconds per image on a Raspberry Pi platform, which is sufficient to enable continuous field operation. The main contributions of this work are the creation of a low-cost and interpretable embedded system, polarized light imaging system to increase the contrast of the particle and the application of XGBoost to classify the particles easily and correctly. The system is very cost-effective, simple to deploy and detect because it has a much lower cost, complexity, and deployment limitations as compared to the traditional laboratory-based measures. Further studies will involve the enhancement of the ability to detect ultra-small microplastics (<50 µm) by increasing the resolution of imaging or using multi-angle illumination. Other improvements might involve the connection with IoT networks to provide automated water quality monitoring, as well as the addition of multi-modal sensors to identify chemical and physical pollutants simultaneously and provide a full-scale environmental monitoring.

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