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AutoSpec-PlastNet: An Integrated AI Pipeline for Automated Microplastic Detection, Size-Based Spectral Proxy Mapping, Polymer Classification, and Environmental Impact Assessment

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I. Introduction

Microplastic pollution has recently been recognized as a significant global environmental issue because of the large-scale production, consumption, and improper disposal of plastic materials. Microplastics are generally defined as plastic particles smaller than 5 mm in size and can be divided into primary microplastics, which are intentionally produced at a microscopic scale, and secondary microplastics, which are produced by the degradation of larger plastic waste. At present, microplastics have been shown to be ubiquitously distributed in marine, freshwater, and terrestrial environments, which has severe implications for their ecological toxicity, bioaccumulation, and potential human health impacts via the food chain and water supply networks.

The primary contribution of this research effort is the design of a fully automated, start-to-finish AI system that integrates imaging, spectroscopy-based selection, polymer identification, and pollution analysis into a single framework. As the proposed system possesses the capability to realistically simulate laboratory decision-making with minimal human intervention, it is expected to offer a scalable, cost-effective, and intelligent solution for microplastic analysis.

Recent breakthroughs in artificial intelligence (AI) and deep learning have shown considerable promise in automating the process of environmental monitoring. Object detection methods, including the You Only Look Once (YOLO) series of algorithms, have been shown to be state-of-the-art in the detection of small and complex objects in complex visual environments, and hence can be applied to the detection of microplastic particles in microscopic images. Deep learning algorithms such as convolutional neural networks have been successfully applied in spectral analysis for the classification of polymers. However, most of the existing literature is focused on microplastic particle detection and polymer classification as separate problems, without an overall pipeline that reflects real-world laboratory practices.

Moreover, the analysis of microplastics in the real world also involves human decision-making, for example, deciding on the appropriate spectroscopy technique to be used based on the size and shape of the microplastic particles. For example, µFTIR spectroscopy is more preferable for larger particles compared to Raman spectroscopy. Most of the current AI research work on microplastic analysis has not taken into account the domain-specific decision-making process in their automated pipelines.

To overcome these challenges, this paper proposes AutoSpec-PlastNet, a novel AI-driven holistic framework for the automated microplastic detection, classification, and environmental impact analysis. The proposed framework starts with the microscopic image input and uses a YOLOv8-based detection model to detect microplastic particles and obtain their bounding box coordinates. Particle size estimation is performed by using a calibrated pixel-to-micrometer ratio, allowing for automated selection of spectroscopy type according to predefined expert rules. As this paper does not involve direct spectroscopic measurement, Raman and µFTIR spectra are proxy-mapped from trusted public datasets using a proxy-based spectral mapping approach, allowing for realistic simulation of spectroscopic analysis.

The spectral information is then preprocessed with baseline correction, noise removal, and normalization methods to improve signal quality. A one-dimensional convolutional neural network is then used for polymer classification, including polyethylene (PE), polypropylene (PP), polyethylene terephthalate (PET), polystyrene (PS), and polyvinyl chloride (PVC). Finally, an environmental impact analysis module is used to aggregate polymer distribution statistics to estimate the severity of pollution and polymer persistence in aquatic environments.

The main contribution of this research work is the development of an entirely automated, end-to-end AI system that combines imaging, spectroscopy-based selection, polymer identification, and pollution analysis into a single framework. Since the proposed system is capable of simulating real-world laboratory decision-making and minimizing human intervention, it is expected to provide a scalable, cost-effective, and intelligent solution for microplastic analysis.

II. Literature Survey

Microplastic pollution has become one of the most serious environmental issues worldwide because these particles are persistent, ubiquitous, and toxic. The standard method of microplastic analysis is based on microscopic imaging followed by FTIR and Raman spectroscopy for chemical characterization. Although these methods have been successful in determining the chemical composition with high accuracy, they are labor-intensive and costly and require specialists, which makes them impractical for extensive environmental monitoring [1].

In recent times, the advent of artificial intelligence has facilitated the creation of automated microplastic analysis methods. Numerous reviews have highlighted the growing role of machine learning and deep learning in microplastic detection and spread quantification [2], [3]. These reviews indicate that AI-based methods could significantly improve both the speed and the precision of microplastic analysis.

Deep learning-based microscopy analysis has been successful in microplastic analysis. Arju et al. have developed a low-cost deep learning-based microscopy system for microplastic analysis and emphasized its potential for implementation in developing countries [4]. YOLO-based object detection models have also been used for microplastic detection in microscopic images with high accuracy and in real time [5]. Other works have used segmentation-based methods to estimate microplastic morphology and size distributions [6].

Spectroscopic methods are still the most reliable for polymer identification. Raman spectroscopy has been shown to be especially appropriate for microplastics smaller than 10 µm, while µFTIR spectroscopy is more efficient for larger particles because of spatial resolution limitations [7]. Nevertheless, spectral analysis is frequently impaired by fluorescence, baseline correction, and noise, making polymer identification more difficult [8].

To overcome these difficulties, deep learning models have been used for spectral analysis. Qin et al. introduced a CNN-based model for Raman spectral classification with high accuracy for polymer identification [9]. Zhou et al. designed a dense CNN model for Raman spectral identification, enhancing resistance to spectral interference [10]. Other works have shown that one-dimensional CNN models can reach classification accuracy above 95% for polymer classification problems [11].

Machine learning-based integrated systems that combine imaging and spectroscopy have also been investigated. Some research works proposed frameworks that combined microscopy-based detection with spectral analysis for microplastic analysis [12]. It has been pointed out by the reviews that morphological as well as chemical data integration is essential for accurate microplastic analysis [13]. Holographic microscopy combined with deep learning has also been used for the precise identification of microplastic fibers and fragments [14].

Various environmental samples, such as freshwater, marine environments, and drinking water systems, have been found to contain microplastics. The authors demonstrated that microplastics are present in freshwater environments everywhere and also warned about the potential risk of microplastic intake through drinking water [15]. The paper stressed the importance of standardized monitoring and automated detection methods for assessing the extent of worldwide microplastic pollution.

Artificial intelligence techniques have also been explored for environmental monitoring purposes. Wu et al. proposed a deep learning-based framework for microplastic detection and classification, showing that automated systems can be more efficient than manual approaches in terms of speed and accuracy [16].

In earlier research, new analytical techniques were introduced for the identification of microplastics. Imhof et al. suggested a technique that uses density separation and FTIR spectroscopy for the identification of microplastics in environmental samples, which formed the basis of microplastic research [17]. Even though the technique is effective, it requires a significant amount of manual work and technical know-how.

Large-scale environmental research too has brought to light the seriousness of plastic pollution. Suaria et al. conducted research on plastic pollution of the Mediterranean Sea and discovered that there was a very high level of microplastic pollution in different marine environments [18]. The paper stresses the necessity for the creation of automated monitoring systems for large-scale environmental studies.

Deep learning algorithms are becoming more and more popular in environmental monitoring and remote sensing applications. Zhang et al. reviewed the use of deep learning models in environmental monitoring and showed the efficiency of deep learning models in the analysis of complex environmental data, including pollution detection and classification [19]. The study indicates the potential use of AI-based systems for real-time environmental decision-making.

Moreover, the study by Silva et al. presented a thorough review of the analysis methods of microplastics, pointing out the drawbacks of the conventional microscopy and spectroscopy analysis methods and underlining the importance of intelligent analysis systems [20]. This review further supports the significance of the combination of artificial intelligence and environmental science for the accurate analysis of microplastics.

III. Proposed System

The proposed system offers an automated and comprehensive artificial intelligence (AI)-based pipeline for microplastic analysis, polymer identification, and environmental pollution analysis based on microscopic images of water samples. The main aim of the proposed system is to reduce human involvement to a minimum while simulating the process followed in a laboratory-based microplastic analysis. The proposed system combines object detection, size calculation, proxy spectroscopy mapping, spectral preprocessing, polymer identification, and pollution impact analysis in a single computational platform.

Unlike traditional laboratory-based pipelines, which involve manual particle separation, operation of a spectroscopy instrument, and analysis by experts, the proposed system offers an automated solution from start to finish. The proposed system is intended to analyze microscopic images of water samples, identify microplastics, calculate their sizes, identify suitable spectroscopy methods, map representative spectral signatures from validated data sources, and classify polymers using deep learning techniques. Additionally, a pollution impact analysis module is used to aggregate polymer data to determine the extent of pollution.

A. Automated Microplastic Detection Module

The initial component of the proposed system is the detection of microplastic particles from microscopic images of water samples. A YOLOv8 object detection algorithm is employed for the detection of microplastic particles and the removal of non-plastic objects such as dust, fibers, and background artifacts. The YOLOv8 algorithm returns the coordinates of the bounding box, confidence levels, and class identifiers of the detected particles. The use of the YOLOv8 algorithm enables real-time detection with high accuracy, which is suitable for high-throughput applications. This module is the core of the system for particle-level analysis.

B. Particle Size Estimation and Spectroscopy Selection

After detection, the size of each microplastic particle is estimated using the size of the bounding box and the calibration parameters of the microscope. A pixel-to-micrometer scale conversion is used to estimate the size of the particles in micrometers (µm). The size of the particles is an essential factor in determining the appropriate spectroscopy analysis for polymer identification.

A rule-based spectroscopy selection mechanism is also introduced to simulate real-world laboratory procedures. Particles with sizes larger than or equal to 10 µm are selected for micro-Fourier Transform Infrared (µFTIR) spectroscopy analysis, while particles smaller than 10 µm are selected for Raman spectroscopy analysis. This decision-making tool ensures that the simulation of laboratory procedures is realistic and does not require actual laboratory equipment.

C. Proxy-Based Spectral Dataset Mapping

As actual spectroscopy equipment is not used in this system, a proxy-based spectral mapping technique is used. The Raman and µFTIR spectra are chosen from verified public spectral databases according to the result of the spectroscopy selection mechanism. This method does not attempt to directly measure the spectra from the detected particles but instead uses a realistic simulation of spectral analysis with verified spectral datasets. The mapped spectra are one-dimensional wavenumber-intensity pairs, which are polymer-specific spectral fingerprints.

D. Spectral Preprocessing and Polymer Classification

The transformed spectra are then subjected to spectral preprocessing to eliminate noise, correct for baseline drift, and normalize intensity. Smoothing filters, baseline correction methods, and Z-score normalization are used for this purpose. The preprocessed spectra are then employed as input to a one-dimensional convolutional neural network (1D-CNN) for polymer classification. The CNN searches for common spectral peak patterns and magnitudes to classify the polymers into broad categories such as polyethylene (PE), polypropylene (PP), polyethylene terephthalate (PET), polystyrene (PS), and polyvinyl chloride (PVC). The classifier gives the type of polymer and the confidence level.

E. Pollution and Environmental Impact Analysis Module

To offer more environmental information than polymer classification, the proposed system incorporates a pollution impact analysis module. This module combines the results of polymer classification for various particles to identify the most prevalent types of polymers, levels of pollution (low, medium, or high), and approximate polymer longevity in water. This module helps to convert technical outputs into useful environmental information for researchers and policymakers.

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F. Integrated System Architecture

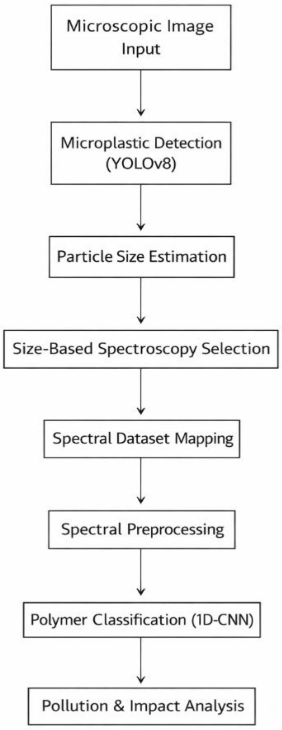

Figure 3.1. System Architecture

The system architecture of the proposed AI-powered microplastic analysis system is shown in Figure 3.1. The microscopic images are first analyzed using the detection module, followed by particle size estimation and spectroscopy selection. Proxy spectral mapping and preprocessing are then carried out, and finally, polymer classification is done using a deep learning model. The pollution analysis and reporting modules then provide interpretable outputs for environmental analysis.

The proposed system provides a completely automated, scalable, and lab-independent solution for microplastic analysis that integrates computer vision, spectral analysis, and environmental analysis into a single AI-powered solution.

IV. Methodology

The proposed AI solution for microplastic detection and polymer identification is an automated multi-step process that employs computer vision, spectral signal processing, deep learning-based polymer identification, and environmental pollution analysis to collectively resemble laboratory microplastic analysis processes in the real world with minimal human intervention.

A. Microscopic Image Acquisition and Preprocessing

The proposed system employs microscopic photos of water samples that may contain microplastic particles. The microscopic photos of water samples may contain noise, background particles, and other non-plastic particles such as dust and fibers. To ensure that the input for the detection model is uniform, the following preprocessing steps are carried out.

The input image is resized to a fixed ratio of pixels. Contrast enhancement and noise removal are carried out to emphasize microplastic particles. The preprocessed image I is given by:

$$I_{norm} = \frac{I - \mu}{\sigma}$$

where μ and σ are the mean and standard deviation of the pixel intensity.

B. Microplastic Particle Detection With YOLOv8

The normalized microscopic image was then fed into a YOLOv8 object detection model to detect microplastic particles. YOLOv8 is one of the latest object detection models that can in one pass predict the bounding boxes and the confidence scores that correspond to the detected particles.

For each detected particle i, the model estimates the bounding box coordinates:

$$B_i = (x_{1i}, y_{1i}, x_{2i}, y_{2i})$$

and confidence score:

$$C_i = P(\text{microplastic} | B_i)$$

Non-maximum suppression (NMS) is a technique that is applied to get rid of the overlapping bounding boxes and retain only the ones with the highest confidence.

C. Particle Size Evaluation

The size of the detected bounding box is then utilized to infer the particle size. The pixel width and height are computed as:

$$W_i = x_{2i} - x_{1i}, \quad H_i = y_{2i} - y_{1i}$$

Using the microscope calibration factor α (µm/pixel), the particle size is estimated as:

$$S_i = \alpha \cdot \sqrt{W_i^2 + H_i^2}$$

This step is critical because the size of the particles is required for polymer identification methods.

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D. Size-Based Spectroscopy Selection

A rule-based spectroscopy selection method is used to simulate real-world laboratory decision-making. For each particle:

$$\text{Technique}_i = \begin{cases} \mu\text{FTIR}, & S_i \geq 10\,\mu m \\ \text{Raman}, & S_i < 10\,\mu m \end{cases}$$

This automated selection helps to achieve realistic spectroscopy assignment without using physical instrumentation.

E. Proxy Spectral Dataset Mapping

As physical Raman or µFTIR instruments are not employed, proxy spectra are chosen from verified public spectral datasets. Each detected particle is mapped to a reference spectrum based on the chosen spectroscopy method.

The spectral signal is modeled as a one-dimensional vector:

$$X = [x_1, x_2, \ldots, x_n]$$

where x_k denotes spectral intensity at the k-th wavenumber.

This proxy-based mapping helps to facilitate research on polymer identification within software-only settings.

F. Spectral Preprocessing

Raw spectral signals are noisy and have a drifting baseline. Hence, preprocessing techniques are employed:

1. Noise removal via smoothing filters
2. Baseline removal
3. Z-score normalization

The normalized spectrum is calculated as:

$$X_{norm} = \frac{X - \mu_X}{\sigma_X}$$

where μ_x and σ_x denote the mean and standard deviation of spectral intensities.

G. Polymer Classification Using 1D CNN

The preprocessed spectral vector is used as input to a one-dimensional convolutional neural network (1D-CNN) for polymer classification. The convolution process for the l-th layer is expressed as:

$$h^{(l)} = \sigma(W^{(l)} * h^{(l-1)} + b^{(l)})$$

where * denotes convolution, $W^{(l)}$ and $b^{(l)}$ are trainable parameters, and σ is the activation function.

The final probability of polymer class k is calculated using the Softmax function:

$$P_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

The model is trained with the categorical cross-entropy loss function:

$$L = -\sum_{k=1}^{K} y_k \log(P_k)$$

where y_k is the ground truth label.

V. Result and Discussion

The proposed AI microplastic detection and polymer identification system was tested and demonstrated to be applicable for microplastic analysis in the environment. The system combines microscopic image analysis, object detection, size estimation, and polymer identification using proxy spectroscopy analysis. The proposed system was tested for usability, microplastic detection accuracy, and polymer identification accuracy using Raman and µFTIR proxy spectroscopy analysis.

A. System Dashboard and User Interface Analysis

The main interface of the proposed system is a web-based dashboard, as shown in Figure 5.1. The dashboard enables users to upload microscopic images of water samples, choose the spectroscopy analysis type (Raman or µFTIR), and start the prediction process automatically. The dashboard provides information on microplastic detection, polymer identification results, confidence levels, and particle size analysis.

The design of the dashboard is simple and ensures that it is user-friendly for non-technical users such as environmental scientists and laboratory technicians. The responsive design of the dashboard shows that the proposed system can be used as a real-time analysis system for microplastic detection.

Figure 5.1. Microplastics AI system dashboard interface for image upload and prediction.

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B. Microplastic Detection and Raman-Based Polymer Prediction

The results of the Raman spectroscopy-based microplastic detection and polymer prediction are shown in Figure 5.2. After uploading the microscopic image, the YOLOv8 model accurately detected multiple microplastic particles and marked them with distinct particle identifiers (MP1, MP2, ..., MPn). The bounding boxes represent the spatial locations of the detected microplastics. For particles with diameters below 10 µm, the system automatically chose Raman spectroscopy and assigned representative spectral information from verified datasets. The 1D-CNN polymer predictor correctly predicted the polymer type as polyethylene terephthalate (PET) with a confidence level of 0.84. The predicted particle size was about 5.18 µm, ensuring that Raman spectroscopy is applicable to small microplastics. The detection of 43 microplastic particles in the sample proves the effectiveness of the proposed system in dealing with densely distributed microplastics. The results show that the combination of object detection and spectral deep learning can achieve accurate polymer prediction without requiring human spectral data collection.

Figure 5.2. Raman-based microplastic detection and polymer prediction results with bounding boxes and particle labelling.

C. Microplastic Detection and µFTIR-Based Polymer Classification

The µFTIR spectroscopy-based results are presented in Figure 5.3. For particles with a size of 10 µm or larger, the system automatically chose µFTIR spectroscopy based on the proposed rule-based selection approach. The YOLOv8 model was able to detect 44 microplastic particles in the uploaded image, and the bounding boxes were created for each detected particle.

The proxy spectral mapping module provided the representative µFTIR spectra, and the 1D-CNN classifier classified the polymer type as polyvinyl chloride (PVC) with a confidence level of 0.85. The estimated particle size was 233.63 µm, which supports the selection of µFTIR for larger particles.

The results demonstrate that the system can dynamically select spectroscopy for particle analysis based on particle size and provide polymer classification results as per laboratory procedures.

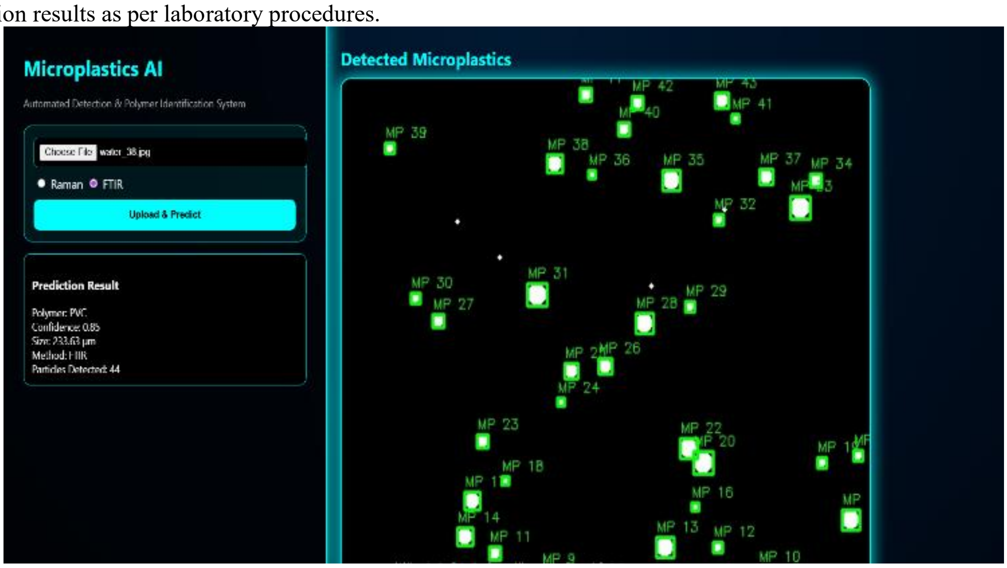

Figure 5.3. µFTIR-based microplastic detection and polymer prediction results with bounding boxes and particle labeling.

D. Discussion of System Performance and Practical Implications

Based on the experimental results, it is clear that the developed AI system is capable of performing automatic microplastic detection, size measurement, polymer identification, and environmental analysis. The YOLOv8 detection model is efficient in microplastic particle detection, even in complex microscopic images. The proxy spectral dataset approach is helpful in polymer identification without requiring costly laboratory facilities.

The use of 1D-CNN in spectral analysis assists the model in learning characteristic spectral features of polymers, thereby improving the classification accuracy. The confidence levels obtained for Raman and µFTIR classifications are indicative of precise polymer classification. In addition, the pollution analysis module helps in consolidating the detected polymer data to estimate the level of contamination and polymer persistence, thus offering significant environmental insights beyond simple classification results. The proposed system, which automates microplastic analysis, is more efficient and less dependent on human effort, time, and equipment compared to the traditional microplastic analysis process. The experimental results clearly show that AI-based microplastic monitoring systems can be used as efficient tools for environmental research and water quality assessment.

VI. Conclusion

This research work developed an automated pipeline powered by AI for microplastic detection, size estimation, polymer identification, and pollution impact analysis from microscopic images and spectral data. The system combines computer vision (detection based on YOLO), rule-based spectroscopy selection, spectral preprocessing, and a deep learning-based 1D CNN polymer classifier, allowing end-to-end automation with less human intervention. By utilizing proxy spectral datasets, the method mimics real laboratory workflows and eliminates the majority of the cost associated with instrumentation and manual analysis. The experiments illustrate that the suggested method is capable of determining microplastic particles, measuring their size, categorizing polymer types, and giving qualitative environmental pollution information; thus, it is very much fit for research and preliminary monitoring purposes.

Future directions will include the integration of real-time Raman and µFTIR instruments to overcome the need for proxy spectral mapping, thus increasing the applicability of the system. The addition of varied environmental samples and other classes of polymers to the dataset will improve the robustness of the model. More sophisticated models like the Transformer and CNN-LSTM models can be investigated for better learning of spectral features. In addition, the development of a cloud-based dashboard with GIS-based pollution mapping and the implementation of the system on edge devices for environmental monitoring will also increase the applicability of the system.

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