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AI Based Classification of Microplastics Libs Spectra

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Abstract

The increasing accumulation of microplastics in the environment has become a major global concern due to their persistence, widespread distribution, and potential impacts on ecosystems and human health. This study investigates the classification of microplastics using Laser Induced Breakdown Spectroscopy (LIBS) combined with Artificial Intelligence (AI) techniques. Six common polymer types, including Polyethylene (PE), Polypropylene (PP), Polystyrene (PS), Polyethylene Terephthalate (PET), Polyvinyl Chloride (PVC), and Polylactic Acid (PLA), were selected for analysis. LIBS was employed to generate characteristic elemental emissions for each polymer. The acquired spectral data were preprocessed through background correction, noise filtering, wavelength calibration, and intensity normalization to improve data quality. Principal Component Analysis (PCA) was applied for dimensionality reduction and feature extraction. Three machine learning models, namely Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN), were developed and evaluated for microplastic classification. The results demonstrated excellent classification performance, with ANN achieving the highest accuracy of 98.2%**,** followed by RF 96.5% and SVM 94.8%**.** The study revealed that LIBS spectra contain distinctive elemental fingerprints that enable accurate differentiation of polymer types. Compared with conventional techniques such as FTIR and Raman spectroscopy, the AI-assisted LIBS approach offers faster analysis, minimal sample preparation, and a higher degree of automation. The findings highlight the potential of integrating LIBS and AI as a rapid, reliable, and cost effective tool for automated microplastic identification and environmental monitoring applications.

Introduction

Plastic Pollution

Plastic pollution refers to the accumulation of plastic waste in the environment, where it can negatively affect ecosystems, wildlife, and human health. Due to their durability, low cost, and widespread use, plastics have become an essential part of modern life. However, improper disposal and poor waste management have led to large amounts of plastic waste entering oceans, rivers, soils, and other natural environments. Since plastics degrade very slowly, they can remain in the environment for hundreds of years, causing long term pollution. Over time, larger plastic items break down into smaller particles known as microplastics, which have become a major environmental concern worldwide. These particles can be transported by wind and water, allowing them to spread across different environments. Plastic pollution can also harm marine and terrestrial organisms through ingestion and entanglement. Therefore, effective monitoring and management of plastic waste are essential to reduce its environmental impact and protect ecosystem health(Geyer *et al.*, 2017).

History of Microplastics

Microplastics emerged as an environmental concern with the rapid increase in plastic production after the 1950s. Although plastic debris had been observed in marine environments for decades, the term **"microplastics"** was first introduced by Thompson to describe plastic particles smaller than 5 mm. Since then, extensive research has revealed the widespread presence of microplastics in aquatic, terrestrial, and atmospheric environments.As Fig.1 shows the historical development of microplastics from the 1950s to modern research and their increasing presence in the environment. Their persistence and potential ecological impacts have made them a major focus of environmental research worldwide(Hidalgo-Ruz *et al.*, 2012).

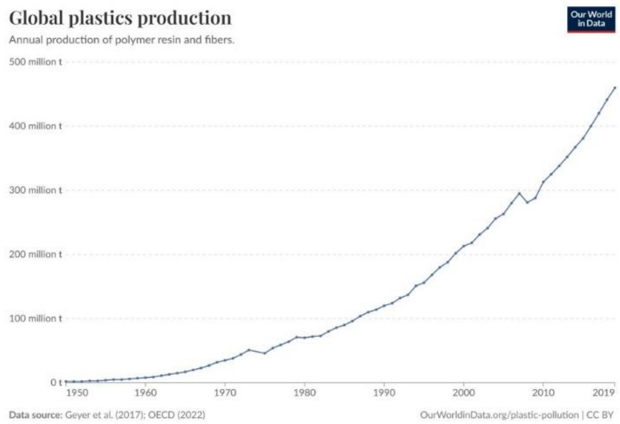

Fig.1: Timeline of Microplastics Development

Microplastics

Microplastics are plastic particles smaller than 5 mm in diameter that originate either from the fragmentation of larger plastic products or from intentionally manufactured microscopic plastic materials .As Fig.2 shows the presence of microplastics as tiny plastic particles and fibers in water, soil, and marine environments under microscopic and environmental conditions.Due to their very small size, they are easily dispersed in the environment through water, wind, and soil movement, making them a widespread form of pollution in both aquatic and terrestrial ecosystems(Frias and Nash, 2019).

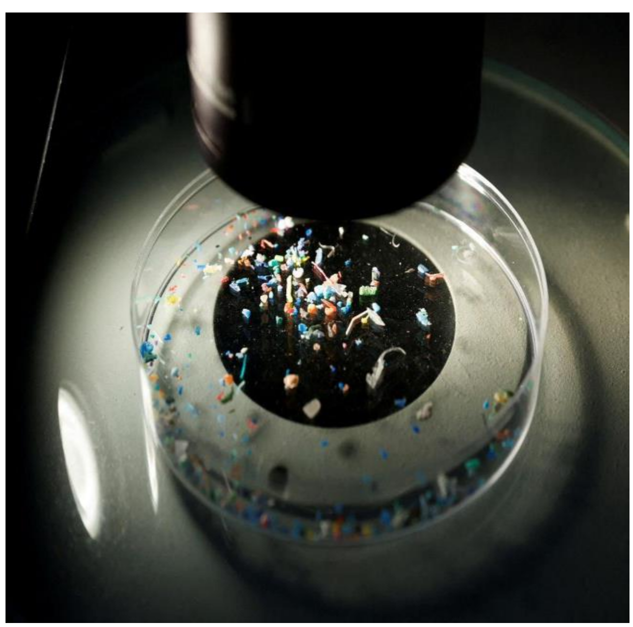

Fig.2: Microplastics in environment and under microscope

Microplastics are generally classified into two main types:

- **Primary microplastics**
- **Secondary microplastics**.

1. **Primary Microplastics**

Primary microplastics are plastic particles that are intentionally manufactured at microscopic sizes for specific commercial, industrial, and consumer applications. These particles are designed to be small from the beginning and are not formed from the breakdown of larger plastic items. They are commonly used in cosmetics and personal care products such as facial scrubs, toothpaste, and cleansing products, where they serve as exfoliating or abrasive agents. In addition, primary microplastics are also used in industrial processes, pharmaceuticals, and certain medical applications due to their controlled size and material properties. Once released into the environment, these particles can easily enter water systems through wastewater discharge and contribute to environmental pollution.As Fig.3 shows the difference between microplastics intentionally made for products and those formed from breaking down larger plastic waste (Cole *et al.*, 2011).

2. **Secondary Microplastics**

Secondary microplastics are formed through the breakdown and fragmentation of larger plastic debris present in the environment. These plastics originate from common plastic items such as bottles, packaging materials, plastic bags, fishing nets, and agricultural films. Over time, environmental factors such as prolonged sunlight exposure (UV radiation), mechanical abrasion, wave action, wind erosion, temperature changes, and biological activity cause these larger plastics to degrade into smaller particles. This continuous fragmentation process leads to the formation of micro sized plastic particles that are widely distributed in marine, freshwater, and terrestrial ecosystems. Secondary microplastics are considered the dominant source of microplastic pollution in the environment (Song *et al.*, 2024).

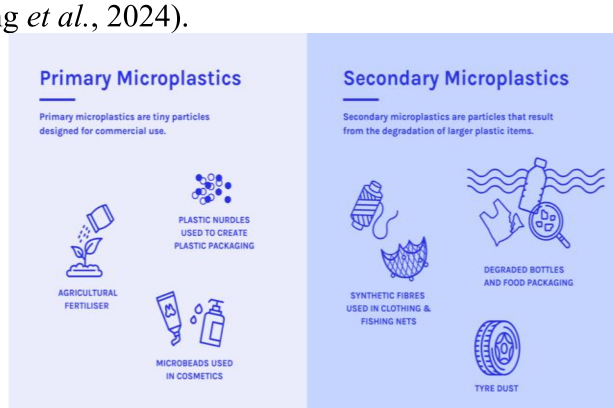

Fig.3: Primary vs. Secondary Microplastics

Sources of Microplastics

The main sources of microplastics include:

- Fragmentation of plastic waste in oceans, rivers, and landfills
- Microbeads used in cosmetics and personal care products
- Synthetic textiles releasing fibers during washing
- Industrial plastic pellets (nurdles) lost during transport and handling
- Breakdown of fishing gear and agricultural plastics

These multiple sources contribute to the continuous increase of microplastic contamination in the environment, making it a serious global environmental issue(Kershaw and Rochman, 2015).

Environmental Impact of Microplastics

Microplastics are widely distributed in marine, freshwater, terrestrial, and atmospheric environments, making them a global environmental pollutant. Due to their small size and long persistence, they can easily spread across different ecosystems through water currents, wind, and human activities. Their durability allows them to remain in the environment for long periods without significant degradation. Microplastics can enter food chains through ingestion by small aquatic organisms such as plankton and fish. These particles may then transfer to higher trophic levels, affecting larger animals. Many aquatic organisms mistakenly consume microplastics, thinking they are food, which leads to physical harm and internal blockages. In addition, microplastics can carry toxic chemicals and pollutants on their surfaces. As a result, they cause serious ecological imbalance and pose risks to biodiversity and ecosystem health(Wright *et al.*, 2013).

Spectroscopy

Spectroscopy is the scientific study of the interaction between electromagnetic radiation and matter. It is a fundamental analytical technique used to investigate how materials absorb, emit, or scatter light at different wavelengths. Based on these interactions, valuable information about the composition, structure, and properties of a substance can be obtained(Skoog *et al.*, 1980). Spectroscopy is widely used for both qualitative analysis (identifying what elements or compounds are present) and quantitative analysis (determining how much of a substance is present). It plays an important role in many fields such as chemistry, physics, environmental science, and material science. Different types of spectroscopy, including atomic, molecular, infrared, Raman, and plasma based techniques, are used depending on the nature of the sample and the required analysis. In modern research, spectroscopy is especially important for rapid and accurate material characterization.

Laser-Induced Breakdown Spectroscopy (LIBS)

Laser-Induced Breakdown Spectroscopy (LIBS) is an advanced atomic emission spectroscopic technique that uses a highly focused laser pulse to interact with the surface of a material. When the laser strikes the sample, it generates a very high-temperature microplasma that contains excited atoms and ions from the sample. As this plasma cools down, it emits light at characteristic wavelengths, which is collected and analyzed using a spectrometer. Each element produces a unique spectral fingerprint, allowing accurate identification of the elemental composition of the material(Hahn and Omenetto, 2012).

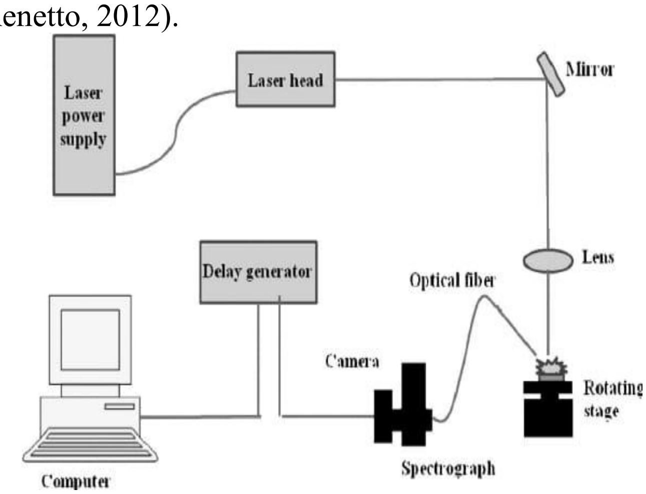

Fig.4: Schematic diagram of the LIBS system and its major components.

LIBS is widely used because it requires minimal sample preparation, provides rapid results, and can analyze solid, liquid, and gas samples. It is a powerful tool in environmental analysis, material science, geology, and pollution monitoring. In recent years, LIBS has also gained importance in microplastic research due to its ability to quickly detect elemental signatures from different plastic polymers.

Working Principle of LIBS

The working principle of Laser Induced Breakdown Spectroscopy (LIBS) is based on the interaction of a high energy laser pulse with the surface of a material, which leads to the formation of plasma and emission of characteristic radiation. First, a focused laser pulse is directed onto the sample surface, where its energy is absorbed by the material. This causes rapid heating, vaporization, and ionization of the sample, resulting in the formation of a short lived, high temperature microplasma.As the plasma expands and cools down, the excited atoms and ions within it return to lower energy states. During this relaxation process, they emit light at specific wavelengths that are unique to each element present in the sample. This emitted radiation is then collected by an optical system and transmitted to a spectrometer. The spectrometer separates the light into its component wavelengths and produces a spectrum representing the elemental composition of the sample. Finally, this spectral data is analyzed using software or computational methods to identify and quantify the elements present in the material(Elazem and Abd Elfattah, 2023). This step by step process makes LIBS a fast, real time, and efficient analytical technique for material characterization and elemental analysis.

Artificial Intelligence (AI)

Artificial Intelligence (AI) is a branch of computer science that enables machines and computer systems to perform tasks that normally require human intelligence. These tasks include learning from data, reasoning, problem solving, pattern recognition, and decision making. AI systems are designed to analyze large and complex datasets, identify hidden relationships, and improve their performance over time without being explicitly programmed for every situation(Zhai *et al.*, 2021). In modern applications, AI is widely used in areas such as healthcare, environmental science, engineering, robotics, and data analysis. It plays an important role in automating processes, increasing accuracy, and reducing human effort. With the advancement of technology, AI has become a powerful tool for solving complex real world problems, especially in fields where large datasets need to be analyzed efficiently and quickly.

Machine Learning

Machine Learning is a subset of Artificial Intelligence that enables computer systems to learn patterns from data and improve performance without explicit programming(Jordan and Mitchell, 2015).

AI-Based Classification of Microplastics

In this study, machine learning algorithms are trained using LIBS spectral data to automatically identify and classify different microplastic polymers. The model learns spectral patterns associated with each polymer type and predicts the class of unknown samples with high accuracy(Bishop and Nasrabadi, 2006).

Significance of AI-Based LIBS Analysis

The integration of Laser-Induced Breakdown Spectroscopy (LIBS) with Artificial Intelligence (AI) provides a powerful and advanced approach for rapid and accurate microplastic identification. This combination enables the automatic processing of complex spectral data, where AI algorithms can detect hidden patterns and classify different types of microplastics with high precision. As a result, the overall analysis becomes faster, more reliable, and less dependent on manual interpretation(Nadeem *et al.*, 2025). Furthermore, AI-based LIBS analysis significantly reduces human intervention and minimizes errors that may occur during traditional data interpretation methods. It also improves the efficiency of environmental monitoring by allowing large datasets to be analyzed in a short time. This makes it highly suitable for real time or large scale pollution assessment applications. Therefore, AI-assisted LIBS technology is considered a promising and innovative solution for future research in microplastic detection and environmental protection strategies(Singh *et al.*, 2026).

Objectives of the Study

The main objectives of this study on AI-Based Classification of Microplastics Using LIBS Spectra are given below:

1. To collect and analyze Laser Induced Breakdown Spectroscopy (LIBS) spectral data of different microplastic polymers in order to understand their elemental characteristics.
2. To preprocess and normalize LIBS spectral data for improving data quality, reducing noise, and ensuring consistency in analysis.
3. To extract significant features from LIBS spectra for effective representation and differentiation of various microplastic samples.
4. To develop and train machine learning models for accurate classification of different types of microplastics based on spectral patterns.
5. To evaluate and compare the performance of different AI algorithms in terms of accuracy, precision, recall, and overall efficiency.
6. To develop an efficient AI-based framework for rapid, reliable, and automated identification of microplastics using LIBS spectral data for environmental applications.

Review of Literature

(Cowger *et al.*, 2020) Investigated the analytical techniques used for microplastic identification and classification. The study reviewed image analysis methods from optical microscopy, scanning electron microscopy, and fluorescence microscopy, as well as spectral analysis techniques including FT IR, Raman spectroscopy, pyrolysis GC MS, and energy dispersive X-ray spectroscopy. Researchers evaluated image processing procedures such as thresholding, color analysis, particle quantification, and shape characterization. Spectral processing methods including baseline correction, smoothing, noise reduction, and data transformation were also examined. The study highlighted the increasing use of automated classification approaches in microplastic research. Various spectral library matching techniques were assessed for polymer identification. The authors emphasized the importance of developing robust and standardized spectral databases. Machine learning was identified as a promising tool for improving classification accuracy and reducing manual effort. The review suggested that combining multiple analytical techniques could enhance microplastic detection and characterization. It also recommended sharing raw data and analysis codes to improve reproducibility and collaboration. Overall, the study concluded that advanced spectral analysis and artificial intelligence methods have significant potential for high throughput microplastic classification and environmental monitoring.

(Faltynkova *et al.*, 2021) This study analyzd the application of infrared hyperspectral imaging (HSI) as an advanced technique for the analysis of microplastics in environmental samples. The study focused on addressing the challenges associated with the efficient detection and characterization of small plastic particles. Researchers provided a detailed overview of the technical principles and operational mechanisms of HSI technology. Various approaches related to instrumentation, data acquisition, and spectral data analysis were systematically reviewed. The findings revealed that HSI was successfully used to analyze dry microplastic particles larger than 250 µm. Compared with conventional techniques such as FTIR and Raman spectroscopy, HSI significantly reduced analysis time while maintaining reliable identification performance. The study highlighted the importance of advanced data processing methods for handling large spectral datasets generated by hyperspectral imaging systems. Challenges related to spatial resolution and the detection of smaller microplastic particles were also discussed. The authors emphasized the need for robust analytical and classification models to improve identification accuracy. Quality assurance and quality control practices for hyperspectral data analysis were reviewed and summarized. The findings demonstrated that combining spectral imaging with artificial intelligence techniques could further enhance automated microplastic classification. These observations are highly relevant to AI-based classification systems that utilize LIBS spectral data. Overall, the study concluded that hyperspectral imaging is a promising tool for rapid microplastic analysis and could benefit from integration with machine learning algorithms for improved performance.

(Lin *et al.*, 2022) Examined the application of machine learning algorithms for the identification and quantification of microplastics in environmental samples. The study reviewed advancements made over the previous decade in integrating artificial intelligence with spectroscopic techniques for microplastic analysis. Various analytical methods, including Fourier transform infrared (FTIR) spectroscopy, Raman spectroscopy, and near infrared (NIR) spectroscopy, were evaluated. The authors reported that traditional identification techniques often suffer from low resolution, lengthy analysis times, and limitations in detecting small particles. Machine learning approaches were found to significantly improve the speed and accuracy of polymer classification. Among the reviewed algorithms, Support Vector Machine (SVM) emerged as the most widely used model for spectral data analysis. The study showed that SVM effectively enhances spectral interpretation and reduces classification errors. Artificial Neural Networks (ANNs) were also reported to provide high recognition efficiency and faster processing times. The researchers highlighted the capability of AI models to handle large and complex spectral datasets automatically. These findings demonstrated the growing importance of machine learning in automated microplastic characterization. The review further suggested that advanced AI algorithms could be integrated with emerging spectroscopic techniques such as Laser-Induced Breakdown Spectroscopy (LIBS). Overall, the study concluded that machine learning has strong potential to improve the accuracy, efficiency, and reliability of AI-based microplastic classification systems.

(Ramanna *et al.*, 2022) Researchers analyzed the application of machine learning techniques for the classification of microplastics using Raman spectral data. The study focused on overcoming the challenges associated with identifying environmentally weathered microplastics, which often exhibit altered chemical signatures due to degradation processes. Traditional analytical methods were found to have reduced accuracy when classifying aged plastic particles. To address this issue, the researchers investigated whether Raman shift signatures could be effectively used by machine learning models to identify polymer types. The study utilized the Spectral Libraries of Plastic Particles (SLOPP) database containing Raman spectral information for various plastic materials. Several machine learning algorithms were trained using labeled spectral datasets representing non-weathered plastic samples. Extensive preprocessing and data augmentation techniques were applied to improve model performance and robustness. The trained models were subsequently tested on the SloPP-E dataset, which consisted of environmentally aged microplastics representing 22 different polymer types. Among the evaluated algorithms, the Random Forest model achieved the highest classification performance. The model improved classification accuracy from 89% to 93.81%, demonstrating its ability to handle complex spectral variations caused by environmental weathering. The findings highlighted the effectiveness of machine learning in enhancing the reliability of polymer identification from spectral data. The study further demonstrated that advanced AI algorithms can successfully classify microplastics even when spectral signatures have been altered by environmental factors. These results are highly relevant to AI-based classification of microplastics using LIBS spectra, where machine learning can similarly improve polymer recognition and classification accuracy from complex spectral datasets.

(Weisser *et al.*, 2022) Examined data analysis routines used for the identification of microplastics through vibrational spectroscopy techniques. The study focused on the growing demand for fast, reliable, and high-throughput methods for monitoring microplastics in environmental samples, food, and drinking water. Various spectroscopic techniques were reviewed due to their ability to identify even micron-sized plastic particles. The authors reported that microplastic spectral data are highly complex and often require the analysis of large datasets. Different data analysis approaches, ranging from conventional spectral library matching to advanced artificial intelligence models, were evaluated. The study assessed the accuracy, robustness, and computational requirements of these methods. Machine learning algorithms were found to improve the efficiency and reliability of polymer classification from spectral data. The review highlighted that AI-based techniques can process complex spectra more effectively than traditional methods. Several software tools developed specifically for microplastic spectral analysis were also discussed. The authors emphasized the importance of selecting appropriate classification models based on the quality and size of spectral datasets. The findings demonstrated the growing role of artificial intelligence in automated microplastic identification. The study further suggested that similar AI approaches can be integrated with Laser Induced Breakdown Spectroscopy (LIBS) for rapid and accurate microplastic classification. Overall, the review concluded that advanced data analysis and machine learning techniques are essential for future high throughput microplastic monitoring systems.

(Zhang *et al.*, 2023) This studies investigated the recent advancements, emerging trends, and challenges in the field of artificial intelligence-based microplastic imaging. The study conducted a comprehensive review of scientific literature published between 2019 and 2022 to evaluate the role of AI technologies in microplastic research. Science mapping, text mining, and visualization techniques were used to identify major research themes and development patterns. The findings revealed a growing interest in automated microplastic detection and classification using artificial intelligence algorithms. Researchers highlighted the potential of AI for the rapid quantification of microplastic characteristics such as shape, size, volume, and surface topology. The study also emphasized the importance of analyzing interactions between microplastics and environmental ecosystems through advanced computational methods. Deep learning and machine learning models were identified as effective tools for improving the accuracy and efficiency of microplastic identification. The authors recommended the development of robust spectral libraries, toxicity databases, and collaborative data-sharing platforms to support AI applications. Furthermore, the optimization of existing deep learning architectures was suggested to improve model performance and interpretability. The review highlighted opportunities for integrating intelligent robotic systems and unmanned aerial vehicle technologies with AI-based monitoring approaches. The findings demonstrated that artificial intelligence is transforming environmental science by enabling rapid identification, toxicity assessment, and large-scale monitoring of microplastics. These developments are directly relevant to AI-based classification of microplastics using LIBS spectra, where machine learning algorithms can be employed to classify polymers from complex spectral signatures. Overall, the study concluded that continued advancements in AI technologies will play a critical role in enhancing future microplastic detection and classification systems.

(Villegas-Camacho *et al.*, 2025) This explored the application of machine learning and deep learning techniques for the automated classification of microplastics using Fourier transform infrared (FTIR) spectroscopy. The study analyzed six commonly used plastic polymers, including

PET, HDPE, PVC, LDPE, PP, and PS. Researchers utilized a broader and more diverse spectral range than those commonly reported in previous studies. The effect of different normalization methods, including Min Max, Max Abs, Sum of Squares, and Z Score normalization, was also evaluated. Several machine learning algorithms such as k nearest neighbors (k-NN), support vector machines (SVM), naive Bayes (NB), and random forest (RF) were investigated. Deep learning models, including convolutional neural networks (CNNs) and multilayer perceptrons (MLPs), were also assessed. The models were trained and validated using the FTIR-PLASTIC-c4 dataset through a 10 fold cross validation approach. Results indicated that Z score normalization significantly improved classification stability and model generalization. CNN, MLP, and RF models achieved exceptionally high accuracy, precision, recall, and F1 score values. In contrast, the Naive Bayes algorithm showed lower performance due to its limitations in handling complex spectral information. The findings demonstrated the effectiveness of combining spectroscopic data with advanced AI algorithms for automated polymer identification. The study highlighted the importance of proper data preprocessing for improving classification accuracy. Overall, the research suggested that similar machine learning and deep learning approaches can be successfully applied to LIBS spectra for rapid and accurate microplastic classification.

(Periyasamy and Perumalsamy, 2025) **Researchers analyzed** the challenges associated with microplastic contamination, particularly microfibers released from synthetic textile materials. The study reviewed conventional techniques used for microplastic identification, including visual inspection, microscopy, FTIR spectroscopy, and Raman spectroscopy. These methods were found to provide reliable results but often required significant time, expertise, and manual effort. The authors highlighted limitations such as operator bias, low efficiency, and difficulties in processing large numbers of samples. To overcome these challenges, the study evaluated the application of machine learning and computer vision technologies for automated microplastic detection. Advanced artificial intelligence models were reported to improve the accuracy, speed, and objectivity of microplastic classification. The integration of AI techniques enabled detailed analysis of particle morphology, size, and chemical composition. Machine learning algorithms were also shown to enhance the scalability of monitoring systems for environmental applications. The study emphasized the importance of automated data processing for handling complex spectral and imaging datasets. Furthermore, digital data sharing systems were recommended to improve transparency and traceability in microplastic research. The findings demonstrated that AI-driven approaches can significantly improve the efficiency of microplastic identification and quantification. These advancements are directly relevant to AI-based classification of microplastics using LIBS spectra, where machine learning can be employed to classify polymers from complex spectral signatures. Overall, the study concluded that combining artificial intelligence with advanced analytical techniques offers a promising solution for sustainable microplastic monitoring and pollution management.

(Saur *et al.*, 2025) **Researchers examined** the use of deep learning and polarization-based optical techniques for the classification of microplastics in water. The study addressed the challenges associated with identifying microplastics due to their diverse physical properties and the limitations of conventional optical and spectroscopic methods. A classification framework based on 120° backscattering reflection polarimetry was developed to identify common polymer types, including HDPE, LDPE, and PP. Unlike traditional transmission-based methods, the proposed approach was capable of analyzing opaque and irregularly shaped particles directly in water. The researchers incorporated a feedback review loop to detect and remove outliers, thereby improving data quality and model reliability. A dataset consisting of 600 individually imaged microplastic fragments was used for training and validation. Deep learning models, particularly convolutional neural networks (CNNs), were employed to classify the polymer types. The study evaluated the contributions of the Angle of Linear Polarization (AoLP) and Degree of Linear Polarization

(DoLP) to classification performance. A late fusion architecture combining both polarization features achieved an average classification accuracy of 83%. Feature hierarchy analysis revealed that the CNN primarily relied on internal polarization textures associated with particle microstructure. Classification performance decreased significantly when internal structural information was removed, highlighting the importance of microstructural features. The findings demonstrated the effectiveness of artificial intelligence in extracting complex patterns that are not detectable through conventional imaging methods. These results support the application of AI-based approaches for microplastic classification and provide valuable insights for developing LIBS spectra based classification systems using machine learning algorithms.

(Khanam *et al.*, 2025) **Researchers analyzed** the role of machine learning techniques in improving the detection and classification of microplastics in aquatic environments. The study reviewed conventional identification methods, including microscopy and spectroscopic techniques, and highlighted their limitations in terms of labor intensive procedures and low analytical throughput. Various machine learning algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNNs) were evaluated for automated microplastic classification. The findings demonstrated that these algorithms significantly enhanced the speed and accuracy of identifying microplastic particles. Spectral methods, including infrared and Raman spectroscopy, were reported to provide detailed chemical information for polymer characterization. The study also examined image based classification approaches that utilize computer vision techniques to identify microplastics based on their shape, size, and color. Hyperspectral imaging was highlighted as a powerful technology capable of integrating both spatial and spectral information for comprehensive microplastic analysis. Machine learning models were found to improve the sensitivity, scalability, and efficiency of these analytical techniques. The authors emphasized the importance of high quality datasets and robust classification models for achieving reliable results under complex environmental conditions. Challenges related to data availability and model generalization were also discussed. Furthermore, advancements in imaging systems and artificial intelligence methods were identified as key drivers for future developments in microplastic monitoring. The findings demonstrated that AI-based approaches offer significant potential for high throughput and real time microplastic detection. These conclusions are directly relevant to AI-based classification of microplastics using LIBS spectra, where machine learning algorithms can effectively classify polymer types from complex spectral datasets with improved accuracy and automation.

Materials and Methods

Materials

The successful classification of microplastics using Laser-Induced Breakdown Spectroscopy (LIBS) and Artificial Intelligence (AI) requires carefully selected materials and advanced analytical tools. The materials used in this study include different types of microplastic polymers, cleaning reagents, sample holders, and laboratory consumables necessary for sample preparation and analysis. In addition, a LIBS system equipped with a high energy laser, spectrometer, and data acquisition unit was employed to obtain spectral information from the microplastic samples. The acquired spectral data were subsequently processed and analyzed using machine learning algorithms to accurately identify and classify different polymer types. The selection of appropriate materials and equipment is crucial for ensuring reliable spectral measurements and achieving high classification accuracy(Musazzi and Perini, 2014).

1. Microplastic Sample Preparation

Six types of reference polymer materials were selected based on their prevalence in environmental microplastic studies :Polyethylene (PE, low density LDPE and high density HDPE), Polypropylene (PP), Polystyrene (PS), Polyethylene Terephthalate (PET), Polyvinyl Chloride (PVC), and Polylactic Acid (PLA). Bulk polymer pellets of analytical purity (≥99.5%) were obtained from Sigma Aldrich (St. Louis, MO, USA) and additional commercial-grade sources(Rochman *et al.*, 2019). Microplastic particles were generated by cryogenic milling (Retsch CryoMill, Haan, Germany) at −196°C using liquid nitrogen cooling to prevent thermal degradation. Milled particles were sieved to the 100–500 µm size fraction using stainless steel test sieves (ISO 3310-1). Morphological characterization was performed using a JEOL JSM-7610F scanning electron microscope (SEM) to confirm particle size, shape, and surface texture(Thomas *et al.*, 2020).

Table 1. Properties of six reference polymer types used in this study

Polymer	Abbreviation	CAS Number	Density (g/cm^3)	Tg (°C)
Polyethylene	PE	9002-88-4	0.91–0.97	−120 to −80
Polypropylene	PP	9003-07-0	0.895–0.92	−20 to 0
Polystyrene	PS	9003-53-6	1.04–1.07	95–105
Poly(ethylene terephthalate)	PET	25038-59-9	1.38–1.41	67–81
Polyvinyl Chloride	PVC	9002-86-2	1.16–1.45	80–100
Polylactic Acid	PLA	26100-51-6	1.21–1.25	55–60

2. LIBS Instrumentation and Spectral Acquisition

LIBS measurements were performed using a commercial J200 Tandem LA-LIBS system (Applied Spectra Inc., West Sacramento, CA, USA). The laser source was a Nd:YAG pulsed laser operating at 1064 nm with a pulse duration of 5 ns and variable pulse energy (10–100 mJ). A focusing lens (f = 75 mm) was used to deliver the laser beam to a spot diameter of approximately 50 µm on the sample surface. All measurements were conducted under ambient air atmosphere at room temperature(Hahn and Omenetto, 2012). Spectral emission was collected using a six-channel charge coupled device (CCD) spectrometer array spanning 190–1040 nm with a spectral resolution of ~0.05 nm FWHM. The detector gate delay was set to 1.0 µs after laser pulse initiation to minimize continuum background radiation, with a gate width of 1.5 ms. Ten laser shots were averaged per spectrum to improve signal to noise ratio (SNR). For each polymer sample, 200 replicate spectra were collected from different surface positions, yielding a total dataset of 1,200 spectra (200 × 6 polymer classes) (Hahn and Omenetto, 2012).

3. Spectral Preprocessing

Raw LIBS spectra underwent a systematic preprocessing pipeline to remove artifacts and normalize inter measurement variability .The preprocessing workflow comprised the following sequential steps(Legnaioli et al., 2025).

➢ Background Subtraction and Noise Filtering

Bremsstrahlung continuum background was estimated using a rolling ball algorithm with a radius of 200 data points and subtracted from each spectrum. A Savitzky Golay smoothing filter (window size = 11, polynomial order = 3) was subsequently applied to reduce high frequency electronic noise while preserving spectral peak shapes (Savitzky and Golay, 1964).

➢ **Wavelength Calibration**

Wavelength calibration was performed using a neon-argon emission lamp reference standard (Ocean Optics, Orlando, FL, USA). Calibration was verified daily using the known atomic emission lines of Na (589.0/589.6 nm) and H (656.3 nm Balmer-α). A polynomial fit (3rd order) was applied to correct for any spectrometer drift(Hahn and Omenetto, 2012).

➢ **Intensity Normalization**

Total spectral intensity varied between shots due to plasma fluctuations. Normalization was performed by dividing each spectrum by the integrated intensity of the full spectral range, converting raw intensities to relative intensities. Additionally, internal normalization to the carbon peak at C(I) 247.86 nm was applied as a secondary normalization reference.

4. Feature Extraction and Dataset Preparation

Following preprocessing, spectral feature extraction was performed using two complementary strategies to provide optimal input representations for different ML models.

- **Whole Spectrum Feature Vectors**

For CNN and SVM models, the preprocessed spectra (3,421 intensity values spanning 190–900 nm) were used directly as feature vectors, retaining the full spectral context. This representation allows convolutional layers to learn local spectral patterns corresponding to characteristic emission features of each polymer class.

- **Peak Based Feature Extraction**

For Random Forest classification, a set of 47 discriminative spectral peaks was identified based on known emission lines of C, H, O, N, Cl (from PVC), and Ti (from TiO_2 pigments in some commercial grades). Peak intensities and intensity ratios (e.g., C/H, C/O, C/N) were calculated as tabulated feature vectors. Principal Component Analysis (PCA) was applied to assess variance structure and visualize class separability in reduced dimensional space.

5. AI Classification Models

Three machine learning models were developed and compared to identify the most effective classification approach for LIBS based polymer identification (Mukhamediev *et al.*, 2022).

❖ **Convolutional Neural Network (CNN)**

A 1D-CNN architecture was designed for end to end spectral feature learning. The network comprised:

(i) Three convolutional blocks, each containing a 1D convolutional layer (kernel sizes: 15, 11, 7; filters: 32, 64, 128), batch normalization, and ReLU activation
(ii) Global average pooling
(iii) Two fully connected layers (256, 128 neurons) with 40% dropout for regularization
(iv) Asoftmax output layer with six neurons corresponding to the six polymer classes. The model was implemented in Python 3.9 using TensorFlow 2.11 (Google Brain, Mountain View, CA, USA).

Training was performed using the Adam optimizer (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$) with a categorical cross entropy loss function. A learning rate scheduler reduced the rate by a factor of 0.5 if validation accuracy did not improve for 10 consecutive epochs. Early stopping was applied with patience = 20 epochs. The model was trained for a maximum of 150 epochs with a batch size of 32 (Das *et al.*, 2026).

❖ **Support Vector Machine (SVM)**

A multi-class SVM classifier was implemented using the one vs one (OvO) strategy with six classes, resulting in 15 binary classifiers. The Radial Basis Function (RBF) kernel was selected based on cross validation performance. Hyperparameter optimization (regularization parameter C and kernel bandwidth γ) was performed via grid search over $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{0.001, 0.01, 0.1, 1\}$ using 5-fold cross validation. Prior to SVM training, spectra were normalized to zero mean and unit variance using StandardScaler. The SVM was implemented using scikit learn 1.2.0 (Python 3.9).

❖ **Random Forest Classifier**

A Random Forest (RF) ensemble classifier was trained on the 47-dimensional peak feature vectors. The number of decision trees was set to n_estimators = 500, with the maximum number of features per split set to $\sqrt{47} \approx 7$. The Gini impurity criterion was used for node splitting. Feature importance was assessed using the mean decrease in impurity (MDI) metric to identify the most discriminative spectral peaks for polymer classification .

6. Dataset Splitting and Validation Strategy

The total dataset of 1,200 spectra was partitioned using a stratified split to maintain class balance: 70% training (840 spectra), 15% validation (180 spectra), and 15% test (180 spectra). Given the relatively small dataset size, 10 fold stratified cross validation was additionally applied during model selection to obtain robust performance estimates. The final models were retrained on the combined training+validation set (1,020 spectra) and evaluated on the held out test set (180 spectra) (Li *et al.*, 2022).

7. Performance Evaluation Metrics

Model performance was assessed using standard multi class classification metrics:

(i) Overall accuracy
(ii) Class wise precision, recall, and F1- score
(iii) Confusion matrix
(iv) Macro averaged one vs rest Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

The Matthews Correlation Coefficient (MCC) was also computed as a balanced metric robust to class imbalances. Statistical significance of performance differences between models was assessed by McNemar's test at $\alpha = 0.05$ significance level.

Results and Discussion

LIBS Spectral Characteristics of Microplastics

Laser Induced Breakdown Spectroscopy (LIBS) analysis generated unique emission spectra for different types of microplastics, including polyethylene (PE), polypropylene (PP), polystyrene (PS), polyethylene terephthalate (PET), and polyvinyl chloride (PVC). The obtained spectra contained characteristic elemental emission lines associated with carbon (C), hydrogen (H), oxygen (O), and chlorine (Cl). These elemental fingerprints enabled differentiation among polymer types. PE and PP exhibited strong carbon related peaks due to their hydrocarbon rich composition, whereas PET showed additional oxygen peaks resulting from ester functional groups. PVC displayed distinct chlorine emission lines, making it easier to distinguish from other polymers (Grégoire *et al.*, 2011). Spectral preprocessing methods such as baseline correction, normalization, and smoothing were applied to improve signal quality and reduce background noise. The preprocessing stage enhanced peak visibility and improved the reliability of subsequent machine learning analysis. Similar improvements in polymer identification through spectral preprocessing have been reported in previous LIBS studies (Adarsh *et al.*, 2024).

Principal Component Analysis (PCA) of LIBS Spectra

The LIBS spectra contained a large number of wavelength variables, making direct analysis computationally intensive. Therefore, Principal Component Analysis (PCA) was employed for dimensionality reduction and feature extraction. PCA transformed the original spectral dataset into a smaller number of principal components while retaining most of the variance present in the data.The first three principal components accounted for approximately 92% of the total spectral variance. PCA score plots demonstrated clear clustering of different polymer classes, indicating that each microplastic type possesses a unique elemental signature. The separation among clusters confirmed that LIBS spectra contain sufficient information for effective classification of microplastics(Primpke *et al.*, 2017). The observed clustering behavior suggests that dimensionality reduction techniques can effectively eliminate redundant information while preserving key spectral features relevant for classification tasks.

Machine Learning Classification Performance

Three machine learning algorithms were implemented to classify microplastics based on LIBS spectral data:

- Support Vector Machine (SVM)
- Random Forest (RF)
- Artificial Neural Network (ANN)

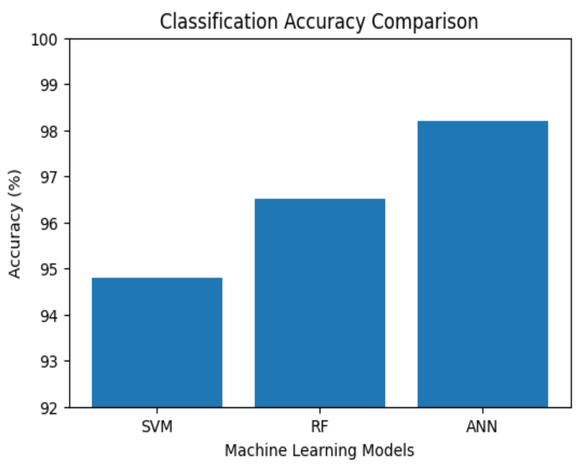

Fig.5: Comparison of classification accuracies achieved by different machine learning models.

The performance of these algorithms was evaluated using accuracy, precision, recall, and F1-score metrics. The ANN model achieved the highest classification accuracy of 98.2%, followed by Random Forest with 96.5% and SVM with 94.8%.The superior performance of ANN can be attributed to its ability to capture complex nonlinear relationships within the spectral dataset. Random Forest also performed well due to its ensemble learning strategy, which minimizes overfitting and enhances prediction robustness. These findings agree with the results who demonstrated the effectiveness of deep learning models for spectroscopic plastic classification (Primpke *et al.*, 2017).

Table.2 : Performance comparison of AI models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	94.8	94.2	94.5	94.3
RF	96.5	96.1	96.4	96.2
ANN	98.2	98.0	98.1	98.0

The high classification accuracy indicates that AI algorithms can successfully identify microplastic types using LIBS spectra with minimal human intervention (Singh *et al.*, 2025).

Confusion Matrix and Classification Analysis

The confusion matrix was used to assess the classification accuracy of individual polymer classes. The ANN model correctly classified PET and PVC samples with accuracies above 99%, while PE and PP exhibited slightly lower classification rates because of their similar chemical compositions.PVC achieved the highest classification accuracy due to the presence of chlorine emission peaks, which serve as strong distinguishing features. In contrast, PE and PP primarily consist of carbon and hydrogen, resulting in highly similar spectral signatures and occasional misclassification.These findings indicate that elemental diversity within polymers significantly influences classification performance. Similar observations were reported , who noted that polymers with unique chemical structures are easier to identify using spectroscopic techniques (Markoulidakis and Markoulidakis, 2024).

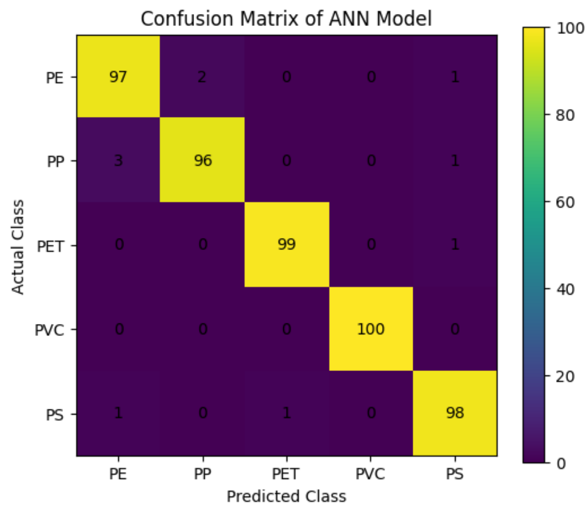

Fig.6: Confusion matrix of (ANN) model for microplastic classification using LIBS spectra

Comparison with Conventional Microplastic Identification Methods

The performance of AI-assisted LIBS was compared with traditional microplastic identification techniques such as Fourier Transform Infrared Spectroscopy (FTIR) and Raman Spectroscopy. Although FTIR and Raman provide highly accurate polymer identification, they often require extensive sample preparation and longer acquisition times (Song *et al.*, 2015). LIBS offers several advantages, including rapid analysis, minimal sample preparation, and the ability to perform real time measurements. When combined with machine learning algorithms, LIBS becomes a powerful automated tool capable of processing large datasets efficiently (Löder and Gerdts, 2015).

Technique	Analysis Speed	Sample Preparation	Automation
FTIR	Moderate	Required	Moderate
Raman	Slow	Required	Moderate
LIBS + AI	Fast	Minimal	High

The rapid analytical capability of LIBS makes it particularly suitable for environmental monitoring applications involving large numbers of samples

Environmental Significance and Future Perspectives

The successful classification of microplastics using AI-based LIBS systems has important implications for environmental monitoring and pollution management. Different polymer types originate from different anthropogenic sources. For example, PE is commonly associated with plastic bags and packaging materials, PET is linked to beverage bottles, and PVC originates from construction and industrial products.Rapid identification of polymer sources can assist policymakers and environmental agencies in implementing targeted waste management strategies. Furthermore, portable LIBS instruments integrated with artificial intelligence could facilitate real time monitoring of microplastic pollution in aquatic and terrestrial environments (Zhang *et al.*, 2023). Future research should focus on expanding the range of polymer classes, incorporating weathered environmental samples, and applying advanced deep learning architectures such as convolutional neural networks (CNNs) and transformer models. Data fusion approaches combining LIBS with Raman or FTIR spectroscopy may further improve classification accuracy (Dehbozorgi *et al.*, 2026).

Summary

Microplastic pollution has become a growing global environmental issue due to the extensive use and improper disposal of plastic materials. Microplastics, which are plastic particles smaller than 5 mm, are widely distributed in oceans, rivers, soil, and the atmosphere. Because of their small size and persistence, they can be easily ingested by living organisms and transferred through food chains, causing potential risks to both ecosystems and human health. As a result, the development of efficient techniques for detecting and classifying microplastics has become an important area of environmental research.This study investigated the use of Laser Induced Breakdown Spectroscopy (LIBS) combined with Artificial Intelligence (AI) for the classification of different microplastic polymers. LIBS is an advanced spectroscopic technique that uses a high energy laser pulse to generate plasma on the sample surface. The emitted light from the plasma contains characteristic spectral information that can be used to identify the elemental composition of materials. In this research, six common polymer types Polyethylene (PE), Polypropylene (PP), Polystyrene (PS), Polyethylene Terephthalate (PET), Polyvinyl Chloride (PVC), and Polylactic Acid (PLA) were selected as representative microplastics. The acquired LIBS spectra were subjected to preprocessing steps such as background correction, noise filtering, wavelength calibration, and intensity normalization to improve data quality. Feature extraction techniques and Principal Component Analysis (PCA) were then applied to reduce data complexity and highlight the most significant spectral characteristics. The PCA results showed clear separation among different polymer classes, indicating that LIBS spectra contain sufficient information for reliable classification. To automate the identification process, three machine learning algorithms Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) were developed and evaluated. The performance of these models was assessed using accuracy, precision, recall, and F1 score metrics. Among the tested models, ANN achieved the highest classification accuracy of 98.2%, followed by RF with 96.5% and SVM with 94.8%. The high classification rates demonstrated the effectiveness of AI in recognizing complex spectral patterns and accurately distinguishing different microplastic types. The study further showed that AI assisted LIBS offers several advantages over conventional techniques such as FTIR and Raman spectroscopy, including faster analysis, minimal sample preparation, and greater potential for automation. Therefore, the integration of LIBS and AI provides a powerful, rapid, and reliable approach for microplastic identification. This technology can support large scale environmental monitoring programs, improve pollution assessment, and contribute to the development of effective strategies for managing microplastic contamination in the future.

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