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AI Based Classification of Microplastics LIBS Spectra

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Abstract
The growing volume of microplastics in the environment is an enormous problem worldwide because of their durability, ubiquity and potential environmental and health effects they may generate. This research aims at the characterisation of microplastics by Laser Induced Breakdown Spectroscopy (LIBS) together with Artificial Intelligence (AI) tools. Here, six types of polymers were chosen for analysis, such as Polyethylene (PE), Polypropylene (PP), Polystyrene (PS), Polyethylene Terephthalate (PET), Polyvinyl Chloride (PVC) and Polylactic Acid (PLA). Using LIBS, characteristic elemental emission spectra for each polymer were created. Acquired spectral data was preprocessed to enhance quality of data by background correction, noise filtering, wavelength calibration and intensity normalization. The technique of Principal Component Analysis (PCA) was used for dimensionality reduction/feature extraction. The three models including Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) were constructed and tested for the classification of microplastic. The results showed that the classification performance was excellent with the highest accuracy was obtained using ANN (98.2%), followed by RF (96.5%) and SVM (94.8%). The study found that LIBS spectra are characterized by differential fingerprint-like spectra of elements which allows the correct identification of different types of polymers. Compared to the traditional methods like FTIR and Raman spectroscopy, AI-assisted LIBS provides a fast analysis time, little to no sample preparation, and increased automation. The results demonstrate the potential of combining LIBS with AI to provide a fast, accurate and low-cost method for the automated identification of microplastics and environmental monitoring applications.

Introduction
Plastic Pollution
Plastic pollution is the buildup of plastic debris, which can have detrimental consequences on the environment, wildlife, and even human health. Thanks to their durability, low cost, and ubiquity, plastics have been integral to modern life. But plastic wastes are mishandled and accumulated by unsound waste management practices in the oceans, rivers, soil and other natural spaces. This degradation can take up to hundreds of years, which means that plastics can pollute the environment for a long period. As time goes by, these bigger pieces of plastic are eventually reduced to smaller ones, which are referred to as microplastics and that are a worldwide issue of concern in terms of the environment. These particles can be blown by wind and washed by water and thus spread over various environments. Also, the impacts of plastic contamination on marine and terrestrial organisms, notably by ingestion and entanglement. Good monitoring and

management of plastic waste are therefore crucial to minimize plastic impact on the environment, and safeguard the health of ecosystem (Geyer et al., 2017).

History of Microplastics:

Microplastics became an environmental issue in the wake of the boom of plastic production as of the 1950s. While it has been decades since plastic wastes were found in marine system, Thompson used the term microplastic to identify plastic that was less than 5 mm. Since then, a vast amount of research has been conducted and it has come out that the microplastic is present everywhere in aquatic, terrestrial and atmospheric environment.The historical evolution of micro plastics from the 1950s up to the current research and their rising occurrence in the environment is shown in Fig.1. Because of their persistence and the potential ecological impacts have made them a subject of intense environmental research all over the world (Hidalgo-Ruz et al., 2012).

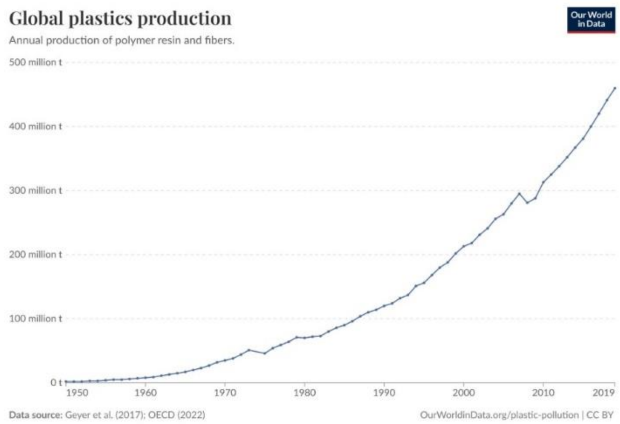

Fig.1: Timeline of Microplastics Development

Microplastics

Microplastics are plastics that are < 5 mm in diameter, such as those that are intentionally manufactured or are a result of the breaking down of larger plastic items.Fig.2 depicts the presence of microplastics in the form of small plastic particles and fibres under microscope and environmental conditions in water, soil and marine ecosystems.Their highly mobile nature due to being very small allows them to travel long distances in water, wind, and soil movement and they are a type of pollution in aquatic and terrestrial ecosystems.

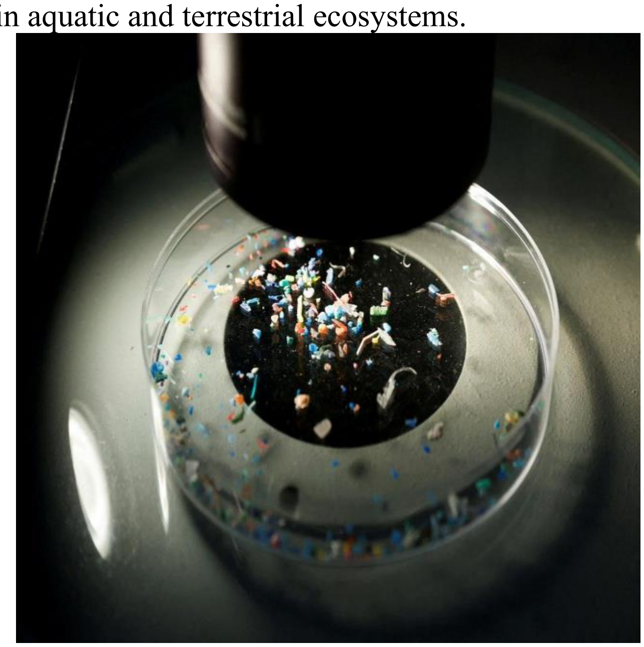

Fig.2: Microplastics in environment and under microscope

Microplastics are generally classified into two main types:

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

1. **Primary Microplastics**

Primary microplastics are plastic particles intentionally produced at the micro level for certain commercial, industrial or consumer uses. These particles are made to be small from the very start—they do not come from the break down of larger plastics. They are frequently added to cosmetics and personal care items, like facial scrubs, toothpaste and cleansing products, as exfoliating or abrasive agents. Additionally, because of their inherent properties and controlled sizes, primary microplastics are used in certain industrial processes, pharmaceuticals and medical applications. After each discharge into the environment, these particles can readily enter in the water system through wastewater discharge and then result an environment pollute.As presented by Fig.3, the difference between the intentional production of micro-plastics for product purposes, and the fragments of larger plastic wastes, which are broken down into micro-plastics (Cole et al., 2011).

Secondary Microplastics:

Secondary microplastics are generated by degradation and fragmentation of the bigger plastic pieces found in the environment. These plastics are derived from various plastics commonly in use including plastic bottles, plastic packaging materials, plastic bags, fishing nets and agricultural films. These larger pieces of plastic break down over time, in the environment, brought about by UV radiation (long-term exposure to sunlight), mechanical abrasion (from weather) and wave action (from the ocean), wind erosion, and even biological organisms. The fragmentation continues, until micro sized plastic particles are formed, which are ubiquitous in marine, freshwater and terrestrial ecosystems. The main source of microplastics in the environment is believed to be secondary microplastic pollution (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

The wide distribution of micro plastics in the marine, fresh water, terrestrial and atmosphere makes it as a global pollutant. They are short-lived and are able to travel long distances between ecosystems, easily dispersed by water currents, wind and humans. They are durable enough to not be degraded significantly over extended presence in the environment. This is because the ingestion of microplastics can enter the food chain via small aquatic organisms like plankton and fish. These particles can then be transferred to higher levels on the trophic level, having an impact on larger animals. Micro plastics are ingested by many aquatic organisms and become a physical hazard to the organism, blocking internal passages. Moreover, microplastics can also be contaminated with toxic chemicals and pollutants on their surface. This results in ecological imbalance which is a threat to biodiversity and ecosystem health and wellbeing (Wright et al., 2013).

Spectroscopy:

Spectroscopy is the science of the interaction of electromagnetic radiation and material. It is a basic tool of analysis that is employed to study the uptake, emission or diffusion of light of different wavelengths by materials. Consideration of these interactions yields useful information on the composition, structure and properties of a substance (Skoog et al., 1980). Spectroscopy is variously employed both for qualitative analysis (what elements or compounds are present) and quantitative analysis (how much of a substance is present). It is significant to numerous areas of science including chemistry, physics, environmental sciences and material sciences. Depending on the nature of the sample to be analyzed, different types of spectroscopy, such as atomic, molecular, infrared, Raman and plasma based spectra are implemented. Spectroscopy is particularly significant for the characterization of materials and is widely used in modern research for fast and accurate characterization.

Laser induced breakdown Spectroscopy (LIBS):

Laser Induced Breakdown Spectroscopy (LIBS) is an advanced technique of atomic emission spectroscopy, which employs a laser pulse with extreme focusing effect on the surface of the material. This very high temperature microplasma will have excited atoms and ions from the sample. This plasma cools off and emits light at specific wavelengths, that are captured and measured by a spectrometer. The spectral fingerprint of each element is distinctly different, and thus, the elemental composition of the material can be determined very well (Hahn and Omenetto, 2012).

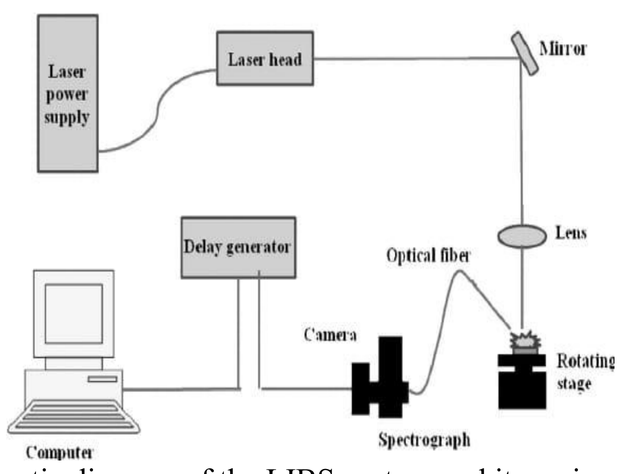

Fig.4: Schematic diagram of the LIBS system and its major components.

The main reasons for the popularity ofLIBS are that it does not need extensive sample preparation, it offers fast results and that solid, liquid and gaseous material can be analyzed. This tool is strong in environmental analysis, material science, geology and the monitoring of pollution. In recent years, LIBS has also been receiving significance for the fast characterization of elemental signature signatures of different plastic polymers for micro-plastic research.

Working Principle of LIBS:

Under the action of a high energy pulse laser, LIBS is a technique based on the interaction between the laser and the surface of the material to produce plasma and emit the characteristic radiation. First, the sample surface is illuminated by a laser pulse of light and the energy of the light is absorbed by the sample. This results in the rapid heating, vaporisation and ionization of the sample leading to the formation of a short-lived, high temperature microplasma.The excited atoms and ions in the plasma tend to settle down into lower energy states as the plasma expands and cools. In this process of relaxation, they produce light that has certain wavelengths which are characteristic of each of the elements present in the sample. This resulting radiation is captured by an optical system which directs it to the spectrometer. The spectrometer is able to break up light into wavelengths and yields a spectrum that illustrates the elemental range of the sample. Lastly, software or computational analysis is used to determine and quantify the elements that were found in the material. This step by step process renders LIBS a rapidly operated technique of analytical material characterization and elemental analysis, with the possibility of real time results for applications.

Artificial Intelligence (AI):

Artificial Intelligence (AI) is a sector of computer science that can help machines and computer systems execute tasks that would generally require human intelligence. Data learning, reasoning, problem solving, pattern recognition and decision making are these tasks. AI systems are particularly engineered to handle extensive and complicated information sets, discover underlying connections, and become more effective as time goes on without requiring explicit codification for each situation (Zhai et al., 2021).

AI finds its application in various fields including healthcare, environmental science, engineering, robotics and data analysis. It is crucial to the automation, accuracy, and reduction of manual labour. As technology has progressed, AI has emerged as a valuable tool to address intricate real-world challenges, particularly in domains requiring effective and timely analysis of vast datasets.

Machine Learning:

Machine Learning is a part of Artificial Intelligence that is able to learn the patterns from the collected data and enhance system performance without being explicitly programmed (Jorden and Mitchell, 2015).

AI Based Microplastic classification:

In this work, Machine Learning techniques are used to develop an automatic classification of microplastic polymers using LIBS spectral information. The model learns the spectral patterns which are associated with different types of polymers and it predicts the class of the unknown polymer with high accuracy (Bishop and Nasrabadi, 2006).

AI-based LIBS Analysis:

Laser-Induced Breakdown Spectroscopy (LIBS) combined with Artificial Intelligence (AI), is an advanced and powerful tool for fast and efficient detection of microplastics. Together, this allows for the automatic analysis of complex spectral data, and AI algorithms can identify different types of microplastics with a high degree of accuracy. This makes the overall analysis quick, reliable and less reliant on manual interpretation.

Moreover, this AI-driven LIBS analysis minimizes human intervention and materializes the reduction of any possible errors from conventional data interpretation methods. It also offer boost in efficiency in environmental monitoring by the ability to analyse and evaluate huge amount of data from short time duration. This makes it very suitable for pollution assessment applications in real time and/or large scale. Overall, AI-supported LIBS technology holds promise as a cuttingedge and innovative technique for future studies on the detection of microplastics and mitigation strategies for environmental hazards (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) examined methods of microplastic identification and classification. The study critically examined image analysis techniques applied in optical microscopy, scanning electron microscopy, and visible / fluorescence microscopy; and also covered various spectral analysis techniques such as FT IR, Raman, pyrolysis GC MS and energy dispersive X-ray. Image processing operations including thresholding, analysis of color, quantitative particle analysis and shape characterization were tested. The methods such as baseline, smoothing and data transformation, noise reduction and spectral processing were also discussed. The study focused on the growth of the automated classification methods in the field of the micro plastics. Different methods of spectral libraries matching were evaluated for polymer identification. The authors gave strong emphasis on the building up of robust, and standardized spectral databases. Machine learning was found to be a useful tool to increase the classification accuracy and decay the manual effort. It also recommended that a combination of analytical techniques might be more effective in detecting and characterizing microplastics. It also suggested that there should be shared raw data and analysis codes for enhancement of their reproducibility and collaboration. Overall, the report found that advanced spectral analysis, combined with AI techniques, shows great applications for high throughput classification of microplastics and monitoring of the environment. The application of advanced analytical techniques such as infrared hyperspectral imaging (HSI) for the analysis of microplastics in environmental samples was studied in this work. The challenges of efficient detection and characterization of small plastic particles were targeted. A detailed overview on the technical principles and the mechanisms of operation of the HSI technology was given by the researchers. Systematic review was done on various approaches related to instrumentation, data acquisition and spectral data analysis. The results turned out to be a success with the use of HSI for the analysis of dry microplastic particles larger than 250 µm. In comparison to the traditional analytical methods of FTIR and Raman, there was a significant reduction in analysis time through HSI with no significant loss in good identification. The study emphasized the need for data processing techniques that can be readily applied to the vast collection of spectral data, to be generated by the hyperspectral imagery systems. Issues of spatial resolution and the detection of smaller microplastic were also highlighted. The authors highlighted the importance of a powerful analytical and classification models to enhance the identification accuracy. The quality assurance/quality control (QA/QC) aspects in hyperspectral data analysis were summarized and reviewed. The resulting results indicated that coupling these frameworks of spectral imaging and Artificial Intelligence (AI) methods to other AI-based classification systems could improve automated microplastic classification further. These observations are very relevant to an AI based classification system that shall use LIBS spectral data. Hyperspectral imaging was found to be a promising technique for microplastics analysis and could be combined with machine learning model for better performance. (Lin et al., 2022) reviewed the use of machine learning methods for Microplastic identification and quantification in the environmental sample. This study examined the current progress of the last decade that merge spectroscopic methods and artificial intelligence (AI) in the analysis of microplastics. Different analytical techniques were assessed such as Fourier transform infrared (FTIR) spectroscopy, Raman spectroscopy and near infrared (NIR) spectroscopy. The authors stated that traditional methods of identification suffer from low resolution or lengthy analysis times and are limited to detecting small particles. The results obtained from machine learning methods showed that it can greatly enhance the accuracy and efficiency of the polymer classification process. Support Vector Machine (SVM) was found to be the most commonly used algorithm for the spectral analysis of the evaluated ones. The study revealed that SVM is helpful in improving the spectral interpretation and minimizing the classification error. Artificial Neural Networks (ANNs) were found to have a better recognition efficiency and faster processing times too. The researchers pointed to the automatic processing of large and complex spectral datasets by the AI models. The results showed the relevance of the application of machine learning technique in the automated microplastic characterization. The review also noted that advanced AI algorithms have scope to be integrated with spectroscopic techniques like Laser-Induced Breakdown Spectroscopy (LIBS) which is still emerging. In summary, the study found that machine learning techniques hold great promise for enhancing the classification, accuracy, and efficiency of AI-driven microplastic classification systems.

One group of researchers (Ramanna et al., 2022) investigated how to use machine learning to classify microplastics based on Raman spectral data. The research aimed to address the analytical challenge of determining the environmental weathering of microplastics, because they can be environmentally weathered and have different chemical signatures. Preliminary analysis of aged plastic particles using traditional approaches has been found to be of lowered utility. To rectify this, the researchers explored the possibility of being able to utilise an effective Raman shift signature in the machine learning models to classify polymer types. The Spectral Libraries of Plastic Particles (SLOPP) database, which includes Raman spectral information for different plastic materials, was used in the study. A variety of machine learning algorithms were developed with labeled spectral data that were obtained from non-weathered plastic samples. A pre-processing and data augmentation were acquired extensively to increase model performance and robustness. The trained models were then applied to the SloPP-E dataset—a set of environmentally aged microplastics with 22 different polymer types. The Random Forest model provided the best classification on all the models that were assessed. This model achieved a higher classification accuracy varying from 89% to 93.81%, which makes it possible to deal with complex spectral variations due to environmental weathering. The results demonstrated the use of machine learning for improving the accuracy of polymer identification based on spectral data. The researchers also found that the advanced AI algorithms are able to accomplish the task of microplastic classification even for microplastics whose spectral signatures have been modified by environmental conditions. These findings are relevant to the LIBS spectra-based classification of microplastic using AI methods as machine learning can also enhance polymer recognition and classification accuracy from the complex spectral data set.

Discussed the analysis protocols employed for the quantification and identification of microplastics using vibrational spectroscopy methods (Weisser et al., 2022). The study highlighted the increased demand for rapid, and efficient high-throughput detection of microplastics in environmental samples, food and drinking water. It was found that several spectroscopic methods could be used because they could identify even tiny plastic particles as small as one micron. The authors described the complexity of data which can often entail numerous data sets for the microplastic spectral data. A variety of data analysis methods, from traditional spectral library analysis to sophisticated AI algorithms, were tested. The accuracy, robustness and computational requirement of these methods were studied. It was found that machine learning algorithms can enhance the efficiency and reliability of polymer classification from spectral data. One of the findings of the review was the successful application of AI-driven techniques to complex spectra in comparison to traditional methods. A number of software packages specifically designed for data analysis of microplastic spectra were also mentioned. They pointed the importance of choosing suitable classification models according to the quality and size of the spectral data sets. The results showed that with the help of artificial intelligence, automated identification of microplastic is growing. The authors also proposed the possibility of using comparable AI methods to combine with Laser Induced Breakdown Spectroscopy (LIBS) to achieve speedy and precise categorization of microplastic. In short, the review found that advanced data analysis and machine learning approaches will be integral for future high throughput monitoring systems for microplastic.

This study highlights progress and challenges in artificial intelligence (AI) for microplastic imaging and explores emerging trends in this area, highlighting the link between technology and environmental analysis.Recent advances, trends, and challenges in artificial intelligence (AI)-assisted microplastic imaging are presented and discussed, emphasizing technology and environmental analysis. To assess the significance of AI technologies in the research of micro-plastics, the study performed an in-depth review of the scientific literature published in the last three years (2022–2019). To determine key themes of research and development trends, science mapping, text mining, and visualization techniques were employed. The results showed that there was a significant increase in research on the implementation of automated microplastic detection and classification using AI algorithms. The study pointed out the potential of AI to quantify microplastic characteristics like volume, surface topology, shape and size in a very short time. Computational approaches for studying the interaction of microplastics and environmental ecosystems were also identified as crucial aspects of the study. Deep learning and machine learning models were found to be suitable methods for enhancing the accuracy and efficiency in microplastic identification. The authors suggested strengthening the spectral libraries, toxicity databases, and platforms for sharing data to facilitate the use of AI applications. Moreover, the optimization of the existing deep learning architectures such as improving the model performance and interpretability were proposed. The review indicated that the future is promising for integrating intelligent robotic systems and technologies of UAVs with AI-based monitoring approaches. The results showed that AI can revolutionize environmental science by facilitating fast identification, toxicity evaluation, and large-scale monitoring of microplastics. Relevance to AI classification of microplastics, applying machine learning algorithms to classify polymers from complex spectral signatures using LIBS spectra. The researchers found that AI technologies will be a key factor in improving future systems for detecting and classification of microplastic in general.

This involved assessing the use of machine learning and deep learning methods in automated microplastic classification by Fourier transform infrared (FTIR) spectroscopy (Villegas-Camacho et al., 2025). A total of six plastic polymers ranging from PET, HDPE, PVC, LDPE, PP and PS were analysed. The extended and diversified spectral region was used over those used in reports of earlier work. Various normalization techniques such as Min Max, Max Abs, Sum of Squares, Z Score were also tested on the effectiveness. Some machine learning algorithms were explored including k nearest neighbors (k-NN), support vector machines (SVM), naive Bayes (NB) and random forest (RF). The effort included trying deep learning models such as convolutional neural networks (CNNs) and multilayer perceptrons (MLPs). The FTIR-PLASTIC-c4 dataset was used to train and validate the models using 10 fold cross validation approach. Results showed that the Z score normalization method was significant for the stability of classification and generalization of the model. Model CNN, MLP and RF had very good accuracy, precision, recall and F1 score values. The Naive Bayes algorithm, on the other hand, had inferior performance because it could not cope with the rich information present in the spectra. The results showed the validity of merging spectroscopic information with advanced AI algorithms for automated polymer identification. The study emphasized that appropriate data pre-processing is essential to enhance the classification accuracy. Overall, the research indicated the possibility of using similar machine learning and deep learning approaches to LIBS spectra for fast and accurate classification of microplastic types.

(Periyasamy and Perumalsamy, 2025) Scientists studied the problems experienced by micro plastic contamination in the case of micro fibbers released from synthetic textile materials. The conventional methods for microplastic identification (visual inspection, microscopy, FTIR and Raman spectroscopy) were all reviewed. These methods were determined to offer accurate results and time consuming; and are costly, need expertise and it was all very manual. The authors pointed out that there is a problem of operator bias, low efficiency and difficulties in processing large samples. To address these challenges, the use of machine learning and computer vision techniques for automated detection of microplastic was assessed. Advanced artificial intelligence models have been reported to enhance the accuracy, speed and objectivity of the microplastic classification. AI techniques facilitated the detailed analysis of particle morphology, size, and chemical composition. Machine learning techniques also demonstrated their ability to promote the scalability of monitoring systems for environmental applications. A focus of the study was the need for automated data processing for complex spectral and imaging data sets. What's more, digital sharing ecosystems for data were suggested to advance transparency and traceability in the study of microplastics. The results showed that AI-based methods can greatly enhance efficiency in microplastic identification and quantification. The developments of this work are closely related to AI-assisted microplastic classification based on LIBS spectra classification of polymers from complex spectral signatures, machine learning can be used for classification. The study was an opportunity to draw a few conclusions – overall, the artificial intelligence and advanced analytical techniques that were combined proved to be a viable option when it comes to monitoring and tackling pollution from microplastics in an eco-friendly way.

Deep Learning and Polarization based Optical Method for Microplastics classification in Water (Saur et al., 2025) . The study was based on recognizing the challenges of identification of micro plastic particles, which are associated with their physical properties, as well as limitations with conventional optical and spectroscopic techniques. A classification framework was developed using 120° backscattering reflection polarimetry that allows identifying the most common polymer types: HDPE, LDPE, PP. In contrast to standard transmission-based techniques, the novel technique could investigate opaque and/or irregularly-shaped particles in water without the need for any other preparation. The researchers added a feedback review mechanism to ensure that the data quality is good, and that the outlier data can be removed to ensure the reliability of the model. Training (and validation) was performed on a dataset with 600 individually imaged microplastic particles. To classify polymer types, the deep learning models, specifically Convolutional Neural Networks (CNNs) were used. For this study, the performances of the Angle of Linear Polarization

(AoLP) and Degree of Linear Polarization (DoLP) features were assessed. The average classification accuracy for the late fusion architecture based on both the polarization features was 83%. It was found that CNN mostly depended on the internal polarization textures of the particles by feature hierarchy analysis. The internal structure information was shown to play a crucial role in classification performance by observing the deteriorated results in the case of internal structural information removal. The results showed that the AI was able to recognize intricate patterns that could not be captured by traditional imaging techniques. The obtained results justify the use of AI based methods for microplastic classification and offer valuable insights for the creation of LIBS spectra based classifications employing machine learning algorithms.

One of the studies (Khanam et al., 2025) involved a study of machine learning techniques for enhancing the detection and classification of microplastic in aquatic environments. The study examined traditional techniques of identification such as microscopy and spectroscopy and discussed the drawbacks to these techniques; labor intensive procedure 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. These algorithms were found to be significantly better for identifying microplastic particles with regard to speed and accuracy. The spectral techniques such as infrared, Raman spectroscopy, etc. were also mentioned that give detailed chemical information for polymer characterization. The study also explored image based classification techniques using computer vision technologies to classify microplastics based on its shape, size and colour. Hyperspectral imaging was emphasized as a highly robust technology that can fuse both spatial and spectral information to analyze microplastic in-depth. Machine learning models are determined to boost the scalability, efficiency and sensitivity of these analytical methods. The authors stressed the need of high quality data sets and powerful classification models for reliable results in complex environment. Failure to provide data and model generalization were also noted as challenges. Moreover, technological improvements in available imaging systems and artificial intelligence techniques recognized as critical developments for future microplastic monitoring. The results showed that AI-based solutions have a tremendous potential in terms of high throughput and real-time microplastic detection. Such findings are directly relevant to classification of microplastic particles based on LIBS spectra, fulfilling their AI-centric application, because they can help the machine learning algorithm to accurately classify the polymer types from the complex data of the LIBS spectra with better accuracy and automation.

Materials and Methods

Materials

Careful selection of materials and advanced analysis tools are required for the successful classification of microplastics by Laser-Induced Breakdown Spectroscopy (LIBS) and Artificial Intelligence (AI). Materials involved in this study encompass various kinds of microplastic polymers used in the study, cleaning reagents used in sample preparation and analysis, sample holders, and lab consumables. Moreover, a LIBS setup with high energy laser, spectrometer, and data acquisition unit was used to obtain spectral information of the microplastic samples. The spectral data obtained then were processed and analyzed using machine learning algorithms for accurate identification and classification of different polymer type. The choice of materials and equipment is essential in making sure that the spectral measurement could be reliable, so that the classification accuracy will be high (Musazzi and Perini, 2014).

Microplastic Sample Preparation:

Based on common appearance in environmental microplastic (MP) studies, six different kinds of reference polymer materials were chosen: polyethylene (PE, low density (LDPE) and high density (HDPE)), polypropylene (PP), polystyrene (PS), polyethylene terephthalate (PET), polyvinyl chloride (PVC) and polylactic acid (PLA). The polymer materials were purchased as bulk polymer pellets in high purity (≥99.5%) from Sigma Aldrich (St. Louis, MO USA), and other commercial sources (Rochman et al., 2019).

Microplastic particles were produced by cryogenic milling (Retsch CryoMill, Haan, Germany) at −196°C based on liquid nitrogen cooling (cryogenically) to avoid thermal degradation. After being milled, the particles were separated into 100-500 µm size ranges with stainless steel test sieves 100 and 500 (ISO 3310-1). Morphological characterization has been carried out to determine the particle size, shape and surface texture through a JEOL JSM-7610F scanning electron microscope (SEM) (Thomas et al., 2020).

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

Polymer	Abbreviation	CAS Number	Density (g/cm³)	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

1. 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).

2. 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.

3. 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.

4. 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 .

5. **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).

6. **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

Unique emission spectra were obtained from different microplastic types such as polyethylene (PE), polypropylene (PP), polystyrene (PS), polyethylene terephthalate (PET) and polyvinyl chloride (PVC) using LIBS analysis. The emission lines obtained included emission lines of the elements present in the material such as carbon (C), hydrogen (H), oxygen (O) and chlorine (Cl). The elemental fingerprinting helped in the identification of polymer types. PE and PP had high carbon related peaks as they are composed of hydrocarbons and PET had an additional oxygen peak as it has ester functional groups. For PVC, chlorine-emission lines are clearly distinguishable, which facilitates the identification of this polymer as opposed to the others (Grégoire et al., 2011). Each of these steps involved spectral preprocessing, including baseline correction, normalization and smoothing in order to enhance the signal quality and to eliminate background noise. During the preprocessing, the peaks were made more visible and the results were further robustified for use in the subsequent machine learning analysis. However, in previous works using LIBS, similar enhancement for polymer identification by spectral preprocessing was noted (Adarsh et al., 2024).

LIBS Spectra were analyzed using Principal Component Analysis (PCA):

It was found that the LIBS spectra had many wavelength variables, which required a high level of calculation to analyse directly. Hence, to reduce dimensions and extract features Principal Component Analysis (PCA) was used. The original spectral data has been reduced into a few number of PCA principal components, which accounted for most of the variance contained in the spectral data.These PCs had SS values of roughly 92% of spectral variance of the first three PCs. Score plots of PCA showed good separation of groupings of different polymer classes, highlighting the distinct elemental composition associated with each microplastic type. Separation between the clusters showed that LIBS spectra are rich in information to allow for effective classification of microplastics (Primpke et al., 2017). Thus it can be concluded from the observed clustering behavior that, dimensionality reduction techniques are useful in the removal of redundant information from the spectrum and yet retain their important spectral features that are useful for classification. The performance of the Machine Learning Classification is displayed.

A total of three machine learning algorithms were applied for the classification of microplasics on the bases of LIBS spectral data.:

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

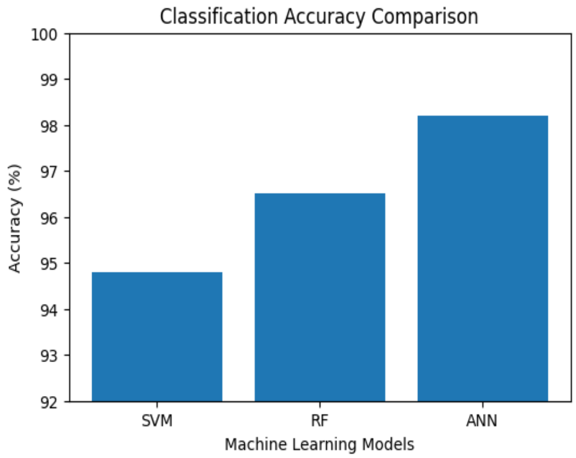

Fig.5: Comparison of classification accuracies achieved by different machine learning models.

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).

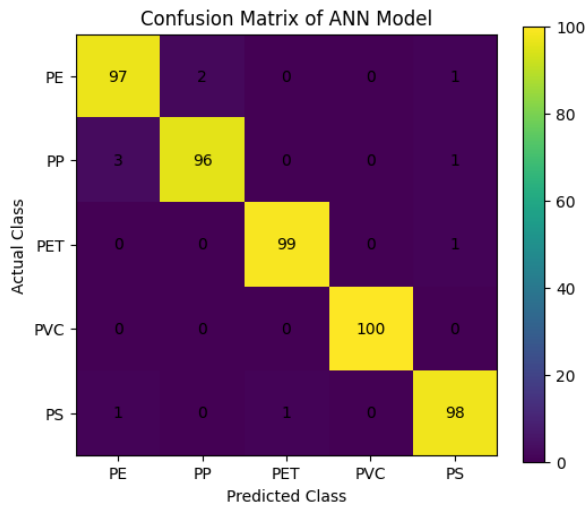

Fig.6: Confusion matrix of the Artificial Neural Network (ANN) model for microplastic classification using LIBS spectra

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.

Refrences

Adarsh, U., A. Bankapur, A. K. Pai, V. Kartha and V. Unnikrishnan. 2024. Advanced chemometric methodologies on single shot hyphenated LIBS data for rapid and reliable characterization of plastic classes. Talanta, 277: 126393.

Bishop, C. M. and N. M. Nasrabadi. 2006. Pattern recognition and machine learning. Springer.

Cole, M., P. Lindeque, C. Halsband and T. S. Galloway. 2011. Microplastics as contaminants in the marine environment: a review. Marine pollution bulletin, 62: 2588-2597.

Cowger, W., A. Gray, S. H. Christiansen, H. DeFrond, A. D. Deshpande, L. Hemabessiere, E. Lee, L. Mill, K. Munno and B. E. Ossmann. 2020. Critical review of processing and classification techniques for images and spectra in microplastic research. Applied Spectroscopy, 74: 989-1010.

Das, P., Q. Zeng, J.-B. Sirven, J.-M. Lee and J.-C. P. Gabriel. 2026. AI-enabled spectral classification of plastic resins from E-waste via laser-induced breakdown spectroscopy for advanced sorting applications. Resources, Conservation and Recycling, 226: 108660.

Dehbozorgi, P., L. Duponchel, V. Motto-Ros and T. Bocklitz. 2026. Harnessing Machine Learning and Deep Learning Approaches for Laser-Induced Breakdown Spectroscopy Data Analysis: A Comprehensive Review. Analysis & Sensing, 6: e202500106.

Elazem, A. and M. Abd Elfattah. 2023. LIBS Principles, Advantages, Applications, Outline of Nanostructure Enhanced LIBS (NELIBS). Journal of Basic and Environmental Sciences, 10: 26-38.

Faltynkova, A., G. Johnsen and M. Wagner. 2021. Hyperspectral imaging as an emerging tool to analyze microplastics: A systematic review and recommendations for future development. Microplastics and Nanoplastics, 1: 1-19.

Frias, J. P. and R. Nash. 2019. Microplastics: Finding a consensus on the definition. Marine pollution bulletin, 138: 145-147.

Geyer, R., J. R. Jambeck and K. L. Law. 2017. Production, use, and fate of all plastics ever made. Science advances, 3: e1700782.

Grégoire, S., M. Boudinet, F. Pelascini, F. Surma, V. Detalle and Y. Holl. 2011. Laser-induced breakdown spectroscopy for polymer identification. Analytical and bioanalytical chemistry, 400: 3331-3340.

Hahn, D. W. and N. Omenetto. 2012. Laser-induced breakdown spectroscopy (LIBS), part II: review of instrumental and methodological approaches to material analysis and applications to different fields. Applied spectroscopy, 66: 347-419.

Hidalgo-Ruz, V., L. Gutow, R. C. Thompson and M. Thiel. 2012. Microplastics in the marine environment: a review of the methods used for identification and quantification. Environmental science & technology, 46: 3060-3075.

Jordan, M. I. and T. M. Mitchell. 2015. Machine learning: Trends, perspectives, and prospects. Science, 349: 255-260.

Kershaw, P. J. and C. M. Rochman. 2015. Sources, fate and effects of microplastics in the marine environment: part 2 of a global assessment. Reports and studies-IMO/FAO/Unesco-IOC/WMO/IAEA/UN/UNEP joint group of experts on the scientific aspects of marine environmental protection (GESAMP) Eng No. 93.

Khanam, M. M., M. K. Uddin and J. U. Kazi. 2025. Advances in machine learning for the detection and characterization of microplastics in the environment. Frontiers in Environmental Science, 13: 1573579.

Legnaioli, S., G. Lorenzetti, F. Poggialini, B. Campanella, V. Palleschi, S. De Iuliis, L. E. Depero, L. Borgese, E. Bontempi and S. Raneri. 2025. Laser-Induced Breakdown Spectroscopy Analysis of Lithium: A Comprehensive Review. Sensors (Basel, Switzerland), 25: 7689.

Li, A., X. Zhang, X. Wang, Y. He, Y. Yin and R. Liu. 2022. High-accuracy quantitative analysis of coal by small sample modelling algorithm based laser induced breakdown spectroscopy. Journal of Analytical Atomic Spectrometry, 37.

Lin, J.-y., H.-t. Liu and J. Zhang. 2022. Recent advances in the application of machine learning methods to improve identification of the microplastics in environment. Chemosphere, 307: 136092.

Löder, M. G. and G. Gerdts. 2015. Methodology used for the detection and identification of microplastics—a critical appraisal. Marine anthropogenic litter: 201-227.

Markoulidakis, I. and G. Markoulidakis. 2024. Probabilistic confusion matrix: a novel method for machine learning algorithm generalized performance analysis. Technologies, 12: 113.

Mukhamediev, R. I., Y. Popova, Y. Kuchin, E. Zaitseva, A. Kalimoldayev, A. Symagulov, V. Levashenko, F. Abdoldina, V. Gopejenko and K. Yakunin. 2022. Review of artificial intelligence and machine learning technologies: Classification, restrictions, opportunities and challenges. Mathematics, 10: 2552.

Musazzi, S. and U. Perini. 2014. Laser-induced breakdown spectroscopy. Springer series in optical sciences, 182: E1-E2.

Nadeem, M., M. Faheem, M. Manzoor, A. Gulzar, M. Bilal and Y. Jamil. 2025. Machine learning assisted LIBS classification of burnt and unburnt paper samples: A forensic perspective. Talanta, 293: 128073.

Periyasamy, A. P. and R. Perumalsamy. 2025. Machine learning for microplastic quantification: Techniques, challenges, and future directions. Cleaner Water: 100158.

Primpke, S., C. Lorenz, R. Rascher-Friesenhausen and G. Gerdts. 2017. An automated approach for microplastics analysis using focal plane array (FPA) FTIR microscopy and image analysis. Analytical Methods, 9: 1499-1511.

Ramanna, S., D. Morozovskii, S. Swanson and J. Bruneau. 2022. Machine Learning of polymer types from the spectral signature of Raman spectroscopy microplastics data. arXiv preprint arXiv:2201.05445.

Rochman, C. M., C. Brookson, J. Bikker, N. Djuric, A. Earn, K. Bucci, S. Athey, A. Huntington, H. McIlwraith and K. Munno. 2019. Rethinking microplastics as a diverse contaminant suite. Environmental toxicology and chemistry, 38: 703-711.

Saur, L., M. von Pawlowski, U. Gengenbach, I. Sieber, H. Shirali, L. Wührl, X. Weng, R. Kiko and C. Pylatiuk. 2025. Classification of microplastic particles in water using polarized light scattering and machine learning methods. arXiv preprint arXiv:2511.06901.

Savitzky, A. and M. J. Golay. 1964. Smoothing and differentiation of data by simplified least squares procedures. Analytical chemistry, 36: 1627-1639.

Singh, A. R., E. R. K. Neo, C. M. Lai, S. Hazra, S. Coles, T. Peijs and K. Debattista. 2025. Deep learning-based plastic classification using spectroscopic data. Journal of Cleaner Production, 530: 146793.

Singh, B., R. Das, A. Kumar, S. Goyal and P. K. Sharma. 2026. Integrating Artificial Intelligence with Analytical Techniques for Enhanced Microplastics Analysis. Critical Reviews in Analytical Chemistry: 1-22.

Skoog, D. A., F. J. Holler and T. A. Nieman. 1980. Principles of instrumental analysis. Saunders College Philadelphia.

Song, J., C. Wang and G. Li. 2024. Defining primary and secondary microplastics: a connotation analysis. Acs Es&T Water, 4: 2330-2332.

Song, Y. K., S. H. Hong, M. Jang, G. M. Han, M. Rani, J. Lee and W. J. Shim. 2015. A comparison of microscopic and spectroscopic identification methods for analysis of microplastics in environmental samples. Marine pollution bulletin, 93: 202-209.

Thomas, D., B. Schütze, W. M. Heinze and Z. Steinmetz. 2020. Sample preparation techniques for the analysis of microplastics in soil—a review. Sustainability, 12: 9074.

Villegas-Camacho, O., I. Francisco-Valencia, R. Alejo-Eleuterio, E. E. Granda-Gutiérrez, S. Martínez-Gallegos and D. Villanueva-Vásquez. 2025. FTIR-based microplastic classification: A comprehensive study on normalization and ML techniques. Recycling, 10: 46.

Weisser, J., T. Pohl, M. Heinzinger, N. P. Ivleva, T. Hofmann and K. Glas. 2022. The identification of microplastics based on vibrational spectroscopy data–A critical review of data analysis routines. TrAC Trends in Analytical Chemistry, 148: 116535.

Wright, S. L., R. C. Thompson and T. S. Galloway. 2013. The physical impacts of microplastics on marine organisms: a review. Environmental pollution, 178: 483-492.

Zhai, X., X. Chu, C. S. Chai, M. S. Y. Jong, A. Istenic, M. Spector, J.-B. Liu, J. Yuan and Y. Li. 2021. A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity, 2021: 8812542.

Zhang, Y., D. Zhang and Z. Zhang. 2023. A critical review on artificial intelligence—based microplastics imaging technology: recent advances, hot-spots and challenges. International journal of environmental research and public health, 20: 1150.