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Research Article

Microplastic Identification Using Impedance Spectroscopy and Machine Learning Algorithms

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Detecting and classifying microparticles in water and other liquid substances is crucial due to their detrimental impact on ecosystems and human health. This is because particles such as microplastics, micropollutants, or heavy metals in water have demonstrated a high impact on the health of ecosystems and a high risk when this water is used for human consumption. Water quality is a critical factor when it comes to human consumption. Currently, some of these pollutants are not correctly detected during water treatment processes or directly in ecosystems, which can carry health risks for humans and animals. From this point of view, the development of tools for detecting these particles is still needed, and research for new strategies for detecting and classifying these microparticles with in situ methods is required. As a contribution to the solution of this problem, this work presents a microplastic detection and classification methodology that uses an electronic tongue system, impedance spectroscopy, and machine learning algorithms for detecting and classifying microplastics. Validation is performed using various sizes of PET (polyethylene terephthalate) microparticles in water to validate the possibility of classification. Results show the advantages of using the methodology, obtaining high accuracy in the classification process.

1. Introduction

Plastics are some of the most used elements in the industry, and their use has been extended since their commercial introduction in the fifties [1]. They are essential in modern life, and their use is a normal practice in society. However, despite their advantages for multiple applications and uses, they are also a problem due to their poor layout. Although there are currently processes focused on optimizing and managing plastic waste [2, 3], these materials continue to be found in different environments, such as bodies of water [4] or fragile ecosystems, promoting the adsorption of other contaminants such as cadmium in plants [5], which can cause significant damage to the trophic chain. In addition to this, the microplastic particles themselves have a considerable impact on the soil because the organisms that inhabit it are affected by these materials [6, 7]. Currently, it would be impossible to ban the use of plastic products in society because of their extended use; however, searching for new ways to replace them is a research [8, 9] area with the same purpose but without affecting the environment. One way to abord this change is by using educational campaigns oriented toward reducing the use of single-use plastics. As an example, multiple countries have banned or created taxes [10, 11] to reduce the use of single-use plastics because these are some of the main contaminants in the environment, such as plastic bottles, food wrappers, plastic supermarket bags, and plastic caps, among others. Although these campaigns and taxes have made the reduction possible, this is a long way, and at the moment, microplastics and plastic debris have been detected around the world in all the major marine habitats [4, 12], including wastewater, air, and food [11].

Different works have been developed for the identification and quantification of microplastics from the marine environment for several years, including the use of different methods such as visual sorting and the analysis of chemical and physical characteristics because of the damage to ecosystems and people [13]. Some studies have demonstrated that microplastics are constantly inhaled and ingested by humans, which represents a potential risk to human health [14, 15]. According to the World Health Organization, in a report called Microplastics in Drinking Water [11], fragments and fibers were found in freshwater, with polyethylene terephthalate and polypropylene as the more common contaminants. From this point of view, detecting and identifying microplastics in water and liquid substances is needed. In situ analysis is desired because it allows an easy and rapid way to detect microplastics by reducing the time required compared to traditional laboratory methods, such as Ramman spectroscopy [16], electron microscopy [17], or selective sampling methods [13]. One of the alternatives to this analysis is the electrochemical method [18]. Electrochemical sensors present some advantages, such as high sensitivity and selectivity, which can be an opportunity to develop intelligent systems compared to traditional analysis methods, which require laboratory analysis and experts. However, developing this kind of system implies instrumentation, electronics, signal processing, and artificial intelligence knowledge. Specifically, using systems such as electronic tongues can be considered a good alternative to this aim.

Several developments exist in the literature where electronic tongues are used; some of them include detecting and classifying heavy metals [19], detection of false and genuine honey [20], food quality monitoring [21, 22], quality control in beverage production [23], chemical deterioration of foods [24], detection of inadequate characteristics of virgin olive oil [25], and analysis of phenolic compounds [26], among others [27]. It has been shown that electrochemical techniques not only serve to measure the properties of a chemical reaction but can also be used for the detection of polymers [28] and contaminants [29]. Additionally, together with the use of artificial intelligence techniques, it is possible to extract and classify the information provided by these techniques.

Electrochemical techniques include potentiometry, amperometry, conductometry, voltammetry, and impedance measurements. The last uses electrochemical impedance spectroscopy which allows measuring the electrochemical properties of an element in a given solution [28]. In terms of microplastics, electronic tongues, and electrochemical methods, the following works are available in the literature: Colson and Michel [30] used impedance spectroscopy and K-NN for the classification of microplastics with a 95% confidence interval. Samples of neutral-density polyethylene and biological specimens such as brine shrimp eggs, brine shrimp nauplii, *Volvox globator* colonies, marine copepods, *Moina*, *Daphnia pulex*, teff, and poppy seeds were used in the validation. Developing a sensor and the configuration setup for detecting microplastics is the aim of this work, and few details are included about the methodology and the preprocessing steps. Du et al. [28] used graphene electrodes to detect microplastics using spectroscopy impedance. The methodology evaluated included principal component analysis and singular value decomposition. Dahl et al. [16] used Raman spectroscopy for detecting and classifying microplastics using spectral signatures. The method was evaluated in three scenarios, including samples from the sea outside Svolvaer, Lofoten, to determine whether it is possible to classify microplastics into water- and sea-influenced pieces. Although these works share common elements with this work, they are primarily oriented toward validating the developed sensors and the use of other techniques which make this work different from those presented herein.

Some approaches other than electronic tongues for microplastic detection are as follows: Sundar [31] used a low-cost approach based on the integration of several elements such as computer vision, neural networks, and IoT communication for the detection of water containing microplastic samples. However, this work had limitations due to the need for databases to train the neural networks. Michelaraki et al. [32] proposed the use of a solvatochromic dye known as Nile red along with fluorescence microscopy as a labeling technique for detecting microplastics. The samples were chosen from sedimented soils, and a specific amount of microplastic particles was added. A process of decanting and filtering was carried out in solutions with a high salt density. Optical techniques were used for detection.

In contrast to the mentioned works, the developed methodology aims to introduce an electronic tongue system for detecting and classifying microplastics. This work is based on the hypothesis that it is possible to use impedance spectroscopy to detect and classify microplastics in water with an electronic tongue. It considers the use of an array of SPE sensors, which are commercial sensors, and we use a sensor network that combines different sensors, impedance analysis, and pattern recognition techniques, as will be shown in the document. The methodology was validated under several water conditions to demonstrate that it has the potential to be used in detecting and classifying polluting microplastics in freshwater. This paper starts with this introduction. The theoretical background is in Section 2, where some key concepts are briefly included. Section 3 introduces the microplastic classification methodology, and the experimental setup and validation are included in Section 4. Finally, conclusions are aborded in the last section.

2. Theoretical Background

This section presents some basic concepts about the methods and terms used in this work. The authors suggest to the readers a review of the references associated with each subsection to go in-depth into the methods if necessary.

2.1. Microplastics. Microplastics are particles of plastic materials; these are generated on most occasions by interacting these elements with their emerging medium. Their size is less than 5 mm [14] and comes from various sources where waste plastics can be generated, such as the textile and cosmetics industries, among others [4, 11].

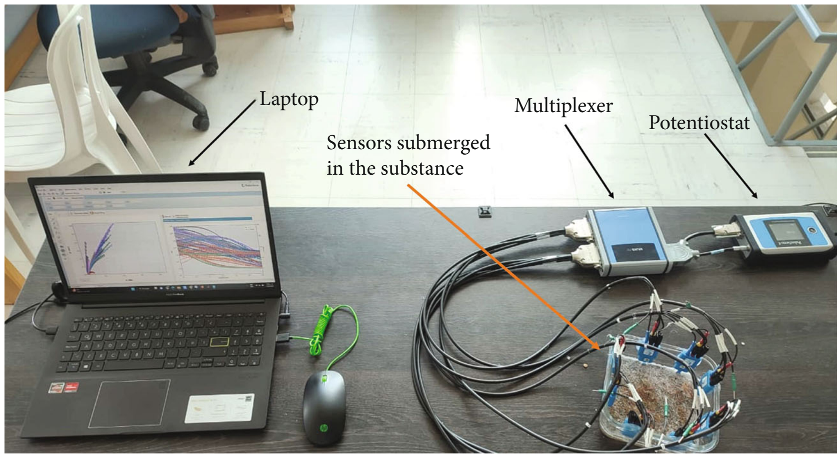


FIGURE 1: Parts of the hardware used in an electronic tongue.

From an environmental perspective [1], the advantages of developing a microplastic monitoring system are numerous.

(i) The detection of microplastics in water can provide insight into the extent of plastic pollution in our environment and help us identify potential sources of pollution

(ii) Early detection can then be used to inform policies and regulations aimed at reducing plastic waste and preventing pollution

(iii) The detection of microplastics can help to better understand the potential impact of these particles on aquatic ecosystems

(iv) This system can be used as an early detection method

(v) It can help to identify areas that may be at a higher risk of contamination, which can then be targeted for further monitoring and remediation efforts

(vi) It can help prevent the spread of pollution and protect both human health and the environment [5]

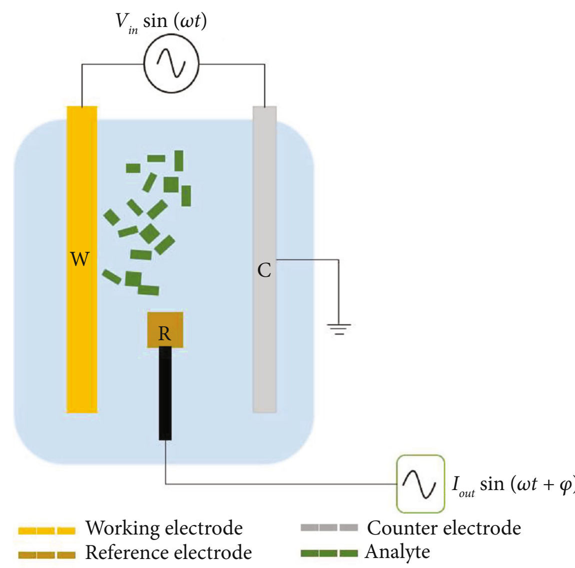
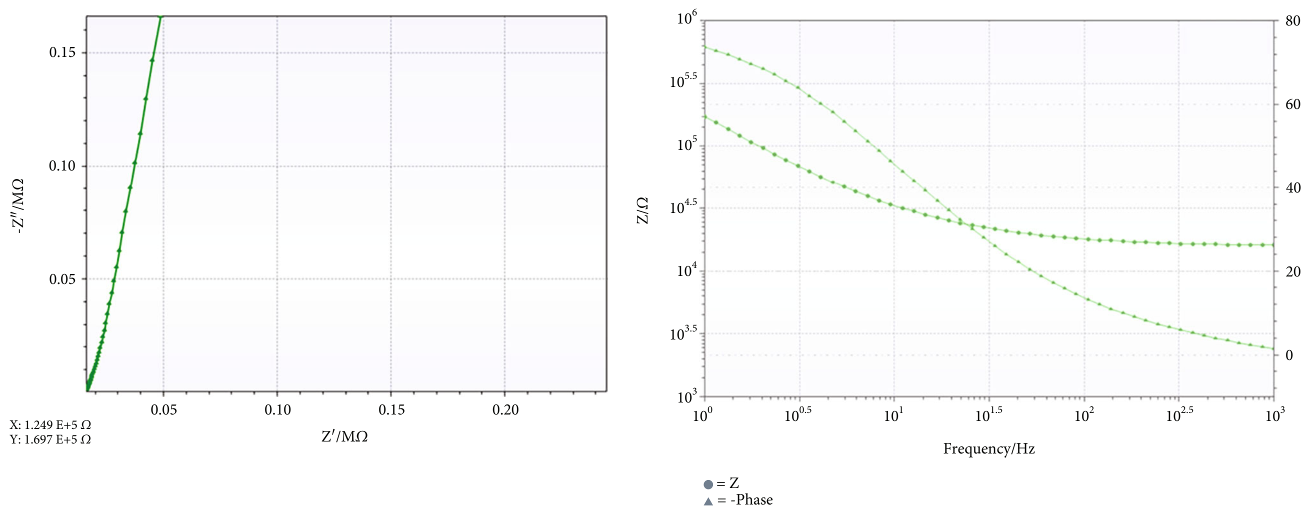


FIGURE 2: Electrode array in an electronic tongue to calculate the impedance spectroscopy method.

2.2. Electronic Tongue System. An electronic tongue system is a multisensor system [33] that uses sensors, a data acquisition system, multivariate analysis, signal processing, and pattern recognition algorithms [34]. Generally, it interacts with the liquid substance through the sensors/actuators by electrochemical inspection and collects the interaction with the substance [35]. Because multiple sensors are used in the inspection, different signals about this interaction are available, and information about the substance or its components can be obtained by processing these signals in a multivariate way [36]. Figure 1 shows a photo of the electronic tongue used in this work. It consists of several sensors submerged in the substance to analyze, and a multiplexer is used for multiplexing the sensors. This is not a need, but in the case of this configuration, it allows us to connect the potentiostat to 8 channels because it has only one channel. The system also uses a potentiostat responsible for applying and collecting the signals and interacting with the sensors. Finally, a laptop is used to apply the developed algorithms to analyze the signals obtained by the sensors.

2.3. Support Vector Machine. A support vector machine (SVM) is a powerful and versatile machine learning algorithm for classification, regression, and outlier detection. SVMs are based on finding a hyperplane that maximally separates the different classes in a dataset. The hyperplane is chosen to maximize the margin between the two classes. SVMs are particularly useful when the data is nonlinearly separable, as they can use *kernel* functions to transform the data into a higher-dimensional feature space where it can be linearly separated. SVMs have been successfully applied in various domains, including image classification, text classification, and bioinformatics [19].



(a) (b)

FIGURE 3: Impedance plot in the (a) complex plane and (b) diagram Bode.

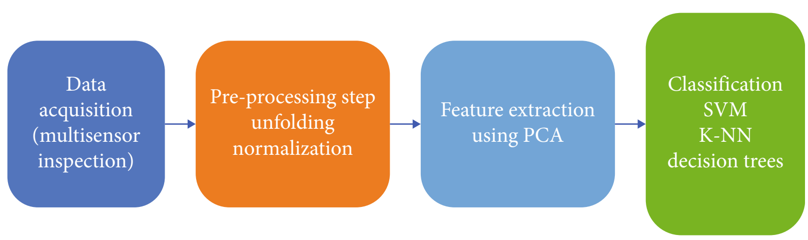


FIGURE 4: Microplastic detection and classification methodology.

2.4. K-Nearest Neighbors. K-nearest neighbors (K-NN) is one of the most basic classification algorithms used in machine learning.

Its applications are oriented toward pattern recognition and data mining [37].

K-NN is a nonparametric and instance-based algorithm, which implies that it does not depend on the functional model of the data (for example, some datasets have a Gaussian distribution); instead, it identifies and uses the training instances of the data to use them in the prediction phase. The algorithm can use different techniques to calculate the distance of its nearest neighbor to group it in a class. Among these techniques are the Euclidean distance, Manhattan distance, or cosine distance. This algorithm has a high computational cost and can be subjected to noise.

2.5. Principal Component Analysis (PCA). Principal component analysis, also known as PCA because of its acronym, is an algorithm that works in the unsupervised domain [38]. This technique aims to study the variables that make up the dataset. For this, PCA applies a linear transformation from n to p variables, where $p < n$. This procedure reduces the dimension with a little loss of information generally associated with redundant information or noise [38, 39].

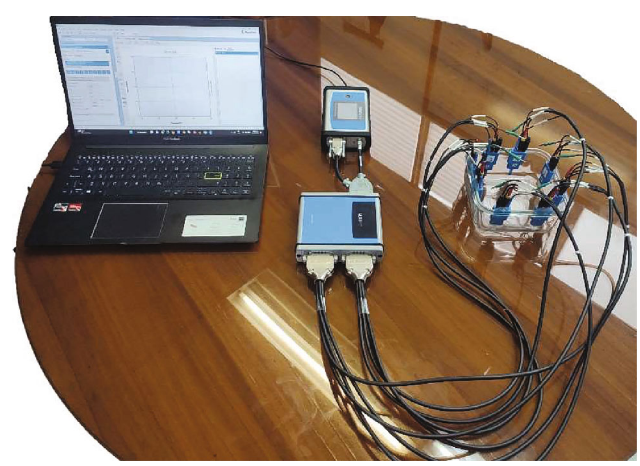


FIGURE 5: Data acquisition system for the electronic tongue in the detection and classification of microplastics.

2.6. Q-Statistic and T^2-Statistic. When analyzing data, it is essential to use appropriate statistical tests to ensure accurate results. Two commonly used statistical tests are the Q-statistic and the T^2-statistic. The Q-statistic is a goodness-of-fit test to determine if an observed frequency

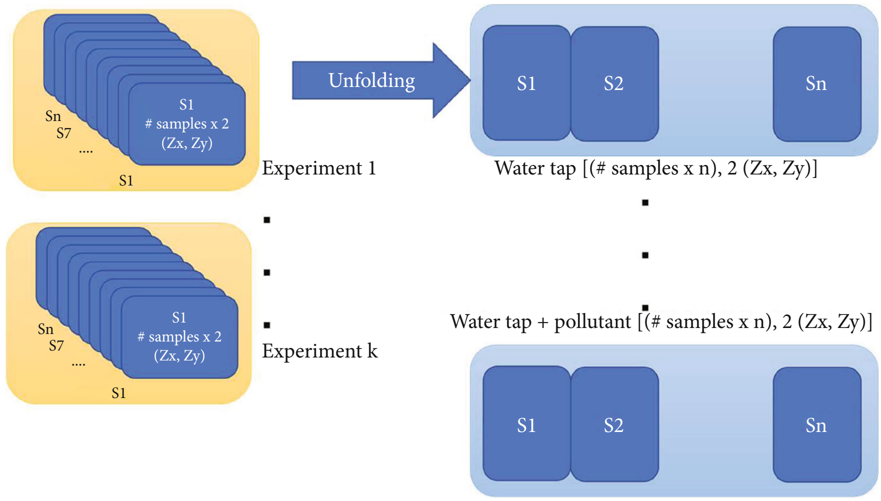


Figure 6: Data organization and unfolding steps.

distribution matches an expected frequency distribution. On the other hand, the T^2-statistic is a multivariate statistical test used to compare the means of two or more groups [39]. Both tests are helpful in different situations and can help researchers draw meaningful conclusions from their data. However, using them correctly and interpreting the results carefully is essential to avoid any potential errors or biases.

2.7. Impedance Spectroscopy. Electrical impedance spectroscopy (EIS) is a technique that allows the characterization of the electrical properties of materials and solutions. It applies a periodic voltage signal, $V_i \sin(t)$, to a medium, such as a solution, between an array of electrodes, as shown in Figure 2.

The response to this signal, which has a specific phase shift angle $I_i \sin(\omega t + \varphi)$, can be measured at a reference electrode. By varying the frequency of the applied signal, the system's response can be analyzed in terms of the impedance variation, which allows for the characterization of the electrical properties of the analyte.

The impedance (Z) can be expressed in terms of the input signal and the response measured at the reference electrode, as shown in the following equation.

$$Z = \frac{V}{I} = \frac{V_i \sin(\omega t)}{I_i \sin(\omega t + \varphi)} = Z_0 \frac{\sin(\omega t)}{\sin(\omega t + \varphi)}. \quad (1)$$

The value of the impedance (Z) can be represented by the Nyquist diagram, which plots the imaginary component of impedance against its real component, or by the Bode diagram, which shows the magnitude and phase of impedance as a function of frequency, as shown in Figure 3.

As the electrode array is immersed in water, microplastic particles are detected by the sensor network, leading to a change in the electrical properties of the liquid and thus the impedance. These changes are detected and classified by AI algorithms to identify microplastic particles.

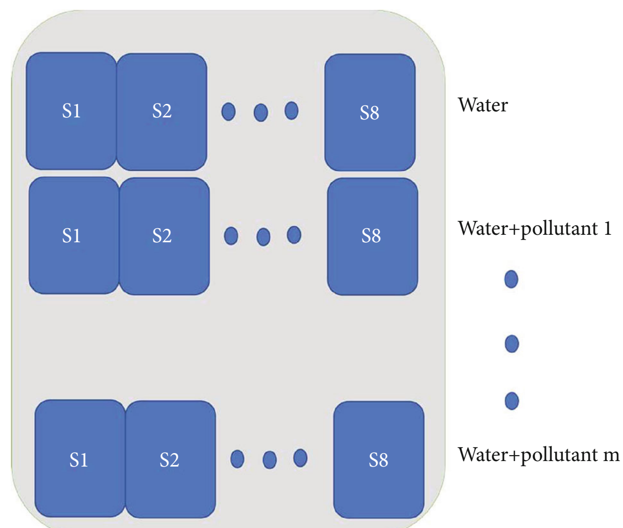


Figure 7: Data organization of the experiments for the water and water with pollutants.

Impedance spectroscopy is a method that reflects an analyte's behavior as a function of its electrical properties, such as resistance, reactance, conductance, inductance, or capacitance [40]. This method can be described as an electrical circuit, and every time it produces a change in the solution established as an analyte, its behavior could be modeled as a specific circuit with its transfer function. However, the variability that can be present in water in the different environments in which it is found represents a challenge when identifying the system to obtain a transfer function that allows modeling the system and comparing it against a model that contains microplastic particles. So the use of algorithms for artificial intelligence lends itself to a great solution because they do not require any representation or identification of the system and can work from the point of view of a pattern recognition system.

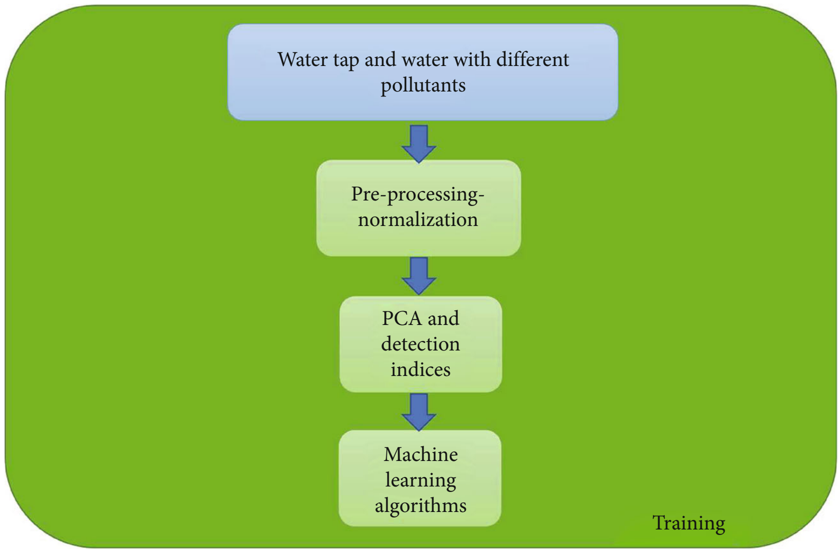


Figure 8: Training process for the electronic tongue.

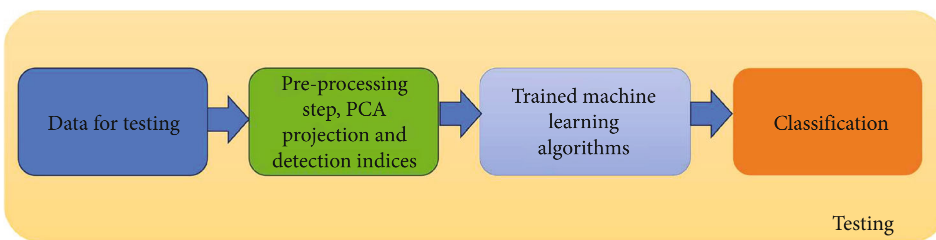


Figure 9: Testing process for the electronic tongue.

3. Microplastic Classification Methodology

The methodology for detecting and classifying microplastics considers, in a general way, four general steps, as shown in Figure 4. The first step considers data acquisition (Figure 5). In this case, multiple sensors are submerged in the liquid samples, with a volume of ≈420 cm^3, and impedance spectroscopy is applied to determine the spectrum of impedances from each sensor. Because multiple sensors are used, multiple different spectrums are obtained. In the case of this work, eight sensors are considered; however, the number of sensors can vary according to the possibilities of the data acquisition system. It is expected that the methodology can be used in the same manner.

In this work, some water samples with different conditions of microplastics and other materials will be considered. These data allow the definition of the baseline and the data to be compared during the pattern recognition analysis. This step ends with the storage of the data and their organization. Figure 6 shows the general scheme of this step. Since n sensors can be used in the acquisition, each sensor collects information with the impedance measure in x and y; that is, each sensor provides a matrix of (samples) rows and two columns (Zx and Zy). As it is shown in Figure 6, n matrices are collected, and each acquisition obtains a three-dimensional matrix. To convert this information into a two-dimensional matrix, the unfolding process is applied, and a new matrix with dimensions $[(\text{samples} \times n), 2]$ is obtained. Because each experiment can be repeated k times, the matrix is organized as $[(\text{samples} \times k \times n), 2]$. This procedure is applied to the collected data. The result is a set of matrices that represent the different types of experiments, which are composed of drinking water and water with different kinds of contaminants (Figure 7). For the case of this work, a network of eight sensors was used.

The next step implies normalization. This is applied to consider the data from all the sensors similarly.

In this case, group scaling was considered after evaluating different normalization methods.

The methodology considers training and testing processes. The first step allows us to create the pattern. A percentage of the data from all the experiments is used. Figure 8 shows the steps followed by the training process.

Principal component analysis is considered a step for the analysis and the feature extraction. This method allows for obtaining a reduced version of the data represented by the components that retain the dataset's variance. Analyzing these components can detect microplastics and elements in the water samples. A traditional way to do this analysis is to use score plot. However, when the variability of the data is high, more than two components are required to represent the information, and a simple plot in two or three

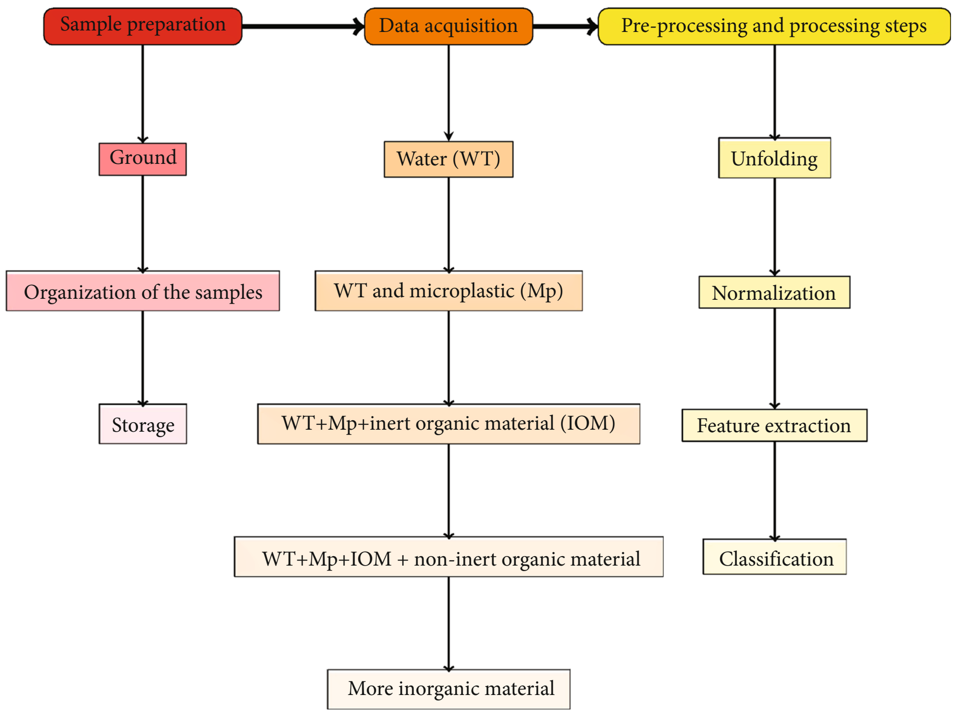


Figure 10: Steps of the methodology applied for detecting and classifying microplastics in water.

dimensions is not enough. These components are the features used as input to the machine learning algorithms.

After the baseline definition and training process, testing is applied. Figure 9 shows the steps to follow during this procedure. The classification result can be verified by using the confusion matrix.

4. Experimental Setup and Validation

To validate the methodology, water and water with different pollutants were considered as the scenarios to classify, and an electronic tongue with eight sensors was used to acquire data from each scenario. Although Section 3 includes a general explanation of the methodology, details about sample preparation and how these are applied to the dataset will be shown in this section. Figure 10 shows in the second and third columns the steps previously explained, showing the cases evaluated in this paper. This figure also includes information about the sample preparation for the validation presented herein.

4.1. Microplastic Samples. Microplastic samples are obtained after shredding plastic materials. From this process, four different sizes were obtained. Details are included in Table 1 and Figure 11.

To determine whether materials other than microplastics should be classified differently, samples of organic, inert organic, and inorganic materials were also studied. "Black earth" was used for the inert organic sample, which contained seed shells. The next sample used was composed of the remains of ground wood. Finally, for the living organic sample, ikura or salmon eggs were used since they have a size similar to that of microplastics, as shown in Figure 12.

Table 1: Size and quantity of polyethylene terephthalate microplastic samples used in the experiments.

Microplastics	Size (m)	Quantity
Sample 1	500 μm < 1000 μm	1.4 g
Sample 2	1000 μm < 1500 μm	1.4 g
Sample 3	1500 μm < 2000 μm	1.4 g
Sample 4	2000 μm < 4000 μm	1.4 g

4.2. Data Acquisition. A potentiostat with a sensor network of eight sensors was used for data acquisition. Using the impedance spectroscopy (EIE) technique, the measurements were made to obtain the electrical transfer curves at different frequencies of the water, the water with the different sizes of microplastics, and the rest of the contaminants. A PalmSens4 potentiostat and the MUX8-R2 multiplexer were used for the data acquisition. Figure 5 shows the architecture used.

Figure 13 shows the impedance curve (in the Nyquist plane) and the Bode diagram in a frequency range from 1 Hz to 1 MHz for water.

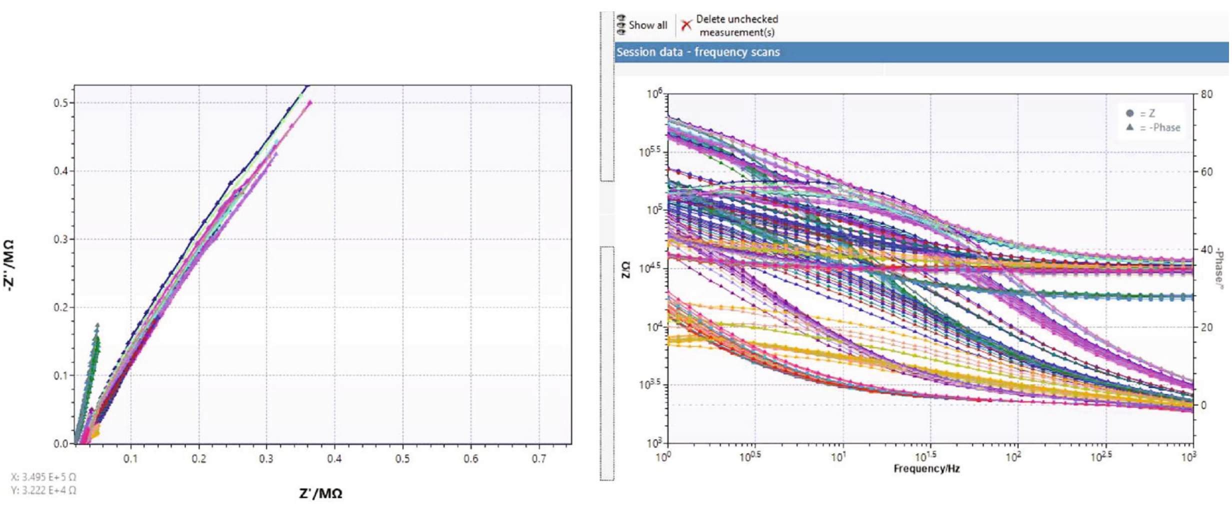
The different impedance curves in the Nyquist plane obey the different sensors and the type of material used in the working electrode. Table 2 shows the types of material used in the detector working electrode.

The dataset obtained consists of 20 experiments per condition, that is, 20 experiments with drinking water and 20 experiments for each of the contaminants added to the drinking water sample.

(a) (b) (c) (d)

Figure 11: Microplastic samples used in the experimental setup. (a) $500\,\mu m < 1000\,\mu m$, (b) $1000\,\mu m < 1500\,\mu m$, (c) $1500\,\mu m < 2000\,\mu m$, and (d) $2000\,\mu m < 4000\,\mu m$.

Figure 12: Organic, inert organic, and inorganic material samples used in the experimental setup.



(a) (b)

Figure 13: Impedance values represented in two types of diagrams: (a) Nyquist and (b) Bode.

After unfolding, all data is normalized using group scaling, as mentioned in Section 3.

4.3. Classification Results. The methodology was validated using three classifiers to compare their performance in two scenarios. The first scenario involved testing water and water with microplastics of various sizes to determine if they could be identified in different classes. The second scenario involved testing water, water with microplastics of different sizes, water with microplastics, and a mixture of living organisms and inert organic and inorganic matter with microplastic particles of various sizes. These simulated environmental conditions are similar to those found in reservoirs that could contain microplastics. The aim was to verify if the

Table 2: Material in the detector working electrode for each SPE sensor used in the electronic tongue.

SPE sensor	Working electrode
1	Gold
2	Platinum
3	Graphite
4	Silver
5	Gold-platinum alloy
6	Gold
7	Gold
8	Platinum

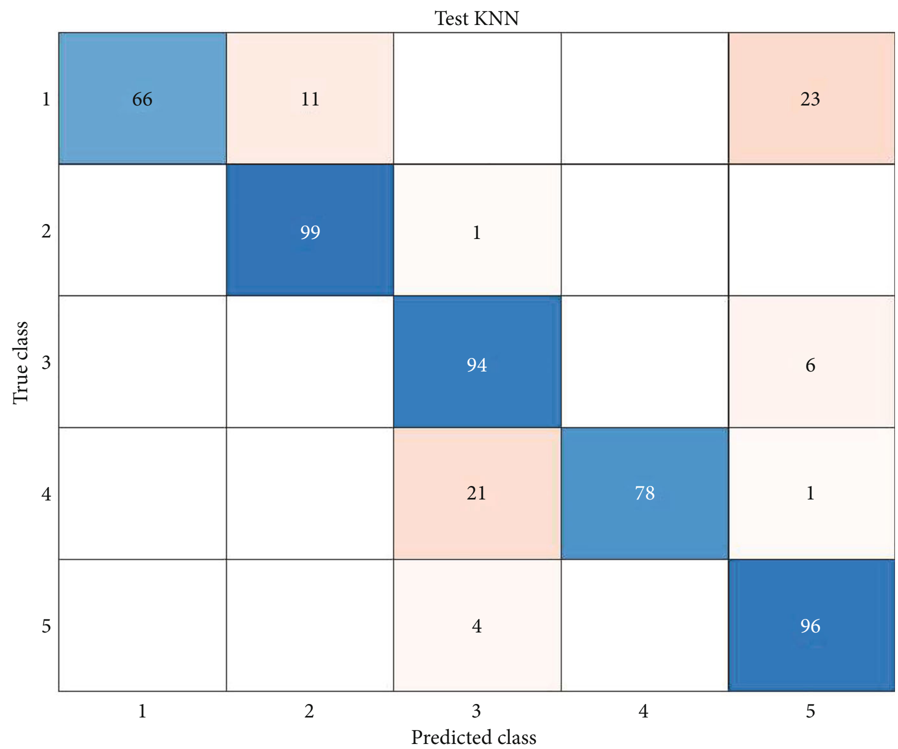


FIGURE 14: Confusion matrix obtained by using K-NN as classifier.

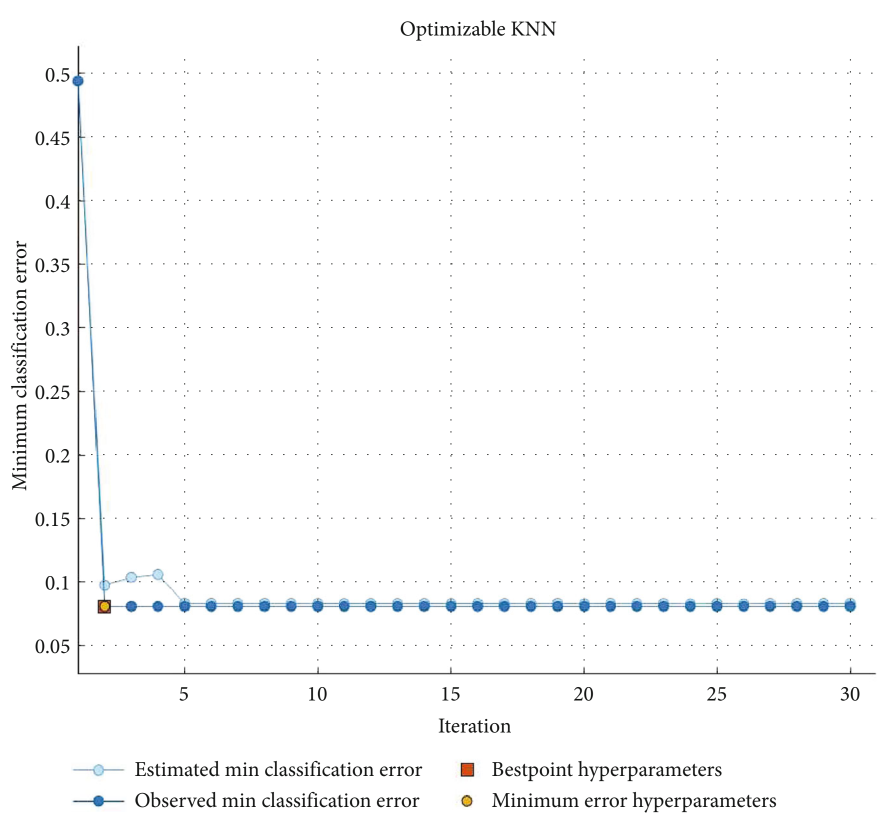


FIGURE 15: Iteration number vs. the classification error for the training step using K-NN.

Table 3: Accuracy comparison for the three algorithms used for the classification of microplastics.

Algorithm	Accuracy	Iteration
SVM	81.2%	18
K-NN	86.6%	4
Decision trees	82.4%	20

Table 4: Materials used to pollute the water in addition to the microplastics.

Used material	Composition	Amount
Living organic material	Salmon eggs	1.4 g
Inert organic material	Earth, rice hulls, and ground wood	1.4 g
Inorganic material	River substrate and yellow sand	1.4 g

electronic tongue system could detect and classify them in a range of sizes.

4.3.1. Water and Water with Microplastics. Figure 14 shows the results in the confusion matrix obtained by K-NN when it is used as a classifier. This type of plot allows a review of the performance of a machine learning model by comparing the predicted values with the actual values in a classification process. The matrix consists of four quadrants: true positives, false positives, true negatives, and false negatives. True positives are the cases where the model correctly predicts positive outcomes, while false positives are the cases where the model predicts a positive outcome but the actual outcome is negative. True negatives are the cases where the model correctly predicts the negative outcomes, while false negatives are the cases where the model predicts a negative outcome but the actual outcome is positive. The best result is expected when all the data is classified along the main diagonal. It means that, from this process, an accuracy of 100% is obtained because all the data is properly associated with a class in the machine.

In Figure 14, the first class represents data from the water without any addition of microplastics, and classes two to five correspond to the four microplastic sizes added to the water, as shown in Figure 11. The accuracy obtained by the methodology using this machine is 86.6%. Accuracy in a classifier refers to how often the classifier correctly predicts the correct class or label for a given input. It is usually calculated as the number of correct predictions divided by the total number of predictions made by the classifier. A high accuracy score indicates that the classifier is performing well and making accurate predictions, while a low accuracy score suggests that the classifier needs improvement.

Figure 15 shows the iteration number vs. the classification error for the training step. Different kernels were used to avoid overfitting, and parameters such as the kernel scale and box constraint level in the same iteration cycle were reviewed using MATLAB's classification learner toolbox. This figure shows the result obtained in terms of the errors and iterations during the training process.

Table 3 summarizes the results obtained by the methodology with the three classifiers for the identification of water and water with different sizes of microplastics. According to these results, the best classification is obtained by the K-NN classifier with 86.6% accuracy. The methodology with this classifier achieves this result in a small number of iterations compared with SVM and decision trees. This result is important because K-NN allows us to obtain good results with a small number of iterations, resulting in a lower computational cost.

4.3.2. Microplastic Identification in Different Conditions. To test the methodology under conditions that closely resemble natural environments where water can be found, samples of water were mixed with various materials (see Figure 12) in equal concentrations to determine if the methodology would be able to detect the microplastic and, if so, in which environments. As in the previous classification process, SVM, K-NN, and decision trees were evaluated to determine which classifier allows to obtain better results in classification accuracy. To evaluate its performance, living organic material (composed of salmon eggs), inert organic material (composed of soil, rice hulls, and ground wood), and inorganic material (a mixture of river substrate and yellow sand) were used in a volume of water of ≈420 cm^3 of water. The proportion of the samples was 1.4 g per kind of material, and Table 4 shows the types of material used to pollute the water.

Microplastic particles of different sizes were added to a part of the mixture to see if the system could detect the presence of these particles. The comparison was also made with the different microplastic samples and validated to determine if they could be classified. Figure 16 shows the confusion matrix with the results obtained using SVM. The first class corresponds to polluted water according to Table 4, but without microplastic. The second to fifth classes correspond to water with the different sizes of microplastic as mentioned in Table 1. The last class corresponds to water with the elements described in Table 4 and microplastics. Results show that an accuracy of 81.2% was achieved using SVM. Similarly, the methodology with K-NN was applied, and the confusion matrix in Figure 17 was obtained. In this case, the accuracy achieved was 89.2%, improving the results with SVM and maintaining better results than in the experiments with water and only water and microplastics.

Finally, decision trees were used in the methodology. Figure 18 shows the results obtained by the confusion matrix.

In this case, the accuracy achieved was 86.0% which is less than K-NN. According to the results, the K-NN algorithm had an accuracy of 89.2% which is the best result in both scenarios. This means that the methodology with this algorithm can accurately distinguish between water with and without microplastics and water containing various added elements.

The results of the use of these classifiers are summarized in Table 5. From the results, it is also possible to determine that all the algorithms have some difficulties when classifying some

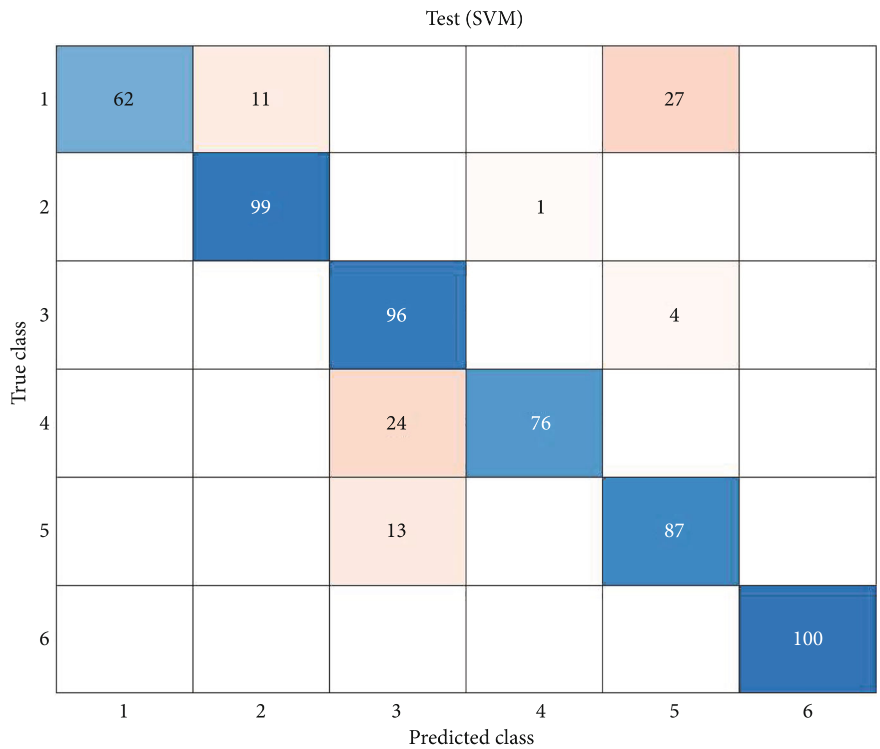


Figure 16: Confusion matrix for microplastic detection under different water scenarios when SVM is used as classifier.

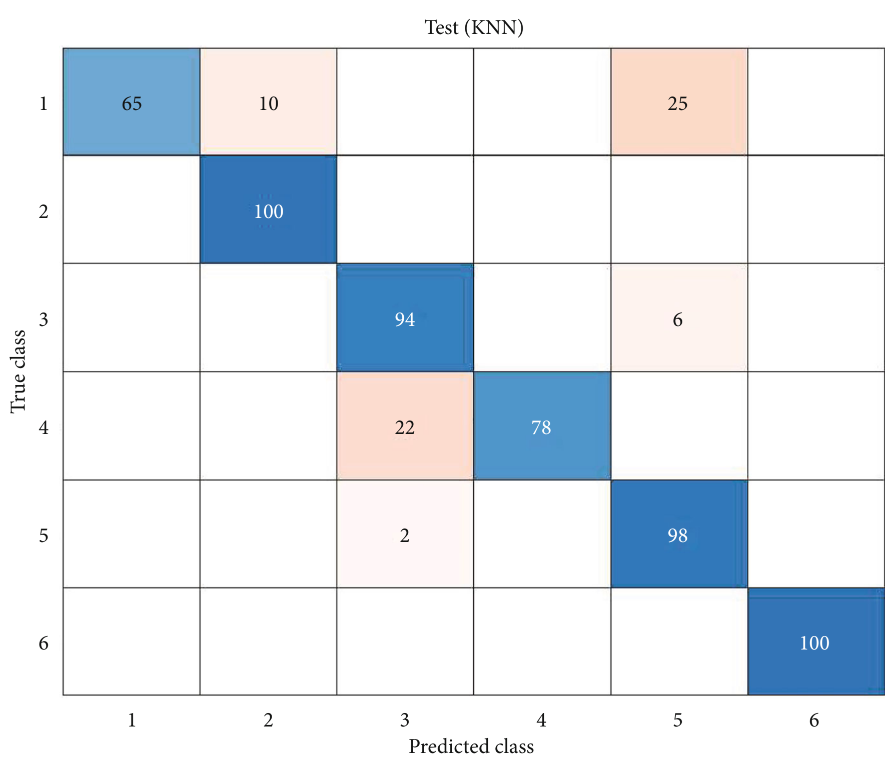


Figure 17: Confusion matrix for microplastic detection under different water scenarios when K-NN is used as classifier.

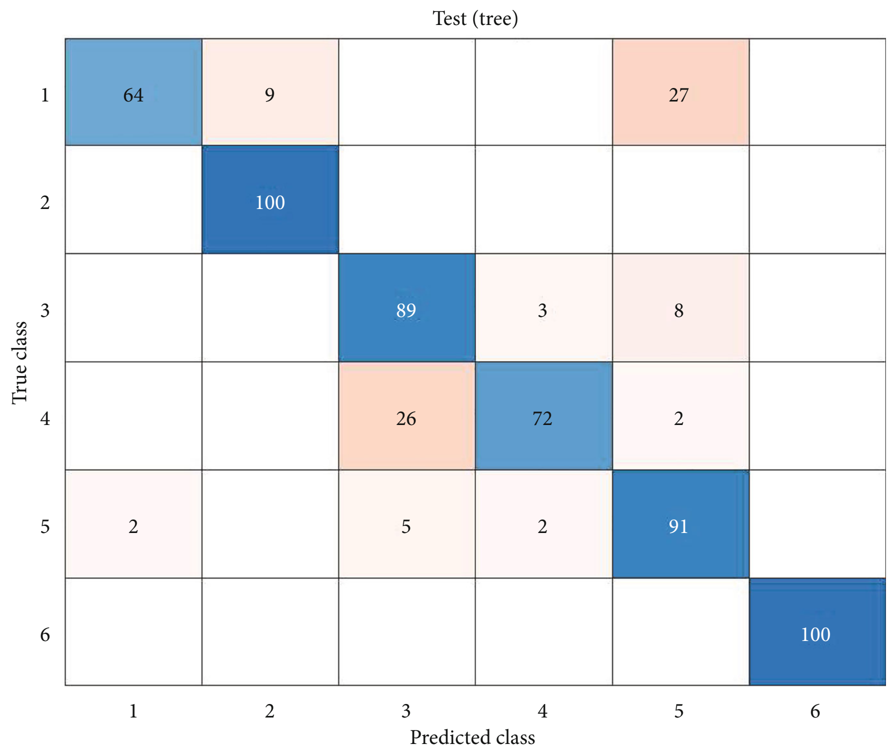


Figure 18: Confusion matrix for microplastic detection under different water scenarios when decision tree is used as classifier.

Table 5: Comparison of the algorithms in terms of accuracy and iterations.

Algorithm	Accuracy	Iteration
SVM	86.7%	26
K-NN	89.2%	15
Decision trees	86.0%	8

sizes of microplastic particles. This is because of the way sensors are distributed in the experiment and the interaction with the different materials. In this sense, it is necessary to evaluate the option of using new sensors or methods to ensure the contact of the sensors with the microplastics.

5. Conclusions

This work presented the results of developing a system for detecting and classifying microplastics in water samples. The approach combines SPE sensors, impedance analysis, and pattern recognition strategies with excellent results. Two scenarios were used to validate the methodology, showing that microplastics can be found in all the scenarios. This methodology was evaluated only with PET as a microplastic at different sizes. However, it is expected that it cannot change with other kinds of microplastics because it was possible to classify other elements in the water samples. Of course, this validation requires more experiments and evaluation to determine differences with the data used in this work.

In general, K-NN presented better results in the classification process. Although the number of iterations was higher than that of decision trees in the second scenario, this is not a big change in the number of iterations. It is important to migrate the methodology in the future to an embedded system because of the time-consuming and computational resource consumption.

Laboratory conditions, including organic and inorganic materials, have allowed for a more accurate emulation of natural conditions and a better understanding of the water in natural environments. These elements provided new classes in the machines, showing the differences in data from the water and the water with microplastics. Interestingly, the microplastics' size significantly impacts the results and how the sensors interact with the water for detection. Although the sensors are better equipped to detect a larger quantity of microplastics, the methodology's true significance lies in identifying microplastics in water regardless of their quality for human consumption.

Since this work does not focus on measuring phenomena related to oxidation-reduction (redox) processes, a stimulus V_{DC} that could cause this phenomenon was not applied. Hence, open-circuit measurements were not carried out to determine the potential E^o in the solution used. However, the degradation of the working electrodes in the sensor network due to the long-term accumulation of ions poses a risk. Therefore, future work will propose implementing algorithms that monitor the stability of the sensors to address this issue.

Although the methodology presented has not been tested on another type of microplastic, it could work if the microparticles pass sufficiently close to the sensor, so one of the limitations is given by the size of the effective area of the sensors as well as the density and volume provided by the microparticles that are intended to be detected. It is also important to clarify that more studies are needed to validate whether the proposed methodology manages to classify different types and sizes of microplastic. Multiclassification should be explored to allow the possibility of simultaneously detecting different types and sizes in a sample of water.

Abbreviations

PCA: Principal component analysis
SVM: Support vector machines
K-NN: K-nearest neighbor.

Data Availability

Data is available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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