Detection of Microplastics in Water Using Electrical Impedance Measurements and Support Vector Machine

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***Abstract*—We propose an approach based on electrochemical impedance spectroscopy (EIS) combined with machine learning for detecting and identifying microplastics in water. The method relies on measuring the complex electrical impedance of water samples over a range of frequencies, capturing both the real and imaginary components of the signal. These impedance responses are represented using Nyquist plots, from which relevant features such as resistance values, peak characteristics, and frequency-dependent behaviour are derived. The classification is carried out in two stages. In first stage, model determines the presence of microplastic in the sample. In second stage, the model detects the type of plastic. EIS signals are processed and transformed into different features, which is used to train support vector machine and XGBoost for identification. The proposed achieves a high accuracy, under controlled condition it shows 95% and in dynamics scenarios it shows 85%-89% and also provides a real-time visualization through a dashboard which makes easier for real time monitoring.**

***Index Terms*—Electrical Impedance Spectroscopy, Support Vector Machine, Fourier Transform Infrared Spectroscopy, Receiver Operating Characteristic Curve**

I. INTRODUCTION

Microplastic pollution becoming a major concern to the environment. It happens by throwing plastics things in our surrounding. Over a certain time, plastics starts breaking down into small pieces and settles down in our environment.[9] These harms human health and ecosystem also. The problem is that microplastics are hard to find because they have chemical structures. Old ways to detect microplastics like Fourier Transform Infrared spectroscopy, are accurate. Need special equipment and a lab, which is expensive and takes a long time. These old ways are not good for real-time monitoring [8]. Detecting microplastics requires collecting, purifying and testing of water samples in lab. This process is a time-consuming, slower and easy to make mistakes. Sometimes this approach may provide inaccurate values. So, there is a need for a fast and automated way to detect microplastics.[7]

Electrochemical sensing is a popular technique to detect microplastics which is simple and can be made small. It calculates the frequencies and finds the properties of the pollutants which lies in that range. But the data from this method is complex and hard to understand.[10] Machine learning improved the detection of microplastics. It uses models like Support Vector Machines to find patterns in datasets. These models easily find the difference between types of plastics like polypropylene and polyolefin. This approach is faster, and provide immediate results.[4][5]

The practical usage of this approach is complex because there is no standard dataset. To address we suggest a way that combines electrical impedance spectroscopy with machine learning. This approach is cheap fast and can be used to detect and analyze microplastics.[1][2][15]

II. RELATED WORKS

Valentin Meiler et al. [1] suggest using impedance spectroscopy and Support Vector Machines to detect microplastics in water. This classifies microplastics with accuracy of 98% for static measurement and 85% fluidity but it has problems with identifying different materials that have similar properties. It also needs laboratory datasets and real water samples. Juan Daniel Sarmiento et al. [2] made a system that uses a tongue with many electrochemical sensors to detect microplastics in water. The system uses impedance spectroscopy and analyzed the presence of microplastics using principal component. This system didn't detection of microplastic contamination.

Almeenu Rasheed and Sovik Das [3] uses electrochemical impedance spectroscopy to detect microplastics in cost effective way. This study used calibration curve to predict the concentration of microplastics. It is efficient but needed a controlled laboratory conditions and difficult to apply environmental samples. Paula V. Morais et al. [4] implemented a Convolutional Neural Network to detect the type of microplastics. The model achieved high accuracy rate and worked efficiently. It needs a big dataset and can have problems with particles that overlap in complex environments. Diogo Gomes et al. [5] uses electrical impedance spectroscopy to detect microplastics, polyvinyl chloride and polyethylene. The model measures impedance and can differentiate between plastic types and concentrations with high accuracy and error rate below 3%. The model struggled to handle complex mixtures and other plastics. Luca Bifano et al. [6] proposed a technique to detect and classify microplastics by integrating impedance spectroscopy and Support Vector Machine. The system detects the microplastic and their concentrations by measuring the impedance. The model required controlled laboratory conditions and struggled to handle real-world samples. Diogo Gomes, et al. [7] develops an approach to estimate microplastics in water using electrical impedance spectroscopy. The model integrates impedance measurement techniques and Support Vector Machines to classify microplastics types. It is quick and accurate. It has problems with factors, like particle size, pH and conductivity of water.

Periyasamy, A. P et al. [8] uses machine learning and deep learning to detect and classify the microplastics. It uses K-means clustering and convolutional neural network for identifying microplastics in water and textiles. Key limitation of this model is sensor technology and data management. Brian R. Coleman [10] developed a machine learning model to predict microplastics in soil, water and sediments. This model uses machine learning and Raman infrared spectroscopy to identify the microplastics. This approach achieved high accuracy but it requires a large data for training. Xiao–Le Han, et al. [16] developed a system which uses deep learning for microplastic identification based on visual data. The model uses neural networks to classify particles. This model requires a large dataset for training and lacks to differentiate the particles which have similar features.

III. METHODOLOGY

The proposed method uses a two-stage classification method. It starts with collecting and preprocessing of electrochemical signals, then dimension reduction to note the key feature. Machine learning model processes the data then detects and classify microplastic effectively.

3.1 About Dataset:

The dataset consists 15,000 samples of different range frequencies from 20Hz to 2MHz. The dataset helps to understand the dielectric and resistive properties of microplastics and consist different types of plastics like polyethylene, polypropylene and polyvinyl chloride. The dataset has features like temperature, conductivity and salinity. We measured impedance in both dynamic modes, which allowed to record how impedance changes under different conditions. It also contains noise and signal drift ensures that model is stable under complex, real-world environments.

3.2 Problem Definition

A. The objective is structured as a two-stage classification task:

1. Binary Classification: Detects whether a sample contains microplastic
2. Multiclass Classification: Identification of plastic category such as Polyolefin (PE, PP), Aromatic (PET, PVC, PS), Synthetic (Nylon, Mixed), and Bio

B. Data Preprocessing and Feature Engineering:

1. Signal Conditioning

The data contains interference and noise. So, we cleaned the data and handled the missing values.

2. Feature Scaling

For stabilizing the data feature scaling is used. By Standard Scaler normalization the features have mean value zero and variance value one, which improves the accuracy.

$$X_{scaled} = (X - \mu)/\sigma \qquad (1)$$

Equation (1) where μ represents the feature mean, σ denotes the standard deviation and X_{scaled} is the transformed feature.

3. Feature Extraction

The complex impedance is represented as

$$Z(f) = Z`(f) - jZ``(f) \qquad (2)$$

From equation (2) uses features like real impedance Z` and imaginary impedance Z`` at different frequencies, phase angle variations ϕ, phase shift variance, and environmental parameters. These features note the electrochemical properties of microplastics.

C. Dimensionality Reduction

For dimension reduction principal component analysis is used for application selection. PCA is used to reduce features and the risk of dimensionality for support vector machine. This ensures minimal loss of information and variance. For the XGBoost PCA is not used. XGBoost is a tree-based, performs internal feature selection and effective at handling raw, non-linear feature spaces. It maintains the original feature space and preserves the physical interpretability of specific frequency responses.

IV. MACHINE LEARNING FRAMEWORK

A. The system follows a two-stage architecture:

1. Stage 1: Binary Classification (SVM)

This stage uses a support vector machine with a radial basis function kernel to establish a non-linear decision boundary for plastic detection. The RBF kernel is formulated as:

$$K(x_i, x_j) = \exp(-\Upsilon \|x_i - x_j\|^2) \qquad (3)$$

The synthetic minority oversampling technique (SMOTE) is implemented during the training phase; it addresses the imbalance between plastic and organic samples.

2. Stage 2: Multiclass Identification (XGBoost)

In stage 1, the model identifies samples has plastic or not. The samples, which were identified as plastic, passed to the XGBoost classifier. We chose XGBoost algorithm as it shows high accuracy and prevention of overfitting. A specific equation is used to assess the risk with prediction. Any values fall below confidence threshold are re-evaluated and this ensures the system to remains stable under challenging environmental conditions.

$$\text{Confidence} = |f(x)| \qquad (4)$$

B. Confidence Calibration and Risk Assessment

The equation (4) is used for risk prediction; low-confidence samples mean manual verification or remeasurement. This ensures the system's readiness in critical environmental conditions.

C. Evaluation Metrics and Visualization

The model performance is validated using a structured split of 80:20 with k-fold cross validation. The visualization metrics is Nyquist Plots shows the relationship between imaginary and real impedance values and helps to analyze the electrical properties of the water sample.

D. Experimental Result

The experimental results evaluate the performance of two-stage hybrid framework for microplastic detection and classification by using enhanced dataset.

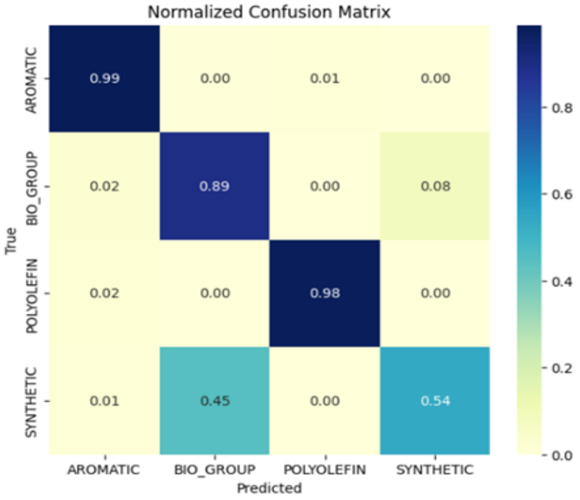

Figure 1

The figure 1 is confusion matrix contains four plastic types - aromatic, biodegradable, polyolefin, and synthetic, to visualize the classification performance by the multiclass models. The model performed well and achieved high accuracy. For Aromatic class and Polyolefin class the accuracy is 99% and 98%. But biodegradable class showed 89% of accuracy and 8% of misclassification and Synthetic class showed 54%.

The reason for misclassification is due both biodegradable materials and synthetic polymers show a similar electrochemical impedance property. This makes the classification process complex.

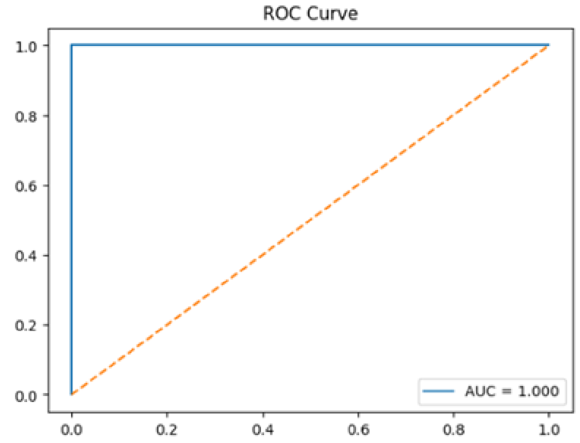

Figure 2

The figure 2 is ROC curve shows binary classification of (plastic vs non-plastic). The model calculates the AUC near 1.0, which is the perfect values for separating plastic and non-plastic samples. The curve lies in the top-left corner, which indicates a high true positive rate and a minimum false positive rate. This clearly proposes that the model is highly effective and reliable in detecting plastic. Such a near-perfect function clearly suggests that binary classification is less complicated than multiclass classification because of better separation within the plastic and biodegradable materials.

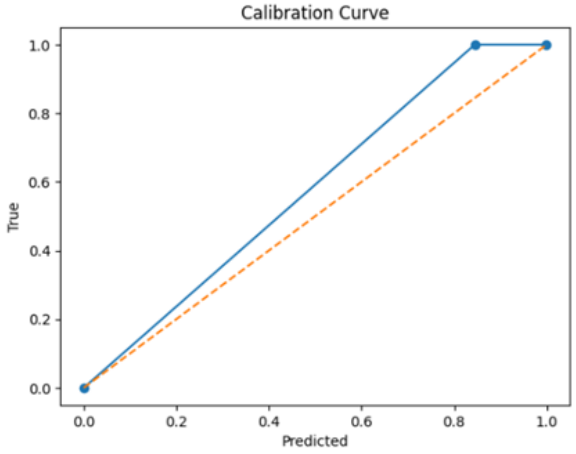

Figure 3

The figure 3 is calibration curve is used to evaluate the predicted probability against the actual outcome. The model shows an almost errorless integration, as the calibration curve closely tracks the diagonal reference line. The curve represents the predicted probabilities are valid and reliable. For example, if a model predicts 80%, then the confidence would closely align with around 80%.

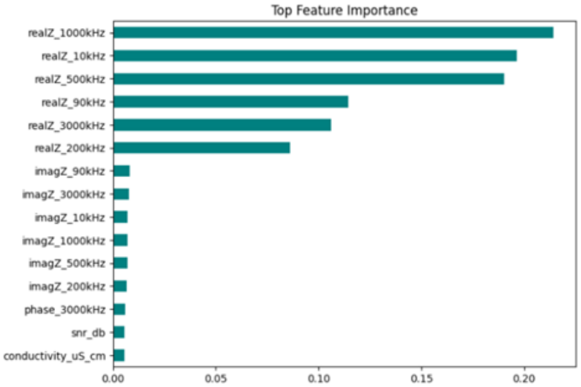

Figure 4

The figure 4 shows feature analysis used to identify the electrochemical parameters to predict accuracy. The results show a controlled real impedance value. At Low and high frequencies, the model captures the physical factors effectively. The imaginary impedance value helps in the model's refinement and compares the frequency-dependent resistance. This analysis confirms that real impedance value classifies the microplastics accurately.

V. CONCLUSION

From this we understand how detection of microplastics in water using Electrical Impedance Spectroscopy (EIS) with machine learning. Traditional signal processing method detects the presence of microplastics, but they are not accurate in identifying different plastic types. This becomes a problem when the concentration is low and the measurements are a bit noisy. This model uses machine learning approach which works well for detecting microplastics and also for classifying different plastic types. In controlled conditions, the accuracy was high, and even when the conditions were dynamic, the performance remained fairly stable. We also noticed that the system gives a rough estimate of the amount of the amount of microplastics present, though it is not always exact.

At the same time, there are some limitations in the current work. The model is trained only on a limited number of plastics types, and real-world water samples are usually more complicated than this. It contains impurities, mixed plastics and changing environmental conditions, which affects the result. So clearly, more testing with real data is needed.

For future enhancement, addition of extra plastics types and some improvement in stability of the model. This approach is simple and cost-effective for detecting microplastics. With some improvements, which is more useful for monitoring in real-time scenario.

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