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ORIGINAL RESEARCH ARTICLE

Laser-induced breakdown spectroscopy with neural network approach for plastic identification and classification in waste management

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ABSTRACT

The threats to the environment and humans are increasing every day due to the use of modern plastics and their improper disposal approaches. Researchers pay more attention to reducing plastic waste through recycling so that it can be used as a raw material. In the recycling chain, grading or identifying different types of plastic is essential. For this, Lase Induced Breakdown Spectroscopy (LIBS) has been established. LIBS is an effective investigation tool that analyzes plastics in a qualitative and quantitative manner. Spectral analysis of different kinds of plastics is performed from the plasma emission obtained from LIBS. In this research work different types of plastic samples are identified using LIBS and classified using back propagation neural network algorithm (BPNN). The research aimed to attain a simple application to detect plastic polymers compared to existing approaches. To validate the better results proposed model performances are compared with existing kNN, SIMCA and ANN based classification models.

Keywords: Laser-induced breakdown spectroscopy (LIBS); plastic classification; Neural network; waste management

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1. Introduction

Plastics are strong, lightweight, corrosion resistant, durable and inexpensive. Plastics are unavoidable in the present era and are used from simple disposable items to large applications. Plastics are involved in daily life as a communication device, footwear, clothing, packing material for food and drinks, etc. For all the above, a large amount of plastic needs to be produced every day. A statistics reports that global plastic production increased from 100 to 367 million metric tons from 1989 to 2019. Among these, 57.9 million metric tons of plastic are produced in Europe and China is the top plastic producer in the world[1]. The performance of virgin plastic polymers increases when they are added with various additives such as silica, carbon, plasticizers, colorings, and flame retardants. Due to the additive components, the properties of plastics are changed. However, it is not sure that all the additive components are nontoxic. A few components, like tributyl tin and lead, are toxic and they produce adverse effects on human and animal populations. The major issue is identifying the additive component quantities and types. Specifically, identify additives like phthalates, BPA, plasticizers, anti-microbial agents, and brominated flame retardants. Since most medical devices, cosmetics, perfumes, computer devices, flooring materials, and food packing materials use phthalates and BPA additive plastics. The weight of PVC increases while using phthalates. Similarly, polycarbonate plastics are made using BPA. These two additive components, including plastic, are unavoidable and pollute the environment as well as humans and animals.

Though plastic provides numerous benefits, the problem associated with plastics is its waste management. The dependence on plastic production resources, the effects of diverse additive components and high plastic utilization introduce various waste management issues. Plastic waste is not only accumulating in industries, it is starting even in households. The major source of household plastic waste is from packaging, different household applications, equipment and vehicles. However, the capacity of waste disposal by landfill also produces adverse effects. Among the total weight of waste collected by local municipalities, ten percent was occupied by plastics and it is increasing gradually. Not only the land, discarded or unused plastic waste contaminates marine and freshwater habitats. Similar to landfills, the accumulated plastic waste quantity in marine is distinctively high. Plastics floating in water are collected water and stored in the marine beds. The plastics escaped from the marine beds accumulate on the shores and cause serious issues in the shore region.

Instead of being unused, the plastic waste is collected for recycling so that the raw material requirement for plastic manufacturing can be reduced. However, it requires an effective identification and classification procedure so that it can be recycled in a large manner. Various techniques are used to identify the plastics, including manual sorting, Inductively Coupled Plasma (ICP)[2], Near Infrared[3], Atomic absorption spectroscopy (AAS)[4], X-ray fluorescence spectrometry[5], and Raman spectroscopy[6]. **Table 1** depicts the summary of available techniques with its remarks. Thank you for the valuable feedback.

Table 1. Techniques available for identification of plastic types.

S. No	Technique	Process	Remarks
1	Manual sorting	Classification based on physical properties	Time consuming, high cost, chances of manual errors are high.
2	Inductively Coupled Plasma	Analyze the liquid samples. Process includes atomization, excitation and ionization	Time consuming due to sample dissolution preparation
3	Raman spectroscopy	Spectroscopic method detects molecule bands	Weak spectrum for analyzing the plastics
4	Near infrared	Widely used spectroscopic method	Not suitable for opaque or colored plastics
5	X ray fluorescence spectrometry	Spectroscopic method detects atoms for plastic identification	Able to identify only chlorine atoms from polyvinyl chloride
6	Atomic absorption spectroscopy	High sensitivity spectroscopic method	Time consuming since the process needs the material to be dissolved in solvents

The above-mentioned techniques have their own disadvantages, so it is essential to obtain a more efficient and faster approach to detecting plastic types so that they can be recycled to produce high quality products. Recently, the use of Lase Induced Breakdown spectroscopy (LIBS) has gained more attention for plastic analysis. The major advantage of LIBS is the laboratory module and it is a nondestructive approach which doesn't require any additional processes. LIBS introduced major changes in analytical chemistry. LIBS include a spectrometer to detect the element specific lines which are emitted due to the plasma decay process. The collected signals are analyzed by observing the intensity and position in the identification process. Different chemical components in the material can be identified by focusing the high-power laser beam and then recorded as a spectrum for material identification. Another advantage of using LIBS is its ability to analyze solid samples with no extra preparation. The simple procedure is highly efficient and minimally invasive. LIBS has been widely used in the metallurgy industry, Raw Materials Quality Monitoring[7], Crime Scene investigation[8], Investigation of electrical, thermal, and mechanical properties of nanocomposites[9], Investigation of Surface Condition[10], Medical applications[11,12], Classification of Aged Epoxy Micro–Nanocomposites[13] and other environmental monitoring applications[14].

Machine learning techniques are widely used in various domains, such as medical image processing, wireless sensor networks, signal processing, etc., due to their numerous advantages. Incorporating machine learning into plastic classification supports waste management so that automated identification and classification models can be obtained. In this research work, a machine learning approach is combined with LIBS for identifying different plastics and classifying them accordingly. The major contribution of this research work is summarized as follows.

- Presented a Lase Induced Breakdown spectroscopy (LIBS) model for plastic polymer identification.
- Presented a back propagation neural network model to classify different types of plastic polymers.
- An intense experimental analysis is presented to demonstrate the performance of the combined approach.

The remaining portion of the article is framed as follows. A short literature analysis is presented in section 2 to discuss the existing methodologies. The proposed Plastic polymer identification and classification process is presented in section 3. Experimental procedure and performance are presented in section 4. The observations are finally concluded in section 5. Thank you for the valuable feedback.

2. Related works

Laser induced breakdown spectroscopy (LIBS) is utilized in various research work to identify different material types. A few recent research works are considered for analysis in this section to describe how LIBS is efficient. Identification of ten different plastic types used in LIBS is reported by Junjuri et al.[15] performs correlation analysis and ratio metric analysis to differentiate plastics. The correction approach utilizes intense carbon, oxygen, nitrogen, and hydrogen lines and performs least discriminant analysis for further classification. The presented research work attains 93% classification accuracy, though it can be improved further using machine learning approaches.

Identification of plastic polymers from electrical and electronic equipment wastes through LIBS is reported by Costa et al.[16]. The residues on printed circuit boards and polymers are identified by incorporating chemometric tools. The collected data is manipulated using data mining techniques to identify polymers in electronic waste. The importance of chemometric models combined with LIBS is detailed by Wang et al.[17] by a demonstration of identifying different plastic samples. Familiar methods such as artificial neural network, k-nearest neighbor, linear discriminant analysis, support vector machine and a few other models are incorporated into the research work to identify plastic types. The analysis reports that neural network and discriminant analysis models outperform other models. However, the performance of the above outperformed techniques can be increased by fine tuning the preprocessing methods.

The LIBS based industrial polymer identification process reported by Tang et al.[18] includes unsupervised learning algorithms for classification purposes. K-means and self-organizing maps are incorporated to classify the polymers. The self-organizing map neural networks are used to separate twenty types of polymers by adjusting the spectral weights. Later, k-means are used to cluster the polystyrene and polycarbonate materials. The acquired classification accuracy is high compared to other polymer classification techniques. Identifying synthetic polymers using LIBS reported by Brunnbauer et al.[19] incorporates principal component analysis and k-means clustering to classify polylactic acid (PLA), polyvinylchloride (PVC), polyethylene (PE), acrylonitrile butadiene styrene (ABS) and polyacrylate (PAK). The presented approach supports direct analysis and it can be used to analyze two-dimensional structured polymers.

Other than plastic type identification, LIBS is widely used to identify different materials. Identifying the copper content in the water is processed using LIBS[20] eliminates the issues in conventional liquid sample analysis. The solid phase copper ions in the water and the parameters that reduce the extraction and detection performance are optimized before proceeding into the identification process. This greatly improves the accuracy and identifies copper contaminants from various samples. Low cost and simple execution are the merits of the research model. Research work[21] addresses the features of LIBS in cement type identification. Ten different cement types are considered for analysis. The diode pumped low energy laser is combined with spectrometers to cover the NIR and UV spectral range. The obtained minimum spectral features are used for classification that is performed using linear discriminant analysis. The accuracy depends on the moisture content in the sample, which is considered as the limitation of the research model.

Identifying heavy metals in microplastics using LIBS is presented by Chen et al.[22] eliminates the requirement for bulk samples which are required in conventional identification techniques. The presented LIBS approach identifies the metals from samples of different shapes and sizes without any pretreatment. The interference in the spectra is reduced by using a thin polyethylene substrate, which increases the identification performance. Examination of Polish banknotes using micro X-ray fluorescence and LIBS approach is presented by Król et al.[23] identifies the characteristic atomic emissions from several elements. Black serial numbers and micro letters are identified using the presented approach. An identification model reported by Malenfant et al.[24] includes LIBS to detect bacterial cells from contaminants based on size. The filter used in the filtration device is exposed to the LIBS process to capture the bacterial deposition and its size. The laboratory procedure is simple and provides accurate results for microbiologists.

The LIBS model reported by Wang et al.[25] combines semi-supervised learning algorithms for explosive identification and classification. The clusters differentiate explosives and improve the accuracy of the classification algorithm. The K-nearest neighbor algorithm used in the research model requires minimum prior information and reduces the data labeling time. Better robustness and reliability are the merits of the presented approach. Other than the above applications, LIBS is used in the medical domain, such as cancer cell classification[26]. The slow, cumbersome sample preparation and imprecision in cancel cell detection can be overcome by the LIBS approach. Other than malignant and non-malignant, the proteins in the abnormal cells are also identified in the research model in an accurate manner. The presence of lead, mercury, and chromium in colon cancer patients is identified so that the patients can acquire early medications. LIBS is used to estimate the nutrient elements in the seed kernels of cucurbits[27]. The presence of magnesium, calcium, sodium, and potassium are identified and processed using principal component analysis for data categorization.

The chemical nature of root soil interactions is analyzed using LIBS[28] to facilitate the next generation of agriculture systems. Organic and inorganic constituents in the root soil are exposed to laser induced breakdown spectroscopy to obtain spatial coordinates for micro and macro nutrients and other matrix elements. The presented approach differentiates the miners and fragments the root and rhizosphere regions. Similarly, LIBS is used for graphite identification from heterogeneous wastes[29] and uranium identification to analyze hydride corrosion. The detection model considers the atomic emission signals of carbon, uranium, oxygen and hydrogen and analyzes their concentration level. From the above survey, it is observed that the performance of the LIBS process is increased using clustering based on machine learning based approaches. K-means clustering is widely used in few research works, but the accuracy of such models is less compared to machine learning technique based classification approaches. kNN, linear discriminant analysis, and principle component analysis are used in a few researches works. Though it provides better results, it is essential to minimize the computation time and increase the classification accuracy. Based on the findings, this research work presents a LIBS approach for identifying different plastic types and classify the plastic polymers using back propagation neural network. Thank you for the valuable feedback.

3. Proposed work

The proposed plastic polymer identification utilizes laser induced breakdown spectroscopy (LIBS). It is a kind of atomic emission spectroscopy that uses a highly focused energetic laser pulse. The pulse converts the sample into plasma, which occurs due to the emission of atoms and ions. The emission lines are captured by a spectrometer so that they can be processed further to detect the material. LIBS is portable and efficient for material analysis. It can be used to detect organic and inorganic components. **Figure 1** depicts the LIBS setup used in the proposed work.

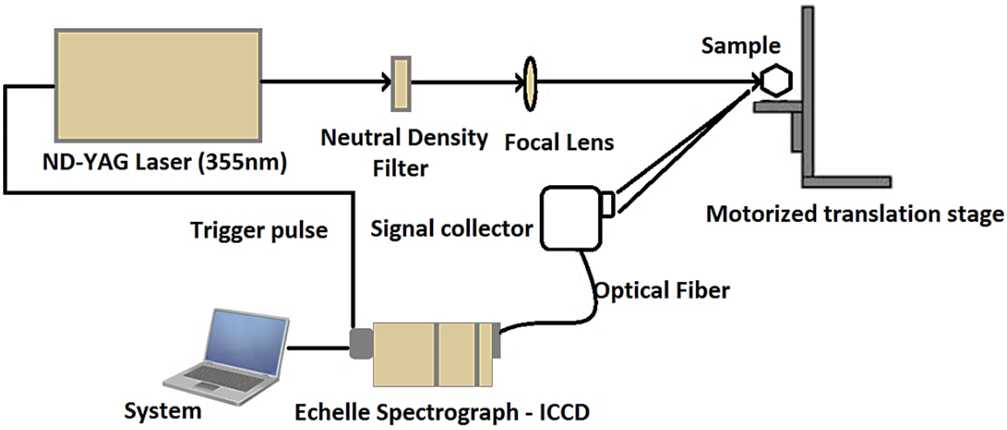


Figure 1. LIBS set up for plastic identification.

The setup depicted above includes a Nd:YAG laser, Neural density filter, focal lens, Echelle spectrometer. Intensifier charge coupled device and other optomechanical components. The specifications of all the devices are listed in **Table 2**. By single-pulse LIBS, atoms are ablated and excited by a single laser pulse. To increase peak intensities without further damaging the sample, double-pulse LIBS uses a second laser pulse that is either perpendicular to or colinear with the first. Portable LIBS analyzers ablating a sample's surface with a focussed laser. When atoms and ions are electrically accelerated, they produce a plasma. As these atoms decay back into their ground states, they have specific wavelengths of light, or "unique fingerprints". LIBS, or laser-induced breakdown spectroscopy, is a very effective analytical method for detecting and characterizing materials. Focusing a powerful laser pulse onto the exterior of something solid or liquid or into the sample volume of a gas or cloud of aerosolized particles is all it takes to conduct LIBS. A laser-plasma is created on or inside the sample during a LIBS measurement, and the resulting light is collected and analyzed spectrally.

Table 2. LIBS specification.

S. No	Device	Specification
1	Nd:YAG laser	Quanta-Ray PRO-230-10
2	Echelle spectrometer	Mechelle, ME5000
3	Intensifier Charge Coupled Device	iStar, DH734-18U-03PS150
4	System	Inter i3, 8GB RAM, 2TB memory

The system specified above is used to process the collected signals. A Neural network algorithm is processed in the system to classify the plastics. The laser in the Nd:Yag produces 355 nm emissions with a pulse duration of 6 ns. The specified pulse duration is mainly used to control the laser energy. A focal lens is used in the setup, which is a biconvex lens and its focal length is 20 cm. The lens is used to obtain the necessary breakdown threshold irradiance for the samples which are used in the testing process. ultraviolet quartz lenses are used in the setup to collect the plasma emissions. Fiber coupling is used to image the collected emissions as a spectrograph. The spectrograph in the setup is an echelle spectrograph which has a focal length of 195 mm so that it covers the wavelength of 200–975 nm. The spectral resolution is 0.05 nm for a slit width of 10 mm. In order to collect the dispersed signal, a thermoelectric cooled Intensifier Charge Coupled Device (ICCD) is used. Similarly, to obtain maximum SNR, a gated detector is used in the setup. The delay between plasma formation and the switch on the ICCD is termed as gate delay. The time taken by the camera to collect the emission is termed as gate width. An oscilloscope and a photodiode are used in the setup to monitor the gate with respect to the laser pulse. The simple setup is used in the research work and the samples are collected under identical conditions.

The collected samples are then processed using a back propagation neural network (BPNN) to classify the plastic polymers. BPNN is one of the familiar neural network approaches which is used to optimize the training process of feed forward neural networks. The proposed neural network has three layers, such as the input layer, hidden layer, and output layer. 100 neurons are present in the input layer to process diverse features. The hidden layer consists of 50 neurons, and finally, the output layer has 5 neurons that represent the class types. **Figure 2** depicts an illustration of the BPNN model.

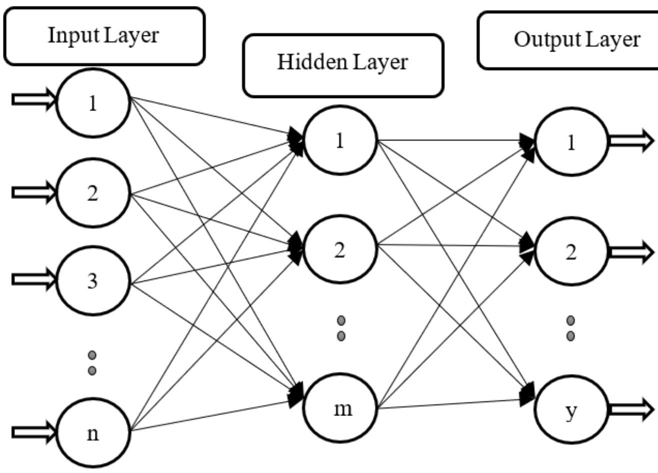


Figure 2. Back propagation neural network model.

The steps in the back propagation neural network are given as follows. The input layer is mathematically represented based on its weight functions. Multiplication of input vector and weight vector is the output of first layer which is provided as input to hidden layer and it is expressed as

$$m = \sum_{i=1}^{n} x(i) \times w(m, i) \tag{1}$$

where the input vectors are represented as *x*, and the weight vectors are represented as *w*. The activation function used in the hidden layer is given as

$$H(m) = \frac{1}{1 + e^{-m}} \tag{2}$$

The final output layer input to process the hidden layer output is obtained is expressed as

$$z = \sum_{i=1}^{m} h(i) \times w(z, i) \tag{3}$$

Finally, the output layer vectors are formulated using the activation function and it is expressed as

$$o(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

The initial weights are selected in the range [−1, 1] and it is used to define how quickly the network converges to attain global minima of error. To obtain a better balance between generalization and memorization, network training is extended until it reaches its minimum error value. Depending on the training patterns, the weights are adjusted and the process is terminated when the error is increased and the network starts to memorize the training patterns. The number of hidden units is obtained based on the input and output functions. The learning rate for BPNN should be considered as a minimum value to avoid losses in the direction of learning when unusual patterns are processed. The process flow of training and testing phases in BPNN is presented in **Figures 3** and **4** respectively.

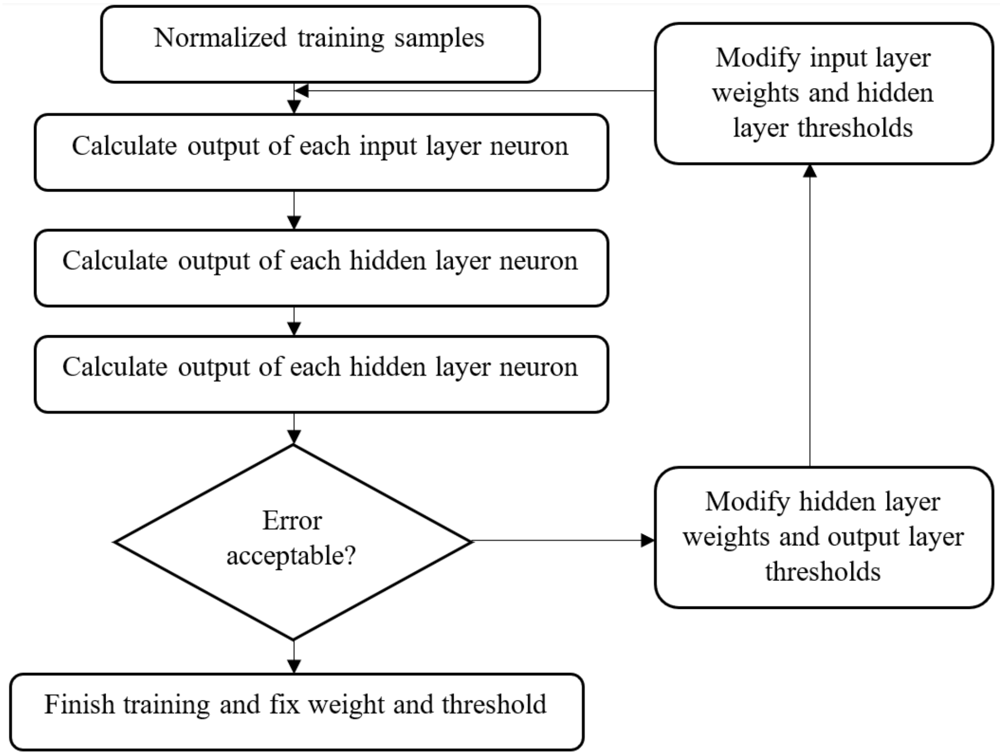


Figure 3. Process flow of training phase in BPNN.

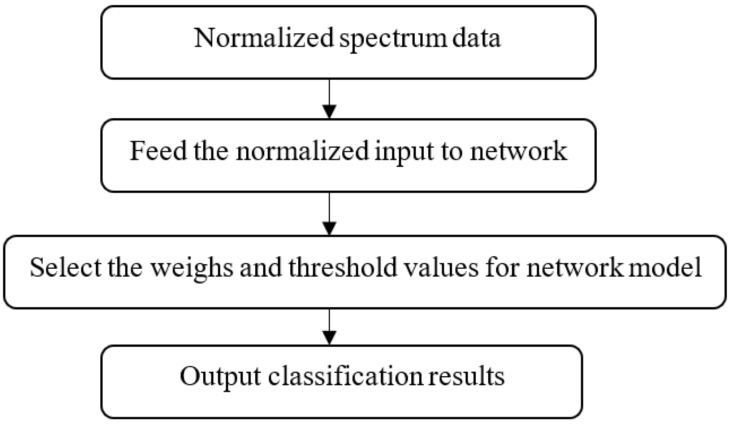


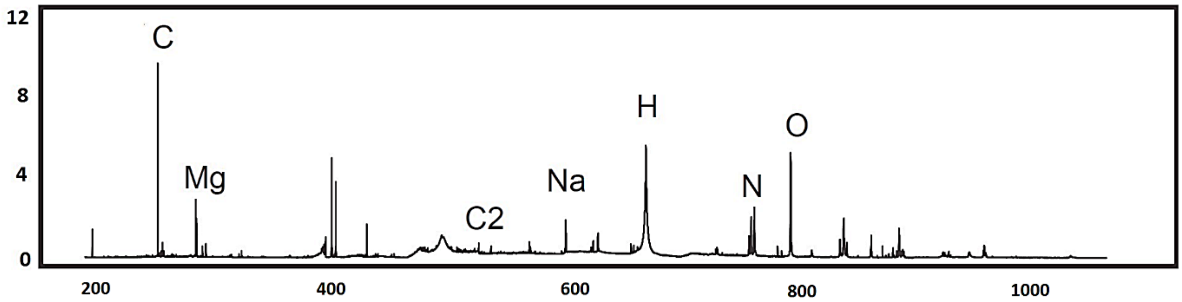
Figure 4. Process flow of testing phase in BPNN.

4. Result and discussion

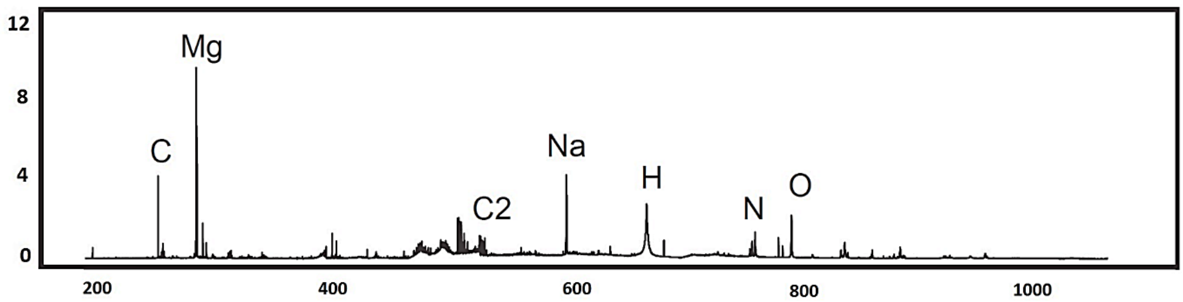
The data for the proposed work is collected from different recyclable polymers with different sizes and colors. Several additives are present in the polymers and these elements are used in type identification. Finally, the polymers are divided into five classes: ABS-PS (Acrylonitrile butadiene styrene-Polystyrene), PC (Polycarbonate), PE (Polyethylene), PA (Polyamide) and PP (Polypropylene). A total of 500 polymer samples are used for analysis, in which 60% of samples are used for training and 40% of samples are used for test and validation purposes. The samples are obtained in a routine manner for the duration of 50 days. The collected data is normalized to compensate for signal variations. The normalized results will be the best results over n pulses. The normalization and classification are performed using MATLAB 14 and emission lines are identified using Aurora software. A total of 500 rows and 10 columns of data are obtained in which the polymer samples are presented as rows and their respective variables are presented as columns. In the polymers, five random points were selected and 10 laser pulses per point were performed. To clean up the surface, a 10 mJ single pulse with a spot size of 250 mm is applied. Principal component analysis is also included in the presented work to evaluate the LIBS abilities in polymer class identification. Based on the intensity ratio obtained between molecular bands and elemental emission lines, variable selection is performed. Five variables are selected as follows: C (350), N (850+817+821), H (760), O (780) and C2 (622). Once the variables are selected, they are processed using a back propagation neural network for further classification.

The instrumental parameters are evaluated based on the interclass distance, so that highly discriminated polymers can be investigated. The combination of interclass distances obtained in the proposed work was calculated as [PE × PC, PS × PE, PA × PE, PS × PC, PA × PC, PA × PS]. The obtained values are converted into geometric averages for experimentation. It is essential for the system to produce minimum random errors so that mean square error is estimated to identify significant differences between mean functions. The proposed model quality is tested through analysis of variance and it is observed that there is no lack of fit. Once the evaluation is completed, the central point is represented as 100 mJ of laser energy with a 0.4 ms delay time and a 120 mm spot size.

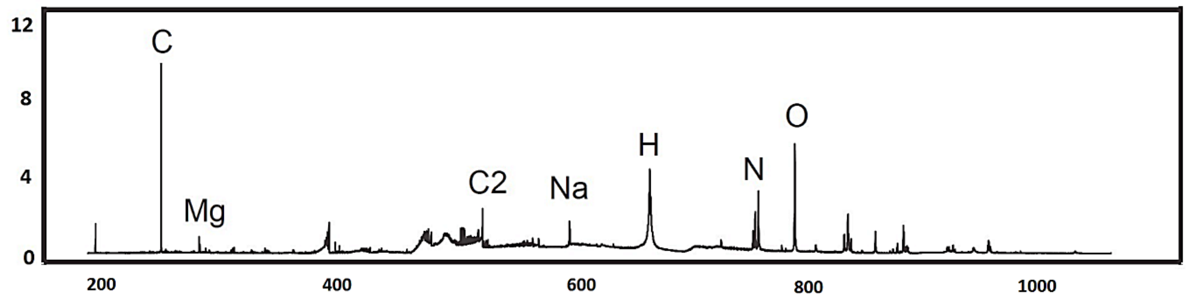
The emission lines and molecular bands are considered for analysis in the proposed work. The spectrum obtained for each polymer is depicted in **Figures 5a–5f**. It is observed from the spectrum that high intensity spectral lines are obtained for hydrogen and carbon. Other than these two high-intensity lines, spectral lines are obtained for Mg, Ca, Na, N, and O. In the analysis, atmospheric oxygen and nitrogen appeared in the spectra, but polymers don't have such components. The intensity emission ratio between molecular bands and emission lines is used for polymer identification qualitatively. The obtained ratios are listed in **Table 3**.



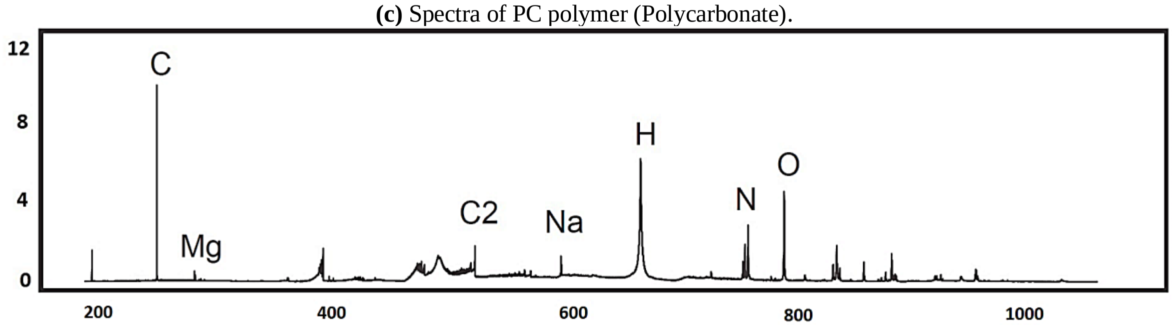
(a) Spectra of PA polymer (Polyamide).



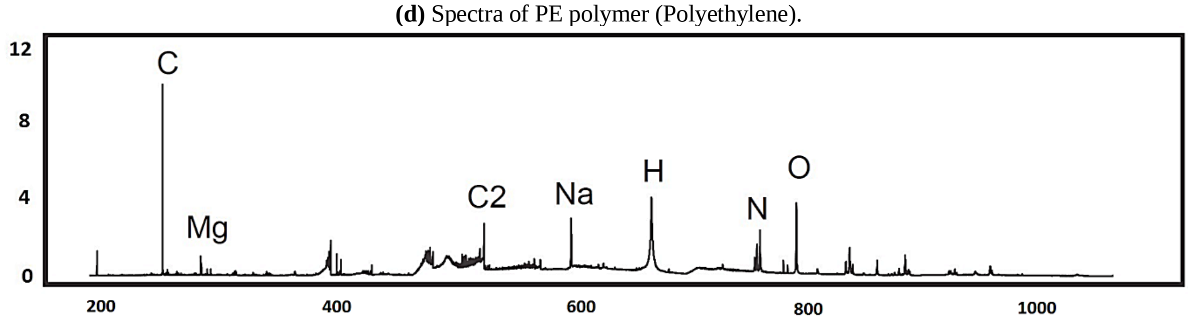
(b) Spectra of PP polymer (Polypropylene).



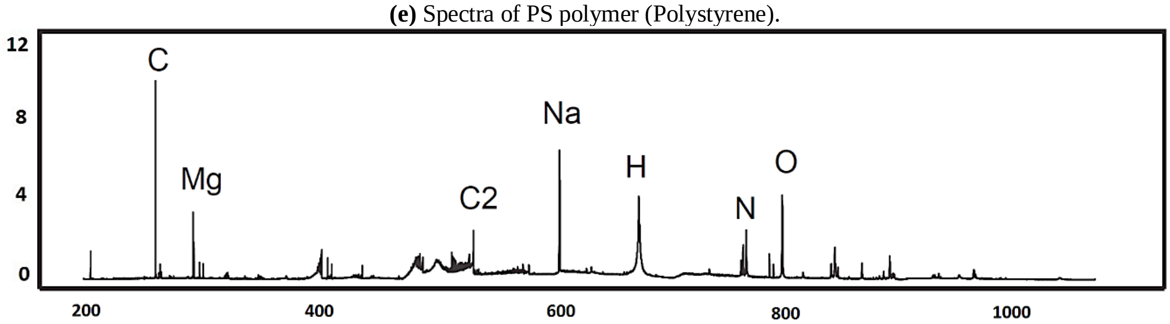
(c) Spectra of PC polymer (Polycarbonate).



(d) Spectra of PE polymer (Polyethylene).



(e) Spectra of PS polymer (Polystyrene).



(f) Spectra of ABS polymer (Acrylonitrile butadiene styrene).

Figure 5. Spectrum of Various Plastics.

Table 3. Polymers average range ratios.

S. No	**Variable Ratio**	**ABS and PS**		**PE**		**PC**		**PP**		**PA**	
		Avg. Ratio	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**
1	C (350)/H (760)	3.2	1.6–4.8	2.4	1.4–3.2	3.2	1.8–5.5	1.8	0.8–2.8	2.1	0.9–3.4
2	C (350)/C2 (622)	5.8	2.4–11.6	9.2	2.8–13.2	8.2	3.2–17.8	7.2	1.8–22.4	24.2	8.4–50.2
3	C (350)/N (850 + 817 + 821)	4.8	2.2–7.6	4.1	1.9–6.2	4.2	2.1–8.2	3.8	1.2–6.4	3.4	1.4–5.8
4	C (350)/O (780)	2.9	1.4–4.6	2.6	1.2–4.2	2.4	1.2–4.4	2.4	0.8–4.2	2.1	0.9–3.5
5	H (760)/C2 (622)	2.1	1.2–3.6	4.9	2.5–6.5	2.6	1.1–4.7	3.7	1.6–9.0	15.5	4.0–32.9

Table 3. (*Continued*).

S. No	Variable Ratio	ABS and PS		PE		PC		PP		PA	
		Avg. Ratio	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**	**Avg. Ratio**	**Range Ratio**
6	H (760)/N (850 + 817 + 821)	1.9	1.5–2.3	2.3	2.1–2.6	1.5	1.0–1.9	2.4	1.7–3.1	1.9	1.4–2.5
7	H (760)/O (780)	1.2	1.0–1.5	1.5	1.3–1.6	0.9	0.7–1.1	1.5	1.1–1.8	1.2	0.8–0.15
8	C2 (622)/N (850 + 817 + 821)	1.2	0.8–1.9	0.5	0.5–1.0	0.8	0.5–1.2	0.9	0.4–1.6	0.17	0.07–0.47
9	C2 (622)/O (780)	0.8	0.5–1.2	0.5	0.4–0.7	0.5	0.1–0.6	0.4	0.1–0.8	0.11	0.05–0.28
10	O (780)/N (850 + 817 + 821)	1.9	1.8–2.1	1.9	1.6–2.1	2.0	1.9–2.1	1.9	1.8–2.1	2.0	1.8–2.2

The obtained data matrix is processed through a principal component algorithm to reduce the dimensionality. The difficulty in separation of ABS and PS is considered in the analysis so that it is treated as a single group. Therefore, five classes of polymers were generated in the analysis. The high intensity principal components are analyzed and depicted in **Figure 6**, which provides the score plot for different samples. The observed variance between the samples is 65.4%. Similarly, considering the molecular bands and emission lines, a loading plot is depicted in **Figure 7** using principal component analysis.

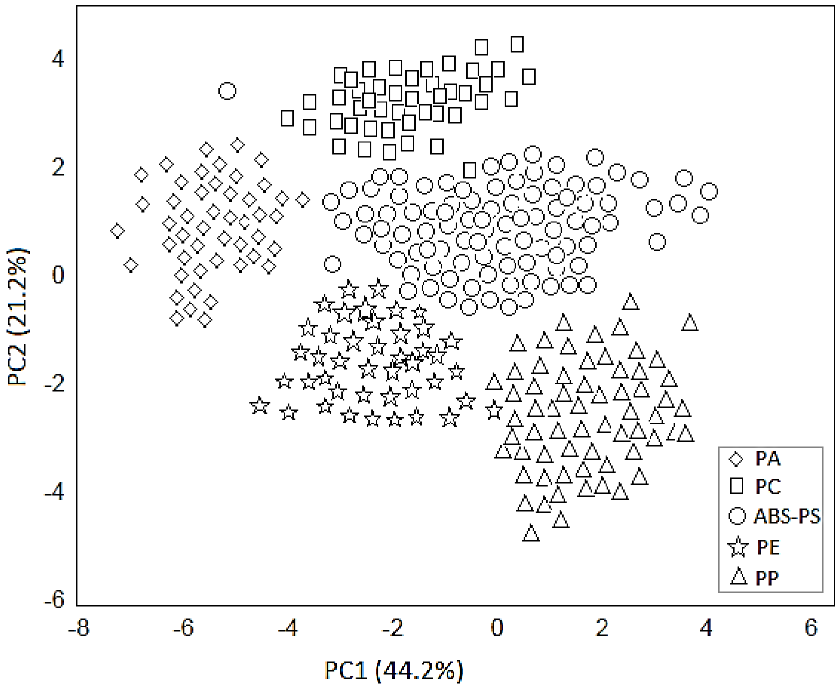


Figure 6. Score plot.

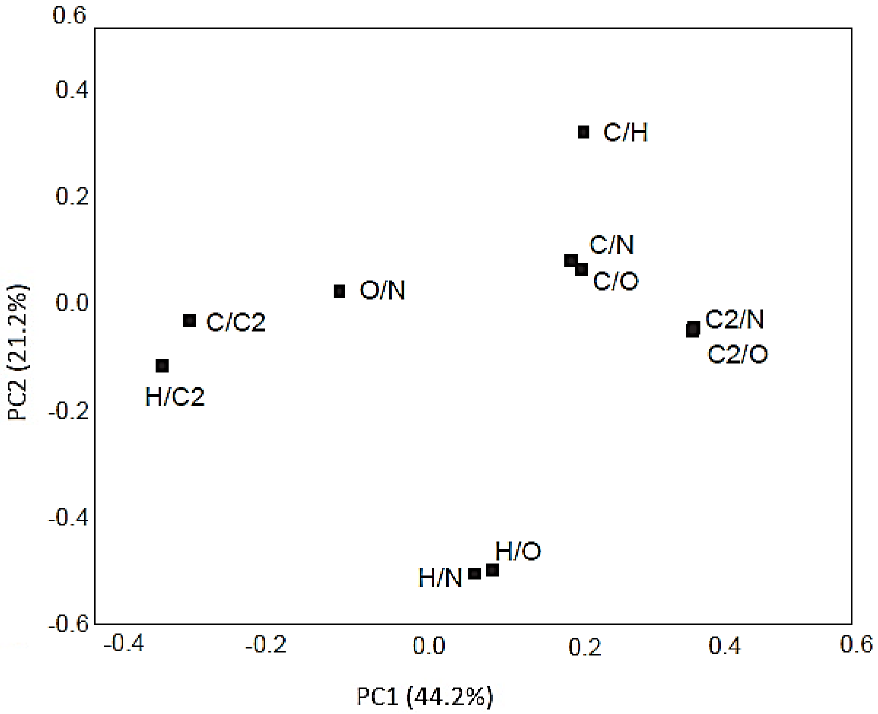


Figure 7. Loading plot.

The proposed method is used to identify and classify plastic polymer samples. A Back propagation neural network is used for classification. The training process is optimized through fivefold cross validation and in each validation the samples are identified among the five classes. The performance of the classification model is validated through parameters such as specificity, sensitivity, and accuracy. The mathematical formulation for the parameters is given as follows.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{5}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Negative} \tag{6}$$

$$Accuracy = \frac{True\ postive + True\ Negative}{True\ postive + True\ Negative + false\ Postive + false\ Negative} \tag{7}$$

The sensitivity analysis of the proposed classification approach and existing methods is comparatively depicted in **Figure 8**. It is observed that the proposed classification algorithm exhibits better sensitivity factors than other techniques. The inability to identify correct polymers from a given sample leads to decreased performance in existing approaches, whereas the proposed approach correctly identifies the samples so that increased performance is attained.

Figure 9 depicts the specificity analysis of all the algorithms used in the classification process. The figure clearly depicts that the proposed BPNN model attains maximum specificity for all polymers and classifies efficiently. However, the performance of SIMCA is much lower than all other models due to the inability to differentiate the polymer types. The performance of KNN and ANN is better than SIMCA, but it is less than the proposed approach.

The classification accuracies of all the four classification models are depicted in **Figure 10**. It is observed based on how many samples the algorithm classified efficiently. It can be observed from the results that the performance of the proposed BPNN is higher than other models. The proposed model classification accuracy is 1% greater than the ANN model and 1.5% greater than the KNN model. Though the accuracy has a minor difference, it will have a huge impact when huge samples are processed. The proposed model could help to identify and classify plastic polymers effectively so that they can be used in recycling plants to categorize different plastics which are required for recycling.

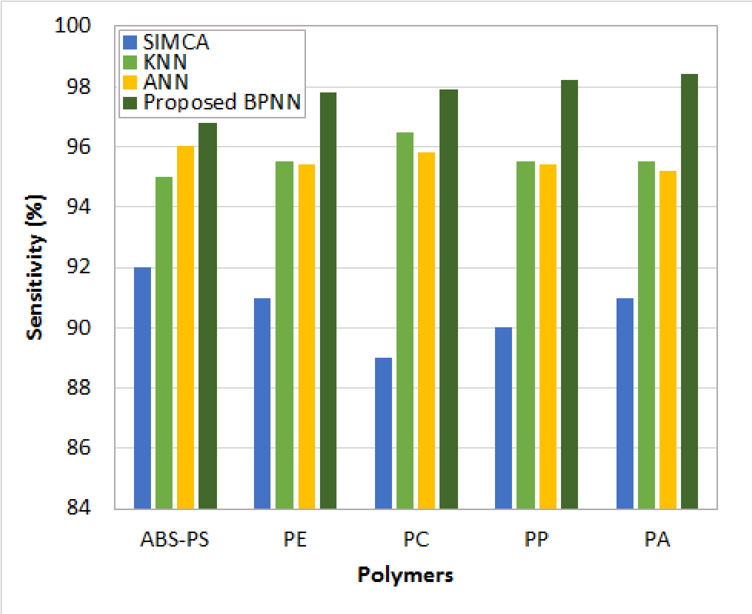


Figure 8. Sensitivity analysis.

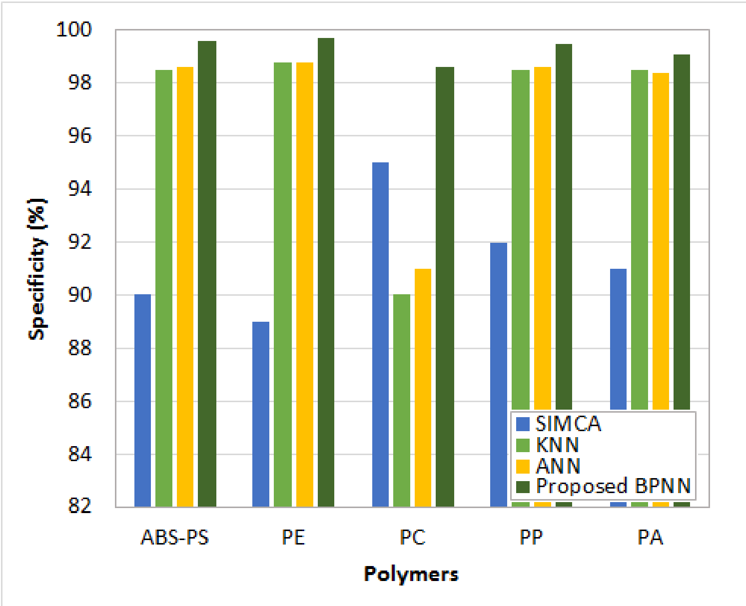


Figure 9. Specificity analysis.

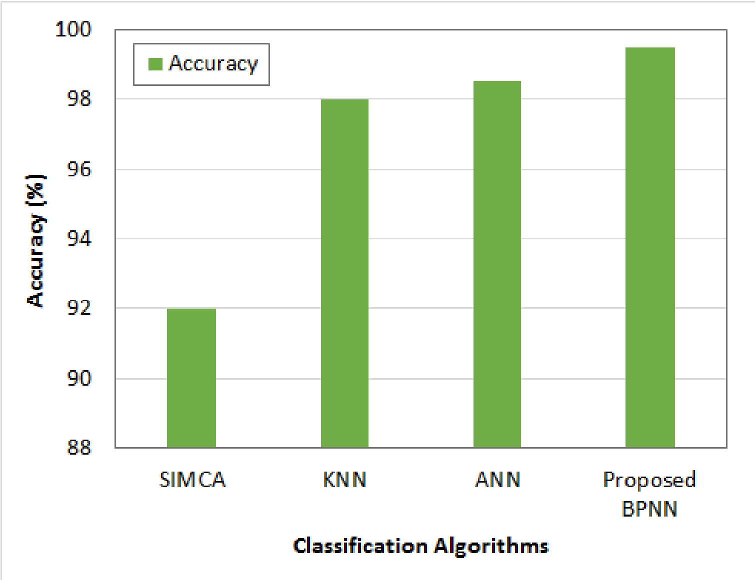


Figure 10. Accuracy comparison.

According to the comments, the accuracy comparison for the different classification models is given.

Precision:

Figure 11 depicts a comparative precision analysis of the proposed categorization technique and the currently used approaches. Precision is the degree to which estimates obtained from separate samples are likely to be similar. The precision of the sample estimate is affected by the kind of sampling (i.e., the method used to pick the examples). Categorization models' selectivity for picking out useful data items. Mathematically, precision is the number of true positives divided by the number of true positives + the number of false positives. Increasing the categorization threshold usually improves accuracy, but this improvement is not guaranteed to be monotonous. It will probably go up. To improve accuracy, increasing the classification threshold often results in fewer false positives.

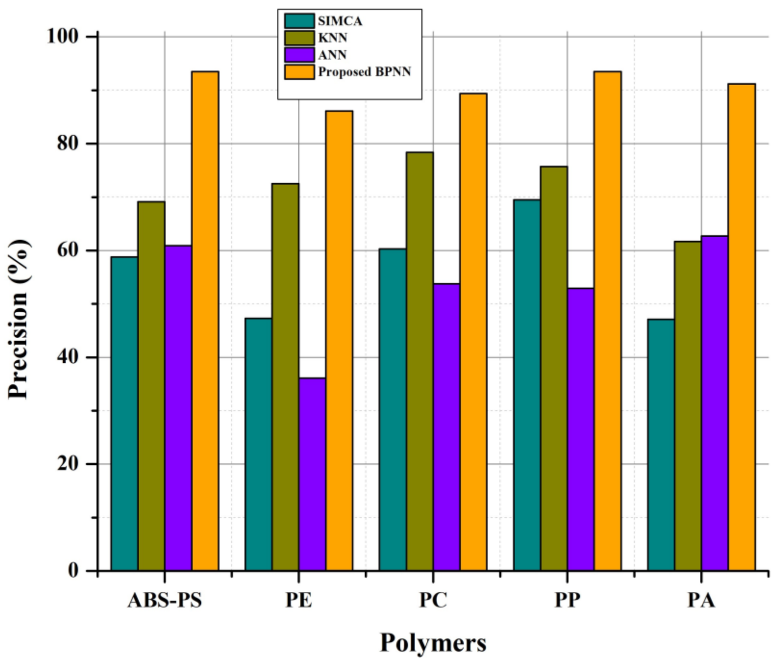


Figure 11. Precision comparison.

Recall:

Figure 12 depicts a comparative recall analysis of the proposed categorization technique and the currently used approaches. One way to evaluate a classifier's performance is by looking at its recall or how well it can track down all positive examples. It is calculated by dividing the number of correct predictions by the total number of predictions (both correct and incorrect). If the detector has a 70% recall rate, 70% of people within the limit will trigger the alarm. A poor recall rate might indicate that drivers with excessive blood alcohol concentrations are evading detection. To have 100% accuracy, a detector must have successfully identified all ground-truth objects. Because of the high number of false positives and low number of actual detections, a detector with low accuracy and recall is likely to miss many ground-truth objects.

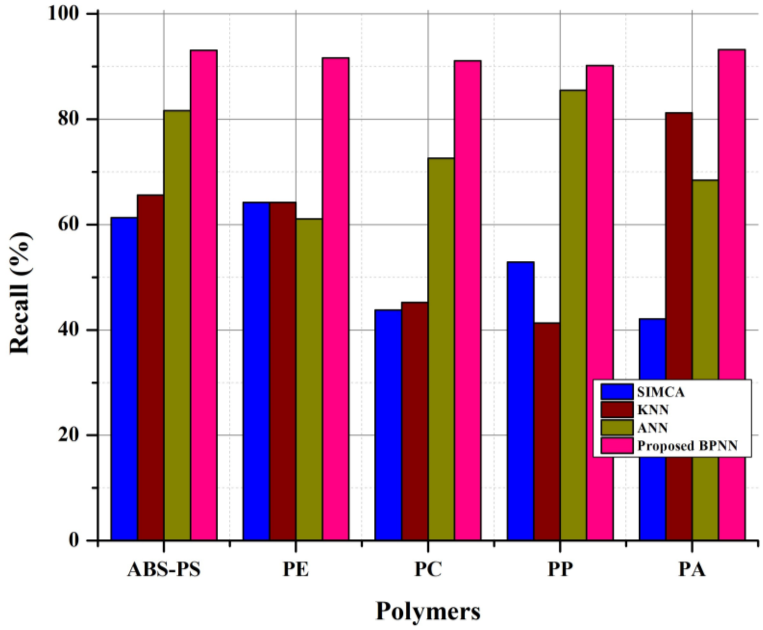


Figure 12. Recall comparison.

5. Conclusion

This research work presents a Laser-Induced Breakdown Spectroscopy with a neural network based plastic polymer identification and classification model for recycling plants. Identifying different polymer samples from plastics is performed using laser induced breakdown spectroscopy and classification is performed using a back propagation neural network. The Nd:YAG laser, Neural density filter, focal lens, and Echelle spectrometer are included in the experimental setup and the collected data is processed using a back propagation model. The performance of the proposed model is verified through parameters such as specificity, sensitivity, and accuracy. Compared to existing classification methods, the performance of the proposed classification model is better. Further, this research work can be extended by introducing deep learning techniques to improve the system parameters. In this work, Laser-Induced Breakdown Spectroscopy (LIBS) was used to determine the composition of the recyclable trash. Four thousand spectra were obtained by preprocessing the gathered LIBS spectra of recyclable waste samples using the bootstrap approach. A new automatic real-time detection method and technology in environmental protection is made possible by combining LIBS with drop-dimension algorithms and machine learning algorithms, allowing for high-precision identification, classification, and subclassification of recyclable waste. LIBS can provide new ideas and methods for waste management, domestic and industrial waste classification, and resource recovery, and is of great value in promoting a green ecology by starting with the generation of waste and ending with the reuse of useful resources.

Author contributions

Conceptualization, PK and JV; methodology, PK and JV; software, JV; validation, PK, JV; formal analysis, PK, JV; investigation, PK, JV; resources, PK, JV; data curation, PK, JV; writing—original draft preparation, PK; writing—review and editing, PK; visualization, PK, JV; supervision, PK, JV; project administration, PK, JV; funding acquisition, PK, JV. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

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