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Evaluation of Plastic Waste Classification Systems

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Authors' contributions

The work was carried out in collaboration between all authors. Author AOA designed the study, took part in the analysis and edited final manuscript. Authors KAJ and OAA worked on the literature and produced first draft of manuscript. All authors read and approved the final manuscript.

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Abstract

Aim: A comparison study of three classifiers was carried out to identify the best classifier which can be utilized to automate and enhance the manual process of identifying and sorting plastic waste.
Place and Duration of Study: Department of Computer Science and Engineering, Obafemi Awolowo University, between April 2014 and September 2015.
Methodology: Collection of plastic wastes data from purposely selected disposal sites was done and the distinguishing characteristics (average spectrum power and shape area) of those plastic wastes were computed and used as feature data. The three classifiers designed using machine leaning and statistical techniques were implemented in the MATLAB environment. The classifiers are Fuzzy inference system, multi-layer perceptron and linear discriminant analysis. The efficiency of the three classifiers was compared using mean square error, mean absolute error and receiver operating characteristics.
Results: It was observed that the classifier designed using artificial neural network had the lowest mean absolute (0.07) and mean square error (0.07), compared to other classifiers. More so, the neural network model had the highest correct classification accuracy of 92.98% as against 87.72% and 75.44% recorded for fuzzy inference system and linear discriminant analysis, respectively.
Conclusion: The study has successfully classified plastic waste data using the spectrum power from the sound signal produced from plastics and the plastic's shape area. Thus, confirming that sound wave signal from plastic could be utilized as feature data in plastic waste identification.

Keywords: Neural networks; fuzzy logic; linear discriminant analysis; performance evaluation; waste.

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1 Introduction

Plastic materials are widely used in many consumable products. They are low performance products like sachet water bags, wrapping products, biscuit wrappers and so on. Plastics account for large amount of wastes generated due to their short lifetime and this has increased the urgency and importance of plastic recycling. The challenge of Municipal Solid Waste (MSW) management is a priority for governments all over the world [1]. Separation and sorting of plastic resins from MSW are the major steps in plastic recycling. Majority of plastic resins create problems for the recycling process because of their incompatibility. The separation of different polymers by type is mandatory because contamination in the recycling of one type with another can cause processing problems [2]. Sorting of plastic resins is usually performed with separation among the major resins namely; Polyethylene terephthalate (PET), High density polyethylene (HDPE), Low density polyethylene (LDPE), polystyrene (PS), polyvinyl chloride (PVC) and polypropylene (PP). Sorting and separation techniques usually involve using chemical, optical or physical property to differentiate between the various plastics to be sorted [3]. Inefficient sorting may probably expose Chlorine-based resins to thermal treatments which could engender the release of hydrochloric gases [4]. Modern recycling plants however, sort plastic containers according to their resin type, and recognition performed using infrared, ultraviolet, and X-ray detectors [5], or through manual means [6]. Though, automated sorting systems treat huge volumes of plastic efficiently with little human intervention, they however require high investments in specific technologies [7,8]. Manual sorting that relies on plant personnel for visual identification and manual classification of plastic containers are however unsuitable for plants with a large throughput, as efficiency of the process will be negatively affected. Nevertheless, in developing countries, manual sorting is cost effective in comparison to the cost of setting up automated systems. Also, manual sorting in recycling plants is still the preferred procedure [9]. Besides, many locally manufactured plastics do not have recycling symbol imprinted on them to aid the automatic identification of such plastics. Classification algorithms can be used to automate the manual sorting of plastic waste. A variety of statistical methods and heuristics from Artificial Intelligence literature have been used in the classification tasks [10]. A variety of statistical methods and heuristics have been used in the classification tasks, but few studies have evaluated the efficiency of algorithms used in the classification of plastic wastes.

Artificial Neural Networks (ANNs) consist of parallel architectures to solve complicated problems through cooperative interconnected artificial neurons. Its processing elements consist of many simple computational elements arranged in layers [11]. Fuzzy inference system can be applied on linear and nonlinear systems. In solving problems, they do not require tedious mathematical models of these systems, but a simple controlling method based on users' experience. Linear discriminant analysis (LDA) is an effective subspace technique which optimizes the Fisher score [12]. It is a useful and simple classifier that do not require tuning of many different parameters but still allow one to achieve competitive accuracy. These good attributes have resulted in its extensive use and exploitation in image classification and feature reduction applications [13], [14]. The classification problems can be solved using models built with FIS, ANNs and LDA since they are convenient and easy to use. The aim of this study is to construct a ANN, FIS and LDA models to classify plastic wastes using physical properties such as the sound generated from the plastic and its shape area (pixel unit). The ANN model with one hidden layer was constructed with the training, testing and validation stages carried out using available test data of 130 different mix of plastic types PET (used for beverages such as mineral water and soda beverages), HDPE (used for oil containers, household cleaning solution bottles, semi-transparent and white coloured bottles such as juice and milk bottles), PP (used for medical containers, battery cases, oil additive containers, bottle labels and caps, combs, etc) and LDPE (used for grocery bags, food industry wrap, dry cleaning bags, etc). The ANN, FIS and LDA models had two input parameters and one output parameter. The efficiency of these three classifiers was compared using mean square error, mean absolute error and receiver operating characteristics.

2 Related Work

Various methods for waste plastics identification and sorting range from manual sorting to advanced automated technologies. A method for identification and sorting of plastics is the optical and spectroscopic-based method [15,5]. In [4], a method for identifying and separating PET and PVC resins from each other using near infrared radiation (NIR) was proposed. This method used two important peaks in absorbance spectra of PET (1660 nm) and PVC (1716 nm) to distinguish between the resins. Unfortunately, NIR sensor is insufficient to produce a high accuracy and precision system since it lacked spatial information to recognize the shape of plastics bottle as well as colour information used to distinguish between label and regions of plastic waste. A visible spectroscopic camera was used in [16] to sort plastics waste in real time. A background subtraction method was employed to locate bottles with regions cropped for building histogram. Region growth algorithm was used to maximize the detected foreground size and filling of gaps. To classify bottle, grey scale histogram of the bottle was used as input to the support vector machine (SVM). SVM has been proven by [17] to be able to distinguish between PET and non-PET materials. The model presented in [16] could perform a real time operation but the grey scale signature used as feature was not enough when the lighting condition is unstable. Any slight variation in the illumination would reduce the accuracy of detection and the SVM requiring retraining to derive a new hyper plane. Artificial neural networks (ANNs) was used to classify PET and non-PET bottles [9], where structuring elements were utilized as input to the ANN classifier. The study in [9] assumed that the shape of PET bottles are more slender than non-PET bottles which are square in shape. This assumption is not generally accurate as shape information alone is not sufficient to get better classification accuracy. Fuzzy logic with template matching algorithm was used in [18] to identify four resin types. Resins with recycling symbol code clearly inscribed were identified using template algorithm and those without symbol code were identified using fuzzy logic method. In [19], a probabilistic white strips approach with shape information was used to recognise PET bottle through neighbourhood information of the reflection area. However, not all white regions have the reflection area, such as a white label or white contaminant. The identification of PVC, polyethylene, and rubber using near infrared– hyperspectral imaging was proposed in [20], while the classification of PET and poly lactic acid with efficiency higher than 98% was reported in [21]. However, as reported in [22], majority of these methods are relatively slow, and most of them involve expensive or complicated apparatus. Five different feature extraction methods (Principal Component Analysis (PCA), Kernel PCA, Fisher's Linear Discriminant Analysis, Singular Value Decomposition and Laplacian Eigenmaps) and Support Vector Machine was used in [22] to achieve the classification task of plastic wastes (PET, HDPE, and PP) with recycling labels. However, this model may be inappropriate in situations where recycling labels are not imprinted on plastics. In [23], the possibility of a combined application of the magnetic density separation (MDS) and the hyperspectral imaging (HSI) for the separation and recognition of PVC from mixed wastes was proposed with a model validation utilizing a Partial Least Square Discriminant Analysis (PLS-DA). The magnetic density separation is effective only if the materials which need to be separated have different densities. The application of MDS and HSI was also used in Polyolefins sorting in the study reported in [24].

In this study, we construct simple but elegant classification models which are not limited to PET as observed in few related work. These models are then evaluated to determine the best for the purpose of automating the manual sorting method. This was with a view to overcome its limitations and improve its efficiency while separating waste plastics.

3 Materials and Methods

This materials and methods used in formulating the classification models are presented in this section.

3.1 Data sample

Data sample (156 in total) containing plastic wastes of different sizes and shape of PET(32%), PP(18%), HDPE(15%), and LDPE (35%) were collected from disposal sites in the city of *Ile-Ife*, *Osun* State, Nigeria. Some of these samples were clear while some were white and coloured. Images of the sample data were taken using a digital camera of high resolution (2048x1536 pixel). The sound wave produced by tapping or rubbing the plastic surface were recorded in a quiet room using microphone available on an Android device. The distribution of the power contained in a sound signal, produced by a plastic waste was determined using equation (1).

$$R_{xx}(0) = \int_{-\pi}^{\pi} P_{xx}(\omega)\, d\omega = \int_{f_{-x/2}}^{f_{x/2}} P_{xx}(f)\, df \quad (1)$$

The average power of a signal over a particular frequency band [ω1, ω2], 0≤ω1≤ω2≤π, was found by integrating the Power Spectral Density (PSD) over that band. This integral is then estimated using a periodogram, a non parametric method. The sound wave is also used as a distinguishing feature since most resins produce sound wave that uniquely identify them for instance; a squeezed nylon produces a unique sound when compared to other resins. Pre-processing operation was carried out on images of the captured plastics to reduce noise and eliminate redundant data. This is to achieve an optimum-quality image. The pre-processing operations (size reduction, image enhancement, morphology, and so on.) were carried out on the acquired images to extract necessary features for identification. The purpose of feature extraction is to represent data in a reduced number of dimensions so as to improve classification through more stable representation. Features such as length, width, and shape area (pixels) extracted from the boundary of plastic object measured in pixel units were computed using the MATLAB '*bwarea'* function. The computed shape area normalized on the scale 0 to 1 are then recorded. The sample data was divided into two subsets. The first set is the training data set (70% of the sample) while the other set is the test data (consisting 30% of the sample). Fig. 1 depicts the characterizing properties of the training data.

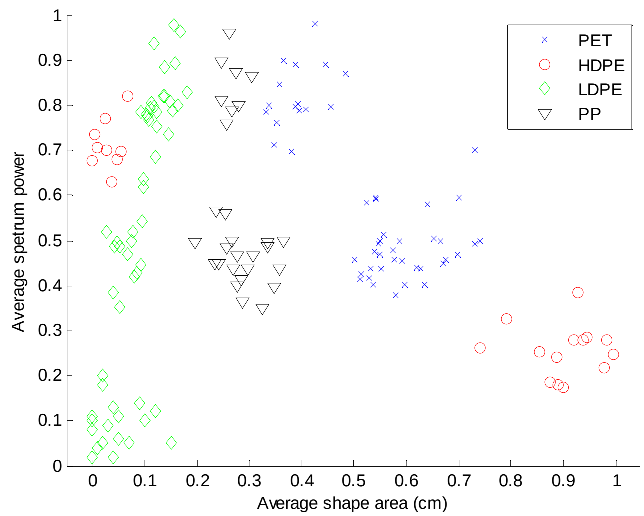

Fig. 1. Characterizing properties of training data set

3.2 Classification models

Classification task entails associating an object with existing classes of objects. Classes are defined as a set of objects, or by a set of rules defining how objects are to be classified into given classes. In this study, the classification of plastic wastes considered only physical properties, which are the plastic's image shape area and the average spectrum power of sound clip produced by tapping the plastic surface. The classification methods used are briefly discussed in the following subsections.

3.2.1 Fuzzy inference system

Fuzzy rules represent classes in terms of linguistic variables. This technique enables approximate reasoning by improving performance of classification systems through efficient numerical representation of vague terms, increased operation range in ill-defined environments and robustness to noisy data. Fuzzy logic-based systems operate on the precise and mathematics of fuzzy set- a fundamental concept that element **x** is a member of set **A** with varying degrees, meaning that each member of the set is characterised by its degree of membership in the set. The degree of membership of element **x** in set **A** is denoted by $\mu_{A(x)}$. A fuzzy set F in

U is usually represented as a set of ordered pairs of a generic element $\boldsymbol{x}$ and its grade of membership function: $F = \{(x,_{\mu F}(x)) | x \in U\}$. Fuzzy inference system does not involve complicated mathematical equations used in modelling certain systems, but only require a simple controlling procedure based on the knowledge engineer experience. The basic structure of a fuzzy inference system consists of following modules: (1) the fuzzifier that converts the crisp inputs into a fuzzy inputs, (2) a knowledge base containing fuzzy rules along with a data base defining the membership functions, (3) an inference mechanism that derives a fuzzy output using a fuzzy reasoning method; and (4), a defuzzifier, which translates the fuzzy output into a crisp value. The Takagi-Sugeno-Kang (TSK) fuzzy model was used as a result of its defuzzification process which is less computational when compared to Mamdani. Besides, Mamdani model lacks accuracy and has high computational cost [9]. The Fuzzy inference model had two input parameters and one output parameter. The input are average spectrum power of sound wave produced from plastic (average s*pectrum power*) and the plastic shape area. The model output variable was the plastic type (PET, HPDE, PP and LDPE). These inputs (average power spectrum, average plastic weight and average plastic area) were classified into nine linguistic variables: Zero, Low, Very Low, Small, Big, Very Big, Medium, High, and Very High). Each linguistic variable was associated with a set of membership function defined over the entire operating range of that variable. Membership function used for the input variables was the triangular-shaped membership function. The number of membership functions and the shape of these functions are an essential part of the knowledge embodied in a fuzzy inference system. The domain expert usually supplies this information. This information when combined with the rules forms the knowledge-base for a given application. The fuzzy rules were carefully constructed to identify any of the four plastic types considered in this study. The rules of the linguistic variables are given in Table 1. The fuzzy inference model is as depicted in Fig. 2.

Table 1. Rules for determining the plastic type

Average spectrum power	**Area**				
	Very small	**Small**	**Medium**	**Big**	**Very big**
Very low	LDPE	LDPE	PP	PP	HDPE
Low	-	PP	PET	LDPE	PET
Medium	-	LDPE	PP	PET	PET
High	-	PP	PET	PET	HDPE
Very high	-	HDPE	PET	PET	HDPE

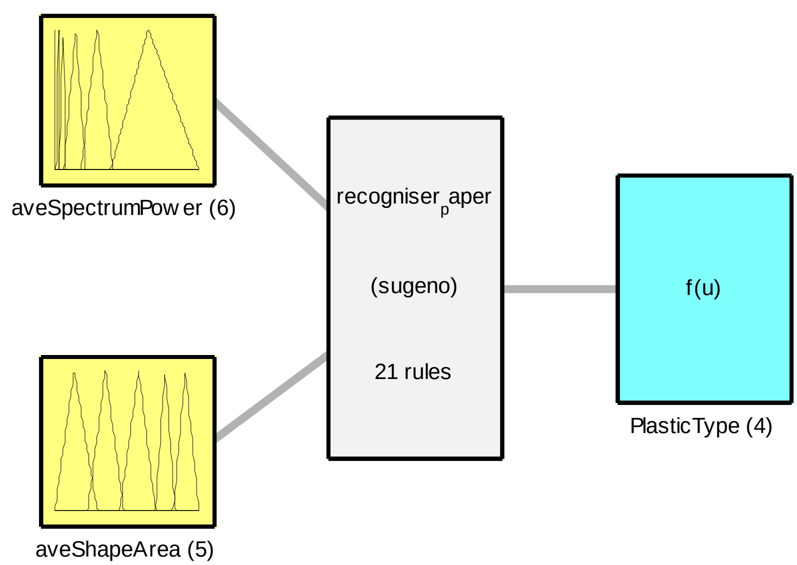

Fig. 2. Fuzzy inference model for plastic waste identification

3.2.2 Artificial neural networks

The multi-layered perceptron (MLP) neural network (see Fig. 3) is employed in this study. The MLP has one input layer, one hidden layers and an output layer. Input layers are in terms of the power spectrum of sound produced by plastic and the plastic's shape area. The output layer is the identified plastic type. Each layer in the MLP architecture has various neurons. Signals flow into the input layer, then through the hidden layers, and finally at the output layer. Each neuron in a layer is connected to the neurons in the adjacent layer with different weights. Except the input layer, each neuron in other layers receives signals from the neurons of the previous layer, linearly weighted by the interconnect values between the neurons. Thereafter the neuron produces its output signal by passing the summed signal through a sigmoid function. The MLP model was trained with the available P (assumed) set of training data using Levenberg–Marquardt (LM) training algorithm. Inputs of $\{i_1, i_2, i_3, ..., i_P\}$ are forced on the top layer. The ANN is trained to respond to the corresponding target vectors,$\{t_1, t_2, t_3, ..., t_P\}$on the bottom layer. The output from neuron i, O_i, is connected to the input of neuron j through the interconnection weight W_{ij}. The state of the neuron m is:

$$O_m = f\left(\sum_i W_{im} O_i\right) \tag{2}$$

where $f(x) \equiv {}^{1}/_{(1+e^{-x})}$ and O_m is the sum of all neurons in the adjacent layer. Given that t is the target state of the output neuron, then the error at the output neuron is defined as:

$$E = \frac{1}{2}(t_m - O_m) \tag{3}$$

Where neuron m is the output neuron. According to the difference between the generated and target outputs, the network's weights $\{W_{ij}\}$ are adjusted to reduce the output error. This error propagates backward to the hidden layer, until it reaches the input layer [25]. The training set (70% of sample data) was used for the training the model. The MLP network model had logarithmic sigmoid and pure linear functions as activation functions for the hidden and output layer neurons, respectively. An optimum number of hidden neurons was determined by starting with a few numbers (5) of neurons and then slightly increasing the number of neurons by five and monitoring the performances of the network models until the mean square error was acceptably small or no significant improvement is observed [26]. In this study, the best performance was obtained from an MLP neural network model with 40 neurons in the hidden layer.

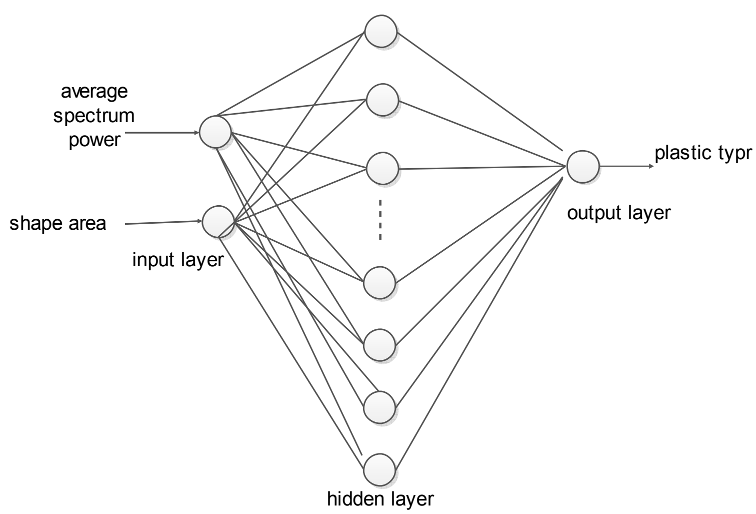

Fig. 3. MLP neural network model for plastic waste identification

3.2.3 Linear discriminant analysis

Linear Discriminant Analysis (LDA) is a method for dimensionality reduction and classification for the purpose of achieving maximum class separability. In addition, it does not require the tuning of free parameters. In many operational domains, where the classification task may be driven from non expert users, it is useful to exploit simple classifiers, which do not require the tuning of many different parameters but will still achieve reasonable accuracy. LDA is a simple classifier which can merge easy implementation and clear physical interpretation with high accuracy. These reasons have resulted in its widespread use and practical exploitation in image classification and feature reduction applications [3,14]. Given a set of *n* labeled samples, $\{x_i, y_i\}_{i=1}^{n}$ where $\mathbf{x}_i \in \mathrm{R}^m$ represents the *m*-dimensional feature vector for the *i*th pixel with label $y_i \in \Omega$, *m* denotes the spectral bands and Ω represents the possible classes in the image. In supervised image classification, the LDA classifier computes a *linear* transformation matrix **G** that reduces an original *m*-dimensional feature vector **x** to an *l*-dimensional vector $a = G^T x \in R^i$, where $l < m$. This low-dimensional feature space is selected to fulfill a given maximization criterion of separability among class distributions [27]. The widely used Fisher criterion [28] is based on maximizing the distance among the means of the classes and, at the same time, minimizing their intra class variances on the basis of the following function, $J(w) = (\mu_2 - \mu_1)^2/(\sigma_2^2 + \sigma_1^2)$. The LDA approach makes use of a linear transformation in reducing the dimension of data in classification problems [29].

4 Results and Discussion

The program used in running the three plastic waste recognition models was written in MATLAB language and test data (30% of sample plastic waste data) were given as inputs to the three classification models. The experiment was conducted on an Intel Core i5 2.50 GHz machine. To compare the results obtained from the three recognition models, the following three performance metrics - mean absolute error (MAE), mean square error (MSE) and receiver operating characteristic (ROC) were used. The metrics are defined as follows. The MAE measures how close the generated outputs are to the targets. It is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|t_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{4}$$

where y_i is the generated output and t_i the true value (target). The mean square error measures the classifier's performance according to the mean of squared errors. It is express as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \tag{5}$$

where $\hat{Y}$ is a vector of n predictions, and Y is the vector of observed values. ROC checks the quality of classifiers by appling threshold values across the interval [0,1] to each classifier's outputs. For each threshold, two values are calculated, the first is True Positive Ratio (TPR), which is defined as the number of outputs greater or equal to the threshold divided by the number of targets that are one, and the second is False Positive Ratio (FPR), defined as the number of outputs less than the threshold divided by the number areof targets that zero. The true positive rate is given by $TPR(T) = \int_T^{\infty} f_1(x)dx$ and the false positive rate is given by $FPR(T) = \int_T^{\infty} f_0(x)dx$. Another measure of how well a classification model has fit the data is the confusion matrix, which was used to visualize the classification performance of the three classification methods.

In evaluating the efficiency of each model in terms of MAE, MSE and ROC, simulation experiments were carried out in which sample from test data consisting of feature data (the plastic shape area and the average spectrum power) representing plastic waste data were presented to each model as inputs. The classification efficiencies of the models using these metrics were recorded. The detailed experimental results are reported in the following tables. Table 2 shows the performance of the three classification models in recognizing plastic waste types used in the study. MLP had the lowest MAE and MSE values of 0.07 compared to MAE(0.16), MSE(0.23) for FIS and MAE(0.44), MSE(1.04) for LDA, respectively. The MLP model also had the highest TPR value of 0.91 compared to 0.81 and 0.72 of FIS and LDA, respectively. Similarly, MLP had the lowest FPR value of 0.03 compared to 0.05 and 0.08 for FIS and LDA, respectively.

The confusion matrix depicted in Table 3, show the percentages of correct and incorrect classifications of the three models. The values in the confusion matrix show the number of correctly or incorrectly classified data. Rows in the matrix refer to the actual class, while the columns refer to the predicted output. Correct classifications are located in the diagonal of the matrix. It is constructed by applying the test data (30% of the sample data) on each classification model. It is observed for the FIS model for instance, that 21 PET data were classified correctly among the 22 PET in the sample, misclassified 3 data. Similarly, the MLP correctly classified 21 PET out 22 PET data in the sample while LDA classified correctly 19 PET data out of 22 present, when the first row of Table 3 is examined. The overall classification accuracy obtained from each classification method is given in Table 4. As shown in Table 4, this study implemented three classification methods to classifies four plastic types (PET, HPDE, LDPE, and PP). It is particularly observed that MLP gives the best recognition performance whereas LDA is the worst among the three classification systems.

Table 2. Efficiency of classification methods

Model	MAE	MSE	ROC	
			TPR	FPR
FIS	0.16	0.23	0.81	0.05
MLP	0.07	0.07	0.91	0.03
LDA	0.44	1.04	0.72	0.08

Table 3. Confusion matrix for the models and the classes

Plastic	FIS				MLP				LDA			
	PET	HDPE	LDPE	PP	PET	HDPE	LDPE	PP	PET	HDPE	LDPE	PP
PET	21	3	0	0	21	1	0	0	19	3	0	1
HDPE	1	10	0	1	0	11	0	0	1	7	0	0
LDPE	0	0	16	2	0	1	16	1	1	1	13	1
PP	0	0	0	3	0	0	0	5	1	1	2	4

Table 4. Percentages of correct and incorrect classification

Model	Plastic type				Classification	
	PET	HDPE	LDPE	PP	Correct (%)	Incorrect (%)
FIS	87.5	83.3	100.0	88.9	87.72	12.28
MLP	95.5	91.7	100.0	88.9	92.98	7.02
LDA	82.5	87.5	60.0	81.3	77.80	22.20

5 Conclusion

In this study, a comparative analysis of the performance of three classification algorithms for plastic wastes was carried for the purpose of automating the manual process of sorting and identifying four plastic waste types (PET, HDPE, Nylon and PP). The feature data for the classification algorithms considered only physical properties, specifically, average spectrum power of sound signal produced by the plastic and the plastic area (pixel unit). The models (FIS, MLP, LDA) were designed, simulated and their efficiency evaluated using the following metrics MAE, MSE and ROC. It was observed that the MLP model had the lowest MAE and MSE values of 0.07 compared to MAE(0.16), MSE(0.23) for FIS and MAE(0.44), MSE(1.04) for LDA, respectively. The MLP model also had the highest TPR value of 0.91 compared to 0.81

and 0.72 of FIS and LDA, respectively. The overall percentages of correct classification by the three classification models were 87.72% (FIS), 92.98% (MLP), and 75.44% (LDA), respectively. The overall percentages of incorrect classification recorded by the three models were 12.28% (FIS), 7.028% (MLP), and 24.56% (LDA), respectively. The study has successfully classified plastic wastes using spectrum power from sound signal produced from plastic and plastic's shape area as physical properties. Thus, confirming that sound wave signal from plastic could be utilized as feature data in plastic waste identification, which was missing in existing models.

More importantly, the results obtained in the study will aid a robot equipped with appropriate actuators to capture necessary input (sound wave produced from plastic and shape area) from the environment, extract relevant feature from such input and use any of the classification model discussed in this study (preferably MLP model), to classify plastic waste. This will ultimately enhance manual sorting and help in reducing environmental pollution in most cities in the developing countries.

Competing Interests

Authors have declared that no competing interests exist.

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