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Classifier Performance in Materials Sorting Using Sound Properties

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Abstract: This paper explores an intelligent classification of different materials from their sound properties irrespective of shape, texture or size. This is towards the building of smart devices particularly useful in waste sorting and recycling. The selected materials are of three broad categories namely metals, glass and plastic. Pre-processing involves filtering noise from the captured sound data, application of principal component analysis (PCA) was carried on extracted frequency and bandwidth feature vectors with the aim of extracting the characteristic properties that contribute the most to variance in order to improve classification accuracy of the training samples. Some common classifiers were tested with the data for accuracy of classification. These include KNN, Random Forest, Adaboost, SVM, Neural Network. KNN gave the best classification accuracy of 96.8%, while the Support Vector Machine (SVM) gave the least performance. By including the band width data for the three materials, it was observed that better identification of materials was achieved.
Keywords: waste sorting; sound properties; features engineering; bandwidth; KNN; Neural Network

1. Introduction

Our world today is in need of smart ways to deal with the ever increasing waste. Recycling of waste is one key way to reduce depletion of raw materials and damage due environmental pollution. The process of recycling begins with sorting or classification of waste and manufacturers seek for cost effective and efficient ways to minimize the time during sorting. One of the properties of materials is the sound they produce when impacted. Sound is ubiquitous in everyday life as objects make contact due to human activity. In this interaction, the human brain has shown the ability to decipher types of materials without visual or tactile information simply from the sounds they produce. For example, it is easy to distinguish glassware that falls on a hard surface from an aluminum plate simply from the resulting sound without seeing the objects. The primary motivation of this work therefore is to explore the sound frequency component and bandwidth of objects that can be used in the sorting of materials of interest.

When an object is struck, the energy of impact causes deformations to propagate through the object, causing its outer surfaces to vibrate and emit sound waves [1].The resulting sound field propagates through and also interacts with the environment before reaching the inner ear where it is sensed. This sound carries important information about the material composition of the object, its shape and size, as well as the type and location of contact on the object [2].What perceptual information is characteristic of a material, and invariant to object shape?

2. Literature Review

Natural sound gives valuable information about the things we cannot see and also contains information about the interaction between the physical objects that generate them. Our auditory sense allows us to infer events in the world that are often outside range of other sensory modalities [3] and auditory perception has been shown to provide insight to everyday listening which consists of perceived properties of a sound's source such as car engine, footsteps etc., rather than the properties of a sound itself (pitch, tone, etc.) [4]. Humans can identify the physical properties of objects from the sounds produce unlike our sense of vision which is always constrained to a particular viewing direction.

Based on theoretical considerations, Wildes and Richards [5] suggested the overall decay time as a significant cue, since it is a direct measure of internal friction in a given material. However, this is only true when a standard anelastic linear solid model is assumed. Lutfi and Oh [6] found that changes in the decay time are not easily perceived by listeners while changes in the fundamental frequency seem to be a more salient cue. On the other hand, Klatzky, Pai, and Krotov [7] showed that decay plays a much larger role than pitch in affecting judgement. Whereas, material classification by subjects is qualitative in accordance with reported measures of internal friction coefficients for these material classes, inter-subject agreement measures have shown that classification is inaccurate for high quality factors, thus suggesting that the overall decay time does not fully account for material properties [8,9]. In [10] the problem of recovering the material type from impact sounds was investigated, and it was proposed to use the internal friction parameter, which is an approximate material property as a characteristic signature of the material. Giordano et al. [11] conducted a study which demonstrated that human beings can accurately recognize an object’s material when listening to the sounds generated when an object is struck [12]. It could be found in the studies of [13-22] and 25] that wavelet, Mel frequency cepstral coefficients (MFCC) have also been explored in feature extraction where Support Vector Machine (SVM) was used to classify the materials sounds with different characteristics, but these methods don’t prove to be consistent for different training samples.

Materials in general, and solid materials in particular generate different sounds resulting from a physical impact. There seems to be an absence of basic research reported in the literature where sound properties such as frequencies and bandwidth are used to identify the material types. Several methods have been investigated to recognize material based on decay parameter. However, none of the reviewed methodologies has computed eigen-frequencies and their bandwidths of the frequencies. In this study, we focus on using sound identification to classify different material types.

 Figure 1:C1 Condense Microphone	 Figure 2: Workstation
 Figure 3: Plastic Cover (P1)	 Figure 4: Glass Bottle (G1)

 Figure 5: Steel Screw (M1)	 Figure6: Exciter (Hard Rubber)
 Figure 7: Metal (M2)	 Figure 8: Metal (M2)
 Figure 9: Metal (M2)	 Figure 10: Metal (M2)

Figure 1-10: Basic equipment and raw sound acquisition from different materials

3. Material and System Design

a. Excitation

To generate sound, a small thick rubber material was used as the exciter to impact the materials. The rubber material essentially was used because of its short decay and dampness which will not contribute much to the sound signal.

b. Sound Signal Capture

Recordings were captured in a sound-treated room using a C1 condenser microphone all-pass setting and a USB 16-bit analog-to-digital conversion system that sampled at a 22 kHz rate. The microphone was suspended directly over the sound source at approximately 1/3 m from the sound source. Each material was hit at different locations to get a random sound signal for the identification of each material. Afterwards, analysis of the sound from the different objects was done based on pattern analysis for classification in the frequency domain. A condenser microphone element transduces the acoustic energy, and low-pass filters cut off the signal at 20 kHz.

c. Data acquisition and processing

Sound recordings of various materials are collected as raw data. Features engineering which identifies the material type, was carried out with Principal Component Analysis (PCA) to extract key distinctive sound features peculiar to a material type.

Properties such as formant frequency and bandwidth were collected as meta-data. The PRAAT software was used to set sampling frequencies, record and save the data.

d. Pre-processing

After the recordings were saved. The pre-processed data was filtered to remove any noise present in the signal. High-pass Filter at 1 kHz was applied to remove the frequencies which account for the size of the material. The filtered and cleaned sample are now passed through an autocorrelation function.

e. Autocorrelation

The autocorrelation of a continuous time signal f(t) is a function of the lag time τ, and defined as the integral

$$Rf(\tau) \equiv \int f(t)\, f(t+\tau)\, dt \quad (1)$$

If f is a sampled signal, with sampling period Δt, the definition is discretized as

$$Rf[\tau] \equiv \sum t\, f[t]\, f[t+\tau]\, \Delta t \quad (2)$$

where τ and $t+\tau$ are the discrete times at which f is defined.

The autocorrelation is symmetric:

$$Rf(-\tau) = Rf(\tau). \quad (3)$$

***f.* Feature Extraction and Dimension Reduction**

The aim of feature extraction is to convert the sound signals into a sequence of feature vectors in order to produce a set of characteristic features that describe the sound signal [26, 27]. The process is as shown in Figure 11:

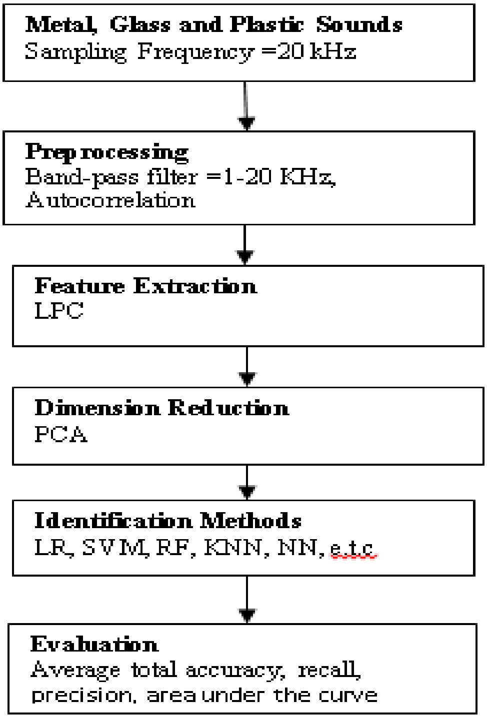


Fig 11: Flow Chart of Process.

g. Linear Predictive Coding (LPC)

Linear Predictive Coding (LPC) is a method, which was used obtain a frequency spectrum. There are various advantages for the use of LPC and they are: (a) LPC proves better approximation coefficient spectrum (b) LPC gives shorter and efficient calculation time for signal parameters and (c) LPC has been able to get important characteristics of the input signals [29]. In LPC, the values of the signal can be expressed as a linear combination of the preceding values.

That is, if $s(i)$ is the amplitude at time i,

$$s(i) = a_1 * s(i-1) + a_2 * s(i-2) + .. + a_p * s(i-p) \quad (4)$$

When the input data from the auto-correlation, this becomes a system of linear equations which can be solved to determine the values of a_1 through a_p. These values are useful to produce a signal which is free from noise and clearly identifies the formants.

Here the Linear Predictive Coding (LPC) of order 4, was used to extract both the formant frequencies and Bandwidth.

The feature vectors were normalizing by centring their mean and scaling by the Standard deviation.

Principal component Analysis (PCA) was performed on the scaled feature vectors to extract the main data that account for the main variance for each material. The Extracted data are now passed for classification and identification as shown in Figure 12.

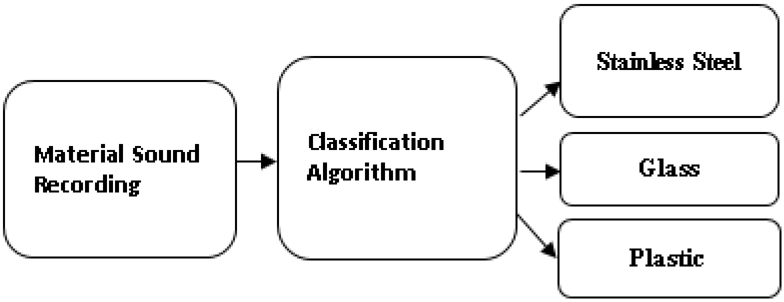


Figure 12: Procedure for the classification system

h. Identification Methods

The identification was done using Orange a data mining software. The widget used is a graphical user interface in which various parameters serve as input and Output.

Classification Algorithms

i. kNN

Predict according to the nearest training instances.
The kNN widget uses the kNN algorithm that searches for k closest training examples in feature space and uses their average as prediction.

<u>Model parameters.</u>
Number of neighbours: 3
Metric: Manhattan
Weight: Distance

Manhattan Distance

$$D(x,y)=\sum_{i=1}^{m}\left|x_i - y_i\right|$$

<u>Data</u>

Data instances: 14055
Features: PC1, PC2
Target: Target

ii. Random Forest

<u>Model parameters</u>

Number of trees: 10
Maximal number of considered features: unlimited
Maximal tree depth: unlimited
Stop splitting nodes with maximum instances: 5

The algorithm
The random forests algorithm is as follows:

1. Draw n_{tree} bootstrap samples from the original data.
2. For each of the bootstrap samples, grow an unpruned classification or regression tree, with the following modification: at each node, rather than choosing the (5) mong all predictors, randomly sample m_{try} of the predictors and choose the best split from among those variables.

(Bagging can be thought of as the special case of random forests obtained when m_{try} = p, the number of predictors.)

3. Predict new data by aggregating the predictions of the n_{tree} trees (i.e., majority votes for classification, average for regression).

iii. AdaBoost

An ensemble meta-algorithm that combines weak learners and adapts to the 'hardness' of each training sample.

The AdaBoost (short for "Adaptive boosting") widget is a machine-learning algorithm, formulated by Yoav Freund and Robert Schapire. It can be used with other learning algorithms to boost their performance. It does so by tweaking the weak learners.

Model Parameters

Base estimator: tree
Number of estimators: 50
Algorithm (classification):Sammer
Loss (regression): Linear

iv. Neural Network

A multi-layer perceptron (MLP) algorithm with backpropagation. The Neural Network used was the sklearn's Multi-layer Perceptron algorithm that can learn non-linear models as well as linear. MLP's uses feed forward and recurrent networks. Multilayer perceptron (MLP) properties include universal approximation of continuous nonlinear functions and include learning with input-output patterns and also involve advanced network architectures with multiple inputs and outputs [27].

Model parameters

Hidden layers: 100
Activation: ReLu
Solver: Adam
Alpha: 0.0001
Max iterations; 200

$$y = wx + b \quad (6)$$

$$error = \grave{y} - y \quad (7)$$

y= true output
$\grave{y}$ = predicted output
w=weight
x=input
B=bias

v. Logistic Regression

Model parameters

Regularization: Ridge (L2), C=1.

Letting Y be the binary response variable, it is assumed that $P(Y=1)$ is possibly dependent on $\vec{x}$, a vector of predictor values. The goal is to model

$$p(\vec{x}) \equiv P(Y=1 \mid \vec{x}). \quad (8)$$

Since Y is binary, modeling $p(\vec{x})$ is really modeling. $E(Y \mid \vec{x})$, which is what is done in OLS regression, with a numerical response.

If we model $p(\vec{x})$ as a linear function of predictor variables, e.g., $\beta_0 + \beta_1 x_1 + ... + \beta_p x_p$, then the fitted model can result in estimated probabilities which are outside of [0,1]. What tends to work better is to assume that

$$p(\vec{x}) = \frac{\exp(\beta_0 + \beta_1 x_1 + ... + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + ... + \beta_p x_p)}, \quad (9)$$

where $x_1,...,x_p$ may be the original set of explanatory variables, but the predictors may include transformed and constructed variables.

vi. Naïve Bayes

Naïve Bayes assumes

$$P(X_1 \dots X_n | Y) = \Pi P(X_i | Y)$$

i.e., that Xi and Xj are conditionally independent given Y, for all i≠j

•Train Naïve Bayes (given data for X and Y) for each value y_k estimate $\pi_k \equiv P(Y = y_k)$ for each value x_j of each attribute Xi estimate

$$\theta_{ijk} \equiv P(X_i = x_{ij} | Y = y_k)$$

prob that word x_j appears in position i, given Y=y_k

• Classify (X^{new})

$$Y^{new} \leftarrow \arg\max_{yk} P(Y = y_k) \prod_i P(X_i^{new} | Y = y_k) \quad (10)$$

$$Y^{new} \leftarrow \arg\max_{yk} \pi_k \prod \theta_{ijk} \quad (11)$$

Additional assumption: Probabilities are position independent and must sum to 1, so there is need to estimate only n-1.

vii. SVM

Support Vector Machines map inputs to higher-dimensional feature spaces.

Support vector machine (SVM) is a machine learning technique that separates the attribute space with a hyperplane, thus maximizing the margin between the instances of different classes or class values. The technique often yields supreme predictive performance results. SVM from the LIBSVM package was used.

<u>Model parameters</u>

SVM type: SVM, C=1.0, ε=0.1

Kernel: Linear

Numerical tolerance: 0.001

Iteration limit: 100

For calculating the SVM we see that the goal is to correctly classify all the data. For mathematical calculations we have,

[a] If Yi= +1;

[b] If Yi= -1; $wx_i + b \leq 1$

[c] For all i; $y_i (w_i + b) \geq 1$

In this equation x is a vector point and w is weight and is also a vector. So to separate the data [a] should always be greater than zero. Among all possible hyper planes, SVM selects the one where the distance of hyper plane is as large as possible. This desired hyper plane which maximizes the margin should also bisects the lines between closest points on convex hull of the two datasets. Thus we have [a], [b] & [c]

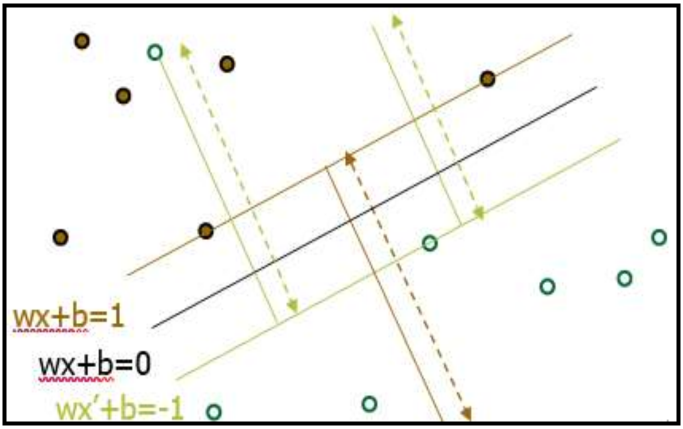


Fig 13: Support Vector Machine.

SVM Classification
DenoteΦ: $\Re^{M} \rightarrow$ F as a mapping from the original M-dimensional attribute space to the highly dimensional attribute space F.

By solving the following dual problem we find α that maximizes

$$\sum_i \alpha_i - \tfrac{1}{2}\sum_i \sum_j \alpha_i \alpha_j y_i y_j \Phi(\mathbf{x}_i)^T \Phi(\mathbf{x}_j) \quad (12)$$

subject to $\sum_{i=1}^{N} \alpha_i y_i = 0,$

$0 \le \alpha_i \le C, \quad \forall i$

The resulting SVM is of the form

$$f(\mathbf{x}) = \mathbf{w}^T \Phi(\mathbf{x}_i) + b = \sum_{i=1}^{N} \alpha_i y_i \Phi(\mathbf{x}_i)^T \Phi(\mathbf{x}) + b \quad (13)$$

Experimental Design
The First Four Formants (Resonant frequencies) coded F1, F2, F3, F4 and bandwidth coded B1, B2, B3, B4 was collected, making a total of 8 feature vectors.
This 8 feature vectors with dimension (15620*8) and 15620 observations was further reduced using the principal component analysis (PCA) to 2Dimension vector with shape (15607*2).
Data gotten from Principal Component Analysis (PCA) which is in 2 dimensions, with the first column representing the most variance followed by the 2nd column for each sound vectors(observation). These values became the input vector for the objects. Since there were three classes, the output vector was labelled (Metal) for metal, (Glass) for glass and (Plastic) for plastic which were used as target output for classification.
Cross Validation of 10 folds in batch was defined in which to partition the data into. Each fold is held out for testing. A model for each fold is trained using a model outside the fold, the model performance is tested using data inside the fold, which was used to calculate the average test error over all folds.

Training Samples.
Glass: 4140 data points.

Metal: 5280 data points.
Plastic: 6200 data points.
In total, 15620 sound observations were trained, 26.5% of which were glass, 33.8% stainless steel and 39.7% plastic.

Test Samples.

Glass: 415 data points.
Metal: 524 data points.
Plastic: 622 data points.
In total, 1561 sound observations were collected, 26.59% of which were glass, 33.57% stainless steel and 39.85% plastic

5. Result and Discussion

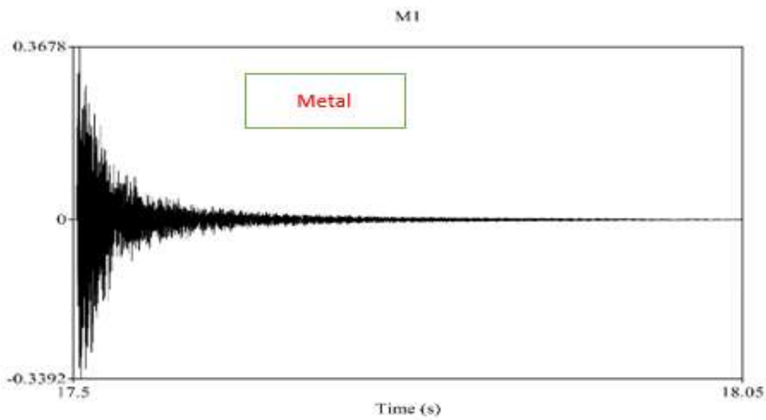


Figure 14: The waveform of the metal material.

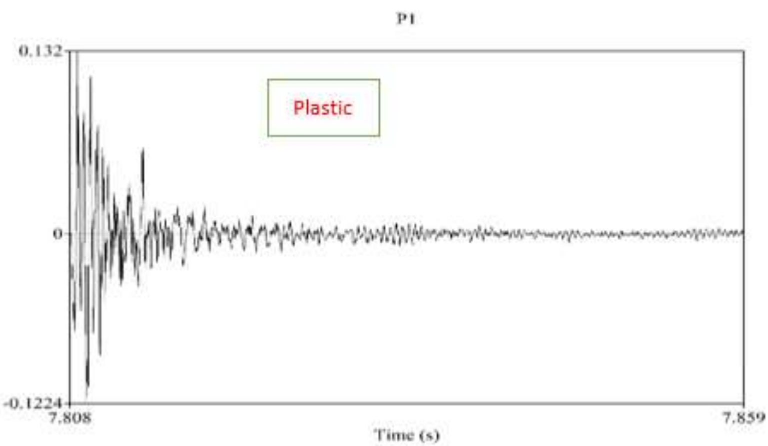


Figure 15: The waveform of the Plastic material

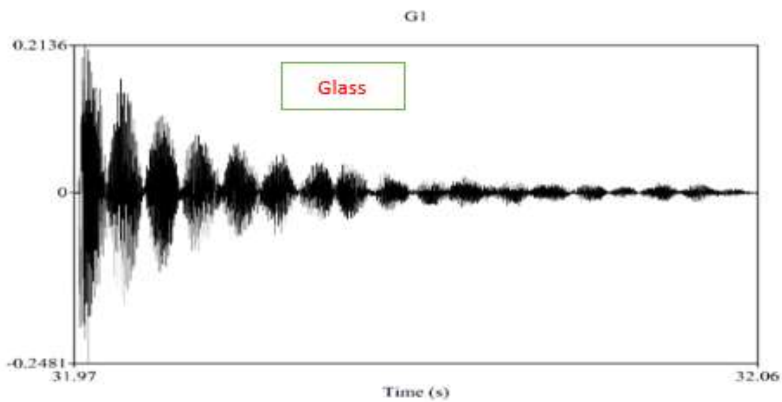
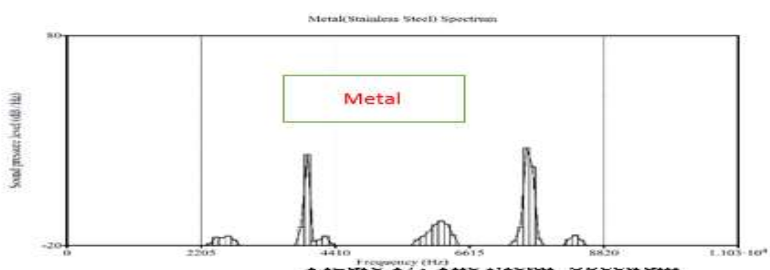
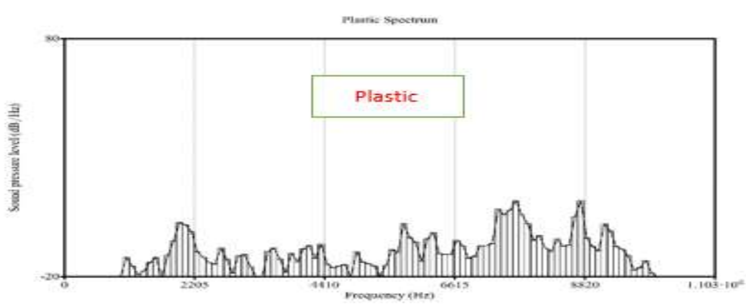


Figure 16: The waveform of the Glass material

a. The Long Term Average Spectrum (LTAS)

In the Figures 17-19 the x axis and y axis represent the Sound Pressure level (dB) and Frequency (Hz) respectively.





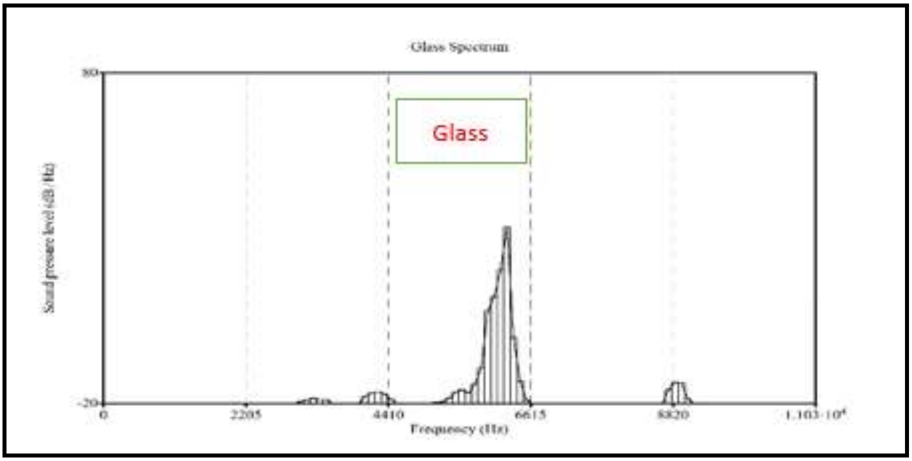


Figure 17 to 19: BAND DENSITIES
METAL ⟶ GLASS ⟶ PLASTICS
ORDER OF DECREASING DENSITIES

From the Figures 17-19, Plastic to metals spectral components have progressively longer decay times, and progressively decreasing bandwidths.
From the result it was found that the bandwidth gave important clues to why a stainless steel, plastic and glass sounds unique. Frequency had a lesser, but significant, contribution.

Training Samples

In Figure 20 the x axis is represents the first principal component (PC1) and the y axis represent the second principal component (PC2)
By visual evaluation, the boundaries of separation for the different materials is visible however it suggests the like hood of misclassification for glass materials, but there is clear line of separation between the metal class and plastic class.

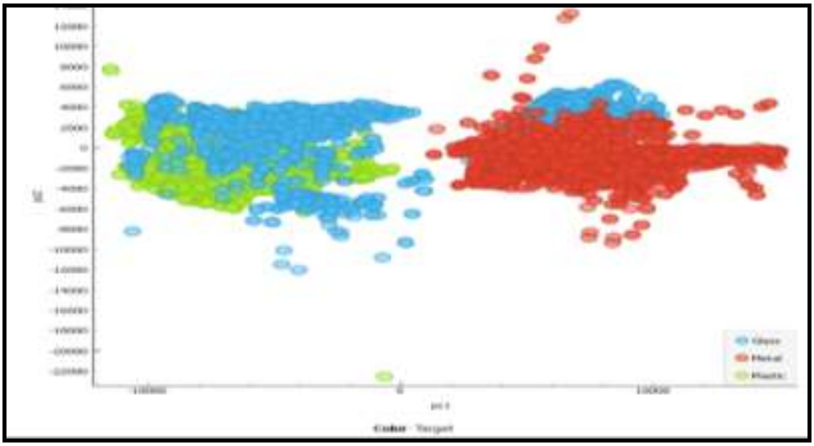


Table 1
Performance Result for different Classifiers.

Scores					
Method	**AUC**	**CA**	**F1**	**Precision**	**Recall**
kNN	0.987	0.967	0.967	0.967	0.967
Random Forest	0.990	0.954	0.954	0.954	0.954
AdaBoost	0.961	0.930	0.929	0.929	0.930
Neural Network	0.985	0.920	0.919	0.920	0.920
SVM	0.889	0.773	0.742	0.754	0.773

Table 2
Confusion Matrix for Training Samples
(Showing number of instances)

	Predicted				
		Glass	**Metal**	**Plastic**	∑
Actual	**Glass**	3773	123	244	4140
	Metal	53	5226	1	5280
	Plastic	87	0	6113	6200
	∑	3913	5349	6358	15620

Sampling type: Stratified Shuffle split, 10 random samples with 90% data.
Target class: Average over classes.

From the Result in Table 1, KNN has the best Classification Accuracy, F1 score, Precision and Recall, with SVM having the least.

Accuracy: The ratio between correctly predicted outcomes and the sum of all predictions.
((TP + TN) / (TP + TN + FP + FN))

Precision: When the model predicted positive, was it right? All true positives divided by all positive predictions.
(TP / (TP + FP))

Recall: How many positives did the model identify out of all possible positives? True positives divided by all actual positives.
(TP / (TP + FN))

F1-score: This is the weighted average of precision and recall.
(2 x recall x precision / (recall + precision))

The Receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The ROC curve is created by plotting the true positive rate against the false positive rate at various threshold settings.

From the ROC Curves in Figures 21-23, it clearly shows the discriminative ability of the different Classifiers, which is seen as the percentage of True Positive rate against the False Positive rate.

b. Text Samples

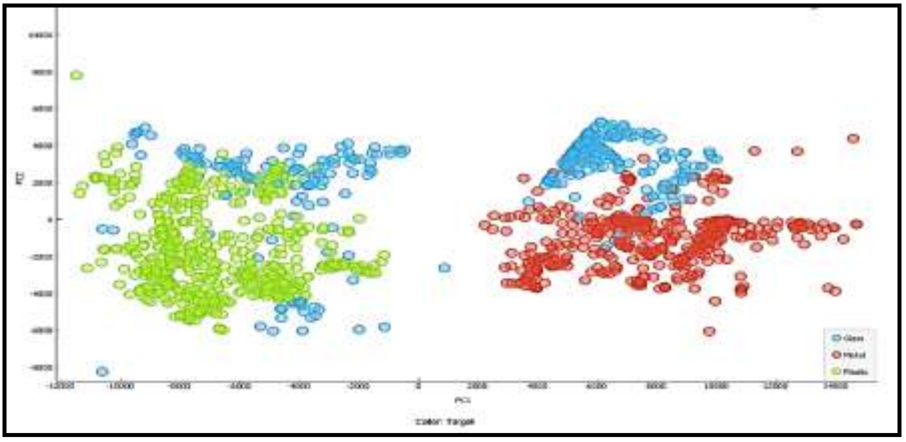


Figure 24: The Scatter Plot of the Test samples.

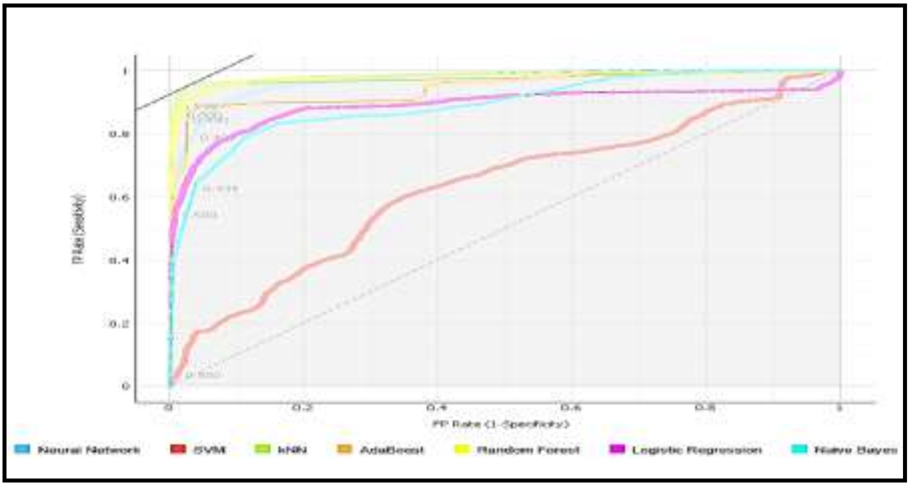


Figure 21: ROC Curve /Glass as Target)

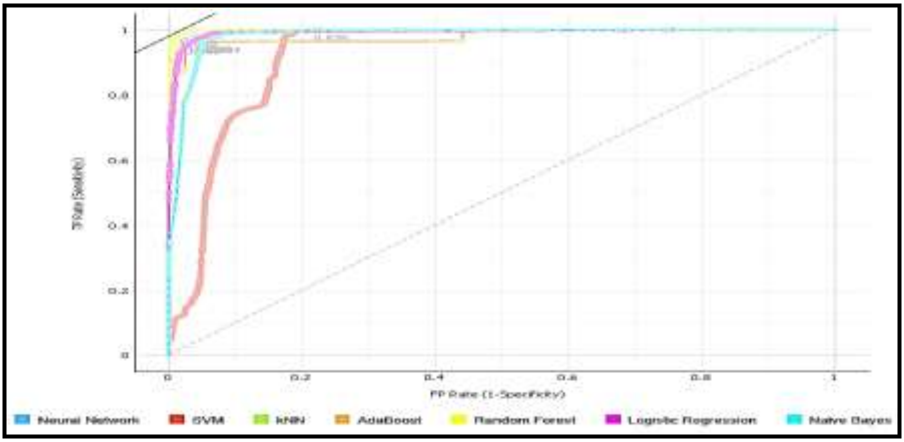


Figure 22: ROC Curve /Metal as Target)

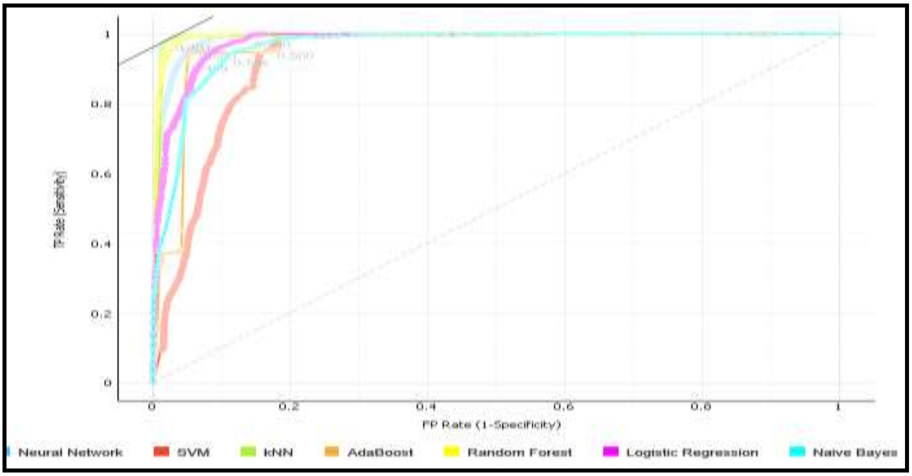


Figure 23: ROC Curve/Plastic as Target)

6. Conclusion

In this paper, we investigated the performance of various classification approaches on the problem of classification of materials from their sound features. The classification results show that KNN has better accuracy when compared to the other classification algorithms.

The difference in band densities has shown to be a distinguishing feature for classifying each material type. Plastic has a dense and broad band, non- harmonic short duration while glass has a narrower band and metals have even a narrower bandwidth and longer duration.

The classification results with band densities show the potential of distinguish glass, metal, and plastic objects using emitted sound waves. This investigation provides insight to the possibility of sorting materials into broad categories where this is sufficient e.g. for the purposes of recycling waste.

Future work will focus on achieving a better representation of the frequency and band density since different materials have different energies in different frequency bands.

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