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MARINE WASTE CLASSIFICATION USING MOMENT INVARIANTS AND NAÏVE BAYES CLASSIFIER

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ABSTRACT

People have transformed marine areas into huge garbage container where other creatures are feeding on it. Plastics as one of major waste produced by human have contaminated food chain. To date, there are no cheap or simple method for managing the waste. In this work, Naïve Bayes Classifier combined with Moment Invariants system is developed to help classifying floating waste on marine areas. This system is implemented in Java by using 2000 sample data from marine and several experimental environments. Several image processings are also used such as resizing, Otsu Thresholding and Histogram Equalization. The results obtained from the proposed system are acceptable in accuracy (69.35%) and False Positive Rate (20.52%) but unreliable False Negative Rate (61.06%). This results are due to overlapping features distribution produced from 10 ranges of Moment Invariants. Although the results are still far from good, the proposed method opens limitless improvements for the next implementations.

Keywords: *Naïve Bayes Classifier; Moment Invariant; Image Processing; Image Classification, Marine Waste*.

INTRODUCTION

Today, plastic has become a potential source of waste. People tend to throw it away after a single use.

Plastic waste managements, including cleaning, finding and separating, are challenging problems. The fact that it is nearly impossible to perform a complete clean-up for plastic waste because of some part of the waste have decomposed (EU Commission's report, 2011). Surprisingly, 60-80 percent of the waste found on marine area are plastics (Barnes and Milner, 2005), (Derraik, 2002). According to literature review, in Indonesia there are no study reports about plastic waste on marine area but estimated 5.4 million ton of plastics are generated every year (ID State Ministry of Environment, 2008). This condition is same as in China where the population is using gas (Hoorweg and Bhada, 2012).

Almost all individuals from seabirds, fish, turtles, mussels and mammals have contaminated by plastic (Ryan et al., 2009).

For observation, ships, small boats, and aerial observations (e.g. plane and satellite observation) are mostly used. However, there are some disadvantages in amount of area of coverage and quantity of waste that can be seen with observation (EU Directorate-General Environment, 2011). As for ascertaining the composition of plastic, people tend to rely on 'Fourier Transform infrared spectroscopy'. This method is classified as a considerably complex and expensive method (Morét et al., 2010).

Moment Invariants. Invariants is a set of quantities that gained from an object. Invariants from a same class must be relatively constant and resistant to kinds of deformation. In contrast, invariants must be slightly different from one class to other classes. This property is called discriminant values.

Mathematically, relation of Invariants (*I*) and Deformations (*D*) from a function (*f*) can be written as;

$I(f) \quad I(D(f))$ ……………………………...(1)

Seven moment invariants of Hu. Hu demonstrated his famous seven moment invariants for rotation.

$\varphi_1 = m_{20} + m_{02}$ ....(2)
$\varphi_2 = (m_{20} \quad m_{02})^2 + 4m_{11}^2$ ....(3)
$\varphi_3 = (m_{30} \quad 3m_{12})^2 + (3m_{21} \quad m_{03})^2$ ....(4)
$\varphi_4 = (m_{30} + m_{12})^2 + (m_{21} + m_{03})^2$ ....(5)

$$\varphi_5 = (m_{30} \quad 3m_{12})(m_{30} + m_{12})((m_{30} + m_{12})^2 \quad 3(m_{21} + m_{03})^2) \quad + \quad (3m_{21} \quad m_{03})(m_{21} + m_{03})(3(m_{30} + m_{12})^2 \quad (m_{21} + m_{03})^2) \text{ .... } (6)$$

$$\varphi_6 = (m_{20} \quad m_{02})((m_{30} + m_{12})^2 \quad (m_{21} \ + \ m_{03})^2) + 4m_{11}(m_{30} + m_{12})(m_{21} + m_{03}) \text{ .... } (7)$$

$$\varphi_7 = (3m_{21} \quad m_{03})(m_{30} + m_{12})((m_{30} + m_{12})^2 \quad 3(m_{21} + m_{03})^2) \qquad (m_{30} \quad 3m_{12})(m_{21} + m_{03})(3(m_{30} + m_{12})^2 \quad (m_{21} + m_{03})^2) \text{ .... } (8)$$

Additional invariant. Flusser (2000) and Suk (2006) showed that Hu's moment invariants are uncompleted. Therefore, they add another invariant for third order moment described below.

$$\phi_8 = \eta_{11}[(\eta_{30}+\eta_{12})^2 \quad (\eta_{03}+\eta_{21})^2] \quad (\eta_{20}+\eta_{02})(\eta_{30}+\eta_{12})(\eta_{03}+\eta_{21}) \text{ .... } (9)$$

Moment computation. Since moments that described before are related for continuous domain, it is needed to describe approximation method for digital image. A rough estimated model is obtained by changing integral notation with sigma (Flusser et al., 2009).

$$m_{pq} = \sum_{i=1}^{N} \sum_{j=1}^{M} i^p j^q f_{ij} \text{ .... } (10)$$

with

f_{ij} = pixel value / grayscale value at (*i,j*) position

NxM = area of image

Naïve Bayes Classifier. Bayes theorem. Bayes Theorem is constructed from interchanging the theorem of conditional probability and the fact that conjunction (∩) is commutative.

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)} \text{ .... } (11)$$

Using Bayes theorem for conditional probability computation is known as Bayesian inference (Neapolitan, 2009).

Bayesian network. Bayesian Network is a graphical model for modelling events' relation. Bayesian network is constructed from nodes and arcs. Node represents event/variable and arc represents relation between events/variables.

Bayesian network is drawn as a DAG (Directed Acyclic Graph) (Korb and Nicholson, 2011). For example, consider a case where an earthquake can trigger an alarm. The case can be drawn as a BN that shown in Fig. 1.

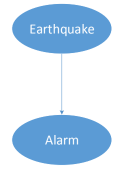

Figure 1. BN of earthquake alarm

BN can be helpful for modeling complex events and their relations

Naïve Bayes Classifier. Naïve Bayes Classifier (NBC) is one of BN modeling structures for classification. NBC consists of one parent node and one or more child nodes. Parent node is known as class variable that describes the classification result. Furthermore, there are child nodes that determine the result. Child nodes are known as attribute variables. All of the attribute variables are assumed independent each other.

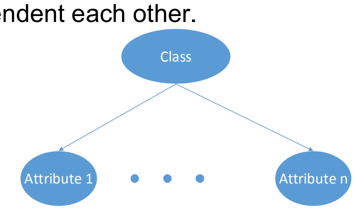

Figure 2. BN of NBC

$$argmax_c P(c|a_1, \dots a_n) = argmax_c \prod_i P(a_i|c)P(c) \text{ .... } (12)$$

Eq. (12) is used to find value of *c* for each class. Class which result maximum value will be the classification result.

METHODOLOGY

System Design. The research is divided into two system processes. The first is classification process and the second is training process. The system begins by checking whether the prototype has been trained or not. If the prototype has been trained, user will be asked to input an image to be classified. If the prototype has not been trained, the prototype will be trained by the process that described later in this chapter.

Classification system begins by converting input image to grayscale. Classification process continue to extracting moments invariant from the image using equation (eq.2 - eq.10). Moments obtained are calculated by NBC as parameters (eq.12) to obtain single result that determine the class of the image.

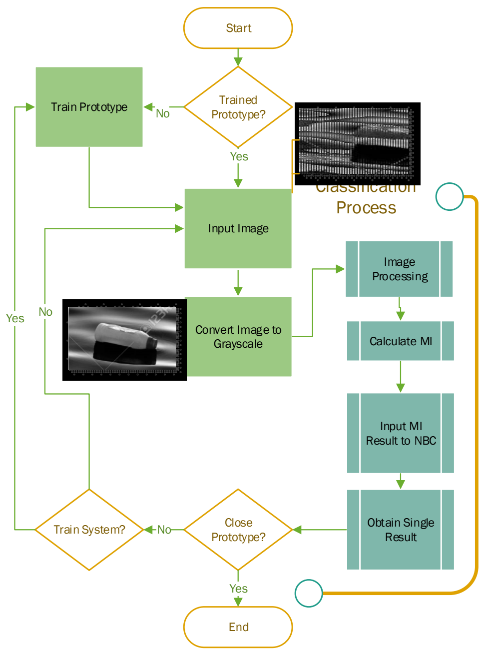

Figure 3. Flowchart of system

As for the training system, moments invariants will be extracted from labelled training images. The images are manually converted to grayscale before the prototype started to increase training speed. Moments invariants are sorted and labelled to be a parameter in NBC system.

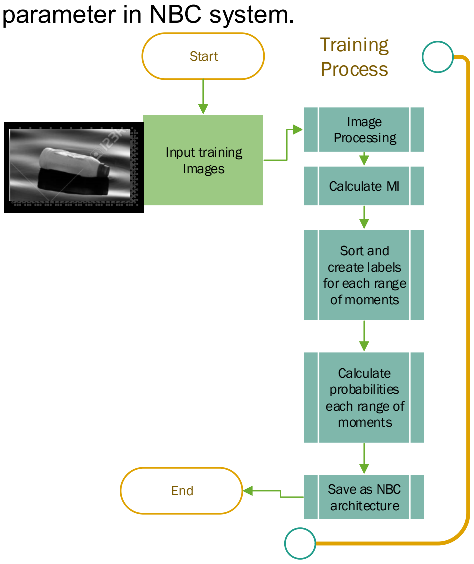

Figure 4. Flowchart of Training

Range of moments are divided and labelled from low to high (mid-range labels are varying to total images in a class that fall in certain moments range). Last process in the training system is calculating probabilities of each moment's range that fall in particular class. The probabilities are calculated for every class to obtain NBC architecture. Training system flowchart can be seen in Fig.4.

Sample Data. The data used for training classifier are images with environments as follows:

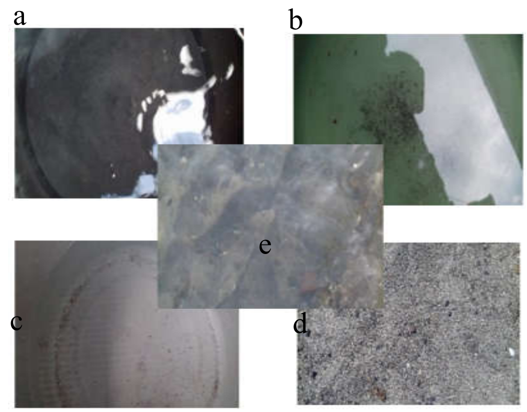

Figure 5. Sample picture of environments

a. Black water bucket filled with ± 10 liters tap water with several generated disturbances (ripples and light reflections)
b. Blue water bucket filled with ± 10 liters tap water with several generated disturbances (ripples and light reflections)
c. Black water bucket filled with ± 10 liters tap water
d. Sands (Natural)
e. Sea 1-10 meters from shore (Natural)

Sample pictures for each environment are shown in Fig. 5.

RESULT AND DISCUSSION

The software program made in this research is called Ice Waste. It was designed to combine Moments Invariants and Naïve Bayes Classification. Several image processes such as converting RGB to Grayscale, resizing, equalizing histogram, and thresholding are included in the system.

User Interfaces. User Interface (UI) consist of Main, Scan File, and Scan Folder forms which are described as follows:

Main form. Main form is the first UI which displayed when the program is run. States of the form can be seen in Fig. 6 such as "Untrained State", "Trained State", "Training State", and "Help Mode State".

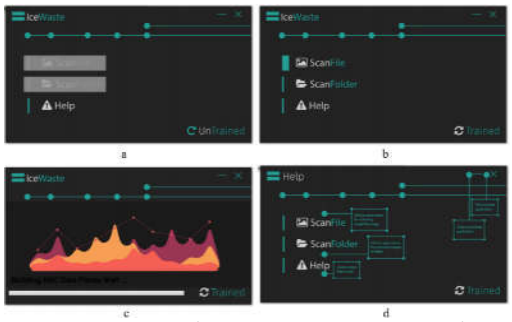

Figure 6. The Main form states. (a) Untrained State, (b)Trained State, (c) Training Process, (d) Help Mode

Untrained state is shown when the software is not trained (Fig. 6a). It is done by checking whether system database has been created or not. In this state, main buttons for inputting data such as Scan File and Scan Folder are disabled. Users only gain access to Help, Train, and Form Control buttons (e.g. Exit and Minimize). In other case, second state (Trained State) is shown when the software is trained and ready to receive input data (Fig. 6b). All buttons can be accessed in this state.

Training State (Fig. 6c) is shown when user clicks on Train button, whether the software is in trained or untrained state. This state shows an animation and a progress bar. A dialog box showing training time is displayed when training process is done and state changes into Second States or First States according to whether the training process have an error or not. Help Mode is shown when Help button is clicked (Fig. 6d). In this state, descriptions for several button in main form are shown. This states designed for new users who need basic information of using the software.

Scan file form. Scan File form is provided for scanning individual file. This form is made to get detailed output of Ice Waste software such as extracted features and output image as can be seen in Fig. 7.

Figure 7. Scan File Form

There are 6 main elements on Scan File menu UI. First element is a Select File button that displays a File Chooser to let users choose a file to be scanned. After choosing an input file, full path to the file is shown at the right side of the button. Second element is Classify button that process the input file when clicked. Moment results are then showed on the third element. Class Result is displayed in fourth element. Fifth element shows time of the process in milliseconds. Last element shows input and result file as an image.

Scan folder form. Scan Folder form is provided to scan images in a folder. This form is made for testing as it provides only the class results of images. The form can be seen in Fig. 8.

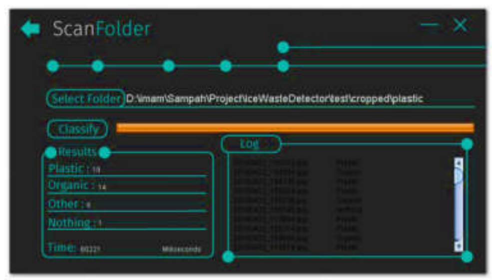

Figure 8. Scan Folder Form

In Scan Folder UI, the two buttons for select input files and process the input are the same as in the Scan File UI, but instead of showing File Chooser for selecting file, Select Folder button displays a File Chooser to select a folder. Results are shown as Results and Log elements. In Results element, users can see a number of files detected for every class. Results element also shows time for the process in milliseconds. Users can see file names and its detected class in Log element.

Preprocessing Results. There are 4 types of preprocessing procedures used in this research. These procedures are used either to get smaller data or to get better extracted features. The procedures are two kinds of initial process, histogram equalization, and Otsu thresholding. All processes include grayscale conversion.

Resize into 10%. This is the first option of the initial procedure in the preprocessing state. This procedure was conducted to get the effect of reducing image pixel to the system performances.

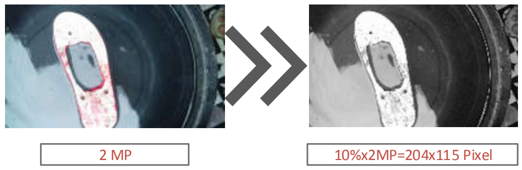

Figure 9. Resize 10% result

This procedure reduces size of images into 10% of its original size. Ratio of the image is maintained in this process. Briefly, the input and output of the process can be seen in Fig. 9.

Resize square 128x128. This is the second option of initial procedure in the preprocessing state. This procedure was conducted to get the effect of reducing image pixel and ratio to the system performances.

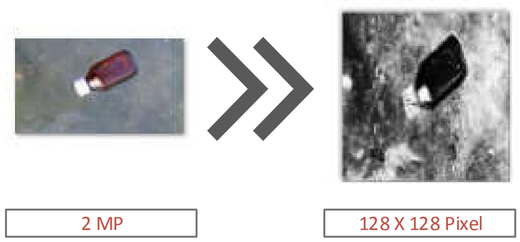

Figure 10. Resize 128x128 result

This procedure reduces size of images into 128x128 pixel. Ratio of images were changed from 16:9 into 1:1. Briefly, the input and output of the process can be seen in Fig. 10.

Histogram Equalization. This procedure is used to get a better distribution of gray scale distribution of input images.

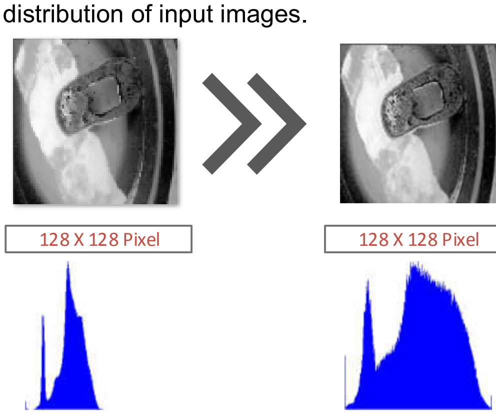

Figure 11. Histogram Equalization result

The Fig. 11 shows that output of histogram equalization provides better contrast and clearer objects. This procedure supposed to bring better performances for the system.

Otsu Thresholding. This process is used to separate object from its background. This process converts image from grayscale into black and white according to Otsu algorithm result. Briefly, the input and output of the process can be seen in Fig. 4.8.

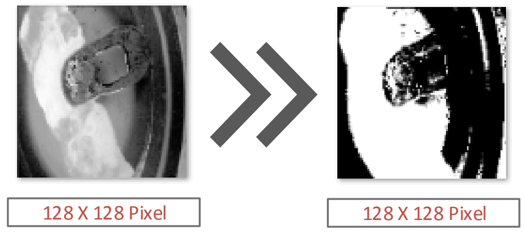

Figure 12. Otsu Thresholding result

The Fig. 4.8 shows that output of Otsu thresholding is a black and white image. The image has more clear pattern of object. This procedure supposed to increase performances by produced better moments extraction values.

Experimental Results. Best result for each environment. Sample data that produce best result environments is a black water filled bucket with minimum reflection.

There were four types of image preprocessing used in this part as seen below.

P1= Without any preprocessing
P2= Resized 128x128
P3= P2+ Histogram Equalization
P4= P3+ Otsu Threshold

Performances of the system such as Accuracy, FPR, and FNR are provided as follows.

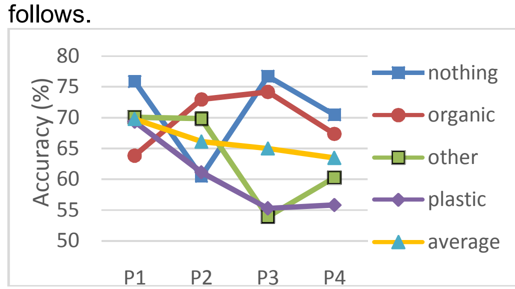

Figure 13. Graph of accuracy for best environment

As seen in Fig.13, all processes tend to decrease the accuracy of the system in average. The best average accuracy is produced by process “P1” or without any process used. Resize process “P2” is decrease all accuracy except for “Organic” class. Process “P3” increase “Nothing” class to maximum and slightly increase “Organic” class. Process “P4” decrease “Nothing” and “Organic” classes and produce the worst accuracy in average. Overall, the system produces reliable results with no accuracy below 50%.

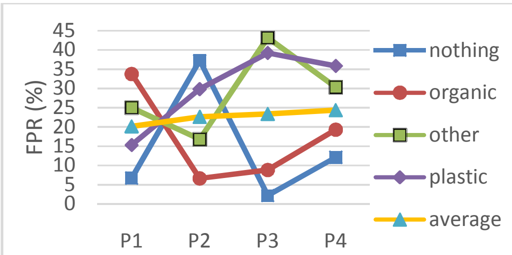

Figure 13. Graph of FPR for best environment

The Fig.13 shows that graph of FPR has similar trendlines as Accuracy. Still, the system produces reliable FPR with no FPR above 50%. This is the first time a system produces reliable results for both Accuracy and FPR

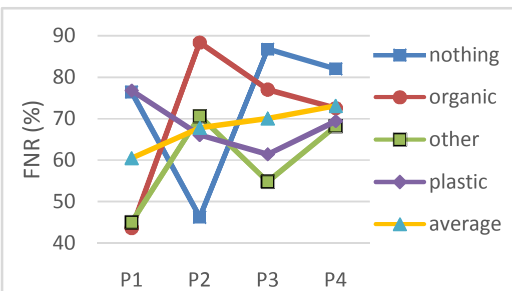

Figure 14. Graph of FNR for best environment

The system with produce poor results for FNR. Acceptable results are only produced by processes “P1” and “P2”. Process “P1” produces two acceptable results which are in “Organic” and “Other” classes. Process “P2” produces only one acceptable result which is in “Nothing” class. Overall the system produced total average for accuracy, FPR, and FNR respectively are 66.09%, 22.61%, and 67.83%

Best Result. There are several methods used in this experiments.

P1=Without any preprocessing
P2=Resized 128x128
P3=Resized 10%
P4=P2+Histogram Equalization
P5= P3+ Histogram Equalization
P6= P4+ Otsu Threshold
P7= P3+ Otsu Threshold

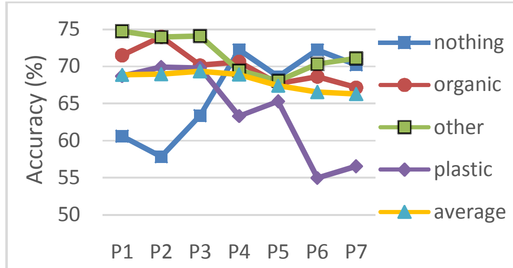

Figure 15. Graph of Accuracy whole data

The Fig.15 shows that the system produces all reliable results. Process “P3” produces best average result. All processes produce slightly differences results with only ~3% margin between minimum and maximum average results.

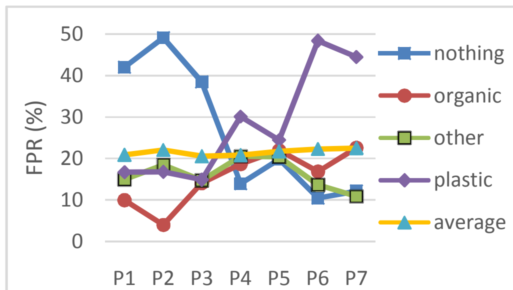

Figure 16. Graph of FPR whole data

The system also produces all reliable results for FPR according to Fig.16. Minimum result again found in process “P3”. The system has ~2.5% margin between maximum and minimum results.

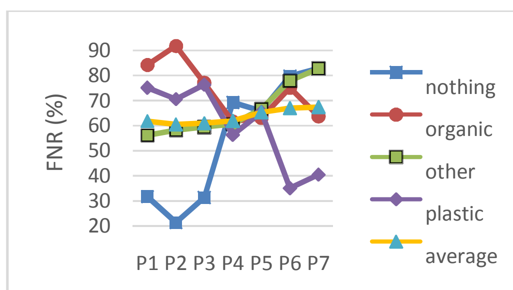

Figure 17. Graph of FNR whole data

The Fig.17 shows that reliable results are only produced in five conditions. Three of the results are in “Nothing” class using processes “P1”, ”P2”, and “P3” whereas two other in “Plastic” class using processes “P6” and “P7”. This time process “P2” produces best average results with “P3” in second position by ~0.5%. Overall the system produced total average for accuracy, FPR, and FNR respectively are

68.04, 21.53, and 63.62. The best system in average is produced by process "P3" with accuracy, FPR, and FNR respectively are 69.35, 20.52, and 61.06. There are increasing results for all parameters compared to the best system with 10% training data which are 66.09%, 22.61%, and 67.83%. The total differences between the best systems is 12.12%. Unfortunately, the research still could not find any reliable FNR.

To find the cause of this problems, research continuous with providing analysis of NBC architecture and moments results for the best system. This analysis hoped to bring a clearer steps and modifications needed for next researches.

Data distribution. To get further detail about the best system produced in this research, best moments distributions.

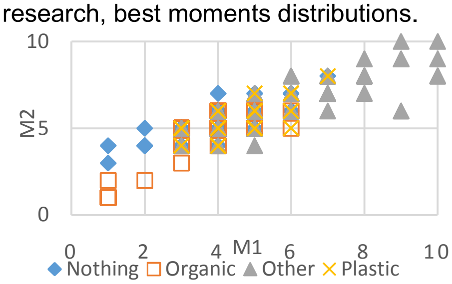

Figure 18. Data distribution M1-M2

The Fig.18 shows that there are no "Plastic" data which does not mix with other classes. "Nothing" and "Organic" data are separable but they mostly mixes with other classes. "Other" data are the most scattered data.

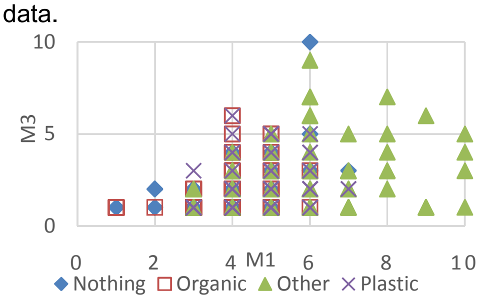

Figure 19. Data distribution M1-M3

The Fig.19 shows that there are no "Organic" data which does not mix with other classes. Only one point of "Plastic" data does not mix with other classes. "Nothing" data are separable but they mostly mixes with other classes. "Other" data are the most scattered data.

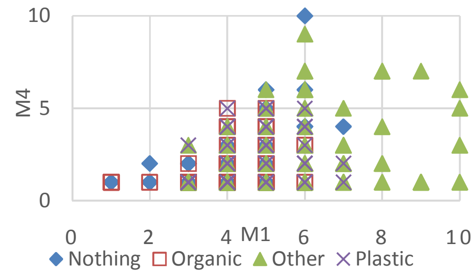

Figure 20. Data distribution M1-M4

The Fig.20 shows that there are no "Organic" and "Plastic" data which does not mix with other classes. "Nothing" data are separable but they mostly mixes with other classes. "Other" data are the most scattered data.

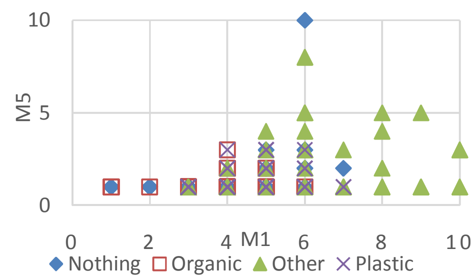

Figure 21. Data distribution M1-M5

The Fig.21 shows that there are no "Organic" and "Plastic" data which does not mix with other classes. "Nothing" data are separable but they mostly mixes with other classes. "Other" data are the most scattered data

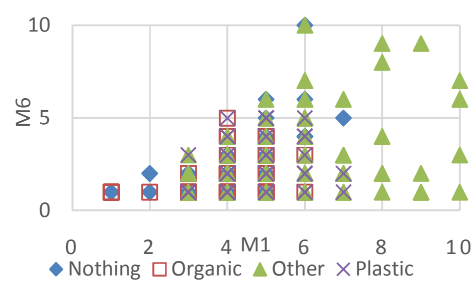

Figure 22. Data distribution M1-M6

The Fig.22 shows that there are no "Organic" and "Plastic" data which does not mix with other classes. "Nothing" data are separable but they mostly mixes with other classes. "Other" data are the most scattered data.

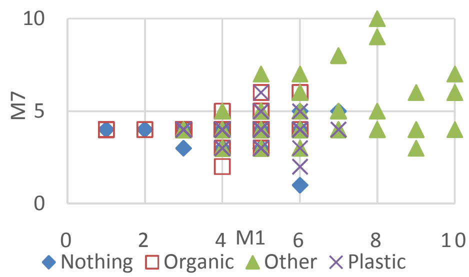

Figure 23. Data distribution M1-M7

The Fig.23 shows that only one point of “Plastic”, “Nothing”, and “Organic” data does not mix with other classes. “Nothing“ data are separable but they mostly mixes with other classes. “Other” data are the most scattered data

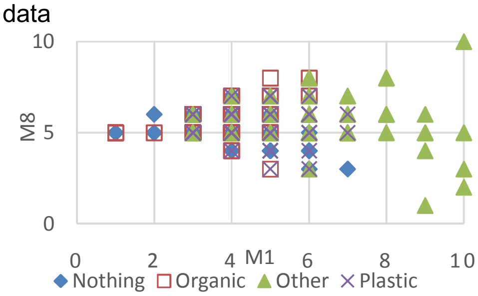

Figure 24. Data distribution M1-M2

The Fig.24 shows that there is no “Plastic” data which does not mix with other classes. Only one point of “Organic” data does not mix with other classes. “Nothing“ data are separable but they mostly mixes with other classes. “Other” data are the most scattered data

Concluding from all data distribution, the system produces poor distribution data with Moment Invariants by range 10. Similar data distributions make it hard to classifying data. There are also grouping data only in 2 and 3 ranges of moments.

Performance per class. To get more detail performances of the best system, classification results for the best system are provided.

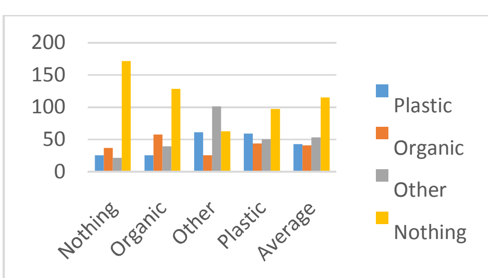

Figure 25. Result per class

As can be seen in Fig.25, Mostly results are in “Nothing” Class and then distributed to other class except for “Other” Class. This fact makes the system good at classify “Nothing” and “Other” Classes which put their classes as most result. For “Organic” and “Plastic” Classes, their classes are put into second most results which produce poor results. In average, “Nothing” class is the most result with more than 100 data in average and “Other” class in second position but half of the average result of “Nothing” class and then separate evenly for the two other classes.

Performances for transparent objects. To get the performance of the best system only for transparent object, 139 transparent data from “Other” and “Plastic” classes are classified. The results are shown in Fig.26.

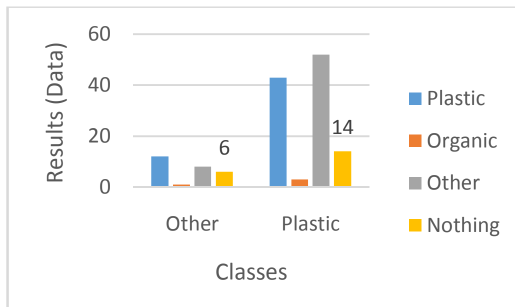

Figure 26. Transparent objects classification results

The Fig.26 shows that only 20 data are classified as “Nothing” class. Accuracy of the system if all objects class merge into one class is 85.61%. This fact shows that the system is reliable for classifying transparent objects

CONCLUTIONS

According to results obtained in this research, it is concluded that:

1. The proposed method was successfully implemented in java platform.
2. The best system produces average Accuracy, FPR, and FNR respectively are 69,35%, 20,52%, and 61,06%.
   - The “Nothing” class Accuracy, FPR, and FNR are 63,33%, 38,44%, and 31,36%.
   - The “Nothing” class Accuracy, FPR, and FNR are 70,17%, 14,08%, and 77,08%.
   - The “Nothing” class Accuracy, FPR, and FNR are 74,09%, 14,72%, and 59,48%.

- The “Nothing” class Accuracy, FPR, and FNR are 69,79%, 14,84%, and 76,32%.

3. Several experiments tend to decrease performance of the system.
4. Environment have significant effect on performances.
5. The best system produces 85,61% accuracy for only transparent objects.
6. NBC produced by the best system have a similar major probability for all classes.

FUTURE WORKS

Future works can be done but not limited by the following conditions:

1. Replacing/modifying methods. These methods including image processing used, moment range divider. More complex image processings such as shadow remover, noise filter, and better thresholding like waterfilling can be used to get better results.
2. Increasing/decreasing/modifying range of moment invariants. This system currently using 10 moment range. Divided equally from minimum to maximum value. This method produces stacking data only to several ranges.
3. Increasing/replacing features extracted from images. This experiment is using only 8 moments as features. Other features such as statistic features and other moment invariants can be used in future works for more parameters.
4. Replacing sample used to data set. This future works can be done to obtain better result of the proposed method. Data set provide more standardized data for testing a classification system. The result can also be compared to previous systems that have used the same data set.
5. Evaluating classes used. This system used 4 class (Nothing, Organic, Other, and Plastic). These classes are choosed based majority waste data from world bank (Organic, Plastic, and Other) (Hoorweg, 2012). Other classes groups based on ingredients, parts, and shapes can be used for more variation.

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