Recyclable Beverages Containers for Reverse Vending Machine Sorting Mechanism using Image Processing Technique

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Abstract –*Waste management is one of the vastest obstacles in society today; thus, reverse vending machine (RVM) is here to deal with this obstacle. Some of the reverse vending machines can classify limited objects since they use sensors as the classification approach. Besides that, the sensor has a minimal lifespan and is expensive. This paper presents a modern image processing technology for the reverse vending machine to carry out classification for sorting mechanism. This approach supports the RVM in classifying three beverages containers which are aluminum cans, drink carton boxes, and polyethylene terephthalate (PET) bottles. Image processing is a standard technology that is used in face detection which provides surveillance and tracking of people in real-time. The method of image processing that used in this project is image enhancement, image segmentation, features extraction, and image classification. The image processing method is highly convenient in classifying the beverages containers because it helps to filter and enhance the image and produce information for machine interpretation. Convolutional Neural Networks (CNNs) is the most popular neural network model used for image classification problems. The CNNs used in this project is ResNet-50, whereas the classification method used is a support vector machine (SVM) classifier. Using both ResNet-50 and SVM classifier, the beverages containers can be classified based on types and segregated accordingly.*

Keywords: *Image processing, MATLAB, Reverse vending machine, sorting, waste classification.*

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I. Introduction

According to Clean Malaysia [1], Malaysia produces roughly 30,000 tons of rubbish per day, and just 5 percent of it is recycled. Malaysia has faced numerous challenges because of this issue. The accumulation of solid trash in the country results in significant land and air pollution, status issues for associations, and hurdles to commercial progress. Combined, the challenge of ordinary waste management in Malaysia is one of the country's most pressing challenges [1]. The Reverse Vending Machine (RVM) idea is created to accomplish the target. RVM is a machine that supports the purchaser to recycle beverages containers and get back points or coins as a profit. The RVM gathers, segregates, and deals with the return of used beverages containers in an automated manner.

Ruveena Singh et al. [2] have proposed a microcontroller-controlled beverage separation system that divides beverages containers into biodegradable and degradable wastes. The microprocessor takes the signal based on the type of beverage, and a servo motor opens the matching dust bin lid to dispose of the garbage.

Andrey N. Kokoulin [3] developed a reverse vending machine that classified PET bottles and aluminium cans using convolutional neural networks. Any other material will be regarded as a forgery. The machine uses a Raspberry Pi camera to capture the object and Python software to code it. Their machine has a feedback system that sends a message to the logistic center, and the user can select the type of reward they desire.

Razali Tomari [4] created a system into a recycle bin while still allowing users to discard their trash traditionally. This study focuses on operating the Bin Processing Unit (BPU) while considering two types of recycling bins: plastic and paper. The user must first scan their SD card before selecting the sort of material to be recycled. Based on the weight of the recycled object, the machine will reward the user with points.

An experimental machine vision device was utilized to recognize and collect recyclable plastic bottles conveyor belts, according to Edgar Scavino [5]. The bottles were photographed with Webcam; then identification was made using their program based on the shape and dimensions of the photos.

This project focuses on the waste classification for sorting mechanism by implementing the image processing method. This RVM allows to classify aluminium cans, PET bottles, and drink carton boxes. This is unlike the previous works [2]-[5], the RVM only can classify limited material. Image processing is an approach to conducting image operations, such as extracting text or data from an image, detecting an image's edge, enhancing a picture, and so on. This approach will help the consumer auto classify the recycled object into their category.

The outline of this paper is as follows. A brief introduction and description of the image processing used in RVM are presented in Section I. Next, the details of the process and the implementation of image processing for beverages containers sorting mechanism are shown in detail in Section II followed by the results and discussion of the simulations in Section III. Lastly, this paper is concluded in the final section IV.

II. Methodology

This part illustrates the details of the proposed reverse vending machine classification technique which is the image processing technique. The summary of waste classification using the image processing part for the RVM is presented in Fig. 1. The details for the image processing will be further described.

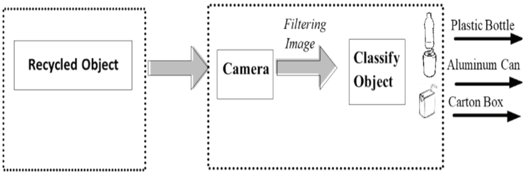

Fig. 1. Summary of Image processing for RVM

The idea for this project is when the consumer inserts the beverages containers, the camera will capture the image. The image will then go through the image processing process such as pre-processing and enhancement, image segmentation, and features extraction. After filtering the image, the image will be used to compare with the stored dataset and lastly perform the classification process. By sorting the beverages containers according to types of materials, it cuts down on the quantity of beverages containers that end up in landfills, freeing up more space. As beverages containers are segregated and handled separately, pollution of the air and water is greatly minimized. This project is divided into three steps which are preparing dataset, image processing, and image classification. The details for these three steps will be discussed in the following section.

A. Dataset Preparation

Before performing the image processing method, the first thing that needs to be done is to prepare the dataset. Since this project needs to classify three types of beverages containers, thus we need to prepare a dataset for these three beverages containers. By collecting more data, it will make the machine perform more accurately, so the data will be collected in different types, sizes, colors, and shapes for all types of beverages container. Each object will be taken from several angles. All the data will be saved into different files according to their materials. Fig. 2 illustrates the proposed algorithms for this project.

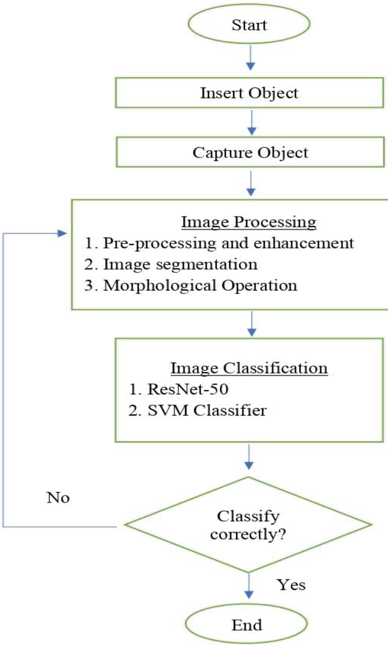

Fig. 2. Proposed algorithms for the system

B. Image Processing

Image processing is a process to enhance the image and to get some helpful information from the image. In this project, image processing is used as the sorting mechanism to segregate three types of beverages containers: aluminium cans, PET bottles, and drink carton boxes for RVM.

The essential step for image processing is the input image. In this project, the camera used is a laptop camera, thus the MATLAB software needs to be connected with the camera by installing a MATLAB support package for USB Webcams and an Image Acquisition toolbox support package for OS Generic Video Interface.

After the image has been captured by the laptop camera, the picture or image needs some pre-processing and enhancement procedures. This step is to enhance or improve the image information and therefore diminish the useless distortions and build up some components for the input image. Each image contains three colour channels: red colour channel, green colour channel, and blue colour channel (RGB). When an image contains these three-colour channels, it contains many unnecessary data that is not required for the process. A grayscale image contains less information, which means that converting the RGB image into a grayscale image will discard any information which is not required for the process. Thus, by using the pre-processing and enhancement process, the RGB image will be changed into a grayscale image, as it has less information and it is ready for the next procedure, which is the image segmentation.

Image segmentation is to perform thresholding on a grayscale image into a binary image. The typical procedure to segment the image is thresholding, which separates the object and background into the black and white district. This is to break up the object from the background in image processing. Any region in the image that lies inside the color channel pixel will be segmented automatically and appear as a significant region in the final binary image by specified the value for each RGB channel.

Morphology refers to a group of image processing methods that work with images depending on their forms. Morphological operations apply a structuring element to an input image and produce a similar-sized output image. By using morphological operation, the value of every pixel in the output image is based on comparing the corresponding pixel in the input image with its neighbors. The morphological opening is used in this project to eliminate all of the small things from the image while keeping the shape and size of the larger object.

C. Image Classification

In this project, both ResNet-50 and support vector machine (SVM) classifier are used to perform image classification. By using both ResNet-50 and SVM classifier, the beverages containers will be classified into aluminium cans, drink carton boxes, and PET bottles. The features extraction is summarized in the steps below. The dataset preparation is the initial phase. Then, the image has to be pre-processed and the dimensions has to be resized. Again, augmentation was employed to match the image size to the network's input size. The features were extracted from the pre-trained network's fully linked layers. The SVM classifier was used to classify the data using deep features. Finally, the model's performance is assessed. Fig. 3 shows the Resnet-50 convolutional neural networks and SVM classifier.

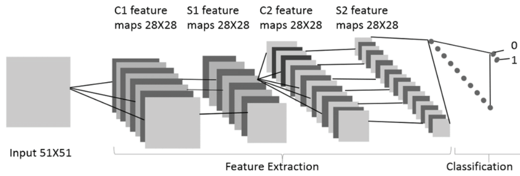

Fig. 3 ResNet50 convolutional neural networks with SVM classifier

ResNet-50 is a pre-trained convolutional neural network which consists of 152 layers deep. ResNet50 is used to extract the image features in this project. Features extraction is a critical technique since it allows to extract the information from an image. As a result, to obtain the data, the ResNet-50 was used to extract characteristics for each type of beverages containers. A feature vector was created by extracting the deep features of ResNet-50 models from a particular layer. The features were fed into an SVM classifier to identify beverages containers. The ResNet-50 model is a multilayer structure network that generates responses at each layer. The layers extract the fundamental visual feature and pass it on to the next layer. ResNet-50 models employ the feature layer and feature vector fc1000 and 1000, respectively. The activation is done in the GPU with a minibatch size of 32 and enough GPU capacity to fit the image dataset. The activation output is in the form of the column to fit in linear SVM training. To train the SVM, the function 'fit class error-correcting output codes (fitcecoc) was used. This function returns the full trained multiclass error-correcting output of the model.

Support vector machine classifier is also known as SVM classifier. In this project, SVM classifier is used to classify three types of beverages containers: aluminium cans, PET bottles, and drink carton boxes. There are three processes in the SVM classifier which are training process, validation process, and classification process [9]. The first step is the training process, which means that the SVM classifier will learn every type of the beverages containers based on their own features, since the beverages containers have different size, shape, colours and angles. Now, the SVM classifier able to complete the learning process from the different features, and the data will be stored by itself. After the training process, the SVM classifier has passed the validation process to compute their performance in the training process. The SVM classifier has recognized the datasets for each beverages containers from the test set in the validation process. The input image for the beverages containers has been processed until the output image can be acquired in the classification process.

The confusion matrix will be used to assess the classifier's performance. The confusion matrix compares the actual target value to those predicted by the machine learning model. The row represented the predicted values whereas the column represented the actual value.

Accuracy, precision, recall, and F-score are the parameters evaluated by the confusion matrix.

The accuracy is calculated as the proportion of cases in the test set that were predict correctly. Precision refers to the percentage of relevant results that are accurately classified by the algorithm. In contrast, recall refers to the percentage of total relevant results correctly that are categorized by the algorithm. F1-score is another name for F-score. The F-score is a metric for determining how accurate a model is on a given dataset. It's also a way of combining the model's precision and recall, and it is defined as the harmonic mean of the precision and recall of the model. Fig. 4 shows the confusion matrix.

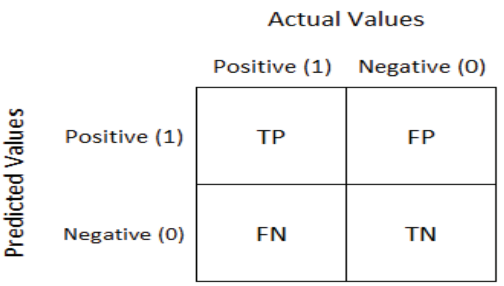

Fig. 4. Confusion matrix

The true positive (TP) is an outcome in which the model predicts the positive class correctly. In the same way, a true negative (TN) is an outcome in which the model adequately predicts the negative class. False positive (FP) is a result in which the model predicts the positive class inaccurately. An FN, or false negative, is an outcome in which the model predicts the negative class inaccurately.

III. Result and Discussion

For this project, the RVM can segregate three types of beverages container which is aluminum cans, drink carton boxes, and PET bottles by using the image processing technique. The result for dataset preparation, image processing, and image classification will be discussed in the following section.

A. Dataset Preparation

By collecting more data, it will make the machine perform more accurately, so the data will be collected in different types, sizes, colours, and shapes for all types of beverages container. Each object will be taken from several angles. All the data will be saved into different files according to their materials. Fig. 5 shows the example image for PET bottles.

To improve or enhance the classification accuracy, all of the data will be collected in different types, sizes, colours, angles, and shapes for all types of beverages containers. Classification accuracy is a metric that measures a classification model's behaviour by dividing the number of correct guesses by the overall number of guesses. It is the most used evidence for evaluating classifier models since it is straightforward to determine and understand. The accuracy for three different amounts of the stored dataset is presented in Fig. 6.

a) PET bottles b) PET bottles

Fig. 5. Example image for PET bottles

This is to compare that which amount of stored dataset will have a higher classification accuracy. The classification accuracy compares between 30 stored datasets, 100 stored datasets, and 500 stored datasets. To get a more precise classification accuracy, each amount of stored dataset is taken three times to take the average number. TABLE I shows the classification accuracy for three different amounts of the stored dataset.

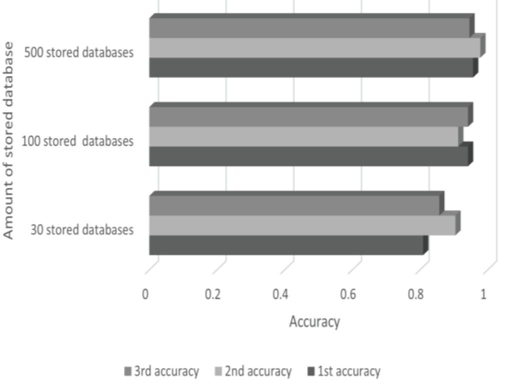

Fig. 6. Classification accuracy for three different amounts of the stored dataset

TABLE I
CLASSIFICATION ACCURACY FOR THREE DIFFERENT AMOUTS OF STORED DATASET

Accuracy	30 stored datasets	100 stored datasets	500 stored datasets
1st accuracy	0.8095	0.9420	0.9570
2nd accuracy	0.8571	0.9130	0.9785
3rd accuracy	0.9048	0.9420	0.9462
Average	0.8571	0.9323	0.9606

According to BrownLee, J. [6], the predictive model is considered good when the classification accuracy is above 90%. The average classification accuracy for 30 stored datasets is 0.8571 or 85.71%. For 100 stored datasets, the average classification accuracy is 0.9323 or 93.23% whereas, for 500 stored datasets, the average classification accuracy is 0.9606 or 96.06%. Both 100 and 500 stored datasets have a good predictive model since their average classification accuracy is above 90%. By comparing these three different amounts of stored datasets, the 500 stored datasets achieve the highest average classification accuracy whereas the 30 stored datasets have the lowest average classification accuracy. This shows that collecting more data will make the machine perform more accurately. Thus, to make the classification become more accurate, 500 datasets in the system will be collected. After the dataset is prepared, the image processing part for waste recognition can be performed using MATLAB.

B. Image Processing

After creating the dataset, the data is required to be derived in MATLAB. The stored dataset is needed to train and test the system. This approach is to train the classifier and therefore determine the classification accuracy. A camera will be applied to capture the beverages containers. Thus, image processing tools are required to perform the image processing. Once the image processing process is completed, the filtered image will be used to make a forecast using the classifier. Fig. 7 describes the coding process for the proposed algorithms.

Fig. 88 until Fig. 110 shows the results for the image processing part. The original image will first be converted into red, green, and blue (RGB) images. The RGB image will then be converted into a grayscale image. The RGB image is a 3-dimensional matrix whereas the grayscale image is only a 2-dimensional image. Thus, the reason to convert RGB images into a grayscale image is that some of the applications in image processing can only be applied to the 2-dimensional image. This step is also to enhance or improve the image information and therefore diminishes the useless distortions and builds up some components for the input image. Fig. 8 shows the original image convert into an RGB image.

After that, a binary image is created by setting a threshold value on the pixel intensity of the original image. This process is to separate an object and background into a black and white district. Any region in the image that lies inside the colour channel pixel will be segmented automatically and appear as a significant region in the final binary image by specifying the value for each RGB channel. Fig. 9 shows the threshold image.

After the thresholding process, the image still has some noises. To overcome this issue, the consistency of regions of interest must be further enhanced by adding a few morphological operators to the image. By complementing the image, the object will turn into white colour whereas the background will turn into black colour. Fig. 100 shows the image after performing the complement operation.

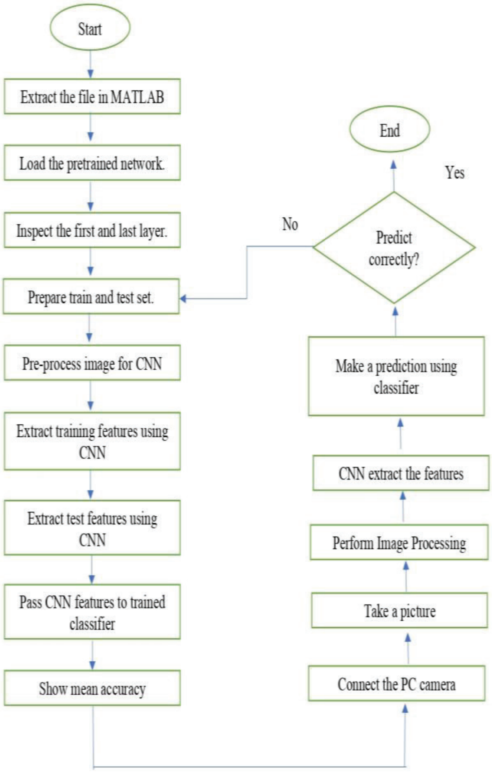

Fig. 7. Coding process for proposed algorithms

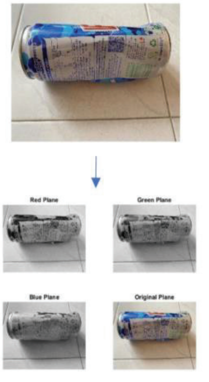

Fig. 8. Converting original image into RGB image

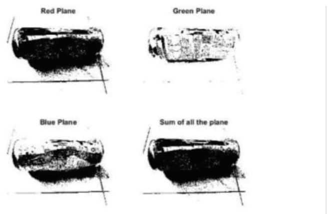

Fig. 9. Thresholding the image

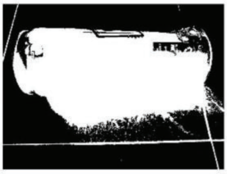

Fig. 10. Image after performing complement operation

After complementing the image, the morphological operation is applied. The purpose of the morphological operation is to remove imperfections by accounting for the form and structure of the image. The morphological opening is used in this project to eliminate all the small things from the image while keeping the shape and size of the larger object. After this image processing procedure, the filtered image will be used to compare with the stored dataset and lastly perform the classification of wastes by using the image classification method. Fig. 11 shows the image after performing the morphological operation.

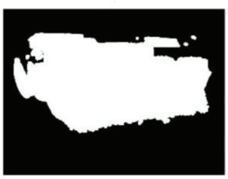

Fig. 11. Image after performing the morphological operation

C. Image Classification

The datastores for this project contain 500 images of beverage containers. 70% of the beverages containers images, which is 350 beverages containers images, will be used for the training set. The training set is a dataset of the datastores that the model will be fitted to. On the other hand, only 30% of the beverage containers images, which is 150, will be used for the validation set. The validation set is a subset of data used to objectively assess a model's fit on the training set while tuning the hyperparameters. Random sampling is used for both training and validation data. The reason to do so is to avoid biasing the result.

The confusion matrix will be used to assess the classifier's performance. The confusion matrix compares the actual target value to those predicted by the machine learning model. Accuracy, precision, recall, and F-score are the parameters that are evaluated by the confusion matrix.

The true positive (TP) is an outcome in which the model predicts the positive class correctly. In the same way, a true negative (TN) is an outcome in which the model adequately predicts the negative class. False positive (FP) is a result in which the model predicts the positive class inaccurately. An FN, or false negative, is an outcome in which the model predicts the negative class inaccurately. The confusion matrix measurement are expressed in equations (1) - (5).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Fscore = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

$$Error = 1 - Accuracy \tag{5}$$

The SVM classifier will be tested for three times to get the average performance which means that the same amount of the datastores will be used and run for three times. The result for every three tests will be shown below and will be described in detail.

Test 1 is the first test to test the performance for the SVM classifier. The confusion matrix for test 1 is presented at Fig. 12. TABLE II shows the SVM classifier performance for test 1.

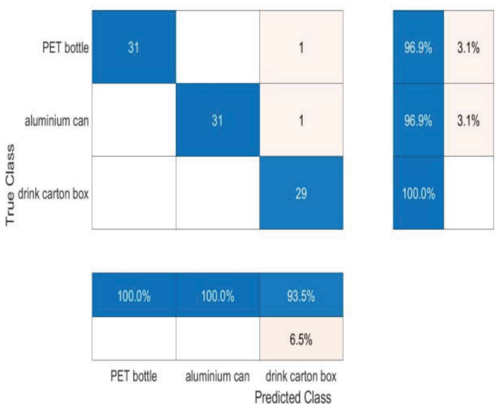

Fig. 12. Confusion matrix for test 1

TABLE II
SVM CLASSIFIER PERFORMANCE FOR TEST 1

Time	24.35 seconds
Accuracy	97.8495 %
Error	2.1505%
Precision	97.92%
F-score	0.9788
Recall	97.85%

For test 1, datasets of the drink carton boxes in the test set have been segregated correctly by the SVM classifier. Unfortunately, two datasets have been segregated incorrectly by the SVM classifier. One dataset from the PET bottles category has been segregated incorrectly under the drink carton boxes category. Then, one dataset from the aluminium cans category has been segregated incorrectly under the drink carton boxes category.

Hence, the row summarization has concluded that 96.9% has been segregated correctly by the SVM classifier while 3.1% has been segregated incorrectly for both aluminium cans and PET bottles datasets. On the other hand, the column summarization for the confusion matrix shows that both aluminium cans and drink carton boxes have reached 100% prediction. In contrast, the drink carton boxes dataset has 93.5% correct prediction by the SVM classifier.

TABLE II provides the summary for the performance of the SVM classifier after test 1. The SVM classifier has achieved 97.8495% accuracy, 2.1505% of error, while the precision is 97.92%, and the recall is 97.85%. In this test 1, the SVM classifier failed to reach 100% for accuracy, precision, and recall. Based on the confusion matrix for test 1, there is only 1 dataset for the PET bottles that have been misclassified under the drink carton boxes category. Thus, there is also 1 dataset for the aluminium cans misclassified under drink carton boxes category. The F-score for test 1 is 0.9788. The SVM classifier took 24.35 seconds to predict all datasets of the beverages containers.

Then, test 2 is the second test to evaluate the performance for the SVM classifier. The confusion matrix for test 2 is presented at Fig. 13. TABLE III shows the SVM classifier performance for test 2.

For test 2, both datasets of the PET bottles and aluminium cans in the test set have been segregated correctly by the SVM classifier. Unfortunately, one dataset from the drink carton boxes category has been segregated incorrectly under aluminium cans category by the SVM classifier.

Hence, the column summarization has concluded that 96.8% has been segregated correctly by the SVM classifier while 3.2% has been segregated incorrectly for the aluminium cans datasets. On the other hand, the row summarization for the confusion matrix shows that both PET bottles and aluminium cans have reached 100% prediction. In contrast, the drink carton boxes dataset has 96.9% correct prediction by the SVM classifier.

TABLE III provides the summary for the performance of the SVM classifier after test 2. The SVM classifier has achieved 98.9247% accuracy, 1.0753% of error, while the precision is 98.96%, and the recall is 98.92%. In this test 2, the SVM classifier is failed to reach 100% for accuracy, precision, and recall. Based on the confusion matrix for test 2, there is only 1 dataset for the drink carton boxes that have been misclassified under the aluminium cans category. The F-score for test 2 is 0.9894. The SVM classifier took 30 seconds to predict all datasets of the beverages containers.

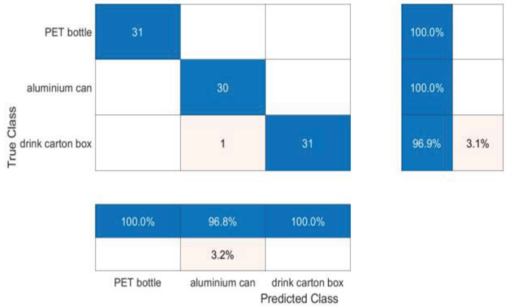

Fig. 13. Confusion matrix for test 2

TABLE III
SVM CLASSIFIER PERFORMANCE FOR TEST 2

Training Time	30 seconds
Accuracy	98.9247%
Error	1.0753%
Precision	98.96%
F-score	0.9894
Recall	98.92%

Test 3 is the last test to evaluate the performance for the SVM classifier. The confusion matrix for test 3 is presented at Fig. 14. TABLE IV shows the SVM classifier performance for test 3

For test 3, datasets of the drink carton boxes in the test set have been segregated correctly by the SVM classifier. Unfortunately, one dataset from the aluminium cans category has been segregated incorrectly under drink carton boxes category by the SVM classifier. Then, one dataset from the aluminium cans category has been segregated incorrectly under the drink carton boxes category.

Hence, the row summarization has concluded that 96.9% has been segregated correctly by the SVM classifier while 3.1% has been segregated incorrectly for both aluminium cans and PET bottles datasets. On the other hand, the column summarization for the confusion matrix shows that both aluminium cans and drink carton boxes have reached 100% prediction. In contrast, the drink carton boxes dataset has 93.5% correct prediction by the SVM classifier.

TABLE IV provides the summary for the performance of the SVM classifier after test 3. The SVM classifier has achieved 97.8495% accuracy, 2.1505% of error, while the precision is 97.92%, and the recall is 97.85%. In this test 3, the SVM classifier is failed to reach 100% for accuracy, precision, and recall. Based on the confusion matrix for test 3, there is only 1 dataset for the PET bottles that have been misclassified under the drink carton boxes category. Thus, there is also 1 dataset for the aluminium cans misclassified under drink carton boxes category. The F-score for test 3 is 0.9788. The SVM classifier took 25.33 seconds to predict all datasets of the beverages containers.

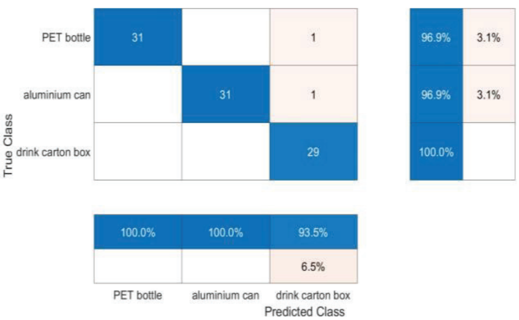

Fig. 14. Confusion matrix for test 3

TABLE IV
SVM CLASSIFIER PERFORMANCE FOR TEST 3

Training Time	25.33 seconds
Accuracy	97.8495%
Error	2.1505%
Precision	97.92%
F-score	0.9788
Recall	97.85%

The average performance for the SVM classifier is shown in TABLE V.

TABLE V
AVERAGE PERFORMANCE FOR SVM CLASSIFIER

Training Time	26.56 seconds
Accuracy	98.2079%
Error	1.7921%
Precision	98.27%
F-score	0.9823
Recall	98.21%

From TABLE V, it can be concluded that the average performance of the SVM classifier has achieved 98.2079% accuracy with 1.7921% of error. For precision, the SVM classifier has a 98.27% positive rate in the datasets of the beverages containers in the test set. Then, the SVM classifier has achieved 98.21% for recall in the classification process for the datasets of the beverages containers. The average F-score is 0.9823. The average training time for the SVM classifier to perform classification is 26.56 seconds.

IV. Conclusion

This paper has described comprehensively an outline for waste classification for sorting purposes for the RVM. Image processing detects the image and thus extracts the characteristic of the image as the output, which will help the reverse vending machine to improve the classification efficiency. By comparison between 30 stored datasets, 100 stored datasets, and 500 stored datasets, 500 stored datasets achieve the highest average accuracy which is 0.9606 or 96.06%. Thus, having more stored datasets will also enhance and increase classification accuracy. The simulation or coding has been tested with the variation of the recycling image. The performance for the SVM classifier was tested by three times with the datasets of the beverages containers in the dataset. The SVM classifier achieves 98.2079% of the accuracy, 1.7921% of error, 98.27% of the precision, and 98.21% of recall. Based on the average performance for the SVM classifier, almost all the dataset of the image for each beverages containers can be classified correctly. The average tine for the SVM classifier to perform classification is 26.56 seconds.

In short, the objective for this project which is to develop a sorting mechanism for reverse vending machine using image processing techniques is achieved. By using the image processing technique, this RVM allows classifying three types of beverages containers which are aluminium cans, drink carton boxes, and PET bottles. As for future work, the Raspberry Pi camera will be recommended to meet the requirement for a real detection and segregate the beverages containers.

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