© Universiti Tun Hussein Onn Malaysia Publisher's Office

IJIE

http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

The Development of an Automated Waste Segregator

Fatin Amanina Azis[1*], Hazwani Suhaimi[1], Pg Emeroylariffion Abas[1]

[1]Faculty of Integrated Technologies,
Universiti Brunei Darussalam, BE1410, BRUNEI DARUSSALAM

*Corresponding Author

DOI: https://doi.org/10.30880/ijie.2023.15.04.002
Received 9 January 2022; Accepted 10 May 2023; Available online 28 August 2023

Abstract: Accumulation of waste is a major global concern, and recycling is considered one of the most effective methods to solve the problem. However, recycling requires proper segregation of waste according to waste types. This paper develops an automatic waste segregator, capable of identifying and segregating six types of wastes; metal, paper, plastic, glass, cardboard, and others. The proposed system employs Convolutional Neural Network (CNN) technology, specifically the Inception-v3 architecture, as well as two physical sensors; weight and metal sensors, to classify and segregate the waste. Overall classification accuracy of the system is 86.7%. Classification performance of the developed waste segregator has been evaluated further using the precision and recall; with high precision obtained for cardboard, metal, and other waste types, and high recall for metal and glass. These results demonstrate the applicability of the developed system in effectively segregating waste at source, and thereby, reducing the need for the commonly labor-intensive segregation at waste facility. Deploying the system has the potential of reducing waste management problems by assisting recycling companies in sorting recyclable waste, through automation.

Keywords: Automatic, waste segregator, CNN, recycling, machine learning, cost-effective

1. Introduction

Waste management is a global challenge and represents one of the most pressing environmental issues that the world is facing today. Many researchers, companies, and government agencies have put a lot of effort into finding better ways to significantly reduce waste as well as manage them effectively. Naturally, as the global population increases and more countries have gradually adopted an urbanized lifestyle [1], the quantity of generated wastes can possibly amount to billions of tons annually, which poses an alarming concern [2]. Some of these wastes end up in landfills, where they are either buried, left slowly to decompose, or occasionally burnt, whilst some end up in the soil, oceans, and rivers, which are a particular problem in developing countries with inadequate waste management systems. Collectively, these lead to global pollution, health issues, and economic issues [3].

Recycling has the potential to alleviate the waste management problem. According to recent studies [4], [5], recycling has been recognised as one of the most effective and significant techniques for managing waste. It has the potential to reduce greenhouse gas emissions and water pollution. At the same time, it can save energy and reduce cost, as recycled materials require relatively lesser processing to convert into usable materials. However, proper segregation is needed for recycling, as different waste types require different treatment processes.

Commonly, in both developed and developing countries, wastes are collected from homes and garbage dump sites and then brought to waste facility centres, where most of the wastes are pre-segregated before they can be recycled. In most cases, the wastes are manually segregated, which can be time-consuming, inefficient and may require large manpower [6]. For this reason, authorities have developed initiatives to enhance recycling efficiency and effectiveness, including initiatives to encourage waste segregation at the source. Segregating waste at the source can potentially reduce the need for manual and tiresome segregation tasks at the waste facility centres. Subsequently, recycling bins

*Corresponding author: 20h8455@ubd.edu.bn

have been made widely available in many public places around the world, with the current typical design of a recycling bin consisting of four compartments. The three compartments of the recycling bins are for common recyclable waste types such as plastics, metal cans, and papers, and another compartment for other waste types, such as wet and non-recyclable wastes. These may come as either a whole or an individual bin. However, papers and cardboards have different treatment processes as they are made from slightly different materials [7], and hence, there is a need to have two separate waste compartments in a recycling bin to facilitate the segregation of the two waste types. Rahim et al. [8] specified that glass is 100% recyclable without loss in quality and purity, indicating that glass should be recycled more often. As such, there is a need to have separate compartments in a recycling bin to segregate papers and cardboards, as well as an additional compartment for glass waste.

For typical recycling bins, users have to manually place their wastes into the appropriate compartments based on the type of waste [9]. However, manual waste sorting may sometimes be ineffective and inefficient. Some users may, intentionally or unintentionally, dispose of their waste into the wrong compartment due to ignorance or some other reasons. Additionally, some wastes are not easily distinguishable by type and thus, may be thrown into the wrong waste compartment. A study in Scotland [10] has found that incorrectly placed waste in dry mixed recycling typically accounts for 19% of the total waste, with glass waste being the most common, accounting for 2.8%of all misclassified waste, which needs to be further segregated at the waste facility centre.

To improve the effectiveness of waste segregation at the source, there is a need to develop an automated recycling bin that can effectively segregate wastes according to their types at the source. This can potentially reduce the requirement of time, energy, and manpower to segregate the waste properly at the waste facility centre, as well as make it cost-effective for potential users. Several techniques have been introduced by different researchers to improve segregation and hence, facilitate the recycling process. The problem can be broken down into the identification of waste types and then segregation. Generally, the techniques adopted involve the utilisation of different sensors, or via machine learning, such as the deep learning approach, to help with the identification of waste, and then automation process for waste segregation [11], [12]. There is a limited number of studies on the optimisation of automatic waste segregator with the integration of deep learning techniques and physical sensors. The integration of the two techniques may significantly enhance the performance of an automatic waste segregator in the future [13].

This paper develops an automated waste segregator by combining the use of cost-effective sensors, specifically for detecting metal and glass, and a deep learning approach using the Inception-v3 model for the identification of waste types. A commercially-off-the-shelf using Raspberry Pi 3B as the processor has been used to ensure the cost-effectiveness of the developed system. Simple automation using several motors is then used to segregate the waste into the appropriate compartments after identification.

2. Related Works

2.1 Automatic Waste Segregation Technologies

Current recycling bins typically consist of, on average, two to three types of waste compartments. In order to help with the identification of the waste type and automated segregation process, several sensor components have been proposed in the literature. In reference [11], Light Dependent Resistor (LDR) and light amplification by the stimulated emission of radiation (LASER) have been used to sort paper and plastic in an automatic waste segregator. Three different types of wastes: glass, metal, and plastic, have been considered [14], with inductive and capacitive sensors used to detect metal and plastic and glass wastes, respectively. Metal and glass are relatively easier to identify, using a metal detector and weight sensor to detect metal and glass, respectively. A metal detector [15] detects metal waste via the principle of electrical induction, whilst glass collected from recycling bins typically is heavier than other types of waste; hence, a weight sensor [16] is utilised to segregate glass waste. Some researchers have also utilised capacitive proximity sensors [17], [18] to identify papers and plastics, as the amount of light passing through each material is different due to their distinct materials and properties. However, using optical sensor may be inaccurate and inefficient as both plastic and paper waste types can have different properties from their normal properties; some plastic can be opaque, and some papers can be thick, which make the determination of waste types using optical sensors to be inaccurate. Other researchers [19] have also utilised X-rays to differentiate plastic materials. However, the method is capital-intensive due to the requirement for specialised X-ray equipment, prohibiting its wide adoption.

Another emerging method that has been proposed by different researchers to solve the waste classification and segregation problems for recycling purposes uses a deep learning approach to identify plastics, papers, and cardboards, which may be difficult to detect using physical sensors. The well-known deep learning technology has demonstrated its superiority over conventional computer vision algorithms, which see objects as a collection of shape and colour features to carry out automation tasks for fast classification [20]. Several studies have been conducted in implementing deep learning techniques to automate the segregation of waste by using image data of the different types of waste. Traditional neural networks, such as Artificial Neural Networks (ANN), are less appropriate for image processing because they have less capacity to handle large data, which are usually needed for image classifications [21]. Convolutional Neural Network (CNN), on the other hand, is a deep neural network that is frequently used to handle large data for image classification and is made up of three main layers; the convolutional, the activation and pooling, and the fully connected layers.

Mao et al. [12] use an optimised DenseNet121 CNN model in the waste classification problem to identify plastic, paper, cardboard, metal cans, trash and glass. The model has been trained on the TrashNet dataset to give an accuracy of 99.6%. Adedeji and Wang [22] use the ResNet-50 pre-trained model trained on four types of waste: glass, paper, plastic, and metal, to give 87% accuracy. DenseNet169 has been used [23] on an NWNU-TRASH dataset consisting of a total of 18,911 images of glass, fabric, paper, plastic, and metal to give an accuracy of 82%. However, these classification methods require a considerable amount of processing power, which can be expensive and impractical to be implemented on a physical bin for the waste classification task. As such, there is a need for a more cost-effective method that can perform a similar task but requires less computational power, thereby allowing it to be more widely implemented in a physical bin.

There are several other CNN architectures that have existed in the literature that can be studied and implemented, including ResNet, VGG, AlexNet, and many more [24]-[26]. Despite these, it is a requirement for the chosen model to have lower computational needs to make it more suitable to be adopted in physical bins. Serengil [27] compares the performance operations of different CNN models, as shown in Fig. 1.

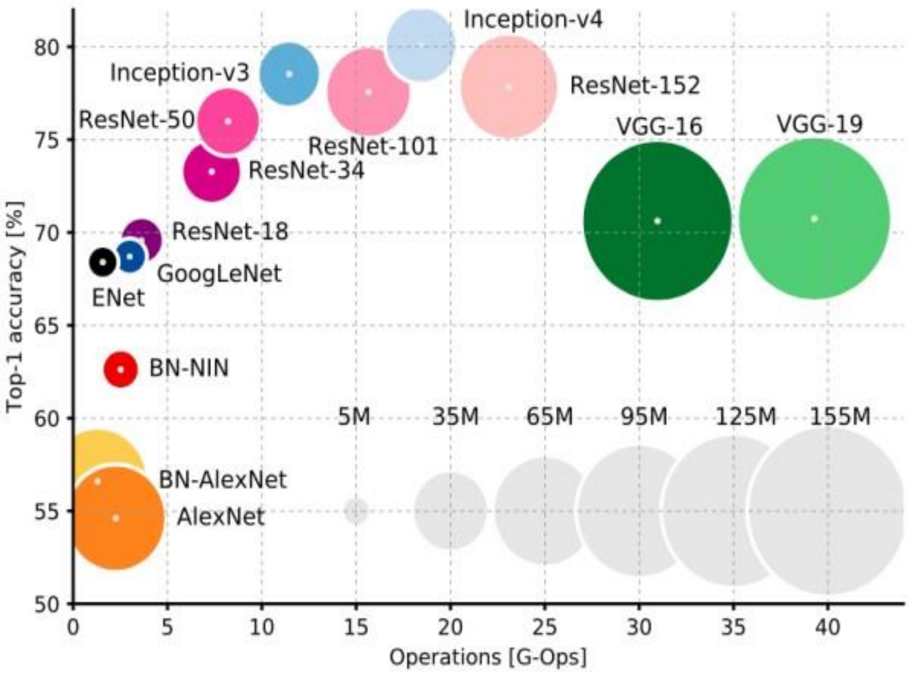


Fig. 1 - Performance comparison of different ImageNet Models [27]

Inception-v3, v4, and Inception-ResNet are all improved versions of Inception-v1 and v2. The idea behind Inception-v3 is to reduce the computational complexity of deeper Nets without influencing the generalisation, and it is used all over the world owing to its efficiency and cost-effectiveness, as well as supplying a reasonable level of model accuracy of more than 75%. It has 24 million parameters where the operations required are about 11 G-Ops shown in Fig 1, which does not require excessively high computational systems and is manageable on a low-cost processor such as a Raspberry Pi microcontroller. In contrast to other CNN model architectures, Inception-v4 performs better with an accuracy of around 80%, but it has a larger number of parameters and operations than the Inception-v3 model. The same is true for VGG models, as both have a large number of classification parameters. The Pi microcontroller is almost incapable of handling the heavily loaded operations required in image recognition processes. On the other hand, AlexNet has a low accuracy of around 55%. This will be in direct opposition to the research goals of developing an accurate automated recycling bin. Ultimately, Inception-v3 is found to be a suitable model architecture to be used for this research study. Nevertheless, researchers are still finding ways to improve the waste classification performance and, at the same time, make the physical bin to be cost-effective.

3. Proposed Method

3.1 Automatic Waste Segregation Technologies

Fig. 2 depicts the full design of the developed automatic waste segregator, which can segregate wastes into 6 waste types: glass, metal, paper, plastic, cardboard, and other types of waste. It is divided into two main parts: the detection chamber and the sorting chamber. The detection chamber detects the types of waste being thrown, whilst the sorting chamber directs the wastes into the appropriate compartments upon classification. There are a total of six compartments to store each of the six waste types. The main specifications of the developed automatic segregator are given in Table 1. A camera is mounted on the inside of the bin and properly angled to capture the image of the waste inside the detection chamber. The detection chamber is wrapped around with a metal detector coil to specifically identify metal waste, whilst a weight sensor is attached beneath the small plate underneath the detection chamber to identify glass waste, which generally is heavier than other waste types. Both the metal and weight detectors, as well as the camera, are used for the accurate identification of waste types. A servo is attached to the small plate beneath the detection chamber to control the release of wastes from the detection chamber to the sorting chamber once the waste has been identified.

The sorting chamber is shaped in a sloping orientation to provide an angle that allows waste to slide through effortlessly, and it is attached to a round wooden plate, which in turn is attached to a stepper motor. This stepper motor is used to direct the identified waste to the exact compartments, depending on the waste types. The round wooden plate can be pivoted smoothly with the help of four rollers that are fixed to the bin's walls, reducing the torque required to rotate the plate and resulting in an efficient and precise rotation. Each of the waste compartments has an equal angle opening of 60°. Once the waste is identified, the stepper motor rotates the sorting chamber to the appropriate waste compartments for the waste to be deposited. Table 2 gives the main parts of the automatic waste segregator and the components used. The processes involved in each step of the segregation process, from detection, classification, and segregation of waste as depicted in Fig. 3, are elaborated in Table 3.

3.2 Metal Detector and Weight Sensors

A metal detector and weight sensor are utilised to detect metal and glass waste, respectively. The metal detector is composed of electrical wires wounded around the detection chamber and a capacitor circuitry; to detect metal cans or other types of metals, with electromagnetic induction occurring as metal waste passes through the coil. Since glass is the heaviest waste type among the six categories considered, a weight sensor is used to detect whether glass has been placed inside the bin by setting a predefined threshold level W_{Th} according to the average weight of glasses to detect glass waste. However, if the waste is neither metal nor glass, the camera is switched on to take the image of the waste, which is then identified using image classification. The inclusion of two physical sensors in the automatic segregation bin is anticipated to reduce the complexity associated with image classification by using simple sensors to identify 2 of the 6 types of wastes, as well as improve accuracy.

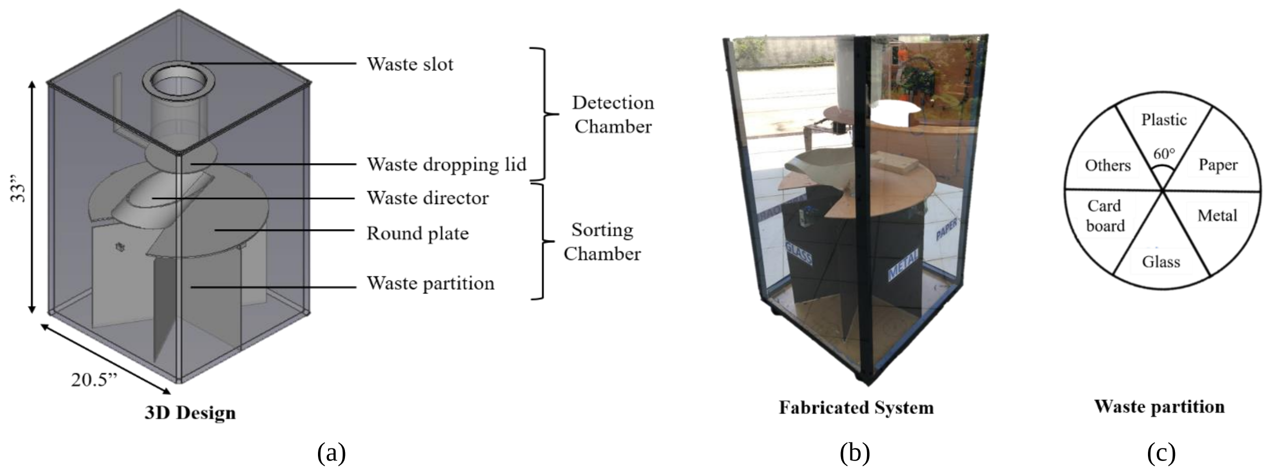
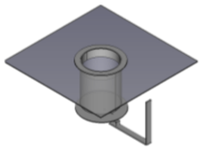
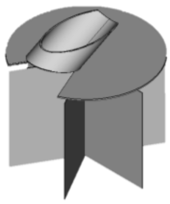


Fig. 2 - (a) 3D design; (b) fabricated system; (c) waste partition of the developed automatic waste segregator

Table 1 - Main specifications of the developed automatic waste segregator

Design Element	Specification
Bin size	33" x 20.5"
Diameter of waste slot	6.0"
Number of waste compartments	6
Size of each compartment	60º
Bin chambers	Two chambers; detection and sorting chambers
Sensors	5MP Raspberry Pi camera sensor, weight sensor, metal sensor
Processor	Raspberry Pi 3B
Deep learning model	Inception-v3

Table 2 - Components associated with each waste chamber

Waste Chambers	Component
Detection Chamber  (a)  (b) a) Isometric view, b) Side view	1. Raspberry Pi 3B 2. 5MP Raspberry Pi camera module 3. Metal detector composed of coils 4. Weight sensor (HX711) 5. Servo
Sorting Chamber  (a)  (b) a) Isometric view, b) Side view	1. Six waste partitions 2. Stepper motor

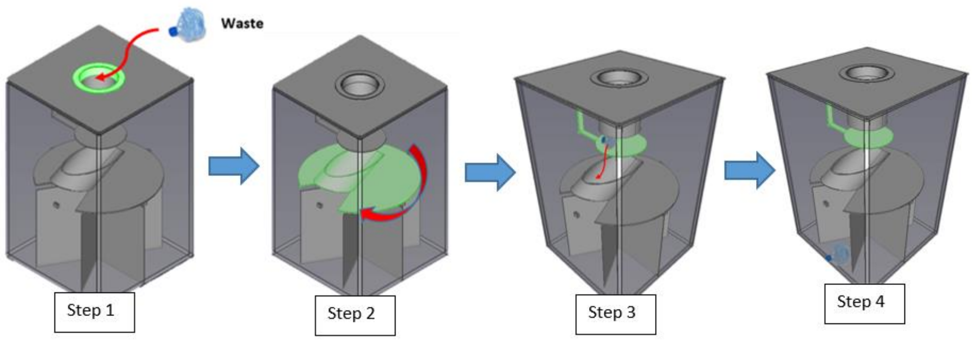


Fig. 3 - Simplified overview of the segregation process

Table 3 - Description of the segregation processes

Step	Process	Description
1	Waste detection and identification	The waste placed inside the detection chamber of the bin is first detected. The waste detection process uses the metal detector to detect metal waste, and the weight sensor to detect heavy glass. If the waste is neither metal nor glass, the camera is switched on and used to detect the waste using image classification.
2	Compartment identification	The sorting chamber is rotated using a stepper motor, according to the output from the waste detection process, to direct the waste to the correct compartment.
3	Waste deposition	Once the sorting chamber is directed to the correct compartment, the servo in the detection chamber releases the waste, to the correct compartment via the sorting chamber.
4	Initialisation	After the waste has been successfully deposited in the appropriate compartment, the electric components start again by default.

3.3 Image Classification Model

The image classifier forms an important component of the automatic waste segregator. However, it is only used if both the metal detector and weight sensor fail to ascertain that the waste is either metal or glass. Image is taken using a Raspberry Pi 5MP camera located inside the bin, arranged to take the image of waste in the detection chamber. After the image of the waste has been taken, the image needs to be processed to determine its waste type, and this is performed using a deep neural network, particularly by utilising the inception-v3 model.

Image classification via the deep neural network requires training of the model using a labelled image dataset before it can be used for testing and waste identification. The former and latter are referred to as the training and testing phases, respectively. The images need to be pre-processed; by cropping, scaling, and adjusting the brightness of the images, to give consistent input to the image classification model during both the training and testing phases. During the training phase, pre-processed labelled images from the dataset containing images of different waste types: plastic, cardboard, paper, metal, glass, and other waste types, are used for training and validating the classification model. The output of the training phase is a trained image classification model.

Once the model has been trained, it may be used for identifying waste from the six different waste types purely from the image captured from the camera. As has been previously mentioned, waste classification from the image is only used if the metal detector and weight sensor are not able to determine that the waste is either metal or glass. This can be due to the waste not belonging to either metal or glass, or it can be that the waste is either metal or glass, but the weight of the glass is actually below the set threshold, or not enough electromagnetic induction has been generated by the metal waste.

In this study, the Inception-v3 architecture shown in Fig. 4 has been utilised for image classification, taking an input image size of 299 x 299 pixels. Consequently, the 512 x 384 input image size from the Raspberry Pi 5MP camera is converted into 299 x 299 as part of pre-processing. The Inception-V3 is made up of multiple convolutions and max-pooling layers, as well as fully connected neural networks. The RGB matrix of the input image is used to generate a 299 x 299 x 3 input image.

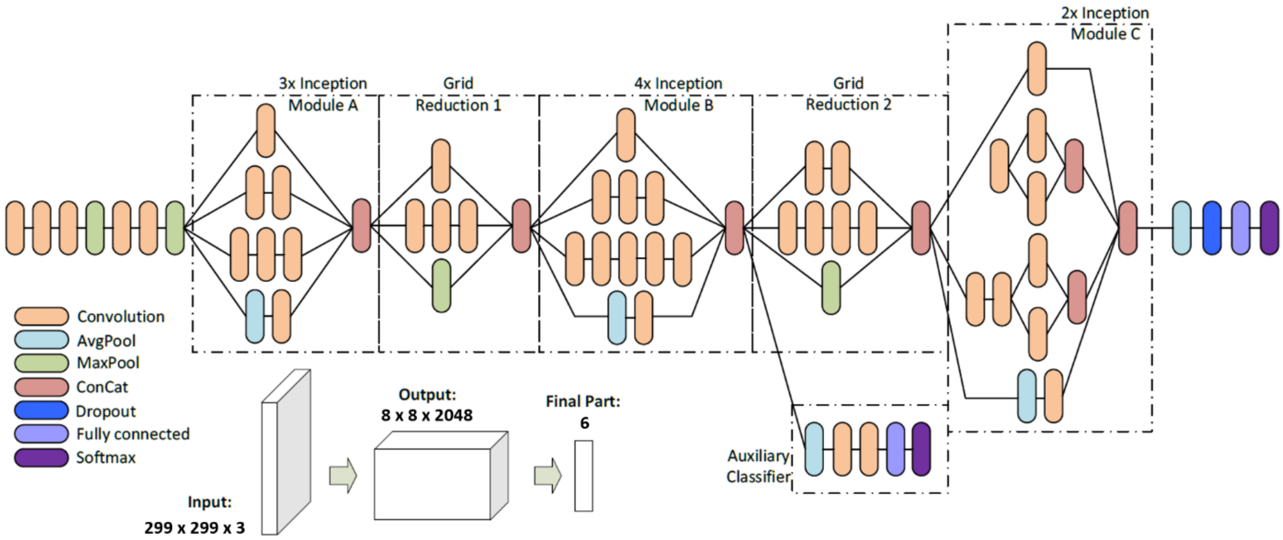


Fig. 4 - Architecture of Inception-v3 model [17]

3.4 Waste Prediction and Segregation

As has been discussed, the first step in the waste classification process utilises the metal detector by coil induction and the weight sensor by setting a threshold, W_{Th}, to help detect metal and glass waste types, respectively. However, if both sensors are unable to determine whether the waste is either metal or glass waste, the camera is then used to take an image of the waste within the detection chamber. The trained image classification model is then used to identify the waste type. Once the waste type has been identified, the stepper motor in the sorting chamber is then used to direct the waste into the appropriate waste compartment by turning the opening of the round plate to the right compartment. The servo under the detection chamber is then used to release the waste into the appropriate compartment. The flowchart in Fig. 5 depicts the conceptual working of the developed automatic waste segregator.

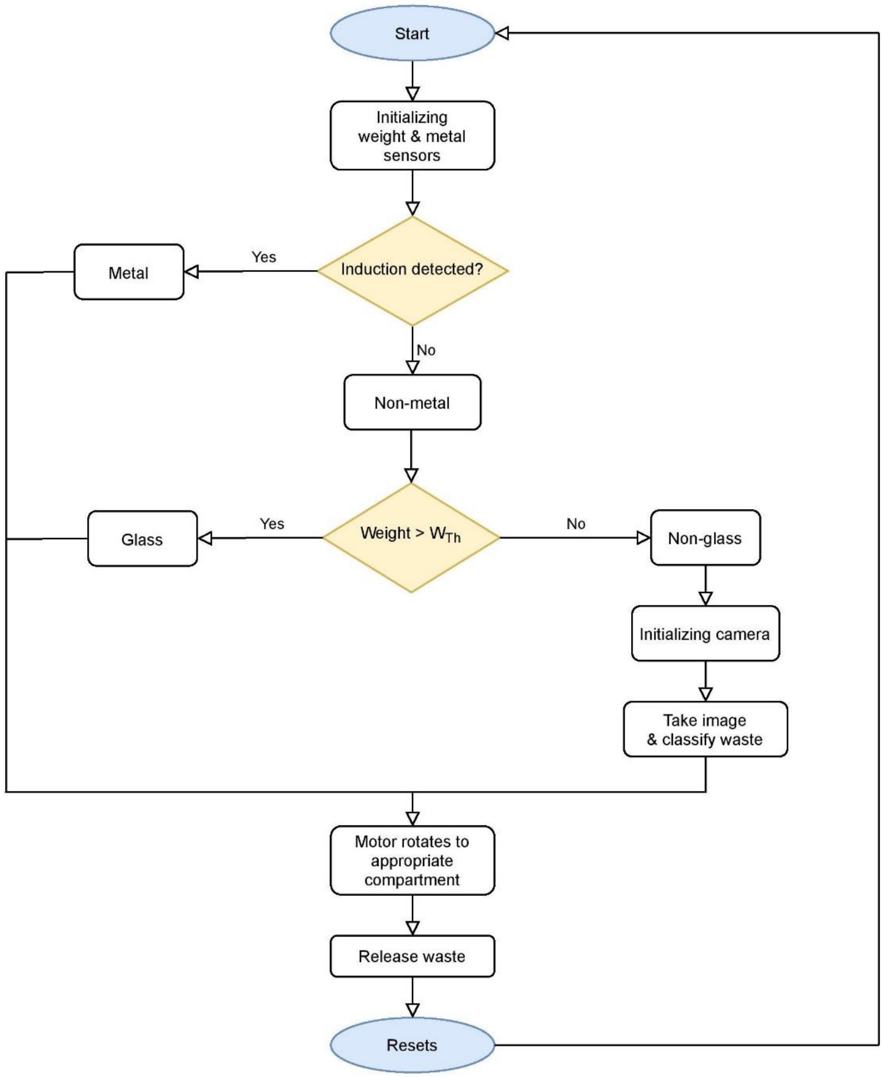


Fig. 5 - Process flowchart of the integration of Inception-v3 and sensors

3.5 Performance Measures

In most cases, classification accuracy is often used as performance evaluation; however, the method is not sufficient to properly measure the performance of a model as a whole. Other metrics such as precision, recall, and F1-measure have been considered and evaluated in this paper. The accuracy measures the exactness of the model in predicting the target classes. While recall measures the correct positive predictions from all of the positive predictions, precision measures the correct positive predictions, and F1-measure weighs the effectiveness of classification using the recall and precision values. The metrics can be easily calculated using a Confusion Matrix which visualises the actual versus model predictions of the target class. In general, each prediction from the model can be either True Positive (TP), True Negative (TN), False Positive (FP), or False Negative (FN). TP is the correct prediction of the actual positive class, and TN denotes the correct prediction of the actual negative class. While FP indicates the incorrect prediction of the actual positive class and FN is the incorrect prediction of the actual negative class. The metrics score; accuracy, precision, recall, and F1-measure can be computed by

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

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

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

$$F1\,measure = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

4. Results and Discussion

4.1 Dataset Used

The designed automatic waste segregator system uses both image classification and physical sensors: metal and weight sensors, to segregate wastes to the appropriate compartments. A comparison of local dry wastes in Brunei indicates that glass waste is the heaviest waste type, and hence, the use of a weight sensor for instant detection of glass waste. This has the potential of saving energy and time by not going through the image classification process. Common residential glass waste in Brunei, including glass bottles and containers, generally weigh more than 190g on average, and as such, a weight threshold W_{Th} has been set to be greater than 190g. Wastes above the threshold are immediately identified as glass and sorted into the glass compartment. Similarly, wastes identified as metal using the metal detector are immediately sorted into the metal compartment.

Additionally, the image classification model needs to be first trained before it can be further used for testing and evaluation. The training image dataset for the six waste categories has been obtained from the TrashNet dataset [28], containing a total of 2,528 images, and this dataset is suitable and manageable for a low-resourced and relatively cheap Raspberry Pi microcontroller with a limited processor speed. Images from the dataset have been captured from different perspectives and have been changed to 299 x 299 pixels before feeding them onto the image classification model for training. Samples from the dataset are depicted in Fig. 6, with training parameters shown in Table 4.

Fig. 6 - Sample of images from TrashNet dataset

Table 4 - Training parameters

Parameter	Value
Learning rate	0.005
Testing percentage	10%
Validation percentage	10%
Training steps	80%
Train batch size	100
Validation batch size	100
Cycles	4000
Input size	299x299

For testing, a different dataset has been used, where a total of 240 images of local waste have been collected and captured, consisting of 40 images from each waste type. These images have been captured using the 5MP Raspberry Pi camera sensor, which has been fixed inside the designed system. Sample images used for testing are given in Fig. 7.

Fig. 7 - Sample of captured test images

At the initial stage, only image classification is used for waste identification, giving the performance of the system in terms of accuracy, precision, recall and F1 measure. The performance of the automatic waste segregator utilising the image only is compared to that of the automatic waste segregator utilising both the physical sensors and image classification using CNN.

4.2 Using the Image Classification Only

A total of 240 local wastes from the six waste types; are plastic, glass, paper, metal, cardboard, and others, have been used to test the constructed automatic waste segregator system using the Inception-v3 image classification model only. Overall prediction accuracy is 84.6%, with the confusion matrix shown in Table 5. The confusion matrix is given in a 6x6 matrix, with rows and columns indicating actual and predicted waste types, respectively. For instance, 2 plastic wastes were wrongly classified as metal wastes whilst 4 metal wastes were wrongly classified as plastic wastes. The network has a high accuracy for each waste ranging from 80% to 87.5%. Cardboard, metal, and paper types give the highest accuracy of 87.5%, predicting 35 of the metal waste types correctly. Glass waste gives 85% accuracy, whilst plastic and other waste types give the lowest accuracy of 80%; misclassifying 8 wastes. In the case of the other waste type, 5 and 3 other wastes are misclassified as plastic and paper, respectively. This may be due to the reflection of light resulting in the distortions on the captured images and thus, causing the misclassification of the mentioned type of waste.

Table 5 - Confusion matrix for testing results with image classification only

		Predicted						
		Cardboard	Metal	Plastic	Glass	Paper	Others	Total
Actual	Cardboard	35	0	1	0	4	0	40
	Metal	0	35	4	1	0	0	40
	Plastic	0	2	32	4	0	2	40
	Glass	0	1	4	34	1	0	40
	Paper	0	0	5	0	35	0	40
	Others	0	0	5	0	3	32	40
	Total	35	38	51	39	43	34	240

Table 6 shows the tabulated results of the statistical measures of the performance. Plastic and paper have higher recall than precision values, which indicates that the model is able to identify and segregate most of the relevant wastes. This is in contrast to cardboard, metal, glass, and others, which have higher precision than recall values, indicating that they are more precise in identifying the targeted waste type, with fewer cross contaminations of waste type. Cardboard and metal achieve considerable F1 measures, which represent a balance between high precision as well as high recall. Overall, an accuracy of 84.6% is obtained.

Table 6 - Performance statistical measures for testing with image classification only

Waste Types	Accuracy %	Precision	Recall	F1 measure
Cardboard	87.5	1.00	0.88	0.93
Metal	87.5	0.92	0.88	0.90
Plastic	80.0	0.63	0.80	0.70
Glass	85.0	0.87	0.85	0.86
Paper	87.5	0.81	0.88	0.84
Others	80.0	0.94	0.80	0.86

4.3 The Integration of Metal and Weight Sensors with Image Classification

The same 240 local wastes from the six waste types; are plastic, glass, paper, metal, cardboard, and others, have been used to test the constructed automatic waste segregator system employing both physical sensors and image classification. Table 7 gives the confusion matrix from the system. The overall accuracy of the system is 86.7%, representing 2.1% higher accuracy than the system which employed image classification only. As expected, similar accuracies are obtained for cardboard, plastic, paper, and other waste types, which utilise the image classification model for their identification. Particularly, for metal and glass waste types, the numbers of correctly classified wastes have increased from 35 and 34 correctly classified waste types to 38 and 36 correctly classified waste types for metal and glass, respectively. 1 metal waste has been incorrectly classified as glass and plastic, whilst 4 glass wastes have been incorrectly classified as plastic. These correspond to accuracies of 95% and 90% for metal and glass waste types, respectively. A few of the metal wastes cannot be detected using the metal detector, as some metal wastes may induce only a very low amount of current, which cannot be properly detected. The weight sensor also poses a slight problem in identifying the waste due to some glasses having a lower weight than the set threshold. These cause the system to resort to using the image classification model, despite the waste being of type metal or glass. However, the improved system, which utilises both physical sensors and the image classification model, has been proven to produce a better accuracy in classifying metal and glass, and, consequently, an overall increase in the accuracy of the system. Table 8 summarises the accuracy, precision, recall, and f1-measure of the developed automatic waste segregator, for different waste types. Metal has the highest accuracy of 95.0%, with plastic having the lowest accuracy of 80.0%. Plastics are found to have the worst prediction results compared to other waste types. Plastic, glass, and paper have higher recall than precision values, in contrast to cardboard and others, which have higher precision than recall values. Again, cardboard and metal achieve considerable F1 measures, which represents a good balance of precision and recall. Ultimately, the overall accuracy obtained is found to be 86.7%, an increase of 2.1% in overall accuracy.

Table 7 - Confusion matrix for testing results with both physical sensor and image classification

		Predicted						
		Cardboard	Metal	Plastic	Glass	Paper	Others	Total
Actual	Cardboard	35	0	1	0	4	0	40
	Metal	0	38	1	1	0	0	40
	Plastic	0	2	32	4	0	2	40
	Glass	0	0	4	36	0	0	40
	Paper	0	0	5	0	35	0	40
	Others	0	0	5	0	3	32	40
	Total	35	40	48	41	42	34	240

Table 8 - Performance statistical measures for testing with both physical sensor and image classification

Class	Accuracy %	Precision	Recall	F1 measure
Cardboard	87.5	1.00	0.88	0.93
Metal	95.0	0.95	0.95	0.95
Plastic	80.0	0.67	0.80	0.73
Glass	90.0	0.88	0.90	0.89
Paper	87.5	0.83	0.88	0.85
Others	80.0	0.94	0.80	0.86

For waste recycling, the precision of classification and segregation of waste types at the source is very important, especially if no further sorting or verification of waste types is performed at the waste facility. On the other hand, recall is more important if the aim is to maximise the amount of a particular waste type that is being collected; although supplementary verification and sorting may be needed at the waste facility after the wastes are collected and transferred to ensure that the collected wastes are of only a particular waste type as well as to reduce contaminations. For the developed automatic waste segregator, cardboard has the highest precision, followed by metal and others. Practically speaking, the collected wastes from the developed automatic segregator of these 3 waste types: cardboard, metal, and others, can directly be processed with no or minimal contaminations of waste types. On the other hand, metal and glass have the highest recall values of 0.95 and 0.90, respectively, with 2 metal and 4 glass wastes have been misclassified.

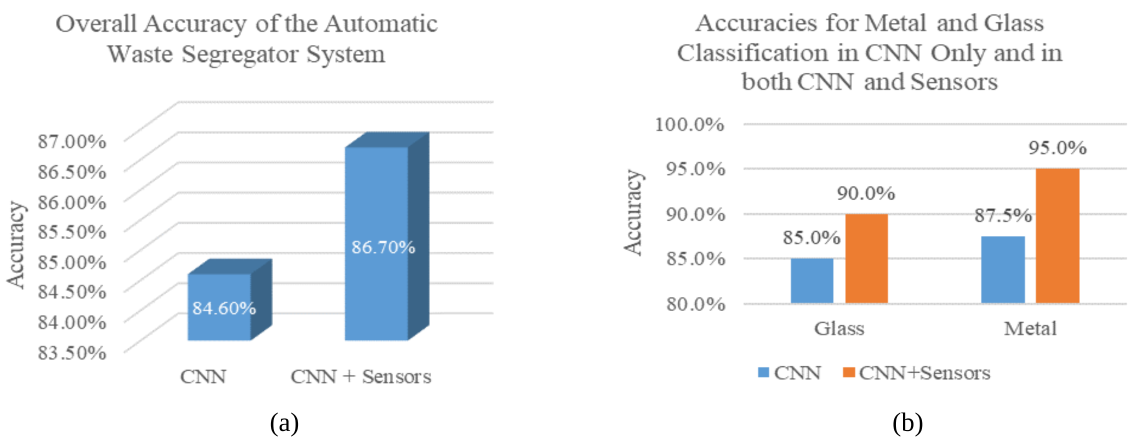


Fig. 8 - (a) Overall accuracy of the developed automatic waste segregator system; (b) accuracies for metal and glass classification in CNN only and both CNN and sensors

A direct comparison between the accuracies of the system with image classification only and the system with both physical sensors and image classification has been made and shown in Fig. 8. Utilising both the physical sensors and image classification gives a higher classification accuracy of 86.7%, as opposed to 84.6% accuracy by utilising the image classification model only, as can be seen in Fig. 8(a). Specifically, the additional utilisation of the physical sensors: metal and weight sensors, increases the accuracies of the two waste types. In the case of glass waste, an increase of 5% is observed, while for metal, an increase of 7.5% is obtained. This shows that the designed waste segregator system has the potential to be adopted for the automatic segregation of waste at the source.

5. Conclusion

With the fast-rising waste accumulation and its associated problems, waste recycling has been touted as one of the most effective solutions for managing waste. However, proper segregation according to waste types is still required to effectively recycle different types of waste and is usually performed manually at the waste facility, which is a labour-intensive and timely process. This paper develops a system for automating waste classification and segregation at the source in order to minimise the need for the laborious segregating process at the waste facility and hence, increase recycling efficiency. Two physical sensors: weight and metal sensors, and a deep learning Inception-v3 model for image classification, have been used for the identification of six waste types: cardboard, metal, plastic, glass, paper, and other waste types. An affordable and commercially-off-the-shelf Raspberry Pi 3B and Raspberry Pi Camera have been used for the identification of waste types using image; where, if the two physical sensors fail to ascertain that the waste is either metal or glass, the image classification shall only be used, to make the system less computationally intensive. The developed automatic waste segregator has an accuracy of 86.7% using both physical sensors and image classification, as compared to only 84.6% using only the image classification. This represents an improvement of 2.1%. Particularly, implementing the physical sensors in addition to the image classification increases classification accuracies of glass and metal wastes by 5% and 7.5%, respectively. The system performances have also been evaluated using precision, recall, and F1-measure scores. High precision values of 1.0, 0.95 and 0.94 are obtained for cardboard, metal and other waste types, respectively, whilst metal and glass waste types give high recall values of 0.95 and 0.90, respectively. These results demonstrate that the developed automatic waste segregator, using both image classification and physical sensors, is able to optimise the performance of the waste segregator in terms of its accuracy, cost-effectiveness, and efficiency for automation in waste classification and segregation. Outcomes from the study indicate that there is a potential to adopt the use of the developed automated waste segregator for waste segregation at the source. The developed product is especially useful in workplaces, schools, and universities; by encouraging and facilitating recycling, and hence, has the potential to ease the global waste problem.

Acknowledgment

The authors fully acknowledged the Faculty of Integrated Technologies, Universiti Brunei Darussalam for supporting this work.

References

[1] UNDP, “Sustainable Urbanisation Strategy,” *UNDP’s support to sustainable, inclusive and resilient cities in the developing world*, pp. 1-54, 2016, [Online]. Available: http://www.undp.org/content/undp/en/home/librarypage/poverty-reduction/sustainable-urbanization-strategy.html.

[2] Z. S. Al-Khafaji, H. K. AL-Naely, and A. E. Al-Najar, “A review applying industrial waste materials in stabilisation of soft soil,” *Electronic Journal of Structural Engineering*, vol. 18, no. 2, pp. 16-23, 2018.

[3] C. Zhang, T. Xu, H. Feng, and S. Chen, “Greenhouse gas emissions from landfills: A review and bibliometric analysis,” *Sustainability (Switzerland)*, vol. 11, no. 8, pp. 1-15, 2019, doi: 10.3390/su11082282.

[4] M. Taušová *et al.*, “Recycling of communal waste: Current state and future potential for sustainable development in the EU,” *Sustainability (Switzerland)*, vol. 11, no. 10, 2019, doi: 10.3390/su11102904.

[5] A. T. W. Yu, I. Wong, Z. Wu, and C. S. Poon, “Strategies for effective waste reduction and management of building construction projects in highly urbanized cities— a case study of hong kong,” *Buildings*, vol. 11, no. 5, pp. 1-14, 2021, doi: 10.3390/buildings11050214.

[6] H. Wilts, B. R. Garcia, R. G. Garlito, L. S. Gómez, and E. G. Prieto, “Artificial intelligence in the sorting of municipalwaste as an enabler of the circular economy,” *Resources*, vol. 10, no. 4, pp. 1-9, 2021, doi: 10.3390/resources10040028.

[7] T. H. Christensen and A. Damgaard, “Recycling of Paper and Cardboard,” *Solid Waste Technology & Management*, vol. 1, pp. 201-210, 2010, doi: 10.1002/9780470666883.ch15.

[8] N. L. Rahim, R. Che Amat, N. M. Ibrahim, S. Salehuddin, S. A. Mohammed, and M. Abdul Rahim, “Utilization of recycled glass waste as partial replacement of fine aggregate in concrete production,” *Materials Science Forum*, vol. 803, no. August 2015, pp. 16-20, 2015, doi: 10.4028/www.scientific.net/MSF.803.16.

[9] F. A. Azis, H. Suhaimi, and E. Abas, “Waste Classification using Convolutional Neural Network,” *ACM*

International Conference Proceeding Series, pp. 9-13, 2020, doi: 10.1145/3417473.3417474.
[10] Zero Waste Scotland, “The composition of household waste at the kerbside in 2014-15 Summary of findings,” no. November 2017, pp. 1-21, 2014, [Online]. Available: http://www.zerowastescotland.org.uk/sites/default/files/The composition of household waste at the kerbside in 2014-15.pdf.
[11] M. H. Russel, M. H. Chowdhury, M. S. N. Uddin, A. Newaz, and M. M. M. Telukder, “Development of Automatic Smart Waste Sorter Machine,” *International Conference on Mechanical, Industrial and Materials Engineering 2013 (ICMIME2013)*, vol. 2013, no. November, pp. 1-3, 2013.
[12] W. L. Mao, W. C. Chen, C. T. Wang, and Y. H. Lin, “Recycling waste classification using optimized convolutional neural network,” *Resources, Conservation and Recycling*, vol. 164, no. August 2020, p. 105132, 2021, doi: 10.1016/j.resconrec.2020.105132.
[13] G. White, C. Cabrera, A. Palade, F. Li, and S. Clarke, “WasteNet: Waste Classification at the Edge for Smart Bins,” 2020, [Online]. Available: http://arxiv.org/abs/2006.05873.
[14] S. M. Samreen, B. Gadgay, V. Pujari, and B. V Pallavi, “Automatic Metal , Glass and Plastic Waste Sorter,” vol. 5, no. Vi, pp. 884-889, 2017.
[15] R. K. Mistri, S. Asheer, P. Kumari, M. Toppo, and A. K. Singh, “Cheap And Efficient Metal Detector,” no. January 2017, 2019.
[16] A. Gilman and D. G. Bailey, “High-speed weighing using impact on load cells,” *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, vol. 2007, no. November 2005, 2005, doi: 10.1109/TENCON.2005.301118.
[17] I. Kabir Ahmad, M. Mukhlisin, and H. Basri, “Application of Capacitance Proximity Sensor for the Identification of Paper and Plastic from Recycling Materials,” *Research Journal of Applied Sciences, Engineering and Technology*, vol. 12, no. 12, pp. 1221-1228, 2016, doi: 10.19026/rjaset.12.2880.
[18] V. T. Widyaningrum, A. S. Romadhon, and R. Safitri, “Automatic Waste Sorter Machine using Proximity Sensor,” no. Himbep 2020, pp. 264-270, 2021, doi: 10.5220/0010331102640270.
[19] B. Ruj, V. Pandey, P. Jash, and V. K. Srivastava, “Sorting of plastic waste for effective recycling,” *Int. Journal of Applied Sciences and Engineering Research*, vol. 4, no. 4, pp. 564-571, 2015, doi: 10.6088/ijaser.04058.
[20] N. O. Mahony *et al.*, “Deep Learning vs . Traditional Computer Vision,” no. Cv.
[21] E. Dominic, “Understand TensorFlow by mimicking its API from scratch,” 2019.
[22] O. Adedeji and Z. Wang, “Intelligent waste classification system using deep learning convolutional neural network,” *Procedia Manufacturing*, vol. 35, pp. 607-612, 2019, doi: 10.1016/j.promfg.2019.05.086.
[23] Q. Zhang, Q. Yang, X. Zhang, Q. Bao, J. Su, and X. Liu, “Waste image classification based on transfer learning and convolutional neural network,” *Waste Management*, vol. 135, no. August, pp. 150-157, 2021, doi: 10.1016/j.wasman.2021.08.038.
[24] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2016-Decem, pp. 770-778, 2016, doi: 10.1109/CVPR.2016.90.
[25] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, pp. 1-14, 2015.
[26] Y. Zhang, J. Gao, and H. Zhou, “Breeds Classification with Deep Convolutional Neural Network,” *PervasiveHealth: Pervasive Computing Technologies for Healthcare*, pp. 145-151, 2020, doi: 10.1145/3383972.3383975.
[27] S. I. Serengil, *Transfer Learning in Keras Using Inception*. 2017.
[28] G. Thung, “TrashNet Dataset,” 2016. https://github.com/garythung/trashnet.