A Deep Learning-Based approach to Segregate Solid Waste Generated in Residential Areas

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Received: 26 January 2023 | Revised: 9 February 2023 | Accepted: 11 February 2023

ABSTRACT

Residential waste is a substantial contributor to solid waste generation, which is approximately around 36.5 million tons annually in India. The waste created in households is not separated at the source. All waste is accumulated in a single waste bin and stashed in a nearby public waste bin, resulting in a massive amount of waste being dumped in landfills and also infused with other types of waste, causing environmental pollution. The core objective of this research is to develop a household waste segregator using the TensorFlow object detection model and Arduino microcontroller. The SSD MobileNet V2 model has been trained with a household dataset consisting of paper, plastic, metal, organic waste, glass, and one more additional empty class to detect whether waste is placed for detection or not. This proposed system can predict the waste class and segregate it into their specific dustbin with mean Average Precision (mAP) and recall of 86.5% and 88.3%, respectively. Waste segregation and recycling can reduce landfills, lower carbon footprints, increase recycling, recover value from garbage, and lower greenhouse gases emitted from waste. Segregation at the source will reduce the cost of the segregation process carried by the municipal solid waste management.

Keywords-deep learning; waste management; computer vision; embedded system; Arduino

I. INTRODUCTION

According to the Indian Central Pollution Control Board's (CPCB) annual report, the country generates 160038.9 TPD (tons per day) of solid waste, of which 152749.5 TPD is collected with a collection efficiency of 95.4%, 79956.3 TPD is processed at 50%, and 29427.2 TPD is landfilled at 18.4%, , and 31.7% (50655.4 TPD), remains unaccounted for [1]. Authors in [2] published a spatio-temporal approach to reduce the waste dumped into landfills. Waste segregation is the biggest issue encountered in solid waste management, which is the process of accumulating, transferring, processing, and discarding solid waste in a municipality under the purview of a municipal authority. The waste could be collected door to door or by placing public trash bins. The collected waste would be transported to the municipal storage area where they will be processed and the unprocessed waste would be dumped into landfill sites (there are 3184 such dumpsites in India). So far, the waste is segregated manually at the storage location. Even though the government takes necessary actions to segregate waste at the source, only a few states can achieve it. In the long run, it is hard for people to maintain separate bins for each waste, so commonly all waste are dropped into a single bin and are handed to the municipal waste collection units. As an outcome, more amount of waste gets dumped into landfills. Authors in [3] proposed a reversal approach to handle the municipal solid waste generated in South Africa. Authors in [4] proposed a real-time deep learning system to sort waste disposed of in public places. Authors in [5] developed a robot that can classify waste as organic and non-organic using computer vision [5].

Over the past decade, the implementation of deep learning in real-time applications has increased drastically. Researchers have been using artificial intelligence techniques to unravel day-to-day problems. Deep learning is the subsidiary of machine learning. Machines can perform tasks such as prediction, classification, pattern recognition, and clustering [6, 7] when trained. Deep learning offers cutting-edge approaches to fully comprehending human behavior [8]. TensorFlow is a free and open-source AI and machine learning software library that is used many scenarios but emphasizes especially on deep neural network training and inference [9]. Nowadays, machines can extract significant information from digital images, videos, and other visual inputs utilizing an area of artificial intelligence termed as computer vision, and they can act based on that information. The model developed in this work will be trained using a learning method named transfer learning. In this method the intelligence of one model is transferred to a new model [10], assuming that the model can be thus trained faster and achieve better results quicker than other training methods. Authors in [11] developed a model using a Convolution Neural Network (CNN) to classify different types of plastics in waste. To improve the classification accuracy, authors in [12] developed the WasteNet model using deep learning with high accuracy. Authors in [13] compared the Support Vector Machine (SVM) with CNN based on waste classification performance. The pre-trained ResNet-34 model [14] was used to classify the waste data collected from the waste bin and the system does not have any segregation unit. Authors in [15] developed a model with transfer learning to classify public waste images. The smart waste separator in [16] has been used to classify waste based on shape. The model was developed using Hu's invariant moments and K-nearest neighbor algorithms. Authors in [17] developed the model RecycleNet to perform classification, especially for recyclable waste with a test accuracy of 81% [17]. Authors in [18] developed a deep learning model that can detect and classify waste into seven categories. In [19], images of solid waste were classified using the Gabor Wavelet Transformation (GWT), which combines an image with Gabor wavelet kernels of various scales and orientations. Authors in [20] implemented a waste segregation model with Internet of Things (IoT) and deep learning. Machine learning and IoT were used in [21, 22] to isolate the biodegradable and non-biodegradable waste and also to detect the presence of harmful gases in the bin. To segregate waste, the model should be trained on the dataset collected from the area in which the segregator needed to be placed. The current work is mainly focused on segregating household waste.

II. MODELING OF THE WASTE SEGREGATION SYSTEM

In this work, an automatic household waste segregator is proposed. This system can classify household waste into five categories, i.e. paper, plastic, organic, glass, and metal. The dimensions of the segregation system are displayed in Figure 1(a). The system has two units: one fixed and one movable as illustrated in Figure 1(b). The movable unit of the segregation system has three major parts: (i) platform, (ii) metal track, and (iii) dustbin. The platform of the waste segregation system can move bi-directionally in a metal track and the dustbins are placed below the track. The position of each dustbin is marked in the aluminum using black color and Arduino can identify the position of the dustbin using an infrared sensor. Waste needs to be placed on the movable platform and the camera placed over the platform would capture the frame and forward it to the custom-trained object detection. The model has been trained in Google Colab using the TensorFlow object detection Application Programming Interface. The object detection model would identify the category of waste and transmit the data to the Arduino through serial communication. Arduino will use infrared sensors and motors to control and modify the position of the platform based on the information collected. The mobility of the platform is controlled by 2 DC motors connected to wheels and 2 more supporting wheels. When the position of the platform matches the position of the dustbin, the waste will be dropped into the dustbin using the slider which is also controlled by the Arduino.

(a)

(b)

(c)

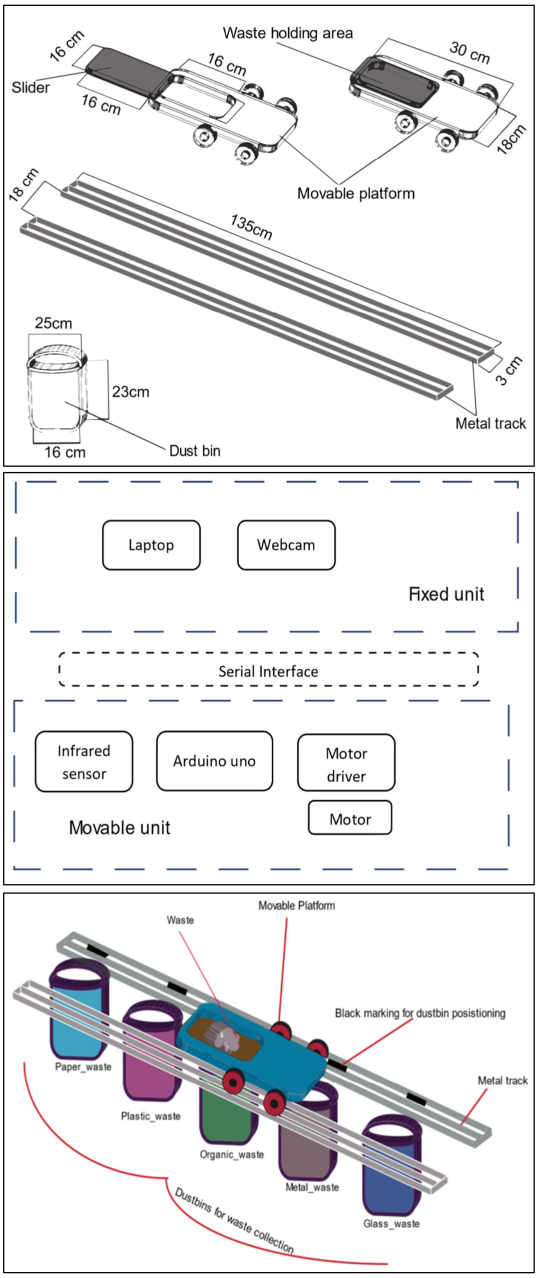

Fig. 1. Waste segregation system: (a) dimensions, (b) block diagram, (c) graphical representation.

III. OBJECT DETECTION MODEL

TensorFlow pre-trained object detection model was used in the automatic household waste segregator. The household waste image dataset was collected using a webcam, with a pixel size of 640×480 and the dataset was trained and tested with 3 pre-trained object detection models. Based on the average precision, average recall, and F1 score, SSD MobileNet V2 FPN Lite 640×640 was preferred for this work. Figure 2 represents the performance evaluation of the models for the household waste image dataset. MobileNet V2 has higher precision, recall, and F1 score than ResNet 50 and EfficientDet D0.

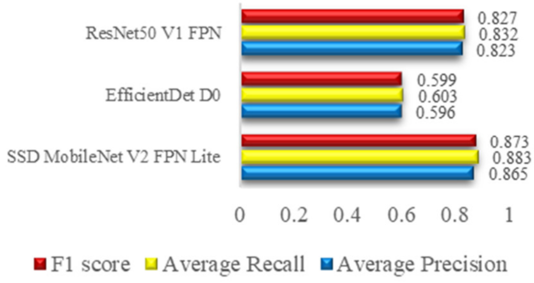

Fig. 2. Evaluation of the pre-trained models.

A. *SSD MobileNetV2*

The MobileNetV2 has been designed to be implemented in low-powered devices with moderate performance on classification, as shown in Figure. 2. MobileNet is small in size and consumes low computing power. While compared to the architecture of the MobileNet V1 model, the main difference is the inclusion of 1×1 Expansion and 1×1 projection layers. Table I represents the transformation of data fed into the bottleneck residual block. Where m×n represents the size of the input block, k is the size of the input and the output channel, and s is the value that represents the stride.

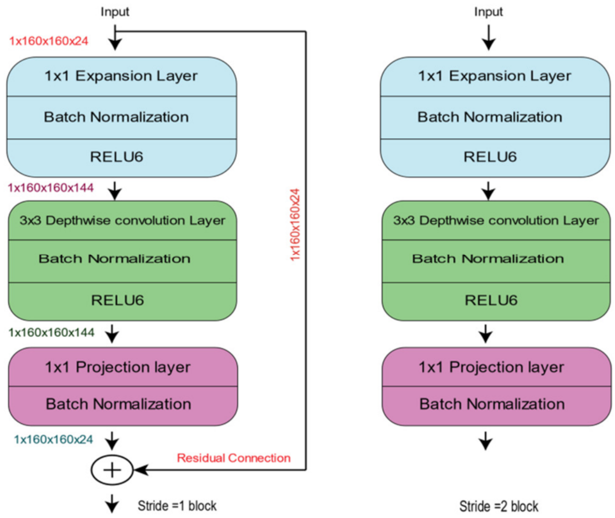

Fig. 3. MobileNet V2 block.

TABLE I. BOTTLENECK RESIDUAL ARCHITECTURE

Input	Operator	Output
m×n×k	1×1 pointwise conv2D, RELU6	m×n×(t k)
m×n×(t k)	3×3, depthwise s=s, RELU6	(m/s)×(n/s)×(t k)
(m/s)×(n/s)×(t k)	1×1 pointwise conv2D	(m/s)×(n/s)×k

The bottleneck residual block has three layers, the 1×1 expansion layer expands the input value based on the expansion factor which has a default value of t = 6.

Consider stride=1 in Figure 3. The input fed to the expansion layer is 1×160×160×24. The input channel 24 is multiplied with the expansion factor and the output of the layer is 1×160×160×144. The output forwarded to the 3×3 Depthwiseconv2D layer applies filters to the input 1×160×160×144, which is forwarded to the 1×1 Projection Layer. In this layer, the input will be reduced to 1×160×160×24 due to the bottleneck feature. In Figure 3, Stride=1 is the Bottleneck residual block and Stride=2 is the formation used to reduce the features of input data [23]. MobileNet base network is used to extract the features from the input image, and the features extracted from the image are forwarded to the SSD network as presented in Figure.4.

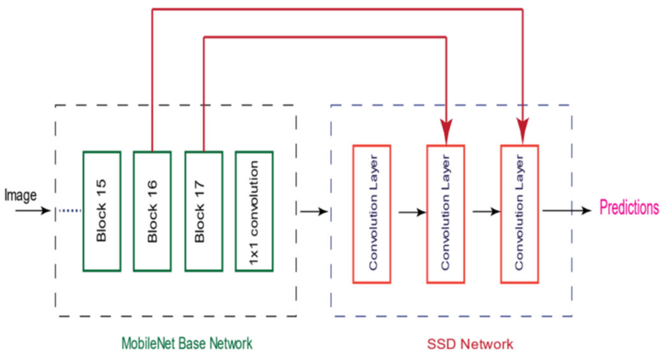

Fig. 4. SSD MobileNet architecture.

B. *Data Collection and Labelling.*

The household waste image dataset was collected using a webcam and the pixel size was determined to be 640×480. The dataset consists of 6 classes, i.e. Organic, Paper, Metal, Glass, and Plastic waste. One additional class (Empty) was included for determining whether the waste holding platform is free. In [24-26], ultrasonic sensor and PIR sensor are used to detect the condition of the platform or waste holding area, to detect whether the waste is placed or not for prediction. This method will eliminate the usage of the ultrasonic sensor in detecting the presence of waste. Altogether 1188 images were collected for training the object detection model. In Figure 5(a), the number of images per class was presented and the images were labelled using labelImg software as shown in Figure 5(b). Once the image was annotated LabelImg will generate an annotation file with an XML extension. For training the object detection model, Google Colab platform was preferred. Google provides 16Gb of workstation GPU free of cost. Training the model using GPU will reduce the training period and correspondingly supports achieving the loss convergence faster. However, authors in [27] suggested an algorithm that can generate better results even in non-GPU machines [27]. The model was trained for 5000 steps with a batch size of 4. The number of training steps was limited to avoid overfitting. A momentum optimizer with a cosine decay learning rate of 0.08 is used in the training process. The model was trained with a batch size of 4, which helps the model to be well generalized and also consumes less GPU. It consumes more time for computation but this offers better results in the case of a low dataset scenario. Training stops when the total loss of the model drops to 0.2. The frozen inference graph was generated after the training and was downloaded from Google Colab.

(a)

(b)

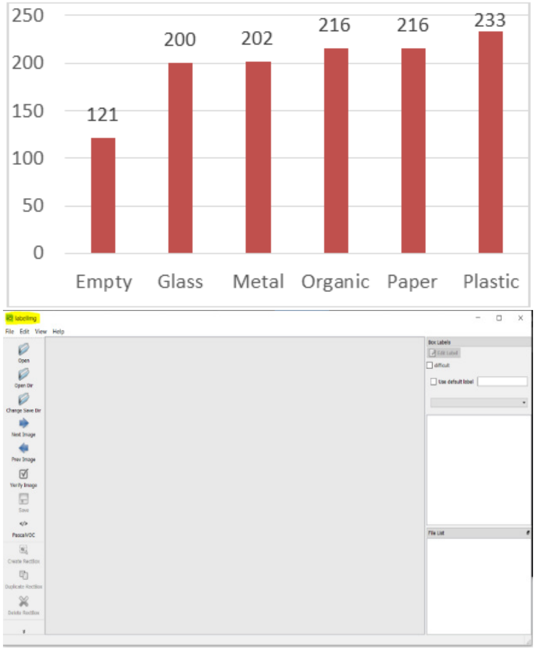

Fig. 5. (a) Dataset distribution, (b) LabelImg interface.

IV. AUTOMATIC HOUSEHOLD WASTE SEGREGATOR PROTOTYPE

A. The Prototype

Most of the parts of the prototype are made up of plastic, except the track which is made up of aluminum. The platform is placed over the track and dustbins were placed below. There is a ridge in the track that holds the wheel of the platform in position. This ridge is responsible for the linear mobility of the platform. The position of the components is shown in Figure 6. The object detection python script was running on the laptop, the webcam captures real-time video from the waste platform. If the waste is not placed in the platform, the object detection model will send class Empty to the controller through serial communication using the PySerial library. The communication takes place with a baud rate of 115200 bps. When a sample waste is placed on the platform, the object detection model sends the prediction results to the controller. From the perspective of the controller side, the controller waits for the incoming serial data. Most of the time the controller receives Empty. During that period, the controller stays still. If the controller receives other class names like Metal, Plastic, Paper, Glass, and Organic as input, the controller will initiate the function to activate the motors in the platform. The infrared sensor in the platform form will locate the position of the respective dustbin with the black mark placed in the tracks. Once the position is reached, the motor of the slider gets activated and the waste will be dropped in the dustbin. After this, the platform moves back to the starting position. Figure 6 illustrates the process of segregation. In Figure 6(a), the platform is in the initial position holding paper waste, whereas in Figure 6(b) the platform moves to the paper waste dustbin.

(a)

(b)

(c)

(d)

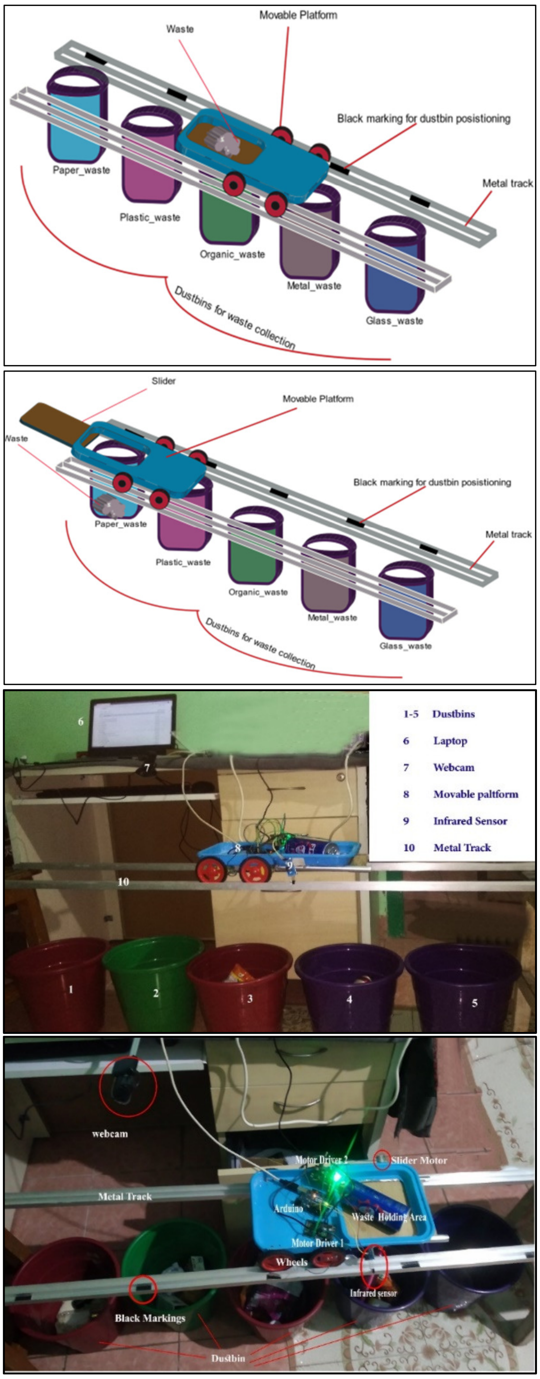

Fig. 6. (a) Initial platform position, (b) platform dropping waste, (c) front view, and (d) top view of the household waste segregation system.

B. The Algorithm

Step 1: Initiate a webcam interfaced with a laptop, and capture video.

Step 2: Predict the video input, and send the predictions to the Arduino controller.

Step 3: Controller reads the serial data.

- if *serial data* = *Empty* then do nothing.
- if *serial data* = *Organic* then put motors forward until Dustbin ID = IR sensor variable=1, slider open, drop waste and close, motor reverse until Dustbin ID = IR sensor variable=1.
- if *serial data* = *Metal* then put motors forward until Dustbin ID = IR sensor variable=2, slider open, drop waste and close, motor reverse until Dustbin ID = IR sensor variable=2.
- if *serial data* = *Glass* then put motors forward until Dustbin ID = IR sensor variable=3, slider open, drop waste and close, motor reverse Dustbin ID = IR sensor variable=3.
- if *serial data* = *Plastic* then put motor in reverse until Dustbin ID = IR sensor variable=1, slider opens, drop waste and close, put motors forward until Dustbin ID = IR sensor variable=1.
- if *serial data* = *Paper* then put motor in reverse until Dustbin ID = IR sensor variable=2, slider open, drop waste and close, motors forward until Dustbin ID = IR sensor variable=2.

Step 4: The controller reads the serial data.

In the track, from the initial position of the platform, there will be 3 markings on the right side and 2 markings on the left side as shown in Figure 6(a)-(b). Figure 6(c) shows the front view and Figure 6(d) the top view of the waste segregation system.

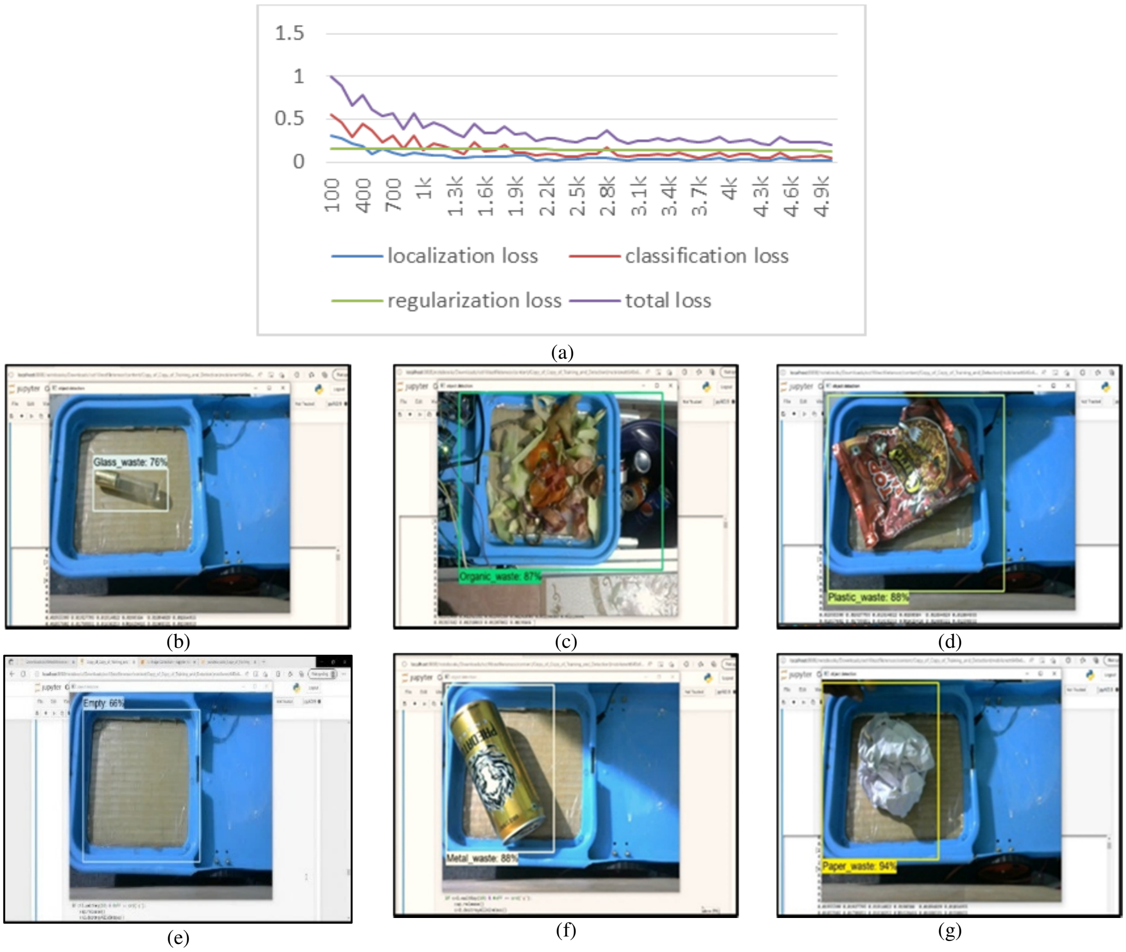

Fig. 7. (a) Loss of the model, (b) glass, (c) organic, (d) plastic, (e) empty, (f) metal, (g) paper.

V. RESULTS AND DISCUSSION

A. Object Detection Model

The model has been trained on the household waste image dataset in Google Colab for 5000 steps. The frozen inference graph generated from the training process was subsequently imported and utilized within Python scripts for object detection. These scripts were executed via Jupiter Notebook on a local machine. The total loss is the sum of classification loss, localization loss and regularization loss. The classification and localization loss are 0.05 and 0.01, demonstrating the model's competence in object classification and localization. The losses at 5000 steps are displayed in Figure 7(a) and Table II. The model performance was evaluated using 120 waste images and was found to have a mean average precision of 86.5% at an Intersection over Union (IoU) threshold of 0.50:0.95, with an average recall of 88% in the same IoU range, as presented in Table III. The model's precision and recall can be improved by increasing the sample size of the dataset or modifying the hyperparameters to increase the model's learning rate and detection efficiency. Figure 7(b)-(g) displays the real-time detection results, with lower confidence scores for the Empty class compared to other classes. This discrepancy is attributed to the comparatively small dataset of 121 images used for Empty class training compared to other classes. Although the confidence score can predict the class more accurately, a confidence threshold of 0.6 was defined for this model, meaning that the bounding boxes are drawn only when the detection confidence score exceeds 60%.

TABLE II. TOTAL LOSS FOR 5000 STEPS

Metrics	Intersection over Union range (IoU)	Value
Mean average precision	0.50:0.95	0.865
Average recall	0.50:0.95	0.883

TABLE III. MEAN AVERAGE PRECISION AND AVERAGE RECALL

Step	Classification loss	Localization loss	Regularization loss	Total loss
5000	0.053084	0.018455	0.130954	0.202493

B. *Segregation of Waste*

When the Arduino microcontroller receives the data from the object detection model, it activates the motor and moves to the corresponding dustbin. The shown above algorithm, programmed in the controller, locates the position of each dustbin based on the black marking placed in the metal track over each dustbin shown in Figure 6(a)-(b), based on the position of the black marking from the center point Dustbin ID was assigned.

The infrared sensor is used to track the corresponding dustbin by detecting the black marks placed, once the platform reaches the destination, the slider will open and waste will drop into the dustbin. Then the slider will close as shown Figure 8(a)-(b). After the waste is segregated into the dustbin, the platform moves back to the initial position and the process is repeated as illustrated in Figure 8(c). In all conditions, Dustbin ID will be the same for reaching the dustbin as and the starting point.

VI. COMPARISON WITH OTHER WASTE MANAGEMENT SYSTEMS

In the existing waste management systems, the work stops after training and evaluation of the deep learning model. Only a few works have developed the hardware for waste segregation. In all segregation systems, the hardware starts the segregation process only after the waste is placed in the waste holding area. The waste placed, can be detected by an ultrasonic sensor and a passive infrared sensor (PIR) [24-26]. A comparison between the proposed and existing systems is shown in Table IV. In the proposed system, the sensor used to detect the presence of waste was eliminated. Instead, images of the empty waste holding platform were collected and included in training, as shown in Figure 7(e). The object detection model itself can detect the presence of waste and also predict its category.

(a)
(b)
(c)

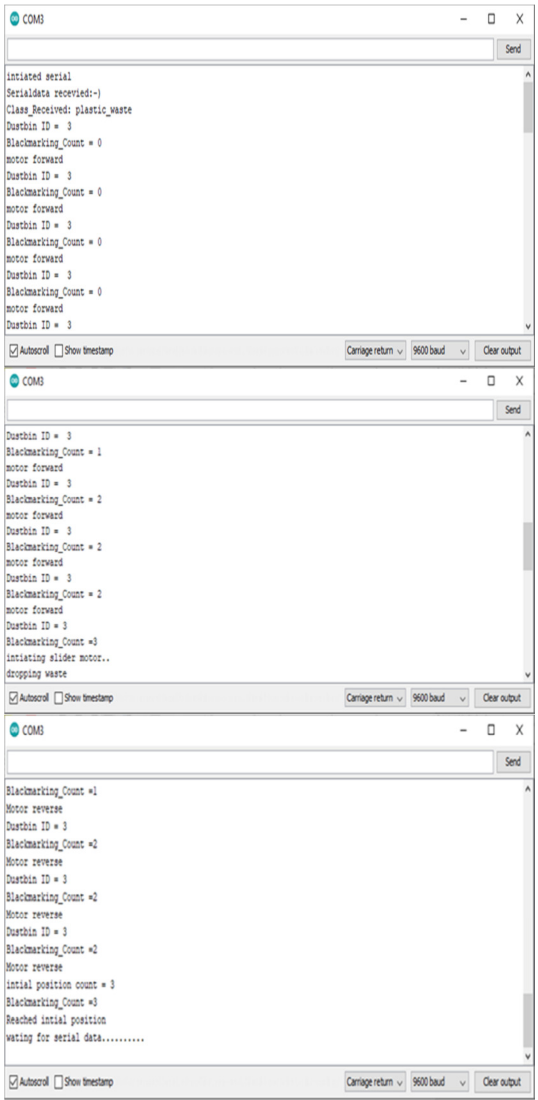

Fig. 8. (a) Controller receives serial data, (b) platform reaches to initial position, (c) comparing dustbin ID with black mark count value to initiate waste drop sequence.

VII. CONCLUSION

This article outlines a household waste segregation system utilizing the TensorFlow-based object detection model, SSD MobileNet V2 640×640. The model is pre-trained and fine-tuned on a custom household waste dataset to enable real-time waste segregation. The dataset is comprised of 6 classes, including five major waste categories, namely paper, plastic, organic, glass, and metal. The sixth class, "empty", was added to detect the presence of waste without the need for an ultrasonic sensor. Within each class, multiple waste items are included, regardless of their features. For instance, the plastic waste category includes images of various products with differing shapes, sizes, and colors, such as dairy product covers, chocolate wrappers, toothpaste tubes, soft drink bottles, hair conditioner containers, water bottles, and grocery product wrappers. This heterogeneity in waste generated by households is a result of varying geographical locations and lifestyles, and thus requires a large and diverse dataset and training in a TPU environment. TPUs demonstrate improved results and faster convergence compared to GPUs, even with larger batch sizes. To optimize the practical implementation of this system, it is necessary to minimize the prototype size. Although the waste segregation process is automated, the disposal process still requires manual intervention, with the segregated waste being handed over to the municipal waste collection unit. In the future, mobility can be added to the dustbin through a path guidance system, and a network connecting household bins to municipal waste collection units can be developed to further automate and improve the reliability of the system.

TABLE IV. COMPARISION OF THE PROPOSED SYSTEM WITH EXISTNG WASTE MANAGEMENT SYSTEMS

Ref.	AI architecture	Segregation mechanism	Methods used to detect the presence of waste	Type of waste
[13]	CNN with 11 layers and SVM	No	-	Metal, paper, plastic, glass, cardboard and general waste
[12]	WasteNet	No	-	Metal, paper, plastic, glass, cardboard and other waste
[28]	-	No	-	General waste
[14]	CNN	No	-	Metal, paper, plastic, glass, cardboard and common waste
[29]	-	No	-	General waste
[21]	-	No	-	General waste
[24]	CNN	**Yes**	**PIR**	Metal, paper, plastic and glass
[25]	MobileNet	**Yes**	**Ultrasonic sensor**	Metal, paper, plastic
[26]	MobileNet	**Yes**	**Ultrasonic sensor**	Metal, paper, plastic, glass, cardboard
Proposed	**MobileNet**	**Yes**	**The object detection model alone can detect the presence of waste**	**Organic, metal, glass, paper and plastic**

AUTHOR CONTRIBUTIONS

The corresponding author contributed in data collection, model training, hardware design, and drafted the manuscript. The second author supervised the process and proofread the manuscript for publication.

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