Deep Learning Model for Enhancing Automated Recycling Machine with Incentive Mechanisms

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***Abstract*—Automated Recycling Machine (*ARM*) can be defined as an interactive tool to flourish recycling culture among community by providing incentive to the user that deposit the recyclable items. To enable this, the machine crucially needs a material validation module to identify the deposited recyclable items. Utilizing combination of sensors for such purpose is a tedious task and hence vision-based YOLO detection framework is proposed to identify three types of recyclable material which are aluminum can, PET bottle and tetra-pak Initially, the 14883 training samples and 937 validation samples were fed to the various YOLO variants for investigating an optimal model that can yield high accuracy and suitable for CPU usage during inference stage. Next the user interface is constructed to effectively communicate with the user when operating the *ARM* with easy-to-use graphical instruction. Eventually, the *ARM* body was designed and developed with durable material for usage in indoor and outdoor conditions. From series of experiments, it can be concluded that, the YOLOv8-m detection model well suit for the *ARM* material identification usage with 0.949 mAP@0.5:0.95 score and 0.997 F1 score. Field testing showed that the *ARM* effectively encourages recycling, evidenced by the significant number of recyclable items collected.**

***Keywords*—Recycling machine; You Only Look Once (YOLO); vision system; interactive recycling; deep learning**

I. Introduction

Recycling is a critical waste management strategy that involves collecting and processing discarded materials into new products. In Malaysia, the recycling initiative began in 1993 and unable to achieve its goals due to lack of significant awareness programs [1]. Consequently, the Ministry of Housing and Local Government launched the National Recycling Program on 2 December 2000, designating 11 November as National Recycling Day to highlight the importance of recycling. Despite numerous efforts, an environmental issue related to waste pollution are a significant concern in Malaysia since it was ranked eighth globally for mismanaged plastic waste [2]. Effective implementation of the 3R (reduce, reuse, recycle) strategies is essential to minimize waste sent to landfills and extend their lifespan. Typically, municipal solid waste in Malaysia consists predominantly of food waste, followed by recyclable materials like plastic, paper, glass, and aluminum cans [3]. Hence, adopting comprehensive recycling strategies is crucial to achieving the effective waste management targets.

Globally, many countries, including China [4], India [5], South Africa [6], Switzerland [7], and Malaysia [8], have adopted systematic waste management techniques. The integration of technology in waste management has gained significant attention, with innovations like the Reverse Vending Machine (RVM) demonstrating the potential to increase recycling activities. Technologies such as RFID [9-11], Wireless Sensor Networks [12], and VANET [13] have shown that they can provide comprehensive waste management solutions and encourage proper waste disposal.

Combining technology with a reward system has proven reliable and effective in supporting recycling initiatives as demonstrated by smart recycle bin [14] [15]. However, the reliance on multiple sensors for identifying recyclable materials prior point issuance requires tedious sensor arrangement, calibration and maintenance, making it unsuitable for long term use. Vision-based technology on the other hand, can recognize a broader range of recyclable items using vast number of features collected from the sample image. One of the works is from [16] in which they introduced ThrashNet dataset and use SIFT feature with SVM and CNN model of AlexNet -like architecture. Andrey et al. [17] developed a reverse vending machine with several CNN classification models, analyzing the effect of training by combining two different dataset clusters. On average their CNN model achieved over 85% accuracy. They further tested the module in real-world implementation by combining weigh sensor with the CNN for fraud detection [18].

Recently, YOLO become trends for recyclable waste detection due to its real-time object detection capabilities and high accuracy. YOLO architecture allows for the simultaneous detection and classification and hence make it ideal for dynamic environments where waste items vary in size, shape, and type. A study from [19] utilized YOLO with a depth camera to accurately determine the type and location of waste in 3D. Additionally, incorporating YOLO in ARMs aligns with broader trends in AI-driven waste management systems, which emphasize the integration of vision-based automated sorting for efficient recycling processes [20] [21]. The effectiveness of YOLO in these applications is further supported by research highlighting its adaptability and performance in real-world scenarios, thereby facilitating the development of intelligent waste management solutions [22] [23]. Currently, there are many types of YOLO variants are available. Detail explanation from the first model which was introduced in 2015 up until the recent one can be found from study [24].

Numerous studies have focused on detection models for recycling waste identification across various applications. However, there is limited research on the real-world implementation of these detection models and their effectiveness when deployed with targeted stakeholders. This paper investigates a detection-based model for optimal implementation in recycling, incorporating a reward system to enhance user engagement. Additionally, it assesses the system feasibility through onsite testing. The paper is organized as follows: Section II details the methodology used throughout this project, Section III and Section IV presents the results and discussion respectively, and Section V concludes the project with final observations.

II. Models and Method

In this section, detailed explanation about model and architecture used throughout this project is explained. It comprises of four main subsections namely dataset preparation, detection model development, and user interface design and automated recycle system formation. To make the automated recycling machine (*ARM*) cost effective, its platform will run on Intel i7 CPU with 16GB RAM and 256GB SSD storage.

A. Datasets Preparation

In this project, samples of recycling images are obtained locally to ensure that the *ARM* model can differentiate the item effectively. The arrangement for capturing the sample images is shown in Fig. 1 in which the camera is positioned 21 cm above the ground with the samples placed 51cm from the camera. A total of 5,872 samples were collected and categorized into three groups, namely PET bottle, aluminum can and tetra-pak as depicted in Fig. 2. These collected images undergo a series of augmentation process which comprises of saturation and brightness adjustment, rotation, blurring and noise contamination and expand the data to 15,820. Once completed, the data were divided into training and validation sets with 14,883 samples for training and 937 samples for validation. Roboflow platform is used to augment, annotate and format the data to well suit the selected version of the detection model. Detailed sample distributions for each cluster can be seen in Table I.

B. Detection Model Development

For detection module, the main structure employed in this project is based on 'You Only Look Once' (YOLO) object detection. Basically, it starts with the forming of grid cells, followed by class prediction across scales, and eventually bounding box location estimation via regression process. The finer grid cell enables smaller target detection and anchor box makes it possible to detect an overlapping object with high accuracy. There are many variants of YOLO model starting from version v1 to version v10. In this project, three recent models which are YOLOv8, YOLOv9 and YOLOv10 were used. Basically, most of the YOLO architecture can be divided into three main components which are backbone, neck and head. The backbone is the part that is responsible for extracting an important feature from the input image. Once the features are extracted, the neck will combine the multi-scale information and channel it to the head section. The head generates predictions based on the extracted information from the backbone and the neck.

YOLOv8 [25] is the architecture evolution from its predecessor YOLOv5 [26] that was developed by Ultralytics. It introduces several enhancements over its predecessors by focusing on improving efficiency, accuracy and ease of use for object detection tasks. The backbone of YOLOv8 was derived and improved from CSPDarknet53 structure which consists of 53 convolutional layers. Apart from that, cross-stage partial connections that facilitate better information flow between layers were integrated. This optimization helps in capturing more detailed features from the input images. In the neck segment, YOLOv8 adopts combination of feature pyramid network (FPN)[27] and path aggregation network (PAN) [28]. This strategy contributes to improving the detection capability of targets at different scales. The head of YOLOv8 utilizes an anchor-free design, which simplifies the detection process and improves overall speed and accuracy. YOLOv8 models are available in five variants which distinguish between number or parameters and accuracy. However, since the aim of this project is focusing on implementation of the model on CPU, three pre-trained models that are well balance between complexity and accuracy were selected which are YOLOv8-n, YOLOv8-s, and YOLOv8-m.

TABLE I. NUMBER OF IMAGE DATASET IN EACH RECYCLE ITEM IMAGE CATEGORY

Image	Training	Validation
Aluminum Can	4005	248
PET Bottle	9054	569
Tetra-pak	1824	120
Total	14883	937

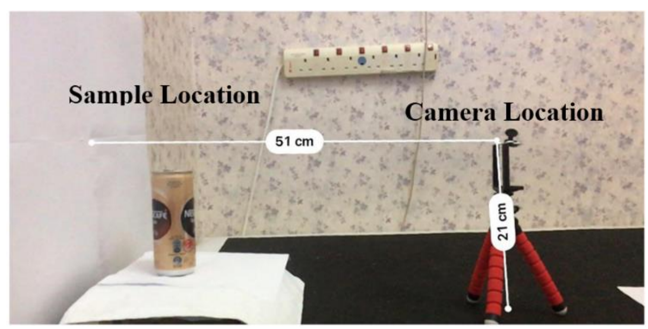

Fig. 1. Setup arrangement for dataset preparation.

Fig. 2. Sample of tetra-pak, PET bottle and aluminum can.

YOLOv9 [29] builds upon the foundations laid by YOLOv7 [30] structures and further refinements to enhance detection capabilities. One of the key features of YOLOv9 is the integration of Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN). The combination has shown strong competitiveness among other models and maintains a balance between reducing the number of parameters and floating-point operations per second (FLOPs) while achieving superior performance compared to earlier versions. For this project a compact model of YOLOv9 known as YOLOv9-c is used as the pre-trained model for the recyclable waste detection assessment.

YOLOv10 [31] introduces significant architectural changes aimed at optimizing performance and reducing complexity. The backbone of YOLOv10 employs enhanced CSPNet which is lightweight design with a rank-guided block architecture that identifies and replaces stages with higher redundancy. This approach reduces the number of parameters and FLOPs, enhancing the model efficiency without compromising performance. The neck of YOLOv10 features improved feature pyramid networks using path aggregation network that better handle multi-scale feature fusion. The head of YOLOv10 is optimized to streamline the detection pipeline, ensuring maximum accuracy and minimal computational overhead. These enhancements make YOLOv10 particularly effective for real-time applications, where computational resources are often limited. YOLOv10 has six final architectures. To balance between speed and accuracy of the system, three YOLOv10 architectures which are YOLOv10-n, YOLOv10-s and YOLOv10-m are further analyzed for the automated recycle waste implementation.

TABLE II. SUMMARY OF YOLO PRE-TRAINED MODEL USE FOR TRAINING THE RECYCLABLE WASTE DATA

Model	Size	Parameters	FLOPs
YOLOv8-n	640	3.2M	8.7G
YOLOv8-s	640	11.2M	28.6G
YOLOv8-m	640	25.9M	78.9G
YOLOv9-c	640	25.3M	76.3G
YOLOv10-n	640	2.3M	6.7G
YOLOv10-s	640	7.2M	21.6G
YOLOv10-m	640	19.1M	59.1G

Table II summarizes the YOLO pre-trained models used to train the recyclable waste dataset. The models are selected based on the current state of the art detection models and have an adequate number of parameters to be used by CPU in the inference stage. From the assessment, a single model that yields a high performance with lower parameters will be selected for fulfilling the needs of an automated waste recycling module system.

C. User Interface Design

To construct the user interface a C# platform along with YoloDotNet v2.0 is utilized. Initially, the optimal weight of the YOLO model is exported to ONNX format to ensure compatibility with the .NET platform. ONNX is an open-source format that is compatible with different deep learning platforms and hence will be convenient for model sharing and deployment. The process using the system will consist of simple four steps as follows:

1) Initiation: Users push the start button in the welcoming screen to initiate the process.

2) Verification: The deep learning module verifies all deposited items.

3) Completion: To end the process, users press the finish button which prompts a screen requesting user information.

4) Point collection: If users wish to collect point, they can enter their phone number or leave it blank, if otherwise.

D. ARM Design and Setup

In this section, design and setup about the *ARM* body structure will be elaborate in detail. An illustration about the machine drawing is depicted in Fig. 3 where the whole structure design is shown on the left side and the chute architecture with camera placement is shown on the right side. The overall dimension of the machine is 1000mm width, 1000mm depth and 1800mm height. Regarding the materials, frame body structure is constructed using 25mm x 25mm hollow steel bars, and the casing is developed using 1mm galvanized steel sheets. Referring to the chute design, a high camera resolution is located 210mm above the chute base and tilted downwards at 45º angle. A 22-inch touch screen is utilized as the information display medium and serves as the user interface input.

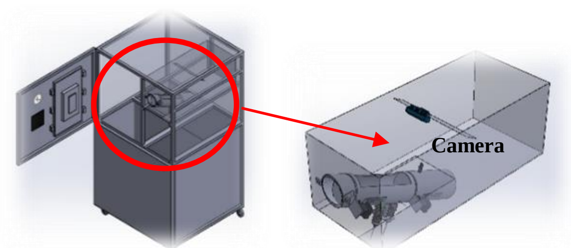

Fig. 3. ARM body design of the machine (left) and detail design of chute with location of camera (right).

III. RESULTS

This section offers a thorough examination of the performance of the detection model and how it was used to automate recycling with an integrated reward system. The three primary components of the analysis are evaluation of the YOLO models, user interface design, and automated recycling module implementation in real-world circumstances, and. The evaluation of the YOLO model involves assessing its mAP, F1 score, and precision in identifying different recyclable materials. The goal of the user interface design is to provide a platform that is simple to use and intuitive so that users can interact with the recycling system. In the end an implementation section describes how the user interface and detection model are combined to create a recycling module that works well in real-world situations.

Fig. 4 illustrates image samples of PET bottles, aluminum cans, and tetra-paks, which have undergone a series of augmentation processes to enhance the sample image for training session. These augmented images are used to train the detection model, ensuring it can accurately identify and classify different types of recyclable materials under various conditions.

Fig. 4. Sample of training batch images where 0 denoted for PET bottle, 1 for aluminum can, and 2 for Tetra Pak.

A. YOLO Model Assessment

This section will elaborate about the experiments conducted to deliberately discuss results obtained for the YOLO detection module framework. There are three versions of YOLO models tested which are YOLOv8, YOLOv9 and YOLOv10. The optimal model is selected based on its performance and medium level complexity to meet the requirement of CPU usage. The metrics considered for analysis are mAP@0.5, mAP@0.5:0.95, F1 Score, and Recall. Table III summarizes the findings.

From the table, among the investigated models, Yolov8-m stands out with a well balance between mAP@0.5:0.95 and F1 score. This model achieves a mAP@0.5 of 0.994, mAP@0.5:0.95 of 0.949, F1 score of 0.997, and a Recall of 0.998. The average mAP@0.5 across all models is 0.994, with a range from 0.994 to 0.995, indicating uniformly high precision across investigated models. However, the distinction in performance is more noticeable in the mAP@0.5:0.95 metric, which averages 0.944, highlighting the model capability to maintain precision across varying thresholds. Yolov8-m is shown to be outstanding for the mAP@0.5:0.95 score of 0.949 and hence capable in detecting objects at different scales more effectively than other models. Additionally, the high F1 score and recall values reflect its balanced performance in precision and recall, which is crucial for robust object detection. All in all, Yolov8-m metrics show a well balance performance and make it the ideal choice for the *ARM* module task.

TABLE III. YOLO MODEL PERFORMANCE TRAINED WITH THREE RECYCLE ITEMS IMAGE CATEGORY

Model	mAP@0.5	mAP@ 0.5:0.95	F1- Score	Recall
Yolov10-n	0.994	0.937	0.997	0.997
Yolov10-s	0.995	0.941	0.992	0.995
Yolov10-m	0.994	0.938	0.991	0.990
Yolov9-c	0.994	0.949	0.996	0.998
Yolov8-n	0.995	0.945	0.998	0.998
Yolov8-s	0.995	0.946	0.997	0.998
Yolov8-m	**0.994**	**0.949**	**0.997**	**0.998**

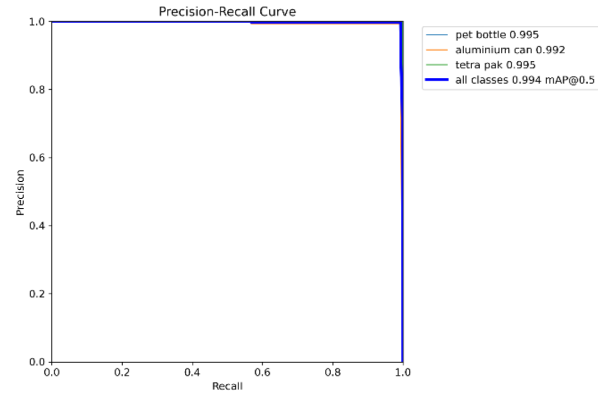

Fig. 5. Precision recall curve of the YOLOv8-m model.

To gain a more detailed insight into the performance of each object class for YOLOv8-m, the precision and recall curves of can be investigated and depicted in Fig. 5. These curves highlight the tradeoff between precision (exactness) and recall (completeness) across various thresholds. By analyzing these curves, one can determine the optimal threshold that maximizes both precision and recall. From the figure, it can be seen that the PET bottle and tetra-pak classes exhibit the highest confidence scores at 0.995, followed closely by the aluminum can at 0.992. On average, the overall performance across all classes achieves a mean average precision (mAP) score of 0.994 at 0.5 confidence threshold. This high mAP score indicates robust detection capabilities.

Apart from the recall and precision performance, Fig. 6 presents the training and validation results of a YOLOv8-m model. From the figure, the top row shows the training metrics, including box loss, classification loss, and DFL (distribution focal loss). All parameters decrease steadily, indicating an improved model performance over epochs. The precision and recall graphs demonstrate that the model achieves high accuracy and recall rates around 10 epochs during the training process and maintaining these high values constantly. The bottom row shows the validation metrics, which mirror the training results, with box loss, classification loss, and DFL loss that decreasing consistently. As for the mAP50 (mean Average Precision at 50% IoU) and mAP50-95 (mean Average Precision across IoUs from 50% to 95%) metrics for both training and validation indicate high performance with values reaching 1.0, showing that the model is effective for detecting the targeted recyclable materials.

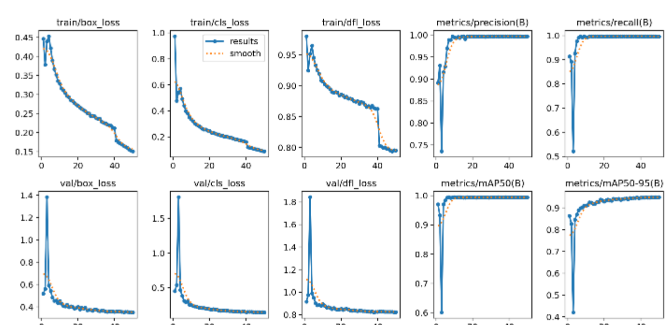

Fig. 6. Result for YOLOv8-m training.

Fig. 7. Sample of YOLOv8-m detection outcome.

Finally, Fig. 7 showcases the resultant images for aluminum can, PET bottle and tetra-pak items after running the inference/testing process with confidence label labelled for each item.

B. User Interface Design Assessment

In this section a snapshot of using the *ARM* system is elaborated and the steps are summarized in Fig. 8. Users can initiate the process by pressing the start button which is represented by the earth icon (see Fig. 8 (a)). This action activates the system and prepares it to receive recyclable materials. Next, recyclable items can be put one by one into the designated slot. As each item is placed inside, the YOLO detection module will scan and detect the material accordingly (Fig. 8(b)). If the system fails to detect an item, the user can remove it and try inserting it again until it is recognized, and if still fails then the material is not acceptable by the system. During this process, the user can monitor each inserted item on the system's screen to ensure proper detection. Once all your recyclable materials have been successfully inserted, the user can press the finish button (Fig. 8(c)) to conclude the recycling process. Eventually, the user can key in a valid phone number into the system to collect any points or rewards associated with the recycling effort. This phone number will typically be used for verification purposes and to credit any recycling points.

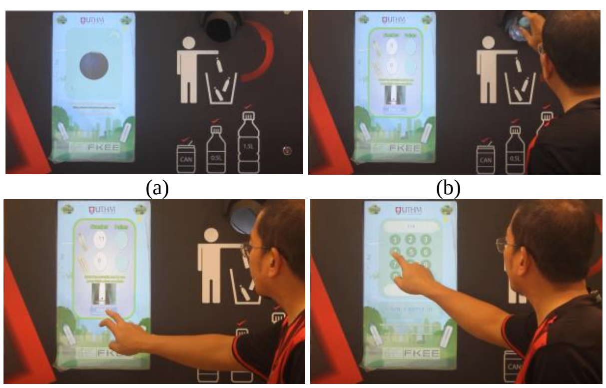

Fig. 8. User interface design consists of four main steps: (a) Start the recycling process. (b) Insert the recyclable items into the recycling system. (c) Finish the recycling process. (d) Enter phone number to claim the points for reward.

C. System Installation and Pilot Testing

Finally, to investigate the feasibility of the *ARM* implementation in actual conditions, the module (Fig. 9(a)) was installed at two different events. In the first case, the module was installed at SWM Pura Kencana (Fig. 9(b)), which is the office of a waste management company in southern Malaysia. In the second case, it was used during an event at a university (see Fig. 10). The installation at the SWM office aimed to study about public acceptance of the module and its effectiveness in encouraging recycling among the community and SWM staff. During the 30 days of implementation, the system managed to collect approximately 21 kilograms of PET bottles and one kilogram of aluminum cans, with snapshots of the collection shown in Fig. 9(c). These results indicate that PET bottles were the dominant item collected and aligning with the goal of reducing plastic waste that ends up in landfills. The system experienced only one instance of downtime due to computer overheating and to address this, a ventilation hole was added to ensure proper airflow within the module.

During implementation of the *ARM* at a showcase event (see Fig. 10), it successfully attracted users to recycle with some of the participants bringing many recyclable items. Primary school students were eager to use the system and deposit most of their plastic bottles into the bin. The one-day event demonstrated that the system could attract first-time users to fully utilize the system. However, to maintain their continuous interest, a different type of reward system should be implemented to sustain their engagement. For instance, integrating point-based reward systems or a lucky draw reward system. Additionally, educational workshops or interactive sessions that explain the importance of recycling and its impact on the environment can further produce a long-term participation.

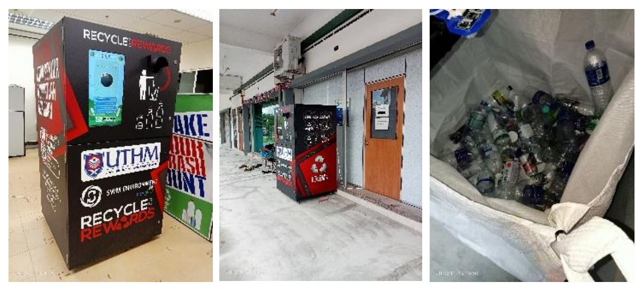

Fig. 9. Automated recycling system module. (a) Complete system module. (b) Installation onsite at SWM Pura Kencana Batu Pahat Johor. (c) Snapshot of collected recycling items.

Fig. 10. Pictures of automated recycle system implementation as a showcase in an event inside university.

IV. Discussion

The key takeaway from the previous analysis of the ARM detection model is that among YOLOv8, YOLOv9 and YOLOv10 architectures, the YOLOv8-m model shows exceptional performance on various object detection metrics for our dataset and hence make it a top choice for waste classification tasks in the ARM module. YOLOv8-m strength in terms of precision (minimizing false positives) and recall (minimizing false negatives), is critical for robust detection in real-world scenarios. To improve these results even further, advanced data augmentation techniques could be used to diversify the training data and reduce overfitting to ensure even better generalization to new, unseen data. Furthermore, experimenting with fine-tuning the hyperparameters of YOLOv8-m could optimize its performance for specific drop-off types or conditions, leading to even higher precision and recognition rates. Apart from that, integrating ensemble methods combining YOLOv8-m with other models could leverage the strengths of the different architectures, increasing accuracy and robustness. Finally, ongoing monitoring and updating of the model with new data can help to maintain its relevance and effectiveness as waste classification requirements evolve.

Integrating YOLOv8-m model into ARM applications involves addressing software and hardware integration with seamless user interface. To maintain cost competitiveness, a CPU is used as the main framework for detecting the recyclable material types. It will also command the Arduino controller for diverting the waste into the respective bin. To illustrate the practicality of YOLOv8-m model for the ARM implementation, a 30-day continuous usage trial reveals the model capability for effectively detecting the inserted materials and delivering to the respective bin. However, the system encounter challenges in outdoor environments due to overexposure from light entering through the chute, which causes the camera to inaccurately capture the shape of object. Such an issue can be overcome by installing a movable lid over the chute to control the amount of light exposure.

V. Conclusion

In this project, a vision-based YOLO detection module of recyclable items was investigated for the automated recycling machine (*ARM*) module. In the assessment stage, three classes of recycle items which are PET bottle, aluminum can and tetra-pak are used during the training and validation stage with total number of 14,883 and 937 respectively. The optimal YOLO structure that can balance between speed and accuracy requirements is integrated in the *ARM* system.

For the detection model assessments, seven state-of-the art YOLO models namely YOLOv8-n, YOLOv8s, YOLOv8m, YOLOv9-c, YOLOv10-n, YOLOv10-s and YOLOv10-m were used to train the recycle dataset. From series of training and fine tuning, it can be concluded that Yolov8-m metrics show a well balance performance with mAP@0.5 score of 0.994, mAP@0.5:0.95 score of 0.949 and F1 value of 0.997. However, it is also worth mentioning that the performance of other investigated models is not too distinct with this model. Since this model yields the highest accuracy, it was further tested under for the ARM inference module that acquired data straight from life feed camera. For the user interface, the flow of using the ARM is easy to follow with simple operation steps with the option for the user to claim the reward points. As for the ARM pilot testing onsite, it shows a promising outcome to attract users to recycle and can be utilized as an interactive tool to ignite recycling culture among communities.

In future, the research can address the current system limitations which lack redemption (incentive) options. Implementing a redemption model aligned with container deposit legislation would enhance user participation. In the absence of such policies, support from entities through corporate social responsibility initiatives is essential for the success of the redemption stage. Apart from that, the detection model can be tested with various public recyclable datasets such as TACO dataset, ThrashNet dataset and WasteNet dataset to investigate the model reliability and scalability.

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