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Turning Trash into Treasure: Developing an Intelligent Bin for Plastic Bottle Recycling

Sirajam Munira, Niloy Paul, Md Ashraful Alam, Md. Mahmudur Rahman*, and M. Shamim Kaiser

Abstract: Plastic pollution has emerged as a major global concern due to its enduring nature and limited recycling options. In response to this critical challenge, this paper presents a novel approach utilizing a Detection-Based Reward System (DBRS) alongside an innovative business model to promote effective plastic waste management, reduce plastic waste accumulation in the nature, and uphold environmental cleanliness. Leveraging the YOLOv5 algorithm for its exceptional accuracy, speed, and open-source availability, plastic bottle detection becomes a pivotal aspect of this system. Users seamlessly enroll in the system, triggering an automated detection process that computes reward points corresponding to their deposited plastic bottles. These reward points are meticulously stored within a centralized database. Beyond its operational facets, this comprehensive system encompasses a robust business model, strategically poised to capture widespread engagement with waste disposal practices, thereby contributing to the realization of Sustainable Development Goals (SDGs) geared towards fostering a healthier environment. Notably, the DBRS attains cutting-edge performance in plastic bottle detection, boasting an impressive mean Average Precision (mAP) of 0.973, underscoring its efficacy in tackling plastic pollution.

Key words: smart environment; reward system; YOLOv5; deep learning; business model

1 Introduction

Plastic pollution is a significant problem affecting the environment, wildlife, and human health. Despite global efforts, plastic still enters the oceans annually, harming marine life and ecosystems. Waste management practices like landfills, incineration, recycling, and composting have helped reduce plastic waste, but they are not perfect. More sustainable and effective practices are needed, and technology can improve waste management and recycling processes.

Recycling conserves natural resources and decreases landfill waste, although it can be energy-intensive and expensive. So, the current situation calls for a systematic and inventive strategy to mitigate the issue of plastic waste, surpassing the constraints of conventional recycling methods and advocating for conscientious plastic consumption. Although recycling activities have been implemented for several decades, their efficacy continues to be constrained by various obstacles, including issues related to contamination, inadequate recycling rates, and inefficiencies in the sorting and processing procedures. Hence, it is imperative to develop innovative strategies that not only amplify recycling practices but also lessen the initial production of plastic litter.

Sensors and Internet of Things (IoT) technologies are increasingly used in waste management, especially for plastic garbage[1], to optimize trash collection routes and save fuel use. Deep learning is also effective in addressing environmental challenges. It can revolutionize plastic waste management by using neural networks. Various deep learning based trash

• Sirajam Munira, Niloy Paul, Md Ashraful Alam, Md. Mahmudur Rahman, and M. Shamim Kaiser are with the Institute of Information Technology, Jahangirnagar University, Dhaka 1342, Bangladesh. E-mail: sirajammunira07@gmail.com; niloy.ipsc89@gmail.com; alamashraful1003@gmail.com; mahmud@juniv.edu; mskaiser@juniv.edu.
∗ To whom correspondence should be addressed.
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identification techniques[2] were applied to reduce waste in natural and urban environments.

The sustainable development goals call for urgent action to address plastic's negative impacts and promote sustainable practices, including proper waste management, infrastructure improvement, and reducing plastic waste. Annually, the global production of plastics for consumption exceeds 3×10^8 t[3], and 10% of all municipal trash contains components made up of plastic[4]. Each year, 25% of plastics are burnt, 20% recycled, and 55% released into the environment. In 2019, Bangladesh improperly handled 6.27 kg of garbage made of plastic per person[5].

The inadequate management and usage of plastic bottles, along with the escalating production of plastic materials, have given rise to environmental issues, such as the contamination caused by plastic and the obstruction of drainage systems in numerous nations (Fig. 1). Despite efforts towards plastic recycling, it has not been sufficient to address this issue. Researchers are studying and developing a machine learning based smart dustbin to encourage proper plastic waste disposal[6, 7].

The main contribution of our Detection-Based Reward System (DBRS) is that it outlines a comprehensive business model for waste recycling that is in line with several Sustainable Development Goals (SDGs). It places significant emphasis on both sustainability and economic feasibility. Additionally, it introduces an advanced deep learning system for the identification of plastic bottles, complemented by a reward system algorithm. This innovative approach has the potential to significantly reduce plastic waste and make a valuable contribution to various SDGs associated with environmental preservation and responsible consumption.

2 Related Work

Throughout all these years, all plastic bottles have been either dumped into nature or collected manually. Recently, much precious research relevant to this project of automated smart bins has been conducted. However, little progress has been made in recycling these dumped bottles. Hence, much research is needed to develop the existing system. Many researchers have developed their models by using different methodologies.

Fig. 1 Plastic waste blocking the drainage system.

2.1 Non-reward-based method

Chowdhury et al.[8] presented biodegradable and non-biodegradable smart containers for trash tracking and disposal. Biodegradable garbage bins use ultrasonic and MQ4 sensors to monitor trash and odor, while non-biodegradable trash cans use only ultrasonic sensors. These sensors notify authorities via app when a threshold is crossed with NodeMCU and ThingSpeak server integration. The software allows locals to text authorities for cleanup, and ThingSpeak alerts the authority to the bin's waste and stink, so a garbage collector is sent.

Namoun et al.[9] used ensemble learning to forecast weekly residential garbage generation in major centers, overcoming limited datasets and missing predictive variables. Hyperparameters were optimised for accuracy using the Optuna method and meta regressor model. The ensemble model outperformed existing approaches like SARIMA, ANN, KNN, SVR, ETS, RF, NARX, and XGBoosting, benefiting city administrators and researchers.

Zhang et al.[10] conducted an investigation aimed at training seven distinct target detection algorithms using the Trash-ICRA19 underwater datasets. The models utilized in this study encompassed YOLOv1−v5, faster region based convolutional neural network, and Single Shot Detector (SSD). The results showed that YOLOv5 achieved the highest performance. Furthermore, Ref. [11] showed that if the YOLOv5 model gets improved, it will perform better than all the traditional detection models.

Jeyalakshmi et al.[12] created a smart shredder and rubbish collector. The rubbish collector employs suction to collect debris from the ground and deposit it in the shredder zone. The shredder shreds trash into small fragments and deposits them in a servo motor-controlled collection box. The storage container has an ultrasonic sensor for garbage measurement. When the maximum threshold is attained, the bin empties its contents by crushing them.

Chitreddy et al.[13] also proposed an ultrasonic waste bin sensor to measure garbage levels. The system alerts authorities when garbage levels approach 75% and suggests the shortest trash collection route using a GPS tracker.

Singhvi et al.[14] developed an IoT system for the purpose of delivering real-time data involving dustbins. The Arduino connects to the GSM/GPRS module and other sensors in the proposed approach. Ultrasonic and gas sensors continuously measure waste level and toxicity, and the data are recorded in a database and displayed on a website with the time and date. The GSM module alerts municipal corporations via mobile phones when the bin is full. Citizens can view the dustbin update status and report any bin or trash management issues on the website.

Sreejith et al.[15] designed an intelligent mobile smart bin that persistently performs the canister level assessment, perilous gas perception, and rain detection using sensors. It moves automatically to the garbage disposal area when it gets filled and returns to the previous position after emptying itself by means of a two-axis robot. The system alerts the users by buzzer and the concerned organization through an alarm message whenever it detects any hazardous gas. The bin automatically closes the top door after sensing rain to avoid rainwater getting into the bin. A web browser monitors the whole system through the ESP8266 Wi-Fi module.

Check the summary of non-reward based methods in Table 1.

2.2 Reward-based method

Vrochidou et al.[16] explored the potential of IoT technology to enhance solid waste management and encourage recycling. The iBIN system, a residential intelligent bin, uses an Arduino microcontroller, sensors, a Wi-Fi modem, and a database to offer weight information for recyclable materials. The system classifies users by recycling activities and may offer discounts or municipal tax reductions. The innovative iBIN system makes recycling more competitive and improves waste management.

Praveena et al.[17] proposed an incentive-based waste monitoring system where a weight detector is used to check and display the weight of thrown garbage. The

Table 1 Review of non-reward-based literature.

Author	Title	Technology	Feature	Year
Chowdhury et al.[8]	Garbage monitoring and disposal system for smart city using IoT	IoT, ultrasonic sensor, and MQ4 sensors	Measure odor and level of waste. Send alerts to authorities. Local citizens can send clean-up requests.	2018
Namoun et al.[9]	An ensemble learning based classification approach for the prediction of household solid waste generation	No mention of physical sensor (use ensemble learning for reducing sensor)	Forecast weekly residential garbage generation in major centers, overcoming limited datasets and missing predictive variables	2022
Jeyalakshmi et al.[12]	Plastic waste management system using metal shredder for clean environment	Arduino, ultrasonic sensor, smart shredder, and rubbish collector	The rubbish collector collects debris from the ground, and the shredder shreds trash into small fragments and deposits them in a servo motor-controlled collection box. When the maximum threshold is attained, the bin empties its contents by crushing them.	2022
Chitreddy et al.[13]	Application of sensors using IoT for waste management system	Ultrasonic sensor, Arduino, GSM module, and LED display	Alert authorities when garbage levels approach 75% and suggests the shortest trash collection route using a GPS tracker.	2019
Singhvi et al.[14]	IoT based smart waste management system: India perspective	GSM/GPRS, ultrasonic sensor, and gas sensor	Ultrasonic and gas sensors continuously measure waste level and toxicity, and the GSM module alerts municipal corporations via mobile phones when the bin is full. Citizens can view and report any bin or trash management issues on the website.	2019
Sreejith et al.[15]	Smart bin for waste management system	Gas sensor, rain detector, buzzer, IoT, and ESP8266 Wi-Fi module	Move automatically when it gets filled and return to the previous position after emptying itself using a two-axis robot. The bin automatically closes the top door after sensing rain to avoid rainwater getting into the bin.	2019

system displays a QR code whenever the garbage weight level exceeds a predetermined lower limit, which is basically used for gifting exchangeable reward points to attract user attention. It also provides an incentive application that stores these reward points for users who achieve QR code scanning. Using blockchain technology, the system ensures the privacy and security of public rewards.

Johar et al.[18] discussed that the increase in waste from various sources has led to a need for management and monitoring of waste in both domestic and public spaces. Inappropriate waste separation, disposal, transportation, and retrieval are identified as issues. The authors proposed a solution that uses solar energy and edge computing to promote initial waste segregation. The proposed system incentivizes the responsible use of public trash cans by awarding users with credits redeemable at the end of each month.

Gaddam and Nikhath[19] proposed a real-time waste monitoring system that checks the validity of thrown trash and displays the result of the check-up through an LCD display message along with a code for correct trash. The system also provides an application that the users use to input the displayed code for collecting a variety of rewards. It sends a notification of bin overload to the concerned authority. The bin has an LED light outside which gets ON whenever the bin becomes full. The system has also ensured rewards for the garbage collectors.

However, the prevailing methodologies predominantly allocate user rewards based on the weight of discarded waste into bins, with a minority considering the count of items disposed of. In contrast, our proposed methodology distinguishes itself by rewarding users through a meticulous calculation of the surface area of the disposed plastic bottles. Our area-based reward system stands out from weight-centric and number-based approaches, as it minimizes the risk of misuse and aligns closely with recycling goals. Unlike number-based systems, our method avoids discrimination by rewarding users based on the actual area of disposed bottles. This eliminates the need for multiple collectors, reducing production costs and the physical footprint. Furthermore, our research includes a comprehensive business plan, offering a detailed financial framework for stakeholders. This enhances the practicality and sustainability of implementing our area-based reward system in recycling infrastructure. Check the summary of reward-based methods in Table 2.

3 Methodology

Object detection algorithms play a crucial role in computer vision by allowing the identification and localization of objects within images or video feeds, thereby facilitating a vast array of applications, such as waste detection. These algorithms use a variety of techniques, including deep learning models such as You Only Look Once (YOLO), Faster R-CNN, and SSD, which have substantially increased detection accuracy and efficiency in recent years. Particularly, YOLOv5 has emerged as a cutting-edge object detection algorithm, offering distinct advantages in terms of speed, computational efficiency, accuracy, and suitability for low-latency real-time detection scenarios.

3.1 YOLOv5 architecture for object detection

YOLOv5 consists of a backbone network and detection devices that collaborate to identify and locate objects within an image. It is designed to be quick and effective and employs a grid-based method to detect objects in various image cells. In addition, it has accuracy-enhancing features such as anchor-free detection and multi-scale training. When predicting a class probability distribution for each box, YOLOv5

Table 2 Review of reward-based literature.

Author	Title	Criteria	User interaction	User identification	Detection method	Business model	Year
Vrochidou et al.[16]	iBIN: Intelligent monitoring system for recyclable materials using Arduino and the IoT	Weight-based	Website	–	–	–	2017
Praveena et al.[17]	A secure incentive based waste monitoring system using IoT	Weight	Incentive application	QR code scanning	–	–	2022
Johar et al.[18]	An edge-based dustbin for smart compacting and segregating	Weight and garbage	–	Application	–	–	2022
Gaddam and Nikhath[19]	Smart dustbin: A reward provider	Waste collector	Mobile application	Confirmation	–	–	2021

uses the class with the highest score as the predicted class for the matching bounding box. The final output is a list of predicted bounding boxes with class predictions and confidence scores, which can be further filtered to enhance precision. The YOLOv5 variant can also be used on edge devices, specifically with Google's Coral Edge TPU accelerator. For operating the Coral Edge TPU[20], a Raspberry Pi 4 variant B with 4 GB memory is suggested. According to Ref. [21], YOLOv5 outperformed EfficientDet and Faster R-CNN in detecting garbage with no background, with a mean Average Precision (mAP) of 0.92 compared to 0.846 and 0.836, respectively. It establishes a nice balance between speed and size, and performance though YOLOv8 has already been established. The YOLOv5 model has a significantly higher inference rate, almost ten times faster, in comparison to the Faster R-CNN model. As a result, it has emerged as the preferred choice for real-time object detection tasks[22]. The YOLOv5 architecture is shown in Fig. 2.

3.2 Convex hull algorithm for reward calculation

The reward calculation methodology in the proposed system involves two major steps: object size detection and reward point calculation. The convex hull algorithm[23] is used to detect the size of the object in the image and calculate the reward points. Let there be K points that are presented in N dimensions. The intersection of all the points will make it convex. There will be N points, each representing S_1, S_2, ..., S_n, so the convex hull can be defined as

$$\text{Convex hull} \equiv \left\{ \sum_{j=1}^{N} \lambda_j s_j : \lambda_j \geqslant 0 \text{ for all } j \text{ and } \sum_{j=1}^{N} \lambda_j = 1 \right\}.$$

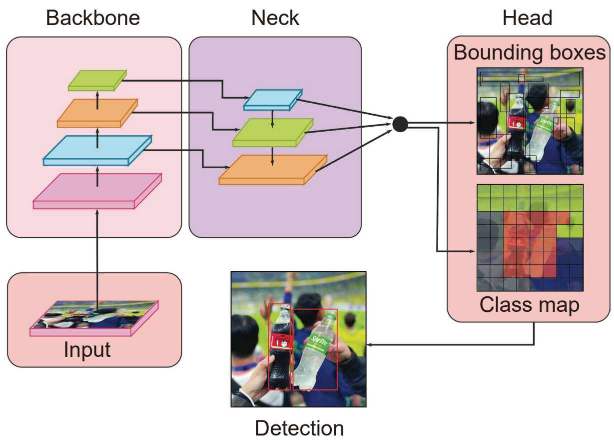

Fig. 2 YOLOv5 architecture for object detection.

This equation states that the Convex hull is the set of all possible weighted combinations of the points S_j, where λ_j are non-negative weights and sum up to 1.

The determination of reward points is linked intricately to the calculated area of the plastic bottle. It is imperative to note that a fixed-position camera is strategically placed in a precise location to align with the terminus where the user's discarded bottle reaches. This system begins by confirming the nature of the waste as a bottle through a reliable detection process. Following this confirmation, the system consistently calculates the area of the bottle. Thus by the stable positioning of the camera at a fixed maintained distance and well-maintained lighting conditions, this area calculation remains uniform for every bottle tossed into the bin, ensuring a reliable and straightforward process for attributing reward points.

Reward calculation: The reward calculation process is fully automated and integrated into the proposed system. The user is not required to engage in any manual calculations or data input in order to receive reward points. Based on the size of the detected object, the system calculates the reward points utilizing our proposed algorithm. The mobile application allows users to access their reward point history and redemption options. Additionally, users will receive notifications whenever reward points are credited to their account. Reward point calculation for plastic bottles is given in Algorithm 1.

Let A be the area enclosed by the convex hull of a detected plastic bottle region. The reward points R assigned to this region can be expressed as a function of A, such as

$$R = kA \tag{1}$$

where k is a constant that determines the conversion rate between area and reward points. The larger the constant k, the more heavily the reward points are weighted towards larger plastic bottle regions.

3.3 Proposed detection-based reward system

The proposed plastic recycling system operates in two independent but interconnected aspects. The initial aspect of the research focuses on creating a reliable plastic bottle detection system. This includes using YOLOv5 techniques to accurately identify and locate plastic bottles inside photos or video streams in order to generate rewards. In the second component, the

Algorithm 1 Reward points calculation for plastic bottle regions

```
function Calculate reward points (image)
    plastic_bottle_regions
  Isolate plastic bottle regions (image)
    reward_points ← []
    for region in plastic_bottle_regions do
        convex_hull ← Find convex hull (region)
        area ← Calculate area (convex_hull)
        reward ← Assign reward points (area)
        reward_points.Append (reward)
    end for
    return reward_points
end function

function Isolate plastic bottle regions (image)
    processed_image ← Apply image processing (image)
    plastic_bottle_regions ←
  Detect regions (processed_image)
    return plastic_bottle_regions
end function

function Find convex hull (region)
    convex_hull ← Convex hull algorithm (region)
    return convex_hull
end function

function Calculate area (convex_hull)
    area ← Calculate enclosed area (convex_hull)
    return area
end function

function assign reward points (area)
    constant_k ← 0.1
    reward ← constant_k · area
    return reward
end function
```

research goes beyond technical concerns to create a holistic plastic recycling business model. The proposed business model describes collection, sorting, and processing procedures for plastic bottles, as well as potential revenue streams from recycled materials.

The suggested system, by merging these two research directives, contributes not only to the growth of product identification technology but also to the creation of a sustainable and economically feasible solution for tackling the plastic waste problem through effective recycling procedures.

3.3.1 Process execution

The system waits to dial the registered user's phone number and shows a welcome message if valid. Deep learning is used to detect if an object dropped in the bin is a bottle or not. If successful, the bottle is pushed inside, and points are added to the user's account. If the user's number is not registered, the system displays a failure message and waits for a registered number.

3.3.2 User interaction

The user starts interacting with the system by dialing his/her registered phone number. Then the user drops an object in the bin, and after the object is identified as a bottle, a reward is added to his/her account. For user interaction, the interface of the mobile application, as shown in Fig. 3, is designed to be simple and intuitive, making it easy for users to view their reward history and redeem points for rewards.

3.3.3 Waste level management

In the process of managing the amount of garbage, a microcontroller and an ultrasonic sensor will work together to determine whether or not the container is 80% full. When the amount of waste reaches the limit, the system will transmit a notification to the appropriate authorities along with the bin's identification number. The garbage collector will then be dispatched, and the trash can will be emptied.

3.4 Business model

Our proposed system focuses on a meticulous business model centered around sustainable microplastic recycling with a unique focus on converting recycled materials into innovative products and toys, thus contributing to the green economy. The model outlines key components starting with needs analysis and system design, followed by revenue streams such as direct sales of recycled materials and a collaborative sponsorship program, promoting green business practices. Also, customers are more interested in incentive-based mechanisms[24]. So, reward redemption in various social works will make people more enthusiastic about collecting plastic waste. An overview of our proposed business model is shown in Fig. 4.

Let us take into account the weight of collected bottles, rewards for collectors, and the associated collection costs, we can denote variables as follows:

W = Total weight of collected plastic bottles (in

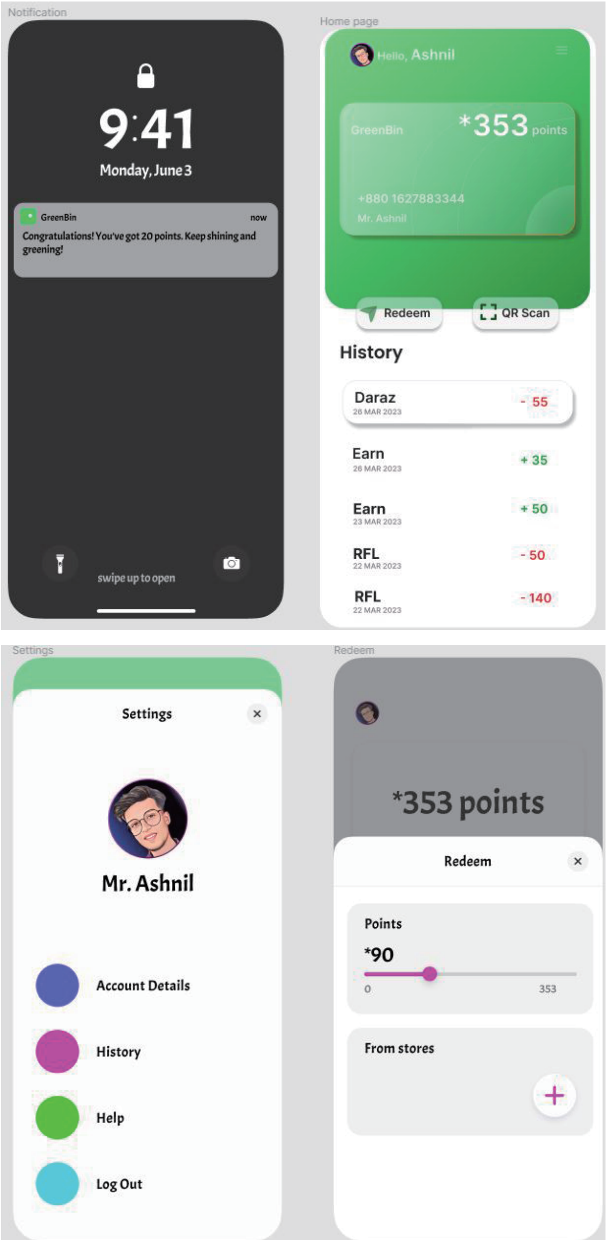

Fig. 3 User interface details.

kilograms).

R = Reward earned for collecting the plastic bottles (in a suitable unit, e.g., points or dollars).

C = Total cost associated with collecting the plastic bottles (in a suitable currency, e.g., dollars).

E = Earned revenue from raw plastic material and minimized collection cost.

Now, we can build a mathematical model combining these factors:

Reward function: Define a function that calculates the reward based on the weight of the collected plastic bottles. This function should encourage collecting more bottles by offering higher rewards for larger amounts of collected plastic. A simple linear function could look like this:

$R(W) = k \cdot W$, where k is a constant that determines the reward per kilogram of plastic collected.

Cost function: It is the cost associated with collecting the plastic bottles. This could include expenses for maintaining smart bins, transportation of waste, labor, and any other relevant costs. The cost function:

$C(W) = b \cdot W$, where b is a constant that represents the cost per kilogram of plastic collected. We can adjust b to reflect the actual cost rate according to the market.

Net benefit function (N_b): We can calculate the net benefit (earned revenue from raw plastic minus sum of all rewards and sum of all costs associated for collection and maintainance) for collection:

$$N_b(W) = \sum E(W) - \left(\sum R(W) - \sum C(W)\right).$$

This function represents the net benefit generated for a given weight of collected plastic bottles.

Redeemable rewards: Ensure that the rewards can be used for various social work like tax rebates or social security aspects.

3.4.1 Key element of business model

We have identified key elements, such as meeting customer needs, revenue streams including direct sales of raw materials and sponsorship programs, and cost structure including salaries, training, installation, logistics, operations, and technology. By addressing these elements effectively, we can ensure the success of our system and achieve sustainable growth.

Key partner: Local authorities and foundations are proposed to join hands to provide community support and vital resources, while partnerships with machinery suppliers ensure access to cutting-edge technology for efficient recycling processes. Engaging with governmental organizations not only facilitates regulatory compliance but also enhances credibility, paving the way for potential funding opportunities. Together, these key partnerships form a robust foundation for our initiative, driving impactful change in plastic recycling and environmental sustainability.

Key activity: In our business model, we propose to

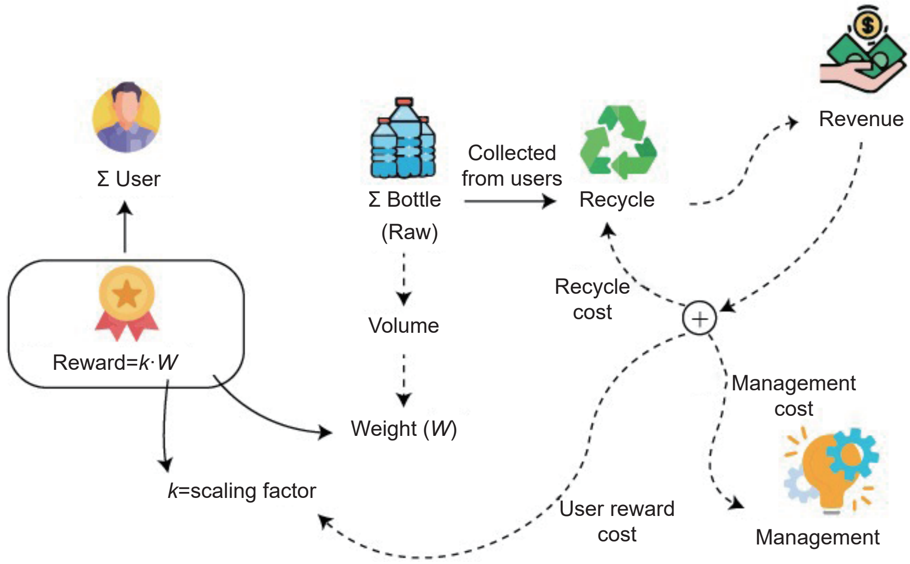

Fig. 4 Proposed business model.

focus on key actions: collecting and transporting waste, sorting and processing materials, and recycling to create new products. These essential steps form the backbone of our sustainable approach to plastic waste management.

Customer relationship: We propose to build strong relationships with shop owners and entrepreneurs, forming the backbone of our customer network. By understanding their needs and collaborating closely, we create a seamless experience. Our goal is to support their efforts in responsible waste disposal and recycling, fostering a partnership that contributes to a cleaner environment while meeting their business objectives.

Customer segment: We propose to serve diverse customer segments, including manufacturing plants, recycling facilities, entrepreneurs, and individuals. By tailoring our solutions to meet the specific needs of each segment, we aim to revolutionize plastic waste management. From providing raw materials to manufacturing plants to supporting entrepreneurs in responsible waste disposal, our approach caters to the varied requirements of different stakeholders. Through simplicity and efficiency, we strive to create a positive impact across these customer segments.

Cost structure: We propose to establish a cost-effective structure by strategically allocating resources. Our focus on essential elements, including personnel, efficient operations, installations, and training, ensures a streamlined process. Investments in cutting-edge technology optimize recycling processes, while logistics are managed judiciously. By prioritizing these key areas, we aim to create a sustainable and financially sound model, maximizing the impact of our initiative on plastic recycling and environmental well-being.

Revenue stream: The system generates revenue by selling the collected plastic waste to recycling companies or manufacturers that use plastic as raw material. Additionally, the system can also sell recycled products such as pellets, flakes, or resin to other companies. Another potential revenue stream is through sponsorship from businesses or organizations that rely on plastic as a raw material for their products or from local governments as part of their waste management and environmental sustainability efforts. The revenue from these streams depends on various factors such as the quality and quantity of plastic waste, market demand, sales channels, and pricing.

The key elements of our business model of DBRS are shown in Fig. 5.

3.4.2 Cost analysis

The cost analysis of the trash bin design listed in Table 3 shows that the estimated cost of the bin is reasonable at 8580 BDT (currency of Bangladesh). This suggests potential for high revenue generation through recycling. However, this is an approximate cost that may fluctuate and have additional costs such as transportation, labour, and maintenance.

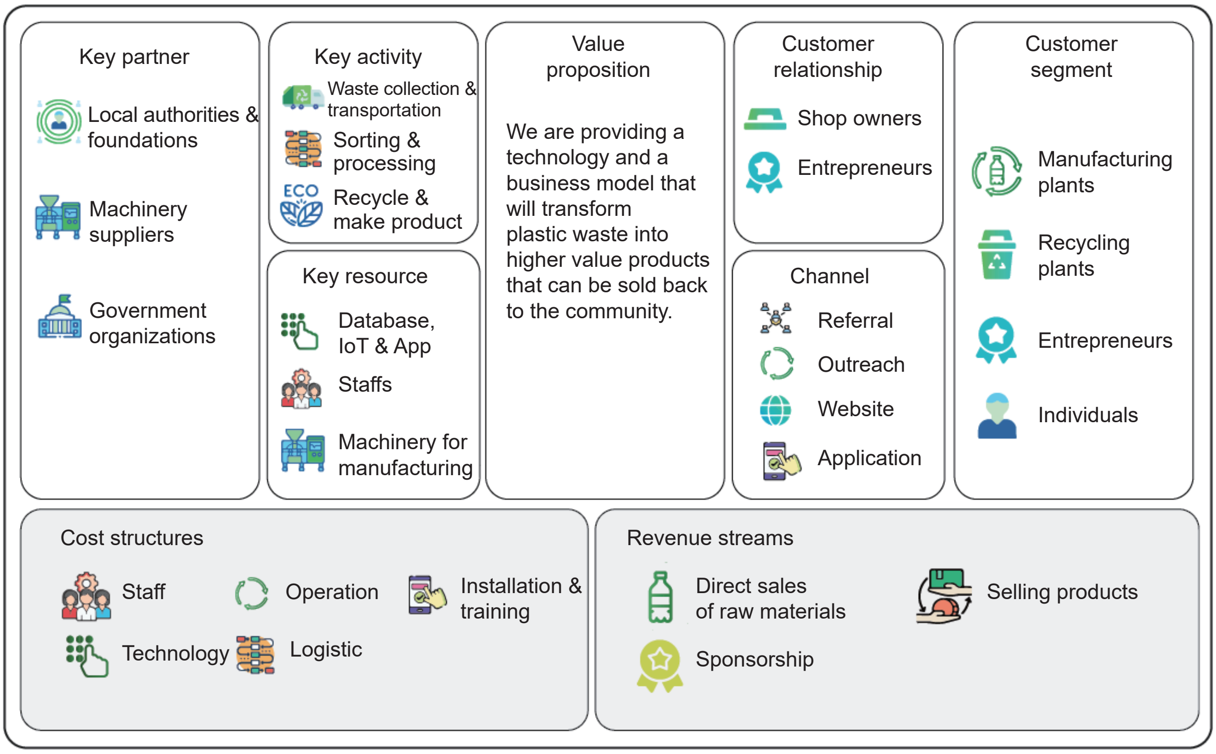

Fig. 5 Key elements of our business model.

Table 3 Cost analysis per bin.

Item	Cost (BDT)
Trash bin	1000
Raspberry Pi	4000
LCD display	230
Ultrasonic sensor	100
Wi-Fi module	400
Servo motor	450
DC-DC converter	100
Printed circuit board	150
Battery	1100
Solar panel	350
Resistors, capacitors, indicators, and connectors	500
Sound chip	200
Total cost per bin	8580

3.4.3 Proposed model of the bin

The proposed physical model of the smart bin is shown in Fig. 6.

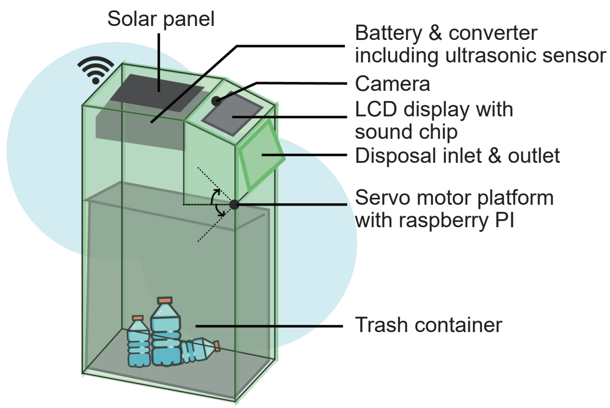

Fig. 6 Proposed physical model of the bin.

4 Experiment

4.1 Used dataset

The experiment incorporates the utilization of many datasets, including the "Bottles Synthetic Images" collection. This dataset has 25 000 diverse photos of various bottle types, such as plastic bottles, wine bottles, and others. In this study, a total of 5000 plastic bottle photos were utilized and selected for their diverse range of lighting circumstances. This selection was made with the intention of facilitating plastic detection in challenging background environments. The dataset titled "Plastic Bottles in the Wild Image Dataset" has 3999 photographs that are accompanied by annotations. Additionally, a self-created dataset consisting of 127 images was produced to facilitate the training and validation of a system's performance.

The details of dataset are given in Table 4.

Our combined datasets comprise around 9000 JPG

Table 4 Dataset details.

Dataset name	Number of total images
Bottles synthetic images[25]	5000
Plastic bottles in the wild[26]	3999
Self created dataset[27]	127

photos, each having a resolution of 640 pixel × 640 pixel. These images were recorded in diverse situations, including indoor and outdoor environments, and were taken under varying lighting circumstances. Some sample training data are shown in Fig. 7.

4.2 Dataset preprocessing

Dataset preprocessing is a set of techniques used to transform and prepare raw data into a format that can be easily analyzed by deep learning algorithms.

In order to enhance the efficacy of our DBRS, we have implemented a resizing technique to adjust the resolution of our training image to 640 pixel × 640 pixel. The dataset was partitioned into two distinct subsets, wherein 7900 photos were allocated for the purpose of training, while 1226 images were designated for testing. The images in our dataset have been annotated using a picture annotation tool known as Roboflow. The photographs have been labeled with the singular class "plastic bottle" in order to enable our detection method to distinguish plastic images from other categories. The training and testing sets were randomly chosen in order to ensure that both sets contained diverse plastic bottle images with distinct backgrounds. In order to facilitate the effective integration of the training process, the dataset format was transformed into the YOLOv5 PyTorch (txt) format.

4.3 Experimental environment and parameter configuration

This study uses YOLOv5 in Python-3.10.9 with the PyTorch-2.0.1 framework for training. The Nvidia RTX 3060 Graphics Processing Unit (GPU), equipped with 12 GB of Video Random Access Memory (VRAM), offers substantial computational capabilities for the purpose of training our dataset. The Ryzen 5600X, a CPU with six cores, exhibits rapid single-core performance, making it highly effective for Python processing. The combined utilization of the GPU's CUDA core and CPU provides a well-balanced training platform that effectively harnesses parallel computation capabilities and high clock rates to enhance the optimization of the model training process with a confidence threshold of 0.45.

4.4 Evaluation metrics

In the context of our model evaluation, the metrics employed include precision, recall, Average Precision (AP), and mAP. The AP is determined by evaluating the integral of the precision curve, the recall rate curve, and the axis, which defines the area enclosed by these components.

$$\mathrm{AP} = \int_0^1 P(r)\mathrm{d}r \tag{2}$$

The mAP is calculated by summing AP values for each category and then dividing this sum by the total number of categories. Significantly, the mAP, which incorporates both precision and recall rates, serves as a comprehensive indicator of the model's performance.

Fig. 7 Plastic bottle training images from combined datasets.

$$\text{mAP} = \frac{\sum_{i=1}^{N} \text{AP}_i}{N} \tag{3}$$

The recall can be defined as the ratio of correctly predicted positive instances to the total number of actual positive instances. The calculation can be determined using Eq. (4).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

Precision refers to the ratio of correctly identified positive predictions to the total number of positive predictions. The calculation can be determined using Eq. (5).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

Here, the abbreviation “TP” represents true positive. The acronym “FP” denotes false positive, while “FN” signifies false negative.

The F-Measure (FM) score refers to the weighted average of recall percentages and precision percentages. As a result, this metric considers the presence of both false positives and false negatives. While FM is more commonly used than precision modulation, the concept of accuracy may not be immediately comprehensible. When the costs associated with false positives and false negatives are similar, accuracy demonstrates strong performance. When the costs associated with false positives and false negatives differ, it is advisable to take into account both recall and accuracy. In relation to favorable outcomes, accuracy refers to the ratio of correctly predicted observations to the total number of expected positive discoveries. The calculation of FM expressed in Eq. (6) takes into account both precision and recall.

$$\text{FM} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{6}$$

5 Result and Discussion

5.1 Training of the dataset

We used transfer learning to train a YOLOv5 model on the dataset, starting with weights learned from the COCO dataset and then refining the model using our combined plastic bottle dataset. To train the model, we utilized a batch size of 32 and 150 epochs. Table 5 describes the configuration parameters of YOLOv5 for our training model.

Table 5 YOLOv5 parameters.

Parameter	Value
Number of epochs	150
Image size	640
Batch size	32
Layer	157
Parameter	7 012 822
Initial learning rate	0.001

5.2 Test results of the model

The DBRS first prompts the user to input a valid registered phone number. Once the number is validated, the object detection process begins. After a successful detection of the bottle, the area of the bottle is calculated. The bottle is kept in a fixed position to ensure that the area is solely dependent on the size of the bottle. The system then adds the corresponding reward points to the user’s phone number, which was provided earlier. Figure 8 shows the result of our proposed system for plastic bottle detection.

Figure 9 shows the precision-confidence, recall-confidence curve, F1-confidence curve, and precision-recall curve. In Fig. 9, “all classes 1.00 at 0.958” means that the confidence value becomes 1.00 when precision value is 0.958.

The main training losses (box loss during validation and objectness loss during validation) decreased overall from around 0.09 to 0.02, indicating the model improved at predicting plastic bottles. The precision and recall metrics fluctuated but increased overall from around 0.3 to 0.9, showing improved object detection performance.

The mAP metrics (the average of mAP at different IoU thresholds 0.5 (mAP_0.5) and the average of mAP at different IoU thresholds ranging from 0.5 to 0.95 (mAP_0.5:0.95)) also increased, further indicating better object detection. The validation losses decreased over time, meaning the model generalized better. The experimental result of our DBRS shows that it can detect plastic bottles with a precision 0.926, recall 0.975, and overall mAP 0.973. The output of the detection process of our system is shown in Fig. 10.

6 Conclusion

The presence of plastic pollution poses significant risks to the natural environment. Our research aims to manage plastic waste and reduce the amount of

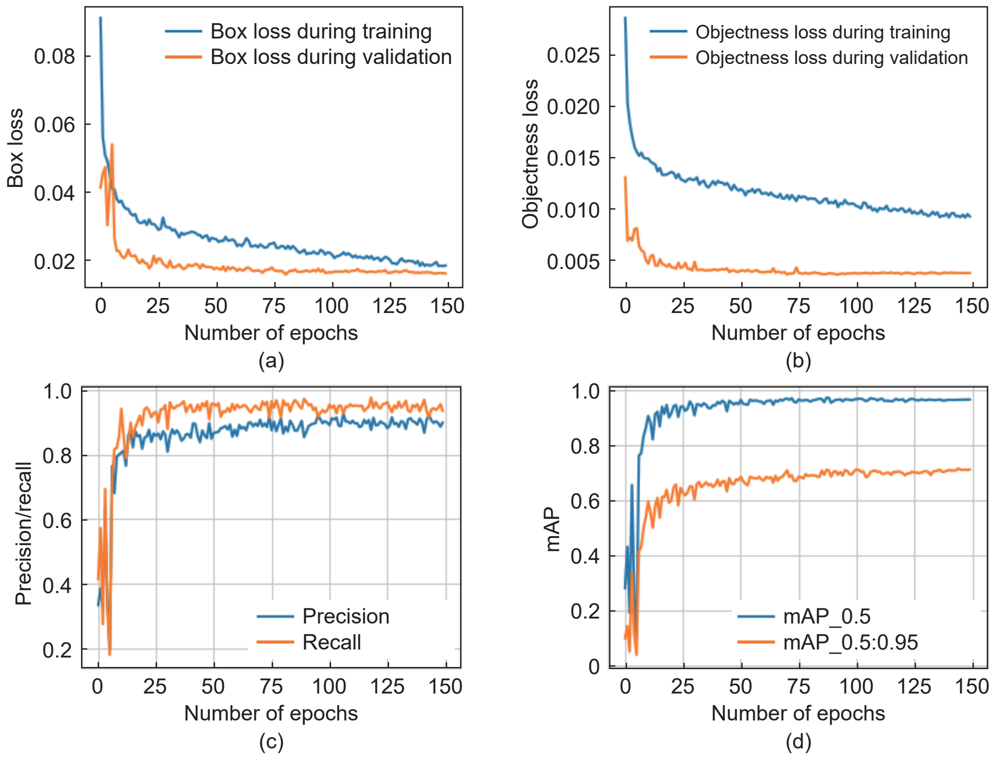

Fig. 8 Results of DBRS.

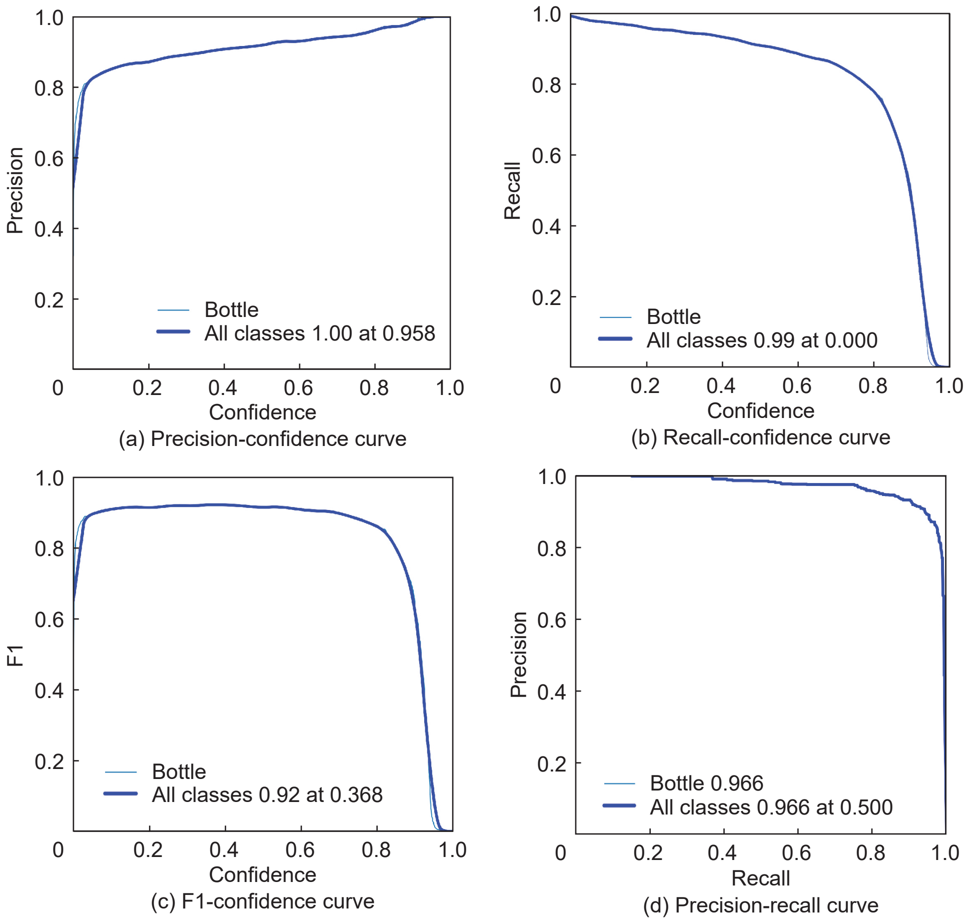

Fig. 9 Different metrics curves of our proposed system.

Fig. 10 Output of our detection system.

dumped and thrown plastic into the environment in a reward-based way focusing on the fact that people like to be rewarded and offered different monetary exchangeable things. Our study has provided evidence of the significant capabilities of deep learning, particularly when utilising the YOLOv5 model, in effectively tackling the pressing concern of plastic bottle detection. With an mAP of 0.973, our model demonstrates its high accuracy and effectiveness in detecting plastic garbage, specifically plastic bottles, across different background settings.

Furthermore, our research extends beyond mere detection as it introduces a novel business model that operates on a reward mechanism. This distinctive methodology not only facilitates the effective reduction of plastic trash but also fosters active engagement from individuals and communities. Our suggested reward-based system presents a sustainable method to address the plastic pollution challenge by providing incentives for responsible plastic disposal and recycling.

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Sirajam Munira received the BSc degree from Jahangirnagar University, Dhaka, Bangladesh in 2023. She currently serves as a software engineer. Her expertise encompasses a range of domains including artificial intelligence, machine learning, human-computer interaction, image processing, and data mining. Her commitment to research and innovation drives her to explore the latest technology and its practical applications.

M. Shamim Kaiser received the bachelor and master degrees in applied physics, and electronics and communication engineering, from University of Dhaka, Dhaka, Bangladesh in 2002 and 2004, respectively, and the PhD degree in telecommunication engineering from Asian Institute of Technology (AIT), Pathumthani, Thailand in 2010. Since 2011, he has been with the Institute of Information Technology, Jahangirnagar University, Dhaka, Bangladesh as an assistant professor, where he became an associate professor in 2015 and a full professor in 2019. He has authored more than 100 papers in different peer-reviewed journals and conferences. His current research interests include data analytics, machine learning, wireless networks and signal processing, cognitive radio networks, big data and cyber security, and renewable energy. He is a senior member of IEEE. He is a life member of the Bangladesh Electronic Society and the Bangladesh Physical Society. And he is a senior member of IEICE, Japan. He is also a volunteer of the IEEE Bangladesh Section. He is the founding chapter chair of the IEEE Bangladesh Section Computer Society Chapter.

Niloy Paul received the BSc degree from Jahangirnagar University, Dhaka, Bangladesh in 2023. His primary research interests lie in artificial intelligence, machine learning, and image processing. His commitment to research and innovation positions him as a valuable contributor to the ongoing evolution of these dynamic fields.

Md Ashraful Alam received the BSc degree from Jahangirnagar University, Dhaka, Bangladesh in 2023. He works as a software engineer, specializing in flutter and android development. He is passionate about artificial intelligence and human-computer interaction, and brings his expertise to the forefront of the software engineering field.

Md. Mahmudur Rahman currently is working as a lecturer at the Institute of Information Technology, Jahangirnagar University, Dhaka, Bangladesh. In 2019, he was awarded a National Science and Technology (NST) fellowship for his master’s research by the Ministry of Science and Technology. His research interests include machine learning, medical image processing, network security, and data mining.