

A Smart System for Segregating Solid Waste using Machine Learning Model

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Abstract : Waste management has problems consisting of the large quantity, variety of waste produced and the nature of the material is very complex and complicated. Recycling is one of the most typical approaches that can be taken. The proposed model involves Convolutional Neural Network (CNN), utilizing YOLO for object detection, and ORB for object tracking. This system can solve problems on a large scale such as districts hence the management becomes centralized and cost-effective. There will be more waste that can be recycled and benefit society. The future framework will have a complete system to become a complete garbage group for reuse, reduce, recycle (3R) use.

Keywords: waste segregation, solid waste, machine learning, YOLO, ORB, algorithm

1. Introduction

Malaysians in 2014 disposed of up to about 33,000 metric tons of waste every day, resulting in the government spending around RM1.2 billion on waste collection [1]. As a result, the country is dependent on landfills with nearly 85% of the waste collected ending up in landfills. In 2019, the recorded waste generated was 4.0 million tons [2]. Power plants, metal refineries, chemical and electrical and electronic industries contributed 57.1 percent (2.3 million tons) of the total waste generated. By 2020, around 49,670 metric tons of waste per day are expected to be generated by Malaysians [3].

On the other side, Malaysia is gradually experiencing a shortage of land available for development [4]. Visvanathan [5] stated that the rapid economic growth by industrialization of developing countries in Asia has created serious problems in waste disposal due to uncontrolled and unmonitored

urbanization. This problem is further exacerbated by the lack of financial and human resources trained in waste management practices in the areas of collection, transport, treatment and final disposal.

Waste management itself has problems consisting of the large quantity, variety of waste produced and the nature of the material is very complex and complicated. This is mainly due to two closely related aspects. The first concerns the increase in the mass of waste with increasing population, economic development, and improving people's welfare. The second is related to the nuisance and threat of waste, especially harmful to the environment, as well as to humans. Therefore, the management that is most likely to be used should always be developed to address the solution.

Besides that waste management continues to be a relevant concern with the human condition. In recent decades, individuals have started to think about controlling waste by increasing its value. Recycling is one of the most typical approaches that can be taken. Despite this, there are still a number of other factors that contribute to it. In light of this fact, it would be interesting to keep studying, researching, and increasing our understanding of the dynamics of the waste. The aim of this project is to develop a system that is able to automatically sort waste into a number of different categories. It is in line with the idea of Zero Net Carbon Emissions.

2. Materials and Methods

2.1 Dataset

The dataset taken from Kaggle.com uploaded by Mostafa Mohamed contains images of several categories of waste including: batteries, brown glass, green glass, white glass, metal, paper, plastic, and cardboard. **Figure 1** shows the snapshot of the dataset example.

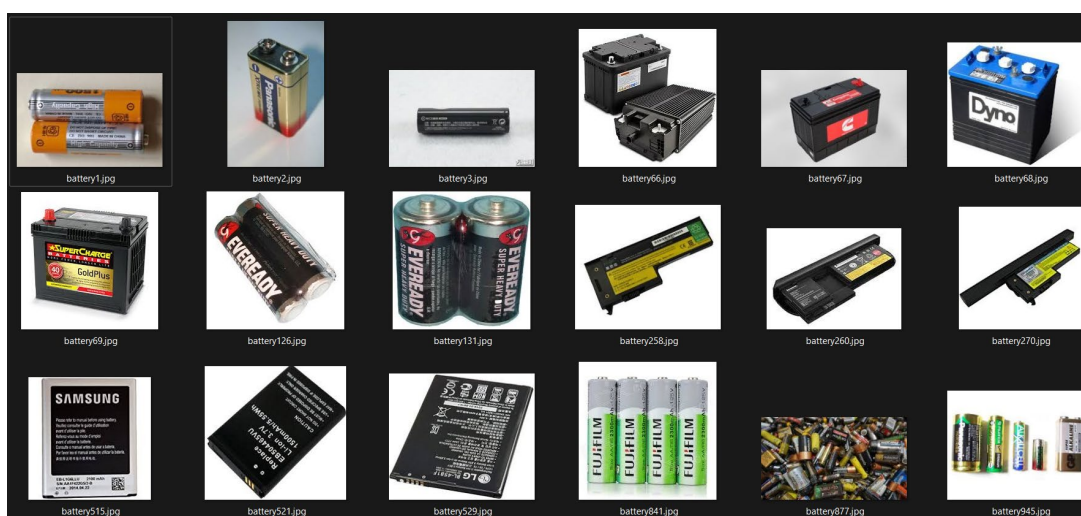


Figure 1: Battery dataset

These are the types of solid waste followed by the total of respective image dataset: battery (945 images), metal (769 images), brown-glass (607 images), green-glass (629 images), white-glass (775 images), plastics (865 images), paper (1050 images), and cardboard (891 images). With such quantity, it is considered sufficient for the system to process the waste classification.

2.2 The system structure

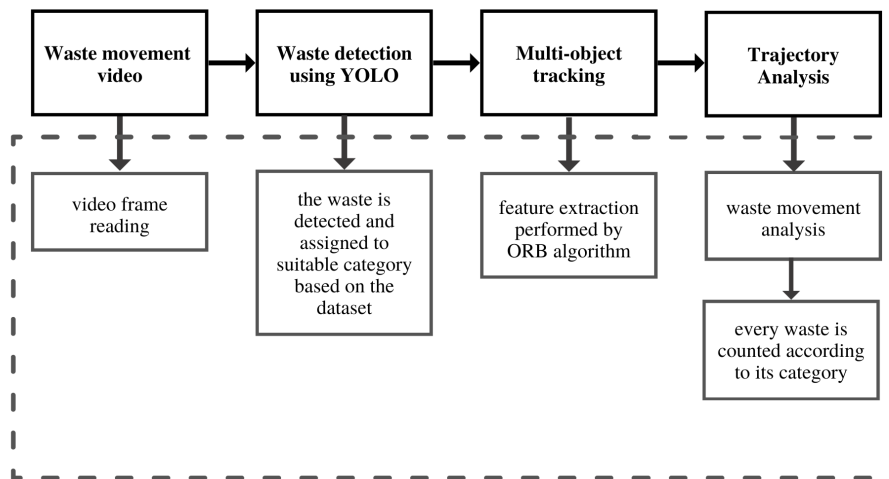


Figure 2: Overall flow of the method

There are some steps that need to be taken to achieve the goal. First, a webcam in real-time provides the system with video input, which is subsequently processed. The video frames are transformed to blobs, pixels are then read, and an object identification model is performed for each blob. Second, the object is then identified using the YOLO deep learning object detection approach. As Nishad [6] on medium.com wrote, You Only Look Once (YOLO) is a real-time item detection algorithm designed to detect the presence of waste. One advantage of YOLO is that it focuses on speed and recognition, instead of detecting objects perfectly. This will be very useful because it will later be used in a waste machine that will run automatically. We expect that the rate of detection will be fast, and the accuracy of detection will be great. Third, ORB feature extraction is conducted on the identified waste box to complete multi-object tracking and collect waste type and amount information. Oriented FAST and Rotated BRIEF (ORB) was developed at OpenCV labs in 2011 as a free-to-use feature detection algorithm. It will be used to extract corresponding features from images and keep the features even when the object moves. ORB can obtain better extraction feature points at a significantly higher speed than SIFT, according to Rublee *et al.* [7]. The ORB method collects the detected box's characteristics and matches them to create a relationship between the same object in many video frames. The trained model recognizes objects and constructs a bound box for each detected object. This technique improves the impact of detecting small objects and solves the problem of objects being difficult to identify owing to quick changes in size. Fourth, a trajectory line is created to determine the waste movement direction and collect quantities of each category. Finally, data regarding the processed results are computed. Later, the statistics obtained from the computations will be utilized in a wide range of analysis.

2.3 Waste detection using YOLO

The implementation of the framework for waste identification utilized the YOLOv3 network. The YOLOv3 algorithm maintains the same fundamental concept as the previous two generations of YOLO algorithms [8]. The convolutional neural network is applied to extract the image's features. The presence of an object is detected in the video frame. The rate of detection is fast and the accuracy of detection is great. The item is surrounded by a bounding box with x and y coordinates, width and height, and the object's category. Using machine learning techniques and multi-label classification, an item is categorized. Using the waste object detection approach to determine the type and location of waste can offer the information required for object tracking. The above information is sufficient for waste

counting, and the waste detection method thus does not detect the specific characteristics of the waste or the condition of the waste.

2.4 Multi-object tracking

Tracking is the process of identifying moving objects in videos over time. In this work, the ORB algorithm was utilized to extract object characteristics. In terms of computing efficiency and matching costs, the ORB algorithm demonstrates higher performance. The ORB technique includes the Features From Accelerated Segment Test (FAST) to identify feature points and the Harris operator to identify corners [9]. After getting the feature points, the BRIEF method is used to generate the descriptor. Taking the feature point as the center of the circle and utilizing the centroid of the point region as the x-axis of the coordinate system establishes the coordinate system. Consequently, when the picture is rotated, the coordinate system may be turned to match the image's rotation, and the feature point descriptor has rotation consistency. When the angle of the image is changed, it is also possible to propose a consistent point. Similar detections with regard to the preceding frame undergo a comparison. After acquiring the binary feature point descriptor, the XOR operation is performed to match the feature points, hence enhancing the efficiency of matching. The procedure is as follows:

1. taking initial set of object detections
2. creating unique ID for each of the detected objects
3. tracking the object over time
4. maintaining the ID assignment

2.5 Trajectory analysis

This section describes the analysis of the trajectories of moving objects and the counting of multiple-object traffic information. In this system, we expect to use a one-directional carousel that will move the waste objects passing the camera. a line/trajectory will be created in the end-part of the camera view. The object that intersects the detection line will be counted and recorded to the database.

3. Results and Discussion

3.1 Waste Classification

The quantity of waste in the landfill is very large, of course, it takes a lot of time to be sorted manually. Therefore, a system for sorting waste is needed to be fast and efficient using machine learning. This machine learning uses YOLO sensors to detect incoming waste, ORB to track the types of waste available in the dataset, then after the waste is sorted by the ORB sensor [10]. Each detected waste will be separated and counted for each type. This report on the amount of waste per type will be used for some data analysis. This system will separate waste based on each type automatically. The types of waste to be sorted include:

3.1.1 Electronic Waste

Electronic Waste is prioritized for sorting. This electronic waste can be in the form of batteries, electric cables, incandescent light bulbs, cell phones, televisions, irons, and other electronic items that we often encounter in our daily lives. This waste contains toxic components that are harmful to human health, such as mercury, lead, cadmium, flame retardant poly bromine, barium, and lithium [11]. These toxic components can cause damage to the brain, heart, liver, kidneys and skeletal system [12]. In addition, e-waste can contaminate groundwater, soil, and the surrounding air, and contribute to

accelerating climate change. Every device ever produced has a carbon footprint and contributes to man-made global warming.

3.1.2 Metal

Metal waste consists of aluminum cans, broken construction steel rods, and old utensils. These waste cans if in a very long time if not separated will contain some heavy metals which can later be carried into the groundwater. Heavy metal compounds such as magnesium or potassium from these rusty cans will fall to the ground, be eroded by water and pollute groundwater [13].

3.1.3 Glass

This glass waste includes jars, medicine bottles, broken cups/jugs, sauce bottles. The system is equipped with color sorting (white, brown, green). This glass waste is classified as hazardous waste if disposed of in any place, because it is feared that it will be stepped on or injure other body parts. Glass waste is also very difficult to decompose in the soil, and it can take hundreds of years to decompose [14].

3.1.4 Plastic

This waste includes PET (mineral water bottles), HDPR (shampoo bottles, crackle or trash bags), PVC (pipes), HDPE (food packaging), PP (glass mineral water), PS (styrofoam) and sachet, pouch packaging waste [15]. For the environment, plastic waste can cause pollution, both in soil, water, and air. Plastic waste can cause soil pollution because it can block the absorption of water and sunlight, thereby reducing soil fertility and can cause flooding.

3.1.5 Paper

This paper waste includes books, newspapers, cardboards, Mixed paper, Boxes, Tetra Packs and various other paper materials. Waste paper is one of the inorganic waste that takes a long time to decompose with the soil, so it needs to be recycled again by separating it from other waste.

3.1.6 Others

Other waste can be diapers, old clothes, ceramics, medicines, and other waste that cannot be categorized above which must be sorted manually after the scanning process is complete.

3.2 Benefits

The benefits of using this system are generally to improve the efficiency of waste management in Northern Malaysia, thereby reducing pollution that is increasing every day. In addition, this system can generate valuable information for several sectors involved in waste management, including the following:

3.2.1 Statistics on plastic consumption in each region. If plastic use is high, policymakers can take the necessary measures to decrease the generation of plastic garbage. For instance, by imposing a pricing policy for plastic bags at supermarkets every weekend, people's dependency on single-use plastic wrap can be reduced. Additionally, it helps improve public awareness of the benefits of reuse products.

3.2.2 The quantity of battery waste can be evaluated by the relevant party. Lithium included in battery disposal can harm ecosystems, especially soil. By understanding how to control it, we can minimize its damaging consequences.

3.2.3 Manufacturers of glass products can track the amount of glass waste generated over time (say, over the course of a month). Green Resource Recovery's employee in Kedah said that glass waste is simply disposed of without further processing in that area. whereas manufacturing glass products from recycled materials can significantly reduce production costs and increase profits.

3.2.4 Similar to the preceding point, the same thing occurs with plastic waste. Plastic waste is one of the 3 R's (reduce, reuse, recycle) primary concerns. If plastic waste can be utilized effectively, it will contribute to sustainable development for all living beings, including humans.

3.2.5 With knowledge of waste generation statistics, the government could establish an institutional and legal framework for solid waste management in their respective regions.

3.2.6 and a variety of other analyses that will prove helpful in the years to come.

3.3 Limitation

3.3.1 Lack of datasets

The first problem is that there is no further system to separate complex waste and waste outside the available datasets. So that more and more complete datasets are needed for faster waste detection and higher accuracy. The lack of datasets can cause the system to not recognize and can cause errors so that the machine cannot run properly. Especially when the garbage has a combination of different types. So in the future if this system is successfully implemented, we will update the system with various garbage outside the datasets regularly. This is done so that the system is always up to date and limitations can be minimized.

3.3.2 System framework

The second problem faced is the absence of a perfectly integrated system framework to completely separate waste comprehensively. The current system is not optimal because there is no hardware that separates waste in real time after processing. Future work will focus on adding this feature to realize a complete framework for separating waste as expected. Software and hardware engineering is required to remove waste properly. This framework also even has a complete system to become a complete garbage group for 3R use.

3.3.3 Garbage personnel

Professional waste personnel are required to control the system and further process the waste once it is detected and provided with data. This control can be done by periodically testing the system and separating dangerous goods such as electronic waste and stored properly by the waste staff manually. Waste that has passed through this system also requires human labor to be processed further to be processed into recycled goods. The future strategy is to train garbage personnel to become professionals, this system will be facilitated with basic standard operations in garbage operations so that it is as expected.

4. Conclusion

This system can solve problems on a large scale such as districts hence the management becomes centralized and cost-effective. By separating waste properly, we can participate in reducing carbon emissions due to waste disposal which is becoming a global issue. There will be more waste that can be recycled and benefit society. Artificial intelligence technologies such as machine learning with some useful libraries like YOLO and ORB were employed in the construction of the models. The neural networks technique used models that were more advanced than those used by the decision tree approach. According to the findings, the deployment of artificial intelligence methods may give a high level of precision for waste detection applications. Communities are able to plan and optimize their waste management operations when they can forecast waste creation. The present study model might be used to automatically detect waste, therefore reducing human involvement, avoiding sickness and also pollution.

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