Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 12
December 2024

Intelligent Solid Waste Management: A Smart Approach for Solid Waste Identification and Segregation

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Abstract

Identifying solid waste is an essential component in achieving a sustainable community. In the case of Northwestern Mindanao State College of Science and Technology, it still relies on hand-sorting and open-burning solid waste methods for waste management despite the growing population. This might result in negative effects on the environment and health among workers, employees, and students. Hence, this paper presents a smart approach to identifying solid waste types by utilizing the real-time object detection and image segmentation model, the YOLOv8. In this approach, the researchers gathered and used the solid waste datasets from Kaggle, GitHub, ShopMetro, and local solid waste images captured by a smartphone. The YOLOv8n model achieved 85.31% average validation accuracy at 50 epochs and 86.50% average validation accuracy at 100 epochs. The result shows that the model achieved an 86.67% multiclass accuracy in identifying solid waste by using 30 samples per waste type at 100 epochs approach. However, the study is still in its initial stages because the hardware for segregation was not developed. Future work will include on adding the hardware feature to complete the system.

Keywords: yolov8, model, dataset, epoch, sustainable and greener future

1. Introduction

Solid Waste Management has always been a challenging task to do in a household, communities, municipalities, cities, and workplaces. Identifying solid waste is a vital component of effective solid waste management. Another challenging task is segregation where wastes are separated into categories like glass, paper, metal, and plastic in relation to the MRF (Materials Recovery Facility). Gathering garbage is a part of waste management [1], and its appropriate disposal at appropriate locations. In this way, structured solid waste management ensures public health and environmental protection.

For instance, one of the universities in the province of Misamis Occidental is Northwestern Mindanao State College of Science and Technology, its growing population signifies an increase in the amount of solid waste on the campus with a current population of 5,632. Most of the solid wastes found in trash bins within NMSCST are unsorted, and unsorted waste will increase the problem for the assigned personnel and waste management. Fig. 1 shows some of the unsorted trash bins of NMSCST. However, the waste management of NMSCST relies heavily on hand-sorting and open-burning methods. The hand-sorting method of the school exposes workers to dangerous materials. Open-burning of solid waste causes negative effects on the environment.

It impacts the health of workers, students, and employees which can cause everything, from headaches and respiratory issues to lung cancer [2]. To address the waste management issue of the school, this paper aims to utilize the recent version of the real-time object detection and image segmentation model YOLO (You Only Look Once), the YOLOv8 to identify solid waste types of NMSCST. The study focuses solely on the utilization of the model for identifying solid waste and later on, integrated into a hardware system that automatically segregates identified solid waste. This method will address the need for effective waste identification and segregation which minimizes manual labor, increases the efficiency of sorting solid wastes, and improves waste categorization accuracy, among other advantages. Some of the contemporary techniques used to design numerous examples that minimize waste generation and management concerns like image processing that advanced significantly as a result of the quick rise in computer power [3], Machine learning (ML), deep learning (DL), and the Internet of Things (IoT) [4], as well as computational intelligence [5].

Fig. 1. Some of the unsorted trash bins of NMSCST

2. Related Literatures

A Smart System for Segregating Solid Waste Using Machine Learning Method (Ihtifazhuddin & Reza, 2023)

This project aims to create a system that can automatically classify garbage into several groups. In this project, the method/approach used a video frame then waste detection using YOLOv3, and then multi-object tracking (ORB). Each sort of waste that is found will be counted and divided. This report on the quantity of garbage by category will be utilized for certain data analysis. This project claims that in large-scale issues, such as those affecting entire districts, can be resolved using their approach, making management more centralized and economical.

Intelligent Solid Waste Classification System Using Deep Learning (Mudemfu, 2023)

To recognize and classify cardboard, glass, metal, paper, and plastic in real-time, this thesis suggests an approach that involves training EfficientNet, VGG16, and YOLOv8. The best accurate model is then deployed to a GPU computer. A procedure known as data augmentation was used to improve model performance and deal with the small number of samples in the TrashNetV2 dataset. This procedure attempted to increase the resilience of the model, minimize the effects of data scarcity, and avoid overfitting. A variety of augmentation techniques were used, including random cropping, random blur effect, random rotation, and random flipping of photos both vertically and horizontally. Pictures were randomly resized to 416 × 416 pixels. The evaluation of the YOLOv8, EfficientNet-B0, and VGG16 architectures was conducted using Adam and stochastic gradient descent (SGD) as the optimizers. When it came to test accuracy, SGD outperformed Adam. YOLOv8 performed the best out of the three models. The YOLOv8 model performs better than EfficientNet and VGG16. In order to attain high levels of accuracy in identifying, categorizing, and tracking the five different types of solid waste materials—cardboard, glass, metal, paper, and plastic—YOLOv8 was selected as the final model to be used in their project. In order to increase the model's performance and accuracy, future development may involve adding other data sources.

Computer-vision-powered Automatic Waste Sorting Bin: A Machine Learning-based Solution on Waste Management (Limsila et al., 2023)

The study implements and assesses an autonomous waste sorting bin driven by computer vision that can quickly and efficiently classify different sorts of waste. In their approach, the camera first takes a picture of the trash, which is then processed using the YOLOv5 model for analysis. To prepare the images, RoboFlow was used. Prior to manually labeling each image in accordance with its classes, every image is first manually taken using a machinefixed camera. This study evaluates the accuracy of YOLOv5 large size by varying the ratio of test to training epochs and epoch count. The ideal set of parameters is 150 epochs with a 93.33% accuracy rate for YOLOv5l (YOLOv5 large). The study has low metal accuracy. Lastly, this study shows how their method can increase the amount of sorted recycled material while decreasing the number of repetitive rubbish sorting.

Smart Waste Management and Classification Systems Using Cutting Edge Approach (Cheema et al., 2022)

The study suggests a state-of-the-art method for intelligent waste management and classification in real time. It classifies and separates waste items in a dump area using deep learning (DL), modern techniques, and the Internet of Things (IoT). The study provides a waste grid segmentation mechanism that divides the waste yard pile into segments that resemble a grid. To create a waste grid, a camera takes a picture of the waste yard and sends it to an edge node. The image segments of the grid cells serve as test images for deep-learning models that have been trained to predict specific waste items. For this study, a deep learning algorithm called Visual Geometry Group with 16 layers (VGG16) was utilized. A cloud server installed at the edge node is used to train the model to reduce overall latency. The trained algorithm has an overall accuracy of over 90%, which is pretty good. Compared to current state-of-the-art solutions, their suggested system yields more accurate results. Existing studies focused on the use of advanced techniques in addition to deep learning algorithms, this paper focuses solely on the utilization of the YOLOv8n in identifying solid waste types. YOLO's Ultralytics supports different YOLOv8 variants, each variant varies in parameter sizes and these are YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), YOLOv8x (extra-large).

3. Conceptual Framework

One benefit of YOLO is that it prioritizes recognition and quickness over precise item detection [6]. With this, the YOLO algorithm is suited for this study which focuses solely on the algorithm alone, and later on, it will be integrated into a hardware system that will automatically segregate the identified captured image of solid waste. Fig. 2 shows the proposed conceptual framework of the study.

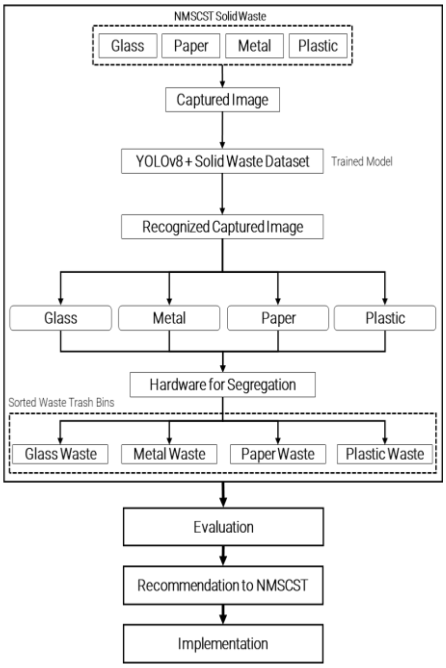


Fig. 2. Proposed conceptual framework of the study

4. Methodology

Location of the Study

The area of study will be restricted to Northwestern Mindanao State College of Science and Technology, Tangub City, Misamis Occidental.

Materials

The researchers utilized the software and hardware specifications indicated in Table 1 for training and testing the model.

Table 1. Utilized Hardware and Software

Hardware (Laptop)	Software
GPU: Intel UHD Graphics **CPU:** Intel Core i5-10210U (4C/8T) @ 1.60 GHz **RAM:** 8 GB DDR4 SODIMM Single-Channel **Storage:** 250 GB Western Digital NVME M.2 **Operating System:** Windows 11 Home Single Language 64-bit	**PyCharm** **YOLOv8n library**

Datasets

The researchers used datasets from Kaggle [7,8], GitHub [9,10], ShopMetro [11], and local waste images captured by smartphone.

The local waste images were actual wastes found in the trash bins of the NMSCST's School of Engineering and Technology Office. However, the researchers captured only 14 plastics and 8 papers which were used for testing. Table 2 shows the number of images per solid waste type. Fig. 3 shows the screenshot of solid waste images dataset used in this paper.

Table 2. Number of images per solid waste type

Waste Type	Training	Validation	Evaluation	Total
Glass	379	132	30	**541**
Metal	673	410	30	**1,113**
Paper	1,594	937	30	**2,561**
Plastic	1,472	1,177	30	**2,679**
Total	**4,118**	**2,656**	**120**	**6,894**

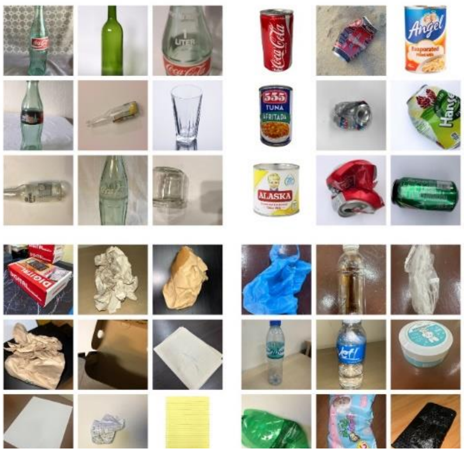


Fig. 3. Sample screenshot of solid waste images across the datasets used

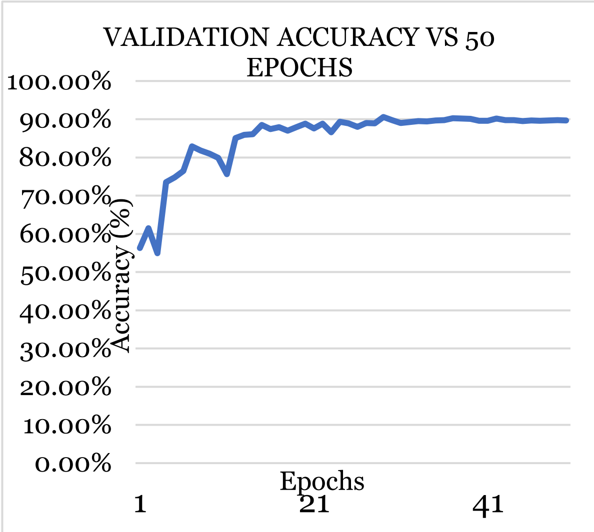
This section discusses the results of this paper.

Training

The model was trained with 50 epochs and a 100 epochs approach. An epoch is the total number of training data iterations in a single model-training cycle which represents the time during which all of the training data is used concurrently [12]. An epoch can also be defined as the number of iterations a training dataset goes through an algorithm [12].

Validation

Fig. 4 shows that the model increased its validation accuracy as the number of epochs went up and stabilized at some point. The 50 epochs approach peaked at the 28th epoch with 90.59% validation accuracy and 85.31% average validation accuracy. For the 100 epochs approach, it peaked at the 33rd epoch with 89.99% accuracy and 86.50% average validation accuracy. Both epochs are almost identical.



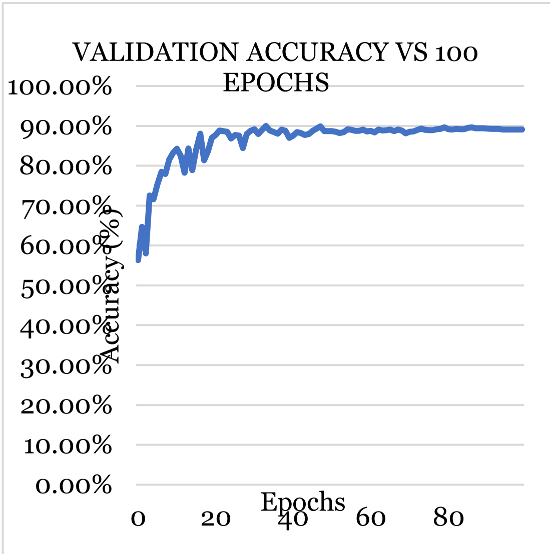


Fig. 4. Validation Accuracy at 50 epochs and 100 epochs

Testing

For testing, the researchers used the 100 epochs approach because of its slightly higher average validation accuracy. For glass waste, 73.33% of the glass waste testing images were identified correctly, 93.33% for metal waste, 93.93% for paper waste, and 90.43% for plastic waste. Among the solid waste types, glass waste has the lowest accuracy of 73.33% which was expected due to the small number of training and validation images with a combined 511 images compared to 1,083 for metal waste, 2,501 for paper wastes, and 2,649 for plastic waste. Overall, a multiclass accuracy of 86.67% of the model was achieved. To get multiclass accuracy, the total number of images correctly identified is divided by the total number of images. Fig. 5 shows the accuracy graph for solid waste types.

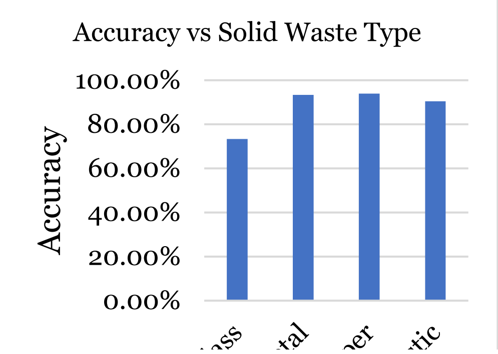


Fig. 5. Testing accuracy graph for solid waste type (30 testing images per waste type)

6. Conclusion

The researchers concluded that utilizing a real-time object detection and image segmentation model like YOLOv8, shows a promising result in identifying solid waste types with a multiclass accuracy of 86.67% at 100 epochs using 30 testing images per waste type. However, the majority of the datasets used were not local datasets. For future work, adding local image datasets for training, validation, and testing may enhance the accuracy. Furthermore, if the input solid waste is not categorized as glass/metal/paper/plastic, another dataset might be added for uncategorized waste. Thus, the vast range of potential datasets is one of the main sources of hindrances in developing a study like this. The researchers recommend to the Northwestern Mindanao State College of Science and Technology the utilization of the YOLOv8n model in identifying solid waste and the funding for the development of hardware segregation must be taken into consideration, in hopes of promoting a sustainable and greener future for the school.

Acknowledgement

The researchers would like to thank the Northwestern Mindanao State College of Science and Technology, Labuyo, Tangub City, Misamis Occidental, Philippines for providing insights regarding waste management.

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