A Recyclable Waste Image Recognition System with YOLOv8 for Children's Environmental Education

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ABSTRACT

Rapid economic growth and increasing urban population have led to a significant increase in waste production, raising serious concerns for countries worldwide. As the population expands, the increase in waste generation poses numerous environmental and public health challenges. This study focuses on educating children about recyclable waste to promote early awareness and proper waste classification habits. Specifically, this study investigates the performance of the YOLOv8 model to embed it into a waste recognition system tailored for children's waste management education. Datasets were obtained from Kaggle and underwent preprocessing. The findings show that a model with 100 epochs, an SGD optimizer, and a batch size of 25 achieved the best performance, with an accuracy of over 94% and a low loss of 0.367. This model demonstrated competitive accuracy in detecting and classifying waste images, highlighting its potential as an effective tool in educational programs aimed at teaching children the importance of waste management and promoting sustainable practices from an early age.

Keywords-recyclable waste; waste management; image recognition; YOLOv8; environmental education

I. INTRODUCTION

The global population, currently at 7.9 billion, is steadily increasing, leading to a surge in economic activities and urbanization. This growth contributes to a significant increase in waste production [1]. Waste production has been projected to increase from 2.24 billion tons in 2020 to nearly 3.88 billion tons by 2050. Malaysia, as a developing nation, is grappling with escalating waste concerns, ranking among the largest contributors to waste in Southeast Asia. The urgency of effective waste management is underscored by the environmental and health challenges posed by increased waste production [1-2].

Artificial intelligence, particularly in image recognition technology, offers a promising avenue to address waste management challenges. Image recognition utilizes computers to interpret visual data, with machine learning models such as Convolutional Neural Networks (CNNs) being a notable technique used for this purpose. In [3-5] image recognition applications were presented to detect and classify waste. The study in [6] explored the potential to incorporate image recognition into educational tools to enhance children's understanding of waste management processes.

Being aware of the importance of waste management is crucial for building environmentally conscious habits in the younger generation [7]. Children's learning processes, driven by play, curiosity, and exploration, lay the foundation for formal education. Parents and teachers play pivotal roles in guiding and supporting children through this learning journey, fostering creativity and love for learning. With a focus on changing habits related to waste management, the role of children's learning processes in shaping environmentally responsible behaviors contributes to a sustainable global society [8, 9]. Waste management, essential for achieving a green and healthy environment, also faces challenges, particularly in Malaysia, where the effectiveness of Reuse, Reduce, and Recycle (3R) methods is hindered by various factors [10]. Despite high awareness and education levels on environmental issues and 3R methods, the community's lack of interest and low awareness about 3R methods results in ineffective waste management practices. To address this issue, research advocates for the education of the next generation, emphasizing the importance of instilling recyclable waste management understanding and practices in children using image recognition and deep learning techniques [11-15].

Significant and noticeable benefits are more likely to come from environmental education, according to the National Pedagogical University, as it teaches kids how to be productive and responsible members of society. Teaching and learning about environmental education accomplish the goals of environmental conservation and protection while also acting as a vital tool in the fight against environmental issues. By sensitizing children to adopt a responsible attitude and respect for the natural world, environmental education is a tool for instilling respect for the environment from an early age. It can also increase their awareness of the importance of recycling and recovery [16]. Thus, this study aims to develop a waste image recognition system to educate children on environmental issues. In summary, the main contributions of this study are:

- Utilizes the YOLOv8 deep learning algorithm to recognize recyclable waste images, improving recognition accuracy.
- Integrates different sources of datasets to reduce biases due to class imbalance.
- The proposed system is designed with point systems to create engaging and effective educational tools for use by children.

II. WASTE MANAGEMENT

The exponential growth of the global population and the simultaneous expansion of economic and industrial activities have resulted in a significant increase in waste production. Effectively managing this escalating waste has become a critical global concern, raising a multitude of challenges on a global scale. Waste management encompasses a series of procedures and actions, from the creation of waste to its ultimate disposal. These procedures involve the collection, transport, treatment, and disposal of waste, with additional considerations for monitoring, regulations, technologies, and economic mechanisms related to waste management.

Unfortunately, when waste production exceeds disposal capabilities, landfill often emerges as a predominant method for waste disposal. Despite their prevalence worldwide, landfills contribute to environmental pollution, unsanitary conditions, and health hazards. In Malaysia, for instance, landfilling is the main waste disposal method, with 88% usage, followed by recycling at 10.5% and composting at 0.7% [11]. The adverse effects of landfills extend beyond immediate health risks to residents and ecosystems, highlighting the urgency of exploring alternative waste management strategies. As an alternative, the 3R program stands as a global initiative to promote sustainable resource utilization. Originating in the late 1980s, the 3R program aims to instill responsible waste management practices, with a focus on waste reduction, reuse of materials, and recycling. To increase recycling rates and achieve Malaysia's federal government target of 40% by 2050, it is necessary to increase community awareness and participation in the 3R program [10]. This multifaceted approach to waste management addresses environmental concerns, economic considerations, and social engagement, laying the foundation for a more sustainable future.

III. IMAGE RECOGNITION

Several studies have delved into image recognition in the context of waste classification, employing various techniques to enhance accuracy and efficiency. In [3], a refined garbage detection system was proposed, called the lightweight Single Shot Multibox Detection (SSD), which integrated the ResNet network for better feature extraction, addressing the issue of gradient disappearance in deep networks. This model, compared to traditional SSD, exhibited a notable increase in mean Average Precision (mAP) to 90.18%, albeit a slight decrease in processing speed to 32.4 frames per second (fps), as shown in Table I.

TABLE I. COMPARISON OF IMAGE RECOGNITION MODELS [3]

Model	Size(M)	mAP(%)	FPS
Faster-RCNN	195.0	89.79	2.5
YOLO v3	237.0	86.41	36.1
SSD	100.0	88.36	34.8
Lightweight SSD	33.5	90.18	32.4

In [5], GC-YOLOv5 was introduced, utilizing the YOLOv5 architecture for waste classification. Achieving more than 99% accuracy in experimental settings and more than 80% in real-world scenarios, this model demonstrated the potential for robust waste identification. In [4], waste classification was performed using Faster R-CNN, focusing on its efficiency compared to other models. This study, employing Inception-V2 and ResNet-101 as backbone networks, achieved promising mAP values of 92% and 83%, respectively, surpassing other methods such as SSD and Region-based Fully Convolutional Networks (RFCN). In [14], real-time pill recognition was performed, evaluating Faster R-CNN, SSD, and YOLOv3 as shown in Table II. While Faster R-CNN exhibited the highest mAP at 87.69%, YOLOv3's superior processing speed of 51 fps rendered it most suitable for real-time applications, showcasing the trade-offs between accuracy and speed.

TABLE II. MODELS' EVALUATION IN FPS [14]

Methods	YOLOv3	Faster R-CNN	SSD
FPS	51	7	32

In [15], deep learning models were used for real-time vehicle detection, highlighting the supremacy of YOLO with 98.19% mAP and 82.1 fps. However, the accuracy of Faster R-CNN and the lightweight nature of SSD were noted. This collective evidence underscores YOLO's dominance in real-time image recognition, due to its balance of speed and accuracy, which has implications beyond real-time applications. Other studies that employed YOLO models for object detection include [17], which focused on detecting customized objects in autonomous driving, and [18-19], which addressed the detection of plant leaf diseases. Thus, for waste recognition efforts, the use of YOLO as the primary deep learning model holds promise for effective waste management solutions. The YOLOv8 model was chosen due to its advanced object detection and image segmentation architecture.

IV. METHODOLOGY

A. Data Collection and Preprocessing

The Garbage Classification dataset was the basis of this research, comprising 2,467 labeled images [20]. Images were classified into six distinct classes, which were cardboard, glass, plastic, metal, paper, and trash. Additional images were obtained from [21-23] to address the class imbalance problem. Data collection also involved collecting images from Pinterest to ensure consistency in the background, as the garbage classification dataset predominantly featured images with white backgrounds. Figure 1 shows sample images from the Garbage Classification dataset.

Fig. 1. Sample images from the Garbage Classification dataset.

The dataset was preprocessed to ensure compatibility and effectiveness in the subsequent training and testing phases. This involved cleaning, formatting, and organizing the data to enhance its suitability for analysis. Key preprocessing steps included resizing all images to a standardized dimension of 640×640 pixels, performing data augmentation to enrich the training dataset, and partitioning it into training and testing sets. These preprocessing tasks were performed using Roboflow, an open-source platform that facilitates dataset annotation and conversion to COCO format, and simplifies tasks such as drawing bounding boxes and labeling, ensuring that it is prepared for robust analysis.

B. Model Design & Evaluation

The model design and development process encompassed several key considerations, beginning with the selection of an appropriate algorithm and techniques for waste image recognition. YOLOv8, renowned for its speed and accuracy in image recognition, was chosen for its compatibility with the task at hand. YOLOv8 employs residual blocks, bounding box regression, and Intersection over Union (IoU) to efficiently identify and classify waste items. Collectively, these techniques enable the system to accurately detect and classify waste objects. In this study, the mAP calculated at the IoU threshold of 0.50 (mAP50) was used to measure the model's accuracy.

The proposed system seamlessly integrated localization and classification tasks, streamlining the detection process. Following waste recognition, pertinent information, such as waste type and user points, is stored in the database, facilitating user engagement and tracking progress. The user interface, designed to attract children's interest, serves as a conduit for displaying relevant information and encouraging active participation in waste management practices. Through these iterative steps, the system not only educates but also incentivizes users to embrace recycling habits, fostering a culture of environmental consciousness from an early age. Figure 2 shows the architecture of the proposed waste recognition system. Python was selected to implement the model architecture, facilitated by its extensive library support. Platforms such as Google Colab and Roboflow were instrumental in training and testing the model, the former providing a robust environment to execute Python scripts. Through meticulous experimentation and hyperparameter tuning, the model's performance metrics, including accuracy and loss, were evaluated to optimize its efficiency in waste recognition.

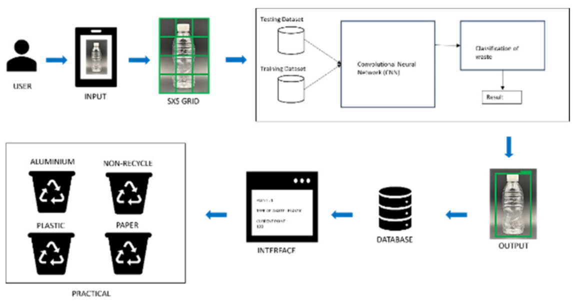

Fig. 2. The architecture of the proposed waste recognition system.

V. RESULTS

A. Evaluation Process

The proposed model involved hyperparameter tuning, including adjustments to epochs, the optimizer, and batch size. Initially, three models were supervised with varying epochs, followed by a second experiment focusing on three models with different optimizers, all set to 100 epochs. Finally, the best hyperparameter values were applied to four models with different batch sizes. Table III shows the details of the hyperparameter tuning for each experiment.

TABLE III. HYPERPARAMETERS FOR EACH EXPERIMENT

Experiment	Hyperparameter	Value
A	Epoch	20, 50, 100
B	Optimizer	SGD, Adam, AdamW
C	Batch Size	10, 15, 25, 40

1) Experiment A: Models with Different Epochs

This experiment focused on evaluating the impact of varying numbers of epochs (20, 50, and 100) on model performance to determine the optimal epoch count to achieve optimal accuracy without over- or under-fitting. The hyperparameter optimizer and batch size remained default, solely focusing on epoch adjustments. The results shown in Table IV indicate a trend of increasing mAP50 scores with higher epoch numbers across models A1, A2, and A3. Model A3 exhibited the highest mAP50 validation of 0.954, surpassing A2 and A1, suggesting that a higher number of epochs improves object detection accuracy.

TABLE IV. COMPARATIVE RESULTS WITH DIFFERENT EPOCHS

Model	Epoch	mAP50	Precision	Recall	Box loss
A1	20	0.918	0.971	0.98	0.3813
A2	50	0.947	0.949	0.98	0.3549
A3	100	0.954	0.974	0.98	0.3504

The precision analysis in Table IV reveals high confidence levels in object localization for all models, with increasing confidence corresponding to higher epoch counts. Similarly, recall scores for models A1, A2, and A3 indicate robust recall abilities, further validating the positive impact of increased epochs on model performance. The bounding box loss scores exhibit a decreasing trend, with model A3 achieving the lowest loss score of 0.3504, indicating its superior ability to correctly predict bounding boxes around objects compared to models A1 and A2.

Figure 3 shows graphs of mAP50, precision, recall, and box loss, indicating that model A3 generated the highest mAP50, precision, and recall, along with the lowest box lost value. This experiment successfully identified 100 epochs as the most suitable epoch count, as evidenced by these results. Model A3's strong performance underscores the effectiveness of utilizing a higher number of epochs in enhancing model accuracy and object detection capabilities.

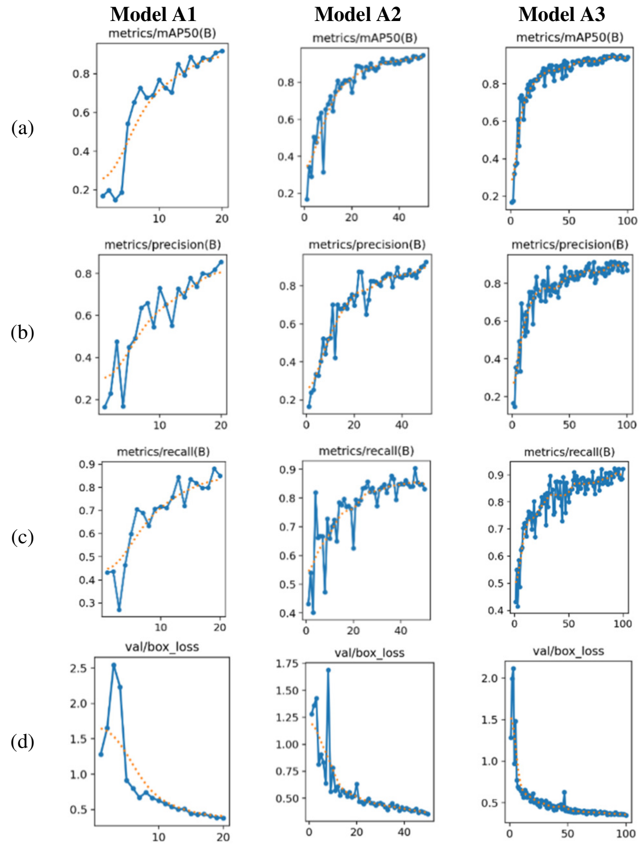

Fig. 3. Performance results of models A1, A2, and A3.

2) Experiment B: Models with Different Optimizers

This experiment focused on evaluating the impact of different optimizers (SGD, Adam, and AdamW) on model performance, using 100 epochs. Table V presents the mAP50, precision, recall, and box loss results for all models in this experiment. Model B1 achieved the highest validation mAP50 score of 0.953, followed by B3 with 0.924, while B2 achieved the lowest mAP50 score of 0.874. Figure 4 shows comparison graphs of mAP50, precision, recall, and box loss results of the models with different optimizers. Model B1 achieved the highest mAP50 and precision results. The steeply increasing trends in precision and recall scores in model B1 suggest its superior performance, indicating higher accuracy and better detection capabilities compared to B2 and B3. Based on Table V, despite the slightly higher box loss value compared to B3, model B1 shows commendable performance in accurately detecting objects. These results show that B1 performed better than the other models, exhibiting the highest mAP50 score, precision, and recall values. Its slightly higher box loss score than B3 indicates an exceptional ability to generalize unseen data.

TABLE V. COMPARATIVE RESULTS FOR MODELS WITH 100 EPOCH AND DIFFERENT OPTIMIZERS

Model	Optimizer	mAP50	Precision	Recall	Box loss
B1	SGD (default)	0.953	0.98	0.98	0.388
B2	Adam	0.874	0.953	0.99	0.400
B3	AdamW	0.924	0.961	0.98	0.369

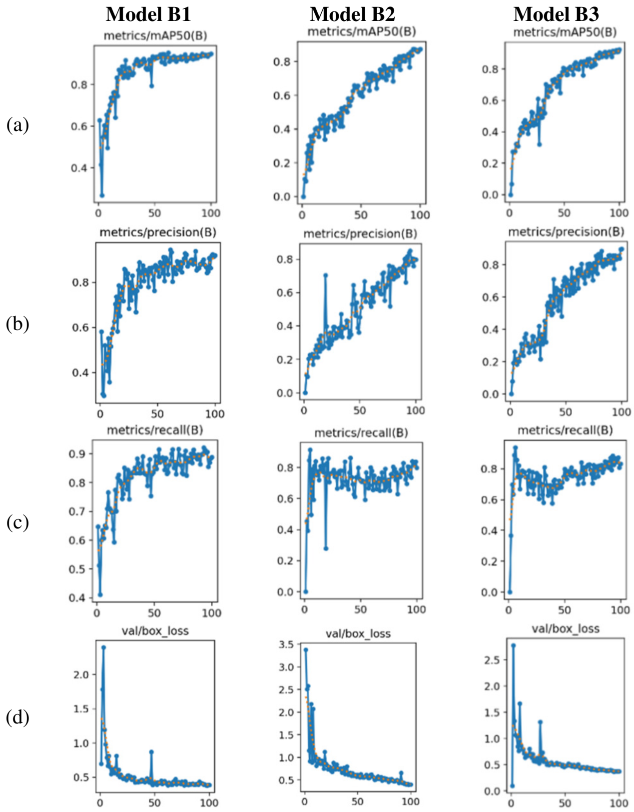

Fig. 4. Performance results of models B1, B2, and B3.

3) *Experiment C: Models with Different Batch Sizes*

Experiment C used models with different batch sizes, using 100 epochs and the SGD optimizer. Recognizing the significant impact of batch size on learning stability, speed, and GPU utilization is crucial. Although the default batch size for the YOLOv8 model is 16, this experiment explored batch sizes of 10, 15, 25, and 40. Table VI presents the mAP50 results for models C1, C2, C3, and C4, demonstrating high accuracy in image recognition across all models. Model C4 achieved the highest mAP50 value of 0.959. However, the precision analysis in Table VI reveals that model C3 exhibits the highest confidence threshold at 0.998 precision, indicating its low false positive rate and greater accuracy in predicting favorable results compared to the other models. A recall analysis emphasizes the superior recall ability of model C3, as it achieved the highest recall score of 0.98. Evaluating bounding box loss results ensures the model's ability to detect objects accurately, with C3 displaying the lowest box loss result of 0.367. This decreasing trend in box loss scores across all models underscores their accuracy in detecting objects. Although C4 has slightly higher accuracy according to mAP50, C3 outperforms it in precision, recall, and bounding-box loss, making it the optimal model among them. Figure 5 shows the performance graphs of the C3 model with different metrics. In conclusion, model C3, with 100 epochs, SGD optimizer, and batch size of 25, emerges as the best-performing model for the waste management system. Its superior precision, recall, and low bounding box loss results highlight its exceptional performance in accurately identifying objects while minimizing false positives and false negatives. Overall, the comprehensive performance of model C3 makes it the most suitable choice for the waste management system.

TABLE VI. PERFORMANCE RESULTS OF MODELS WITH 100 EPOCHS, SGD OPTIMIZER AND DIFFERENT BATCH SIZES

Model	Optimizer	Batch Size	mAP50	Precision	Recall	Box loss
C1	SGD (default)	10	0.948	0.973	0.97	0.376
C2		15	0.942	0.992	0.97	0.379
C3		25	0.949	0.998	0.98	0.367
C4		40	0.959	0.973	0.97	0.373

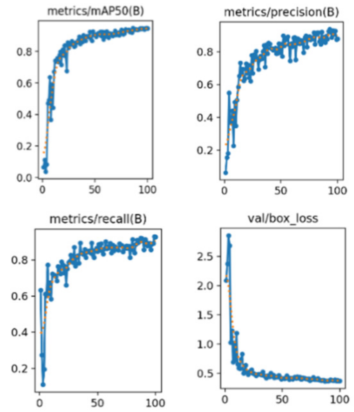

Fig. 5. Performance results of model C3.

B. *User Interface*

A system was developed using HTML, CSS, and XAMPP for the point system. CSS was used to make the user interfaces more attractive and appealing to the children. The system provides the necessary information to the user to capture the image of the waste object and inform its class. Figure 6 shows the system login page, while Figure 7 shows the waste recognition page. On this page, the user can capture the waste image and display its class. The user gets two points for each detected waste object. This approach can create engaging and effective educational tools to help children understand the importance of proper waste classification and recycling. By integrating AI technology into educational programs, the next generation can be empowered to actively participate in waste management practices, fostering a culture of sustainability and resilience that is essential to address the environmental challenges posed by rapid economic growth and urbanization.

Fig. 6. The login page of the waste recognition system.

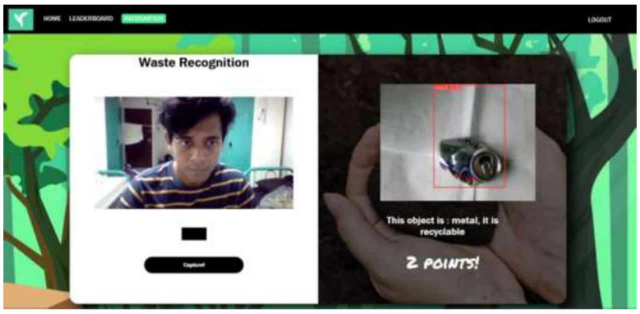

Fig. 7. The waste recognition page.

C. Limitations and Future Improvements

This study demonstrates several limitations. First, the dataset lacks diversity in object images, particularly in terms of common waste items found in school compounds, potentially affecting the model's predictive accuracy and leading to overfitting due to irrelevant images. Second, the study confines itself to using only the YOLOv8 object detection algorithm without comparing it with alternative algorithms such as SSD and Faster R-CNN, limiting understanding of its relative performance. Last, the requirement for images with a white background restricts the model's adaptability to diverse backgrounds, limiting its ability to detect objects with other background colors. Future research should expand the dataset to include a broader variety of common school compound objects to enhance the model performance by facilitating better learning of object features and improving generalization to unseen data. Moreover, experimenting with alternative neural network algorithms along with YOLOv8 would provide valuable insights into their comparative performance, including factors such as speed, accuracy, sensitivity, robustness, and ease of implementation. Furthermore, transitioning to a waste dataset with random rather than solely white backgrounds could mitigate the model's sensitivity to background variations, allowing it to focus more on object features and adapt more effectively to diverse image backgrounds.

VI. CONCLUSION

This study investigated the performance of YOLOv8 in recyclable waste image recognition and developed a system for children's environmental learning. The goal is to instill sustainable waste management habits from an early age. This study integrated different datasets to reduce biases due to class imbalance. The model with SGD optimizer, 100 epochs, and a batch size of 25 achieved the best results, with 99.8% precision, 98% recall, and 0.367 low bounding-box loss. The performance of YOLOv8 is exceptional compared to other versions of YOLO in image recognition. This study highlighted several strengths, including the high accuracy of the proposed system in the classification of recyclable waste and the incorporation of gamification elements to improve children's engagement in environmental education. The proposed system features a point system to create engaging and effective educational tools for children. By accurately recognizing waste types and incentivizing participation through point-based systems, waste management education can be enjoyable for children. Focusing on the younger generation, this study aims to foster long-term behavioral change and increase awareness of waste management practices, offering a potential solution to ongoing waste management challenges in Malaysia. It is hoped that this initiative not only will impart knowledge to children but will also instill the habit of waste classification, thus raising awareness and potentially boosting recycling rates. These efforts will significantly contribute to the promotion of sustainable waste management practices, thereby fostering a cleaner and greener future.

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REFERENCES

[1] S. Kaza, S. Shrikanth, and S. Chaudhary, "More Growth, Less Garbage," *World Bank Publications - Reports*, Jul. 2021, [Online]. Available: https://ideas.repec.org/p/wbk/wboper/35998.html.

[2] I. S. Arumdani, A. S. Puspita, and M. A. Budihardjo, "MSW handling of top 5 leading waste-producing countries in Southeast Asia," *IOP Conference Series: Earth and Environmental Science*, vol. 896, no. 1, Aug. 2021, Art. no. 012003, https://doi.org/10.1088/1755-1315/896/1/012003.

[3] J. Fang, "SSD-based Lightweight Recyclable Garbage Target Detection Algorithm," *Innovation in Science and Technology*, vol. 1, no. 1, pp. 40–45, Aug. 2022, https://doi.org/10.56397/IST.2022.08.05.

[4] A. I. Middya, D. Chattopadhyay, and S. Roy, "Garbage Detection and Classification using Faster-RCNN with Inception-V2," in *2021 IEEE 18th India Council International Conference (INDICON)*, Guwahati, India, Dec. 2021, pp. 1–6, https://doi.org/10.1109/INDICON52576.2021.9691547.

[5] Z. Wu *et al.*, "Using YOLOv5 for Garbage Classification," in *2021 4th International Conference on Pattern Recognition and Artificial Intelligence (PRAI)*, Yibin, China, Dec. 2021, pp. 35–38, https://doi.org/10.1109/PRAI53619.2021.9550790.

[6] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using YOLO: challenges, architectural successors, datasets and applications," *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9243–9275, Mar. 2023, https://doi.org/10.1007/s11042-022-13644-y.

[7] S. M. Anua, N. N. K. Anwar, N. Mohd Zain, W. N. W. Abd Rahman, N. A. Hamzah, and H. Abdul Rahman, "Reduce, Reuse and Recycle (3r) Awareness Programme to Increase the Knowledge, Attitude and Practice on 3r among Primary School Students," *International Journal of Academic Research in Business and Social Sciences*, vol. 12, no. 13, pp. 62–74, Jun. 2022, https://doi.org/10.6007/IJARBSS/v12-i13/14144.

[8] P. Mupa and T. I. Chinooneka, "Factors Contributing to Ineffective Teaching and Learning in Primary Schools: Why Are Schools in Decadence?," *Journal of Education and Practice*, vol. 6, no. 19, pp. 125–132, 2015.

[9] H. A. Rahman, "Efforts and Challenges in the Application of Environmental Education in Malay," *Asian Journal of Environment, History and Heritage*, vol. 1, no. 2, 2017.

[10] "Malaysia Waste Management Solutions," *International Trade Administration - U.S. Department of Commerce*, Aug. 23, 2022. https://www.trade.gov/market-intelligence/malaysia-waste-management-solutions.

[11] F. S. M. Zabidi, N. A. M. Kasim, S. Ahmad, and N. H. Miskan, "Factors Influencing Waste Management in Malaysia," *Journal of Business Innovation*, vol. 7, no. 1, 2022, Art. no. 100.

[12] F. S. M. Zabidi, N. A. M. Kasim, S. Ahmad, and N. H. Miskan, "Factors Influencing Waste Management in Malaysia," *Journal of Business Innovation*, vol. 7, no. 1, pp. 100–107, 2022.

[13] S. M. Kamaruddin, M. H. Sharif, A. Misni, and P. Ahmad, "Subang Jaya Residents' Awareness and Practice of Biomass Waste Management," *Asian Journal of Quality of Life*, vol. 3, no. 12, pp. 147–155, Jul. 2018, https://doi.org/10.21834/ajqol.v3i12.151.

[14] S. Sulistyawati, T. W. Sukesi, S. A. Mulasari, F. Tentama, and S. N. Djannah, "Knowledge, Attitude and Practice towards Waste Management among Primary School Children," *Asian Journal of Education and Social Studies*, pp. 24–30, Jun. 2020, https://doi.org/10.9734/ajess/2020/v8i430234.

[15] J. Kim, J. Y. Sung, and S. Park, "Comparison of Faster-RCNN, YOLO, and SSD for Real-Time Vehicle Type Recognition," in *2020 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia)*, Seoul, Korea (South), Nov. 2020, pp. 1–4, https://doi.org/10.1109/ICCE-Asia49877.2020.9277040.

[16] V. Gizzi, S. Di Dio, and D. Schillaci, "Junkbox, a waste management educational game for preschool kids," *Interaction Design and Architecture(s)*, no. 40, pp. 46–56, Apr. 2019, https://doi.org/10.55612/s-5002-040-003.

[17] T. Saidani, "Deep Learning Approach: YOLOv5-based Custom Object Detection," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12158–12163, Dec. 2023, https://doi.org/10.48084/etasr.6397.

[18] E. Iren, "Comparison of YOLOv5 and YOLOv6 Models for Plant Leaf Disease Detection," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13714–13719, Apr. 2024, https://doi.org/10.48084/etasr.7033.

[19] H. M. Zayani *et al.*, "Deep Learning for Tomato Disease Detection with YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13584–13591, Apr. 2024, https://doi.org/10.48084/etasr.7064.

[20] "Garbage Classification." Kaggle, https://doi.org/10.34740/kaggle/ds/81794.

[21] A. Ouedraogo, "Waste Images." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/angelikasita/waste-images.

[22] "waste_pictures." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/wangziang/waste-pictures.

[23] A. Shrivastav, "Most Common Recyclable and Non-Recyclable Objects." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/ashwinshrivastav/most-common-recyclable-and-nonrecyclable-objects.