Development of Covid Medical Waste Object Classification System Using YOLOv5 on Raspberry Pi

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Abstract*— The increase of COVID-19 cases had affected the increase of medical waste, reaching 12,740 tons in Jakarta. Medical and hazardous waste are often found in the community environment, due to poor waste management and improper waste segregation before disposal. Based on these problems, studies have been carried out regarding waste classification. However, there were some limitations in the proposed method. The use of Convolutional Neural Network (CNN) method with model compression has a significant drop in accuracy. The application of Single Shot MultiBox Detector (SSD) method with TensorFlow framework also has low level of accuracy. Results of other studies using YOLOv4 method showed that the accuracy of this model was lower when running on Raspberry Pi. In the context of classifying objects in general, You Only Look Once (YOLO) is interesting and potential. Therefore, this study proposed the development of areal-timee hazardous waste classification system using YOLOv5 method. Based on the test results on the Raspberry Pi 3b+, YOLO produced 85% and 96% accuracy at image size of 128x128 and 25x320 pixels within 1-5 seconds of computational time. With the development of a new framework for sorting waste, it is expected to be an alternative method that can be applied by other researchers in waste classification.

***Keywords*— Internet of Things, Object Detection, Raspberry Pi, Smart Trash Bin, YOLOv5m**

I. INTRODUCTION

Waste is an unavoidable problem in life because most daily human activities generate waste [1]. According to a study [2], every year the world generates about 1.47 billion tons of municipal waste. If waste is not treated and managed properly, this problem will become even more serious [3]. One result is waste accumulation [4]. Apart from creating piles of uncontrolled waste, this also has the potential to become a medium for spreading viruses or diseases [5].

Case of COVID-19 pandemic is one of the factors causing the problem of medical waste in the health sector. The amount of medical waste has increased as the results of preventive measures [6], such as implementing social distancing, requiring the use of masks, gloves and face shields, as well as lockdowns to prevent the spread of the COVID-19 virus [7]. The use of protective masks is one of the factors that significantly increased medical waste in the community as a preventive necessity from COVID-19 [8]. As of 60 days after the first case of the COVID-19 in Indonesia, 12,740 tons of medical waste was generated in Jakarta [9].

According to a study [10], medical waste is a factor in the transmission of COVID-19 because the viruses and bacteria can move through media that have physical contact and last a long time, especially on plastic surfaces. Thus, waste such as bottles, tissues and spoons are categorized as hazardous waste [11]. In addition, the medical waste is often found in the community as it is mixed with ordinary household waste [12]. It is mainly caused by the improper segregation of medical waste [13]. This leads to a higher risk of virus transmission because mixed medical waste can contain active virus particles [13].

Based on these problems, studies have been carried out [14]–[16] in regard with waste classification. A study using Convolutional Neural Network (CNN) based on deep learning was applied to classify waste into nine categories [14]. Another study used Single Shot MultiBox Detector (SSD) with TensorFlow framework as waste classification and LoRa as data transmission media [15]. A study applied webcam and real-time You Only Look Once (YOLO) object detection in Raspberry Pi to detect and classify the recyclables waste into the correct categories [16].

In general, the proposed methods have shown good performance in waste classification. However, the evaluation shows that the waste classification method using CNN with model compression has a large negative impact on the classification accuracy and speed of object classification. This is because the decrease in image quality affects the model's ability to classify with high accuracy so it takes a long time [14]. Subsequent evaluations show that the SSD method with TensorFlow framework has less accurate level of classification due to the lack of sample data and also cannot detect two objects at once. [15]. The results of other studies using YOLOv4 method show that when trained with a smaller number of images and run on the Raspberry Pi, the accuracy of this model is lower, but without the Raspberry Pi it has higher accuracy. In addition, this study has a longer classification speed, which is 507.38 ms [16].

On the other hand, in the context of general object classification, YOLOv5 has also become an interesting and potential approach in the field [17]. YOLOv5 method imposed on deep learning techniques and real-time object detection by processing the entire image in one step [18]. Compared to other approaches that require more complex processing steps, YOLOv5 can provide high speed and efficiency in detecting and classifying objects in real time. [19].

There are several studies [20]–[21] that applied YOLO method as object detection. In this study [20], a comparison of the results of object detection using the YOLOv3, YOLOv4, and YOLOv5 methods with YOLOv5 obtained an average precision level greater than YOLOv3 and YOLOv4. In this study [22], YOLOv5 method was used with modified YOLOv5s method by optimizing YOLOv5s backbone

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network structure, CNN replaced with Ghostbottleneck module to increasethe occlusion recognition rate. A study used a modified YOLOv5m to detect smoke by adding mosaic enhancement method and hybrid attention mechanism to improve detection performance [21].

Based on these previous studies, this research proposed a system that focuses on detecting and classifying waste objects as hazardous or not using YOLOv5 method to be applied to the smart trash bin system [23]. The main contributions of this research are as follows:

- A proposed framework for classifying waste objects with the implementation of the YOLOv5 method.
- A real-time object detection algorithm on Raspberry Pi 3B+.

Furthermore, this article explains the materials and methods in section 2, the results and discussion in section 3, and finally the conclusion in section 4.

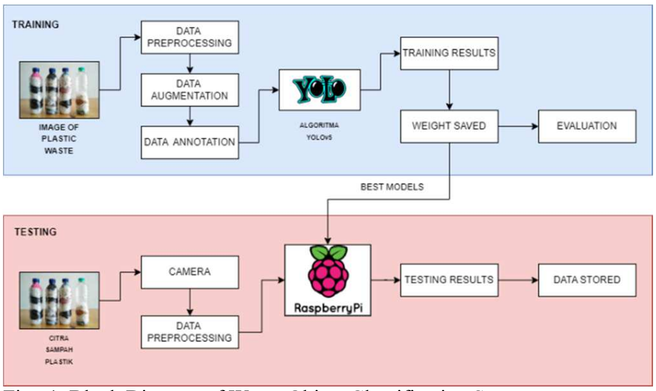

Fig. 1. Block Diagram of Waste Object Classification System

II. METHODS

A. Framework

In general, the system consists of two main processes: training process and testing process. The training process consists of several stages in the form of data processing, data augmentation, data annotation, and training with YOLOv5. In the testing process, the system was built using a USB Camera device as an input device to capture images of waste objects in real time, then the image data is received by the Raspberry Pi 3B+ microcontroller device and image processing will be carried out by the YOLOv5 method to perform object detection processing using the model that has been trained. Then the output of the detection process is the classification results and status of the type of waste. Fig. 1. shows the block diagram of proposed system framework.

1) Pre-Process

In the Pre-process data section, initial image dataset was collected as a reference. The dataset should include images of various waste objects, including hazardous and non-hazardous waste. The number of image datasets used affects the results of model training, the use of a small image dataset tends to produce a small quality model, so that in the Pre-process data section, the initial image dataset needs to be increased using an augmentation process. In the augmentation process, the initial image dataset with an initial number of 25 images was multiplied. There were several augmentation methods used in this study including image rotating of 90 degrees, 180 degrees, and 270 degrees, scaling of 200%, and adding noise of 50% [24].

2) YOLO Configuration

Before carrying out the training process to model the waste object detection system, YOLO was configured first. The pre-processed dataset was divided into 2 different folders based on dataset requirements, namely the training dataset and the validation dataset, with a ratio of 80 (Training): 20 (Validation). In addition to dividing the dataset before training, the label configuration for the types of waste objects were adjusted according to the type of waste to be detected, into 7 labels.

3) YOLO Training

In the process of selecting YOLOv5 method to be used, several YOLOv5 methods were trained with the same number of batch, epoch, and image size to find out the comparison between batch size of 50, 100 epochs, and image size of 64x64 pixels. The YOLOv5 method training process used the free Google Collab Research platform, with a configuration that had been adjusted to the needs for the design and construction of a waste object classification system which configuration was based on the configuration documentation provided by YOLOv5.

4) Object Detection Testing

Testing was conducted to assess the performance of the proposed framework. There were several measurement parameters used in the test, namely accuracy, precision, recall, F1-score and computational speed. The accuracy test was used to examine the accuracy of the system in detecting the type and classification of waste objects using image data, video and real-time captured data via a webcam device. In calculating the accuracy value, true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values were required. Accuracy is a comparison of the ratio of correct predictions with the ratio of wrong predictions. The accuracy value was calculated using formula (1).

$$Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)} \quad (1)$$

The second test was precision. Precision is the ratio of TP value to the amount of data that is predicted to be positive (TP + FP). The smaller the FP, the greater the precision. The precision value was calculated using the formula (2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

The third test was recall. Recall is a comparison of TP with the amount of data that is actually positive. The smaller the FN, the greater the recall. Recall value was calculated using the formula (3).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

The fourth test was F1-Score or F1-Measurement. F1-Score is a comparison metric between the average precision and recall values. If the precision value is large but the recall value is small, the prediction from the model will be accurate but cannot cover all possibilities. The F1-Score value was calculated using the formula (4).

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

The final test was computational speed testing. Computational time is an important performance indicator used to determine whether an algorithm can be executed within a reasonable time frame [25]. Speed testing used a computational time testing method, which focused on testing the speed level of the system in detecting the type and classification of waste objects in image data, video and real-time captured data via a webcam device.

B. *Implementation Environment*

The framework for detecting and classifying waste objects that had been designed in the previous stage was implemented using hardware and software as shown in Table I.

TABLE I. IMPLEMENTATION ENVIRONMENT

Item	Specification
Laptop (Asus TUF FX505DT)	Processor AMD Ryzen 5 ~2.2GHz with Random Access Memory (RAM) 8 GB
YOLO	YOLOv5m
Raspberry Pi 3 B+	Microprocessor Broadcomm BCM2837 64bit Quad Core Processor Random Access Memory (RAM) 1 GB
USB Camera	Device for capturing images of waste objects
Google Colab	Platform for YOLO model testing
Makesense.ai	Platform for image labeling

III. RESULT AND DISCUSSION

This section contains an explanation regarding the dataset and test results. First, the creation of the used dataset is discussed. Second, a comparison of testing the accuracy of the waste object classification system is discussed. Third, a comparison of Computational Time testing is carried out on two devices, namely laptop and Raspberry Pi.

A. *Dataset*

A dataset is a data structure generated from merging database tables, processing and collecting raw data, and storing it in a single database table [26]. The collection of image data for this research involved creating a dataset of garbage objects to be classified. Fig. 2 shows several examples of images used, with the type of waste classified as garbage images and the number of classes detected being 7.

Each object class in Fig. 2 has an initial set of 25 image data, and these images are subsequently augmented to ensure an equal number of images in each class. After the augmentation process, the total number of image data used in the object detection with the model training process is 1050.

Fig. 2. Garbage Object Initial Image Dataset

B. *Test Results*

The YOLO model training and testing process on a laptop involves comparing the Confusion Matrix values generated from each model training process. The YOLOv5 model has several versions such as YOLOv5x, YOLOv5l, YOLOv5m, YOLOv5n, and YOLOv5s.

In selecting the YOLOv5 model, each model will be trained with the same number of batches, epochs, and image sizes to obtain valid comparisons. This study used a Batch size of 50, an Epoch of 100 times, and an Image Size of 64x64 pixels. Fig. 3 shows the results of comparing precision, recall and F1-score for each YOLOv5 model.

Based on Fig. 3, the YOLOv5m model emerged as the chosen option for a sorting system in the research on a garbage object classification system using YOLO on a Raspberry Pi. This model stood out as the chosen option because YOLOv5m yields the highest level of Confusion Matrix from the Recall and F1-Score parameters when executed with the lowest image size parameter, namely 64 pixels.

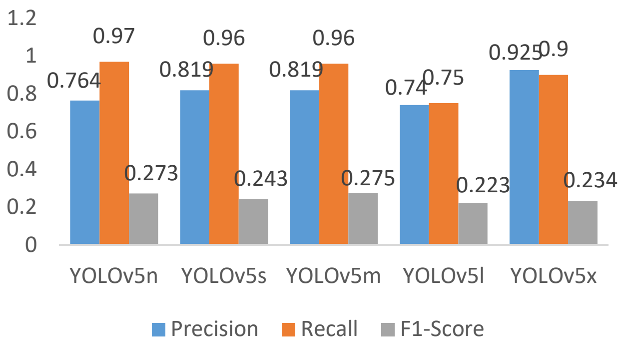

Fig. 3. Comparison Diagram of the Convusion Matrix on the YOLOv5

Before implementing the dataset, the dataset undergoes an augmentation process. In this process, the dataset gets reproduced by rotating images by 90 degrees, 180 degrees, and 270 degrees, scaling them by 200%, and adding noise by 50%. Fig. 4 shows an example of the augmentation process carried out. Based on Fig. 4, the original image undergoes rotation by 90 degrees and 270 degrees. Then the image is also scaled by 200%. Finally, added noise of 50%.

The test was carried out by comparing the performance of the object detection system on two devices with different specifications and running the object detection system with several image size parameters, namely 256x320 pixels and 128x128 pixels. Testing on both sizes of these image parameters is used as a reference because the Raspberry Pi device cannot run the detection system at an image size of 640x640 pixels.

In testing the accuracy of the garbage object classification system using the Convusion Matrix method, the detection system tests all data. Then from each detection result, the number of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) is calculated. The Convusion Matrix method will measure the quality of these four values, providing outputs that can assess them in the form of four parameters: accuracy, precision, recall, and F1-score.

TABLE II. DATA CONVUSION MATRIX TEST (256X320 PIXEL)

Detect : 256x320					
No	Kind of Waste	ACCURACY	PRECISION	RECALL	F1-SCORE
1	Face mask	96%	96%	77%	85%
2	Spoon	96%	89%	80%	84%
3	Tissue	95%	92%	73%	81%
4	Bottle	100%	100%	97%	98%
5	Gloves	98%	88%	100%	94%
6	Antigens	95%	91%	70%	79%
7	Other Garbage	90%	61%	73%	67%
AVERAGE		96%	88%	81%	84%

Based on Table II, the YOLOv5m model has an image size of 256x320 pixels. The average accuracy rate of 96% indicates that the model can recognize the type of waste with a high success rate. In addition, the average precision of 88% indicates that the model tends to give a small amount of error in classifying the type of waste. However, there are variations in classification performance between different waste types. Some types of waste, such as masks, bottles and gloves, have a very high accuracy rate, while other types of waste have a slightly lower accuracy rate.

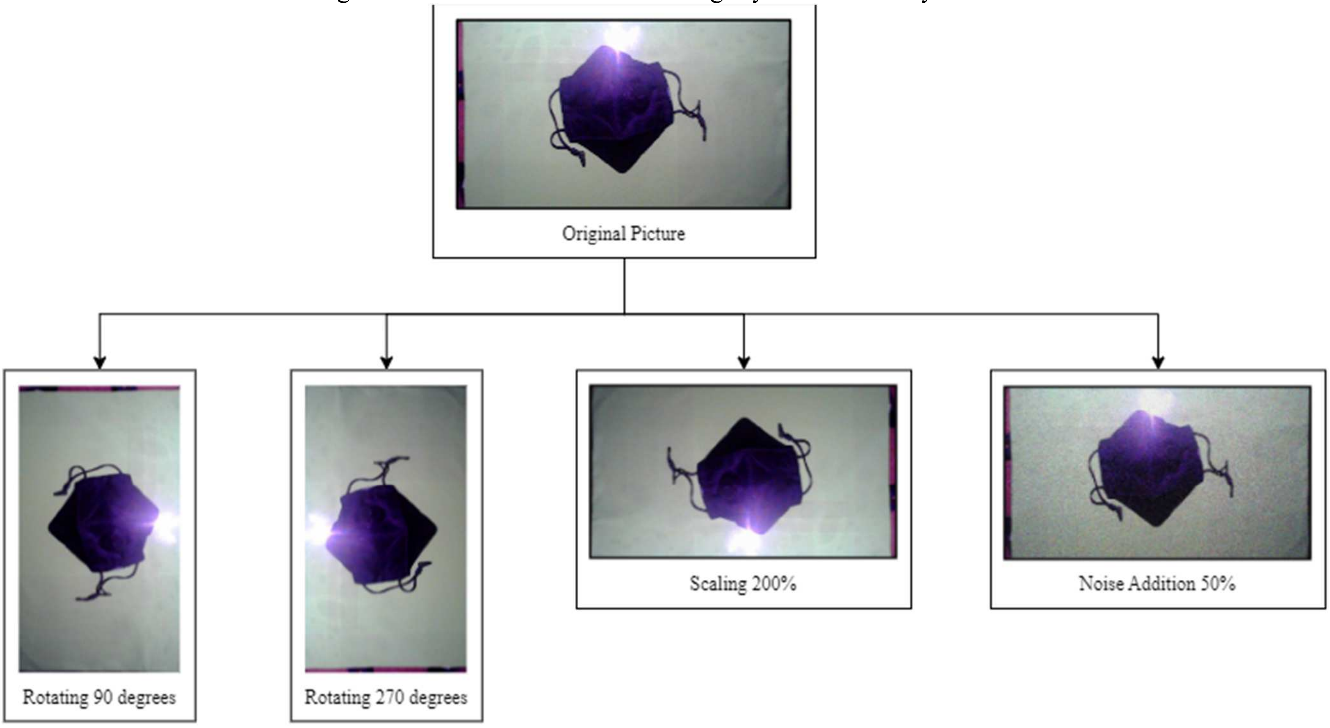

Fig. 4. YOLOv5m Implementation Diagram on Raspberry Pi

Based the Table III, the YOLOv5m model in the garbage object classification system shows a relatively good level of accuracy at an image size of 128x128 pixels, with an average of 85%. However, there are significant differences in classification performance between different types of waste, as spoons and antigens have high accuracy rates, reaching 95% and 94%, respectively. However, other types of waste, such as masks, tissues, gloves and other waste, have a lower accuracy rate, with a figure below 90%.

TABLE III. DATA CONVUSION MATRIX TEST(128X128 PIXEL)

Detect : 128x128					
No	Kind of Waste	ACCURACY	PRECISION	RECALL	F1-SCORE
1	Face mask	88%	58%	63%	60%
2	Spoon	95%	83%	80%	81%
3	Tissue	89%	63%	50%	56%
4	Bottle	91%	80%	53%	64%
5	Gloves	55%	24%	100%	39%
6	Antigens	94%	78%	82%	81%
7	Other Garbage	86%	50%	17%	25%
AVERAGE		85%	62%	64%	58%

In addition to accuracy, the level of precision, recall, and F1-score also provide an overview of classification performance. The average precision of 62% indicates that the model provides accurate results in recognizing some types of waste, such as spoons, but tends to have a higher error rate for other types of waste. The average recall rate of 64% indicates the model's ability to recognize garbage objects as a whole, although there are variations in the recall rate between different types of waste. The average F1-score of 58% illustrates the balance between precision and recall in classifying garbage objects.

Based on testing between image sizes of 256x320 pixels and 128x128 pixels on the Yolov5m model, there is a significant decrease in the accuracy of the classification of garbage objects. At an image size of 256x320 pixels, the model achieves an average accuracy rate of 96%, while at an image size of 128x128 pixels, the average accuracy rate drops to 85%. It shows a significant effect of decreasing image resolution on classification performance. In addition, there is a difference in accuracy for certain types of waste between the two image sizes. For example, types of waste such as masks, tissues, gloves, and others have a lower accuracy rate at 128x128 pixels compared to 256x320 pixels.

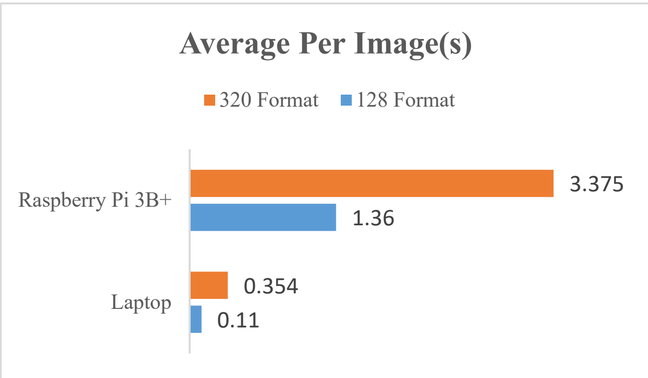

Fig. 5. Computational Time Per Image Test Result Diagram

C. *Computational Time Test Results*

Computational Time testing was conducted on two devices, a Laptop and Raspberry Pi Model 3B+, using 10

Images for each garbage object. The purpose of testing on two different devices is to determine the effect of device architecture and specifications on the computing speed of the garbage object detection system. Fig. 5 shows the diagram of the results of the average object detection time per 1 image. The test results obtained on the Raspberry Pi device showed a computation time of 1.36 seconds for a size of 128x128 pixels and 3.375 seconds for a size of 256x320 pixels. Meanwhile, the computing time on laptop devices is 0.11 seconds at a size of 128x128 pixels and 0.354 seconds at a size of 256x320 pixels.

IV. Conclusion

In this study, YOLOV5 method was applied to detect waste object. From the results of testing process of the waste object classification system, it can be concluded that higher-resolution images (256x320 pixels) generally yield better detection performance for waste objects, with improved accuracy, precision, recall, and F1-score. However, if computational speed is a crucial factor, using smaller pixels (128 format) can provide a substantial increase in detection speed, albeit at the cost of reduced accuracy and precision, particularly for smaller and more complex objects like "Glove". With the development of a new framework for sorting waste, it is expected to be an alternative method that can be applied by other researchers in waste classification.

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References

[1] S. K. Tripathi and M. D. Fruits, “Time to Modify Operating Software (OS), Database (DB) and TCP/IP Protocols for Data Trash Elimination, Based on User Defined Shelf Life of Data,” *Int. J. Comput. Eng. Technol.*, vol. 10, no. 1, pp. 138–156, 2019.

[2] X. Shen, B. Chen, M. Leibrecht, and H. Du, “The Moderating Effect of Perceived Policy Effectiveness in Residents’ Waste Classification Intentions: A Study of Bengbu, China,” *Sustain.*, vol. 14, no. 2, 2022, doi: 10.3390/su14020801.

[3] S. Dharmaraj *et al.*, “The COVID-19 pandemic face mask waste: A blooming threat to the marine environment,” *Chemosphere*, vol. 272, p. 129601, 2021, doi: 10.1016/j.chemosphere.2021.129601.

[4] A. S. Luyt and S. S. Malik, *Can biodegradable plastics solve plastic solid waste accumulation?* Elsevier Inc., 2018.

[5] J. Wang *et al.*, “Disinfection technology of hospital wastes and wastewater: Suggestions for disinfection strategy during coronavirus Disease 2019 (COVID-19) pandemic in China,” *Environ. Pollut.*, vol. 262, p. 114665, 2020, doi: 10.1016/j.envpol.2020.114665.

[6] T. Chowdhury, H. Chowdhury, M. S. Rahman, N. Hossain, A. Ahmed, and S. M. Sait, “Estimation of the healthcare waste generation during COVID-19 pandemic in Bangladesh,” *Sci. Total Environ.*, vol. 811, p. 152295, 2022, doi: 10.1016/j.scitotenv.2021.152295.

[7] J. Peng, X. Wu, R. Wang, C. Li, Q. Zhang, and D. Wei, “Medical waste management practice during the 2019-2020 novel coronavirus pandemic: Experience in a general hospital,” *Am. J. Infect. Control*, vol. 48, no. 8, pp. 918–921, 2020, doi: 10.1016/j.ajic.2020.05.035.

[8] Y. T. Tesfaldet, N. T. Ndeh, J. Budnard, and P. Treeson, “Assessing face mask littering in urban environments and policy implications: The case of Bangkok,” *Sci. Total Environ.*, vol. 806, p. 150952, 2022, doi: 10.1016/j.scitotenv.2021.150952.

[9] F. C. Mihai, “Assessment of COVID-19 waste flows during the emergency state in romania and related public health and environmental concerns,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 15, pp. 1–18, 2020, doi: 10.3390/ijerph17155439.

[10] D. E. Corpet, “Why does SARS-CoV-2 survive longer on plastic than on paper?,” *Med. Hypotheses*, vol. 146, p. 110429, 2021, doi: 10.1016/j.mehy.2020.110429.

[11] Q. Liu and J. Schauer, “Airborne microplastics from waste as a transmission vector for COVID-19,” *Aerosol Air Qual. Res.*, vol. 21, no. 1, pp. 1–5, 2020, doi: 10.4209/aaqr.2020.07.0439.

[12] H. Zhou *et al.*, “A deep learning approach for medical waste classification,” *Sci. Rep.*, vol. 12, no. 1, pp. 1–9, 2022, doi: 10.1038/s41598-022-06146-2.

[13] B. A. Khan, A. A. Khan, H. Ahmed, S. S. Shaikh, Z. Peng, and L. Cheng, “A Study on Small Clinics Waste Management Practice, Rules, Staff Knowledge, and Motivating Factor in a Rapidly Urbanizing Area,” *Int. J. Environ. Res. Public Health*, vol. 16, no. 20, pp. 1–15, 2019, doi: 10.3390/ijerph16204044.

[14] C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, “A smart municipal waste management system based on deep-learning and Internet of Things,” *Waste Manag.*, vol. 135, no. January, pp. 20–29, 2021, doi: 10.1016/j.wasman.2021.08.028.

[15] T. J. Sheng *et al.*, “An Internet of Things Based Smart Waste Management System Using LoRa and Tensorflow Deep Learning Model,” *IEEE Access*, vol. 8, pp. 148793–148811, 2020, doi: 10.1109/ACCESS.2020.3016255.

[16] A. B. Wahyutama and M. Hwang, “YOLO-Based Object Detection for Separate Collection of Recyclables and Capacity Monitoring of Trash Bins,” *Electron.*, vol. 11, no. 9, 2022, doi: 10.3390/electronics11091323.

[17] M. Chiriboga *et al.*, “Rapid DNA origami nanostructure detection and classification using the YOLOv5 deep convolutional neural network,” *Sci. Rep.*, vol. 12, no. 1, pp. 1–13, 2022, doi: 10.1038/s41598-022-07759-3.

[18] A. Aboah, M. Shoman, V. Mandal, S. Davami, Y. Adu-Gyamfi, and A. Sharma, “A Vision-based System for Traffic Anomaly Detection using Deep Learning and Decision Trees,” *IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work.*, pp. 4202–4207, 2021, doi: 10.1109/CVPRW53098.2021.00475.

[19] J. Yao, J. Qi, J. Zhang, H. Shao, J. Yang, and X. Li, “A Real-Time Detection Algorithm for Kiwifruit Defects Based on YOLOv5,” *Electron.*, vol. 10, no. 14, 2021, doi: 10.3390/electronics10141711.

[20] U. Nepal and H. Eslamiat, “Comparing YOLOv3, YOLOv4 and YOLOv5 for Autonomous Landing Spot Detection in Faulty UAVs,” *Sensors*, vol. 22, no. 2, pp. 1–15, 2022, doi: 10.3390/s22020464.

[21] Z. Wang, L. Wu, T. Li, and P. Shi, “A Smoke Detection Model Based on Improved YOLOv5,” *Mathematics*, vol. 10, no. 7, 2022, doi: 10.3390/math10071190.

[22] D. Hu, J. Zhu, J. Liu, J. Wang, and X. Zhang, “Gesture recognition based on modified Yolov5s,” *IET Image Process.*, vol. 16, no. 8, pp. 2124–2132, 2022, doi: 10.1049/ipr2.12477.

[23] I. Hermawan, A. Kurniawan, R. Hanafi, A. Fierelio Sumarsono Kinandes, and M. Arlan Ardiawan, “Rancang Bangun Alat Mobile Smart Trash Bin Menggunakan Raspberry Pi,” *J. Politek. Caltex Riau*, vol. 9, no. 1, pp. 19–30, 2023.

[24] P. Oza, P. Sharma, S. Patel, F. Adedoyin, and A. Bruno, “Image Augmentation Techniques for Mammogram Analysis,” *J. Imaging*, vol. 8, no. 5, pp. 1–22, 2022, doi: 10.3390/jimaging8050141.

[25] A. Anton, N. F. Nissa, A. Janiati, N. Cahya, and P. Astuti, “Application of Deep Learning Using Convolutional Neural Network (CNN) Method For Women’s Skin Classification,” *Sci. J. Informatics*, vol. 8, no. 1, pp. 144–153, 2021, doi: 10.15294/sji.v8i1.26888.

[26] M. Efremova, M. Vento-Tormo, S. A. Teichmann, and R. Vento-Tormo, “CellPhoneDB: inferring cell–cell communication from combined expression of multi-subunit ligand–receptor complexes,” *Nat. Protoc.*, vol. 15, no. 4, pp. 1484–1506, Apr. 2020, doi: 10.1038/s41596-020-0292-x.