E-ISSN: XXXX - XXXX

Networked Knowledge and Research in Informatic

Networked Knowledge and Research in Informatic
Vol. 1 No. 1 (2026) : 32-43
Available online at : https://ejournal.unuja.ac.id/index.php/NKRI

Detection of Sellable Non-Organic Waste Using YOLOv4 Based on Flask Web

Luthfi Nurul Huda [1]
[1] Universitas Amikom Yogyakarta, Indonesia
luthfinurulhuda@students.amikom.ac.id [1]

Doi

Submitted: 01 Sep 2026 Revision: 15 Sep 2026 Accepted: 25 Sep 2026 Published: 30 Sep 2026

Abstract Non-organic waste management in Islamic boarding school environments requires a sorting system that is fast, accurate, and easy to use, particularly for waste types that have selling value. In the Al-Hasyimiyah area of Nurul Jadid Islamic Boarding School, waste sorting has been implemented to help maintain environmental cleanliness and support the reuse of economically valuable waste. However, the sorting process still faces challenges because some students are not yet able to distinguish types of non-organic waste based on category and selling price. This study aims to develop an image-based non-organic waste detection system to estimate selling prices using the You Only Look Once version 4 (YOLOv4) method implemented in a Flask-based web application. The dataset consisted of 1,170 JPG images and one MP4 video with five waste classes: aluminium, mixed plastic container, plastic bottle, plastic cup, and cardboard. The dataset was divided into 819 training data, 234 validation data, and 117 testing data. The research stages included problem identification, dataset collection, preprocessing, image resizing to 416 × 416 pixels, annotation using LabelImg, data splitting, YOLOv4 training, model testing, selling price estimation, and Flask web implementation. The experimental results showed that the best configuration was obtained using batch 64 and max_batches 2500, achieving an mAP of 90.70%, precision of 79%, recall of 89%, and F1-score of 84%. Testing on 251 objects produced 226 detected objects and 25 undetected objects, resulting in an overall accuracy of 90%. The findings indicate that YOLOv4 can be effectively used as a supporting tool for detecting and estimating the selling price of non-organic waste.

Keywords *Computer Vision; Flask; Non-Organic Waste; Price Estimation; YOLOv4*

1. INTRODUCTION

Waste is one of the environmental problems that continues to increase along with human activities. Non-organic waste requires special attention because it is difficult to decompose naturally and needs more directed management. Waste types such as plastic, aluminium, cardboard, and metal materials can cause negative impacts when left unmanaged, but they may also have economic value when properly sorted and processed. Therefore, non-organic waste management needs to be carried out through a more innovative, educational, and sustainable approach (Ramadhani et al., 2021). In the Al-Hasyimiyah area of Nurul Jadid Islamic Boarding School, waste management is an important part of maintaining cleanliness, health, and the beauty of the dormitory environment. Since November 2021, the Al-Hasyimiyah area has implemented a waste sorting system to separate sellable waste from waste that must be discarded. Sellable waste can be reused, sold, and the proceeds can support regional cleaning needs. However, the implementation of waste sorting still faces challenges because not all students understand the differences among non-organic waste types based on category and selling price.

Sellable non-organic waste in the Al-Hasyimiyah area is classified into five types: aluminium, mixed plastic container, plastic bottle, plastic cup, and cardboard. Each type of waste has different visual characteristics and selling prices. When sorting is conducted manually, waste disposal site officers need more time to identify waste types and estimate their selling value. This condition indicates the need for a technology-based support system that can help detect waste types and estimate selling prices more quickly.

The development of computer vision and deep learning provides opportunities to build digital image-based object detection systems. Object detection enables computers to recognize objects in images or videos, determine object classes, and display bounding boxes around detected areas (Aini et al., 2021). Several previous studies have applied deep learning methods for waste identification, such as Faster R-CNN for plastic waste identification (Faizal et al., 2023), Mask R-CNN for detecting organic and non-organic waste based on Flask Web (Ramadhany, 2023), and SSD-MobileNet for real-time waste type detection (Muttaqin & Ramadhan, 2023). YOLOv4 is one of the object detection methods known for its high speed and accuracy. This method processes images in a single detection stage, making it suitable for fast object detection needs. YOLOv4 combines backbone, neck, and head components in an efficient object detection architecture and has been widely used in real-time detection cases (Bochkovskiy et al., 2020). Previous studies have shown that YOLOv4 can be applied to face mask detection with high accuracy (Yu & Zhang, 2021) and household waste detection and classification (Guo et al., 2023).

The research gap addressed in this study lies in the need for a non-organic waste detection system that not only identifies object types but also provides additional information in the form of selling price estimation. Previous studies generally focused on waste classification or object detection, whereas this study integrates YOLOv4 detection results with selling price and estimated object weight information. In addition, the trained model is implemented in a Flask web application so that it can be used more practically by students and waste disposal site officers.

This study aims to develop a sellable non-organic waste image detection system using the YOLOv4 method based on Flask Web. The developed system is expected to help students recognize waste types, support waste disposal site officers in estimating waste selling prices, and improve the efficiency of waste management in the Al-Hasyimiyah area of Nurul Jadid Islamic Boarding School.

2. RESEARCH METHODS

This study used an experimental approach based on deep learning with the YOLOv4 method. The research stages included problem identification and literature study, problem analysis, dataset collection, preprocessing, YOLOv4 implementation, model testing, selling price estimation, Flask web implementation, and conclusion drawing.

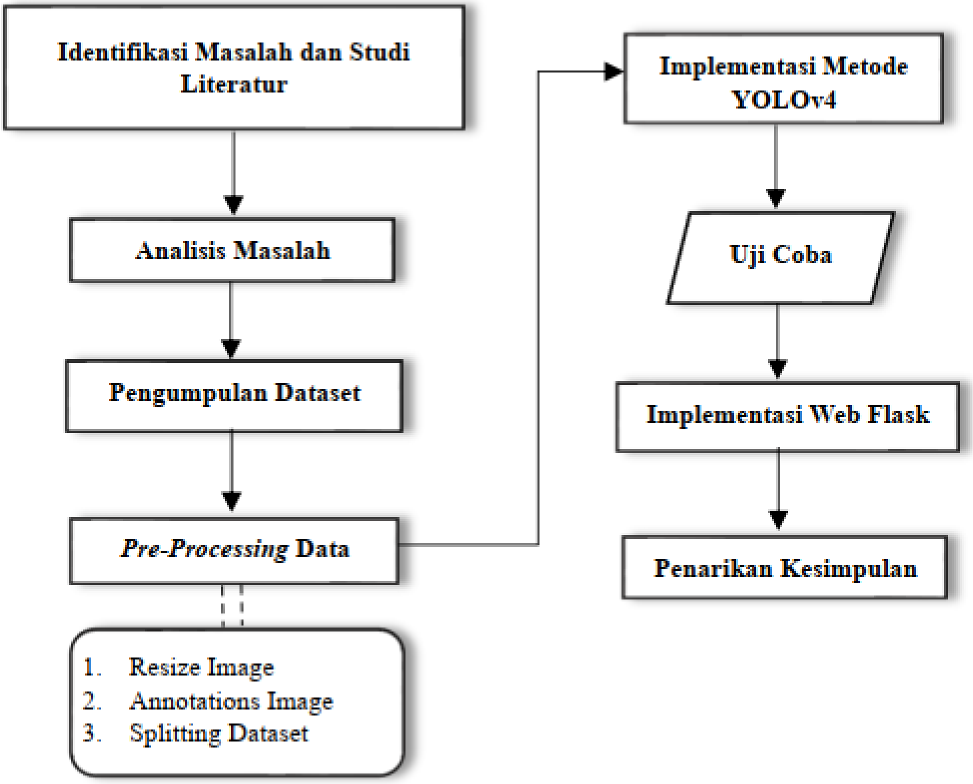


Figure 1. Research Framework

2.1. Research Object and Dataset

The research object was sellable non-organic waste in the Al-Hasyimiyah area of Nurul Jadid Islamic Boarding School. Data were collected by directly capturing images using a Vivo Y21 smartphone and by using datasets from previous research. The total dataset consisted of 1,170 JPG images and one MP4 video. The waste types used in this study consisted of five classes: aluminium, mixed plastic container, plastic bottle, plastic cup, and cardboard. These classes were selected because they are sellable waste types commonly found in the Al-Hasyimiyah area. Room.

Table 1. Sample Dataset of Non-Organic Waste Based on Selling Price

No	Waste Class	Object Examples

1	Aluminium	Cans and iron hangers
2	Mixed Plastic Container	Scoops and plastic buckets
3	Plastic Bottle	Mineral water bottles
4	Plastic Cup	Plastic beverage cups
5	Cardboard	Used cardboard

2.2. Dataset Splitting

The dataset was divided into three parts: training data, validation data, and testing data. Training data were used to train the model, validation data were used to monitor model performance during training, and testing data were used to evaluate the final model performance on unseen data.

Table 2. Dataset Splitting

Data Type	Percentage	Number of Data
Training	70%	819 images
Validation	20%	234 images
Testing	10%	117 images and 1 video
Total	100%	1,170 images and 1 video

2.3. Preprocessing and Annotation

Preprocessing was conducted to ensure that all images were ready for YOLOv4 training. The first stage was image resizing, which changed the image size to 416 × 416 pixels. This size was selected because it matches the YOLOv4 input requirement and can help accelerate the computational process. The next stage was image annotation using LabelImg. At this stage, each waste object was given a bounding box and class label according to its type. The annotation results were saved in TXT format according to the YOLO standard. After the annotation process was completed, the dataset was divided into training, validation, and testing folders.

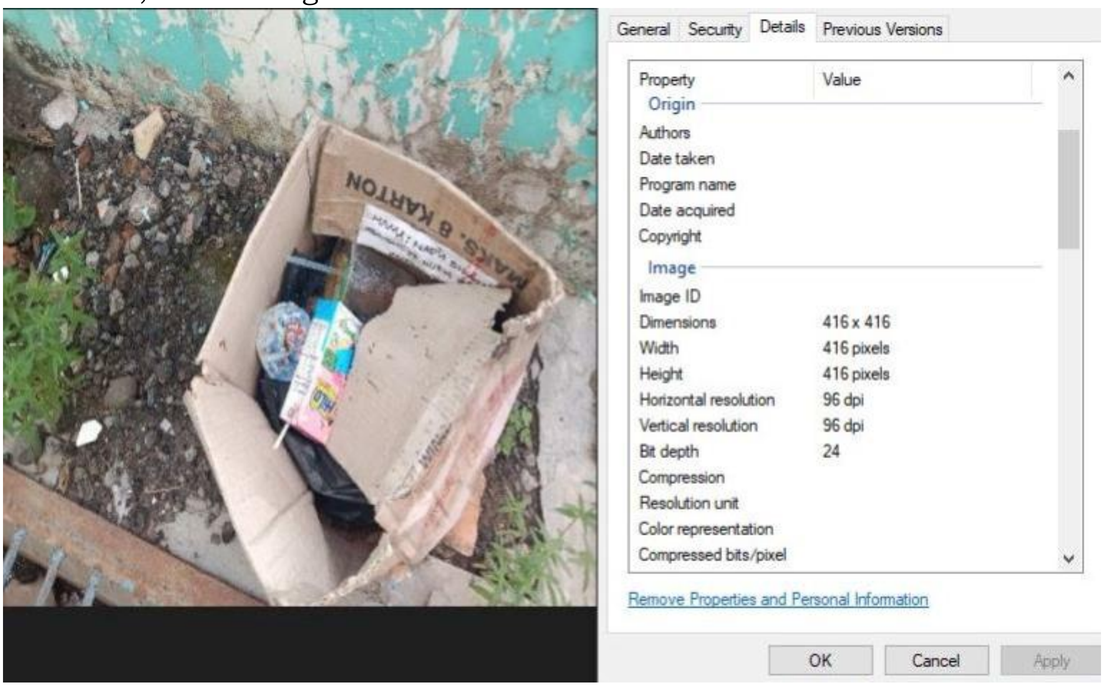


Figure 3. Dataset Image Resizing Process

Figure 4. Dataset Annotation Process Using LabelImg

2.4. YOLOv4 Implementation

YOLOv4 implementation was carried out using Google Colaboratory with GPU support. The dataset and configuration files were stored in Google Drive and connected to Google Colaboratory. The implementation process included cloning the Darknet repository, modifying the Makefile to support GPU and OpenCV, copying configuration files, copying obj.names and obj.data files, and downloading the initial YOLOv4 weights. The model was trained using the pre-trained yolov4.conv.137 file. Training was performed using several combinations of batch and max_batches parameters to obtain the best configuration. The best parameters were selected based on average loss, precision, recall, F1-score, and mAP.

Table 3. Basic YOLOv4 Implementation Configuration

Component	Description
Method	YOLOv4
Detection framework	Darknet
Training platform	Google Colaboratory
Web implementation tool	Visual Studio Code
Web framework	Flask
Input image size	416 × 416 pixels
Number of classes	5 classes
Initial weights	yolov4.conv.137

2.5. Price and Weight Estimation

In addition to detecting objects, the system also displays estimated weight and selling price for each waste object. The estimation was performed using a price list per kilogram and an estimated number of objects per kilogram for each category. With this approach, the system can calculate the estimated price per object based on the detected waste type.

Table 3. Basic YOLOv4 Implementation Configuration

Waste Class	Price per Kg	Estimated Number of Objects per Kg	Estimated Weight per Object	Estimated Price per Object
Aluminium	Rp10,000	35	28.57 grams	± Rp286

Mixed Plastic Container	Rp1,600	10	100 grams	± Rp160
Plastic Bottle	Rp2,500	65	15.38 grams	± Rp38
Plastic Cup	Rp2,000	130	7.69 grams	± Rp15
Cardboard	Rp1,100	20	50 grams	± Rp55

The estimation is an initial approximation. Actual selling prices may change depending on the physical condition of the waste, real weight, collector policy, and local market prices.

2.6. Model Evaluation

The model was evaluated using precision, recall, F1-score, mAP, and detection accuracy on the testing data. The mAP value was used to evaluate the model's performance in detecting objects across all classes. Meanwhile, testing accuracy was calculated based on the number of successfully detected objects compared with the total number of test objects.

The detection accuracy formula used is as follows.

Accuracy = ∑Testing Data ∑Correct Data×100%

where:

∑Correct Data

represents the number of correctly detected objects, while

∑Testing Data

represents the total number of objects in the testing data.

2.7. Flask Web Implementation

After the model was trained and tested, the system was implemented in a web application using Flask. The application was designed to allow users to upload waste images, after which the system displays detection results including waste class, confidence score, estimated weight, and estimated selling price. This implementation aims to make the model easier for students and waste disposal site officers to use without manually running the code.

3. RESULTS

3.1. Dataset and Preprocessing Results

The dataset used in this study consisted of 1,170 non-organic waste images and one testing video. The images were collected from the Al-Hasyimiyah area and the waste disposal site, so the dataset reflects real field conditions. The dataset consisted of five sellable waste classes: aluminium, mixed plastic container, plastic bottle, plastic cup, and cardboard. The preprocessing process successfully standardized image sizes to 416 × 416 pixels. After that, the images were annotated using LabelImg by assigning bounding boxes to each waste object. The annotated dataset was then divided into training, validation, and testing data. This process produced a dataset ready to be used for YOLOv4 model training.

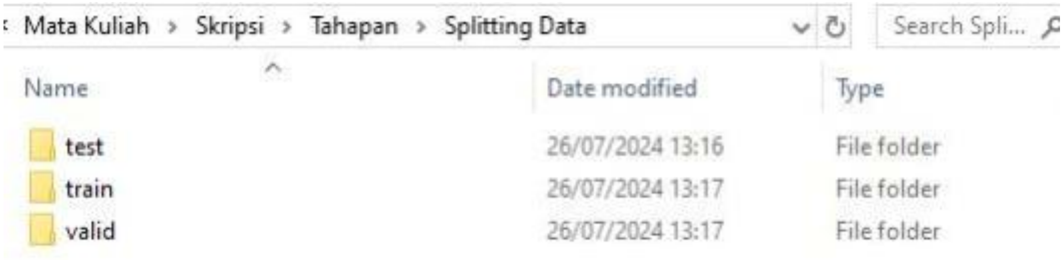


Figure 5. Dataset Splitting Folder

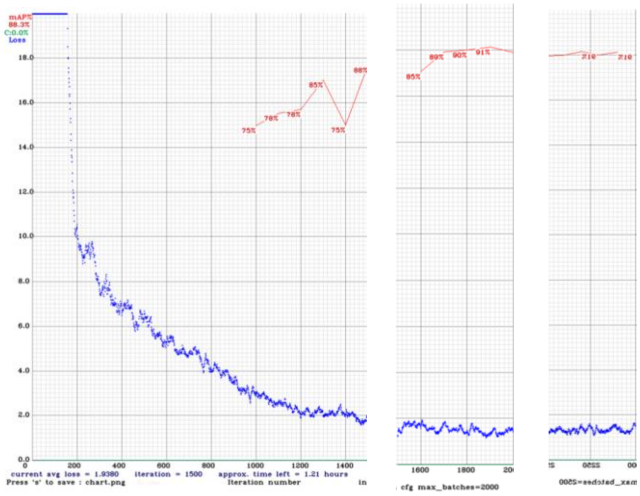
3.2. Training Results

OLOv4 training was conducted using several parameter trials to obtain the best model. The tested parameters included combinations of batch 64 and batch 32 with max_batches 2000 and 2500. The comparison results are shown in Table 5.

Table 5. Summary of YOLOv5 Training Results

No	Parameter	Avg Loss	Time	Precision	Recall	F1-Score	mAP
1	Batch 64, Max_Batches 2000	1.9380	1.42 hours	78%	88%	83%	90.64%
2	Batch 64, Max_Batches 2500	1.1324	2.07 hours	79%	89%	84%	90.70%
3	Batch 32, Max_Batches 2000	2.3012	1.11 hours	72%	83%	77%	82.26%
4	Batch 32, Max_Batches 2500	1.4859	1.22 hours	74%	87%	80%	88.16%

Based on Table 5, the best configuration was obtained using batch 64 and max_batches 2500. This configuration produced the lowest average loss of 1.1324, with an mAP of 90.70%, precision of 79%, recall of 89%, and F1-score of 84%. These values indicate that the model has good detection capability and a reasonably balanced performance between object detection coverage and prediction correctness.



3.3. Detection and Price Estimation Results

The testing results showed that the system was able to detect non-organic waste objects and display additional information in the form of estimated weight and selling price. The displayed information included object class, confidence score, estimated weight, and estimated price per object. These results indicate that the model functions not only as an object detection system but also as a supporting tool for estimating the economic value of waste.

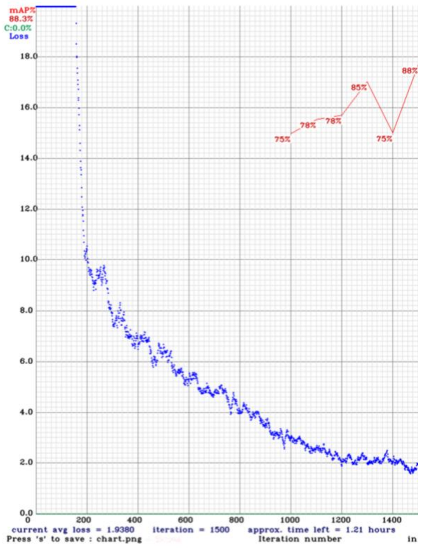


Figure 7. Waste Detection Result with Estimated Price and Weight

During the detection process, confidence scores may differ between testing using Darknet and OpenCV. This difference may occur due to variations in preprocessing, model execution, and post-processing. Therefore, the confidence score is used as an indicator of model certainty, while final decisions may still consider object conditions and officer verification.

3.4. Testing Results

Testing was conducted on 117 testing images containing various non-organic waste objects. From those 117 images, there were 251 test objects. The results showed that 226 objects were successfully detected, while 25 objects were not detected. Thus, the overall detection accuracy reached 90%.

Table 5. Summary of YOLOv5 Training Results

No	Class	Number of Test Objects	Detected	Undetected	Accuracy
1	Aluminium	51	49	2	96%
2	Mixed Plastic Container	10	7	3	70%
3	Plastic Bottle	71	64	7	90%
4	Plastic Cup	107	94	13	87%
5	Cardboard	12	12	0	100%
Total		251	226	25	90%

Based on Table 6, the Cardboard class obtained the highest accuracy of 100%, followed by Aluminium at 96%, Plastic Bottle at 90%, Plastic Cup at 87%, and Mixed Plastic Container at 70%. The lowest accuracy in the Mixed Plastic Container class may be influenced by varied object shapes, image backgrounds, lighting conditions, and visual similarity with other plastic waste types. Overall, the model produced good detection results across the five non-organic waste classes.

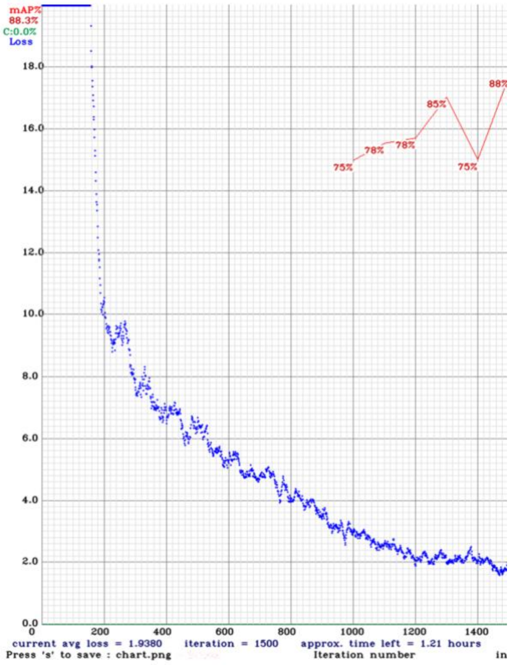


Figure 8. Non-Organic Waste Grouping

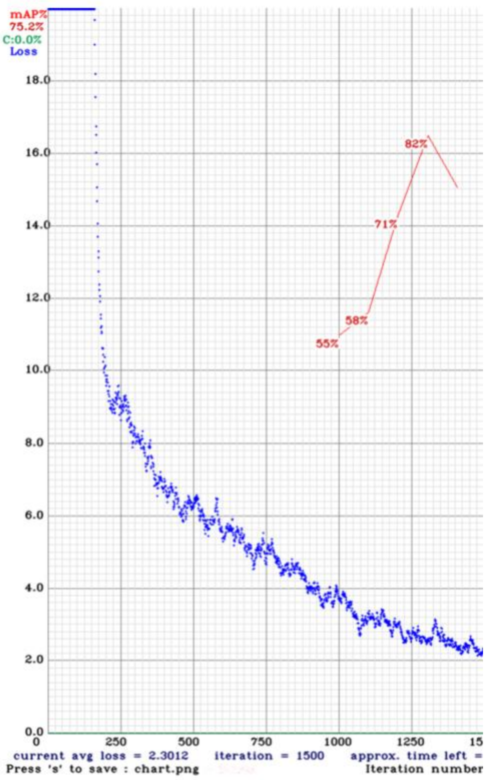


Figure 9. Non-Organic Waste Object Detection Result

3.5. Flask Web Application Results

The trained YOLOv4 model was then implemented in a Flask-based web application. This application provides image upload, image processing, object detection, and estimated selling price display features. Users can upload waste images through the web page, and the system displays the detection results along with class, weight, and estimated price information.

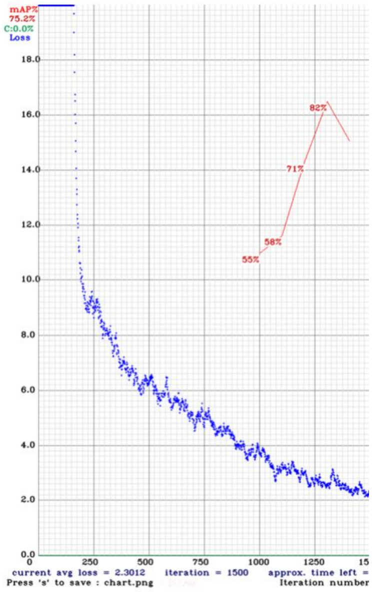


Figure 10. Flask Web Implementation Result

The Flask web implementation shows that the YOLOv4 model can be used in a more practical application form. This system can help students recognize non-organic waste types and assist waste disposal site officers in estimating the selling value of sorted waste. However, the displayed selling price estimation remains supporting information because the actual price can be affected by waste condition, actual weight, and collector pricing.

4. CONCLUSIONS

This study successfully developed a sellable non-organic waste image detection system using the YOLOv4 method integrated with a Flask-based web application. The system was designed to support waste sorting in the Al-Hasyimiyah area of Nurul Jadid Islamic Boarding School by detecting five waste classes: aluminium, mixed plastic container, plastic bottle, plastic cup, and cardboard. The dataset consisted of 1,170 JPG images and one MP4 video. The dataset was divided into 819 training data, 234 validation data, and 117 testing data. The preprocessing process included resizing images to 416 × 416 pixels, annotating images using LabelImg, and splitting data into training, validation, and testing folders. The training results showed that the best parameters were obtained using batch 64 and max_batches 2500, with an average loss of 1.1324, precision of 79%, recall of 89%, F1-score of 84%, and mAP of 90.70%. In the testing stage, out of 251 test objects, 226 objects were successfully detected and 25 objects were not detected, resulting in an overall detection accuracy of 90%. The Cardboard class achieved the highest accuracy of 100%, while the Mixed Plastic Container class obtained the lowest accuracy of 70%. The Flask web implementation enables detection results to be presented more easily through a web interface. The system can display waste class, confidence score, estimated weight, and estimated selling price. Therefore, this system can serve as a supporting tool for non-organic waste management, especially in supporting waste sorting and estimating waste selling value. Future research is recommended to increase dataset variation, add more data to classes with lower accuracy, test the model in other areas, and compare YOLOv4 performance with newer detection models such as YOLOv5, YOLOv8, Faster R-CNN, or SSD. In addition, selling price estimation should be developed using actual weight measurement so that the generated price values become more precise.

5. REFERENCES

Aini, Q., Lutfiani, N., Kusumah, H., & Zahran, M. S. (2021). Deteksi dan pengenalan objek dengan model machine learning: Model YOLO. CESS (Journal of Computer Engineering, System and Science), 6(2), 192. https://doi.org/10.24114/cess.v6i2.25840

Alfarizi, D. N., Pangestu, R. A., Aditya, D., Setiawan, M. A., & Penelitian, M. (2023). Penggunaan metode YOLO pada deteksi objek: Sebuah tinjauan literatur sistematis. Jurnal Sistem dan Teknologi Informasi, 1(1), 54–63.

Arnita, Marpaung, F., Aulia, F., Suryani, N., & Nabila, R. C. (2022). Computer vision dan pengolahan citra digital (A. B. Surya, Ed.). Pustaka Aksara. www.pustakaaksara.co.id

Aziz, F. (2021). Deteksi objek menggunakan metode You Only Look Once (YOLO) untuk identifikasi penyakit padi [Thesis].

Bochkovskiy, A., Wang, C., & Liao, H. M. (2020). YOLOv4: Optimal speed and accuracy of object detection.

Cholissodin, I., & Soebroto, A. A. (2020). AI, machine learning & deep learning: Teori dan implementasi. http://bit.ly/3piOnnU

Darmawan, A. C. (2022). Pengembangan aplikasi berbasis web dengan Python Flask untuk klasifikasi data menggunakan metode Decision Tree C4.5. Jurnal Pendidikan Konseling, 4(5), 5351–5362.

Faizal, L., Yuyun, Y., & Hazriani, H. (2023). Identifikasi sampah plastik menggunakan algoritma deep learning. Jurnal Ilmiah Sistem Informasi dan Teknik Informatika (JISTI), 6(2), 162–171. https://doi.org/10.57093/jisti.v6i2.176

Gunawan, T. S., Ashraf, A., & Riza, B. S. (2020). Development of video-based emotion recognition using deep learning with Google Colab. TELKOMNIKA, 18(5), 2463–2471. https://doi.org/10.12928/TELKOMNIKA.v18i5.16717

Guo, D., Cheng, L., Zhang, M., & Sun, Y. (2023). Garbage detection and classification based on improved YOLOv4. Journal of Physics: Conference Series. https://doi.org/10.1088/1742-6596/2024/1/012023

Holiyanti, R., Sukmawati, Fahmi, I., & Rozikin, C. (2022). Pendeteksi sampah metal untuk daur ulang menggunakan metode Convolutional Neural Network. Jurnal Teknik Informatika dan Sistem Informasi, 8, 261–274. https://doi.org/10.28932/jutisi.v8i1.4492

Mahasin, M., & Dewi, I. A. (2022). Comparison of CSPDarkNet53, CSPResNeXt-50, and EfficientNet-B0 backbones on YOLOv4 as object detector. Jurnal Teknologi Informasi, 2(3), 64–72.

Muttaqin, M. R., & Ramadhan, Y. R. (2023). Deteksi jenis sampah secara realtime menggunakan metode Single Shot Multibox Detector (SSD). Jurnal Mahasiswa Teknik Informatika, 7(3), 1890–1895.

Ramadhani, R. D., Thohari, A. N. A., Kartiko, C., Junaidi, A., & Laksana, T. G. (2021). Optimasi akurasi metode Convolutional Neural Network. Jurnal RESTI, 5(2), 11–12. https://doi.org/10.29207/resti.v5i2.2754

Ramadhany, A. (2023). Deteksi sampah organik dan non-organik menggunakan metode Mask R-CNN untuk mendukung kampanye zero waste di lingkungan Pondok Pesantren Nurul Jadid berbasis Web Flask.

Sihananto, A. N., Muharrom, M., Haromainy, A., Sari, A. P., Mubarrok, A. H., & Ramadhan, D. (2022). Pemilahan jenis sampah menggunakan algoritma CNN. Jurnal Ilmiah Teknologi Informasi, 17.

Yu, J., & Zhang, W. (2021). Face mask wearing detection algorithm based on improved YOLOv4.

Yusup, R. M., Anugrah, A. F., Muslimah, D. D., Widya, M., Permana, N., & Yuliani, S. (2024). Pendeteksian objek menggunakan OpenCV dan metode YOLOv4-Tiny untuk membantu tunanetra. Journal of Computer Science and Information Technology, 1(2), 59–68.