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Prototype Model For Plastic Bottle Waste Detection Using Yolov8s

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ABSTRACT: Plastic bottle waste is one of the most common types of inorganic waste found in the environment and has become a serious environmental problem. Along with the rapid development of artificial intelligence technology, object detection methods based on deep learning can be utilised to automatically detect plastic bottle waste in digital images. This study aims to develop a prototype model for plastic bottle waste detection using the YOLOv8s algorithm. The research method used is descriptive quantitative with several stages including dataset collection, preprocessing, model training, testing, and evaluation. The dataset used consisted of 1001 images of plastic bottle waste obtained independently using a smartphone camera and additional datasets from Kaggle. The dataset was labelled and processed using Roboflow with image resizing to 512×512 pixels and divided into training, validation, and testing datasets. Model training was carried out using the Ultralytics library on Google Colab with parameters of 5 epochs, image size 512×512, and batch size 8. The results showed that the YOLOv8s model was able to detect plastic bottle objects properly in various environmental conditions, backgrounds, and lighting variations. Evaluation results indicated that the model achieved good performance based on precision, recall, mAP50, and mAP50-95 values. Therefore, YOLOv8s can be effectively implemented as a lightweight and real-time object detection model for plastic bottle waste detection.

Keyword : Deep Learning, Object Detection, Plastic Bottle Waste, YOLOv8s, Computer Vision

I. INTRODUCTION

Environmental pollution caused by plastic waste has become one of the major global environmental issues due to its negative impact on ecosystems and human health [1]. Plastic bottle waste is one of the most common types of inorganic waste found in public environments because it is difficult to decompose naturally and can persist in the environment for hundreds of years [2].
Improper plastic waste management can lead to environmental degradation, water pollution, and ecosystem imbalance [3]. Therefore, an effective waste detection and management system is

needed to help identify plastic bottle waste automatically and support environmental cleanliness efforts [4].

Along with the rapid development of computer vision and artificial intelligence technology, object detection methods based on deep learning have shown significant progress in recognising and locating objects in digital images [5].

Deep learning methods have become increasingly popular because they can automatically learn object features from large datasets with high accuracy [6] One of the most widely used object detection algorithms is YOLO (You Only Look Once), which is known for its fast detection speed and strong accuracy in real-time applications [7].

YOLO performs object detection using a single-stage detection mechanism, enabling efficient processing compared to traditional detection approaches [8] Several previous studies have implemented YOLO-based methods for waste detection systems. Rosanti et al. reported that YOLOv8 achieved high accuracy in bottle detection tasks under various testing conditions [9] Ramadhan et al. implemented YOLOv4-tiny for plastic bottle waste detection in water environments and obtained satisfactory real-time detection performance with accuracy ranging from 67% to 80% [3], [4] Purwasih et al. applied YOLOv7 for plastic bottle classification and achieved precision of 93.9%, recall of 91.6%, and mAP50 of 96.5% [5].

Another study conducted by Dwi Prasetya et al. implemented YOLOv8 for waste classification and achieved precision of 0.883 and recall of 0.903 [6] Other studies also showed that YOLO-based models provide efficient object detection performance for various waste classification tasks and environmental monitoring systems [6]

However, most previous studies focused on general waste detection or used heavier object detection models that require higher computational resources [7]. In addition, some models are less suitable for lightweight real-time implementation on devices with limited hardware specifications [8]. Therefore, this research focuses specifically on detecting plastic bottle waste using YOLOv8s, a lightweight variant of YOLOv8 designed for efficient real-time detection with lower computational requirements [7].

his study aims to develop a prototype model for plastic bottle waste detection using YOLOv8s and evaluate its performance in detecting bottle objects under different environmental conditions.

II. RELATED WORK

Research on object detection using deep learning methods has been widely conducted in recent years due to the increasing capability of convolutional neural networks in image processing tasks [9]. YOLO-based algorithms are among the most frequently used methods because they provide a good balance between detection speed and accuracy [10]. Rosanti et al. implemented YOLOv8 for bottle classification and reported that the model achieved 100% detection accuracy under certain image distance conditions [11]. Ramadhan et al. used YOLOv4-tiny for detecting plastic bottle waste in water environments and obtained detection accuracy ranging from 67% to 80% with efficient real-time performance [4]. Purwasih et al. implemented YOLOv7 for plastic bottle classification and achieved precision of 93.9%, recall of 91.6%, and mAP50 of 96.5% [12]. Another study conducted by Dwi Prasetya et al. used YOLOv8 for waste classification and obtained precision of 0.883 and recall of 0.903 [13]. Research conducted by Redmon et al. also showed that YOLO-based methods provide faster object detection performance compared to region-based detection approaches [14]. In addition, Bochkovskiy et al. developed YOLOv4, which improved object detection performance through optimisation of convolutional neural network architectures [10]. Jocher et al. further introduced YOLOv8 as an advanced object detection model with improved efficiency and lightweight implementation capabilities [15]. Based on these previous studies, YOLO algorithms have proven effective in object detection tasks, especially for waste detection systems [16]. However, most previous research focused on broader waste categories or required higher computational resources [17]. Therefore, this study specifically applies YOLOv8s as a lightweight object detection model for real-time plastic bottle waste detection.

III. METHOD

In this study, bottle waste detection was performed using the YOLOv8s method to recognize bottle objects in digital images. The dataset in this study was systematically processed through several stages, starting with data collection and input, dataset labeling, dataset size adjustment, dataset division, model design and training, and analysis of the prediction results.

A. Research Object

In this study, images of plastic bottle waste were used as research data to detect bottle objects using the YOLOv8s method. The dataset used was obtained through a data collection process taken directly using a mobile phone camera independently and from Kaggle dataset sources. The dataset collection was carried out in May 2026. The total number of datasets used in this study was 1001 images of plastic bottle waste.

The dataset is then labeled, resized, and divided into three parts: training data, validation data, and testing data. At this stage, the collected dataset is further separated into training, validation, and testing data. The labeling, resizing, and dataset division processes are performed using the Roboflow library to ensure proportional and structured data distribution automatically. Through this process, the dataset is automatically labeled, resized, and separated into three main folders: train, val, and test, which are then used in the training and evaluation process of the detection model.

B. Tools and Materials

he tools that will be used in this research consist of hardware and software which will be explained in the following table:

Tabel 1. Research tools and materials

No	Type of Tool	Name/spesification	Information
1	Hardware	*Handphone* Redmi 10 2022 Storage 4/64 GB	Used for image/picture capture
2	Hardware	Leptop	Used for the training and testing process of the YOLOv8s Algorithm.
3	Software	Processor: Intel Corei5 Memory: 8192MB RAM GPU: NVIDIA GeForce Sistem: Windows 10 Pro 64-bit	The main operating system used

		Python 3.11.0 Google colab Ultralitic	
4	Dataset	image of plastic bottle waste	used for detection

C. *Research Stages*

The research will be conducted in stages, from data collection to analysis of the results. The research stages can be seen in the following image:

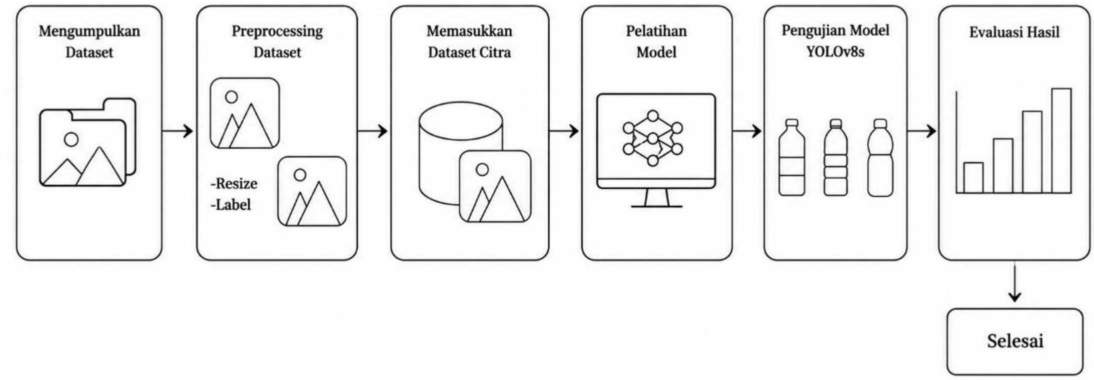

Figure 1. Research stages

1. Collecting Dataset

This research will begin with the stage of collecting a dataset of plastic bottle waste images. The dataset is obtained by taking photos directly using a cellphone camera, under various environmental conditions. Therefore, at this stage, the plastic bottle waste images are photographed together with various other objects in the surrounding area so that the collected data can train the detection model. An example of a plastic bottle waste image dataset can be seen in Figure 2.

Figure 2. Image of Plastic Bottle Waste

2. Insert Image Dataset

In this stage, researchers will input the image dataset into the detection program to demonstrate the initial data processing process. The collected dataset will then be fed into a previously created detection system or program. At this stage, the dataset is prepared for use by the YOLOv8s model.

3. Preprocessing

In the preprocessing stage, the plastic bottle waste image is resized to 512x512 pixels to standardize the model's input dimensions. Furthermore, the plastic bottle object labeling process is also carried out using the Roboflow platform so that the model can recognize the object's position in the image. In the preprocessing stage, the image size is changed from the initial resolution of

3048x4064 pixels to 512x512 pixels so that the dimensions of the entire image are uniform according to the needs of the YOLOv8s model. In addition to the resizing process, object labeling is also carried out by annotating the plastic bottle parts using a bounding box. This process aims to enable the model to recognize the location and shape of objects during the training process. The results of this preprocessing and labeling are then used as the main dataset in the training and evaluation process of the plastic bottle waste detection model.

4. Model Training

During the model training phase, the training process was carried out using the YOLOv8s method, utilizing the Ultralytics library within the Google Colab environment. The pre-prepared dataset—formatted for YOLO—was used and configured via the `data.yaml` file. The training parameters employed included the number of epochs, input image size, and batch size.

5. YOLOv8s Model Testing

The next stage is testing using the YOLOv8s model, which is the core of this prototype. It involves testing the dataset using the YOLOv8s algorithm. At this stage, the model detects plastic bottle objects by displaying a bounding box, a "bottle" class label, and a confidence score. These detection results are used to assess the model's performance in automatically recognizing and localizing plastic bottles.

6. Evaluation of Result

The results evaluation phase is conducted after the YOLOv8s model testing process is complete. At this stage, the performance of the plastic bottle detection model is analyzed based on several key parameters, such as detection accuracy, confidence score, and the model's ability to detect plastic bottles under various environmental conditions. The evaluation also includes observations of detection errors, such as undetected bottles. Furthermore, the model's speed is analyzed to ensure the system's ability to operate in real time. The evaluation results are then used as a basis for assessing the capabilities of the developed prototype and as considerations for making improvements or further developments to make the plastic bottle waste system more accurate and efficient.

Figure 2. Images of fresh and unfresh tilapia eyes

IV. RESULT AND DISCUSSION

1. Model Training

The model training results are displayed graphically, with evaluation values such as precision, recall, mAP50, and mAP50-95 for each training epoch. These values are used to determine the model's ability to accurately recognize bottles. The YOLOv8s model training results can be seen in Figure 3. below.

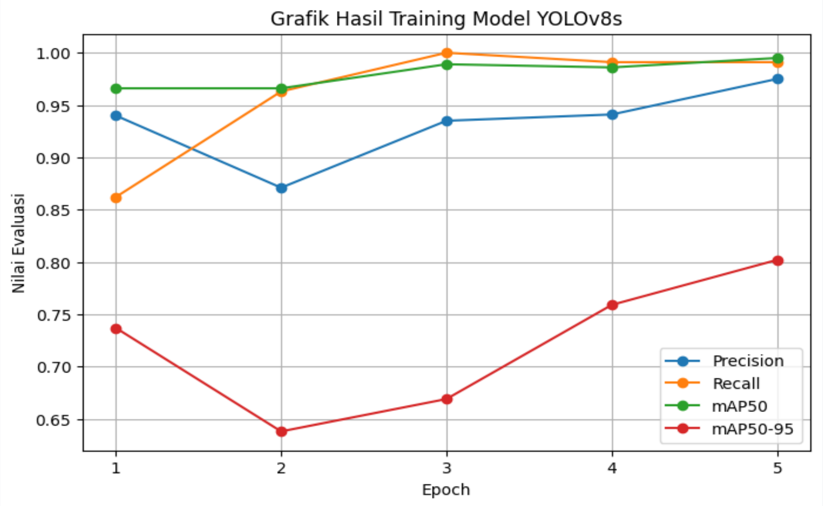

Figure 3. Graph of YOLOv8s model training results

Figure 3. shows a graph of the YOLOv8s model training results conducted over 5 epochs. The graph displays the development of model evaluation values in the form of precision, recall, mAP50, and mAP50-95 at each epoch during the training process. Based on the graph, the model's performance has improved at each epoch. The precision and recall values indicate the model's ability to detect plastic bottle waste objects with a high level of accuracy. In addition, the mAP50 and mAP50-95 values also increased, reaching the best results at the 5th epoch. These results indicate that the YOLOv8s model is able to learn object patterns well and produces optimal detection performance on the used dataset.

2. Object Detection Result

After the model testing process is complete, the detection results for plastic bottle waste objects are displayed in the form of image visualizations using the Python library. This visualization aims to facilitate observation of the YOLOv8s model's prediction results for each preprocessed test image. Through this visualization process, the model's prediction results for plastic bottle waste objects can be analyzed based on the bounding box and detection results for each test image. The YOLOv8s prediction results can be seen in Figure 4. below.

Figure 4. Object detection results

Figure 4.4 shows that the YOLOv8s model is capable of detecting plastic bottle waste objects in several test images by assigning bounding boxes, object class labels, and confidence scores to each detected object. Based on these test results, most plastic bottle objects were successfully recognized despite varying background conditions, positions, and lighting. The displayed confidence scores indicate the model's confidence level in the detected objects.

Furthermore, the detection results indicate that the model is capable of automatically recognizing more than one bottle object in a single image. However, some images still have low confidence values due to small object size, unclear object position, or complex environmental conditions. Overall, the test results indicate that the YOLOv8s model can be used to detect plastic bottle waste quite well under various image conditions.

3. Prediction Result Analysis

The following are the results of testing the YOLOv8s model on previously prepared test data. At this stage, the model automatically performs a prediction process to detect plastic bottle objects in each test image. The prediction results display the number of objects detected, the image size used in the inference process, and the time required for the model to detect each image.

This prediction output is used to determine the YOLOv8s model's ability to recognize plastic bottles in various image conditions, including single objects, multiple objects, and images without plastic bottles. Furthermore, the test results also demonstrate the model's detection speed during the inference process. The results of the prediction analysis can be seen in Table 2. below.

Table 2. Prediction results

No	Keterangan	Jumlah
1	Jumlah botol terdeteksi	205
2	Jumlah botol tidak terdeteksi	54
3	Jumlah botol sebenarnya	259

Table 2. shows that the YOLOv8s model used to detect plastic bottle waste successfully detected 205 bottles out of a total of 259 bottles actually found in the test dataset. Based on these results, there were 54 bottles that were not detected by the system. These test results indicate that the model has quite good detection capabilities with an accuracy rate of around 79.15% in recognizing plastic bottle objects in the test images. However, there were still several objects that were not

detected, which were likely caused by factors such as lighting, object position, the size of the bottle being too small, or unclear image conditions.

V. CONCLUSION

Based on the research results, it can be concluded that the YOLOv8s method can be used to automatically detect plastic bottle waste objects in digital images. The research process began with dataset collection, preprocessing, data labeling, dataset division, model training, and the testing and evaluation stages of the detection results. The dataset used consisted of 1,001 images of plastic bottle waste obtained through self-capture using a mobile phone camera and from Kaggle dataset sources. In the preprocessing stage, all images were resized to 512x512 pixels and object labeling was performed using the Roboflow platform to ensure the model could accurately recognize the position of the plastic bottle objects. The dataset was then divided into 70% training data, 15% validation data, and 15% testing data to support the model's training and evaluation processes proportionally.

The training results showed that the YOLOv8s model experienced improved performance at each epoch based on precision, recall, mAP50, and mAP50-95 values. During the testing phase, the model successfully detected most plastic bottle objects under various image conditions, including lighting, object position, and background. Based on the evaluation results, 205 bottles were successfully detected out of a total of 259 actual bottles, achieving an accuracy rate of 79.15%.

These results indicate that the YOLOv8s method is quite effective in automatic plastic bottle waste detection systems. However, some objects were not detected due to small size, unclear position, and complex environmental conditions. Overall, this study demonstrates the potential application of YOLOv8s as a solution in the development of computer vision-based plastic bottle waste detection systems.

REFERENCE

[1] Z. Aromi, O. A. Putri, and R. Rahayu, “Pengelolaan Sampah Plastik di Kota-kota Indonesia,” *Jurnal Ekologi, Masyarakat dan Sains*, vol. 5, no. 2, pp. 251–255, Dec. 2024, doi: 10.55448/5f7d0846.

[2] Alfarros Amar Amanu, Alya Puspita Zahrani, Fitrin Aeni Ristaatin, Alfin Riski Ardillah, and Denny Oktavina Radianto, “Pengaruh Limbah Mikroplastik Terhadap Organisme dan Upaya Penanganannya,” *Manufaktur: Publikasi Sub Rumpun Ilmu Keteknikan Industri*, vol. 2, no. 2, pp. 12–24, May 2024, doi: 10.61132/manufaktur.v2i2.293.

[3] N. Trisnawati, Y. N. E. Putri, N. T. Rahma, E. M. Sari, and A. T. Yulinda, “Pelatihan daur ulang sampah botol plastik menjadi celengan di desa air hitam kabupaten mukomuko,” *Jurnal Ilmiah Mahasiswa Kuliah Kerja Nyata (JIMAKUKERTA)*, vol. 2, no. 1, pp. 153–159, Jan. 2022, doi: 10.36085/jimakukerta.v2i1.2542.

[4] A. Ramadhanu and H. Syahputra, “Pengenalan teknologi pengolahan citra digital (digital image processing) untuk santri di rahmatan lil’alamin international islamic boarding school,” *Communnity Development Journal*, vol. 3, no. 2, pp. 1239–1244, 2022.

[5] O. Purwasih, W. Widhiarso, and M. R. Pribadi, “Bulletin of computer science research Klasifikasi Citra Sampah Botol Plastik Jenis HDPE dan PET Menggunakan Algoritma YOLOv7,” *Media Online)*, vol. 5, no. 4, pp. 714–723, 2025, doi: 10.47065/bulletincsr.v5i4.654.

[6] B. Dwi Prasetya, E. Putri Amalia, P. Devita Juliana, and R. Kumalasari Niswatin, “Implementasi Object Detection Berbasis Web untuk Klasifikasi Jenis Sampah Menggunakan YOLOv8,” 2025.

[7] S. Kako *et al.*, “Remote sensing and image analysis of macro-plastic litter: A review,” *Mar. Pollut. Bull.*, vol. 222, p. 118630, Jan. 2026, doi: 10.1016/j.marpolbul.2025.118630.

[8] R. Prateep Na Talang and S. Sirivithayapakorn, “Environmental and financial assessments of open burning, open dumping and integrated municipal solid waste disposal schemes among different income groups,” *J. Clean. Prod.*, vol. 312, p. 127761, Aug. 2021, doi: 10.1016/j.jclepro.2021.127761.

[9] F. Xiao, H. Wang, Y. Li, Y. Cao, X. Lv, and G. Xu, “Object Detection and Recognition Techniques Based on Digital Image Processing and Traditional Machine Learning for Fruit and Vegetable Harvesting Robots: An Overview and Review,” *Agronomy*, vol. 13, no. 3, p. 639, Feb. 2023, doi: 10.3390/agronomy13030639.

[10] Z. Huangfu, S. Li, and L. Yan, “Ghost-YOLO v8: An Attention-Guided Enhanced Small Target Detection Algorithm for Floating Litter on Water Surfaces,” *Computers, Materials & Continua*, vol. 80, no. 3, pp. 3713–3731, 2024, doi: 10.32604/cmc.2024.054188.

[11] N. Rosanti, R. Latifah, S. Munir, and I. A. Q. Maududi, “Pengaruh Jarak Objek Citra pada Model Deteksi dan Klasifikasi Botol Plastik menggunakan YOLO,” *Jurnal Teknologi Terpadu*, vol. 10, no. 1, pp. 63–69, Jul. 2024, doi: 10.54914/jtt.v10i1.1247.

[12] P. Objek Merek Sampah Botol Plastik Heru Purwantoro, T. Al Mudzakir, and S. L. Arum Puspita, “Penerapan Algoritma YoloV5 Dalam,” no. 1, p. 18, 2024, [Online]. Available: www.makesense.ai

[13] B. Dwi Prasetya, E. Putri Amalia, P. Devita Juliana, and R. Kumalasari Niswatin, “Implementasi Object Detection Berbasis Web untuk Klasifikasi Jenis Sampah Menggunakan YOLOv8,” 2025.

[14] H. Wu *et al.*, “Weak surface defect detection for production-line plastic bottles with multi-view imaging system and LFF YOLO,” *Opt. Lasers Eng.*, vol. 181, p. 108369, Oct. 2024, doi: 10.1016/j.optlaseng.2024.108369.

[15] J. Pei, S. Li, and Y. Li, “A real-time surface defects detection model via dual-branch feature extraction and dynamic multi-scale fusion attention,” *Digit. Signal Process.*, vol. 152, p. 104582, Sep. 2024, doi: 10.1016/j.dsp.2024.104582.

[16] “Implementasi Algoritma Pengolahan Citra Digital untuk Perbaikan Kualitas Gambar”.

[17] A. M. Metry, M. S. Mostafa, and H. M. Ebied, “Evaluating YOLOv8 Variants for Object Detection in Satellite Image,” *International Journal of Intelligent Computing and Information Sciences*, vol. 25, no. 2, pp. 18–31, Jun. 2025, doi: 10.21608/ijicis.2025.374419.1387.