

Implementation of Organic and Inorganic Waste Detection Modeling in School Waste Bins Using Yolov11

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Waste management in the school environment poses a significant challenge due to the high volume of mixed organic and inorganic waste, which hinders the recycling process. The utilization of object detection technology can offer a solution. However, previous studies employed older YOLO architectures, which still have room for improvement. This research aims to implement a detection model to differentiate between organic and inorganic waste within the school environment, with a focus on the implementation of the YOLOv11 architecture. The method used is a Convolutional Neural Network (CNN) featuring the YOLOv11 architecture, utilizing a public dataset from Kaggle that is divided into 7 waste classes. The research stages include image preprocessing, image augmentation, and dataset partitioning using Stratified K-Fold Cross Validation. The model's performance will be evaluated using mean Average Precision (mAP), precision, recall, and F1-score metrics. Subsequently, the model will be developed into a desktop-based system application. The result of this study are expected to provide an accurate and efficient waste detection model to assist in recognizing the types of waste present in the school environment.

Keywords: Waste Detection; YOLOv11; Organic and Inorganic Waste.

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1. Introduction

Waste is the final residue that no longer has further utility or has lost its economic value. The prevailing perception of waste still carries negative connotations; therefore, a shift in mindset is necessary to enhance public awareness regarding the importance of proper waste management [1].

Based on data from the National Waste Management Information System (SIPSN), as reported on the official SIPSN website in 2024, Indonesia generates approximately 35.3 million tons of waste annually, reflecting a decrease of 1.11% or about 390,000 tons compared to the previous year. However, only 38.63% or around 13.64 million tons of waste per year is properly managed. This volume corresponds to an estimated waste generation rate of approximately 0.342 kg per person per day. These figures indicate that Indonesia is currently facing a significant waste management crisis, representing a major challenge that requires collective action [2].

School environments constitute one of the largest daily waste producers, generated from the activities of students, teachers, and administrative staff [3]. Waste bins provided within school premises are often not used according to their intended purpose, resulting in the mixing of organic and inorganic waste. Environmental cleanliness, including attitudes toward waste issues, is therefore the responsibility of all members of the school community [4].

To address waste management challenges in schools, technological approaches play an essential role in assisting school communities in identifying and classifying different types of waste. In particular, image

processing techniques enable automatic waste identification by providing detailed information regarding waste categories [5].

Previous research has developed object detection models using Convolutional Neural Networks (CNN) with the YOLOv8 algorithm to detect floating waste on the surface of the Ciliwung River. The dataset used in the study was collected from Google Images, YouTube, and direct smartphone photography, and was divided into 547 training images, 60 validation images, and 190 testing images. The model was trained under three experimental configurations with different epoch settings (50, 100, and 200 epochs), achieving optimal performance at the 177th training epoch. The best-performing model produced evaluation scores of 84.02% precision, 91.03% recall, 77.6% accuracy, and an F1-score of 87.38% [4].

Another study conducted by Dewangga et al. (2025) aimed to detect and classify organic and inorganic waste using the YOLOv9 object detection model. The dataset consisted of 392 images collected through direct video recording and internet sources, which were subsequently divided into 70% training data, 20% validation data, and 10% testing data. The model was trained for 100 epochs to recognize eight different waste classes. Evaluation results demonstrated excellent performance, with an average precision of 0.937, recall of 0.924, mAP50 of 0.957, and mAP50–95 of 0.888 [6].

Previous studies have confirmed the effectiveness of the YOLO framework for various waste detection tasks. Research by [7] successfully implemented YOLOv8 for floating waste identification, achieving an F1-score of 87.38%. Findings from Dewangga et al. (2025) indicate that the adoption of the YOLOv9 architecture significantly improved waste classification performance, as demonstrated by an mAP@50 value of 0.957. This trend confirms that successive updates in YOLO architectures consistently provide substantial improvements in detection accuracy for similar problem domains [8].

Based on this positive trend, the present study proposes the use of the YOLOv11 architecture, one of the most recent versions that potentially offers improved accuracy and efficiency for the specific application of detecting organic and inorganic waste in school waste bins, thereby enhancing the detection capability of previous models.

The proposed study primarily focuses on addressing previously identified challenges by developing a waste object detection model tailored to the characteristics of the dataset and the specific research context, namely waste generated in school environments. Several prior studies provide empirical evidence regarding waste composition in schools. Research by Auliya Akrae Littaqwa et al. (2025) reported that the dominant waste types in a school in Mataram City consisted of plastic waste (42.71%), organic waste (42.30%), and paper waste (8.95%). Similar findings were reported by Muhammad Sawaludin and Lalu Auliya [9], who identified plastic waste (50.2%), paper waste (21.2%), and organic waste (20%) as the primary waste components at Yayasan Pesantren Islam Ittihadul Abror NWDI Mercapada . Additionally, Sari et al. (2023) provided more detailed quantitative data from State Elementary School 02 in Bengkulu City, showing that inorganic waste such as styrofoam, plastic bottles, plastic packaging, and plastic straws reached approximately 6 kg per day, while organic waste including food scraps, paper, leaves, and plant materials ranged from 5 to 8 ounces per day.

Based on these references, this study focuses on the most dominant waste types in school environments and constructs a dataset categorized into two main classes: organic and inorganic waste. The proposed model employs the YOLOv11 architecture, leveraging its latest features to enhance detection accuracy and object detail recognition. YOLOv11 is selected due to the introduction of new architectural components designed to improve detection performance, particularly for objects with diverse shapes, textures, and visual characteristics. The trained detection model will be implemented into a desktop-based application system to support automatic waste classification within school environments.

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2. Literature Review And Problem Statement

Object detection technology based on deep learning has experienced rapid development, particularly through the Convolutional Neural Network (CNN) paradigm, which demonstrates strong capability in extracting visual features automatically and accurately. The YOLO (You Only Look Once) framework has become one of the most widely adopted real-time detection approaches because it integrates object localization and classification into a single-stage process, enabling high detection speed while maintaining competitive accuracy (Redmon et al., 2016). Continuous architectural improvements, from earlier YOLO versions to more recent generations, have consistently enhanced detection performance through the introduction of improved backbone structures, feature fusion strategies, and optimization mechanisms [10]. Empirical studies further confirm that YOLO-based models are effective for waste detection tasks, achieving high precision and recall in various environmental contexts, including open-area waste monitoring and automated waste classification systems [11]. These findings indicate that the integration of advanced YOLO architectures provides a reliable foundation for building automated waste classification systems.

Despite these developments, several limitations remain in existing studies. Most previous research focuses on general waste detection scenarios or employs earlier YOLO architectures, while limited studies specifically address detection systems adapted to school environments with simplified class structures suitable for educational implementation [12]. Furthermore, the application of newer architectures such as YOLOv11 has not been extensively explored for organic and inorganic waste classification in controlled environments such as school waste bins, where object characteristics may vary significantly in texture, shape, and lighting conditions [13]. Based on this research gap, the problem addressed in this study is formulated as follows: How can the implementation of the YOLOv11 architecture improve the accuracy and reliability of automatic detection of organic and inorganic waste in school environments? Accordingly, this study proposes the hypothesis that the implementation of the YOLOv11-based detection model, supported by appropriate pre-processing and augmentation strategies, will produce higher detection performance compared with earlier YOLO-based implementations in similar waste classification tasks.

3. Metode

This study begins with the development of a methodological framework designed to ensure that the research process is conducted systematically while minimizing the possibility of errors. The research stages are as follows:

1. Literature Study
The initial stage of the research involves reviewing various scientific literature relevant to the topic of organic and inorganic waste detection.
2. Dataset Collection
Public datasets are collected from several Kaggle repositories and categorized into two groups, namely organic waste and inorganic waste.
3. Model Design
At this stage, a detection model is designed using a Kaggle dataset consisting of seven waste classes (four organic and three inorganic). Data partitioning is performed using Stratified K-Fold Cross Validation with $K = 10$. Preprocessing includes image resizing and normalization, followed by image augmentation to increase data variability and balance, such as flipping, rotation, scaling, cropping, and adjustments of brightness, contrast, and saturation. The augmented dataset is then trained using the YOLOv11 architecture with pre-trained weights. Model training is conducted through hyperparameter experimentation, including the Adam optimizer, 50 and 100 training epochs, a batch

size of 16, and a learning rate of 0.001. Model testing is performed using the testing dataset with a specified confidence threshold to balance precision and recall. Model performance is evaluated using mean Average Precision (mAP), which includes accuracy, precision, recall, and F1-score metrics, and the final model is subsequently developed into a desktop-based application system. The design scheme is illustrated in Figure 2.

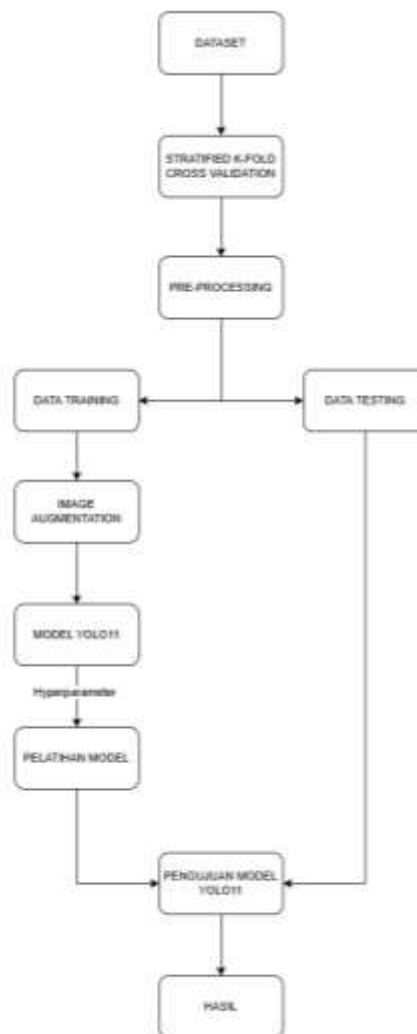


Figure 1. YOLOv11 Architecture Design Scheme

4. Implementation

At this stage, the designed model is implemented to perform waste recognition and detection using the processed training dataset.

5. Testing

The testing phase is conducted using the testing dataset by setting a confidence threshold to evaluate detection results. Model performance is assessed using the mean Average Precision (mAP) method, which includes precision, recall, and F1-score metrics. Precision indicates the accuracy of predicted waste categories, recall represents the model's ability to detect waste objects, while the F1-score is the harmonic mean of precision and recall.

4. Results and Discussion

Data Pre-processing Stage

During the preprocessing stage, resizing and normalization were applied to the entire Kaggle dataset [14]. The preprocessing results generated through Roboflow produced a technically standardized dataset. All waste images that previously had varying dimensions were standardized to a uniform size of 640 × 640 pixels, with normalized pixel intensity values. Structurally, the dataset was evenly distributed into 10 folds without altering the essential feature information contained in the images. The final output of this stage consisted of a collection of image files and corresponding labels in .yaml format, fully compatible with the YOLOv11 architecture and ready to proceed to the augmentation stage to enrich the variability of the training data [15].

Augmentation Stage

The augmentation stage was conducted to increase data variability, resulting in a more diverse dataset that enhances the model’s flexibility in responding to real-world conditions [16]. The Horizontal Flip technique produced mirrored images, enabling the model to recognize waste objects regardless of their orientation [17]. Through the Rotation technique, images were rotated at various angles to simulate irregular waste positions [18]. The application of Scaling and Cropping generated variations in object size and partial image regions, allowing the model to identify objects even when they appear partially visible or at a distance [19]. In addition, adjustments to Brightness, Contrast, and Saturation ensured that the model maintained detection accuracy under different lighting conditions and color intensities, enabling effective detection even when image quality is imperfect, as shown in Table 1.

Table 1. Augmentation Details

Augmentation Technique	Parameter Details	Detection Purpose
Outputs per training example	3	Triples the number of training samples to enrich data variability.
Flip	Horizontal, Vertical	Enables recognition of waste objects from different orientations (top–bottom, left–right).
90° Rotate	<i>Clockwise, Counter-Clockwise, Upside Down</i>	Allows the model to recognize objects positioned at perpendicular rotations.
Crop	<i>0% Min Zoom, 20% Max Zoom</i>	Enables detection of objects even when partially visible or captured from different distances.
Rotation	Between -15° and +15°	Simulates random tilting positions of waste objects in real-world environments.
Grayscale	Applied to 15% figure	Trains the model to recognize waste shapes without relying on color intensity.
Hue	between -15° and +15°	Handles variations in object color caused by differences in brand or material type.
Saturation	between -25% and +25%	Addresses variations in color intensity ranging from faded to highly vivid.
Brightness	between -15% and +15%	Maintains detection accuracy under both low-light and very bright conditions.

Model Testing and Evaluation Results

The testing of the organic and inorganic waste detection model was conducted using the YOLOv11 architecture with a Stratified K-Fold Cross Validation scheme (K = 10) and a training duration of 100 epochs. Implementation of Organic and Inorganic Waste Detection Modeling in School Waste Bins Using Yolov11. Feriyanto et.al

This approach was applied to ensure the stability of model performance evaluation while minimizing data distribution bias in the dataset, which consists of 3,347 images across seven waste classes [20]. As presented in Table 2, the results represent the average performance values of the YOLOv11 model across the 10-fold evaluation.

Table 2. YOLOv11 Model Evaluation Results (10-Fold)

No	Evaluation Metric	Average Value
1	Precision	0.9577
2	Recall	0.9408
3	F1-Score	0.9491
4	mAP@0.5	0.9730
5	mAP@0.5:0.95	0.9147

Based on Table 2, the YOLOv11 model demonstrates excellent performance in detecting organic and inorganic waste. The precision value of 0.9577 indicates that the majority of detected objects are correctly identified as waste, resulting in a low false-positive rate. This is essential to ensure that the system does not perform incorrect classifications during the waste sorting process [21]. The recall value of 0.9408 shows that the model is capable of detecting most waste objects in the testing images. With a high recall value, the risk of undetected waste objects (false negatives) can be minimized, making the system more reliable for real-world implementation [22].

The balance between precision and recall is reflected in the F1-score of 0.9491, indicating that the model exhibits stable performance in detecting and classifying waste objects. This value confirms that the model is not only accurate but also consistent across various testing scenarios. In addition, the mAP@0.5 value of 0.9730 indicates that the model achieves highly accurate bounding-box localization at an Intersection over Union (IoU) threshold of 0.5. Meanwhile, the mAP@0.5:0.95 value of 0.9147 demonstrates that the model maintains strong performance across stricter IoU thresholds.

Overall, the comprehensive evaluation results presented in Table 2 indicate that the YOLOv11 model delivers accurate, stable, and reliable detection performance, highlighting its suitability for use as a supporting system for the detection and classification of organic and inorganic waste in school environments [23]. The following section presents the best-performing model results.

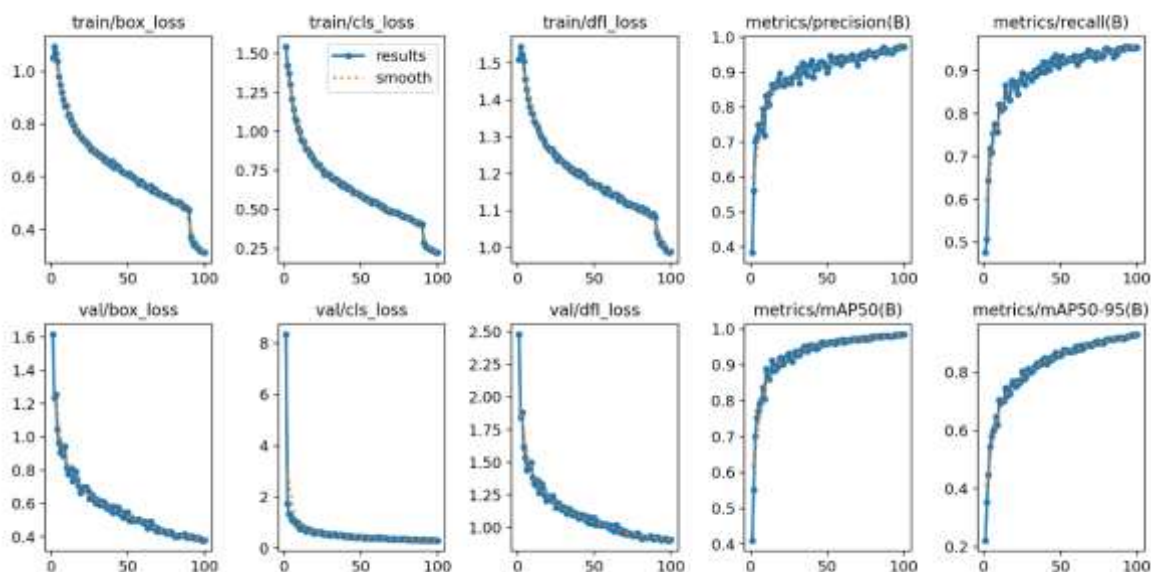


Figure 2. Precision-Recall Curve Fold 9

Based on the evaluation results using the 10-Fold Cross Validation scheme, Fold 9 was selected as the best model because it showed the most superior performance compared to the other folds. In Fold 9, the YOLOv11 model obtained a precision value of 0.9731, a recall of 0.9542, and an F1-Score of 0.9636, which indicates a very high level of accuracy and consistency in detecting trash objects. In addition, the mAP@0.5e value of 0.9847 indicates that the model in Fold 9 is capable of detecting and localizing objects with excellent accuracy at an Intersection over Union (IoU) threshold of 0.5. Meanwhile, the mAP@0.5:0.95s value of 0.9305 indicates that the model maintains superior performance at various stricter IoU levels.

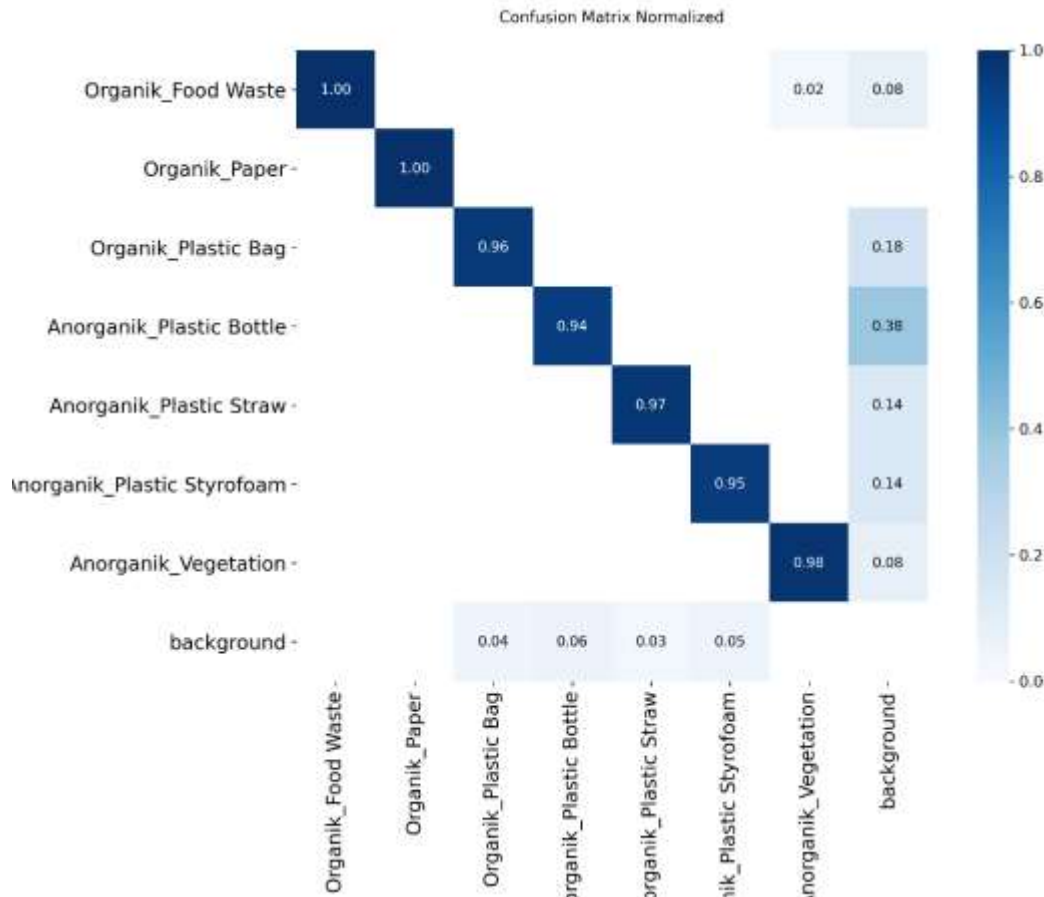


Figure 3. Confusion Matrix Normalized

The model evaluation results were confirmed through a Normalized Confusion Matrix to measure the classification performance for each waste category in detail. Based on this data, the model showed a very high level of accuracy with dominant values on the main diagonal, where the Organic Food Waste and Organic Paper classes achieved perfect accuracy of 100% [24]. In general, most inorganic classes such as Plastic Straw, Plastic Styrofoam, and Vegetation had a classification success rate above 95%. This indicates that the texture and shape features of these objects have been well extracted by the model, thereby minimizing prediction errors between waste categories. However, there is an anomaly in the Inorganic Plastic Bottle class, which shows a false negative rate of 38% against the background label [25]. This indicates that the model has difficulty distinguishing plastic bottles, which tend to be transparent, from the background of the testing environment. In addition, the background category shows a small spread of errors (misclassification) to several plastic classes, triggered by the visual similarity between background elements and the physical characteristics of inorganic materials [26]. Overall, despite the challenges in detecting transparent objects, the model remains highly reliable in separating organic and inorganic waste with a very solid average accuracy value per class.

5. Conclusion

Based on the results of the study, it can be concluded that the implementation of the YOLOv11 architecture combined with the Stratified K-Fold Cross-Validation technique demonstrates a high level of effectiveness in detecting organic and inorganic waste in school environments. The best-performing model was obtained in Fold 9, achieving an mAP@0.5 value of 0.985 and an F1-score of 0.96. The incorporation of the latest features in the YOLOv11 architecture has been shown to improve object localization accuracy, even though the dataset used contains diverse variations. These findings indicate that the developed model has strong potential to be integrated into a desktop-based decision-support system as an educational tool for automatic and accurate waste sorting, although several object classes still exhibited detection errors. Based on the outcomes of this study, the following recommendations are proposed for future research: Increase the diversity of the dataset to reduce bias and minimize misdetections, particularly in cases of mixed waste objects. Implement the detection model in a mobile-based application (Android/iOS) to facilitate easier access for interactive waste-sorting education.

6. Referensi

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