EdgeTech Insights Journal
Vol.1, 1 (Juni, 2025), pp. 13-23
ISSN: xxxxx EISSN: xxxxx, DOI: xxxxx

DETECTION WASTE USING YOLOV5

Lasro Simbolon[1] , Betrand Samuel Pandiangan[2], Janwollver Sirait[3]
[1]Lancang Kuning University, Pekanbaru, Indonesia ; Simbolonlasro82@gmail.com
[2]University of Medan, Medan, Indonesia ; Betrandpandiangan@gmail.com
[3]University of Padang, Padang, Indonesia ; janwollversirait11012006@gmail.com

ARTICLE INFO

KEYWORDS:
Waste Detection, Waste Classification, Organic Waste, Inorganic Waste, YOLOv5, Smart Waste Management, Artificial Intelligence (AI), Recycling, Waste Sorting, Sustainable Waste Management, Web Technology, Real-Time Object Detection

Article history:

Received 2021-08-14
Revised 2021-11-12
Accepted 2022-01-17

ABSTRACT

One of the most important factors in city development in the past has been the efficient use of organic and inorganic waste. This research aims to improve detection and classification systems using the YOLOv5 method implemented on a web-based system. This system is designed to increase the efficiency of the recycling process while simplifying the automatic waste separation process. The YOLOv5 algorithm is one of the most effective artificial intelligence (AI) methods for detecting objects in real-time in image data sets with labels for organic and inorganic samples. The results of the system analysis show that the YOLOv5 model has a high level of accuracy in classifying the two types of waste, so it can help the general public in handling waste more quickly and easily. This web-based system also provides clear information regarding the types of waste that need to be discussed, as well as waste optimization at the local level using web-based smart technology. This research is expected to have a positive impact on technology-based waste management, increase public awareness of the importance of effective waste management, accelerate the waste management process, and increase the efficiency of the recycling system.

Corresponding Author:
Lasro Simbolon
Lancang Kuning University
Simbolonlasro82@gmail.com

1. INTRODUCTION

Waste has become an increasingly serious environmental issue in Indonesia. As one of the countries with the largest population and the fastest rate of urbanization, Indonesia faces major challenges related to waste development (Abdillah et al., 2024). According to a World Bank report, global production will increase from 2.01 million tons in 2018 to 3.4 million tons in 2050, and developing countries such as Indonesia will contribute significantly to this increase. Indonesia is also known as the largest producer of plastic waste in the world, where most of this waste ends up in the oceans and damages aquatic ecosystems (Abdillah et al., 2024).

Currently, waste management in Indonesia is still far from ideal, with only 66.24% being carried out effectively and 33.76% not being carried out at all. This data shows that not all waste in Indonesia is utilized effectively, which highlights the need for innovation and improvements in the waste management system to improve the environment and public health (Labibah & Pulungan, 2025).

The main challenge in modern waste management is the abundance of organic and inorganic waste that has existed since the beginning of production, making it difficult to sort and process. (Sistem et al., n.d.). Instability in sorting also has a negative impact on environmental sustainability and can increase the risk of pollution if not handled well (Maya Sabilla et al., 2024). Therefore, the development of a more efficient and automated waste management system with modern technology is very important to increase recycling efficiency and minimize environmental damage.

Separating organic and inorganic waste is an important step to make waste management more efficient. Although this separation is done by hand, it is often unsuccessful and takes a long time Therefore, computer vision and deep learning based technologies can be used to automate waste separation (Fathurrahman & Akbar, 2024). YOLO (You Only Look Once) is a technology that has proven effective at detecting objects in real-time. YOLOv5, the latest version of YOLO, allows you to find objects quickly and accurately. This makes it the best choice for web-based waste management applications (Abo-Zah had & Abo-Zah had, 2025)In addition, waste management can become more integrated and efficient with the use of YOLOv5-based technology. This technology not only speeds up the waste separation process, but also allows data and information on the types of waste generated to be more easily analyzed. This data is very valuable for developing more effective waste management strategies and for mitigating the impact of waste management activities (G et al., n.d.). With web-based applications, this system enables better data integration between the community, government and other related parties in the local and national waste sector.

Although various studies have applied YOLO-based models for waste detection and classification, most existing research focuses on controlled datasets or single-source data, with limited discussion on dataset variability derived from real landfill environments combined with public datasets. In addition, several studies emphasize model accuracy without providing sufficient analysis of training stability, loss convergence, and mAP consistency during the learning process.

While YOLO-based models for garbage identification and classification have been used in a number of studies, the majority of current research concentrates on controlled datasets or single-source data, with little attention paid to dataset variability coming from real landfill sites paired with public datasets. Furthermore, a number of research focus on model correctness without adequately analyzing training stability, loss convergence, and mAP consistency during the learning process. Additionally, while the use of cloud-based platforms for end-to-end training, validation, and inferencelike Roboflow has not been thoroughly examined in terms of its viability and performance consistency for real-world waste detection scenarios, many prior YOLOv5 implementations in waste classification focus on standalone model performance.

2. METHOD

A. Technique Dataset Collection

The graphic dataset used in this study was collected through two main methods: direct image creation in the field and the use of additional datasets from Roboflow Universe. Field collection was carried out to obtain samples that accurately reflect the situation, especially in the Muara Fajar landfill environment which is affected by various types of organic and inorganic waste (Prasetio & Pratiwi, 2025). On the other hand, the Roboflow Universe dataset is used as supporting data to increase object variability, so that the model has broader learning capabilities. All data is then transferred to a cloud-based storage service (Google Drive), which provides accessibility and allows for more structured and risk-free dataset management.

The collected dataset contains a variety of sample objects, ranging from organic materials such as leaves, food scraps and twigs to inorganic materials such as plastic bottles, cans, packaging plastic and glass-based materials (Ramadhan et al., 2025). This sample diversity is very important because it aims to provide a realistic illustration of the surrounding conditions so that the detection model developed can accurately describe objects in various situations. In addition, organizing data in a neat folder structure ensures that researchers can identify and process files efficiently, especially when the number of images has increased.

After that, each image is annotated using the LabelImg tool. In this phase, researchers create bounding boxes around objects and label them according to their respective categories. The annotation process is carried out manually to ensure high accuracy in object classification (Abdillah et al., 2024). Annotation quality directly impacts model performance. LabelImg was chosen because of its ability to generate annotation files in various formats that are compatible with the model analysis flow. This phase is a crucial component in computer vision research because it will improve the system's ability to perform automatic classification in a more precise way.

B. Pre-processing

After the dataset is collected, the first step in the data processing process is pre-processing. At this stage, the images taken have varying sizes, so they need to be adjusted to a standard size to facilitate further processing. All images are resized to 320x320 pixels to ensure consistency in processing. In addition, the images are also normalized to ensure the distribution of pixel values is within the range expected by the YOLOv5 model. This process also involves augmentation to increase the amount of data, such as image rotation, flipping, and brightness changes, to make the model more robust to image variations.

C. Training Data

In this study, the YOLOv5 model was developed using the Roboflow Train 3.0 platform, which provides a variety of features, from dataset analysis to automatic model analysis processes. Before the study began, the annotated dataset was sent to Roboflow and processed through an internal validation system to ensure that each file complied with standards, regardless of image format or annotation structure (Hesananda et al., 2024). This phase is very helpful in maintaining data integrity so that there are no weak images or unreadable annotations.

After the validation process is complete, Roboflow automatically converts all annotations to a format compatible with YOLOv5. In addition, this platform offers configurable augmentation functions including rotation, lighting adjustment, inversion and scale variations (Hesananda et al., 2024). This augmentation feature is used to increase the diversity of the dataset without the need to add data from the field, allowing the model to handle more complex visual conditions when applied to a textual environment. With this augmentation, the YOLOv5 model can understand more complex visual patterns and reduce the risk of overfitting. In the training phase, Roboflow implements a workflow that has been optimized for YOLOv5 (Xu & Yu, 2024). Users can compare parameters such as the number of epochs, batch size, input resolution and model type. Roboflow displays interactive performance graphs, such as loss, precision, recall, and mAP (Mean Average Precision), during the process (Hesananda et al., 2024). This information makes it easier for researchers to monitor model development in real-time and determine whether the process is running as well as possible. After the training process is complete, Roboflow provides the test result model in several formats so that it can be easily integrated into applications or detection systems that are being developed (Abdillah et al., 2024).

D. System implementation

The implementation of the waste detection system in this study was carried out entirely through the Roboflow platform, without the development of web-based applications or interfaces. The YOLOv5 model that has been developed in Roboflow is then implemented using the Inference feature available on the platform. With this capability, users can upload images to the Roboflow dashboard, and the system will automatically process the images using the previously developed model (Prasetio & Pratiwi, 2025).

Each image is processed in real-time, where Roboflow runs an inferential flow to generate bounding box predictions, category labels (organic or inorganic), and confidence values from each detected object. All of this is done in the cloud, so there is no need to install additional software on the research computer. The use of the Roboflow platform also makes model evaluation easier because users can easily compare prediction results with original analysis or assess model performance with new images that are not included in the study data set.

E. Testing

Testing is a crucial step in understanding how a model can function when applied to data not used during the analysis process. In this phase, the previously validated dataset is used to generate an objective model performance graph. This data analysis ensures that the model's ability to generalize various graphic variations that may arise in real-world situations is strengthened,testing also helps identify the model's resilience when facing less than ideal real-world conditions. Dataset validation usually includes various lighting conditions, differences between image capture, and object appearances. Therefore, this step evaluates the model's ability to analyze objects, even if their appearance differs from the examples used during the research. This is important because in the field, objects are often overlapping, partially covered, or in unstructured environments, requiring a model that is highly adaptive to visual changes.

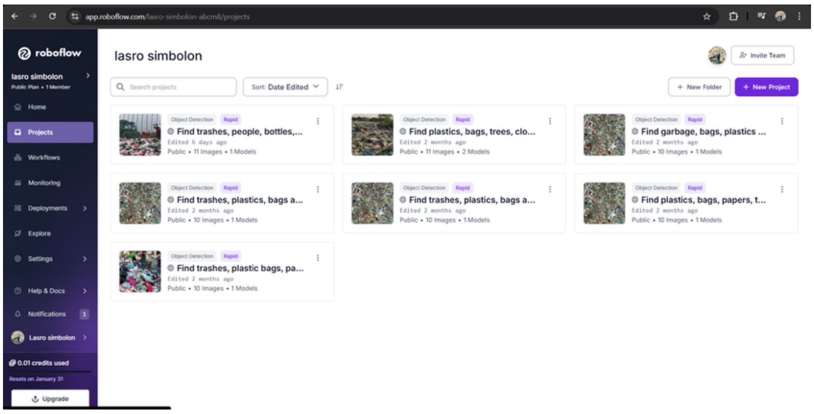
In addition, the test results are presented in the form of a graph that illustrates the consistency of the model's performance in analyzing visual objects up to data not included in the analysis process. This evaluation shows that the model is able to stabilize detection and classification performance on many variations of object appearance, which indicates that the previous learning process has produced a very strong feature representation. As a result, testing not only serves as a performance verification tool but also as an indicator of the model's success in learning the general characteristics of objects from the dataset used.

Testing provides an illustration of the model's ability to change current visual conditions. In some cases, overlapping or relatively small objects can affect the confidence level in the model's predictions. This condition allows for challenges commonly found in real-world environments, making the results of this research an important indicator of how well the model can adapt to visual complexities that are not fully optimal.

The test results show that the validation and analysis processes carried out previously have a significant impact on the stability of the model's performance. The consistency of the evaluation metric values indicates that the model not only performs well on the training data but also has the ability to compare performance with test data. This shows that the dataset analysis strategy, including the validation and data collection process, has been carried out in an appropriate way to support the objective evaluation process. This condition shows that the model is able to learn feature representations that are common and do not appear in current patterns that only appear in research data. As a result, the model has a good generalization ability to handle the variability of visual objects found in the test dataset. This generalization ability is an important factor in ensuring that the model can be used to analyze images with different characteristics, such as lighting segments, shooting angles, or background complexity.

3. RESULTS AND DISCUSSION

This research focuses on the detection and classification of organic and inorganic materials using the YOLOv5 method, which is implemented through the Roboflow platform. The system is designed to distinguish two types of waste based on digital images, namely organic and inorganic waste, with the aim of simplifying the waste production process automatically and efficiently.



Object Detection Rapid
Find trashes, people, bottles,...
Edited 6 days ago
Public • 11 Images • 1 Models

Object Detection Rapid
Find plastics, bags, trees, clo...
Edited 2 months ago
Public • 11 Images • 2 Models

Object Detection Rapid
Find garbage, bags, plastics ...
Edited 2 months ago
Public • 10 Images • 1 Models

Object Detection Rapid
Find trashes, plastics, bags a...
Edited 2 months ago
Public • 10 Images • 1 Models

Object Detection Rapid
Find trashes, plastics, bags a...
Edited 2 months ago
Public • 10 Images • 1 Models

Object Detection Rapid
Find plastics, bags, papers, t...
Edited 2 months ago
Public • 10 Images • 1 Models

Object Detection Rapid
Find trashes, plastic bags, pa...
Edited 2 months ago
Public • 10 Images • 1 Models

Figure 1. Project page view on the *Roboflow platform*

Based on Figure 1, it can be seen that several object detection projects have been developed on the Roboflow platform to improve the waste classification process. Each project presents a dataset and YOLOv5 model used to analyze objects with different visual characteristics. The results of some of these projects show that the research process is not limited to one configuration, but is carried out methodically by analyzing the dataset and model to achieve more stable performance.

All waste images used in the projects mentioned above go through a pre-processing stage. This step includes resizing the image to 320 x 320 pixels, normalizing pixel size, and augmenting data. The purpose of this pre-processing procedure is to standardize data and improve the model's ability to analyze the variability of visual objects. The results of this phase ensure that the images used in each Roboflow project are in a condition that is appropriate for the YOLOv5 model testing process.

Each project developed uses the Roboflow Train 3.0 feature on the YOLOv5 model. During the training process, the model is used to learn visual patterns of organic and inorganic waste based on previously established bounding box annotations. The confidence level towards detected objects, bounding boxes, and class labels are the result of the training process reflected. After the final analysis process, the model is evaluated using the cloud-based inference feature provided by Roboflow. In this phase, waste images are processed in real-time without requiring additional software installation. The model can identify objects in various visual conditions, such as differences in lighting and background, which indicates the model's ability to generalize to new data outside the research dataset.

The research results show that the YOLOv5 model can accurately detect waste objects and provide predictions such as bounding boxes, class labels, and confidence values. This model can identify organic and inorganic objects in image tests, even if the objects are located in different lighting conditions or different backgrounds. This shows that the dataset augmentation and validation process has an impact on the model's generalization ability.

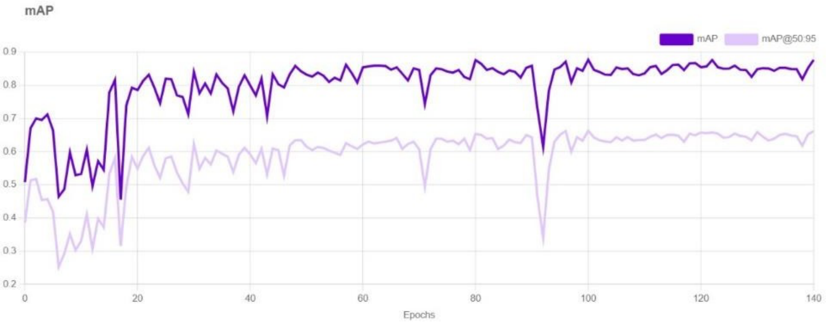


Figure 2. mAP graph

Based on Figure 2, it can be observed that the mAP value experienced a significant increase at the beginning of the research. In the first few epochs, the mAP curve shows relatively large fluctuations, which indicates that the model is still in the early stages of learning and the network weights correspond to the visual waste objects found in the dataset. This situation shows that the YOLOv5 model gradually analyzes organic and inorganic characteristics, such as shape, texture, and visual differences between objects.

As the number of epochs increases, the mAP value shows an increasing trend and begins to form a more stable pattern. This shows that the model has successfully learned more consistent visual representations, making it easier to detect and classify objects. The stability of the mAP curve at this stage indicates that the model learning process has reached a convergent state, where performance growth is not drastic but more consistent.

Conversely, the mAP@50–95 curve shows an increasing pattern that is closer to the standard mAP. This can be interpreted as the model's adjustment process in predicting the location of the bounding box more precisely at various Intersection over Union (IoU) thresholds. Although the value is smaller than mAP, the stability of the mAP@50–95 curve in the next epoch indicates that the model has consistency in determining the position of the object accurately, not only at one IoU threshold but also at a wider range of thresholds.

Slight fluctuations over several epochs indicate that the model continues to make internal adjustments during testing, which is a common condition in the deep learning training process. However, there was no statistically significant decrease in performance, therefore it can be concluded that the model did not experience extreme overfitting during the testing process. Overall, the mAP and mAP@50–95 curve patterns in Figure 2 show that the YOLOv5 model has stable performance and the ability to consistently detect and classify organic and inorganic materials after the testing process.

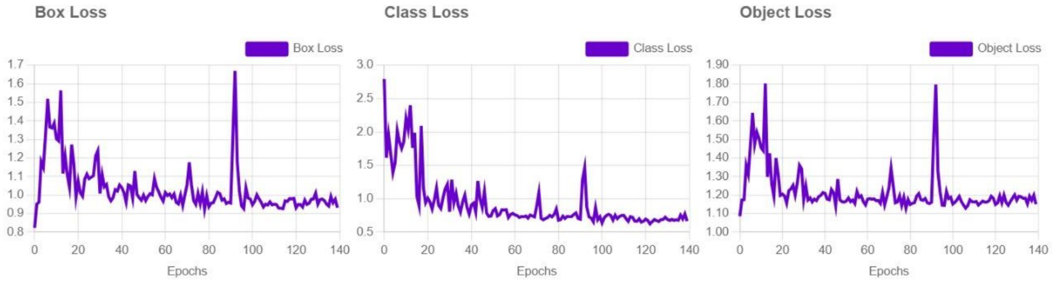


Figure 3. Graphs of Box Loss, Class Loss, and Object Loss against the number of epochs in the YOLOv5 model training process

Based on Figure 3, the Box Loss graph shows a very high loss at the start of the analysis and very large fluctuations throughout the first few epochs. This condition indicates that the model is still experiencing difficulties in predicting the location of the bounding box accurately during the initial phase. As the number of epochs increases, Box Loss tends to decrease and creates a more stable pattern. This decrease shows that the model can predict the position of the bounding box against the waste object more accurately, thus reducing the difficulty in finding the object. The Class Loss graph in Figure 3 illustrates a significant decrease at the beginning of the analysis process. This indicates that the model quickly learns the differences in visual characteristics between organic and inorganic classes. After a certain number of epochs, the Class Loss value stabilizes with small fluctuations, indicating that the object classification process has reached a somewhat optimal state. This stability indicates that the model can maintain consistency in separating the two classes of waste during continuous testing.

On the other hand, the Object Loss graph shows a gradual decrease in loss values as the epoch progresses, although there are still fluctuations at several points at this time. This indicates that the model continues to make adjustments in determining the presence of trash objects in the image. Fluctuations in Object Loss are a common feature in deep learning research, especially when models encounter variations in the shape, size, and location of objects in the dataset. However, the tendency for loss values to remain relatively stable in subsequent epochs indicates that the model has been able to recognize the presence of objects consistently.

Overall, the reduction and stabilization of Box Loss, Class Loss, and Object Loss in Figure 3 indicate that the YOLOv5 model analysis process ran smoothly. This model not only improves the accuracy of object location predictions but also demonstrates increasingly consistent object classification and detection capabilities. This indicates that the model has reached a stable learning condition and does not show extreme overfitting indicators during the testing process, so it can be used in the inference and testing stages. The stability of the loss values in the final stage of the study also shows that the model has successfully adjusted its internal parameters ideally to the characteristics of the dataset used, such as variations in the shape, size, and position of objects.

Figure 4. Training Data Results

Based on the completed data analysis results, the YOLOv5 model demonstrates excellent capabilities in detecting and classifying objects in real-world images. This can be seen from the model inference results displayed in the graph, where the model successfully identified various commonly found waste objects. The most common objects found in the images are plastic bags and general waste, which are often identified with bounding boxes and confidence levels in the form of percentages.

Based on the results of the study, the model was able to identify a number of plastic bag objects with varying degrees of confidence. Some objects had confidence levels between 52% and 55%, while others had higher confidence levels, such as 61%, 72%, and up to 73%, as indicated by the inference label. In addition, objects classified as trash also have confidence levels between 61% and 72%. This percentage variation limits the differences in the visual conditions of objects, such as object size, overlap level, and the influence of the background on the image.

The model's success in detecting multiple objects with a relatively consistent confidence level indicates that the YOLOv5 model can function well in complex and unstructured environments. Even though the objects are ink-based, partially covered, and have uneven lighting, the model is still able to provide classes and confidence levels that can be interpreted visually. Overall, these inference results show that the developed YOLOv5 model has the ability to detect and classify inorganic waste in natural environments. With detection results based on the confidence percentage of each object, this model can be evaluated more closely on new data and can be used as a component of a digital automatic waste detection and classification system.

4. CONCLUSION

This study shows that implementing the YOLOv5 method through the Roboflow platform can effectively classify organic and inorganic samples based on digital data. The model results are not affected by the data collection process, which combines field and supporting data, as well as careful manual analysis to improve the quality of model instructions. The data collection process, which combines field and supporting data, as well as accurate manual annotation, is an important factor in improving the performance of object detection models, as also mentioned in research on YOLO-based waste classification (Abdillah et al., 2024; Ramadhan et al., 2025).

Pre-processing steps, such as image size adjustment, normalization, and data augmentation, have been shown to improve the model's ability to generalize across different visual conditions, as observed in other detection studies using the YOLO model (Aditya Azis et al., n.d.; Sulistyo et al., 2025) The results of the study, which showed mAP convergence and loss reduction and stabilization, indicate that the model successfully learned optimal feature representations, in contrast to previous research findings that highlighted the importance of evaluation metric stability in deep learning models (Abo-Zahhad & Abo-Zahhad, 2025). The model's ability to perform real-time object detection under various test conditions demonstrates a high level of adaptability to complex environments, as demonstrated in the YOLO implementation research for smart waste based on computer vision (Abdillah et al., 2024; Sulistyo et al., 2025) Overall, the results of this study support the idea that the use of YOLOv5 can be an effective solution in an automatic waste detection and classification system, as well as potentially increasing the efficiency of artificial technology-based waste management as stated in previous studies (Abo-Zahhad & Abo-Zahhad, 2025; Gelar et al., 2025). In addition, other studies that developed the YOLOv5s model for waste classification also showed results indicating that this model can achieve high detection performance, such as competitive accuracy and mAP on more complex waste datasets, which indicates good generalization ability across various types of waste and complex datasets (Flores, 2023)

Several other studies have shown that YOLOv5-based object detection also produces consistent and significant results in various waste classification applications. For example, the YOLOv5 model has been used to classify various waste categories, such as glass, plastic, and metal, with high accuracy and high average precision on more complex waste datasets, demonstrating the model's ability to effectively handle a wide range of visual object variability (Zhao & Hu, 2024) Another study using YOLOv5 in the context of waste classification through a server application and user interaction also highlighted the model's success in accurately analyzing and classifying waste, which increases the potential for implementing this method in automated waste monitoring and management systems. Furthermore, the implementation of YOLOv5 in waste environments, such as rivers, demonstrated that this model can handle complex real-world visual conditions (Flores, 2023).

In addition, other research using YOLOv5 in a server-based sampah classification system and user interaction also highlights the model's success in accurately analyzing and classifying sampah types, increasing the method's potential for implementation in an automated sampah classification system. In summary, the implementation of YOLOv5 in complex language environments, such as sungai areas that are affected by limbah, indicates that this model is capable of enhancing deteksi performance even in the face of visual challenges, such as dinamis latar belakang and non-seragam pencahayaan(Flores, 2023)

5. REFERENCE

Abdillah, H., Naufal Syahbana, A., Ishaq, G., Husain, A., & Agustin, S. (2024). Detektif Sampah : Klasifikasi Jenis Sampah Organik dan Anorganik Menggunakan Metode YOLOv5 Berbasis Website. In *Agustus* (Vol. 3, Issue 2).

Abo-Zahhad, M. M., & Abo-Zahhad, M. (2025). Real time intelligent garbage monitoring and efficient collection using Yolov8 and Yolov5 deep learning models for environmental sustainability. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-99885-x

Aditya Azis, B., Azis Wardana, A., & Harjoko, A. (n.d.). ANALYSIS OF PRE-TRAINED YOLO MODEL AND DATA AUGMENTATION FOR WASTE CLASSIFICATION Analisis Pre-Trained Model YOLO dan Augmentasi Data Untuk Klasifikasi Sampah. http://etd.repository.ugm.ac.id/

Fathurrahman, A. A., & Akbar, F. (2024). Perancangan Sistem Identifikasi Jenis Sampah Menggunakan Tensorflow Object Detection Dan Transfer Learning. Jurnal Nasional Teknologi Dan Sistem Informasi, 10(1), 64–71. https://doi.org/10.25077/teknosi.v10i1.2024.64-71

Flores, J. C. (2023). A YOLOv5s Model for Classification of Garbage. www.sajst.orgwww.sajst.org

G, S. S., Uthaman, M., & Professor, A. (n.d.). Automated Waste Classification And Recycling Optimization Using AI. In International Journal of Environmental Sciences (Vol. 11, Issue 24). https://theaspd.com/index.php

Gelar, T., Fitriani, S., & Rachmat, S. (2025). A Systematic Literature Review of YOLO and IoT Applications in Smart Waste Management. Green Intelligent Systems and Applications, 5(2), 123–139. https://doi.org/10.53623/gisa.v5i2.706

Hesananda, R., Noviani, I. A., & Zulfariansyah, M. (2024). Implementasi YOLOv5 untuk Deteksi Objek Mesin EDC: Evaluasi dan Analisis. BIOS : Jurnal Teknologi Informasi Dan Rekayasa Komputer, 5(2), 104–110. https://doi.org/10.37148/bios.v5i2.127

Labibah, L., & Pulungan, M. A. (2025). Evaluasi Pengelolaan Sampah Menggunakan Pemodelan Sistem Dinamis di Kabupaten Ponorogo. JURNAL Al-AZHAR INDONESIA SERI SAINS DAN TEKNOLOGI, 10(1), 24. https://doi.org/10.36722/sst.v10i1.3316

Maya Sabilla, A., Musfiroh, L., & Prasetya Adi, N. (2024). ANALISIS DAMPAK TIMBUNAN SAMPAH TERHADAP PENCEMARAN LINGKUNGAN DI TPA SAMPAH WONOREJO KABUPATEN WONOSOBO. In Jurnal Kajian Ilmiah Interdisiplinier (Vol. 8, Issue 7).

Prasetio, B., & Pratiwi, N. (2025). Deteksi Sampah Organik dan Anorganik Menggunakan Model YOLOv8. JIPI (Jurnal Ilmiah Penelitian Dan Pembelajaran Informatika), 10(1), 494–506. https://doi.org/10.29100/jipi.v10i1.5965

Ramadhan, U., Santoso, N., Gamar, F., Mekanika, D., Energi, D., Terapan, S., Mekatronika, T., Elektronika, P., & Surabaya, N. (2025). Deteksi Sampah Botol Plastik di Perairan Menggunakan YOLO v4-Tiny. 7(1). https://doi.org/10.47233/jteksis.v5i1.1744

Sistem, P., Sampah, K., Berbasis, O., Buatan, K., Mendukung, U., Limbah, P., Berkelanjutan, Y., Putri, T. A., Sari, T. N., & Daniati, E. (n.d.). Prosiding SEMNAS INOTEK (Seminar Nasional Inovasi Teknologi) 2025 479 (Vol. 9). Online.

Sulistyo, B., Nurpulaela, L., Simanjuntak, A. H., Faizal, R. A., & Louhanapessy, H. M. (2025). Implementasi YOLOv5n untuk Deteksi Sampah Sungai Berbasis Computer Vision. Jurnal Ilmiah Teknik Mesin, Elektro Dan Komputer, 5(2), 433–442. https://doi.org/10.51903/juritek.v5i2.5036

Xu, B., & Yu, S. (2024). Improving Data Augmentation for YOLOv5 Using Enhanced Segment Anything Model. Applied Sciences (Switzerland), 14(5). https://doi.org/10.3390/app14051819

Yunefri, Y., Sutejo, Y. E., Fadrial, K. A., Ramadhani, M., & Hardianto, R. (2022). Implementation of object detection with you only look once algorithm in limited face-to-face times in pandemic. *Journal of Applied Engineering and Technological Science*, *4*(1), 400-404.

Zhao, H., & Hu, X. (2024). Garbage Classification and Recognition Model based on YOLOv5. In Journal of Theory and Practice in Engineering and Technology (Vol. 1, Issue 2). https://www.woodyinternational.com/https://woodyinternational.com/index.php/jtpet/article/view/43