Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Inorganic Waste Detection Application Using Smart Computing Technology with YOLOv8 Method

Yozika Arvio[1)*], Dine Tiara Kusuma[2)], Iriansyah BM Sangadji[3)]
[1,2,3)]Faculty of Energy Telematics, Institut Teknologi PLN, Jakarta, Indonesia
[1)] yozika@itpln.ac.id, [2)]dinetiara@itpln.ac.id, [3)]iriansyah@itpln.ac.id.ac.id

Submitted :Aug 17, 2024 | **Accepted** : Aug 24, 2024 | **Published** : Oct 8, 2024

Abstract: Waste and renewable energy are critical issues in Indonesia, with the government aiming for renewable energy (RE) to contribute 23% to the national energy mix by 2025. This research focuses on developing a waste processing system through the TOSS (Tempat Olah Sampah Setempat) method to convert waste into biomass, such as briquettes and pellets for fuel. However, manual waste sorting remains time-consuming, prompting the need for a real-time detection system. You Only Look Once (YOLO) is an object detection approach that utilizes Convolutional Neural Networks (CNN) for object detection, making it one of the applications of intelligent computing in the field of computer vision. the latest version of YOLO is YOLO v8 offering several improvements over the previous version, can be employed in a real-time detection system to separate organic and inorganic waste. In this study, the dataset used consists of 2.000 images comprising five classes of inorganic waste: plastic bottles, plastic, glass, cans, and Styrofoam. The research highlights that YOLOv8 performs exceptionally in detecting inorganic waste, using the same objects for detection as those in the dataset. With direct testing resulting in an average accuracy of 98%, and model evaluation showing 99.33% accuracy, 99.63% precision, 96.53% recall, and a 98.03% F1-score, these findings demonstrate YOLOv8's ability to greatly enhance and streamline the waste sorting process. This advancement supports the conversion of waste into renewable energy. The study offers a practical solution and is anticipated to be a valuable reference for future research.

Keywords: Object Detection; Inorganic Waste; Renewable Energy; Smart Computing; Yolov8.

INTRODUCTION

Two major issues need to be addressed by all stakeholders of the Unitary State of the Republic of Indonesia, namely the national waste problem and the energy problem. The utilization of renewable energy is considered a solution, the government aims for renewable energy (RE) to contribute 23% to the national energy mix by 2025. Based on data from 111 regencies/cities in Indonesia in 2023, the waste accumulation reaches more than 17 million tons per year, with the composition of waste in Indonesia consisting of 41.3% organic waste (food scraps, twigs, leaves), 48.7% inorganic waste (plastic, paper, and others), and the household waste being the largest contributor.

To address this issue, a waste processing system known as TOSS (Tempat Olah Sampah Setempat) has been developed, which does not require complex initial sorting stages. This method successfully transforms waste into biomass in the form of RDF/SRF with the resulting products being briquettes and pellets, which is suitable for use as a fuel source for domestic needs as well as the industrial sector.

Currently, the waste collection and sorting process is still done manually by human at waste area, which takes a long time to detect organic and inorganic waste. Metal, glass, and toxic waste will not be processed in the subsequent stages, as this type of waste cannot be converted into electrical energy. On the other hand, waste with a high organic content is recommended for immediate processing through biological waste treatment to produce methane gas. Plastic and Styrofoam waste requires pre-processing, which involves drying, shredding, and molding into waste pellets.

Waste detection applications, especially for large-scale implementations, require systems that are efficient in terms of energy and computing. Deep learning models such as CNNs often require large computing power, which is not always ideal for edge or mobile devices that are limited in terms of power and processors. Based on research conducted by Alkalaev et, al, research is still needed in developing lightweight and computationally efficient models, but still able to provide high accuracy in waste detection (Konstantin Alkalaev & Xavier Bekaert, 2019)

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117
e-ISSN : 2541-2019
p-ISSN : 2541-044X

To build a real-time detection system, an object detection system using cameras is required. Object detection is a process used to determine the presence of specific objects in a digital image (Ahmad & Rahimi, 2022). Basically, You Only Look Once (YOLO) is an object detection approach that utilizes Convolutional Neural Networks (CNN) for object detection, making it one of the applications of intelligent computing in the field of computer vision (Arvio, Kusuma, et al., 2023; H C, 2020).

In this research, the object detection system uses the YOLOv8 (You Only Look Once version 8) method, which is the latest version of YOLO, offering several improvements over the previous version, YOLOv5 (Terven and Cordova-Esparza, n.d.) thus, YOLOv8 was chosen for this research. It is hoped that this study will provide solutions to the issues raised, assess the performance of YOLOv8 in detecting inorganic waste, and help expedite the waste sorting process. Additionally, this research is expected to serve as a reference for future studies.

LITERATURE REVIEW

YOLOv8 implements several techniques such as advanced data augmentation and customized loss functions, all aimed at improving object detection performance under various conditions including a more advanced and efficient architecture (Hussain, 2023). Compared to YOLOv5, YOLOv8 offers advantages in terms of flexibility and efficiency (Wang et al., 2023). With the anchor-free approach, users no longer need to manually configure anchor boxes, which simplifies the training process and adapts the model to various datasets. Additionally, optimizations in the architecture and training techniques make YOLOv8 more adaptable to modern object detection challenges, making it an ideal choice for applications such as autonomous driving, surveillance systems, and robotics. Several studies have applied YOLOv8, such as research on (Rasjid et al., 2024) to detect objects with 7 sample classes, namely: bottle, chair, person, pot, gallon, trash can, and bucket, the evaluation results show that the YOLOv8 model performs very well. Additionally, it also handles high-speed objects like drones effectively(Kim et al., 2023), license plate recognition system (Naureen et al., 2024) and an intelligent fire detection system for urban areas (Talaat & ZainEldin, 2023). Overall, YOLOv8 represents a significant evolution in object detection algorithms, maintaining the speed and accuracy advantages that are characteristic of YOLO (Jiang et al., 2021; Ragab et al., 2024), while also introducing new innovations that enhance its performance across various application scenarios. With these improvements, YOLOv8 continues to solidify its position as one of the leading algorithms in the field of computer vision.

In the research on (Arvio, Tiara Kusuma, et al., 2023) Product Defect Detection for Masks using YOLOv5, weights were obtained with a MAP (Mean Average Precision) value of 0.92, and all mask objects were detected accurately with a precision rate of 97.1%. Subsequently, research (Soerya et al., 2022) explains the implementation of YOLOv3 for identifying and classifying office waste such as paper, plastic bottles, and cans, achieving an object detection accuracy of 94%. Previously, there was also research related to the development of a prototype for separating organic and non-organic waste using a microcontroller (Ichsan et al., 2019). he novelty of this research lies in the detection of inorganic waste within organic waste piles with greater detail based on the categories of inorganic waste used as training data for the neural network. The final outcome is the identification of waste that does not pass the sorting process for conversion into renewable energy. YOLOv8 has been effectively utilized in systems for detecting transparent plastic bottles, incorporating depth information to improve sorting accuracy in recycling processes (Hyuntae Cho, 2024). The algorithm has also been adapted for real-time garbage classification, enabling efficient categorization of diverse waste types through live camera feeds (Urlamma et al., 2024). Pan et al in 2024 successfully developed a Model that was applied in various environments, including smart waste bins and recycling facilities, to address the urgent need for effective waste sorting solutions (Songzhe Pan et al., 2024).

To find out the objects in a digital image, there are several digital image processing processes. The following is the image processing process flow in the YOLOv8 method available in figure 1.

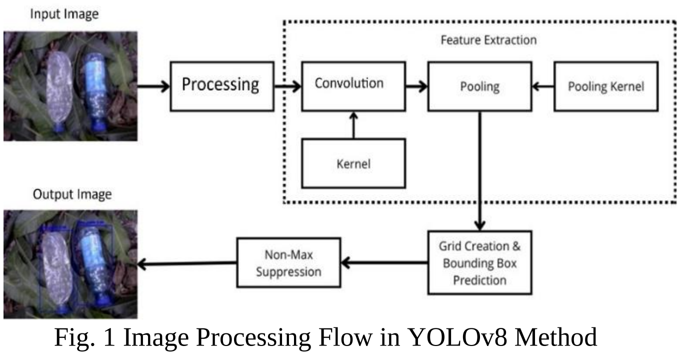


Fig. 1 Image Processing Flow in YOLOv8 Method

According to Figure 1, to determine objects in digital images, several processes are involved. First is the process of inputting the image to be detected as input for the model. Next is image preprocessing, where the image is prepared for the detection stage, such as resizing or image augmentation. Third, feature extraction involves

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117

e-ISSN : 2541-2019
p-ISSN : 2541-044X

extracting important features from the image using convolutional and pooling layers. Fourth, grid creation and bounding box prediction is the process of dividing the image into grids, with bounding boxes and class predictions made for each grid. Following that is the non-max suppression process, which removes redundant or overlapping bounding box predictions, leaving only the most relevant boxes. Finally, the output stage where the model provides the final bounding boxes and class labels for each detected object.

In the object detection process, there are several stages, one of which is image feature extraction. These processes include convolution and pooling. The convolution process is used to extract image features, while pooling is used to reduce the image dimensions without losing its features. A 4x4 image is used as the input image, which will undergo a convolution process using a 3x3 filter, resulting in a 3x3 image. To clarify the convolution process, the illustration of the process is provided in Figure 2.

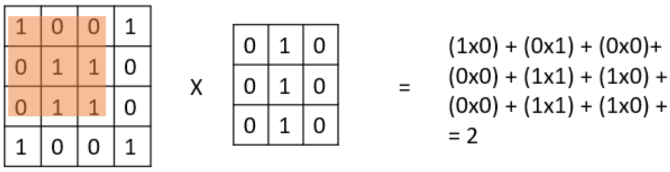


Fig. 2 Illustration of Image Convolution Process

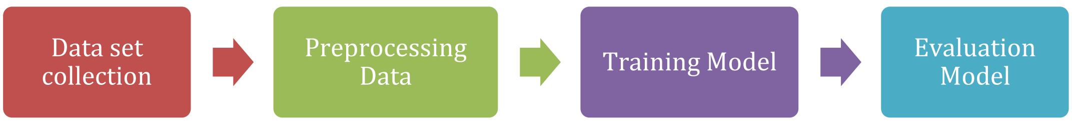
In the convolution process, the entire image will be convolved with the filter gradually. The filter will move around the digital image and the convolution process will be carried out slowly as in Figure 3. From the convolution process, the image which was originally 4x4 will change to 2x2. After the image undergoes convolution, pooling can be applied. The most commonly used pooling is usually max pooling. Max pooling is an operation used to reduce the size of the image within the scope of the kernel used by selecting the largest value. From the max pooling process with an initial image size of 2x2, a 1x1 image is obtained with a pixel value of 2, which is the highest value within the 2x2 max pooling kernel.

Thus, from the convolution and max pooling process, which forms the basis of the YOLO method, with a 4x4 input image, a 1x1 image is produced. These filters and operations are part of the image processing in the YOLO method, stored in the model's weights. These weights will later be used as data for image processing, so that objects in the image are detected, marked by a bounding box as an indicator, along with the object's class and confidence level.

METHOD

2.1 Research Stage

The development of an inorganic waste detection system for the waste sorting process using the YOLOv8 (You Only Look Once version 8) method involves several stages there are :



2.1.1. Dataset collection

To create an object detection system using the YOLOv8 method, a dataset is required. A dataset is a collection of data used as reference data during the model training process. In this study, the dataset used consists of 2.000 images comprising five classes of inorganic waste: plastic bottles, plastic, glass, cans, and Styrofoam. The dataset was collected by photographing inorganic waste objects to be detected. This collection was done manually using a Logitech C270 webcam, which is the same webcam that will be used in the system, ensuring that the data collected is of good quality and consistent with the conditions during the system's comprehensive testing. In addition to direct data collection, secondary data sourced from the internet, in the form of inorganic waste images, was also included. Examples of the collected dataset are shown in table 1.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Table 1 Dataset Classification

No	Classification	Object figure	No	Classificatiom	Object figure
1.	Plastic bottle		4.	Glass	
2.	Plastic		5.	Styrofoam	
3.	Can				

2.1.2. Data Preprocessing

After the dataset is obtained, the data needs to be preprocessed first, a stage known as preprocessing. The preprocessing stage involves labeling or marking each data point that will be used for training. Labeling aims to mark the objects to be detected. This marking includes the object's class and its position, indicated by a bounding box. The documentation of the dataset labeling process is shown in figures 3.

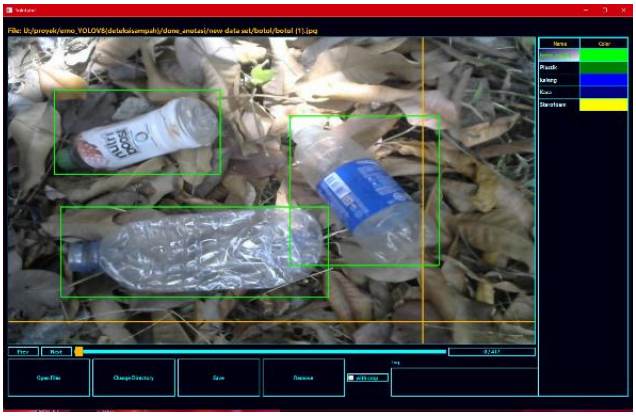


Fig. 3 Process in Yolo Label Application

From the labeling process that has been completed, an annotation file in .txt format is generated, containing the location and class of each object in every dataset image. This file will be used as a reference in the training process to determine which objects will be detected, allowing the model to understand the characteristics and uniqueness of each object. After completing the dataset annotation process, the final step in dataset preparation is dataset splitting. The dataset is split into two parts: training data and validation data.

From the dataset split configuration image, the dataset is divided into two main folders: train and val, with an 80% split for training data and 20% for validation data. Each of these folders contains two subfolders: images and labels. The images folder holds all the dataset images, while the labels folder contains the .txt files resulting from

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

the labeling process. During training, the data in the train folder will be used to train the model weights, and the data in the val folder will be used to validate the weights.

2.1.3. Training Model

In the model development process, the training phase is crucial. This phase is the most important as it determines the model's ability to detect objects. Here are the parameters used in training the model:

Table 2
Parameter Training Model

Parameter	Description
Epoch	150
batch	8
Varin bobot	Yolov8s

Next, the YOLOv8 model training is performed using Google Colab to ease the workload on the computer.

2.1.4. Evaluation Model

To evaluate the performance of the YOLOv8 model, several metrics are used, including accuracy, precision, recall, and F1-score. These metrics are assessed using the following equations:

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

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

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

$$F - 1\ Score = \frac{(2 * Recall * Precision)}{(Recall + Precision)} \quad (4)$$

With True Positive (TP) representing the interpretation of predicting positive and being correct. True Negative (TN) refers to the interpretation of predicting negative and being correct. False Positive (FP) is Type 1 error, where the prediction is positive but incorrect. Finally, False Negative (FN) is Type 2 error, which is very dangerous as it involves interpreting a prediction as negative when it is actually incorrect.

RESULT

The entire data set that has been formed is 2000 data which is divided into 1600 training data and 400 validation data, after carrying out the training process which produces a YOLOv8s model. The model training process was carried out for 2 hours 56 minutes with epoch 150, and batch 8.

The training model cannot be used directly in the system, it is necessary to evaluate the model first using a confusion matrix. The use of the confusion matrix is used to evaluate the model using the parameters accuracy, precision, recall and f1-score. The following is the confusion matrix resulting from the YOLOv8 model training in this research, available in figure 4.

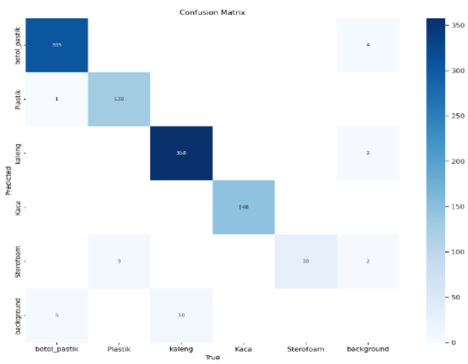


Fig. 4 Confusion Matrix Validation Results

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Based on the results of the confusion matrix in Figure 4, there are two sides, namely predicted and true. Predicted is the result of model predictions on validation data, while true is the truth label, on each side there are 6 classes. Background class is a class that arises due to an error in object detection, for example another object is detected even though the object is not part of the object that should be detected. The background class is usually a representation of the FP (False Positive) and FN (False Negative) conditions. From these results, accuracy, precision, recall and f-1 scores can be calculated. The following is the calculation of accuracy, precision, recall and f-1 score for the plastic bottle class.

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

$$Accuracy = \frac{(305+666)}{(305+4+6+666)}$$

$$Accuracy = 98.98\%$$

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

$$Precision = \frac{(305)}{(\ 305+ 4)}$$

$$Precision = 98.71\%$$

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

$$Recall = \frac{305}{(305 + 6)}$$

$$Recall = 98.07\%$$

$$F - 1\ Score = \frac{(2 * Recall * Precision)}{(Recall + Precision)}$$

$$F - 1\ Score = \frac{(2 * 98.07\% * 98.71\%\ )}{(98.07\% + 98.71\%)}$$

$$F - 1\ Score = 98.39\%$$

According to the calculations carried out, the plastic bottle class has an accuracy value of 98.98%, precision 98.71%, recall 98.07% and f-1 score of 98.39%. Then, testing for other classes is also carried out using the same calculations, the following detailed results of the YOLOV8 model evaluation calculations are available in Table 3

Table 3. YOLOv8 Model Evaluation Results

Class	**Accuracy**	**Precision**	***Recall***	**F1-Score**
Plastic Bottle	98.98%	98.71%	98.07%	98.39%
Plastic	99.08%	100%	93.53%	96.65%
Can	98.78%	99.44%	97.28%	98.35%
Glass	100%	100%	100%	100%
Styrofoam	99.79%	100%	93.75%	96.77%
Average	99.33%	99.63%	96.53%	98.03%

According to the calculation results, the YOLOv8 model has a good level of performance with performance values above 90% for all evaluation parameters. The best model in detecting glass objects has 100% accuracy, 100% precision, 100% recall and 100% f1-score. Thus, the model can be said to be suitable for use in inorganic waste detection systems.

To find out the actual performance of the YOLOv8 model that has been applied to the inorganic waste detection system, an inorganic waste detection system interface was created, which is presented in Figure 5 determine the actual performance of the YOLOv8 model which has been applied to the inorganic waste detection system.

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 4, October 2024
DOI : https://doi.org/10.33395/sinkron.v8i4.14117
e-ISSN : 2541-2019
p-ISSN : 2541-044X

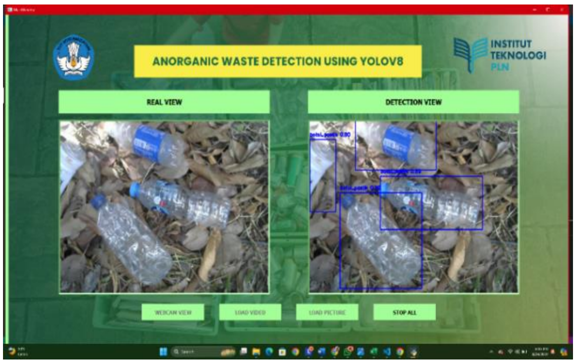


Fig. 5 Interface Inorganic Waste Detection System

From Figure 5 it can be seen that the system can detect inorganic waste objects in the form of plastic bottles which are marked by the formation of a bounding box that detects the waste object.

DISCUSSIONS

The results of this study highlight the effectiveness of the YOLOv8 method in detecting inorganic waste with model evaluation, including an average accuracy of 99.33%, precision of 99.63%, recall of 96.53%, and an F1-score of 98.03%, it is evident that YOLOv8 provides a high level of reliability in classifying and detecting inorganic waste.To further understand the test results directly, they are presented in Table 4.

Table 4. Direct Detection Test Results

Testing to	Number of Objects	Detection Results		Accuracy
		True	False	
1	1	1	0	100%
2	1	1	0	100%
3	1	1	0	100%
4	1	1	0	100%
5	1	1	0	100%
6	5	5	0	100%
7	4	4	0	100%
8	1	1	0	100%
9	2	2	0	100%
10	2	2	0	100%
11	10	10	1	90.91%
12	10	10	0	100%
13	10	10	0	100%
14	10	10	1	90.91%
15	10	9	1	90.00%
16	10	10	0	100%
17	10	8	2	80.00%
18	3	3	0	100%
19	3	3	0	100%
20	3	3	0	100%
Average Accuracy				98%

The test results presented in Table 4 show that the model can detect objects with an accuracy of 98%. However, there are still errors that occur, there are two errors that occur during testing, namely the object failed to be detected which occurred in the 15th and 17th tests and then the error condition caused by the background being detected as an object as happened in the 11th and 14th tests. From all test results, the YOLOv8 model can detect inorganic waste well with an accuracy of 98%. Thus, the YOLOv8 method is very effective in detecting inorganic waste objects of 5 classifications, namely plastic bottles, plastic, cans, glass and styrofoam.

CONCLUSION

After carrying out all the testing stages, a conclusion can be drawn that the YOLOv8 method can work well in inorganic waste detection systems. YOLOv8 has very good performance as shown by the results of model evaluation using the confusion matrix with an average accuracy of 99.33%, precision of 99.63%, recall of 96.53%, and f1-score of 98.03%. Furthermore, from direct testing results, the YOLOv8 model has an average accuracy of 98%. With these results it can be concluded that by using the YOLOv8 method inorganic waste can be detected well and has high accuracy. So it can simplify and speed up the process of sorting waste as renewable energy fuel.

ACKNOWLEDGMENT

The authors would like to extend their heartfelt thanks to Institut Teknologi PLN and DIKTI for their support, which was instrumental in completing this research as part of its outcomes. We also appreciate the relevant organizations for granting us the opportunity to gather the data needed for this study.

REFERENCES

Ahmad, H. M., & Rahimi, A. (2022). Deep learning methods for object detection in smart manufacturing: A survey. *Journal of Manufacturing Systems*, *64*, 181–196. https://doi.org/https://doi.org/10.1016/j.jmsy.2022.06.011

Arvio, Y., Kusuma, D. T., Sangadji, I., & Dewantara, E. K. (2023). *Penerapan Metode Convolution Neural Network (CNN) Dalam Proses Pengolahan Citra Untuk Mendeteksi Cacat Produksi Pada Produk Masker*. *16*(4), 340–350. https://doi.org/10.30998/faktorexacta.v16i4.20073

Arvio, Y., Tiara Kusuma, D., & Sangadji, I. B. (2023). *PENDEKATAN ALGORITMA YOLO V5 UNTUK MENDETEKSI CACAT PRODUK MASKER YOLO V5 ALGORITHM APPROCH FOR THE FACE MASK DEFECT DETECTION*. http://jurnal.dinarek.unsoed.ac.id

H C, D. (2020). An Overview of You Only Look Once: Unified, Real-Time Object Detection. *International Journal for Research in Applied Science and Engineering Technology*, *8*(6), 607–609. https://doi.org/10.22214/ijraset.2020.6098

Hussain, M. (2023). YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection. In *Machines* (Vol. 11, Issue 7). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/machines11070677

Hyuntae Cho. (2024). Transparent Plastic Bottle Detection and Depth Decision Method using YOLOv8 in Recyclable Waste Segregation Systems. *2024 IEEE International Conference on Omni-Layer Intelligent Systems (COINS)*.

Ichsan, T. J., Gunawan, T., Kom, M., Handayani, R., & St, S. (2019). *PROTOTIPE PEMILAH SAMPAH ORGANIK DAN NON-ORGANIK*.

Jiang, P., Ergu, D., Liu, F., Cai, Y., & Ma, B. (2021). A Review of Yolo Algorithm Developments. *Procedia Computer Science*, *199*, 1066–1073. https://doi.org/10.1016/j.procs.2022.01.135

Kim, J. H., Kim, N., & Won, C. S. (2023). High-Speed Drone Detection Based On Yolo-V8. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, *2023-June*, 1–2. https://doi.org/10.1109/ICASSP49357.2023.10095516

Konstantin Alkalaev, & Xavier Bekaert. (2019). Towards higher-spin AdS2 / CFT1 holography. *High Energy Physics - Theory*.

Naureen, A., Krishna, K. C., Teja, N. S., Mahesh, L., & Vamshi, K. (2024). College Bus Number Plate Registration Detection Using YOLO-V8. *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT)*, 1–7. https://doi.org/10.1109/easct59475.2023.10392472

Ragab, M. G., Abdulkadir, S. J., Muneer, A., Alqushaibi, A., Sumiea, E. H., Qureshi, R., Al-Selwi, S. M., & Alhussian, H. (2024). A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023). *IEEE Access*, *12*, 57815–57836. https://doi.org/10.1109/ACCESS.2024.3386826

Rasjid, A. A., Rahmat, B., & Sihananto, A. N. (2024). Implementasi YOLOv8 Pada Robot Deteksi Objek. *Journal of Technology and System Information*, *1*(3), 9. https://doi.org/10.47134/jtsi.v1i3.2969

Soerya, O., Utomo, N., Utaminingrum, F., & Widasari, E. R. (2022). Implementasi YOLO versi 3 untuk Mengidentifikasi dan Mengklasifikasi Sampah Kantor berbasis NVIDIA Jetson Nano. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *6*(6), 2829–2834. http://j-ptiik.ub.ac.id

Songzhe Pan, Ning Wang, Yuyun Lin, & Jianhao Tang. (2024). Based On YOLOV8 Intelligent Trash Can Garbage Classification Detection Algorithm. *Mathematical Modeling and Algorithm Application*, *2*(1), 28–32.

Talaat, F. M., & ZainEldin, H. (2023). An improved fire detection approach based on YOLO-v8 for smart cities. *Neural Computing and Applications*, *35*(28), 20939–20954. https://doi.org/10.1007/s00521-023-08809-1

Terven, J. R., & Cordova-Esparza, D. M. (2023). *A COMPREHENSIVE REVIEW OF YOLO ARCHITECTURES IN COMPUTER VISION: FROM YOLOV1 TO YOLOV8 AND YOLO-NAS PUBLISHED AS A JOURNAL PAPER AT MACHINE LEARNING AND KNOWLEDGE EXTRACTION*.

Urlamma, Amani, Mounika, & Devakumari. (2024). Automatic Garbage Classification Using YOLOV8. *International Advanced Research Journal in Science, Engineering and Technology*, *11*(3), 110–115.

Wang, M. H., Yu, Y., Lin, Z., Zeng, P., Liu, H., Liu, Y., Hu, W., Fang, X., Jiang, X., Chen, G., Hou, G., Chong, K. K., & Yu, X. (2023). Optimizing Real-Time Trichiasis Object Detection: A Comparative Analysis of YOLOv5 and YOLOv8 Performance Metrics. *2023 9th International Conference on Systems and Informatics (ICSAI)*, 1–5. https://doi.org/10.1109/ICSAI61474.2023.10423285

*name of corresponding author