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Detection of Plastic Bottle Waste Using YOLO Version 5 Algorithm

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Abstract: Plastic bottle waste management has become one of the most pressing environmental issues, especially in countries with high plastic usage rates, such as Indonesia. This research uses the YOLOv5 (You Only Look Once version 5) algorithm to detect plastic bottle waste automatically. The YOLOv5 algorithm was chosen because it has efficient detection performance and high accuracy in small object recognition. The dataset consists of 500 images of plastic bottles obtained through cameras and internet sources. The data is processed through several stages: annotation (bounding box and labeling using Roboflow), split dataset (70% for training, 20% for testing, and 10% for validation), pre-processing (resizing images to 460x460 pixels), and augmentation (adding data variations to improve model performance). Training and evaluation of the YOLOv5 model using the precision metric of 89.8% indicates the ability of the model to accurately identify plastic bottles from the overall prediction, recall of 83.1% indicates the success of the model in detecting the majority of plastic bottles in the test data, and mean average precision (mAP) of 89.2% represents the average precision at various prediction thresholds. Test results on varied bottle image test data obtained detection accuracy between 82%-93%, indicating the model can recognize plastic bottles consistently. Sometimes, this model needs help detecting overlapping picture objects. However, this research proves the potential of the yolov5 algorithm as an automated litter detection solution that will be integrated with a system and support faster and better plastic waste management.
Keywords: *Detection, Plastic Bottle Waste, YOLOv5*

INTRODUCTION

In daily life, waste is an inseparable aspect of human, animal, and plant activities. Waste is material left over from living things that are no longer used and will continue to increase every day. Based on research conducted by Priana, Indonesia is the second largest contributor of plastic waste in the world after China, with a total of 3.21 million tons or 80% of plastic waste ending up in the sea, which causes water pollution and poisons fish (Priana & Karyawati, 2023). In line with this research, the results of research from *Sustainable Waste Indonesia* (SWI) quoted from Republika.co.id noted that the recycling rate in Indonesia is still below 10%, this can create the potential for a higher increase in plastic bottle waste (Ratna Puspita, 2019). Plastic bottle waste has a large amount of increase, along with the popularity of plastic bottle packaging for various types of drinks in the current era. Plastic packaging is considered more practical because it is lightweight and easy to carry anywhere. However, often, the packaging that has been used is thrown away carelessly, causing an ever-increasing accumulation of plastic waste. It is estimated that around 182.7 billion plastic bags are used in Indonesia. Plastic waste can have a negative impact on the environment if not managed properly. Because it is difficult to decompose, elastic, and does not absorb water, plastic waste can inhibit water absorption and air circulation into the soil. Hence, the accumulation of plastic waste has the potential to reduce environmental quality (Utami & Fitria Ningrum, 2020). Separating plastic waste and waste by type takes a long time because waste is often mixed and must be sorted individually. Limited storage facilities mean temporary storage is only sometimes sufficient, and workers need to manually remove waste, increasing processing time. Waste-sorting workers are also susceptible to diseases due to hazardous substances such as heavy metals, biological pathogens, and toxic chemicals in waste (Elamin et al., 2018).

Technology is needed to overcome these problems and help the waste sorting process be more efficient and safe. One solution that can be used to speed up the waste sorting process is to apply an algorithm integrated with specialized technology to detect and distinguish plastic bottles from other types of waste. This technology speeds up processing, improves accuracy compared to manual methods, and reduces risk exposure for workers

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(Purwantoro, Mudzakir,. 2024). You Only Look Once (YOLO) is the algorithm chosen to support the solution. Because plastic bottle waste is included in the image or visual data category, an object recognition method with high accuracy is needed to detect it. YOLO is one of the most commonly used Deep Learning algorithms in digital image processing due to its high speed and accuracy. This algorithm efficiently divides the image into small grids and provides predictions in bounding boxes and object labels (Hassadiqin & Utaminingrum, 2023).

The YOLO (You Only Look Once) method is an innovation in object detection systems, using a single neural network for direct object detection and recognition and predicting the class and bounding box in one evaluation step. This method speeds up the detection process compared to other methods (Abdillah et al., 2025). The YOLO algorithm design process begins with a preprocessing stage, where the input image is resized into a grid of size s×s. Each object in the image is annotated with the corresponding class label, and the algorithm predicts the bounding box along with the relevant values. Each bounding box is predicted by the grid and assigned a confidence value, which is the confidence level that the bounding box contains objects of a particular class (Choi et al., 2019). The algorithm receives plastic bottle images as input in plastic bottle waste detection. The previously trained dataset will detect newly uploaded plastic bottle images. Plastic bottles that are successfully detected will be displayed in the form of a bounding box that includes the name of the object with the class “bottle plastic", along with the confidence value of the object. This confidence value determines the confidence level of the detection and affects how the object will be displayed based on the detection results by YOLOv5 (Yusuf et al., 2024a).

The YOLO algorithm was chosen because it is superior to other methods and has a high level of accuracy. This is evidenced in research conducted by Ardieka Fahmi Radhitya; the YOLO method can detect faster than the Faster R-CNN model, which shows a longer computation time per image than the YOLOv5 model (A. F. Radhitya et al. 2023). In line with research conducted by Agung Selamet Riyadi with the title “*Perbandingan Metode ResNet, YOLOv3, dan TinyYOLOv3 pada Deteksi Citra dengan Pemrograman Python*”, it was found that the YOLOv3 model provides the best accuracy rate of 96.79%. This is due to YOLOv3's ability to thoroughly detect every object in the image. In contrast, the TinyYOLOv3 model only achieved an average accuracy of 65.96% and ResNet 86.96% (Riyadi et al., 2022). In research by Sahla with the title “*Perbandingan Analisis YOLOv3, YOLOv4, dan YOLOv5 untuk Deteksi Tanda Bahasa*,” Sahla Muhammed Ali conducted a comparison between the three YOLO algorithms. The results showed that the F1 values of YOLOv3, YOLOv4, and Yolov5 were 0.53, 0.63, and 0.65, respectively. For the mAP value, each algorithm obtained 0.46, 0.607, and 0.633. The comparison results show that YOLOv5 is more accurate than previous versions of YOLOv3 and YOLOv4 (Ali, 2021). This is in line with research conducted by Olorunshola Oluwaseyi in “A Comparative Study of YOLOv5 and YOLOv7 Object Detection Algorithms", which states that the results of research conducted on a custom dataset for Remote Weapon Station show YOLOv5 has superior performance compared to YOLOv7 in terms of precision and mAP (Olorunshola et al., 2023). In research conducted by Dito Hafidzulrahman titled "Comparison of YOLO Algorithm Version 5 with Version 8 in Hilal Detection.” The YOLOv5 model shows superior performance, and this is due to the higher recall value of YOLOv5 compared to YOLOv8. YOLOv5 can detect objects as a whole better than YOLOv8 (Hafidzulrahman, 2024).

Based on various studies on the use of the YOLO algorithm, overall, it has proven superior to other methods such as Faster R-CNN, TinyYOLOv3, and ResNet in terms of accuracy, speed, and overall object detection capability. Of the various YOLO versions compared, YOLOv5 is the superior choice as it has higher precision, recall, and mAP than previous versions, such as YOLOv3 and YOLOv4, and performs better than YOLOv7 and YOLOv8. This makes YOLOv5 a reliable algorithm for object detection applications, including in the context of plastic waste management. Despite its high accuracy, the YOLOv5 algorithm sometimes needs to improve the detection of overlapping objects, especially if they have similar colors or textures. However, these weaknesses can be overcome with improvements in preprocessing, more accurate and detailed annotations, and more diverse data augmentation.

METHOD

This research uses 500 image data, which will be divided into *training*, *testing*, and *validation* data. The method used is object detection. This technique is based on artificial intelligence, where computers are trained to see as humans see, known as *computer vision*. For object detection, the YOLOv5 model is used from the *Convolutional Neural Network* (CNN) algorithm. Through the object detection process, *mean average precision* (mAP) is the metric used (Purwantoro, Mudzakir, 2024). Roboflow is a platform used in *object detection* that provides features to label or annotate images. In addition, Roboflow allows users to upload their datasets according to their needs, making it easier to label and prepare data for object detection models (Mustofa et al., 2023). In completing this research will go through a series of stages and processes described in the flowchart in Figure 1 below.

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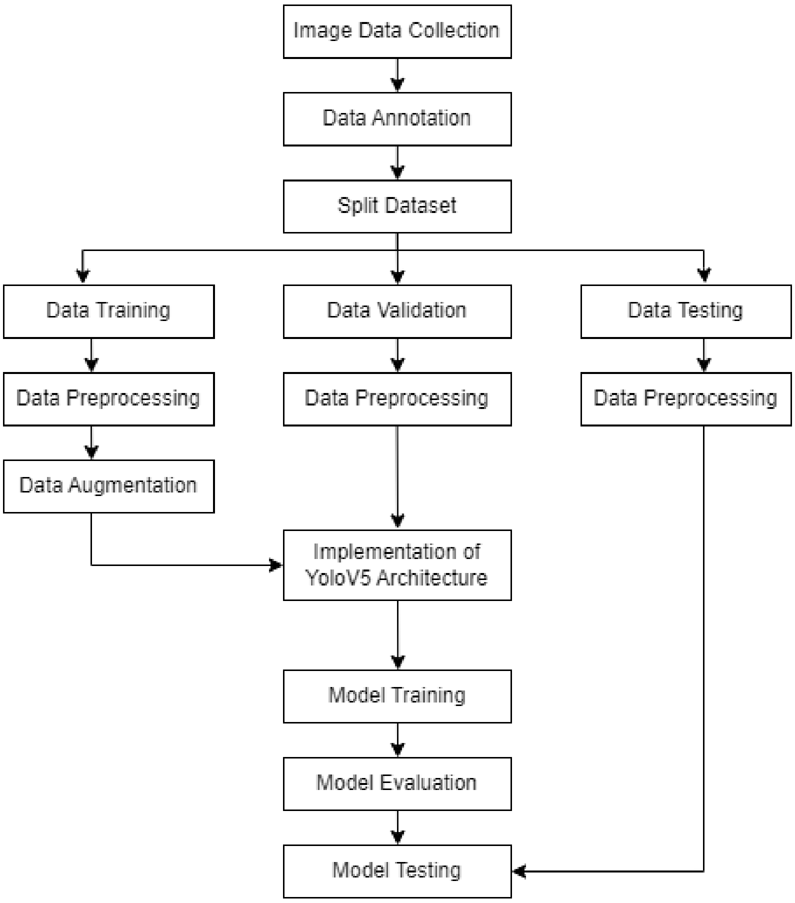

Figure 1. Research Design

1. Image Data Collection
   Image data collection was obtained through two main sources. First, plastic bottle image data was taken directly using a cell phone camera at the Addainuriyah Dua Islamic Boarding School landfill. Then, to increase the number of datasets, several plastic bottle images taken from internet sources were added. The amount of data collected from plastic bottle images was 208 images.
2. Data Annotation
   After the dataset is collected, the annotation process is carried out with the Roboflow platform. Roboflow provides various features for annotating objects in the image to be detected. The annotation process includes providing *bounding boxes* and labels. The *bounding box* is a rectangle that surrounds the object in the image, serving to identify the position of the object. The next step is labelling. Each *bounding box* object will be labelled with the class "*bottle plastic*," indicating that the detection process focuses on plastic bottles. The label "*bottle plastic*" will appear on images that are detected to contain plastic bottles (Yusuf et al., 2024).
3. Spilt Dataset
   After the data annotation is successfully processed, the dataset division stage (*split dataset*) is grouped into three categories. The 208 datasets are divided into 70% for *training* data, 20% for *testing* data, and 10% for *validation* data from the entire dataset. *Training data* is used to train the model, *and validation* data serves to evaluate the model during training but does not participate in the training process. In contrast, *testing* data is used to measure the overall performance of the model after the training process is complete.
4. Data Pre-processing
   Each image in the initial dataset is still of a random size. Therefore, pre-processing is carried out for *training* data, *validation*, and *testing* data, namely by changing the image size to 460 x 460 pixels. Image files are reduced to reduce file size and speed up the model training process. Lower-resolution images allow the model to process the data more quickly and efficiently, as less memory and computational resources are required. This contributes to the improvement in overall model training (Setiyadi et al., 2023). In addition, the *auto-orient* feature is also applied in the data pre-processing stage. This feature is used to perform adjustments automatically, allowing the rotation or orientation of an object or image to be adjusted in a more detailed direction as desired by the user (Fauzi et al., 2024).

5. Data Augmentation on Training Data
Data augmentation is implemented on the *training* data to increase the variety of images so that the trained model becomes more robust and can recognise patterns better. This augmentation stage goes through various manipulation techniques, such as *flipping*, where the image is flipped horizontally and vertically. 90-degree rotation, where the image is rotated by 90 degrees, *cropping*, where some areas of the original image are cut or taken, usually from the center area or randomly, *shear* where the image is shifted at a certain angle so that the object appears tilted, *grayscale* where a color image is converted to *grayscale* (black and white), leaving only intensity information without color, *noise* addition where random disturbances, such as dots or color variations, are added to the image and *cut out* where a portion of the image area is removed or covered with a black box to hide some visual information from the model. This technique is very good to apply to small datasets, as it is able to increase the diversity of the data without the need to increase the original data (Chan Uswatun, Angkin, 2023). In the data augmentation method performed through the Roboflow platform, the number of image variations was only increased by three times due to limited user access in Roboflow.
6. Architecture of YOLOv5
YOLO (You Only Look Once) is an algorithm developed for live object detection. It processes an image with a focus on recognizing objects in it and applies a model to various positions and sizes in the image. The area that obtains the highest detection score will be considered as a successfully detected object. YOLO uses *convolutional neural network* (CNN) architecture with *deep learning to* detect the presence of objects in images. In the application, the YOLO CNN consists of only convolutional and pooling layers. The number of convolutional layers is adjusted to the expected number of classes and prediction boxes (Geraldy & Lubis, 2020).
The YOLO algorithm processes the input image by dividing it into a 460×460 grid. If the centre of an object is located in one of the cells in the grid, it will detect the object. Each grid cell then generates several bounding box predictions along with confidence values for each frame. Each bounding box yields five parameters, four of which indicate the position and size of the box (x, y, w, h) and one confidence value. The coordinates (x, y) indicate the location of the centre of the bounding box relative to the edge of the grid cell, while w and h indicate the width and height of the box relative to the overall size of the image. A grid cell that detects an object also estimates the class probability for that object, regardless of the number of bounding boxes generated (Khairunnas, Yuniarno, and Zaini 2021). YOLOv5 has a smaller file size compared to YOLOv4 and previous versions, making it more practical to implement on embedded devices. In addition, YOLOv5 offers higher accuracy and superior performance in detecting small objects compared to previous versions of YOLO (Imran, 2023). Based on the research mentioned in the Introduction section, the YOLOv5 algorithm was chosen because it is superior to other methods, such as Faster R-CNN, TinyYOLOv3, and ResNet, in accuracy, speed, and detection capability. Compared to YOLO version 3,4,5,7,8, YOLOv5 shows higher precision, recall, and mAP, making it a reliable algorithm for object detection, including plastic waste management.
The YOLOv5 architecture has three main components, namely, *Backbone, Neck*, and *Head*. *Backbone* uses *CSPDarknet53* as a convolutional neural network to extract features from images, which improves the accuracy and efficiency of the model by minimizing the number of parameters. *The Neck* plays a role in processing the extracted features before passing them to the prediction layer. YOLOv5 uses FPN (*Feature Pyramid Network*) and PANet (*Path Aggregation Network*) to improve small object detection capability and enrich information from higher layers. The *Head* is responsible for predicting the bounding box as well as the class of the detected object, like the structure in YOLOv3 and YOLOv4. It generates three different feature maps to improve accuracy at various object sizes. Overall, YOLOv5 uses CSPDarknet53 to perform feature extraction from images, combines it with PANet, and uses *Head* to detect objects with high efficiency (Riva & Jayanta, 2023). Overall, the architectural structure of YOLOv5 is shown in Figure 2 below.

*name of corresponding author

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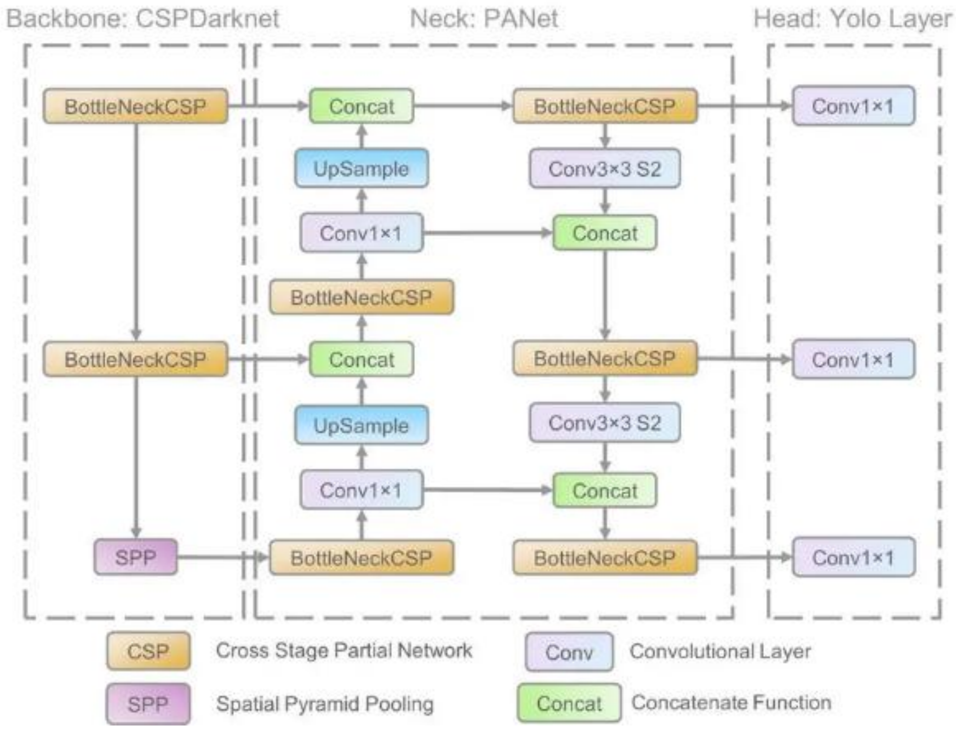

Figure 2. YoloV5 Architecture (Riva & Jayanta 2023)

7. YOLOV5 Model Training
From the dataset that has been collected, the modelling stage using the YOLOv5 algorithm to detect plastic bottle waste is carried out through the Google Collab platform. The YOLO V5 algorithm performs model training for the detection of data defined in the data.yaml file. Data.yaml contains the dataset configuration, such as the path to training data, validation data, and the number of classes. In the training stage, the YOLOv5 model serves to train the algorithm to recognize and detect plastic bottles in images or videos. In this process, the model learns from the *training* dataset (images of plastic bottles that have been labelled) to identify patterns and features typical of plastic bottles. If the resulting model reaches an accuracy level above 70%, then the model will be used for the plastic bottle waste detection process. Conversely, suppose the accuracy of the model is less than 70%. In that case, further evaluation will be carried out on the dataset used to increase the accuracy value of the training data modeling (Arvio, Kusuma, and Sangadji 2024).
8. Evaluation of the YOLOV5 Model
Furthermore, to evaluate the performance of the algorithm used, testing is carried out using the confusion matrix. This test aims to determine how well the model can detect objects from the trained dataset. This stage also aims to produce a model with a high accuracy and low error rate and measure the performance of the model by calculating *precision*, which is the ratio between the correctly predicted objects compared to the overall results predicted by the model, and *recall*, which is the ratio between the correctly predicted objects compared to the overall actual results. In addition, *mean average precision* (mAP) is calculated using the *precision* and *recall* values to provide an overview of the model performance (Gelar Guntara, 2023).
9. Testing the YOLOV5 Model
After the model training and evaluation process is complete, the next step is to test the model using images uploaded to Google Collab. This test uses new data that has yet to be used in the model training stage. The purpose of this test is to evaluate the system's ability to detect plastic bottle waste with high accuracy and low error rate (loss). Initial testing was done by uploading image files to Google Collab to see the success rate of the YOLO method (Hassadiqin & Utaminingrum, 2023).

RESULT

1. Data Pre-processing
After the data has gone through the pre-processing stage as described in the research method, the results, as presented in the table below, are obtained.

Table 1. Data pre-processing results

Input Image	Pre-processing Data

*name of corresponding author

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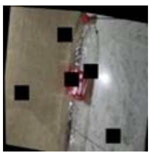
2. Data Augmentation
   After the image has gone through the pre-processing stage, the next step is to increase the variety of datasets from the pre-processed data through the augmentation process. Due to limited user access in Roboflow, the augmentation process has only increased by three times. The following are the results of data augmentation.

Table 2. Data Augmentation Results

Input Image	Data Augmentation Results		
			
			

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3. YoloV5 Model
   In this stage, the YOLOv5 model preparation process uses Google Collaboratory. It includes cloning the YOLOv5 repository from GitHub, installing the required libraries, setting up the working directory, and initializing the supporting libraries to ensure the environment is ready to be used in training and testing the object detection model.
4. Model Training
   The training process lasts for 16 minutes using 100 *epochs*, which means the entire dataset will be processed 100 times for the model to learn the patterns more deeply from the given data as well as refine the weights and improve its accuracy. The batch size is set to 16, which means 16 images will be processed in each training iteration. If the trained model achieves an accuracy level above 70%, then the model will be used for the plastic bottle waste detection process. Conversely, if the model accuracy is less than 70%, then further evaluation will be carried out on the dataset used to increase the accuracy value of the training data modeling (Arvio, Kusuma, and Sangadji 2024). From the training process that has been carried out, the accuracy results above 70% are detailed in Table 3 below.

Table 3. Model Training Results

Evaluation Indicator	**Percentage (%)**
Precision	89.8%
Recall	83.1%
Mean Average Precision (mAP)	89.2 %

The Yolo V5 algorithm model's training results obtained a *precision* (P) value of 0.898, *recall* (R) of 0.831, mAP@0.5 of 0.892, and mAP@0.5-0.95 of 0.663. These results show that the model performs fairly well in detecting objects at various *threshold* levels.

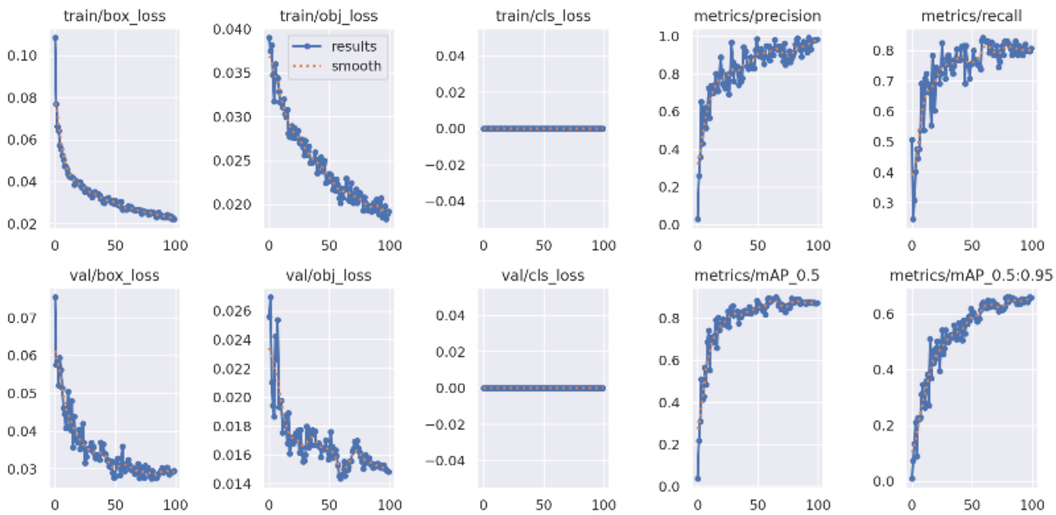

Figure 3. Visualization of Training Results

*name of corresponding author

Figure 3 is a graph of the YOLOv5 model training results. It can be seen that the box loss value for both training and validation has decreased significantly, indicating an increase in the model's ability to predict the bounding box of plastic bottle waste objects. In addition, the train/object loss and val/object loss also decreased consistently, indicating an improvement in object detection. The classification values (train/class loss and val/class loss) remained almost constant around zero, indicating no significant classification problems. The precision metric increases steadily, reflecting that the model rarely generates false positives, while recall also shows improvement, indicating that the model is getting better at detecting all object instances. Finally, the mean Average Precision (mAP) value at threshold 0.5 increased during training, with mAP@0.5:0.95 showing good, albeit slightly lower, detection performance. These results show that the YOLOv5 model has a good ability to detect objects with high accuracy.

5. Model Evaluation

Furthermore, the algorithm's performance is evaluated using the *confusion matrix*. This test aims to determine how well the model can detect objects from the trained dataset.

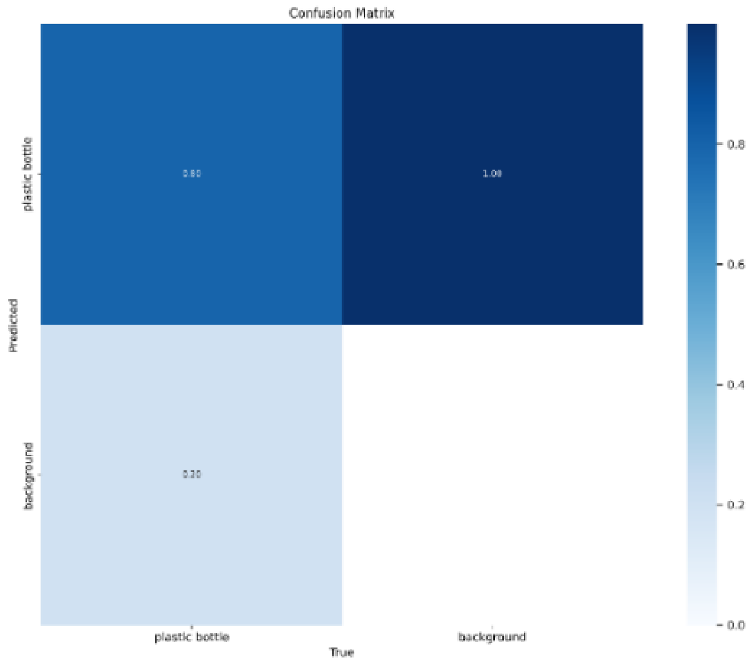

Figure 4. Confusion Matrix

Figure 4 shows the evaluation results showing that the model can correctly identify 80% of the samples that are plastic bottles. In comparison, there are still 20% errors where plastic bottle samples are misclassified as background. Based on the evaluation results using *the confusion matrix*, the *True Positive* value reaches 80%, which means that the model succeeds in correctly predicting plastic bottles when they really are. In contrast, the *False Negative* value of 20% indicates that the model misclassified the sample as not a plastic bottle when, in fact, it was a plastic bottle. The *True Positive* value that reaches 80% indicates that the model already has a fairly good level of accuracy in detecting plastic bottles.

6. Model Testing

After the model training and evaluation process is complete, the next step is to test the model using images uploaded to Google Collab. This research tests the model that has been trained using those that have never been used in the model training stage. The purpose of this test is to assess the system's ability to detect plastic bottle waste with high accuracy and low error rate (*loss*). The first test was carried out using image files uploaded on Google Collab to determine the success rate of the YOLO method (Hassadiqin & Utaminingrum, 2023). Detection of plastic bottles using the YOLOv5 method runs well, resulting in a high level of accuracy. The following are the detection results for plastic bottles and non-bottle images.

*name of corresponding author

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Table 4. Model Testing Results

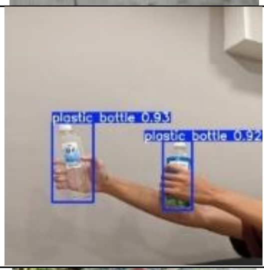
Model Testing	Accuracy
	84% - 92%
	92% - 93%
	91%

Table 4 shows the results of testing the model, with accuracy ranging from 84% to 93%. This shows that the model has a consistent level of accuracy on varied test data and can recognize objects well in that data range. Therefore, by applying the YOLOv5 algorithm, the resulting detection model is adequate and feasible to use in the plastic bottle waste management process.

DISCUSSIONS

The results of this study show that the YOLOv5 algorithm can detect plastic bottle waste with a high level of accuracy, as reflected by the precision value of 89.8%, recall of 83.1%, and mAP of 89.2%. These values confirm that YOLOv5 not only can correctly identify plastic bottles but also consistently detects most of the target objects in the test dataset. This accuracy is obtained through the training process using annotated data and through pre-processing. Comparisons with previous studies also show the superiority of YOLOv5 in efficiency and accuracy over other algorithms, such as YOLOv3, YOLOv4, Faster R-CNN, TinyYOLOv3, and ResNet. The use of Google Collab as a training platform also supported the optimal results, proving that cloud-based infrastructure can be an efficient alternative for large-scale data processing. Overall, this research confirms the potential of YOLOv5 to be implemented in an automated and real-time plastic bottle waste sorting system, providing a practical solution that can support plastic waste management in Indonesia.

CONCLUSION

This research successfully uses the YOLOv5 algorithm for plastic bottle waste detection as a solution in the waste management process. By using YOLOv5, the system can perform real-time detection with high accuracy. Training the model on Google Colab resulted in a Precision value of 89.8%, which means the model has a high level of accuracy in identifying plastic bottles from all predictions generated. In addition, the recall value reached 83.1%, indicating that the model could detect most plastic bottles in the test data. Mean Average Precision (mAP) shows a value of 89.2%, the average precision at various threshold levels. Hence, the model can identify and distinguish plastic bottles from other objects. In the final test, the detection accuracy ranged from 84% to 93%, indicating that the model performed well on varied test data. This research contributes to supporting the automation of plastic bottle management, reducing reliance on manual methods, and accelerating plastic recycling efforts in Indonesia, making it an innovative solution that has the potential to be applied in the waste management industry

*name of corresponding author

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and environmental policies. However, this research has several limitations, such as a limited dataset that does not represent a wide variety of plastic bottle conditions and challenges in detecting overlapping bottle images. For future research, it is recommended that this algorithm be integrated with a technology-based system capable of detecting plastic bottle waste to be implemented directly in the real world. In addition, it is essential to develop a broader dataset that is not limited to plastic bottle waste but includes various other types of waste to increase the flexibility and coverage of the model.

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