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Identification Types of Plastic Waste Based On The Yolo Method

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Abstract

Plastic is still widely used in the daily lives of Indonesian people. As well as being an inexpensive material, plastic is characterized by weather, lightweight and corrosion resistance. In Indonesia, awareness of waste is still very low, resulting in the indiscriminate accumulation of garbage. Some people don't know the material from the type of plastic used These issues can be solved by using artificial intelligence advancements, such as computer vision. The yolov3 Tiny method was used to identify the type of plastic. The types of plastic used in this study were PET, PP, and HDPE. This method is implemented in a desktop-based application. The system is successful with an average accuracy value of 53.3%. The system easily recognizes the PET type, with an accuracy rating 70% greater than the other varieties. Whereas for the PP type, the result is 60% and for the HDPE type, it gets a value of 30%. For researchers, in turn, it may add a greater number of data slices and vary to be even more accurate in their identification.

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I. INTRODUCTION -

Plastic is still widely used in the daily lives of Indonesian people. As well as being an inexpensive material, plastic is characterized by weather resistance, light weight and corrosion resistance. In Indonesia, awareness of waste is still very low, resulting in indiscriminate accumulation of waste [1]. According to J. Meijer, L. J et al, Indonesia ranks fifth in the world in terms of dumping plastic waste into the sea [2]. The world is working to reduce plastic waste in many ways, from reducing plastic consumption to recycling.

Plastic recycling cannot be arbitrary because plastic has many distinct types based on the type of plastic or its composition, so sorting plastic before recycling is required. Currently, the sorting of plastics in industrial environments still requires human operations, such as observing symbols or levels of hardness. Therefore, the application of human labor usually has some drawbacks, such as relatively high costs,

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inefficiencies, and inconsistent results. The situation is different when sorting is carried out by machine action, which brings several advantages, such as reducing labor cost, efficient and consistent in delivering results. There are some people who do not know the material from the type of plastic used [3].

However, if you look closely, plastic shows properties that can distinguish one type of plastic from another. As a result, we require a system that can identify the type of plastic using photos and provide information on the type of plastic. These problems can be overcome by implementing artificial intelligence innovations, one of which is computer vision. Computer vision can mimic the workings of human vision although it cannot accurately mimic the human eye because the working system of the human eye and brain is still not fully understood [4].

You Only Look Once (YOLO) is a method developed by Joseph Redmon for object detection. YOLO performs object detection effectively [5]. When compared to other object detection systems, YOLO has higher Mean Average Precision (MAP) and Frames Per Second (FPS) [6].Based on the YOLO model, transfer learning can be performed on the model so that the model can detect and classify new objects. Previous research has shown that using the Yolo v5 approach to detect plastic waste at railway crossings can significantly increase the effectiveness of security cameras [7]. The YOLOv3 Tiny method was utilized in this investigation to determine the type of plastic. PET, PP, and HDPE were the plastics employed in this investigation. This technique is implemented in a desktop application.

II. YOU ONLY LOOK ONCE (YOLO)

The YOLO is algorithm for object detection that is different from other algorithms. The YOLO method applies a neural network to all images [8]. YOLO is inspired by the google net image classification model. YOLO itself has 24 convolution layers and 2 combination layers. YOLO can run at 45 fps (frames per second) on Titan. There are several versions of YOLO such as YOLOV1, VOLOV2, YOLOV3 and YOLOV4 with different accuracy and detection speed [9], [10]. In YOLOv3, bounding box prediction is done by using the cluster dimension as the anchor box. Each Bounding Box will predict 4 coordinates and predict class using multilable classification. The value of an object is predicted based on the value in each box using logistic regression without softmax [11]. During the training process, a binary cross-entropy loss function is used to predict the class.Yolov3-tiny uses two different detection scales to predict objects. The proportions given are 13x13 and 26x26. The architecture used in yolov3-tiny is similar to yolov2, namely Darknet-19, the difference between yolov3 Tiny and yolov2 is that it does not have a multiscale detector. YOLOv3 [12]formula:

$$NxN \text{ X } [B \text{ X}5 + C] \tag{1}$$

Where N is a feature ratio, B is the number of bounding boxes, and C is the number of classes. Tiny YOLO is lighter and faster than YOLO while surpassing other models in accuracy [13]. The tinyyolov3 network can be used for object detection and classification. This model is trained on the Coco dataset and can recognize up to 80 classes.

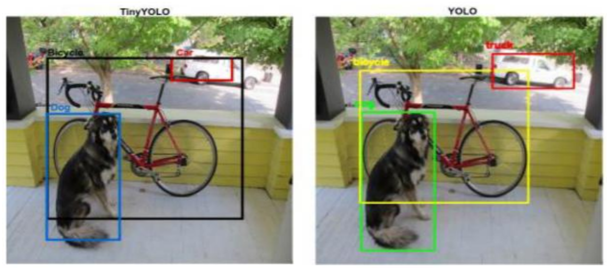

Figure 1. YOLO Model

YOLO v3-Tiny utilizes pooling layers and reduces the number of convolutional layers. It generates predictions as a 3D tensor that includes target points, bounding boxes, and class predictions at two different scales. The image is segmented into cells within an S×S grid. During final detection, bounding boxes with suboptimal objectivity values are discarded. In the YOLO v3 Tiny input preset, the maximum convolutional layer and the union layer are used for feature extraction [14]. For each bounding box, yolov3-tiny evaluates 4 bounding box coordinates with symbols(tx,ty,th,tw). Here is the equation for bounding-box:

$$Bx=\sigma(Tx)+cx \tag{2}$$

$$By=\sigma(Ty)+cy \tag{3}$$

$$Bw=pw.C\text{^}Tw \tag{4}$$

$$Bh=ph.C\text{^}Th \tag{5}$$

Where (tx,ty) represents the center of the bounding box,(tw,th) is the size of the bounding box, (pw,ph) describes the dimensions of the segmentation anchor box, and (cx,cy) s the coordinate offset. Due to normalization, the coordinate values range between 0 and 1 [12]. Yolov3-tiny estimates the object value in each of the 3 anchor bounding boxes [B x (5 + C)] based on each scale.

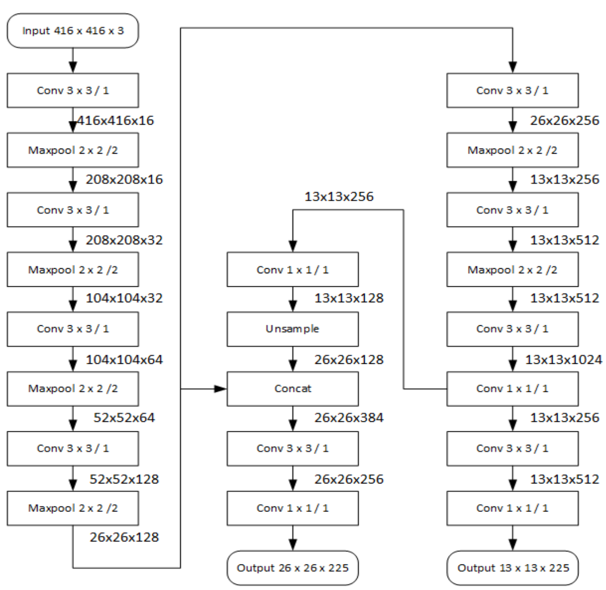

Figure 2. Architecture of YOLO v3-Tiny

III. METHODS

The research to be conducted focuses on the development and implementation of solutions for problems identified in previous studies. The method used to identify plastic waste involves YOLO (You Only Look Once) version 3 Tiny algorithm.

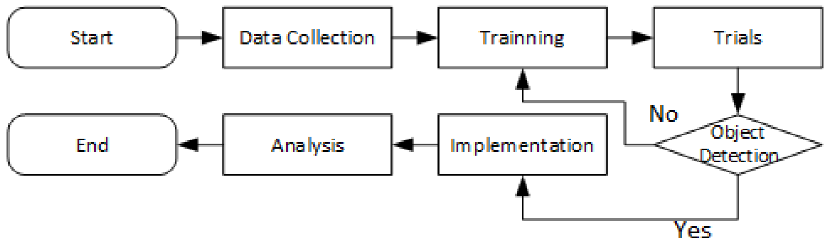

Figure 3. Research Stage

A. Data Collection

Collecting the dataset for this study from pictures of PET, PP and HDPE plastics from the internet. Each image in the data set is annotated to get data about the object being trained. In addition, the dataset is processed with the YOLO v3 Tiny technique.

B. Plastic

Plastic is one of the most widely used items in human life. Generally, plastic has characteristics that are easily shaped or molded, which are lightweight and flexible, lightweight, unbreakable, invisible, electric and thermal insulation, and severely volatile [7]. Each form of plastic has its own use and properties.Plastic differences also affect the recycling process [9]. Here are the types of plastic that are often used in everyday life there are 7 varieties including (PET), (HDPE), (PVC), (LDPE), (PP), (PS) and other (O).

C. You Only Look Once (YOLO)

YOLOv3 introduces the concept of anchor boxes, which are generated from the clustering process on the training dataset. Each anchor box adjusts itself to the different aspect ratios of objects within the dataset, enabling YOLOv3 to predict the location and determine the size of objects accurately. For each location in an image, YOLOv3 predicts several bounding boxes along with confidence scores, with these scores reflect the model's confidence in whether the box contains an object and the accuracy of the object's classification. YOLOv3 enhances detection accuracy by utilizing binary cross-entropy loss for classification and a specialized loss function that combines mean squared error and intersection over union (IoU) for bounding box prediction. This approach helps optimize the prediction of location and object classification simultaneously.

D. Training Process

Training process is a process in which a neural network is trained to recognize or learn patterns so that it can perform the expected object recognition with high accuracy. The initial step is to link Google Colab to Google Drive. Next, download the configuration file from the Darknet GitHub repository and enable GPU and OpenCV support. The following step involves setting up the Darknet network with YOLOv3 and extracting the images from the zip file and run a training process to generate weight measurements. The result is a weight value stored in google drive.

E. Testing Process

To determine the accuracy of the YOLOv3 Tiny method for identifying plastic waste, the researchers conducted a testing process. This testing process involved presenting the object in front of the camera, providing adequate lighting, and analyzing images.

F. Application Design

An application is a program in the form of software that runs on certain systems and is useful for supporting various functions performed by humans on the system [15]. At the application design stage is the stage where from designing the flow, ui/ux, and program algorithms.

In this research to design an application using pyqt5 which is owned by python so that this application is desktop-based. The following is the flow of using the application.

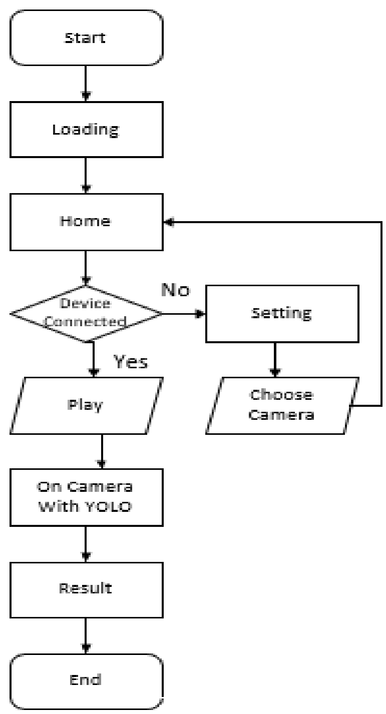

Figure 4. Flowchart Application

IV. RESULTS AND DISCUSSIONS

A. Pre-Processing Result

This investigation began with the collection of image data with three different types of plastic obtained over the internet. Next, label each image using the labelling application. The labeling process is giving a frame to an image and providing a description.

Figure 5. Labeling image

B. *Training Result*

In this investigation, three varieties of plastic were used, with 300 photos of each type used for training. In the training process using darknet53 configuration. The level of accuracy achieved with the YOLOv3 Tiny model of 6000 iterations results in an average loss value of 0.59.

```
6000: 0.643525, 0.599113 avg loss, 0.001000 rate, 1.565759 seconds, 384000
images, 0.048402 hours left   .
```

Figure 6. Output Batch

The lower the value the better, at least the average loss value is less than 0.60.

C. *Testing Result*

After completing the training results, the next step is the testing phase. The purpose of the tests conducted is to assess the accuracy level of the developed model. The level of accuracy generated by the system is based on the results of image classification observations. In the conducted tests, the results can be seen in the table below. If the bottle has been identified, the display on the application will display the type, value and marked with a bounding box.

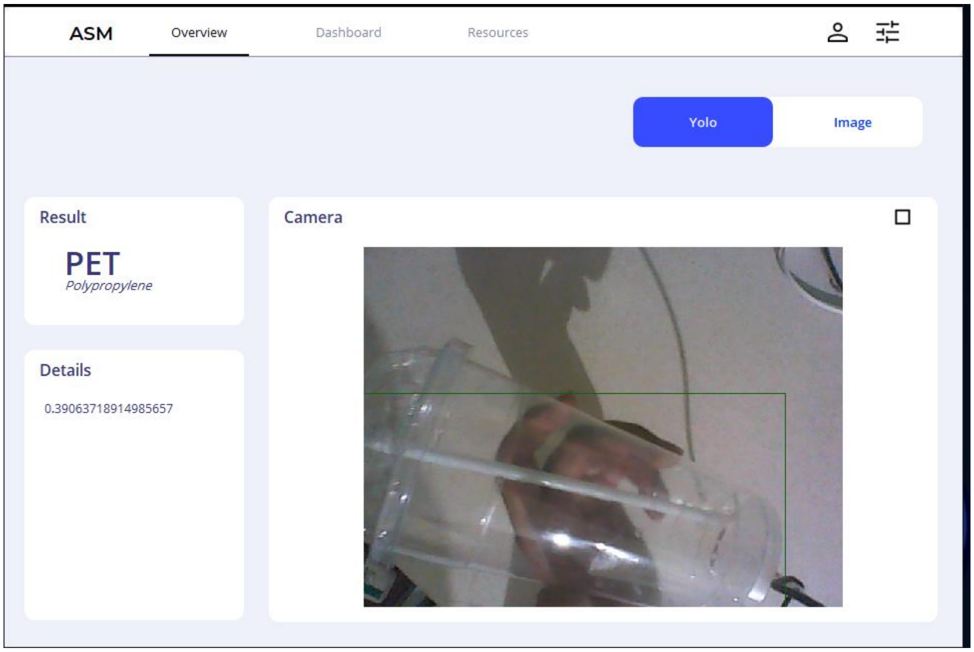

Figure 7. Experimental result of YOLO v3-Tiny

After completing the preprocessing, training, and testing processes on the desktop application we developed, the next phase involves analyzing the trial data. We compiled a table with the outcomes from 50 experiments, each incorporating 5 distinct types of plastics. For analytical purposes, we subdivided the experiments into batches of 10 for closer examination. The data showcased in this document represents a sample from these 10 experiments.

Table 1. Result of PET Plastic Testing

No	Test Results			Success
	System	Manual	Value	
1	PET	PET	0.23	Yes
2	PP	PET	0.39	No
3	PET	PET	0.20	Yes
4	PET	PET	0.21	Yes
5	PET	PET	0.35	Yes
6	PP	PET	0.27	No
7	PET	PET	0.20	Yes
8	PET	PET	0.28	Yes
9	PET	PET	0.32	Yes
10	PP	PET	0.39	No

Table 1 showcases the outcome of 10 trials focusing on 5 distinct types of PET plastics, with data acquisition carried out through both automatic and manual readings via a custom-developed desktop application. The process encountered several inaccuracies in PET plastic identification, primarily attributed to two factors. Firstly, the transparency of PET plastics occasionally hindered the system's edge detection capabilities, leading to misidentification. Secondly, the background used during the readings sometimes caused the system to mistakenly classify PET plastics as PP (Polypropylene), indicating that both the material's transparency and the choice of background significantly impact the accuracy for plastic identification system. To enhance the system's precision, it is crucial to refine the edge detection algorithms and carefully select a background that minimizes interference, thereby improving the reliability of PET plastic classification.

Table 2. Result of PP Plastic Testing

No	Test Results			Success
	System	Manual	Value	
1	PP	PP	0.77	Yes
2	PET	PP	0.31	No
3	PET	PP	0.39	No
4	PP	PP	0.38	Yes
5	PP	PP	0.27	Yes
6	PP	PP	0.32	Yes
7	PP	PP	0.29	Yes
8	PET	PP	0.24	No
9	PET	PP	0.21	No
10	PP	PP	0.34	Yes

Table 2 displays the results of 10 trials focused on 5 different types of PP plastics, with data collection conducted through both automatic and manual readings via a specially developed desktop application. This process encountered several inaccuracies in the identification of PP plastic, primarily due to two factors similar to those encountered with PET plastic types. First, the transparency of PP plastic occasionally impeded the system's edge detection capability, leading to misidentification. Second, the background used during readings sometimes caused the system to misclassify PP plastic as PET and vice versa, indicating that the transparency of the material and the choice of background significantly impact to accuracy of the plastic identification system. To enhance the system's precision, it is crucial to refine the edge detection algorithm and carefully select a background that minimizes interference, thereby improving the reliability of PP plastic classification. If we examine the data from manual trials, we obtain much better results. This is because we can adjust the edge detection process and select the appropriate colors, resulting in much more accurate data.

Table 3. Result of HDPE Plastic Testing

No	Test Results			Success
	System	Manual	Value	
1	HDPE	HDPE	0.22	Yes
2	PP	HDPE	0.21	No
3	PP	HDPE	0.41	No
4	PP	HDPE	0.97	No
5	HDPE	HDPE	0.20	Yes
6	PP	HDPE	0.58	No
7	PP	HDPE	0.27	No
8	PP	HDPE	0.23	No
9	PP	HDPE	0.54	No
10	HDPE	HDPE	0.32	Yes

Table 3 showcases the outcomes of 10 experiments focusing on 5 different types of HDPE plastics, with data collection executed through both automatic and manual readings using a specifically developed desktop application. Throughout these trials, several inaccuracies in the identification of HDPE plastics were observed. A notable factor contributing to these inaccuracies is the similarity in color between PP and HDPE plastics, which complicates their distinction.

Additionally, the detection of edges and the reflection of light captured by the camera significantly influence the accuracy of object readings. Remarkably, manual testing yielded far superior results. This improvement is attributed to the ability to fine-tune the edge detection process and adjust color saturation appropriately, leading to data that is significantly more precise and reliable. This underscores the importance of optimizing detection settings to enhance the overall accuracy of plastic identification.

The subsequent section details the outcomes of the conducted experiments, as depicted in Table 4, which showcases the results from testing 10 samples. This testing phase illustrates the performance of the system in identifying different types of plastics. Specifically, for PET plastics, the system achieved a success rate of 70% with 7 successes and 3 failures. In the case of PP plastics, the success rate was slightly lower at 60%, with 6 successful identifications and 4 failures.

The most challenging type to identify proved to be HDPE plastics, where the system only managed a 30% success rate, successfully identifying 3 samples correctly but failing to identify 7 accurately. This data highlights the varying levels of the system's proficiency in recognizing different plastic types, indicating a need for further optimization to improve its accuracy, especially for HDPE plastics.

Table 4. Result of Testing

No	Type	Sample Number	System Test Result		Accuracy (%)
			Success	Fail	
1	PET	10	7	3	70
2	PP	10	6	4	60
3	HDPE	10	3	7	30

Based on the data derived from the test results presented, the system achieved an average accuracy rate of 53.3%. Detailed analysis of the table reveals that objects made of PET (Polyethylene Terephthalate) were identified with greater accuracy compared to those made of HDPE (High-Density Polyethylene). Notably, the system frequently misclassified HDPE objects as being made of PP (Polypropylene). This suggests that while the system demonstrates a certain level of proficiency in distinguishing between different types of plastics, there remains a significant challenge in accurately identifying HDPE materials, often leading to their incorrect classification as PP. The discrepancy in identification accuracy underscores the need for further refinement of the system's algorithm to enhance its ability to differentiate more effectively between HDPE and PP materials.

V. CONCLUSIONS AND RECOMMENDATIONS

According to the research findings, the system successfully detected and classified plastics based on their types, achieving an average accuracy of 53.3%. The system demonstrated high performance in recognizing PET plastics, with an accuracy of 70%, which is significantly higher than that of other types. In comparison, the PP type achieved an accuracy of 60%, while the HDPE type only reached 30%. This disparity in accuracy may be attributed to the dataset's limited variance or insufficient number of samples for each plastic type.

Despite these challenges, the YOLOv3 Tiny model proves to be a viable tool for sorting and detecting plastic waste. Its effectiveness in distinguishing PET and PP plastics shows potential for practical applications in waste management systems. For future research, expanding the dataset to include a greater variety of samples and increasing the overall number of images could enhance the system's accuracy. Such improvements would contribute to more reliable identification of different plastic types, leading to more efficient sorting and recycling processes. Researchers are encouraged to diversify and enlarge their datasets to improve the precision of plastic identification systems.

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