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# A YOLOv5s Model for Classification of Garbage

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***Abstract –****As a result of great economic and social progress, domestic waste production has risen dramatically. Environmental problems will become prevalent without efficient waste management, impeding sustainable growth. Waste classification management is a critical and crucial aspect of resolving this issue. Traditional waste classification technology is inefficient and unreliable. This work presents a waste detection and classification model based on YOLOv5 to enhance the efficiency and accuracy of waste classification. To begin, the researcher obtained the Trashnet Garbage classification dataset, which has 2527 images classified as glass, metal, plastic, paper, cardboard, and trash. This study trained a YOLOv5s model for garbage detection and classification using the dataset. Finally, the performance of the trained model was evaluated. The results indicate that the YOLOv5 garbage classification model achieves an accuracy of 90.2 %, a recall of 91.6 %, and a mean average precision (mAP) of 95.2 %. The model could accurately classify all sorts of waste and achieve a high detection rate.*

***Keywords*** *– Computer Vision, Deep Learning, Garbage Classification, Waste Management, YOLO algorithm*

## INTRODUCTION

In the existing literature, waste generation is linked to urbanization, economic development, and population growth. It is argued that expanding urbanization and lifestyle changes are responsible for rising rates and consumption behaviors, all of which inevitably lead to larger greenhouse gas emissions (Dickella Gamaralalage et al., 2015; Kaza et al., 2018) and produce a variety of the solid waste that devastates our natural environment (Sapuay, 2016).

In 2015, the world's daily trash production was estimated to be around 39,422 tons, but this figure is expected to triple by 2025 (EMB, 2016; Hoornweg & Bhada-Tate, 2012). These concerns, if not addressed, may aggravate pre-existing issues such as leachate infiltration into groundwater tables, changes in climate patterns, and increasing catastrophic risk exposure.

In the Philippines, the country's population is 100.98 million, up 8.64 million from previous estimates in 2010 and 24.47 million since 2000, according to the most recent census in 2015 (Philippine Statistics Authority, 2016). In addition, recent waste projections indicate that yearly waste production will increase from 13.48 million tons in 2010 to 14.66 million tons in 2014 and then to 16,63 million tons in 2020 (DENR, 2018).

According to DENR data from 2015, biodegradable waste accounts for approximately half (52.27 %) of Municipal Solid Waste, while recyclable waste accounts for nearly a third (27.87 %); the remainder consists of special wastes such as household and healthcare waste, waste electrical and bulky waste (1.93 %), and residuals (17.98 % ). Food waste accounts for 45.05 % of organic waste, while yard trash accounts for 7.22 %. Recyclable garbage includes plastics (10.56 %), paper and cardboard (8.61 %), glass (2.43 %), metal (4.22 %), textiles (1.61 %), rubber and leather (0.44 %) (DENR, 2018).

If garbage is not effectively handled, environmental issues will increase over time, posing the greatest obstacle to sustainable growth. Municipal solid waste contains numerous recyclable components; recycling minimizes waste emissions, provides value, and cuts expenses. Classification and management of waste will be the most effective solution to handling it properly (Zhang et al., 2021).

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Currently, several researchers recommend computer vision and deep learning-based intelligent waste recognition and classification systems for recycling operations (Vo et al., 2019). This methodology can realize automatic waste classification through machine recognition of waste images in order to reduce labor costs, save human resources, and further improve resource reuse rate, thereby addressing the vexing issues of manual waste sorting, such as heavy workloads, the tendency of workers making errors, and poor sorting efficiency. The current waste recognition and classification technique based on machine learning use variables such as color and texture to recognize waste images. On the other hand, traditional image recognition algorithms use a relatively single dataset, have limited generalization capacity, and need to be improved in terms of accuracy and operating economy (Rad et al., 2017).

Rapid development and refinement of image classification and object detection algorithms are being achieved. Various detection algorithms differ in accuracy and speed (Lin et al., 2020; S. Liu et al., 2018; Rezatofighi et al., 2019; Q. Wang et al., 2020). General target identification algorithms are classified into two types: two-stage and one-stage. The two-stage models use the algorithm network to generate a series of sparse matrix candidate frames, which are subsequently classified and regressed to detect the target. This model is exemplified by the faster RCNN and SPP-net, both of which have low speeds but great precision (Ren et al., 2017). Based on regression, one-stage models execute uniform high-density sampling at numerous places inside images, extract features utilizing a convolutional neural network (CNN) model, and carry out classification and regression. Examples include the single-shot multibox detector (SSD) and you only look once (YOLO) series (Ying et al., 2022), which are significantly faster than two-stage models and, therefore, more suited for real-time industrial applications.

Additionally, data augmentation and properly fine-tuned hyper-parameters for the fully-connected layer of CNNs may boost their efficiency (Al-Hyari & Areibi, 2017; Frid-Adar et al., 2018). Image affine transformation, white-box, and black-box methods are all approaches for data augmentation. For example, random vertical and horizontal image flipping during the affine transformation process could increase the variety of images in the training dataset for CNNs (Tong et al., 2019).

The YOLO algorithm series is precise and fast, and it has been utilized in a variety of object identification applications (Kuznetsova et al., 2020). The YOLO system also computes and anticipates all of the image's features. YOLOv5 is the fifth Python-based version of the YOLO model (Cengil & Çinar, 2021). According to various studies, YOLOv5 surpasses the other YOLO models in terms of accuracy and speed (Cengil & Çinar, 2021; Kuznetsova et al., 2020; Thuan, 2021).

In recent studies, YOLOv5 was utilized to identify a variety of objects. Kong et al. (2021) used YOLOv5 to detect grass carp and fish culture in real-time. A recent study using YOLOv5 devised and executed a visual depiction, video detection, and real-time identification of whether a person is wearing a helmet (Guan et al., 2022). The YOLOv5 model was employed to recognize apples in orchards using harvesting robots. Both tests significantly improved detection speed and accuracy compared to existing YOLO systems (Kuznetsova et al., 2020; Pan & Yan, 2020). Compared to YOLOv3 and YOLOv4, the YOLOv5 model correctly recognized any mold on the food surface and had higher precision, recall, and average precision (AP) (Jubayer et al., 2021). A modified YOLOv5s model was also used to detect wire braided hose faults. Experimental findings indicated that the model's accuracy and identification efficiencies were 92.2% and 23 frames per second, respectively (Ying et al., 2022).

This study examines the following categories of recyclable garbage: paper, cardboard, metal, plastic, glass, and trash. Based on YOLOv5, this research provides a waste classification model to detect waste accurately and identify its type.

## OBJECTIVES OF THE STUDY

This study aimed to utilize the YOLOv5 algorithm to detect and classify recyclable garbage such as paper, cardboard, metal, plastic, glass, and trash. This objective sought to incorporate recent technological developments to accurately detect and classify recyclable wastes using vision systems and deep learning.

## MATERIALS AND METHODS

### System Architecture

Fig. 1 depicts the architectural framework of this paper. First, waste images were acquired using the Trashnet garbage classification dataset for the input. Second, in Roboflow, the garbage dataset was pre-processed, annotated, and augmented. The pre-processed and augmented garbage dataset was then utilized for

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training a custom YOLOv5 model for garbage classification. Finally, the performance of the trained custom YOLOv5 model was evaluated. Afterward, an inference with trained weights was run on the test datasets.

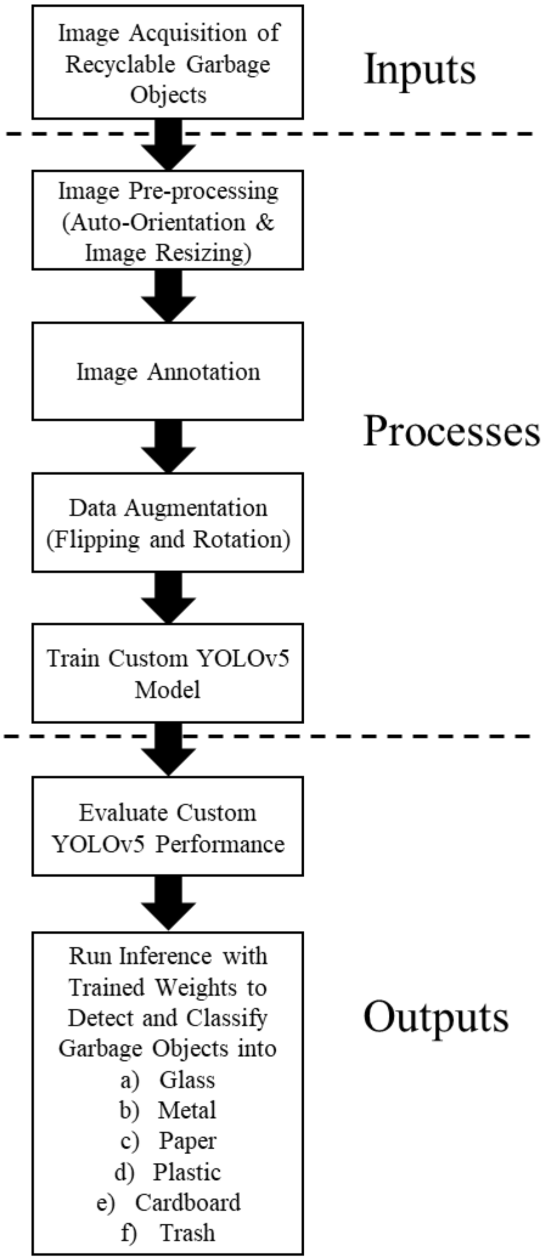


Fig. 1. System Architecture of the Study.

**Dataset Pre-processing and Annotation**

The dataset for this study was obtained from the Trashnet Garbage Classification dataset (Thung & Yang, n.d.). The dataset obtained from the repository is divided into six categories: glass, paper, cardboard, plastic, metal, and trash. The garbage dataset was uploaded and pre-processed in Roboflow, where auto-orientation and image-resizing techniques were applied. The garbage dataset is summarized in Table 1. The images were labeled using the Roboflow Annotation tool, and annotated values for YOLOv5 Pytorch were generated. Fig. 2 shows some of the images in the dataset.

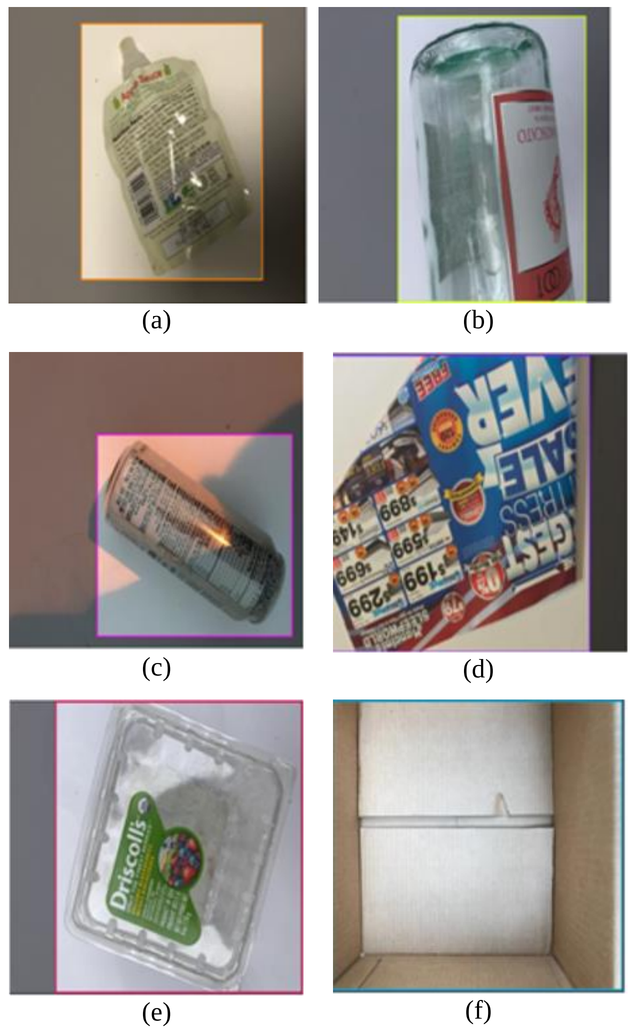


Fig. 2. Sample images in the dataset: (a) trash, (b) glass, (c) metal, (d) paper, (e) plastic, (f) cardboard.

**Data Augmentation**

Following pre-processing and annotation, the data set was augmented in Roboflow. Data Augmentation was performed to increase the amount and

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diversity of data. It helped to reduce overfitting in small datasets. A few data augmentation techniques, such as flipping and rotation, were applied to the garbage dataset to produce new images. The dataset was randomly split as follows: 70% for Training, 20% for Validation, and 10% for Testing.

**YOLOv5**

Define abbreviations and acronyms the first time they are used in the text, even after they have already been defined in the abstract. Properly and formally cited using APA Format (Salcedo, 2018). Leave one space before and after the major headings as well as one space before and after the sub-headings.

The YOLO algorithm (You Only Look Once) is a one-stage detection algorithm created by Joseph Redmon and colleagues (He et al., 2014) to address the demands of real-time and high-accuracy detection. It converts a detection task into an end-to-end regression problem. The bounding box probabilities and coordinates were accurately predicted, improving detection performance for multiple-label targets. When its released, the YOLO algorithm provided impressive specifications outperforming the leading algorithms in terms of speed and accuracy for detecting and calculating object locations (Redmon et al., 2016).

The YOLOv5 series and its network architecture are the most recent versions. The YOLOv5 model is comparable to the YOLOv4 model in architecture. As illustrated in Fig. 3, the three major parts of YOLOv5 are the Backbone, the Neck, and the Head (Xu et al., 2021; Zhu et al., 2020). The Backbone collects critical features from a picture provided as input. CSPDarknet53 serves as the Backbone of YOLOv5, gaining enlightenment via a cross-stage partial network (CSPNet) based on Darknet53. Compared to the Darknet used by YOLOv3, CSPDarknet53 has significantly improved processing speed and has the same or even better detection accuracy (C. Y. Wang et al., 2020).

The four modules of CSPDarknet53 are Focus, CBL, CSP, and spatial pyramid pooling (SPP) (He et al., 2014). The Focus module duplicates and splits the input image four times. They combine Concat layers to form a 320 × 320 x 12 feature map, which is then convoluted with 32 kernels to get a 320 x 320 x 32 feature map. The Focus aims to minimize the number of layers to optimize performance, not to raise mAP. One convolutional layer (Conv), one batch normalization layer (BN), and one Leaky-Relu activation function comprise the CBL module (Lowe, 2004).

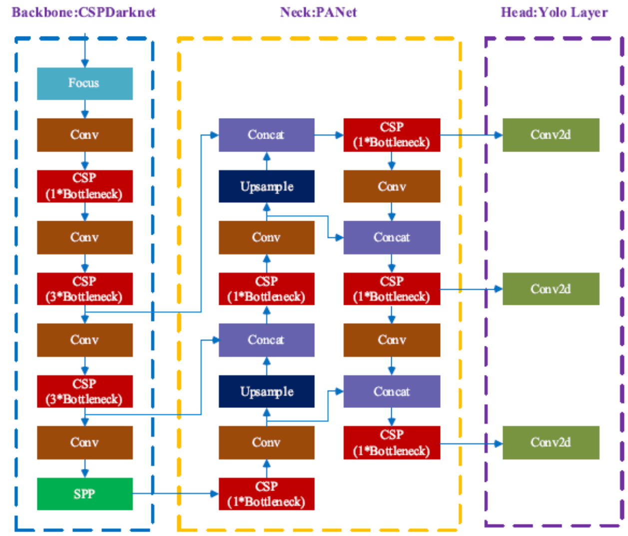

Figure 3. YOLOv5 Architecture (Fang et al., 2021)

The Neck is mostly used to create feature pyramids, which aid YOLOv5 in generalizing object scaling to recognize objects of varied sizes and scales. In YOLOv5, Neck utilizes a Path Aggregation Network (PANet) as a parametric polymerization technique for various bone and detector levels. The adaptable feature pools supplied by PANet connect the feature grid to all the feature layers (Cheng & Zhang, 2020; Y. Liu et al., 2020). Additionally, the PANet structure is employed to transport enhanced characteristics from the bottom to the top of the prediction layer (the Head portion), increasing network feature aggregation capability (S. Liu et al., 2018).

As with previous YOLOv3 and YOLOv4 versions, the final detection occurs in the Head section. Head generates final output vectors with class probabilities and bounding boxes for identified objects, as well as anchor boxes for feature maps (Fang et al., 2021) .

PyTorch is used to compile YOLOv5 fully and provides higher adaptability and efficiency than previous detection algorithms. In YOLOv5 networks, there are four types of models: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. YOLOv5s was chosen for this study due to their smaller size and greater speed than the alternatives.

**Training YOLOv5 using Garbage Dataset**

Environment

The Garbage Classification dataset was utilized for training a YOLOv5 model using Roboflow's Google Colab Notebook (Solawetz, 2021). Google Colab provides free access to powerful GPUs.

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Install Requirements

The YOLOv5 architecture was cloned from the GitHub repository made by Ultralystic, installed the requirements, and imported Python libraries.

```
!git clone https://github.com/ultralytics/yolov5
%cd yolov5
%pip install -qr requirements.txt
%pip install -q roboflow

import torch
import os
from IPython.display import Image, clear_output


print(f"Setup complete. Using torch {torch.__version__
} ({torch.cuda.get_device_properties(0).name if torch.c
uda.is_available() else 'CPU'})")
```

Preparing the data set for Training

The Waste Classification dataset was exported from Roboflow in YOLOv5 Pytorch format and set up the environment.

```
from roboflow import Roboflow
rf = Roboflow(model_format="yolov5", notebook="ultr
alytics")

os.environ["DATASET_DIRECTORY"] = "/content/da
tasets"

!pip install roboflow

from roboflow import Roboflow
rf = Roboflow(api_key="Z1fCKYPyPdT890ud9xO6")
project = rf.workspace().project("waste-trainer")
dataset = project.version(5).download("yolov5")
```

Train Custom YOLOv5 Model

100 epochs were used to train the model, which took around 5.283 hours. There is a 'train.py' file in the YOLOv5 directory for training the YOLOv5 model. The model was trained accordingly using the bash command '!python train. py parameters'.

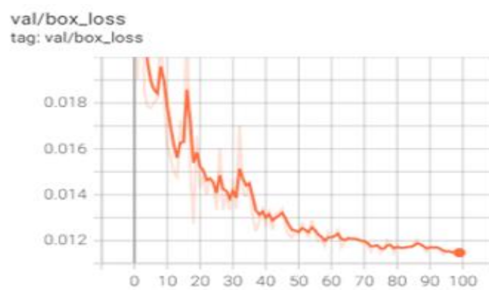
```
!python train.py --img 416 --batch 16 --epochs 100 --
data {dataset.location}/data.yaml --weights yolov5s.pt –
cache
```

The details of training the YOLOv5 model are as follows:

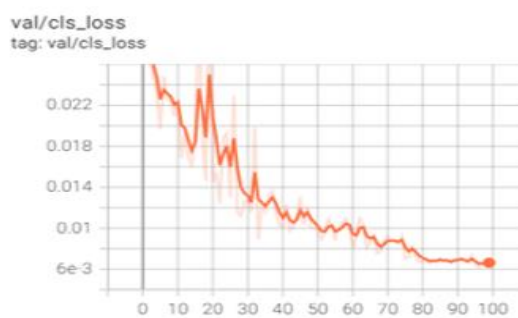
Image Size: 416
Batch Size: 16
Data description:
YOLO Model: YOLOv5s.yaml
Weights: yolov5s.pt

## RESULTS AND DISCUSSION

Each iteration of the training process can be separated into two parts. The data from the training set were initially input into the model, and the weight was then adjusted automatically based on the loss value. The validation set's data was then applied to the model. The validation set's data was then applied to the model. As a result, the loss value was computed using the most recently updated weight. The loss value obtained from the validation set data served as an essential metric to assess the model's performance.




(a)




(b)

Fig. 4. Validation Loss VS Epoch Graph: (a) val/box_loss, (b) val/cls_loss.

The average time required to complete the training procedure on 16 batches was 183 seconds for one epoch. On the garbage dataset, which contained 5280 training images and 502 validation images, the total

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execution time was 5.283 hours. The training was completed after 100 epochs, and a 14.4 MB weight file was obtained. Figs. 4a and 4b illustrate the validation dataset loss during training. As can be seen in the graphs, both the box_loss and cls_loss curves continue to drop consistently despite the appearance of an oscillation. After 100 epochs, the loss remained relatively consistent and progressively approached 0.115 and 0.00656, respectively, for box_loss and cls_loss. The box loss curve indicates that the predicted bounding boxes are close to the ground truth object. In contrast, the cls_loss curve indicates that the loss in classification correctness for each predicted bounding box diminishes.

**Dataset Detection Performance**

Trained weights can identify and classify waste in any image. Suppose a waste object is detected in the image. In that case, a bounding box is drawn to enclose it, determine its waste classification, and display the probability that the object is a specific type of waste.

The command below was used to detect waste using the trained weights. The detect.py file will be compiled, and the architecture used in training will be rebuilt. For the waste images, trained weights will be used to predict objects and limit boxes.

```
!python detect.py --
weights runs/train/exp/weights/best.pt --img 416 --
conf 0.1 --source {dataset.location}/test/images
```

Fig. 5 depicts the outcomes of six random samples. The waste object was detected and classified using a bounding box. The confidence coefficients were also shown at the top of the bounding box. The trained YOLOv5 accurately detects and classifies waste objects. The detection findings in this study demonstrated that YOLOv5 could recognize and classify waste.

Table 2 summarizes the training outcomes for the YOLOv5 model. All 257 waste images were correctly detected and classified. Overall, the recall rate was 90.2 %, precision was 91.6 %, mAP@.5 was 95.2%, and mAP@.5:.95 was 77.82%. The trained model performed excellently in terms of target detection and classification.

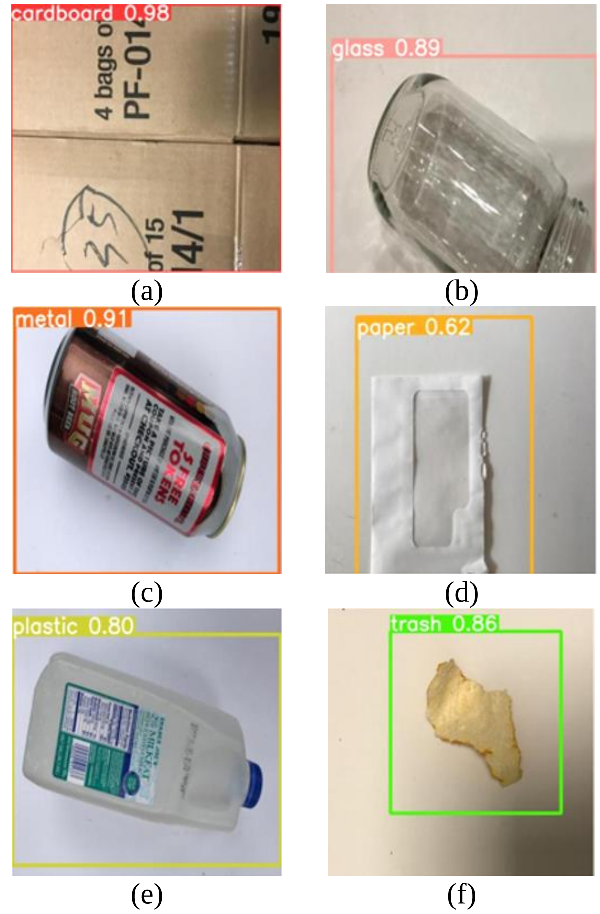


Fig. 5. Detection results of some samples: (a) cardboard, (b) glass, (c) metal, (d) paper, (e) plastic, (f) trash.

Table 2. Detailed Results of the Trained YOLOv5 Model

| Class | Precision | Recall | mAP@.5 | mAP@.5:.95 |
|---|---|---|---|---|
| all | 0.916 | 0.902 | 0.952 | 0.778 |
| cardboard | 0.95 | 0.959 | 0.986 | 0.875 |
| glass | 0.932 | 0.888 | 0.979 | 0.752 |
| metal | 0.867 | 0.973 | 0.963 | 0.812 |
| paper | 0.966 | 0.946 | 0.982 | 0.803 |
| plastic | 0.923 | 0.903 | 0.947 | 0.758 |
| trash | 0.861 | 0.741 | 0.855 | 0.666 |

The F1 and PR curves were acquired using YOLOv5s weight training after model training, as illustrated in fig. 6 and 7. Trash has the lowest F1 and PR scores of the six waste categories, whereas cardboard has the best F1 and PR ratings. The model's recognition capability for a particular class can be enhanced by including sample data from that class. Nonetheless, the results demonstrated that YOLOv5 could learn sufficient information from the training set to classify and identify waste correctly.

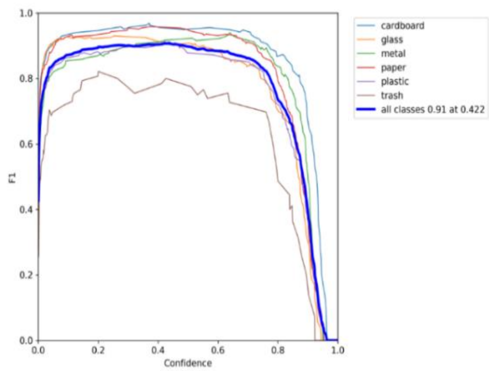


Fig. 6. F1 Curve.

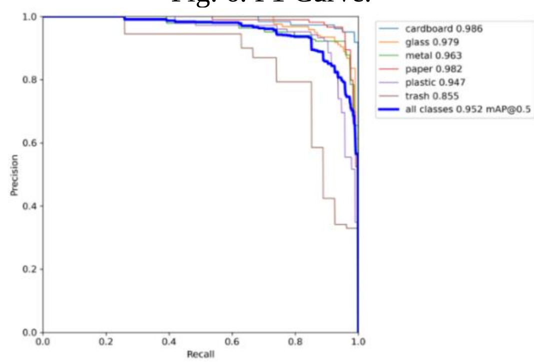


Fig. 7. Precision-Recall Curve.

**Comparison of Deep Learning Approaches for Garbage Classification**

Table 3 compares the results of this study with other deep learning models, including previous versions of the YOLO models, focusing on garbage classification task. The data illustrates that there is an improvement of deep learning models' performance over the recent years. Although the YOLOv5 algorithm used in this study does not achieve the highest accuracy compared to other cutting-edge methodologies, it nevertheless demonstrate a good performance. The different versions of YOLO algorithm has shown to have a strong performance in classification tasks.

The performance of the YOLOv5 model could be further improved by conducting the training on a more powerful computing devices. By overcoming the limitations of Google Colab and leveraging the computational resources of powerful computing devices, the model could achieve a better performance.

Table 3. Comparison of Deep Learning Methodology for Garbage Classification

| Author | Methodology | Accuracy |
|---|---|---|
| Mengistu, 2017 | Faster R-CNN | 68.30% |
| Knowles et al., 2018 | OscarNet (CNN) | 88.42 |
| Y. Liu et al., 2018 | YOLOv2 | 89.2% |
| Vo et al., 2019 | DNN-TC | 94% |
| Ruiz et al., 2019 | Inception-ResNet | 88.60% |
| Ye et al., 2020 | YOLO-VAE | 69.70% |
| Chen & Xiong, 2020 | YOLOv4 | 64% |
| Kumar et al., 2021 | YOLOv3 | 92.50% |
| This Study | YOLOv5 | 90.2% |

## CONCLUSION AND RECOMMENDATION

A computer vision approach based on YOLOv5 was utilized to detect and classify garbage. The results indicated that the YOLOv5 model could attain 90.2% precision, 91.6% recall, and 95.2% mAP. The results indicate that this waste classification model can accurately classify all types of garbage and achieve high detection accuracy. There is still plenty that can be done to improve the garbage detection and classification model. The model can be enhanced further to detect additional types of garbage. Once the system detects a broader garbage classification, the model could be used to sort recyclables and non-recyclables in a Materials Recovery Facility, or it can be integrated into a Smart Waste Sorter Machine.

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