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A Machine Learning Approaches For Smart Garbage Detection And Collection

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Abstract:

Rapid industrialization, urban growth, and increasing global population have amplified waste pollution and environmental harm. Proper waste sorting remains a widespread challenge from homes to disposal sites. This research proposes a solution using deep learning algorithms—specifically YOLOv4 and YOLOv4-tiny with Darknet-53—for object detection. The dataset includes 3870 images categorized into glass, metal, paper, and plastic. Testing involved images, videos, and webcam inputs. Hyperparameter experiments on YOLOv4-tiny included subdivision values and mosaic data augmentation. Results show YOLOv4 outperforms YOLOv4-tiny in detection accuracy (mAP 89.59%, precision 0.76, recall 0.90, F1-score 0.82, Avg IoU 64.01%), despite YOLOv4-tiny being faster computationally. Optimizing with smaller subdivisions and mosaic augmentation enhances model performance.

1.Introduction

In Indonesia, waste production has surged, reaching 67.8 million tonnes in 2020, posing challenges due to slow degradation of mixed organic and inorganic waste. Effective sorting and recycling from households to disposal sites are crucial (KLHK, 2020; Devi et al., 2018; Sakr et al., 2016).

Object detection, a computer vision technique, identifies objects in images or videos, pivotal in waste classification. Prior methods like SURF-BoW, Multi-Class SVM, CBIR, K-NN, and K-mean faced accuracy limitations (Y. Liu et al., 2018; Chinnathurai et al., 2016; Torres-García et al., 2015; Deepa & Roka, 2018).

Convolutional Neural Networks (CNNs), including YOLOv4 and YOLOv4-tiny, excel in real-time object detection, outperforming other CNN variants. This research enhances YOLO's performance through hyperparameter experiments on subdivision and mosaic data augmentation.

Accessible via website, Google Colab, or local PCs, this study integrates inputs from images, videos, and webcams. Sections cover introduction, literature review, methods, experiments, results, discussion, and conclusions for future directions.

YOLO (You Only Look Once) is a real-time object detection algorithm developed by Joseph Redmon in 2016 (Redmon et al., 2016). It uses Convolutional Neural Networks (CNNs) to detect objects swiftly from images, videos, and live webcams. YOLOv2, introduced in 2017, improved accuracy and speed (Redmon & Farhadi, 2017), followed by YOLOv3 in 2018, further enhancing performance (Redmon & Farhadi, 2018). YOLOv4, released in 2020 by Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Lio, introduced advancements like CSPDarknet53 backbone and Bag of Freebies for better accuracy without increased inference costs (Bochkovskiy et al., 2020).

Using a single-stage approach, YOLO divides images into grid boxes, predicting bounding boxes and probabilities for objects within each grid. It surpasses traditional methods like SSD and faster R-CNN in simplicity and speed, making it efficient for real-time applications. YOLO models are adaptable, with variants like YOLOv4-tiny tailored for mobile and embedded devices (Jiang et al., 2020).

YOLO's impact spans diverse applications from agriculture to waste management, demonstrating high accuracy in detecting objects such as wheat heads, citrus, and waste containers with mAP scores exceeding 90% (Gong et al., 2020; Wenkang Chen et al., 2020; Valente et al., 2019). Its robust performance and versatility make it a leading choice in modern computer vision tasks.

2.Literature Review and Related Work

The colossal increase in environmental pollution and degradation, resulting in ecological imbalance, is an eye-catching concern in the contemporary era. Moreover, the proliferation in the development of smart cities across the globe necessitates the emergence of a robust smart waste management system for proper waste segregation based on its biodegradability. The present work investigates a novel approach for waste segregation for its effective recycling and disposal by utilizing a deep learning strategy. The YOLOv3 algorithm has been utilized in the Darknet neural network framework to train a self-made dataset. The network has been trained for 6 object classes (namely: cardboard, glass, metal, paper, plastic and organic waste). Moreover, for comparative assessment, the detection task has also been performed using YOLOv3-tiny to validate the competence of the YOLOv3 algorithm. The experimental results demonstrate that the proposed YOLOv3 methodology yields satisfactory generalization capability for all the classes with a variety of waste items.

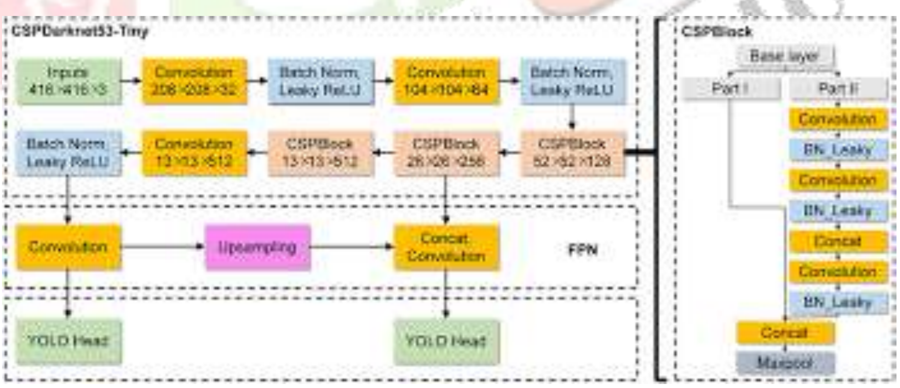

Fig1. Yolo Network

The technique of image recognition algorithm is used to conduct an in-depth study and analysis of the intelligent classification and recycling system of solid waste and to optimize the design of its system. The network structure and detection principle of the YOLO target detection algorithm based on convolutional neural nets are analysed, images of construction solid waste are collected as a dataset, and the image dataset is expanded using data enhancement techniques, and the target objects in the dataset are labelled and used to train their own YOLO detection models. To facilitate testing the images and to design a YOLO algorithm-based construction solid waste target detection system. Using the detection system for construction solid waste recognition, the YOLO

model can accurately detect the location, class, and confidential information of the target object in the image. Image recognition is a technique to recognize images by capturing real-life images through devices and performing feature extraction, and this technique has been widely used since its inception. The deep learning-based classification algorithm for recyclable solid waste studied in this paper can classify solid waste efficiently and accurately, solving the problem that people do not know how to classify solid waste in daily life. The convolutional layer, pooling layer, and fully connected layer in a convolutional neural network are responsible for feature extraction, reducing the number of parameters, integrating features into high-level features, and finally classifying them by SoftMax classifier in turn. However, the actual situation is intricate and often the result is not obtained as envisioned, and the use of migration learning can be a good way to improve the overfitting phenomenon. In this paper, the combination of lazy optimizer and lookahead can improve the generalization ability and fitting speed as well as greatly improve the accuracy and stability. The experimental results are tested, and it is found that the solid waste classification accuracy can be as high as 95% when the VGG19 model is selected and the optimizer is combined.
Haitao Chen, Optimization of an Intelligent Sorting and Recycling System for Solid Waste Based on Image Recognition Technology.

Due to the increasing development of cities' populations, which has resulted in massive garbage output, waste management systems in urban areas are confronting issues. The ravage of possessions can be employed powerfully with the incorporation of the internet of things (IoT), TensorFlow based deep learning model, as conventional ravage managing system are extremely uneconomical. The major goal of this study is to create a smart waste management system based on a deep learning model that optimizes trash isolation and allows for bin status monitoring in an IoT context. Yolo real time object detection algorithm is employed and educated with a dataset that includes paper, cardboard, glass, metal, and plastic for garbage sorting and grouping. Yolo algorithm enhances the detection speed and yields precise findings with low background noise. Yolo uses convolutional neural network to detect the object. The camera module detects garbage and the servomotor linked to a plastic board, categorizes the waste into the appropriate waste cubicle using the educated model on TensorFlow Lite and Raspberry Pi 4. The garbage fill is monitored by an ultrasonic sensor, and the latitude and longitude are obtained in real time by a GPS module. The smart bin's LoRa module transmits the bin's status to the LoRa receiver at 915 MHz. The smart bin's electronic mechanisms are safeguarded by an RFID-based locker that can only be opened with a registered RFID badge for maintenance or upgrades. This work is framed out of the technologies such as Robotics, neural network, Internet of Things and deep learning algorithm. The garbage detection system is more precise and faster than the other existing methods. The YOLO algorithm can predict objects in real time, which speeds up detection. It's a prediction method that produces exact results with little background noise. The algorithm has outstanding learning capabilities, allowing it to learn and apply object representations to object detection.
Usha S M1, Mahesh H B2 Accurate and High Speed Garbage Detection and Collection Technique using Neural Network and Machine Learning, Materials Science and Engineering.

3.Research Method

In this research, the initial step involved collecting a dataset from Kaggle (Garbage Classification) consisting of 3870 images, each 299 x 299 pixels in .jpg format. The dataset was divided into 3126 training images and 744 validation images, categorized into four waste types: glass, metal, paper, and plastic.

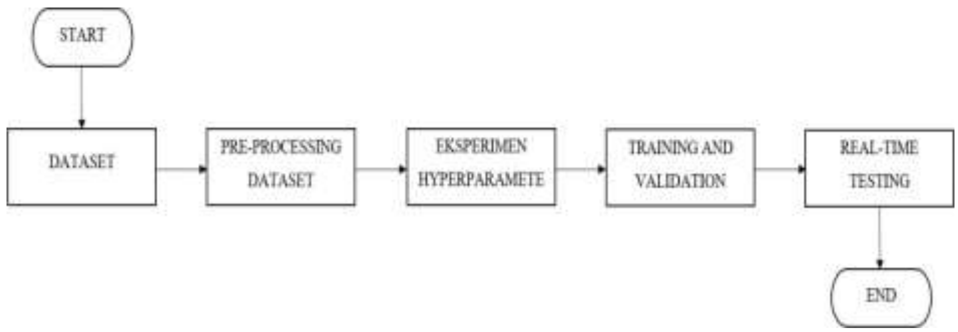

Fig2. Flowchart of process

The next step included dataset preprocessing using the Label Img annotation tool to label images and generate .txt files containing image details. Data augmentation techniques were also applied, including mosaic augmentation, which combines four training images to enhance dataset variability without requiring large batch sizes.

Following preprocessing, the research focused on hyperparameter experiments to optimize the YOLO architecture's performance. Key variables tested included standard parameters like batch size 64, network size 406x406, and filters 27, alongside experimental variables such as subdivision values of 16 and 8, with and without mosaic augmentation, across a range of training steps and batch settings.

In the training and validation stages conducted on Google Collaboratory, the focus was on preparing and fine-tuning the YOLOv4 model for effective object detection. Using pre-prepared training and validation datasets, the goal was to generate weights files crucial for real-time testing.

This phase involved transfer learning, leveraging models pretrained on the COCO dataset available from the AlexeAB repository. Specifically, yolov4.conv.137 was utilized for YOLOv4, while yolov4-tiny.conv.29 served for YOLOv4-tiny, optimizing their performance for object detection tasks.

After identifying the optimal model weights from training and validation, the focus shifted to real-time testing. This phase involved testing the yolov4 and yolov4-tiny models using input from images, videos, and webcams.

```
   layer   filters  size/strd(dil)      input                output
   0 Create CUDA-stream - 0
 Create cudnn-handle 0
conv     32        3 x 3/ 1    416 x 416 x   3 ->  416 x 416 x  32 0.299 BF
   1 conv     64       3 x 3/ 2    416 x 416 x  32 ->  208 x 208 x  64 1.595 BF
   2 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   3 route  1                                      ->  208 x 208 x  64
   4 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   5 conv     32       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  32 0.177 BF
   6 conv     64       3 x 3/ 1    208 x 208 x  32 ->  208 x 208 x  64 1.595 BF
   7 Shortcut Layer: 4,  wt = 0, wn = 0, outputs: 208 x 208 x  64 0.003 BF
   8 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   9 route  8 2                                    ->  208 x 208 x 128
  10 conv     64       1 x 1/ 1    208 x 208 x 128 ->  208 x 208 x  64 0.709 BF

                                 ...

 151 route  147                                        ->   26 x  26 x 256
 152 conv    512       3 x 3/ 2     26 x  26 x 256 ->   13 x  13 x 512 0.399 BF
 153 route  152 116                                ->   13 x  13 x1024
 154 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 155 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 156 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 157 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 158 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 159 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 160 conv     27       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x  27 0.009 BF
 161 yolo
```

Fig. 3. YOLOv4 Structure

4.Result and Discussions

The training and validation process involved two phases using Google Colab. First, YOLOv4 was configured with parameters such as Batch 64, Subdivision 16, Network Size 416x416, Max_batches 8000, Steps 6400 and 7200, Filters 27, Classes 4. This process took 15 hours to complete 8000 iterations. Second, YOLOv4-tiny was configured with the same parameters, completing in just 2 hours (13 hours faster than YOLOv4). YOLOv4 achieved a best mAP of 89.59% with an average loss of 0.766, while YOLOv4-tiny reached a best mAP of 81.84% with an average loss of 0.218.

From YOLOv4, the best results were obtained with yolov4-obj_3000.weights, showing AP values of Glass 96.89%, Metal 82.56%, Paper 95.60%, Plastic 83.30%. YOLOv4-tiny's best results came from yolov4-obj_best.weights, with AP values of Glass 91.15%, Metal 75.61%, Paper 82.58%, Plastic 78.00%.

When compared to previous studies using the TrashNet Dataset, the YOLOv4 model developed in this research achieves higher accuracy. Research by Jardosh et al. (2020) using YOLOv3 obtained a best mAP of 84.44%, which is 5.15% lower than the YOLOv4 model in this study that incorporates Mosaic data augmentation. Similarly, Mittal et al. (2020), using CNN, achieved an accuracy of 87%, 2.59% lower than our YOLOv4 model with Mosaic. This study also includes computation speed results, a metric not reported in the previous research.

Following the training and validation phases, the next step involves real-time testing using images inputs. Both YOLOv4 and YOLOv4-tiny models are tested using the best weights obtained from the training and validation process for comparative analysis.

Dataset Comparison

TrashNet	Dataset in This Research
Glass 501	Glass 953 (+ 452)
Paper 594	Paper 998 (+404)
Cardboard 403	-
Plastic 482	Plastic 900 (+418)
Metal 410	Metal 1019 (+609)
Trash 137	-

4.1 Input Images

Testing conducted on Google Colab using the command 'detector test' with a threshold of 0.5. The input images used represent each waste class: glass, metal, paper, and plastic. indicate that YOLOv4 achieves better prediction probabilities, though YOLOv4-tiny demonstrates faster prediction times. Specifically, YOLOv4 processes predictions in 20.37 ms, whereas YOLOv4-tiny operates faster at 4.89 ms.

Furthermore, waste classification and image detection can also be executed on a local laptop or PC. This process requires several files: weights file, .cfg file, and obj.names file.

Additionally, the classification and detection of waste using image inputs are facilitated through a website created by the author using the Flask framework.

Training Images

5.Conclusion

In this research, we developed a waste classification model capable of real-time object detection, displaying bounding boxes and prediction probabilities in images. The model runs effectively on Google Colab, local PCs/laptops, and a Flask framework-based website, accommodating inputs from images, videos, and webcams.

Results indicate that the simpler YOLOv4-tiny architecture exhibits faster computation speeds compared to YOLOv4, although with slightly reduced prediction accuracy. YOLOv4 achieves an mAP of 89.59%, precision of 0.76, recall of 0.90, F1-score of 0.82, and Average IoU of 64.01%. In contrast, YOLOv4-tiny achieves an mAP of 81.84%, precision of 0.59, recall of 0.83, F1-score of 0.69, and Average IoU of 48.35%. This comparison highlights a trade-off between speed and accuracy in model performance.

Further analysis shows that adjusting the subdivision value can enhance mAP by up to 2%, and activating mosaic data augmentation can improve mAP by approximately 1%, albeit with increased processing time.

Future research recommendations include expanding the dataset size to improve model performance, increasing the number of waste types classified in real-time, and exploring newer versions of the YOLO algorithm, such as YOLOv5.

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