YOLO-BASED MULTI-MODEL ENSEMBLE FOR PLASTIC WASTE DETECTION ALONG RAILWAY LINES

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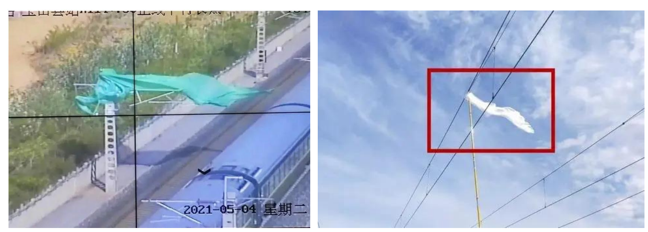
ABSTRACT

A rapidly increasing amount of plastic waste not only cause serious environmental issues but also pose a considerable threat to the rail transportation. It is important to monitor the intrusion of floating plastics into the railway area. In this article, we propose to detect plastic waste using You Only Look Once-v5 (YOLO-v5) algorithm and model ensemble through surveillance cameras installed along railway lines. Experiments on the size of YOLO-v5 model were carried out to find the optimal size to detect plastics. The model with large size (YOLOv5l) outperformed with an overall accuracy (OA) of 82.6% and mean Average Precision (mAP) of 0.822. Two ensemble modelling strategies were implemented considering different size combination of YOLO-v5 models including 1) nano, small and medium sizes; 2) nano, small, medium and large sizes. The latter one achieved the best result with the OA equal to 85.4% and the mAP equal to 0.834. The results indicate that YOLO-based ensemble model can effectively improve the performance of detection plastic waste using surveillance cameras and the acquired knowledge has great potential to UAV- and satellite-based high-resolution imagery.

Index Terms— YOLO, model ensemble, plastic waste, railway

1. INTRODUCTION

Currently plastic materials are extensively used including food packages, greenhouse, tunnel covering films, shading and protective nets. Several million tons of plastic waste per year is generated worldwide, raising concerns on the pollution of soil, air and water resources [1]–[4]. Remote sensing techniques have been adopted to detect marine plastic waste. Most plastics are typically transparent in the visible spectral range, hyperspectral imaging from unmanned aerial vehicles was employed to detect marine plastic litter by supervised learning of a linear classifier [5], [6]. Activities in agriculture contribute to huge quantities of plastic waste. Agricultural plastic waste map is the basic information for waste management to define the position of collections, which could be obtained via UAV- or satellite-based imagery [7]–[10]. Methods including support vector machine, object-based image analysis and convolutional neural networks have been experimented for detecting agricultural plastics.



(a) (b)

Fig 1. Illustration of the intrusion of floating plastics to railway areas. (a) plastic film in green color; (b) plastic film in white color marking with a red square.

The floating plastics pose a considerable threat to the safety of high-speed train operation. They could hang on the overhead line of the high-speed railway driven by wind as

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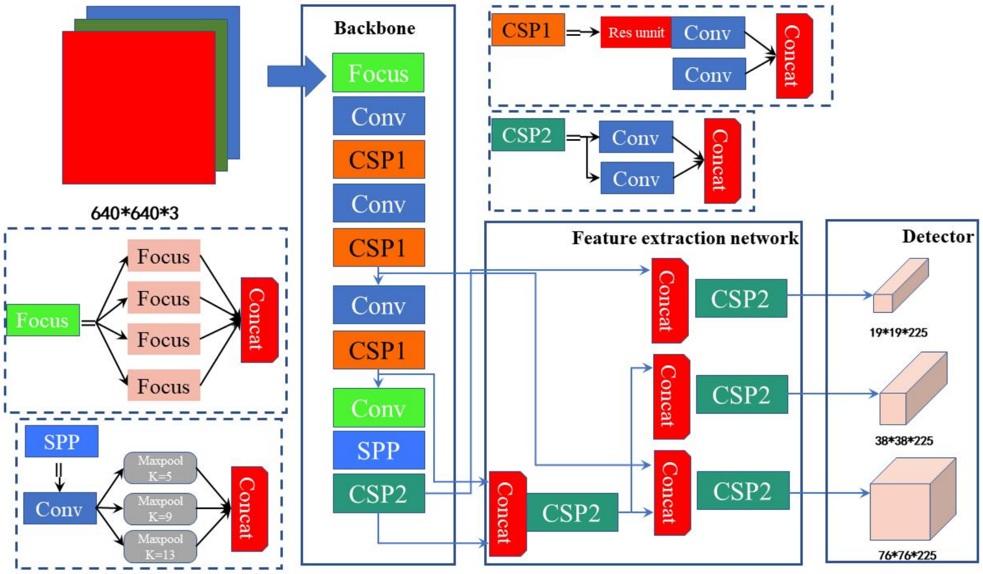

Fig 2. The network structure of the YOLO algorithm

shown in Figure 1. As the voltage of electric locomotives and high-speed railways is very high, once these foreign objects are winded on the railway power supply overhead line, they will affect the normal power collection of the pantograph of the train, resulting the train being delayed. In order to ensure the safety of railway lines, it is vital to monitor the intrusion of floating plastics into the railway area, which has been few studied.

In this paper, we primarily focus on using the data from surveillance cameras on the ground along railway lines, detecting plastic waste using You Only Look Once-v5 (YOLO-v5) algorithm [11], [12]. YOLO models with different sizes are considered and model ensembling strategy is implemented to achieve the best approach for real-time detection of plastic waste.

2. METHODOLOGY

2.1 YOLO

YOLO is a popular object detection algorithm because of its speed and accuracy. It divides images into a grid system, and each cell in the grid is responsible for detecting objects within itself. The network structure of the YOLO algorithm is illustrated in Figure 2. The whole network structure is composed of two fully connection layers and 24 convolution layers. The final detection result can be obtained by regressing the detection box position and judging the category probability. The YOLO method performed not well on small targets as there tends to be multiple targets in the same grid without detailed grid division. Thus, the YOLO-v5 algorithm is considered in this study. YOLOv5 includes five different model sizes: YOLOv5n (smallest), YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x (largest). When the size of input images is equal to 1280 pixels, the number of parameters for each YOLOv5 model is listed in Table 1.

Model	Input size(pixels)	Params(M)
YOLOv5n	1280	3.2
YOLOv5s	1280	12.6
YOLOv5m	1280	35.7
YOLOv5l	1280	76.7
YOLOv5x	1280	140.7

Table 1. The number of parameters for different YOLOv5 models with the input size as 1280 pixels (M=million, n=nano, s=small, m=medium, l=large, x=extra-large).

2.2 Ensemble modeling

Ensemble modeling is capable of aggregating the prediction of each base model and results in the final prediction. For YOLOv5 ensembling gathers detections from all sources prior to non-maximum suppression. The performance of each single model was evaluated as baselines and then two strategies were implemented considering different size combination of YOLO-v5 models including 1) nano, small and medium sizes; 2) nano, small, medium and large sizes. The accuracies on test dataset were compared.

2.3 Evaluation

We randomly split the dataset as 80%, 10% and 10%. The first part is used for training and the rest are for validation and test. To evaluate the performance of YOLO-based models, several metrics are considered in this study, including overall accuracy (OA), precision, recall and mean Average Precision (mAP).

3. RESULTS AND DISCUSSION

In the pilot study, a total number of 87 images were collected between 21-23 July 2021 via surveillance cameras installed along the railway line. To rich the dataset, additional 87 images were collected via the camera in an experimental area. These images were manually labelled by experts. The model training and testing were done with a workstation operated under Ubuntu 18.04 operation system. The workstation is equipped with16-core Intel Xeon 5218@2.3GHz processor, 256 GB of RAM and NVIDIA RTX3090 GPU.

The overall accuracies for YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x were 74.8%, 73.3%, 77.6%, 82.6% and 77.8%, respectively. YOLOv5l outperformed among these five models and it took 3 hours and 25 minutes for the training. Loss curves for training and validation were depicted in Figure 3, and the mAP@0.5 curve were shown in Figure 4.

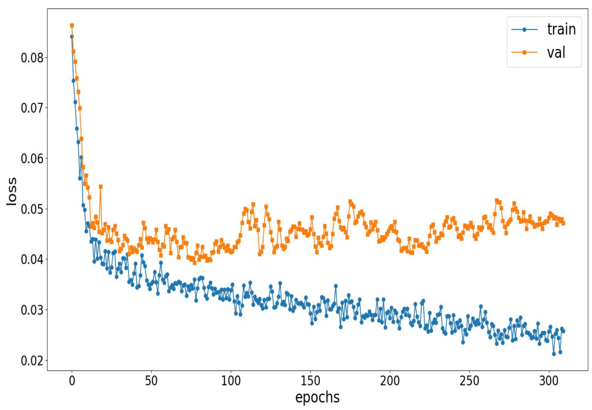

Fig 3. Loss curves for training and validation for the YOLOv5l model

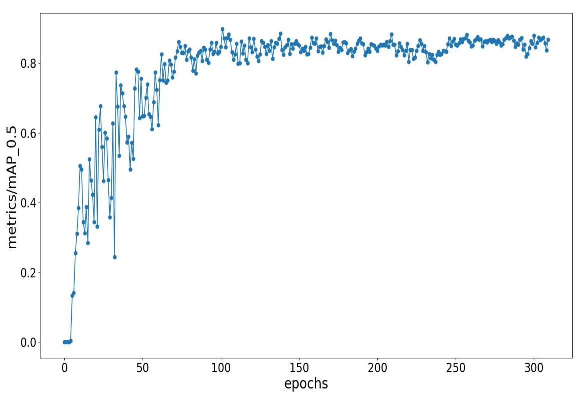

Fig 4. The mAP curve for validation for the YOLOv5l model

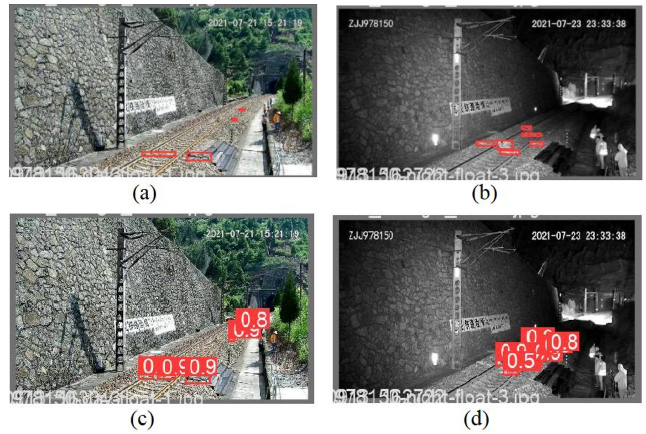

Fig 5. Training and prediction examples with detected plastic waste obtained from surveillances cameras along the railway line. (a) image obtained in the daytime condition with plastic waste marking by red squares; (b) image obtained in the nighttime condition with plastic waste marking by red squares; (c) detected plastic waste in the daytime image labelled with the confidence; (d) detected plastic waste in the nighttime image labelled with the confidence.

Model	OA	mAP	Precision	Recall
Ensemble-1	83.6%	0.822	0.939	0.884
Ensemble-2	85.4%	0.834	0.925	0.917

Table 2. Ensemble modelling results for two strategies. Ensemble-1: YOLOv5n, YOLOv5s and YOLOv5m; Ensemble-2: YOLOv5n, YOLOv5s, YOLOv5m and YOLOv5l.

Ensemble modeling is an effective method to improve the performance of object detection. We first considered three models having relatively small model size as base models, which are YOLOv5n, YOLOv5s and YOLOv5m. The ensemble results achieved an OA of 83.6% and mAP of 0.822. The accuracy increased compared to the performance of each single model. Then the model of YOLOv5m was also included as the second ensemble strategy, and the OA was further improved to 85.4% and the mAP to 0.834 as shown in Table 2. Examples of detecting plastic waste were shown in Figure 5. It can be seen that the YOLO-based ensemble model performed well on the detection of plastic waste along railway lines and the accuracy for images acquired in the daytime condition is better than the ones acquired in the nighttime condition.

4. CONCLUSIONS AND FUTURE WORK

Floating plastics driven by wind could hang on the overhead lines supplying power for electric locomotives, affecting the normal power collection of the pantograph of the train. Thus, it is vital to identify plastics along railway lines. As a pilot study of detecting the intrusion of floating plastics, this paper explored the potential of YOLO algorithm for plastic waste detection along railway lines using surveillance cameras. The results demonstrated that YOLOv5 with large model size outperformed with an OA of 82.6% and mAP of 0.822. When considering ensemble modelling strategy, integrating multiple YOLO-based models with small, nano, medium and large sizes achieved the best result with the OA equal to 85.4% and the mAP equal to 0.834. For future work, UAV- or satellite-based high-resolution data will be considered for detecting floating plastics along railway lines. The YOLO-based approach will be adapted to such overhead imagery to map the distribution of plastic waste along railway lines, identifying the potential threat to the safety of train operation.

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