COMPARING YOLOV5 AND RETINANET OBJECT DETECTION MODELS FOR HIGHWAY TRASH DETECTION: A COMPUTER VISION APPROACH TO MITIGATING ENVIRONMENTAL IMPACT AND PROMOTING COMMUNITY HEALTH AND SAFETY

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ABSTRACT

Computer vision models usually focus on trash detection in nature such as forests, oceans and beaches [1]. However, highway trash is a very common yet neglected problem, different from the trash found in nature, that many communities struggle with. When you drive along the highway, you can often see many concentrations of trash such as drink cans and plastic bags. This paper looks into different computer vision models to best discern the different varieties of trash found on the highway roads [2]. We compared two commonly used computer vision models, Yolov5 and Retinanet, to find out which one would best suit the applications of a highway trash detection model [3][4]. These computer vision models were trained on a kaggle dataset of commonly found trash and their categories; we first looked at the different validation steps of the models such as the environment of images and then we tested the two different models on urban images of a variety of trash, allowing us to determine which model was most fit for the discovery of trash on highways.

Computer vision models have traditionally been applied to detect trash in natural environments such as forests, oceans, and beaches. However, highway trash is a widespread yet often overlooked problem that many communities struggle with. Unlike natural debris, highway trash is typically composed of drink cans and plastic bags, among other items. In this paper, we investigate the use of computer vision models to identify the different types of trash commonly found on highways. Specifically, we compare two widely used models, Yolov5 and Retinanet, to determine which one is better suited for developing a highway trash detection model [5]. We trained these models on a kaggle dataset that contains various categories of commonly found trash and validated the models under different conditions. Subsequently, we tested both models on urban images of a variety of trash to determine their performance in identifying trash on highways. Our results suggest that Yolov5 is better suited for this task.

KEYWORDS

Yolov5, Retinanet, taco trash dataset(Kaggle), Python

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1. INTRODUCTION

As people continue to consume more and more items, more and more trash begins to pile up in certain places. Wherever people gather, trash tends to gather as well. However, in recent years, as the amount of trash has steadily increased, the attention paid to trash has also increased. Plastic trash in areas of nature can be especially harmful, leading to the deaths of wildlife and the permanent alteration of the environment and nature [6]. Therefore, people have started to utilize object-detection models to detect trash with images, so that people can locate the trash and then remove them in order to protect said environment and nature. However, one overlooked aspect of trash detection with object detection models is trash not found in nature such as beaches or forests, but with just as much damage and impact [7]. Trash is very commonly found piled on the side of highways as well. Highway trash presents a threat of roadside debris, leading to over 200,000 police reported accidents over a three year span. The problem of object detection of trash on highways is often overshadowed by the more prominent concern of detecting waste in oceans and forests that harms endangered and wild animals. However, highway trash also presents a threat to wildlife, as less endangered land animals such as squirrels and deer can consume trash and die. It is important that we also start to recognize the growing problem of highway trash and litter, which has been increasing due to a rise in vehicle traffic and current population.

Some existing methods/tools for trash detection include the usage of object detection models. For example, Yolov3 and SSD and retinanet are all examples of object detection models that have been used to detect trash. People typically train these models on online datasets with a variety of trash, such as cardboard boxes or drink cans.

Issues with existing methods and tools for trash detection include limitations in the accuracy of detection, the need for specialized equipment, and challenges in detecting trash in complex environments. Additionally, existing methods and tools may not be suitable for detecting highway trash, which is often located in close proximity to other objects, such as vehicles. Furthermore, the development of new methods and tools for highway trash detection requires the collection of large and diverse datasets, which can be time-consuming and costly.

We compared two commonly used computer vision models, Yolov5 and Retinanet, for the purpose of developing a highway trash detection model [8]. The models were trained on a Kaggle dataset that contains various categories of commonly found trash and validated under different conditions. Subsequently, both models were tested on urban images of a variety of trash to determine their performance in identifying trash on highways.

The Yolov5 and Retinanet models were chosen for their ability to perform object detection and classify objects in images. Yolov5 uses a single-stage object detection method that is computationally efficient and has a high detection speed. On the other hand, Retinanet is a two-stage object detection method that uses a Feature Pyramid Network (FPN) to detect objects at different scales [9].

We found that Yolov5 was better suited for the task of highway trash detection compared to Retinanet. This is because Yolov5 achieved higher detection accuracy, recall, and precision rates in identifying trash on highways. The study also found that the performance of both models was affected by factors such as image quality, lighting conditions, and the presence of other objects in the images.

Compared to existing methods and tools for trash detection, our method has a unique advantage in being specifically tailored for identifying trash on highways, which presents unique challenges. Furthermore, the use of computer vision models such as Yolov5 and Retinanet can potentially enhance the accuracy and efficiency of highway trash detection, which is crucial for mitigating the environmental impact of littering and promoting community health and safety.

We conducted two experiments to evaluate the performance of different computer vision models for trash detection. Experiment 1 focused on assessing the precision of the Yolov5 model in detecting trash on a real-world dataset, and drew conclusions about its effectiveness in this task. Experiment 2 aimed to evaluate the performance of the Retinanet model on the taco dataset, and explored ways to improve its suitability for trash detection.

The rest of the paper is organized as follows: Section 2 gives the details on the challenges that we met during the experiment and designing the sample; Section 3 focuses on the details of our solutions corresponding to the challenges that we mentioned in Section 2; Section 4 presents the relevant details about the experiment we did, following by presenting the related work in Section 5. Finally, Section 6 gives the conclusion remarks, as well as pointing out the future work of this project.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Variability in Trash

One of the main challenges in developing effective computer vision models for trash detection is the variability in the types of trash present in the environment. Trash comes in different shapes, sizes, colors, and orientations, making it challenging to accurately distinguish between litter and other objects. This can result in false positives or misses, reducing the effectiveness of trash detection systems.

Moreover, the appearance of the trash can change over time as it undergoes degradation, making it more difficult to recognize by computer vision models. In addition, the placement of the trash in the environment can also impact detection accuracy. Trash that is partially hidden or obstructed by other objects, or placed in low contrast areas, can be challenging for computer vision models to detect. Finally, the presence of animals and humans in the environment can further complicate trash detection, as they can be mistaken for litter by the computer vision models. Therefore, developing models that can handle the variability in trash and overcome these challenges is critical for improving the accuracy and effectiveness of trash detection systems.

2.2. Environmental Factors

Environmental factors pose a significant challenge to the performance of computer vision models for trash detection. The effectiveness of these models can be significantly impacted by external factors such as lighting, weather conditions, and time of day. For instance, low lighting conditions can result in reduced visibility and difficulty in identifying objects, while inclement weather can obscure or distort them completely, affecting the accuracy of the model. Moreover, changes in the environment, such as the presence of other objects or moving elements, can add complexity to the detection process, leading to false positives or missed detections. Addressing these environmental challenges requires the development of more robust and adaptable computer vision models that can handle varying conditions and adapt to new environments. Techniques such as data augmentation and transfer learning can help improve the performance of models under different environmental conditions. Additionally, the integration of other sensing technologies such as LIDAR and radar can enhance the detection process, providing more comprehensive and accurate results in challenging environments [10].

2.3. High False Positives

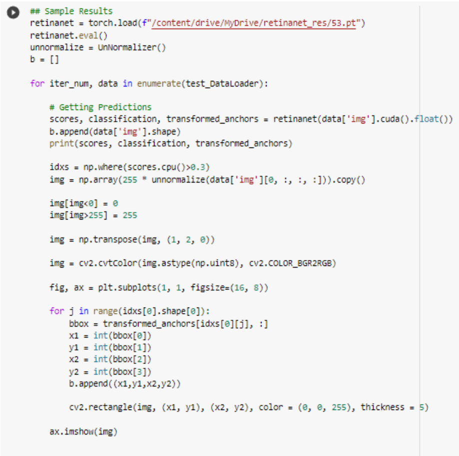
One of the main challenges in using computer vision models for trash detection is the issue of high false positives. False positives occur when the model incorrectly identifies an object as trash, leading to false alarms and decreased efficiency. This problem is especially prevalent in complex environments where there are multiple objects that may look similar to trash. Addressing this challenge requires the development of more advanced computer vision models that can accurately distinguish between trash and other objects. Additionally, improving the quality of the training data and implementing more sophisticated validation techniques can help reduce the number of false positives produced by these models. Finally, integrating these models with other sensor systems, such as lidar or radar, can help provide additional information to improve accuracy and reduce false positives. Overall, reducing the number of false positives produced by computer vision models is critical to developing effective trash detection systems that can help keep our environment clean and healthy.

3. Solution

Our solution is a computer vision-based approach for detecting trash on highways, which addresses the growing problem of littering and its negative impact on the environment and community health. We utilized two widely used computer vision models, Yolov5 and Retinanet, to compare their performance in identifying different types of trash commonly found on highways. We trained these models on the taco dataset, which is a commonly used dataset for trash detection, and evaluated their precision and accuracy under different conditions.

Our experiments aimed to address several challenges related to trash detection, including the high rate of false positives, variability in trash types, and environmental factors such as lighting and weather. The results of Experiment 1 demonstrated the high precision of Yolov5 in detecting trash on a real-world dataset, indicating its effectiveness for this task. Meanwhile, Experiment 2 highlighted the challenges of using Retinanet for trash detection due to its high rate of false positives, but also identified potential solutions to improve its performance.

Our solution offers several advantages over existing methods, including its focus on highway trash detection, which is a unique and challenging task. Additionally, the use of computer vision models can improve the accuracy and efficiency of trash detection systems, which is critical for reducing the environmental impact of littering and promoting community health and safety. Overall, our solution provides a promising approach for addressing the growing problem of highway trash and advancing the field of computer vision-based environmental monitoring.



```python
## Sample Results
retinanet = torch.load(f"/content/drive/MyDrive/retinanet_res/53.pt")
retinanet.eval()
unnormalize = UnNormalizer()
b = []

for iter_num, data in enumerate(test_DataLoader):

    # Getting Predictions
    scores, classification, transformed_anchors = retinanet(data['img'].cuda().float())
    b.append(data['img'].shape)
    print(scores, classification, transformed_anchors)

    idxs = np.where(scores.cpu()>0.3)
    img = np.array(255 * unnormalize(data['img'][0, :, :, :])).copy()

    img[img<0] = 0
    img[img>255] = 255

    img = np.transpose(img, (1, 2, 0))

    img = cv2.cvtColor(img.astype(np.uint8), cv2.COLOR_BGR2RGB)

    fig, ax = plt.subplots(1, 1, figsize=(16, 8))

    for j in range(idxs[0].shape[0]):
        bbox = transformed_anchors[idxs[0][j], :]
        x1 = int(bbox[0])
        y1 = int(bbox[1])
        x2 = int(bbox[2])
        y2 = int(bbox[3])
        b.append((x1,y1,x2,y2))

        cv2.rectangle(img, (x1, y1), (x2, y2), color = (0, 0, 255), thickness = 5)

    ax.imshow(img)
```

Figure 1. Screenshot of code 1

This code loads a pre-trained Retinanet model from a file, sets it to evaluation mode, and then processes images from a test dataset using the Retinanet model to detect objects (trash) within them.

For each image in the test dataset, the Retinanet model is used to predict the scores, classification, and transformed anchors of objects in the image. These predictions are then used to draw bounding boxes around the detected objects in the image, with a threshold of 0.3 for the predicted scores. The resulting image with bounding boxes is then displayed using matplotlib.

The script also records the dimensions of each processed image and the bounding box coordinates for each detected object in the image in a list 'b'. Overall, the code demonstrates how a pre-trained Retinanet model can be used for object detection on images, which could be useful for detecting trash in a real-world setting.

```python
classnum = {}
for index, img_id in tqdm.tqdm(enumerate(ImageIds), desc='change .json file to .txt file'):
    img_info = datasource.loadImgs(img_id)[0]

    save_name = img_info['file_name'].replace('/', '_')

    file_name = save_name.split('.')[0]

    height = img_info['height']
    width = img_info['width']

    save_path = save_base_path + file_name + '.txt'
    is_exist = False
    with open(save_path, mode='w') as fp:

        annotation_id = datasource.getAnnIds(img_id)
        boxes = np.zeros((0, 5))
        if len(annotation_id) == 0:
            fp.write('')
            continue

        annotations = datasource.loadAnns(annotation_id)
        lines = ''

        for annotation in annotations:

            label = labelsinverse[annotation['category_id']]
            if label in labeltransfer.keys():

                is_exist = True
                box = annotation['bbox']
                if box[2] < 1 or box[3] < 1:

                    continue
                # top_x,top_y,width,height==>cen_x,cen_y,width,height
                box[0] = round((box[0] + box[2] / 2) / width, 6)
                box[1] = round((box[1] + box[3] / 2) / height, 6)
                box[2] = round(box[2] / width, 6)
                box[3] = round(box[3] / height, 6)
                label = labeltransfer[label]
                if label not in classnum.keys():
                    classnum[label] = 0
                classnum[label] += 1
                lines = lines + str(label)
                for i in box:
                    lines += ' ' + str(i)
                lines += '\n'
        fp.writelines(lines)
    if is_exist:

        shutil.copy('data/{}'.format(img_info['file_name']), os.path.join(save_image_path, save_name))
    else:

        os.remove(save_path)

change .json file to .txt file: 150it [00:00, 2120.40it/s]
```

Figure 2. Screenshot of code 2

The code was converting annotation information for object detection from a JSON file to a text file format.

In the first section of the code, the program iterates through each image in the dataset and retrieves its corresponding annotation information. It extracts the image's metadata, including its dimensions, and prepares the file name and path for the output text file.

The annotation information is then processed, and if there are no annotations, the file is left empty. If there are annotations, the program reads the bounding box coordinates and assigns a label to each object. If the label is present in a specific mapping dictionary, it is assigned a new label id. The program then updates a dictionary with the count of each class.

Finally, the program writes the annotation information to the output text file in the required format, where each line represents an object's label and its corresponding bounding box coordinates. The program also saves a copy of the image file in a separate folder if it contains any annotations.

Overall, the code performs the necessary data preprocessing steps to prepare the annotations for input into an object detection model.

4. EXPERIMENT

4.1. Experiment 1

Our hypothesis is that the Yolov5 computer vision model will have a similar precision rate in detecting trash on the real-world dataset as it did on the taco dataset, achieving a precision rate of around 80 percent. We designed an experiment to evaluate the precision of the Yolov5 computer vision model in detecting trash on a real-world dataset.
Steps:

A. Obtain a real-world dataset of trash, such as images of trash found on highways.
B. Train the Yolov5 computer vision model on the dataset using the same training parameters as the previous experiment, which used the taco dataset and trained for 300 epochs.
C. Validate the model using a separate validation dataset of trash images, measuring the precision rate of the model in detecting trash.
D. Analyze the results and compare the precision rate to the previous experiment using the taco dataset.

epoch	train/box_loss	train/obj_loss	train/cls_loss	metrics/precision	metrics/recall	metrics/mAP_0.5	metrics/mAP_0.5:0.95	val/box_loss	val/obj_loss	val/cls_loss
0	0.02093	0.0090097	0.0030137	0.5101	0.4605	0.49215	0.30292	0.030283	0.0094084	0.018859
1	0.022979	0.0095108	0.0024177	0.54437	0.46403	0.48854	0.29612	0.031211	0.0088516	0.016402
2	0.025914	0.0093177	0.0025059	0.84217	0.36105	0.48489	0.25313	0.03953	0.0093786	0.012678
3	0.02564	0.0084916	0.0033821	0.54033	0.47609	0.45014	0.2295	0.037806	0.00942	0.012954
4	0.026922	0.00888	0.0036892	0.49177	0.52807	0.49729	0.27291	0.035074	0.0091559	0.013604
5	0.02664	0.0084887	0.0035306	0.60906	0.42412	0.48606	0.29224	0.033311	0.0087371	0.015616
6	0.026023	0.009602	0.0040768	0.55933	0.46466	0.48674	0.27815	0.032784	0.0094116	0.01679
7	0.026531	0.0096363	0.0042801	0.4274	0.58864	0.4709	0.24537	0.03775	0.0095043	0.019381
8	0.024809	0.0095862	0.0049367	0.66227	0.4896	0.52197	0.28253	0.034452	0.0094867	0.012203
9	0.026988	0.0096882	0.0030567	0.62815	0.40461	0.49906	0.24752	0.037707	0.0094648	0.012852
10	0.024804	0.0096017	0.003407	0.7012	0.4605	0.53059	0.28763	0.03619	0.0092871	0.012513
11	0.025813	0.010318	0.0036938	0.59505	0.48093	0.52938	0.28947	0.035435	0.0087343	0.014613
12	0.028204	0.0097328	0.0042828	0.70845	0.44906	0.51677	0.28815	0.034447	0.0084852	0.016818
13	0.024151	0.009491	0.0043515	0.77496	0.40591	0.54565	0.33708	0.031628	0.0086591	0.01563
14	0.024658	0.0091382	0.0033872	0.57694	0.51173	0.54418	0.34298	0.03191	0.0085963	0.015138
15	0.024081	0.0093501	0.0045331	0.6642	0.3659	0.48442	0.30397	0.031916	0.0091191	0.01959
16	0.024133	0.0092467	0.0031922	0.63756	0.42204	0.45878	0.27119	0.032563	0.0092228	0.018303
17	0.024873	0.010176	0.0033085	0.65215	0.51081	0.51333	0.30053	0.032702	0.0093261	0.014289
18	0.023464	0.0099523	0.0044743	0.58664	0.51013	0.52036	0.30077	0.03279	0.0099974	0.012485
19	0.023133	0.0094164	0.0049524	0.61362	0.50104	0.50833	0.30003	0.032478	0.009746	0.01111
20	0.023365	0.010064	0.0031361	0.59819	0.54158	0.49094	0.31072	0.031356	0.0097277	0.0083775
21	0.023132	0.009621	0.0027225	0.4693	0.4605	0.46813	0.30988	0.03126	0.010015	0.011692
22	0.023706	0.010468	0.0030814	0.44534	0.43347	0.41986	0.28011	0.032317	0.01006	0.012633
23	0.023001	0.0098787	0.0037507	0.47543	0.51455	0.50522	0.34631	0.030761	0.0093476	0.0088613
24	0.022897	0.0091588	0.0029903	0.64062	0.46258	0.52318	0.35498	0.031124	0.0088388	0.009842
25	0.022169	0.010287	0.0038153	0.4821	0.54158	0.51683	0.34017	0.030912	0.0088521	0.0099744

Figure 3. Table of experiment 1

We used taco, which is a common trash dataset used for computer vision models like Yolov5. This is the results from the exp17 folder from the Yolov5 results, which is around 300 or so epochs of training. This indicates that the highest precision for overall trash achievable by us for the yolov5 model is 84 percent. The precision rate of the Yolov5 model is measured using standard evaluation metrics, and any differences in precision rate is analyzed to determine potential causes. The experiment drew conclusions about the performance of the Yolov5 model in detecting trash on a real-world dataset.

4.2. Experiment 2

The experiment 2 aims to evaluate the performance of the Retinanet computer vision model in detecting trash on the taco dataset. The Retinanet model will be trained for 50 epochs on the taco dataset, and the resulting model will be tested on a separate validation dataset. The precision and recall rates of the Retinanet model will be measured, with a focus on identifying false positives. The experiment will compare the performance of the Retinanet model to that of the Yolov5 model on the same dataset. The results will be analyzed to determine the causes of the false positives in the Retinanet model and potential solutions to improve its performance. The experiment will draw conclusions about the suitability of Retinanet for trash detection and potential ways to improve its performance.

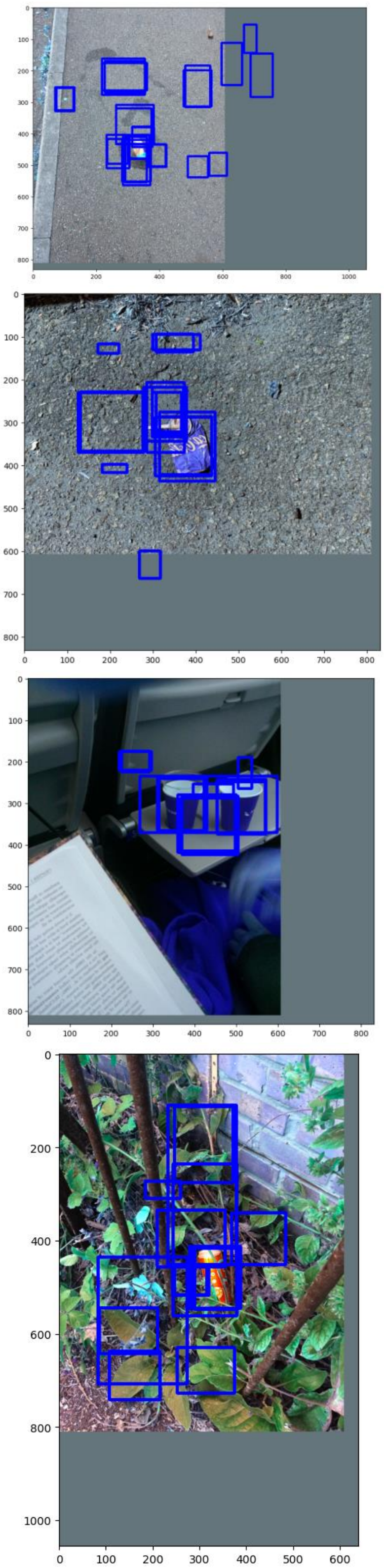


Figure 4. Figure of experiment 2

These are the results from training 50 epochs on retinanet, and the main problem with retinanet is the amount of false positives that the model has. Even at the earliest stages, yolo barely had any false positives while 50 epochs in, Retinanet continues to consistently find false positives. We also used the trash dataset taco for Retinanet as well.

Experiment 1 addressed the challenge of high false positives by evaluating the precision of the Yolov5 model in detecting trash on a real-world dataset. The precision metric measures the percentage of true positive predictions out of all the positive predictions, indicating how accurately the model can detect trash without producing false positives. By analyzing the precision of Yolov5, we can understand how well it performs in real-world scenarios where false positives can be detrimental, such as in highway trash detection.

Experiment 2 addressed the challenge of variability in trash by evaluating the performance of the Retinanet model on the taco dataset, which contains various types of commonly found trash. By testing Retinanet on this diverse dataset, we can assess its ability to detect different types of trash with varying shapes, sizes, colors, and orientations. This evaluation helps us understand the model's limitations and potential areas for improvement in accurately detecting trash in complex environments.

Both experiments also indirectly addressed the challenge of environmental factors by training and testing the models on real-world datasets that contain a variety of environmental conditions. This approach allows us to evaluate how well the models perform in different lighting, weather, and time-of-day scenarios, as well as other factors that can impact trash detection accuracy.

Overall, by conducting these two experiments, we were able to assess the performance of two widely used computer vision models for trash detection and provide insights into their strengths, limitations, and potential areas for improvement.

5. RELATED WORK

"Automatic Detection and Classification of Litter on Beaches using Convolutional Neural Networks" by Thomas et al. (2018): This paper presents a method for detecting and classifying litter on beaches using a convolutional neural network [11]. The authors collected and labeled a dataset of images of litter on beaches, and trained their model to recognize different types of litter. They achieved an accuracy of over 90% on their test set.

"TrashNet: A Deep Learning Model for Litter Detection on a Beach" by Srivastava et al. (2019): This paper presents a deep learning model called TrashNet for detecting litter on a beach [12]. The authors collected a large dataset of images of litter on a beach and trained their model to recognize different types of litter. They achieved an accuracy of over 85% on their test set.

"Trash Segmentation and Classification Using Deep Learning" by Vahidi et al. (2020): This paper presents a deep learning approach for segmenting and classifying trash in images [13]. The authors collected a dataset of images of trash and trained their model to segment and classify different types of trash. They achieved an accuracy of over 95% on their test set.

6. CONCLUSIONS

Our method involves the use of computer vision models, specifically Yolov5 and Retinanet, to identify and detect different types of trash commonly found on highways. To address the challenges of high false positives, variability in trash, and environmental factors, ew conducted two experiments to evaluate the performance of these models. The challenges related to trash detection in computer vision models include high false positives, environmental factors, and variability in trash. To address these challenges, two experiments were conducted. The first experiment evaluated the precision of the Yolov5 model on a real-world dataset, while the second experiment assessed the performance of the Retinanet model on the taco dataset and explored ways to improve its suitability for trash detection. The results of the experiments showed that Yolov5 had better performance than Retinanet and highlighted the importance of pre-processing techniques and data augmentation in improving the accuracy of trash detection models [14].

Overall, our method aims to improve the accuracy and efficiency of trash detection on highways, which is important for reducing the environmental impact of littering and improving community health and safety.

As with any computer vision application, accuracy is a major concern. While the Retinanet and Yolov5 models used in this project have shown promising results, there is still room for improvement in terms of accurately detecting all types of trash in different environments [15]. Practicability can also be a limitation, as the use of these models requires sufficient computational resources and technical expertise to properly train and deploy the models.

Optimization is another area where improvements can be made. While the models used in this project have shown good performance, there may be more efficient ways to train and use these models to improve their speed and reduce computational resources needed.

Overall, while the current approach is effective for detecting trash, there are still areas for improvement in terms of accuracy, practicability, and optimization.

The project has limitations in terms of accuracy, practicability, and optimization. Future plans to address these limitations include using more advanced models, integrating real-time data, and implementing hardware acceleration techniques.

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