The Green Verge Project

Litter awareness from GPS enabled dashcam footage

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Abstract

The allocation of resources to combat litter is currently a manual process. However, dashboard-cameras are being more common in motoring, and potentially offer a mechanism by which litter can be more thoroughly monitored. The Green Verge project seeks to implement a robust system that can automatically detect litter from dashcam footage, register the detected litter and geospatial coordinates, and produce a user-friendly mapping solution that highlights regions of high litter concentration.

Introduction

- Littering has **detrimental effects** on both the **natural environment**, with the breakdown of litter releasing chemicals, and the wildlife that inhabits it [2].
- Litter has been shown to be an **increasing problem** in the U.K [3].
- The cost of combating litter is estimated to be about **£700 million a year** to local authorities [1].

Recent consultations with local authorities highlighted a demand for the development of a computer vision based system that can process, and identify litter within video footage to allow for better allocation of resources.

- **Dashboard-cameras** (dashcams) have become fairly **ubiquitous** in modern motoring, being fitted as standard in many new cars. Furthermore, they are **already fitted** to many local authority vehicles, like refuse collection trucks.
- Dashcams provide **inexpensive** mechanism for **autonomously** collecting video footage from the environment, and many are **GPS enabled**.

In this project, we seek to build a *deep-learning* based system that is able to accept GPS embedded vehicle dashcam footage, and **robustly** identify litter within it.

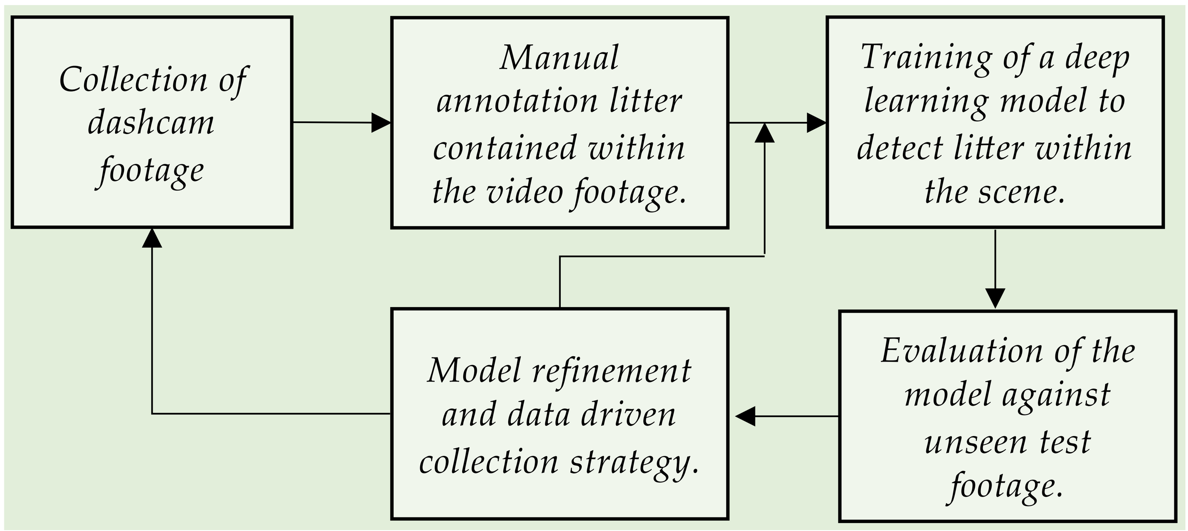

Figure 1. Overview of training pipeline adopted in the green verge project.

Work Overview

The Green Verge project has been split into work packages (WPs); in this poster we present the work conducted to-date on WP1: ***dataset creation and model training***. The training pipeline adopted for WP1 is shown in Figure 1. Our main aims in this work are:

1. Construct an annotated **dataset** of litter from dashcam footage.
2. Use our dataset to train a **deep learning model** to detect litter in dashcam footage.

Future work will consider WP2: *litter visualisation and mapping*.

Dataset Construction

Our dataset is constructed from 4K dashcam footage, collected in Lincolnshire between February and April 2022. Video footage was annotated with bounding boxes, for the single class we refer to as `litter`, using the open-source annotation tool CVAT [6]. We also label each video according to the weather and lighting conditions seen, to aid with our data driven collection strategy (Fig. 1).

In total, our dataset collected so far consists of **8997 frames** (constructed as a subset of the **32 hours** of total footage captured). The size of our dataset is compared to other related work in figure 2. With augmentation techniques, we increase the size of the training dataset to **15,065 frames** and include domain specific inductive bias (e.g. vehicle motion blur), without the costly need of annotating further frames.

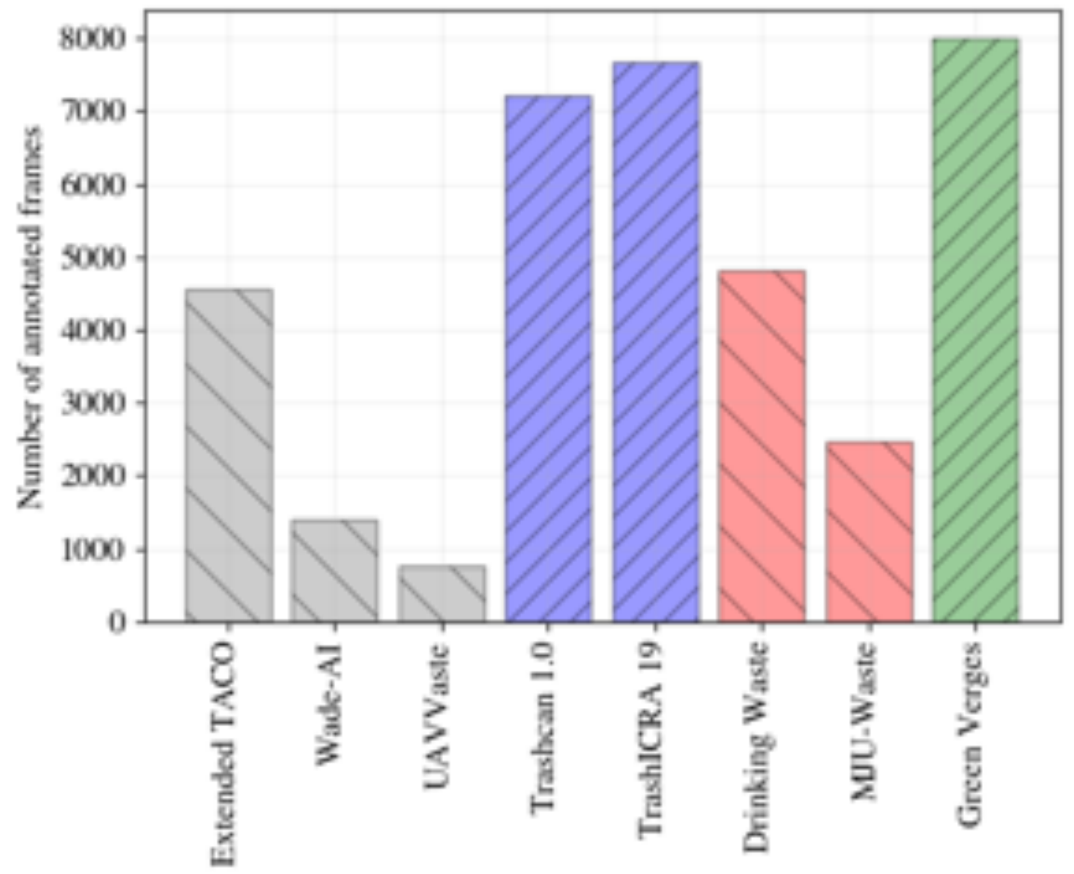

Figure 2. Comparison of the size of our dataset compared with related works; grey columns represent datasets with litter captured in urban/outdoor environments, blue represents datasets captured underwater, and red represents datasets captured indoors.

Deep Learning Model

For model development, we have implemented a **baseline model** using the SOTA method for object detection - YOLOv5 [5]. We used weights pretrained from the COCO dataset, with fine-tuning first conducted on the UAVVASTE dataset [4], then further trained on our dataset until optimal results where obtained. This initial model has managed to achieve mean average precision (mAP), at a 50% intersection over union threshold, of 44%. A testing demo can be viewed via the QR code.

Challenges faced so far include largely varying photometric appearance of litter and various noise; such as pedestrians, passing cars or light reflections. The results achieved via a baseline model demonstrated the challenges we face ahead. We will seek to address these in our future work.

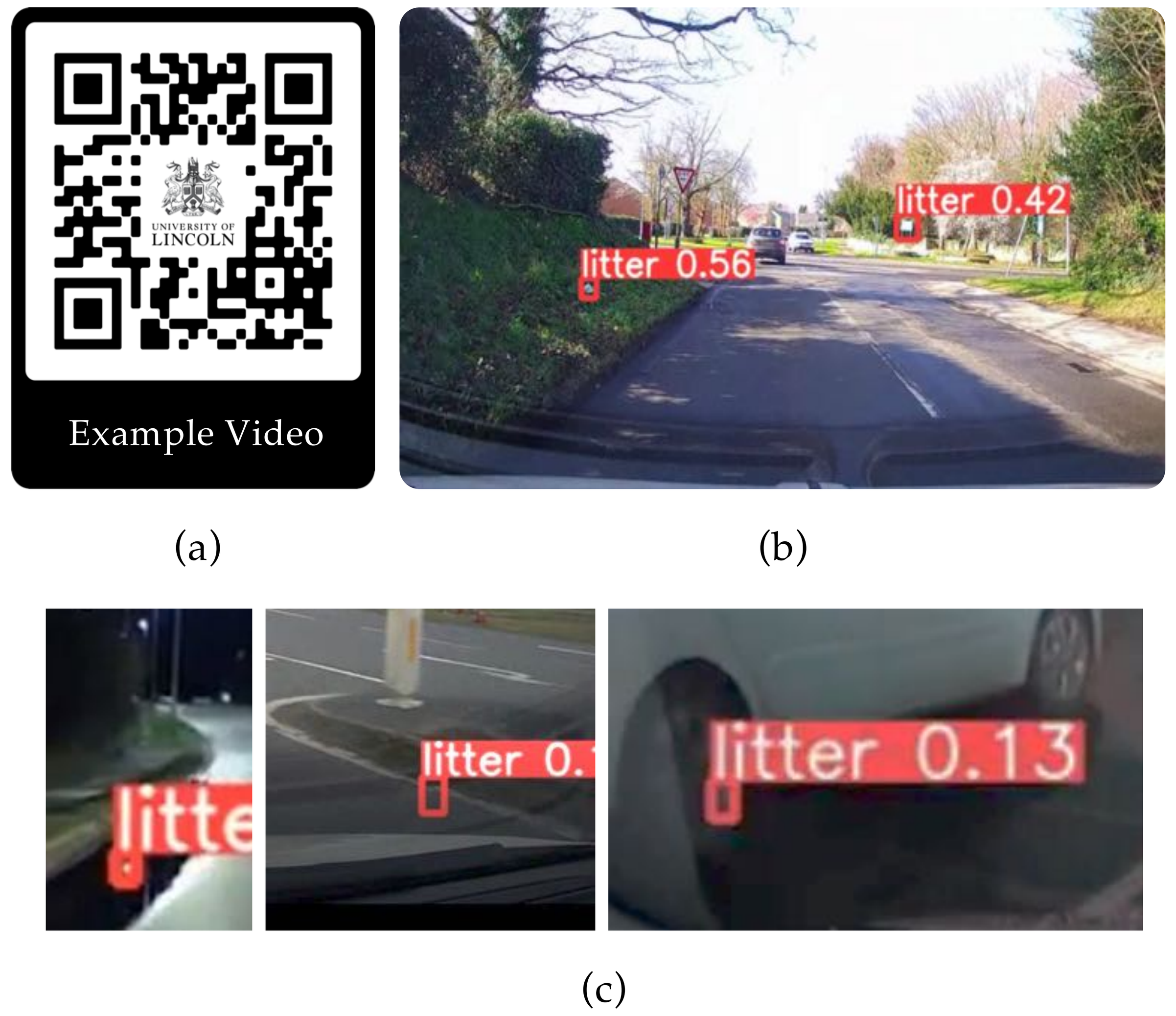

Figure 3. (a) Example test video with our current implementation. (b) Example of where litter is correctly and incorrectly detected in a single frame. (c) Examples of challenging frames for the network to deal with: reflections in water, road markings, moving vehicles.

References

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[2] Frederic Gallo, Cristina Fossi, Roland Weber, David Santillo, Joao Sousa, Imogen Ingram, Angel Nadal, and Dolores Romano. Marine litter plastics and microplastics and their toxic chemicals components: the need for urgent preventive measures. *Environmental Sciences Europe*, 30(1):1–14, 2018.

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