Litter Detection Using UAV

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Abstract
Limited supervision over uncharted litter scattered for long duration, account to environment linked problems. Present resolutions to mitigate these effects include awareness program like "Swachh Bharat abhiyan" and also an app (Swachhata) that enables user to report such problems [1]. This paper introduces the concept of micro-unmanned aerial vehicle (UAV) to detect litter from real-time video surveillance footage via machine learning models.
Keywords – litter, UAV, machine learning

I. INTRODUCTION

Litter by meaning itself is small debris such as paper, cans, and bottles that are scattered in public place. Uncharted litter scattered in public not only causes problem to humans but also causes the problem to inhabitant animals, most of the animals consume the litter or get entangled in it etc. Most of the day-to-day litter that gets accumulated is non-biodegradable waste; in a way it also effects the environment. The litter also causes foul smell, resulting in distressed breathing behavior. These litter carried away through sewage water, has greater chance to end up in a river and eventually in ocean that results in devastating effects on marine life. For example, reports of a dead whale found by the shore having plastic in their stomach, most of seals, turtles die every year by entangling themselves in disposed fishing nets etc.

Today, India is considered one of the countries in the world to dispose most garbage. The landfills or the dump yards can have deadly materials, including plastics and chemicals. According to recent reports, India is generating about 130 million tons of e-waste and the numbers are expected to get doubled by 2020 [9]. There are many city based initiatives taken to prevent improper disposal of litter. For example, Bengaluru stands among first cities in India to take an initiative to segregate solid waste at household level before collection. The Hon. Prime minister of India launched Swachh Sarvekshan mission to rank cities based on sanitation and cleanliness. The MoUD added that under Swachh Bharat Mission, it incurred the cost of about Rs.62,009 crore ($9.4 billion) on solid waste management [11]. Mysuru City Corporation framed a report stating that the city produces about 402 metric tons of waste every day [10]. Mysuru city has also put a lot of efforts to prevent improper disposal of litter. It includes door-to-door collection of solid waste, segregating them as recyclable waste and also produce huge amount of compost from biodegradable waste. Mysuru has bagged the cleanest city in India for over two times and is always at top five cleanest cities in India. Though its efforts of monitoring waste disposal, there is a loophole in the plan and hence it is losing its top position of being the cleanest city.

This paper demonstrates an effective solution that can bring out significant changes to the existing monitoring plan of litter. By automating the process of detecting litter through UAVs, can be a better strategy by reducing human efforts and by saving the critical amount of time compared to traditional method. By adopting this effective method of detecting litter, Mysuru will hold its position of cleanest cities.

II. BACKGROUND

Micro-UAV

These are miniature version of UAVs. The advantage of choosing micro-UAV to collect data is because of it is portable and inexpensive compared to standard size drones. Due to its miniaturization, it can navigate easily through narrow space in order to detect litter. Due to its flexibility, it is able to monitor vast colonies with ease. This project made use of Cheerson CX-10WD-TX models that can be remotely controlled over Wi-Fi and is equipped with high-definition First Person View (FPV) cameras. The drones are employed for real-time broadcasting of video and image data to be evaluated by the litter detection model. The drone can also be controlled via a remote controller as shown in figure1.

Figure 1 – Cheerson CX-10WD-TX micro UAV [5]

Computer Vision and Machine learning

Machine learning is the technique to instill knowledge to the computer program about the different tasks via a large amount of data about the task. Hence the computer improves its performance progressively on that task [6]. Computer vision is automated task of human visual system. It deals with providing computer a high-level understanding by extracting high dimensional data from the digital images or videos [7]. Machine learning and computer vision are core part of computer science. By combining the power of both the disciplines we can create robust and sophisticated applications. The automated litter detection system is the result of combination of both machine learning and computer vision.

Python

[8] Python is a high-level general-purpose programming language that supports object-oriented programming and consists of large comprehensive libraries. It emphasizes on code reliability. It has collection of Libraries such as NumPy, SciPy and Matplotlib that has its application in scientific computing. Python also has libraries such as Tensor Flow, Keras and Scikit-learn that facilitate in many artificial intelligence projects. Python also provides library for computer vision, for example openCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library that has a common infrastructure for computer vision applications.

Tensor Flow

It is an open source software developed by Google Brain team. Tensor Flow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.

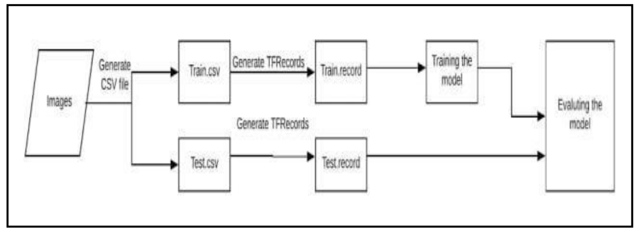

Figure 2 – Tensor flow architecture

Classifier

Convolution Neural Network:

CNN belongs to class of deep neural network finds its application in analysing visual imagery.

Different layers of the convolutional neural network used are:

• Input Layer: The first layer of each CNN used is 'input layer' which takes images, resize them.

• Convolution Layer: which act as filters for images, hence finding out features from images and also used for calculating the match feature points during testing.

• Pooling Layer: This layer takes large images and shrinks them down while preserving the most important information in them.

• Flattening: here Convolution and pooling are repeated until a single dimensional array is produced.

• Fully Connected Layer: The final layer is the fully connected layers which takes the high-level filtered images and translate them into categories with labels.

Detectors

You Only Look Once (YOLO):

You Only Look Once (YOLO) is an object detection algorithm in machine learning that is used to finds objects in an image. The objects in the images are determined by creating a series of bounding boxes and with the highest probability containing the object. Unlike other algorithms, YOLO generates all its predictions at once, hence the name, as it only processes the image once. The ideology behind this algorithm is as follows,

- First it divides an image into a grid of S^2 squares where S is a constant value.
- If a square of the grid lies upon an object, then that square is responsible for creating bounding boxes on

the object. The bounding boxes also are paired with a confidence score.

- YOLO generates a confidence score by assessing how certain it is that a bounding box contains an object or part of an object.
- If there is no object in a bounding box, then the confidence score should be 0.

While the YOLO lags in accuracy when compared with other algorithms, it quickly detects the objects in the image. Hence it is well suited for devices will low computation power [2].

Single Shot Multibox Detector (SSD):

Single Shot Multibox Detector (SSD) is a machine learning algorithm that detects objects by generating and finding a matching box with the ground truth box around an object in a single forward pass of the network.

- First, SSD creates multiple bounding boxes, in each cell on the pre-annotated image using the Multibox algorithm.
- Afterwards, as more convolutional layers are generated, it uses small convolutional filters to create multi-scale feature maps and thus computes the location and class scores of the object.

Higher resolution feature maps are responsible for detecting small objects and, lower resolutions are used to detect large objects. The number of filters applied around each location in a feature map is calculated with the following equation:

$$(c+ 4)\ k$$

Where, c is the number of classes

k is the number of bounding boxes.

SSD predictions are classified as positive matches or negative matches. The intersection over the union (IoU) is an evaluation metric used to determine positive and negative matches. If the IoU is greater than 0.5 between the predicted bounding box and the ground truth box, then the match is positive [2].

Fast R-CNN:

Image is processed with conv layers to produce feature maps. Then, a fixed-length feature vector is extracted from each region proposal with a region of interest (RoI) pooling layer. Each feature vector is then fed into a sequence of FC layers before finally branching into two sibling output layers. One output layer is responsible for producing soft max probabilities for all C + 1 categories and the other output layer encodes refined bounding box positions with four real-valued numbers. All parameters in these procedures are optimized via a multi-task loss in an end-to-end way [22].

III. EXISTING SYSTEM AND ITS DEMERITS

Though there are mechanisms for cleanliness maintenance, it is inadequate and not so efficient. There are so many complaints registered by the public about the litter found in the city. It is only sometimes being resolved by the respective authorities. The complaint thus entered is being handed over to the cleanup crew. One way is the respective authority to move around the city only to detect litter and take care of the same issues by making use of so many resources. A new digital way of reporting complaints is through app called “Swacchata”. The Swachhata-MoHUA is the official app of Ministry of Housing and Urban Affairs (MoHUA), GOI. The app enables a citizen to post a civic related issue (eg; a garbage dump) which is then forwarded to the city corporation concerned and thereafter assigned to the sanitary inspector of the particular ward.

Figure 3 - Swachhata app

The main demerit of the existing system is that:

- Retaining cleanliness is challenging
- Lot of manpower is been wasted
- Lot of time is invested in the same

IV. ABOUT LITTER DETECTION USING UAV

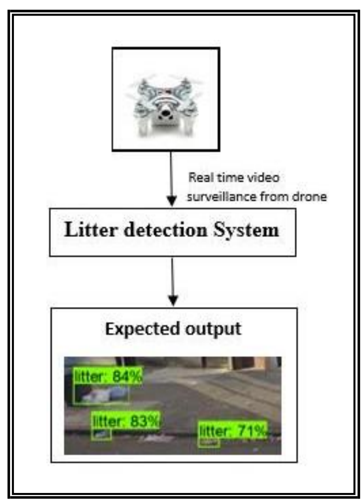

Figure 4 – Flow diagram [14]

Litter will be recorded via image acquisition from an Unmanned Aerial Vehicle (micro-UAV), while an automatic processing of the high volume of imagery will be developed through machine learning, employed for debris detection and classification.
Some of the advantages are:

- Just one worker driving a mobile base while drones fly alongside scanning for litter. That is, it reduces amount man power required.
- An area that would take hours to cover on foot could be cleared by drones in minutes. That is, its time efficient as well.

V. CHALLENGES

The below are few challenges with respect to UAV: [1]

Legislation:
There are rigid rules and regulation that does not permit to operate autonomous UAVs for commercial applications. Once the regulations are refined, then this type of use of UAVs can be allowed.

Weather:
Poor weather conditions are major hurdles for UAVs as they might get deviated from their original path. In such situations, there might also be damages caused on UAVs which end up failing in their task.

Energy Limitations:
It is the most fundamental challenge when dealing with drone as it depends on battery to power its components. Battery consumption in UAV is mainly used for hovering, wireless communications, data processing and image analysis.

Theft:
The major concern of using UAVs for gathering data wirelessly are cyber liability and hacking. UAVs must be guarded against the malicious software seeking to abduct the sensitive information it carries.

The below are few challenges with respect to automating the use of aerial imagery: [4]

Flat and meager view of Objects:
Computer vision algorithms and datasets are devised to evaluate images captured by humans that are usually horizontal and consist of all the features required to process the image in the lab. In contrast, the UAV imagery captured are usually vertical in nature, thus hiding most of the features possessed by the objects of interest. For example, image of a house captured from a UAV, shows only the view of the roof by hiding other features like doors, windows, and walls.

Difficulty in labeling data:
Even though we congregate the images, we need to label those images manually. This task demands precision and accuracy. There is no easy way of doing it rather than by hand.

Object overlap:
In some circumstances the process of detecting objects that are very close to each other, results in overlapping bounding boxes.

VI. LITERATURE SURVEY

Application of UAV to detect litter in the coastal area:
The UAV was used to detect the litter along the side of a beach in Saudi Arabia. The litter were recorded via images collected from an UAV. An automatic processing of the high volume of imagery was developed through machine learning. The results were discovered to be 39-time faster beach coverage than with a standard approach where a beach is screened by walking. The system achieved 61.8% accuracy [16].

Application of UAV to detect poachers in the wildlife sanctuary:
UAVs equipped with long wave thermal infrared cameras are used to identify rangers of poaching activity because there is increased poaching activity at night. The animals and humans are warm and emit thermal infrared light, this is used to detect their presence. There was considerable increase in the precision of detecting poachers using SPOT in contrast with EyeSpy Novice (ESN), and EyeSpy Expert (ESE) [17].

Application of UAV to detect individuals engaged in violent activities:
UAV can detect one or more individuals engaged in violent activities from aerial images. The framework first uses the FPN network to detect humans after which the proposed SHDL network is used to estimate the pose of the humans. The estimated poses are used by the SVM to identify violent individuals. It attained an average accuracy of 60-65% [18].

Application to recognize airplane:
The class of object "airplanes" was created. The open-source tool known as Bounding Box Label was used to label all airplane instances in this dataset, creating ground truth bounding box. CNN was able to recognize "airplane" objects in the data set with 97.5% of accuracy [19].

Application for rescue operation in disaster area:
UAV based monitoring system and object detection technique is proposed in order to enhance the search and rescue operation in a disaster area [20].

Application for moving object detection:
Moving objects detecting and tracking is important for future Unmanned Aerial Vehicles. Here the global-motion of the background by tracking features selected by KLT algorithm from frame to frame. In order to avoid features located on the foreground objects participating in motion estimation, feature effectiveness evaluation is employed [21].

VII. IMPLEMENTATION

Gather images
The dataset used for training is congregation of around 4500 images, most of them sourced from google. The dataset is classified as ten classes namely, plastic bags & covers, tetra packs, wrappers, bottles, cans, cigarette buds, plastic cups & spoons, cardboards, rubber, wire & cables etc. The composition of dataset also includes "trashnet" dataset, & some images from Garbage in image (GINI) dataset [14]. All images collected are of different colors, backgrounds, contrast which helps learner model to detect litter effectively in testing phase. Furthermore, the preferred image size was kept at less than 300KB in order to reduce computation time. Finally, the dataset was randomly split into 80:20 ratio as train and test data respectively.

Table 1 – class of litter in the dataset

Label images
Labelling is probably most tedious and time-consuming task in developing a model. In order to reduce this time-consuming task, there are variety of browser and desktop-based annotation tools available off the shelf to accomplish this task. LabelImg is a graphical annotation tool used for labelling images via bounding boxes [12].

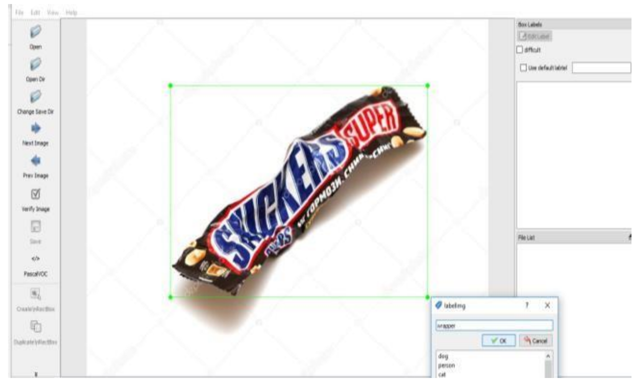

Figure 5 – LabelImg application for labelling images

Train model
The SSD and R-FCN models were built using the Tenserflow object detection API. The R-FCN was built from the Tensorflow R-FCN InceptionV2 model and the SSD was built using the Tensorflow SSD InceptionV2 model. In order to use the Tensorflow Object Detection API the images and image annotations needed to be converted from PASCALVOC format to tfrecord files. A simple script was written in python to convert the training and testing annotations into tfrecord files.

Test & integrate
Obtaining the live feed from micro-UAV to a computer was another hurdle in the project. The micro-drone came with an app that had functionalities of control it, and also obtaining real time feed, take pictures, record video etc., from a smartphone; thus, it was known that the drone had some level of a communication protocol. However, the software for controlling the micro-UAV was not publicly available. Therefore, an open-source project named Hack-a-Drone was made use of in order to control and receive video stream from the drone directly to a computer.
Hack-A-Drone enables to control drone through the keyboard, and it also has an auto-pilot feature that lets the drone to fly the preset route.

Table 2. Hardware requirement for the CPU and the GPU used in this experiment

	CPU	GPU
Manufacturer	Intel	NVIDIA
Model	I7	Geforce GTX680
Architecture	Sandy Bridge	kepler
Clock Frequency	3100 MHz	1002 MHz
Cores	4	1200
DRAM	8 GB DDR3	4 GB DDR5

VIII. RESULTS AND DISCUSSION

	SSD	R-FCN
Plastic	0.72	0.83
Paper	0.82	0.87
Foil	0.73	0.71
Metal	0.65	0.60
Cigarette	0.70	0.67
Glass	0.62	0.68
Cardboard	0.70	0.80

Table 3. Experimental results

From the above table, we can see that the results obtained by R-FCN are better compared to SSD. Therefore, we can conclude that R-FCN provides better results for this project.

IX. CONCLUSION

This implementation has achieved 73.71% accuracy in detecting the debris. This can be considered as a feasible and long-term solution for the existing problem of proper detection of litter and their disposal. This prototype can be added to “Swachh Bharath Abhiyan” so that the results expectancy of the mission may also be met through this project.

X. FUTURE ENHANCEMENT

Drones can be devised to automate the phenomenon of congregating the litter. In this scenario, it flies at a low altitude to detect-pick-deposit the debris to respective bins. The feature of a GPS can be tied to the drones enabling it to report the accurate location of litter [2]. Additionally, path planning for drones can help drones to scan only the regions of area of interest [3]. The application of mission planning for drones gives a way for an autonomous flight feature, which enables it to navigate with ease and without human intervention. Last but not the least feature is to add decision making capability to drones in order to return to nearest charging stations based on the power available in the battery.

ACKNOWLEDGMENT

The authors of this paper would like to thank and express their heartfelt gratitude to project mentor Prof. Suman Jayakumar for her valuable guidance. Our sincere gratitude to Vidya Vikas Institute of Engineering and Technology, Mysuru (VVIET) for making it possible to conduct this project.

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