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# **Identification of Products in Plastic Waste using Object Detection**

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Abstract: The scope of the proposed project is to trace back the plastic products from the garbage dumps to the manufacturers. The project aims to deliver a portal to the citizens to report the nuisance of plastic waste that has been generated at a specific location and at a given time. The aim is that the entire system is automated with the citizens having to make minimal effort to capture images of the scene. The project will then provide comprehensive data regarding distribution of plastic waste by different brands/products in different locations along with time dimension.

The following paper provides a solution as an android application (client) to provide the public accessibility to the solution along with Deep Learning model-YOLOv3 at the server to automate the process of accepting the input image and identifying the brand and counting the trail of plastic products. User's location and time will be captured in the android application. If a plastic product is detected in the given input, the corresponding data is pushed into the database (MySQL) for storage and timely analysis of location specific and brand specific plastic.

Index Terms - Deep Learning, Plastic Waste Profiling, Object Detection, YOLOv3

#### I. Introduction

# 1.1 Background

During 1979, retail for plastics was blooming in the Indian Petro-Chemical. In the year 1994, plastic bottles of different emerging beverage brands marked the beginning of the plastic nuisance. Plastic waste has been a mainstay for the humblest waste pickers who try to scrape together livelihoods through the most vulnerable ways in this domain.

Plastic utilization in India is 11 kg, 10% of the United States and one-third of China's, as indicated by PlastIndia 2015. The anticipated high development paces of GDP and proceeding with quick urbanization propose that India's direction of plastic utilization and plastic waste is probably going to increment.

According to the current trends in plastic production, it is expected that polymer consumption from 2017 to 2022 is likely to increase at 10.4%, wherein the consumption and consequent waste generation of one-time-use plastic is higher. On India's independence day of 2019 (i.e 15th of August) as well as in the G7 Summit held on 26th of August 2019, the then Prime Minister of India vowed to free the country from single-use plastic.[1] 80% of plastic in India is discarded as waste material. Also, forty percent of plastic waste is rendered uncollected. This degree of pollution is damaging – not only to the environment, but to health as well.[2]

Top manufacturers of soft drinks and soda, including Coca-Cola, PepsiCo and Bisleri, have started to print a buyback appreciation on all Polyethylene terephthalate (PET) bottles sold in Maharashtra in order to agree to new guidelines and help inspect littering. Buyers will be allowed to return empty plastic containers and will be charged according to the bottle-printed buyback estimate. Whilst the administration has enabled organizations to maintain adjustable buyback esteem, most organizations have chosen Rs 15 for every kg of PET containers, and Rs 5 for wrappers every kg.[3]

Swachh Bharat Mission was launched to provide complete sanitation solutions for all of India's 4041 statutory towns. India became the 18th nation to enforce prohibition on the use of plastic after the Maharashtra government issued the ban on Plastic and Thermocol Products on 23rd of March, 2018. A majorly important reason behind banning plastic and corresponding plastic products was the Buy-Back scheme of plastic products failed.

#### 1.2 Proposed Solution

The above mentioned problem can be aided by a system/software which can analyze the brands of plastic packaging and track identity footprint of the manufacturers. The system will have the following dimensions:

i. Take photos of garbage dumps or collection points The algorithm should be capable of identifying the discarded packaging of consumer goods such as chips, cookies, cold drinks, etc.

ii.Based on the identified label, a plastic and litter profile of the manufacturer can be created over a period of time or over a collection of locations

For example, common litter elements include wrappers of chocolate chip packets or empty bottles of cold drinks used and packaging disposed of by analyzing these items, the algorithm will aim to create a profile for different plastic waste as well as litter brands.

The solution's goal is an algorithm that can create a profile for commodity brands plastic products so that brand plastic waste profiles can be created. Ability to identify brand / s for common litter objects thrown into garbage.

#### 1.3 Related Work

After doing lots of literature study about detecting products/brands we have learned that Deep Learning[4] models can aid in a number of cognitive automation tasks by reducing human intervention after a series of past experience/training. There are loads of potential in modifying currently present work patterns efficiently by making use of Deep Learning, Image Processing and AI. Detection, Localization and Classification of objects on retail and in market places has been studied before.

Normally, for identification and/or classification of different brands and corresponding products, extracting and using Image Processing features such as SIFT[5] and Harris corners[6] have been used.[7]

With the increasing trend in the field of Deep Neural Networks (DNNs)[8], the implementation of Regions since CNN features (R-CNN)[9] acquires a benefit. DNNs in that they behave differently than usual. We have deep architectures with the ability to learn features that are more complex than the ones with less layers.

More complex and hence, more reliable training algorithms also enable the learning informative object representations without the need to design features manually[10].

With the introduction of R-CNN, a large number of enhanced models have been proposed, such as Fast R-CNN, which aims at optimization of classification and bounding box regression tasks[11], Faster R-CNN, which uses an additional subnetwork to generate regional proposals[12] and YOLO, mainly for performing detection of object through fixed-grid regression[13].

#### II. TECHNIQUES

#### 2.1 YOLOv3

YOLO is the only neural network having structure similar to ResNet that makes predictions in the form of bounding boxes which provide class probability from images in a single evaluation. Optimization can be made end-to-end directly on performance of detection.[13]

The network of YOLO is completely feature-based equipped with seventy five convolution layers. It doesn't have a fully-connected layer. This structure aids in handling images of any size. Also, no layers of pooling are used. Instead, a convolution layer with step 2 is used to downsample the feature map, passing the size-invariant feature forward. In addition, the ResNet-like structure and the FPN-like structure are also key to improving its accuracy.

Our model is based on Tiny-YOLOv3 which has 53 layers in contrast to YOLOv3 which has 106 layers. This may prove to degrade the accuracy but offers lesser requirement of training time and GPU resources. With an acceptable trade-off for accuracy, Tiny-YOLOv3 is suitable in real-time environment as it gives faster and quicker results.[14]

#### 2.2 Speed v/s Accuracy

The results obtained by measuring speed and accuracy in terms of metric mAP (Mean Average Precision) for different Metaarchitecture combinations and function extractors and found an inverse relationship between the two; the accuracy results in speed decrease and vice versa.[15] Table 1 provides the conclusive result for the same.

Factors Considered while choosing the Deep Learning Model:

- i. Feature Extractors (DarkNet, ResNet, VGG16)
- ii. IoU (Intersection over Union) threshold
- iii. Number of Proposals
- iv. Use of multi-scale images in training or testing
- v. Training configurations

Table 1 Comparison between different deep learning models

Model	mAP	FPS	Batch size	#Boxes	Input Resolution
Faster R-CNN	73.2	7	1	~6000	~1000 x 600
Fast YOLO	52.7	155	1	98	488 x 488
YOLO	66.4	21	1	98	488 x 488
SSD512	76.8	19	1	24564	512 x 512

#### III. DATASET

#### 3.1 Dataset Generation

The dataset used in this paper has two fundamental sources. Firstly, use the Python package *google\_images\_download* to scrape images from the web. Also, around 4,000 images were produced physically to train the dataset model. Using the application FFMPEG was most effective by taking direct videos of plastic debris with variation in angle(rotation), distance(depth), light, noise, etc.

#### 3.2 Dataset Annotation

The tiny-yolov3 model requires annotation in VOC format. LABELIMG is a tool wherein the images were annotated with appropriate class and instances with bounding boxes. These annotations are stored in XML text format and are then used for training and testing purposes.

#### 3.3 Dataset Augmentation

By application of OpenCV, various disturbances and variations were introduced in the existing dataset. Common practices that were used here included performing rotations (30°, 40°, 60, 90°, 120°, 150°, 180°, etc), changing contrast, zooming, resizing, smoothing, sharpening, etc

#### IV. METHODOLOGY

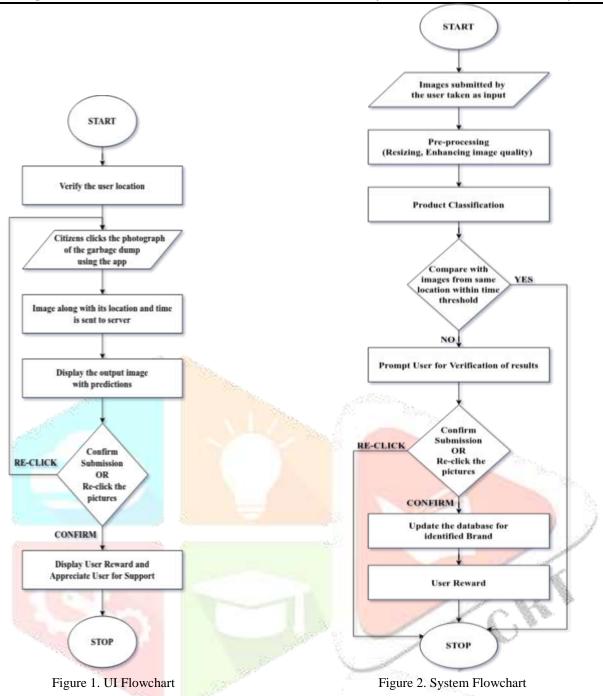
#### 4.1 Proposed Approach

The initial user interface provides access to the following screens:

- i. Camera: Enables the user to capture the scene of interest. The user will have a 30-second window to submit the capture image.
- ii. User Profile: To highlight the basic information along with points awarded to the user for the number of submissions and consequent trails of plastic detected.
- iii. Product Statistics: Gives information about most detected plastic products and their brands specifically in that region.

# 4.2 System Flow

- i. User Login/Registration: User Authentication through Google Sign-in Authentication
- ii. Capture and Transfer of Image from Android Application to Server:
  - a. Verify User Location
  - b. Capture scene of interest using Phone Camera
  - c. User has 30 second window to submit captured image
  - d. Send Image to server using HTTP client from Android



iii. Image-in-image search: The image-in-image is used to find the subjected image as a subset/segment of other images. Algorithm results are successful when the given image is found anywhere in the provided dataset. Thus, whenever one user clicks a picture with the same geotag as another within threshold time, there is an automatic check to see if either image isn't just the sub-image of the other.

iv. Plastic Product Classification: Received image will be passed to an image processing algorithm to crop and resize the image based on predefined parameters.

The image is further sent to a convolutional neural network(CNN) for extraction of features and classification of the image. As a result this will help to detect brands of plastic and update the entry of identified brands in the database.

v. User Reward: Users get rewards based on the type and number of submissions of the waste.

# V. RESULTS

#### 5.1 Object Detection using YOLOv3

Figure 3 is a snapshot taken from Google Colab (Python Notebook) while testing a particular image using tiny-YOLOv3 Model. The trained weights can successfully identify the two instances (trails) of parle-g wrapper in the provided image as seen in Fig.4.

Figure 5 is the corresponding visualization of data created by detection of products (Balaji and Parle-G) from various locations. The tool used is PowerBI.

```
vo Anto
Total BFLOPS 5.449
Loading weights from tiny-yolov32_24000.weights...
seen 64
Done!
Enter Image Path: /content/darknet/obj/b(238).jpg
/content/darknet/obj/b(238).jpg: Predicted in 1237.178000 milli-seconds.
balaji: 100%
Not compiled with OpenCV, saving to predictions.png instead
Enter Image Path:
```

Figure 3. Training and Testing tiny-YOLOv3 on Google Colab



Figure 5. Map-visualization of data using PowerBI

# 5.2 ANDROID SCREENS (UI)

The following figures describe the work flow of the system in the view of the user. Figure 6 is the home screen for the user which gives information regarding previous submission made by the user and their current rewards. Figure 7 is to confirm the location from the user before they can capture an image. Figure 8 is the upload screen wherein user has 30 seconds to submit the image to the server. The submitted image is then processed at the server and a result image such as Fig.4 is generated. Figure 9 is the screen which displays the corresponding result to the user.

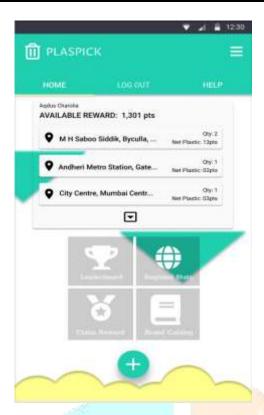


Figure 6. Home Screen

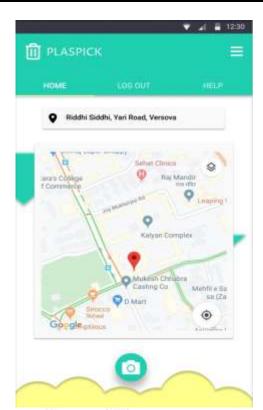


Figure 7. Confirm Location Screen

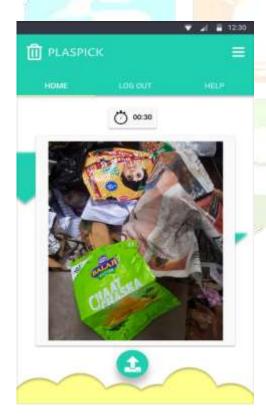


Figure 8. Upload Image Screen with Timer

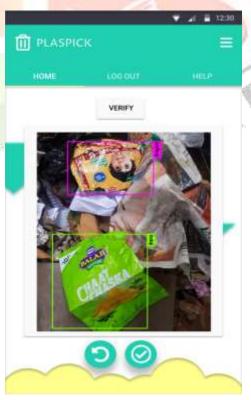


Figure 9. Result Screen

# VI. CONCLUSION

For the proposed paper we have gathered around 6000 images of plastic wrappers, which were used for training Tiny-YOLOv3 model to get desired predictions. We were able to get an accuracy of 87% on products by using Tiny-YOLOv3 model. In order to get faster predictions we have used less number of layers which trade-off with lower accuracy. An android application portal was created using a trained model.

We have successfully created a system which aids in implementing a profile of companies that contribute to plastic pollution by using data generated from application portals. The application portal is available for the general public/individuals who can contribute/submit images of plastic waste by using their smartphones. In order to detect multiple branded plastic products, the given deep learning model can be further trained, which in turn increases the scope of applications. The given solution was implemented as a

proof of concept and we can further expand this solution to a larger scale where we can significantly reduce plastic pollution in our country and throughout the world.

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