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Sustainable Waste Management through ML-based Real-Time Trash Bin Prediction

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Abstract

Waste management has been an issue due to low awareness among people of any country to lead major environmental contamination, tragic accidents, and unfavorable working conditions for landfill workers. The Lack of precise and efficient object detection could be a barrier in the growth of computer vision-based systems. As per the latest research articles, pre-trained models could be used for Trash Bin detection in real time and for recommending appropriate actions after detection. Using a unique validation dataset made up of predicted trash items, the two classes of acceptable object identification models, YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector), are then contrasted. It is concluded that SSD performs noticeably better than YOLO in identifying trash objects based on several performance metrics computed utilizing multiple open-source research projects. The model is then built up to recognize several trash object types after being pre-trained using Microsoft's COCO (Common Objects in Context) dataset. Our initiative intends to enhance sustainable waste management, make trash sorting incredibly simple, and guard against serious illnesses and accidents at landfill and garbage disposal sites.

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1. Introduction:

As the world continues to urbanize and the population grows, waste management has become an increasingly critical challenge. Inefficient garbage collection and disposal can lead to environmental pollution, health hazards, and economic losses. The traditional method of collecting garbage relies on a fixed schedule, irrespective of the amount of trash present in the bins. This often results in overflowing bins or unnecessary collections of partially filled bins, which not only increases the cost of waste management but also leads to unpleasant odors, unsanitary conditions, and potential health hazards.To tackle these issues, researchers have explored the use of machine learning and computer vision techniques to optimize waste collection schedules. One such approach is garbage detection, which uses object detection algorithms to predict the level of trash in a bin. This enables waste management services to optimize their collection schedules and reduce the number of unnecessary collections, leading to improved efficiency, cost savings, and environmental benefits.

Garbage detection involves training machine learning models to recognize and locate objects within an image or video. In the case of garbage detection, cameras or sensors placed on trash bins capture images of the bin's contents, which are then analyzed using object detection algorithms. The model can predict the amount of trash in the bin based on the objects detected, and this information can be used to optimize waste collection schedules. The use of machine learning and computer vision techniques in garbage detection has several advantages over traditional waste management methods. First and foremost, garbage detection can reduce the number of unnecessary collections, which saves time and money for waste management services. It also reduces the amount of waste that goes to landfills, which is essential for environmental conservation. By accurately predicting when bins are likely to fill up, garbage detection can also help to reduce litter and maintain clean public spaces. Garbage detection is a complex process that requires the development of accurate object detection models. The accuracy of the models depends on the quality of the images captured and the complexity of the objects within the bin. This means that the models need to be continually updated to improve their performance. Additionally, there are privacy concerns associated with capturing images of people's garbage, and these need to be addressed through appropriate policies and regulations. The success of garbage detection depends on the accuracy of the object detection model. There are several object detection techniques, including YOLO (You Only Look Once), RCNN (Region-based Convolutional Neural Networks), and SSD (Single Shot Detector). These techniques are based on deep learning algorithms, which have been shown to achieve state-of-the-art performance on object detection tasks. The choice of the algorithm depends on the application, and each technique has its advantages and limitations.

Structure of the paper is as follows: Review of literature is covered in section 2. Research methodology for object detection and recognition is considered in section 3. Dataset description and ground truth and detection annotations are discussed in section 4 and 5 respectively. Model comparison and error visualization is done in section 6. SSD modification and implementation is discussed in section 7. Conclusion and future scope is covered in section 8.

2. Litelature Review

Most of the research work done to tackle the problem of waste management till now involves the use of mechanistic models and IoT [1], [2], [3]. These systems not only take a lot of time to be constructed, but are also expensive, inefficient, and inaccurate. All such proposed models have a major drawback that they cannot be used for managing mixed waste but can work for wastes of one category only. Some of them such as [3] have a limitation of size. Only those solid waste objects which can comfortably fit into the system can be used. Deep learning is a breakthrough in the field of artificial intelligence. Reviews of previous research models done by scholars have suggested that most waste management problems are complex, and traditional methods don’t provide an adequate solution for them. They have stated that artificial intelligence methods have a great potential to provide an alternative effective approach to build systems that can operate in the real world and make waste segregation easier, reliable and more accurate [13],[14], [15], [16][18].Many existing machine learning models for waste management are based on image classification, but their main drawback is that they only classify one single object in an image- they can only tell if the object is dry or wet [5], or biodegradable or non-biodegradable [6], or identify the class which the object belongs to. But in real world situations, garbage piles have several waste objects belonging to different categories at one place, and hence image classification is not successful in such cases. We have therefore implemented object detection in our proposed solution which can detect multiple waste objects within the same image. Studies have shown that waste segregation is a task which needs an accurate and fast model for detection of objects. Many scholars have proposed a model based on the Convolutional Neural Network (CNN) [7], [4], [17] or the You Only Look Once (YOLO). The former can be accurate, but since it requires a lot of resources to operate, it gives results after a long delay and can only reach up to a speed of 5-7 FPS (Frames Per Second). The latter is a fast and lightweight solution [8] capable of detecting objects at a rate of 40-90 FPS, but it compromises greatly on accuracy due to which it is a poor choice for applications such as waste object detection, because incorrect detection will lead to wrong trash bin prediction which will increase the problem rather than providing a solution for it. We have therefore utilized a newer and powerful object detection model called Single Shot Detector (SSD) whichachieves a great balance between speed and accuracy [9]. Its implementation is more straightforward than CNNs and we can enjoy a much faster speed of 22-46 FPS with precise predictions [10]. The research work in [11] proposes a novel open-source toolkit for evaluating an object detection model by comparing the output of the object detection model and the ideal expected output. The toolkit calculates various metrices and plots several graphs to evaluate the model and hence is a great tool for comparing the performance of two or more models. This work has been used for selecting the appropriate object detection model for detecting waste items. Another toolkit introduced in [12] helps to visualize in depth the various errors and faults of an object detection model. It plots charts and graphs providing quantitative analysis of the model and gives useful insights about the components and features that the model lacks so that it can be improved on them. This toolkit is applied on the detection results of the YOLO model that has been compared with the SSD model in this work, to analyze the main limitations of the model. These results may be considered while planning improvements for this work in future. Also, the existing solutions are only deployed on local systems, but our proposed system is completely an online web-app deployed on a web server and is available for the entire public for free for their personal and commercial use, and is hence more accessible.

3. Research Method

The selection of an object detection model to be used for any task largely depends on the application it is applied in [9]. This study aims to build an online web-app for garbage object detection and to identify the correct trash bin for it. This task requires a model having high precision value because waste item misclassification will lead it to the wrong trash bin type and will hence not solve the problem of improper waste management and environmental and health complications associated with it.

The Convolutional Neural Networks (CNN) based models - RCNN, Fast-RCNN, Faster-CNN are very accurate but they operate at very slow speeds. The YOLO V3 has high detection speed but its size is 250 MB which is undesirable. Other models available cannot be easily deployed on the browser and cannot be used. This leads to the following four models shown in Table 1 which are appropriate for the application. All these models can be deployed on the web, have suitable size under 60 MB and are trained on the most appropriate dataset (Microsoft's COCO dataset having 80 classes). From this list of suitable models, two classes of models are identified - YOLO and SSD. The latest models of these classes - the Tiny YOLO V3 and SSD Lite, Mobile Net V2 are selected for the final comparison.

Table 1: Object Detection Model Suitable for Waste Detection

Name	Format	TrainingDataset	Size
SSDLite MobileNet V2	Tensorflow	COCO	17.9 MB
Tiny YOLO V3	Tensorflow	COCO	44.9 MB
Tiny YOLO V2	Tensorflow	COCO	34 MB
Tiny YOLO VI	Tensorflow	COCO	60B

3.1 DATASET DESCRIPTION

To compare the SSD Lite, Mobile Net V2 and Tiny YOLO V3 object detection models, a validation dataset has been prepared. The dataset contains 100 real images of expected garbage objects. All the images are captured using a 64 Megapixel camera. Most of images have a resolution of 3456 px by 4608 px and the size of this raw dataset is 285 MB. These dimensions and size are quite large to be used as an object detection model validation dataset and hence, they need to be resized.

To perform image resizing and to reduce the size of the dataset, an AI-based open-source project called Katna has been used. The Katna image module executes the image resizing task

It supports three down sample factor values - 8, 16 and 32. One of these values can be set based on the image resizing task being implemented. Since the validation dataset contains images of resolution greater than 2000 px by 2000 px, a high value of 16 is set for the down sample factor so that it takes less time for resizing the dataset. The output resolution of each image is set to 640 px by 480 px. This is an appropriate resolution because it is small and therefore can be easily processed by the web-based object detection models. It is also large enough to perform manual ground truth annotations on them. The final size of the dataset is 8.47 MB with each image approximately 87 KB in size. Fig. 1 shows the result of applying Katna to our dataset images.

3.2 GROUND TRUTH AND DETECTION ANNOTATIONS

The next step in model comparison is the preparation of ground truth annotation of the dataset. Ground truth annotation is the manual outlining of each image in the processed and resized dataset. This is done in order to have an ideal detection data so that the automatic outlining of the images performed by any object detection model can be compared against it and the accuracy and errors in the model can be evaluated and visualized. The Intel's novel digital data annotation tool for object detection - CVAT (Computer Vision Annotation Tool) has been used to perform the ground truth annotations.

Figure 1: Original (left) and resized (right) garbage objects

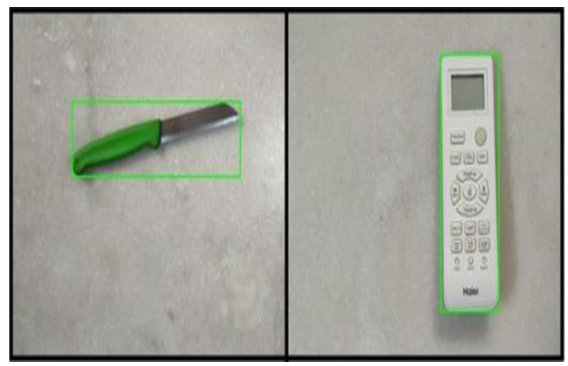

Figure 2: Ground truth annotations using CVAT

Since CVAT supports in-browser annotation instruments, the complete dataset is first uploaded on the server. There are five common types of annotation formats. The bounding box format for ground truth annotation is used because the detection annotations by object detection models used also have the same format. Each image is annotated by manually drawing a rectangular outline around the target object and then locking the box. 100 bounding boxes have been drawn for 100 images. These are shown by green rectangular outline around the garbage objects - knife (metal) and remote (e-waste) as shown in Fig. 2. There are several output formats, such as YOLO, txt (text file), PASCAL VOC, COCO, etc. for storing the ground truth annotations. The COCO format for ground truth annotations, which uses a single JSON output file is used in this project. All the 100 ground truth annotations are stored in this JSON file. For each annotation, five parameters are noted. These are the width of the box, its height, x and y coordinates and the category of target object.Figure3showsthenumberofgroundtruthboundingboxesper class for our dataset. The dataset includes image samples of 14 classes.Preparation of the detection annotation file is the last step before the object detection models can actually be compared and evaluated. Since there are two models to be compared, one detection annotation file for each of the models is prepared.

The ML5 library's COCO-SSD object detection model, which uses the SSD Lite Mobile Net V2 architecture in its implementation, is used to obtain the detection of each image in the dataset for the SSD annotation file. Since the dataset contains 100 images, this model is also applied 100 times to get the results.

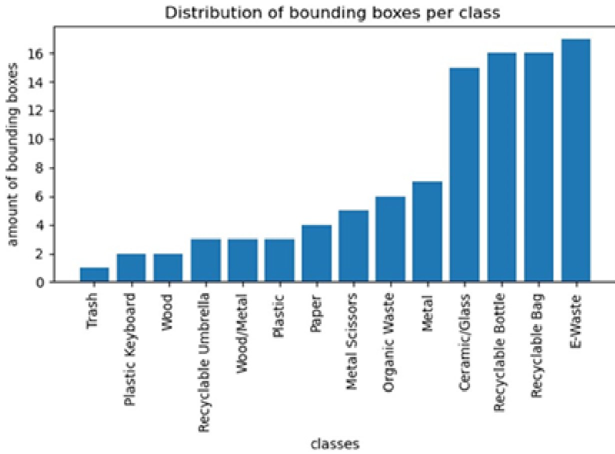

Figure 3: Ground truth bounding boxes per class

Figure 4: YOLO (top) and SSD (bottom) annotations - JSON form

For the YOLO detections, an open-source project maintained by the developer Zqingr, featuring Tiny YOLO V3 detections on static images is used to get the detections on our dataset. For both SSD and YOLO detection results, the width, height, x and y coordinates of the detected bounding boxes and the category of the detected object along with the confidence scores of each image have been noted. These values are then used to prepare the detection annotation files for each model in the COCO format. Hence, these annotations are also stored in a JSON file like the ground truth annotations. These detection annotations for the class - recyclable bag for both SSD and YOLO detections is shown in Figure 4.

4. Results And Discussion

The ML5js SSD model used is trained on Microsoft's COCO (Common Objects in Context) dataset to identify the objects. The COCO dataset contains 328K image samples and identifies them in 80 classes or labels. In order to make the best use of this dataset for the purpose of detecting solid waste objects, these 80 classes are merged into the following classes relevant to the application as shown in Table 4.These modifications are achieved by manipulations in the original ML5 JavaScript file that contains code for the model. The modified model is then implemented in an attractive browser-based app built using P5js. The PC’s webcam or mobile phone camera is used to provide a live video feed of suitable resolution to the detector. The bounding boxes of appropriate trash bin color are drawn around the garbage item with the class label it belongs to. The same color of dustbin also pops up on the screen so that user can immediately know which bin it should be thrown in. The web-app is deployed on Netlify and can be visited at the url: https://admiring-aryabhata- 37592b.netlify.app/.

4.1 Metric Terms

Having both the ground truth and detection annotation files ready, this section aims to cover the evaluation of the models based on these files. Following three parameters as Intersection over Union (IOU), Precision and Recall were used in metrics evaluation as given in equation no 1 to 3.

$$IOU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \quad \text{……………………………..(1)}$$

$$Precision = \frac{TP}{TP+FP} \quad \text{…………………………………(2)}$$

$$Recall = \frac{TP}{TP+FN} \quad \text{…………………………………………….(3)}$$

4.2 Metric Evaluation

Three metrics are calculated using the novel toolkit proposed in [11] for both the object detection models - the SSDLite, MobileNet V2 and the Tiny YOLO V3. These are the COCO metrics, the PASCAL VOC metrics at IOU threshold of 0.5 and at IOU threshold of 0.75. Table 2 shows some of the common measures that the toolkit provides.

Table 2: Detection Measures for SSD and YOLO

Model	Ground Truth Boxes	Total Ground Truth Area	Detection Boxes	Total Detection Area	Correct Classes	Incorrect Classes
SSDLite M. V2	100	112657.71 100 px	100	112531.25 px	100	0
VOLO V3 Tiny	100	112657.71 42 px	42	67964.43 px	41	1

Table 3: COCO and PASCAL Matrices for SSD and YOLO

Model	COCO Metric Precision	PASCAL PASCAL Metric Metric Precision @ 0.5 IOU	PASCAL PASCAL Metric Metric Precision @ 0.75 IOU
SSDLite MN V2	78.97 %	100.00 %	85.81 %
Tiny YOLO V3	14.99 %	24.27 %	15.92 %

Figure 6 and Figure 7 show examples of significant localization and miss detection errors by the YOLO model against SSD while performing comparison of the models on the dataset images, providing practical proof of the low precision value of the YOLO model.

The results show that YOLO V3 is far less accurate than the SSD model, and hence the SSDLite Mobile Net V2 model is finally implemented in the paper.

4.3 Error Visualization

The research work by Bolya, Daniel et al. [12] proposing TIDE (Toolbox for Identifying Object Detection Errors) toolkit has been implemented on the YOLO V3 annotations to find out where the loss in precision in the COCO metrics, which is 85% loss, comes from and visualize the errors.

The results of this toolkit are shown in Figure 8 below. Most of the error comes from the false negatives or misses in detecting the ground truths, and as can be seen from the TIDE evaluation, these are close to 60. Since there was only one mis-classification in the YOLO detections, the graph below shows just 1 unit for classification error, which is also the same as false positive error.

5 Conclusion And Future Scope

This study proposes a fast and accurate garbage item detection web application implemented using ML5js SSD object detection model that uses the SSDLite MobileNet V2 model in its architecture. For the selection of the appropriate model, many models that can fit into this application are surveyed. The latest versions of the YOLOand SSD class of models are chosen for comparison.A validation dataset of 100 images is prepared for this purpose which is resized to suitable resolution. Then the ground truth annotations and the detection annotation files are prepared in the COCO format. These files are fed into the metrics evaluation toolkit and three popular metrices are calculated. The precision values of all the metrices point out that SSD outperforms the YOLO model and hence it is implemented. Various error components that led to the loss of precision in the YOLO model are also visualized. The web app uses the webcam of the device to provide a real time feed to the detector, which recursively processes the video feed. The model, originally trained on the COCO dataset having 80 categories, is modified to output 16 categories relevant to expected solid waste items. The model identifies the category of the item and predicts if it is recyclable or not. The corresponding trash bin color is then displayed for easy waste segregation.

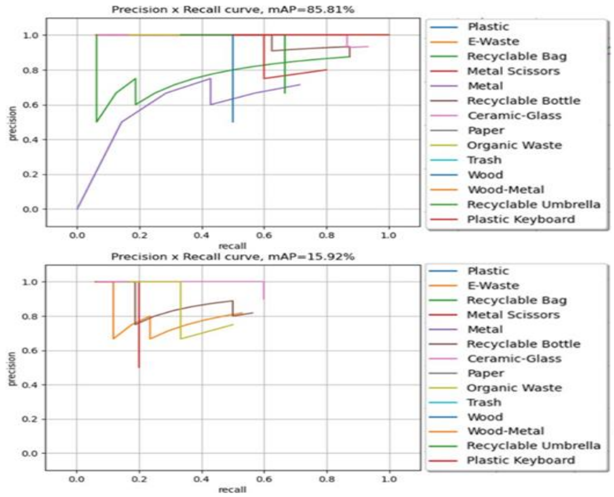

Figure 5: Precision-Recall Curve For SSD (Top) - YOLO (Bottom)

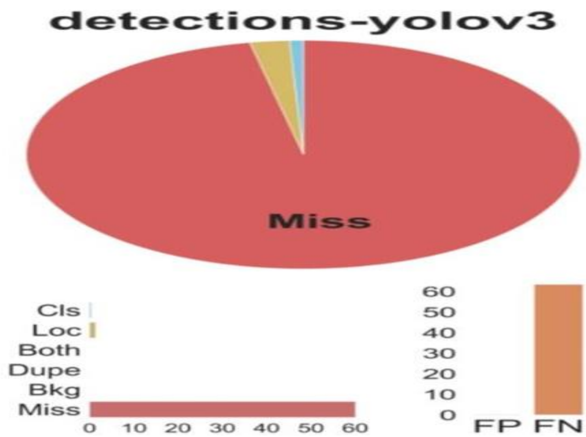

Figure 6: Error Visualization Of YOLO Using TIDE

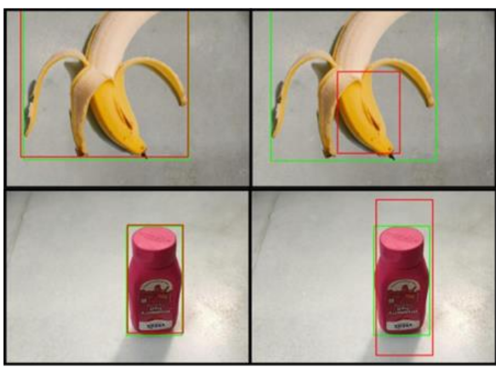

Figure7: Localization errors for SSD (left) and YOLO (right)

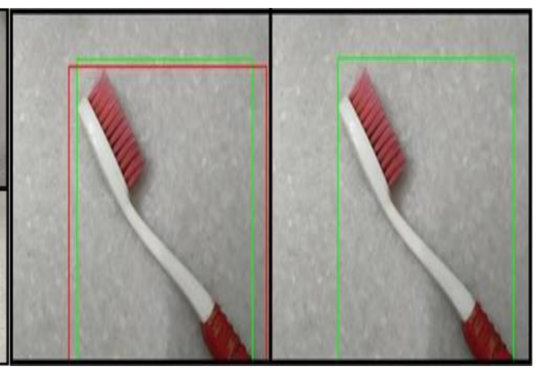

Figure 8: Correct detection by SSD (left) and miss by YOLO

Table 4: Categorization of Objects Used

Object Class Created	Material	Recyclable/ Biodegradable	Trash Bin Color
Paper	Paper	Recyclable	Blue
Plastic	Plastic	Recyclable	Blue
Organic Waste	Organic Matter	Biodegradable	Green
Bottle	Glass/ Plastic	Recyclable	Blue
Electronics	Hazardous	Recyclable	Black
Metal , Scissors	Metal	Recyclable	Blue
Glass	Glass	Recyclable	Blue
Wood	Wood	Recyclable	Blue
Ceramic	Ceramic	Recyclable	Blue
Trash	*	Not-Recyclable	Blue
Wood/ Metal	Wood/ Metal	Recyclable	Blue

Bag, Keyboard	Textile/ Plastic	Recyclable	Blue
Ceramic/ Glass	Ceramic/ Glass	Recyclable	Blue
Sports Ball	Rubber, Cork	Recyclable	Blue

The proposed model is very unique in its implementation because all other works on garbage classification and segregation are based on Python, but we have implemented JavaScript code with recently developed libraries, which is never used before in this area. The working model requires no packages, IDE, command line interaction or expensive equipment and can simply be executed using a click-and-use web URL on PC, Android or IOS devices. Hence, it is the most easy-to-use object detection modelwhich is not just available locally, but is globally accessible and can be used by multiple users at the same time. Another distinct feature is that it not only classifies the garbage objects, but also identifies the appropriate trash bin for it.

A lot of work has been done on the backend and frontend of the web application. However, there are some drawbacks too. One of the main disadvantages of this application is that it can only detect the images which come under one of the categories listed in the COCO dataset. This means that this web-app can only detect objects which the model is trained on. Though the COCO dataset supports 80 categories of objects, it would have been even better if the training dataset consisted of objects specifically containing several images of different classes of solid waste items, so that this application could be applied to even broader categories of garbage items. Another drawback is that sometimes an object which is also present in the training dataset is not detected at all or is detected only at a particular angle at which the object is positioned. The object may also be misclassified by the model occasionally, which can lead to the object being thrown in the wrong bin. This can be avoided by creating a really rich dataset for training the model. These additions may be covered in future to make it a more practical problems.

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