Municipal Waste Segregation Using Densenet

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Abstract — One of the most difficult issues facing contemporary civilization is the correct management of trash. Municipal Solid Waste (MSW) must be divided into many categories, such as bio, plastic, glass, metal, and paper. The most effective methods up to this point have been neural networks. The present deep learning methods that have been suggested to categorize garbage have been thoroughly summarized in this paper. This article suggests a system for dividing litter into the six categories listed in the benchmark techniques. Convolution neural network was the categorization architecture. These models, which Google has suggested, are based on compound scaling, have an accuracy range of 74% to 84 %, and they have been pretrained on the model. For effective categorization, this study suggests Densenet 201 model adjustment for pictures relevant to particular demographic regions. This kind of model tuning through transfer learning offers a unique classification model that is highly tuned for a specific area. Furthermore, through fine-tuning over region-specific litter photos, it led to improvised classifications.

Keywords: Waste Segregation, Densenet 201, Compound Scaling

I. INTRODUCTION

The disposal of waste is a significant environmental problem that presents a serious challenge in practically all industrialized and developing nations. It turns out to be the biggest obstacle to ecological harmony and sustainable growth. Since it is their mission to act in the public interest, a number of non-governmental organizations (NGOs) are actively pursuing this cause and directing the focus of government organizations in this direction. The World-Wide Fund for Nature (WWF) is the leading organization in this field outside NGOs [1,2]. People across the world who value intelligence and the environment work to further these goals within their local communities through organizations. Due to the massive production of disposable goods [3] in almost every industry, the real worry of trash bins has gotten much worse in recent years. This options are endless and includes everything from foam to medical waste to lightbulbs to plastic bags and potable drinking water packaged in plastic bottles. The need for ecological equilibrium, which has already been severely disrupted by civilization just in the last 200 years, is the main driver behind effective waste management. We used the data from the United States Environmental Protection Agency (US-EPA) as a starting point [1]. According to estimates, 292.4 million tons of municipal solid waste (MSW) are produced year, or 2.22 kg per individual.

MSW refers to the assortment of products that people discard after using them. Cans, bottles, single-use glasses, snack packs, meals, couches, chairs, laptops, tires, and refrigerators are all included. MSW contains goods that fall into the categories of both hazardous and non-hazardous, disposable and non-disposable materials, as was previously mentioned. The suggested usage of different sorts of (non)disposable objects follows the hierarchy depicted in Figure 1.1, even if there are specialized strategies for different forms of disposal.

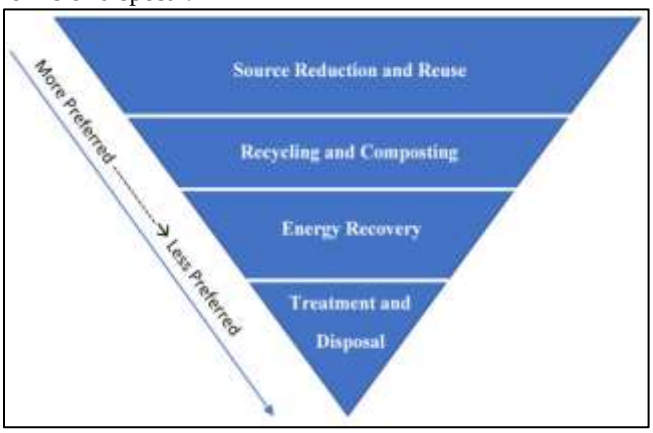

Fig. 1: Preferred model of waste management.

The correct disposal of trash is a difficult problem for governments working at the levels of nations, states, and municipal authorities functioning at the level of towns. This covers both recovering produced garbage for recycling, composting, or other processes and reducing waste at the source before it enters the waste stream. Additionally, it comprises landfilling procedures that adhere to existing regulations or newly developed waste conversion technologies, as well as ecologically appropriate waste management through burning with energy recovery and conversion.

Generally speaking, only 10% of materials are recycled, as seen in [1]. The circular economy is presented as a potential remedy for this. In the most abstract terms possible, we extract resources from the planet, process them, and then dispose of them as garbage. It is a linear process. The circular economy, on the other hand, advocates for a system in which there is no line's end but rather a loop that returns garbage to the earth once it has been appropriately transformed. A circular economy is a set of concepts and strategies for addressing issues including pollution, waste management, and the global environment. The waste produced in the context of plastic materials must be recyclable, compostable, or both. . The goal is to keep the plastic products in use so they don't end up in the environment and the economy.

According to US-EPA figures from 2018 [4], Figure 2 depicts the categorization of garbage into its several kinds. The graph provides a concise breakdown of all waste kinds that fall within representative classes, together with their shares of the total MSW produced in 2018.

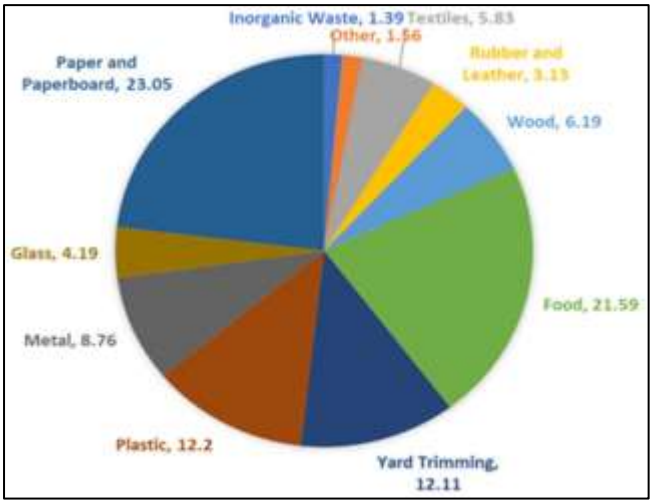

Fig. 2: Types of Municipal Solid Waste (MSW) Types.

Recycling is the term for a group of procedures used to turn garbage into new products. Energy and/or usable resources may be recovered throughout the aforementioned procedure. Only when a material can regain its original state qualities can it be said to be recyclable.

The natural conversion of organic materials into manure is known as composting. The two most popular methods for managing solid waste are recycling and composting. According to US-EPA figures from 2018.

The aforementioned factors unmistakably show the rationale behind the creation of methods for the effective treatment of MSW products. This procedure must be automated in order to save money and human labor. The accurate categorization of MSW items is one of the key features of this technology. The Deep Learning Technique based on Densenet is one of the cutting-edge methods for classifying solid waste [5]. The deep-learning Densenet model is widely employed for image recognition. By using this method, a certain image may be labeled appropriately. Although deep learning is still a research topic, it has moved from academic institutions into the commercial mainstream and revolutionized a number of application fields. For the categorization of the litter among the photos and for the subsequent classification of the litter, a framework of image processing algorithms over the current dataset is taken into consideration.

II. LITERATURE REVIEW:

With a degree of accuracy up to 75%, the authors of [1] suggested a deep learning architecture employing a two-stage detector to recognize and categorize rubbish into seven categories. With the aid of EfficientDet-D2, the first stage handles the localisation of litter without concentrating on its class type, and the second phase divides the recognized trash into seven categories while semi-supervisedly utilizing unlabeled photos to train the classifier. The plan recommends a mobile application that uses deep learning to precisely identify the waste item's categorization.

The model discussed in [7] takes into account a TrashNet dataset that is examined for the categorization of garbage images. With the aid of a multilayer hybrid convolution neural network, a straightforward, effective trash categorization approach with fewer parameters has been suggested, with an accuracy of up to 92 percent. In order to examine the best classification and accuracy, the basic model has been proposed with four subsequent upgraded versions back-to-back. To accomplish rich feature extraction, a suitable Heat Map comparison in the form of photos is also provided. The suggested technique has also been compared to current ones in terms of accuracy, parameters, and complexity.

III. METHODOLOGY

A. Dataset

	Organic	Recyclable
Training data	12565	9999
Testing data	1401	1112
Total	13966	11111

Table 1: Number of Waste Images in the Dataset.

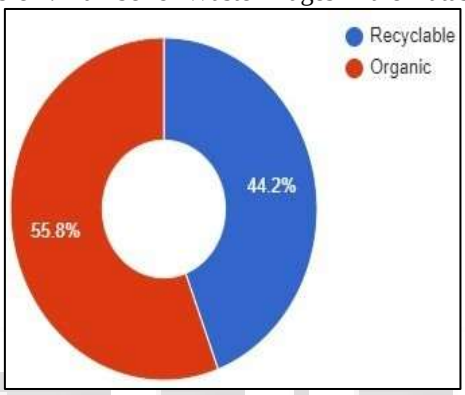

Fig. 3: Distribution of waste images in dataset

as seen in Fig. 2, were primarily captured on mobile phones. While our server controls the annotations and regularly runs a crawler to collect additional possible data, Flickr manages and stores these.

The writers contributed to this study as Independent Researchers.

Fig. 4: Cropped annotated images from dataset

Pictures of trash. Furthermore, we have picked a few pictures from [6]. All pictures are segmented and annotated by users using our web tool under free copyright licenses:

In order to define the backdrop of photos, scene tags are used, as shown in Fig. 4, and litter occurrences are divided and labeled using a hierarchical taxonomy with 60 types of litter that correspond to 28 super (top) categories, as shown in Fig. 3. This includes a special category: For items that are either unclear or not included in the other categories, there is unlabeled litter. When compared to other datasets (like COCO), where class differentiation is crucial, this is fundamentally different. Here, all objects can be in fact classified as one class: litter. Furthermore, it may be impossible to distinguish visually between two classes, e.g., plastic bottle and glass

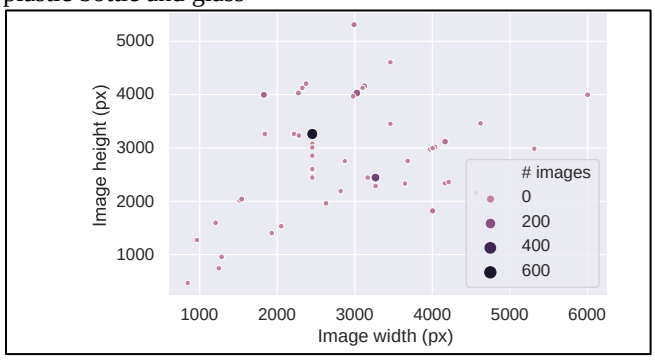

Fig. 5: Distribution of image resolutions

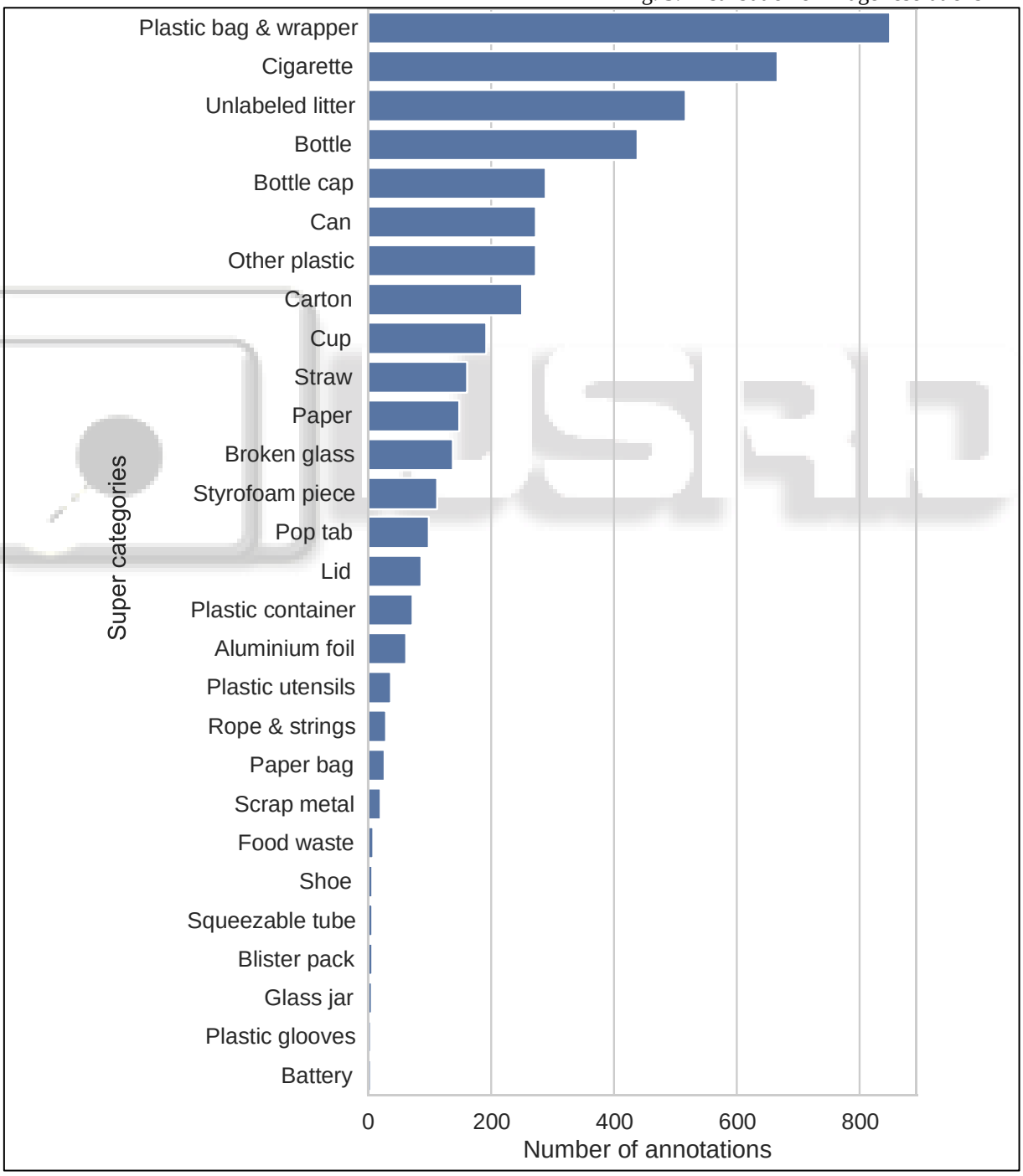

Fig. 6: Number of annotations per super category provided by Dataset's current version

The size diversity of the annotations per category for this new taxonomy is shown in Fig. 4.4 and Table 10. The majority of cigarettes—the third-largest class—have an area that is smaller than 64 x 64 pixels, as can be shown. Our findings will demonstrate how this may be problematic.

B. Garbage transplants

If the mask segmentations are accurate enough, transplantation may be a useful method of expanding the dataset by including additional underrepresented backgrounds. This is particularly important if we operate under closed-set settings (i.e. specific environment). Imagine that we want to run litter detection on a river containing crocodiles to ensure that they do not lead to false positives, but there isn't much trash there to photograph and contribute to our dataset, and we definitely don't want to disturb their environment. ! As seen in figure 6, one could simply copy and paste DATASET segmentations into photos containing crocodiles. However, because the masks are not perfect, this will result in artifacts around the edges. Therefore, as shown in Fig. 6, we suggest utilizing a binary mask's truncated distance transform to pixelwise combine the transplanted item and the target picture. This smooth mask successfully blurs the silhouette.

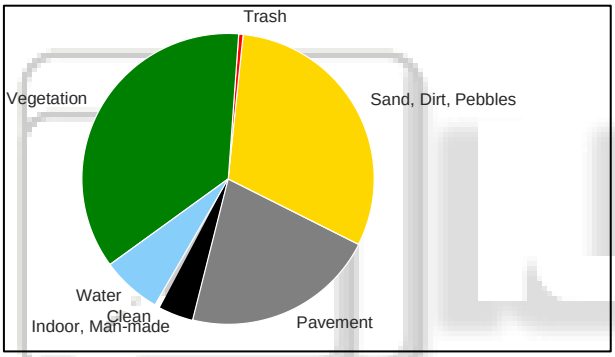

Fig. 7: Proportion of images by background tag.

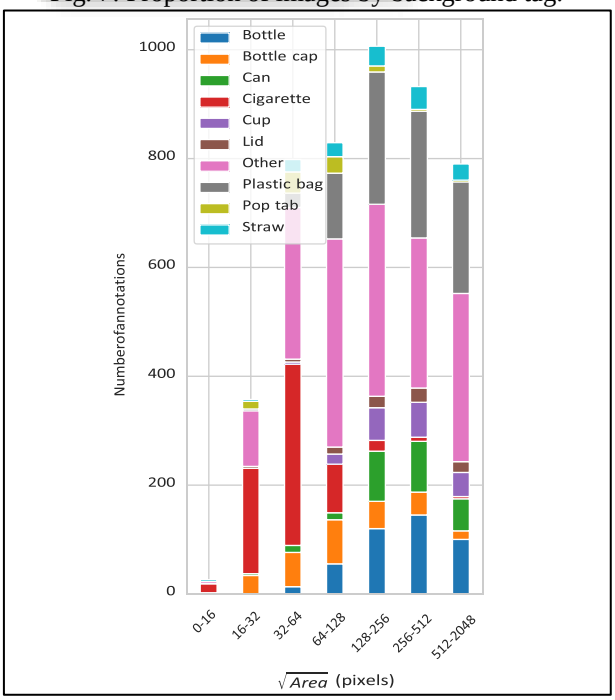

Fig. 8: Histogram of bounding box sizes per category for DATASET.

This tool, together with other characteristics to facilitate simple and smooth transplanting, is included into our suggested GUI, seen in Fig. 7. Although technique can make transplanting appear natural, it neglects numerous lighting and camera variables to make it realistic. It should also be noted that this does not work well with translucent things (such as plastic films).

Figure 9 Soft vs hard transplant

Object was moved to a new picture using a soft mask that was created using a distance transform, as shown on the bottom-left. A more even silhouette may be seen..

Fig. 10: Our proposed GUI to transplant dataset segmentations

We tested Densnet 201 on two distinct tasks (i.e. taxonomies): I DATASET, classless litter detection where the goal is to only detect and segment litter items; and (ii) DATASET, detection and classification to distinguish these 10 classes of litter in order to evaluate the performance of litter detection and segmentation using Dataset.

Due to this dataset's modest size. All quantitative findings are presented for a cross validation of four times. The dataset is randomly divided for each fold into an 80 percent training set, a 10 percent validation set, and a 10 percent test set. We examined several scores to rank the predictions as detailed in Section III-B and use the standard Average Precision (AP) [7] averaged across Intersection-over-Union (IoU) criteria as our assessment metric. The implementation and training specifics for our Densent 201 are covered in the next sections.

C. Implementation

By [8], we had implemented the -densenet 201. With an input layer size of 10241024 pixels, we employed the default

Resnet-50 in a Feature Pyramid Network as the backbone by scaling and padding the pictures appropriately. Models were trained using SGD for 100 epochs on the dataset, with a batch size of 2 pictures, and a learning rate of 0.001. Mask R-CNN weights learned on the dataset [9] were used to begin the weights. Although the validation error does not appear to be reduced, longer training continues to minimize the training error. For data augmentation, we rotated pictures between and around the annotated bounding boxes during training, introduced Gaussian blur and AWG noise, adjusted image brightness and contrast, and cropped photos around the annotated bounding boxes to ensure that a litter object is always visible. We additionally transplanted 320 instances from the training set to Flickr photographs using tags based on the scene tags presented in Fig. 4 to further enlarge the training set.

1) Prediction Scoring

The score used to rank the predictions has a major impact on AP, as shown in [10], and the greatest class confidence level may not be the optimal option. As a result, we investigated employing 3 distinct scores from the output of the Densenet classification head to fit our two jobs. Using the following scores, we compared the class probabilities provided by this head, where P = p1, p2,..., pN+1 where N is the number of classes and pN+1 is the likelihood of being background.

$$Score = \begin{cases} \max_i p_i, & class\_score \\ 1 - p_{N+1}, & litter\_score \\ \frac{\max_i p_i}{p_{N+1}+\epsilon}, & ratio\_score \end{cases} \quad (1)$$

While class_score is the established score, ratio_score expresses both the confidence on a class and the confidence on being litter, where is just a small scalar to avoid NaN. That is, ratio_score allows us to say "This model is ratio_score times more confident that given object is class X than not being litter."

IV. Simulation and Results

The provided data represents the results of training and evaluating a waste segregation model using a Densenet architecture. The model was trained on 2527 data examples, and various experiments were conducted by adjusting the batch size and the number of epochs. Here's a breakdown and description of the observations from these experiments:

S.no.	Batch Size	No .of epochs	Validation loss	Validation accuracy	Image browsed	Type of waste detected
1	32	5	1.6473	0.2885	cardboard	Paper
2	32	10	1.6474	0.2668	Glass	Paper
3	32	40	1.4257	0.5356	Glass	Glass
4	32	60	1.4941	0.4763	Metal	Metal
5	32	80	1.4503	0.5435	Paper	Paper
6	32	100	1.5280	0.5119	Trash	Trash

S.no.	Batch size	No. of epochs	Validation loss	Validation accuracy	Image browsed	Type of waste detected
1.	16	5	1.6803	0.2767	cardboard	paper
2.	16	10	1.6268	0.3043	glass	glass
3.	16	30	1.4193	0.4407	metal	metal
4.	16	50	1.5283	0.4130	plastic	plastic
5.	16	80	1.7145	0.2332	trash	paper
6.	16	100	1.9624	0.4644	paper	paper

Three distinct situations and three different batch sizes are used to evaluate the waste segregation Densenet model, which was trained using 2527 data examples. When the batch size is increased, the accuracy of the model increases to 51%, but when the batch size is decreased to 50% of the original batch, the accuracy drops to 41%, which is lower than the original test but higher than the second test

V. Conclusion

We demonstrated the application of the Dataset and technologies for trash identification. Many academics, primarily graduate students and business owners, who began working on this issue but were having difficulty locating enough datasets to represent it, gave us positive comments. Although Densenet is a fine place to start, it is obvious that our dataset needs a lot more labeled photos, thus we welcome the reader to use our tools to add annotations to CNN by using Densenet 201

Furthermore, employing our network setup produces subpar identification results for small items (like cigarettes), which negatively impacts the AP as a whole. As a result, future study should develop better models and techniques to fully use the high resolution of DATASET photos. One could just raise the input resolution, but doing so would dramatically increase memory use. A sliding window approach may also be used to run Densenet 201 and then fuse predictions, but this would lose context from the neighboring windows. Consequently, a more effective and lossless technique is needed

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