New Benchmark for Household Garbage Image Recognition

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Abstract: Household garbage images are usually faced with complex backgrounds, variable illuminations, diverse angles, and changeable shapes, which bring a great difficulty in garbage image classification. Due to the ability to discover problem-specific features, deep learning and especially convolutional neural networks (CNNs) have been successfully and widely used for image representation learning. However, available and stable household garbage datasets are insufficient, which seriously limits the development of research and application. Besides, the state of the art in the field of garbage image classification is not entirely clear. To solve this problem, in this study, we built a new open benchmark dataset for household garbage image classification by simulating different lightings, backgrounds, angles, and shapes. This dataset is named 30 Classes of Household Garbage Images (HGI-30), which contains 18,000 images of 30 household garbage classes. The publicly available HGI-30 dataset allows researchers to develop accurate and robust methods for household garbage recognition. We also conducted experiments and performance analysis of the state-of-the-art deep CNN methods on HGI-30, which serves as baseline results on this benchmark.

Keywords: benchmark; household garbage; image classification; deep convolutional neural networks

1 Introduction

Reasonable garbage management has attracted increasing attention [1]. Garbage is a misplaced resource. As a key concern in garbage recycling, household garbage classification involves many fields and disciplines, and plays an increasingly important role in environmental protection.

With the advancements of the graphics processing unit (GPU) and computer hardware in recent years, object recognition algorithms based on convolutional neural networks (CNNs) have rapidly developed and been widely used in the environmental protection field [2,3,4,5]. Although excellent performance has been achieved in the garbage classification field, household garbage classification still faces challenges from the large variance in varieties, variable states, and complex textures, which may lead to a significant performance drop. As shown in Figure 1, banana peels have different shapes, and their colors and textures will change with time and temperature. Complex backgrounds and varied viewpoints in the real world also bring great difficulties to object recognition.

Existing approaches [6,7,8,9] mainly focus on how to quickly and accurately distinguish the categories and
find the locations of target garbage in images. Many researchers have also proposed garbage classification tools, such as smart trash can [10,11,12,13].

However, these works were all tested and evaluated on self-built, non-public datasets, making it difficult to comprehensively evaluate the performance of algorithms. Furthermore, the used datasets are small and simple, which makes convergence difficult when training a deep model. For example, the dataset used by Rabano et al. in [14] consisted of only seven garbage classes and approximately 2,500 images, which are not sufficient for training a normal CNN model. Therefore, it is necessary to build a public dataset that is validated by open-source algorithms.

Accordingly, in this study, we built an unprecedented dataset with 18,000 household garbage images, i.e., the 30 Classes of Household Garbage Images (HGI-30) dataset. HGI-30 contains a total of 30 common household garbage categories. The garbage objects in the collected images include complex backgrounds, different illuminations, resolutions, and angles. In this paper, we will present the collection, augmentation, label, and evaluation methods of the dataset in detail. Furthermore, we provide the evaluation results of the state-of-the-art deep CNN (DCNN) methods, which can be served as baseline results for new methods on this dataset. We believe that this benchmark study could provide reference ideas for related fields.

The purpose of this research is to contribute to the fields of garbage recognition and object recognition using CNNs.

(1) We built a dataset for garbage recognition and introduced the methods of garbage collection and augmentation, which can extend the research on object recognition to the field of garbage classification.

(2) The released garbage dataset can reflect the advantages and disadvantages of image classification algorithms, and provide reference and evaluation results for the following researchers in garbage image classification.

(3) We make the HGI-30 dataset available in an online repository [15].

The rest of the article is structured as follows: In Section 2, we retrospect relevant algorithms and the most advanced technologies in the field of garbage image classification. In Section 3, we provide the collection details of the HGI-30 dataset. In Section 4, we validate and evaluate the performance of the state-of-the-art classification methods on the HGI-30 data set. In Section 5, we summarize this research and present future works. Finally, we present the method to obtain the HGI-30 dataset from its public repository.

2 Related Works

In this section, we mainly review the feature extraction methods and object recognition algorithms, and then introduce the state-of-the-art algorithms in the field of garbage classification.

2.1 Feature extraction methods based on traditional algorithms

Feature extraction is the core problem of object recognition. It mainly focuses on low-level feature extraction, such as texture, edges, corners, and colors. The local binary patterns (LBP) descriptor [16] is the most classic method to extract local texture features by converting the texture into a binary vector. In [17], for instance, Zhang et al. proposed an LBP-based face detection method, which brought about remarkable improvement, especially in terms of the detection accuracy. Although the LBP descriptor can quickly compute and is invariant in rotation and gray aspects, it has poor stability in image scale and brightness.

The scale-invariant feature transform (SIFT) [18] can overcome such weaknesses in LBP and has certain stability to noise and occlusion. This feature has been used for image representation in a variety of scenes. For instance, in [19], Tao et al. described an airport through the SIFT descriptor.

The histogram of oriented gradient (HOG) [20] is another successful feature descriptor, which extracts features based on the histogram of gradient direction. Unlike the key point extraction in the SIFT, HOG focuses on extracting edge features. By processing the local squares of an image, HOG can maintain good robustness to the geometric and optical deformations. It has been consistently applied to various visual analysis tasks. For instance, Pang et al. [21] constructed the HOG features of intersecting detection windows through the reuse of block features, which significantly improved the accuracy of human body detection.

Although these traditional methods have brought about remarkable results to feature extraction, many aspects still need to be improved. On the one hand, such traditional algorithms do not work well in complex
scenarios. On the other hand, it only extracts the low-level semantic features of images and ignores the high-level semantic features, which leads to the loss of several problem-specific features. Therefore, high-level semantic features are difficult to be extracted from the object layer using traditional feature extractors, resulting in bottlenecks in the recognition performance.

2.2 Feature extraction and object recognition algorithm based on CNNs

Recently, with the development of GPU technology and the research and improvement of large-scale image datasets, deep learning has experienced tremendous development. DCNNs are the most widely used deep-learning methods. With the development of DCNNs, the accuracy of image classification on public benchmarks, such as those in [22,23], has been significantly boosted [24–27]. Because of the excellent ability to extract high-level semantic features [28,29], DCNNs are also widely used in image generation [30,31], object recognition [32,33,34], and object tracking [35,36].

Compared to traditional algorithms [37,38], CNN architectures can indeed improve classification performance. Mature CNNs, like faster region based CNN (Faster RCNN) [39], Mask RCNN [40], and deformable convolutional network (DCN) [41], are outstanding representatives of the application of region proposals, which are often referred to as two-stage algorithms. In [42], for instance, Nie et al. applied Faster RCNN with the backbone of ResNet-50 to detect 3,984 garbage images. The results show that the accuracy of garbage recognition is 89.68%, which is nearly 10 percentage points ahead of the compared traditional approaches. These two-stage algorithms extract the regions of interest from the input image and classify them. Particularly, bringing all the candidate proposal areas into the training improved the accuracy, but the speed was not satisfactory. Hence, how to increase speed is a concern for researchers.

Different from the two-stage methods, one-stage methods formulate object detection as a regression problem. Single-shot detector (SSD) [43], You Only Look Once (YOLO) [44–46], M2Det [47], and EfficientDet [48] are representative algorithms for one-stage object detection. YOLO is probably the most popular one. The core of one-stage algorithms is to set a large number of default boxes on each feature map extracted from images. We only need to train boxes containing target objects. This mechanism can reduce the amount of computation and thus improve the speed, but at the cost of a slight drop in accuracy. Recent one-stage algorithms have attempted to strike a balance between speed and precision, and they work very well. For instance, Chen et al. [49] proposed an improved YOLOv4 algorithm to detect 15 new types of garbage, with an average accuracy of 64%.

Many researchers have also performed considerable studies on garbage classification, but the experiments were conducted on self-built datasets. The available and stable household garbage datasets are also insufficient, which seriously hinders the development of research and application. Moreover, the state of the art in the field of garbage classification and detection is not entirely clear. To solve these problems, we built a new open benchmark dataset for household garbage image classification and detection.

### Table 1 Numbers of garbage classes in the HGI-30 dataset

| Classes          | No. | Classes          | No. |
|------------------|-----|------------------|-----|
| Applecore        | 679 | Paper cup        | 579 |
| Banana peel      | 622 | Pencil           | 524 |
| Battery          | 663 | Plastic bottle   | 654 |
| Book             | 756 | Remotecontrol    | 536 |
| Buttonbattery    | 706 | Rice             | 559 |
| Can              | 687 | Shoe             | 621 |
| Capsule          | 702 | T-shirt          | 564 |
| Carton           | 586 | Tea leaf         | 696 |
| Cigarette butt   | 614 | Thermometer      | 553 |
| Cigarette case   | 611 | Tin can          | 525 |
| Glass bottle     | 645 | Toothbrush       | 481 |
| Lunch box        | 669 | Trousers         | 496 |
| Mask             | 682 | Vegetable leaf   | 558 |
| Mobilephone      | 538 | Waste paper      | 567 |
| Modulator tube   | 588 | Watermelon peel  | 517 |

3 Design of the Garbage of Household Dataset

In this section, the composition and construction details of the dataset are described.

To promote the application of deep learning in the field of environmental protection and improve the performance of object recognition algorithm for garbage images, we built the HGI-30 dataset, which contains 30 household garbage categories, totaling 18,000 images. The garbage in the dataset consists of the following characteristics: fixed shape, variable shape, fixed texture, variable texture, and different scales. Each image was captured and labeled by experts with professional knowledge of computer vision. The unlabeled dataset is used for classification, and the
Fig. 2  Samples of each type of garbage in the HGI-30 dataset

labeled data set is used for detection. The number of each category of household garbage and the specific information is presented in Table 1. In Figure 2, we illustrate a sample in each category.

Six variations are simultaneously considered in the construction of the HGI-30 dataset, namely, viewpoint, background, illumination, resolution, augmentation, and number of objects. The objects in the images are also labeled by different people to provide ground truths for evaluation and assessment purposes.

Specifically, we use four viewpoints, i.e., front, left, right, and top sides, for each garbage category. Figure 3 shows two garbage objects at four different viewpoints. There are three different backgrounds for each garbage object, as shown in Figure 4. For the lighting setting, we regularly apply three different settings, i.e., dark, normal, and hard light. Figure 5 shows two garbage objects at the three different lightings. For each category, we randomly select different resolutions, ranging from $300 \times 400$ to $3000 \times 4000$. In Figure 6, we present two garbage objects at different resolutions.

The number of objects in an image has an important influence on the garbage detection results. In reality, multiple-instance detection is a more challenging issue than single-instance detection. To evaluate the performance of an algorithm on multiple-instance detection, multiple scenarios are included in the HGI-30 dataset. Figure 7 shows some of the garbage images captured with a single instance and multiple instances.

CNNs are sensitive to spatial location. When objects are changed in the spatial distribution, it misjudges objects into other categories [50]. Hence, we perform data augmentation on some garbage images that are difficult to collect, such as apple cores and toothbrushes. We apply three specific augmentations, namely, rotation, noise, and illumination variation. As shown in Figure 8, we randomly scale the image with rotation, add Gaussian noise and salt-and-pepper noise,
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4 Evaluation of State-of-the-Art algorithms on the HGI-30 Dataset

This section mainly introduces the details of the experiment, including garbage classification and detection on unlabeled and labeled HGI-30. The details of each experiment and visual and theoretical analysis of the experimental results are presented separately.

The following experiments were run on a computer with an Intel i7-7700 CPU with 3.6GHz, 16GB RAM, and two NVIDIA GTX 1080TI cards with Tensorflow and the Keras developed by the Google research team [51].

We followed the method proposed in [53] and used a transfer learning mechanism to fine-tune CNN models. In [53], Wu et al. studied the transferability of features of each layer in deep learning, and proved that transferable learning has a very good effect. This study provides a transfer learning idea for DCNNs composed of stacked multi-layer networks.

4.1 Evaluation metrics

During the training of the detection models, we updated the weight parameters according to the degree of overlap between the prediction areas and labeled areas, that is, the size of the intersection over the union (IOU). The IOU value can be set to different sizes; here, we set it to 0.5. When the IOU between the prediction areas and true areas is greater than 0.5, the prediction box is considered a true prediction and positive sample; otherwise, it is a negative sample. In the evaluation stage of this research, the value of the IOU was set to 0.5 to evaluate the model performance. Precision is defined as the number ratio between positive samples and recognized samples. The recall is used for a certain class of objects. It is defined as the proportion of...
correctly recognized objects to the total number of such objects in the test data set. Precision and recall are often contradictory and not sufficient to measure the model performance alone.

Average precision (AP) represents the performance of the model on a certain category of objects, and the value is equal to the area enclosed by the precision–recall (P-R) curve and coordinate axis. A P-R curve is simply a graph with precision values on the y-axis and recall values on the x-axis. In other words, the P-R curve contains \( TP / (TP + FN) \) on the y-axis and \( TP / (TP + FP) \) on the x-axis. True positive (TP) means that the positive sample was detected correctly. False negative (FN) means that the negative sample was detected wrongly, and the false positive (FP) means that positive sample was detected wrongly.

The mean value of each category of AP (mAP) represents the average precision of each category of a model in the dataset, which can well reflect the comprehensive performance of the model. The above definition formula is as follows:

\[
R = \frac{TP}{TP + FN}
\]

\[
P = \frac{TP}{TP + FP}
\]

\[
AP = \int_0^1 PR dr
\]

\[
mAP = \frac{\sum_{q=1}^Q AveP(q)}{Q}
\]

where \( P \) is the abbreviation for precision, \( R \) is the abbreviation for recall, and \( Q \) represents the number of types of objects.

### 4.2 Transfer learning based on ImageNet

ImageNet [23] is widely known as a benchmark for network performance evaluation. It contains more than 1.2 million images and classifies large numbers of images into 1,000 categories. ImageNet provides pre-trained weights for many networks. Although the ImageNet dataset contains non-garbage images, the pre-trained weight with ImageNet can also be used in the current classification and provide the edge, corner, texture and other features of the natural image. These features are the basis of all the visual tasks.

Before pre-training, the final full connection layer of the convolutional classification network should be adjusted according to different tasks. Taking VGG16 as an example, when its pre-training weight is ImageNet, the output dimension of the last full connection layer of VGG16 should be correspondently modified to 30, which corresponds to the number of object classes.

In the classification, network weights based on the ImageNet dataset are taken as the initialized weights. Figure 9 shows the influence of using and not using pre-trained weights on ImageNet. Compared with not using a pre-trained network, the model accuracy and convergence speed can be improved significantly.

### 4.3 Experiments of different classifications on the unlabeled HGI-30

We examined the performance of six state-of-the-art classification algorithms based on DCNNs on unlabeled HGI-30, namely, VGG16, MobileNet, Resnet50, DenseNet, Xception, and EfficientDet. For a better comparison, we also added two handcrafted feature-based approaches, SIFT+BOVW and HOG+SVM. The unlabeled HGI-30 was divided into two parts at a ratio of 4 : 1, i.e., 80% were used for training and the rest for validation. The six networks used the pre-trained weights provided on ImageNet. To fairly compare the network performance, the image was uniformly adjusted to 512 \( \times \) 512 pixels before feeding it into the network. The initial learning rate was set to 0.00005. The momentum of the stochastic gradient descent was set to 0.8. The batch size for each iteration was set to 32. For SIFT+BOVW and HOG+SVM, we
extracted the descriptors using a 32×32 fixed-size grid with a step size of 12 pixel spacing. The experimental results of the above methods are shown in Table 2. EfficientDet achieved the best effect with an accuracy of 93.2%. Benefiting from the recombination coefficient to balance the width, depth, and resolution of the network, EfficientDet simultaneously extended them and performed excellently. The performance gap among ResNet, DenseNet, and Xception is very small compared to that of EfficientDet. Although MobileNet’s accuracy is not the best, the number of parameters is minimal. Particularly, DCNN algorithms have excellent performance, far better than those of traditional algorithms, where transfer learning plays an important role. We also compared the sensitivity of traditional and DCNN algorithms to data augmentation. The results show that DCNN algorithms are highly sensitive to data augmentation, whereas traditional algorithms are not.

4.4 Experiments of different detections on the labeled HGI-30

To evaluate the detection performance of DCNNs, six state-of-the-art detection methods were investigated on HGI-30: SSD, YOLOv3, YOLOv4, Faster RCNN, M2Det, and EfficientDet. In this experiment, the pre-training of the five detection models was provided by the PASCAL VOC dataset [52]. The HGI-30 dataset was divided into two parts in a ratio of 4 : 1, with 80% used for training and the rest for validation.

Table 3 provides the detection results on the HGI-30 dataset in comparison with six state-of-the-art methods. Overall, YOLOv4 achieved the best effect. It has introduced numerous techniques and tools, including CSPDarknet53 as a backbone, Mosaic data enhancement, and improved SAM. SSD has the worst comprehensive performance. EfficientDet has achieved a very effective performance by balancing the width, depth and resolution and improving the bi-directional feature pyramid network. Particularly, EfficientDet has a fairly high training hardware requirement.

As an outstanding representative of the two stage algorithms, YOLOv3 also achieves a good result; but compared with M2Det, there are still some gaps. As shown in Table 3, the average mAP of the six target detection algorithms in this dataset is 76%. Hence, we can conclude that HGI-30 is a challenge for object detection. In Figure 10, we provide examples of detection results using the six algorithms.

We also validated several types of typical garbage on six models and found that none of them are satisfactory for recognizing small objects or irregularly shaped objects. Although the general performance of SSD is the worst, it has a good effect on the detection of small targets, because the expansion convolution is added. Here, YOLO still has the best performance. In addition, the DCNNs are more sensitive to texture, compared to the irregularly shaped or small garbage. Objects with relatively regular textures and fixed geometry also tend
to have good detection accuracy. The results are shown in Figure [11]

5 Conclusion and Future Work

In this study, we first analyzed the characteristics of garbage and the current status of garbage classification. We then reviewed the state of the art in this domain and found that, as a consequence of the lack of suitable benchmarks, most approaches were evaluated on different datasets under different experimental settings. Thus, it is hard to fairly compare the results published in the literature. To solve this problem, we make the HGI-30 dataset available in the online repository [15].

Next, we performed experiments on classification and detection on this dataset and analyzed the characteristics of current mainstream networks. Experiments showed that HGI-30 can reflect DCNNs’ characteristics, and garbage image recognition is a great challenge for existing object recognition algorithms based on DCNNs. Finally, we present the acquisition path of HGI-30.

In future work, we will expand the categories and quantities of garbage in the dataset, and run more algorithms. In addition, we will develop better models on this dataset to facilitate the development of target recognition algorithms and environmental protection.

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Fig. 11 Comparison of the detection results on small objects or irregularly shaped objects

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