



Design of Deep Learning-Based Models for Intelligent Waste Classification Using Single-Label and Multi-Label Approaches

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ABSTRACT

Today, with the rapid growth of technology, especially deep learning, the importance of using novel methods has become more evident than ever. Environmental issues such as waste management likewise require new, intelligent approaches that can reduce costs, accelerate operations, and minimize human error. Waste classification, as one of the fundamental and important aspects of waste management and recycling, is the main focus of this research. In this study, two deep learning models were trained on images from the Realwaste dataset, which includes about 4,200 images across the categories of metal waste, glass waste, paper waste, cardboard waste, food organic waste, plastic waste, vegetation waste, and textile waste, in order to advance intelligent waste sorting. The resulting models are a single-label model and a multi-label model. The base model uses the EfficientNetB0 architecture introduced by researchers at Google, but it was redesigned and trained through transfer learning to suit the specific problem addressed in this study. To increase data diversity, artificial data augmentation techniques such as rotation, lighting changes, and image blending using the CutMix and MixUp methods were employed. In addition, to address data imbalance, class weights were calculated based on the frequency of each class. The training and validation data were split at a ratio of 70% to 30%, and all programming was carried out in Python within the Visual Studio Code environment using the Scikit-learn and TensorFlow libraries. The experimental results showed that both models performed well in the intelligent classification of waste images. For images containing a single waste type, the single-label model sometimes provided higher confidence in identifying the correct category; however, the multi-label model, which exhibited better control of overfitting during training, delivered better overall performance. The multi-label model's average confidence in identifying the correct category in the experimental test, 0.875, was higher than that of the single-label model, 0.855. In the analysis of an image unrelated to waste, the multi-label model, with a confidence below 0.25, also made a smaller error than the single-label model, which had a confidence of 0.29. Finally, in the experimental test on images containing several waste types simultaneously, it was found that the EfficientNet architecture is not as reliable for analyzing images containing multiple waste types as it is for analyzing images containing a single waste type.

Introduction

Rapid progress in artificial intelligence, machine learning, and especially deep learning has transformed how unstructured data, particularly images, are analyzed, with convolutional neural networks remaining one of the main foundations of image classification. Environmental challenges such as excessive waste generation call for intelligent solutions, and waste management and sorting have drawn considerable global attention, as population growth, urbanization, and industrial expansion increase household, commercial, industrial, and agricultural waste volumes. Traditional waste separation is usually manual and rule-based, an approach difficult to scale and labor-intensive; applying artificial intelligence, by contrast, can increase classification accuracy and reduce operating cost and time, with approaches such as smart bins and sorting robots proposed as effective directions. Building on this motivation, the present study develops a single-label model and a multi-label model, both based on EfficientNetB0 and transfer learning, trained on RealWaste data, and compares their performance across a range of test images. EfficientNet was chosen as the base architecture because this family of models balances depth, width, and image resolution well, and EfficientNetB0, despite far fewer parameters than earlier architectures such as VGG16, is generally a more optimized and accurate model. Persian-language and domestic research specifically centered on intelligent waste sorting with the help of deep learning and image processing is not abundant, and the present study also aims to inform future research in this direction, including the potential contribution of object-detection models such as YOLO for images containing several waste types at once.

Method

The RealWaste dataset, containing more than 4,700 images across nine categories, was released in late 2023 and used as the basis for this study. The miscellaneous-trash category was excluded so training could focus on precisely labeled images, leaving eight target categories: metal, glass, paper, cardboard, food organics, plastic, vegetation, and textile waste, comprising roughly 4,200 images. Further images matching each category were downloaded from the internet, bringing the working image pool to approximately 5,000 images. Because RealWaste images generally each focus on a single waste item, single-label images were also combined into composite images to give the multi-label model better training conditions, alongside rotation and brightness variation; class weights based on category frequency were applied, since image counts differ considerably across categories. For both models, EfficientNetB0, pretrained on roughly 1.2 million images across about 1,000 classes, served as the starting point, so it's already-learned visual features could be reused here; the original 1,000-class output layer was replaced with an 8-class layer. Early layers, capturing general image features, were kept frozen while newly added layers trained on the project's data; some previously frozen layers were later unfrozen for closer adaptation to waste imagery. Both models used independent sigmoid outputs, so each class receives a value between 0 and 1 that need not sum to 1; this same design was used for the single-label model too, keeping the two architectures consistent for easier comparison. Accordingly, the single-label model reports only the label with the highest value, while the multi-label model displays every label exceeding a 0.25 threshold, adjustable in the model's test code. Training and validation data were split 70:30; Adam was used instead of RMSProp, originally used for EfficientNetB0, for more stable, faster convergence on this smaller dataset; all programming was done in Python, in Visual Studio Code, using Scikit-learn and TensorFlow. Over training, the single-label model showed some widening between training and validation loss, a mild but not severe degree of overfitting; the multi-label model, trained with fewer epochs partly in response, showed a more balanced loss, without clear overfitting or underfitting.

Results

Both trained models were tested on new images not seen during training, downloaded from the internet. The first four test images each showed a single type of waste — paper, textile waste, food organics, and plastic — and both models identified the correct category in every case, though confidence values differed. On the paper image, the single-label model reported higher confidence (0.84 versus 0.76); on the remaining three, the multi-label model reported higher confidence (0.87 versus 0.80 for textile waste, 0.93 versus 0.87 for food organics, and 0.94 versus 0.91 for plastic). On the food organics image, the multi-label model produced two labels, food organics and textile waste, with the correct category, food organics, receiving much higher confidence (0.93) than the second label (0.31). Averaged across these four images, the multi-label model's confidence in the correct category was 0.875, compared with 0.855 for the single-label model. On an image unrelated to any of the eight trained categories, the multi-label model's confidence stayed below 0.25 for every category, while the single-label model reported 0.29 confidence for one category, metal; the multi-label model therefore performed better on this image. On a composite image formed by combining five different waste types, the multi-label model correctly identified two categories, food organics and glass, at 0.35 and 0.30 confidence, respectively; one of these, food organics, was also identified by the single-label model, at 0.28 confidence, and the multi-label model's higher confidence on this shared category is why it performed better on this image. Overall, confidence levels were low on this image containing several waste types at once, a pattern suggesting that object-detection architectures such as YOLO may be better suited to such images.

Conclusions

Both models performed adequately in classifying waste images, and the multi-label model was overall more accurate than the single-label model across the test images used. The multi-label model also performed better on the image unrelated to the trained categories and on the composite image containing several waste types, although the single-label model occasionally reported higher confidence on individual single-waste-type images. Because of its greater flexibility in identifying more than one class in a single image, the multi-label approach appears better suited to real-world recycling lines that handle a wide variety of waste, though the EfficientNetB0 architecture, in either its single-label or multi-label form, is not a fully reliable choice for analyzing complex images containing multiple waste types at once. Beyond the models themselves, this comparison of single-label and multi-label performance on a waste-classification task adds to the literature on deep learning applications in environmental management, and, subject to further validation, the developed models could support recycling lines and smart waste-management systems, helping reduce cost, speed up operations, and reduce human error. Future work in this direction could focus on increasing the size and diversity of the training data, particularly in lighting, angle, and image quality; using genuinely composite images, rather than synthetically combined ones, to further improve the multi-label model for real-world scenarios; incorporating object-detection architectures such as YOLO for complex, multi-waste images; and, before training, setting aside a separate test set on which to report standard metrics such as accuracy, precision, recall, and F1, allowing a more rigorous evaluation than the qualitative testing carried out here.

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