Using Convolutional Neural Networks to Classify Organic and Recycle Materials

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1 Introduction

Recycling waste is important step to protect the environment from being polluted and harmed. Inappropriate waste management could lead to water pollution and decease transmission. However, the most popular waste disposal method worldwide is through landfills[2]. It is expected that waste generation will increase by 50% in 2030 and 70% in 2050 if no proper actions are taken. Manual sorting proves to be more efficient than mechanical sorting[4] as human are very capable of identity types waste. But human resources are expansive since there were health concerns about hand picking hazardous materials.

Recent development in computer vision, in particular, convolutional neural network (CNN), makes it possible to automate waste classification. We aim to show that a reliable automated system based on CNN that identifies and classifies types of wastes is possible. We focus on applying some of the best practices in designing CNN algorithms, e.g., data augmentation and dropout, to improve the accuracy of our models.

2 Methodology

2.1 Overview

We use empirical approach to investigate the abilities of waste classification of various deep learning algorithms. The classification is of two classes: organic and recyclable materials. Our approach, as illustrated in Figure 1, including feeding each CNN the same dataset with sigmoid classifier and comparing the results from each CNN based on test accuracy.

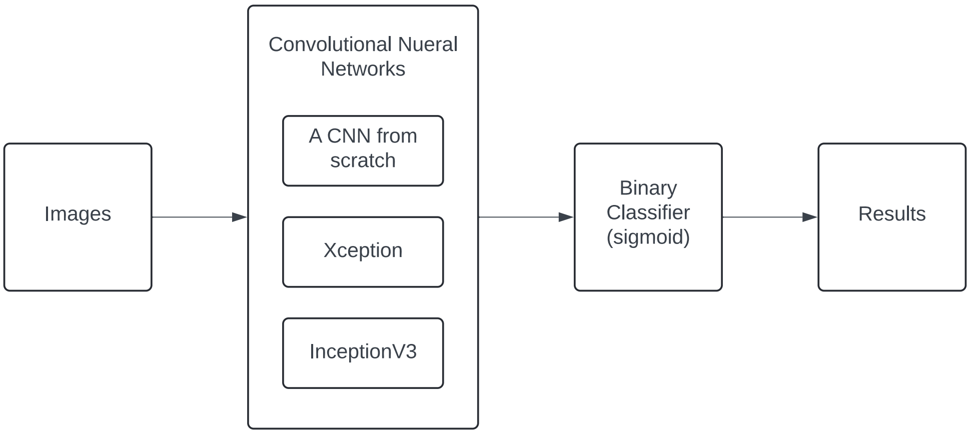

Figure 1: Methodology

2.2 Dataset

The dataset is from Kaggle (click) which contains 22500 images of organic and recyclable objects that are spitted into train data (85%) and test data (15%). We take 40% of the train data as validation dataset. The images are preprocessed to $223 \times 223 \times 3$ size.

2.3 Data Augmentation & Dropout

Deep learning model often require a large dataset in order to achieve a considerable generalization power. Data augmentation produces more training data and thus is a powerful technique for mitigating overfitting in computer vision [3][1]. We used position augmentation including Flipping, Rotation, and Zooming. Color augmentation, for instance, Contrast and Brightness, are not considered since Organic and Recyclable may have significant different colour spaces and so adding color augmentation would break the colour spaces, thus making it harder for the model to generalize.

Dropout is one of the most effective and most commonly used regularization techniques for neural networks[1]. Dropout is added to all the models in our experiments with dropout rate set to 0.5.

2.4 A CNN Model from Scratch

We build a CNN model from scratch and experiment the test accuracy with/without data augmentation. The structure of this model is shown in Figure 2.

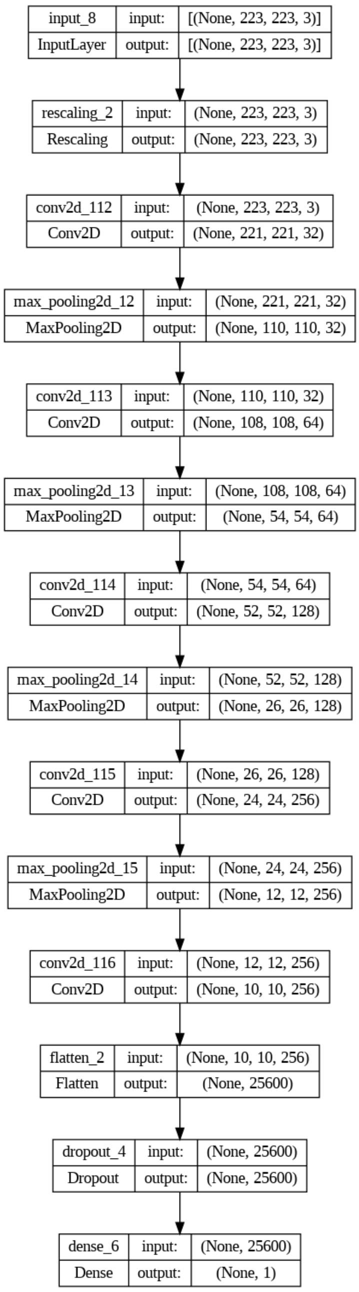

Figure 2: A CNN build from scratch

3 Results

The first experiment is to investigate the improvement of test accuracy by adding augmentation layer to our manual defined model. Both models in this experiment were trained for 50 epoches with RMSProp optimizer. The training progress and results are shown in Figure 3 and 4, and Table 1 respectively.

	Test Accuracy	Test Loss
Model with Data Augmentation	88.7%	0.3123
Model without Data Augmentation	90.6%	0.2666

Table 1: Results from Manually Defined Model

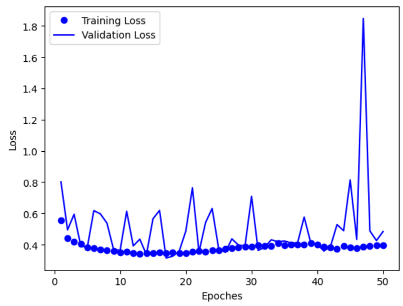

Figure 3: Training vs. Validation Loss (Data Augmentation)

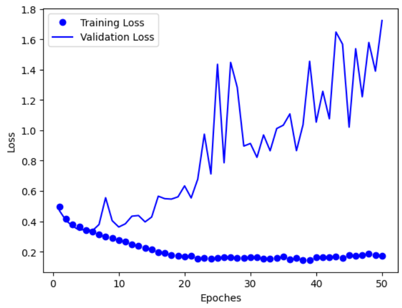

Figure 4: Training vs. Validation Loss (No Data Augmentation)

We expected that the model with Data Augmentation would return a better test accuracy, however, this is not the case. There could be various reasons, we suspect that the reason is that the model with data augmentation merely perform worse on the test dataset but may achieve higher accuracy on a general dataset, or that more epoches are required since it is unsure overfitting has occurred in Figure 3 while the model without Data Augmentation overfitted almost immediately as shown in Figure 4.

To further improve the accuracy, we conduct the second experiment, in which we fine-tune two pretrained models, InceptionV3 and Xception, with weights trained on ImageNet. Both of the trainings consists of 50 epcohes, using RMSProp optimizer with 10^{-5} learning rate and sigmoid classifier. The results are shown in Table 2.

Pretrained Model	Test Accuracy	Test Loss
Xception	90.3%	0.2504
InceptionV3	91.4%	0.239

Table 2: Results of Fine Tuning with Xception and InceptionV3

4 Conclusion

In our study, we aimed to identify a reliable model for classifying two types of materials: organic and recyclable. By training various models and evaluating their test accuracies, we discovered that Data Augmentation significantly mitigates overfitting (See Figure 3 and Figure 4). In our second series of experiments, we fine-tuned the Xception and InceptionV3 models, which resulted in higher validation accuracies. However, improvements in test accuracy were minimal, likely due to the limitations of the test dataset's robustness. Our findings underscore the necessity of advanced fine-tuning and optimization techniques to develop an effective automated waste classification system that can handle multiple classes.

5 Limitations and Possible Improvements

A primary limitation of our current study is its focus on binary classification, which does not fully represent the complexities of actual waste management systems that deal with a variety of materials.

Implementing a more comprehensive dataset, similar in scale and diversity to "ImageNet", could allow for the development of a robust multi-classification model adept at extensive waste classification tasks.

Moreover, our models, Xception and InceptionV3, demonstrated early signs of overfitting, likely due to their extensive parameter sets. Utilizing a larger dataset could help in delaying or preventing this overfitting, enabling more sustained learning.

Lastly, our research was restricted to fine-tuning only two pretrained models. Expanding our study to include additional models such as NASNet-Large and Inception-ResNet-V2 could further enhance accuracy and model robustness, leading to more reliable waste classification solutions.

References

[1] Francois Chollet. *Deep learning with Python*. Simon and Schuster, 2021.

[2] Silpa Kaza, Lisa Yao, Perinaz Bhada-Tata, and Frank Van Woerden. *What a waste 2.0: a global snapshot of solid waste management to 2050*. World Bank Publications, 2018.

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[4] Steven Saar, Markus Stutz, and Valerie M Thomas. Towards intelligent recycling: a proposal to link bar codes to recycling information. *Resources, Conservation and Recycling*, 41(1):15–22, 2004.