Trash Material Classification via Deep Learning

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Abstract

Trash material classification is an interesting task that helps save the environment in its applications. In my project, I tackle the material classification problem using deep learning in search of the best ways to classify trash material for environmental purposes. A good convolutional model can help create useful application for sorting trash material without the need of human contact with recycling equipment. In my experiments, I will try out several methods and networks, including different optimization techniques and different network architectures in order to find the best and most accurate convolutional models for the trash material classification task on benchmark datasets. I will rely mostly on fine-tuning existing models in order to spend more time exploring and comparing different methods.

(a) TrashNet dataset

(b) MINC-2500 dataset

(c) FMD dataset

Figure 1. Samples from benchmark datasets used. Columns from left to right: glass, metal, plastic.

1. Introduction

1.1. Motivation

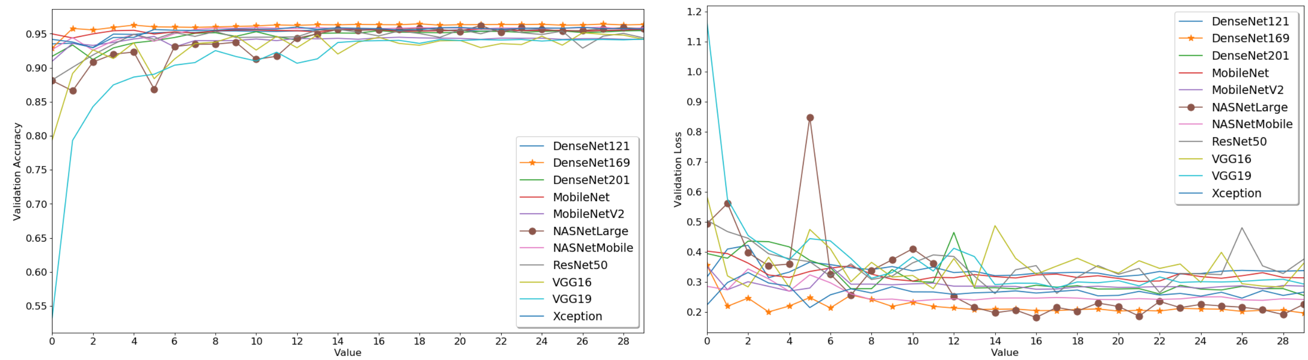
Waste management is a very important task to preserve the environment. Environment and natural materials played an important function in the development of human societies and in history on the whole [1]. Therefore, trash material classification helps a lot with achieving the goal of a better environment by applying deep learning methods to help us build useful applications dedicated for categorizing different types of materials given suitable datasets.

1.2. Problem Statement

In this project, I try to find the best and most efficient approaches to image classification suitable for trash material classification, applied on benchmark datsets that will be introduced in a later section. My hope in this project is to implement and develop very accurate and efficient classifiers for the task of material classification.

2. Related Work

Schwartz et al. [13] explored the difference between different material types and their properties from an image recognition point of view, illustrating how different materials show different textures and smoothness and how their features can be useful in image recognition tasks. Another interesting paper is by students from Stanford University [17] where they explored computer vision and deep learning approaches to classify trash material using a dataset that they acquired by hand for the purpose of their project. This dataset is used as a benchmark dataset in this project. Bircanoglu et al. [3] introduce their own RecycleNet architecture dedicated for recycling material classification and also some experimintations with other networks. In addition to these related papers, I explore different networks as base models in my experiments, such as ResNet50 [8], DenseNet [10], and others in hopes of finding the most suitable clas-



(a) Validation Accuracy

(b) Validation Loss

Figure 2. **Validation accuracy and loss during training using different fine-tuned architectures on the TrashNet [16] dataset.** NASNetLarge and DenseNet169 seem to perform similarly as the epoch number increases during training. When evaluating the models during the test phase, NASNetLarge perfroms the best on average.

sifier for trash material classification.

3. Datasets

In this project, I focus on trash material classification. In order to look for a suitable model of classification for such material, I collected three datasets that have been used for similar tasks. Benchmark datasets used in this project include the TrashNet dataset [16], the Flickr Material Database (FMD) [14] and the Materials in Context Database (MINC-2500) [2]. These datasets will be used to experiment with different convolutional models. Experimnets so far have been done using the TrashNet dataset which contains 2527 images of trash material (labels: paper, plastic, cardboard, glass, metal, and uncategorized).

4. Methodology

4.1. Convolutional Neural Networks

I rely mostly on fine-tuning existing models in the deep learning industry. In this case, I take different existing architectures pre-trained on ImageNet [5] and fine-tune them to do the task of trash material classification. Networks to be considered along with their tests results are shown in Table 1.

4.2. Data Augmentation

Augmentation to the data is applied on the training set and the test set to increase classification accuracy. Augmentation techniques include shifting images horizontally and vertically, rotation by a 45 degree angle, horizontal flipping, shearing, and zooming.

5. Results

5.1. Performance

For performance evaluation, I decided to use the following metrics: categorical accuracy, categorical cross-entropy loss, mean squared error, mean absolute error, and mean squared logarithmic error. Test results for these metrics are shown in Table 1.

5.2. Experiments

I chose to use Adam as an optimizer in the experiments done so far. I also implemented learning rate reduction on plateau to help the training process get a little boost if no real progress was made for 5 epochs during training. All experiments are run for 30 epochs with a batch size of 32 except for dense networks due to hardware limitations such as NASNetLarge in which I used a batch size of 4, Xception in which I used a batch size of 8, and DenseNet201 in which I used a batch size of 16.

6. Conclusion

NASNetLarge seemed to perform the best among all architectures used. I speculate that I can get even better results given better hardware. A larger batch size would definitely bump up the accuracy.

7. Future Work

I intend to dig deep into the architectures in order to find reliable methods to increase classification accuracy. I will analyze and compare my methods to the ones introduced in [3] and [17] and try to beat them. I will also experiment with the other two material datasets introduced in this project. For optimization, experiments will include different optimization algorithms such as Stochastic Gradient Descent

Architecture	$\delta\uparrow$	cce↓	mse↓	mae↓	msle↓	Parameters	Batch Size
ResNet50 [8]	0.880	1.088	0.036	0.040	0.016	25m	32
VGG16 [15]	0.852	1.090	0.042	0.050	0.020	15m	32
VGG19	0.859	1.062	0.041	0.049	0.020	20m	32
MobileNet [9]	0.875	1.258	0.039	0.044	0.019	4m	32
MobileNetV2	0.866	1.062	0.039	0.046	0.019	3m	32
DenseNet121 [10]	0.870	1.146	0.041	0.045	0.020	7m	32
DenseNet169	0.885	1.123	0.035	0.039	0.017	13m	32
DenseNet201	0.881	0.945	0.035	0.040	0.017	18m	16
Xception [4]	0.880	0.806	0.033	0.042	0.016	23m	8
NASNetMobile [18]	0.877	0.987	0.035	0.041	0.017	5m	32
NASNetLarge	**0.901**	**0.791**	**0.031**	**0.038**	**0.015**	88m	4

Table 1. **Comparisons of test results of different fine-tuned architectures on the TrashNet dataset.** Rows from left to right: architecture, test accuracy, categorical cross-entropy, mean squared error, mean absolute error, mean squared logarithmic error, number of trainable parameters in millions, and batch size. The reported numbers are real results from the experiments.

Architecture	$\delta\uparrow$
DenseNet121 (TrashNet)	**0.95**
Deep-TEN (MINC-2500)	**0.813**
FV-CNN (FMD)	**0.824**

Table 2. **State-of-the-art test accuracies.** DenseNet121 performance was reported by [3].

[12], Adam [11], RMSprop [7], Adamax [11] and Nadam [6]. I also aim to implement my own convolutional network and try to optimize it to beat state-of-the-art results shown in Table 2. A graphical user interface will be presented at the end of the semester to demo and test the performance of the trash classifier.

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