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Waste Classification using Transfer Learning with Convolutional Neural Networks

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Waste Classification using Transfer Learning with Convolutional Neural Networks

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Abstract. With the aim to tackle the issue of waste classification for different categories of misspend substances, the authors, with a limited availability of dataset have processed a highly accurate model to classify garbage into 7 different categories using the CompostNet dataset. Experiments were carried out on pre-trained models of MobileNetV2, ResNet34 and Densenet121 model, previously trained on ImageNet dataset. The accuracies obtained were 96.42%, 96.27% and 96.273% respectively for the Densenet121, mobilenetv2 and resnet34 models. Within 60 epochs, the neural network model accurately categorizes waste materials provided in the input image. The results of the experiments are compared with other previous work done in the same field. The applications of the experiments conducted in this research aims at providing better waste categorization and also follows the United Nations goal for Responsible Consumption and Production towards sustainable development.

1. Introduction

With the huge amount of garbage produced by consumers every day all over the world, the waste materials are mixed with each other without proper categorization and segregation. As per the reports of the Indian government's MHUA (Ministry of Housing and Urban Affairs), solid waste generation in total is approximately 150 thousand metric tons per day in India. Only 90% of this is collected out of which, only 1/5th of it stands processable and the remaining waste goes to the dump sites with all sorts of harmful e-wastes, plastic, liquid waste, partially consumed food, unfinished water bottles, variety of metals, poly-ethene bags, etc. This diversified accumulation of waste materials makes it extremely hard for useful materials such as bio-degradable and recycle-able items to be categorized and gathered to be utilized.

The problem of garbage or solid waste accumulation is assuming high proportions at a constant growth rate. At present, people of India in specific produce about 62 million metric tons of solid-waste annually. About 68% percent of the solid waste production in the United States are a combination of plastic, glass, metals, waste compost matter and paper [1]. According to reports, one-third of the food produced across the globe goes to waste [2]. The lack of awareness of the correct grouping of meal waste, plastics, compost, etcetera is a vital contributor of accumulation and mis-categorization of waste.

With the advancement of deep learning and technology in specific, humans tend to utilize them for the good and for a social cause for the betterment of society and eventually integrate the same with the goals of sustainable development and less exploitation of materials on earth.

1.1. Motivation

The work aims at bringing in attention to the consumers, the concern of waste categorization and the rapid increase in the production of the same. A global organization such as the United Nations aims at substantially reducing waste generation through the goals to prevent, reduce, recycle and reuse [3]. It also aims to encourage organizations, especially large and multinational corporations, to adopt sustainable practices and to integrate the same into their reporting cycle [3]. With the advancement of technology, it becomes our responsibility to provide the environment and the citizens, both, at the same time, with helpful solutions to tackle this problem.

According to a report, some of Asia's cities produce about 80% of the economic GDP of their country. These technologically advanced and growing cities are huge contributors in producing harmful wastes and lack the tantamount rate of appropriate disposal of waste while at the same time generating harmful greenhouse gases through deluge of solid waste [4].

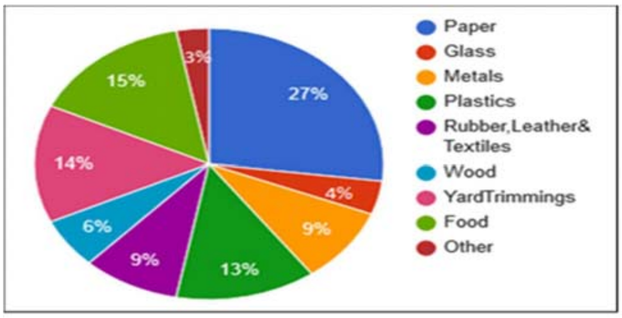

Figure 1. Composition of Municipal Solid Waste generated by the United States in the year 2013 [1]

1.2. Overview

Contributions are located in the field of Deep Learning and Image classification through the use of Convolutional Neural Networks. The concept of Transfer Learning is used. Techniques and methodologies adopted in tackling the subject matter of work is mentioned in study. Starting from dataset selection, CompostNet dataset is chosen as the primary dataset for the model to be trained on, which is an extension of the TrashNet dataset.

Three models are presented which provide in the experiments that follow that show better results than the research conducted by Gary Thung and Mindy Yang [6] which makes use of Neural Networks with SVM Classifier. Author's results are compared with the work carried with CompostNet [5], which makes use of Neural Networks with a SoftMax classifier. Comparisons of the results with the ones provided by Umut Ozkaya & Levent Seyfi [8] are also mentioned which show high accuracy on the Trashnet dataset with fine-tuned Convolutional Neural Network [9] models through SoftMax classifiers.

2. Related Work

Image classification plays a very vital role in the field of Deep Learning. With the boom of Deep Learning in the recent years, image classifiers have been studied in the field of Convolutional Neural Networks (CNNs) [9]. CNNs are a class of neural networks which are commonly used to analyse images. CNNs have been used in various applications such as Image classification, Object detection, Semantic and Instance Segmentation, Generative Adversarial Networks, Autoencoders, and many more. Having their applications in fields related to image and video processing, they had to be the best choice to go for Image Classification in this case to categorize waste materials.

Authors make use of supervised learning of visual images using Image classification techniques to eventually classify the input images into different categories. Supervised Image classification techniques make use of inputs to the CNNs as an image along with a corresponding label data with the image to help train the Neural Network model to classify images as per the input image to a corresponding output class.

3. Waste Classification

The issue of waste classification can be addressed through social and environmental awareness, labelled dustbins or dumping areas for categorized wastes, educating citizens to be responsible and aware about waste categorization. The CNNs can be otherwise used with little effort in promoting awareness and incorporating people to follow a certain custom into dumping objects in the right dustbin. The Dataset provided by Gary Thung and Mindy Yang [6] along with the TrashNet model provided by them categorizes waste materials into 6 different categories. CompostNet concentrates on categorizing food waste and compostable waste separately into 7 different categories.

The Spot-Garbage [10] mobile application made by the researchers at Indian Institute of Technology makes use of a CNN architecture known as GarbNet and helps at spotting garbage on the grounds of Indian urban areas. Though GarbNet doesn't categorize waste materials, it identifies the waste material and constructs a region of interest to mark on the image for the same without categorizing the waste. Their results show high accuracy on classifying garbage in images.

4. Model and Dataset Specifications

4.1. Dataset used

The CompostNet dataset [5], extended by the TrashNet dataset [7] forms a total of 7 categories of waste, namely, Paper, Cardboard, Metal, Glass, Compost, Trash and Plastic. The TrashNet dataset [7] consists of 2527 images with 6 categories: paper, cardboard, metal, glass, plastic and trash. Each image has dimensions of 512x384 pixels and is taken against a white poster board background.

The CompostNet [5] dataset consists of an additional 175 photos in the food waste and 49 photos of landfill waste, forming a total of 2751 images in all 7 categories. The CompostNet dataset [5] has two versions: version-A and version-B.

The version-A of the dataset consists of images of sizes 300x400 pixels and the version-B on the other hand consists of images of shape 224x224 pixels. Images are then reshaped to images for waste classification technique to the dimensions of 512x384 pixels according to TrashNet dataset [7] opted by Gary Thung and Mindy Yang.

Figure 2. Example images from the CompostNet dataset

4.2. Transfer Learning

Transfer Learning is a method used to leverage weights from a pre-trained model to get better accuracy on a related but different task with a different dataset. Transfer Learning has proven to provide better results when there is a lack of dataset availability. In this case, 2751 images in total are available in the dataset. The lack of dataset size might lead to a model which might have low accuracy. For that very reason, it was opted to look for better results on waste classification through transfer learning.

The pre-trained weights of MobileNetV2 [11], ResNet34 [12] and DenseNet121 (all trained on the ImageNet dataset) are loaded on their respective architectures to classify the 7 categories of images available in the dataset.

4.3. Training & Learning Rate Specifications

In order to find a suitable learning rate for the model to train on, the logarithmic learning rate against the training loss for the 1st epoch was plotted with the pretrained model. The minimum and maximum values chosen for the search of learning rate were 1e-6 and 1e1 respectively. The learning rate started from a small value of 1e-6 and after every mini-batch increased by a small value with a batch size being specified to 16 for the experiments. The best learning rate would be the one that minimizes the loss while at the same time prevents the loss from diverging or exploding. The experiment was conducted for 1 epoch to find a suitable learning rate. With every iteration, learning rate is increased and the learning rate (in logarithmic scale) is plotted against the training loss of the model. The learning rate used was the one just before where the loss starts diverging. Training was conducted using pre-trained models which were fine-tuned for 60 epochs.

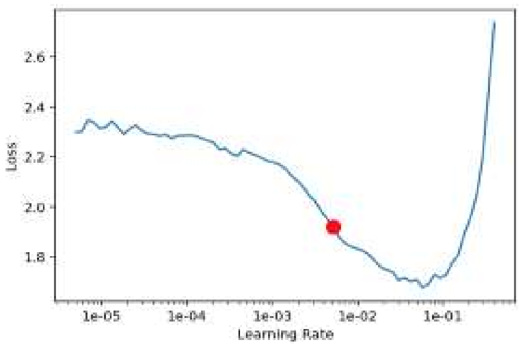

Figure 3. Training loss plotted against logarithmic learning rate

The red dot in Figure 3. specifies the learning rate of 5.13e-03. This was the learning rate that was chosen for the experiments. The dataset was split in the ratio of 75:25 to form training and testing sets and the model was trained for 60 epochs. Adam Optimizer [13] was used with SoftMax output classifier with a value of 0.95 & 0.99 for the exponential decay rate parameter for the first and second momentum estimates, respectively. The experiments were conducted on Google Colab [14] on a Tesla T4 GPU with 12 GB RAM.

4.4. Data Augmentation

Data Augmentation was used to add data points to the training dataset and to introduce variation to the dataset which was limited in size. The data augmentation process makes the model generalize well and have more data points to be trained upon. The Augmentation process opted for in the training included horizontal and vertical flips and a maximum rotation of 25 degrees for the DenseNet121 and ResNet34 [12] model training process. The MobileNetV2 [11] model showed a higher accuracy on test data for a maximum rotation of 50 degrees rather than 25 degrees.

5. Results, Comparisons and Evaluation

5.1. Previous work

Gary Thung and Mindy Yang achieved an accuracy of 75% using their CNN TrashNet [6]. While CompostNet [5] achieved an accuracy of 77.3% with their version-A (CompostNet) and version-B achieved an accuracy of 22.695% (MobileNet). The experiments conducted by the authors aimed at achieving a higher accuracy than TrashNet [6], CompostNet [5], and Umut Özkaya1 and Levent Seyfi's fine-tuned model's results [8].

5.2. DenseNet121

The CompostNet dataset [5] was split into 75% for training and 25% for testing phase. The model was trained for 60 epochs with a batch size of 16. The author's approach achieved an accuracy of 96.428%. The results of the densenet121 model fine-tuned on a model pre-trained on ImageNet shows better results than Umut Özkaya1 and Levent Seyfi [8]. The confusion matrix depicts the actual labels on the y-axis against the predicted labels of the test images on the x-axis. The diagonal boxes of the confusion matrix represent the correctly predicted images in the test set of the dataset. The rest of the boxes depict the wrongly predicted outputs. It can clearly be seen that the most misclassified object in the experiment was glass, which was predicted as metal.

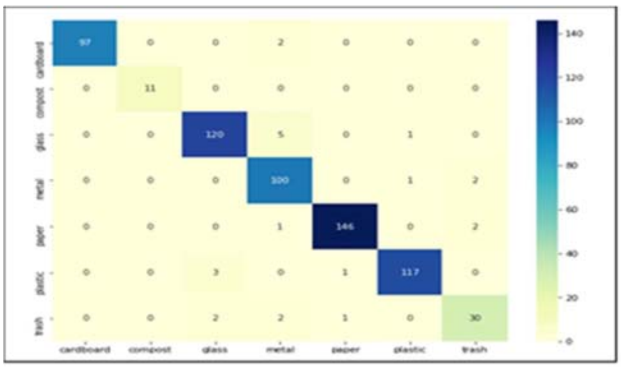

Figure 4. Confusion Matrix for the DenseNet121 model on the test set

5.3. MobileNetV2

The same training to testing dataset split ratio was used for MobileNetV2 model as well to be fine-tuned on the CompostNet dataset [5]. The model was trained for 60 epochs with a batch size of 16 and approached an accuracy of 96.27% on test set. CompostNet version-A (MobileNet) displayed an accuracy of 77.3% against the author's highly accurate 96.27% on the test set.

5.4. ResNet34

The experiments conducted on ResNet34 show a high accuracy in just 60 epochs as compared to 200 epochs of Umut Özkaya1 and Levent Seyfi [8]. Finding a suitable learning rate for the model made the training process much more efficient and hence the study shows high accuracy on categorizing waste from input images.

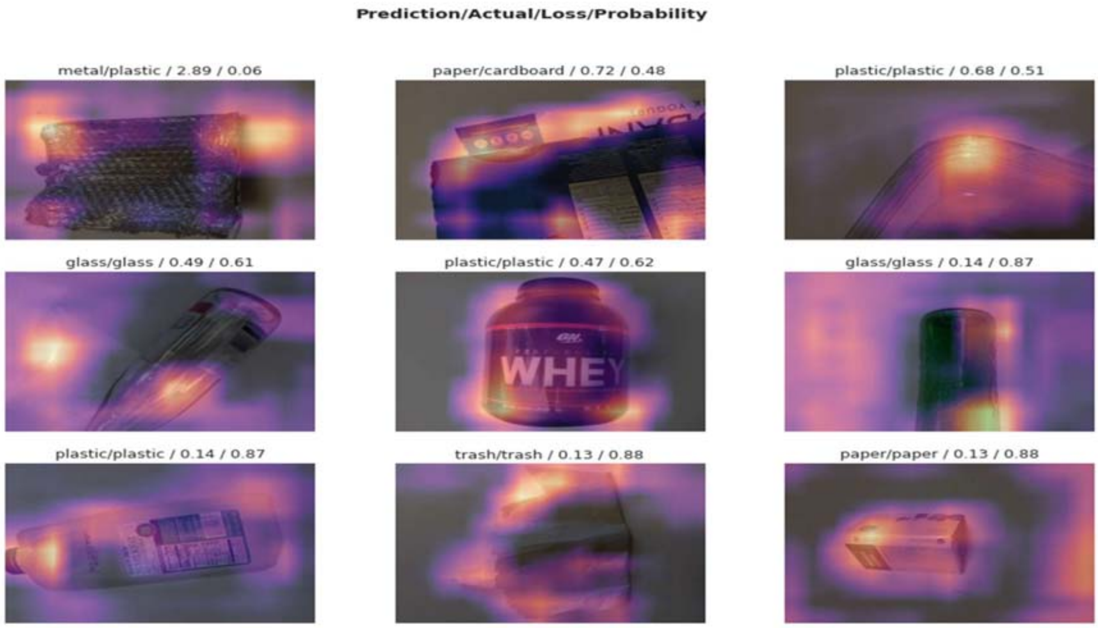

Table 1. Comparison on CompostNet

Model	Test Acc. (%)	Epochs
ResNet34(Proposed)	96.273	60
DenseNet121(Proposed)	96.428	60
MobileNetV2(Proposed)	96.270	60
CompostNet(Version-A)	77.3	20
CompostNet(Version-B)	22.965	20

Training for more epochs and adjusting the hyperparameters of the models or adding images to the dataset might lead to better results and higher accuracy. For the model to be practically used on edge devices in the areas where they could be utilized and benefited from, it might require more dataset variation, additional images and categories.

6. Conclusion

Solutions for waste categorization were provided through different models that show highly accurate and promising results to categorize waste materials into 7 different categories by the authors. The authors look forward for this model to be deployed on edge devices to eventually be integrated with dust-bins for waste classification to categorize the input waste of the dustbin and segregate the material according to different categories. This will result in better and easy segregation of waste materials for future, when the materials are removed from the dustbins for processing, recycling process, for reuse or for disposal of the same. This research could help people of all the communities to understand the solutions and the seriousness of the issue of waste management.

Table 2. Comparison of Models Trained

Model	Test Acc. (%)	Epochs	Dataset	Classes
ResNet34(Proposed)*†	96.273	60	CompostNet	7
DenseNet121(Proposed)*†	96.428	60	CompostNet	7
MobileNetV2(Proposed)*†	96.27	60	CompostNet	7
GoogleNet*	88.10	200	TrashNet	6
VGG-16*	90	200	TrashNet	6
ResNet*	89.38	200	TrashNet	6
DenseNet121*†	95	200	TrashNet	6
RecycleNet[15] †	81	200	TrashNet	6
MobileNet	76	500	TrashNet	6

* Transfer Learning applied in the training process.
† Data Augmentation applied in the training process

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