Classification of TrashNet Dataset Based on Deep Learning Models

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***Abstract*—Waste recycling is very important in terms of economy and climate balance of the world. For this reason, classifying recyclable garbage is an important goal for humanity and Deep Learning models can be used for this purpose. In this study, we tested well-known Deep Learning models to provide the most efficient approach. In this study, Densenet121, DenseNet169, InceptionResnetV2, MobileNet, Xception architectures were used for Trashnet dataset and Adam and Adadelta were used as the optimizer in neural network models. Based on the findings obtained in this study, Adam provided better test accuracies compared to Adadelta. Besides, the data augmentation process was applied to increase classification accuracy because of limited samples of the Trashnet dataset. As a result of the conducted experiments, the best results were found in the DenseNet121 using fine-tuning with a test accuracy rate of 95%. A similar success rate was also found in the InceptionResNetV2 model using fine-tuning with a test accuracy of 94%.**

***Keywords*—Deep learning, CNN, image classification, waste, recycling**

I. Introduction

Rapid urbanisation, the increasing human population and also industrialisation cause environmental pollution all over the world. An increase in production and marketing activities, caused by these processes, has made the intensive use of natural resources inevitable, while the waste products that are produced due to ever-increasing consumption tendencies have reached levels that threaten the environment and human health in terms of both quantity and harmful contents [1], [2]. Waste products can be classified based on various factors such as consumption, production, and chemical and physical properties. Waste products are the materials that must be disposed of in a regular manner in terms of human and environmental health.Briefly, not prioritising recycling can cause financial losses as well as a waste of natural resources [3].

Solid wastes are an environmental and human problem; they directly or indirectly interact with the environment and human beings in the cycle of waste, from where they are produced until the last stage of expulsion.

Inadequate cleanliness and waste management practices and lack of awareness of the relationship between environment and human health can be clearly observed in undeveloped and developing countries.

In the globalising world, with the influences of industrialisation and urbanisation, resources are used unconsciously, which leads to the formation of consumption wastes.

In order to establish a model description or machine learning system with classical machine learning techniques, the feature vector must first be extracted. In order to extract the feature vector, specialists are needed [4], [5]. These transactions require a great deal of time and experts are often very busy. These techniques cannot be used to process raw data without pre-processing and without expert help. Deep Learning has made great progress by eliminating this problem, which employees in the field of machine learning have been struggling with for many years. Deep nets carry out the learning process on raw data, unlike traditional machine learning and image processing techniques [6].

Deep Learning is a machine learning form that enables computers to learn from experience [7]. It allows computational models consisting of multiple processing layers to comprehend a representation of data with multiple abstraction layers. These approaches enable us to develop the cutting edge technology in such many different areas as the recognition of speech, visual objects, drug discovery and genomics. Deep Learning explores the complexity of large datasets using a rewriting algorithm to display how a machine can alter internal parameters utilized to calculate the representation of each layer that are based on the representation of former layers. Deeply convolutional networks have contributed significantly to the improvements in image, video, speech and sound processing, while repetitive networks enlighten sequential utterances like text and speech [8].

Our work has been applied to the environmental issues of solid waste management and recycling. In order to contribute to this field, recyclable materials have been dealt with using a deep learning approach.

The datasets used in this study are images in which a single object is presented on a clean white background. We use Deep Learning to classify images into six categories of rubbish classes. In this way, we can predict the category of rubbish that an object belongs to using just an image [9], [10].

In recent years, researchers have carried out a number of image classification research projects based on neural networks; however, there have been insufficient rubbish classification projects using computer vision and neural networks.

The most similar project to this study is 'Auto-Trash', from the 2016 TechCrunch Disrupt Hackathon [11]. The project consisted of an auto-sorting rubbish bin that could contradistinguish between compost and recycling using a Raspberry Pi-powered module and camera. Auto-Trash was well-constructed using Google's TensorFlow [11].

We have found another analogous project in the form of a smartphone application. This study was designed to roughly classify a pile of rubbish shown in an image. The main aim of the smartphone application is to allow people to follow up on rubbish they see in their local area and report it. The authors used Bing Image Search to create their dataset and used the resulting images to train their network [12].

In this study, we use computer vision and Deep Learning to improve the process of identifying recyclable materials. Our dataset was obtained from a study by Stanford University students [9].

II. Deep Learning Models

A number of models have developed by researchers due to the success of deep learning and the models we used were described in this section.

A. Xception

Xception architecture is based on depthwise separable convolution layers extensively. Mapping of cross-channels connections and spatial connections in the property maps of convolutional neural networks can be thoroughly set apart in this architecture. Xception, which is a stronger version of the underlying Inception architecture, has 36 convolutional layers building the property extraction base of the network. All convolutional layers are structured into 14 modules, all of which have linear remnants relation around them, outside of the first and the last modules. Briefly, this architecture is very easy to describe and change because it is a linear heap of depthwise separable convolution layers with residual relations [13].

B. MobileNet

MobileNet is a model recommended by the Google research team. MobileNet consists of in-depth separable convolutions initially used in the Inception model. The reason for this is to reduce the number of first computations in the first few layers. The MobileNet structure was built on depth-wise separable convolutions. However, the first layer is out of this because the first layer is full convolution. MobileNet performs a depth-wise separable convolution after the full convolution. Thus, a high accuracy rate can be achieved with a small number of hyperparameters. MobileNet is a useful model because it can be trained faster with fewer resources [14].

C. Densely Connected Convolutional Networks

DenseNets, contain very short connections between input and output layers, are very efficient convolutional neural network structures. One of the big advantages of these nets are improved flow of information and gradients throughout the network. Thus, they tend to yield consistent improvement in accuracy with growing number of parameters, without any signs of performance degradation or overfitting. Therefore, DenseNets necessitate considerably fewer parameters and less computation to attain novel performances [15].

D. Inception V4 (Inception-ResNet-V2)

Recently, very deep convolutional networks have become crucial in the progress in image recognition performance. Inception architecture was proven to perform well at relatively low computational costs. Inception-v4 is the advanced version of the Inception-v3 and a hybrid of inception modules and residual connections. In inception-v4, batch normalization takes place on the top of traditional convolutional layers. Due to this property, inception block size has been increased [16].

III. Experimental Results

A. Dataset

Detection of recycling materials is very important for humanity and civilization. In addition, the value of the world ecosystem and its importance for a livable world is an undeniable fact in today's world. In this work, it is aimed to classify the recycling of materials such as glass, paper, cardboard, and metal.

The TrashNet dataset was used for this work [9], [12]. This dataset contains paper, glass, plastic, metal, carton and garbage subclasses. The images on this dataset consist of photographs of garbage taken on a white background. The different exposure and lighting selected for each photo include the variations in the dataset. Each image was resized to 512 x 384 pixels and the original dataset is nearly 3.5 GB in size.

This dataset contains 2527 images in total. The content of the dataset is as follows:

- 594 paper
- 501 glass
- 137 trash
- 410 metal
- 482 plastic

- 403 cardboard.

For this work, 70% of all images were used for training, 17% for testing, and 13% for validation.

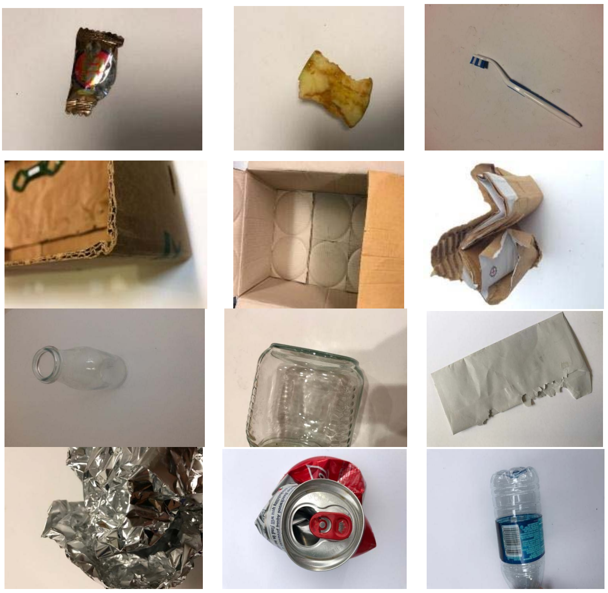

Figure 1. Sample Images of the Dataset [12]

B. Results

All the experiments of this study were performed using Keras library with TensorFlow version 2.1.4 backend on Google Colaboratory platform [17]. The experiments were performed using Tesla K80 GPU.

We implemented training models for the experiments from scratch, training data, validation during training, and used these weights for the experiments. Our experiments and the results were shown in Figure 4.

The most successful test accuracies were shown in Table I.

Table I. Most Successful Test Accuracies

Model	Epoch	Test Accuracy
Inception-V4	100	89 %
DenseNet169	150	84 %
MobileNet	150	84 %

During the training of all models, we used simple data augmentation methods.

The reason we implemented data augmentation is that there are relatively few images available. In some experiments, the data augmentation resulted in overfitting, but for the most part, the data augmentation was very successful. Furthermore, we performed fine tuning experiments on some models and fine tuning using weights of the pre-trained model on ImageNet dataset. After a small step of pre-training of ImageNet trained weights containing model, fine-tuning was performed with stochastic gradient descent with 0.9 Nesterov momentum and the learning rate was set to 0,0001. During the training of all models, we utilized simple data augmentation methods such as horizontal and vertical flip and 15 degrees or 20 degrees rotation. The learning rate of the Adam optimizer was set at 0.001, the default value of Keras was used in all experiments.

For the training experiments of DenseNet models, the batch size was selected as 8. As for other training experiments, the batch size was selected as 32. For DenseNet, Xception and MobileNet training experiments, the input size was selected as 224x224. For the Inception-ResNet-V2 model training experiments, the input size was selected as 299x299. The results of the trained models were shown in Figure 4.

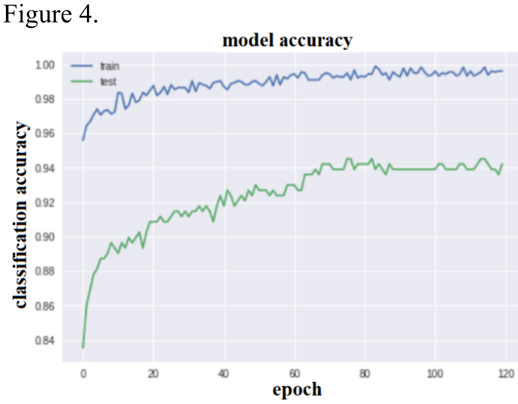

Figure 2. Accuracy Graphic for fine-tuned Inception-V4 model: 94% Test Accuracy

Inception-v4 model was applied to 10 epoch in pre-training phase. At the next training phase, 200 epochs were applied and 89% test accuracy was achieved. When we analyzed the validation results during the training of the Inception-V4 model, we noticed that the validation test results dropped after the seventh epoch in the pre-training phase. After this evaluation, in the next experiment, we decided to finish the pre-training phase in seven epochs and increase the subsequent training phase. Then, we set the training phase to 120 epoch and with this trial, we achieved 94% test accuracy. The results of the training with InceptionResnetV2 model 7 + 120 epoch were shown in Figure 2.

Figure 3. Accuracy Graphic for Densenet169: 95% Test Accuracy

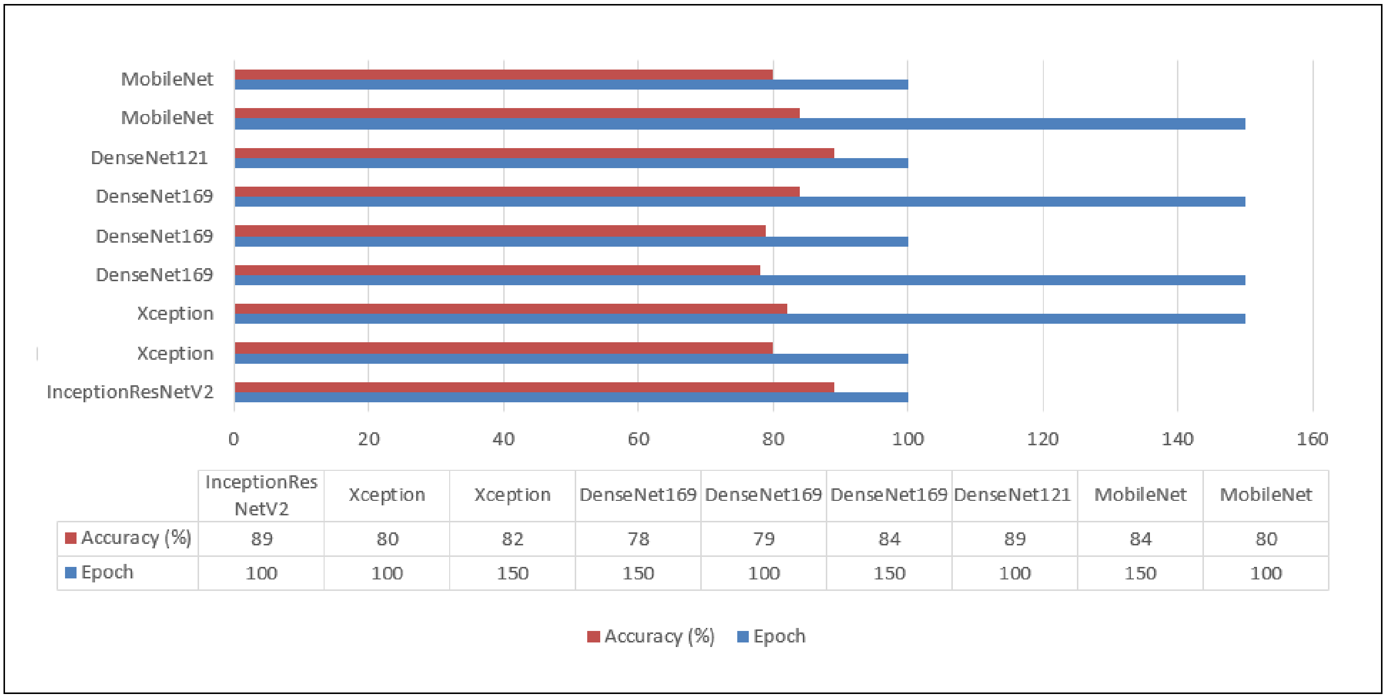

Figure 4. Comparison of Deep Learning Models

With these results, we applied the same experiment on DenseNet-169 Model. In this experimental result, we achieved a 95% of test accuracy with DenseNet-169 model. The result of the training with 7 + 120 epoch of DenseNet169 model were shown in Figure 3.

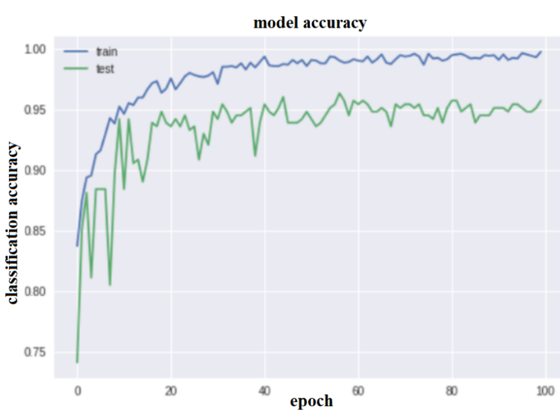

Figure 5. Accuracy Graphic for Densenet121: 95% Test Accuracy

In the experiment we performed with the Densenet121 model, we executed the training with 100 epochs after pre-training with 10 epochs. As a result, we achieved a 95% of test accuracy. The results of the training with DenseNet-121 10 + 100 epoch were shown in Figure 5 and the results of fine-tuned models were shown in Figure 6. By applying fine-tuning to the models, the best test results were obtained.

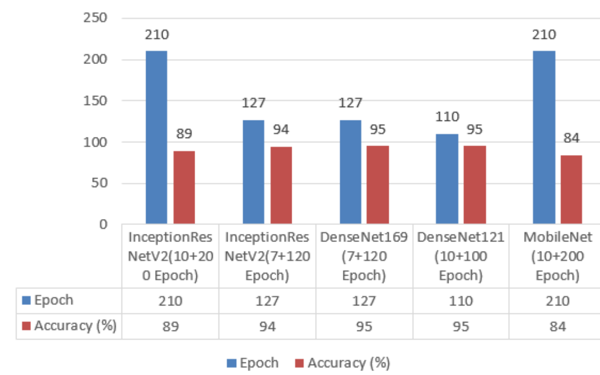

Figure 6. Test Accuracy Results of Fine Tuned Models

IV. Conclusion

In this study, the experiments were performed on known CNN models. As a result of these experiments, the applied deep learning models achieved more than 76% test accuracy. The Inception-ResNet-V2 model with 100 epochs achieved a 89% of test accuracy. Densenet-169 model with 150 epoch, we achieved a 84% of test accuracy. The highest test accuracy with MobileNet model is 84%, with 150 epochs. Fine-tuned model results were shown in Table II.

Table II. Fine Tuned Models Results

Model	Epoch	Test Accuracy
DenseNet121	10+100	95 %
DenseNet169	7+120	95 %
Inception-V4	10+200	89 %
Inception-V4	7+120	94 %
MobileNet	10+200	84 %

As a result, the most successful test accuracy rates were achieved with the fine-tuned Densenet-121 and Densenet-169 models. In the selection of the optimizer, Adam and Adadelta optimizers were tried with 100 epochs in InceptionResNetV2 model. As a result of this experiment, a higher test accuracy was obtained in the Adam optimizer. Thus, the Adam optimizer was used in all training sessions.

In the light of the conducted experiments, it can be said that deep learning algorithms can be used to classify recyclable waste. For this purpose, we performed some experiments on known deep learning models. However, the success rate in real-time systems can be low due to the relatively small amount of data and the white background of all the images. In the next study, size of the dataset will be increased to obtain more successful results. It will also aim to realize various improvements on the models.

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