Avrupa Bilim ve Teknoloji Dergisi
Özel Sayı 36, S. 73-77, Mayıs 2022

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
Special Issue 36, pp. 73-77, May 2022

Research Article

Garbage Classification Using Pre-Trained Models

Selim Sürücü[1*], İrem Nur Ecemiş[2]

[1*] Çankırı Karatekin University, Faculty of Engineering, Departmant of Computer Engineering, Çankırı, Turkey, (ORCID: 0000-0002-8754-3846), selimsurucu@karatekin.edu.tr

[2] Çankırı Karatekin University, Faculty of Engineering, Departmant of Computer Engineering, Çankırı Turkey, (ORCID: 0000-0001-9535-2209), iremnurecemis@karatekin.edu.tr

(1st International Conference on Engineering and Applied Natural Sciences ICEANS 2022, May 10-13, 2022)

(**DOI:** 10.31590/ejosat.1103628)

ATIF/REFERENCE: Surucu, S., Ecemiş, İ. N. (2022). Garbage Classification Using Pre-Trained Models. *European Journal of Science and Technology*, (36), 73-77.

Abstract

With the increase of urbanization, the garbage accumulated in the cities has become a big problem. While all of the accumulated garbage is classified as unnecessary, today, with the development of recycling technologies, most of the materials in the garbage are considered recyclable. Recycling recyclable materials in our daily lives is essential both for material development and for creating the life cycle of existence in the world in ecological terms. Different studies are carried out in almost every country to separate recyclable materials from the garbage. Being able to detect recyclable materials automatically with artificial intelligence will benefit from cost, human resources and time. This decomposition issue appears as a new field of study in the literature. This study aims to classify garbage by automatically using the transfer learning method. By using different transfer learning methods, it was seen that the Resnet50-V2 model showed a high success rate of 97.07% in the results.

Keywords: Garbage Classification, Pre-Trained Models, Image Classification

Önceden Eğitilmiş Modeller Kullanılarak Çöp Sınıflandırması

Öz

Şehirleşmenin artmasıyla birlikte şehirlerde biriken çöpler büyük bir sorun haline geldi. Birikmiş çöplerin tamamı gereksiz olarak sınıflandırılırken, günümüzde geri dönüşüm teknolojilerinin gelişmesiyle birlikte çöpün içindeki malzemelerin çoğu geri dönüştürülebilir olarak kabul edilmektedir. Geri dönüştürülebilir malzemelerin günlük hayatımızda geri dönüşümü hem malzeme gelişimi için hem de ekolojik anlamda dünyadaki varoluşun yaşam döngüsünü oluşturmak için elzemdir. Geri dönüştürülebilir malzemeleri çöpten ayırmak için hemen her ülkede farklı çalışmalar yapılmaktadır. Geri dönüştürülebilir malzemeleri yapay zeka ile otomatik olarak tespit edebilmek, maliyet, insan kaynağı ve zamandan fayda sağlayacaktır. Bu ayrıştırma konusu literatürde yeni bir çalışma alanı olarak karşımıza çıkmaktadır. Bu çalışma, transfer öğrenme yöntemini kullanarak çöpleri otomatik olarak sınıflandırmayı amaçlamaktadır. Farklı transfer öğrenme yöntemleri kullanılan bu çalışmada, Resnet50-V2 modelinin sonuçlarda %97,07 gibi yüksek bir başarı oranı gösterdiği görülmüştür.

Anahtar Kelimeler: Çöp Sınıflandırma, Pre-Trained Models, Görüntü Sınıflandırma

[*] Corresponding Author: selimsurucu@karatekin.edu.tr

1. Introduction

Many waste materials emerge as the residue of the products used in our daily lives. Some of the waste materials create toxic effects over the years and reach the human body differently and become harmful to human health. In order to reduce the harm of these products to health as much as possible, harm-reducing actions should be taken by gathering them together again. On the other hand, some waste materials can be reused in human life thanks to the different structures they contain. In the beginning, the products that could be offered for reuse were paper, glass, plastic, and metal. These and similar products should be separated from organic or non-recyclable waste.

In recent years, when urbanization and the use of cheap materials have increased, the recycling of waste products has been of great importance to reduce ecological damage. Therefore, many studies are carried out on computers to increase recycling. The first of these is the Automatic Garbage Classification System made by Rao et al [1]. In the system created here, ResNet-50 was chosen as the main algorithm, and changes were made to this algorithm to obtain better results by performing operations on this algorithm. Furthermore, an improved algorithm based on ResNet-50 is proposed. In this way, a neural network whose further improved activation function part gave higher results. As a result of the studies, almost 95% accuracy results were obtained with six types of garbage.

In another study [2], the VGG16 model defined and classified garbage. The OpenCV library was used to find and then select objects on the dataset in the study. Here, preprocessing was applied to 224x224 RGB images. Then, the operations continued by using different functions and adding layers to the network. As a result, a deep learning-based VGG16 convolutional neural network model is proposed. At the end of the study, the garbage was divided into four different groups hazardous garbage, kitchen waste, recyclable garbage, and others. As a result of the tests, it was seen that the accuracy rate of the system created was 75.6%, and it is thought that this result meets the daily needs for household garbage.

In another study [3], the MobileNet convolutional neural network model classified general garbage into six categories: metal, cardboard, glass, paper, plastic, and other garbage. With the model, the test accuracy rate was 87.2% with 500 training steps on a dataset with 2527 garbage images. Optimization and quantification were carried out in the model Android application development part. Confidence in the optimized model was higher than in the quantized model. The model was installed on the Samsung Galaxy S6 Edge+ mobile phone, and it was seen that high success was achieved in the test definitions made afterward.

2. Material and Method

2.1. Dataset

The dataset used for the study was taken from the Kaggle website [4], which is open-sourced to users. There are a total of 6 different classes in the dataset, which is publicly shared with the name "Garbage Classification". These classes are cardboard, glass, metal, paper, plastic, and garbage. There are 2527 different images in the dataset, 403 in the cardboard class, 501 in the glass class, 410 in the metal class, 594 in the paper class, 482 in the plastic class and 137 in the garbage class. It was an important point to use a clean dataset so that the garbage can be trained for pre-trained models in the work to be done, and this dataset was used to show the characteristics of each class and was deemed appropriate for our study. Dataset example is shown in Figure 1.

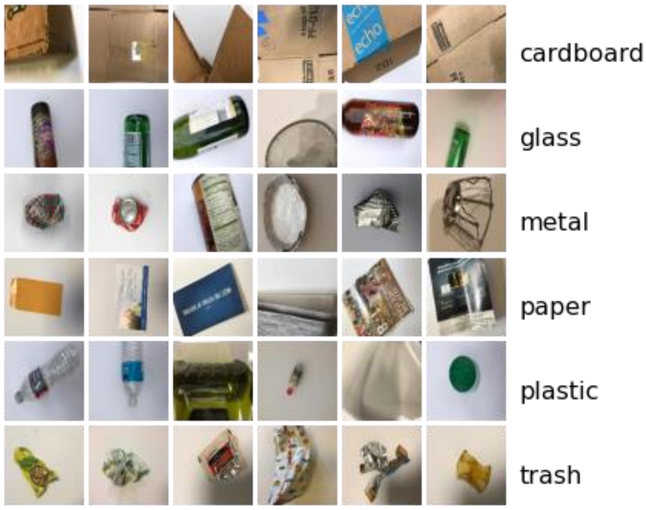

Fig. 1 Sample images from the dataset

2.2. Methodology

As a first step in the study, the dataset was divided into 5 different subsets using the K-fold cross-validation method. We thought that running the models on these subsets—one in each fold as test data and the remaining 4 as training data—would provide efficiency to the dataset. Thanks to this method, there would be no data in our dataset that the models used could not test as test data.

In the next step, we applied transfer learning models. Transfer learning is starting the learning process from a previously taught model for another problem rather than starting from scratch. The term pre-trained model is used in computer vision instead of the name transfer learning. It is seen that pre-trained models are used in many different areas, from disease detection [5] to the classification of plant leaves [6] in different sectors.

This study carried out training in 20 epochs, and 5 pre-trained models were used. Our first model is EfficientNetB7 [7]. The EfficientNetB7 is the latest released model among the Efficient models. The basic building block in EfficientNet models is the inverted bottleneck (MBConv). It combines computation with a separable convolutional structure compared to traditional layers, using shortcuts between bottlenecks that connect far fewer channels. For example, while EfficientNetB0 has around 10 million total parameters, EfficientNetB7 has around 23 million parameters.

Another model of ours is the Inception V3 model. This model consists of multiple convolutions (with 1x1,3x3,5x5 filters) and 3x3 maximum pooling steps [8]. Also, in the final stage, a fully connected layer was added. While the Inception V3 model does not allow the number of parameters to be high, it allows for the formation of deeper networks. An accuracy of 78.1% was obtained in the ImageNet dataset.

Our other model, NaSNet-Large, is a convolutional neural network trained on more than one million images, with input dimensions of 331x331 [9]. Despite achieving the most advanced result in the ImageNet competition, the computational power required is enormous.

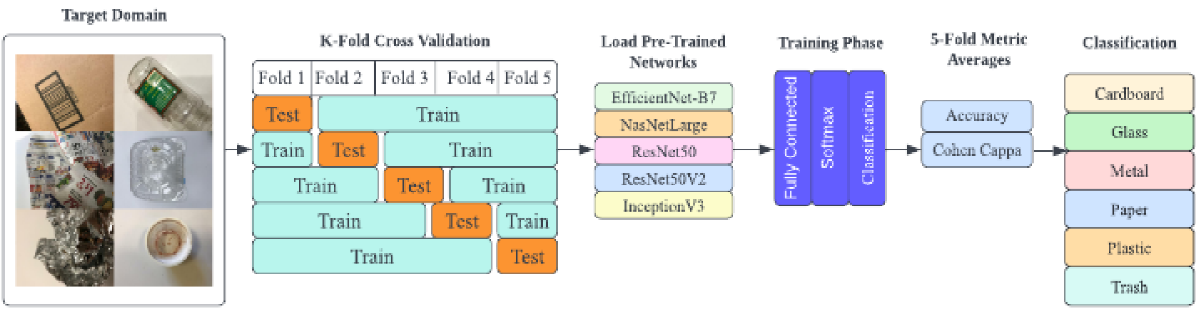

Fig. 2 Flow Chart

ResNet models are an acronym for residual neural networks that aim to solve the performance degradation problem of CNN networks. It is an advanced version of CNN models. It adds shortcuts between layers to solve the performance degradation problem. In this study, we used the ResNet50 and ResNet50-V2 models. The number 50 in the names represents the number of layers. The difference between the ResNet50-V2 model and the first version, the ResNet50 model, is weight layers in the pre-activation process instead of post-activation [10]. The output of the append operation between V2 identity mapping and residual mapping is passed to the block for further processing. However, in V1, the output of the addition operation is transferred to the next block after the ReLU activation.

A fully connected layer is added to the continuation of the pre-trained methods, and after this layer, a softmax layer with 6 has been added as processing is done on 6 classes. This layer constitutes our classification result. Two metrics were used to analyze the results. These metrics are Accuracy and Cohen Cappa.

Accuracy is obtained by dividing the correct predictions of a model by the entire dataset.

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Cohen Kappa is a metric that measures inter-interpretive reliability [11]. Calculation of Kappa;

$$K = \frac{p_0 - p_e}{1 - p_e}$$

- p_0 = relative agreement among those evaluated
- p_e = hypothetical probability of agreement

The result of 5 folds is summed and divided by 5 to find the average result for each metric.

3. Results

The first training results we obtained in our study can be seen in the accuracy and loss graphs shown in Figure 3-7. When these graphs are examined, it is seen that the best results are obtained in ResNet50-V2 and InceptionV3, and the worst results are obtained in EfficientNetB7. Confusion matrix results (Figure 8-12) are also given to show the pre-trained models' results in the classes' training process. When examining the confusion matrix, the numbers corresponding to the diagonals are expected to be the highest number in that row. High numbers on the diagonal mean that the result is good. In Figure 10 and Figure 11, it is seen that the numbers in the diagonals are high. When these two graphs are compared, it is seen that better results are obtained in InceptionV3 for the Trash class. When the confusion matrix results are examined, it is seen that it produces vertical results for 2 pre-trained models. This result means that it produces incorrect results for the 2 models.

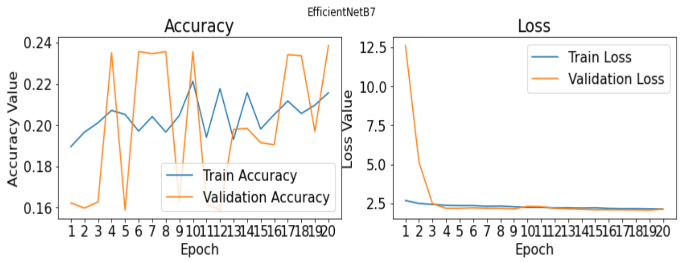

Fig. 3 *A*ccuracy and loss results of the EfficientB7

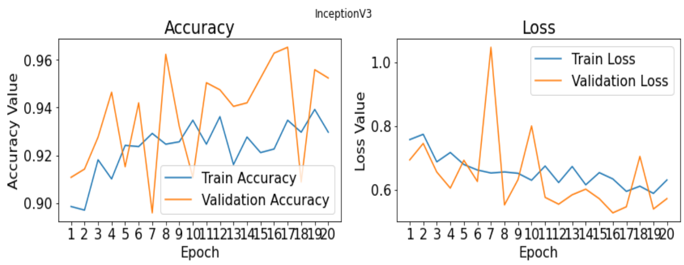

Fig. 4 Accuracy and loss results of the InceptionV3

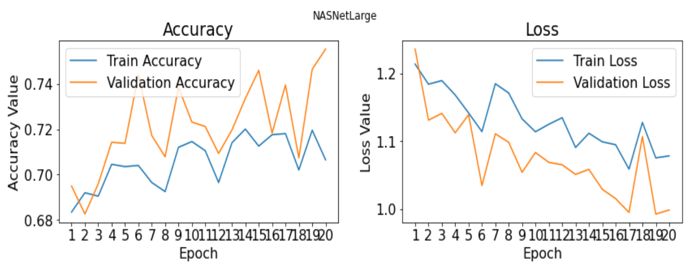

Fig. 5 Accuracy and loss results of the NasNet-Large

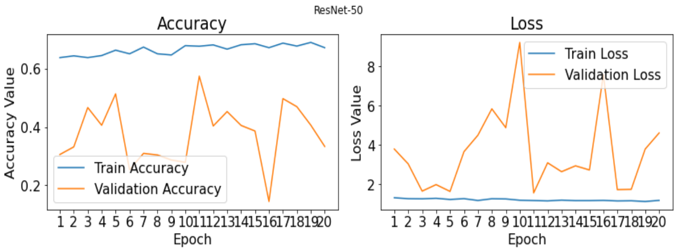

Fig. 6 Accuracy and loss results of the ResNet50

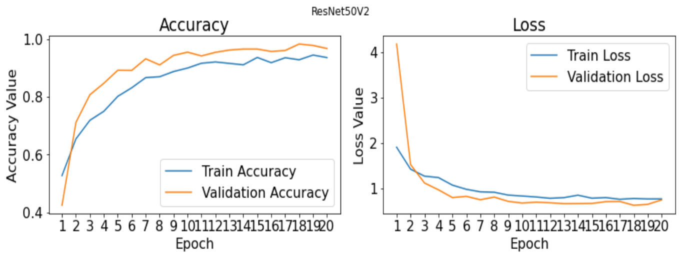

Fig. 7 Accuracy and loss results of the ResNet50-V2

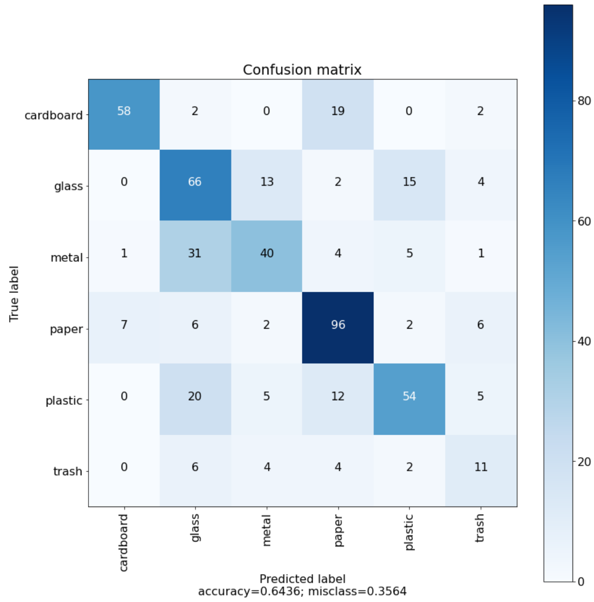

Fig. 10 Confusion matrix of NasNetLarge

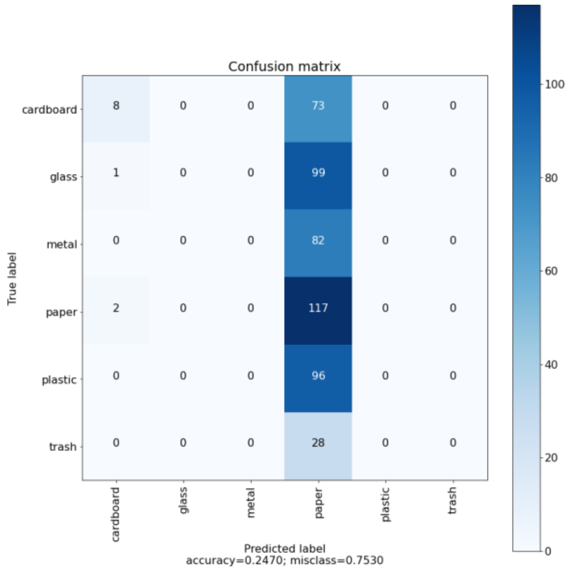

Fig. 8 Confusion matrix of EfficientNet-B7

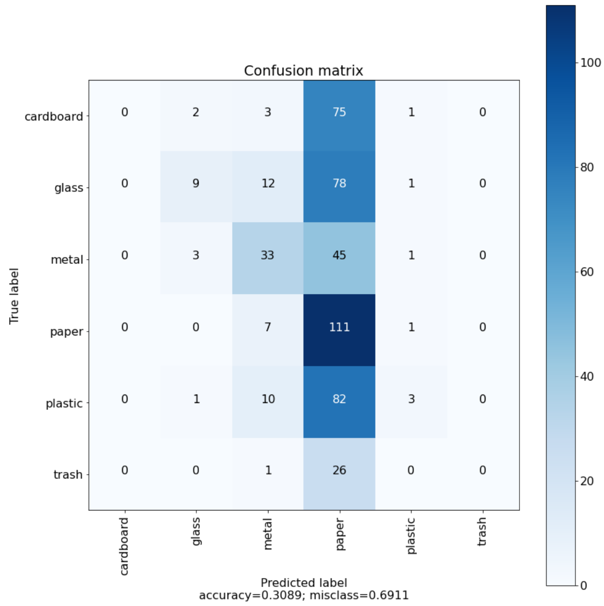

Fig. 11 Confusion matrix of ResNet50

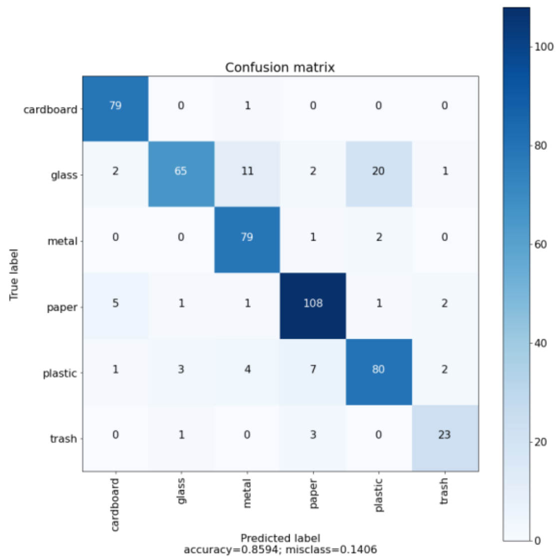

Fig. 9 Confusion matrix of Inception V3

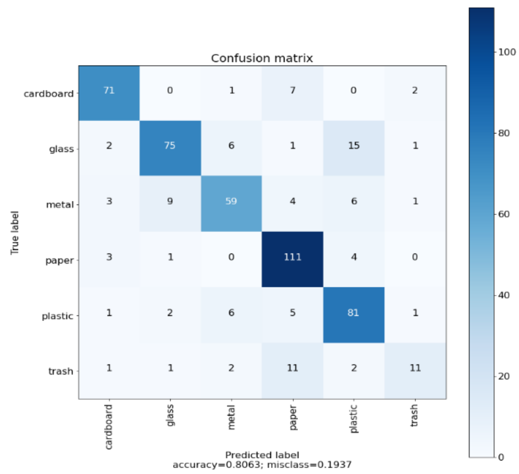

Fig. 12 Confusion matrix of ResNet50-V2

Table 1 shows the results from the test data. As the graphical results mentioned above show, this table shows that Inception-V3 and Resnet50-V2 produce good results. As the graphical results mentioned above show, this table shows that Inception-V3 and Resnet50-V2 produce good results. While ResNet50-V2 achieved an accuracy of 97.07%, the best result for Cohen Cappa was obtained with the InceptionV3 model.

Table 1. Test results of models

Method	Accuracy	Cohen Cappa
EfficientNetB7	0.2445	0.0176
InceptionV3	0.9469	0.8277
NASNet-Large	0.7376	0.5603
ResNet50	0.3348	0.1090

References

[1] M.V. Rao, K.N.V.R. Sekhar, B. Jayanth and K. Santosh." An Automatic Garbage Classification System" in *2021 JETIR*, 2021, vol. 8, pp.4-9.

[2] H. Wang, "Garbage Recognition and Classification System Based on Convolutional Neural Network VGG16," 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), 2020, pp. 252-255, doi: 10.1109/AEMCSE50948.2020.00061.

[3] S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios and E. J. Calilung, "Common Garbage Classification Using MobileNet," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), 2018, pp. 1-4, doi: 10.1109/HNICEM.2018.8666300.

[4] Dataset website. [Online]. Available: https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification

[5] H. H. Mohammed, S. Sürücü and R. Choupani, "Lung Inflammatory Classification of Diseases using X-ray Images," 2021 6th International Conference on Computer Science and Engineering (UBMK), 2021, pp. 548-553, doi: 10.1109/UBMK52708.2021.9558905.

[6] E. Kiliç, İ. N. Ecemiş and H. O. İlhan, "Narenciye Ağaç Yaprak Hastalıklarının Evrişimli Sinir Ağları ile Sınıflandırılması," 2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 2021, pp. 452-456, doi: 10.1109/ISMSIT52890.2021.9604631.

[7] M. Tan and Q. V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." *ArXiv* abs/1905.11946 (2019): n. pag.

[8] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2818-2826, doi: 10.1109/CVPR.2016.308.

[9] Z. Barret, V. Vasudevan, J. Shlens and Q. V. Le. "Learning Transferable Architectures for Scalable Image Recognition." *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition* (2018): 8697-8710.

[10] H. Kaiming, X. Zhang, S. Ren and J. Sun. "Deep Residual Learning for Image Recognition." *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2016): 770-778.

[11] J. Cohen. "A Coefficient of Agreement for Nominal Scales." Educational and Psychological Measurement 20, no. 1 (April 1960): 37–46. https://doi.org/10.1177/001316446002000104.