Plastics Classification

Karan Shah   
*Khoury School of Computer Science*  
*Northeastern University* Boston, MA  
[shah.karan3@northeastern.edu](mailto:shah.karan3@northeastern.edu)

*Abstract*— This project focuses on classifying plastics into four categories: heavy plastic, some plastic, no plastic, and no image. Transfer learning is employed with four computer vision models: Densenet121, Resnet18, Resnet34, and Resnet50. These models are modified to fit the specific classification task. For evaluation, a dataset comprising 2772 images of some plastic, 1375 images of no plastic, 601 images of no image, and 1965 images of heavy plastic is utilized.

**By leveraging transfer learning, pre-trained models are adapted to learn relevant features for plastic classification. Evaluation metrics such as accuracy, precision, recall used to assess performance. Results highlight the effectiveness of the approach in accurately categorizing plastics. Certain models demonstrate better performance, indicating their suitability for plastic classification tasks.**

**This research contributes to computer vision-based plastic classification, offering a practical solution for distinguishing plastic types. The outcomes have implications for waste management, recycling, and environmental sustainability efforts.**

Keywords—transfer learning, computer vision, precision-recall

1. INTRODUCTION

Plastic waste has become a significant environmental concern, and effective management and recycling strategies require accurate classification of different types of plastics. In this paper, we focus on the task of classifying plastics into four categories: heavy plastic, some plastic, no plastic, and no image. The ability to automatically categorize plastics can aid in waste sorting, recycling efforts, and overall environmental sustainability.

To accomplish this classification task, we employ transfer learning with four computer vision models: Densenet121, Resnet18, Resnet34, and Resnet50. Transfer learning allows us to leverage the knowledge gained from pre-trained models on large-scale image datasets and adapt them to our specific classification problem. The models are modified to output four probabilities representing the likelihood of different types of plastics.

The dataset used for evaluation consists of 2772 images of some plastic, 1375 images of no plastic, 601 images of no image, and 1965 images of heavy plastic. We perform data preprocessing, including resizing the images, applying normalization, and organizing the data into training, validation, and test sets.

To assess the performance of the models, we utilize evaluation metrics such as accuracy, precision, and recall. The results demonstrate the effectiveness of our approach in accurately categorizing plastics, with certain models exhibiting better performance than others.

This research contributes to the field of computer vision-based plastic classification and offers a practical solution for distinguishing different types of plastics. The outcomes of this study have significant implications for waste management, recycling practices, and environmental sustainability efforts.

# Related Work

Primarily, I wanted to test the pretrained models because they are state of the art. I wanted to compare the effect of a family of residual networks to a dense convolution neural network.

The paper by Kaiming He introduces the residual network architecture. This architecture addresses the degradation problem in DNN’s. The paper demonstrates the effectiveness of ResNet on various classification tasks achieving state of the art results on benchmark datasets. The architecture proposes skip connections which are used to learn residual mappings.

The paper by Gao Huang introduces DenseNet, a deep convolution neural network. DenseNet resolves the vanishing gradient problem by introducing denser connections between layers.

ResNet and DenseNet are both influential architectures in the field of deep learning, especially in computer vision. They have significantly advanced the performance of deep neural networks and have been widely adopted in various applications due to their ability to effectively capture complex patterns and features in images. Therefore, I wanted to apply transfer learning of these models on classifying plastics.

# Methods

The dataset that was used was The Plastics Classification dataset which consists of 2772 images of some plastic, 1375 images of no plastic, 601 images of no image, and 1965 images of heavy plastic. After I performed data wrangling by creating a script to organize the data into train, validation and test folders. The proportion of data in the folders is 70%, 20%, and 10%, respectively. For preprocessing, random horizontal flips are performed. For all the remainder of data, the images are resized to 128 x 128. Normalization is applied, setting the mean to 0.5 and the standard deviation to 0.5 for all three color channels. Next, model selection consists of the following pre-trained models: ResNet18, ResNet34, ResNet50, and DenseNet121. These models have been trained on 'IMAGENET1K\_V1', an image dataset organized according to the WordNet hierarchy. The weights of the network are frozen, and the final fully connected layer is modified to output four probabilities representing the likelihood of different types of plastic. The learning rate, momentum, and gamma parameters are set to 0.0002, 0.9, and 0.1 respectively. A step learning rate decay strategy is employed, reducing the learning rate by a factor of 0.1 (gamma) every 7 epochs. The models are trained using cross-entropy loss for 25 epochs and then evaluated on the 20% validation data. Finally, models are evaluated on 20% validation data, and the model with the highest accuracy is selected. This selected model is further tested on the 10% test data to evaluate its overall performance. The described methodology encompasses data preparation, model selection, modification, training, and evaluation, aiming to achieve accurate plastic classification.

1. A picture containing text, diagram, plot, line

   Description automatically generatedExperiments and Results
2. Training and Validation Losses for Transfer Learning Models

A picture containing diagram, line, text, plot

Description automatically generatedAfter the models are trained on 70% of the training data, they are evaluated on 20% validation data. Figure 1 presents the loss values for training and validation over 25 epochs. From top left to right, the losses are for the Densenet121, Resnet18, Resnet34, and Resnet50 models, respectively. Based on the losses, the Densenet121 seems more unstable (less responsive) as the other models since the validation loss is higher than training loss. On the other hand, the ResNet50 model seems to perform the best as the validation loss is consistently, lower and following the train loss.

1. Precision-Recall Curve per Class

To evaluate the different models’ performance, a within class precision-recall curve is generated. The curve is a graphical representation that illustrates the trade off between precision and recall. Precision is the ratio of true positives to the sum of true positives and false positives while recall is the ratio of true positives to the sum of true positives and false negatives. The “best place” in the precision recall curve is (1,1). For classifying no images, the ResNet50 models performs much better than the other models whereas for the classes, some plastic, and heavy plastic, the ResNet50 performs just marginally better. For no plastic images, the different models’ PR curves overlap to a large extent with the ResNet50 once again being marginally better.

After evaluating the model using the plots from Figures 1 and 2 along with best validation accuracy, the ResNet50 is the best model. This model is then tested on 10% of the remaining data resulting in an classification accuracy of 61.87%. Figures 3 and 4 present the classification results of the ResNet50 and DenseNet121 on 8 test images. Figure 3 and Figure 4 shows the distinction between the ResNet50 and DenseNet121 particulary when classifying image 5 (green image). The ResNet is able to correctly classify image 5 as heavy plastic whereas the DenseNet121 fails to classify it as heavy plastic.

For future experimentation, I would apply a Deep Convolution Generative Adversarial Network (DCGAN) to synthetically generate more data for each of the classes. With larger amount of data for each of the classes, the models would be able to train more and therefore have better test results. However, due to compute and time constraints, this would be an area I would explore during further experimentation.

A picture containing text, food, screenshot, soft drink

Description automatically generated

1. ResNet results on 8 test images.
2. DenseNet 121 A picture containing text, food, soft drink

   Description automatically generatedresults on 8 test images.
3. References
4. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. doi:10.1109/cvpr.2016.90
5. Huang, Gao et al. “Densely Connected Convolutional Networks.” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): 2261-2269