Enhancing Plastic Recycling through Machine Learning and Computer Vision: A Case Study on Plastic Bottles

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Abstract

Enhancing recycling efficiency remains a challenge due to many contemporary innovations' cost and organizational constraints. Conventional methods of plastic categorization are not scalable for plastic recycling due to extreme costs for multiple sets of hardware, such as different types of sensors. However, in this project, I propose a new method of classifying plastic based on computer vision. As a case study, I decided to focus on creating a model for identifying different kinds of plastic in plastic bottles. I used this model to increase accuracy of identifying and classifying different kinds of bottles, such as clear and blue plastic bottles, and was able to find that with a neural network, the model could classify the bottle at a high rate compared to the baseline. The results of my study show the potential of this technology in context of economically sustainable recycling. My model displays an ability to distinguish between different types of bottles, surpassing my baseline by a significant margin of 58.83%. This improvement in accuracy has large implications for improving recycling efficiency and plastic waste management. These findings highlight the potential of integrating machine learning with computer vision for cost-effective and efficient recycling methods.

1 Introduction

As the accumulation of plastic in our ecosphere persists, efforts have increasingly shifted towards recycling rather than producing new plastic. However, this approach is fraught with challenges. One major issue is the sheer variety of plastics, making categorization and sorting a complex task [Sul]. This complexity, coupled with the enormous volume of plastic produced, makes the recycling process highly problematic and difficult to manage effectively. Consequently, a significant portion of plastic intended for recycling ends up in landfills, as illustrated by Figure 1.

In this project, I propose an alternate method of classifying plastics by using machine learning algorithms and computer vision. I am motivated by the fact

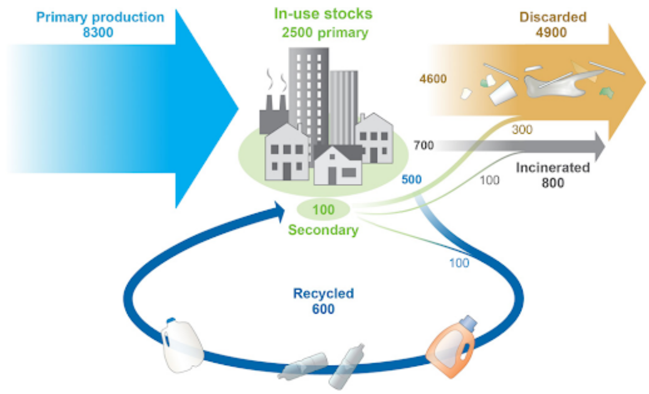

Figure 1: Global production, use, and fate of polymer resins, synthetic fibers, and additives (1950 to 2015; in million metric tons). [GJL17]

that even though I believe that recycling helps the environment, the rates of recycling still fall short compared to what I need to make a difference. My hypothesis is that using a neural network for a machine learning algorithm would result in an algorithm that would be able to classify plastics based on how they look. To test this hypothesis, I applied the example first to plastic bottles, one of the most used forms of plastic [OSM]. By using computer vision, I was able to test out my hypothesis on a sample dataset from Kaggle. My procedure started with inputting and rescaling the images I got from my dataset, and after that, splitting them into a validation and training dataset. After that, I continued by putting them through a neural network, and then measuring the performance of the network.

2 Related Works

In this section, I examine research in the area of waste management, with a particular focus on addressing issues related to efficiency.

A project on AI usage in waste management, authored by Praveen Kumar Gupta, Vidhya Shree, Lingayya Hiremath & Sindhu Rajendran [GSHR70], takes a broader perspective on the issues surrounding waste management. It highlights the importance of advanced technologies, especially machine learning and artificial intelligence (AI), in addressing the many challenges associated with waste management. The paper highlights the increasing need for intelligent waste management systems, particularly in urban environments struggling with population growth and environmental concerns. By harnessing the power of machine learning and AI, this research proposes strategies to optimize waste collection, sorting, and recycling processes. Such optimization not only has the potential to bring down environmental pollution but also improve the overall efficiency of waste management practices.

Another project about general waste management, by Bingbing Fang, Jiacheng Yu, Zhonghao Chen, Ahmed I. Osman, Mohamed Farghali, Ikko Ihara, Essam H. Hamza, David W. Rooney, and Pow-Seng Yap [FYC+23], extends the discussion to a broader spectrum of waste management. This comprehensive review examines the application of artificial intelligence across various aspects of waste management, including waste-to-energy, smart bins, waste-sorting robots, waste generation models, waste monitoring and tracking, plastic pyrolysis, logistics, disposal, resource recovery, and more.

The project demonstrates how artificial intelligence can reduce transportation distance, cost, and time in waste logistics while improving accuracy in waste identification and sorting. Furthermore, it explains how AI-enhanced chemical analysis improves waste pyrolysis, carbon emission estimation, and energy conversion. The paper highlights how artificial intelligence can improve efficiency, reduce costs, and contribute to smart waste management systems in the context of smart cities.

To sum up, these two research papers collectively emphasize the potential of artificial intelligence in addressing waste management challenges, from enhancing efficiency and cost savings to improving environmental sustainability and public health in modern waste ecosystems.

While the two papers discuss how to address waste and plastic management, some solutions that are being implemented are too costly for a majority of government run waste plants. A lot of waste plants do not have the money for expensive equipment, such as sensors on every trash can and package. However, a camera-based system is much cheaper to implement than an array of sensors, due to the fact that there only needs to be at least one camera at the processing site for categorization. This system would also be smaller and easier to implement than a lot of other systems, as it only needs to be one more step in processing. By adding cameras and computer vision, waste management plants can get an easy to implement and cost-effective solution to categorizing recyclables.

3 Data

The WaRP dataset [PWY+] used in this research originates from a recycling plant and is comprised of images depicting various recyclable bottles made from different plastics. This dataset was specifically curated to facilitate research and analysis in the field of waste management, recycling, and computer vision. The data was collected with a camera with different image sizes and formats.

3.1 Data Labels

Moreover, the data is organized into 20 sub-categories for the different types of bottles that are given in the dataset. Each subsection contains over 600 images for each type of bottle. See figure 2 for a couple sample categorizations.

3.2 Data Preprocessing

The dataset underwent a couple preprocessing steps to ensure uniformity and quality. These steps included rescaling the images to make sure that they match the same size, and feeding the image into the model, which then transforms the image into a vector after using max-pooling to focus the model. The preprocessing was applied consistently to all subsets to avoid bias.

3.3 Data Split

To facilitate the training of the machine learning model, the dataset is divided into two subsets: a training set and a validation set. The split ratio is 80% training and 20% validation, ensuring that models can be trained on a substantial portion of the data while having separate sets for model validation and evaluation.

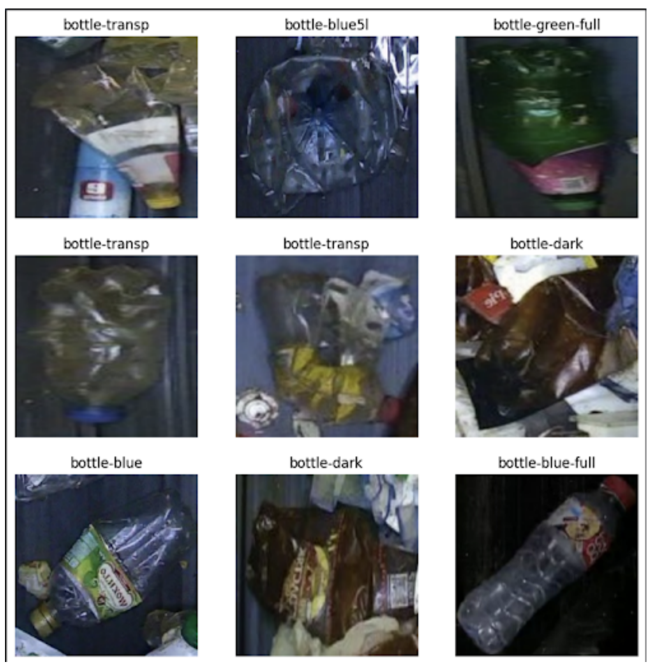

Figure 2: Sample of different images from the WaRP Dataset

4 Experiment Setup

In this section, I outline the experimental setup for my machine learning research, using a sequential model with 8 layers to classify bottles into 20 separate categories and focusing on the accuracy of the model. The following subsections describe the dataset, preprocessing steps, model architecture, and evaluation metrics used in this study.

4.1 Model Architecture

The chosen machine learning algorithm for this task is a convolutional neural network, implemented using the TensorFlow Keras libraries. The model architecture consists of 8 layers: a rescaling layer, a convolutional layer, a max pooling layer, a second convolutional layer, a second max pooling layer, a flattening layer that transforms the layer into a vector, and two dense layers. See figure 3 for a complete figure of the model. The model was trained using the Adam optimizer, with a batch size of 5868 images and 24 epochs.

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 32)	0
flatten (Flatten)	(None, 59168)	0
dense (Dense)	(None, 128)	7573632
dense_1 (Dense)	(None, 20)	2580

Total params: 7586356 (28.94 MB)
Trainable params: 7586356 (28.94 MB)
Non-trainable params: 0 (0.00 Byte)

Figure 3: Model Network Diagram

4.2 Evaluation Metrics

To assess the performance of the model, I used the accuracy on the validation set. The accuracy was selected as the appropriate metric due to the use of the validation set in determining overfitting and early stopping. This metric was therefore selected to evaluate the model's ability to classify different types of recyclable bottles.

5 Results and Analysis

This section presents the results obtained from my experiments and provides an analysis of these findings.

5.1 Model Performance

In assessing the performance of my model, I conducted a thorough evaluation of the performance on the validation dataset to gauge its capabilities in recognizing different bottles.

On the training dataset, my model exhibited a great ability to analyze the patterns found within the data. With a training score of 97.68%, and a validation score of 62.9%, the model seems capable of making good predictions, especially considering that random chance, in 20 categories, would be 5%. Running against a different simple random baseline model, the accuracy of the predictions stays flat at 4.07%. For more information about my simple model, consult figure 4. With a difference of 58.83%, these results on the datasets demonstrate the capabilities of my model in determining different kinds of bottles. Figure 5 shows the accuracy of the model as the number of epochs rises.

```
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_4 (Rescaling)     (None, 180, 180, 3)       0

 flatten_1 (Flatten)         (None, 97200)             0

 dense_3 (Dense)             (None, 128)               12441728

 dense_4 (Dense)             (None, 20)                2580

=================================================================
Total params: 12444308 (47.47 MB)
Trainable params: 12444308 (47.47 MB)
Non-trainable params: 0 (0.00 Byte)
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Figure 4: Baseline Model Network Diagram

5.2 Analysis

Upon reviewing the results, one key observation emerges. I note that increases in accuracy start to slow down and decline after 18 epochs, so I stop training here. This observation provides valuable insights into the limitations of my model, as after 18 epochs, we cannot extend my current model further.

However, I notice that my model has a significantly higher accuracy than random choice. Since there are 20 different variables, random choice would give us around a 5% chance, however, the model has around a 65% chance to select the correct object. This substantial improvement in accuracy highlights the

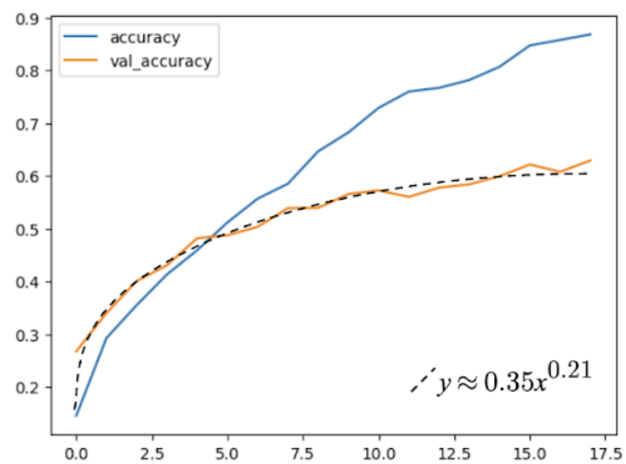

Figure 5: Graph of Epochs (x) versus Accuracy (y)

potential of my approach, with large, cost-effective applications in the recycling industry.

6 Conclusion

In summary, this project has explored the application of machine learning and computer vision in addressing the complexities associated with plastic recycling. The delicate problem of managing plastic waste is compounded by the massive array of plastic materials, which has made traditional sorting methods less effective, causing a significant portion of plastics to end up in landfills [Uni].

My approach employs a neural network within a machine learning framework, and has demonstrated promise with plastic classification. Through experimentation, particularly focusing on plastic bottles, I have shown that machine learning algorithms, driven by visual cues, can progress in plastic categorization.

The results of my study show the potential of this technology in practical contexts. My model demonstrates an ability to distinguish between different types of bottles, surpassing random selection and my baseline by a significant margin of 58.83%. This improvement in accuracy has large implications for improving recycling efficiency and changing plastic waste management. Further implications of this research may change the landscape of different plastic recycling not only in bottles, but in other plastic products. My research shows how a combination of machine learning and computer vision could change the avenue of recycling with increased efficiency and lower cost while protecting the environment.

7 Code

Project Github: https://github.com/rachit-j/recycling-project

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