JOURNAL OF
EMERGING INVESTIGATORS

Article

Class distinctions in automated domestic waste classification with a convolutional neural network

Atharv Goel[1], Bibit Bianchini[2]
[1] The Harker School, Saratoga, California
[2] GRASP Laboratory, University of Pennsylvania, Philadelphia, Pennsylvania

SUMMARY

Over the last two decades, there has been little improvement in recycling practices. However, there have been increasing efforts to address this issue with neural networks, specifically in the waste classification task. Currently, the recycling process is dependent on people sorting waste into a set of categories that can feed into recycling centers where the bulk of the recycling process occurs. By using neural networks to sort waste instead of human judgement, any issues with human subjectiveness or lack of knowledge can be circumvented. Most research to date has focused on the varying levels of success of different algorithms in sorting recyclables. However, the importance of the dataset itself has largely been ignored. Many datasets used in waste classification research have classes that do not sort the data efficiently. The goal of this study was to develop a comprehensive dataset and explore how different classification schemes affect accuracy. We hypothesized that adding more classes would improve the accuracy of the model. We generated five models for each of the four different types of classification schemes we used. Additionally, we ran half of the same models on TrashNet, another waste classification dataset. We concluded there is a high likelihood that there exists no correlation between the classification schemes and the resulting accuracies for the waste classification task.

INTRODUCTION

From 1985 to 2005, the recycling rate in the US tripled as awareness grew and the first recycling programs were implemented (1). However, after 2005, that rate began to plateau, increasing an average of only 0.3% annually for the next 12 years (1). Despite the low statistics, the Environmental Protection Agency (EPA) has established a goal of recycling 50% of total recyclables by 2030 (2). Recyclables are items that can be used again, while trash refers to items that can only be disposed. To reach the goal, the EPA created a plan known as the "National Recycling Strategy", which they planned on implementing starting 2021, but all their objectives currently remain under the status of "Not Started" (3, 4).

The low recycling rate in the US can be attributed to three main issues. The first is a lack of accurate information on recycling. Approximately 7% of the US population already does not believe that recycling has any significant environmental impacts (5). On top of this, companies, especially big oil and gas corporations, present plastic as an essential and easily recyclable material through well-funded public campaigns. These campaigns often overlook that most plastics still end up in the landfill, as recycled plastic would be detrimental to the companies' manufacturing industries (6). On the other hand, overenthusiastic environmentalists will sometimes misclassify garbage as recyclable in a process referred to as "aspirational recycling" (7). This group of people, while understanding the importance of recycling, unintentionally subvert recycling efforts because of their lack of accurate information.

The second problem is inconvenience. Making the effort to sort between recyclables and trash takes time and energy that people may be too busy to dedicate, even if they understand its importance (5, 8). Curbside recycling programs are automatically provided to an estimated 50% of households in the US, yet only an estimated 70% of people who have access take advantage of the services (9). For the 50% of people who do not have access to automatic curbside pickup services, their only other significant alternative are drop-off services (9). However, instead of dropping off their trash, recyclables, compost, electronics, and other Municipal Solid Waste (MSW) at different centers, it is individually efficient for people to simply throw everything into the trash.

The last problem with recycling is the ambiguity of waste (5). Besides some specific categories of MSW, like aluminum cans, over 60% of people are unaware or unsure of which bin many items belong in (7, 8). Additionally, depending on location within the country, what is considered recyclable may differ based on what processing centers that region offers (10). At that point, people would have to spend significant time searching for answers on the internet, which feeds back into the inconvenience problem.

One solution that may circumvent most of these issues is automated waste sorting. Instead of a person having to do the work of sorting their waste, a machine could reliably do it. This kind of system does exist in some mixed waste processing facilities. These are centers that sort waste through some combination of manual or mechanical processes. However, they also require more funding to cover the operating costs, and recyclables also have a much higher chance of getting contaminated due to long periods of close contact with trash (11). An automated and accessible sorting system that targets at the source, for use in homes, schools, or offices, would both minimize contamination and help distribute costs amongst consumers.

Machine learning-based neural networks are a popular method to do classification tasks. These networks learn by training on a set of inputs and outputs (a dataset) to construct a model that can predict outputs of new inputs. There are many implementations of neural networks, and they can

https://doi.org/10.59720/24-245

reach higher or lower accuracies depending on the input data, desired speed, and other constraints. We chose a convolutional neural network (CNN) because they historically have a higher accuracy rate at classifying image data than other types of neural networks (12). CNNs are adept at capturing and preserving spatial dependencies in data, making them ideal for processing grid-like data that images contain. These outputs are referred to as classes.

Currently, several attempts have already been made to use CNNs for waste classification. These attempts focus on using different algorithmic techniques to try and improve the accuracy. For example, many have attempted using transfer learning, which is when a network that had already been trained on one task is then swapped to a new task, minimizing the number of parameters that must be fine-tuned (13). It has had varying results, but many have started reaching accuracies above 85-90% when transferring specific networks like DenseNet (14-18). Transfer learning has also proven suitable for related tasks such as classification of construction or disaster waste (19, 20).

An alternative factor that has yet to be focused on is the effect of the dataset. The learning process of the network is heavily dependent on the training dataset, so dataset changes can cause major changes in resulting accuracy. TrashNet was one of the first datasets made for waste classification, with the following classes: cardboard, glass, metal, paper, plastic, and trash (21). Notably, while the first five classes, which are all recyclables, have around 400 images each, the trash class has less than half of that (21). That means neural networks may choose to prioritize the recyclable classes, which contribute to higher weight over the trash class, to achieve the highest possible accuracy even if that means identifying trash as recyclable. Misclassifying trash can have much greater real-world consequences, though, because recyclables in close proximity to trash can become contaminated. In other words, putting trash in a recycling bin can convert all the true recyclables into more trash (22). Unfortunately, since TrashNet was one of the first datasets created for this waste classification issue, much of the research is based on it. There are other alternative datasets that have been used, but their categorizations often seem arbitrary and/or exclusive. For example, the Home Garbage Classification Dataset separates green glass, brown glass, and white glass as three out of twelve categories, while its trash category is made up almost exclusively of toothbrushes, masks, and diapers (23).

As such, we decided to focus on the effects of different classifications of the dataset in the waste classification task. Prior research indicates that differentiating data points into more classes can have both a positive and negative effect on the resulting accuracy (24). This is because weak, yet significant, features might remain hidden in coarse classification but become prominent in finer classification (24). If these features exist, the accuracy may increase. If these features do not exist or if the model cannot identify them while training, then the model may be unable to distinguish between the finer classes, decreasing the accuracy. In the context of waste classification, the broadest classes can be defined as recyclables and trash (ignoring organic waste). As mentioned earlier, the distinction between these two classes is critical because trash can contaminate recyclables. The major subcategories of recyclables are defined well by TrashNet: cardboard, glass, metal, paper, and (recyclable) plastic (18). These categories cover all the common recyclables that the EPA lists, excluding organic waste and items that must be specially recycled like electronics (25). Defining subcategories for trash is more difficult, and most garbage datasets keep trash as a singular class without breaking it down. For this paper, we define the subcategories of trash as: broken glass, (non-recyclable) plastic, food wrappers, soiled paper/cardboard, chemically treated wood, and soiled fabrics/textiles. These subcategories are based on the end products of commonly recyclable materials as well as other significant waste categories identified by the EPA (1). This list is not meant to be truly comprehensive, but it does represent some of the common types of trash within the United States.

For this paper, we investigate how these different classifications affect the accuracy of the waste classification. In order to be a constant standard, accuracy will simply refer to distinctions between recyclable and trash. Thus, even if an image of cardboard is misclassified as paper, it will still be considered valid. This lines up with the EPA's primary classification of recyclable versus trash (ignoring organic waste that must be composted). In this paper, we will compare four different classification schemes and compare accuracies. The schemes that we test will be recyclable vs. trash, subcategories of recyclable vs. trash, recyclable vs. subcategories of trash, subcategories of recyclable vs. subcategories of trash (**Table 1**). We hypothesize that finer classification of the dataset, i.e. adding more classes, will improve the accuracy of the model. This is because each of the subcategories of recyclable and trash are visually different to a human and these significant visual distinctions may be features that the model will learn to distinguish.

RESULTS

In the data collection stage, we collected 30 pictures for each class, splitting them 17% for testing and 83% for training. After training, we employed the models in two experiments.
In the first experiments, we compared all four classification schemes on the 55-image testing dataset. To accomplish this, we ran all 20 models on our testing dataset and compiled their results with respect to the corresponding classification to which they belonged. The average results for each of the four different classifications are in confusion matrices (**Tables 2-5**). The columns represent the number of images from the dataset that belong to each category. These were the images that were fed into the models to test their performance. The

Scheme 1	Scheme 2	Scheme 3	Scheme 4
Recyclable	Cardboard	Recyclable	Cardboard
	Glass		Glass
	Metal		Metal
	Paper		Paper
	Plastic		Plastic
Trash	Trash	Broken Glass	Broken Glass
		Nonrecyclable Plastic	Nonrecyclable Plastic
		Soiled Paper	Soiled Paper
		Soiled Fabric	Soiled Fabric
		Food Wrappers	Food Wrappers
		Wood	Wood

Table 1: Classification schemes. Each column represents one of the classification schemes being tested. Blue indicates recyclable categories, and yellow indicates trash categories.

https://doi.org/10.59720/24-245

		True	
		Recyclable	Trash
Predicted	Recyclable	22	3
	Trash	3	27

Table 2: Averaged results for recyclable/trash models. Confusion matrix detailing the average number of images for each column's category classified as the row's category by the models with the classifications scheme recyclable/trash. Color coding: blue indicates a correct subcategory match (target score is 5) and yellow indicates no match (target score is 0).

rows are the models' prediction of what class the image belongs to. To reflect this, we implemented a color coding: blue signifies a perfect classification (e.g. classifying cardboard as cardboard), white signifies a subcategory misclassification where the coarse category is still correct (e.g. classifying cardboard as paper since they are both recyclable), and yellow signifies a complete misclassification (e.g. classifying cardboard as soiled paper since the latter belongs to the trash coarse category).

We computed the accuracies by dividing the number of correct coarse category classifications (color coded green and yellow in the confusion matrices) by the total number of classifications (**Table 6**). Seventeen of the accuracies fell within a range of 85% to 90%, while the last three fell in the range of 90% to 95%. We used a one-way ANOVA on these accuracies to obtain a *p*-value of 0.6366, indicating any differences caused by changing the classifications did not statistically significantly affect accuracy.

In the second experiment, we compared the recyclable/trash models and the cardboard/glass/metal/paper/plastic/trash models with TrashNet. The other classification schemes required the subcategorization of the trash category, but this was not possible due to the limited number of subcategories of trash images in TrashNet. All the accuracies fell in the

		Cardboard	Glass	Metal	Paper	Plastic	Trash
Predicted	Cardboard	4.4	0	0	0.6	0	2
	Glass	0	2.8	0	0	0	0.2
	Metal	0.2	1.4	2.8	0.4	0	0
	Paper	0	0	0	3	0	0.2
	Plastic	0.4	0.6	0.2	0	4	0.4
	Trash	0	0.2	2	1	1	27.2

Table 3: Averaged results for sub-categorized recyclable/trash models. Confusion matrix detailing the average number of images for each column's category classified as the row's category by the models with the classifications scheme cardboard/glass/metal/paper/plastic/trash. Color coding: blue indicates a correct subcategory match (target score is 5), white indicates a correct coarse category match (target score is 0), and yellow indicates no match (target score is 0).

https://doi.org/10.59720/24-245

		True						
Predicted		Broken Glass	Non-recyclable Plastic	Soiled Paper	Soiled Fabric	Food Wrappers	Wood	Recyclable
	Broken Glass	4.4	0	0	0	0	0	0
	Non-recyclable Plastic	0	4.2	0	0.4	0.4	0	0
	Soiled Paper	0	0	3.6	0.6	0	0	0
	Soiled Fabric	0	0	0	3.8	0	0	1.4
	Food Wrappers	0	0	0	0	4.6	0.6	0.4
	Wood	0	0	0	0	0	3.4	0.6
	Recyclables	0.6	0.8	1.4	0.2	0	1	22.6

Table 4: Averaged results for recyclable/sub-categorized trash models. Confusion matrix detailing the average number of images for each column's category classified as the row's category by the models with the classifications scheme broken glass/nonrecyclable plastic/soiled paper/soiled fabric/food wrappers/wood/recyclable. Color coding: blue indicates a correct subcategory match (target score is 5), white indicates a correct coarse category match (target score is 0), and yellow indicates no match (target score is 0).

range of 70-80%, and a one-way ANOVA calculated a non-significant *p*-value of 0.1622 (**Table 7**). Even though the accuracies were around 10% lower compared to the results from the first test, the *p*-value still suggests that there was no significant difference between the different classification schemes.

Overall, our results indicate that while different classification schemes yielded slightly varying accuracies, these differences were not statistically significant.

DISCUSSION

For a waste classification model, achieving the best results means understanding the algorithms, data, and training parameters that must appeal to recycling centers where the primary process of recycling takes place. While we decided to focus on just distinguishing between simply recycling and trash, there has been a growing movement towards multi-stream recycling, where different categories of recyclables are kept separate to facilitate sorting and improve efficiency. Especially as recycling processes and infrastructure continue to develop, digitalized neural networks can quickly adapt to evolving requirements.

We hypothesized that classifying a trash dataset more finely would improve its accuracy because the model would learn based on the material and visual differences of each class. This mimics a human's own classification process, where we determine a piece of waste's component materials, structure, and contaminations along with our own background knowledge to determine a corresponding course of action. However, there was not a statistically significant difference (0.6366 *p*-value exceeds the 0.05 significance threshold) between the three groups with different numbers of classes, which does not support our hypothesis. In other words, for the waste classification task of separating recyclables and trash, this experiment suggested that it does not matter how coarse or fine classification is.

https://doi.org/10.59720/24-245

		True										
		Cardboard	Glass	Metal	Paper	Plastic	Broken Glass	Non-recyclable Plastic	Soiled Paper	Soiled Fabric	Food Wrappers	Wood
Predicted	Cardboard	4.4	0	0	0.6	0	0	0	1.4	0	0	1
	Glass	0	2.6	0	0	0	0.4	0.6	0	0	0	0
	Metal	0.2	1.6	4.4	0.4	0.2	0	0	0	0	0	0
	Paper	0	0	0	3	0	0	0	0	0.6	0	0
	Plastic	0.4	0.8	0	0	3.8	0	0.6	0	0	0	0
	Broken Glass	0	0	0	0	0	4.6	0	0	0	0	0
	Non-recyclable Plastic	0	0	0	0	0	0	3.8	0	0	1.2	0
	Soiled Paper	0	0	0	0	0	0	0	3.6	1	0	0
	Soiled Fabric	0	0	0.2	1	0	0	0	0	3.4	0	0
	Food Wrappers	0	0	0.2	0	0.6	0	0	0	0	3.8	1
	Wood	0	0	0.2	0	0.4	0	0	0	0	0	3

Table 5: Averaged results for sub-categorized recyclable/sub-categorized trash models. Confusion matrix detailing the average number of images for each column's category classified as the row's category by the models with the classifications scheme cardboard/glass/metal/paper/plastic/broken glass/nonrecyclable plastic/soiled paper/soiled fabric/food wrappers/wood. Color coding: blue indicates a correct subcategory match (target score is 5), white indicates a correct coarse category match (target score is 0), and yellow indicates no match (target score is 0).

These results were further corroborated by the experiment where we compared some of the models against TrashNet. Since TrashNet has the same recycling subcategories but no trash subcategories, only the recycling/trash and the cardboard/glass/metal/paper/plastic/trash models were tested. The non-significant *p*-value of 0.1622 suggests that the different classification schemes had no comparable differences on the resulting models (**Table 7**). Thus, the major advantage of using finer classification would be to cater more to recycling centers that offer dual or multi-stream recycling. If recycling and trash are the only two options, though, then just classifying between those two categories yield ideal results.

Both the highest and lowest accuracies belong to models from the classification scheme with the trash subcategories but not the recycling subcategories. Interestingly, the standard deviations do vary largely between the classification schemes (**Table 6**). This effect could be due simply to the random seeded training. However, it could also mean that there do exist latent features, and that the CNNs were only able to find them in some scenarios. Further trials would have to be done to explore this.

The models did exhibit another noticeable trend where they classify on visual differences similarly to how a human does (**Table 5**). Consider the significant number of misclassifications of soiled paper/cardboard and treated wood as cardboard (1.4/5 and 1/5). In these examples, the misclassified pieces of waste have textured brown appearances that may have confused the model. Nonrecyclable plastic (which includes clear plastic bags) and broken glass were also often classified as glass, which visually matches when considering the slightly shiny, transparent appearance.

Much of the research conducted in garbage classification has been oriented towards smaller systems, like smart home bins for homes. One logistical issue with the mechanical

https://doi.org/10.59720/24-245

p=0.6366	Recyclable/Trash	Sub-categorized Recyclable/Trash	Recyclable/ Sub-categorized Trash	Sub-categorized Recyclable/ Sub-categorized Trash
Trial 1	0.8909	0.8364	0.8364	0.8909
Trial 2	0.9091	0.8545	0.8909	0.8545
Trial 3	0.8909	0.9455	0.8909	0.8545
Trial 4	0.8909	0.9273	0.8909	0.8727
Trial 5	0.8727	0.8545	0.8545	0.8727
Std. Dev.	0.0129	0.0492	0.0257	0.0152

Table 6: Accuracies for all models. Columns detail each of the four different classification schemes, and rows represent each of the five trials and the standard deviation for that classification. *p*-value of 0.6366 computed using one-way ANOVA.

portions of these is that they must fit multiple “sub-bins” for the different types of trash or recyclables that they sort. Without making the total system too big to replace conventional trash bins, and the “sub-bins” too small to fit items, these systems might only be able to sort between a few different classes. One implication of our study is that if these sorting systems are only able to sort between trash and recyclable, that will not lead to any loss in accuracies. Processing facilities may still need to do further classification in a later stage, but contamination from contact between recyclables and trash would be significantly reduced.

Further work can be done in testing other classification schemes, using different subcategories of trash and recyclables, and including other MSW like food waste. For example, perhaps one model first classifies the object by its material, and then a second model built purposefully for that material decides whether the object is recyclable or not. Our study was oriented towards examining the difference between classification schemes, but it is possible that results differ in approaches other than transfer learning. Using other input data like weight or even sound from a microphone tapping the objects may prove helpful in distinguishing between materials as well. Other types of neural networks entirely, such as recurrent neural networks, transformer-based models, and graph neural networks, could have different results also.

p=0.1622	Recyclable/Trash	Sub-categorized Recyclable/Trash
Trial 1	0.8103	0.7818
Trial 2	0.7777	0.7978
Trial 3	0.7996	0.7647
Trial 4	0.7944	0.7940
Trial 5	0.8116	0.7858

Table 7: Accuracies for recyclable/trash and sub-categorized recyclable/trash models on TrashNet. Columns detail the two different classification schemes, and rows represent each of the five trials. P-value of 0.1622 computed using one-way ANOVA.

Thus, while this study does strongly insinuate that there is no relationship between the classification scheme and the accuracy, it is impossible to completely rule out the possibility. If there is indeed no correlation, then that could aid in collecting and sorting data by removing the work required to do finer classifications depending on the specific task. Further work that can be done in this sector of waste classification is building a large and truly comprehensive dataset. This may entail regional surveys to examine MSW trends in different locations and tailoring neural networks to fit each of those different places.

MATERIALS AND METHODS

Data Collection and Splitting

In the data collection stage, we generated 30 pictures for each of the 11 classes (**Figure 1)**. The objects for the trash subcategories were of used condition such that they would likely be thrown away soon. The objects for the recycling subcategories were in much more varied conditions, where some would likely be thrown away soon (e.g. scrap cardboard), and some could have kept being used for longer (e.g. a glass). All were picked as objects that an average U.S. consumer may use, but this dataset was not meant to be fully comprehensive.

The images were split into 17% testing and 83% training. The testing dataset included 5 images from each class, for a total of 55 images. This testing dataset would be the standard

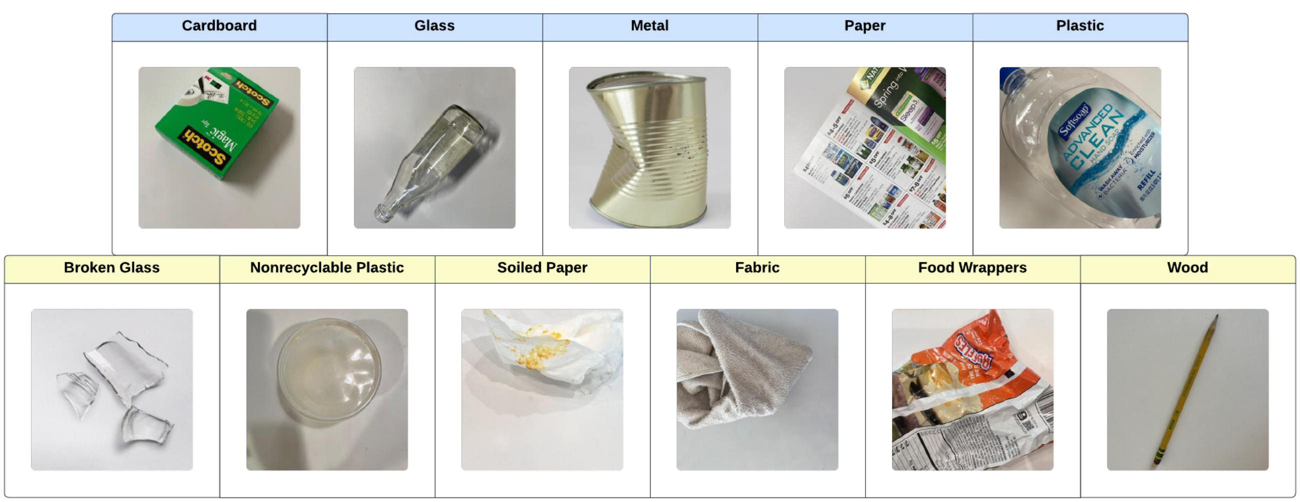

Figure 1: Examples from Image Dataset. Each image correlates to a different category of recyclable (title in blue) or trash (title in yellow). This dataset was used for training the CNNs to sort between recyclables and trash.

https://doi.org/10.59720/24-245

that each of the final models would be compared against to procure the accuracies. We used the rest of the images in the training process for the models, generating 5 models for each of the 4 classification schemes.

Model Architecture

Four copies of the same model were used for each of the classification schemes. For the model, we chose to employ transfer learning in the form of EfficientNetV2B2 since transfer learning is popular in other research for waste classification. EfficientNet was trained on a trimmed version of the ImageNet dataset containing 1000 classes and 1.2 million images (26, 27). EfficientNet was created to reach high levels of accuracy, while being much smaller and faster than alternatives (26). As a model originally trained on ImageNet, EfficientNet is far too complex to be used for a maximum of 11 classes. Thus, to avoid overfitting, we froze the first 300 layers, only allowing the final 40 layers to be edited during training. The initial layers of a network tend to be for general feature detection, while the later layers are more suitable for identifying features specific for a particular task (28). The alterations we added were some data augmentation layers at the beginning to enlarge the datasets and increase variation. These were a random horizontal flip, a random rotation between -π and π radians, and a random zoom between -30% and 30% on both the horizontal and vertical axes. We also added a pooling layer and a dropout layer after EfficientNetV2B2 with a rate of 0.2 to decrease overfitting by reducing co-dependency, and a dense layer at the very end to modify the output vector dimension to match the number of classes: 2, 6, 7, or 11 (**Figure 2**).

Model Training and Testing

The models were trained using Python (version 3.11.0) and TensorFlow version 2.13.0 (29). They trained for one hundred epochs, using an eighty-twenty training-validation split. Once finished training, we tested these models in two different sets of experiments. The first set compared the four classification schemes on the 55-image testing dataset. The models were run on the testing dataset, and the results compiled. This process was done for each of the four different classifications with five trials done for each.

As a further secondary test, we used TrashNet as another testing dataset. However, since TrashNet only has the categories cardboard, glass, metal, paper, plastic, and trash, we could only test half of the models on it. These were the models belonging to the classification scheme with recyclable/trash and cardboard/glass/metal/paper/plastic/trash. The other two require trash to have subcategories which was not possible since TrashNet's trash category was too small and limited.

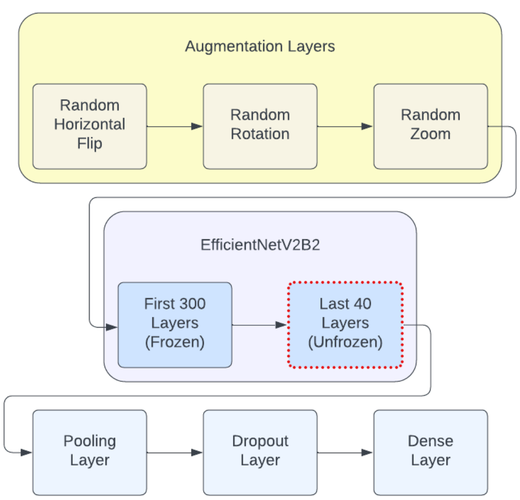

Figure 2: Model Architecture for CNNs. Diagram explaining the layout of the model used for sorting between the different categories. EfficientNetV2B2 was employed in the form of transfer learning, so only the last forty layers of it were editable during training, indicated by the red border.

Received: July 24, 2024
Accepted: December 9, 2024
Published: April 29, 2025

REFERENCES

1. "National Overview: Facts and Figures on Materials, Wastes and Recycling." *Environmental Protection Agency*. www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials. Accessed 15 July 2024.
2. "U.S. National Recycling Goal." *Environmental Protection Agency*. www.epa.gov/circulareconomy/us-national-recycling-goal. Accessed 15 July 2024.
3. "National Recycling Strategy." *Environmental Protection Agency*. www.epa.gov/circulareconomy/national-recycling-strategy. Accessed 15 July 2024.
4. "Circular Economy Implementation Plan Online Platform." *Environmental Protection Agency*. www.epa.gov/circulareconomy/circular-economy-implementation-plan-online-platform. Accessed 15 July 2024.
5. SAP and Qualtrics. "The Climate Progress Survey: Business & Consumer Worries & Hopes." *World Economic Forum*. 2021, www3.weforum.org/docs/SAP_WEF_Sustainability_Report.pdf. Accessed 12 July 2024.
6. Sullivan, Laura. "How Big Oil Misled The Public Into Believing Plastic Would Be Recycled." *National Public Radio*, 11 Sept. 2020, www.npr.org/2020/09/11/897692090/how-big-oil-misled-the-public-into-believing-plastic-would-be-recycled. Accessed 20 July 2024.
7. Albeck-Ripka, Livia. "6 Things You're Recycling Wrong." *The New York Times*, 29 May 2019, www.nytimes.com/2018/05/29/climate/recycling-wrong-mistakes.html. Accessed 20 July 2024.
8. Ipsos. "Household Waste and Recycling Research Report." *New South Wales Environment Protection Authority*, 2016, www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/waste/ipsos-waste-and-recycling.pdf. Accessed 13 July 2024.
9. "2020 State of Curbside Recycling Report." *The Recycling Partnership*, 13 Feb. 2020, www.recyclingpartnership.org/wp-content/uploads/dlm_uploads/2020/02/2020-State-of-Curbside-Recycling.pdf. Accessed 22 July 2024.
10. Blanco, Christian, *et al*. "America's Broken Recycling System." *California Review Management*, 2023, cmr.berkeley.edu/2023/05/america-s-broken-recycling-system/. Accessed 18 July 2024.
11. Rogoff, Marc. "Processing Technologies." *Solid Waste*

Recycling and Processing. 2nd ed., William Andrew, 2014, pp. 43-111, https://doi.org/10.1016/B978-1-4557-3192-3.00004-X.
12. Rawat, Waseem and Zenghui Wang. "Deep convolutional neural networks for Image Classification: A Comprehensive Review." *Neural Computation*, vol. 29, no. 9, Sept. 2017, pp. 2352–2449, https://doi.org/10.1162/neco_a_00990.
13. Zhuang, Fuzhen, *et al*. "A Comprehensive Survey on Transfer Learning." *Proceedings of the IEEE*, vol. 109, no. 1, Jan. 2021, pp. 43–76, https://doi.org/10.1109/jproc.2020.3004555.
14. Laksono, Pringgo, *et al*. "Deep learning implementation using convolutional neural network in inorganic packaging waste sorting." *Franklin Open*, vol. 8, 2024, https://doi.org/10.1016/j.fraope.2024.100146.
15. Böhmer, Lili. "Optimizing recycling using automated image-based classification : a machine learning approach for improved waste management." July 2024, hdl.handle.net/10400.14/46198.
16. Fu, Bowen, *et al*. "A Novel Intelligent Garbage Classification System Based on Deep Learning and an Embedded Linux System." *IEEE Access*, vol. 9, 22 Sept. 2021, pp. 131134-131146, https://doi.org/10.1109/ACCESS.2021.3114496.
17. Yang, Jianfei, *et al*. "GarbageNet: A Unified Learning Framework for Robust Garbage Classification." *IEEE Transactions on Artificial Intelligence*, vol. 2, no. 4, Aug. 2021, pp. 372-380, https://doi.org/10.1109/TAI.2021.3081055.
18. Rismi, Rismiyati, *et al*. "Xception architecture transfer learning for garbage classification." *2020 4th International Conference on Informatics and Computational Sciences (ICICoS)*, Nov. 2020, https://doi.org/10.1109/ICICoS51170.2020.9299017.
19. Li, Zuohua, *et al*. "An intelligent identification and classification system of decoration waste based on deep learning model." *Waste Management*, vol. 174, Feb. 2024, pp. 462-475, https://doi.org/10.1016/j.wasman.2023.12.020.
20. Pitakaso, Rapeepan, *et al*. "Optimization-driven artificial intelligence-enhanced municipal waste classification system for disaster waste management." *Engineering Applications of Artificial Intelligence*, vol. 133, part F, July 2024, https://doi.org/10.1016/j.engappai.2024.108614.
21. Thung, Gary and Mindy Yang. "Trashnet." *GitHub*, 8 Apr. 2017, github.com/garythung/trashnet. Accessed 10 July 2024.
22. Rosenthal, Sonny and Noah Linder. "Effects of bin proximity and informational prompts on recycling and contamination." *Resources, Conservation and Recycling*, vol. 168, May 2021, https://doi.org/10.1016/j.resconrec.2021.105430.
23. Wang, Jianfei. "Application research of image classification algorithm based on deep learning in household garbage sorting." *Heliyon*, vol. 10, no. 9, 15 May 2024, https://https://doi.org/10.1016/j.heliyon.2024.e29966.
24. Abramovich, Felix and Marianna Pensky. "Classification with many classes: challenges and pluses." *Journal of Multivariate Analysis*, vol. 174, https://doi.org/10.1016/j.jmva.2019.104536.
25. "Frequent Questions on Recycling." *Environmental Protection Agency*, www.epa.gov/recycle/frequent-questions-recycling. Accessed 19 July 2024.
26. Tan, Mingxing and Quoc V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." *Proceedings of the 36th International Conference on Machine Learning*, vol. 97, June 2019, pp. 6105-6114. https://doi.org/10.48550/arXiv.1905.11946.
27. "ImageNet," www.image-net.org. Accessed 19 July 2024.
28. Iman, Mohammadreza, "A Review of Deep Transfer Learning and Recent Advancements." *Technologies*, vol. 12, no. 2, Mar. 2023, https://doi.org/10.3390/technologies11020040.
29. Abadi, Martín, *et al.* "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," 2015, https://doi.org/10.5281/zenodo.14919893.