Data-Driven Solutions for Single-Stream Recycling Optimization: A Case Study

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Abstract

The amount of waste produced across the world is not sustainable. Optimizing materials recovery facilities (MRFs) through artificial intelligence, machine learning, and computer vision improves recycling efficiency and reduces waste. We evaluated over 300 unique models from four of the most popular convolutional neural network (CNN) modeling architectures and recommended an optimal model to optimize recycling sorting operations at MRFs. We found that ResNet50 was the most viable CNN architecture for MRF applications. The best ResNet50 model achieved 86.22% accuracy against the test dataset and returned predictions in 0.2046 seconds. This case study provided a foundation for enhancing trash and recycling sorting applications and a framework for conducting image recognition analysis with transfer learning.

Keywords: waste, recycling, materials recovery facility, waste management, artificial intelligence, machine learning, computer vision, convolutional neural network, ResNet, DenseNet, Vgg, classification

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Chapter 1: Introduction

Background

Across the world, different countries are deploying waste management strategies to a varying degree of success. The world's waste production continues to grow as the population grows. A more modern solution is needed because existing waste segregation processes are often manual, inefficient, and hazardous to human health. The trash industry and environmental groups are working on promising and innovative solutions that use artificial intelligence and machine learning to mitigate this problem. However, widespread adoption is lagging due to the many challenges associated with waste management.

Problem Statement

The world produces more than two billion tons of solid waste each year. That is a daily average of roughly 1.63 pounds per person. (Narayan, 2021) This statistic is even more troubling because experts expect solid waste production to increase significantly. The World Bank has estimated that global waste will grow to 3.4 billion tons by 2050. Despite having more capital to tackle the problem, high-income countries are the largest contributors to the global waste problem. For example, Americans produce more than 254 million tons of waste every year. Approximately 75% of American waste is recyclable, yet only 30% gets recycled (Awe et al., 2017, 1, *Municipal Solid Waste, US EPA*, 2016). Furthermore, experts estimated that daily per capita waste generation in high-income countries will increase by 19 percent by 2050. (*Can New Technology Solve a Trillion-Pound Garbage Problem?*, 2021)

Waste that is not recycled correctly goes to incinerators or landfills. Both destinations pose problems for the environment. Despite efforts to filter out harmful waste, landfills leach toxic liquids into the soil and groundwater. Incinerators release greenhouse gases that contribute to the climate crisis. (Tarun et al., 2019, 1)

Many municipalities have tried rolling out public education campaigns and providing incentives for recycling, but the ratio of contaminated recyclables keeps growing. According to the National Waste and Recycling Association, America's recycling contamination rate went from 7% to 25% in ten years. China has stopped buying and processing these "dirty" recycling streams, directly impacting the number of dirty recyclables ending up in landfills. (Koerth, 2019)

Traditionally, the segregation phase has been the most challenging aspect of waste management. Since single-stream recycling has become more popular, segregation needs have changed. In most cases, waste segregation is a machine and sensor-aided process, but there is still a lot of manual effort. In some developing countries, the process is entirely manual - wherein "ragpickers" sift through mountains of trash to find anything of value (including recyclables) and sell it to others for reuse. Advances in automation with AI and Computer Vision provide an enormous opportunity to improve and optimize the trash segregation process and limit the health risks to those who work with the trash.

Conceptual Framework

We expect to employ a Data Science solution using Artificial Intelligence, Computer Vision, and the Internet Of Things (IoT) to classify items in the recycling waste stream accurately. The proposed models boost efficiency while organizing recyclables and reduce waste by improving the overall recycling rate. Classifying waste is very complex and sometimes involves hundreds of attributes. However, certain features of the pictured item like size, color, texture, and edges are the most significant in the prediction process.

The key performance indicator for this work is the recycling rate, and the goal is to maximize the ratio of clean recyclables to "black tag" or "municipal" solid waste (MSW).

Purpose and Significance

The purpose of this case study is to publish a framework and findings that contribute to the effort of mitigating the worldwide trash crisis by enabling and improving large-scale waste classification systems. This case study describes several automated waste classification systems directly applicable to this work. The goal is to demonstrate how to leverage modern technology, data science modeling techniques, and data analysis tools to help mitigate the Global Trash Crisis through data-driven recycling pipelines. This report will help society achieve a more sustainable balance of renewable to non-renewable resources and educate the audience about materials recovery challenges. There is simply too much MSW going into landfills, and it is not sustainable for our future. Furthermore, improvements to waste segregation will reduce the risk of health issues for the individuals who work hands-on with garbage streams.

Project Objectives

1. Research, apply and compare the effectiveness of candidate models to identify and segregate trash items.
2. Assess the improvement in trash classifying model accuracy with the integration of transfer learning.
3. Assess the model’s ability to predict the classification of an item quickly and decide if it is viable for use at an MRF.

Definition of Terms

Understanding the relevant terms and acronyms relating to garbage and technology is essential. Municipal solid waste (MSW) refers to everyday items we use and then dispose of in trash or recycling containers, such as leftover food, packaging, beverage containers, paper, and batteries. Most people refer to MSW as "trash" or "garbage." (*Municipal Solid Waste | Wastes | US EPA*, 2016) Single-stream recycling is a system for collecting reusable MSW (recyclables) from homes, businesses, and public areas in dedicated bins. A material recovery facility (MRF) is where our recyclables are delivered, sorted, and processed for resale on commodity markets (Waste Management, 2011). Its inputs are raw, unsorted trash; its outputs are large square "bales" of segregated material for use as inputs in secondary markets.

Artificial intelligence (AI) is a field of computer science concerned with building computers that can perform tasks traditionally designated for intelligent beings. Machine learning (ML) is a branch of artificial intelligence that allows computers to learn from themselves with little to no manual intervention or training from humans. Deep learning is a sub-field of machine learning that incorporates layered processing. Insights gathered about each layer are passed to their successors to extract detail about high-level features. A convolutional neural network (CNN) is a specialized deep learning architecture designed to process structured data arrays. CNNs have many applications for image recognition since an image's pixel data is a structured data array. Computer vision is a field of AI that enables computers and systems to derive meaningful information from digital images, videos, and other visual inputs. (IBM, n.d.) In the context of this case study, computer vision refers to the algorithms and models that take inputs from cameras (pictures of garbage) and process them into meaningful information. Transfer learning is the concept of reusing the knowledge from an existing, pre-trained model for a different, related problem. For example, one related study used a model trained explicitly for brand and label recognition to help classify items in a recycling stream.

Scope

This study will assess various artificial intelligence and machine learning techniques to recommend an optimal model for classifying recyclables. We train, test, and optimize each of the candidate models similarly. However, we do not integrate the recommended computer vision solutions with mechanical or robotic components.

Assumptions and Limitations

Although optimizing the existing waste stream through technological means is a worthwhile endeavor, the success or failure of a recycling program also depends on people's attitudes, behaviors, and habits. One study about recycling behavior found seventy percent of all UAE respondents recycle, but 48 percent admitted they contaminate the recycling stream by throwing waste in recycling bins (AlHaj Ali et al., 2021). An Earth Day study from Covanta found that only 31 percent of Americans say they always recycle. Others practice "aspirational recycling," which means they accidentally contaminate the recycling stream with items they believe are recyclable but are not. Factors like education level, proximity to recycling bins, lack of time, and lack of information were important in determining a person's recycling behavior. Surprisingly, young respondents were less likely to recycle than older respondents. (*Covanta Survey: "Americans Don't Know How to Recycle,"* 2019) Considering this, a comprehensive effort to improve the recycling rate must include a plan to educate and encourage the general public to recycle more efficiently, which is outside the scope of this case study.

Another limitation of this study is its inability to distinguish "clean" or "pure" recyclables from "dirty" recyclables. Purity standards differ among MRFs, and the TrashNet dataset used in this paper consists of only clean items. For example, we can categorize a pizza box as cardboard, but we cannot assess its purity based on how much grease is on it. TrashNet is also limited to

2527 images, which seems relatively tiny considering Americans generate more than 250 million tons of MSW each year. (Awe et al., 2017) To supplement TrashNet, we tried to access a much larger dataset with millions of images from WasteNet, but could not get the academic approval required to use the dataset.

Even if we acquired access to the WasteNet dataset, we would have run into a bottleneck with processing power because we are limited to the cloud compute available through Google Colab’s service. Models deployed in MRFs need to return predictions very quickly (within seconds) to keep up. Due to this lack of computing resources, the study has limitations on how quickly it can produce results and the number of layers available to the deep learning models. We assume real-life implementations will have the funds and resources to devote more resources, which allow for deeper neural networks and faster response times.

Moreover, this study assumes the utility of the proposed models will continue to be applicable as the waste stream evolves. The waste stream is constantly changing with new packaging materials, and science is finding ways to reuse items that were once considered unrecyclable. Others have suggested embedding RFID tags in objects which could significantly reduce the need for computer vision solutions.

Chapter 2: Literature Review

Many prominent waste collection businesses in rich countries have mature collection and segregation systems. Waste Management is the largest waste disposal company in America and they started doing business in 1968. The company's mission is "to maximize resource value while minimizing - and even eliminating - environmental impact so that both our economy and our environment can thrive." (Waste Management, 2022) Their market share (and profits) grew because they reinvested in technologies to help mitigate the complex problems of a continuously evolving waste stream. Waste Management uses artificial intelligence and data science to run its MRFs with integrated conveyors, sensors, cameras, and mechanical equipment. (Blomberg, personal communication, Feb 08, 2022) Learning about Waste Management's single-stream recycling workflow will help us understand the depth and breadth of the waste sorting problem.

Waste Management (WM) Recycling Overview

Single-stream recycling is a simplified system that has gained popularity, wherein recyclables are not sorted into paper, plastic, and metal before collection by the truck. Instead, various "commingled" items go into a single waste bin collected outside the residence. Single-stream recycling simplifies the consumer's recycling process and increases recycling participation rates. Waste Management estimates single-stream recycling has increased the participation rate by over 50 percent. (Waste Management, 2011) By learning about Waste Management's single-stream recycling process, we can identify gaps to address with AI and computer vision.

For Waste Management customers, the journey of a recyclable begins as garbage trucks empty individual recycling bins into their hoppers. Next, the garbage trucks deliver the recyclables to an MRF and dump them onto a warehouse floor. Dozer-loaders scoop the material off the floor and drop it onto a giant conveyor belt. Here, a team of individuals monitors the stream of recyclables and picks off contaminated items. As the recyclables travel down the conveyor belt, conveyor screens and disc streams separate the paper and cardboard from the stream. The paper and cardboard are re-directed to large storage bunkers, where a team of individuals manually check the item for quality again. Next, the paper and cardboard stream goes through another system of conveyor belts, and paper is separated using a series of agitators. The agitators put the paper on yet another conveyor belt where the paper products are sorted for quality and classified into bins based on quality.

Steel items and scrap metal are removed from the conveyor belt using large magnets suspended above the waste stream. Magnets collect the metal items off the conveyor and drop them into a dedicated bin for further processing.

After removing paper, cardboard, and steel, most remaining items are plastic and aluminum containers. Infrared sensors scan them to determine their thickness and spectral characteristics. Waste Management's models are proprietary, so we cannot know precisely how Waste Management classifies its plastics. (Blomberg, personal communication, Feb 08, 2022) However, Zhu et al. conducted a plastic identification study to demonstrate how SVM (Support Vector Machine) can identify the type of plastic (PP, PS, PE, PMMA, ABS and PET) based on the spectral reading from an infrared sensor. (Zhu et al., 2019) Waste Management’s MRFs have real-time integration between similar plastic predicting models and a "computerized air-jet." The air jet shoots targeted bursts of air at the plastic items (milk jugs, water bottles, detergent bottles) to blow them off the conveyor belt and into the correct bin.

Aluminum cans get a negative charge from an eddy current so that magnets can repel them out of the stream and into a dedicated bunker for storage. Each bin with segregated material gets a final manual review for quality. Then, compactors create "bales" from the material in the bin. The bales are loaded back onto trucks and delivered to buyers who use them as raw material in their manufacturing processes. Waste Management expected 95 percent quality and purity of materials from its machines, and they attributed the extra 5 percent boost in quality from the employees' manual effort. (Waste Management, 2011)

Waste Management devoted a huge amount of resources and research to build automation into its state-of-the-art MRFs. Despite its success in processing more than 20,000 tons of recyclable material each month, Waste Management still strives for tiny improvements at every stage. (Blomberg, personal communication, Feb 08, 2022) Across the world, there are many less sophisticated recycling centers and reclamation facilities that operate on a smaller scale, with less efficiency, and with more manual intervention. The ideas proposed in this case study will help improve the design of waste segregation solutions at MRFs and recycling centers across the world. The Global Trash Crisis is a worrisome topic for many individuals and organizations. Due to heightened interest, plenty of academic studies were available to review regarding artificial intelligence as a solution to waste management challenges.

Smart Waste Bins

Many of the academic studies on artificial intelligence for waste management use a similar methodology, wherein pictures of trash are separated into testing and training datasets, and then a machine learning algorithm is run against them to do supervised learning. Then the model's accuracy is determined based on the rate it predicted the pictured item's classification correctly.

A common theme amongst a few of the studies was to design a smart waste bin to be used in people's homes or in public places – the first step in the waste stream. The authors maintain that classifying items at the time they are disposed of will reduce the complication of sorting them downstream. An “IoT-based smart trash box” study uses sensors, a camera, a Raspberry Pi microcontroller, and an Android app to classify TrashNet waste images into two categories: digestible and indigestible. The authors experimented with three CNN architectures: AlexNet, VGG16, and ResNet34. ResNet34 (96.1%) and VGG16 (94.2%) achieved similar accuracy measures against the test data, but ResNet34 produced the result in less time, making it the obvious choice. AlexNet performed poorly, classifying 82.9 percent of the items correctly. (Rahman et al., 2020)

A Pittsburgh-based company called Trashbot built on the idea from this study to create AI-powered garbage cans for areas where lots of waste is generated, like airports, shopping malls, and stadiums. Testers put objects into the Trashbot, and then they were scanned and analyzed by machine learning models. Then, rotating chutes inside the Trashbot redirected the objects to the correct storage bin with 90 percent accuracy. The Trashbot could also extract liquid from the recyclables to improve the items’ purity. (Greenwalt & Karidis, 2017)

Wang et al. installed sensors and Bluetooth-connected cameras on nine different trash bins connected to one central processing controller. They experimented with seven different CNN architectures and identified Xception and MobileNetV3 as the best candidates. The smart trash bin system could identify items that were placed into an incorrect bin (kitchen waste going into the plastics bin), but it could not prevent the incorrectly classified material from entering the bin. The smart system notified its users if the bin became too full or unsafe due to gas buildup. (Wang et al., 2020)

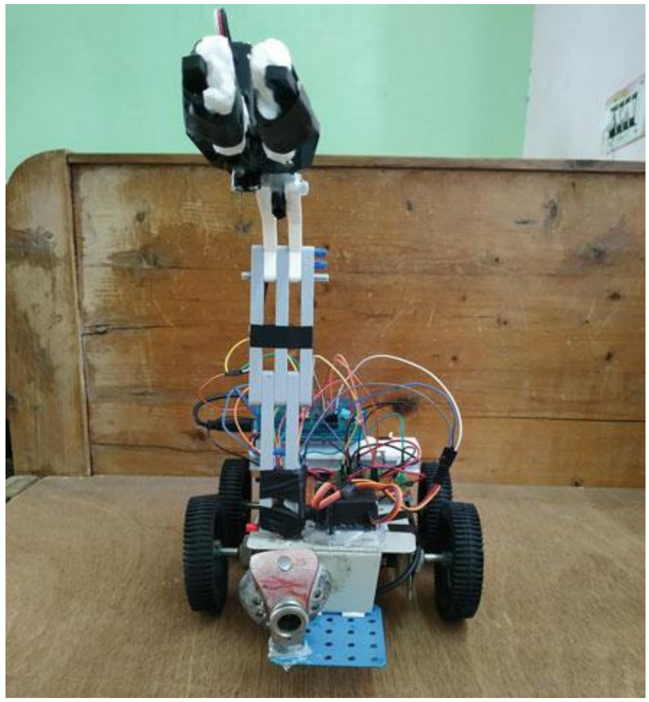
There are a few more limitations of the proposed smart waste bin that will make widespread adoption difficult: 1) many large items don't fit inside the waste bin, 2) the waste bin becomes unstable when one section is full and the other sections are empty, 3) the lenses, sensors, and any other electronic equipment inside would become constricted or blocked by trash residue over time, leading to inferior performance and frequent maintenance/cleaning, and 4) the lack of natural light inside the container would reduce image quality significantly. Keeping lenses and sensors clean is an ongoing challenge with all waste segregation solutions. Many companies tried to gain an edge on the competition by marketing their waste segregating machinery as "easy to clean" or "easy to maintain." (Barker, 2021)

Mobile Trash Sorting Robots

Zurada et al. implemented a creative "autonomous trashbot" idea. Like many other solutions in this section, it used sensors and cameras to identify the trash through artificial intelligence and machine learning. The "trashbot" was different because it was mobile; it traveled to the trash. It looked like a high-tech remote-control car. The design includes a RaspberryPi and two servo motors to move a mechanical arm and position the car. A Vgg16 model was used for classification because the authors found that it performed the best out of the four candidate models they tested; ResNet34, ResNet50, Vgg16, and Vgg19. (Zurada et al., 2020)

Figure 1

Zurada et al. Autonomous Trashbot



Note. From Zurada, J. M., Raman, B., Gunjan, V. K., & Gangadharan, G. R. (Eds.). (2020). *Modern Approaches in Machine Learning and Cognitive Science: A Walkthrough: Latest Trends in AI*. Springer International Publishing.

The "IOT based Sun Tracing TrashBot" study was a variation of the autonomous trashbot from the previous study. The distinguishing factor was its solar-powered engine and the trash bin attached to the back of the robot. Due to its small size, the Trashbot had very limited uses. It could not lift any items taller than 20 centimeters (about twice the length of the long edge of a credit card) or heavier than a juice container. (Sharadhi & Madhu, 2020) Mobile trashbots showed promising innovation, but their size and lifting power severely limited them. Due to these limitations, they have not gained much traction. Most commercially available trash segregating solutions work at the macro level and handle hundreds of thousands of items in a day. Mobile trashbots could not handle that much volume, but we could apply them in other settings like public parks or roadside ditches for litter cleanup.

Since the studies mentioned above aim to classify the items at the time they are disposed of, a one-by-one approach to classification seems feasible. However, some may argue that the cost of a robotic waste bin will deter consumers. There is a valid counter-argument that IoT-enabled smart appliances are already becoming more mainstream, so the idea of the smart waste bin in the household is viable. The London-based environmental engineering company Recycleye began its business venture with smart bin applications, but they switched to a robotics-oriented solution to sort waste at MRFs. According to the CEO, Recycleye abandoned the smart bin idea because they were “too expensive for the customer” and could only sort into a few classifications. (Stower, 2021)

The smart waste bin concept has a few shortcomings, but a lot of the same technology can be used applied to sorting at a larger scale. Tarun et al. tried to solve this problem outside of a waste bin by designing their waste segregation system with a conveyor belt, which is more like the automated processes in America’s MRFs. They used predictions from a CNN model to control a windshield wiper attached to a conveyor belt to do a binary classification: plastic or non-plastic. Their system achieved an accuracy of 97.8% and an f1 score of 0.945, but they did not report any information about the sample size or nature of the items used in testing. (Tarun et al., 2019) The lack of information about the sample items makes it difficult to assess the viability of the model for actual trash segregation applications. If a disproportionate amount of the items in the sample were the same class (ex: clear plastic bottles), the model is likely over-fitted.

Conveyor belts, mechanical equipment, and integrated robotics are incredibly useful for trash segregation, but working with large or awkwardly-shaped items is a challenge for even the most intricate robotics. Modern robots use tools like suction cups, claws, and cones – but they are not precise enough to identify a piece of gum sticking to the top of an aluminum can, for example. (Ahmed & Asadullah, 2020) Although detecting the gum is useful because it will help us determine the can is "dirty", we cannot expect the robots to pick the gum off the top of the can and make it "clean". Many of the commercial solutions struggle to pick paper and lightweight packaging for the same reasons. As a result, more manual sorting is required on paper lines. (Pyzyk, 2019) Other items like bicycles, fire hoses, wire, and rebar pose similar challenges which require manual presorting. Furthermore, different municipalities have different standards for what's considered a "clean recyclable," so there is no one-size-fits-all solution. VARISORT+ is a German optical sorting system that accounts for different standards; it allows operators to set a certain threshold on the algorithms that determine the quality of the recyclables to fine-tune the quality measures. (Barker, 2021)

Classification Methods

Most literature on waste classification does not include machinery or robotics. Instead, it focuses solely on different artificial intelligence methods and architectures that could be used to sort trash. Most (but not all) studies involve some variation of CNN for classification.

Bircanoğlu et al. used seven variations of three different CNN architectures: 1) MobileNet, 2) ResNet, and 3) DenseNet. Adam (adaptive moment adaptation) and Adadelta optimization were used to work around some of the sensitivity to hyperparameter selection based on the somewhat small sample size of the TrashNet dataset used. The authors achieved better than 75% accuracy for all the model variations they tested. The best model was a pre-trained, 121-layered DenseNet model which achieved 95% accuracy. However, due to relatively slow prediction times, this model was not a good candidate for real-time implementation in a Material

Recovery Facility. Some layers were removed, and other changes were made to the network architecture to make it run 46% percent faster and increase its real-time viability. (Bircanoğlu et al., 2018)

Özkaya & Seyfi built on the work of Bircanoğlu et al. by improving the accuracy of the models by switching the final CNN layer (aka fully connected layer) from the traditional SoftMax layer to a Support Vector Machine (SVM) layer. (Özkaya & Seyfi, 2018) Using SVM instead of SoftMax in CNN is a widely debated topic. The difference is that SoftMax maximizes the likelihood of predicting an individual item's classification correctly, whereas SVM maximizes the ability to distinguish between the different classes. (Tang, 2013) Using TrashNet as a dataset, the authors found a significant increase in predictive ability by using SVM in the final layer instead of SoftMax.

Gyawali et al. conducted a comparative analysis study. They assessed model performance using the TrashNet dataset for Vgg16, ResNet50, and ResNet18. ResNet18 was the best performing model, and it performed especially well for classifying paper. The authors had limited computational power, so they opted for a pre-trained model and limited the number of epochs to 25. (Gyawali et al., 2020)

Azhaguramyaa et al. used a different spin on traditional CNN algorithms by adding "contextual information" and "photometric changes" to the layers. This approach is called "Histogram of Oriented Gradients". Histogram of Oriented Gradients works by dividing the image into many small regions called cells. Each pixel in the cell is analyzed pixel-by-pixel for any changes in gradient (color shade). Then, cells are combined into "blocks" and the cells in the block are analyzed to measure the intensity of the change in gradient. The authors added the extra contextual features because it improved prediction for objects like trash items, which are diverse in sizes, colors, and dimensions. Similar to Rahman et al., the authors designed their algorithm to predict only two classifications: biodegradable (food) and non-biodegradable (plastics). They tested it using a small prototype that consisted of an infrared processor, a Raspberry Pi microcomputer, and a camera. Although they didn't integrate with any external components or robotics, the suggested model could be a critical component to the success of any automated system. The study reported a "very high accurate detection and classification rate," but no specifics were given. (Azhaguramyaa et al., 2021)

Huang et al. developed a Vision Transformer Model as an alternative to Convolutional Neural Networks. The authors make a case that their Vision Transformer Model improves upon CNN by dividing the image into several "patches" to form sequential data. The sequential data is run through an encoder (similar to how natural language processing works), which assigns a weight to each patch. The weights on the patches determine which portions of the image are the most important toward identifying the image. (Huang et al., 2021)

Some of the studies above were able to achieve very good accuracy measures, in part because images are classified into binary categories (digestible/indigestible). Robust real-time applications in MRFs require the ability to classify items into multiple categories. Another common theme amongst these studies is comparing various candidate models. Despite using similar models and the same dataset (TrashNet), the results and recommendations between the studies mentioned differ greatly. There is very little agreement between them about which modeling architecture is best for waste classification. The results were highly dependent on whether the models were pre-trained, what hyperparameters were used, the training/test split, the number of epochs run, and how the input data was prepared. Furthermore, some studies used transfer learning and others did not. Since RecycleNet is a pre-optimized model which simplifies thousands of parameters to classify recyclables, I was surprised when I learned that some models that implemented transfer learning with RecycleNet did not perform as well as the alternatives.

Multi-Stage Classification

Zhang et al. recognized the need for breaking down classifications into stages (categories and subcategories). The authors designed their “two-stage” solution to break down items into four categories and thirteen subcategories. For example, “hazardous waste” was broken down into separate categories for batteries and medicine. The categories and subcategories they chose were compliant with the local regulations in Shanghai, China. Using a customized dataset of 1040 images, they achieved a 93.8 percent average accuracy on the first stage, and 94.7 percent accuracy on the second stage. This study proved that more classification decisions with fewer categories perform better than fewer classification decisions with more categories. (Zhang et al., 2021) Majchrowska et al. implemented two-stage classification to improve accuracy in classifying litter. Recall how Waste Management uses multi-stage segregation – first to separate plastics from the single-stream recycling, then to separate PP (polypropylene) plastics from the other types.

Imperfect Images

Thus far, all the literature I covered had limited scope and practicality because they all used a dataset that included only good quality images of whole items (typically on solid white background). In practice, these items are simply dumped off a truck into a bin that feeds a conveyor belt. So, it is not likely that items would be isolated enough to be photographed individually without manual intervention. When item A is partially covered or obfuscated by item B, it is difficult to determine the dimensions of both the items (especially if items A and B share the same features). We could expect the same classifiers to underperform when processing commingled recyclables on a conveyor belt at an MRF.

Figure 2

Comingled Plastic Recyclables Entering a Mechanical Sorter

Note. From Ahmed, A. A. A., & Asadullah, A. (2020, 05 10). Artificial Intelligence and Machine Learning in Waste Management and Recycling. *Engineering International*, *8*(1), 43-52. https://doi.org/10.18034/ei.v8i1.498

Figure 3

WM Line Workers at Philadelphia MRF

Note. From Waste Management. (2011, April 4). *Waste Management Single-Stream Recycling: Take a tour of our Philadelphia MRF*. YouTube. Retrieved February 28, 2022, from https://www.youtube.com/watch?v=_GP3JuiX5BY

There were two advanced studies we encountered that tested the proposed solutions with overlapping items and poor-quality images. "Smart Trash Net: Waste Localization and Classification" is one of them. The authors used python to randomly generate "piles" of trash by stitching and merging multiple single-item images together into a single image with multiple items. They used a pre-trained, Faster R-CNN model to identify and classify each of the pieces of waste as either 1) landfill, 2) recycling, or 3) paper. Since the requirement was to classify multiple items in a single image, the model is more complicated than the previous versions. It works by finding the "ground truth" or "anchor" of each item in the image. Using the anchor, which is typically near the center of the item, the algorithm identifies the edges of the image and draws a boundary. Using these item boundaries, it can distinguish where one item ends and another begins. The proposed model achieved a mean Average Precision (mAP) of 0.683 against the merged images, but accuracy suffered significantly (no explicit accuracy measures were provided). (Awe et al., 2017)

The Recycleye study took a different approach to diminish the quality of the images; they darkened them to account for poor lighting conditions and blacked out half of the images to simulate partial objects. Using the unaltered, undamaged images' accuracy rate of 97.78 percent as the baseline, the accuracy decreased nearly 9 percent under poor lighting and 20 percent when half the images were visible. Recycleye also supplemented its traditional waste classification algorithms by integrating with the Flickr Materials Database (FMD) and the WaBaDa database of plastic waste images. The WaBaDa database was designed to represent the "typical contents of municipal waste", but it also includes brand and labels identification. The additional brand-level recognition introduced through WaBaDa integration boosted accuracy. In fact, Recycleye was tested against manually curated images of 45 different varieties of beverage cans photographed from different angles and perspectives. If the photo did not show the brand label, the item was much more likely to be misclassified. They used FMD to train the model against images of items belonging to common material categories like fabric, glass, plastic, wood, water, and foliage. Model accuracy fluctuated based on the level of damage to the items. For example, accuracy decreased for aluminum cans that were crushed or dented versus undamaged items of the same kind. (Dewulf, 2017)

Recycleye was a very interesting study about new technologies in waste classification. It also bridged the gap between academia and industry. The Recycleye publication cited above was created in 2017 to prove the concept of artificial intelligence as an affordable system to solve the trash crisis and "drive a waste data revolution." The company Recycleye was founded in 2019 using the same ideas from the "Application of machine learning to waste management" paper published through the Imperial College of London. They currently sell two major platforms: a computer vision solution called "Recycleye Vision" and an integrated robotics solution called "Recycleye Robotics". These offerings have already generated more than 4M pounds in revenue. (Waste360, 2021) Recycleye is fulfilling its mission by maintaining an open-source database called WasteNet which holds more than 2.5 million training images – far more than TrashNet, which has about 2500 images. The WasteNet dataset is being used to help develop partnerships between robotics companies and AI/computer vision providers. Unfortunately, I was not able to get access to the dataset and use it in my testing because, despite its open-source nature, it requires academic approvals that I was not able to acquire.

Commercial Waste Sorting Applications

Recycleye is one of many businesses trying to capitalize on the massive opportunity to optimize the waste stream with artificial intelligence and robotics. An article by WasteDive highlighted the growing adoption of automation and robotics in MRFs. The major players in the market are Machinex, ZenRobotics, Waste Robotics, AMP Robotics, and Bulk Handling Systems. (Pyzyk, 2019)

According to Peter Rashio, Marketing Manager for Bulk Handling Systems (BHS), artificial intelligence solutions are the key enabler for applying robotics and automation to the waste and recycling space. (Pyzyk, 2019) AI is being used within optical sorters to identify the composition and classification of objects, as well as in downstream robotics to do quality control. The embedded AI also provides real-time data to operators about changing trends with materials in the waste stream. (Barker, 2021) Veolia, USA's second-largest waste management company, partnered with Bulk Handling Systems and Machinex to create the “Max AI” robotic sorting system. Veolia has a dedicated Artificial Intelligence department with more than 200 employees. (Stower, 2021) According to Machinex's VP of sales, their machines have made MRF automation significantly better by improving plastic purification and fiber automation over the last ten years. Machinex’s key market differentiators are their “hyperspectral cameras” and the ease of maintenance on their sorting machines. (Barker, 2021)

The founder of AMP Robotics got his idea for his business after he visited a Materials recovery facility and he noticed how inefficient the process was and how difficult the work is. (Clifford, 2021) After only six years of operation, AMP Robotics achieved a milestone of successfully processing over a billion recyclables in one year through their machines. Their “AMP Neuron AI Platform” uses machine learning and computer vision to classify waste of all different shapes, sizes, textures, and colors. It excels at separating plastic recyclables into their sub-groups (PET, HDPE, LDPE, etc.) (Smalley, 2020)

Beyond computer vision and AI, other organizations like the FMCG (fast-moving consumer goods) consortium are pushing an initiative to add smart tags (RFID) into consumer product packaging to improve trash segregation. RFID is a better alternative to barcodes because barcodes are not always visible to the sorting system's cameras, but they cost up to 10 cents more per item. (Dewulf, 2017) Considering the large market for fixing inefficiencies at MRFs and the massive amount of waste generated daily, small improvements will save a lot of money and contribute significantly toward protecting the planet. (Stower, 2021)

The Finnish company ZenRobotics was one of the first to create robots to sort waste at a large scale; they called their solution "The Recycler." It used adaptive algorithms that are optimized to "maximize the monetary value" of the recovered objects. It was programmed with an extra layer of complexity to prioritize picking the largest, and purest items over smaller, dirty items. It uses machine learning not only for material recognition but also for object manipulation to help reduce the workload of the manual sorters (employees). The system is continuously trained and optimized by manually entered feedback about misclassified items. (European Commission - Eco-innovation Action Plan, 2021; Zenrobotics Recycler, 2014)

As mentioned previously, some studies are limited to good-quality images of single items. TOMRA, a Swedish recycling equipment manufacturer, reduces the problem of overlapping items by using mechanical and air technology to pre-process the items prior to sorting so they are more evenly distributed on an MRF's conveyor belt. According to Mark Neitzey, Sales Director at Van Dyk Recycling Solutions, their "Deft Air" solution has an enormous impact on the operating speed and accuracy of the sorting systems. (Barker, 2021)

Themes

A common theme amongst nearly all the literature I reviewed is that automation in the waste industry is critical to achieving sustainability. It is a common belief that AI and machine learning are fundamental to the success of waste stream optimization and automation. The waste stream is continually evolving, so the best solutions will be those with feedback loops that increase efficiency over time. Although the human element will never be completely removed, any effort to reduce human intervention should increase productivity and profitability.

Regulations and standards are pushing many businesses and governments across the world to improve waste stream optimization. Large corporations are subject to ESG ratings, which assess a company's waste management practices and sustainability. Since some investors heavily consider ESG ratings, it is in a corporation's best *financial* interest to reduce waste. (Blomberg, personal communication, Feb 08, 2022) Financial and societal pressure are driving companies to implement "zero waste" initiatives. This continued pressure toward sustainability will encourage more innovation and promote more studies like the one outlined in this case study.

Chapter 3: Methodology

Modeling Architecture Rationale

This case study used computer vision solutions to conduct image classification for segregating recyclables efficiently. Image classification takes images as inputs and assigns each a label based on its features. Convolutional Neural Networks (CNNs) are an effective architecture for image classification because their multi-layer design can detect an object's features by breaking an image into layers and detecting its edges. Calculations from one layer get passed on to succeeding layers to improve feature extraction.

CNNs are popular in the computer vision domain because they can detect essential features in an image without human supervision. They systematically reduce input image parameters while maintaining the model's quality, making them an appropriate choice for recycling image classification. CNN is also flexible; adding, removing, and modifying layers is relatively easy. Layers can also use customized activation functions that combine the benefits of other computer vision techniques. (Huang et al., 2021) CNN outperforms many competing architectures when using massive datasets as inputs because the number of parameters increases far slower than other architectures. We chose CNN as our primary architecture because it can scale for large datasets and its prevalence in the reviewed literature. (Lee et al., 2020; Shi et al., 2021)

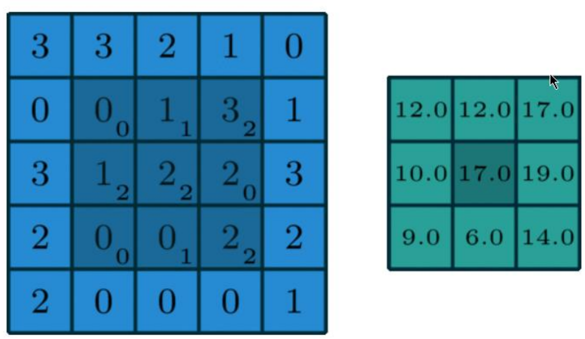
We considered several alternative computer vision modeling techniques in our analysis. Among them were support vector machine (SVM), scale-invariant feature transform (SIFT), and histogram of oriented gradients (HOG). These alternatives are suitable for smaller datasets, as their parameters increase linearly with the dataset. We did not evaluate them because recycling classifiers need to scale for millions of images. (Ahmed & Asadullah, 2020; Yang & Thung, 2016)

CNN Components

CNNs consist of many layers. Our CNN classification models primarily consisted of varying degrees and configurations of the four most common layers: convolutional layers, pooling layers, dropout layers, and fully-connected layers. The convolutional layers broke down the images using “strides” of one pixel and multiplying the RGB values by their corresponding weights. Figure 4 illustrates this concept. The Pooling layers “downsampled” or summarized the features in the input and protected against overfitting. (Rahman et al., 2020)

Figure 4

Convolutional Layer Example with Weights and Stride



Note. From Sharma, P. (2021, June 6). *PyTorch Conv2D Explained with Examples - MLK*. Machine Learning Knowledge. Retrieved April 8, 2022, from https://machinelearningknowledge.ai/pytorch-conv2d-explained-with-examples/

Candidate Models

Many pre-built CNN architectures exist today. This case study involved building a customized CNN model and testing it against three of the most popular CNN architecture families (ResNet, DenseNet, VGG) using transfer learning. We used transfer learning techniques to adapt the ResNet, DenseNet, and VGG models to the trash classification problem. Many families of CNN are freely available to use in transfer learning. This case study uses ResNet, DenseNet, and VGG because they are significantly different, and they are among the most popular architectures used in computer vision today. (Zhang et al., 2021) We tested each model using the same framework. The framework established the same hyperparameter options, loss function, metrics, epochs, and fully-connected layer configuration for each model. The final, fully-connected layer is a special dense layer that uses a softmax activation function to determine the confidence of each predicted class (see Figure 5). Softmax is appropriate for this case study because it assumes each image belongs to exactly one class.

Using the same framework ensured fairness in evaluation while allowing each model the freedom to choose and optimize its hyperparameters. The ResNet, DenseNet, and VGG models were pre-trained on the ImageNet dataset. ImageNet contains more than 14 million images and 20 thousand categories. The pre-trained layers in these models were frozen to preserve the original model's weights and prevent keras from attempting to optimize them further.

Figure 5

Softmax Activation Function Formula

$$y_i = \frac{e_i^x}{\sum_{j=1}^{n} e_j^x},$$

- where ***yi*** is the probability of each class
- ***n*** is the number of classes (6)
- ***xi*** and ***xj*** are the inputs

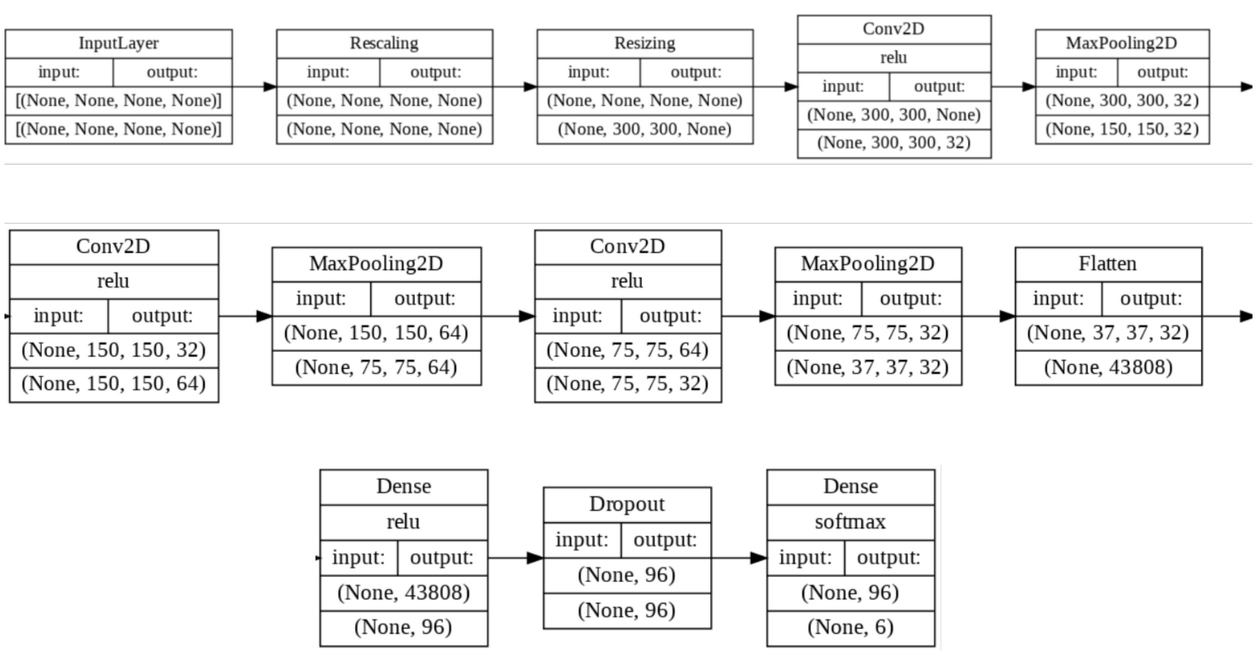
Note. From Masand, A., Chauhan, S., Jangid, M., Kumar, R., & Roy, S. (2021). ScrapNet: An Efficient Approach to Trash Classification. *IEEE Access*, *9*, 130947-130958. 10.1109/ACCESS.2021.3111230.

Custom CNN

We developed a customized baseline CNN model that consisted of six layers: three convolutional layers and three max-pooling layers. This configuration followed the standard best practice of adding a pooling layer after each convolutional layer. The pooling layers cut the size of the feature map in half at each hop by reducing the image's pixels by a factor of two. The pooling layers used the rectified linear activation function (ReLU). The custom CNN was initialized without pre-trained weights, allowing the neural network to determine appropriate weights independently.

Figure 6

Customized CNN Architecture Diagram

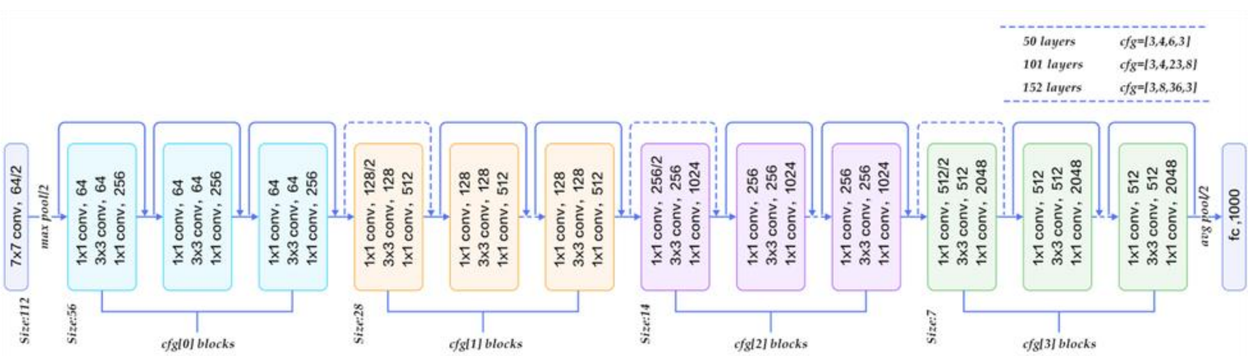


ResNet

Residual Neural Networks (ResNet) are different from traditional “feed-forward” CNNs because they use the concept of shortcuts to skip layers when necessary. Skipping layers can reduce model complexity and allows for faster training. ResNet had the added benefit of lowering degradation and training error due to vanishing gradients. There are many variants of ResNet that range from 18 layers to 1202 layers. We selected ResNet50, which has 48 convolutional layers, a max-pooling layer, and an average pooling layer. Figure 7 shows a sample of the layering scheme for ResNet50.

Figure 7

ResNet Architecture Diagram



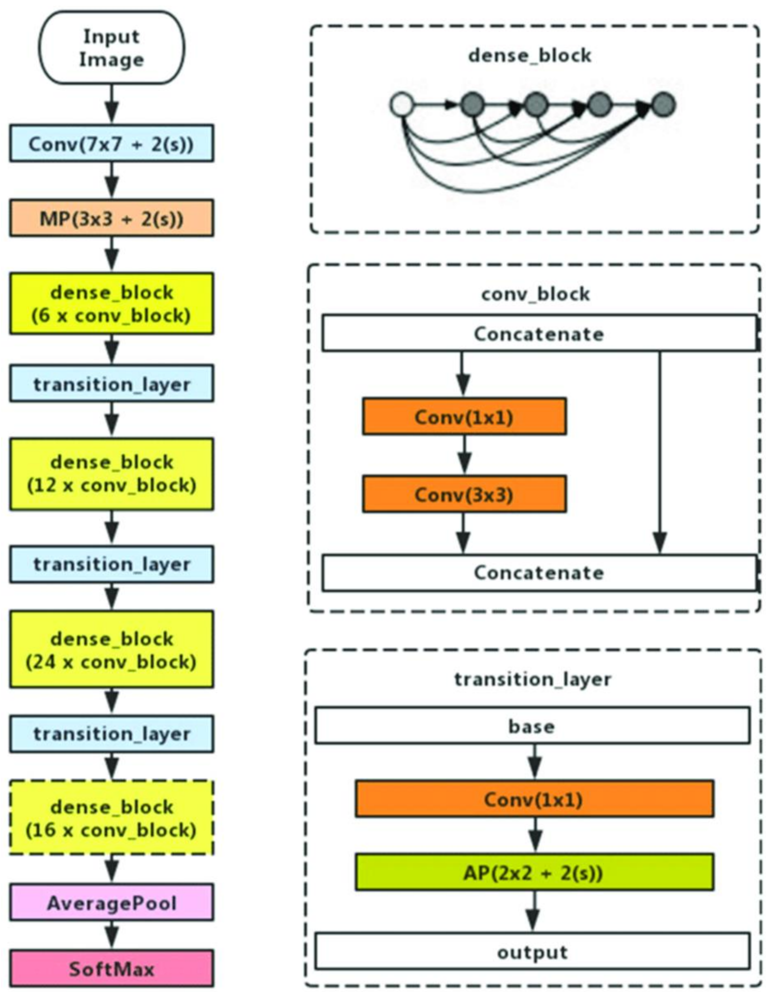
Note. From He, K., Zhang, X., Ren, S., & Sun, J. (2017). Deep Residual Learning for Image Recognition. IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC). https://doi.org/10.48550/arXiv.1512.03385

DenseNet

The creators of DenseNet wanted to improve on ResNet architecture. ResNet allows for skipping a single layer, whereas DenseNet allows multiple parallel jumps to bypass layers while maintaining a direct, “dense” connection between all layers and their subsequent layers. (Huang et al., 2017) The added connections between layers increase the model's ability to predict, but DenseNet models are more prone to overfitting and require more compute resources due to the additional links. (Liu & Zeng, 2018) Due to these constraints, we chose DenseNet121, which has the fewest layers of the available DenseNet models.

Figure 8

DenseNet Architecture Diagram



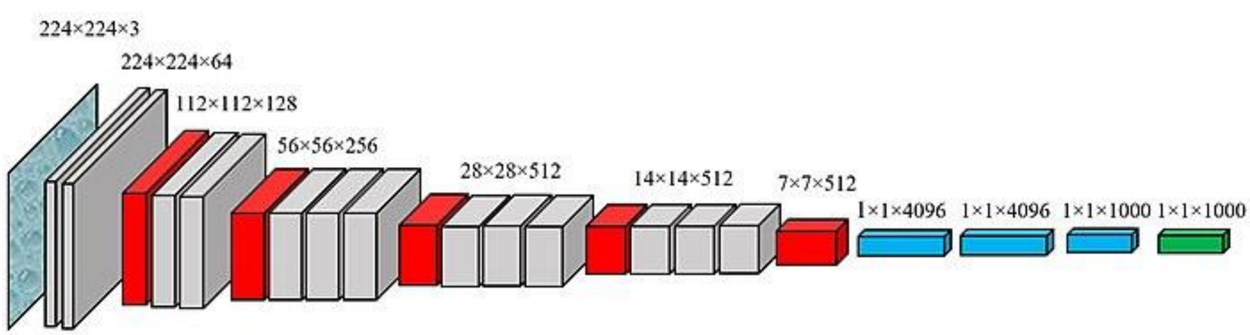
Note. From Ji, Q., Huang, J., He, W., & Sun, Y. (2019, Feb). Optimized Deep Convolutional Neural Networks for Identification of Macular Diseases from Optical Coherence Tomography Images. *Algorithms*, *12*(3), 51. 10.3390/a12030051

VGG

Visual Geometry Group (VGG) is another commonly used CNN for image classification. VGG models consist of several “blocks.” Blocks contain one or more convolutional layers and a max-pooling layer, and they are connected linearly. VGG is a relatively simple model, but it is very powerful. It consists of 3x3 convolutional layers that build on each other with increasing depth. There are two variations of VGG models: VGG19 and VGG16. We chose VGG16, which has 13 convolutional layers and 3 dense layers. VGG models have fewer layers than many other neural networks because they are prone to the vanishing gradient problem. The vanishing gradient problem occurs when the gradient becomes so tiny that the layer’s weights never change their values. (Majchrowska et al., 2022; He et al., 2017; Liu & Zeng, 2018; Huang et al., 2017)

Figure 9

Vgg16 Architecture Diagram



Note. From *VGG Net*. (2020, August 21). EverybodyWiki Bios & Wiki. Retrieved April 7, 2022, from https://en.everybodywiki.com/VGG_Net

Dataset

We used the open-source TrashNet dataset in this case study. TrashNet is a repository of 2527 images of miscellaneous trash items classified into six categories: cardboard (403), glass (501), metal (410), paper (594), plastic (482), and trash (137). The images are of a single item on a white background. Some objects were photographed in their entirety; others were only partially shown. The photos were taken from different perspectives to increase variety.

Figure 10

Sample TrashNet Images

Data Preparation

We used a standard 80/20 train/test split for the recycling classification case study. We split the 80% training data further into 80% training data and 20% validation data. The result is 1614 training images, 405 validation images, and 508 testing images. Splitting data in this manner is an industry best practice. (Masand et al., 2021; Zhang et al., 2021; Awe et al., 2017)

There are multiple ways to split the data using built-in python libraries like sklearn and keras, but we needed more control over the output of the data than what these pre-packaged solutions offered. We wrote a custom function to split the dataset into testing, training, and validation subsets for reproducibility and ease of use. The custom function builds a folder structure consistent with the ImageNet standard; two levels of subfolders exist: one for train, valid, and test - then another for each classification (cardboard, glass, metal, etc.)

The images have three channels (red, green, blue); each pixel in the picture is a set of 3 RBG color values on a scale of 1 to 255. For simplicity, the images are optionally "rescaled" or "normalized" (based on the value of the preprocess rescale hyperparameter) using preprocessing functions, so the RGB data is on a scale of 0 to 1 instead of 1 to 255.

The original TrashNet images are 512x384 in size. During data preparation, we resize the images into smaller squares. VGG, DenseNet, and ResNet prefer images of size 224x224, whereas the other models didn't have a documented preference. In the absence of image size restrictions, we also tested with 300x300 images.

Hyperparameter Tuning

Each candidate model had a huge number of hyperparameters available for tuning. We selected a few of the most critical hyperparameters for each candidate model. Then we decided on a small subset of the most appropriate values for those hyperparameters. Table 1 shows all possible values in the hyperparameter search space used in the tuning phase. Using the keras tuner library, we used two alternative hyperparameter optimization algorithms to identify a "best model."

First, we used HyperBand searching to conduct a tournament-style, bracket-based elimination of all the candidate models to identify a high-performing model. HyperBand trains many candidate models in early rounds and carries forward the top-performing half of models to the tournament's next round. It uses early stopping to preserve time and resources to converge on a winning model quickly.

Next, we used the random search method to conduct hyperparameter optimization. Random search chooses any combination of hyperparameter values at random. Then, it builds and tests the model. It saves metrics about each model it tests in its "search space" and stores the model that maximized the performance metric. In our case, the performance metrics were validation accuracy and categorical cross-entropy. Based on the parameters in Table 1 below, there are 7680 possible parameter combinations, so we set a limit of 50 on the random search to ensure the process would complete within two hours.

Hyperparameter Search Space

Table 1

Hyperparameter Search Space

HyperParameter	Datatype	Values
Model Type	string	basecnn, vgg16, densenet121, resnet50
Preprocess Rescale	boolean	true/false
Preprocess Random Flip	boolean	true/false
Batch Normalization	boolean	true/false
Dense Units	integer	32, 64, 96, 128, 160, 192, 224, 256
Dropout Rate	float	0.0, 0.1, 0.2, 0.3, 0.4, 0.5
Learning Rate	float	0.01, 0.005, 0.001, 0.0005, 0.0001

HyperParameters Detail

- See *Modeling Architecture* section for details about each of the model types.
- The *preprocess rescale* layer normalizes the image's RGB values for more efficient classification.

- *The preprocess random flip* layer inverts the image on both axes to create different views of the same object.
- *Batch normalization* standardizes the data between layers to reduce bias. After batch normalization, image data has the same range of values, reducing bias.
- The *dense units* hyperparameter is the output size of the dense layer. The dense layer takes input from all the neurons of its input layer and changes the dimensions to output a consolidated dimensional vector. The dimensional vector has the number of parameters defined by the dense units hyperparameter. (Huang et al., 2017)
- *The dropout rate* is the percentage of output to be randomly removed from the layer and temporarily ignored. By thinning the inputs, the downstream nodes become more robust and correct some mistakes from prior layers to reduce overfitting. (Garbin et al., 2020)

Optimizer

We used the Adam optimizer to further optimize parameters with gradient descent and decaying gradients to navigate the search space. We chose the Adam optimizer over other alternatives like Adadelta and RMSprop because it combines the benefits of these optimizers and uses adaptive momentum to find an optimal learning rate for each parameter. Adam tends to converge faster than many other optimizers, and most of the studies from our literature review recommended it. (Lee et al., 2020; Masand et al., 2021)

Model Training

The “best model,” was the model that produced the lowest loss and highest validation accuracy in the hyperparameter tuning phase. We loaded the saved best model from cloud storage and re-trained it using the best hyperparameter values. To enhance the model, we increased the number of epochs from 20 in the hyperparameter tuning phase to 50 in the training phase. After each training epoch, we invoked a callback function that stored the best version of the model to the filesystem and stopped the training process after five consecutive epochs without improving the error rate (early stopping).

Model Evaluation

Evaluation Metrics

Validation Accuracy. Accuracy against the validation subset measured the model's ability to correctly classify items at a high level (correct versus incorrect classification). Accuracy is simple to understand because it is binary; each item was either classified correctly or not. For classification problems, accuracy is the ratio of correct predictions to total predictions.

Categorical Cross Entropy. We used categorical cross-entropy as the loss function in model evaluation. Cross entropy was a more robust metric than accuracy because it quantifies how close (or far) the model was from predicting the correct class. Categorical cross-entropy calculates the sum of loss for each correct class's probability per observation. As the predicted probability of the right class diminishes, the loss increases according to the loss formula below in Figure 11. Figure 12 shows two images that the ResNet50 model classified correctly. Notice the paper sample (probability 99.67%) had a much smaller loss than the metal sample, which had a probability of 77.26%.

Figure 11

Formula for Calculating Categorical Cross-Entropy

$$-\Sigma_{c=1}^{M} y_{i,c} \log(p_{i,c})$$

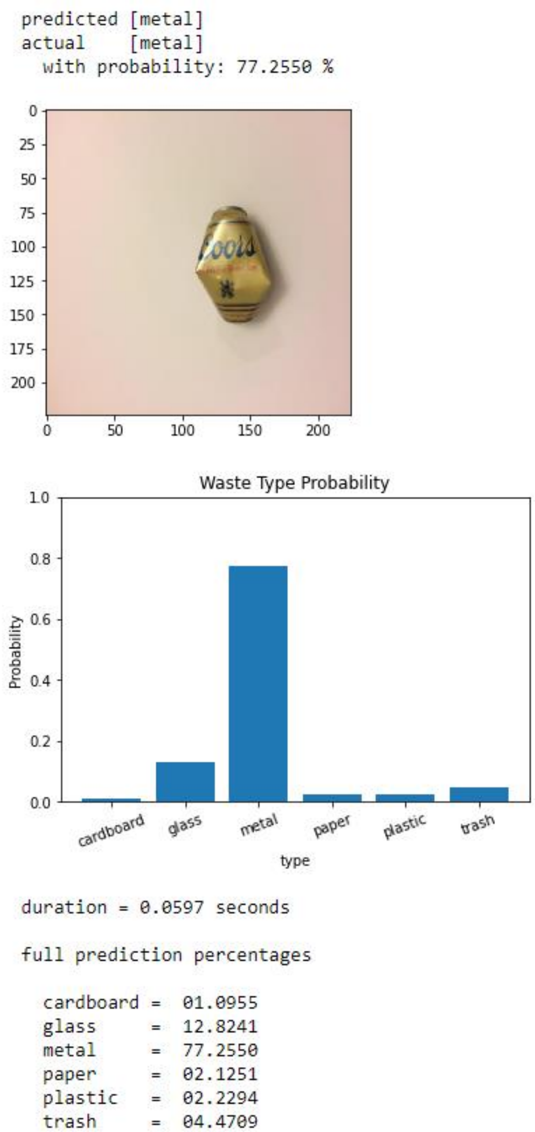
- where ***M*** is the number of classes

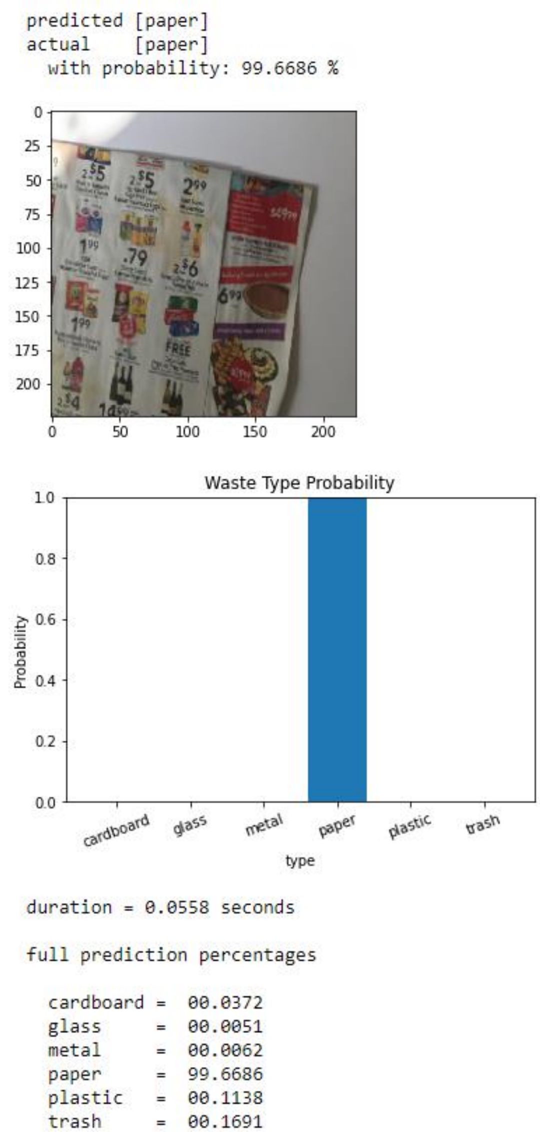
- ***yi,c*** is a binary indicator for whether ***c*** is the correct class
- ***pi*** is the predicted probability between 0 and 1.

Note. Formula image from Gomez, R. (2018, May 23). *Understanding Categorical Cross-Entropy Loss, Binary Cross-Entropy Loss, Softmax Loss, Logistic Loss, Focal Loss and all those confusing names*. Raúl Gómez blog. Retrieved April 7, 2022, from https://gombru.github.io/2018/05/23/cross_entropy_loss/

Figure 12

Example Predictions with Classification Probabilities





Prediction Time. Accurately classifying a recyclable is critical to the application's success. Accordingly, we considered the time it takes to return the prediction as a key performance metric. For a model to be useful in large-scale recycling classification applications, it needs to return predictions quickly. In the context of recycling classification, a model that predicts with 100% accuracy would not be helpful if it takes more than a half-second to return the prediction. In many cases, it would be appropriate to forego a model that predicts more accurately for another that predicts faster.

Model Evaluation Process

The best models from the tuning phase were evaluated against the test dataset using keras' evaluate function. We omitted images from the test dataset during the tuning and training phases to prevent bias in the final model evaluation. To assess prediction time, we took the average of the duration to predict ten individual images using the most accurate model for each model type. The timing framework used python's "time" package to capture start and end times.

Environment Setup

Training waste classification models on our local machines was not sufficient. Heavy image processing requires GPU to run quickly, so we turned to Google Colab and Kaggle as they are free compute options for students. Both Google Colab free and Kaggle enforced a session limit. Session limits made it difficult to run the extensive hyperparameter search outlined above, so we upgraded to Google Colab Pro, which allows for "High-RAM GPU" runtimes and twelve-hour session limits. The Google Colab Pro high memory runtime was sufficient for the processing and analysis outlined in this case study. The details of the development environment used can be found in Table 2.

Table 2

Development Environment Specifications

Name	Value
Programming Language	Python 3.7.13
Compute Platform	Google Colaboratory Pro
RAM	27.3 GB
Hardware Accelerator	GPU / High-RAM
Operating System	Linux/Ubuntu 18.04 (x86_64)
CUDA Version	11.2
Python Libraries	tensorflow, tersorboard, keras, keras-tuner, numpy, matplotlib

Conclusion

Chapter 3 explained the similarities and differences between several popular candidate model families and modeling techniques used to classify images. We demonstrated how we adapted pre-existing models to our specific use case and described the rationale for training and evaluating the models. We also justified our decisions and weighed them against the alternatives. Chapter 3 illustrated why TrashNet images are adequate for supervised machine learning because they are a good proxy for items in the recycling stream at an MRF. The methodology and framework described above were the foundation for conducting our analysis in a reproducible and unbiased way. We ran all trials using a shared python notebook with minimal configuration changes for each model type. The results were stored outside of Colab's temporary storage in Google Drive cloud storage for checkpointing and reusability. Chapter 4 summarizes and describes the findings and results from applying the above approaches, techniques, and methodologies.

Chapter 4: Results

Introduction

This chapter outlines the results of our case study's analysis on recycling optimization through computer vision models using convolutional neural networks. The first section outlines the general performance and viability of each model type we tested (base CNN, DenseNet121, ResNet50, Vgg16). The second section compares the hyperparameters and performance metrics for the best model of each of the model types found in the tuning phase. In the third section, we evaluate the two hyperparameter optimization algorithms' ability to identify the top-performing model. Finally, we review the performance metrics and recommend a "best of the best" model to deploy at materials recovery facilities and explain its advantages over the other candidates.

Model Type Viability

The primary objective of this case study was to "research, apply and compare the effectiveness of candidate models to identify and segregate trash items." After running an extensive search to identify the best-performing models for each model type, we determined that DenseNet121 and ResNet50 models were the most viable modeling architectures according to our gathered performance metrics. Vgg16 was the third best, and the base CNN model was the least feasible. Table 3 shows the top 25 candidate models from the hyperparameter tuning phase. The top 25 candidate models were all of model type DenseNet121 (12) or ResNet50 (13). The best Vgg16 model was ranked #51 with a validation accuracy of 0.8333. The best base CNN model was ranked #117 with a validation accuracy of 0.6536.

Table 3

Top 25 Models from Tuning Phase

Rank	Model Type	Rescale	Random Flip	Batch Norm	Dense Units	Dropout Rate	Learning Rate	Tuner Type	Val. Acc.
1	densenet121	TRUE	TRUE	TRUE	224	0.1	0.001	random_search	0.8932
2	resnet50	FALSE	TRUE	FALSE	64	0.1	0.001	random_search	0.8750
2	resnet50	FALSE	TRUE	TRUE	224	0.5	0.005	random_search	0.8750
2	densenet121	TRUE	TRUE	TRUE	160	0.4	0.001	hyperband	0.8750
5	resnet50	FALSE	TRUE	FALSE	96	0.3	0.0005	random_search	0.8698
5	densenet121	TRUE	FALSE	FALSE	160	0.5	0.001	random_search	0.8698
5	densenet121	TRUE	TRUE	FALSE	256	0.1	0.005	random_search	0.8698
8	resnet50	FALSE	FALSE	TRUE	128	0.4	0.01	random_search	0.8672
9	resnet50	FALSE	TRUE	TRUE	192	0.1	0.01	random_search	0.8646
9	resnet50	FALSE	TRUE	TRUE	256	0.3	0.005	random_search	0.8646
9	densenet121	TRUE	TRUE	TRUE	192	0.3	0.005	random_search	0.8646
9	densenet121	TRUE	FALSE	TRUE	224	0.5	0.001	random_search	0.8646
9	densenet121	TRUE	TRUE	FALSE	256	0.2	0.001	random_search	0.8646
14	densenet121	TRUE	FALSE	TRUE	160	0.2	0.005	random_search	0.8620
14	densenet121	TRUE	FALSE	FALSE	224	0.4	0.005	random_search	0.8620
16	densenet121	TRUE	FALSE	FALSE	160	0.2	0.001	hyperband	0.8594
16	densenet121	TRUE	TRUE	TRUE	256	0.4	0.01	random_search	0.8594
18	resnet50	FALSE	TRUE	TRUE	192	0	0.005	hyperband	0.8568
18	densenet121	TRUE	TRUE	FALSE	128	0.3	0.01	random_search	0.8568
20	resnet50	FALSE	FALSE	TRUE	64	0.5	0.01	random_search	0.8542
20	resnet50	FALSE	TRUE	FALSE	128	0.1	0.005	random_search	0.8542
20	resnet50	FALSE	TRUE	FALSE	160	0.3	0.01	random_search	0.8542
20	resnet50	FALSE	FALSE	TRUE	224	0.2	0.001	random_search	0.8542
20	resnet50	FALSE	TRUE	FALSE	192	0.2	0.001	random_search	0.8542

The second objective of this case study was to "assess the improvement in trash classifying model accuracy with the integration of transfer learning." We can unequivocally conclude that integrating transfer learning into our models improved the results. The ResNet50, DenseNet121, and Vgg16 models all used transfer learning, and they outperformed the base CNN model that we built without integrating transfer learning. The gap in accuracy between the base CNN model and the 3rd best transfer learning model was over 13 percentage points. Since the authors of the transfer learning models trained them against hundreds of thousands of ImageNet images, it makes sense that they would predict more accurately than our base CNN model. We achieved our objective of proving we could successfully adapt the transfer learning models to our recycling classification problem.

Optimal Hyperparameters

There were no apparent patterns or commonalities between the hyperparameter values of the top 25 models. For example, we did not observe that any specific hyperparameter value was more prevalent in the top-performing candidate models. However, there were some commonalities amongst the hyperparameter values of the best model by model type (see Table 4). The best-performing model for each model type used 1) random flipping during the preprocessing, a relatively low dropout rate (0.1 or 0.3), and a learning rate of either 0.001 or 0.0005.

Table 4

Best Model Hyperparameter Values By Model Type

Model Type	Rescale	Random Flip	Batch Norm	Dense Units	Dropout Rate	Learning Rate
basecnn	TRUE	TRUE	FALSE	96	0.3	0.0005
vgg16	FALSE	TRUE	TRUE	160	0.3	0.001
densenet121	TRUE	TRUE	TRUE	224	0.1	0.001
resnet50	FALSE	TRUE	FALSE	64	0.1	0.001

Hyperparameter Optimization Algorithms

The random search hyperparameter optimization found the best model for ResNet50. Random search was far more effective at finding optimal hyperparameters than Hyperband. Random search identified 22 of the top 25 models - Hyperband identified the remaining three models. Random search took 104 minutes to complete 50 trials, whereas Hyperband took 41 minutes to complete 30 trials. Random search trials averaged 124 seconds to finish; Hyperband trial averaged 82 seconds. Hyperband tested more models quickly because it uses very few epochs in the early “rounds” of each tournament-style “bracket.”

Since CNNs rely on connections between layers, changes to a hyperparameter that affects one layer can drastically change the optimal values of the hyperparameters related to subsequent layers. We believe this is another reason random search outperformed Hyperband in finding optimal hyperparameters.

Model Performance

We built, trained, and evaluated each of the best models for each model type from Table 4 against the test dataset. We collected the following performance metrics during the training and evaluation processes: accuracy, loss, evaluation duration, training duration, and time to predict. Table 5 shows accuracy, loss, evaluation duration, and training duration. Table 6 summarizes the time to predict.

Table 5

Best Model Performance Metrics By Model Type

Model Type	Accuracy	Loss	Evaluation Duration*	Training Duration*
basecnn	0.6693	1.1739	00:15	04:09
vgg16	0.8012	1.9548	00:20	**03:23**
densenet121	0.8425	0.3846	00:23	09:39
resnet50	**0.8622**	**0.3587**	**00:11**	05:23

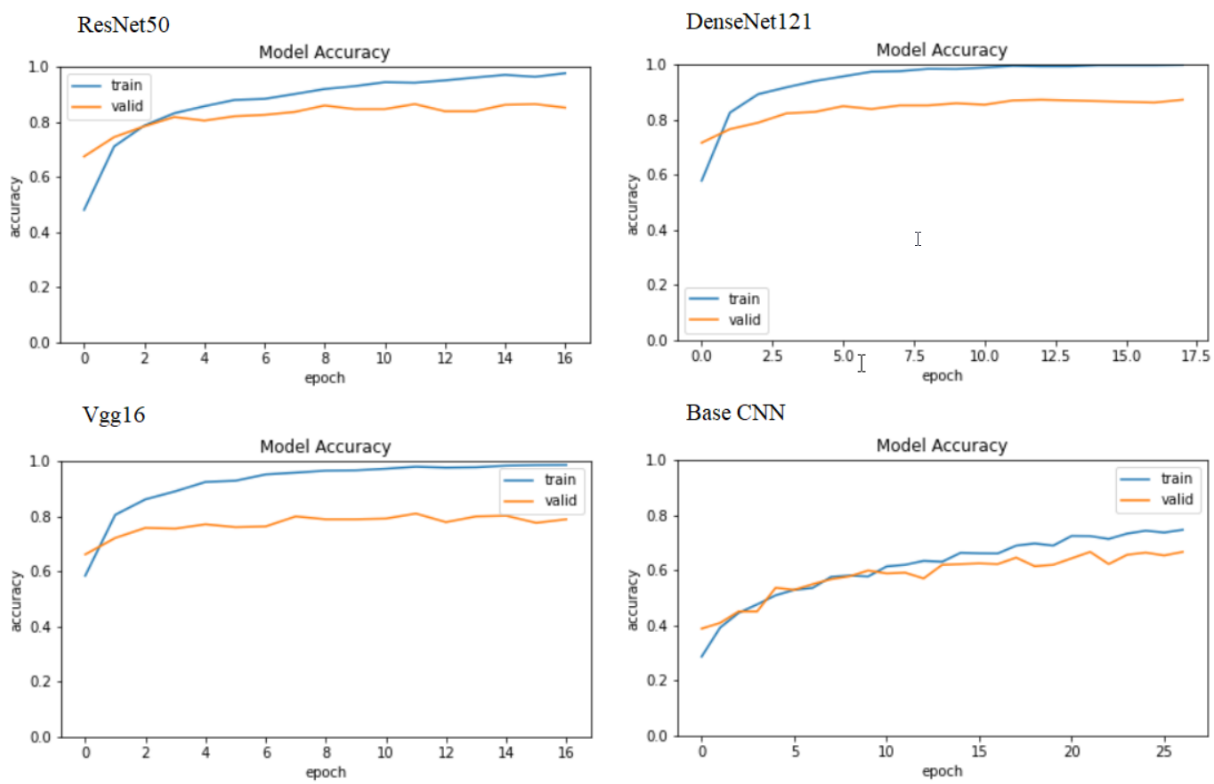
* Note: Values are in minutes:seconds format

Accuracy

Figure 13 shows the training and validation accuracy of each of the best models for each model type from the training phase. As expected, training accuracy was better than validation accuracy, and test accuracy was very similar to validation accuracy in all cases. We emphasized test accuracy for the final model evaluation because there is less potential for bias than validation accuracy. ResNet50 had the best test accuracy measure at 0.8622. DenseNet121 was a close second place with 0.8425.

Figure 13

Best Models Accuracy



Loss

We used categorical cross-entropy to quantify a model's loss during the model evaluation phase. We found that the training loss is consistently less than the validation loss except for a few early epochs. Again, ResNet50 (0.3597) and DenseNet121 (0.3846) had significantly better loss metrics than Vgg16 (1.9548) and base CNN (1.1739). We can conclude that ResNet50 and

DenseNet121 were not only better at predicting the correct class, but they were also closer to predicting the correct classification (the probability for the correct classification was higher) when predicting an incorrect class. The large gap in Vgg16's accuracy (0.8012) and loss (1.9548) means it correctly predicted many images, but it was off by a wide margin when it predicted incorrectly.

Figure 14

Best Models Loss

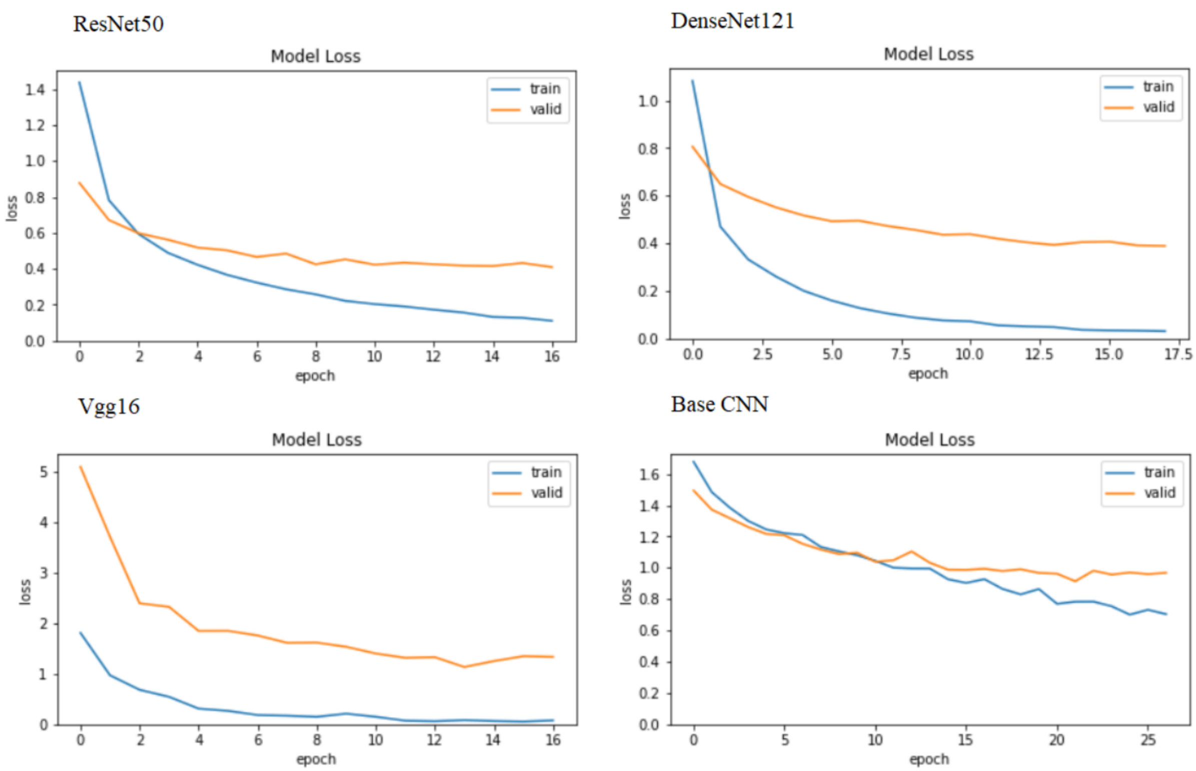
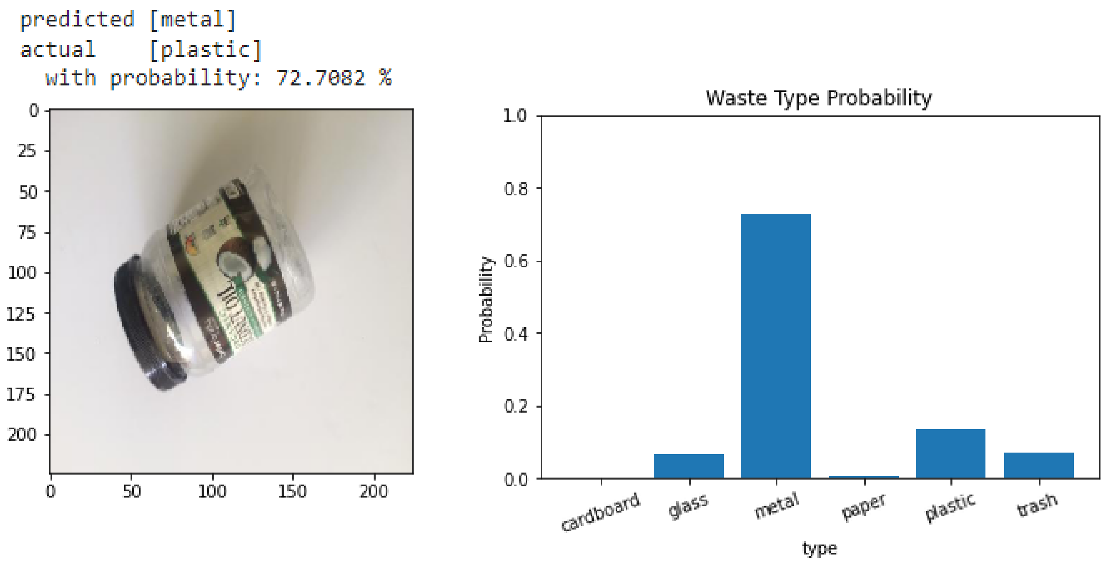


Figure 15 shows one such example with high loss. The sample is plastic, but the model predicted metal and assigned the probability of plastic as only 0.1325.

Figure 15

Example Prediction with High Loss



Prediction Time

Our third objective was to "assess the model's ability to predict quickly and decide if it is viable for use at an MRF." We collected the timings from predicting an image from each class in Table 6. We used the same images for each model type to ensure fairness. The base CNN model returned its predictions the fastest (0.0839 seconds), and DenseNet121 returned its predictions the slowest (0.4853 seconds). ResNet50 (0.2046 seconds) and Vgg16 (0.2119) had similar timings. ResNet50 was the fastest of the three transfer learning models, which agrees with Rahman et al., 2020.

Ahmed & Asadullah reported that employees at an MRF traditionally pick 20 to 40 items per minute, while machines from Bulk Handling Systems can pick 60 to 80 items per minute. On average, each model type returned predictions in less than half a second, so they can all predict at least 120 items per minute. However, we must consider the time it takes for machines to pick up the item and drop it into the proper bin. We could not find any data on how long it takes machines to process each item, but we can assume it varies widely based on the number of machines, bins, the conveyor belt's size, and the conveyor belt's speed. We estimate that

ResNet50 can predict 293 items per minute on the current infrastructure, whereas DenseNet121 can predict 124 items per minute. ResNet50 can predict roughly 2.4 times faster than DenseNet121.

The timings we collected are simply a baseline. Running on an upgraded system or a better network will produce faster predictions, so it is plausible that any of the models we discussed could be viable for MRF operations. For example, Bircanoğlu et al. found DenseNet121 was too slow to run at an MRF, so they removed some layers and upgraded the system specifications to make it run faster. (Bircanoğlu et al., 2018)

Table 6

Time Taken to Predict Single Image of Each Class (seconds)

Test Image	ResNet50	DenseNet121	Vgg16	Base CNN
cardboard4.jpg	0.9450	2.5843	0.9831	0.2606
glass32.jpg	0.0637	0.0647	0.0543	0.0472
metal4.jpg	0.0537	0.0653	0.0584	0.0467
paper2.jpg	0.0554	0.0658	0.0616	0.0473
plastic4.jpg	0.0546	0.0663	0.0591	0.0512
trash131.jpg	0.0549	0.0653	0.0550	0.0504
Mean	0.2046	0.4853	0.2119	0.0839
Est. Items per Minute	293	124	283	715

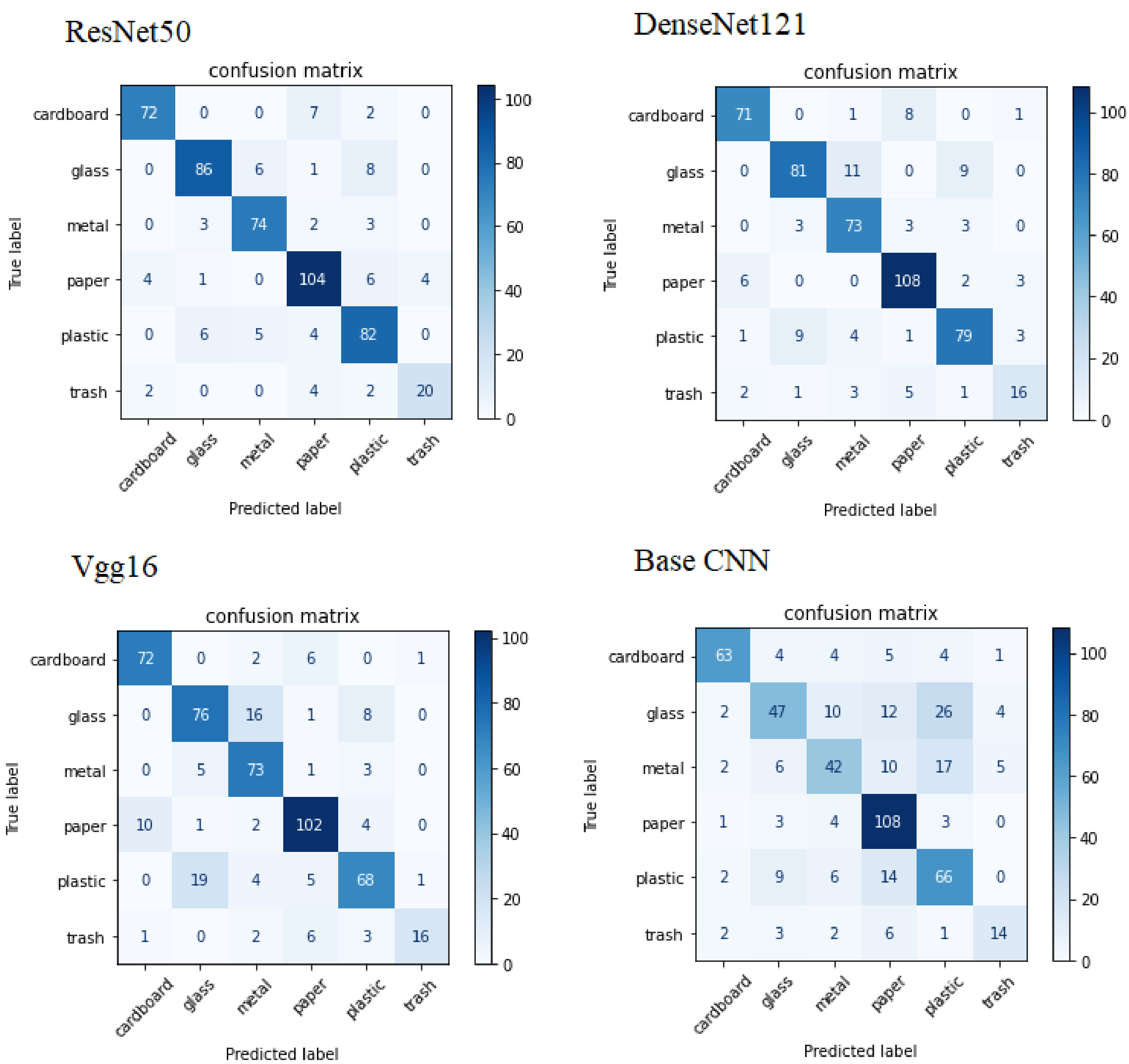
Confusion Metrics

Figure 16 shows how each of the four best models excelled in predicting some classes while struggling to predict others. Each model had difficulty distinguishing glass from plastic and glass from metal. The base CNN model performed well against paper samples, but it struggled to classify glass and metal correctly. Vgg16 did not recognize the difference between cardboard and paper as well as the other models. ResNet50 did not perform as well as

DenseNet121 on paper samples, but it performed better on glass, cardboard, metal, plastic, and trash.

Figure 16

Best Models Confusion Matrices



Recommended Model

Summary and Justification

Based on the above performance metrics, we recommended a ResNet50 model with the hyperparameters listed in Table 7 for single-stream recycling sorting applications at materials recovery facilities.

Table 7

Recommended Model Hyperparameters

Hyperparameter Name	Value
Model Type	ResNet50
Preprocess Rescale	FALSE
Preprocess Random Flip	TRUE
Batch Normalization	FALSE
Dense Units	64
Dropout Rate	0.1
Learning Rate	0.001

Out of more than 320 model variations evaluated through Hyperband and random search, we determined ResNet50 with the hyperparameters from Table 7 to be the “best of the best” for a few key reasons: 1) it had the best accuracy against the test dataset, 2) it had the lowest loss against the test dataset, 3) it is likely to operate fast enough for an MRF because it can predict 293 items per minute and 4) it performs reasonably well in classifying each of the six classes, 5) it converged faster than the other candidate models. Although Table 3 shows DenseNet121 as the top-ranked model, the recommended ResNet50 performed better against the test dataset.

Our recommended model used transfer learning to adapt the original ResNet50 model to our recycling classification problem. Recall from Chapter 3 that the original ResNet50 model was trained against the ImageNet database. To keep the pre-trained weights, we froze the

ResNet50 layers in the model's definition to prevent the tuners from attempting to optimize them in the tuning and training phases.

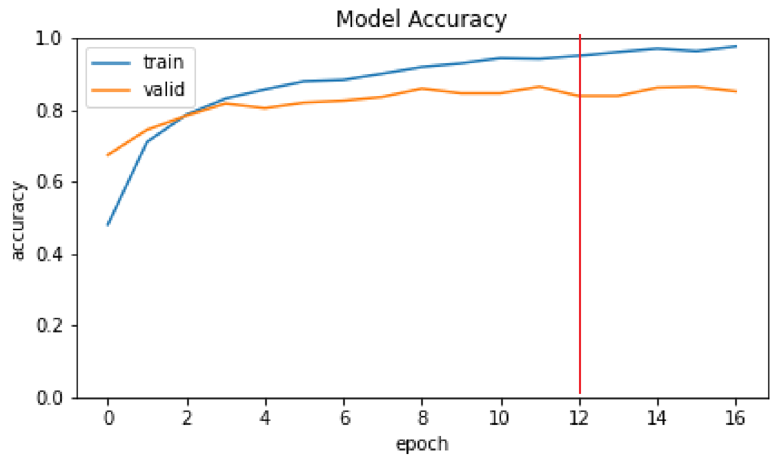
Training and Convergence

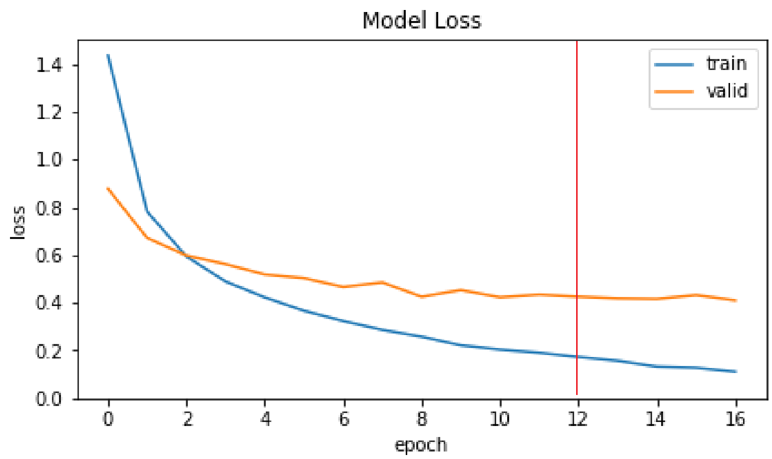
The recommended model converged after 12 epochs, and it completed training in 5 minutes and 23 seconds, which was significantly less than DenseNet121 (09:39). Model training stopped early to prevent overfitting since the validation accuracy did not improve from 0.8697 between epochs 13 and 17. In this case, we recommend training the ResNet50 model for 12 epochs before deployment. Any additional training beyond 12 epochs will likely cause overfitting against the TrashNet dataset.

Since the scale of single-stream recycling at MRFs is so massive, minor improvements will translate to enormous savings for waste management companies and the environment, even if it is only a tiny fraction of a percent. Due to this requirement, we configured early stopping after five epochs of no improvement to validation accuracy. From the accuracy and loss metrics shown in Figure 17, we saw an increase in performance against the training dataset, while the validation dataset metrics did not improve after epoch 12.

Figure 17

Recommended Model Metrics by Epoch





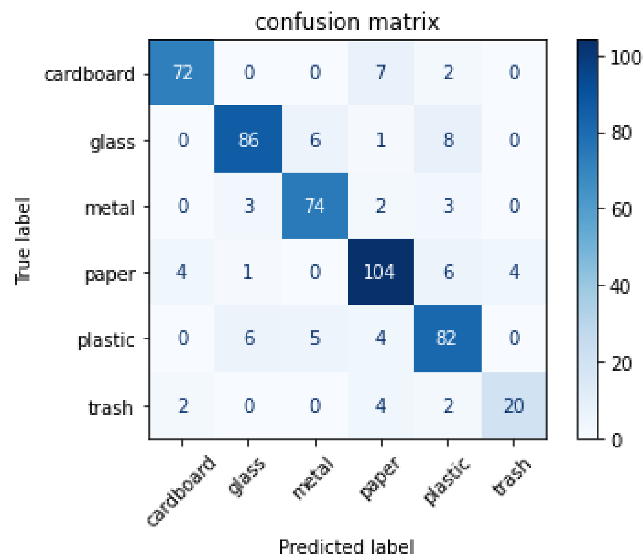
Confusion Metric Detail

The ResNet50 model classified cardboard (0.91) and metal (0.87) most accurately. The lowest f1 scores belong to trash (0.77) and plastic (0.82). The relatively small sample size might have diminished the model's ability to predict trash for trash versus the other classes. There were only 137 trash samples; all the other classes had at least 403 samples.

Using Figures 24 and 25, we determined the recommended model mispredicted plastic more than any other class. Plastic was confused with trash, glass, and paper 7.14%, 7.92%, and 5.04% of the time, respectively. However, the model incorrectly classified trash as paper for 14.29% of the test samples - the most among all combinations.

Figure 18

Recommended Model Confusion Matrix with Classification Report



classification report:

	precision	recall	f1-score	support
cardboard	0.92	0.89	0.91	81
glass	0.90	0.85	0.87	101
metal	0.87	0.90	0.89	82
paper	0.85	0.87	0.86	119
plastic	0.80	0.85	0.82	97
trash	0.83	0.71	0.77	28
accuracy			0.86	508
macro avg	0.86	0.85	0.85	508
weighted avg	0.86	0.86	0.86	508

Table 8

Recommended Model Misclassification Rate Relative Percentage

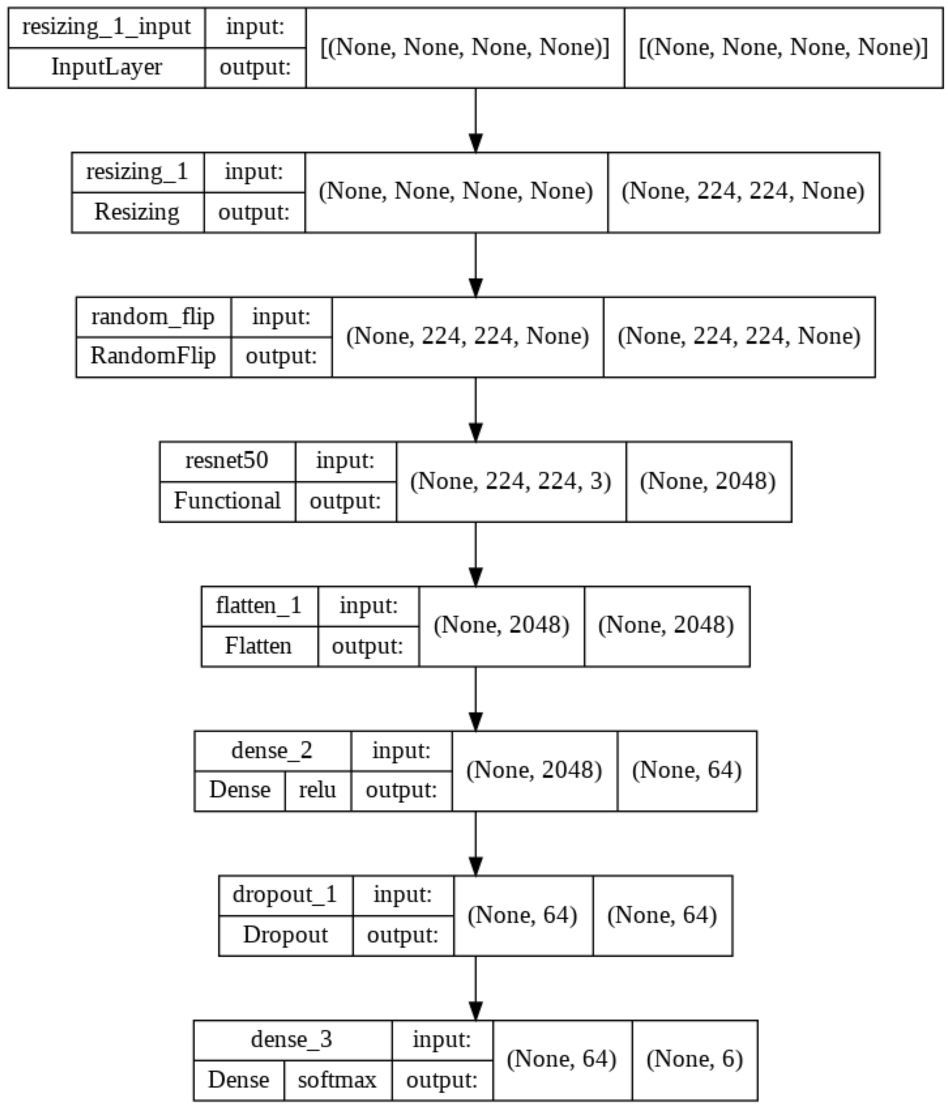
Misclassification Rate

predicted label

true label	cardboard	glass	metal	paper	plastic	trash	TOTAL
cardboard	N/A	0.00%	0.00%	8.64%	2.47%	0.00%	11.11%
glass	0.00%	N/A	5.94%	0.99%	7.92%	0.00%	14.85%
metal	0.00%	3.66%	N/A	2.44%	3.66%	0.00%	9.76%
paper	3.36%	0.84%	0.00%	N/A	5.04%	3.36%	12.61%
plastic	0.00%	6.19%	5.15%	4.12%	N/A	0.00%	15.46%
trash	7.14%	0.00%	0.00%	14.29%	7.14%	N/A	28.57%
TOTAL	10.50%	10.68%	11.10%	21.84%	23.76%	3.36%	

Figure 19

Recommended Model Summary Diagram



Conclusion

Our recommended ResNet50 model is the product of analyzing all the performance metrics gathered in the training, tuning, and evaluation phases. We believe the suggested model is a great starting point for sorting recycling streams. Refer to the appendix to review the source code used to conduct the analysis. Although the scope of this case study is somewhat limited, our findings provide a strong foundation for further work and development of computer vision CNN models for recycling and other similar use cases. Chapter 5 discusses the next steps for this case study and highlights some of its shortcomings.

Chapter 5: Discussion

Study Significance

Reducing municipal solid waste is a complex problem requiring a complex solution. There are two main ways to reduce the amount of non-renewable waste: produce less and reuse more. This paper focused solely on developing technology to increase recycling, but it did not address ways to reduce the amount of MSW created. From that perspective, it may seem like we focused on treating the symptom and not the cause. However, experts expect global waste to grow to 3.4 billion tons by 2050, so society will need to attack this problem from both angles to reduce unrecycled waste significantly.

Optimizing the waste stream is a win-win proposition for all parties. The everyday customer benefits from the reduction in environmental harm caused by landfills and incinerators. The waste management company benefits from additional sales of recycled materials and a reducing costs associated with landfilling and incineration. Buyers of recycled materials on the secondary market benefit because they get a purer product which requires less quality control. Although implementing computer vision solutions at an MRF would require heavy investments in technology and robotics, we believe the high accuracy of our models proves machine learning, computer vision, and CNN are incredibly useful in the waste management industry. Automation is becoming an attractive alternative in the waste management industry because it increases ROI by combatting rising wages, mitigating employment shortages, and reducing worker safety risks.

Many of the largest waste management companies have deployed computer vision solutions with teams of data engineers and data scientists to oversee them. They have realized the benefits, and their models continue to grow and improve. Their models are proprietary, so we could not relay any specifics. (Blomberg, personal communication, 2022). Still, our study paves the way for smaller waste management companies with fewer resources to optimize their waste streams.

We anticipate a growing need for recycling optimization solutions because industry experts expect recycling rates to increase due to eco-friendly consumer trends and increased efforts to reduce carbon emissions. (Ahmed & Asadullah, 2020)

Limitations and Suggestions

We designed our models assuming an MRF would filter the items based on the class with the highest predicted probability. A classifier might treat an item with as little as 18% probability the same as an item with 99% probability. Most MRFs have a quality threshold. The models should be configurable to default the item as trash unless there is at least 50% confidence. Since different MRFs have different quality standards and regulations, it would be beneficial to tweak the classification framework to allow configuring minimum probabilities for each class to reduce contamination.

One of the biggest challenges for single-stream recycling is dirty recyclables. Unfortunately, the TrashNet dataset did not include any images of contaminated recyclables, so we could not incorporate them into our models. Imagine if we tested our models with a half-full peanut butter jar. The jar would probably get classified correctly as plastic, yet we cannot recycle it. Therefore, it would be best if the models classified the dirty peanut butter jar as trash. Adding a "dirtiness" element to the model would undoubtedly make classification more complicated, but it is a necessary next step to increase the utility of the model. Since dirtiness characteristics can be widely different amongst the classes, we recommend adding a two-stage classification for each non-trash category. The first stage would identify the item's composition (plastic, paper, glass, cardboard, metal). The second would be a binary predictor to indicate whether the item is clean enough (according to a configurable threshold) to be recycled.

To make the training images more representative of the actual recycling stream, we plan to scale, shear, rotate and reduce brightness on the TrashNet images. As mentioned in the literature review, the photos from TrashNet are of much higher quality than we can expect from all MRFs. Since some items may overlap or blend in with the background, CNN will not be able to identify them as well. With this in mind, we should not assume that deploying our ResNet50 model will result in 86% accuracy when deployed in an MRF setting.

The scope of this case study was limited to four different model families: base CNN, DenseNet, ResNet, and VGG. We can consider many other model families for transfer learning like Xception, GoogleNet, AlexNet, and MobileNet. Furthermore, some model families have multiple variations to consider (ResNet34, ResNet50, ResNet101). Likewise, we could have considered alternative activation functions on the fully-connected layer. Our models used the softmax activation method, but our studies have demonstrated that implementing SVM, SIFT, and HOG activation within CNNs can produce better performance. Overall, this case study provided a baseline and a framework to test any of these models in future iterations easily.

To increase the models' utility, we also plan to implement multi-stage classification for plastics and metals. Plastics need further sorting into their respective categories: polyethylene terephthalate (PET), polystyrene (PS), polypropylene (PP), polymethyl methacrylate (PPMA), and acrylonitrile butadiene styrene (ABS). (Zhu et al., 2019) Metals also need another sorting layer to segregate steel, copper, aluminum, brass, gold, and silver. We may also consider combining similar classifications in an initial stage to test for better performance. Since paper and cardboard are fibrous materials that our models may confuse, we can consider combining them into a “fibers” category. Then, the subsequent stages would further divide the fibers category into paper and cardboard.

We also plan to experiment with different values for the early stopping parameter. Some may argue that our resulting models are overfitting because early stopping did not occur even though there was minimal accuracy gain and loss reduction. Referring to Figure 17, there is a strong case that the optimal model takes place at epoch 3, not epoch 12.

Lastly, we plan to experiment with deploying our model using positive sorting versus negative sorting. This case study assumed positive sorting since it is the method used in most MRFs today. Positive sorting is designed to assume all items on the conveyor belt are valid and clean recyclables. With positive sorting, the MRF’s systems use a quantity-oriented system that filters out dirty or misclassified things that do not belong. Since many recyclable items are not correctly filtered (false negatives), quality issues can arise with the final product. Removing dirty recyclables from the recycling stream is so tricky that some MRFs have changed to a quality-oriented negative sorting approach. Negative sorting treats all items as dirty unless the MRF’s systems can identify them as valid and clean. The net effect of negative sorting is a final product that is smaller but purer. The secondary market prices for recycled goods increases as the purity of the recyclables increases. (Pyzyk, 2019)

Alternative Use Cases

Although we designed our trash-classifying CNN models for MRFs, they could also be used to report the composition of our waste stream. These models will allow us to collect metrics on the amount of waste created and show trends about which waste categories are growing. This information would be helpful in public education and recycling initiatives to help save the environment.

However, we need to be aware of the potential ethical issues with collecting data about trash. Any users of these models should take care to deploy them without intruding on an individual’s privacy. It is not permissible to search through someone’s garbage bin, so it is also not acceptable for waste companies to build customer profiles using data about a household’s trash composition.

Conclusion

This case study demonstrated how to build, train, and evaluate various machine learning computer vision models using CNN for recycling classification. Transfer learning using ResNet50 was the best performing model of the four candidate modeling architectures. Integrating transfer learning models trained on ImageNet significantly improved our base CNN model results. Using Google Colab's Pro tier, we estimate the recommended model can classify nearly 300 items per minute, sufficient for MRF deployment. The framework and dataset used to train and evaluate the models are somewhat limited. Still, our methodology and findings provide an excellent reference for others to build on and contribute to the greater goal of reducing the amount of non-recyclable waste. Like many artificial intelligence and machine learning solutions, the proposed models need more training data and more time to learn and reach their full potential.

Appendix

Source Code

The following python notebooks were used to setup the training data, define the models, run the hyperparameter search, determine the best model, evaluate the model, and print figures. There is a dedicated python notebook for each of the model types. Each notebook shares the same code framework with a different "MODEL_TYPE" parameter.

- basecnn_recycling_classifier.ipynb
- densenet121_recycling_classifier.ipynb
- resnet50_recycling_classifier.ipynb
- vgg16_recycling_classifier.ipynb

Model Diagrams

- basecnn model
- densenet121 model
- resnet50 model
- vgg16 model

Tables

The following excel file contains all of the tables included in this report

- capstone-recycling-classification-tables.xlsx

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