WASTE IMAGE CLASSIFICATION WITH DEEP LEARNING TECHNIQUES

George Liu
Student# 1006849341
georgedev.liu@mail.utoronto.ca

Kathy Lin
Student# 1007620166
kath.lin@mail.utoronto.ca

Viet Minh Nguyen
Student# 1007503989
nvmichael.nguyen@mail.utoronto.ca

Chris Shih
Student# 1008298272
chris.shih@mail.utoronto.ca

ABSTRACT

This project focuses on utilizing deep learning frameworks to classify images of landfill waste from sources into their respective material classes, with the final goal of optimizing recycling processes by transferring materials to their appropriate recycling facilities. This proposal document will outline the following: the neural network's architecture, its training and testing datasets, data processing steps, prior studies and developments relating to the project, and how the development team will collaborate and distribute work fairly.

—-Total Pages: 6

1 INTRODUCTION

With the rapid modernization and growth of the world's population, waste and pollutant generation has increased dramatically. The World Bank (Bank, 2022) estimates that the world's annual waste generation is poised to break 3.88 billion tonnes in 2050 - a 73% increase from 2020. Recycling has always been a great option to help us beat this statistic, but with a shockingly low recycling rate of 27% for discarded glass and 8% for discarded plastic (Cho, 2020), there is a clear need for improvement. Cho (2020) mentions a contamination risk if waste is deposited into the wrong bin or sent to the wrong facility, preventing large batches of materials from being recycled.

This project will seek to minimize this risk by leveraging deep-learning models for image classification. The neural network will be able to process an input image of a piece of waste and reliably predict the material that the waste consists of. With this information, large batches of waste can now be separated into material classes, which can then be sent to their respective processing facilities.

Deep learning, more specifically with Convolutional Neural Networks (CNNs), has been a popular choice for solving image classification problems. Krizhevsky et al. (2012) mention that CNNs have a tendency to make strong, yet accurate assumptions about the nature of images and are easy to train on large datasets, which can be attributed to having fewer parameters and connections. Additionally, with highly accurate and complex pre-built neural networks being so widely accessible, utilizing transfer learning becomes a possibility. All of these factors contributed to the decision to train a CNN for this task.

2 ILLUSTRATION / FIGURE

Our idea is to build the classification algorithm for an automatic garbage classification system, as illustrated in Figure 1. The image of an object is used as input to the previously-trained CNN, which performs feature extraction processes to classify the object's class (e.g., paper, glass, metal, plastic).

As part of the implementation of the model in reality, the trained model can be used as part of a classification system inside any garbage bins. A means of collecting object images is needed (e.g., a camera with sensors to take immediate pictures whenever there's an object thrown inside the bin). The image is then input to the model. The resulting classification from the CNN can send signals to additional machines (e.g., robotic arms, conveyor belts, trap doors) that can send the trash to the appropriate trash bin.

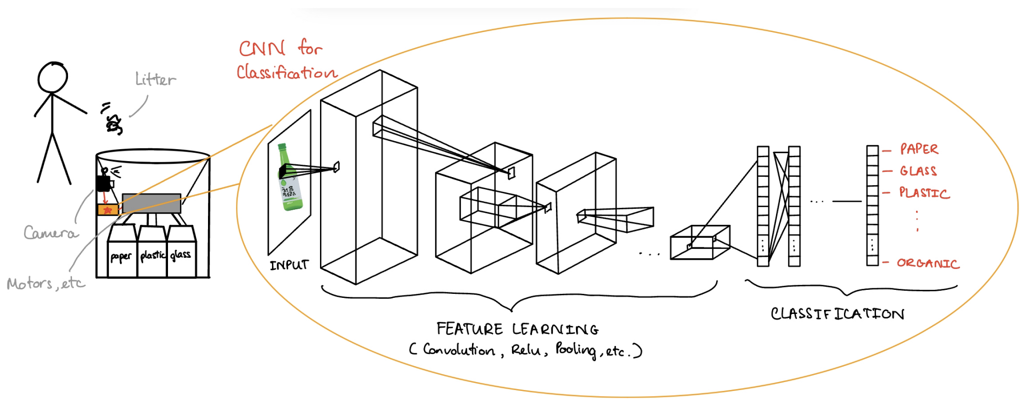

Figure 1: Project idea sketch

3 Background and Related Work

Image classification is one of the most widely researched areas in the field of computer vision. With the recent advancements in hardware, frameworks, and scalability, naturally, deep learning models have become very popular. However, there are still traditional, non neural network-based models that we can use as baselines for our own CNN. Lin et al. (2011) developed a way of training large image datasets with support vector machine (SVM) classifiers by first leveraging parallel processing techniques and hundreds of mappers to extract features from images, then by utilizing an averaging stochastic gradient descent (ASGD) algorithm. The model achieves a 52.9% accuracy score on the ImageNet dataset — state-of-the-art at the time the paper was published, but completely outclassed by modern neural networks.

However, convolutional neural networks can still take large amounts of time and computing resources to train. Fine-tuning weights and parameters on previously trained image classification neural networks like AlexNet (Krizhevsky et al., 2012) and ResNet (He et al., 2016) can help reduce training time, and since these models have been trained on large and varied datasets (i.e. ImageNet), this can result in improved model generalization performance (Hosna et al., 2022).

As for works on recycling and material sorting, Bircanoğlu et al. (2018) trained the DenseNet family of models (pre-trained on ImageNet) to obtain a 95% test accuracy on the TrashNet dataset. However, due to their focus on real-time implementation, they proposed their own model, RecycleNet, to accelerate inference times. This architecture altered the number of connections in the DenseNet model, offering a 46% inference time improvement on the CPU. As for hardware topics, Li & Grammenos (2022) developed a prototype for a "smart recycling bin", leveraging embedded systems (Jetson Nano, K210) and sensors to classify and segment waste at the time of disposal. Sorting materials is also a prominent topic in robotics — Koskinopoulou et al. (2021) proposes a robotic material categorization system trained on the Mask R-CNN architecture, utilizing cameras and sensors to segment, identify, and retrieve waste. Although this project will not be encompassing image segmentation, this remains a relevant topic in regard to the real-world implementation of our image classification CNN.

4 Data Processing

4.1 Data sources

The data for the project consists of two datasets. Each dataset contains images of different types of garbage along with their labels (Table 1).

Table 1: Number of examples in each class for each dataset

Dataset	Paper	Glass	Metal	Plastic	Trash	Misc	Total
Mohamed (2021)	1941	2011	769	865	697	9323	15606
Chang (2018)	997	501	410	482	137	0	2527
Total	2938	2512	1179	1347	834	9323	18133

4.1.1 Dataset 1: Garbage Classification (12 classes) (Mohamed, 2021)

- Classes: Battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, white glass
- Size: 15,606 images
- Errata: Some image sizes and formats appear not to be standardized and some samples contain watermarks (view biological100.jpg)

4.1.2 Dataset 2: Garbage Classification (Chang, 2018)

- Classes: cardboard, glass, metal, paper, plastic, trash
- Size: 2,527 images
- Errata: Images appears to be properly cropped at a standard aspect ratio and size

4.2 Cleaning the Dataset

- Comb through each dataset, removing images with watermarks and unclear labels
- Resize and crop images to a common aspect ratio and resolution
- Merge and organize the datasets into the following classes: Paper, Glass, Metal, Plastic, and Trash, removing any classes that do not belong to any of the above categories
- Ensure there is no bias among classes by removing training examples from classes that have excess training samples until there are equal numbers of samples in each

4.3 Data Augmentation

Given that the datasets we use are on the smaller side, we will use data augmentation to improve model robustness. We will apply the following transformations available to us in PyTorch Contributors (2017).

- Randomly crop onto different parts of the images
- Randomize brightness of the images
- Random horizontal/vertical flipping
- Random color jitter

5 Architecture

We will use a Convolutional Neural Network as is standard for image classification-type problems. The following table 2 describes the components of the model architecture and a short description of its purpose in relation to the overall model.

Table 2: The components/layers that the team will use in the model architecture

Layer type	Description
Convolutional Layer	Uses a learnable kernel which finds patterns in image data
ReLU activation	A standard non-linearity used in ML
Max-Pooling Layer	Determines the relevant features in the previous layer
Fully Connected Layer	Uses the flattened activations of the previous layer to determine the logits
Softmax output	Converts the logits to probabilities for classification

6 Baseline Model

The team elected to choose a simple Support Vector Machine model, which will serve as our baseline model. The SVM model was chosen as it works well on high-dimensional inputs like images and has existing implementations in popular ML libraries like SciKit Learn (Pedregosa et al., 2023).

7 Ethical Considerations

The main ethical issue of the system is that it can unintentionally guide users to violate established garbage sorting rules, which could worsen the environment and recycling rates. This is primarily because most of the images we use have a white background, which is not the case in real-world scenarios. This also raises questions about users' environmental responsibilities. In addition, privacy concerns might arise due to the datasets we use, which are collected by taking pictures of people's garbage and scraping the web, potentially capturing their personal information.

8 Project Plan

To make sure the project will be completed in time, we have set clear internal deadlines for each deliverable, Project Plan (PP), Progress Report (PR), Final Report (FR), and Video Presentation (VP) (Table 3) and have scheduled a weekly online meeting on Thursday at 6 pm to review each other's progress and address any challenges encountered. Our team will use a group chat to communicate everything that is related to the project and provide regular updates on assigned tasks to make sure everyone understands what is going on in the team. To prevent each other's code from being overwritten, we will divide each big task into sub-tasks so that only one person is responsible for one function. If someone has ideas to make that function better, then that person will first discuss with the person in charge of the function.

Table 3: Tasks, assigned person, and internal deadlines

Task	Assigned Person	Internal Deadline
PP Abstract, Introduction, Background and Related Work	Chris	Oct. 13
PP Data Processing, Architecture, Baseline Model	George	Oct. 13
PP Illustrations, Risk Register	Michael	Oct. 13
PP Ethical Consideration, Project Plan, Colab Link	Kathy	Oct. 13
Coding Data Processing	George	Oct. 22
Coding Baseline Model Architecture	Chris	Oct. 22
Coding CNN Architecture	Kathy	Oct. 22
Coding Baseline Model Testing	George	Oct. 29
Coding Training (one qualitative and quantitative result)	Michael	Oct. 29
PR Brief Project Description	Michael	Nov. 2
PR Individual Contributions and Responsibilities	All	Nov. 2
PR Notable Contribution (Data Processing)	George	Nov. 2
PR Notable Contribution (Baseline Model)	Chris	Nov. 2
PR Notable Contribution (Primary Model)	Kathy	Nov. 2
FR Introduction, Background and Related Work	Chris	Nov. 29
FR Baseline Model	Chris	Nov. 29
FR Illustration, Quantitative Results, Qualitative Results	Michael	Nov. 29
FR Data Processing, Discussion	George	Nov. 29
FR Architecture, Evaluate model on new data	Kathy	Nov. 29
FR Ethical Considerations	Kathy	Nov. 29
FR Project Difficulty / Quality	Chris	Nov. 29
VP Problem	Michael	Nov. 29
VP Data Processing	George	Nov. 29
VP Model	Chris, Kathy	Nov. 29
VP Results	Chris	Nov. 29
VP Discussion	Kathy	Nov. 29

9 Risk Register

There are multiple possible scenarios that can affect the team's progress. We came up with a set of procedures to both prevent and resolve these situations.

- Absence of a team member: A team member is sick, leaves the team (drop the course), or unable to participate in a deliverable for some reasons.
  - Every person is responsible to notify other team members way ahead of time or immediately when such occasions happen (or is expected to happen).
  - If the next team meeting is not within 48 hours, or the deadline is near, arrange an emergency team meeting to address the situation. Redivide work in such a way the quality of output is unaffected. Have additional team meetings to meet the final deadlines.
- Any team member does not meet internal deadlines
  - Use weekly (more frequent if needed) team meetings to check-in on the progress.
  - Update the task divisions or assign other members to support if necessary, with unanimous decision by all team members.
  - If the deadline is not met for personal reasons (not because of unequal task division), the entire team will address the issue in the next team meetings to avoid similar problems.
- Technical Emergency (lose work progress or cannot submit assignment)
  - For known scheduling conflicts or other issues, team members are expected to communicate such issues before they occur at least 24 hours in advance

- Do backups every 2 hours of working by pushing the code and related documents to shared GitHub. Draft on Google Docs for written assignments so version history is visible.
- Submit assignments at least 1 hour before deadlines (hard internal deadline) to avoid submission issues.

- Low training/test performance of model
  - All team members should fully attend lectures, tutorials, and lab sections to keep up with course materials and have the knowledge to contribute to the project.
  - Plan and follow the project timeline closely, leaving space for possible low performance result scenarios.
  - Raise the issue as soon as possible and discuss ways to address them as a group. Prepare sufficient documentations/presentations to seek help from Professor/TAs.

If any situation is not mentioned above, the team will hold an emergency meeting and come to a consensus on how to proceed.

10 Link to Colab Notebook

We use Colab Notebook to store all codes for this project, which can be found at `https://colab.research.google.com/drive/1I5NHdVTj9E4rGB1ZUWz5O2dzfYJAriOt?usp=sharing`.

11 Link to GitHub

We use a shared private GitHub to backup project codes and related documents `https://github.com/michael-ngx/garbage-classifier.git`.

References

The World Bank. Solid waste management, 2022. URL `https://www.worldbank.org/en/topic/urbandevelopment/brief/solid-waste-management#:~:text=In%202020%2C%20the%20world%20was,3.88%20billion%20tonnes%20in%202050.` Accessed on October 11, 2023.

Cenk Bircanoğlu, Melvin Selim Atay, Fuat Beser, Ozgun Genc, and Merve Ayyuce Kizrak. Recyclenet: Intelligent waste sorting using deep neural networks. 07 2018. doi: 10.1109/INISTA.2018.8466276.

C Chang. Garbage classification, 2018. URL `https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification/data`. Accessed on October 13, 2023.

Renee Cho. Recycling in the u.s. is broken. how do we fix it?, 2020. URL `https://news.climate.columbia.edu/2020/03/13/fix-recycling-america/`. Accessed on October 11, 2023.

Torch Contributors. Transforming and augmenting images, 2017. URL `https://pytorch.org/vision/main/transforms.html`. Accessed on October 13, 2023.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016. doi: 10.1109/CVPR.2016.90.

Asmaul Hosna, Ethel Merry, Jigmey Gyalmo, Zulfikar Alom, Zeyar Aung, and Mohammad Azim. Transfer learning: a friendly introduction. *Journal of Big Data*, 9, 10 2022. doi: 10.1186/s40537-022-00652-w.

Maria Koskinopoulou, Fredy Raptopoulos, George Papadopoulos, Nikitas Mavrakis, and Michail Maniadakis. Robotic waste sorting technology: Toward a vision-based categorization system for the industrial robotic separation of recyclable waste. *IEEE Robotics & Automation Magazine*, PP: 2–12, 04 2021. doi: 10.1109/MRA.2021.3066040.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C.J. Burges, L. Bottou, and K.Q. Weinberger (eds.), *Advances in Neural Information Processing Systems*, volume 25, pp. 1. Curran Associates, Inc., 2012. URL https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf.

Xueying Li and Ryan Grammenos. A Smart Recycling Bin Using Waste Image Classification At The Edge. *arXiv e-prints*, art. arXiv:2210.00448, October 2022. doi: 10.48550/arXiv.2210.00448.

Yuanqing Lin, Fengjun Lv, Shenghuo Zhu, Ming Yang, Timothee Cour, Kai Yu, Liangliang Cao, and Thomas Huang. Large-scale image classification: Fast feature extraction and svm training. In *CVPR 2011*, pp. 1689–1696, 2011. doi: 10.1109/CVPR.2011.5995477.

Mostafa Mohamed. Garbage classification (12 classes), 2021. URL https://www.kaggle.com/datasets/mostafaabla/garbage-classification/data. Accessed on October 13, 2023.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Support vector machines, 2023. URL https://scikit-learn.org/stable/modules/svm.html. Accessed on October 13, 2023.