WASTE SEGREGATION USING CNN MODEL

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ABSTRACT

The Group 27 Project Team plans to create a Deep Learning application using a Convolutional Neural Network model that can predict the waste disposal category that any given input image of a waste material belongs to. In this report, we illustrate the overall model of our project, explore related work, express our data processing mechanisms, identify a baseline model, explore ethical issues surrounding our project, outline our project milestones, and plan for risks that we may encounter. —–Total Pages: 7

1 INTRODUCTION

The rise in global temperature has been a source of caution for scientists as its implications on humanity could be catastrophic in the future. Effects of global warming include rising sea levels, an increased outreach of various diseases as well as more frequent tropical storms that are higher in magnitude as well [1]. Greenhouse gases such as Methane and Carbon Dioxide play a primary role in global warming by inducing an effect that prevents heat from leaving the Earth's atmosphere [1]. Landfills also mainly produce Methane and Carbon Dioxide through anaerobic decomposition of the wastes within the landfill [2]. With Methane being one of the biggest contributors to greenhouse gas emissions [3] as well as being a primary by-product of decomposition present in landfills, attempts to reduce these emissions will have a significant impact on slowing down global warming. Recycling is effective in reducing the waste that would end up in landfills, leading to lasting beneficial impacts such as reduced methane production (through reduced decomposition), conservation of natural resources and energy as well as reduced air pollution (through reduced incineration of landfill waste) [4]. For these reasons, the goal of our project is to design a system that would help users categorize their waste in ways that would allow, promote and ensure proper disposal.

Common methods of disposal that are present in most households. Using the city of Toronto as an example, there are various bins that are designed to collect different types of waste such as recycling waste through the Blue bin recycling program, organic waste through the green bins, and other forms of garbage [5]. Drop-off Depots are also present for items such as electronic waste, yard waste and metal waste. Many regions have mobile applications, such as TOwaste, that include search wizards and databases for which ways to dispose of waste. One limitation to these applications is that searching within these databases provides general guidelines that are limited. With consumer products varying heavily on materials used for various components, it becomes hard to dispose of these components properly through the use of a general database. This can potentially be solved with the use of a system that is able to classify waste through the means of a picture (of the waste) to instruct the user on how to dispose of it. This feature is something that currently does not exist through these applications and something we hope to implement through deep learning.

Deep learning would be ideal for this problem as models can be trained and used for classification through data sources such as images. In this case, the user of the application can take a picture of the item they would like to dispose of, our trained model will be able to classify what kind of waste it is, and be able to instruct the user to dispose of it correctly. Creating a manual database would be impossible to maintain as there are countless materials and products out there to classify. With deep learning, this classification can be performed quicker and in a more accurate way based on the training we implement on the model. Our model will be trained through pictures of various kinds of waste in order to be able to identify and classify them. With this implementation, users will be able to accurately know how to dispose of their items without having to search through databases for these answers.

2 Illustration

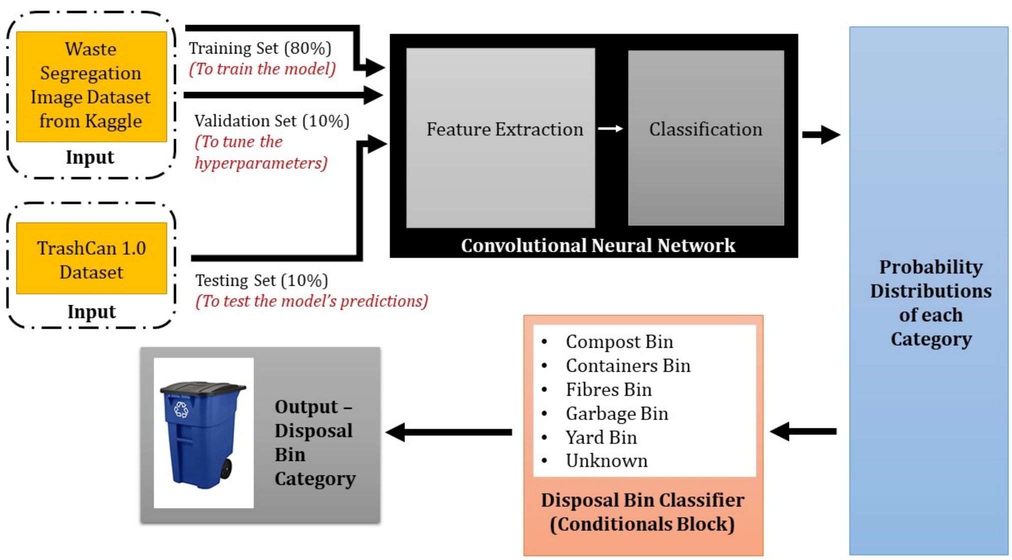

Figure 1: Overall Model for Project

3 Background and Related Work

The most common methods used to determine the correct bin for waste are from city resources. These resources include paper notices and the city website [5]. The resources often contain a list of common waste items and the corresponding bin to dispose of them. With the adoption of technology by cities, cities are creating more online tools and applications to aid residents with waste classification. Examples of this in Toronto are the Waste Wizard and the TOwaste App [6]. The Waste Wizard is an online tool that can be accessed through the web or through the TOwaste App to help with the classification of waste. The user inputs the item they are disposing of in the text box, and the tool responds back with the correct waste bin for the item. The TOwaste App is an application created for residents to aid with waste disposal. The Towaste App contains the Waste Wizard as well as other features(collection schedules, map of drop off location for hazardous materials, etc. . .) in order to make the waste disposal process less challenging.

Although the most common methods today used for waste classification do not use AI, there have been developments in waste classification using AI in the last couple of years. One example of this is from a paper titled "An Automatic Garbage Classification System Based on Deep Learning" [7]. The paper features a design that incorporates AI and hardware to create a garbage bin that classifies the disposed item as either recyclable or non-recyclable and then disposes of the item in the correct bin. The design of the garbage bin consists of three layers. The first layer uses a camera inside the bin that is used to determine the classification of the item. The second layer uses the classification from the first layer in order to select which bin the item will go into. The third layer is where the item will be disposed to. This layer is made up of two bins, one for recyclables and one for non-recyclables. The selection of which bin to dispose of is determined by the second layer.

The project will be similar to the first layer in the "An Automatic Garbage Classification System Based on Deep Learning" design. The design will prompt the user to take a picture of the item to dispose of and classify the item to the correct bin. In the paper, the classification is either recyclable or non-recyclable. For the project, the classification is one of the following five bins: Compost, Containers, Fibres, Garbage and Yard.

4 Data Processing

We will be using the Waste Segregation Image Dataset from Kaggle [8] to train and validate our model. Having already inspected the data for outliers and aberrations, we know that this dataset has around 1.05GB or 14,165 images for train data and 133MB or 1,201 images for validation data. Typically, training and validation data is split into a 80:20 ratio [9]. Our ratio comes out to be approximately 10%. In order to accommodate for the lack of validation data and the addition of test data, we plan to repurpose the large train data in this dataset and combine data from other sources [10]. Our plan to repurpose the large train data consists of taking train data from each biodegradable and non-degradable category and putting them to their respective categories in the validation data. We will achieve a ratio of 12800 train data:2566 validation data, which gives the 80:20 ratio. Ultimately, the validation data is used to adjust the hyperparameters of the model and doesn't allow us to test the model on new data. This is why we also will use organic and recyclable waste data from the collection of datasets in the TrashBox Github [10], namely the TrashCan 1.0 dataset which has 7,212 images and the TrashBox dataset which has 17,785 images. We, as data scientists, can choose how much testing data we will use obviously and are not limited to using just these sources or all this data. In conclusion, the collection of testing data coupled with the repurposing of our Kaggle training data to validation data will allow our model to sufficiently fine tune the hyperparameters before performing classifications on new, unseen data.

5 Architecture

As previously discussed in our Background and Related Work, we identified a gap in which people have a difficult time segregating their waste and must resort to manually searching up classifications online. This method is dependent on the individual identifying and classifying their waste themselves, which can be unreliable. Our implementation will bridge this gap of manual uncertainty by using a Convolutional Neural Network (CNN). Through our illustration, we showed how our CNN is a black box in which we take an image of waste as an input and output the classification of the bin in which the waste belongs. CNN's are effective for image classification as the concept of dimensionality reduction suits the huge number of parameters in an image [11]. CNN's have the innate ability to extract features from images which is why we opted to choose it over a normal neural network. Normal neural networks cannot handle complex and large images due to computational constraints and overfitting. CNN's typically consist of three layers: convolutional layer, a pooling layer and a fully connected layer [12]. For now, we do not know the number of layers and the hyperparameters of our CNN; these will be modified through the duration of the project.

6 Baseline Model

The baseline model the project will use to compare the neural network against is the random forest classifier. The random forest algorithm works well with classification problems and with large datasets which will make it a good choice for the baseline of the project [13].

The random forest is composed of multiple decision trees. Each tree is created using a random sample of the training dataset making each tree unique. When an input is given to the random forest, each individual tree outputs a class. The output of each tree is tallied and the class with the most tallies is the random forest's prediction. The low correlation between the models(tree) allows the random forest to ideally converge on the correct class making it a strong baseline for classification problems. Since each tree is created using a random subset of the training set, it also allows the random forest to be a model that can be used with large datasets.

The goal of the random forest baseline is for it to be a benchmark to the project's model. The success of the project will be measured by the comparison of the test accuracy between the baseline and CNN model. The CNN model should be performing better than the baseline in order for it to be considered a success.

7 Ethical Considerations

As our project is based on classifying images of waste, not much user information is required or collected that would potentially breach privacy or cause ethical concerns. Our project is aimed to improve current existing waste disposal applications. This would require the added permission of the user device's camera and potential collection of the user's location to target the methods of disposal for the specific region they are located in.

From an environmental aspect, our model will not be able to classify waste that was not used in the training set. As an example, our model won't be able to classify yard waste until we have trained it to do so. Hence, our model will be limited to being able to classify waste in those categories that we have trained it for, which could result in potential misclassification. This misclassification for classes we have not trained can have environmental impacts that we are hoping to avoid .

8 Project Plan

8.1 Team Logistics

The team will meet twice every week together in-person on Tuesday from 5-6 pm Thursday from 4-5 pm. We will communicate with each other via a Facebook Messenger group chat and hold online meetings through Messenger if needed. Since we are using Colab as the basis for the project, there is an obvious threat of rewriting others' code without permission. However, we plan to mitigate any inconveniences by ensuring that after everyone is done working on the Colab at their preferred time, they must download an ipynb file to their computer to ensure they have a working copy of the code at their disposal. Furthermore, the ability to see revisions on Colab will allow us to identify code changes with user edits and timestamps. We will also ensure we communicate with each other with our intended coding tasks before making changes on Colab to ensure that everyone is aware of proceedings.

8.2 Task Table

Table 1: **Task Table**

Tasks	**Deadline**	**Assigned Team Members**	**Status**
Dataset and project selection	October 4, 2022	Full Team	Done
Project Proposal	October 13, 2022	Full Team	Done
Acquiring, cleaning, and combining dataset and determining the training, validation, and test set splits	October 18, 2022	Full Team	In progress
Working on the Baseline model	October 24, 2022	Abdurrafay, Athavan	In progress
Testing the Baseline model	October 28, 2022	Nafio, Shadman	Not Started
Creating the CNN	November 1, 2022	Abdurrafay, Athavan	Not Started
Creating the associated functions required to train, validate, and test the CNN	November 5, 2022	Nafio, Shadman	Not Started
Creating the Disposal Bin Classifier Function	November 6, 2022	Abdurrafay, Athavan	Not Started
Training the CNN model	November 11, 2022	Nafio, Shadman	Not Started
Write the Progress Report	November 13, 2022	Full Team	Not Started
Tuning the hyperparameters of the CNN model	November 14, 2022	Abdurrafay, Athavan	Not Started
Testing the CNN model	November 17, 2022	Nafio, Shadman	Not Started
Create Project Presentation Script	November 19, 2022	Full Team	Not Started
Record Project Presentation	November 23, 2022	Full Team	Not Started
Write Project Report/Final Deliverable	November 30, 2022	Full Team	Not Started

9 Risk Register

This section explores five risks that the project team may encounter during the project and provides potential solutions to mitigate these risks.

Likelihood:	Team's Potential Solution
Risk 1: A project team member misses a deadline	
Likelihood:	Team's Potential Solution
- Assumed to be a low risk as the team consists of driven individuals that want to do well. -Team acknowledges the possibility of this risk as members can have other unanticipated events and duties that may hinder their ability to meet a deadline.	- Team will establish our own internal deadlines that are before final course deadlines to give us time to complete tasks before the course's deadline. - Team will meet to decide their course of action to finish these incomplete tasks before the final deadline. For example, more resources in the form of team members may be allocated to work on finishing an incomplete task.
Risk 2: A project team member drops the course	
Likelihood:	Team's Potential Solution
- Assumed to be a low risk as team consists of individuals who are excited to work on this project and have done semesters in the past with a similar workload - Team acknowledges the possibility that a member may encounter unexpected events that could lead to him needing to drop the course.	- Team will discuss the redistribution of the tasks among the remaining project team members. - Team will establish an open environment to allow team members to feel comfortable disclosing their decision to drop the course prior to them doing it.
Risk 3: A team member gets sick (catches a virus such as COVID)	
Likelihood:	Team's Potential Solution
- There is always a possibility that a team member may get sick, especially as weather conditions change and we get into flu season.	- Team will hold online meetings so that team members will be able to contribute without having to be present in person. - Team will discuss ways to decrease the sick team member's workload through a redistribution of tasks in the case that they are having a difficult time managing their load.
Risk 4: Longer than estimated neural network training time	
Likelihood:	Team's Potential Solution
- Assumed that there is a high possibility of this risk as the project team members are not extensively experienced with training neural networks. - Team acknowledges that the datasets that we plan to use are large and can lead to long training times.	- Team will update the project plan/timeline to better reflect the longer training time. - Team will decide on ways in which the hyperparameters or datasets can be changed to decrease the model's training time.
Risk 5: The neural network model struggles to categorize a specific item	
Likelihood:	Team's Potential Solution
- There is a possibility that the model might have a difficult time classifying items that look similar but are of different categories as they may have similar patterns/features in their appearance.	- Team will discuss how to fine tune the hyperparameters of the neural network. - Team will discuss if any change in the training dataset is required to better train the model to properly categorize that item.

Table 2: **Risk Register Table**

10 Link to Github or Colab Notebook

Here is the link to the Colab Notebook:
https://colab.research.google.com/drive/1Nnw4fn8m7WoKmVK3m1wz0nQPWzUeCRJv

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