AI in Recycling Final Paper

1. Abstract

The plastic pollution issue is an issue that has been plaguing the earth for the past half century and longer. Despite this, it has only been brought to light in the 21st century, and technology to help solve the issue is still new and largely undeveloped. Being someone who is passionate about environmental conservation, I wanted to create a tool that could be used to more easily sort recycling items. By using a machine learning algorithm, we have been able to create a tool that can detect what type of material an item is and determine whether it is recyclable or not. This tool can be applied to many different industry sectors, whether it is sorting items in a recycling plant, building it into an app for people to use day to day, or even aiding the plastic oceans cleanup effort. By creating this tool, we help do our part in protecting our planet and helping those who are less educated in the field to do so as well. We have approached the problem by using various machine learning algorithms to identify the material of items in a dataset. Using a KNN and CNN algorithm, we created a tool that became more and more accurate in identifying the material of an item. After testing the KNN and the CNN algorithm, we found that the CNN algorithm was much more accurate reaching a 68 % accuracy compared to 46% accuracy

2. Introduction

When thinking of ways to sort recycling, it seems reasonable to just look for a recyclable logo or one of those recycling signs with the designated numbers to know what to do. However, it is important to consider that many recyclable items don't always have the recycling logos or maybe are partially recyclable, with other parts of it not being so. Furthermore, it is important to consider that in recycling facilities or even in some bins, items are required to be sorted into different material groups. Why do that manually when an AI can do that for you? That is why we decided for our AI to identify based on material type rather than whether it had a recycling logo or something similar. That is why we chose to use a Convolutional Neural Network (CNN), as it works by getting an image, weighing different parts of it, and then comparing it to other images in the data set to find similarities. This allowed us to train an algorithm to recognize patterns within images of certain material types and then use that training to identify the material of an image. Then, using that information, we can classify the item as recyclable or not. This will be a useful tool for any company trying to recycle more efficiently, especially in plants where workers are still sorting manually.

3. Background

Due to this being a space where technology is still being developed, not many studies or applications of AI have been made in the space. We used a large dataset with thousands of images of items made of different materials in order to train our dataset. We referenced other studies like one by Pratima Kandel[1], which focuses on classifying waste with machine learning. CNN was used within the study paired with data augmentation to achieve an 82% accuracy. However, the dataset used by the study was small and therefore limited the accuracy that was achievable by the CNN algorithm. Another study by Desi Tomalessi[2] had a similar aim and also used a CNN to sort the items into categories and identify them. It achieved a good accuracy of 86.7% on the trained dataset but only 68% on a personal dataset. Once again, the dataset used to train was limited and therefore also limited the accuracy achievable by the algorithm. Finally, a study by Mindy Yang and Gary Thung [3] aiming to use computer vision to classify waste used an SVM and a CNN to process their data. Their SVM process performed much better than their CNN process with the SVM achieving 63% accuracy and the CNN only achieving 22%. They acknowledged that for a system like this one to work more efficiently, a continuously growing database of waste pictures was needed.

4. Dataset

The dataset that we chose was a garbage classification dataset that contained 15,150 images of 12 different classes of household garbage; paper, cardboard, biological, metal, plastic, green-glass, brown-glass, white-glass, clothes, shoes, batteries, and trash.

Figure 1 : Plastic Bottle

Figure 2: Soda Can

We reduced this down to just 600 for each category as that was near the amount of images in the smallest category. Each category had to have the same amount of images to be balanced and for the algorithm to work. Furthermore, any more than that would have just taken way too long to process for the computer, that's why we decided to reduce it to 600 images for each category to train the algorithm evenly. We also noticed that the images in the dataset were all a different size, which was problematic for the algorithm as the algorithm required images of the same size. Therefore, we shrank each image down to a uniform 50 x 50 pixels to make all the images the same size for the CNN to process as well as improve the processing speed.

5. Methodology/Models

The machine learning algorithms that we used to create our tool were KNN Classifier and CNN Classifier. The KNN Classifier works by looking at how similar pixel values across an image are, and determines how many different images are considered. We split the dataset into 80% training and 20% testing, which resulted in 5760 total images for training and 1440 total images for testing. Since we had 12 classes, the KNN trained on an equal number of samples from each of the 12 classes where each class had 480 images for training and 120 images for testing. We chose to test the data with 1 to

30 neighbors with the algorithm reporting back the accuracy with each amount of neighbors. We then graphed the accuracy in comparison to the number of neighbors.

The CNN Classifier is a Deep Learning algorithm that works by taking an input image, assigning importance to parts of the image, and differentiating it one from other images. The structure of the CNN was inspired by the structure of the visual cortex and is comparable to the human brain. It assigns black and white values to each image and uses a kernel to process the image. In the convolution layer, a kernel hovers over a portion of the image and applies an element-wise multiplication operation to the assigned color values of the image, producing an output value. The kernel then moves to the right across the entire image collecting output values. Once it covers the entire width, it moves down to the next row and repeats the entire process. Finally, all these output values are formed into a squashed one-depth channel Convoluted Feature Output. The primary objective of the convolutional layer is to find low-level features like edges, color, gradient-orientation, etc from the base image. The CNN can also have many different layers, with later layers focusing on high-level features. Following the convolution layer, there is a pooling layer. The pooling layer finds features that do not change positional or rotational and also scales down the convolved feature to make it easier for the computer to process. In a CNN, there is max pooling and average pooling. We chose to use max pooling for our algorithm. Max pooling not only reduces noise in the image but also returns the maximum value from the kernel. It typically performs better than average pooling. The base layer of the Convolutional Neural Network is formed by the convolution layer and the pooling layer. These layers can be increased to get more detail out of an image but will also take longer for the computer to process. Following that, a fully-connected layer is added in order to achieve a flattened final output. Non-linear combinations of the high level features, the output from our convolution layer are found using a fully connected layer. Now the image is in the right form for a multi-level perceptron, but it still needs to be flattened into a column vector. To do that, a feed-forward neural network and backpropagation is applied to the image. This process is run over multiple epochs and dominating and certain low-level features in the image are distinguished and classified using the Softmax Classification technique. We first combined the images that we imported from each category into one large class list that ended up with 7200 images. Then, we defined y as the class list and x as the np.array of the same class list. The np.array of the class list gave us the raw data of the list like how many images and image dimensions. We decided to run it 30 epochs to see how much more accuracy we could get from the CNN Classifier. We then plotted the validation accuracy and raw accuracy compared to the number of epochs. Validation accuracy is important as it aims to combat the issue of overfitting. Overfitting is a serious issue where the model will fit the learning data, but is unable to make accurate predictions of data that it has never seen before. This is where validation accuracy comes in. The data is split into the training set, which is used to train the data and the validation set, used to evaluate the data. A higher validation accuracy means a similarly high accuracy when processing new data.

6. Results and Discussion

From our KNN Classifier, we only got an average accuracy of 0.46 or 46% which shows that using the KNN Classifier for this task was not the correct choice. Meanwhile when using the CNN Classifier with 30 epochs we managed to get up to 68% accuracy and 56% validation accuracy with model 2. Due to our accuracy in model 1 being an inaccurate representation of the models ability, we added dropout layers to compensate and make it a more realistic representation of its ability. As we can see in the graph below, it starts to plateau with the validation accuracy shown in blue and the accuracy shown in orange. The validation accuracy shows us that it starts to learn itself which is not accurate of the models actual ability to detect the materials of an image.

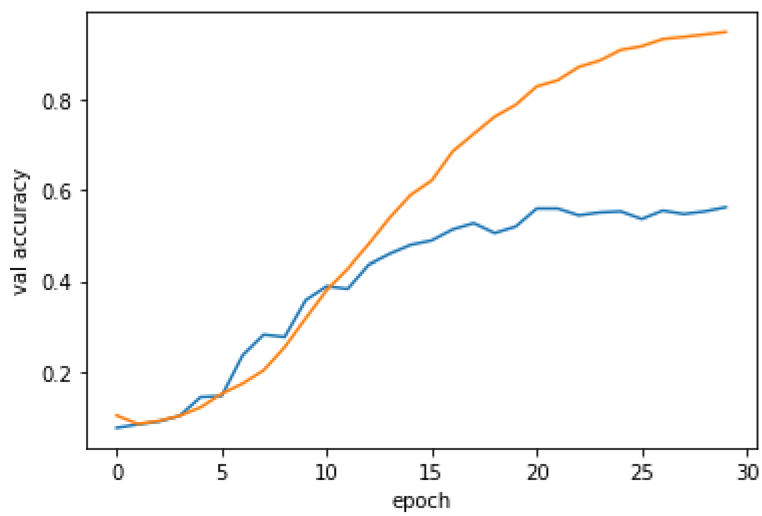

Figure 1: Training Curve for CNN Model 1

(Orange : Raw Accuracy, Blue : Val Accuracy)

Due to the overfitting present in this graph, we added dropout layers and observed an increase in the validation accuracy as seen below

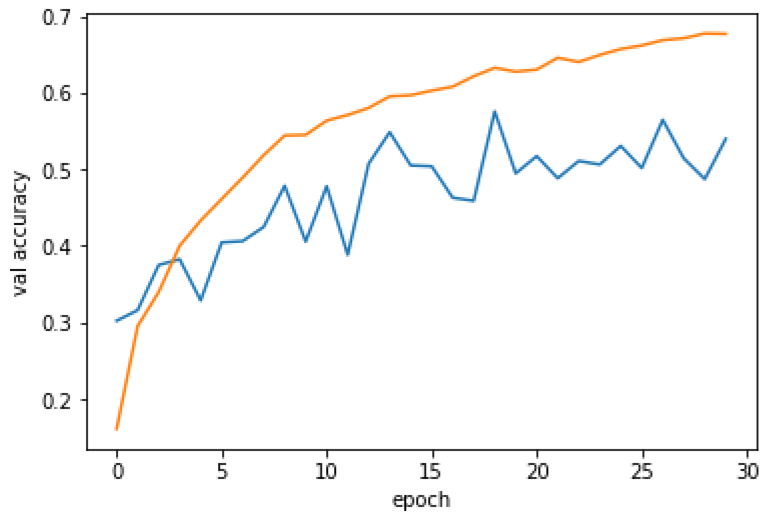

Figure 2: Updated Training Curve for CNN Model 2

(Orange : Raw Accuracy, Blue : Val Accuracy)

Furthermore, the model may not be good at detecting differences between materials like the different glasses and plastic, especially since it is using black and white color. The main concern is with the plastic and the glass as those two are recycled very differently and not being able to tell the difference could be a major flaw in the model.

7. Conclusion

In this paper, we addressed the problem of classifying different types of garbage using computer vision and machine learning algorithms. We cleaned and modified an image dataset, and applied CNN and KNN algorithms to create a product that can detect the material of a common household trash. We achieved an identification accuracy of 46% with KNN and an accuracy of 68% with our best CNN model. Future work would include expanding the dataset used as well as further hyperparameter optimization for the convolutional neural network. The accuracy at the moment is a promising start, but it would be crucial for the AI to reach an accuracy closer to 90% for it to be feasible to use recycling plants or in apps. AI will slowly be incorporated into more and more daily systems and this technology will be greatly beneficial to the recycling industry.

8. Acknowledgements

I want to thank Shreyas Muralidharan for mentoring me in carrying out this research as well as aiding in the writing of this paper.

9. References

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