Robotic Sorting of Shredded E-waste: Utilizing Deep Learning

Hamidreza Karbasi, Adam Sanderson, Alireza Sharifi¹, and Carl Wilson
School of IT and Engineering
Conestoga College Institute of Technology and Advanced Learning
Cambridge, Ontario, Canada
hkarbasi, asanderson1, asharifi1, cwilson3891@conestogac.on.ca
¹Contact Author

Abstract— In this study, a deep learning technique has been introduced to enable a novel robotic application in shredded electronic waste (e-waste) sorting. The main objective is the classification of three material groups: circuit boards, plastics, and wires; commonly found in shredded e-waste. Speed and accuracy are the key factors in this process. The desired industry requirement for the segregation purity is 95% in this application. Due to this requirement, we applied a relatively deep model using a combination of the Faster R-CNN algorithm with a ResNet101 feature extractor. Using this combination, we are able to reach an overall purity rate of 98%. Using only one Graphics Processing Unit (GPU) our neural network implementation can infer images at a rate of approximately 20 frames per second. This meets the original requirements for e-waste sorting process in which a conveyor belt carries the shredded pieces at a speed of 1 meter per second. A high-speed parallel robot is utilized to sort the materials into separate bins. The promising result of this study will pave the road to addressing the shortcomings of current e-waste sorting technologies in terms of efficiency and liability.

Keywords: Electronic Waste Recycling; Robotic Sorting; Neural Networks; Machine Learning; Deep Learning.

Submission Type: Regular Research Paper

I. INTRODUCTION

In recent decades, consumer electronics have become an integral part of daily life, revolutionizing the way we communicate, retrieve information, and entertain ourselves. Waste management and resource recovery for electrical and electronic equipment, such as computing/display devices and mobile telecommunications devices, includes waste stream sorting, chemical separation and treatment, decontamination, and waste logistics. Another key segment includes material recovery: metal recovery and plastic recycling contribute to both economic and environmental sustainability [1].

Waste Electrical and Electronic Equipment (WEEE) is the fastest-growing sector of solid waste, with 40-50 million tonnes generated globally each year. Only 15-20% of WEEE is recycled; the rest ends up in landfills, riverbanks and deserts, or is exported to Third World countries where it is incinerated to liberate precious metals. In the U.S. alone, 2.2 million tonnes of electronic waste (e-waste) is disposed annually [2].

The main challenge for current recycling technologies is identifying and classifying waste [3]. Machine Learning algorithms are purposefully designed for identifying and classifying data with tolerable cost and error rates. There are many techniques that have been developed, such as Convolutional Neural Networks (CNN) which are used to classify images. With the availability of more data and powerful computational engines like Graphic Processing Units (GPU), CNNs can have multiple layers which can potentially result in a more accurate classification algorithm. CNNs with multiple layers, called Deep Learning (DL) networks [4], have been implemented in many different libraries and programming languages. TensorFlow, which was developed by Google, is one such library used to implement DL [5].

There are many applications of CNNs for classification problems that are currently being utilized by companies and universities [6]. In recycling applications though, traditional Artificial Neural Networks (ANN) have been applied. Image and color of objects are used as the input data to the ANN to solve the municipality or cloth recycling classification problems [7]. In some recycling applications in which the visible range imaging is not effective, other types of sensing technologies such as Infrared Spectral Analysis might be used [8].

In e-waste recycling, automated object classification is currently a significant challenge due to huge diversity in shape, type, and model. In e-waste recycling facilities, in-take items are manually dismantled and components that are reusable, toxic, or explosive are removed first. Then the remaining materials are shredded and sorted to produce high yields. The upstream of shredded e-waste objects includes precious metals, circuit boards, plastics, and wires. First, metals are separated from the stream by magnet and Eddy current separators. Then the main challenge of downstream process is to identify and segregate circuit boards, plastics, and wires into separate bins at high purity. To realize this task automatically, three major subsystems are needed: sensors to capture the materials’ information, an intelligent algorithm to identify materials, usually based on color, shape, chemical or more detailed features, and mechanical actuators to separate the different types of materials into their designated bins. All three subsystems must be capable of running at high speeds to maximize the throughput. Shredded e-waste objects entering the sorting systems are usually dirty, and the surrounding environment is also contaminated with dust contributing to the complexity of any automated system. Due to the randomness of...
shredded object shapes, the classification process needs the use of algorithms that have learning and generalization capabilities. They need to learn from actual material samples and be able to generalize when they encounter a material that is not exactly in the same condition as the material that they had been trained with. Artificial Intelligence (AI) algorithms seem to be good candidates as they have both learning and generalization capabilities. Moreover, because of the high number of features we are looking for to distinguish different objects, we have to utilize distinctive neural networks with deep layers. Deep learning neural networks became an option just recently after having advancement in the production of inexpensive GPUs.

In this paper, we explain the design and development of a high-speed identification and classification system that is used to classify different shredded e-waste objects. The goal defined by the industry partner is a minimum overall purity rate of 95% and the conveyor speed of 1 m/s. The purity rate can be examined for each specific type of shredded e-waste objects or for the overall network. Category specific purity rate is defined as the number of correctly classified objects over all of the objects classified in the specific category. The purity rates of the three categories are used to calculate the overall purity rate.

By successful completion of this research to identify shredded e-waste objects, robotic sorting systems can be added to the shredding lines to maximize precious metals and plastics recovery rate and reduce the cost and health risk associated with the current manual process.

In Section 2, we study the architecture of the neural network model and the algorithm we chose and tuned for the separation problem. Then in Section 3 we show the results for different datasets of e-waste objects. Finally, we conclude in Section 4.

II. CONVOLUTIONAL NEURAL NETWORKS

A. Deep Neural Network Architecture

There is a large variety of circuit boards, plastics, and wires that the neural network must be able to identify. This means we have to use deep networks to identify enough features to classify the e-waste objects. Deeper neural networks are more difficult to train. We choose ResNet101 as the neural network architecture [9]. ResNet101 has 44.5 million parameters which allowed the neural network to capture adequate features from the e-waste objects. In addition, ResNet101 explicitly reformulates the layers as learning residual functions with reference to the layer inputs, which helps increase the accuracy and decrease the loss of deep networks when compared to traditional stacked convolutional neural networks. There are many objects in each image we feed to the neural network model. We need to use a region proposal network as the feeder to the object detection network. Because of that we choose Faster R-CNN [10] as our object detection algorithm.

B. Data processing and the Neural Network

The process began with a pre-trained network which was trained on the Microsoft COCO dataset [11]. The pre-trained network provides us with pre-existing parameters which allow us to train our network more quickly without losing accuracy.

1) Data Augmentation

Data augmentation is done to the data during the imaging process. Light bars are used to project light across the surface of the conveyor belt. The camera (Basler acA1300-200uc) does not take in a lot of ambient light, so the light bars are required to give the data the definition that our network requires.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classes</td>
<td>Circuit boards, plastics, and wires.</td>
</tr>
<tr>
<td>Image Size</td>
<td>1280x1024 and 1920x1080. The 1920x1080 images are resized to 1280x720 during training while maintaining the aspect ratio.</td>
</tr>
<tr>
<td>Weight Regularization</td>
<td>L2 regularization with a value of 0.001. This value is subtracted from or added to model weights to prevent models from overfitting. This helps the model generalize data that it has not been trained on.</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>The learning rate is set to 0.003 for the duration of the training, with no decay. This value has proven to work well with the data we have.</td>
</tr>
<tr>
<td>Number of Training Objects</td>
<td>9083</td>
</tr>
<tr>
<td>Number of Validation Objects</td>
<td>576</td>
</tr>
<tr>
<td>Number of Test Objects</td>
<td>651</td>
</tr>
</tbody>
</table>

Data augmentation is also done during training using TensorFlow’s preprocessor library. This network uses 4 data augmentation options: random jitter boxes, random horizontal flip, random vertical flip, and random rotation 90. Each option has a 50% chance of occurring per iteration.

The random horizontal flip, random vertical flip, and random rotation 90 options give us potentially 8 (the power set of all three options; $2^3$) different images that the network can train on. These options are the best options for this network because they do not change the size or color of the images.

The random jitter boxes option changes the size of the bounding boxes very slightly. This helps the network learn that the edges of the data don’t need to be exact. This way, when the
network evaluates data that it has not been trained on, it is able to find the edges much more accurately.

In total, the network trained on 4 data augmentation options. This can potentially multiply the size of our training dataset by 16 (the power set of all four options; $2^4$).

2) Network Parameters

Table 1 shows the selected parameters we tune for the neural network. We have access to more objects to add to our objects datasets, but the purity rate does not change significantly when we increase the number of objects. We determined that the shown numbers in Table 1 are the minimum number of objects required to achieve a high purity rate.

3) Training Phase

Before the CNN can be used to identify the e-waste object types, it must be trained. The network is trained in a supervised manner, by showing the network the input data, and the proper output that it should generate. To facilitate this in the actual setting, a conveyor belt is loaded with one type of e-waste objects and is then scanned. This process is to be completed for each type of e-waste objects. In an ideal scenario, input data from e-waste type 1 (e.g. circuit board) should result in a value of 1.0 at the first output, and 0 of the other two outputs. This would mean that e-waste type 1 (e.g. circuit board) is the winner in this competition. Therefore, when training the network, the input values with ideal output values are used. The same process is then repeated for the other types of e-waste, until the network is trained for all three types of e-waste.

When training the neural network the Faster R-CNN algorithms iterates (propagates) through the training samples to calculate the ResNet101 parameters (forward and backward propagations) to minimize the smooth-L1 loss function calculated values [10].

4) Identification Phase

The trained neural network can then be used as a classifier. Now, a mixture of e-waste objects of different types will be placed on the conveyor belt and scanned.

III. RESULTS

A. Training Results

Loss graph is a metric for measuring how a neural network is trained. When training the neural network, we iterate through all of the parameters in the network in both forward and backward propagation to minimize the loss function. In this study, we trained the neural network with a batch size of 1 (number of samples being propagated through the neural network model per iteration when training). The total loss showed a good rate of convergence and ended up at approximately 0.100 loss, which proves that the training was successful. Figure 1 shows the loss value for up to 75000 iterations.

B. Evaluation Results

Figures 2 through 5 are the purity rate graphs. The graphs show the results of inference performed on different datasets. Three different datasets were evaluated: Training, Test, and Validation. The Training dataset is the data that the network trained on. It is expected that these values will be the highest of all three datasets. The other two datasets, Validation and Test, contain data that the network was not trained on. These two datasets represent what the actual performance of the network would be on data it has never seen before. The validation dataset can be used as a metric for choosing the best sets of parameters based on the purity rate of the neural network. The set of the neural network parameters (called checkpoint) are stored for defined iterations and are evaluated for both training and validation datasets. Based on the optimum purity rate of the chosen checkpoint on training and validation datasets, then the neural network model is tested against the test dataset. In this paper we are reporting the purity rates of all three datasets, training, validation, and test, over the stored checkpoints in the interval of 70000 to 75000 iterations. The best purity rates achieved for all three datasets in the shown interval.

In Figures 2 through 5, the vertical axis shows the purity rate and the horizontal axis shows the number of iterations the neural network has been trained for calculating the network parameters (we only show the interval of 70,000 to 75,000 steps in order to see the purity rate precisely.) The blue line shows the training dataset, the orange line shows the validation dataset, and the red line shows the test dataset. As we expected, the purity rate of the training datasets for all of the classes is close to 100%.

Circuit boards showed very good results, with a purity rate above 98% for all three datasets.

Plastic showed the best results of all three classes, with a purity rate above 99% for all three datasets.
The purity rate of wires is approximately 94% for the Test and Validation sets.

The overall training, validation, and test purity rates are 100%, 98%, and 98%, respectively.
The neural network can infer approximately 20 frames per second, which meets the original requirements that include a conveyor belt speed of 1 m/s.

Figure 6 shows an example of a test dataset image. The neural network draws boxes around the e-waste objects and identifies them with quite high certainty. This information will be sent to a parallel robot to pick and place the shredded e-waste objects into assigned bins. A scenario that this robotic setup might be used for, could be further purifying plastics from circuit boards and wires which known as contaminations. Figure 7 shows a robotic setup under development with a parallel robot (Adept Hornet 565) and a conveyor. The robot will be tasked to purify plastics from the circuit boards and wire contaminations based on the output result of our trained neural network. This will result in a very clean plastic output and replace a tedious and inefficient manual task.

### IV. CONCLUSIONS

We have demonstrated the most accurate convolutional neural network to be used for e-waste classification. As it is shown in Table 2, plastics and circuit boards resulted in purity rates in excess of 98% on every dataset, which surpasses the 95% that was originally discussed. Wires show purity rate of over 94%. The lower rate with wires stems from the size and shape differences for each wire. However, the overall purity rate is over 98%.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Training</th>
<th>Validation</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circuit board accuracy</td>
<td>100%</td>
<td>100%</td>
<td>98.5%</td>
</tr>
<tr>
<td>Plastic accuracy</td>
<td>100%</td>
<td>99.5%</td>
<td>99%</td>
</tr>
<tr>
<td>Wire accuracy</td>
<td>100%</td>
<td>96%</td>
<td>94%</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>100%</td>
<td>98%</td>
<td>98%</td>
</tr>
</tbody>
</table>

By successful completion of this research to identify shredded e-waste objects, robotic sorting systems can be added to the shredding lines to maximize precious metals and plastics recovery rate and reduce the cost and health risk associated with the current manual process. Furthermore, this study will pave the road for development of innovative robotic solutions for pre-sorting and dismantling outdated electronics that will tremendously help the industry to increase their efficiency and eliminate the health and safety risk involved with the current manual processes.

### ACKNOWLEDGMENTS

The authors of this paper would like to thank our industry partner Shift Recycling for providing material samples and technical insights, Conestoga College for dedicating resources and lab space, Natural Sciences and Engineering Research Council of Canada (NSERC) and Ontario Centers of Excellence (OCE) for funding the project. The authors are also indebted Ms. Amber White for her help in editing the paper.

### REFERENCES