Segregating Hazardous Waste Using Deep Neural Networks in Real-Time Video

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***Abstract*—Sustaining a society requires reusing, reducing, and recycling waste. Waste disposal has always been a problem in developing countries because of inadequate infrastructure. By utilizing artificial intelligence to detect hazardous waste, more individuals will be protected from the negative effects of it. To help mitigate this problem, we experimented with Keras, to create a convolutional neural network, and OpenCV, to create real-time videos, that identifies hazardous waste from other recyclable materials. Through the use of machine learning, our model is able to categorize different recyclable materials with about 90% accuracy. Objects within the video receive a prediction for 3 classifications which includes batteries, syringes, and nonhazardous waste. Then, the category with the highest category is what the network will classify it as. In conclusion, the model is able to identify hazardous objects and recyclable items within a pile of trash to help protect all individuals.**

I. Introduction

Sustaining an economy requires reusing and recycling waste since wastes have always been a problem in many communities by how people dispose of wastes. For years now, humans have been dealing with different kinds of wastes and the common methods include burying, burning, and keeping in places where wastes should not exist. This is especially evident in the Yucca Mountain in which trash is stored within the mountain [56]. While trash exists, the most threatening type of trash is hazardous waste. Dealing with hazardous wastes has become a challenging project for waste disposal and recycling sites since it is made up of material that has the characteristics to damage the environment and its properties and create a potential hazard to human health. [65] Hazardous waste usually isn't handled effectively as many don't understand what harm it can do to the environment if thrown away into the trash can and discarded into a landfill. It is most apparent in developing countries as they don't have the equipment and laws necessary to regulate disposing of hazardous waste in their community. [40] Therefore, the establishment of efficient and safe hazardous waste management and recycling is a fundamental part of sustainable environmental protection. [11] Humans have to be able to come up with a way to dispose of waste in order to help the economy become a better place to live. Furthermore, human workers have created smart sorting ways in many developed countries, which means the intelligent systems could replace manual labors. With more intelligent systems, fewer humans will be exposed to hazardous wastes. However, many developing countries don't have this option and therefore, novel hazardous waste segregation methods are urgently needed for development [11], [55]. Our goal is to set up an approach for identification and separation of syringes and batteries from target wastes through employing deep neural network to achieve a part of hazardous waste segregation.

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II. Related Works

Proper disposal of waste and recycling is necessary to sustain an economy. During the 19th century, modern industrial waste recycling took place as a result of a shortage of materials due to an economic crisis known as the Great Depression [6]. Since then, many countries have been making an effort to develop and set up more modern sorting systems instead of using manual laborers to help with what they have experienced during the economic crisis. The employing of workers to recycle or get rid of common wastes such as glass, paper, cardboard, plastic, metal, and other trash is harmful to not only the worker as they are the ones handling the hazardous waste but also the environment since that is where the trash will end up. Especially among these wastes, hazardous materials can not only cause severely damaged properties, but it can also create a potential risk to human health and the environment when not managed properly. [67]

In order to automatize the recycling process along with advanced composting and incinerators, proposing intelligent systems to detect the waste components correctly is vital for not only the economy but also the world around us. Intelligent systems can help humans not be harmed as much since they don't have to be the ones touching the hazardous waste. However, it can cause individuals lose their jobs because artificial intelligence will be replacing those jobs. [34] In addition, segregating hazardous waste through intelligent sorting systems has become an increasingly challenging and disruptive task to many societies as it is difficult for societies to come up with a way to do this. Many countries don't have the money to afford these new contraptions since they have a lack of resources [14] and are not as industrialized and because these new inventions are way out of their range to be able to afford one of these.

In the relevant reported works of literature regarding syringes and batteries sorting problems as below: A review from Abdul Mujeeb et al. for injection equipment recycling practices in Pakistan by studying highly-trafficked clinical laboratories in Karachi [51]. Of these clinical labs, only 9% of recycled syringes are recycled with healthcare waste recyclers. All other labs are disposing of needles in ways that expose humans to hazardous waste, with the possibility of causing injuries and spreading disease. These locations include government collected waste systems, and community waste sites and neither of these is designed to collect medical equipment. Furthermore, these locations have humans hand-sorting trash, either as employees or as scavengers which may be harmful to themselves. The paper points out necessary improvements that must be made to help dispose of lithium batteries in a non-harmful way and the limitations of the infrastructure preventing those changes since Pakistan is a developing country with less industrialization than some of the more industrialized ones.

Similarly, syringes are a major problem as they are thrown into the streets or flushed down public toilets. An article written by Wenger et al. points out the problems associated with the disposal of syringes as there is improper waste disposal of syringes [66]. They are also trying to examine the ways that syringes are being disposed of. Through studies in San Francisco, California, they found that 13% of the syringes found were disposed improperly as some were found on the streets, Golden Gate Park, and in self-cleaning toilets that were public to everyone. The improper way of syringe disposal can lead to hepatitis and HIV to the community if it spreads from the syringe. They used the Geographic Information System to be able to map out the blocks in which they were planning on going to study and observe. Out of the 2411 blocks, they chose to study 1000 of those blocks. Within these blocks, they were able to figure out that 53% of the syringes were found in the trash. In addition, they estimated that about approximately 108 of those syringes were disposed improperly. However, a limitation to there study is that they did not study all 2411 of those blocks which means that their study could have been more accurate if they studied all of those blocks.

The need for identifying hazardous waste is apparent. Another review from Daniel Hsing Po Kang et al. discusses the disposal of lithium batteries in society and the implications this causes on the environment and human health [43]. This study outlines the measured toxicity of lithium batteries and highlights the lack of proper recycling procedure for these batteries. Since these lithium batteries are so prevalent in society, many of these batteries end up being thrown away as people don't know how to dispose of them, therefore causing them to exist as hazardous waste in the landfill. In addition, these pollutants within these batteries can leach into the groundwater which harms the drinking water for all humans. [61] This problem is exacerbated in parts of the world that lack the infrastructure for streamlined solid waste collection, especially in the developing countries where they have less standard laws of where to throw away trash and dispose of them. The call to action is that we, as a society, need strategies to identify and assist in adequately disposing on lithium-ion batteries.

Additionally, in an article written by Josh Cabrido illustrates the idea of how batteries have become needed to be recycled and how there are many issues regarding the disposal of batteries [13]. Disposal of used batteries right now, in many developing countries, is still done in an illegal as well as improper way as it harms not only humans doing the recycling but also the environment as all batteries contain toxic and hazardous wastes along with nonrenewable resources. Few regulations and standards have been implemented in developing countries to regulate their disposal of batteries, especially in China and Mexico. Over 20 million recycled lead-batteries in the United States have been shipped over to Mexico, particularly Naucalpan de Juârez. There, it was seen that it included 5 times more lead than the limit that the United States had implemented in the lawn. Even though about 96% of all lead-batteries are being recycled, the recycled batteries are becoming smaller pieces and then reused again which harms the environment. Additionally, the newly created batteries from the recycled parts still contain around 60-80% lead and plastic. Therefore, there needs to be a more efficient way to dispose of all of these batteries to help make the world a better place.

Although the detrimental problems above have existed for a long time, there is no applicable sorting method for solving these problems. Reported in the paper below is the Intelligent Waste Sorting which is currently being developed for the common waste sorting [11], [55], [57], [88]. One article focuses on a robotic grasping system that uses deep learning and machine vision to sort garbage. This new system is more efficient than manual sorting as manual sorting still exists in many developing countries. In the paper, it demonstrates a new technique that estimates the poses of the grasping machine by using deep neural networks. The system requires three significant components and can be performed in a complex background. The objects detection can precisely locate and classify single items. The team also achieved to segregate target objects that have a 30 percent coverage. This shows how the robotic arm can function and perform tasks even though image recognition is only part of the whole technology. [88]Automating the recycling process by using intelligent systems is significantly important. [33] Their dataset ImageNet focused on the most common recyclable materials such as glass, cardboard, paper, metal, and plastic while everything else is classified as trash. They looked at five models: Deep Residual Networks, MobileNet, Inception-ResNet(Inception-v4), Densely Connected Convolutional Networks, and Xception. Additionally, many of them also looked at a couple of optimization approaches: Adam and Adadelta in which they rotated the images. The most recent paper [11] reported that current Computer Vision and Deep Learning techniques could play an essential role in the automatic finding and classification of waste types for further recycling tasks. In this work, the TrashNet dataset was used to train and compare different deep learning architectures for automatic categorization of garbage types. Particularly, several Convolutional Neural Networks

(CNN) structures were analyzed: VGG, Inception, and ResNet. The best results for categorization were achieved through a combined Inception-ResNet model that yielded 88.6% of accuracy [69]. Other works include [2]–[5], [7]–[10], [15]–[20], [22]–[32], [35]–[39], [41], [42], [44]–[50], [53], [54], [58]–[60], [62]–[64], [68], [70]–[87]. Based on the above literature reviewing, there is lacking an intelligent method for sorting hazardous wastes particularly syringes and batteries as they are continuously being classified as trash and not being disposed of properly. Therefore, the establishment of novel approaches for segregating syringes and batteries using deep neural networks establishes the main goal of this paper.

III. Dataset

Category	# of pictures
Batteries	223
Syringes	91
Non-hazardous Trash	1984

Fig. 1. Pictures per category

Fig. 2. Picture of battery, syringe, and paper

The purpose of creating neural networks is to recognize hazardous wastes from common types of trash and be able to recycle them properly. Our focus is on syringes and batteries. Our dataset contains the Trashnet dataset and some hazardous waste images we gathered. Fig.1 shows what the dataset contains: three types of wastes and the number of pictures each category includes. The Trashnet Dataset has a total of 2527 images, we deleted some pictures and our total number of images of non-hazardous waste is 1984.

We used the Trashnet dataset created by Gary Thung and Mindy Yang. [69] Every picture in the dataset is resized to 512 x 384 and taken in front of a white background with moderate lightings. Because the dataset does not contain any hazardous waste images, we added pictures of syringes and batteries labeled for non-commercial reuse with modification from the web and took some of our own as shown in Fig.2. We collect different types of batteries and took pictures of them in different perspectives and angles on white papers. In total, we added 314 images to the Trashnet Dataset, including 223 pictures of batteries and 91 pictures of syringes. We divided the dataset into a training set which contains 90% of the images, and a testing set that has 10% of the pictures. The dataset we used in total has 2298 pictures of three different categories of wastes, which include batteries, syringes, and nonhazardous waste.

IV. Model and Methods

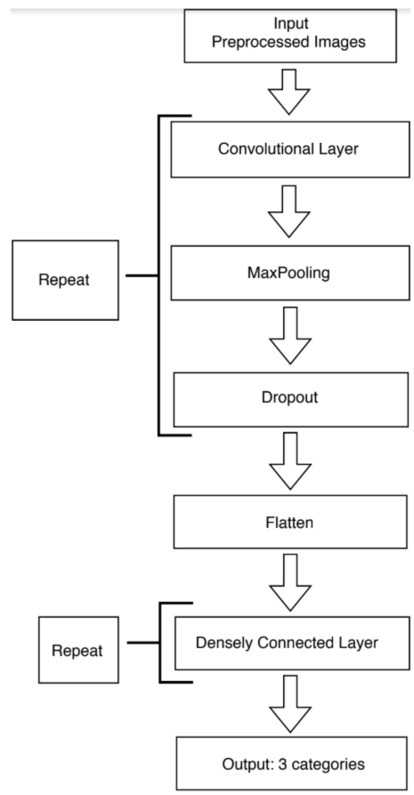

Fig. 3. Model of the convolutional network

Fig.3 shows the convolutional neural network (CNN). The CNN was created using the code shown in Fig. 4. This CNN using the code shows the process that we are using in order to classify the pictures taken from the real-time video. The pictures are taken from the video and the frames taken from the videos are put into the neural network with 24 frames per second. With each picture put into the neural network, these images are classified into 3 different categories which are batteries, syringes, and nonhazardous waste. At the end of classification, one of these categories has the highest accuracy which represents what the network classifies it as. The higher the accuracy the neural network classifies the picture, the better it is since we want the video to be able to identify these waste and be able to categorize them into the right type of material.

```
Data: images from dataset
Result: trained model to categorize objects into correct categories

begin
    Import keras
    Import keras models and layers
    Import preprocessed images from keras
    Declare number of classes
    Resize pictures using Image Data Generator in Keras
    for train generator and validation do
        Pull dataset from directory
        Rescale
        Use categories
        Divide into batches
    end
    Model images passed down sequentially
    for convolution layer do
        Declare nodes and kernel
        Maxpool 3/4
        Dropout 20%
        Flatten from 2D array to 1D
        Form dense layer with 7 nodes
    end
    Use Softmax to declare the highest accuracy class of the dense
     layer
    Use optimizer Adam on the selected category
    Adjust to layers and learn
    Save model
end
            Algorithm 1: Model code
```

Fig. 4. Psuedocode for trash segregation model

Therefore, they can be used for those people who live near landfills or recycling plants to help protect themselves from hazardous waste. Through the use of a CNN, the real-time video is able to help classify what images are being sent through and what the images are representing.

For the images that are used in the convolutional neural network, they are first being preprocessed so that pictures are changed into a variety of shapes which can be used in the model. First, the images are put into the Image DataGenerator in Keras which uses Tensorflow [1]to back it up and [21] will be able to help make the images readable for the CNN. After being put into the generator, the pictures are changed into a size of 100 by 100 and it has a scale of 0-1 by dividing it by 255. Within this generator, it creates 16 different copies of each image so that the neural network can learn and train from these pictures. The generator shears 0-20% and also flips the image horizontally as well randomly. Once the images are able to be used in the CNN, it first goes into the convolutional layer of the neural network which creates the images into another 128 forms that can be further analyzed. This helps the later layers be able to train with the images and learn from them since the convolutional layer is the building block of the CNN as it does most of the challenging computations before it transfers the images to Max pooling. After the many hundreds of pictures arrive in the Max pooling, the Max pooling helps to reduce and lower the dimensions in order to make better accuracy and make assumptions about the different regions of the picture to be able to determine what the outcome is since it is a sample/image based discretization process. Next, the pictures go the dropout layer which is a technique in which some of the neurons in the training set are ignored and dropped out in order to prevent the CNN from becoming too crowded. As more and more pictures are being transferred, the dropout layer is there to prevent overfitting and help to keep the neural network stable. The steps of using the convolution layer, Max pooling, and dropout can be repeated as needed until the image is ready to be moved on. When the image is ready, then the images go to the flattening layer. The flattening layer is where the images are changed and formatted in a certain way so that the dense layer can interpret the image and provide the outputs of the 3 different categories. Finally, the images go to the dense layer which is another layer fully connected and full of layers. The dense layer helps to classify each of the pictures given by the convolutional layers and being reduced by the Max pooling to be able to determine which category the picture goes into. This step may be repeated as needed to help classify the images that are given to the layer. The dense layer is what categorizes each of the images into what it believes is the best category with a 0-100% accuracy available. At the end of this process, the frames of 24 per second are able to be classified into the right category.

V. Real-Time Video

```
input  : captured real time frame
output: prediction of category from model
Import cv and numpy
Load trained model
Start video capture
Declare fps of camera
Read frame
Update frame
Save frame
Re-size frame to fit model
Send frame through model
Run model prediction
Check which category the prediction belongs
if q is pressed then
    Stop running
    Close all windows and the camera
end
            Algorithm 2: OpenCV code
```

Fig. 5. Psuedocode for the OpenCV

For the creation of a real-time prediction video, we used OpenCV. [12] OpenCV stands for Open Source Computer Vision Library; it is a library that provides real-time computer vision codes. We utilized OpenCV to push individual frames through the trained convolutional neural network to predict the category of the current item in each frame of the video as shown in Fig.5. It shows the algorithm used to create the OpenCV video. Any parts of computation we got done from

OpenCV are done and computed in numpy. [52] For example, we prepossessed the images using numpy. The webcam we used in our research incorporated the use of 24 frames per second. Furthermore, all webcams with any frame rate can be used for this. The output screen contains the following components: the updated frame from the webcam, the text representing the predicted category, and the predicted category percent for each item that traveled through the trained convolutional neural network.

Our program runs by starting the video capture from the default camera. The camera then updates the current frame continuously. If the user presses the “c” key, the current frame is captured and resized to fit the prediction model. Then the frame is sent through our model and gives a predicted output. The prediction model has three different categories, and the category with the highest predicted percentage is added to the frame along with its predicted percentage, which is the output. Pressing the “q” key breaks the running process and closes all the video windows.

VI. Results

Fig. 6. The accuracy of the CNN classifying the battery, non-hazardous trash, and syringe

All of our findings were done in Keras and OpenCV to create a model that could identify an object. For our results, we were able to create a real-time video that could identify what the object was in the image by using a convolutional neural network. The video could recognize the different objects that were put under the camera such as cardboard, paper, glass, metal, plastic, and hazardous waste (specifically batteries and syringes). Most importantly, this artificial intelligence is able to identify the difference between hazardous waste and other trash and be able to classify them into the right category. The neural network that the real-time video uses has about 90% accuracy as shown in Fig.6 for categorizing what the object in the image is. In addition, this model is able to be used in any kind of machine available for use since it can classify the different images it sees in its camera into the right category.

VII. Conclusion

In conclusion, hazardous waste needs to be separated from normal trash since they are harmful to all organisms and the environment. Therefore, using artificial intelligence to do the job will protect the individuals who work at the dump yards and sorting centers. That is the motivation behind our research on segregating hazardous waste from normal trash. Our goal was to have an accuracy of at about 100%, however, our real-time video can classify the images with about 90% which was a little below our expected result. To improve accuracy, we attempted converting our pictures to black and white or even making the pictures bigger in size. It can categorize most images into the right category just not with the accuracy desired. The dataset used for the neural network was modified in order to help provide more images for the training and testing sets. The use of a convolutional neural network to interpret the images and give an output of which category the image was a significant part of our research.

With the real-time video, it can classify each of the images into the 6 categories with the speed of the webcam used. It is able to identify the object found within the video with the use of bounding boxes to outline the object. The best implementation would be able to install it within an robotic arm that can pick out the batteries and syringes from the pile of trash. The robotic arm will put the batteries and syringes piles of batteries and can be transported to sites to where the batteries and syringes will actually be recycling and no thrown into a landfill.

VIII. Future Work

For the future, the accuracy of the video needs to be improved to where there is about 98-100% so that the neural network can categorize the images better. Right now, the real-time video can classify an object that is located in the middle of the video and is on the surface of the pile of trash. It needs to be modified to where it can classify multiple objects within a pile of trash accurately and efficiently so that it can be used in any kind of machine. Moreover, it needs to be able to identify images that are behind other trash or hazardous waste and be able to classify them accurately as well. In addition, having the model within the robotic arm to segregate hazardous waste from normal trash would be most ideal. Fewer people will get hurt from hazardous waste since a robotic arm is doing all of the work and not the individuals.

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