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Method for Identifying Recycled Materials by Means of Convolutional Neural Networks (CNN)

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Abstract—

This project aims to improve municipal trash collection by using deep learning and image processing methods to enhance waste detection in public areas. The findings of this research will contribute to better smart city infrastructure and waste management systems. Two Convolutional Neural Networks (CNNs) were constructed using the AlexNet network architecture. One CNN was trained to identify trash in images, while the other was trained to separate recyclable items from landfill trash. Proving the concept's practicality, the two-stage CNN system was trained and tested using the industry-standard TrashNet indoor picture dataset. After collecting external photos for the intended use case, the authors trained and tested the system. In an initial test using an image database of various garbage objects to distinguish between non-trash and trash, the first convolutional neural network (CNN) trained on the external image dataset had a success rate of 93.6%. Our accuracy went improved from 89.7 percent to 93.4 percent—a total of 92.2 percent—after training an extra convolutional neural network (CNN) to differentiate between trash and recyclables. A clever garbage can robot equipped with a camera might sense when trash is close by and gather it automatically.

Keywords—CNN, AlexNet, Image Classification, Deep Learning, Object detection.

INTRODUCTION

When the city is clean and well-maintained, the residents really enjoy it. With an ever-increasing urban population comes an inevitable increase in garbage, making it more difficult to keep cities clean. We may get a feel for the difficulty level by looking at the South Asian nations. Although some governments can afford to set up and run complex waste management systems, the vast majority of people on Earth reside in countries that just do not have the resources to do so. Because of this, waste management has become an urgent concern in several regions around the globe. When a nation lacks resources, its garbage cans are always full. Plus, rather of putting their rubbish inside the container, residents in these nations often just throw it outdoors. Garbage cans are ideal environments for the growth of germs. After that, there are worries about dirtiness and pathogens. Because it is unwelcoming to strangers, painful for humans, and particularly hazardous for children and the elderly, it is not a smart idea to leave a garbage can out on the highway in such a condition. Littering along roadsides and other forms of uncollected waste endangers human health, diminishes the beauty of industrialized nations, and damages the ecosystem. An estimated 842,000 people die every year as a result of "unsafe water supply, sanitation and hygiene," according to the World Health Organization [1]. Nearly all of the world's 361,000 children under the age of five reside in nations with relatively low per capita income. Garbage collection is an expensive affair for nations both rich and poor. But with autonomous garbage collection systems, public health will improve and costs will go down. According to CBSNewYork, for instance, the annual cost of garbage collection in New York City is $300 million [2].
In recent times, deep learning researchers have achieved remarkable progress in computer vision. When it comes to detection, segmentation, and classification of images, convolutional neural networks (CNNs) rank well among the top deep-learning algorithms [3-6]. The article concludes by

suggesting CNN for garbage detection and identification. In order to classify rubbish that people leave in public places in cities, Chu et al. [7] suggested a multilayer hybrid deep-learning system (MHS). Wastebaskets and similar containers may have their contents automatically sorted by the gadget. The AlexNet CNN [3] and optical sensors were used to discover more numerical feature information, and key visual features were recovered. In order to sort the trash can item, this system made use of multilayer perceptrons (MLP), which aggregated input from many sources. The suggested MHS averaged an accuracy rate of over 90% even though the system could only identify garbage in public places to a limited extent. Park and roadside pranks would not be considered under their method. Bai et al. [8] demonstrated a robot that could detect lawn debris with high accuracy and no human assistance needed. They guided the robot's movements and garbage detection using a ResNet deep neural network-based navigation system [9]. The robot can clean parks and schools autonomously thanks to its garbage-identifying and navigational abilities. Over 95% of the time, they were able to correctly identify garbage. On the other hand, the robot is limited to detecting waste on grass. Consequently, the bot was unable to distinguish between different types of urban waste. When the city is clean and well-maintained, the residents really enjoy it. With an ever-increasing urban population comes an inevitable increase in garbage, making it more difficult to keep cities clean. We may get a feel for the difficulty level by looking at the South Asian nations. Although some governments can afford to set up and run complex waste management systems, the vast majority of people on Earth reside in countries that just do not have the resources to do so. Because of this, waste management has become an urgent concern in several regions around the globe. When a nation lacks resources, its garbage cans are always full. Plus, rather of putting their rubbish inside the container, residents in these nations often just throw it outdoors. Garbage cans are ideal environments for the growth of germs. After that, there are worries about dirtiness and pathogens. Because it is unwelcoming to strangers, painful for humans, and particularly hazardous for children and the elderly, it is not a smart idea to leave a garbage can out on the highway in such a condition. Littering along roadsides and other forms of uncollected waste endangers human health, diminishes the beauty of industrialized nations, and damages the ecosystem. An estimated 842,000 people die every year as a result of "unsafe water supply, sanitation and hygiene," according to the World Health Organization [1]. Nearly all of the world's 361,000 children under the age of five reside in nations with relatively low per capita income. Garbage collection is an expensive affair for nations both rich and poor. But with autonomous garbage collection systems, public health will improve and costs will go down. According to CBSNewYork, for instance, the annual cost of garbage collection in New York City is $300 million [2].

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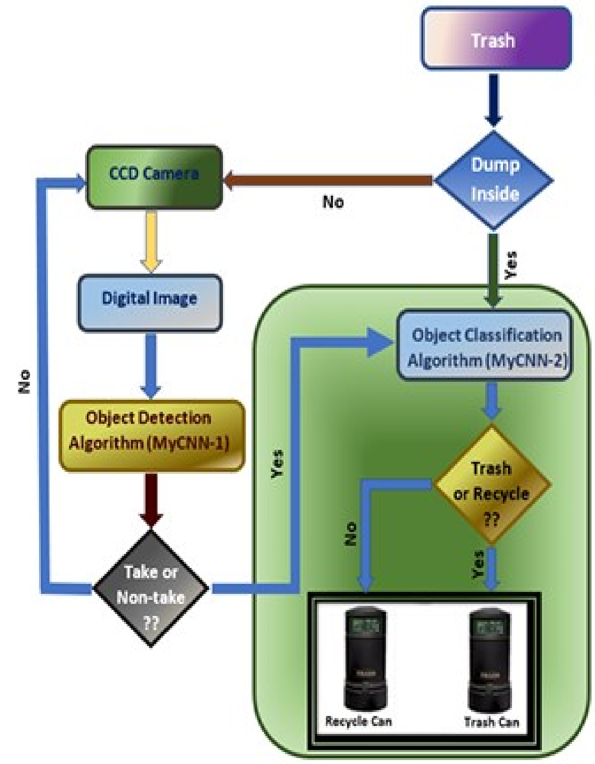

distinguishes between picture characteristics by applying learnable biases and weights to each. In order to identify and categorize objects in digital photos, other researchers have used convolutional neural networks (CNN) [3-6]. Following training, convolutional neural networks (CNNs) may filter and classify pictures into multiple classes based on the input-output pairings, replacing rudimentary approaches like filtering by a hand-engineered procedure. Convolutional neural networks (CNNs) are designed to mimic the way neurons in the human brain communicate with one another. A number of layers, including convolutional, pooling, fully connected, and normalizing layers, make it up [3-6]. The input picture is convolved with moving kernels in the convolutional layers using certain window size and stride size, and each kernel then outputs a feature map. After applying the rectifier linear unit (ReLU) to the output, which prevents the gradient from disappearing, we use the pooling algorithm to lower the feature dimensions and noise. Following a series of convolutional layers and pooling, the features are deflated before being input into the fully connected layers. These layers are composed of sets of artificial neurons (nodes) arranged in columns, with the output of each layer's activation neurons being mapped to the input of every layer below it. Equations for forward pass and backward pass propagation rules may be used to define the fully linked function in mathematical form [9]. Layer 1's outputs, which make up the input vector x, are defined as $a(1) = xb$, with j=1, 2, 3…., $n1$ and $n1$=n being x's dimensions. The output of neuron i's calculation in layer l is provided by

$$z_i(l) = \sum_{j=1}^{n_{l-1}} W_{ij}(l)a_j\,(l-1) + b_j(l) \qquad (1)$$

This is created by adding together all the outputs from layer l-1 and represents the net input to neuron i in layer l, where i=1,2, 3,..., nl and l=2,..., L. The ith neuron in the lth layer is related with the bias value $b(l)$. For any value of i from 1 to nl, the activation value of neuron i in layer l may be expressed as $a(l)$ =h($zi(l)$), where h is an activation function. For any integer i from 1 to $n\mathbf{O}$, the value of the network output node i is (L) = h ($zi(L)$). In a fully linked feedforward network, these are the only operations needed to convert input to output. Any neuron's output and net input in any layer (apart from the first layer's j(l)) is directly related to each other, and the same holds true for any hidden layer's node j.

$$\delta_j(l) = \frac{\partial E}{\partial z_j(l)} \qquad (2)$$

Refining the CNN's local architectural structure and dimensional parameters may improve its accuracy [8]. In recent years, a wide variety of convolutional neural network (CNN) designs have appeared [3]. The in-field processing capabilities and cheap computing cost of AlexNet [3] make it an ideal choice for our study. The 2012 ImageNet Challenge (ILSVRC) was the venue for the introduction of AlexNet [3]. The top-5 mistake rate for picture categorization was down from 26% to 15.3% thanks to it. Its very competent design has earned it much renown. The MATLAB® version of AlexNet, which has 25 layers altogether (five convolutional and three fully connected) was used in this investigation. The exact number of layers is shown in Table 1. In order to extract the necessary picture characteristics, several Convolutional Kernels are used. In a single convolutional layer, several identically sized kernels are used. The 1000-way softmax function, which corresponds to 1000 class labels, is fed the output of the final Fully Connected Layer. Along with the fourth and eighth levels comes the cross-channel normalization layer. Following the sixteenth layer and the Cross-Channel Normalization levels come the max-pooling layers. Each convolutional layer is followed by the ReLU nonlinearity. Each completely linked layer has 4096 neurons that communicate with every neuron in the layer below [3]. As mentioned in

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Section III, the number of categories is adjusted to 2 in the final Fully Connected Layer (layer 23).

. Table 1: MATLAB AlexNet Layer Configuration

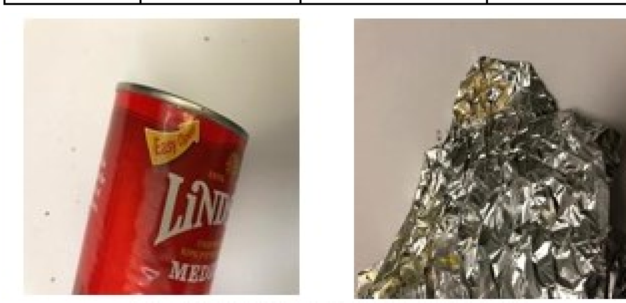
Layer	Type
1	Data (227x227x3 Size Images)
2	96 kernels of size 11x11x3 Convolutions
3	ReLU
4	Cross Channel Normalization
5	3x3 Max Pooling
6	256 kernels of size 5x5x48 Convolutions
7	ReLU
8	Cross Channel Normalization
9	3x3 Max Pooling
10	384 kernels of size 3x3x256 Convolutions

METHOD AND RESULTS

We developed a set of procedures for training a Convolutional Neural Network (CNN) to classify objects as either trash, recyclable or other. We used the AlexNet CNN architecture and trained it with take or not take images on the public spaces for a smart robot trash can to decide to grab an object or not. More specifically, “take” means the identified item is a trash item to be grabbed, and “non-take” means the identified item is not a trash item that should not be grabbed. We trained AlexNet to perform a set of four tests as follows: 1. Trained AlexNet with TrashNet [11] images and tested the resulting CNN with a subset of TrashNet images in 5 categories (metal, plastic, glass, paper, cardboard). 2. Tested the same CNN using an indoor camera in real time focusing of trash objects. 3. Trained AlexNet with outdoor images to classify as either “take” or “non-take”. Tested the resulting CNN with a subset of outdoor images. 4. Trained AlexNet with outdoor images to classify as either landfill trash or recyclable. Tested the resulting CNN with a subset of outdoor images. Tests 1 and 2 were preliminary tests to confirm accuracy of the AlexNet CNNs. We downloaded a publicly available CNN called Deep Learning Toolbox Model for AlexNet Network [12] for use in developing an algorithm in MATLAB. We modified the AlexNet architecture by changing the number of neurons in the last Fully Connected Layer to suit our requirements. We also downloaded a publicly available database, named TrashNet [11], of trash images taken in an indoor environment and separated over 2000 images into 5 categories (metal, plastic, glass, paper, cardboard) to train the CNN. The preliminary training results on the TrashNet indoor images confirmed the applicability of CNN in this application with good accuracy. Tests 3 and 4 are practical tests that could be implemented on the final trash robot design. The outdoor “take” and “non take” images were all taken by us from the surroundings of human living areas on a college campus. Every image used to

train the CNN is a real scenario of trash in our area. For the second task, we trained another AlexNet CNN using the “take” item images to further classify the items into landfill trash or recyclable. The detailed procedure concerning each of these tests are described below. Test 1 – Five Categories in a Controlled Indoor Setting As a primary test, deep learning methods for implementing Convolutional Neural Networks (CNN) in MATLAB were used to train AlexNet in the 5 categories (metal, plastic, glass, paper, cardboard) of images. We tested the accuracy of our trained version of AlexNet using a subset of the TrashNet images. Results are shown in Table 2. Accuracy of detection exceeded 80 % for all 5 categories. It should be noted that the images used in this test were taken in a controlled indoor environment with a consistent lighting background. That helps to explain why the results shown above are very accurate. Several examples of the images used in the test are shown in Figure 2. Table 2: Results of CNN classification using TrashNet indoor images

Category	Total count of images	Count of correctly detected images	Accuracy (%)
Metal	41	39	91.68
Plastic	48	38	81.25
Paper	59	53	89.83
Cardboard	40	37	92.5
Glass	50	46	92
Overall	238	213	89.50



(a) Example of training images used as metal

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(d) Example of training images used as cardboard

(e) Example of training images used as glass

Figure 2. Examples of training images used for the detection of five types of recyclable materials. Part 2: A Real-Time Camera Test in Five Areas Next, we went to an inside workplace with a camera that was focusing on a white display board backdrop, taking pictures of thirteen different things. A total of 260 photos were obtained by rotating each item to capture it from 10 distinct points of view. Figure 3 shows the results of a single object test using a set of ten photos. We ran each picture through our trained AlexNet model (from Test 1), which sorted them into one of five groups: metal, plastic, glass, paper, and cardboard. Table 3 displays a synopsis of the test findings. The trained AlexNet achieved an accuracy of 90% or higher when identifying 7 of the 13 things, and an accuracy of 70% to 80% when identifying 3 of the 13 objects. Three items caused the CNN some trouble: orange plastic box, clear glass, and brown paper. The earthy linen

was wrongly categorized as having 70% cardboard and 30% plastic due to a mix-up between the two materials. The fact that the CNN cannot see the difference between paper and cardboard because to their similar colors is one probable explanation. According to CNN, 60% of clear glass is glass and 40% is plastic. One possible explanation is that plastic and glass both reflect light in the same way. Even with a transparent plastic cup, the issue persisted. The real-time detection was implemented in the MATLAB program. The actual item that was recognized is given in the figure title, which shows the real-time picture. Figure 4 displays the recorded pictures of the thirteen items used to evaluate the convolutional neural network (CNN). These graphs illustrate a few representative outcomes. A plastic bag, for instance, is appropriately classified as plastic in Figure 4 object 1. A number of things are shown in Figure 4. A few have been accurately named, but others have not.

Figure 4: Example of images of 13 objects for use in evaluation Part 3: Outdoor Image Classification (Take/Non-Take) We classified 1054 digital photographs of outdoor settings as "take" or "not take" in order to build training for such images. We mostly took pictures of things on grass, sidewalks, roads, and flower beds for the first outside test. After that, we used these 1054 photos to train AlexNet. Images tagged with "take" featured both recyclable and non-recyclable materials. Pictures of grass, birds, trees, sidewalks, etc., were included in the "non-take" category of images. We put the CNN through its paces using 316 photos that were comparable across the two sets (210 "take" images and 106 "non-take" images). Categorization accuracy

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was 93.6% overall. Nearly all of the "take" items (97.6%) and almost all of the "non-take" products (85.8%). The results of this test are shown in Table 4. Outdoor item categorization examples using training and test photos are shown in Figures 5 and 6, respectively. Figure 7 shows the outcome of the CNN algorithm's choice to "take" or "non-take" when tested with a specific picture. The title of the image then indicates the result.

Table 4: Results of CNN classification using outside images with 2 categories

Category	Total count of images	Count of correctly detected images	Accur (%
"take"	210	205	97.
"non-take"	106	91	85.
Overall	316	296	93.

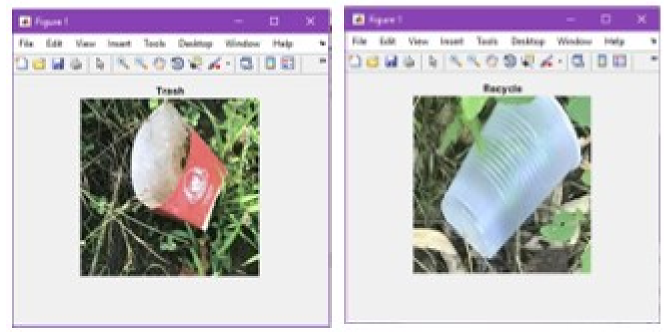
"take" images "non-take" images

(a) Take image on grass (b) Non-take image on road

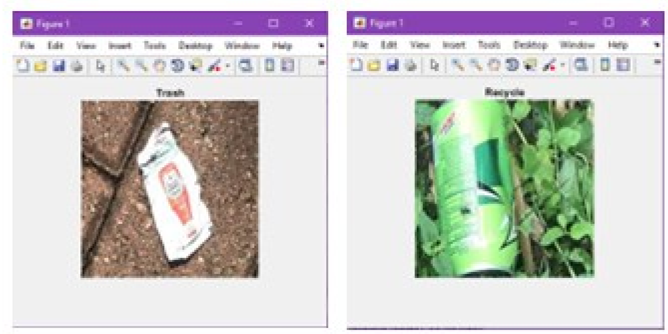
The fourth test is to determine if outside images are recyclable or trash. Then, we used 700 outdoor photos from the "take" category to train an additional AlexNet CNN after sorting the database into "trash" and "recyclable" sections. After sorting the photos into two groups, we ran the CNN through its paces on 175 examples (107 "trash" images and 68 "recycle" images). As previously demonstrated in Table 5, the findings were correct. Its total accuracy in classifying was 92%. Correct identification of "Recycle" goods was 89.7 percent, while "Trash" items were 93.5 percent accurate. Figure 8 displays a number of examples of output graphics where the caption either says "trash" or "recycle," indicating the user's selection.

Table 5: Results of CNN classification using outside images with 2 categories

Category	Total count of images	Count of correctly detected images	Accuracy (%)
"recycle"	68	61	89.7
"trash"	107	100	93.5
Overall	175	161	92



(a) Correct detection of trash object on grass (b) Correct detection of recycle object on grass



(c) Correct detection of trash object on sidewalk (d) Correct detection of recycle object on grass

Figure 8: Sample output of test images for outdoor object classification

CONCLUSION

In this project, we created a convolutional neural network (CNN) algorithm to identify recyclables and landfill goods inside the garbage category, and to distinguish between trash and non-trash objects. The goal was to create an automated trash can. This license is only valid for usage at Zhejiang University. Collection system; restrictions apply. The detection accuracies ranged from 89.7 percent to 93.5 percent, and the results were positive. Compared to the current methods utilized by road sweeper trucks or vacuum cleaners, smart trash cans that include this categorization based on image processing are more suited to cleaning public places of rubbish. The results of the experiments shown that the suggested

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algorithm is capable of properly distinguishing between trash and recycled materials. This algorithm may be a useful resource for creating a garbage can robot that can mow a large grass at a school or park. Using our two-stage trained CNN in an algorithm that can communicate with a microcontroller and a camera, our next work will include programming a garbage can robot to navigate public spaces, detect objects on the ground, and collect and sort waste according to recyclables or landfills.

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