Technology of Autonomous Subaquatic Waste Acquiring and Pre-processing Unit (ASWAP)

The Aquation Team

Abstract – This report provides information on the machine learning technologies ASWAP utilizes.

I. Introduction:

We aim to accelerate the rate at which we are collecting waste in the seas, so that we can enjoy cleaner beaches and animals can live a healthy life.
By reducing marine debris safely and efficiently, we hope to slow down the rapid decrease in subaquatic plants due to water pollution. This way, we will be able to slow down marine warming thus protecting the ecosystem.

Our solution is the first autonomous underwater cleanup product. Using a weakly supervised object detection model aboard a versatile drone, we locate and collect waste in areas that are inaccessible to humans.

Because it would be ineffective to hold on to the waste, it will be stored in an inflatable container, which once full, will float to the surface to easily be picked up by a cleanup crew aboard a cleanup boat.

When the debris of the collection area is collected, the cleanup boat along with the drones either continue to the next preprogrammed collection area or return to the docking station if offload or charging is needed.

One of the greatest issues faced in the ocean cleanup projects today is the handling of waste after it is collected. We use advanced classification models to sort garbage in our docking stations so that it can be recycled and resold.

II. Methods and Materials:

A. Datasets

As datasets are one of the most important parts of a successful machine learning product, trash image datasets both for classification and detection were needed.
For the waste detection model, we used images from the Deep-see Debris Database which was created by JAMSTEC. This is a small dataset which consists of 3644 images. A sample of the dataset is shown in Fig. 1.

Fig. 1:

For the waste classification model, we used images from two datasets [2] by Arkadiy Serezhkin and Kivicode. We had a total of 10,532 images which we divided into 4 different waste classes: paper, plastic, glass, metal. A sample of the combined dataset is shown in Fig. 2.

Fig. 2:

B. Artificial neural networks

An artificial neural network (ANN), in its essence is a sequence of simulated neurons, linking together to create exponentially complex functions, which could not be written out manually. Despite its seemingly complex nature, an ANN can easily be broken down into building blocks, which can then be reassembled to form a comprehensive picture of its functioning. A model, is the term used to refer to the network as a whole, made up of all its neurons. A way we can see this is that the neural network is modeling the way a brain would get from one selection of data to another. Each model, in itself is composed of layers, a line of neurons within the model.

C. Convolutional neural networks

A convolutional neural network (CNN or ConvNet) is a type of multilayer neural network specialized to analyze and classify images (in this case, video footage is fragmented into many images). It convolves the input image, which is abstracted to a feature map, using windows sized 3x3, extracting features of the objects and classifying them accordingly.

D. ResNet-50

The fine-tuned CNN structure ResNet-50 was trained on millions of ImageNet images for 1000 classes. It consists of 50 layers, enabling it to extract essential features from the images.

III. Results:

1. Waste detection model

Due to a lack of datasets for underwater garbage detection, we were unable to implement a classical object detection model. Instead of this, we used weakly supervised learning which means that we implicitly trained the model to find an object in the image while learning to classify that object. To do this, we first pulled some images of different types of waste from an online dataset and trained an Xception model (originally created by Francois Chollet)[3] to classify the images. The algorithm we used to then locate the object is called grad-CAM. The idea behind this is to calculate the gradient between the last convolutional layer and the model's final output. In Layman's terms, we figure out how much the model uses each pixel to determine what is in the image. One of the downsides of this is that we cannot truly determine the accuracy of our model as with this algorithm, classification accuracy does not always equate to object detection. However, we have found that our model achieves very good results without much training. One advantage of this type of approach is that we can easily tell if there is no waste in the image as the classification model will have a very low certainty.

e.g. Detection and location of a plastic bottle underwater

2. Waste classification model

With sufficient data, we developed the classification model based on the ResNet-50 pre-trained model. Here, we utilized transfer training. Enabling us to achieve fast and accurate results using little data: We removed the top classification layer and added a layer using SoftMax regression for the multiple-class classification.

We tried to obtain the highest classification accuracy by testing multiple pre-trained CNNs such as InceptionV3, InceptionResNetV2 and multiple approaches. The highest accuracy was obtained from transfer training the ResNet-50 Network and retraining using selected portions.

We were able to achieve a train accuracy of ~96%, a validation accuracy of ~94% and a test accuracy on a completely new real-world dataset of 92%.

With a 92% accuracy, we can confidently assume that the classification of trash in our system is possible and efficient. The remaining 8% can be compensated using traditional sorting methods such as but not limited to weight and various sensors.

References:

[1] http://www.godac.jamstec.go.jp/catalog/dsdebris/e/index.html

[2]https://www.kaggle.com/arkadiyhacks/drinking-waste-classification , https://www.kaggle.com/szdxfkmgnb/waste-classification

[3] https://github.com/kwotsin/TensorFlow-Xception