

# ROBOTIC INFERENCE – UDACITY

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**Abstract** – This paper aims to present the application of robotic inference in cleaning up beaches of solid waste deposits. Also, implementation of multi class classification network in a real time scenario, proposed to be used for environmental waste clean up is shown. An analysis of the network in recognizing a dirty beach with the performance gives a fair idea of how the network would perform when based on an actual moving vehicle. Results based on testing the network with a separate validation set actual proved the same. Finally, the scope of application of this concept to different requirements that focus on the environment has been highlighted.

## 1. Introduction

One of the worst problems that mankind faces today is cleaning up after themselves in the literal sense. The new York Times reports that the US Government spends 2% of its GNP to clean up the environment[1]. Reports estimate that it would cost around 489\$ million per year to clean up a million square kilometres of the great Pacific Garbage Patch[2]. Hence it will suffice to say that it is high time that technology, specifically Robotics and Machine Learning join hand in hand to resolve this issue.

## 2. Background

The author will now attempt to explain how this issue can be approached. This solution will be implemented by installing the Jetson TX2 pack on a moving terrain vehicle developed specifically for this purpose. The data feed into the camera would be live during operation. Model LeNet was used to train the model due to its high flexibility in processing black and white images. The standard 3 layer LeNet is sufficient to help classify the images with 5 epochs. Although a larger number of epochs would have been preferred in case of a bigger dataset, optimizing this parameter was necessary to avoid overfitting.

## 3. Data Acquisition

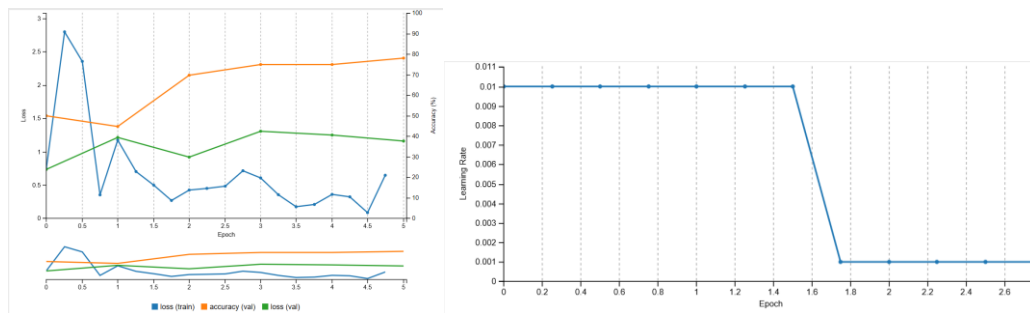
Although there was no image dataset available to represent clean and dirty beaches, the ones available in Google was made use of. A classification dataset was created by downloading images into categories Clean\_Beach and Dirty\_Beach. A number of 200+ images were downloaded and labelled for each category. Apart from this, there was a validation dataset of around 25 images taken as well. The reason black and white images was chosen was based on the uniformity in the color gradient in case of a clean beach. In case of a dirty beach, there were a lot of discrepancies that marked the image. At the same time, a clean beach can also have discrepancies like people, animals, shells and umbrellas. The model was trained taking all this into consideration. That is, when training the model, the clean beach dataset contained pictures of beaches with families, animals and other allowed objects. Partly, this idea was inspired from Udacity's Rover Sim project, which calculates navigable terrain based on the color.



## 4. Results

This is a challenging undertaking since a clean beach can not be defined based on the dataset provided alone. Hence a separate set of images apart from the training set was used to test the model. But, pleasantly, the inference was highly successful with 4 out of 5 images being successfully labelled. Also, the accuracy was reported to be ~79%. Also, the dataset was trained for 8 epochs, but the model overfitted itself. Hence the number of epochs had to be reduced to 5. Also,

the image manipulation used was the squash option, alleviating the issue of loss of data. After all, there is no particular shape or structure expected of a beach, clean or dirty.



## 5. Discussion

Training the model with black and white images was done based on the fact that a clean beach does not have a varying gradient. Also, apart from the presence of animals and humans, there is nothing else that is expected to be present. Hence LeNet was chosen to train the model due to its high degree of flexibility with processing black and white images. Upon validating the inference with images that were not part of the training dataset, the result was really satisfactory. Although not upto the mark, 3 out of 5 images were marked in the correct category.

BeachModel Image Classification Model



| Predictions |        |
|-------------|--------|
| Dirty Beach | 88.75% |
| Clean Beach | 1.25%  |

BeachModel Image Classification Model



| Predictions |       |
|-------------|-------|
| Clean Beach | 71.4% |
| Dirty Beach | 28.6% |

BeachModel Image Classification Model



| Predictions |        |
|-------------|--------|
| Clean Beach | 95.52% |
| Dirty Beach | 4.48%  |

At this point, only speed was deemed more important than accuracy since the focus is not on identifying what the waste is or what object is present. The only 2 classification required is presence or absence of plastic waste deposits. To overcome this, the agent can be enhanced to include learning what kind of objects are present.

## 6. Conclusion/Future Work

Although the current scope of the work is limited to just recognizing, this can be easily expanded to include object recognition as to what is actually present in the surface. That way, it easier for the bot to infer the object present in the environment. Taking it a step further, an underwater bot can be developed to recognize plastic floating in the ocean and extract the same. Another enhancement can be deploying a swarm of robots to do this job, making it easier to accomplish the task and enable learning from one another.

## References:

[1] <https://www.nytimes.com/1990/12/23/us/2-of-gnp-spent-by-us-on-cleanup.html>

[2] <https://response.restoration.noaa.gov/about/media/how-much-would-it-cost-clean-pacific-garbage-patches.html>

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