Tracking and identifying floating marine debris

Kyriaki Kylili[1], PhD student in Electrical Engineering
Alessandro Artusi[2], Ioannis Kyriakides[1] and Constantinos Hadjistassou[1]
[1]Department of Engineering, University of Nicosia, Cyprus;
[2]KIOS Research and Innovation Center of Excellence, University of Cyprus

Introduction

It is estimated that a minimum of 5.25 trillion plastic objects weighing 268,940 tons are found in the world's oceans [1]. Techniques such as ship observations, net trawling and water filtration help estimate the amount of plastic debris at the local scale [2].

The main goal of this research is to devise an automatic method for detecting and classifying marine debris. To this end, we are using two machine learning methods:

A. Bag of Features
B. CNN using Bottleneck

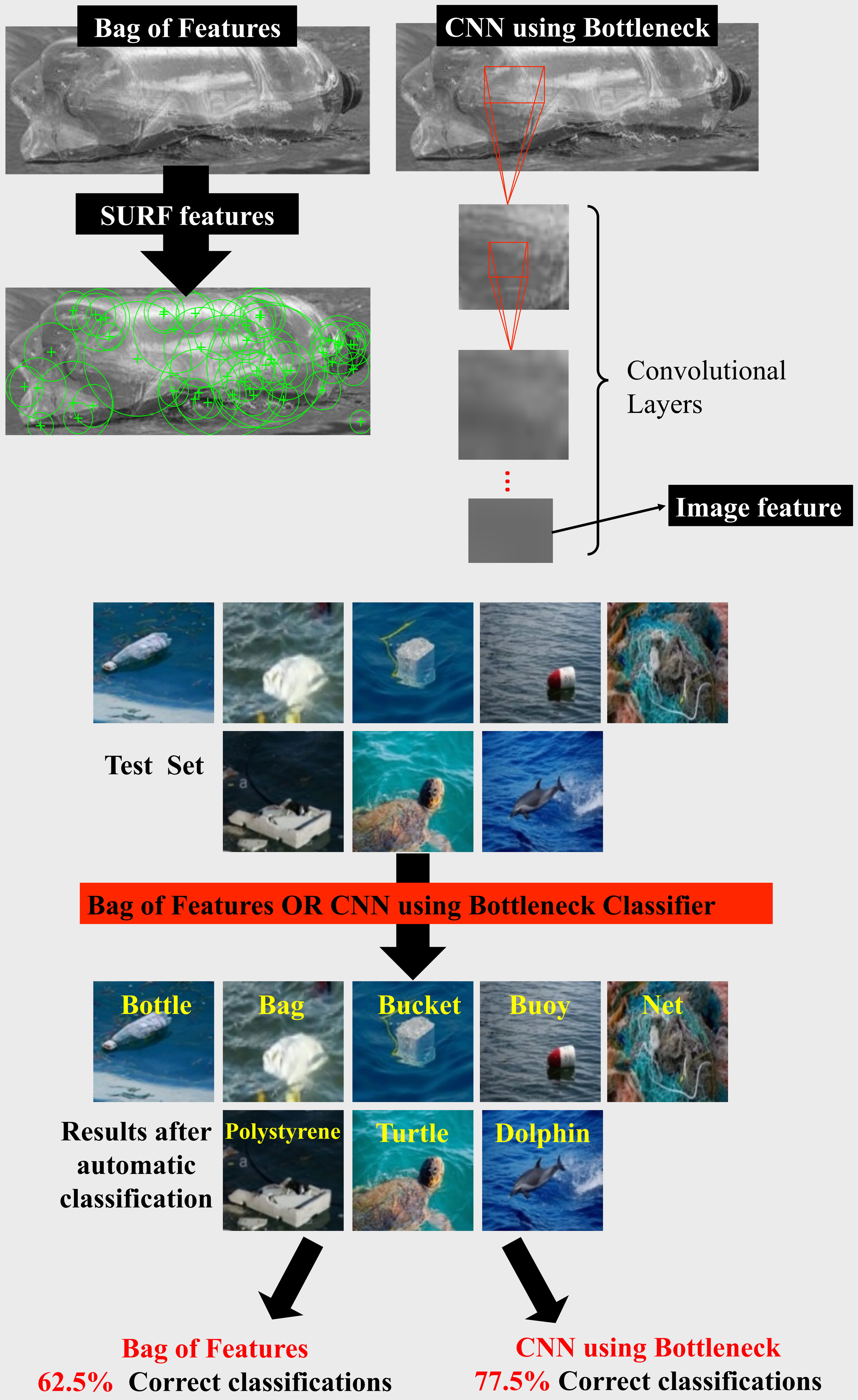
to create classifiers able to classify images of marine debris in respective categories.

Methods

The two machine learning techniques differ in the way they extract image features. Both of the methods train their classifiers using a training set of 8,000 images consisting of six categories of plastic marine litter and two classes of marine life. Below are the two methods:

A. Bag of Features Method:
- i. Is a conventional machine learning method;
- ii. Utilizes the SURF algorithm to extract image features from the training set;
- iii. Constructs a visual vocabulary generating a histogram of visual word occurrences that represent the training set;
- iv. Trains the image category classifier using the visual vocabulary [3].

B. CNN using Bottleneck Method:
- i. Is a Deep Learning approach;
- ii. Is based on a Convolutional Neural Networks (CNN) architecture, a feedforward procedure that extracts image features from the training set. Each layer of neurons employs convolutional operations to extract information from overlapping small regions from the previous layers [4].
- iii. Uses the VGG16 model pre-trained on the ImageNet dataset to boost accuracy.



Bag of Features Code - MatLab

```matlab
bag = bagOfFeatures(trainingSet);
img = readimage(imds, 1);
featureVector = encode(bag, img);
figure
bar(featureVector)
title('Visual word occurrences')
xlabel('Visual word index')
ylabel('Frequency of occurrence')
categoryClassifier = trainImageCategoryClassifier(trainingSet, bag);
confMatrix = evaluate(categoryClassifier, trainingSet);
confMatrix1 = evaluate(categoryClassifier, validationSet);
mean(diag(confMatrix1));
img = imread(fullfile('F:\Queries\test_bucket.jpg'));
[labelIdx, scores] = predict(categoryClassifier, img);
categoryClassifier.Labels(labelIdx)
```

CNN using Bottleneck Code - Python

```python
model = applications.VGG16(include_top=False,
weights='imagenet')
bottleneck_features_train = model.predict_generator(
    generator, nb_train_samples // batch_size)
np.save(open('bottleneck_features_train.npy', 'wb'),
bottleneck_features_train)
model = Sequential()
model.add(Flatten(input_shape=train_data.shape[1:]))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(num_classes, activation='softmax'))
model.compile(optimizer='adadelta',
loss='categorical_crossentropy', metrics=['accuracy'])
```

Method	Bag of Features	CNN using Bottleneck
Correct predictions	62,5%	77.5%
Computational time	~ 1h	~ ½ h

Results and Future Work

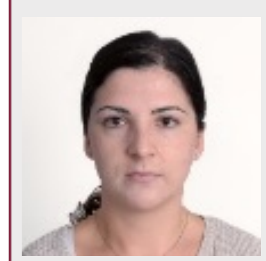
The capabilities of Bag of Features and CNN using Bottleneck methods were examined in classifying marine debris to their categories. Testing the two methods on the same image set we report that the Deep Learning approach reaches a classification accuracy of 77.5% compared to 62.5% for the Bag of Features. The better performance of CNN method is based on the use of the VGG16 model, that is pre-trained on the ImageNet dataset and it has already learned features that are useful for most computer vision problems. Moreover, its CNN architecture automatically discovers the representations of images needed for the classification task. The key aspect of the CNN method is that the important image features needed for the training of classifier are not designed by human operators but are learned using a general-purpose learning procedure. Finally, the computational time of the CNN method is the half of the time needed for the Bag of features method.

Our future plans are to instruct the CNN method to read videos of marine debris and automatically detect floating plastics. Subsequently, to classify debris into different categories and tag important information such as geospatial characteristics which will permit the spatial mapping of marine debris.

I want to express my gratitude to Universitas Foundation, A. G. Leventis Foundation and University of Nicosia for their generous financial support.

References

[1] M. Eriksen et al., PLOS ONE, 9(12):1-15, 2014.
[2] F. Galgani et al., Ices J Mar Sci, 70(6):1055–1064, 2013.
[3] S. O'Hara et al., CoRR, 2011.
[4] Y. LeCun et al., Nature, 521(7553): 436-444, 2015.



Kyriaki Kylili, PhD student