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AquaVision: Automating the detection of waste in water bodies using deep transfer learning

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ABSTRACT

Water pollution is one of the serious threats in the society. More than 8 million tons of plastic are dumped in the oceans each year. In addition to that beaches are littered by tourists and residents all around the world. It is no secret that the aquatic life ecosystem is at a risk and soon the ratio of plastic/waste to the marine life particulary fish will be 1:1. Hence, in this paper, we have proposed a dataset known as AquaTrash which is based on TACO data set. Further, we have applied proposed state-of-the-art deep learning-based object detection model known as AquaVision over AquaTrash dataset. Proposed model detects and classifies the different pollutants and harmful waste items floating in the oceans and on the seashores with mean Average Precision (mAP) of 0.8148. The propose method localizes the waste object that help in cleaning the water bodies and contributes to environment by maintaining the aquatic ecosystem.

1. Introduction

Rising level of pollution around the globe is becoming one of the major concerns of people, polits, and environmentalists. A lot of efforts are being made to reduce the air, and water pollution levels. Humans are the main contributor to the raising of the level of various types of pollution. The effect of which one can find trash everywhere on the earth whether it is a remote area, Himalayas, or the Indian Ocean. Presently, around 5.25 trillion litter objects are present in the oceans, this quantity is steadily increasing with every pass of the day [1]. There is strong evidence that among these litter objects there are several harmful waste items that have adverse effects on the marine ecosystem. These harmful waste items include plastics, bottles, chemical objects, and many other toxic pollutants in the oceans and other water bodies. These pollutants create pollution which imposes a threat to the marine ecosystem and results on severe effects to the environment [2–4]. The degradation of the marine ecosystem will not only affect the environment but is also very dangerous to the small scale economic activities related to marine life. It is estimated that around 90% of the world's fisheries have already been oppressed [5, 6]. Now, it has been predicted that the ratio of fish to plastic waste will be 1:1 by 2050 compared to 1:5 in 2014 [7]. This implies that we are heading on to a very dangerous path and need to manage the degradation, as it is the need of the hour.

1.1. Significance of research in marine life and reduction of water pollution

Detection of waste in the water is not a new issue, researchers of different domains like civil engineers, biomedical, etc. have been significantly contributed to different aspects. In the present era when most of our daily world problems are trained and tested by Artificial Intelligence (AI) models. So, this major environmental cannot be lacked. Therefore, this research proposed a state-of-the-art deep learning object detection model called 'AquaVision'. This enables us to detect and classifies the trash objects in the marine including seashore, oceans for assisting in mapping the waste items, and cleaning of water bodies. Furthermore, this assists in cleanup activities and reducing the water pollution level, which will be a great help to aquatic life.

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2. Role of deep learning in environmental engineering

Deep learning-based techniques are being significantly used to solve many real-world problems to make the system more accurate and efficient. These techniques can be implemented in almost every domain like medical, health, security, automation, and many more [8–15]. Deep learning-based applications can also be seen in environmental engineering for the detection and prediction of the waste in the water [16–19]. There are several studies that bring awareness and provide solutions for systematic management of waste in water. Shafi et al. [20] have applied four machine learning classifiers known as k-Nearest Neighbour (kNN), Support Vector Machine (SVM), single-layer neural network, and deep neural network (DNN). They have used these classifiers to classify the water quality. In their obtained results, it is found that DNN is more capable as it provides higher accuracy in comparison to other i.e., 93%. Liu et al. [21] in order to check quality Guazhou Water Source, Yangtze River deep learning based Long Short Term Memory(LSTM) network is used, their predictive model can predict the drinking water for the next 6 months. Some research studies have used the TrashNet dataset for classification and detection of objects [22–25]. Aral et al. [22], Vo et al. [23] have applied deep learning methods to classify waste and recycle. For this, TrashNet dataset has been used on various architectures such as Mo- bileNet, DenseNet121, DenseNet169, InceptionResNetV2, Xception. Along with them, they have tested two optimizers Adam and Adadelta. In the obtained results, Adam has outperformed the Adadelta on test accuracies. As the TrashNet dataset is limited in numbers, therefore, data augmentation is used to increase classification accuracy. Their experimental results represent that DenseNet121 provides better predictions with a test accuracy of 95%.

Next, Vo et al. [23] have used the VN-Trash dataset which consists of images for classes like Organic, Inorganic, and Medical waste in Vietnam. They have used a Deep neural network architecture known as DNN-TC which is just a better version of ResNet architecture. The proposed neural network performs better on both datasets–TrashNet and VN-Trash. obtained results provide 94% accuracy for TrashNet and 98% accuracy for VN-Trash dataset. Awe et al. [24] have classified waste as recycling, landfill, and paper from a jumbled waste image dataset generated by stacking single waste images from the TrashNet dataset. They have used Faster R–CNN pre-trained on the PASCAL VOC dataset to get the region of interest (ROI) and then to classify them. They have obtained mean Average Precision (mAP) of 0.683 on the classification of waste images. Yang and Thung [26] have applied SVM with scale-invariant feature transform (SIFT) and Convolutional neural network(CNN) to classify waste from images with only a single piece of waste material in it and then classified into six different classes known as glass, paper, metal, plastic, cardboard, and trash. Obtained experimental results reveal that SVM with 68% classification accuracy has outperformed the CNN with only 22% classification accuracy.

3. Dataset information

Several public available datasets are available on object detection from the water. TrashNet [26] and TACOS [27] are the most prominently used datasets in deep learning and machine learning research purposes. In order to test our model we also created another dataset known as AquaTrash which is available on the server [28].

3.1. TrashNet

For training TrashVision, we have used a publicly available dataset known as TrashNet made available by Yang and Thung [26]. The dataset consists of 2527 images of garbage items categorized into 6 different categories namely glass, paper, cardboard, plastic, metal, and trash. The original dataset takes around 3.5 GB of disk space. After using a python script to compress and downsize the dataset, the size has been reduced to around 50 MB with very little loss in image quality.

Table 1
A comparison of two open source Trash datasets available with proposed dataset.

Parameters	TrashNet [5]	TACO [6]
Number of Images	2527	~1500
Number of Annotations	Labeled Data	~4784
Mode of annotation	None	Crowd-source
Categories	6	~28 (excluding sub- categories)
Size	~3.5 GB	~2.63 GB
Background	Plain	Random

Fig. 1. A sample image from AquaTrash dataset with a yellow box as Ground Truth Label. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.2. TACO

TACO dataset or Trash Annotation in Context dataset made by Proen,ca and Simõ̃es [27], it is publicly available containing 1500+ annotated images of litter thrown into streets and forests made available. The annotation is done manually and is open for everyone to contribute. It is a growing dataset and new images are added and annotated frequently.

3.3. AquaTrash

There are very few open-source datasets available which consist of a large number of garbage images and could be used for the proposed study. A comparative study as displayed in Table 1, has been done between the two available datasets – TrashNet [26] and TACO [27] dataset. Both the datasets have some shortcomings such as either the annotations were crowdsourced and unreliable or there were no annotations at all. So, we have proposed an-other dataset AquaTrash to perform various experiments using the proposed AquaVision model. We have also released an open-source dataset AquaTrash which consists of 369 images from 4 different categories related to various litter items. All the images

Table 2
Object detection results in the form of Average precision by state-of-the-art approaches when applied on COCO Dataset.

Methods	Backbone	Average Precision
Two-stage methods		
Faster R–CNN w TDM [25]	Inception-ResNet-v2- TDM	36.8
Faster R–CNN w FPN [34]	ResNet-101-FPN	36.2
One-stage methods		
DSSD513 [31]	ResNet-101-DSSD	33.2
RetinaNet [32]	ResNet-101-FPN	39.1

Table 3
Hyperparameters used to train AquaVision Dataset.

Epochs	Batch size	Steps	Time per step	Train/Test size
20	8	500	4 s/step	80/20

in the AquaTrash are manually annotated to obtain accuracy in the results. AquaTrash dataset consists of 369 images from the TACO dataset and rep-resents manually annotated trash objects in each image. AquaTrash dataset is an open-source dataset, distributed under the MIT license and all the files are available at repository [28]. The technical description of the proposed dataset has been presented in Fig. 1.

In brief, the technical description of the AquaTrash dataset altogether it has 4 categories namely – { ('glass' : 0), ('metal' : 1), ('paper' : 2) , ('plastic' : 3) } they are stored in a .csv file format. And these images are associated with a .csv file containing all the annotations in the format < file path >, < x min >, < y min >, < x max >,< y max > , < class >.

Where, < file path >: The path where the images are stored. If the images are stored in the same folder as your .csv file then the path is nothing but the name of the image, for example "sample img.jpg"

< x min >: x co-ordinate of the image

< y min >:y co-ordinate of the image

< x max >: x + height

< y max >: y + width

< class >: The name of the class to which the particular bounding box belongs to. For example, ¨metal" or ¨glass". are available at repository [24].

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< *x max* >: x + height

< *y max* >: y + width

< *class* >: The name of the class to which the particular bounding box belongs to. For example, "metal" or "glass".

4. Proposed approach with experiments

Most of the recent studies have used a two-stage approach model for object detection like RCNN or faster RCNN [24,29,30]. In contrast, one-stage approaches like DSSD513 [31] and RetinaNet [32] have proved to be more effective while doing object detection. As highlighted in Table 2 shows that the results of different state-of-the-art approaches when applied to the COCO dataset [33], and one-stage based RetinaNET outperforms with an average precision of 39.1. The hyperparameters are used to train the Aquavision dataset has been presented in Table 3.

4.1. RetinaNet

We have used RetinaNet, developed at Facebook AI Research (FAIR) to train the proposed model [32]. Resnet-50 [35] has been used as a backbone for the proposed model. It has several loss functions that can identify the losses after each step during training. It is a one stage detector that uses Focal Loss over general Cross-Entropy or Weighted Cross Entropy loss functions to improve the prediction accuracy [32]. Lower loss is stated by easy negative samples while the other loss focuses on hard samples. It uses Resnet50 and FPN as the backbone models and outperforms the Faster R–CNN by using two sub-networks for classification and one region proposal regression. One stage detector provides 100k object locations in an image that are regularly sampled across all images and densely cover all the position with aspect ratios. Since RetinaNet is a single-shot detector unless FasterRCNN which is a two-stage method, on the COCO dataset competition RetinaNet has been proved to give better accuracy. Therefore, it is capable to detect *waste items from the oceans* much faster and more.

4.2. Evaluation of water waste object detection

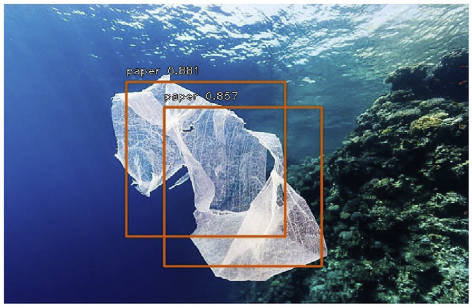
In water waste object detection, the use of AP (Average Precision) in measuring accuracy is quite popular. Average precision defines the average precision value for recall value over 0 to 1. Precision is the ratio of true positives (TP) to the cases that are predicted as positive i.e., true positive and false positive (FP). It gives the accuracy of our predictions. i.e., the percentage of correct predictions as shown in Equation (1).

$$Precision = \frac{True\ Positive\ (TP)}{True\ Postive\ (TP) + False\ Positive\ (FP)} * 100 \tag{1}$$

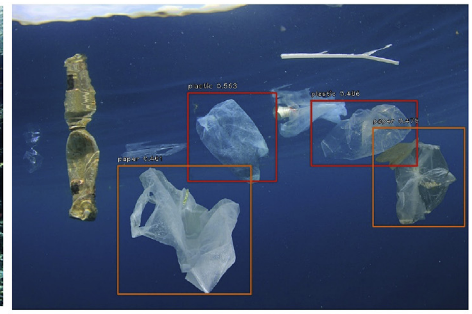
Recall gives how good are all the positives which depends on the percentage of total relevant cases correctly classified by the model.

$$Recall = \frac{TP}{True\ Postive\ (TP) + False\ Negative\ (FN)} * 100 \tag{2}$$

IoU (Intersection over Union) is a ratio between the area of overlap and area of union as shown in Equation (3). Since, we know humans are very good at detecting different boxes in images, we keep the bounding box annotated by a human as the Ground Truth. And then the area of Union of the predicted bounding box and area of Intersection of the predicted bounding box with the Ground truth bounding box is measured and then their ratio is calculated which is also known as Jaccard Index or IoU. It measures the overlapping of real object boundary (ground truth)



(a) A paper bag detected in Ocean with an accuracy of 88%



(b). Plastic detected in the Ocean.

(c) A plastic cup detected in the ocean with

(d) General Waste Detected

Fig. 2. (a) A paper bag detected in Ocean with an accuracy of 88%. (b). Plastic detected in the Ocean. (c) A plastic cup detected in the ocean with (d) General Waste Detected.

with the prediction boundary.

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{3}$$

4.3. Results and predictions

We have applied predictions on random images by using the AquaVision method. As the proposed model was trained for non-aquatic images still able to detect and classify trash objects even in the aquatic images. The obtained predicted results are highlighted in Fig. 2 which shows that the model is able to identify the waste objects from the water and trash with confidence up to 88.1% and even though the model is trained on very few images it has shown great results when the prediction is applied on random images. After training AquaVision for 16 epochs on 369 images we were able to achieve a mean Average Precision (mAP) of 0.8148. The average precision of different classes is also provided in Table 4.

5. Discussion

Waste items in different water bodies and seashores result in water pollution and affect the aquatic life in these water bodies. In this paper, we have successfully detected and classified the various waste items with utmost accuracy. Obtained result represents a self-curated waste image dataset [28] inspired by the TACO dataset and applied a RetinaNet detection model that outperforms Faster RCNN on the TrashNet dataset used by Awe et al. [24] providing mean Average Precision (mAP) of 0.814. This analysis is also used by some automated devices to clean water bodies. The same is also deployed in cleaning devices like drones for mapping waste in water bodies and beaches and waste after collection that can be segregated into different categories for recycling later with the proposed classification model. Proposed model saves a lot of time and human resources. In this way, one can clean the various water bodies more efficiently and can save the aquatic ecosystem.

Table 4
Average Precision and Mean Average Precision calculated for the 4 classes included in AquaTrash.

Class	Average Precision
Glass	0.7353
Metal	0.8427
Paper	0.8589
Plastic	0.8223
mAP (mean of Average Precision)	**0.8148**

6. Conclusion

In this paper, we have applied a deep transfer learning approach to detect waste in water bodies. The proposed AquaVision model detects various waste items with the help of AquaTrash dataset on a single stage detector Reti-naNet which uses Resnet50 as the backbone and FPN. Obtained results rep-resents that AquaVision model provides results in a more efficient manner in spite of limited training data. This method can also find applications in aerial waste detection and the classification which will eventually help in cleaning various water bodies with less human efforts and great precision. In the future, some more annotated images will be included of different waste items in AquaTrash dataset to increase the accuracy of the detection of waste from the water.

Declaration of competing interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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