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Conserving Oceans from Plastic Waste using Convolution Neural Network Model

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ABSTRACT

Plastic Pollution is posing a serious threat to the ocean and its diversity to an extreme level. The number of plastic bags, bottle and other plastic materials which are disposed into the ocean not only pollute its water, tend to change its properties but also can kill marine animals and cause the marine diversity to degrade. Internet of Things (IoT) is a new technology which has sensing capabilities and work in a real-time environment. Aquatic IoT sensors can be used in order to detect and tract these plastic objects in the water. By this method, the cleaning of oceans can be done in an effective manner. There are various deep learning models that have the potential to classify the objects in a real-time environment either on land or in water. These models can be used in order to detect plastic waste from marine debris. In this paper a two-step approach has been adopted with the aim to detect and classify plastic objects under ocean water. Firstly, the IoT sensors are deployed deep into the ocean which take pictures of the different regions in the ocean. Next, the VGG16 CNN (Convolutional Neural Network) deep learning model has been adopted for this paper which takes these pictures as input and classify them into plastic, plants, animals and other objects so that amount of plastic waste can be detected. The approach showed 96.5% accuracy as compared to other object detection and classification approaches. More effectiveness in the proposed work can be added by ensembling the random boost classifier and decision tree approach in the future.

Key words: *Plastic pollution, Internet of Things, Deep Learning, CNN, Object detection, Marine diversity.*

Introduction

By 2050, plastic will cover 88% of ocean surface and be found in every third fish, causing a quadrupling of 22 million tonnes of plastic pollution by 2060 (Khalil *et al.*, 2021). It emphasizes the need for systematic strategies and budget allocation to tackle global plastic pollution, particularly in developing economies with inadequate waste management systems (Kumar *et al.,* 2018). The Ocean Cleanup, a nonprofit group, is employing IoT technology to tackle five major ocean rubbish patches, including The Great Pacific rubbish Patch, with the assistance of 120 specialists (Qiu *et al.,* 2020). TOC uses U-shaped barriers and technology to intercept debris at river mouths in gyres, capturing 80% of ocean plastic. The Interceptor Original, a solar-powered shuttle, counters traditional IoT projects by capturing river rubbish (Qiu *et al.*, 2020 and D'Asaro *et al.*, 2018 and Bai *et al.*, 2018).

Recycling marine plastic trash can reduce ocean pollution by reducing the annual entry of 8 million tonnes of plastic into the oceans. IoT devices using recycled ocean plastic are being explored for housing, buttons, switches, cabling, and electrical parts. However, issues with consistency and quality per-

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sist, necessitating pyrolysis and chemical recycling procedures (Dinesh *et al.,* 2020). Since 1950, over 8 billion tonnes of plastic have been produced, with only 9% recycled and over half ending up in landfills. China, Turkey, Japan, and Germany have implemented initiatives to reduce plastic trash, with Germany decreasing to 6.68 million tonnes by 2016 (Jambeck *et al.*, 2016).

Underwater drones and UUVs are revolutionizing ocean conservation by mapping ocean floor, identifying new marine species, and creating protected zones. They also collect plastic waste, enhancing sea preservation approaches (Law *et al.,* 2020). The O-CNN Model, a deep learning Convolution Neural Network, accurately classifies plastic marine debris on three datasets, achieving 96.5% accuracy. The model's L1 and L2 regularizers' influence was assessed at both single-level and multi-level scaling.

Related Work

Plastic pollution from land, maritime activities, poorly managed household garbage, industry, and runoff contributes to stormwater runoff, wastewater effluent, agricultural runoff, and rivers reaching the ocean (Jambeck *et al.*, 2015). The author explains that population growth, individual plastic waste generation, and poorly managed trash contributed to the 4-12 million tonnes of plastic debris entering the ocean in 2010 (Jambeck *et al.,* 2015). Researchers estimate plastic emissions using global models, local estimates, and materials flow studies, considering factors like waste commerce, illegal dumping, and river-related sources (Law *et al.,* 2020 and Schmidt *et al.*, 2017). Studies consider microplastic emissions due to large estimations and small ocean plastic amounts, but double counting is challenging due to polymer degradation over time (Lau *et al.,* 2020). Microplastic emissions from marine paint, cosmetics, road paint, textiles, pre-production pellets, and tires contribute to 8% to 12.5% of ocean plastic pollution, with 14% coming from marine sources (Foley, *et al.,* 2018 and Eunomia, 2016). Subtropical gyres are contaminated by plastic from ocean currents, causing increased beaching and sinking beneath the ocean's surface. Concerns arise about plastic's impact on world cycles, biodiversity, ecosystem health, climate, and the widespreadness of plastics in ecosystems (Kaandorp *et al.,* 2020 and Brahney *et al.,* 2020). The rise in marine plastic garbage, causing significant harm to the marine ecosystem, is causing public concern due to the increasing amount of plastic dumped into the ocean each year (Rochman, 2016 and Jambeck, 2015). Despite extensive studies estimating floating plastic density and weight in seas, long-term monitoring remains limited, with IoT technologies aiding in finding floating marine plastic (Andrady *et al.,* 2009 and Andrady, 2015). Water's unique physical characteristics, light transmission, and absorption make it more effective in detecting various types of reflectance than plastic, as demonstrated in a study using hyperspectral remote sensing (Eriksen *et al.*,)The study suggests that the Internet of Things (IoT) can aid in locating and mapping marine plastics. Aerial photographs and spatial analysis have been used to map trash along Hawaiian Islands beaches. Combining high-resolution images with machine learning can accurately quantify litter and map maritime debris (Goddijn-Murphy *et al.,* 2018 and Martin *et al.,* 2018).

Proposed Methodology

The VGG16 CNN model uses a selective search algorithm to analyze real-time images, focusing on color and intensity. It uses 3X3 receptive field filters and ReLU units for spatial resolution. The model uses pooling layers for feature mapping and dimensionality. The mAP measure was used to evaluate the proposed O-CNN Model, with results for plastic object detection using the VGG16 CNN model compiled in a table.

Table 1. Summary of Plastic Material Type and its recycling nature

Summary of Plastic Material Type and its recycling nature Polymer Type	Use	Recyclable?
Polyethylene Tetraphthalate	Plastic Bottles	Yes
High-Density Polyethylene	Milk, shampoo, Bleach Bottles	Yes
Polyvinyl Chloride	Piping, Vinyl Flooring, Cabling Cover	Often
Low-Density Polyethylene	Plastic food covers	No
Polypropylene	Food tube, Bottle lids, Houseware, Medical purposes	Often
Polystrylene	Food containers, cutlery	No
Others	Cups, coolers, etc	No

VGG16 CNN is the best task classification model, but training takes longer due to inceptions and strip connections. Tensor Flow, an open-source framework, is used for plastic waste recognition in ocean water using datasets like Trashnet, Tacos, and Aquatrash. Trashnet and Aquatrash display marine, organic, and street trash images. Images are tagged, categorized, and organized for model training. Small errors in categories don't affect model evaluation accuracy, as they fall into specific groups.

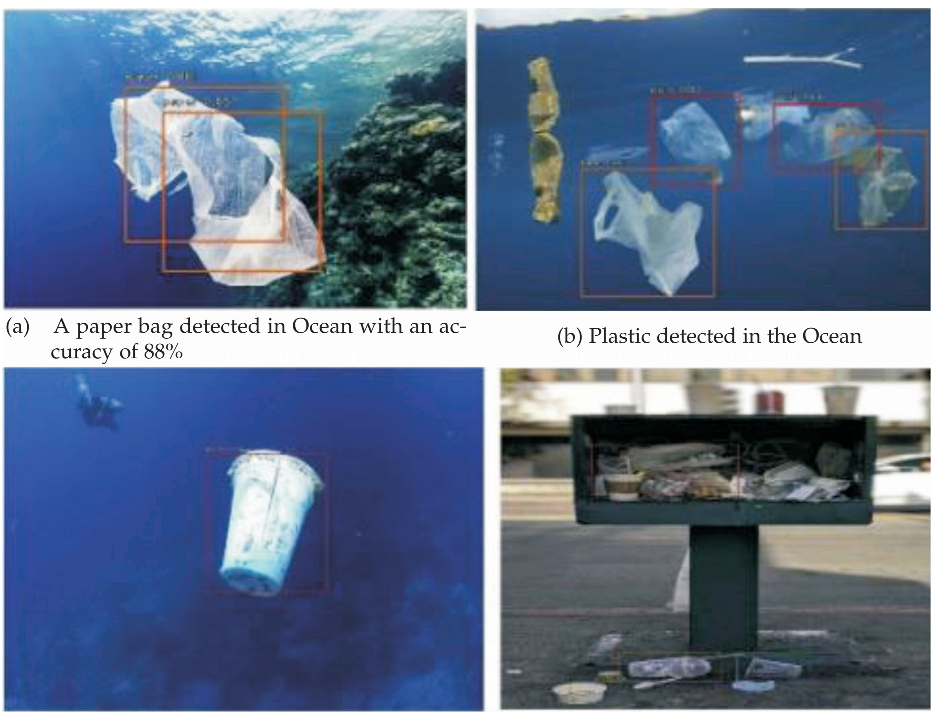
The model is trained on 200 KB image types for dimension reduction, and then analyzed using convolutional layers to extract features, typically vector image representations of the input image. The output displays desired picture portions, and objects are grouped for labeling and weighting, resulting in a learned model. The model is reloaded for testing, using unlabeled realtime testing pictures, and repeated for each session. Firstly, the ReLU activation function can be given as:

$$f(x) = max\ (0, x) \qquad ..\ (1)$$

where, x is output weight. The SoftMax function is used to calculate the probability of each target class C as follows:

$$f(x)_i = \frac{e^{x_i}}{\sum_j^C e^{x_j}} \qquad ..\ (2)$$

Next, the Average Precision (AP) method has been used to measure the accuracy for a recall value of 0 to 1. The precision (P) is calculated as the ratio of True Positives (TP) to False Positives (FP) in order to finally calculate the model's accuracy.



(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

(c) General Waste Detected

Fig. 1. Image Training Set Snapshots from Aqua Trash Dataset

Table 2. Summary of mAP values for various deep learning

S. No	Approach	Plastic Bottle	Plastic Bag	Straws and Containers	Other
1	O-CNN	100.0	78.3	85.5	87.6
2	EdgeLens	99.8	77.8	85.0	87.0
3	NodeMCU	99.9	77.3	84.6	86.8
4	SSD	83.5	76.9	83.9	86.3

$$P = \frac{TP}{TP + FP} * 100 \quad .. (3)$$

The VGG16 model uses data augmentation to improve the accuracy of recognizing real-world images of plastic garbage in water. The model uses a classifier that inputs fresh plastic waste photographs during training, and uses various color tints to increase accuracy due to demographic differences in ocean water colors. The study investigates five color schemes to enhance object detection processes and accuracy in identifying plastic trash, influenced by water pollutants and oil spills, using test images from a dataset.

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The accuracy (A) of the model can be calculated as follows:

=((98+96+95+97)/400)×100%

$$A \frac{TP}{FP} \times 100\%$$

=(386/400)=96.50%

The results as shown in the table proves that high accuracy is obtained in normal color tons of the images and in a semi-transparent ocean water color while the lowest accuracy as obtained in bandicoot color tone. The maximum average accuracy of the proposed model is 96.5.

Results and Discussion

The study utilized 9,000 annotated photographs for training and 2,000 for testing, collecting data for 40 epochs. The models were validated and measured over 40 epochs. The study uses an NVIDIA Quadro K2400 GC Card and Intel Xeon CPU for simulation, achieving 100% accuracy in training and testing, with L1 and L2 for feature selection in sparse and non-sparse categories.

According to the first case different kinds of regularizers are being used in the training process. The use of regularizers help to assign penalty weights to the adopted parameters in various layers of the model. These weighted penalties are used to calculate the cross entropy (CE) for loss function, which can be formulated as follows:

Table 3. Summary of training and testing accuracy for O-CNN under various color hues

	Plastic Bottle and other Marine Debris				
Plastic Bag	Normal	Sepia	Bandicoot	Grayscale	Total
Normal	98	1	1	0	100
Sepia	1	96	2	1	100
Bandicoot	1	2	95	2	100
Grayscale	0	1	2	97	100
Total	100	100	100	100	400
Accuracy	96.50%				

Table 4. Summary of O-CNN Accuracy under Regularizer and Non-Regularizer Mode

	Training			Testing		
Case	Accuracy	80%	20%	30%	40%	50%
Without Regularizer	Training	99.58%	99.97%	99.5%	99.39%	98.92%
	Testing	98.97%	97.99%	97.78%	98.93%	98.99%
L1	Training	100%	98.97%	98.92%	99.48%	98.98%
	Testing	98%	97.90%	97.91%	96.53%	96.92%
L2	Training	89%	99.73%	98.12%	99.77%	99.93%
	Testing	82%	98.90%	97.93%	98.83%	98.78%
L1 U L2	Training	98%	99.9%	98.94%	98.98%	98.77%
	Testing	96%	99.3%	98.13%	97.73%	98.92%

$$CE\ (Loss(f)) = \sum_{C=1}^{IG} y_{Ob,C} \log\ (pr_{Ob,C}) \quad ..\ (4)$$

where, IG is the total number of images, y is an indicator where y = ε [0,1], C stands or class and Ob is the observed classification set. Regularizer effectively avoids overfitting and fluctuation issues in training data. 30% of 5500 photographs were used in four scenarios, evaluating model effectiveness and accuracy.

The test accuracy is highest in Case 1 without regularizers, but the model's loss value increases. Regularizers L1 and L2 improve performance, with L1UL2 case yielding best object tracking results. The model performs better in 20% cases, especially for training scenarios with 80% fed value.The model performed better than the union of L1 and L2 regularizers in examining the accuracy and loss impact on the VGG16 model for a 20% test set.Next,

Table 5. Summary of mAP values for various deep learning approaches for object detection.

VGG16 Config	Small Scale Side		Top-1 Error	Top-5 Error
	α	β	(%)	(%)
A	256	256	28.3	10.11
A-LRN	256	256	28.7	10.03
B	256	256	27.4	9.9
C	256	256	26.4	10.8
	384	384	27.1	9.7
	[256;512]	384	27.9	9.63
D	256	256	28.3	9.9
	384	384	25.4	10.4
	[256;384]	384	26.9	9.2

the model is being analyzed for its accuracy under Single-Scale (SS) and Multi-Scale (MS) parameters. Firstly, for SS, let α denote the test scale and β denote the train scale where, α = β for an ideal case and $\alpha=0.5(\beta_{min}-\beta_{max})$ for jittered $\beta \in [\beta_{min}-\beta_{max}]$ as seen in the table.

As from the above table it can be seen that in the case of A-LRN the model accuracy does not improve therefore this case is avoided and its results are not considered for the deeper layers. As we go deep into layer 11 in A to 19 in E, the error % decreases and thus it performs well for larger datasets. It has also been analyzed that the top-1 error is 7% higher than that of top-5 error rate as compared in 5X5 and 3X3 conv. filters. At the time of training the scale jittering used were α ∈ [256, 512].

The above table is used to assess the model's accuracy under MS mode. The analysis is done over annotated and augmented image dataset under different 5 values. The model is trained for a fixed α value for three image sizes where $\alpha = \{\beta - 32, \beta + 32\}$. At training time wider scalar value for β has been considered where $\alpha \in [\alpha_{mi}n, \alpha_{max}]$ and $\beta = [\alpha_{min}, 0.5(\alpha_{max}), \alpha_{max}]$. Total three proposed approaches namely EdgeLens [33], NodeMCU[31] and SSD[32] has been considered to illustrate the improved accuracy of the proposed O-CNN Model.

For every Epoch Session the bandwidth utilization is shown in Fig 3 (a). As can be seen, a highly accurate performing model is having the maximum network bandwidth consumption. This is because 1.0-1.5 MB data images are transmitted at every instant of time in this mode. Next in Figure 3 (b) an analysis of Jitter has been illustrated. Jitter can be defined as the variation in total delay caused and

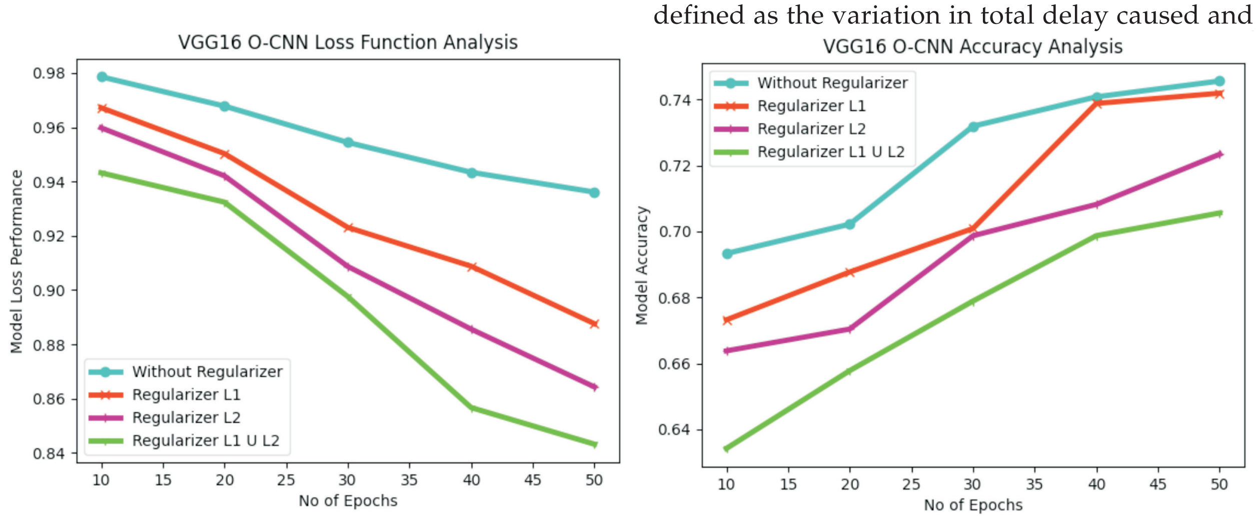

Fig. 2. Model Accuracy and Loss Function Analysis for O-CNN Approach for Regularizers

Table 6. Summary of mAP values for various deep learning approaches for object detection.

VGG16 Config	Small Scale Side		Top-1 Error (%)	Top-5 Error (%)
	α	β		
B	256	224,256,288	28.4	9.2
C	256	224,256,288	27.9	8.9
	384	352,284,416	28.1	8.9
	[256;512]	256,384,512	25.9	8.3
D	256	224,256,288	26.2	8.4
	384	352,384,416	26.4	8.4
	[256;384]	256,384,512	24.3	7.3
E	256	224,256,288	25.9	8.8
	384	352,84,416	26.3	8.9
	[256;384]	256,384,512	24.3	7.3

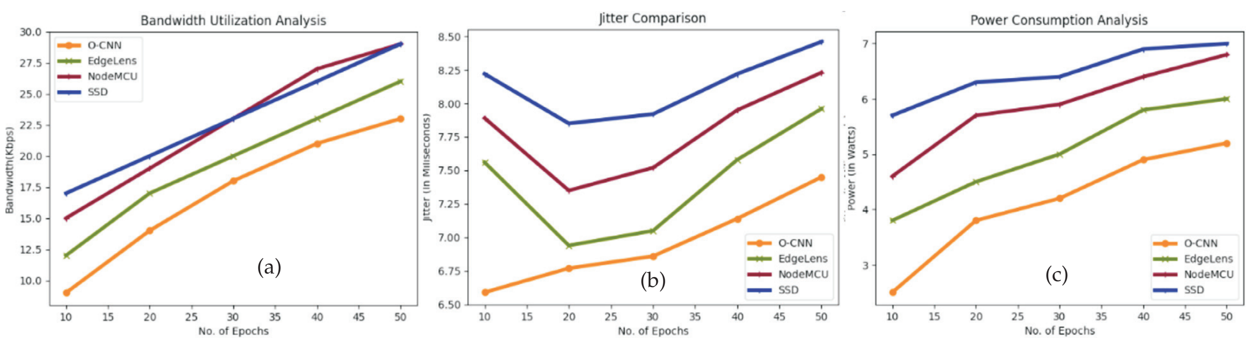

Fig 3. O-CNN Analysis under (a) Bandwidth Utilization, (b) Jitter, (c) Power Consumption

serves as an important factor for real-time applications. It can clearly be seen that the highest jitter has been caused in SSD approach while the proposed approach causes the lowest jitter. Lastly, an analysis of power consumption has been illustrated in Figure 3 (c) where SSD approach again consumes the maximum power as compared to the proposed approach.

Conclusion

Extreme levels of plastic pollution pose a major danger to the ocean's biodiversity. The quantity of plastic bottles, bags, and other things dumped into the oceans not only contaminates the water and tends to alter its characteristics, but also has the potential to harm marine life and reduce marine variety. A new technology called Internet of Things (IoT) can percept things around it and operate in real-time. This approach makes it possible to effective remove plastic materials from the oceans. Different deep learning models may be able to categorize the items in a real-time setting, whether on land or in water. These models may be applied to the detection of maritime debris containing plastic garbage. This article uses a two-step technique to identify and categorize plastic items submerged in ocean water. First, the IoT sensors are placed deep below the water, where they take photographs of the various oceanic zones. The VGG16 CNN (Convolutional Neural Network) deep learning model has then been used in this article to categorize the input images into plastic, plants, animals, and other items in order to determine the amount of plastic trash. In comparison to previous object identification and classification algorithms, the method demonstrated 96.5% accuracy. The presented work can be made more successful in the future by combining the random boost classifier with decision tree technique.

References

Andrady, A.L. and Neal, M.A. 2009. Applications and societal benefits of plastics. Philosophical Transactions of the Royal Society, B: *Biological Sciences*. 364: 1977-1984.

Andrady, A.L. 2015. Persistence of plastic litter in the oceans. In: Marine Anthropogenic Litter. Cham: Springer; pp. 57-72.

AquaTrash Kaggle. https://www.kaggle.com/datasets/

harshpanwar/aquatrash garythung/trashnet: Dataset of images of trash; Torch-GitHub." https://github.com/garythung/trashnet

Bai, M., Zhu, L., An, L., Peng, G. and Li, D. 2018. Estimation and prediction of plastic waste annual input into the sea from China. *Acta Oceanologica Sinica.* 37(11): 26–39, https://doi.org/10.1007/s13131-018-1279-0.

Brahney, J., Hallerud, M., Heim, E., Hahnenberger, M. and Sukumaran, S. 2020. Plastic rain in protected areas of the United States. *Science.* 368(6496): 1,257–1,260, https://doi.org/10.1126/science.aaz5819.

Dinesh, M.H. 2020. Design and Fabrication Model is Used to Extract Waste Plastic to Bio Oil. *International Journal of Engineering and Management Research.* 6: doi: 10.35291/2454-9150.2020.0708.

D'Asaro, E.A. Ocean convergence and the dispersion of flotsam. *Proceedings of the National Academy of Sciences of the United States of America.* 115(6): 1162–1167, Jan. 2018, doi: 10.1073/pnas.1718453115.

Eriksen, M., Lebreton, L.C., Carson, H.S., Thiel, M., Moore, C.J. and Borerro, J.C. 2014. Plastic pollution in the world's oceans: More than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea. *PLoS One.* 9:e111913.

Eunomia, 2016. Plastics in the Marine Environment. Eunomia Research & Consulting Ltd, Bristol, UK, 13 pp.

Foley, C.J., Feiner, Z.S., Malinich, T.D. and Höök, T.O. 2018. A meta-analysis of the effects of exposure to microplastics on fish and aquatic invertebrates. *Science of the Total Environment.* 631: 550–559, https://doi.org/10.1016/j.scitotenv.2018.03.046.

Goddijn-Murphy, L., Peters, S., van Sebille, E., James, N.A. and Gibb, S. 2018. Concept for a hyperspectral remote sensing algorithm for floating marine macro plastics. *Marine Pollution Bulletin.* 126: 255-262.

Jambeck, J.R., Geyer, R., Wilcox, C., Siegler, T.R., Perryman, M., Andrady, A., Narayan, R. and Law, K.L. 2015. Plastic waste inputs from land into the ocean. *Science*. 347(6223): 768–771.

Kaandorp, M.L., Dijkstra, H.A. and E. van Sebille, 2020. Closing the Mediterranean marine floating plastic mass budget: Inverse modeling of sources and sinks. *Environmental Science & Technology.* 54(19):11,980–11,989, https://doi.org/10.1021/acs.est.0c01984.

Khalil,R.A., N. Saeed, M. I. Babar, and T. Jan, "Toward the internet of underwater things: recent developments and future challenges. *IEEE Consumer Electronics Magazine*. 10(6): 32–37, Nov. 2021, doi: 10.1109/mce.2020.2988441.

Kumar, P.M. and Gandhi, U.D. 2017. A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases. *Computers & Electrical Engineering*. 65: 222–235, Jan. 2018, doi: 10.1016/j.compeleceng.2017.09.001.

Kvale, K.F., Friederike Prowe, A.E. and Oschlies, A. 2020. A critical examination of the role of marine snow and zooplankton fecal pellets in removing ocean surface microplastic. *Frontiers in Marine Science* 6:808, https://doi.org/10.3389/fmars.2019.00808.

Law, K.L., Starr, N., Siegler, T.R., Jambeck, J.R., Mallos, N.J. and Leonard, G.H. 2020. The United States' contribution of plastic waste to land and ocean. *Science Advances.* 6(44):eabd0288, https://doi.org/10.1126/sciadv.abd0288.

Martin, C., Parkes, S., Zhang, Q., Zhang, X., McCabe, M.F. and Duarte, C.M. 2018. Use of unmanned aerial vehicles for efficient beach litter monitoring. *Marine Pollution Bulletin.* 131:662-673.

Pavan Sankeerth, V., Santosh Markandeya, V. and Sri Ranga, E. "Smart Waste Management System Using IoT. *Inventive Computation Technologies*, doi: 10.1007/978-3-030-33846-6_71.

Rochman, C.M., Browne, M.A., Underwood, A., Franeker, J.A., Thompson, R.C., Amaral-Zettler, L.A. 2016. The ecological impacts of marine debris: Unraveling the demonstrated evidence from what is perceived. *Ecology.* 97: 302-312.

Schmidt, C., Krauth, T. and Wagner, S. 2017. Export of plastic debris by rivers into the sea. *Environmental Science & Technology.* 51(21): 12,246–12,253, https://doi.org/10.1021/acs.est.7b02368.

Qiu, T., Zhao, Z., Zhang, T., Chen, C. and Chen, C.L.P. Underwater Internet of Things in Smart Ocean: system architecture and open issues. *IEEE Transactions on Industrial Informatics*. 16(7): 4297–4307, Jul. 2020, doi: 10.1109/tii.2019.2946618.