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Advancing Plastic Pollution Detection in Underwater Environments Using CNN Architectures

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***Abstract*—Most of the plastic debris from land that ends up in the ocean originates from human waste, making ocean pollution one of the most serious environmental problems. The creatures, the local economy, and the equilibrium of the marine ecosystem are all at risk from these contaminants. Aquatic life and humans will undoubtedly be impacted by this. Various advanced models and approaches are used to detect and measure plastic pollution in the water. This research focuses on a number of well-known methods, such as VGG16, MobileNetV2, DenseNet, and a bespoke convolutional neural network (CNN) architecture. Using these cutting-edge models, we want to improve the precision and effectiveness of plastic garbage detection in underwater environments. MobileNetV2, which demonstrated its better performance with 80% accuracy and computational efficiency in this setting, produced the most promising results among the tested models.**

***Index Terms*—Plastic Pollution, Ocean Contamination, Marine Ecosystem, Aquatic Life, CNN, Plastic Waste Detection, Environmental Impact, Detection Models.**

I. Introduction

Marine life and ecosystems are seriously threatened by the widespread issue of plastic waste in our seas and other bodies of water. Innovative approaches are needed to solve this problem, such as using deep learning technologies to identify and track plastic waste underwater. Deep learning has potential for detecting and tracking plastic garbage below the water's surface, especially in the areas of object detection and picture recognition. The goal of this project was to create a computer vision system that can automatically identify plastic garbage in underwater photos or videos, aid in prompt response, and support conservation initiatives. This technology can help marine researchers, environmental organizations, and legislators understand and reduce plastic pollution in aquatic habitats by utilizing deep learning skills. This will help to preserve and safeguard our seas [1].

The widespread issue of plastic pollution in our seas and other bodies of water is a serious hazard to ecosystems and marine life. Deep learning technology must be used in creative ways to solve this problem. In order to precisely detect and track plastic waste underwater, models are essential. Because of their high expense, labor-intensive nature, and propensity to harm marine species, traditional technologies such as manta trawls and marine vehicles confront difficulties. Using a large undersea dataset, we assessed a number of deep learning models in our study, including CNN, VGG16, MobileNetV2, and DenseNet. MobileNetV2 outperformed the others in terms of accuracy, proving its efficacy and computational efficiency. This technology facilitates rapid response and conservation efforts by helping with a variety of activities, including the detection, inspection, and reconstruction of scenes, including plastic trash.

Even though deep learning models for underwater plastic detection have advanced significantly, issues like consistent benchmarking processes and datasets still exist. By addressing these issues, these technologies will become even more successful, helping to safeguard and preserve our oceans.

Remotely operated vehicles (ROVs) present a viable substitute with their sophisticated computer vision systems. Underwater objects, including plastic waste, can be detected and their movements tracked by these vehicles [2].

Despite notable advancements in the use of deep learning models for underwater plastic detection, there are still a number of important research gaps. First, evaluating and comparing the performance of various detection algorithms is made extremely difficult by the absence of defined benchmarking techniques and datasets. Progress towards more efficient detection techniques is hampered by this inconsistency, which makes it challenging to identify the relative advantages and disadvantages of different approaches.

In this work, we use a carefully annotated dataset to assess how well deep learning models, including CNN, MobileNetV2, DenseNet, and VGG16, detect plastic waste in underwater environments. MobileNetV2 showed the best accuracy among these models.

II. RELATED WORK

For underwater marine debris identification, Khriss et al. (2023) carried out a thorough comparison analysis of cutting-edge deep learning models, such as Faster R-CNN, SSD, YOLOv8, and YOLOv9. They evaluated performance parameters like accuracy, precision, recall, and mean average precision (mAP) across various object classifications and environmental circumstances using the TrashCAN and DeepTrash datasets. According to their results, YOLOv9 continuously performed better than the other models, exhibiting higher mAP, precision, and recall. The research also demonstrated YOLOv9's stability and convergence behavior throughout training, highlighting its efficacy as a reliable tool for environmental monitoring and intervention initiatives in underwater ecosystems [3].

Using an improved low-sample-size dataset, Fernando et al. (2021) created a deep transfer learning method to tackle the difficulties of underwater marine plastic waste detection. Enhancing detection performance in situations with little labeled data was the main goal of the study. They improved the model's capacity for generalization by utilizing transfer learning approaches, which allowed it to detect plastic garbage with high accuracy in a variety of underwater circumstances. The findings show how transfer learning can help environmental monitoring applications overcome data shortage issues [4].

An enhanced YOLOv5n model designed for underwater plastic waste detection was presented by Xu and Hu (2022). Their strategy aimed to increase detection accuracy and efficiency while maintaining real-time applicability. They improved the model's capacity to identify plastic garbage in intricate underwater environments by implementing architectural changes and fine-tuning parameters. The model's lightweight design, which makes it appropriate for deployment in real-time systems with limited resources, was highlighted in the study. The enhanced YOLOv5n offered a workable solution for the identification of plastic garbage beneath water by striking a balance between computational effectiveness and detection performance [5].

In [6], they have used object detection models like YOLOv4 and YOLOv5 that have shown significant effectiveness in detecting plastic in marine sites. In another work [7], they have demonstrated and broken down polymers for providing a way to reduce the concentration of nano and microplastics. In [8], a deep learning model has been used to identify underwater trash, helping autonomous underwater vehicles (AUVs) detect and remove debris.

III. METHODOLOGIES

The suggested research detects plastic garbage underwater by using deep learning techniques. Given their effectiveness and precision in object detection tasks, we used models like MobileNetV2, CNN, DenseNet, and VGG16 in our project. The purpose of this device is to help sea divers locate plastic litter more effectively by dynamically identifying it underwater. Our method can precisely identify plastic garbage by utilizing these cutting-edge models, which helps with water resource management and environmental preservation.

A. Dataset Description

The dataset consists of pictures showing underwater environments tainted by trash that has been dumped and debris that has contaminated the seas. The dataset was preprocessed using the Dark Prior Channel technique to increase image contrast, which made it easier to identify and detect the debris. The files are arranged in three main directories: the Train Directory, which has 3,628 photos and their labels; the Validation Directory, which has 1,001 images and labels; and the Test Directory, which has 501 images and labels. Along with a class name, the labels indicate the bounding box coordinates (e.g., width, height, x-coordinate of the top-left corner, y-coordinate of the top-left corner). There are fifteen classes in the dataset, including mask, can, cellphone, electronics, gbottle, glove, metal, miscellaneous, net, pbag, pbottle, plastic, rod, sunglasses, and exhaust. A data sample has been shown in **Figure** 1.

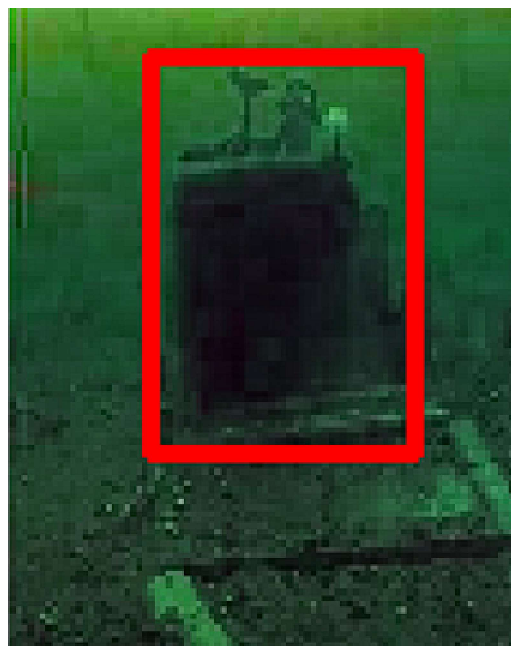

Fig. 1. Plastic Detection Sample

B. Methodology

1) Dataset Loading and Preprocessing : To guarantee consistency, we loaded the dataset and performed preprocessing. This entails normalizing pixel values, scaling photos to a consistent size, and formatting labels according to the model training specifications. The complete process has been shown in **Figure** 2.

2) Data Augmentation: We have used data augmentation strategies to make our training data more varied. Images have been rotated, flipped, scaled, and shifted in order to improve the model's generalization.

3) Model Selection: Deep learning models like CNN, DenseNet, VGG16, and MobileNetV2 have been used in our study. In tasks involving object detection and picture recognition, these models are renowned for their effectiveness and precision. We have trained these models on various hyperparameter settings for the classification task.

4) Evaluation: The trained models have been tested on a different dataset for validation or testing. We have determined performance criteria, including recall, accuracy, precision, and F1-score, to evaluate each model's efficacy.

IV. EXPERIMENTAL RESULT AND ANALYSIS

MobileNetV2 was the best model in the evaluation of different models for plastic identification, with an F1-Score of 80%, accuracy of 80%, precision of 78%, and recall of 82%. Then, with a 79% F1-Score, 80% recall, 79% accuracy, and 77% precision, DenseNet showed impressive performance. Additionally, the basic CNN (2D) model demonstrated strong performance, attaining a 76% F1-Score, 76% accuracy, 74% precision, and 77% recall. In contrast, VGG16, despite being well-known for its deep architecture, trailed somewhat with 71% accuracy, 69% precision, 73% recall, and 71% F1-Score. MobileNetV2 and DenseNet shone out for their greater accuracy and resilience in managing challenging picture identification tasks, even though all models performed well overall. An overview of our findings has been given in **Table** I.

TABLE I
PERFORMANCE METRICS OF DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1-Score
CNN (2D)	76%	74%	77%	76%
VGG16	71%	69%	73%	71%
DenseNet	79%	77%	80%	79%
MobileNetV2	80%	78%	82%	80%

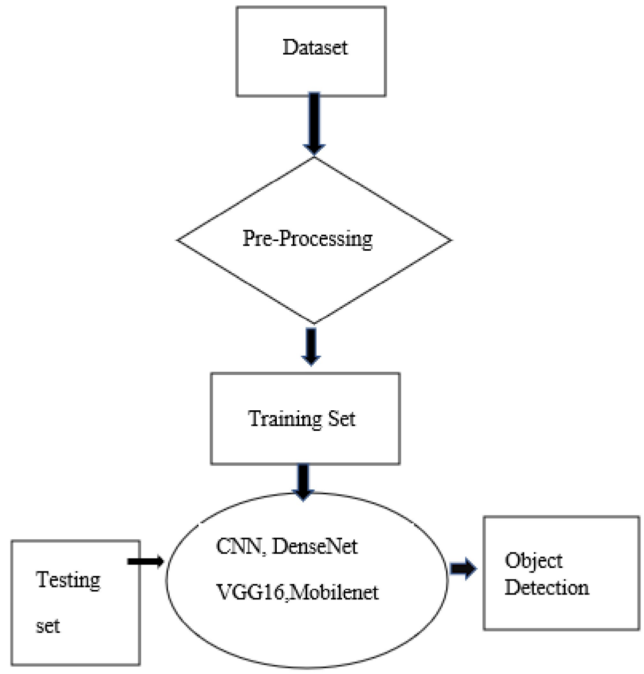

Fig. 2. Proposed Methodology.

V. FUTURE WORK

Future research in the field of plastic detection should concentrate on improving picture resolution in order to better capture microplastics, which are frequently difficult to detect because of their small size. Additionally, sophisticated picture preprocessing methods like contrast enhancement and noise reduction might boost the detection of microplastics in aquatic environments. By combining spectroscopy data with image-based detection, a more precise identification based on chemical composition can be obtained. Combining semi-supervised learning approaches with cutting-edge models like EfficientNet and vision transformers can greatly improve performance and increase model accuracy. Strong training datasets can also be produced by sophisticated data augmentation methods or synthetic data synthesis with GANs, which improves generalization. Active learning frameworks can be used to improve model performance by concentrating on the most instructive labeling samples. Also in the real-life world, there are plenty of challenges like low visibility, light refraction, and underwater sensor compatability for detecting the plastic object in the ocean. Future studies that focus on these regions can significantly enhance the identification and detection of macro- and microplastics, leading to more potent responses to the plastic pollution problem.

VI. CONCLUSION

Sophisticated deep learning models such as CNN, MobileNetV2, VGG16, and DenseNet have greatly enhanced the ability to detect plastic waste underwater. These models provide strong frameworks for monitoring in real time and successfully handle issues like a lack of labeled data and a variety of maritime habitats. Using these models together improves ecological monitoring and conservation initiatives, which in turn lessens the negative impacts of plastic trash on marine ecosystems and fosters a more wholesome ocean environment.

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