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Automated Marine Debris Detection: A Deep Learning and Ensemble Approach with Web Deployment

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Abstract

Objectives: To propose a scalable, real-time detection framework for existing ocean debris detection systems using deep learning. **Method:** Convolutional Neural Networks (CNNs) and Random Forest (RF) classifiers are combined to increase the detection accuracy and to provide a robust monitoring solution. The performance of the CNNs, the RF classifier, and their ensemble is compared to evaluate their performance. **Findings:** The results show that the ensemble model outperforms individual models by achieving a higher accuracy and F1 score of 95.1% and 0.95, respectively. Furthermore, object detection is performed using the Clarifai API, integrated into a Voila-based web application. **Novelty:** The web based application allows users to upload images and receive detection results. The proposed method provides a practical, scalable tool for monitoring and mitigating plastic pollution in the world's oceans.

Keywords: Convolutional Neural Networks; Random Forest classifier; Ensemble algorithm; Debris detection system; Clarifai API

1 Introduction

Plastic pollution is one of the century's biggest environmental challenges. Millions of tons of plastic waste enter marine environments each year originating from land-based activities, fishing industries, and shipping operations. Once plastic degrades into micro plastic, it can remain for decades, infiltrating food chains and posing severe threats to marine ecosystem stability, biodiversity and human health. Reports from the United Nations Environment Programme (UNEP) emphasize that without immediate intervention, plastic debris in the oceans could outweigh the fish population by 2050. Traditional methods of detecting and quantifying marine debris rely on manual surveys, ship-based sampling, and aerial image analysis. These existing methods are costly, labor-intensive, and lack scalability, offering limited ability to provide real-time output in large-scale monitoring. This problem demands innovative and automated solutions across different marine environments to provide effective monitoring.

Even though deep learning is becoming more popular for marine debris detection, most of the existing methods employ single-model architectures. Single model architectures struggle with high variability, occlusion, and spectrum ambiguity that are common in marine environments. Current ensemble methods rarely utilize the hybrid combination of deep feature extraction and conventional machine-learning decision mechanisms. The proposed method presents a novel ensemble architecture that combines CNN for strong feature representation with a RF classifier for better decision fusion. This CNN–RF ensemble is specifically designed for detecting marine debris. The combination of CNN-RF makes classification more stable and accurate in challenging coastal images. We evaluate three models a CNN, a Random Forest classifier and their ensemble. The ensemble algorithm provides better accuracy and F1-scores. Furthermore, object detection capabilities are implemented using the Clarifai API, which is integrated into a Voila-based web application to provide an interface for real-time image inputs and debris identification. This study contributes to environmental awareness and provides a practical, long-term solution for monitoring plastic pollution by combining artificial intelligence techniques with user friendly deployment.

2 Related Work

Recently, researchers explored a wide range of deep learning algorithms for marine debris detection. Deep learning algorithms focus on improving object detection performance under challenging environmental conditions. Several methods utilized transfer learning and data augmentation to overcome dataset limitations to enhance debris detection accuracy[(1)]. Significant attention has been given to real-time object detection models. YOLOv8 has been used on embedded devices such as the Jetson Nano and Raspberry Pi to detect debris under challenging environmental conditions[(2)]. Furthermore, YOLOv5 and YOLOv7 have been utilized specifically for underwater and ROV-based marine debris detection[(3)],[(4)]. Studies have demonstrated the effectiveness of YOLOv8 in handling varying illumination[(5)], BoT-SORT algorithm on YOLOv8[(6)], and lightweight neural models outperforming traditional marine debris detection models such as Faster R-CNN, SSD, and YOLOv5/v8/v11/v12[(7)]. Additionally, Aerial-Aquatic Speedy Scanner (AASS) integrated with Super-Resolution Reconstruction (SRR)[(8)], and SRR with an optimized object detection model[(9)], improved the detection capability of YOLOv8. Comparisons among techniques such as Faster R-CNN, Mask R-CNN, YOLO NAS, and YOLOv6/YOLOv8 have further demonstrated the potential of deep learning for underwater debris detection[(10)]. More recently, specialized variants such as YOLO11-YX[(11)] and improved YOLO backbones were proposed for floating marine debris detection in low-visibility waters[(12)].

Research beyond YOLO-based detectors has also been conducted. Transformer-based models have been applied to detect marine debris in high-resolution aerial images[(13)] and combined semantic segmentation–object detection frameworks demonstrated better debris detection in complex environments[(14)]. Dataset contributions have also played a vital role, including the SeaClear Marine Debris Dataset[(15)], hydrodynamic laboratory experiments comparing sensor modalities for debris detection[(16)], and hybrid AI approaches integrating clustering with fully convolutional networks for debris detection[(17)]. Systems built with Scikit-Learn, Keras, and TensorFlow have demonstrated early potential for debris detection[(18)], and ResNet-based architectures have achieved strong precision and F1-scores in debris detection[(19)]. Sentinel-2 satellite images have been widely used, in approaches such as the modified infrared normalized difference vegetation index (INDVI)[(20)], the MADOS dataset for joint debris oil spill detection[(21)], and CNN-based models for identifying debris of varied shapes and sizes[(22)]. Additional works have explored deep feature–based classification frameworks[(23)], confidence-adjusted SSD detectors[(24)], and hybrid CNN–LSTM models to improve debris detection performance[(25)]. U-Net and its variants have been specifically used for segmentation tasks in Sentinel-2 images[(26)], and the MARIDA benchmark has become a standard for evaluating debris detection performance from satellite images[(27)]. Furthermore, IoT-based marine debris management systems[(28)], general deep learning applications for marine monitoring[(29)], large-scale detection architectures[(30)],[(31)], and Lightweight Spatial and Spectral Hyperspectral CNN (LSS-HCNN)[(32)] have been used to detect marine debris.

The proposed method aims to revolutionize maritime debris monitoring through deep learning algorithms and computer vision. Existing methods are expensive, time-consuming, labor-intensive, and inflexible. This makes the real-time monitoring of debris across oceans difficult. However, the proposed system identifies and measures marine debris in real time in a scalable and cost-effective manner. The proposed ensemble method requires CNN models tailored for marine debris detection. The CNN model is trained on labeled images to detect marine debris effectively. Furthermore, the proposed system overcomes the drawbacks of individual models and improves overall detection accuracy. Statistical metrics such as precision, recall, F1-score are used to measure the performance of deep learning models. These metrics provide useful information about accuracy in detecting maritime debris. Statistical analysis will assist in fine-tuning and optimizing the model's performance for real-world applications. Furthermore, the proposed system implements algorithms to estimate the percentage of marine debris present in the ocean. The system will be able to detect marine debris by analyzing images and tracking changes over time. The percentage estimation provides vital insights into the level of plastic pollution in maritime areas and provides a better understanding of the problem and helps design targeted solutions.

3 Methodology

The flow diagram of debris detection using ensemble algorithms is shown in Figure 2. A diverse dataset of marine environment images, including both debris and non-debris was collected from SeaClear dataset[15] and self-collected images. The sample images are shown in Figure 1. The dataset includes 1240 underwater images from both public and self-collected images. From the dataset, 780 images were debris, and 460 images were non debris images. Preprocessing was performed to ensure uniformity and high variability in the dataset using techniques such as resizing, normalization, and data augmentation. The dataset was split using a stratified approach into 70% for training, 15% for validation, and 15% for testing. The proposed CNN architecture is constructed using three convolutional pooling blocks, 128-unit dense layer and a softmax layer. The convolutional pooling blocks consists of 32, 64, and 128 filters, 3x3 kernals, and ReLu activation. A Max-pooling layer is used for down sampling to avoid overfitting. The dropout rate is applied at the rate of 0.25 and 0.5. The CNN architecture trained for 30 epochs using Adam optimizer and xavier initialization. Furthermore, 128-dimensional feature vectors were extracted and fed as input to the RF classifier. The Softmax layer was used for multi-class classification and to differentiate debris and non-debris classes.

Fig 1. Sample Images of Debris and Non-debris

The CNN was trained on the training dataset and optimized using its hyperparameters such as optimizer, learning rate, batch size, epochs, loss function and weight initialization. Furthermore, the performance of CNN was measured using different statistical parameters. Features such as color histograms and texture descriptors were extracted from the images. The extracted features were fed as input to the Random Forest model. Preprocessing was performed to ensure uniformity and high variability in the extracted features. The RF classifier was trained on the training dataset and evaluated on the testing dataset to assess its performance on unseen data. The performance of the RF classifier was optimized using different combinations of hyperparameters such as the number of trees, tree depth, splitting criterion, minimum samples split, minimum sample per leaf, bootstrap sampling and random state. Furthermore, hyperparameters were adjusted to improve the performance metrics.

The ensemble model improves performance by combining the predictions from multiple individual models. The proposed ensemble approach is a hybrid feature-level ensemble, combining a CNN for deep feature extraction and RF for final classification. The CNN model extracts feature from each image in the dataset. The extracted deep features from the CNN model were fed as input to the RF classifier. The optimal hyperparameters for CNN and RF are shown in Table 1. The efficiency of the ensemble model in detecting marine debris was assessed using the testing dataset.

Table 1. Hyper parameters of CNN and RF

CNN Hyperparameters	Value	RF Parameters	Value
Optimizer	Adam	Number of Trees	300
Learning Rate	0.001	Splitting Criterion	Gini impurity
Batch Size	32	Maximum Depth	None
Epochs	30	Minimum Samples Split	2
Loss Function	Categorical Cross-Entropy	Minimum Samples per Leaf	1
Weight Initialization	Xavier uniform	Bootstrap Sampling	Enabled
		Random State	42

The CNN model used Uniform Manifold Approximation and Projection (UMAP) to visualize the characteristics of the extracted features. The CNN acquired significant feature representations when features from various classes were clustered

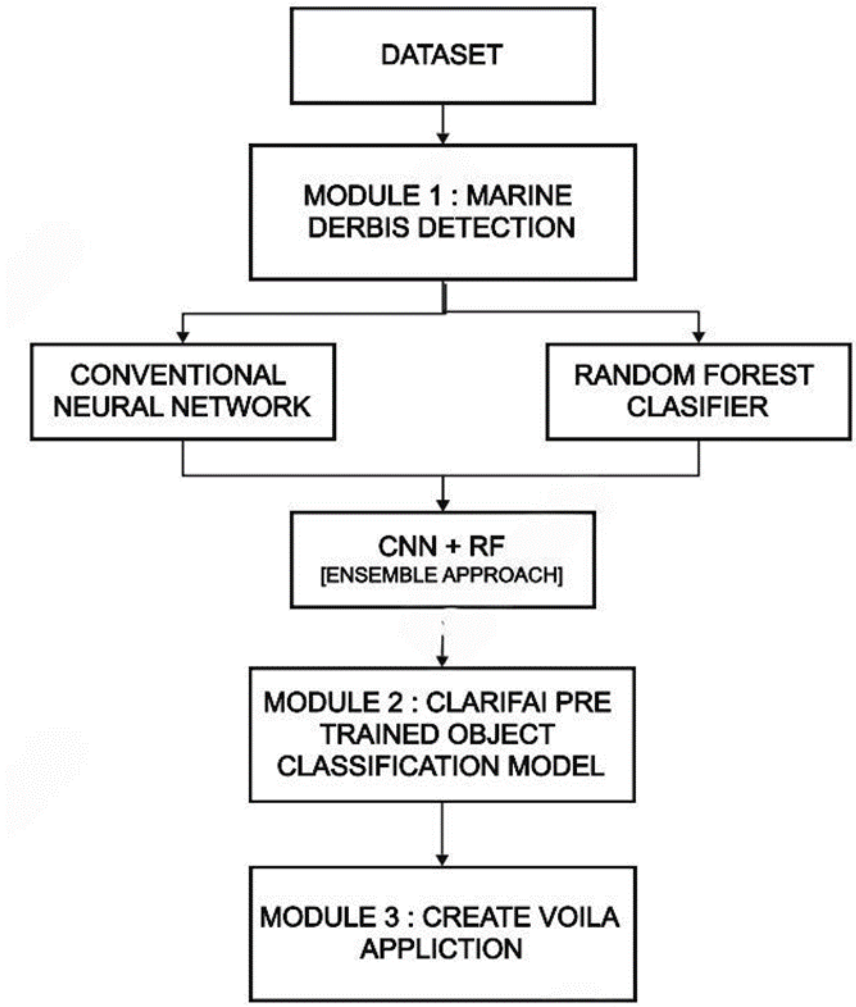

Fig 2. Flow diagram of Debris Detection using Ensemble Algorithm

using UMAP. In noisy images, features from multiple classes overlapped and the features extracted from complicated and noisy images were less separable. Noisy images require modern architectures for debris detection. The Clarifai API has been adapted to improve the system capabilities. The Clarifai API offers pre-trained models for different applications such as concept extraction, classification, and object identification. Hence, developers can incorporate vision features using the Clarifai API. The Clarifai API is used in the proposed system to increase the capabilities of the marine debris detection system. A user-friendly Voila application was developed to provide a graphical interface for the marine debris detection system. This app allows users to interact with the system without needing to write code. Users can upload underwater images and view real-time results using a Voila interface. This application abstracts the complexity of the models and ensures accessibility and practical usability for researchers, environmentalists, and policymakers.

4 Results and Discussion

The proposed marine debris detection system was tested on various underwater images. This system proved its ability to accurately identify and measure marine debris. The proposed system combines CNNs, RF and ensemble learning with an object detection API, and performs consistently better than existing systems. Figure 3 shows the sample outputs of marine debris detection using ensemble algorithms. The system outlines detected debris with bounding boxes and estimates their percentage in each image. In Figure 3(a), marine litter covers about 71.23% of the scene, showing a significant amount of pollution. Figure 3(b) and 3(c) show the system accurately finding floating plastic items like bottles and packaging, which are

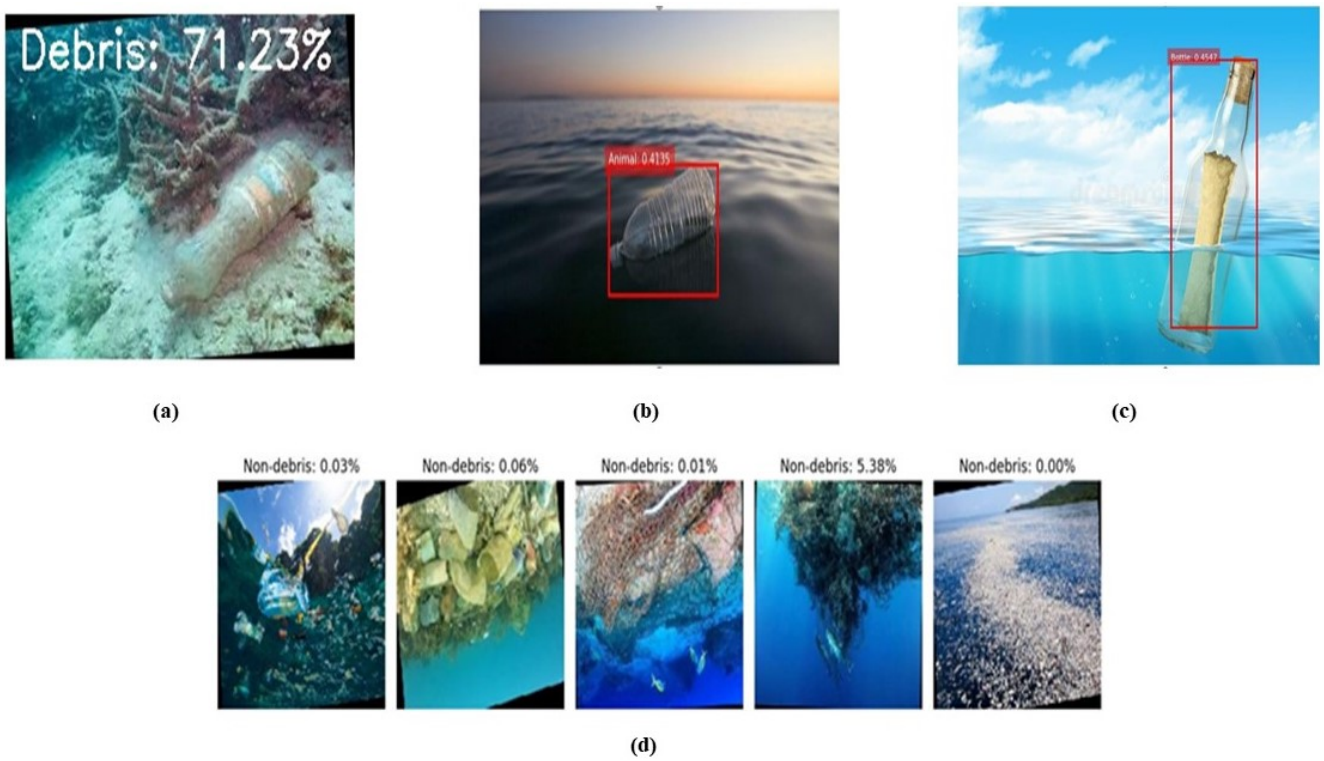

Fig 3. Sample outputs of Marine Debris Detection using Ensemble Algorithm

marked with red bounding boxes. Figure 3(d) shows different marine settings and their corresponding "non-debris" percentage ranges from 0.13% to 6.00%. Figure 3 demonstrates the system's ability to perform on various images under different conditions and differentiate plastic from natural elements. The ensemble approach uses CNNs and RF to effectively identify various types of debris. Furthermore, the ensemble approach provides high accuracy and reliability. Real-time and web-based functionality makes the proposed ensemble system a practical tool for environmental monitoring.

Table 2. Statistical Analysis of (a). CNN (b). Random Forest (c). Ensemble

Method	Accuracy	Precision	Recall	F1-Score
CNN	89.6%	0.78	0.23	0.36
RF	84.4%	0.75	0.71	0.73
CNN-RF Ensemble	95.1%	0.95	0.95	0.95

The marine debris detection was performed using three models such as a CNN, a RF classifier, and their ensemble. The statistical analysis of these models performance is shown in Table 2. Table 2 highlights the comparative strengths of each approach. Accuracy indicates the total number of correct predictions across all classifications. The harmonic sum of precision and recall is known as F1 score. In instances of class imbalance, the F1 score is the best way to measure the performance of a model. This metric shows how well the ensemble model can find positive cases. The CNN model achieved an accuracy of 89.6% and a F1-score of 0.36 on the test dataset. The accuracy indicates the proportion of correctly classified samples and the F1-score balances precision and recall by providing a single metric for overall model performance. The low F1 score suggests that the CNN model needs improvement. False positives and false negatives need to be balanced to achieve high F1-score. The RF classifier achieved an accuracy of 84.4% and a F1-score of 0.73. Even though the RF classifier exhibited lower accuracy compared to the CNN, it balances precision and recall well with significantly higher F1-score. The statistical values of the RF classifier suggests that it effectively detects marine debris with minimized misclassifications. Furthermore, the combination of the basic CNN and RF models performs well with outstanding accuracy and F1 score of 95.1% and 0.95 respectively. The significant improvement over the CNN and RF models shows that a more reliable and accurate maritime debris detection system can be constructed using the advantages of RF classifier and CNNs. The ensemble model improved performance through the

CNN's feature extraction capabilities with the RF's decision-making ability. The utility of these models is seen in the debris detection visualizations as in Figure 3. The proposed method discovers and measures debris in real time with great accuracy. The ensemble model works quite well, making it a good choice for a web-based program that can be used to monitor maritime pollution in real time on a large scale.

Table 3. Performance comparison of marine debris detection methods

Method	Accuracy	Precision	Recall	F1-Score
YOLO11-YX [11]	62.3%	0.60	0.61	0.60
Transformer model [13]	81.5%	0.79	0.82	0.80
Hybrid AI Method [17]	98.3%	0.98	0.98	0.98
YOLOv5 [24]	91%	0.90	0.91	0.90
Faster R-CNN [24]	88%	0.87	0.88	0.87
ResUNext [27]	85%	0.84	0.85	0.84
CNN–RF Ensemble (Proposed)	95.1%	0.95	0.95	0.95

The ensemble method combines CNN-based feature extraction with a Random Forest classifier to overcome the limitations of conventional single model detection methods. The performance accuracies of different marine debris detection methods were compared as shown in Table 3. The proposed ensemble method outperforms most of the existing algorithms with an accuracy of 95.1% and a F-1 score of 0.95. The integration of Clarifai's object detection API with a Voila-based web interface provides end-to-end real time marine debris detection. The proposed method provides a more scalable practical solution compared to existing methods.

5 Conclusion

This paper presents a resilient and scalable system for marine debris detection using a hybrid deep learning methodology. The proposed ensemble model combines CNNs with Random Forest classifiers. The ensemble model demonstrates clear quantitative improvements over individual models and outperforms the existing methods, achieving a higher detection accuracy and a F1 score of 95.1% and 0.95 respectively. The ensemble method effectively enhances feature discrimination and reduces misclassification, validating the model's superiority over existing literature. Furthermore, the integration of Clarifai's object detection API with a Voila-based web application provides a practical and real-time detection through a simple user interface. This implementation highlights the systems scalability and potential for operational deployment. Results show that AI-driven methods might improve the efficiency of marine debris detection systems. The results are limited by small datasets and lack of evaluation on broader benchmarks. Future work will focus on evaluating the ensemble models using larger datasets such as MARIDA and MADOS. Integrating the architectures such as transformer-based backbones, contrastive feature learning, and uncertainty estimation can address the issues related to turbid water, low-light, and occluded conditions. Furthermore, the debris detection system can be implemented on Unmanned Aerial Vehicle (UAV), Autonomous Underwater Vehicle (AUV), hyperspectral and satellite images for large-scale marine debris monitoring.

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