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Detection of Plastic in Water using Image Processing

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ABSTRACT

The anthropogenic activities are contaminating the natural water bodies which have adverse effects on humans as well as the environment. Pollution in water caused by sewage, industrial waste, and various bacteria and viruses damage inhabitants in water and affects the entire biosphere. The main purpose of this study is detection of plastic contents in water and save the lives of aquatic region. As water is one of the major resources which we consume directly and indirectly, so it must be protected. To avoid this water quality degradation, it is required to construct the real-time monitoring system which determines the quality of water by assessment of pollutants present. In order to get improved quality of images, color correction method is used to remove casts and histogram equalization is used to enhance contrast. In this work, the following techniques are used viz. Image Processing and deep learning neural network models(CNNs). CNNs are especially effective at image classification because they are able to automatically learn the spatial hierarchies of features, such as edge detection, textures, and shapes, which are important for recognizing objects in images. In this study, the real-time monitoring system which consists of computer vision, image processing toolbox which takes images of polluted water as input has been developed and examined to assure the adaptability of monitoring the pollutants (plastic) in water.

Keywords: Pollution, Image Processing, Deep Learning, Neural Network, plastic detection, computer vision.

INTRODUCTION

In this study the main goal is to detect and analyze floating pollutants in aquatic environments. Unlike conventional methods that often struggle to discriminate between pollutants and natural features, our algorithm leverages the power of immune-inspired extremum region analysis to enhance accuracy and reliability. The algorithm identifies extremum regions within the image, focusing on areas that exhibit significant variations in pixel intensity. This selective approach helps distinguish floating pollutants from the surrounding water and natural elements. The most common method to measure ocean pollution is to collect samples from different depths of ocean and them in laboratories. Several other detection methods such as remote sensing technologies are used to capture where the response of the electromagnetic interaction with water is checked. Underwater vehicles are used widely for monitoring underwater images. The parameters we are considering for analysis are plastic, oil spills & chemicals, fishing net and dead corals. Corals are not able to sustain the rise in temperature of the ocean. Even a Small Changes in temperature lead to large number of dead coral reefs. In addition, fishing nets break coral reefs and make them vulnerable to diseases. Entanglement of dolphins and other species in the net is a threat to their lives. The parameters we are considering for analysis are plastic, oil spills & chemicals, fishing net and dead corals. Corals are not able to sustain the rise in temperature of the ocean Plastic pollution in water is a major environmental problem. Microplastics, which are plastic particles smaller than 5 millimeters, are particularly harmful because they can be ingested by marine life and enter the food chain. Image processing can be used to detect plastic particles in water, including microplastics. Faster R-CNN beats other masks in terms of computation precision and mean precision. Pollutants have been determined by feature extraction using gray level co-occurrence matrix. It extracts the features based on entropy, homogeneity, contrast, energy calculations to identify texture of an image for classification.

Fig 1.1 RGB to Grey

LITERATURE SURVEY

Yu, X., Ye, X., & Zhang, S. (2022) study said that Detection of floating pollutants on water surfaces was crucial for environmental protection and water resource management. Conventional image processing techniques often faced challenges in accurately extracting pollutant targets due to factors such as varying illumination, complex water surface patterns, and the presence of non-pollutant objects. The IER algorithm drew inspiration from the immune system's ability to identify and eliminate foreign substances. It utilized the concept of extreme regions, which were areas in an image that exhibited significant intensity variations compared to their surroundings. Its ability to handle complex real-world scenarios made it a valuable tool for environmental monitoring and water resource management.[1]

Kshirsagar, S., Ghodke, S., & Shriram, R. (2021, March) said that Machine learning and computer vision algorithms were often used for pollution classification and detection. Image segmentation techniques were applied to separate the water from other objects and identify regions of interest. This may have involved methods such as thresholding or more advanced segmentation algorithms.This early awareness allowed for prompt intervention and mitigation measures. More than 50 freely available images were used on the net for each class with resolution in the range of 640480-1200900 that were taken from different sites. Image processing allowed for large-scale and automated monitoring of ocean pollution. This was particularly valuable for assessing the extent and distribution of pollutants over vast areas, which would have been challenging through manual surveys alone.[2]

Faisal, M., Chaudhury, S., Sankaran, K. S., Raghavendra, S., Chitra, R. J., Eswaran, M., & Boddu, R. (2022) said that Faster R-CNN methodology was used to detect plastic waste objects at sea. A pre-trained Faster R-CNN model, such as one trained on COCO (Common Objects in Context) or another relevant dataset, was chosen. This model was fine-tuned on a specific plastic and turtle dataset. The Faster R-CNN model was trained using the annotated dataset. This involved adjusting the model's weights to improve its ability to detect plastic and turtles. This contributed to faster and more targeted detection of plastic garbage, enabling timely interventions for turtle preservation. The average accuracy of all types of images tested was 96.50%.[3]

Lin, F., Hou, T., Jin, Q., & You, A. (2021) said that the pre-trained YOLOv5s model was the most useful for plastic detection in rivers in UAV imagery. The pre-trained YOLOv5s model used the Houy Mak Hiao dataset. The main purpose of YOLO (You Only Look Once) was to perform real-time object detection in images and video streams. The detection accuracy on the dataset of the North Canal was 88.0%. After training and testing the merged dataset, the detection accuracy of the model was 82.3%, and the detection speed was 28 FPS. The Faster R-CNN algorithm was employed for turtle detection. Total of 92,998 images used for training. Dataset consists of 22,461 images of plastic bags and 69,996 images of plastic bottles. An automated method using deep learning for monitoring plastic pollution was developed. It achieved a reliable estimate of plastic density with 68.7% precision. [4]

van Lieshout, C., van Oeveren, K., van Emmerik, T., & Postma, E. (2020) said that the automated method for monitoring plastic pollution was developed. The method successfully distinguished plastics from other elements. The Faster R-CNN was trained on the river image data set. Training the optimized method with 24k images was expected to yield a precision of around 73%. Automated systems could detect plastic waste in rivers as soon as it appeared, allowing for prompt intervention and cleanup. The collected images or video frames were annotated to label instances of plastic waste in the river. This annotated dataset was used for training the deep learning model. Faster R-CNN could be used to detect and classify objects.[5]

Fig 2.1: Graphical Representation of Papers and Year

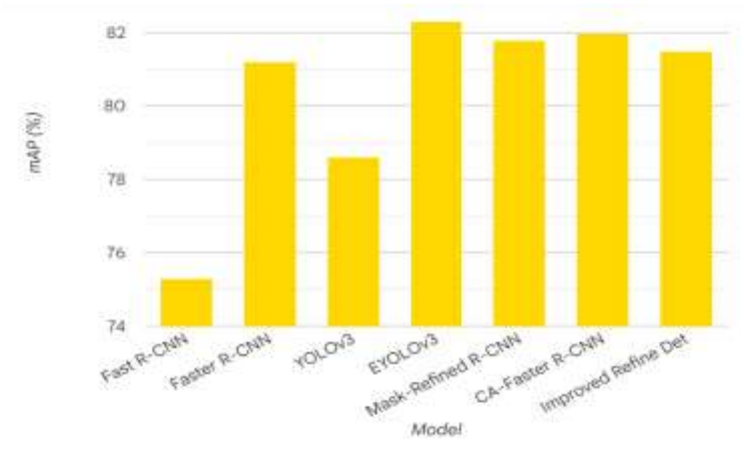

Fig 2.2: Graphical Representation of methods and mAP

Table 2.1: Table of Literature Survey

	Title	year	Objectives	Limitations	Advantages	Performance metrics	Gaps
1	"Floating pollutant image target extraction algorithm based on immune extremum region"	2022	detect and extract pollutant targets or objects from images	lack the flexibility to adapt to different types of images or scenes.	capable of handling a wide range of pollutant types, image conditions 2. scalable to handle large datasets	The accuracy of the research is 0.9436	algorithm fails to extract the target in different lighting conditions, weather conditions
2	"Ocean pollution detection using image processing"	2021	involves preprocessing images to enhance features relevant to plastic detection.	The accuracy of image processing algorithms in identifying and quantifying pollutants can vary.	image processing can be more cost-effective for large-scale monitoring	giving accurate results with up to 80% to 90 % accuracy	
3	"Faster R-CNN algorithm for detection of plastic garbage in the ocean: a case for turtle preservation"	2022	The primary objective is likely to detect and identify plastic garbage.	Object detection algorithms may produce false positives	Faster R-CNN is known for its high accuracy in object detection tasks.	The average accuracy of all types of images tested is 96.50.	
4	"Improved YOLO based detection algorithm for floating debris in waterway"	2021	The study may aim to accurately localize the detected debris.	The effectiveness of any object detection algorithm depends heavily on the quality and diversity of the training dataset.	Improvement in detection performance for floating debris in waterways	The FMA-YOLOv5s model obtains the mAP of 79.41%	A comprehensive and diverse dataset is crucial for training and evaluating object detection algorithms.
5	"Automated River Plastic Monitoring Using Deep Learning and Cameras"	2020	Goal of making it accessible and affordable for broader use in monitoring plastic waste in rivers.	Environmental conditions in rivers can change over time due to seasonal variations or human activities.	Deep learning-based systems can process large volumes of image data quickly.	The method achieves a reliable estimate of plastic density with a precision of 68.7% .	
6	"Detection of River Plastic Using UAV Sensor Data and Deep Learning "	2022	To improve the accuracy and efficiency of plastic detection compared to traditional manual	The accuracy of detection heavily relies on the quality of the UAV sensor data	It has the potential to provide early warnings of pollution events	The highest mAP achieved without transfer learning is 0.81 for the Houay Mak Hiao dataset using the YOLOv5s model .	Potentially enhancing the performance of plastic detection.
7	"Plastic debris in rivers"	2019	To assess the scope and scale of plastic pollution in rivers, including the types of plastic debris	Research on plastic debris in rivers can be limited by the availability of comprehensive and up-to-date data	Papers in this field may discuss innovative solutions for mitigating plastic		Many people are still unaware of the extent and consequences of plastic

					pollution in rivers		pollution in rivers
8	"UAV-BASED RIVER PLASTIC DETECTION WITH A MULTISPECTRAL CAMERA"	2022	To develop and evaluate a method for detecting plastic debris in rivers using UAVs and a multispectral camera.	Multispectral cameras typically have a limited number of spectral bands.	The use of UAVs allows for remote sensing of river environments.		Weather conditions, such as wind and rain, can affect the flight stability and image quality of UAVs.
9	"EYOLOv3: An Efficient Real-Time Detection Model for Floating Object on River"	2023	To propose and evaluate an efficient object detection model	Object detection models often face challenges related to false positives.	Reducing hardware requirements and operational costs.		Poor data quality due to factors like sensor limitations or environmental interference can lead to detection errors.
10	"RANDOM FOREST-BASED RIVER PLASTIC DETECTION WITH A HANDHELD MULTISPECT"	2021	To create a robust and accurate detection model using Random Forest.	The performance of the camera and the detection algorithm may be affected by weather cons.	Random forests are known for their ability to provide accurate classification and detection	Validation of the RF allowed to obtain an accuracy performance of 98%	Variability in data quality can affect the performance of the random forest model.

METHODOLOGY

Reference 1:

Kshirsagar, S., Ghodke, S., & Shriram, R. (2021, March). Ocean pollution detection using image processing. In 2021 International Conference on Emerging Smart Computing and Informatics (ESCI) (pp. 408-412). IEEE.

Methods:

- ❖ Global thresholding method for coral reef classification
- ❖ DWT and GLCM for feature extraction and classification

Explanation:

1) **Input image**: The user inputs a digital image.

2) **Color Correction Method**:

- ❖ It uses white balancing process to remove color casts (unwanted tint) of particular color and restores original color. It restores white and gray shades of gray image.

3) **RGB to Gray Conversion** :

- ❖ Convert the RGB color image to grayscale image because the color does not help us identify many important features such as edges.

4) **Histogram Equalisation**:

- ❖ Histogram is a graphical representation of tonal distribution i.e. intensity levels of an image. It is a technique used for obtaining a uniform histogram. Gray levels are spread over different ranges for different types of images.

5) **Discrete Wavelet Transform**:

- ❖ Wavelet Transform is one of the approved and popular tool in image processing and computer vision, giving accurate results with up to 80% to 90 % accuracy.

6) **GLCM Feature Extraction**:

- This gray-level co-occurrence matrix (GLCM) can be used to disclose definite properties about the spatial distributions of the grey levels in an image. This is the technique which is used in the texture analysis for the images.

7)**Neural Network Trained and classified in 4 classes:**

- After this we have trained our DNN to classify these images in one of the 4 classes (plastic, fishing net, oil spills and coral reefs). First stage of neural networks is to train the data. Here the output is automatically compared with the trained data
- The input image is given to the neural network and then processing is done according to weights which are adjusted while training the data.

8) If the image matches with any of the above mentioned classes we predict that the ocean is polluted. Otherwise, for images of clean water and fishes it gives output as out of database and we determine that the ocean is unpolluted.

Novelity:

- Introduces a novel and economical method for ocean pollution prediction.
- Uses DWT and GLCM for feature extraction and neural networks for pollutant classification.
- The use of image processing allows for automated detection and continuous monitoring of ocean pollution events. This automation significantly reduces the need for manual observation and analysis, providing a real-time and scalable solution.

Reference 2:

Faisal, M., Chaudhury, S., Sankaran, K. S., Raghavendra, S., Chitra, R. J., Eswaran, M., & Boddu, R. (2022). Faster R-CNN algorithm for detection of plastic garbage in the ocean: a case for turtle preservation. *Mathematical Problems in Engineering*, *2022*.

Methods:

- Region Convolutional Neural Network (R-CNN) used for object detection.
- Faster R-CNN recognition method used for detection.

Novelity:

- Algorithm for turtle preservation using computer vision.
- Object detection and recognition using Faster R-CNN.

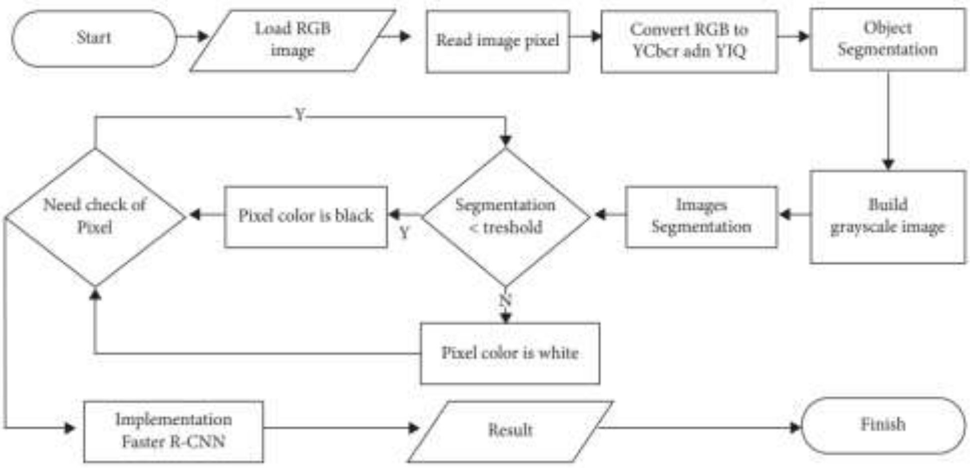

Fig 3.3: Flowchart of Segmentation with Faster R-CNN

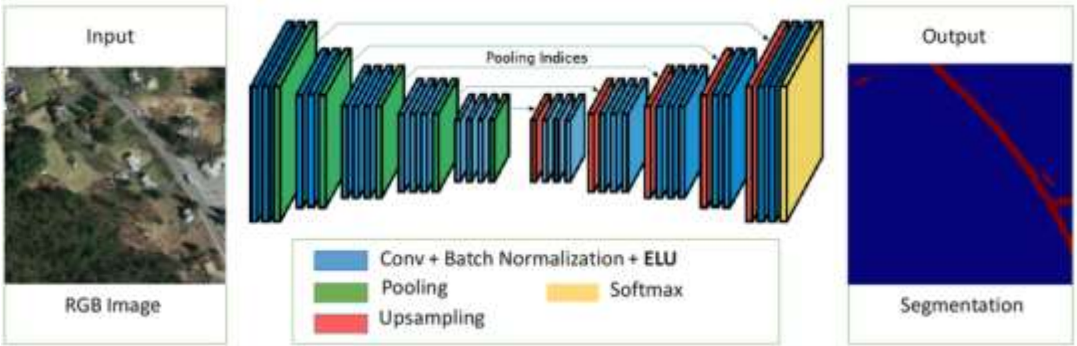

Fig 3.4: Architecture of Object Segmentation in Faster R CNN

This flowchart outlines a process for image processing and segmentation using various techniques, including color space conversion and object segmentation through Faster R-CNN (a machine learning model for object detection):

1. **Start**: The initial step in the process.
2. **Load image**: The raw image is loaded into the computer using an image processing library, such as OpenCV.
3. **Read image pixel**: Each pixel in the image is read using the image processing library. A pixel is a single point in an image and is represented by three values: red, green, and blue (RGB).
4. **Convert RGB to YCbCr and YIQ**: The RGB color space of the image is converted to the YCbCr and YIQ color spaces. The YCbCr color space is a luminance-chrominance color space, which means that it separates the brightness of the image from its color information. The YIQ color space is also a luminance-chrominance color space, but it is more perceptually uniform than the YCbCr color space.
5. **Segmentation images:** The image is segmented into different regions using an image segmentation algorithm. Image segmentation is the process of dividing an image into different regions, or segments, based on their features, such as color, texture, and intensity.
6. **Check if pixel color is black**: If the pixel color is black, the pixel is set to gray. This is because black pixels have no color information, so they can be safely converted to gray without losing any information.
7. **Segmentation threshold**: If the pixel color is white, the pixel is set to gray if the segmentation threshold is met. The segmentation threshold is a value that determines whether a pixel is considered to be part of a foreground object or a background object. If the pixel color is greater than the segmentation threshold, the pixel is considered to be part of a foreground object and is set to gray. If the pixel color is less than the segmentation threshold, the pixel is considered to be part of a background object and is not set to gray.
8. **Build grayscale image:** The grayscale image is built from the segmented images. This is done by simply averaging the pixel values of all the pixels in each segment.
9. **Output**: The grayscale image is output to the user. This can be done by displaying the image on a screen or by saving the image to a file.

RESULTS AND DISCUSSIONS

S. No	Name	year	Methodologies	Datasets Used	Performance metrics
1	Yu, X., Ye, X., & Zhang, S. (2022).	2022	Region feature extraction based on artificial immune algorithm Multi-scale Gaussian function image illumination correction	--	The accuracy of the research is 0.9436
2	Kshirsagar, S., Ghodke, S., & Shriram, R. (2021, March	2021	Global thresholding method for coral reef classification DWT and GLCM for feature extraction and classification	--	giving accurate results with up to 80% to 90 % accuracy
3	Eswaran, M., & Boddu, R. (2022)	2022	Region Convolutional Neural Network (R-CNN) used for object detection. Faster R-CNN recognition method used for detection.	1. Total of 92,998 images used for training 2. Dataset consists of 22,461 images of plastic bags and	The average accuracy of all types of images tested is 96.50.

				69,996 images of plastic bottles	
4	Lin, F., Hou, T., Jin, Q., & You, A. (2021)	2021	FMA-YOLOv5s algorithm with feature map attention layer Mosaic data augmentation for training dataset expansion.	1.Dataset with labeled target objects 2. Background images of clean river surface	The FMA-YOLOv5s model obtains the mAP of 79.41%
5	van Emmerik, T., & Postma, E. (2020)	2020	Deep learning for detecting floating macro plastics Experimental evaluation using bridge-mounted cameras at different river locations	Floating plastic dataset used for training	The method achieves a reliable estimate of plastic density with a precision of 68.7% .
6	B. M., Dailey, M. N., Shrestha, S., & Nakamura, T. (2022)	2022	Deep learning models (YOLOv3, YOLOv4, YOLOv5) Transfer learning from one location to another	Houay Mak Hiao River Dataset	The highest mAP achieved without transfer learning is 0.81 for the Houay Mak Hiao dataset using the YOLOv5s model .
7	van Emmerik, T., & Schwarz, A. (2020).	2019	Plastic tracking, active sampling, passive sampling, visual observations, and citizen science.	1.100k "Plastic" pixels 2. 500k "Other" pixels	
8	Cortesi, I., Masiero, A., Tucci, G., & Topouzelis, K. (2022)	2022	Machine learning tool based on random forest classifiers	1.100k "Plastic" pixels and 500k "Other" pixels 2. Unbalanced training datasets for the two classes	-
9	Zhang, L., Xie, Z., Xu, M., Zhang, Y., & Wang, G. (2023).	2023	YOLOv3	--	
10	Cortesi, I., Masiero, A., De Giglio, M., Tucci, G., & Dubbini, M. (2021).	2021	Random Forests and Support Vector Machine classifiers	--	Validation of the RF allowed to obtain an accuracy performance of 98%
11	Zhang, L., Wei, Y., Wang, H., Shao, Y., & Shen, J. (2021).	2021	Improved RefineDet model	Datasets constructed from river monitoring videos.	The improved RefineDet has higher detection accuracy 75.6%
12	Taddia, Y., Corbau, C., Buoninsegni, J., Simeoni, U., & Pellegrinelli, A. (2021)	2021	Hyperspectral sensors (potential future research)	RGB orthomosaics	AMD over 2.5 cm was collected every time and further analyzed to create a ground truth dataset.
13	Bhardwaj, P., Sharma, S., & Sarker, I. H. (2020)	2020	AquaVision: deep learning-based object detection model.	1.TrashNet Dataset 2.TACO Dataset	mean Average Precision (mAP) of 0.8148
14	Tasseron, P. F.Schreyers, L., Peller, J., Biermann, L., & van Emmerik, T. (2022)	2022	Support Vector Machine (SVM) algorithm Multispectral or hyperspectral imaging of plastics	1.Lab and field-based input data 2. Riverbank-harvested plastics obtained in the lab	Plastic detection in field-based images, user accuracies for plastics to up to 93.6%.
15	Hassanien, A. E., & Snasel, V. (2015)	2019	Flight conveyor Scooping arm with basket	--	The proposed classification approach achieved 95.41%accuracy

Tab 5.1: Results of individual study

Model Name	**Precision**	**Recall**	**mAP**	**FPS**
Fast R-CNN	79.8%	78.5%	75.3%	4
Faster R-CNN	88.6%	84.9%	81.2%	13

YOLOv3	83.2%	80.4%	78.6%	35
EYOLOv3	87.4%	85.7%	82.3%	35
Mask-Refined R-CNN	86.9%	85.1%	81.8%	16
CA-Faster R-CNN	89.5%	83.6%	82.0%	20
Improved Refine Det	88.3%	85.0%	81.5%	28

Tab 5.2: Performance Metrics Table

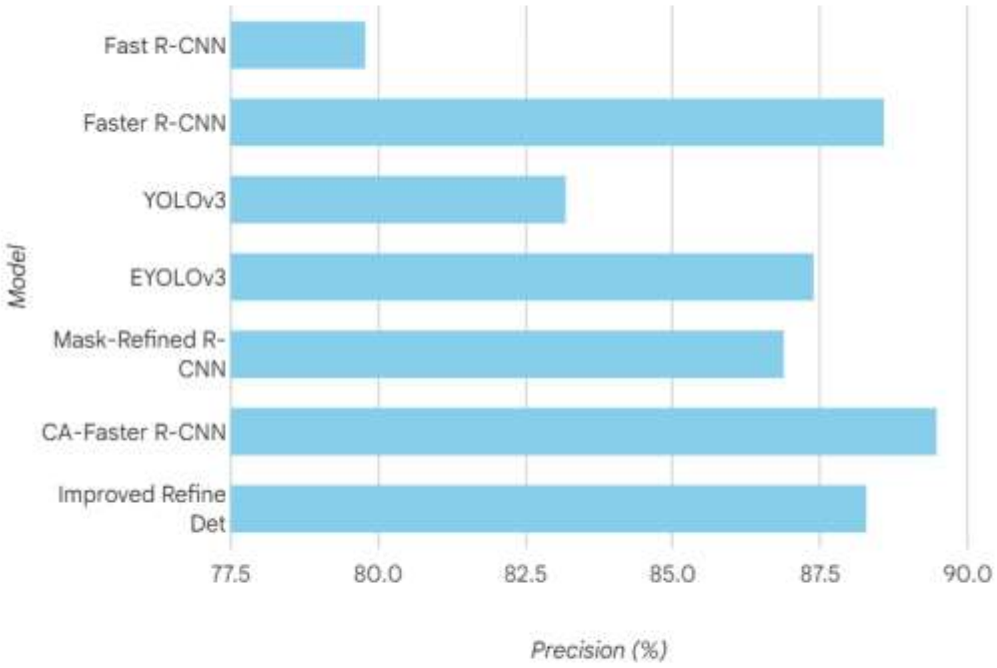

Fig 5.1: Graphical representation of Models and Precision

The graph shows the performance of different object detection models on the VOC 2012 dataset. The models are evaluated in terms of precision, recall, mAP, and FPS.

Precision is the fraction of detected objects that are actually present in the image.

Recall is the fraction of objects that are present in the image that are detected.

mAP is the mean average precision across all classes of objects.

FPS is the number of frames per second that the model can process.

As you can see, the CA-Faster R-CNN model has the highest mAP, followed by the Mask-Refined R-CNN and Faster R-CNN models. The Improved Refine Det model has the highest FPS, followed by the EYOLOv3 and Faster R-CNN models. The trade-off between precision and recall is apparent in the graph. Models with higher precision tend to have lower recall, and vice versa. This is because models that are more precise are more likely to only detect objects that are actually present in the image, but they are also more likely to miss objects that are present. Conversely, models with higher recall are more likely to detect all of the objects that are present in the image, but they are also more likely to detect objects that are not present.

CONCLUSION

The primary objective of the research is to address the challenge of accurately extracting floating pollutant targets from images, a task crucial for environmental monitoring and pollution control. The authors propose a novel algorithm based on the immune extremum region to enhance the precision and efficiency of target extraction. The immune extremum region algorithm draws inspiration from immunology, utilizing principles of immune systems to detect and isolate pollutant targets in images. The research methodology involves the development and implementation of the proposed algorithm, followed by a comprehensive evaluation of its performance. The authors compare the results of their algorithm with existing methods, assessing key metrics such as accuracy, computational efficiency, and robustness. The findings indicate that the proposed immune extremum region-based algorithm outperforms other approaches, demonstrating superior accuracy in extracting floating pollutant targets from images. One noteworthy aspect of the study is the integration of immunological principles into the algorithm design. The immune extremum region algorithm leverages the concept of extremum seeking, mimicking the immune system's ability to identify and prioritize regions of interest in the context of pollutant extraction. This unique approach contributes to the advancement of image processing techniques for environmental applications. The results of the study have implications for environmental monitoring and pollution management. The enhanced accuracy and efficiency offered by the proposed algorithm can significantly improve the identification and extraction of floating pollutant targets in various environmental settings. This, in turn, contributes to a more effective and timely response to pollution events, aiding in the mitigation of environmental risks. However, it is essential to acknowledge potential limitations and areas for future research. The study's evaluation may benefit from further validation across diverse datasets and environmental conditions to assess the algorithm's generalizability. Additionally, the computational complexity of the proposed algorithm should be considered, especially in real-time applications. In conclusion, the research by Yu, Ye, and Zhang presents a promising contribution to the field of environmental image processing. The immune extremum region-based algorithm demonstrates notable advantages in floating pollutant target extraction, showcasing potential applications for improved environmental monitoring and pollution control. The integration of immunological principles in algorithm design marks a distinctive aspect of this study, opening avenues for further exploration in the intersection of computational techniques and environmental science.

REFERENCES

1. Yu, X., Ye, X., & Zhang, S. (2022). Floating pollutant image target extraction algorithm based on immune extremum region. *Digital Signal Processing*, *123*, 103442.
2. Kshirsagar, S., Ghodke, S., & Shriram, R. (2021, March). Ocean pollution detection using image processing. In *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)* (pp. 408-412). IEEE.
3. Faisal, M., Chaudhury, S., Sankaran, K. S., Raghavendra, S., Chitra, R. J., Eswaran, M., & Boddu, R. (2022). Faster R-CNN algorithm for detection of plastic garbage in the ocean: a case for turtle preservation. *Mathematical Problems in Engineering*, *2022*.
4. Lin, F., Hou, T., Jin, Q., & You, A. (2021). Improved YOLO based detection algorithm for floating debris in waterway. *Entropy*, *23*(9), 1111.
5. van Lieshout, C., van Oeveren, K., van Emmerik, T., & Postma, E. (2020). Automated river plastic monitoring using deep learning and cameras. *Earth and space science*, *7*(8), e2019EA000960.
6. Maharjan, N., Miyazaki, H., Pati, B. M., Dailey, M. N., Shrestha, S., & Nakamura, T. (2022). Detection of river plastic using UAV sensor data and deep learning. *Remote Sensing*, *14*(13), 3049.
7. van Emmerik, T., & Schwarz, A. (2020). Plastic debris in rivers. *Wiley Interdisciplinary Reviews: Water*, *7*(1), e1398.
8. Cortesi, I., Masiero, A., Tucci, G., & Topouzelis, K. (2022). UAV-based river plastic detection with a multispectral camera. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 855-861.
9. Zhang, L., Xie, Z., Xu, M., Zhang, Y., & Wang, G. (2023). EYOLOv3: An Efficient Real-Time Detection Model for Floating Object on River. *Applied Sciences*, *13*(4), 2303.
10. Cortesi, I., Masiero, A., De Giglio, M., Tucci, G., & Dubbini, M. (2021). Random forest-based river plastic detection with a handheld multispectral camera. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 9-14.
11. Zhang, L., Wei, Y., Wang, H., Shao, Y., & Shen, J. (2021). Real-time detection of river surface floating object based on improved refinedet. *IEEE Access*, *9*, 81147-81160.
12. Taddia, Y., Corbau, C., Buoninsegni, J., Simeoni, U., & Pellegrinelli, A. (2021). UAV approach for detecting plastic marine debris on the beach: A case study in the Po River Delta (Italy). *Drones*, *5*(4), 140.
13. Panwar, H., Gupta, P. K., Siddiqui, M. K., Morales-Menendez, R., Bhardwaj, P., Sharma, S., & Sarker, I. H. (2020). AquaVision: Automating the detection of waste in water bodies using deep transfer learning. *Case Studies in Chemical and Environmental Engineering*, *2*, 100026.
14. Tasseron, P. F., Schreyers, L., Peller, J., Biermann, L., & van Emmerik, T. (2022). Toward Robust River Plastic Detection: Combining Lab and Field-Based Hyperspectral Imagery. *Earth and Space Science*, *9*(11), e2022EA002518.
15. Sweidan, A. H., El-Bendary, N., Hegazy, O. M., Hassanien, A. E., & Snasel, V. (2015). Water pollution detection system based on fish gills as a biomarker. *Procedia Computer Science*, *65*, 601-611.