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Enhanced Underwater Fish Detection: A Deep Learning Approach using Faster R-CNN with MobileNet

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ABSTRACT: Underwater species detection is key to marine conservation, fisheries control, and ecologic studies. It utilizes modern technologies like AI, computer vision, sonar, and acoustics for detecting and locating marine species in real time. Live images are captured by high-resolution underwater cameras, LiDAR, and thermal sensors, while sonar identifies species based on sound waves. AI and machine learning handle these data in real-time, either locally through edge computing or from a distance through cloud servers, allowing for speedy decision-making. Underwater species detection remains particularly challenging, however, due to environmental conditions such as light scattering, refraction, and absorption, which cause image clarity to deteriorate. Other challenges, such as high turbidity, changing illumination, background noise, and visual clutter, further hamper accurate detection and classification. In order to overcome these challenges, a deep learning method based on Faster R-CNN with MobileNet is used. This technique provides high-accuracy real-time object detection and is very effective in underwater applications. The robust feature extraction of Faster R-CNN and the light architecture of MobileNet enable efficient and accurate identification of marine life even in adverse underwater conditions.

KEYWORDS: Deep learning, Faster R-CNN, MobileNet, Object detection, Feature extraction.

I. INTRODUCTION

Underwater fish detection is important for marine ecosystem monitoring, conservation of biodiversity, and management of fisheries. Underwater environments, however, pose challenges in the form of low visibility, turbidity of water, and complex backgrounds, which make it challenging to accurately identify species. Object detection models based on deep learning, including Faster R-CNN, have proven to be effective tools in overcoming these challenges by offering accurate and efficient detection of marine organisms. Faster R-CNN is a two-stage object detection framework with an RPN coupled with a classification network for precise species localization and identification. To make it more efficient, MobileNet is used as the feature extractor backbone, providing a light but efficient solution to underwater detection based on deep learning. The model is conditioned on a multi-decker dataset of sea creatures, to which image enhancement and data augmentation methods are applied to enhance detection ability in different underwater conditions. The aim is to further advance underwater fish detection through the optimization of Faster R-CNN with MobileNet, enhancing its accuracy, robustness, and applicability to real-world underwater settings. This study adds to marine conservation by facilitating improved species monitoring, assisting scientists and researchers in comprehending aquatic biodiversity, and solving some of the most significant underwater object detection challenges.

II. LITERATURE SURVEY

[1] Uma N. Dulhare, Mohd Hussam Ali Muffakham Jah, "Underwater human detection using faster R-CNN with data Augmentation", Elsevier, Vol. no.80, 2023.

The paper focuses on underwater human detection using Faster R-CNN with data augmentation. Drowning is a serious public health threat, with 3,74,000 lives claimed annually. Detecting humans in underwater videos is

challenging due to various factors like noise, camera limitations, and illumination changes. The paper proposes using Faster R-CNN and data augmentation techniques to address this issue.

[2] Luciano Ortenzi, Jacopo Aguzzi, Corrado Costa, Simone Marini, Daniele D’Agostino Aguzzi, Corrado Costa, Simone Marini, Daniele D’Agostino, Laurenz Thomsen, Fabio C. De Leo, Paulo V. Correa, Damianos Chatzievangelou, “Automated species classification and counting by deep-sea mobile crawler platforms using YOLO”, Elsevier, Vol. NO. 82, 2024.

YOLO algorithms, known for speed and low computational cost, on autonomous platforms. Edge computing, processing data closer to the source, offers a solution. YOLO algorithms, known for speed and low computational cost, have been used in fixed-camera settings for single-species detection. However, applying YOLO to multi-species classification and counting on mobile platforms like benthic crawlers, while addressing challenges like moving backgrounds and variable illumination, represents a significant have been used in fixed-camera settings for single-species detection.

[3] Ahsan Jalal, Ahmad Salman, Ajmal Mian, Mark Shortis, Faisal Shafait, “Fish detection and species classification in underwater environments using deep learning with temporal information”, Elsevier, Vol. No.57, 2020.

It reviews existing methods, highlighting challenges like poor lighting, water murkiness, and camouflaged fish. Previous approaches included image processing techniques focusing on texture and outline features, Support Vector Machines (SVMs) with various feature extractors, and Gaussian Mixture Models (GMMs) for background subtraction. More recently, deep learning methods like Convolutional Neural Networks (CNNs), including YOLO and ResNet, have been applied, showing improved accuracy but still facing limitations.

[4] Linlin Liu, Chengxi Chu, Chuangchuan Chen, Shidong Huang, “MarineYOLO: Innovative deep learning method for small target detection in underwater environments”, Elsevier, Vol No. 104, 2024.

The literature on underwater object detection reveals a shift from two-stage methods (like R-CNN variants) towards faster, one-stage approaches (like YOLO and SSD). Two-stage methods, while accurate, suffer from computational limitations unsuitable for real-time applications in underwater environments. One-stage methods offer speed advantages but often struggle with small object detection, a significant challenge due to poor lighting and image quality in underwater setting.

III. PROPOSED METHODOLOGY

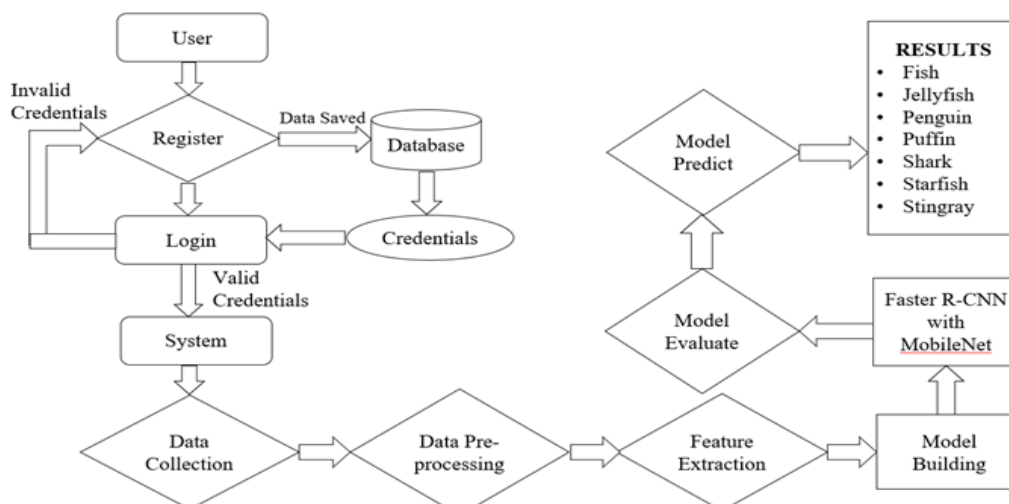


Figure 1: Flow Chart

The above figure illustrates the underwater fish detection process using Faster R-CNN with MobileNet. It starts with user login and registration, followed by data gathering, pre-processing, and feature extraction. Then the model is constructed, tested, and applied for prediction, giving results for different marine animals.

1. Data Collection and pre-processing

The module pools the images of sea creatures, such as a dataset containing varied marine life like sharks, starfish, puffins, penguins, jellyfish, fish, and stingrays. Pre-processing involves:

- Image Enhancement for visibility under low-light conditions.
- Data Augmentation (adjusting brightness, flipping) to enhance model generalization.
- Image Normalization to normalize pixel values for uniform input to the DL models.

2. Faster R-CNN with MobileNet

Faster R-CNN takes a two-stage detection strategy where it initially generates region proposals in order to detect possible objects and subsequently classifies and refines the detected objects. The RPN sweeps across the extracted feature maps and generates bounding boxes around possible object positions. MobileNet is used as the backbone network, offering a light yet potent feature extraction system. Faster R-CNN utilizing MobileNet has been optimized for performance in underwater environments with differing lighting, turbidity, and particulate.

3. Feature extraction

The framework derives relevant visual features from underwater images based on CNN-based architectures. The backbone network of Faster R-CNN derives spatial features to produce elaborate feature maps. Region Proposal Network (RPN) of Faster R-CNN produces region proposals, which aid in localizing fish species with high accuracy. ROI (Region of Interest) pooling normalizes the chosen regions by resizing them to a specified size for accurate classification and bounding box refinement.

4. Model training

Faster R-CNN model is trained, validated and tested with a dataset of labelled images of marine organisms to provide precise object detection. Hyperparameter tuning is done by modifying batch size, learning rate, and IoU threshold to attain maximum performance. GPU acceleration with NVIDIA CUDA accelerates training, greatly minimizing computational time. Faster R-CNN continually improves object localization and classification through iterative updates in training.

5. Model detection and recognition

The Faster R-CNN model examines underwater images to identify marine species by finding important features like edges, shapes, patterns and colours. Trained Faster R-CNN model examines underwater images to identify and classify species like fish, sharks, jellyfish, and stingrays. Bounding boxes are placed on identified species with a confidence score of prediction certainty. Faster R-CNN deals with occlusions and overlapping objects effectively, enhancing classification accuracy.

6. Performance analysis

The Faster R-CNN model is tested using typical object detection metrics to quantify performance.

- Precision & Recall to quantify detection accuracy.
- Mean Average Precision (mAP) for general detection performance.
- FALSE POSITIVES & FALSE NEGATIVES to quantify misclassification.
- IoU (Intersection over Union) to quantify bounding box accuracy.

IV. EXPERIMENTAL RESULTS

A. Performance metrics

The images shown below are the results of the fish detection process that illustrates the detected fish with bounding boxes and confidence score, picturizing how efficiently the detection by Faster RCNN model.

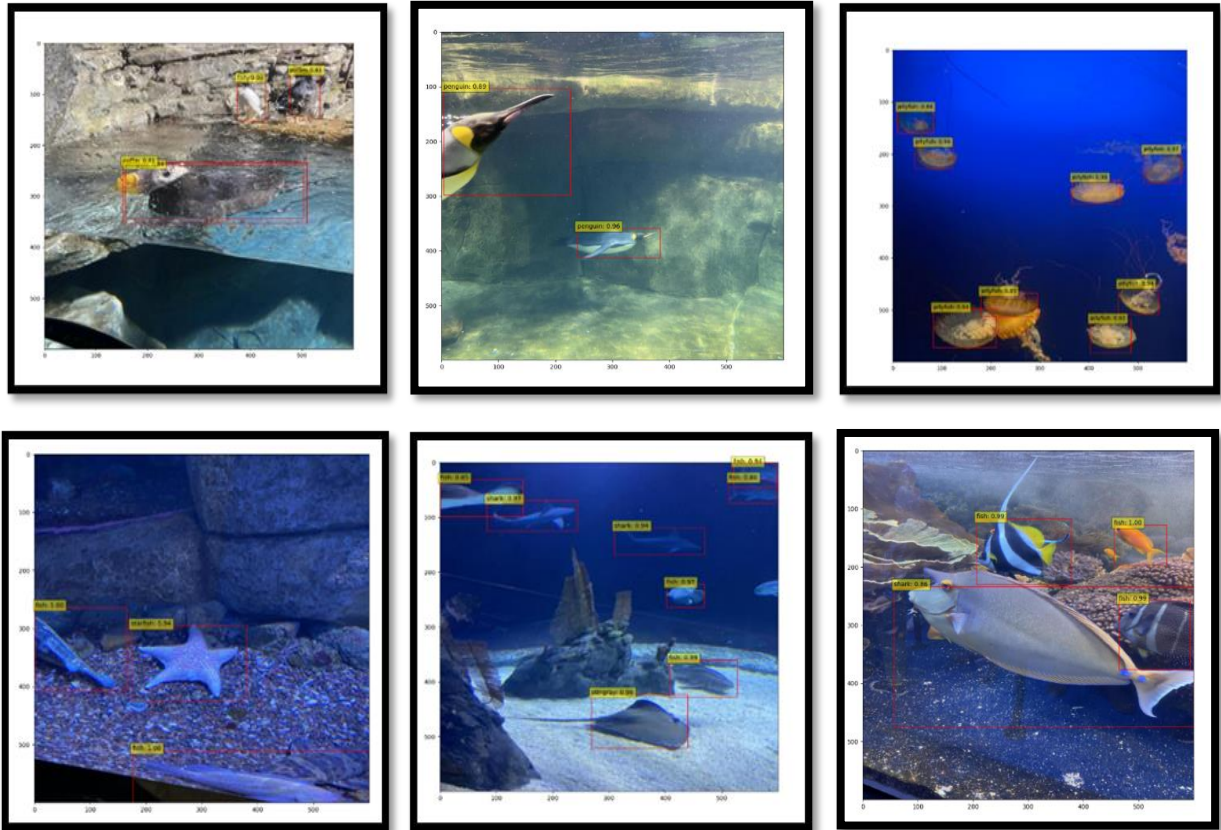


Figure 2: Detected underwater fishes

B. Comparative analysis

Metric	YOLOv9	Faster R-CNN
Precision	81.6%	93.02%
Recall	70.7%	85.11%
Training Value	77.1%	85.71%
False Positive (FP)	124	30
False Negative (FN)	229	70

The experimental results shows that Faster R-CNN yields very accurate underwater fish detection and species classification. YOLOv9 and Faster R-CNN were evaluated against major parameters like precision, recall, and total detection accuracy. The comparison indicates that Faster R-CNN consistently dominates YOLOv9 with greater

accuracy and fewer false positives and false negatives. Because of its powerful feature extraction ability and strong object detection, Faster R-CNN is seen to yield more precise results in underwater fish detection and species classification. This makes it the model of choice for applications that demand high precision and reliability, particularly in complicated underwater environments.

V. CONCLUSION

The MobileNet-based Faster R-CNN model has shown efficient performance in underwater species detection and classification, even under adverse conditions like low visibility, turbidity, and occlusions. Utilizing sophisticated feature extraction methods, it identifies marine species with accuracy, such as fish, jellyfish, sharks, starfish, and stingrays. The two-stage detection mechanism of the model, aided by a Region Proposal Network (RPN) and ROI pooling, provides accurate object localization and classification. Pre-processing methods of data like image enhancement and augmentation also enhance model robustness and generalization. Moreover, GPU acceleration enhances training efficiency by increasing computation speed. Faster R-CNN's capacity to manage overlapping objects and diverse environmental conditions also makes it more reliable in practical applications. Its capability for real-time monitoring supports marine biodiversity conservation as it facilitates early detection of ecological changes. Overall, this system presents a strong and reliable solution for detecting fish underwater, thus it is a useful resource for research, marine conservation, and automated underwater monitoring systems

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