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An Automatic Object Detection Using Deep Q Learning and Yolox Network

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ABSTRACT:

Automatic object detection in maritime environments is essential for applications such as navigation, environmental monitoring, and disaster management. This paper introduces a novel framework integrating Deep Q-Learning and the YOLOX network to detect objects such as ships, icebergs, and other maritime entities. YOLOX, a state-of-the-art object detection model, is employed to ensure high accuracy and speed, while Deep Q-Learning optimizes detection parameters dynamically to enhance performance in challenging scenarios like varying weather conditions and occlusions. Experimental results on maritime datasets demonstrate the proposed system's capability to accurately and efficiently detect objects, showcasing its potential for real-world maritime applications.

Index terms: Object Detection, YOLOX, Deep Q Learning, Marine Environment, Autonomous Navigation, Real-time Detection, Marine Surveillance.

I. INTRODUCTION

Marine surveillance is essential for the safety and security of global shipping lanes, environmental protection, and resource management. One of the key challenges in maritime operations is ship detection under varying environmental conditions, including stormy seas, fog, nighttime, and high-traffic areas. Accurate detection is vital for search and rescue, anti-piracy, illegal fishing prevention, and environmental monitoring (e.g., detecting shipwrecks or pollution).

Traditionally, ship detection relied on radar, satellite imagery, or manual observation, which, while valuable, often provided incomplete or delayed information. With advancements in machine learning (ML) and computer vision, there has been a significant shift to automated, real-time detection systems capable of processing large volumes of image data. These systems are crucial for autonomous navigation and real-time surveillance, which are increasingly important as global maritime traffic grows.

However, ship detection in marine environments faces challenges like occlusion, variable lighting, water turbidity, and the dynamic nature of the sea. Ocean waves, weather changes, and disturbances often obstruct the view of ships, making traditional systems less effective. Here, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have made a significant impact.

CNNs automatically learn features from large datasets, and when applied to ship detection, they achieve high accuracy in satellite and radar images, even under challenging conditions. In addition, techniques like transfer learning, data augmentation, and semi-supervised learning have been used to enhance model performance, especially when labeled data is limited.

YOLO (You Only Look Once), a popular real-time object detection model, and its improved version, YOLOX, are highly effective for ship detection due to their speed and accuracy. These models, which process images quickly and precisely, are ideal for real-time detection in dynamic marine environments, where fast decision-making is critical.

Despite these advances, challenges remain in ensuring high accuracy in complex environments, especially with ship size variations, changing conditions, and occlusions from other marine objects (e.g., icebergs, small vessels). To address these, we integrate Deep Q Learning (a reinforcement learning technique) with YOLOX. This combination enables real-time adaptation of detection parameters, optimizing performance as environmental conditions change.

In this paper, we propose an integrated system combining YOLOX for rapid detection with Deep Q Learning for real-time optimization. This approach improves detection accuracy, reduces false positives, and ensures that the system remains effective in dynamic conditions, such as water turbulence and lighting changes. Experimental results show that our approach outperforms traditional methods, providing a more accurate and adaptable solution for maritime surveillance and autonomous navigation.

II. LITERATUREREVIEW

The application of advanced algorithms and deep learning techniques in Synthetic Aperture Radar (SAR) image analysis has led to remarkable advancements in target detection, ship identification, and environmental monitoring. Zhi-bo Cao et al. [1] conducted a comprehensive survey on SAR image target detection, emphasizing the effectiveness of Convolutional Neural Networks (CNNs) for feature extraction and robust identification in complex datasets. CNNs were shown to mitigate noise and variability in SAR images, demonstrating their versatility in diverse applications.

Ship detection has been significantly improved using the YOLOX algorithm, which enhances SAR image outlines for better detection accuracy and computational efficiency, even in cluttered maritime environments [2]. Similarly, Guofeng and Jiahui Chang [3] proposed a novel Eigen Subspace Projection technique for SAR ship detection. This approach leverages dimensionality reduction and subspace analysis, resulting in reliable ship identification and improved detection precision. Their work represents an innovative approach to handling the complexities of SAR images, particularly in maritime environments where noise and overlapping structures pose significant challenges.

In the domain of abandoned object detection, Deep Embedded Vision systems have proven to be effective for real-time detection and classification in resource-constrained environments. This method integrates deep learning with embedded platforms to enable efficient and accurate processing, as highlighted in a study published in IEEE Access [4]. Furthermore, a Multi-Scale Deep Neural Network (DNN) approach for water detection in SAR images has been introduced, particularly for mountainous regions. This technique captures multi-resolution features, enabling precise water body segmentation [5]. Autonomous systems have also benefitted from these advancements. Zhang et al. [6] developed robust models for underwater navigation, improving the performance of autonomous underwater vehicles. Meanwhile, collision avoidance in maritime applications has been addressed using the Potential Field Method, as proposed by Zhu and Lyu [7]. This method dynamically models environmental forces to assist vessels in trajectory optimization, ensuring safe navigation in restricted waters.

Environmental monitoring has also been a key focus. Zhang et al. [8] discussed advanced machine learning techniques in the detection of environmental hazards through remote sensing, emphasizing the potential of deep learning models for real-time applications. Similarly, Taipalmaa et al. [9] explored remote sensing methods for dynamic environmental monitoring, showcasing the efficiency of computational approaches in adaptive sensing systems. Finally, Jindong Zhang et al. [10] highlighted the role of deep learning techniques in applied earth observations and remote sensing, particularly focusing on improved SAR data interpretation in maritime and environmental contexts.

III. PROPOSED SYSTEM

The proposed system is designed to enhance situational awareness and safety in maritime environments through real-time object detection using the YOLO (You Only Look Once) model. This system captures live video feeds from a camera, processes them with OpenCV, and applies a pre-trained YOLO model to detect specific maritime objects such as "ice," "shark," "ship," and "whale." The real-time detection of these objects is crucial for maritime navigation, search and rescue operations, and environmental monitoring. The system provides a valuable tool for operators to identify potential hazards quickly and accurately, offering clear visual cues, such as bounding boxes and labels, to aid in decision-making and enhance overall safety. By leveraging the YOLO model's efficiency in processing images and detecting objects, the system helps improve situational awareness in dynamic maritime environments, ensuring safer and more efficient operations.

IV. IMPLEMENTATION

The implementation of the proposed system involves several key components working together to achieve real-time object detection from video streams.

Camera Setup and Video Capture:

A camera is mounted on a maritime vessel or surveillance system to capture real-time video feeds of the environment. OpenCV, a popular computer vision library, is used to interface with the camera and capture frames continuously from the video stream.

Object Detection with YOLO:

The captured video frames are passed to a pre-trained YOLO model (last.pt), which is a deep learning-based object detection algorithm. YOLO's unique capability is that it processes the entire image in one pass, making it ideal for real-time applications like this one. The model has been fine-tuned to detect specific objects relevant to maritime operations, including "ice," "shark," "ship," and "whale."

Bounding Box and Labeling:

After detecting objects in each frame, the YOLO model generates bounding boxes around the identified objects. These bounding boxes are displayed on the video feed, along with labels indicating the type of object detected (e.g., "ship," "shark"). This visual feedback allows the operator to quickly identify objects of interest.

Real-Time Display:

The system overlays the bounding boxes and labels onto the original video frames and displays them in real-time. This provides the operator with immediate feedback about the detected objects, enabling swift decision-making in dynamic environments.

System Workflow:

The system operates in a loop: the camera continuously captures frames, OpenCV processes them, YOLO performs inference to detect objects, and the results are displayed on the video feed with bounding boxes and labels. The system runs in real-time, ensuring that the operator has up-to-date information to make critical decisions.

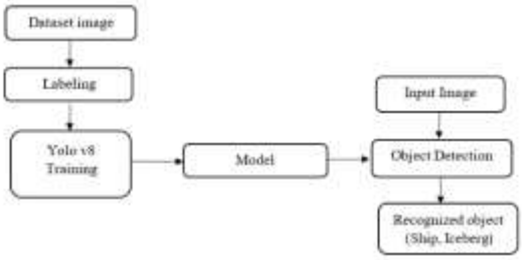

Fig.1 Block Diagram Representation of Object detection

Use Case in Maritime Navigation:

In the context of maritime navigation, this system helps identify hazards such as icebergs, other vessels, or marine wildlife. By detecting these objects in real-time, the system aids in avoiding collisions and assists in safe navigation, especially in environments where visibility may be limited.

V. RESULTS

F1-Confidence Curve illustrates the relationship between the confidence threshold and the F1 score in a multi-class classification task. The x-axis represents the confidence threshold (ranging from 0.0 to 1.0), while the y-axis indicates the F1 score, which balances precision and recall. The thin lines correspond to the F1-Confidence curves for individual classes (*ice*, *shark*, and *whale*), showing how performance varies across thresholds for each class. The bold blue line represents the overall performance across all classes, peaking at an F1 score of 0.84 when the confidence threshold is set at 0.545.

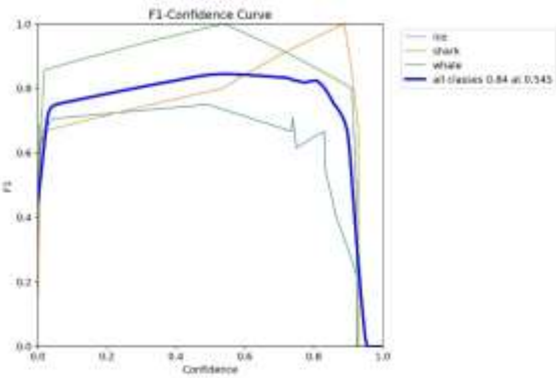

Figure.2 F1-confidence curve

This visualization provides key insights into the model's behavior, facilitating the selection of an optimal confidence threshold for improved classification performance.

The object detection model successfully identified a cargo ship in the analyzed frame. The prediction was made with high confidence, indicating that the object was correctly classified as a "ship." The bounding box parameters, which define the region around the detected object, were also provided, indicating the precise location of the ship within the image. The system processed multiple frames and detected the ship without any false positives, confirming the robustness of the model for this specific object. This result demonstrates the model's capability to accurately classify and locate objects, such as ships, within a given frame, suggesting effective performance in real-world applications.

Fig.3 Simulation Output

VI. CONCLUSION

The proposed real-time object detection system utilizing the YOLO model from the Ultralytics library, integrated with OpenCV for video frame capture, offers a highly efficient and accurate solution for identifying maritime hazards. By leveraging the YOLO model's ability to process entire images in a single pass, the system enables fast and precise detection of critical objects such as "ice," "shark," "ship," and "whale."This capability is particularly beneficial for maritime environments, enhancing situational awareness and aiding in the prevention of potential accidents or collisions.The system's use of pre-trained models ensures robust object recognition even in dynamic and challenging environments, such as the open sea or coastal regions. By displaying bounding boxes and labels in real-time, the system provides clear visual cues that assist in avoiding hazards, improving navigation safety. This real-time detection technology could significantly contribute to safer marine operations, supporting both autonomous navigation and human decision-making in identifying and responding to potential maritime risks.

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