30th
International Maritime Lecturers Association Conference
Split Croatia
www.imla30.org

International Maritime Lecturers Association

FACULTY OF MARITIME STUDIES

NAVIGATIONAL SAFETY ENHANCEMENT USING AI-BASED OBSTACLE DETECTION FOR SHIPS

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Abstract. Maritime collision avoidance is a vital component of ensuring the safety and efficiency of ship navigation. This study presents a novel collision avoidance system utilizing the YOLOv9 object detection model, achieving an exceptional accuracy of 99.9%. The primary objective of this research is to develop a robust system capable of real-time detection and classification of critical maritime objects such as breakwaters, buildings, buoys, mountains, ships, sky, water, and vegetation, under diverse environmental conditions. To ensure the model's stability and generalizability, the dataset was carefully selected to contain a variety of environmental situations, including different light levels, weather patterns, and observation angles. To improve the quality of the input photos preprocessing methods such as noise reduction and data augmentation were used. Because of its high real-time object recognition performance, minimal processing overhead, and capacity to handle numerous classes at once, the YOLOv9 model was selected. The unique aspect of this work is when it detects any obstacle at a good amount of distance through the camera operated by Artificial Intelligence (AI) prior to the warning signal.

Keywords: Maritime Obstacle Avoidance; Ship Collision Prevention; AI-Based Navigation Safety; YOLO.

https://doi.org/10.7225/imla30.47

1. INTRODUCTION

The marine transport is critical to international trade, transportation, and economic growth. As global marine traffic rises, so do the issues of protecting navigational safety especially in full waterways, limited technology, and low-visibility locations (Weijun, I. et al., 2023). Traditional navigation aids function, such as Radar systems, sonar, Automatic Identification Systems (AIS), Global Positioning System (GPS), Electronic Chart Display and Information System (ECDIS), magnetic and gyro compasses, and human visual monitoring. Radar, AIS, and ECDIS are particularly important for contemporary marine navigation because they give real-time situational awareness, collision avoidance, and route planning assistance. Radar is essential for obstructions in low visibility; AIS allows vessel-to-vessel data exchange and ECDIS provides integrated digital chart-based navigation (Sonnenberg, G. J. 2013). One of the major worries is the potential for collision with objects like fishing boats, floating debris, icebergs, or undiscovered ships. These catastrophes not only cause significant damage to ships and environmental degradation, but they also create problem in global supply lines (Dominguez-Péry, C. et al., 2021). Artificial Intelligence (AI) approaches like computer vision models, particularly deep learning-based object identification frameworks, have demonstrated enormous potential for accurately detecting barriers (Manakitsa, N. et al., 2024). YOLO is a very strong and efficient real-time object detection technique making it ideal for real-time obstacle detection aboard ships. This includes impressive processing making it ideal for real-time obstacle detection (Anguchamy&Palanisamy, 2025). The use of AI-based object detection systems in marine circumstances improves situational awareness and allows both human and autonomous navigation. Such systems can recognize likely obstructions, analyse hazards, and take quick avoidance actions to avoid accidents and ensure navigational safety (Thombre, S.et al., 2020). This is especially critical with operating without direct human supervision. In addition, the usage of edge computing combined with AI provides effective processing of video and sensor data, enhancing real-time decision-making capabilities (Rashid&Kausik, 2024). Regardless of these advances, this approach designed to function in real time and with high detection accuracy and integrate seamlessly with onboard navigation systems (Vagale, A. et al., 2021). It aims to provide an intelligent support layer to traditional methods, enabling safer and more efficient maritime operations, as illustrated in Figure 1.

2. LITERATURE REVIEW

Currently lot of work is done on the machine learning and deep learning applications across various transport modes road, rail and ship improving safety and operational efficiency. It highlights transferable methods like Artificial Neural Network (ANN), Support Vector Machines (SVM), Hidden Markov and Bayesian models (Tselentis, D.I. et al., 2023). AI technologies are enhancing maritime safety through applications like risk analysis, predictive maintenance, and intelligent navigation. It discusses real-world implementations such as Wartsila's Fleet Operations Solution and ABB Ability™ Marine Pilot Vision (Durlik, I. et al., 2024). The transformative impact of real-time AI agents on autonomous maritime systems, highlighting their roles in safety, efficiency, and sustainability. It examines AI agent architecture, safety mechanisms like collision avoidance, and regulatory compliance, while also addressing challenges such as computational limits and ethical concerns (Durlik, I. et al., 2025). A computationally efficient algorithm for

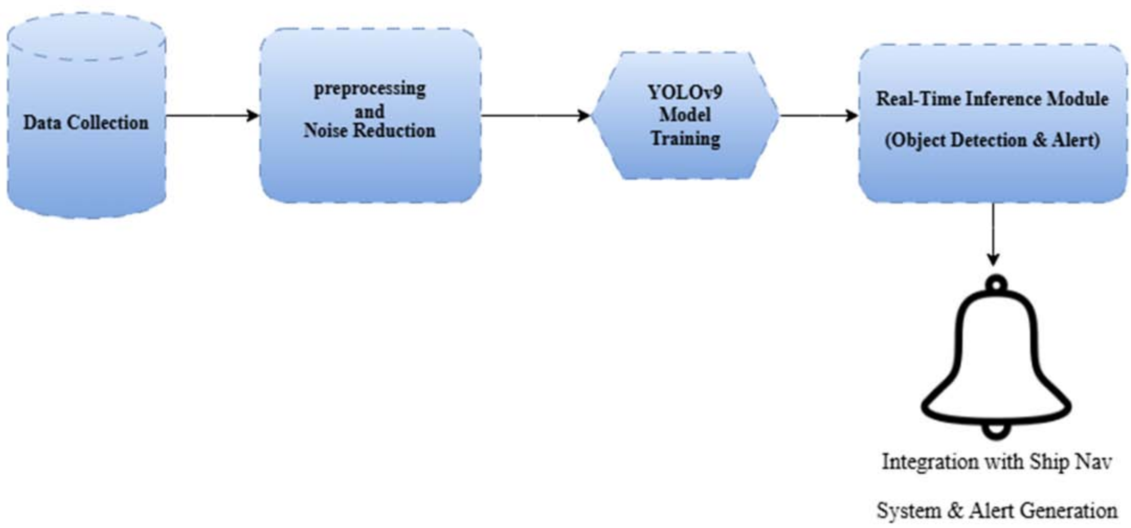

Figure 1. Show the workflow diagram for the project

detecting maritime obstacles using raw LiDAR data. the method effectively identifies simple-shaped objects like buoys and totems by offering a fast, practical solution for safe navigation (Saglam&Papelis, 2023). An AI-based autonomous surface vehicle (ASV) system for continuous surveillance in Marine Protected Areas (MPAs), using cloud and edge computing. The system features a smart algorithm that dynamically selects the best AI processing source cloud or edge based on latency and accuracy needs to optimize mission outcomes without human input (Molina-Molina, J.C. et al., 2021). This study explores how autonomous ships and artificial intelligence (AI) are reshaping the shipping industry by improving efficiency, safety, and sustainability. It highlights advancements in sensor-based navigation and decision-making systems, while also addressing challenges like regulatory gaps, cybersecurity, and public acceptance (Riyadh, M. 2024). The current work deals with enhancing the navigational safety using AI model.

3. METHODOLOGY

The structures in Figure 2 shows the step-by-step method to develop the model, which includes the six most important phases, from collecting data to model representation. These sections mentioned below address each phase of the proposed methodology.

This study delivers a complete and systematic approach to developing an AI-powered real-time maritime obstacle recognition system. This involves recording real-time detection from AI-powered cameras placed on the vessel. This AI base cameras has 360 degrees rotational ability which gives itself an edge in detecting different class of objects.

3.1. Data Collection

The dataset for this study is collected from Roboflow which is a wen platform (https://roboflow.com), It contains 1,115 images captioned images reflect important barrier categories typically encountered during ship navigation. The data set contains the important features like, including breakwaters, buildings, buoys, mountains, ships, the sky, and vegetation. These images were chosen effectively to build the AI model. Below is the (Table 1) that represent the data set description of this work.

Table 1. Shows the Dataset Description (Roboflow)

Sl. no.	Object Class	Number of Instances
1	Breakwater	120
2	Buildings	140
3	Buoys	180
4	Mountains	95
5	Ships	200
6	Sky	115
7	Vegetation	85
8	Water	180

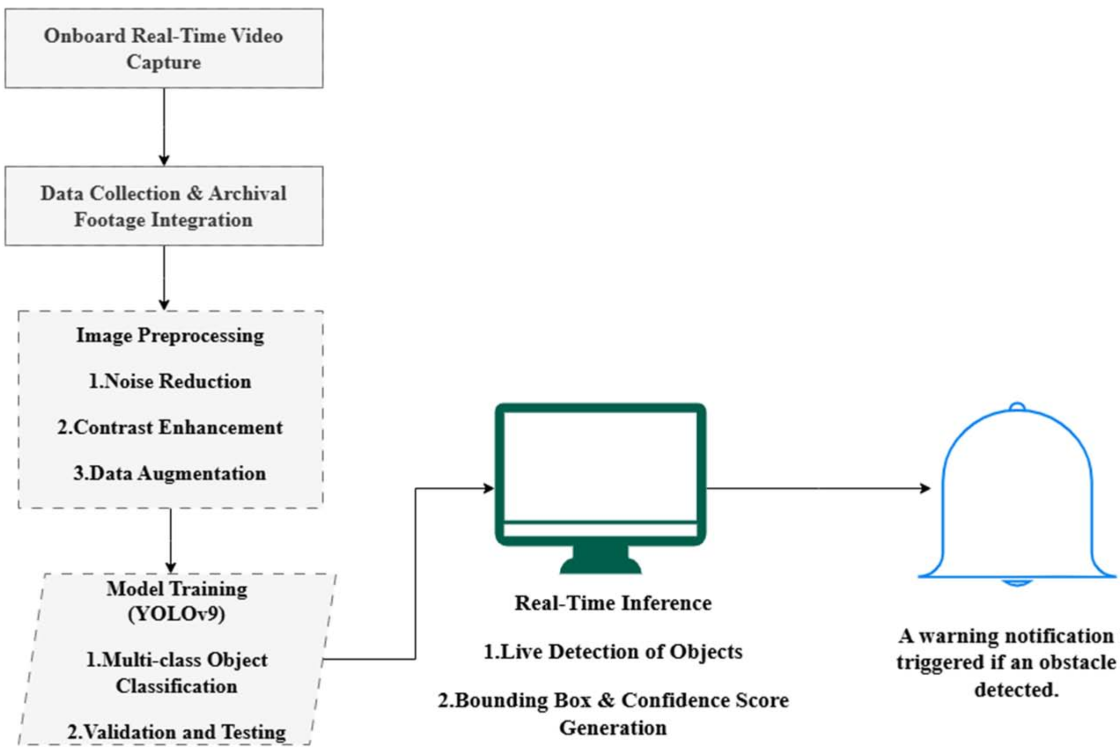

Figure 2. Proposed architecture for AI-based obstacle detection for ships

3.2. Data Preprocessing

The dataset is already stream lined when we collect it from Roboflow web platform. All the images are properly scaled to a fixed input resolution of 640×640 pixels, as per YOLOv9 requirement. The scaled images were transformed to the necessary YOLO format for training.

3.3. Model Selection

The YOLOv9 model was chosen for its high object detection skills and capability for marine conditions which is the novelty of the work. Among the several accessible detection frameworks, YOLOv9 is built for fast, precise, and multi-object recognition system which is vital for collision avoidance in marine operations. The key aims of this study is real-time object, detection with high accuracy with the trained model and high computing version. This technology allows the system to function efficiently even under the processing situations seen on devices.

3.4. Model Training

The model training process was conducted using Jupiter Notebook with a Python-based implementation. Training was carried out A GPU-enabled system was used for training, which Quickly improved the method of learning and efficiently handled large batches of marine image data. The model was trained over 15 epochs using the data set which been scaled to 640×640 pixels, with a batch size of 600. In order to ensure optimal ensure and generalization across wide range of marine situations, To avoid overfitting and preserve model stability, loss values and validation performance measures were continuously monitored during the training process. the final YOLOv9 model was developed successfully and demonstrated good detection reliability. For real-time deployment on ship's to delete the obstacle edge-based processing system, enabling live detection.

3.5. Deployment and Real-Time Prediction

The model was integrated into a real-time video analysis pipeline that continuously monitored the maritime environment. The camera sensor system is directly installed on the ship's onboard computer unit, with real-time forecasts. When the system detected any barrier, it sent out an instant notification to the bridge duty officer. These warnings were seen in the installed device in the bridge, which displayed the obstacles, with class names. In addition to visual feedback, the device produced visual warning signs, enhancing situational awareness and preventing accidents. This real-time decision support of model operated automatically simultaneously assisting manual navigation by giving accurate, timely information to ship operator. Although the dataset did not indicate the particular camera type, the system is compatible with marine-grade security cameras like the FLIR M364C (Forward Looking Infrared Radiometer). These cameras are ideal for shipboard usage because of their high-resolution images ,infrared and thermal capabilities for low-light environments, and waterproof (IP67/IP68) and corrosion-resistant casings. They also have wide dynamic range optical zoom, and high frame rates, which are required for spotting distant or fast-moving hazards in dynamic marine situations. The deployment of such cameras guarantees that the AI model receives consistent, real-time information, improving obstacle detection ability even in tough situations like as fog, rain, or stormy seas.

4. RESULTS & DISCUSSIONS

The YOLOv9 model was evaluated on a test dataset comprising of the total 1,115 images. The evaluation focused on key metrics such as precision, recall. The model achieved an outstanding accuracy of more than 95%, across all object classes. The real-time detection performance was validated on GPU based edge device, where the model continuous video streams. These results confirm the model's suitability for real-time obstacle detection in dynamic maritime conditions. AI-based obstacle detection system offers several advantages for maritime navigation. It provides real-time monitoring, automatic detection, and instant alerts, enhancing navigational safety and reducing the reliance on human vigilance, especially in low-visibility conditions. The system improves situational awareness on the bridge and assists crew members in making faster, data-driven decisions. However, there are not able limitations. The effectiveness of detection extreme weather conditions (e.g., heavy fog, high sea spray), and the safety distance at which an obstacle is detected depends on camera quality and installation angle. In some cases, the system may detect obstacles too late for evasive action. Additionally, false positives or missed detections can still occur, particularly with floating debris or small objects. The figures (Figures 3 and 4) illustrate the system's detection outcomes, showcasing how the model effectively identifies of obstacle detection activities.

Figure 5 shows the precision-confidence connection for several marine item classifications recognized with a YOLO-based AI model. The graph depicts how accuracy varies with confidence criteria for each class, including water, sky, ship, flora, and more. Classes

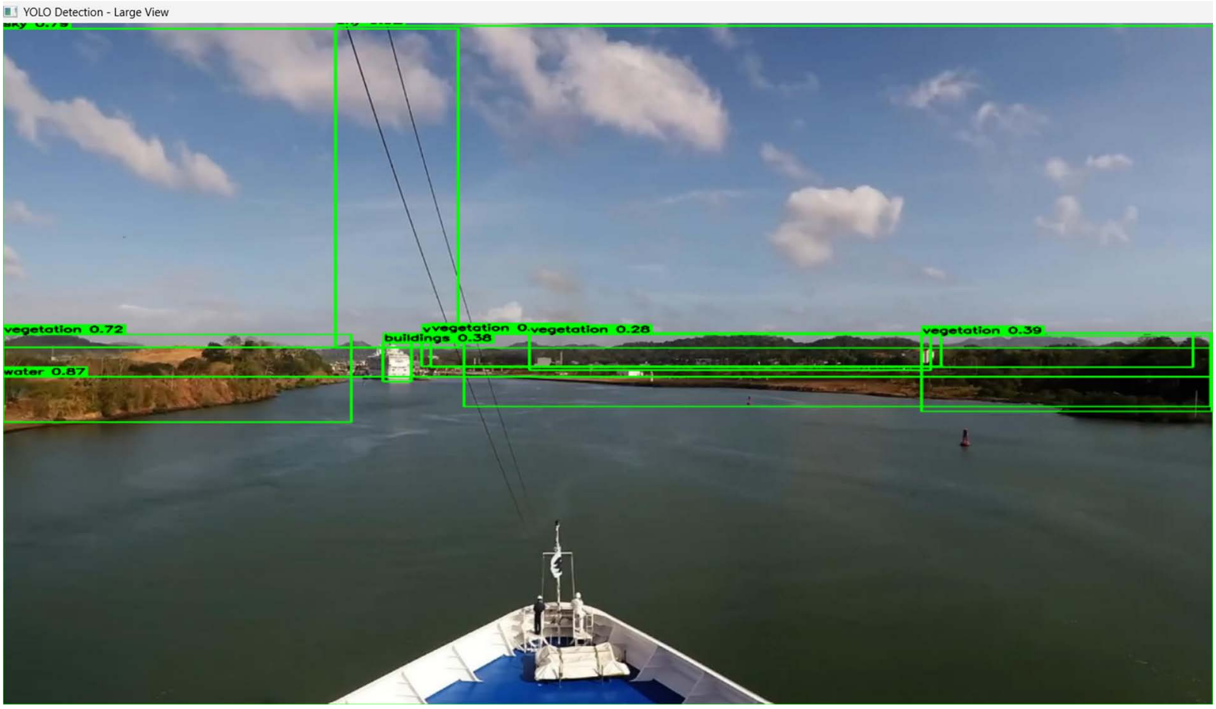

Figure 3. Shows the Real-time object detection using YOLO enhances situational awareness for maritime vessels by identifying key elements such as water and vegetation

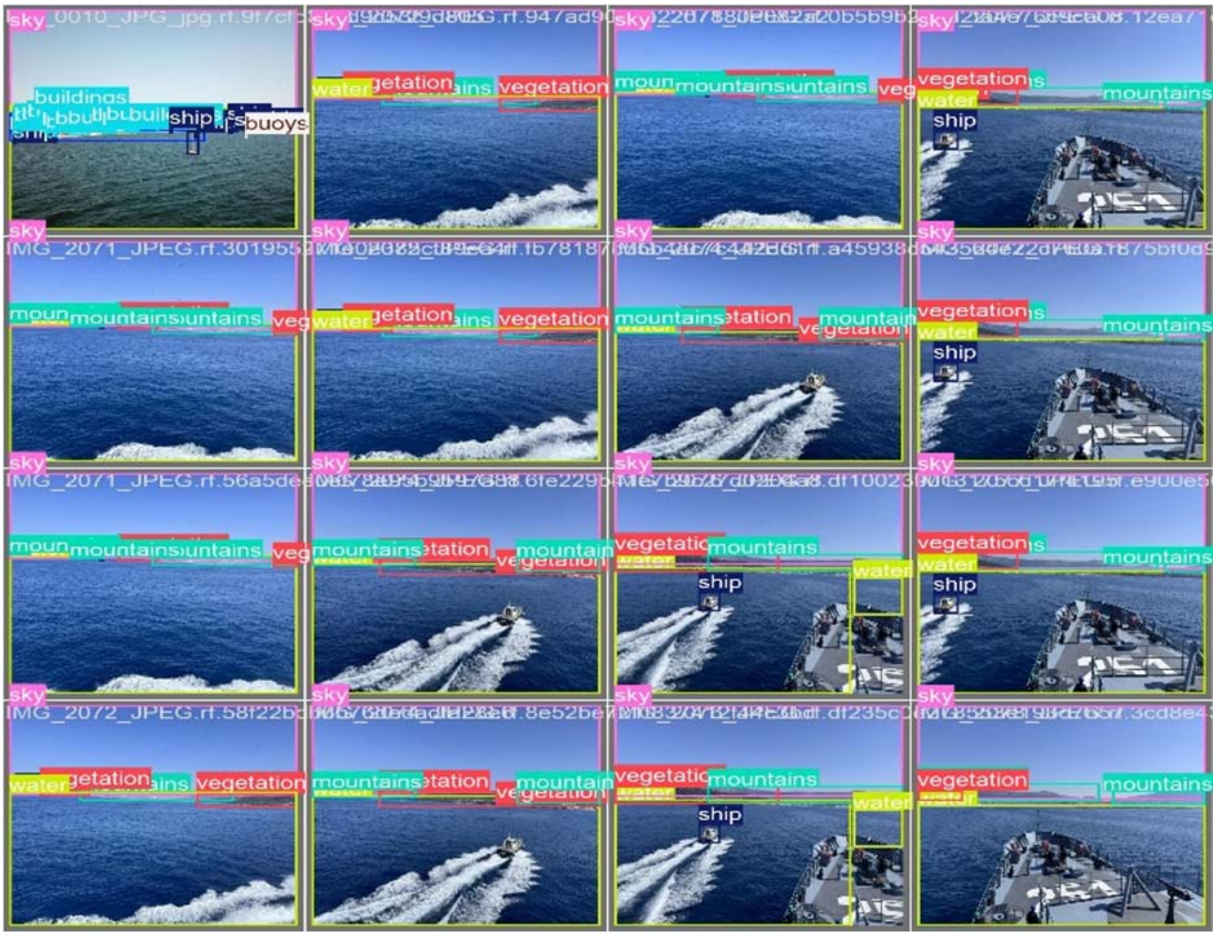

Figure 4. Shows the Batch detection output from a YOLO model

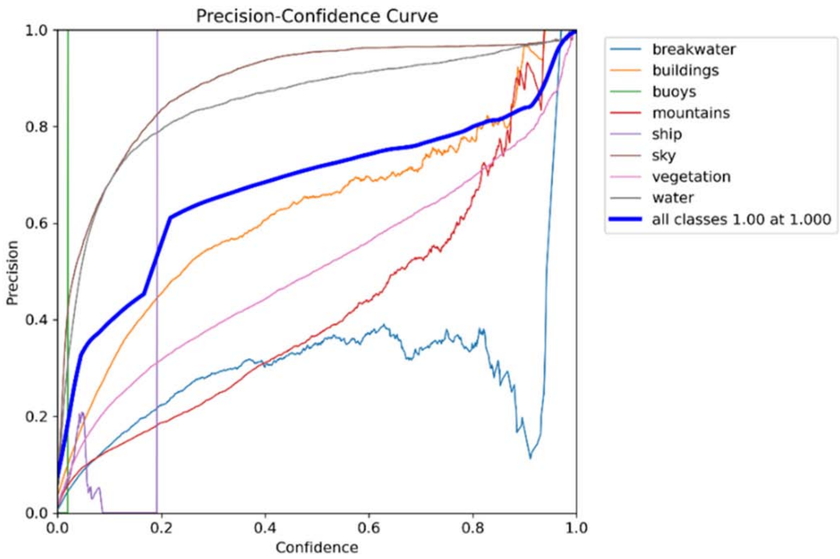

Figure 5. Precision Curve for Maritime Object Detection

like sea and sky shows great precision across all confidence levels, but ship and breakwater show poorer consistency. The bold blue line shows the averaged accuracy across all range.

5. CONCLUSION

The AI-powered obstacle detection system performed well in detecting objects divided into various classes. The data set were taken from the robo flow web platform. The YOLO based AI model implemented to real time video integration also showed good results. The precision curve test showed a model accuracy of more than 95%. Still there are some limitations like limited detection range, which means that the object may be detected too late for safe evasive action, particularly at high vessel speeds. This highlights the need of clearly defining the system's working scope. In its current configuration, the system is best suited for navigation, sea lanes, and as a support tool for human lookouts, rather than as a stand-alone long-range navigation assistance.

6. FUTURE SCOPE

The model study should focus on increasing the dataset to include new types of maritime obstacles, which are typical collision hazards. Multi-spectral and thermal imaging can help to enhance detection accuracy in challenging conditions such as dark or dense fog. Another interesting possibility would be to link the system with navigation modules and have early warnings as well automated path re-planning and crash-avoidance. Model compression and optimization would make the system more deployable on resource-constrained ships, focusing on energy efficiency and robustness. Use of an embedded cloud-edge system could be considered to outsource heavy computations to the cloud if internet is available but ensuring that local edge nodes are still responsive in the real time. Finally, broad commercial practice and long-term ship-borne operation need to be performed on both of cargo and passenger ships to test the scalability, robustness and effectiveness of the system under dynamic marine environment. Future implementations may include combining radar, AIS, and ECDIS data with computer vision models to improve real-time decision-making. Furthermore, implementing adaptive warning thresholds depending on vessel characteristics, such as speed and turning radius, can aid in fine-tuning alert time for safe navigation.

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