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Research Article

EURMARS: Use of Satellite Imagery as an Asset for Maritime Environment Rapid Mapping and Object Detection in Large Areas

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ABSTRACT:

The increasing complexity of maritime risks and threats requires accurate and timely identification for environmental and human safety. Satellite observations enable comprehensive surveillance of large maritime areas, which is essential for detecting and responding to environmental changes and potential threats. The Horizon Europe project EURMARS aims to develop and validate a multi-purpose observation platform to enhance detection capabilities for various risks and threats. This paper introduces a novel Earth Observation (EO) algorithm based on Object-Based Image Analysis (OBIA), employing a You Only Look Once (YOLO) -v9 model to process data from open-access satellites (Sentinel-1, Sentinel-2, Landsat 8, 9) and video from the microsatellite NEMO-HD. Automatic Identification System (AIS) data are used to ensure comprehensive monitoring and validate the method's results. Satellite imagery with AIS data integration is a critical element of the vessel tracking methodology, significantly improving the accuracy and reliability of maritime surveillance. Real-life demonstrations have confirmed the method's effectiveness in enhancing maritime security and facilitating early detection and response to threats.

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1. Introduction

1.1 Aim and Scope

Monitoring and managing the maritime environment are crucial and challenging due to its vast size and continuously changing conditions.[1] Traditional surveillance methods, such as land-based or ship-based observation, often fail to provide comprehensive and timely data over wide areas. In contrast, remote sensing technologies, particularly satellite imagery, offer a powerful solution to these challenges by providing extensive coverage and efficiently capturing high- or medium-resolution data. The vessel detection using satellite imagery can be further enhanced by the transmitters' data integration, which offers valuable information on vessels' position and direction. The Automatic Identification System (AIS) is a widely used vessel tracking system that provides continuous location updates.[2]

When it comes to satellite imagery, both optical and Synthetic Aperture Radar (SAR) data are particularly effective for detecting vessels, offering improved accuracy and reliability in maritime surveillance.[3] Regarding vessel detection in optical images, key factors affecting the results include the size of the detected objects and weather conditions. Vessels must cover a sufficient number of pixels in the image, depending on its spatial resolution, to be detected accurately. However, adverse weather conditions such as clouds or waves can hinder the detection capability.[4] Additionally, the reflection of sunlight in the waves can create areas of high contrast in images, which can be misinterpreted as vessels.[5] On the other hand, SAR data is a reliable method for detecting vessels at sea, as they provide good results regardless of weather conditions. Moreover, larger vessels, being metallic structures, reflect more radar signals. However, SAR images can have high levels of noise and sensitivity in the air, which can prevent the accurate detection of vessels.[6] In addition to the satellite imagery, the Slovenian microsatellite NEMO-HD enhances vessel detection with its high-resolution multispectral imagery and HD RGB video capabilities. Equipped with an advanced guidance, navigation, and control system, NEMO-HD can track non-linear paths, such as coastlines, or focus on a specific ground target for several minutes.[7-8] Despite its high orbital velocity, NEMO-HD maintains orientation towards a selected Earth area, enabling the recording of HD video. The ability to capture motion-tracked video from space introduces a new dimension to maritime traffic monitoring.

This paper presents an integrated algorithm for processing EO data using OBIA for vessel detection in multispectral and SAR images and RGB video. The algorithm includes the development of a component that collects satellite data, processes them, and finally performs vessel detection via YOLO-v9 model. The proposed end-to-end method and the technologies have been validated through the integration of data from AIS positioning systems and real-world experiments, demonstrating their effectiveness in terms of rapid threat response and improved maritime security.

1.2 Relative Literature Review

Since the launch of the first optical and SAR satellites fifty years ago, the number of satellites capturing images of the Earth has increased significantly. These satellites are classified according to the spatial resolution of their images into four groups: very high, high, medium, and low resolution. Among those that provide open access to their data, Sentinel satellites offer high-resolution imagery, while Landsat satellites provide medium-resolution data.[9]

Recent studies have focused on vessel detection using data from Sentinel-1[10-18] and Sentinel-2[19-23] satellites, often in combination with other data sources. For instance, in a study,[2] Sentinel-1 data with AIS datasets were integrated, leading to the development of a database and web-based tool for detecting "dark vessels"—vessels not transmitting AIS signals, potentially engaged in illegal activities. This tool visualizes detections from both data sources. Additionally, another study[6] proposed a Polarimetric Combination-based Ship Detection (PCSD) method to address challenges such as speckle noise in SAR data, achieving an overall detection rate of over 85 % and over 42 % for small vessels. Further advancements in vessel detection have been made using optical satellite imagery. An algorithm employing object detection techniques has been developed for identifying vessels under 20 meters in length, which typically lack AIS. This method has demonstrated the capability to detect vessels 8 meters in length.[24] A study demonstrated the importance of Landsat 8 using its visible and infrared bands to validate the proposed ship detection method, showing that its multi-resolution images significantly increase the detection accuracy compared to classical methods.[25] Another study developed a ship detection method using spectral and thermal fusion, with experiments on Landsat 8 data showing effective, clutter-resistant ship detection.[26]

These advancements in satellite remote sensing technology and the integration of various data sources have significantly enhanced the accuracy and efficiency of maritime monitoring and vessel detection.

2. Methods

2.1 Model Training

Datasets Overview

Optical Dataset

Four publicly available optical datasets were used for the training, testing, and validation of the vessel detection model. The first dataset, the TGRS-HRRSD Dataset[27] (Figure 1a) contains 21,761 images sourced from Google Earth and Baidu

Map. The second dataset is simply referred to as ship-detection.[28] The third dataset, namely Ship Detection from Aerial Images,[29] consists of 621 images specifically for ship detection, and the fourth, Ships in Google Earth,[30] comprises 794 images obtained from Google Earth, which are split into two groups—training and testing. All these datasets are openly accessible and contain optical images of vessels, providing a robust foundation for training the optical detection model.

SAR Dataset

In addition to optical data, a SAR image dataset[31] was also used to train and test the detection model. This dataset includes a labelled collection of 102 images from the Chinese Gaofen-3 satellite (Figure 1b) and 108 images from Sentinel-1, both of which were cropped into smaller 256x256 pixel segments, resulting in a total of 39,729 image chips.

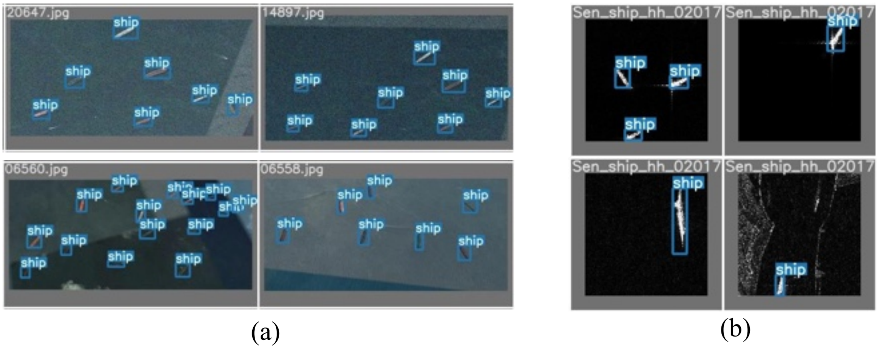


Figure 1: Sample images from (a) TGRS-HRRSD optical dataset and (b) Chinese Gaofen-3 and Sentinel-1 datasets.

YOLOv9

In recent years, deep learning models have significantly outperformed older AI systems in areas such as object detection, language processing, and speech recognition, thanks to advances in architectures such as Convolutional Neural Networks (CNNs), transformers, and perceptrons.[32] Research is increasingly focused on enhancing learning methods and optimising model training, including improving loss functions and label assignment.[33] Traditional approaches often overlook information loss, leading to prediction inaccuracies. Early deep learning models like R-CNN and Faster R-CNN used a two-step process: locating and classifying objects.[34] While accurate, they were too slow for real-time applications, processing only about 7 frames per second (fps). In contrast, one-step models like YOLO predict both object location and category simultaneously, achieving speeds around 45 fps in the original YOLO and up to 140 fps in newer versions like YOLOv5.[35] This efficiency enables near-real-time detection of vessels in radar images, which is crucial for maritime surveillance. Given the proven effectiveness of YOLO models for real-time detection, such as improved identification and localization of exact positions and targets,[36] we have chosen to implement YOLOv9-E, fine-tuned for our vessel detection model. In comparison with relative publications,[32,37] it has been proven to be improved in many aspects as it needs fewer parameters and calculations and also has a significant improvement in Average Precision (AP).

Parameters Selection

Several parameters were meticulously selected to optimize performance when applying the YOLO-v9 model for vessel detection. The batch size was determined based on hardware capabilities equal to 6, which required 25.6 GB of graphics memory, demonstrating the relationship between batch size and hardware resources - larger batch sizes can speed up training but require more GPU memory. Hyperparameter tuning was conducted through hyperparameter evolution to enhance the model's performance. Validation was used for this hyperparameter evolution and model evaluation after each epoch, utilizing 10% of the total dataset, and ensuring that no images from the training or test datasets were included. While most hyperparameters, such as image size and epochs, were set to default values, the image size for the SAR vessel detection dataset was specifically adjusted to 256x256 pixels due to the resolution limitations of the dataset. The training environment was equipped with robust hardware, including an CPU AMD Ryzen 7 5800X 8-core processor, 32 GB of DDR4 3200MHz RAM, and an NVIDIA GeForce RTX 3090 with 24 GB GPU, ensuring efficient computations. YOLO-v9 employs a composite loss function that combines components for bounding box regression, object classification, and confidence score prediction, ensuring precise localization and accurate detection. The test dataset, also comprising 10% of the total data, was used to evaluate the model's performance every 100 epochs to determine convergence. This test set did not overlap with the training or validation datasets. If no improvement was observed on this test dataset, the training process was halted, signifying that the model had converged.

Performance Metrics

The model was trained and tested using 90% of the dataset. After repeating the training and testing process multiple times, the model with the best performance across all iterations was selected for final validation. To evaluate its effectiveness during both the training and testing phases, several key metrics were used, such as precision, recall, F1 score, and mean average precision (mAP). These metrics assessed various aspects of the model, such as how accurately the bounding box captures the detected object, the probability of an object being correctly identified in a specific area, the precision of the detection, the percentage of correct predictions, and the overall model's performance.

2.2 Component development

The component developed in this study for vessel detection operates through several critical steps. First, it searches for new image products by continuously searching the Copernicus and USGS Earth Explorer product catalogue within a predefined area of interest for Sentinel-1, Sentinel-2, and Landsat 8,9 images. This search is performed on a ten-minute basis. An API facilitates the image acquisition process by allowing users to browse available products based on several parameters such as sensor type, product layer, area of interest, cloud coverage, and acquisition date.

Once an image is detected, the algorithm automatically downloads it and performs a series of preprocessing steps to optimize it for the detection step. These preprocessing steps are essential to ensure data quality and include subset cropping of images, noise reduction, masking to highlight the area of interest, and applying spectral or geometric transformations to prepare the image for accurate vessel detection. Preprocessing of SAR images (Figure 2a) was fully implemented using SNAP software, whereas for optical images (Figure 2b), steps 1-3 were processed in SNAP, while the remaining steps were developed manually.

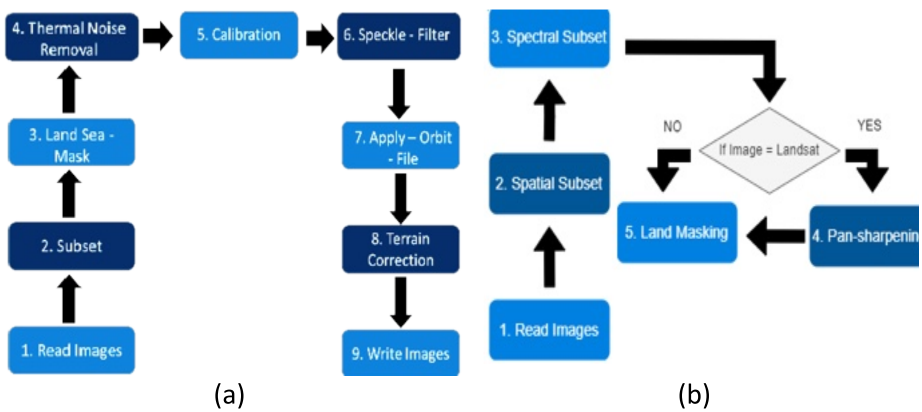


Figure 2: Workflow of the image dataset preprocessing (a) SAR, (b) optical imagery.

After the preprocessing, the SAR image has GeoTiff format with SigmaVV and SigmaVH bands. The VV and VH bands are read, and outliers are removed (after some testing, keeping the values of 0.01 to 0.1 removes most of the sea noise and enhances the vessel's footprint), after that the values are stretched to a range of 0-255 and with these values a grayscale PNG image is created with the help of the library rasterio. In accordance with the SAR image, the optical image has a format of GeoTiff with RGB bands. The RGB bands are read, and outliers are removed; the values are stretched to a range of 0-255, and with these values an RGB PNG image is created with the help of the library rasterio.

Although the YOLO-v9 model was trained and tested on very high-resolution images, the algorithm was implemented on high- and medium-resolution images. However, adjustments were made to ensure high training accuracy without negatively impacting the results, including procedures such as scale invariance and data augmentation. Specifically, for scale invariance, the model was trained using images where the detected object's bounding box occupied 10% or less of the image area. If it covered more than 10 % of the image, the image was discarded from the training dataset.

The vessel detection process involved generating bounding boxes around the identified vessels, each characterized by a confidence level. The approach for detecting vessels varied slightly between optical and SAR images.

The algorithm was fully developed in Python 3.10 within the Visual Studio code environment. The libraries employed for processing include Or, Tarfile, dotenv, Numpy, Rasterio, SnapPy, Geopandas, PIL, SQLAlchemy, and OpenCV. These libraries facilitated the handling of satellite image data and the generation of accurate vessel detection results.

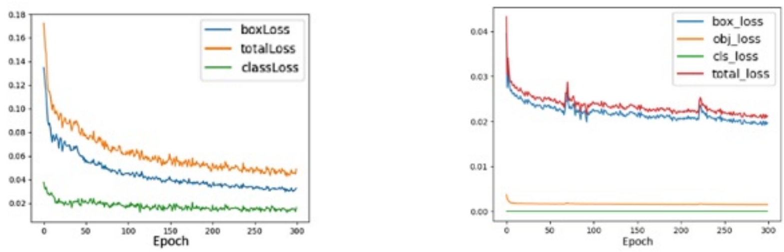
2.3 Application on Sentinel, Landsat, and NEMO-HD data

In the scope of the project, the developed algorithm was applied to satellite data from Sentinel-1, Sentinel-2, Landsat 8-9, and to the microsatellite NEMO-HD data to evaluate its performance in real-world scenarios. Sentinel-1, launched in 2014, captures Synthetic Aperture Radar (SAR) images with a spatial resolution of up to 5 meters, providing high-quality data irrespective of weather conditions or time of day.[38] Sentinel-2, on the other hand, offers multispectral optical observations across 13 spectral bands with a spatial resolution of up to 10 meters, making it suitable for applications such as land cover change detection, coastal monitoring, emergency response, and maritime surveillance.[39] Landsat 8 and 9 continue the Landsat program's legacy, which began in 1972, providing moderate spatial resolution in global, synoptic, and repetitive Earth surface coverage. These satellites enable the detection and monitoring of both natural and human-induced changes over time.[40] The NEMO-HD microsatellite provides high-resolution video in the visible spectrum, with a spatial resolution of 2.8 x 2.8 meters and a ground footprint of 3x5 kilometers. The video can be acquired globally, and when the Area of Interest (AOI) is within range of the ground station in Slovenia, it can be transmitted in real-time. For AOIs beyond this range, the video is stored onboard and transmitted during the next contact with the ground station, ensuring timely access to critical information.[41] This combination of datasets allowed for comprehensive testing and validation of the algorithm while demonstrating its effectiveness in diverse real-world maritime monitoring scenarios.

3. Results

3.1 Performance and Score

To illustrate the performance of the YOLO-v9 model's training (Figure 3a) and testing (Figure 3b) in vessel detection, several diagrams created represent the evolution of the loss function, broken down into its components: box loss, total loss, and class loss. These plots provide insight into how the model's predictions improve during the epochs, with each loss function representing different aspects of the bounding box prediction and object classification.



(a) (b)

Figure 3: Loss function diagrams for (a) training phase and (b) testing phase.

The evaluation of training results for both optical and SAR images was conducted using several metrics. Figure 4 and Figure 5 illustrate the model's performance over 300 epochs.

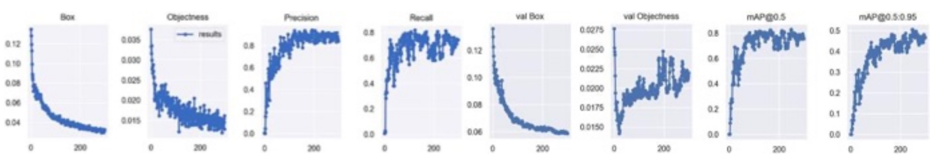


Figure 4: Training evaluation metrics of optical images

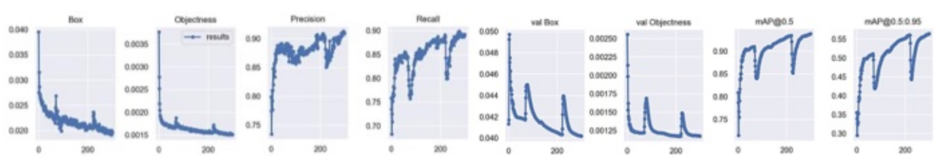


Figure 5: Training evaluation metrics of SAR images.

In addition, confidence plots, including accuracy, recall and F1 score curves, illustrate the model's ability to detect vessels at various confidence levels. These diagrams contribute to the evaluation of model performance, both for training (Figure 6) and testing (Figure 7), as precision measures the quality of positive predictions, recall indicates the model's ability to detect true positives, and the F1 score balances both.

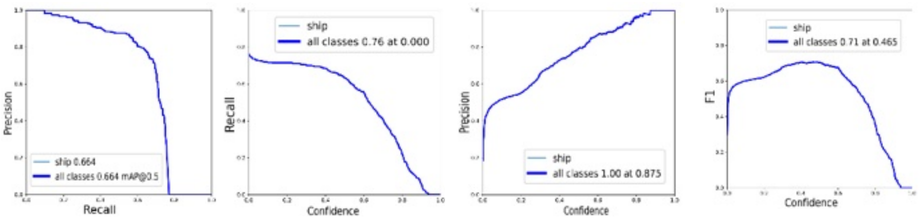


Figure 6: Confidence plots for training phase.

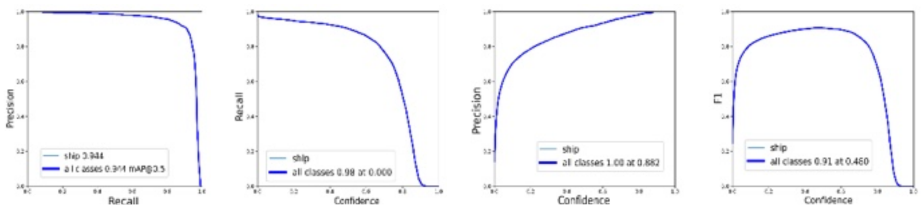
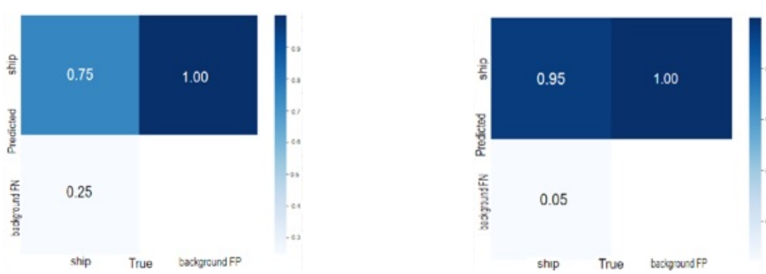


Figure 7: Confidence plots for the testing phase.

Figure 8a displays the prediction accuracy in the optical images during the model's testing with a true positive rate of 75 % for the "ship" class, while 25 % of the predictions were falsely classified as "background." Additionally, in Figure 8b the confusion matrix shows the testing prediction accuracy for vessels in the SAR images. The model attained a true positive rate of 95% for the "ship" class, while 5% of the predictions were falsely classified as "background." Vessel detection results are shown in Figure 9 (a-c).

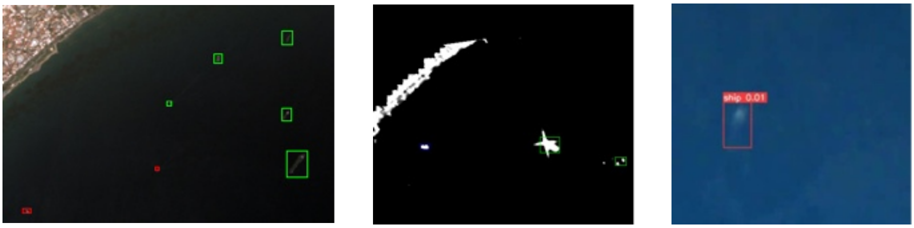


(a) (b)

Figure 8: Confusion matrix for model testing for vessel detection in (a) optical images and (b) SAR images.

3.2 Demonstration of the Pilot Use Case

As part of the EURMARS project, demonstration experiments were performed to assess and validate the developed methods and technologies in real-time conditions, with the primary objective of leveraging multiple sensors for sea object detection via data fusion. This study specifically focused on merging satellite imagery and AIS data to improve detection accuracy at sea.



(a) (b) (c)

Figure 9: Application of vessel detection algorithm on (a) Sentinel-2 image, (b) Sentinel 1 image, (c) NEMO HD video.

The first demonstration took place in Varna, Bulgaria, in April 2024. On the first day, the Sentinel-2 satellite passed over the area of interest, followed by the NEMO-HD satellite the next day. Although both the satellite images and video experienced dense cloud coverage (approximately 90%), the area of interest had only light cloud coverage (Figure 10a). For the Sentinel-2 image, the results indicated one true positive and two false positive detections (Figure 10b), primarily due to the dense cloud coverage, where small clouds were misidentified as vessels. The NEMO-HD satellite captured a one-minute video over this area and was able to detect one vessel in a duration of 8 seconds with a confidence >0.025 (Figure 11). The detection bounding boxes in both cases included the image's metadata, such as detection time, vessel coordinates, and object dimensions.

(a) (b)

Figure 10: (a) Sentinel-2 image (b) Detections on Sentinel-2 image.

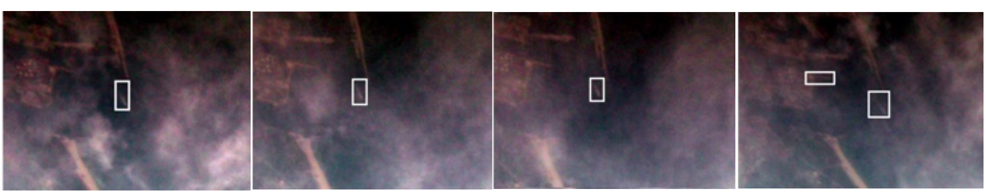


Figure 11: Detections on NEMO-HD video frames.

To validate the detection results, vessel positions were recorded using two methods (Figure 12a). First, an AIS antenna was installed in the Varna region to capture and transmit vessel position signals (Figure 12b). Additionally, GNSS tracker devices were given to the vessels and recorded their position (Figure 12c).

(a) (b) (c)

Figure 12: (a) Two vessels appeared on the image; (b) Vessel 1 position with AIS; (c) Vessel 2 position with GNSS tracker.

A noted issue with detected vessels is that the algorithm occasionally misidentifies the wake of a moving vessel as part of the vessel, leading to an overestimation of its size. Additionally, when two vessels are close to one another, one vessel may be incorrectly assigned to the bounding box of the other, causing both to be represented in a single box. Integrating AIS data can enhance accuracy by offering additional information to differentiate between overlapping or closely spaced vessels, thereby improving detection results.

4. Discussion

In this article, an algorithm for vessel detection integrating optical and SAR satellite imagery with AIS data is presented, automating the entire process from image retrieval to vessel detection and ensuring a continuous workflow without requiring user intervention. Initially, the vessel detection algorithm automates the search and acquisition of satellite images, followed by preprocessing to improve image quality. It then detects vessels within these images. The model exhibits high accuracy during the validation phase, achieving a true positive rate of 75 % for optical images and 95 % for SAR images. Notably, the model performs better with SAR images, which may be attributed to the greater diversity of testing samples for optical images. Compared with relevant works [42,43] where YOLO models were used for vessel detection, our model performs adequately, given the weather conditions that may affect the detection of vessels at sea.

The integration of satellite images with AIS data is crucial for verifying vessel positions. The possibility of identifying mismatches between AIS data and satellite detections enhances the accuracy and consistency of vessel identification significantly, reducing ambiguity and uncertainty in vessel positions and saving time.

The implementation in real-world experiments within the EURMARS project exemplifies a robust approach to evaluating maritime object detection fusion techniques. The integration of various sensors, including satellite imagery and AIS data, underscores the importance of cross-referencing multiple data sources to improve detection accuracy. The demonstration in Varna highlighted the challenges and successes of the project. Validation with AIS data and GNSS trackers ensured accurate verification, though issues such as detecting vessel wakes and merging close-range vessels into a single bounding box indicate areas for improvement. These findings reinforce the value of real-time, multi-sensor data fusion in maritime surveillance and highlight the need for further refinement of the EURMARS project's vessel detection algorithm.

5. Conclusion and Future Work

In this paper, we introduced our work developed under the Horizon Europe project EURMARS, in which maritime object detection, more specifically – vessel detection, was performed. A framework in which YOLO-v9 was exploited for object detection integrates image acquisition, preprocessing, vessel detection, and result outputs for the purpose, based on both optical multispectral images and SAR images. Four maritime datasets were used to fine-train the YOLO-v9 models for optical images from a number of remote sensing satellites, whilst one dataset was employed for SAR images from two satellites. Validation and testing results have shown that the developed algorithm can achieve excellent vessel detection accuracy of 75 % and 95 % for optical images and SAR images, respectively. In the demonstration testing, Sentinel-2 images and NEMO-HD video were captured in experiments associated with AIS. With more demonstrations throughout the EURMARS project, we will further explore the robustness of the developed algorithm and enhance its resilience to deal with different scenarios in maritime environments. For vessel detection models, valuable training data may be generated from the targeted satellites to increase the detection accuracy. We may also consider modifying the model architectures to fit better for maritime object detection in light of scenarios with more tests in real conditions.

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