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Sistemas automáticos de reconhecimento de alvos aplicados em diferentes contextos da Oceanografia Operacional

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por

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Aos que me guiam e me guardam.

"Think globally, act locally".
***Patrick Geddes**.*

Resumo

Nas últimas décadas, a Oceanografia Operacional passou por uma quebra de paradigma. Antes a escassez de dados *in situ* era um dos maiores desafios para o desenvolvimento de pesquisas marinhas; atualmente, a capacidade de processamento de grandes volumes de dados se tornou uma das peças-chave nos programas de monitoramento. Nesse contexto, o uso de ferramentas assistivas, como o aprendizado de máquinas, surgem como solução para lidar com grandes volumes de dados em tempo (quase) real. Com base no exposto, este trabalho tem como objetivo principal investigar o desempenho de sistemas de detecção automática de alvos (ATR, sigla em inglês) em duas matrizes de dados distintas com aplicação para a Oceanografia Operacional. A primeira abordagem metodológica é baseada em um modelo adaptado do YOLOv8+SAHI, integrando um rede neural convolucional, dados do Sistema de Identificação Automática e imagens de satélite, com potencial de aplicação em programas de monitoramento do tráfego marítimo, a fim de aumentar a consciência situacional marítima através da detecção de embarcações não cooperativas. A segunda abordagem insere-se no contexto da Guerra de Minas e baseia-se na customização da rede neural YOLOv11 para detecção de minas navais a partir de dados de sonar de varredura lateral. Ambas abordagens demonstraram resultados promissores para detecção em tempo real de alvos de interesse nas diferentes matrizes de dados. Com base das estatísticas de treinamento e validação das redes neurais, bem como no tempo de latência, ambas tem grande potencial de aplicação em programas operacionais de monitoramento dos oceanos.

Palavras chave: embarcações não colaborativas; guerra de mina; minas navais; monitoramento oceanográfico; redes neurais.

Abstract

In recent decades, Operational Oceanography has undergone a paradigm shift. Previously, the scarcity of *in situ* data was one of the greatest challenges marine research development; currently, the capacity to process large volumes of data has become one of the key elements in monitoring programs. In this context, the use of assistive tools, such as machine learning, has emerged as a solution to deal with large volumes of data in (near) real time. Based on the above, this work aims to investigate the performance of automatic target detection (ATR) systems in two distinct data matrices with application to Operational Oceanography. The first methodological approach is based on an adapted model of YOLOv8+SAHI, integrating a Convolutional Neural Network, Automatic Identification System data and satellite images, with potential for application in maritime traffic monitoring programs, in order to increase maritime situational awareness through the detection of non-cooperative vessels. The second approach is part of the Mine Warfare context and is based on the customization of the YOLOv11 neural network for detecting naval mines from side-scan sonar data. Both approaches demonstrated promising results for real-time detection of targets of interest in different data matrices. Based on the training and validation statistics of the neural networks, as well as the latency time, both have great potential for application in operational ocean monitoring programs.

Keywords: non-collaborative vessels; mine warfare; naval mines; oceanographic monitoring; convolutional neural networks.

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Memorial Descritivo

1.1 Contextualização

Na era da informação, a oceanografia operacional tem experimentado uma transformação significativa impulsionada pelo avanço das tecnologias de sensoriamento e capacidade computacional. Atualmente, uma variedade de plataformas – como satélites, boias de monitoramento, sistemas autônomos e programas integrados – gera quantidades massivas de dados que abrangem desde medições físico-químicas até imagens de alta resolução dos ambientes marinhos (UNCTAD, 2022; Molinari *et al.*, 2021). Essa abundância de informações oferece um potencial sem precedentes para o entendimento dos processos oceânicos e para a gestão sustentável dos recursos marinhos, mas também impõe desafios críticos na integração, processamento e validação dos dados brutos.

A heterogeneidade dos dados, oriundos de diferentes sensores e distribuídos em múltiplas escalas temporais e espaciais, dificulta a extração manual de informações relevantes por especialistas. Soma-se a isso à presença de ruídos, lacunas e inconsistências que comprometem a qualidade das análises, tornando inviável um processamento pontual e manual. Diante desse cenário, torna-se imprescindível o desenvolvimento de soluções automatizadas que consigam transformar os dados coletados em informações confiáveis e acionáveis para a tomada de decisão (Silva *et al.*, 2023; Ferreira *et al.*, 2022).

Nesse contexto, técnicas de inteligência artificial, especificamente algoritmos baseados em redes neurais profundas, emergem como ferramentas poderosas para enfrentar essa problemática. Estudos recentes demonstram a eficácia de abordagens baseadas em deep learning na interpretação de grandes volumes de dados provenientes de diversas fontes (Caricchio *et al.*, 2025). Tais métodos possibilitam não apenas o processamento em tempo real, mas também a validação automatizada dos dados captados, assegurando que apenas informações com alta qualidade e confiabilidade sejam disponibilizadas para operadores e gestores.

A convergência entre a abundância de dados provenientes de múltiplas fontes e a aplicação de métodos automatizados de processamento e validação representa, portanto, uma área de extrema relevância e oportunidade (Silva *et al.*, 2023). A integração de técnicas avançadas de IA, combinada com estratégias de data fusion e algoritmos robustos de reconhecimento de padrões, tem o potencial de transformar a maneira como os dados oceanográficos são utilizados para monitoramento ambiental, segurança marítima e gestão de recursos naturais (Dwyer *et al.*, 2024; Tziolas *et al.*, 2020). Essa abordagem não apenas aprimora a acurácia na detecção de eventos operacionais, mas também contribui para a construção de sistemas informacionais resilientes e adaptáveis às variações das condições marinhas.

Diante desse cenário desafiador e dinâmico, a presente dissertação propõe desenvolver e validar métodos baseados em inteligência artificial para o processamento e a interpretação dos grandes volumes de dados oceanográficos. Ao combinar algoritmos de redes neurais com técnicas de integração e validação de dados de múltiplas fontes, o trabalho busca superar as limitações dos métodos tradicionais e contribuir para a construção de sistemas de informação robustos e eficientes, aptos a transformar dados brutos em *insights* estratégicos operacionais.

1.2 Objetivos

O principal objetivo deste trabalho é investigar o desempenho de sistema de detecção automática de alvos (ATR, sigla em inglês) em matrizes de dados distintas com aplicação para a Oceanografia Operacional. Como objetivos específicos são listados:

- Propor uma abordagem metodológica baseada em um modelo adaptado do YOLOv8+SAHI, integrando CNN, dados AIS e imagens de satélite, a fim de aumentar a consciência situacional marítima através da detecção de embarcações não cooperativas;

- Propor uma abordagem metodológica baseada na rede neural YOLOv11 customizada para detecção, em tempo real, de minas navais a partir de dados de side scan sonar.

1.3 Estrutura

Em acordo com o regimento interno do Curso de Pós-graduação em Geofísica da Universidade Federal da Bahia (Deliberação Normativa 01/2019), esta Dissertação está estruturada no formato de compilação de dois artigos científicos, os quais um já foi aceito e publicado em revista conceito 1A QUALIS da CAPES e o segundo artigo encontra-se submetido, aguardando parecer dos revisores.

Cada artigo corresponderá a um capítulo da Dissertação, cujo conteúdo equivale à totalidade de cada trabalho. Este manuscrito está organizado da seguinte maneira. No "Capítulo 2" apresentamos um Estudo de Caso sobre o uso da rede neural YoloV8 para detecção de embarcações não colaborativas usando dados SAR do Sentinel-1: (artigo publicado na *IEEE Geoscience and Remote Sensing Letters* – https://doi/10.1109/LGRS.2024.3508462). Ao passo que no "Capítulo 3" realizamos uma Avaliação Operacional de dados de Sonar de Varredura Lateral aplicados à Detecção de Minas Navais usando um Algoritmo de Reconhecimento Automático de Alvos (artigo submetido na *IEEE Geoscience and Remote Sensing Letters*). O "Capítulo 4" discute os principais resultados dos capítulos anteriores e traz uma conclusão geral ao trabalho.

2

Artigo 1

YoloV8 neural network application for non-collaborative vessel detection using Sentinel-1 SAR data: A Case Study

Citation: Caricchio, C., Mendonça, L. F., Lentini, C. A., Lima, A. T., Silva, D. O., and e Góes, P. H. M. (2024). YoloV8 neural network application for non-collaborative vessel detection using Sentinel-1 SAR data: A Case Study. IEEE Geoscience and Remote Sensing Letters, doi:10.1109/LGRS.2024.3508462.

2.1 Abstract

Non-collaborative vessels are usually involved in illegal activities and actively monitoring these vessels is one of the most challenging task. This study introduces a methodology that combines AIS data and SAR images into a YOLOv8+SAHI-based approach, as a decision aid tool for non-cooperative vessel detection, to improve maritime domain awareness. It was used 1958 augmented images to custom train the YoloV8 neural network. For the study case, 16 Sentinel GRDH-IW SAR images were used. During the training, the custom model achieved excellent performance with satisfactory statistical results (mAP@.5: 94.3%, precision: 92.5% and recall: 91.9%), especially when compared to similar previous studies. The model was able to correctly distinguish between vessels and non-vessel features, such as islands, rivers or coastlines. In the study case, the false negative detection rate was 95.4%, similar to mAp@0.5 results found at the training and validation step and the Recall was 95.6%, considered excellent results. The Recall improvement in the study case shows that the model's performance in real-world scenarios is better than initially expected for

application in non-collaborative vessel detection systems. The model presented showed very promising results for the operational detection of darkships using, simultaneous, SAR images and AIS data.

Index Terms—convolutional neural networks (CNNs), Dark ships, IUU fishing, Machine Learning.

2.2 Introduction

Non collaborative vessels, also known as dark ships, are those vessels that do not voluntarily report their position to avoid regular maritime surveillance systems (Prasad *et al.*, 2023). They are usually involved in drug smuggling and weapons trafficking, as well as in Illegal, Unreported, and Unregulated (IUU) fishing activities (Liddick, 2014), nearly 90% of illegal vessel activity goes undetected (Milios *et al.*, 2019). Only the IUU fishing activity alone costs the global economy at least 41 billion dollars per year, threatening economic security, natural resources critical to global food security, and biodiverse ecosystems (Temple *et al.*, 2022). In this context, coastal states are increasing their efforts to improve their maritime situational awareness to curb such illegal activities in their exclusive economic zones and international waters (Fujii *et al.*, 2021; Doumbouya *et al.*, 2017; Siousiouras and D. Dalaklis, 2009).

On the other hand, active ocean monitoring is a major challenge due to the vastness of the ocean and the limitations of tracking systems (Thoya *et al.*, 2021; Gjerde, 2012). In remote areas beyond the reach of coastal radars, efforts have focused on satellite imagery (Heiselberg, 2020) or Automatic Identification System (AIS) data, which can be disabled or spoofed. AIS is an automatic tracking device that uses transceivers on ships and is used by Vessel Traffic Services (VTS) to report the ship's position.

Over the past two decades, the availability of satellite data has increased significantly because of government initiatives, first with the release of the Landsat Program archive in 2008 and more recently with the Copernicus Program, which provides free and open super spectral imagery data (Milios, 2019; Tziolas *et al.*, 2020). SAR imagery can provide all-weather and day/night monitoring of vessels, including small vessels (20-30 m), that are not easily visible in optical imagery (Franceschetti and Lanari, 2016). In this way, SAR and AIS data can be combined to improve the ship's surveillance capability (Zhao *et al.*, 2014).

Recent technological developments, which have significantly increased the availability of satellite data, have also brought to attention the problem of analyzing and accessing the information behind the enormous amount of available data (Ferreira *et al.*, 2022). Therefore, using neural networks to analyze such data represents a turning point in remote sensing and spatial image processing, identification, and target detection (Maggiori *et al.*, 2016). The study conducted by Abburu and Golla (2015) pointed out that although manual satellite image classification methods are considered robust and effective, they can consume significant time and depend on the analyst's familiarity and knowledge, turning it into an ineffective operational method.

On the other hand, neural networks can process and interpret large volumes of high-resolution data and automatically identify features and objects of interest with improved accuracy (Alam *et al.*, 2020). In particular, the application of convolutional neural networks (CNNs) has revolutionized the ability to detect patterns in multispectral and radar imagery, facilitating tasks such as land use classification, environmental monitoring, and object detection (Tziolas *et al.*, 2020). The efficiency and flexibility of the CNNs allow them to obtain deeper information and make faster and more reliable assessments, thus significantly advancing knowledge in Earth Observing Systems (Ferreira *et al.*, 2022). Taking the monitoring of oil spills at sea as an example, Singha *et al.* (2013), using an Artificial Neural Network on SAR images, obtained a correct identification of 91.6% of reported oil spills, while Kadhim and Abed (2019) using Deep CNN obtained 94.01

Based on the above, due to its higher accuracy, faster speed, less human intervention, ship detection with artificial intelligence in synthetic aperture radar images had become a research hotspot. Although the topic has already been studied over the last two decades (Zhang, 2020; Schwegmann *et al.*, 2016; Leung *et al.*, 2002), the constant evolution of the neural networks computational capacity still requires new studies to establish an optimal methodology for detecting ships from SAR images (Ren *et al.*, 2023; Tang *et al.*, 2024; Lv *et al.*, 2024; Humayun *et al.*, 2024).

This paper proposes a novel comprehensive methodology integrating CNN, AIS data, and satellite imagery target detection. The main objective of this fusion is to propose a YOLOv8+SAHI-based approach to enhance maritime domain awareness through the localization of non-cooperative vessels, thus preventing unlawful activities at sea. The major contribution of this article is the proposal of a combined methodology using YOLOv8 and the SAHI module for the detection of small ships in large SAR images, with which the original image slicing into small frames allows better inference results with YoloV8. The experiment conducted in the Case Study demonstrates that the YOLOv8+SAHI detects ships with competitive results in comparison with some previous works. This paper is organized as follows. Section 2 presents the dataset and methods used in this study. Section 3 describes the results of the custom training of the neural network and discusses its use, fused with AIS data, on a set of SARimages as a case study. Finally, Section 4 provides a brief conclusion and suggestions for future works.

2.3 Data and Methods

This study can be divided into two phases: Phase 1 is the development and adaptation of a custom-trained network, while Phase 2 evaluates these results in a practical case study. The flowchart of the methodology is shown in Fig. 2.1.

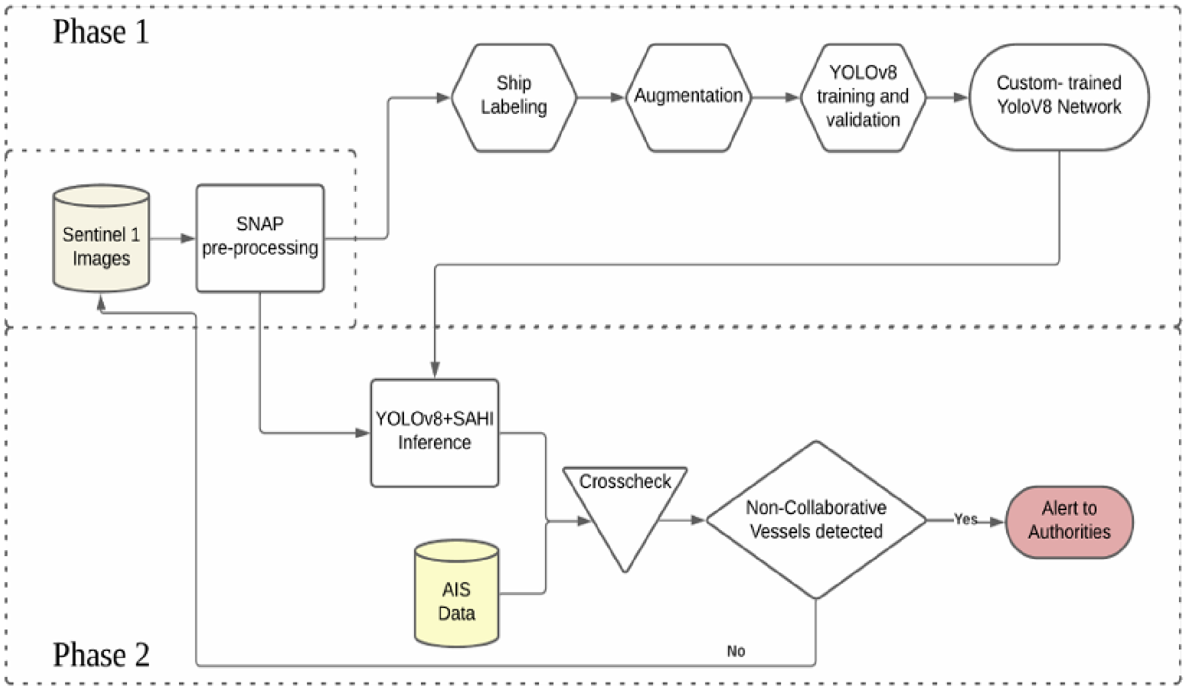

Figura 2.1: Non-collaborative vessel detection system workflow using remote sensing imagery.

Synthetic Aperture Radar images from the Sentinel-1 mission conducted by the European Space Agency have been used to train the algorithm. This SAR data consists of a constellation of two polar-orbiting satellites (S1A and S1B) with a 6-day repeat cycle, operating in almost all-weather conditions day and night. Given our interest in categorizing and discriminating small targets, we focus on analyzing the processed level-1 high-resolution ground range detected (GRDH) interferometric wide (IW) swath S1 images with a pixel spacing of 10 m and resolution of 20×22 m.

Our non-collaborative vessel detection strategy focuses on improving detection performance in near real-time, particularly for small ships. To achieve this, we use a computationally less expensive med-size YOLO-V8-M model (hereafter YoloV8) (Glenn, 2023) coupled with a Slicing Aided Hyper Inference (SAHI) module to run the inferences and to improve the obtained results. The SAHI module slices a large image into smaller regions, each representing a local crop of the original image. Small targets in the original image become relatively more prominent than their local crops. This provides better visual details for the YoloV8 model. As a result, the combination of YoloV8+SAHI allows for better detection of small targets (Akyon *et al.*, 2022). A detailed explanation of the applied methodology can be found in Ye *et al.* (2024).

Before using the SAR images to train and validate the neural network, they were preprocessed with the SNAP software to improve their quality due to speckle filtering and data conversion. The SNAP software and its various toolboxes are freely available on the ESA's webpage (https://step.esa.int/main/download/snap-download/) for download. After augmentation, a subset of 1958 images with 640 x 640 pixels were used to train and validate the YoloV8 neural network. The model was trained on a GPU for 300 epochs, a batch size of 32, and a learning rate of 0.01. All the images were annotated using Roboflow (Dwyer *et al.*, 2024).

For the case study, 16 Sentinel GRDH-IW SAR images were used. More information about the images can be found on the supplementary material. The targets identified in the YoloV8+SAHI inference of the SAR images were then compared with simultaneous AIS data in the same area. Since the AIS data was mainly from satellite sources, it was considered simultaneously within a one-hour interval of SAR imagery collection to ensure a significant number of vessels. Furthermore, a 50 km uncertainty radius was used to correlate the detected target by the neural network with an AIS data spot. Vessels without correspondence with the AIS source were classified as non-collaborative vessels, and this result, as part of a decision aid tool, should be reported to marine traffic authorities for further analysis.

To evaluate our results, we rechecked the YoloV8+SAHI inference and the AIS data using a manual classification to ensure the framework's effectiveness.

2.4 Results and Discussion

2.4.1 YoloV8+SAHI Custom Training Model

The mean average precision (mAp@.5), metrics precision (P), and recall (R) are used to evaluate the detection performance of the model. The customized model obtained an excellent performance with satisfactory statistical results (mAP@0.5: 94.3%, P: 92.5%, and R: 91.9%), especially when compared to similar previous studies (Table 2.1).

Table 2.1: Comparison of mAP@.5, P, and R with previous studies using CNN to detect vessels from SAR imagery.

	mAp@.5	**Precision (P)**	**Recall (R)**
This study	94.3%	92.5%	91.9%
Yu and Shin (2023) [31]	93.6%	93.9%	87.7%
Patel *et al.* (2022) [32]	65%	70%	63%
Tang *et al.* (2021) [33]	90.1%	70.8%	92.65%
Sun *et al.* (2021) [34]	93.9%	94.8%	93.9%
Devadharshini *et al.* (2020) [35]	-	89%	80%

We attribute the superior performance of our system to the improved accuracy and speed of YoloV8 compared to the earlier versions of YOLO and other deep-learning detection systems. Furthermore, the SAHI module allows the slicing of original SAR images into small blocks, increasing the Yolo network's classification capacity.

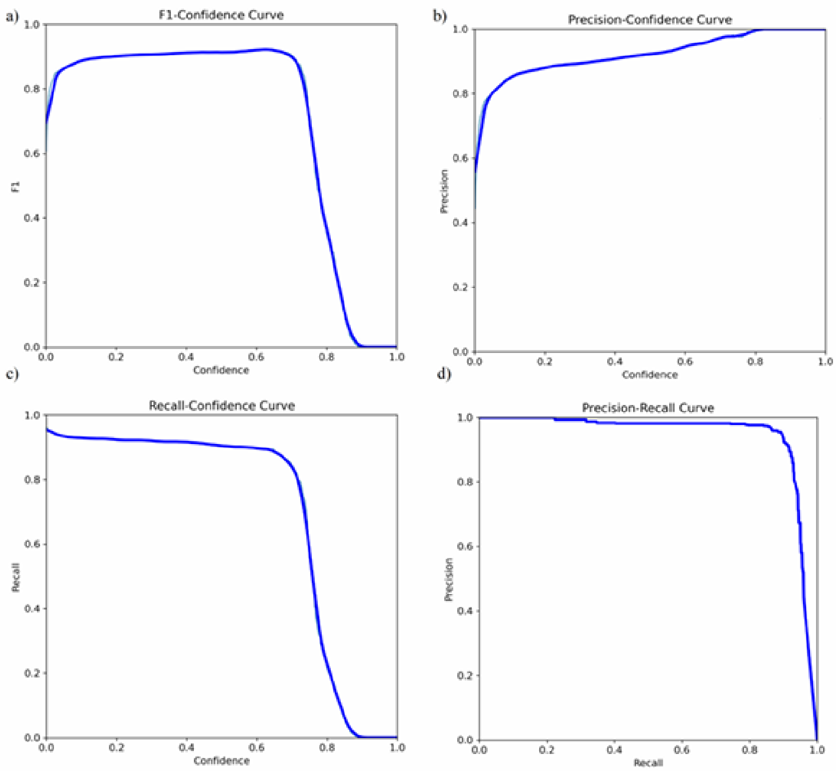

Figura 2.2: Results of the model training: (a) F1-Confidence Curve, (b) Precision-Confidence Curve, (c) Precision-Recall Curve, and (d) Recall-Confidence Curve.

The normalized confusion matrix of the YoloV8 model obtained in the test set shows the model correctly identified 95% of the ships and failed to identify only 5%. The F1-Confidence curve shows the best F1 score of 0.92 with a confidence threshold of 0.471 (Fig. 2.2a). Still, as soon as the Precision and Recall-confidence curves also have a plateau shape (Fig. 2.2b and 2.2c), with the sharp drop only after the 0.6 confidence level, we assumed the threshold of 60confidence as the optimum level to be used in the inferences of the case study.

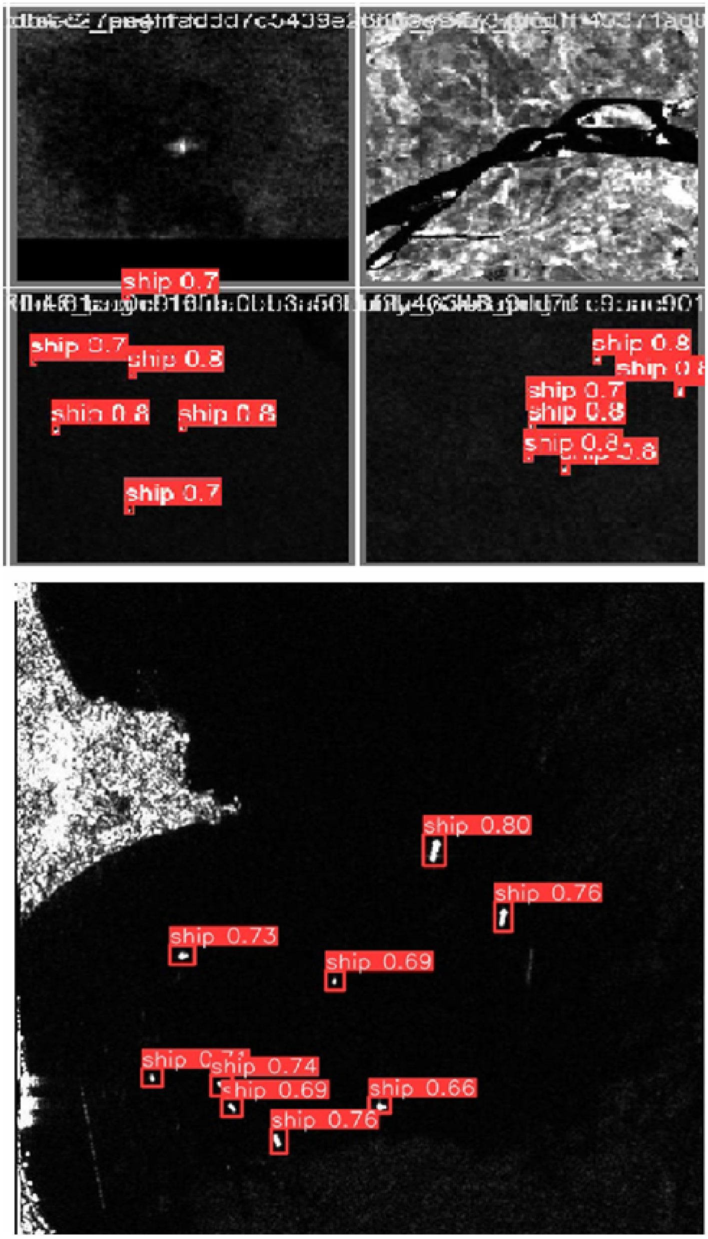

Figura 2.3: Examples of the YoloV8+SAHI raw output: (a) validation batch showing the network's ability to correctly classify ship and non-ship features and (b) a zoomed image with anchored vessels and their respective detected confidence levels. This satellite image is centered on Lat. 12.97ºS and Long. 38.52ºW, near Salvador Harbour Area, Brazil.

Fig. 2.3 shows examples of the YoloV8+SAHI outputs. The model can correctly distinguish between vessels and non-vessel features, such as islands, land, rivers, or coastline (Fig. 3a). Taking a closer look at the inference (Fig. 3b), it can be observed the bounding boxes with the respective confidence values that the network detected nine ships in an anchorage area. All the vessels identified had a confidence level higher than 0.6, confirming the above-proposed threshold of 60% for the pilot project.

2.4.2 Case Study

On average, the YoloV8+SAHI model took 13.2 minutes to run the inference on the 16 images selected for this case study. Figure 2.4 shows an example of the post-processed output, where the red pins represent a possible non-collaborative vessel and the green pins represent a target with an AIS correlation.

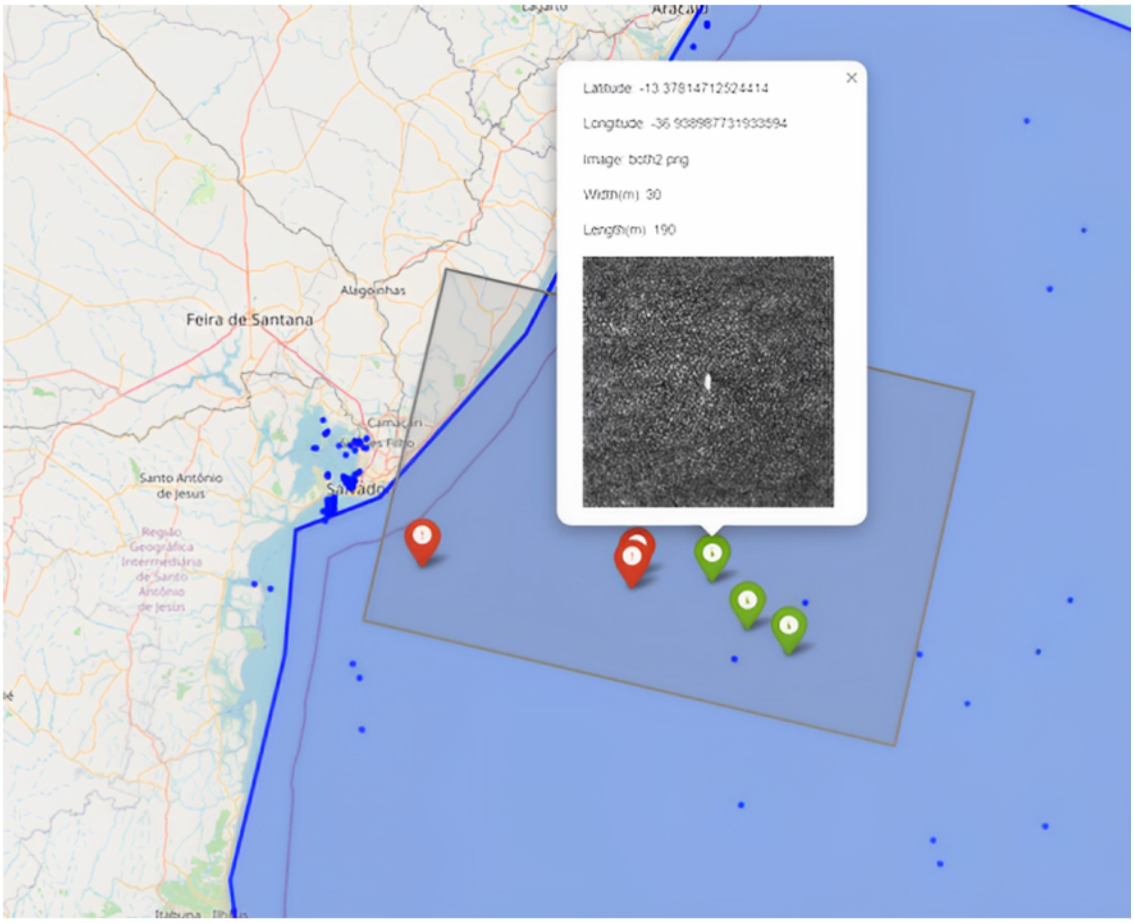

Figura 2.4: Inference results and simultaneous AIS data crossed output. Green pins represent a target with an AIS correlation, and red pins represent a possible non-collaborative. This satellite image is centered on Lat. 13.09ºS and Long. 38.37ºW, coast of Bahia, Brazil.

A total of 230 targets were identified after the inference, of which 172 (74.8%) were correlated with a collaborative vessel (with AIS signal), and 58 targets (25.2%) did not have an AIS correlation (i.e., probable non-collaborative vessel). From the visual analysis of the 58 probable dark ships, 18 (31%) were not vessels; they represented clouds or land features with high reflectance in the SAR image. Although the error rate for False Positives (FP) may initially be considered high, a human analyst can easily discard an FP, so such results do not significantly impact the model's outcome, which is to develop a decision-aid tool to increase maritime situational awareness. The False Negative (FN) detection rate was 95.4%, similar to mAp@0.5 results at the training and validation phases. In the 16 selected SAR images, 175 vessels were visually identified, whereas the model correctly identified 167 out of this total. To evaluate the model's performance, we used the Recall variable, a critical metric since not detecting a non-collaborative vessel (FN) is more harmful than identifying different features as vessels (FP).

$$\text{Recall} = \text{TP} \ / \ (\text{TP} + \text{FN})$$

Using the above formula to calculate the Recall in the Study Case inferences, a score of 95.6% was obtained. Theimprovement of this metric in the Study Case compared to the Recall obtained during the model training part, shows that the model's performance in real-world scenarios is better than initially expected for application in non-collaborative vessel detection systems.

2.5 Conclusion

This paper discussed how a customized YoloV8+SAHI neural network could help increase maritime situational awareness and how it can be used as a decision-aid tool for non-collaborative vessel detection. The methodology presented here showed promising results in simultaneously detecting non-collaborative vessels using Sentinel-1 SAR images and AIS data. The proposed neural network used the YoloV8 concomitantly with the SAHI module (YoloV8+SAHI) to effectively balance lightweight design with high accuracy and speed in detecting small targets such as vessels in large satellite radar images. Furthermore, it is essential to highlight that for further studies, some opportunities for improvement were identified, such as using a more extensive training dataset that could may reduce the False Positive rate and introduce a maritime traffic density analysis to help improve the ability of the system to identify and classify the non-collaborative vessels.

3

Artigo 2

Operational Assessment of Side Scan Sonar data applied to Naval Mine Detection using an Automatic Target Recognition Algorithm

Citation: Caricchio, C., Mendonça, L. F., Lima, A. T. and Lentini, C. A. (submitted). Operational Assessment of Side Scan Sonar data applied to Naval Mine Detection using an Automatic Target Recognition Algorithm. IEEE Geoscience and Remote Sensing Letters.

3.1 Abstract

Mine Warfare (MW) and Mine Countermeasures (MCM) have become strategic options to ensure national sovereignty and the safety of maritime commercial routes, which is the primary logistics system for international trade. As an asymmetric weapon, locating and neutralizing a naval mine becomes a great challenge for the worldwide Navies. In this context, this work proposes an object detection model based on YOLOv11 for automatic and real-time detection of naval mines in harbour areas using Side Scan Sonar (SSS) data. The main objective of this tool is to apply it to Unmanned Maritime Vehicles (UMVs) to enhance the mine detection efficiency during minehunting operations. Secondarily, this study aims to evaluate the effects of operational parameters, oceanographic and meteorological conditions on the SSS data quality for naval mine detection. All the data used to train the neural network were real and obtained in a test area, mimicking a port area, a strategic environment in the context of MW. The model performed with satisfactory statistical results (mAP@0.5: 0.84, P: 0.93, R: 0.83, and, F1 Score: 0.88). Based on the results provided in this study, the 0.70 confidence level can be safely used in future operational inferences using this customized

model. From the operational evaluation of SSS data quality, the ideal condition for data acquisition is using an intermediary range and high-frequency sonars with calm seas and low speeds. Despite the recent advancements in the field of machine learning, it is unlikely that neural networks will fully replace human operators in MCM missions in the short to medium term. However, they serve as a valuable tool for decision support, enabling rapid analysis of large datasets and filtering information to present only the most relevant data to human analysts, such as potential sea mines.

Index Terms— Machine Learning, Maritime Mine and Countermeasure, Mine Warfare, Target Detection, YOLO.

3.2 Introduction

According to the UNCTAD (2022), global maritime trade carries over 802.1the maritime context, imply higher shipping costs and lower maritime connectivity, leading to higher inflation, shortages of food and interruptions of supply chains, which are relevant factors for a global crisis. In this context, as a single mine inserted strategically in a harbour area or in a shipping route can stop maritime movements for days while the entire area is swept (Léonard *et al.*, 2013), MW and MCM are strategic components for the worldwide Navies to ensure national sovereignty and the safety of maritime commercial routes (Lluy, 1995).

Sea mines are a cost-effective weapon for asymmetric warfare in the maritime domain. MW has shaped many conflicts throughout the twentieth century (Huberman, 2021) and is responsible for most US ship casualties after World War II (NRC *et al.*, 2000). Launching a naval mine into the sea is an operation that involves minimal risks and low cost; on the other hand, MCM operation requires costly specialized equipment, qualified human resources, and high-casualty risk (Huberman, 2021). Furthermore, the cost of mine hunting and clearance is totally out of proportion with the cost of placement, and the process is extremely slow, providing yet another asymmetrical advantage (Donohue, 1994). Sea mines can be used as defensive or offensive weapons, and due to their low cost, they are a key element for the Navies of developing countries for anti-access, area denial, and maritime control strategies and operations (Truver, 2012).

MCM operations are conducted by Sweeping or Minehunting vessels and, recently, by unmanned platforms. Sonars are the primary data source for identifying potential sea mines in the minehunting (Léonard *et al.*, 2013). During World War II, the progress of sonar systems was driven by the urgent need to detect enemy submarines, leading to the introduction of technologies such as active and passive sonar (Holt, 2008). Inventions such as the side scan sonar (SSS) allowed for more effective detection, wide coverage, high resolution, and reliable imaging capabilities, resulting in a significant impact on naval battles (Verbrugge, 2017; Wei *et al.*, 2009). In the post-war period, sonar research continued to advance, developing more sophisticated systems, such as multi-beam and synthetic aperture sonar, which improved resolution and underwater imaging capabilities. Theseinnovations transformed military tactics and opened new opportunities for scientific research and ocean exploration (Lurton, 2011).

Small objects, like sea mines, often have weak acoustic signatures that can easily blend into the surrounding noise or get obscured by complex seabed topography (Zheng and Tian, 2018). Developing advanced detection systems to overcome these barriers is pivotal for maritime safety, scientific exploration, and military operations. Innovative solutions like high-resolution sonar technologies, enhanced acoustic processing techniques, and advanced machine-learning algorithms are being developed to address these challenges. These tools aim to refine detection accuracy and improve system efficiency, enabling them to differentiate between real targets and environmental interference (Zou *et al.*, 2025).

The evolution of sonar has not only revolutionized naval operations but has also served as a catalyst for developing UMVs (Bae and Jungpyo, 2023). These UMVs are equipped with advanced sonar systems, allowing real-time data collection for many research fields, such as oil and gas, bathymetry, shipwrecks, underwater archeology and the presence of artificial structures or sea mines (Fahlstrom *et al.*, 2022). Compared with the financial and human resources costs of a minehunting vessel operation, the UMVs are considered a low-cost option with high efficiency, sonar accuracy, and no human risks (Li *et al.*, 2023), being a big bet for the future of MCM.

Underwater UMV operations provide a challenging environment; in particular, the communication windows and bandwidth are restricted (Sariel *et al.*, 2008), leading the UMVs to need onboard decision-aid tools to ensure real-time and accurate data analysis. Considering the high resolution of SSS and the dimensions of a survey area, the volume of data collected simultaneously in a mine search operation is exceptionally high (Zou *et al.*, 2025). In this way, detailed analysis and real-time data processing become key factors and, simultaneously, a bottleneck in the operation's success. On the other hand, with the fast evolution of machine learning and artificial intelligence techniques, detection algorithms have been developed to assist sonar operators in filtering and detecting targets of interest in an agile and precise manner (Udaya et al., 2024).

The convolutional neural network (CNN) YOLO (from the acronym You Only Look Once, referring to the fact that it is an algorithm capable of carrying out the detection task with a single pass through the network) is a fast and efficient approach to object detection, being an excellent option for real-time target detection tasks (Wang and Hong-Yuan, 2024) due to its low-latency characteristics (Tian *et al.*, 2025). YOLO is a single-pass detector that uses a CNN for image processing (Ahmed et al., 2024). Its first version, presented in 2016 (Redmon *et al.*, 2016), has undergone several iterations lately. The YOLOv11 version significantly improves real-time target detection, achieving remarkable gains in processing speed and substantially enhancing real-time performance capabilities (Khanan and Hussain, 2024). The efficiency of the previous versions of YOLO is scientifically proven for application in surveillance systems, autonomous vehicles, and real-time video processing (Shafiee *et al.*, 2017; Zacchini *et al.*, 2020; Narejo *et al.*, 2021) and even for detecting submerged targets in real time (Zou *et al.*, 2025; Wang *et al.*, 2021; Steiniger *et al.*, 2021). According to the review by Jegham *et al.* (2024), computationally the YOLOv11 is recommended for constrained environments, real-time monitoring, and rapid response scenarios, all characteristics present on MCM missions using unmanned vehicles.

Therefore, the primary goal of this paper is to propose an object detection model based on YOLOv11 for automatic and real-time detection of naval sea mines in harbour areas using SSS data. The main objective of this tool is to apply it on UMVs to enhance the mine detection efficiency during minehunting operations. Secondarily, as an unprecedented publication, this study aims to evaluate the effects of operational parameters and meteorological conditions on the SSS data quality for naval mine detection.

The manuscript is organized as follows: Section 2 presents the dataset and methods used, Section 3 describes the results with a discussion, and Section 4 provides a brief conclusion and suggestions for future works.

3.3 Data and Methods

Using a Klein 3000 (100/500 kHz) and a Edgetech 4125 (400/900 kHz) dual frequency SSS, a parameterized test was conducted to evaluate the SSS performance in detecting mines and mine-like objects (MLO). Different SSS frequency, range parameters, navigational speed and direction and, also, meteoceanographic conditions were tested to assess which configuration allows the SSS to provide the best data quality for visually detecting naval mines in shallow waters.

For the YOLOv11 training step, all the SSS images were based on real data obtained in a test bay area in shallow and protected waters (less than 30 m depth), mimicking a port area, a strategic environment in the context of MW. The SSS dataset was composed of data from different SSS models and frequencies to provide the neural network with as much variability as possible for the target discrimination capacity.

The test area was planted with real subsurface exercise mines (Fig. 3.1a) and bottom MLO (Fig. 3.1b). The availability of a sufficient amount of data to train and validate the model is a well-known problem in this science field (Munteanu *et al.*, 2022; Denis *et al.*, 2017). Therefore, it was decided to compose the MLO and the real exercise sea mine images into a single class to improve the number and variety of images. Also, augmentation techniques, such as mosaic, blur, noise, flip and brightness, were applied using Roboflow (Dwyer *et al.*, 2024).

The training of the convolutional neural network (CNN) architecture YOLOv11 (You Only Look Once, version 11) was performed utilizing an NVIDIA T4 GPU, over 900 epochs with a batch size of 16, targeting a single-class detection problem focused on naval mines. YOLOv11, a real-time object detection model based on a fully convolutional backbone with embedded residual and attention modules, was trained using a curated dataset of annotated sonar images. These images were selected to ensure variability in size, contrast, and background complexity, enhancing the generalization capability of the model. The training and validation phases employed a medium size model configuration to balance detection accuracy and computational efficiency. Model performance was quantitatively assessed using standard object detection metrics, including mean Average Precision at Intersection over Union threshold 0.5 (mAP@0.5), Precision (P), Recall (R), and F1-score, along with confidence threshold optimization and latency time measurements, aiming at operational suitability for real-time mine detection tasks in maritime environments.

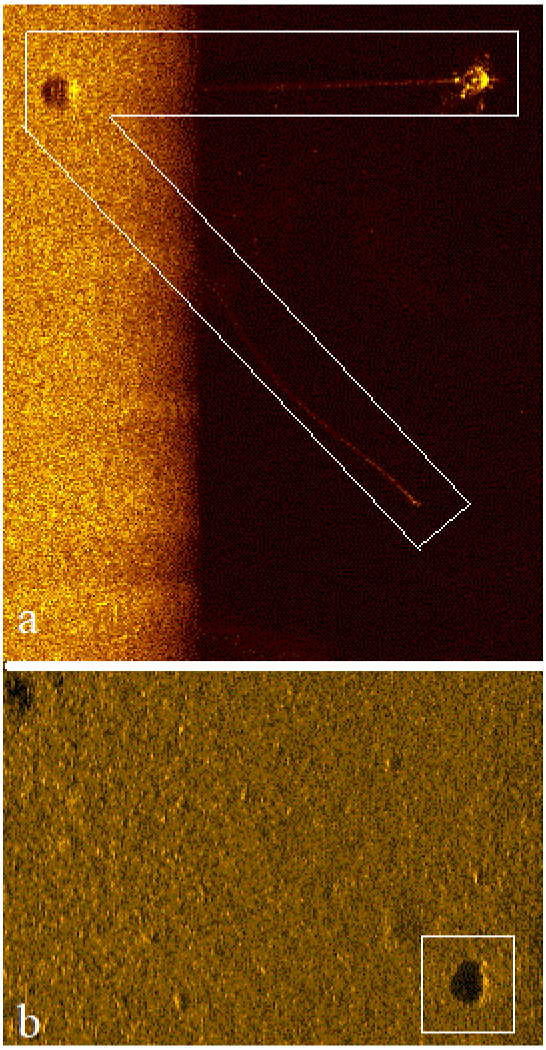

Figura 3.1: Example of a (a) subsurface exercise mine and a (b) bottom MLO images used for model training.

3.4 Results and Discussion

In the context of MW, the results of the sonogram analysis should focus not only on the hit rate (True Positive (TP) or True Negative (TN), but mainly on the rate of critical errors, i.e., False Negatives (FN), which would imply, in practice, that a mine would not be identified, nor neutralized, incurring serious life-threatening and damage to navigation. Although they are also considered errors, False Positive (FP) results, as long as they are not in large amounts, do not imply serious consequences for MW, only increasing the operating time for target rectification or confirmation.

Based on the above, Recall is the most critical metric in the context of convolutional neural networks (CNNs) applied to naval sea mines detection tasks, as it measures the ability of the model to correctly identify all relevant positive instances - specifically, the proportion of true positives relative to the total number of actual positives in the dataset. In practical terms, a high recall indicates that the network is effectively reducing false negatives, which is of paramount importance in naval mine classification scenarios where failure to detect a target can lead to serious operational hazards. Consequently, high Recall values directly increase the trustworthiness of the system for MCM applications, ensuring that the detection framework prioritises safety by maximising sensitivity to real targets.

3.4.1 Parametric evaluation on SSS data quality

Fig. 3.2 shows the effects on the data quality regarding the parameters analyzed during the parametric evaluation. In the data collected in more adverse conditions (i.e., waves above 1 m and winds above 15 knots), the negative effects of environmental conditions on the data quality create dark stripes on the sonograms and, consequently, increased the degree of difficulty to detect small objects, especially on abeam navigation (Fig. 3.2, middle).

Optimising survey lines, preferably towards the bow or stern of the vessel, avoiding cross-track navigation and using platforms with inertial measurement units (IMUs) can improve sensor stability and reduce the effect of sway on the acoustic images. The use of convolutional neural networks trained in different sea conditions through data augmentation also contributes to the robustness of the model, making it more efficient at detecting targets in adverse conditions.

A negative effect was observed regarding navigation speed on the data collected at speeds above 6 knots. The speed-generated interference zones in the sonogram could hide the target due to its dark bands (Fig. 3.2, bottom). In a real situation, this would be a critical error, i.e., FN, due to errors in the data acquisition parameters.

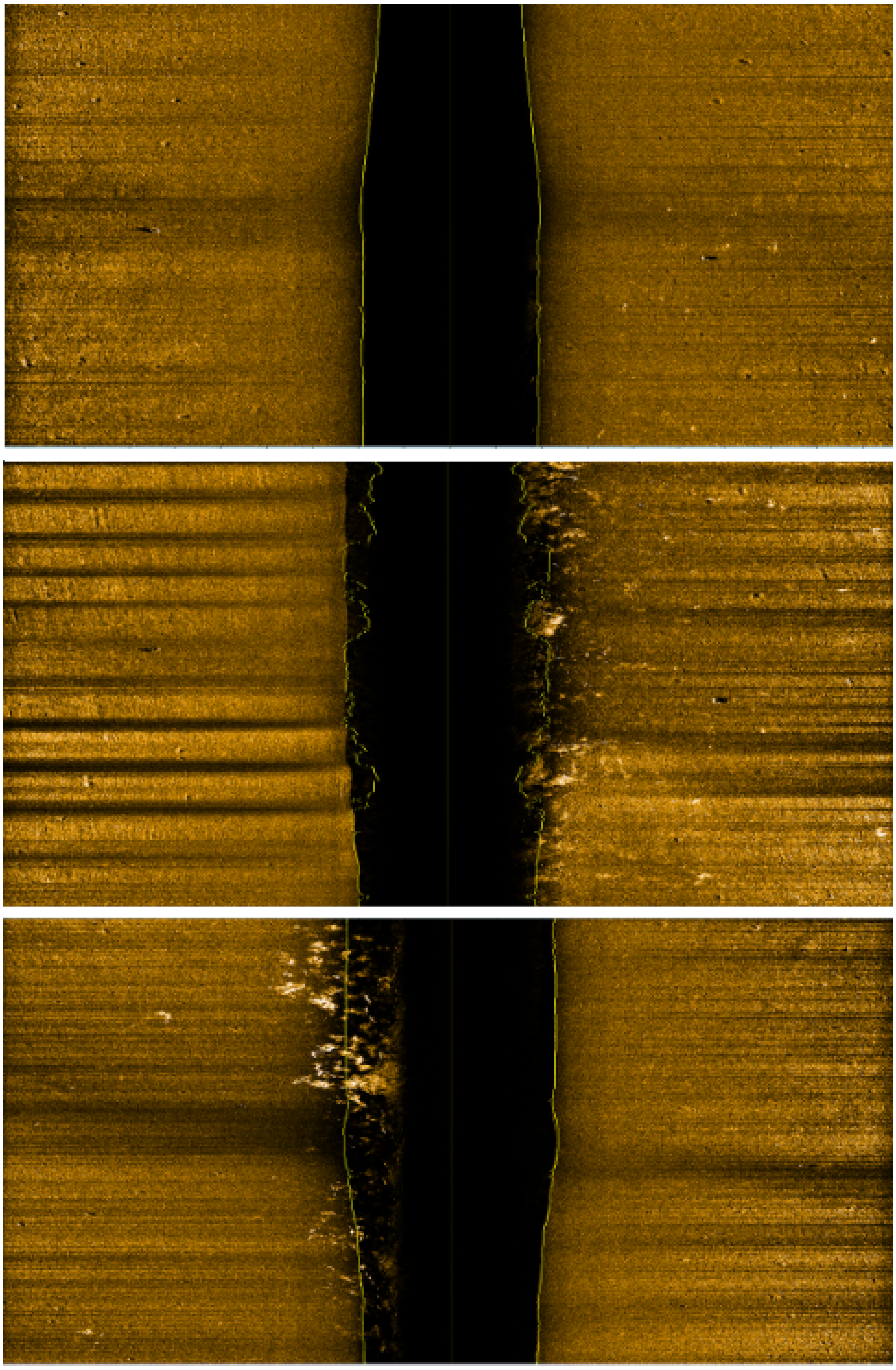

Figura 3.2: Example of SSS data with high quality (top panel), meteoceanographic interference (middle panel), and velocity interference (bottom panel).

In the operational range, the relative size of the targets was reduced when using the 75-m range. Although this range covers a larger area (i.e., fewer probing lines and,consequently, less time for the search stage), the reduced size of the targets makes their detection difficult. Thus, as already presented in previous studies (Ludwig, 2000), the 75-m range could be applied when searching for large objects or a preliminary sweep of the minefield. In the SSS data acquired within the 37-m and 50-m range, qualitative differences were not observed in the retrieved images. Therefore, based on the results obtained in the present study using high-frequency SSS (900 kHz) in a standard sweeping mission conducted in shallow water environments, the 50-m range would be the most suitable configuration since it allows good visualization of targets with 1-m dimension, in addition, to optimize the minefield sweeping time when compared to the 30-m range.

3.4.2 YOLOv11 model

The model performed with satisfactory statistical results (mAP@0.5: 0.84, P: 0.93, R: 0.83, and F1 Score: 0.88), even when compared to recent studies using improved versions of YOLOv11 (Zou *et al.*, 2025), where the metrics obtained in the detection of small objects from SSS data were mAP@0.5 = 0.83, P = 0.93, R = 0.70.

Based on the F1 Score, R and P confidence curves (not shown here), it was possible to obtain the best F1 Score, R, and P at 0.68, 0.86 and 0.89 of confidence levels, respectively. Therefore, based on those results, the 0.70 confidence level is proposed to be safely used in future inferences using this customized model.

On Fig. 3.3 it is presented, as an example, a validation batch with 16 different sea mine and null images. The network correctly interpreted 13 images as TP and 3 as TN, giving a 100threshold of 70results align well with the metrics obtained during the neural network training.

Regarding the latency time, the customized model took, on average, 25.1 ms per image to run the inference. For SSS data, this low latency is good enough to ensure sea mine operational detection in a real MCM scenario, where the ping rate is 3-12 ms and the waterfall window data has more than 450 pings.

Comparing the present paper with previous YOLO applications (Redmon *et al.*, 2016; Guan, 2023; Kang and Kim, 2023), the results suggest that the customized model may be aligned with the best practices in the field, even without relying on the most recent or complex versions of the YOLO algorithm.

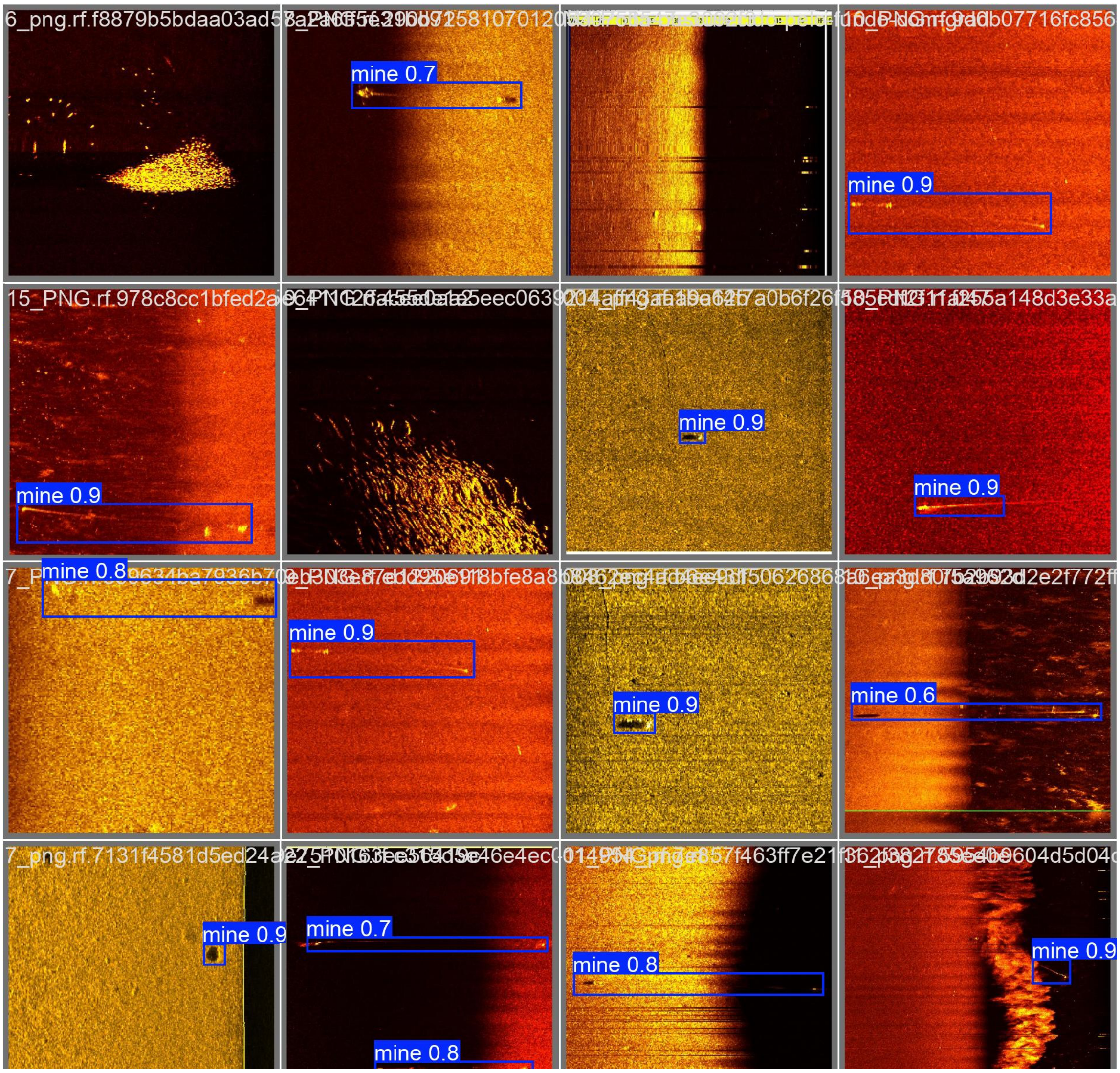

Figura 3.3: Batch validation consisted of 16 different images with eminent results, where all the targets were correctly identified by the network with a high confidence level.

3.5 Conclusion

This study presented a customized YOLOv11-based model for real-time detection of naval mines using SSS data. The results demonstrated statistically satisfactory metrics, reinforcing the feasibility of applying this approach in operational mine countermeasures missions. Furthermore, the literature's unprecedented parametric analysis highlighted the ideal conditions for acquiring high-quality data with SSS, which is essential for accurately identifying naval mines. This analysis is expected to serve as a basis for future discussions and public reviews on this topic.

Despite the promising results and rapid advancements in the field of machine learning, it is unlikely that neural networks will fully replace human operators in MCM missions in the short to medium term. Neural networks, however, serve as a valuable tool for decision support, enabling rapid analysis of large datasets and filtering information to present only the most relevant data to human analysts, such as potential sea mines. When embedded in unmanned vehicles, this technology mitigates risks to human life and enables operators to focus on verifying real targets, thereby enhancing the effectiveness of MCM operations.

Additionally, for future works, potential improvements have been identified, including the use of more extensive training datasets that could enable the differentiation between bottom mines and subsurface mines as distinct classes. This approach would facilitate more detailed results and, ultimately, contribute to reducing model errors.

The high-speed development of machine learning techniques and AI-based detection algorithms offers transformative potential in naval mine detection. These tools, embedded in UMVs, not only enhance data filtering and analysis, but also significantly assist human operators in identifying objects of interest with agility and precision. While technology continues to advance, the irreplaceable expertise of human operators remains a cornerstone of effective MCM missions. By harnessing this synergy between human judgement and AI-driven innovation, future advancements can focus on refining detection methods, expanding training datasets and ensuring operational safety during mine hunting missions.

4

Considerações Finais

No contexto da Oceanografia Operacional, esta Dissertação apresentou duas aplicações da rede neural convolucional YOLO (versões 8 e 11) em diferentes matrizes de dados (imagens satelitais SAR e sonar de varredura lateral - SVL) para detecção automática de alvos de interesse.

As principais descobertas e contribuições foram resumidas nos parágrafos a seguir.

4.1 Deteccção de embarcações não-colaborativas a partir de imagens SAR

Este trabalho propôs uma nova metodologia abrangente integrando uma rede neural convolucional, dados AIS e imagens de satélite SAR. O principal objetivo desta fusão dessa abordagem baseada em YOLOv8+SAHI foi propor uma ferramenta de auxílio à decisão para a detecção de embarcações não colaborativas visando aprimorar a consciência situacional marítima, prevenindo assim atividades ilícitas no mar. A metodologia apresentada mostrou resultados promissores na detecção simultânea de embarcações não colaborativas usando imagens Sentinel-1 SAR e dados AIS. OS resultados estatísticos foram considerados excelentes (mAP@0,5: 94,3%, P: 92,5% e R: 91,9%), especialmente quando comparado a estudos anteriores semelhantes.

O experimento conduzido no Estudo de Caso demonstra que o desempenho do modelo proposto para detecção de embarcações não colaborativas, em cenários do mundo real é melhor do que o inicialmente previsto na fase de treinamento. A rede neural proposta utilizou o YoloV8m concomitantemente com o módulo SAHI (YoloV8+SAHI) para equilibrar um design leve com alta precisão e velocidade na detecção de pequenos alvos, como embarcações, em grandes imagens satelitais SAR.

4.2 Sistema Automático de Detecção de Minas Navais

Este estudo apresentou um modelo personalizado baseado em YOLOv11m para detecção em tempo real de minas navais utilizando dados de SVL. O principal objetivo desta ferramenta é aplicá-la em veículos marítimos não tripulados visando aumentar a eficiência da detecção de minas durante operações de caça a minas. Secundariamente, como uma publicação inédita, este estudo avaliou os efeitos de parâmetros operacionais e condições meteorológicas na qualidade dos dados SVL para detecção de minas navais. Os resultados demonstraram métricas estatisticamente satisfatórias (mAP@0.5: 0.84, P: 0.93, R: 0.83, F1 Score: 0.88 e tempo de latência: 25.1 ms/imagem), reforçando a viabilidade da aplicação dessa abordagem em missões operacionais de Contramedidas de Minagem. Além disso, a análise paramétrica destacou as condições ideais para a aquisição de dados de alta qualidade com SSS (i.e. 900 kHz; 50m de alcance lateral, velocidade $<$ 6 nós, mar calmo), fator chave para a identificação precisa de minas navais.

Apesar dos resultados promissores e dos rápidos avanços no campo do aprendizado de máquina, é improvável que as redes neurais substituam totalmente os operadores humanos em missões de Contramedidas de Minagem a curto e médio prazo. Enquanto a tecnologia continua a avançar, a expertise insubstituível dos operadores humanos permanece um pilar fundamental para missões de Contramedidas de Minagem eficazes. Ao aproveitar essa sinergia entre o julgamento humano e a inovação impulsionada pela IA, os avanços futuros podem se concentrar em refinar os métodos de detecção, expandir os conjuntos de dados de treinamento e garantir a segurança operacional durante missões de caça minas.

4.3 Conclusão

O presente trabalho, ao investigar o desempenho de sistemas de detecção automática de alvos em imagens SAR e dados de SSS, demonstrou a capacidade do uso das ferramentas de aprendizado de máquinas para análise e processamento de grandes volumes de dados oceanográficos em tempo real. Ao mesmo tempo, o mesmo representa apenas um pequeno vislumbre do potencial de utilização de ferramentas assistivas em programas oceanográficos de coleta de dados e disseminação de informações. Desta forma, sugere-se, para futuros trabalhos, o uso de redes neurais em diferentes matrizes de dados oceanográficos para detecção de anomalias ou feições de interesse como, por exemplo, a identificação de condições meteoceanográficas com grande potencial de formação eventos extremos, ou detecção de *boom* de algas em oceano aberto a partir de dados de satélite.

Por fim, este trabalho foi uma proposta ancorada tanto no seu potencial de aplicação prática, que pode transformar o *modus operandi* de operações de segurança marítima, quanto na contribuição acadêmica ao aprofundar o conhecimento na intersecção entre inteligência artificial, processamento de imagens e oceanografia operacional. Em um mundo cada vez mais desafiado por ameaças assimétricas e pela necessidade de proteger rotas cruciais para a economia global, avanços científicos nessa área podem representar um diferencial estratégico significativo.

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