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Marine Ships Detection based on Yolov11 Algorithm: Enhancing Maritime Surveillance and Safety

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Abstract:

Maritime surveillance is crucial to ensuring the safety, security and management of maritime activities due to the increasing complexity of maritime risks and potential threats. Detecting ships in satellite images helps monitor illegal activities and protect marine environments. This study focuses on deep learning applications by leveraging the latest state-of-the-art YOLO algorithm, YOLOv11, for ship detection. It evaluates the performance of the model on kaggle_ships_in_google_earth dataset. To ensure a robust evaluation, this study employs a comprehensive set of metrics, where the result indicates that, the model achieved a remarkable balance of accuracy and efficiency in term of precision, recall, and mAP50 and mAP50-95, scoring 0.96, 0.84, 0.94, and 0.69 respectively. These results demonstrate the effectiveness of the model in practical applications. Its ability to demonstrate high accuracy in detecting and locating different types of ships under diverse environmental conditions suggests that it can be integrated into video surveillance, which greatly enhances maritime surveillance capabilities and provides accurate and effective ship detection.

Keywords: Ship Detection; Maritime Surveillance; Deep Learning; YOLOv11

1. Introduction

Maritime ship monitoring plays a pivotal role in ensuring maritime surveillance and safety, particularly in regions facing challenges such as high ship density and illegitimate activities like smuggling, piracy, carrying migrants, and illegal fishing [1]. Accurate ship detection systems are critical to ensuring maritime efficiency and security, as well as timely identification of unauthorized or suspicious ships. Traditional methods based on radar systems and manual visual surveillance often face significant challenges, especially in complex maritime environments with low visibility, variable illumination, dynamic weather conditions, and background clutter [2]. In this context, the advancements in artificial intelligent and deep learning technologies have provided significant improvements in the field of object detection. Thus, integration of deep learning into maritime applications provides transformative solutions, enhancing the accuracy and efficiency of ships detection and maritime traffic monitoring [3].

In recent years, deep learning technologies, a branch of machine learning, has revolutionized various fields particularly in computer vision by enabling the development of highly accurate and efficient algorithms to automatically extract and recognize features from images [4]. Among these technologies, the YOLO (You Only Look Once) family of algorithms, has received a significant attention for its capabilities in real-time object detection. The YOLO framework was introduced by Redmon et al. in 2016, and has gone through several iterations, with each version improving upon its predecessor in terms of speed and accuracy [5]. The latest version in the Ultralytics YOLO series, YOLOv11, has shown remarkable performance on various object detection and classification tasks, making it a suitable candidate for marine ship detection [4]. Building upon the impressive advancements of previous versions, YOLOv11 includes advanced innovations such as improved transformer units and convolutional structures. These improvements enable the algorithm to detect objects in real time while maintaining high accuracy, even in dynamic and resource-constrained environments. Additionally, the improvements make it capable of processing multi-scale feature maps, making it particularly suitable for identifying ships of different sizes and shapes in diverse maritime scenarios [6]. YOLO as a Single-Shot Multi-Box Detector, extracts features directly from the entire image to predict the object's location and class, delivering faster inference times and performs identity classification and predicts the bounding box of the detected objects, integrating multiple steps through a solitary neural network [7].

Integrating YOLOv11 into maritime surveillance systems offers transformative benefits by leveraging its speed and efficiency, enabling faster emergency response times, improved tracking of illegal activities, and improved navigational safety. This makes it generalizable across diverse datasets, including high-resolution satellite imagery and aerial surveillance, delivering superior performance compared to traditional deep learning models [8].

This research scrutinizes the efficacy of the state-of-the-art You Only Look Once version 11 (YOLOv11) algorithm in the detection of marine ships utilizing the Google_Earth imagery dataset. This dataset encompasses images of ships captured under diverse conditions and environments, thereby offering a comprehensive framework for evaluating the algorithm's robustness and precision. The importance of this investigation is underscored by its prospective contributions to the enhancement of maritime surveillance and safety. By capitalizing on the capabilities of the YOLOv11 algorithm, the study aims to provide a reliable and efficient solution for real-time ship detection, which can be integrated into existing maritime monitoring systems.

The remainder of this paper is organized as follows. Section 2 conducts a review of the related work within the domain of ship detection. Section 3 provides an overview of YOLOv11 algorithm. Section 4 describes the methodology employed in this study, encompassing the dataset description, model selection and training, as well as evaluation metrics. Section 5 articulates the results and dissection, highlighting the performance of the YOLOv11 algorithm in detecting ships within the dataset. Ultimately, Section 6 concludes the paper by encapsulating the key contributions and proposing directions for future inquiry.

2. Literature Review

Previous studies in ship detection have focused on using deep learning techniques, particularly YOLO algorithms. Enhanced models such as YOLOv4 and YOLOv5 were developed to increase the accuracy of detecting small ships in images. Improvements included integrating new modules to enhance performance. The studies utilized diverse datasets, including satellite imagery, resulting in significant improvements in accuracy and retrieval rates while maintaining detection speed. Results demonstrated the effectiveness of these models in addressing challenges such as varying ship sizes and changing lighting conditions, reflecting continuous progress in this field and its potential application in maritime surveillance and port management.

In [9], the researchers present an important study on ship detection using Synthetic Aperture Radar (SAR) imagery, evaluating the performance of the YOLO11 algorithm. This study is the first of its kind to test YOLO11 on SAR images, focusing on challenges in both open ocean and coastal environments. The results show that YOLO11 achieved Precision, Recall, and mean Average Precision (mAP) values of 0.865, 0.813, and 0.792, respectively, with better performance in open ocean settings compared to coastal ones.

This study highlights YOLO11's effectiveness in detecting ships under complex imaging conditions, underscoring its relevance for future maritime surveillance applications.

The paper [10] conducted a study titled "Ship detection based on YOLO algorithm for visible images". This study focuses on improving ship detection in visible images using the YOLOv4 model, where a new dataset known as Inland Ships Data Set (ISDS) was developed to enhance research in this field. The authors proposed an improved model called YOLOv4-MSW, which integrates multi-scale features to enhance the accuracy of small ship detection. Results showed that the new model achieved an improvement in average precision (AP) by 4.87% and recall rate by 10.03% compared to the original model, reflecting the effectiveness of the proposed model in addressing challenges associated with ship detection in various environments.

In [11], the researchers conducted a study to address challenges in marine vessel detection by applying YOLOv5 network improved with lightweight convolution and attention mechanism. The study focused on solving issues of insufficient feature extraction, low precision, and recall rates in ship detection. The researchers proposed YOLOv5 Network to the YOLOv5 algorithm by integrating a receptive field enhancement module (RFE), spatial pyramid rapid pooling module, and coordinate attention mechanism. They added a slim-neck module using lightweight convolution (GSConv) and replaced the CIoU loss function with SIoU. Experimental results using the seaShips dataset demonstrated that the improved YOLOv5 algorithm achieved significant performance improvements in model evaluation metrics while maintaining detection speed and without substantially increasing the number of model parameters, effectively addressing detection challenges in complex marine environments.

Moreover, in the research conducted by A. Ataee and J. Kazemitabar [12], a Real-Time YOLOv5-based deep convolutional neural network used to detect ships in the enriched dataset. The study utilized two well-known datasets, SeaShips and ABOships, and supplemented them with a self-collected dataset comprising 13,129 images categorized into six classes: passenger ships, military ships, cargo ships, container ships, fishing boats, and crane ships. The proposed algorithm achieved remarkable results, detecting ships in real-time from videos at 135 frames per second with 99% precision. This study highlights the effectiveness of YOLOv5 in addressing challenges such as varying lighting conditions, ship types, angles, and backgrounds in real-world scenarios.

A comparison of different versions of the YOLO algorithm (YOLOv3, YOLOv4, and YOLOv5) for ship detection conducted by Krishna Patel et al. in 2022 [13]. This study focused on developing an automatic ship detection approach using deep learning techniques to analyze the Airbus Ship Dataset, which consists of approximately 40,000 satellite images. The results demonstrated that YOLOv5 outperformed the other versions, achieving an accuracy of 99%, compared to 98% for YOLOv4 and 97% for YOLOv3. This highlights the effectiveness of YOLOv5 in addressing challenges related to ship detection from satellite imagery, such as variability in shape, size, and environmental conditions.

3. YOLOv11 Algorithm Overview

3.1 What is YOLOv11?

The YOLO algorithm has reached new heights with the introduction of YOLOv11, marking a significant advancement in real-time object detection technology [14]. This latest version builds on the strengths of its predecessors while introducing innovative features that broaden its applicability across various computer vision (CV) tasks. YOLOv11 stands out for its enhanced adaptability, supporting a wider array of tasks beyond traditional object detection, including posture estimation and instance segmentation. Designed to balance power and practicality, YOLOv11 aims to tackle specific challenges faced by different industries with improved accuracy and efficiency. The model exemplifies the ongoing evolution within real-time object detection technology, pushing the boundaries of what is achievable in CV applications. Its versatility and performance enhancements position YOLOv11 as a crucial development in the field, potentially paving the way for new real-world applications across diverse sectors.

3.2 Architectural footprint of Yolov11

The YOLO framework has transformed the field of object detection by introducing a unified neural network architecture that performs both bounding box regression and object classification tasks simultaneously. This integrated approach represents a significant shift from traditional two-stage detection methods, providing end-to-end training capabilities thanks to its fully differentiable design. Central to the YOLO architecture are three key components: the backbone, which acts as the primary feature extractor using convolutional neural networks to convert raw image data into multi-scale feature maps; the neck, which serves as an intermediate processing stage that employs specialized layers to aggregate and enhance feature representations across various scales; and the head, which functions as the prediction mechanism, generating final outputs for object localization and classification based on the refined feature maps. Building on this established architecture, YOLOv11 enhances the foundation laid by YOLOv8 by introducing architectural innovations and parameter optimizations that aim to achieve superior detection performance. The following sections will detail the key architectural modifications implemented in YOLOv11 [15].

Building on the established architecture, YOLOv11 enhances the foundation set by YOLOv8 by introducing innovative architectural features and optimizing parameters to achieve superior detection performance. The following sections will provide a detailed overview of the key architectural modifications incorporated into YOLOv11. in Figure 1 The following sections detail the key architectural modifications implemented in YOLO11:

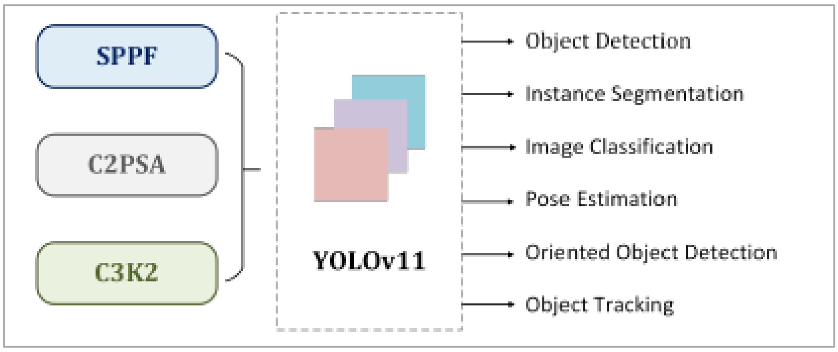


Figure 1: Key architectural modules in YOLO11 [15]

4. Methodology

In this section the dataset used for the purpose of the ships detection in satellite images, and the evaluation metrics used, are explained.

4.1 The Dataset Overview

In this paper, the "kaggle_ships_in_Google_earth" dataset was utilized due to its comprehensive collection of satellite images. The dataset was collected by the Rob flow platform, ensuring a diverse and high quality set of images [16]. This dataset consists of

1644 satellite images with a pixel resolution of 640x640 for one class named "ship". The images in the dataset show a variety of marine environments, including ships with port area, land, and open seas, and under different weather conditions and times of day, as shown in Figure 1. Each image contains one or more ships of varying sizes and types, providing a diverse dataset for training robust models.

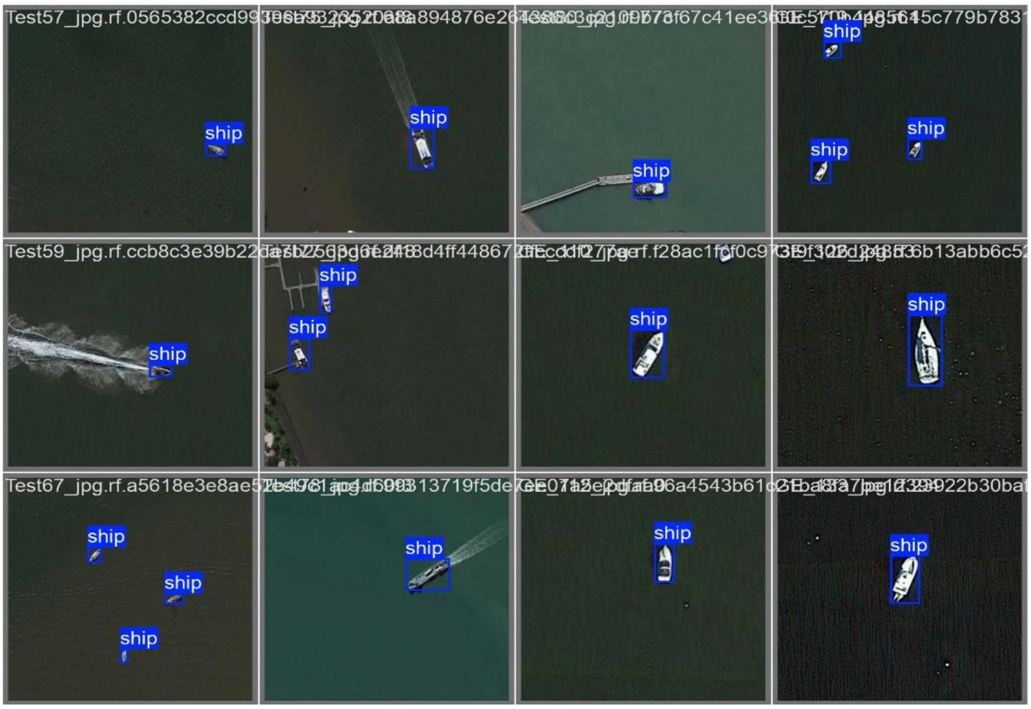


Figure 1: Sample Images from kaggle_ships-in-google-earth Dataset

Each image is annotated with bounding boxes that identify the ships within the images and their locations. These annotations are critical to training deep learning models to accurately detect ships in satellite imagery. The annotated dataset was divided into training, testing and validation sets, with approximately 85.5% of the images allocated for training, 11% for testing and 3.5% for validation. The dataset distribution is shown below in the Table 1.

Table 1: kaggle ships_in_google_earth Dataset Distribution

Data Sets	**Number of Samples**
Training Set	1406
Validation Set	182
Testing set	56
Total	1644

4.2 Model Selection and Training

The YOLOv11 algorithm was utilized in this study for marine ships detection due to its high efficiency and accuracy in real-time detection tasks, such as improved identification and localization of exact positions and targets.

To train the model, the open-source Google Colab was used, leveraging its GPU capabilities to accelerate the process. This platform provided the necessary computational resources to handle the large dataset effectively. Several parameters were used during training the YOLO11n model including: The size of the input images for experiment is 640 × 640 pixels and the Epochs are set to 200. All other parameters were set to default values of the YOLOv11n model such as, the batch size is set to 16 and the learning rate which is initialized at 0.01, with adjustments made based on validation performance. Three primary loss functions were monitored during training: box loss, classification loss, and distribution focal loss.

4.3 Evaluation Metrics

In the target detection task of the YOLOv11 model, the performance evaluation is based on the detection of the bounded box (Metrics(B)), which evaluates the model's ability to accurately identify the target.

In this study, to comprehensively evaluate the model performance, four critical metrics are employed including: precision, recall, and mean average precision (mAP) parameters. These metrics assessed various aspects of the model. Among them, precision, shown in Equation (1), measures the proportion of true positive detections among all samples predicted as positive, reflecting the ability of the model to correctly identify detected targets.

Recall, as illustrated in Equation (2), denotes the proportion of true positives detected among all actual positive samples, measuring the effectiveness in detecting all relevant targets. mAP, shown in Equation (3) was calculated at two levels: mAP50, represents the mean average precision computed at a 50% Intersection over Union (IoU) threshold and mAP50-95, represents the mean AP calculated across IoU thresholds from 50% to 95%.

These values are between 0 and 1, where the larger value of mAP represents better detection accuracy.

(1) $$\text{Precision} = TP/\ TP + FP$$

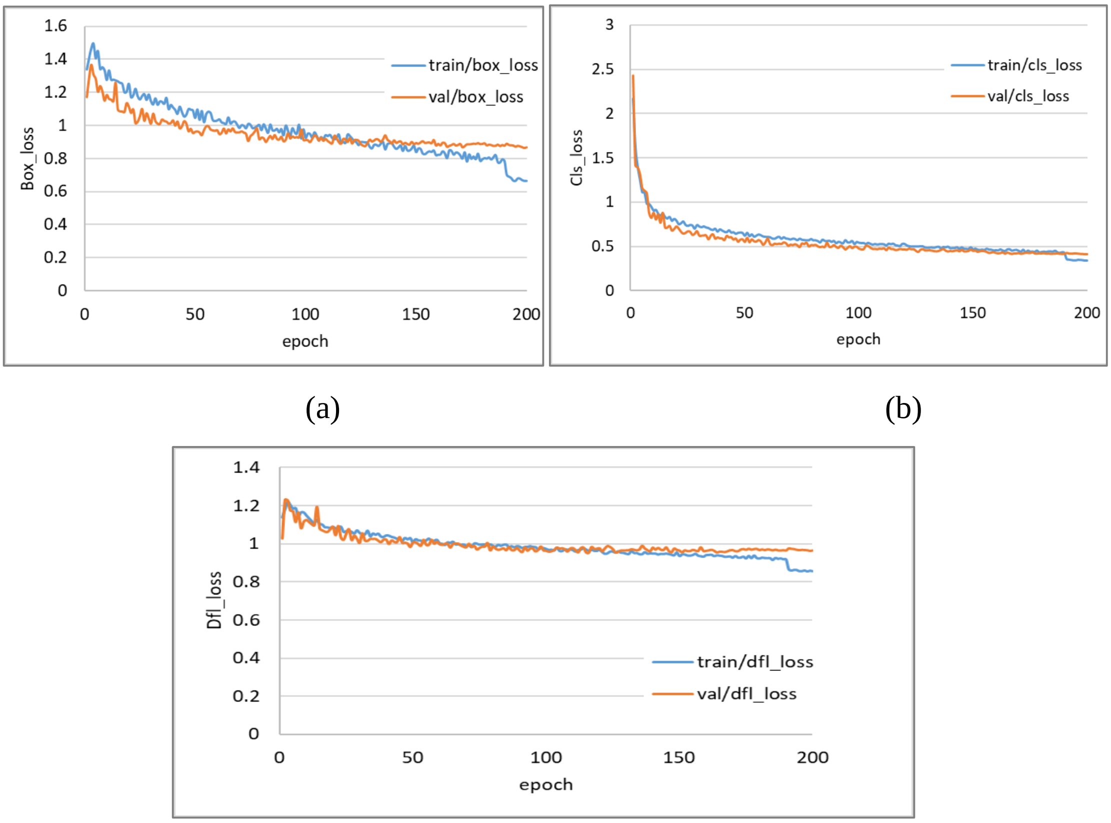
$$\text{Recall} = TP/TP + FN \tag{2}$$

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{3}$$

In the above equations, TP (True Positive) represents the number of correctly identified positive samples (true target detections). FP (false positive) represents the number of incorrectly identified negative samples as positive (false detections). FN (false negative) represents the number of Positive samples missed by the model (missed detections). AP represents the area of the precision–recall curve calculated by interpolation for category i at an IoU threshold.

5. Results and Discussion

To clarify the training and testing performance of the YOLO11 model in ship detection which was performed on Google Colab using a Tesla T4, various diagrams were created as illustrated in Figure 2, representing the evolution of the loss metrics, including: box_loss, Classification Loss (cls_loss), and Distribution Focal Loss (dfl_loss). These diagrams depict how the model improves predictions over 200 epochs.



(c)

Figure 2: Training and validation Loss Metrics Over 200 epochs (a) Box_loss, (b) Cls_loss, and (c) Dfl_loss.

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Each loss function represents different aspects, where box_loss measures target localization accuracy, cls_loss enhancs classification accuracy, and dfl_loss increases the model robustness to handle small targets and complex backgrounds.

During the training process, Box_loss decreased from approximately 1.34 to 0.6 over 200 epochs, indicating a significant improvement in the localization accuracy of the bounding boxes. Similarly, cls_loss dropped from arround 2.16 to 0.34, reflecting improved classification performance by the model. Also, dfl_loss reduced from 1.34 to 0.85, suggesting increased confidence in the predicted bounding boxes. This indicates that, the YOLOv11 model has effectively learned the features during the training process, resulting in a significant improvement in its performance in ships detection task.

In the validation set, the box_loss decreased from 1.17 to 0.86, which confirms the model's ability to generalize to unseen data. This reduction suggests the model is becoming better at predicting the locations of bounding boxes for objects in the validation set. In term of Cls_loss, which measures the classification error, significantly decreased from 2.42 to 0.41. This substantial reduction further validates the model's robustness and its improved accuracy in correctly classifying objects. Moreover, the dfl_loss decreased from 1.03 to 0.96. Although this reduction is not as pronounced as the other losses, it still indicates consistent model performance across different datasets. These improvements in the validation set losses demonstrate that the model’s generalization ability has significantly enhanced, making it more reliable and effective in handling new data.

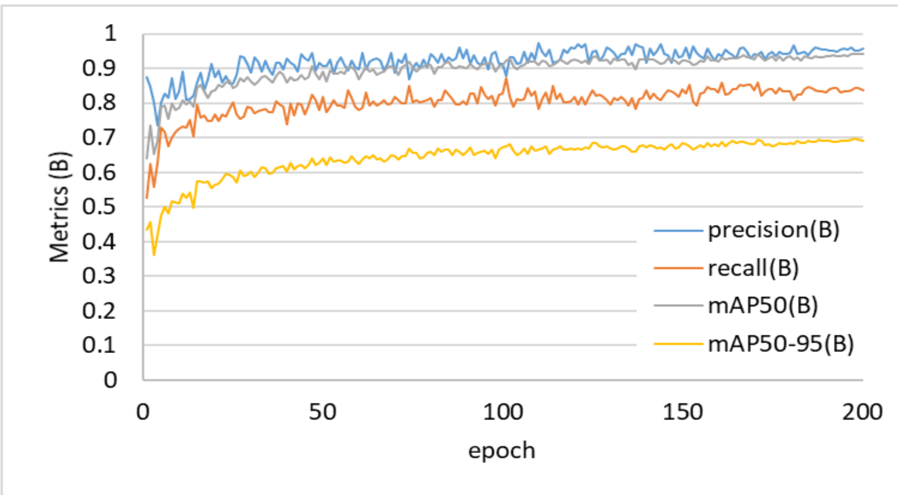

Figure 3: The accuracy curves of Metrics(B).

Figure 3, shows the evaluation of the model performance over 200 epochs. The precision(M) reaches 0.957, indicating a high proportion of true positive predictions. In other words, a high precision indicates that the model produces few false positives, meaning most predicted targets correspond to actual targets.

Recall stabilizes around 0.8, reflecting the model's ability to identify a significant portion of true positives. mAP50 improves to around 0.7, indicating strong model performance in object detection at an IoU threshold of 0.5, while mAP50-95 stabilizes around 0.5, indicating good performance at higher IoU thresholds with room for improvement. Overall these matrices, the model shows significant progress in learning and performance improvement. Table 2 compares these metrics at different stages of training.

Table 2: Ship Detection Performance at different stages of training

Stage	Precision	Recall	mAP50	mAP50-95
Early Stage	0.82	0.71	0.76	0.52
Middle Stage	0.91	0.82	0.90	0.66
Late Stage	0.96	0.84	0.94	0.69

Figure 4 shows the prediction accuracy for ship in the dataset images during the model's testing with a true positive rate of 91 % for the "ship" class, indicating that 91% of the actual ships in the images were correctly identified. While 0.9 % of the predictions were falsely classified as "background".

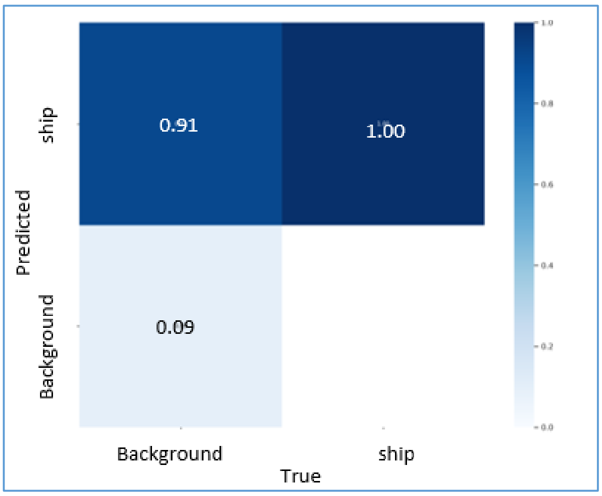

Figure 4: Confusion matrix for model testing for ship detection

In addition, confidence curves presented in Figures 5 and 6, including Precision–Recall and F1 score curves respectively, illustrate the model's ability to detect ships at various confidence levels. These curves contribute to the evaluation of model performance, as precision measures the quality of positive predictions, recall indicates the model's ability to detect true positives, and the F1 score balances both. The high precision-recall curve, with an average precision of 0.943 for the "ship" class and a mAP value of 0.943 across all classes at a threshold of 0.5, reflects the model's balanced approach in achieving both high precision and recall and demonstrates the model's strong performance. Furthermore, the F1-score further illustrates the model's reliability, with a score of 0.90 at a confidence level of 0.530 for the "ship" class.

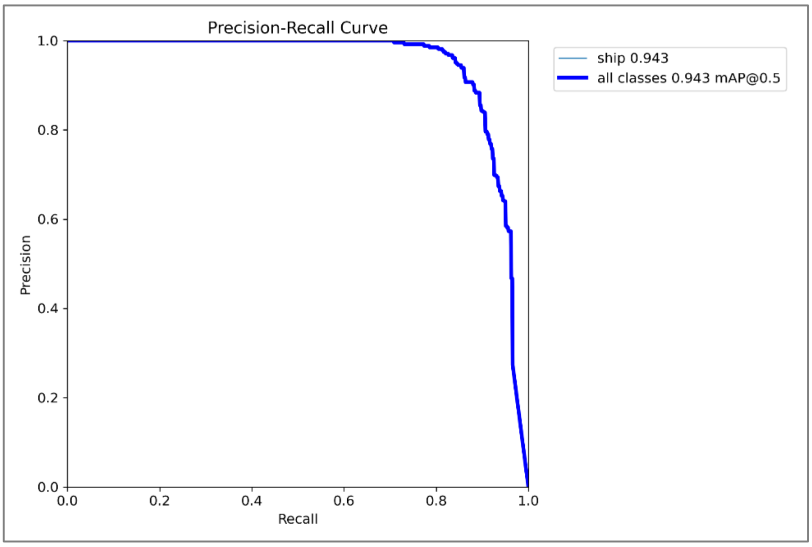

Figure 5. P–R Curve

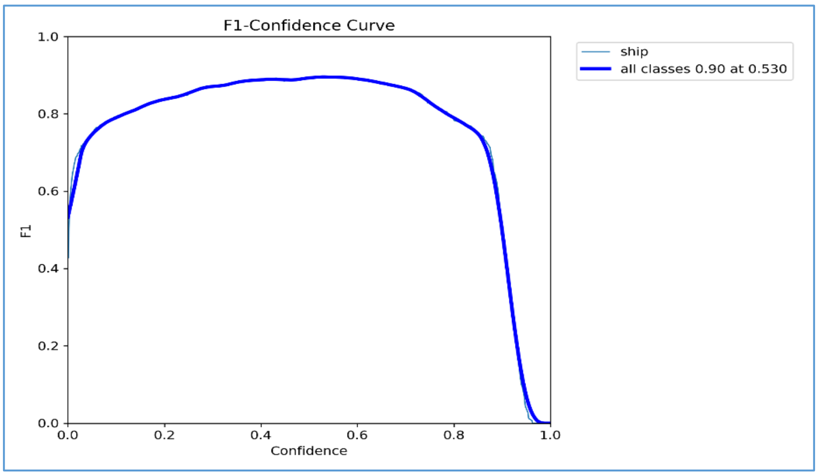

Figure 6. F Score Curve

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To further evaluate the performance of the YOLO11 model, this study used a new set of ship satellite images sourced from Google Images, to gain deeper insights into its effectiveness and potential real-world applications in maritime surveillance and safety. Figure 7 shows the detection results on a new ship images. The results show robust performance with confidence scores ranging from 0.35 to 0.95, indicating the model's ability to identify ships in a variety of conditions. In conclusion, the results confirm the model's robustness and accuracy in ship detection, even in diverse and challenging scenarios, proving its potential usefulness in practical applications.

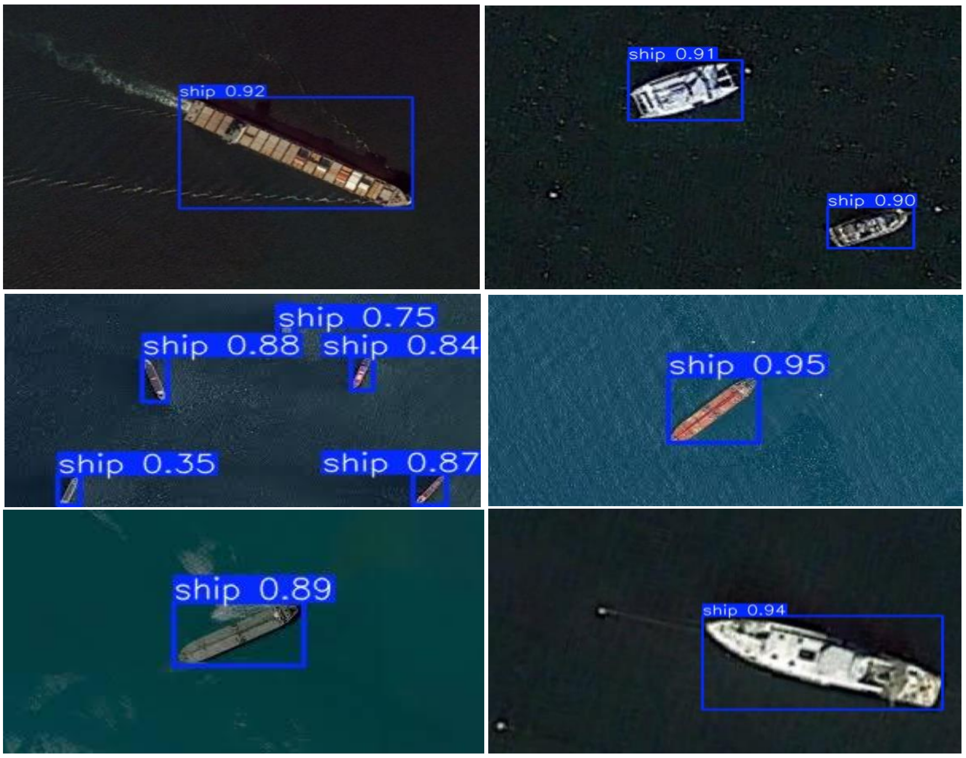

Figure 5: Results of ship detection for unseen images

6. Conclusion

In conclusion, this study demonstrates the effectiveness of the YOLOv11 algorithm in enhancing maritime surveillance through accurate ship detection in satellite imagery. By leveraging a diverse dataset of satellite images, the YOLOv11 model achieved impressive performance metrics, including precision, recall, and mean Average Precision (mAP), with scores of 0.96, 0.84, and 0.94 respectively. These results underscore the model's capability to detect and locate various types of ships under different environmental conditions, indicating its potential for real-time applications in maritime monitoring systems. The advancements presented by YOLOv11 including improved transformer units and convolutional structures, allow for efficient processing and high accuracy, making it suitable for dynamic maritime environments where traditional detection methods may struggle. This research highlights the transformative impact of integrating deep learning technologies into maritime applications, paving the way for enhanced safety and security in marine operations.

In future studies, the YOLOv11 model can be evaluated on larger imagery datasets including different types of ships such as cargo ships, oil tankers, fishing boats, and marine vessels. Collecting images from different geographical locations such as open oceans, coastal areas, and ports would enhance the robustness of the model. Additionally, future research lines will focus on further improving the model and exploring its integration with existing observation systems to effectively address ongoing marine challenges. The study contributes significantly to the field of maritime surveillance, offering a reliable solution for ship detection that can aid in monitoring illegal activities and ensuring navigational safety.

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