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Advanced Maritime Vessel Detection in Satellite Imagery Using Masati-V2

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Abstract – Maritime vessel detection in satellite images address real time issues such as maritime security, illegal fishing and environmental monitoring, which require efficient tracking of vessels in large scale. Maritime vessel detection is challenged by limited annotated satellite datasets, varying sea conditions, and the presence of small or overlapping vessels. YOLOv10 is best for maritime vessel detection in satellite images due to its high accuracy, speed and efficiency in handling complex environments. It is able to detect small vessels against vast and cluttered backgrounds. YOLOv10 addresses these challenges through architectural features, which able to detect small objects like ships. It is scalable for tasks like illegal fishing detection and coastal security using satellite images. Using Masati-V2 dataset we have trained algorithms like YOLOv10s and YOLOv10m which are family of YOLOv10.Evaluation is performed using performance metrics which include precision and recall. According to our research, YOLOv10m model gives the best prediction for maritime vessel detection in satellite imagery. Future research will concentrate on enhancing classification models to identify various vessel types, including smaller or overlapping ones, under diverse environmental conditions and also need to explore real-time vessel tracking using temporal data and predictive analytics can be explored to monitor vessels continuously across multiple satellite images for improved situational awareness.

Keywords – Satellite images, YOLOv10s, YOLOv10m, Maritime Vessel, YOLOv10.

I. Introduction

In the context of oceanic and coastal domains, maritime refers to activities and operations associated with the sea or ocean, including transportation, naval defence, resource exploration, and environmental monitoring. The technique of discovering and identifying ships or boats in optical or radar data, especially in maritime contexts is known as maritime vessel detection. Given the vastness of the ocean and the increasing need for maritime safety, satellite-based maritime vessel detection has become a critical task in ensuring maritime situational awareness, border control, and illegal activity monitoring. Maritime surveillance plays a key role in ensuring national security, facilitating naval defence operations, assisting with environmental conservation initiatives, and combating illicit activities like smuggling and unregulated fishing. In marine safety and security, the ability to rapidly, autonomously, and accurately detect and identify ships is the highest priority. [1]. By facilitating efficient navigation, eliminating collisions, and ensuring timely reactions to potential threats or emergencies at sea, accurate ship identification enhances maritime safety. Using satellites to capture images of the earth's surface for various purposes such as monitoring light-scattering aerosols is known as satellite imagery. [2]. Since satellites can cover huge areas quickly, provide synoptic views and high-resolution spatial details, and gather multi-spectral information, they are widely used in the maritime domain. These work effectively for monitoring marine traffic and patrolling the sea against illegal activities. [3].

It is inherently difficult to detect vessels in satellite imagery because of things like small object size, and changing environmental conditions. Challenges arising from the dynamic nature of the background, absence of static cues, presence of small objects in distant backgrounds, and varying illumination conditions collectively contribute to the complexity of maritime vessel detection. [4]. Although they work efficiently in many instances, traditional monitoring systems like radar and optical sensors suffer from numerous drawbacks. Their effectiveness can be hindered by adverse weather conditions and line-of-sight constraints, resulting in significant surveillance gaps. [5].

Despite obstacles such as vessel concealment and fabricated documents, shipping is an essential part of international trade. Regulatory enforcement and marine safety are at risk due to these problems. For safe and effective marine operations, effective ship detection is crucial. [6]. Particularly in expansive marine settings, traditional ship identification techniques frequently suffer from processing speed and accuracy issues. For prompt decision making in applications like rescue and surveillance, real-time detection is essential. As a result, the need for detection algorithms that are accurate and quick. [7].

Object detection has become a key component of contemporary computer vision, that allows computers to precisely discover and recognize objects in images. Finding and detecting objects in an image is known as object detection, and it is essential to many artificial intelligence tasks. Strong and effective object detection models that can manage complicated environmental conditions are of vital importance especially in the maritime and aerial domains, as remote sensing and satellite imagery become more widely available. Maritime Situational Awareness (MSA) is essential for duties including illegal activity monitoring, disaster response, coastal surveillance, and naval defence. However, due to occlusions, low contrast, and varying weather conditions, identifying objects such as ships, coastlines, and marine regions in aerial images poses special difficulties. Real-time object identification has made deep learning-based models popular, especially those in the YOLO (You Only Look Once) family. Among several object detection algorithms, YOLO's architecture and performance improvements have made it more well known. Due to its scalability YOLO is a popular choice for real-time object detection tasks. YOLO is well-suited for various industrial applications. YOLO offers in-depth analysis in development and practical applications in various industries. [8]. YOLO is highly adaptable, making suitable for various applications in diverse domains. Moreover, YOLO is designed to work efficiently with limited computational resources and is suitable for deployment on edge devices.

One-stage models like YOLO (You Only Look Once) are best because of high processing speed and effectiveness, which is best for real-time applications. While they strike a balance between accuracy and speed, they face challenges with small-object detection in complex environments. [9]. YOLO is a deep learning algorithm that performs object detection as a single classification regression task which enables real-time performance. It's simple architecture and fast computation makes it ideal for applications that requires fast and efficiency. [10]. The most recent development in the YOLO series, YOLOv10, is intended to enhance real-time detection using a smaller model and fewer parameters. It is appropriate for areas with limited resources since it increases speed and efficiency without sacrificing precision. Additionally, YOLOv10 offers architectural enhancements that help with small object recognition in intricate settings. YOLOv10 advancements include handling of dynamic and cluttered backgrounds, which can significantly improve its performance in complex environments such as maritime detection. These enhancements make YOLOv10 not only faster and more efficient but also more robust in challenging detection scenarios. [11].

YOLOv10s and YOLOv10m are optimized variants of YOLOv10, designed for different trade-offs between speed and accuracy. YOLOv10s offers a lighter, faster model with fewer parameters, making it ideal for environments with limited computational resources. YOLOv10m strikes a balance between efficiency and detection performance, providing improved accuracy for complex tasks. [12] YOLOv10s and YOLOv10m are variants of YOLO family, each designed to meet performance and deployment model. These models are part of YOLOv10's broader goal of unifying the object detection pipeline with speed, postprocessing, and improving small object detection performance. Moreover, both YOLOv10s and YOLOv10m support training on datasets and can be easily fine-tune the domain-specific tasks such as maritime vessel detection. The model integrates several optimization techniques for speed and post-processing efficiency. YOLOv10 has optimized to improve detection of small objects which is important for maritime vessel detection, where small boats and ships can be easily missed due to less precise models. This adaptability makes YOLOv10s and YOLOv10m excellent choices for applications beyond maritime surveillance and other real-time object detection tasks where efficiency and accuracy are both crucial.

II. MATERIALS AND METHOD

In this research, two YOLOv10 models will be used to assess precision and recall. A comparative analysis will be carried out to evaluate the effectiveness of YOLOv10s and YOLOv10m models in maritime detection of satellite images. It will focus on optimizing detection accuracy for small vessels and also consider real-time processing capabilities. Furthermore, performance metrics such as inference speed will be analyzed to determine each model on large scale satellite image processing.

Table 1. Environmental setup for YOLOV10s and YOLOv10m training.

Parameter	Value
GPU	NVIDIA A100
GPU RAM	40 GB
CUDA version	12.3
Batch size	16
Number of epochs	150
Input image size	640 pixels
Rotation	10 degrees
Translation	0.1
Scaling	0.5

Precision: The accuracy of a model's positive predictions is made using a statistic called precision. It is particularly crucial when false positives cause more problems than false negatives.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: The model's recall, also known as sensitivity or true positive rate (TPR), determines how well it can identify each relevant occurrence in a dataset.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Mean Average Precision (mAP): The performance of object detection models is assessed using a metric called Mean Average Precision (mAP), which is especially useful for tasks like object recognition and picture classification. In order to calculate it, the average precision (AP) values for each object class in a dataset are averaged.

$$MeanAveragePrecision = \frac{1}{M}\sum_{i=1}^{M} \text{AveragePrecision}_i$$

where n is number of classes, APi is Average Precision for class i.

mAP50: The mean Average Precision at an Intersection over Union (IoU) threshold of 0.50 is known as mAP50 in object detection. The accuracy of object detection models—more especially, how successfully they find and categorize objects—is assessed using this measure.

$$\mathbf{mAP}_{50} = \frac{1}{M}\sum_{i=1}^{M} \text{AveragePrecision}_{i,\text{IoU}\geq 0.50}$$

where M is number of classes, IoU is Intersection over Union at threshold 0.50.

mAP50-95: The mean average accuracy, which ranges from 0.50 to 0.95, computed at different IoU thresholds.

$$\mathrm{mAP}_{50:95} = \frac{1}{10M}\sum_{i=1}^{M}\sum_{j=0}^{9} \mathrm{AveragePrecision}_i @\mathrm{IoU} \geq 0.50+0.05j$$

where M is number of classes, IoU is Intersection over Union at threshold 0.50 to 0.95.

These metrics are calculated after each epoch to track model performance of training and validation sets.

A. LITERATURE REVIEW

The application of deep learning to remote sensing has gained prominence in recent years, especially for the comprehension of maritime scenes. Traditional object detection methods like Support Vector Machines (SVMs) and Histogram of Oriented Gradients (HOG) have demonstrated limited effectiveness in maritime environments due to complex backgrounds, varying illumination, and the small scale of targets. [13]. Recent research has addressed these issues by concentrating on lightweight models, such as YOLOv5n, YOLOv6, and MobileNet based detectors that enable real-time inference without significant accuracy trade-offs. Since the release of Convolutional Neural Networks (CNNs), deep learning models have significantly improved the accuracy of object detection in aerial and satellite imagery. [14]. Among these, the You Only Look Once (YOLO) group of detectors has shown exceptional performance in balancing speed and accuracy. YOLOv3 and YOLOv5 have been successfully applied to ship detection tasks in earlier studies. [15][16]; however, in dynamic maritime settings, they frequently encountered difficulties distinguishing small or closely spaced objects.

Datasets like SeaDronesSee and Airbus Ship Detection have facilitated the development of ship detection models. [17][18], but they are lacking in scene diversity, especially when it comes to multi-class identification in mixed or coastal situations. This gap is filled by the MASATI V2 (Maritime Satellite Imagery) dataset, which offers annotated satellite images in several categories, including as land, sea, coast, ship, multi, and coast-ship, allowing for a more thorough assessment of identification methods.

With the evolution of deep learning models, object detection has advanced significantly, especially with the introduction of the YOLO (You Only Look Once) family. YOLO was initially presented by Redmon et al. as a real-time object identification model that balanced accuracy and speed. Since then, better backbone architectures, anchor-free techniques, and feature pyramid networks have improved performance in a number of versions, including YOLOv3 through YOLOv8. Recent advancements in the YOLO series, including YOLOv7, YOLOv8, and the latest YOLOv10, have introduced architectural improvements that enhance performance for real-time detection with low latency. [19]. Specifically, YOLOv10 provides a variety of model sizes from YOLOv10n to YOLOv10x, meeting various deployment requirements while preserving high accuracy on object detection benchmarks. Through increased efficiency and architectural improvements, the most current YOLOv10 models further optimize detection, making them appropriate for deployment in contexts with limited resources. Techniques for data augmentation are also essential for improving detection models' capacity for generalization. Methods such as horizontal and vertical flipping, rotation, scaling, translation, and colour jittering have been widely adopted to simulate real-world imaging variations and prevent overfitting. [20].

Overall, even while models and datasets for maritime object recognition have advanced significantly providing high-resolution pictures, a variety of environmental conditions, and more reliable algorithms current techniques continue to encounter difficulties. Class imbalance, a lack of labeled datasets, and challenges identifying small or overlapping objects in complex backdrops are a few of them. There are still limitations in generalization across marine environments and integration with real-world applications, even with the effectiveness of datasets like MASATI and models like YOLO in real-time detection. To enable more dependable, flexible, and scalable solutions for environmental monitoring and marine surveillance, future research must address these problems.

B. DATA SET

In this study, we utilized the MASATI v2 (MAritime SATellite Imagery dataset), a publicly available collection of high-resolution satellite images offering visible spectrum optical aerial images of maritime areas. The MASATI dataset consists of colour images of various dynamic maritime settings, which can be evaluated by ship detection methods. One or more targets under various lighting and weather situations may be present in each image. The dataset has 7337 satellite images which are labelled with seven classes-land, coast, sea, ship, multi, coast-ship, and detail. Additionally, there is labelling for the vessels' position along with the bounding box. For our work, the dataset was divided into 70% for training, 20% for validation and 10% for testing. We employed data augmentation techniques such as translation, rotation, scaling, horizontal flipping, and vertical flipping to increase model's robustness and generalization. This dataset is essential for comparing how well object detection models work in actual maritime situations since it provides a realistic and varied range of challenges aligned with applications for satellite-based monitoring and surveillance.

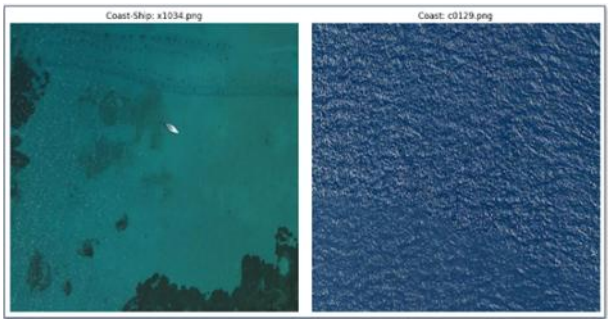

Fig. 1 Ship and Sea

Fig. 2 Coast-ship and Coast

III. RESULTS

In our work, we assessed the efficacy of YOLOv10 models in maritime detection in satellite imagery. The dataset contained maritime images which consists of three labels - images, labels and output. YOLOv10m and YOLOv10s models were trained and evaluated on this dataset. The precision achieved by YOLOv10s was 84.58%, while YOLOv10m achieved a higher precision of 89.43%. Training and validation loss curves for YOLOv10s and YOLOv10m are shown in Fig. 3 and Fig. 6, respectively. Fig. 4 and Fig. 7 illustrate the precision and recall of the models. The performance comparison of predicted versus actual labels is shown in Fig. 5 for YOLOv10s and Fig. 8 for YOLOv10m.

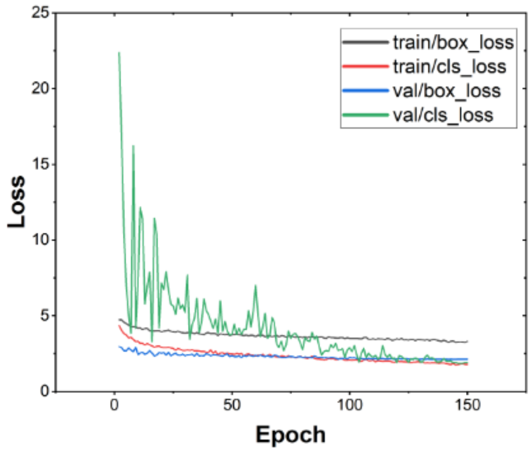

Fig. 3 Training & Validation Loss Curves (YOLOv10s)

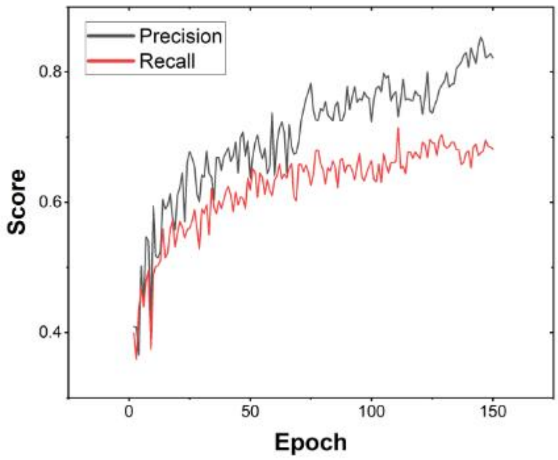

Fig. 4 Precision and Recall Over Epochs (YOLOv10s)

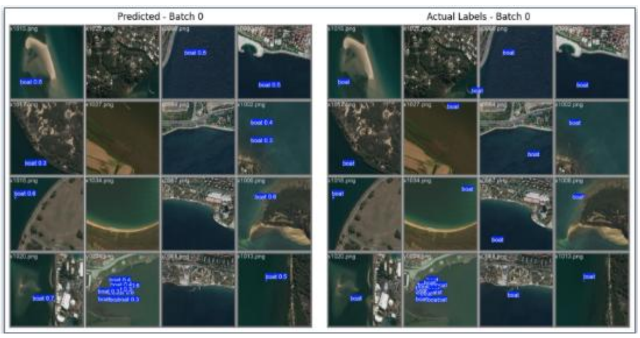

Fig. 5 Predicted Labels Vs Actual Labels of YOLOv10s

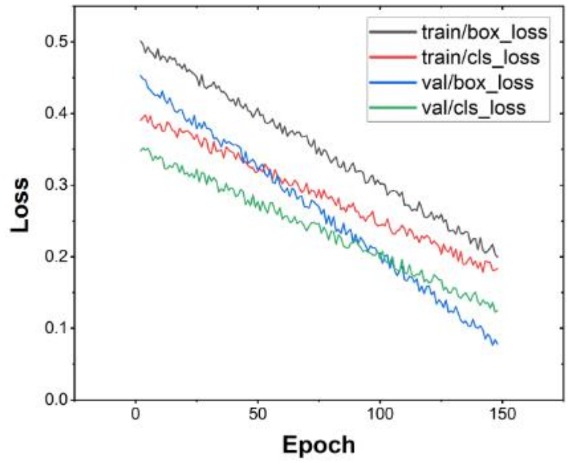

Fig. 6 Training & Validation Loss Curves (YOLOv10m)

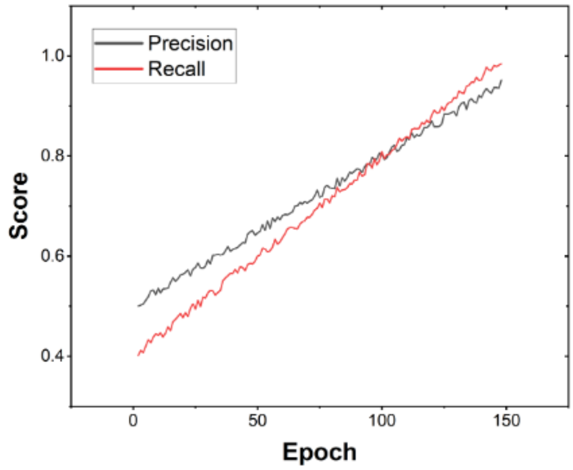

Fig. 7 Precision and Recall Over Epochs (YOLOv10m)

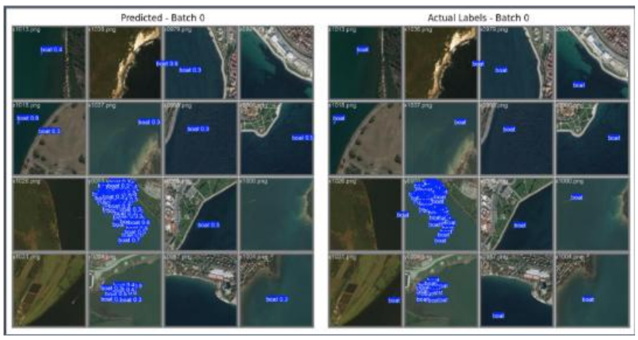

Fig. 8 Predicted Labels Vs Actual Labels of YOLOv10m

IV. DISCUSSION

The experimental findings show that YOLOv10m performs better than YOLOv10s in terms of accuracy, with a 4.85% improvement. Because tiny vessels are typically hard to spot because of their low contrast against oceanic backdrops, YOLOv10m's greater ability to detect them is the reason for this improvement. Vessel size, shape, and edge contrast were shown to be crucial elements that contribute to precise detection. Because of its architecture, the YOLOv10m can balance computing efficiency with detection accuracy, which makes it ideal for real-time maritime applications where it's critical to recognize small objects in dynamic sea settings. Satellite-based marine detection has advanced significantly with the YOLOv10m model, as compared to previous models or smaller variants such as YOLOv10s. Its robust yet lightweight design makes it ideal for use in situations that call for both speed and accuracy, such search and rescue missions, marine traffic management, and naval surveillance.

V. CONCLUSION

In conclusion, this work uses the MASATI-V2 dataset, which contains complex aerial and marine sceneries, to offer a thorough evaluation and compare YOLOv10s and YOLOv10m object detection algorithms. The YOLOv10m model achieved a high performance with a precision of 0.8943, recall of 0.6783, and mAP@0.5: 0.7873. In comparison, the YOLOv10s model achieved a precision of 0.8458, recall of 0.6436, and mAP@0.5 of 0.7641. The accuracy and resilience of YOLOv10m in high-confidence detection circumstances are highlighted by its precise and dependable localization capabilities. According to these findings, YOLOv10m is a good fit for practical applications that value accuracy and selective detection, such as target tracking and maritime surveillance, where accurately recognizing important items is more crucial than finding every instance. Building on the results of this study, future research will concentrate on investigating ensemble strategies to integrate the strengths of YOLOv10s and YOLOv10m. Future initiatives will encompass domain adaptation, real-time deployment on edge devices, and the incorporation of explainability techniques to enhance comprehension of model choices. Incorporating multimodal data, such radar or thermal imagery, could improve detection performance in complex or low-visibility maritime conditions.

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