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Ship detection and identification for maritime security and safety based on IMO numbers using deep learning

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ABSTRACT

In marine safety and security, the ability to rapidly, autonomously, and accurately detect and identify ships is the highest priority. This study presents a novel approach using deep learning to accurately identify ships based on their International Maritime Organisation (IMO) numbers. The performance of various sophisticated deep learning models, such as YOLOv8, RetinaNet, Faster R-CNN, EfficientDet, and DETR, was assessed in accurately identifying IMO numbers from images. The RetinaNet and Faster R-CNN models achieved the highest mAP50-95 scores of 70.0% and 64.1%, respectively, with inference times of low scale. On the other hand, YOLOv8, with a slightly better mAP50-95 of 65.1%, showed an exceptional balance between accuracy and speed (9.20 ms), making it well-suited for real-time applications. However, models like EfficientDet and DETR experienced difficulties achieving lower mAP50-95 values of 33.65% and 48.7%, respectively, especially when analysing low-resolution images. Following detection, the Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) was used to improve the clarity of extracted IMO digits. It is followed by applying Easy Optical Character Recognition (EasyOCR) for accurate extraction. Despite the enhancements, minor identification errors continued, suggesting a requirement for additional refinement. These findings reveal the capacity of deep learning to significantly augment maritime security by enhancing the efficiency and precision of ship identification.

Keywords: Marine Security, Ship Detection, Deep Learning, Real-Time Object Detection, IMO Number Identification.

1. INTRODUCTION

In marine safety and security, the capacity to recognise ships rapidly, automatically, and accurately is essential for both military and commercial purposes. Conventional systems such as the Automatic Identification System (AIS) have notable limitations as they depend on the ship's active involvement and are frequently insufficient in complex and variable marine settings [1]. This paper introduces a novel approach that uses deep learning models to detect and identify ships from images using their International Maritime Organisation (IMO) identifiers [2]. The IMO number is a unique identifier that must be attached to a ship's deck for the whole duration of its operating lifetime. It functions as a reliable means of tracking ships, even when there are changes in ownership or flags. This research uses a specialised deep-learning model to identify these numbers, which are usually small and may be hidden or affected by the ship's motion or construction [3]. Several works inspired us to use a specialised deep-learning model to identify them, as deep learning has transformed the science of computer vision by offering tools capable of accurately and efficiently processing and analysing low-quality data [4]. For example, applying convolutional neural networks (CNNs) in ship movement classification based on AIS data shows significant improvements in reliability and accuracy compared to conventional approaches [5]. In another work, a framework was proposed to evaluate the environmental consequences of operational shipping and focused on the significance of precise ship detection for pollution management and accordance with regulations [6]. Using computer vision and deep learning techniques to detect ships engaged in illegal operations, such as trafficking, is essential for improving maritime security. By precisely detecting and identifying ships based on their IMO numbers, these technologies are crucial in monitoring and avoiding criminal activity at sea, thus enhancing worldwide maritime safety [7].

This work proposes a framework to identify ships based on their IMO numbers, consisting of IMO detection, IMO region extraction, image enhancement, and IMO digits extraction. Firstly, five popular object detection models are studies in performing end-to-end identification of IMO numbers on ships, focusing on overcoming issues related to the low positioning accuracy of small-sized tags and ship identity verification [3]. Models like YOLO (You Only Look

Once) [8] and RCNN (Region-based Convolutional Neural Networks) [9] have been proven to be excellent in tasks requiring real-time processing and high precision due to their rapidity and robustness. An improved YOLO network has been developed to identify ships, including multiple optimisations to improve accuracy and performance [8]. RetinaNet, an advanced model, provides improved abilities in recognising individual instances, making it well-suited for recognising small and complex items such as IMO numbers [9]. The effectiveness of DETR (Detecting Transformer) and EfficientDet models is compared in ship-detecting tasks. These models are known for detecting objects accurately in many situations and environments [10]. Secondly, To improve the identification and classification of IMO numbers, the upgraded Super-Resolution Generative Adversarial Network (ESRGAN) [11] is utilised to enhance image resolution. At the same time, Easy Optical Character Recognition (EasyOCR) [4] is employed to extract the IMO numbers from the upgraded images precisely. The combination of methodologies guarantees exceptional accuracy and dependability, even in difficult situations [4][12].

The main contributions made in this work include:

1. ***Dataset Collection and Augmentation:*** Updated and augmented a collection of ship images, including obvious IMO numbers.
2. ***Evaluation of Object Detection Models:*** Developed and evaluated five object identification models (YOLO, RCNN, RetinaNet, DETR, EfficientDet) to accurately identify both ships and IMO numbers.
3. ***Framework Development:***
    - ***Ship and IMO Detection:*** Used deep learning algorithms to identify ships and IMO areas.
    - ***IMO Region Extraction:*** Separated and reduced IMO number areas.
    - ***Image Enhancement***: Enhanced the resolution of IMO regions using ESRGAN.
    - ***Digit Recognition:*** Extracted and recognized IMO digits using EasyOCR.

2. RELATED WORK

Conventional ship detection methods depend on radar and the Automatic Identification System (AIS), which utilise radio waves and require active ship involvement. Although IMO numbers can be obtained through this system, these approaches are passive and could show insufficient coverage and security concerns, particularly in complex maritime environments [13]. While some work focuses on active solutions for identifying IMO numbers, some work has been done in vehicle license plate detection and recognition. Previous car license plate number identification approaches were based on conventional image processing techniques, such as edge detection and template matching, without using machine learning concepts. These traditional techniques served as the basis until the arrival of more sophisticated deep learning-based technologies [14]. The dramatic development of machine learning, particularly deep learning, has significantly enhanced the precision and robustness of object detection. For example, a study shows that deep learning-based EasyOCR can achieve over 95% accuracy in character recognition [15]. Another deep learning-based approach was developed for license plate detection and recognition in unconstrained environments, demonstrating substantial improvements over traditional methods [16]. Detecting and identifying IMO numbers is more challenging due to poor lighting conditions, complex sea conditions, and the small dimensions of numbers. Deep learning methods could provide notable enhancements in automated identification from images, increased precision, durability in various situations, and quicker processing speeds that are ideal for real-time applications [17].

3. METHODOLOGY

In the workflow shown in Figure 1, images of ships are gathered and later undergo pre-processing and augmentation to enhance the data quality. Next, a machine learning model is used to analyse these processed images and recognize and bring out the area that includes the IMO numeric value. The identified IMO region is subjected to resolution enhancement using ESRGAN to enhance the image's clarity. Following that, the precise region with the IMO number is cut out using the bounding box determined by the model. Finally, the numerical values of the IMO number are found using EasyOCR.

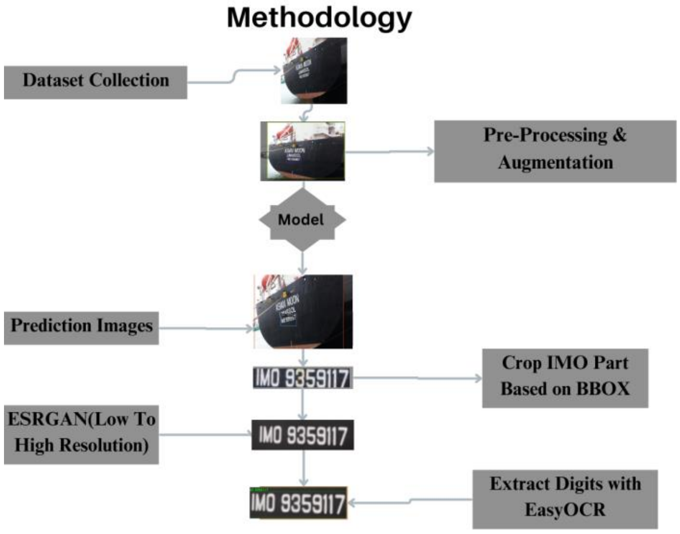

Figure 1. Workflow of the proposed ship detection and identification system, including IMO number detection, region extraction, image enhancement using ESRGAN, and digit extraction using EasyOCR.

3.1 Dataset Collection

The dataset used in this study came from the BalticShipping database, which offers detailed information about ships based on their name or IMO number [18]. Initially, 80 unique pictures were gathered, showing various ships in different situations. The images underwent pre-processing by applying the auto-orient function and scaling them to dimensions of 640×640 pixels. Each image was subjected to augmentation to improve the dataset, which involved using three different transformations, including random rotations ranging from -19° to +19°. This process resulted in a total of 437 images. Due to their low quantity, more than half of the original images were assigned for training to optimise the model's learning capacity. The dataset was divided into 390 images (about 89%) for training, 31 images (7%) for validation, and 16 images (4%) for testing. The choice to assign a substantial proportion of the images to the training set was motivated by the necessity of providing the deep-learning models with a large quantity of data from which to gain knowledge, particularly given the complex and varied nature of the ship's images [19]. Consistency was maintained in this research by using the same dataset for all deep learning models, ensuring the results were similar and valid.

3.2 Training Approach

Detection Models: The object detection task involved fine-tuning five models, including YOLOv8, Faster R-CNN, RetinaNet, DETR, and EfficientDet. These models were trained using pre-trained architectures. Except for DETR, all models utilized a learning rate of 0.001. YOLOv8, Faster R-CNN, RetinaNet, and EfficientDet employed the Adam optimizer, whereas Faster R-CNN and RetinaNet opted for SGD. The primary model of DETR was trained with a learning rate of 0.0001 using the Adam optimizer, while the learning rate of its backbone was 0.00001. The training process involved training all models for 100 epochs using 640×640-pixels images and a batch size of 8. The validation process utilized a confidence level of 0.80 and an Intersection over Union (IoU) criterion of 0.50. The dataset types used were XML for YOLOv8, COCO for Faster R-CNN, RetinaNet, DETR, and TFRecord for EfficientDet.

Image Enhancement and Digit Extract Models: The Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) was used to improve the resolution of the extracted areas of interest (ROIs) of IMO by the detection model. This phase was critical in enhancing the clearness and complexity of the visuals, which affected the accuracy of the subsequent text/digits recognition procedure. Next, EasyOCR was utilised to extract the IMO numbers from the enhanced images. The OCR procedure used a pre-trained model with a recognition threshold 0.70 to guarantee high confidence in the recovered digits. The objective of this combined method, which involves enhancing images and then performing text recognition, is to optimise accuracy in identifying and reading IMO numbers from images with different levels of quality.

3.3 Measures

Accuracy: Precision and recall [20] are essential measures for assessing the performance of object detection algorithms. Precision is a metric that measures the correctness of identified objects by estimating the percentage of true positives out of the total false positives. The recall metric assesses the model's capacity to identify all relevant objects by using the ratio of true positives to the combined total of true positives and false negatives.

The model's performance was assessed by measuring the mean Average Precision (mAP) across a broad range of IoU thresholds, namely mAP50-95 [21]. The precision and recall of ship and IMO number detection are evaluated using this metric across a wide range of IoU criteria, from 50% to 95%. The evaluation extensively assesses the model's accuracy and consistency by simply measuring mAP50-95, thereby subjecting it to more strict detection criteria. Implementing mAP50-95 guarantees that the model's performance remains consistent across a range of detection strictness, showing its capacity to achieve high levels of object detection accuracy. These metrics evaluate the model's object detection performance, with precision representing the detection accuracy and recall indicating the quantity of detection completed. Examining precision and recall at different IoU levels thoroughly assesses the model's abilities [20].

Time efficiency: The inference speed, estimated in milliseconds (ms), was used to evaluate the processing speed of each model for a 640×640 pixel image. This benchmark is essential for assessing the fit of the models for real-time applications.

4. RESULT

4.1 Validation Results

Table 1 presents a competitive analysis of the performance of YOLOv8 [8], RetinaNet [9], Faster R-CNN [9], DETR [10], and EfficientDet [10] in detecting ship and IMO numbers on the validation data. The RetinaNet model achieved the highest mAP50-95 score of 70.0%, making it a highly suitable option for tasks prioritising accuracy. The Faster R-CNN model achieved a mAP50-95 percentage of 64.1%, slightly smaller than YOLOv8's 65.1%. While new, DETR showed a significantly lower mAP50-95 of 48.7% than the previous three models, indicating the need for further optimisation. The EfficientDet model achieved the lowest mAP50-95 index of 33.65%.

Table 1. Validation performance comparison of different object detection models for ship and IMO number identification. The results are evaluated using mAP50-95.

Metric	**RetinaNet**	**Faster RCNN**	**YOLOv8**	**DETR**	**EfficientDet**
mAP50-95 (Final)	70.0%	64.1%	65.1%	48.7%	33.65%

Figure 2 shows the individual accuracy of ship and IMO number detection. It can be seen that RetinaNet and Faster R-CNN achieved ideal stability between IMO and ship detection, with mAP values of 61.1% and 56.2% for IMO detection and 78.9% and 72.0% for ship detection, respectively. YOLOv8, although having a lower IMO accuracy of 45.6% mAP, showed exceptional performance in ship detection with a mAP of 84.6%. DETR had a similar mAP with YOLOv8 in IMO detection. However, its ship detection was worse than the latter. EfficientDet had difficulties detecting IMO (14.6%).

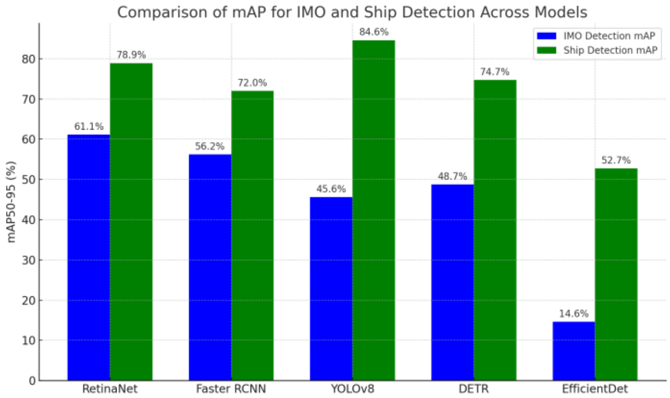

Figure 2. Comparison of the mean Average Precision (mAP) for ship and IMO number detection across different models.

4.2 Test Results

Table 2 presents the performance comparison of five different models on the test data, specifically focusing on metrics related to precision, recall, and inference speed per image.

Precision and Recall: The YOLOv8 model [8] achieved a precision of 100%, indicating its perfect ability to accurately detect objects without incorrectly classifying negative instances as positive. However, the recall rate of YOLOv8 is 78%, suggesting that although it shows high precision, it falls short of identifying quite a few of the reality items within the sample. The gap between precision and recall can give rise to possible challenges in practical applications, while the model shows low error rates. RetinaNet [9] achieves a more equal balance between precision and recall, reaching 75.3%. These findings indicate that RetinaNet could be more dependable for applications that need detecting many objects, even if it involves allowing a small number of false positives. Faster R-CNN [9] shows a comparable balance but somewhat lower scores (71.9% for precision and recall), indicating a steady but slightly less precise performance than RetinaNet. On the flip side, DETR [10] and EfficientDet [10], due to their lower precision and recall, may encounter difficulties detecting missing objects and accurately recognising them, reducing their value for high-stakes or accuracy-critical applications.

Table 2. Test performance comparison of YOLOv8, RetinaNet, Faster R-CNN, DETR, and EfficientDet models based on precision, recall, and inference speed per image.

Metric	**Retinanet**	**FasterRCNN**	**Yolov8**	**DETR**	**Efficientdet**
Precision	**75.3%**	**71.9%**	**100%**	**48.7%**	**43.5%**
Recall	**75.3%**	**71.9%**	**78%**	**56.2%**	**48.5%**
Inference Speed Per Image	**84.57 ms**	**98.77 ms**	**9.20 ms**	**69.90 ms**	**17.50 ms**

Inference Speed Per Image: YOLOv8 [8] shows a faster inference speed than other models, achieving an impressive 9.20 ms per image. It indicates its high suitability for real-time applications. EfficientDet [10] showed remarkable performance in this aspect, achieving an inference speed of 17.50 ms per image, indicating a robust balance between efficient processing and acceptable precision. In contrast, RetinaNet [9] (84.57 ms), Faster R-CNN (98.77 ms), and DETR [10] (69.90 ms) show slowed inference speeds, so underlining the natural compromises between speed and accuracy. Despite its longer inference time, RetinaNet maintains an edge through its superior precision and recall, making it an ideal choice for applications that prioritise accuracy, even if it requires giving up speed.

Prediction Result: Figure 3 shows the comparative detection performance of YOLOv8, Faster R-CNN, RetinaNet, EfficientDet, and DETR on a collection of test images. The YOLOv8 model shows difficulty in detecting IMO numbers, frequently with lower confidence levels. It indicates difficulties in providing precise identification of smaller text sections. The Faster R-CNN and RetinaNet models maintain high confidence levels in detecting ships and IMOs across all images. The consistency seen may suggest that the test set fails to correctly represent more complex real-world situations. The EfficientDet algorithm compromises speed and precision, although it displays variability in detecting IMO. The DETR model shows variable performance, occasionally failing to include IMO numbers and ultimately stressing the requirement of a varied and demanding test set to assess the model's capacity accurately.

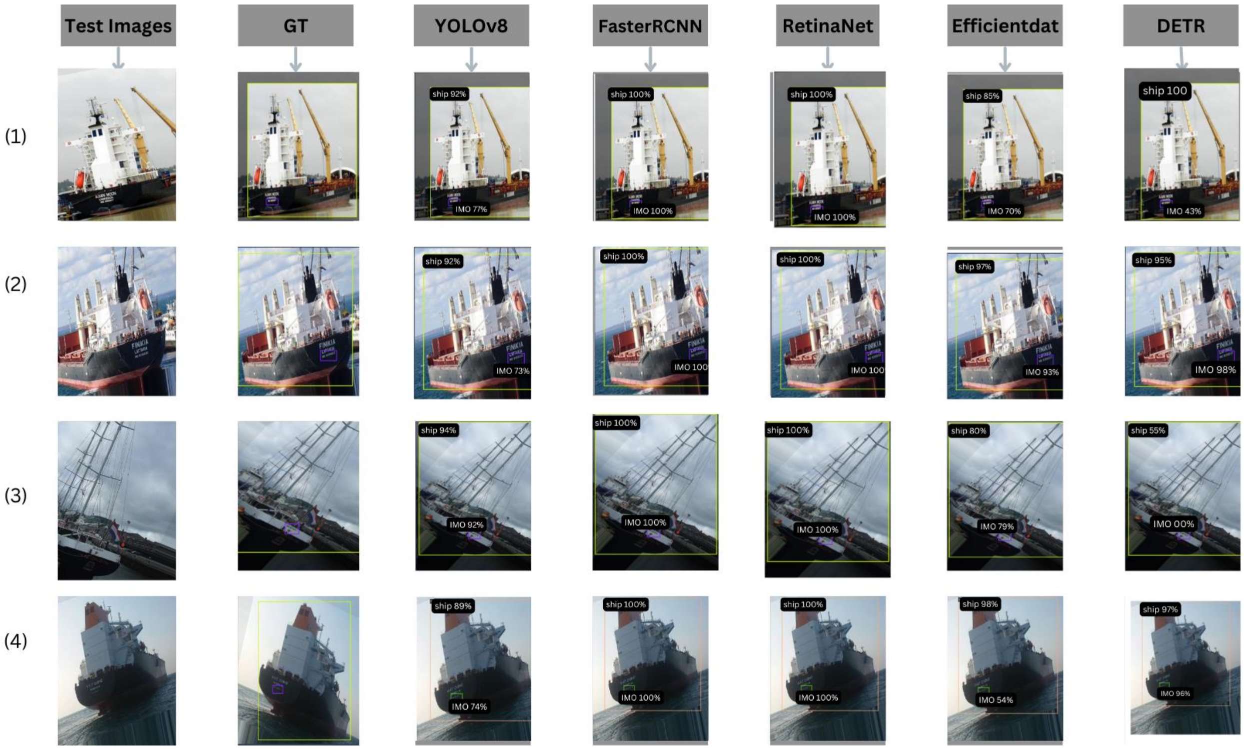

Figure 3. Detection performance comparison of YOLOv8, Faster R-CNN, RetinaNet, EfficientDet, and DETR on test images.

4.3 RoI and Digit Extraction

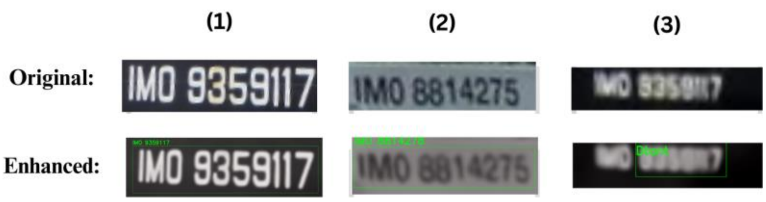

Figure 4. Enhancement and OCR of Low-Resolution IMO Numbers Using ESRGAN and EasyOCR. (1) clear image, (2) noisy image, and (3) badly blurred image.

The effects of EasyOCR and ESRGAN on low-resolution IMO number images are shown in Figure 4. The enhanced images are displayed in the bottom row ("Enhanced"), while the top row ("Original") displays the original images. In column 1, the proposed models successfully enhanced the original image and extracted the accurate OCR of "IMO

9359117". Column 2 shows that ESRGAN denoised the original image. However, EasyOCR misread "IMO 8814275" as "IMO 8814278", confusing a "5" for an "8". Therefore, EasyOCR sometimes misread characters, especially when the original image quality is poor. Both models failed for the badly blurred image in column 3, misreading the number as "Dtant", which exposes issues in this condition.

5. DISCUSSSIONS AND CONCLUSION

This study examined the performance of deep learning models in detecting ships and IMO numbers in difficult maritime situations. RetinaNet and FasterRCNN have shown exceptional accuracy. While Yolov8 showed outstanding speed, making it ideal for real-time applications. However, models such as DETR and EfficientDet faced difficulties when dealing with low-resolution images when applying ESRGAN upgrades. It was recognised that there is a requirement for additional improvement in image processing and model optimisation to achieve real-time deployment. These findings highlight the potential of deep learning to enhance marine safety and security. Future research should prioritise improving the reliability and practicality of these methods.

While successful, the concepts and methods utilised in this study had limits, especially when identifying IMO numbers under challenging conditions. The high processing requirements and longer inference durations of models like RetinaNet and FasterRCNN pose difficulties for real-time deployment, especially on platforms with limited facilities such as marine systems. YOLOv8 showed outstanding speed, but its accuracy of IMO detection needs improvement. The use of ESRGAN to enhance image resolution provided positive results. However, it could not eliminate recognition mistakes, as evidenced by the misclassification of digits in some cases. In addition, to boost the accuracy of identifying IMO numbers, mainly when image quality is poor, it is essential to explore additional improvements to image super-resolution methods such as ESRGAN. Possible approaches could involve domain-specific modification to more effectively address the visual attributes of marine situations, such as the reflection of light on water and the changing illumination conditions. Finding a compromise between accuracy and computing effectiveness is necessary in real-time applications. Investigating improvements such as model reduction or employing more lightweight architectures would be beneficial in enhancing the possibility of deploying models like RetinaNet and Faster R-CNN in real-time on ships.

Future research should concentrate on several significant areas to improve the approach and efficient use of marine detection systems. Enhancing the model's capacity and applicability requires an extension of the dataset to include a bigger and more diverse collection of marine situations. Adding dropout to reduce overfitting and batch normalization to stabilize and accelerate training will be essential for enhancing training methodologies. Implementing sophisticated techniques to enhance blurry images can greatly improve the accuracy of digit detection. The combination of optical data with AIS information would significantly improve the accuracy of detection. Refining OCR algorithms and investigating hybrid models is essential to enhance IMO number detection, especially in low-quality images. Conducting detailed evaluations of the models under different marine situations thoroughly explains their practical efficiency and limitations.

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