Implementation Of Deep Learning For Ship Detection In Aerial Images

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***Abstract*— The accurate detection of ships in satellite imagery holds immense significance for maritime security and diverse applications like traffic monitoring, military activity surveillance, and combating illegal fishing. However, achieving precision and efficiency in detection remains a persistent challenge. Artificial Intelligence (AI) has emerged as a valuable tool for ship detection in satellite imagery, although obstacles persist. This study employs the YOLOv7 algorithm, a specialized tool for ship detection, aiming to enhance detection accuracy and efficiency compared to previous methods. Leveraging the most recent ShipRSImageNet dataset, this research anticipates delivering a substantial contribution to advancing the efficiency and accuracy of ship detection in the realm of maritime security and its associated applications.**

Keywords— Satellite imagery, You Only Look Once (YOLO), Deep Learning, AI, ShipRSImageNet, aerial images.

I. INTRODUCTION

The detection and recognition of ships in satellite imagery have garnered attention in maritime security and traffic control applications because ships are the primary means of operations at sea [1]. The use of satellite imagery in ship detection holds significant importance in managing maritime traffic, defense and intelligence, as well as fisheries management. Remote monitoring plays a crucial role in ship monitoring due to its wide operational range and extensive monitoring capabilities [2].

Furthermore, in civilian environments, this serves as the foundation for marine resource management, monitoring of illegal fishing activities, surveillance of marine pollution, and maritime rescue assistance. In a military context, this technology can be utilized for patrolling territorial maritime zones, protecting interests and rights, and monitoring important ports and targets.

In the past, this was accomplished with the aid of the Automated Identification System (AIS), which utilizes very high-frequency radio signals to wirelessly transmit vessel location, destination, and identification information to receiving devices on other ships and on land [3]. This system has proven highly effective in monitoring vessels obligated to install VHF transponders but falls short in identifying non-compliant vessels, including those that disable their transponders, such as small boats commonly used by coastal communities and typically lacking AIS systems.

Given these circumstances, it is important to conduct research on this matter. Ship detection and classification have crucial strategic value in various situations beyond monitoring ships without VHF transponders. It is beneficial for tactical situations to expedite decision-making processes and provide situational understanding of water environments. Advances in remote imaging technology have enabled extensive monitoring across maritime regions. This has sparked researchers' interest in developing maritime target detection and classification technology. Automating ship detection has significant benefits in various applications. To date, research has continuously progressed in ship detection in satellite imagery to enhance the detection system's output. This study aims to achieve better accuracy using the YOLOv7 approach. It is hoped that the results from this model will enhance the efficiency and accuracy of ship detection in satellite imagery.

II. LITERATUR REVIEW

The detection of oriented targets in remote sensing imagery has gained significant prominence in recent years. Conventional approaches typically use horizontal bounding boxes (HBB) for target identification, but they often face accuracy challenges, especially when dealing with targets featuring diverse orientation angles, dense distributions, and significant aspect ratios. The introduction of Oriented Bounding Box (OBB) addresses these challenges by incorporating rotation angles into the bounding boxes.

A study conducted by Guozhi Miao et al. showcases the effectiveness of this innovative approach, achieving a high detection accuracy with a mean Average Precision (mAP) of 86.29%, based on experiments conducted on HRSC2016 and UCAS-AOD datasets [4]. Detecting ships with varying aspect ratios proves challenging using horizontal bounding boxes, necessitating an approach with rotating bounding boxes. N. Su, Z. Huang et al. Zhou introduced an arbitrary-oriented detector to swiftly determine ship positions in large-area images. They utilized a novel feature extraction network called DCNDarknet25, adhering to the You Only Look Once (YOLO) principle, resulting in improved speed and accuracy. This approach effectively identifies rotations without relying on angle regression, enabling swift detection of ships in extensive monitoring images. Testing on the HRSC2016 dataset and their own large-area image dataset (LARS) demonstrated excellent accuracy with an mAP of 88.28% [5].

C2-YOLO, a rotation-based target detection network using YOLOV5, improves accuracy by 3.52%, resulting in an mAP of 85.65% for small targets in remote sensing images. X. Cheng and C. Zhang utilized CARAFE and CA modules for feature fusion and object location focus. Experiments on the DOTA and HRSC2016 datasets validated performance comparable to state-of-the-art methods [6].

In their journal, L. Zhang and H. Yin compared three ship detection algorithms in remote sensing images: Faster R-CNN, YOLOv4, and SSD using HRSC2016 dataset. The performance varies depending on ship size and type. SSD is the fastest, YOLOv4 is accurate for small ships. The choice of method should align with target characteristics and priorities, considering both detection accuracy and speed [7].

Ship detection technology is crucial for maritime traffic safety and waterway management. This paper proposes an enhanced YOLO-based ship detection method, introducing ASPP and CBAM attention mechanisms to improve foreground-background discrimination. Focal Loss is utilized to enhance accuracy in detecting challenging targets. Experiments conducted by X. Zhang and Z. Zhang demonstrate the superiority of our method, achieving an average accuracy of 96.8% in real-time ship detection using the ShipsNet dataset [8].

III. Material and Method

The steps in this research are illustrated in Figure 1. The methodology employed in this study begins with data collection, data preprocessing, model training, model testing, followed by analysis and evaluation. Ship detection in aerial images was developed using the You Only Look Once - V7 (YOLO-V7) algorithm.

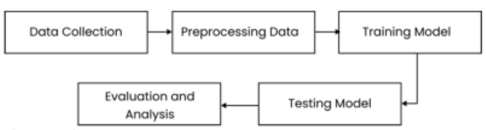

Fig. 1 research steps

A. Aerial Image

An aerial image, obtained from an elevated perspective using aircraft, drones, or satellites [9], offers a broad view of the landscape. Aerial images find applications in mapping, environmental monitoring, agriculture, security, and more. They provide valuable spatial data, particularly for mapping and environmental monitoring, aiding in observing changes in natural areas like forests and rivers. In agriculture, they assist in crop observation, pest detection, and resource optimization. Aerial images are also utilized in security for surveillance and law enforcement. Despite the benefits of detailed information and extensive coverage, challenges include complex data processing, coordinating image capture, and managing costs and resources for acquisition and analysis.

B. Dataset

The dataset to be used in this research is a public dataset known as ShipRSImageNet [10]. This dataset is an aerial image processing dataset used for ship detection and classification, as shown in Figure 2. The dataset consists of 3,435 images sourced from various sensors, satellite platforms, and locations, namely:

The xView Dataset uses imagery from the WorldView-3 satellite, providing a resolution of 0.3 meters. The images have been resized to 930 x 930 pixels, resulting in a total of 532 images in this dataset.

1) The High-Resolution Satellite Collections 2016 (HRSC2016) Dataset consists of 1,057 images.
2) The Fine-Grained Ship Detection (FGSD) Dataset is composed of 1,846 images.
3) The Airbus Ship Detection Challenge Dataset comprises 21 images.
4) The GeoFen-2 and JiLin-1 Satellites Dataset includes 17 images.

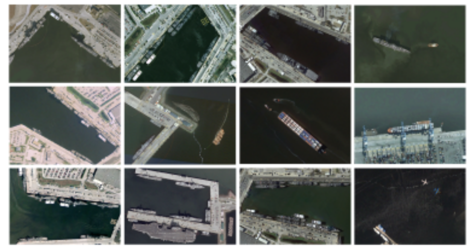
Fig. 2 Dataset

C. Pre-processing Data

in the Pre-processing stage, the dataset is divided into training and testing datasets with a split composition of 80% for training data and 20% for testing data, utilizing a total of 3,435 images for model development (2,748 images for the training dataset and 687 images for the testing dataset).

The ShipRSImageNet dataset initially utilized PascalVOC and COCO formats. However, since the YOLO model has a different label format, namely the YOLO format, the labels from the original format need to be converted and adapted to the YOLO format. This was done to make the dataset compatible with the YOLO model. This process involves converting the labels from the initial PascalVOC format to the YOLO format. The YOLO dataset label format consists of 5 main columns: object class, bounding box width and height, and the coordinates of the bounding box's center point with respect to the object (x and y-axis coordinates of the bounding box's center point).

D. Model Architecture

You Only Look Once (YOLO) is an object detection algorithm that emerged from the advancement of Convolutional Neural Network (CNN) [11]. Originally introduced by Redmon et al. in 2016, YOLO stands out due to its unique detection approach utilizing regression for object detection by assigning values to various parts of the image [12]. The algorithm is highlighted in their paper as an efficient real-time object recognition method [13]. YOLO excels in speed when it comes to object detection, employing a distinct strategy compared to conventional detection systems. Previous methods typically utilize classification for detection and then perform checks at various locations using the model, considering regions with high scores as detections. In contrast, YOLO divides the image into multiple regions and predicts bounding boxes and probabilities for each region. These bounding boxes are then weighted by the predicted probabilities. The workflow of YOLO is illustrated in Figure 3.

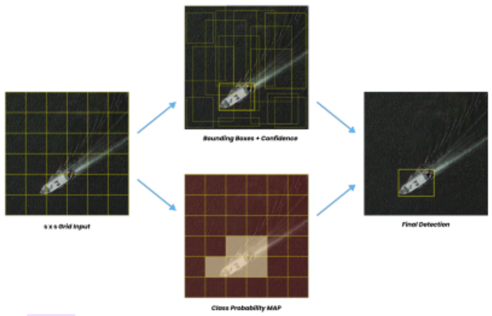

Fig. 3 YOLO workflow

In Figure 3, it can be observed that YOLO essentially takes the input image and transforms it into a grid divided into several small sections (typically 19x19 or 13x13). Each cell in the grid is responsible for predicting five components: x, y, w, h, confidence. These five components form a bounding box that encloses an object, as shown in Figure 4.

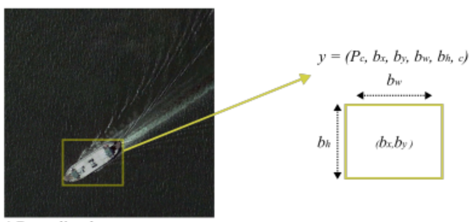

Fig. 4 Bounding box components

In Figure 2, it can be observed that the arrangement of the bounding box on an object. In this bounding box arrangement, the values *bx* and *by* represent the coordinates of the center of the box relative to the boundaries of the network cell. The values *bw* and *b*h represent the width and height of the box relative to the entire image, and the value *c* represents the confidence or confidence score. To calculate the confidence, it can be defined as Formula (1).

$$confidence = \mathrm{P}(object)\, x\, IoU \frac{truth}{pred} \quad (1)$$

In Formula (1), P(object) denotes the likelihood of an object's presence, while IOU (intersection over union) serves as an evaluation metric for gauging the object detector's precision. In this context, "truth" signifies the ground truth or actual value, and "pred" signifies the anticipated value. This can be depicted as depicted in Figure 5.

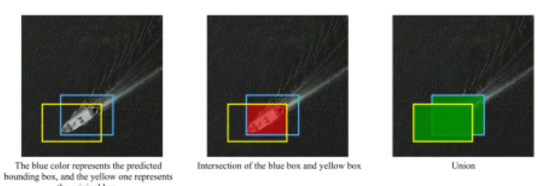

Fig. 5 Intersection over union

In Figure 5, it illustrates an overview of IoU (Intersection over Union), where the IoU value ranges from 0 to 1. If the IoU has a value of 1, it means the bounding box and the ground truth box overlap perfectly, resulting in high accuracy. Here is the IoU equation as shown in Formula (2).

$$IoU = \frac{area\ overlap}{union\ area} \quad (2)$$

In Formula (2), It is evident that the intersection point represents a proportion. The overlapping area pertains to the region between the bounding box and the ground truth box. On the other hand, the union area corresponds to the area encompassed by the predicted bounding box.

You Only Look Once (YOLO)–V7 is one of the latest versions of the YOLO algorithm. With an efficient hardware-friendly design and high performance, this version has seen several improvements compared to its predecessors. One of the major enhancements is the utilization of anchor boxes [14].

In this study, we implemented a deep learning model using the You Only Look Once v7 (YOLOv7) method. The YOLOv7 method was chosen because it is suitable for deep image detection cases, particularly for image classification models. YOLOv7 has an architecture that combines elements from YOLOv4 [15], Scaled YOLOv4 [16], and YOLO-R [17], resulting in a new and improved YOLOv7 method.

In YOLOv7, the primary computational unit within the YOLOv7 backbone is the Extended Efficient Layer Aggregation Network (E-ELAN), which processes network features. E-ELAN is derived by adapting and modifying the ELAN architecture, illustrated in Figure 6.

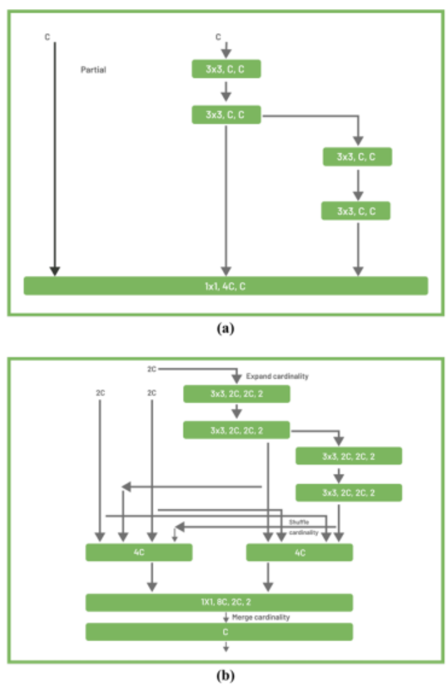

Fig. 6 (a) ELAN architecture, (b) E-ELAN

In Figure 6 (a), the leftmost connection illustrates cross-stage connections, while the parallel connections on the right are stacked within a computational block.

The result of these modifications is an improvement in the model's learning capability without disrupting the gradient flow. These modifications occur within the computational block, while the transition layers continue to use the ELAN architecture. In E-ELAN, group convolutions are utilized to expand the channels and cardinality of the computational block. Each computational block is shuffled into groups of a specific size, and the results are combined. By combining shuffled group features, E-ELAN efficiently performs feature fusion within the network. These changes enhance the feature fusion capabilities in YOLOv7 and improve the model's performance.

When constructing an object detection model, factors typically considered include network depth, network width, and the image resolution used in network training. In the case of YOLOv7, this method increases both the depth and width of the network simultaneously by combining the layers of the model into a cohesive unit, as seen in Figure 7.

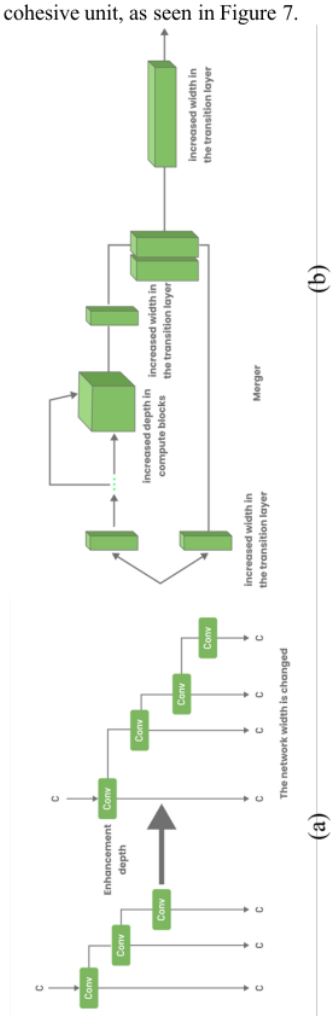

Fig. 7 (a) model scaling, (b) Model Compound Scaling

In Figure 7, it can be seen that this model architecture consists of layers combined simultaneously. Therefore, when increasing the depth of the computational block, it is necessary to calculate the changes that occur in the output kernel. Furthermore, considering an increase in width by the same amount as the calculated changes in the output kernel. This way, this composite scaling approach maintains the existing properties in the original architecture and preserves an optimal structure.

E. Evaluation and Analys

Evaluation is conducted to measure the performance of the developed model. The performance of a model is considered good if the model has high metric values. In this study, Confusion Matrix will be used as a tool to measure the model's performance. The Confusion Matrix generates a table that compares predicted values with actual values, from which accuracy, precision, recall, and f1-score can be calculated. In the performance of the confusion matrix, there are four classes that represent the results of the classification process:

1) True Positive (TP): The prediction is accurate, and it corresponds to the actual true value.
2) True Negative (TN): The prediction is inaccurate, and it matches the actual false value.
3) False Positive (FP): The prediction is inaccurate, suggesting a true value when it's actually false.
4) False Negative (FN): The prediction is inaccurate, suggesting a false value when it's actually true.

Accuracy is the ratio of true predictions to the total actual values. In other words, accuracy illustrates how accurately the model classifies images correctly, as shown in formula (3).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (3)$$

Precision is the ratio of true positive predictions to the total positive predicted values. It represents how many of the correctly predicted positive classes out of all the predicted positive values. This is depicted in formula (4).

$$Precision = \frac{TP}{TP + FP} \qquad (4)$$

Recall or sensitivity is the ratio of true positive predictions to the total actual positive values. It represents how many of the actual positive values were predicted correctly. This is depicted in formula (5).

$$Recall = \frac{TP}{TP + FN} \qquad (5)$$

The F1-Score is a measure calculated as the harmonic mean of precision and recall. An ideal F1-Score is 1, indicating a perfect balance of precision and recall. In Formula (6), it is evident that a higher F1-Score signifies a model with strong precision and recall performance, while a lower F1-Score suggests a weaker balance between these metrics.

$$F1\text{-}Score = 2 \times \frac{Recall * Precision}{Recall + Precisioin} \quad (6)$$

IV. Results

In the results section, we will showcase previous studies related to ship detection in images. These prior studies serve as the foundation for our further research. The insights gained from these previous studies provide a basis for enhancing ship detection accuracy in aerial images, which is the main focus of our research. The accuracy comparison results with previous studies are presented in Table 11.

Work	Dataset	Methode	Hasil
Jingrun Li, Jinwen Tian∗, Peng Gao, Linfeng Li [18]	DOTA[23]	Fine-grained Clasification Network	mAP: 0.72%
S Wei, H Chen, X Zhu, H Zhang [19]	HRSC2016[24]	Faster R-CNN *with Dilated Convolution*	mAP : 70.85%
X Wu; Y Zhou [20]	HRSC2016[24]	*improveed* YOLOv5	mAP: 72.6%
G Miao, X Ren, R Guo, Z Peng [4]	HRSC2016[24]	*improved* Resnet101	mAP : 86.29%
Nan Su, Zhibo Huang, Yiming Yan, Chunhui Zhao, Shuyuan Zhou [5]	HRSC2016[24]	DLAO	mAP : 88.28% & 77.8%
X Cheng, C Zhang [6]	HRSC2016[24]	C 2 -YOLO	MAP: 85.65%
B V R Zalukhu, A W Wijayanto, M I Habibie [21]	ShipRSImageNet [25]	YOLOv5x6	Precision: 75.18%.
L Zhang, H Yin [7]	HRSC2016[24]	YOLOv4	mAP: 96.04%
Abhinaba H.; P. Jidesh [22]	ShipRSImageNet [25]	*Faster* R-CNN	*Accuracy:* 92.93%
X Zhang, Z Zhang [8]	Shipsnet[26]	*improved* YOLOv5	mAP: 96.8%

In Table 2.1, it can be observed that research on ship detection has shown progress each year. Not only precision and accuracy have improved, but also the datasets concerning ship images have advanced. Additionally, the methods used in the development of this research are also evolving.

This research has reached a significant stage of progress, including the accomplishment of more accurate dataset labeling. Currently, the focus of the research has shifted to the next phase, where the model is undergoing training using the latest version, YOLOv7. This step reflects the researchers' dedication to updating and enhancing the ship detection methodology, presenting the potential for significant improvements in accuracy and reliability of detection.

V. Conclusion

In our future work, we plan to utilize the YOLO-v7 method to achieve more accurate object detection in aerial images. We hope that the proposed method can enhance the bounding box capability to detect class objects. In the previous versions of YOLO, the method was capable of detecting and identifying various types of ships in the water, such as cargo ships, bulk carriers, cargo vessels, container ships, fishing boats, passenger ships, and more. With the latest version and additional modifications, we aim to improve the accuracy in ship detection in aerial images. We will also collect a more diverse range of ship samples to enhance the model's generalization ability.

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