Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 235 (2024) 1793–1802

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering (ICMLDE 2023)

Ship Detection in Synthetic Aperture Radar Imagery: An Active Contour Model Approach in Computer Vision Deep Learning

Tripty Singh[a,*], Tina Babu[b], Rekha R Nair[b], Prakash Duraisamy[c]

[a] *Department of Computer Science and Engineering, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India*
[b] *Department of Computer Science and Engineering, Alliance University, Bengaluru, India*
[c] *University of Wisconsin-Green Bay Wisconsin, USA*

Abstract

The utilization of Synthetic Aperture Radar (SAR) images for ship recognition holds significant importance within the realm of maritime surveillance and security. SAR images are useful for ship detection and recognition because they can penetrate through clouds and capture detailed information about ships, such as their size, shape, and orientation. In the context of ship recognition using SAR images, the primary objective is to employ automated methods for the identification and categorization of ships present in SAR imagery. The detection of ships in SAR images is a significant research area, but it remains challenging due to speckle noise, land clutters, and low signal-to-noise ratio. Researchers have developed various approaches to overcome this challenge, such as adaptive filtering, speckle reduction, and segmentation techniques. Hence, a ship detection method is devised that combines the active contour method and the YOLO-v8 model using deep learning techniques. In the first step, the SAR images undergo pre-processing and normalization, and the model is trained with the backbone network. The YOLO-v8 model, renowned for its proficiency in object detection, is applied to delineate precise bounding boxes around ships within the images. The results obtained from experiments conducted on a variety of SAR images convincingly demonstrate that the suggested approach attains proficient ship target detection, striking a balance between accuracy and comprehensiveness. This approach represents a promising solution to enhance ship detection in challenging SAR scenarios.

Keywords: SAR ship detection; YOLO models; active contour; deep learning ;bounding box

1. Introduction

SAR is a remote sensing technology that has garnered substantial interest in recent times owing to its capability to deliver high-resolution images of Earth's surface under diverse weather and lighting conditions. [1, 2]. SAR has many

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000.
E-mail address: tripty_singh@blr.amrita.edu

10.1016/j.procs.2024.04.170

applications, including ship detection and recognition in maritime surveillance and security [3]. Ship recognition using SAR images is an important task in maritime surveillance, which involves automatically identifying and classifying ships in SAR images [4]. This task is challenging due to the complex nature of the SAR images, which often contain high levels of noise and clutter. However, using SAR images for ship recognition offers several advantages over other imaging technologies, such as optical imaging, including the ability to penetrate clouds and capture images of ships even in adverse weather conditions. In recent years, there has been growing interest in developing accurate and robust ship recognition algorithms using SAR images [5]. As a consequence, a multitude of methodologies have emerged, encompassing techniques like feature extraction, machine learning, and deep learning. These methods have displayed considerable potential in enhancing the precision of ship recognition when employing SAR images. Ship recognition using SAR images has several practical applications, including maritime surveillance, search and rescue operations, and piracy prevention. As the technology continues to evolve, SAR ship recognition is expected to become an increasingly important tool in maritime security and surveillance. Furthermore, developing large-scale datasets for training and evaluating recognition algorithms is crucial for advancing the state-of-the-art in SAR ship recognition [6]. Continued research and development in this field is expected to improve ship recognition accuracy and robustness, making it a vital tool in ensuring maritime security.

SAR technology has revolutionized remote sensing in the maritime domain due to its all-weather capability, day-and-night operation, and independence from solar illumination. SAR sensors provide high-resolution images that detect and identify various objects, including ships, in large ocean areas [7]. Ship detection in SAR imagery has garnered significant attention in recent years due to its crucial role in maritime surveillance, environmental monitoring, and maritime safety. The detection of ships in SAR imagery is a challenging task due to the complex nature of the marine environment. SAR images often exhibit high clutter and noise levels caused by wave reflections, surface roughness, and atmospheric conditions. Moreover, ships come in various sizes, shapes, and orientations, making designing a universal ship detection algorithm difficult. In recent years, considerable progress has been made in developing detection techniques for SAR imagery. These methods can be broadly categorized into model-based, statistical, and machine learning-based approaches [8]. Model-based methods exploit known ship characteristics and use sophisticated mathematical models to detect ships. Statistical techniques focus on identifying statistical anomalies in SAR images to distinguish ships from clutter [9]. Machine learning-based methods leverage the power of artificial intelligence algorithms to learn ship patterns from a large training dataset.

The objectives of this paper are the following:

- To provide a comprehensive overview of these ship detection techniques in SAR imagery.
- To analyze the strengths and weaknesses of each approach and highlight potential avenues for future research.
- To discuss performance evaluation metrics and benchmark datasets that facilitate comparing and assessing different ship detection algorithms.

The subsequent sections of the manuscript are structured in the following manner. Section 2 provides an in-depth exploration of the existing literature, while Section 3 offers a comprehensive elucidation of the proposed methodology. The experimental results, analysis and discussion is mentioned in Section 4. The manuscript is concluded with future scope in Section 5.

2. Literature Review

Numerous strategies have been used, ranging from more sophisticated methods like Convolutional Neural Networks (CNN) [10] and Deep Learning architectures [11] to more classic algorithmic approaches like Support Vector Machines (SVM) [12] and Random Forests (RF) [13]. The evaluation of these algorithms' performance is conducted using metrics such as accuracy, precision, recall, and F1-score [14]. Clutter suppression techniques are crucial to enhance the detection performance by reducing false alarms caused by background noise in SAR images [15]. Different methods have been proposed to mitigate clutter effects, including adaptive filtering, statistical modeling, and thresholding techniques. These approaches aim to enhance the visibility of ships while suppressing the clutter from waves, land, and other non-ship objects. Another important aspect of SAR ship detection is the availability of benchmark datasets. Many publicly accessible datasets, like MSTAR and TerraSAR-X, have been used to assess how well ship detection algorithms work [16]. These datasets provide a standardized platform for benchmarking and facilitating fair comparisons among different techniques. In this review, we analyze and compare various SAR ship detection techniques published in the literature.

In the realm of target detection, Dong et al. [17] made improvements to the Faster RCNN model. They replaced the traditional nonmaximum suppression (NMS) method in the regional proposal network phase with Sig-NMS. This modification significantly reduced the chances of missing smaller targets. Additionally, Cui and colleagues proposed a detection technique built upon the concept of an Intensive Attention Pyramid Network (DAPN) [18]. This approach entails the extraction of comprehensive features, which encompass both high-resolution details and semantic information, with the aim of augmenting detection capabilities for ship targets at varying scales.

Li and colleagues introduced a residual network referred to as R3-NET, designed for the detection of vehicles from various orientations in remote sensing images and videos [3]. This network demonstrated significant robustness and accuracy. In the domain of dense target detection, Wang and their research team made advancements by incorporating the Spatial Group-wise Enhancement (SGE) attention module into the CenterNet model. This addition allowed for the efficient detection of closely located ships [19]. However, even though these methods have made significant strides in improving detection accuracy, they still present challenges in terms of computational requirements, time consumption, and compatibility with deployment on devices possessing restricted computational memory and resources capacity.

In the realm of object detection, there are primarily two approaches. The initial category is the single-stage detection technique, demonstrated by models such as the SSD (Single Shot MultiBox Detector) and the YOLO (You Only Look Once) series algorithm [20, 21]. This approach employs regression techniques to directly forecast the confidence in a category and pinpoint the target's position within an image.

The second approach is the two-stage model. In this method, a regional proposal network is employed to generate a set of candidate boxes that may contain potential targets. Subsequently, this model further identifies the target's category and refines the boundary boxes.

By understanding the current state-of-the-art and research trends, researchers can focus their efforts on addressing the challenges and advancing SAR ship detection for improved maritime surveillance and security. In addition to feature extraction, classification algorithms, clutter suppression, and benchmark datasets, other important aspects of SAR ship detection have also been investigated in the literature. These include polarization analysis, multi-temporal analysis, and fusion techniques. Polarization analysis explores the potential of utilizing the polarization information in SAR data for ship detection [22]. Polarimetric SAR (PolSAR) data provides additional information about the scattering properties of the observed targets. Several studies have investigated the use of polarimetric features, such as the coherency matrix and polarization entropy, to improve ship detection accuracy. Multi-temporal analysis involves the exploitation of SAR images acquired at different time instances to detect ships.

By reviewing and analyzing the related work in SAR ship detection, this paper aims to provide a comprehensive understanding of the current state-of-the-art techniques, identify research gaps, and propose potential avenues for future research. The insights gained from this review will contribute to the advancement of SAR ship detection methodologies and ultimately improve maritime surveillance and security capabilities.

3. Proposed Model

This paper proposes a total of 6 object detection models that are discussed below. We start by creating a custom dataset for training the models, and a testing dataset is created to test the trained models. Using deep learning object detection models, we get good accuracy for each model for the testing data provided to the model.

To operationalize our model for real-time applications, we employed advanced deep learning techniques in conjunction with computer vision to identify and categorize ships within SAR images. Our primary goal was to enhance the accuracy of our deep learning models by implementing a multi-layered approach. We addressed this challenge by investigating six distinct deep learning models: YOLOv5, YOLOv8, Detectron2, YOLOv3 Pytorch, Tensorflow2, and YOLOv5 Oriented Bounding Boxes. Through this comprehensive exploration, we aimed to optimize the accuracy of our deep learning models, thereby improving their performance in ship detection and classification tasks within SAR imagery.

The model architecture is illustrated in the accompanying Figure 1, while the pre-training process of the network model is visualized in Figure 2. Our approach involves the creation of a deep learning model capable of self-training

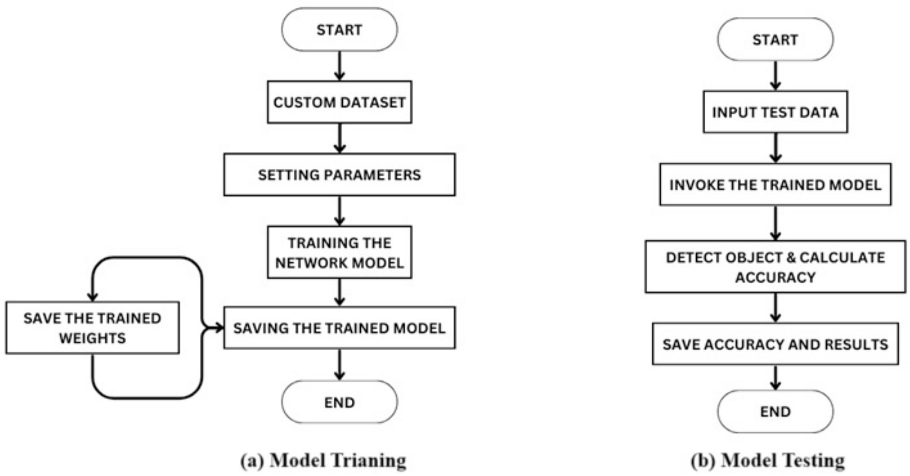


Fig. 1. Object detection Model (a) Training (b) Testing.

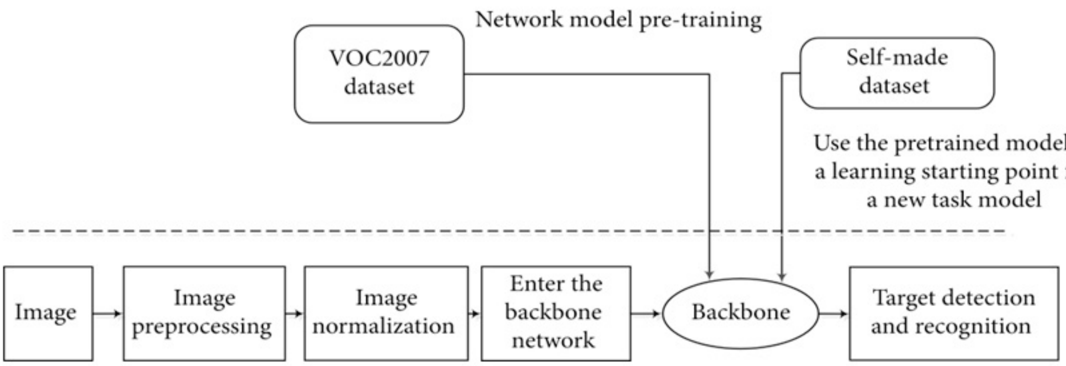


Fig. 2. Pre-training of the network model.

with the supplied dataset, yielding results in the form of mean Average Precision (mAP) scores. This model's outcomes offer insights into achieving high prediction accuracy utilizing only a subset of the dataset. This strategy holds significant potential for addressing diverse data-related challenges prevalent in today's world.

The following models were analysed for the detection.

3.1. YOLOv5

YOLOv5 is an object detection model that has gained significant popularity in the computer vision community [23]. It stands for "You Only Look Once," referring to its ability to perform object detection in real-time by looking at the entire image only once. YOLOv5 has also been adapted for Synthetic Aperture Radar (SAR) ship detection. Training YOLOv5 for SAR ship detection involves collecting a dataset of SAR images that contain annotated ship instances.

The model is trained using a technique called supervised learning, where it learns to detect ships by minimizing the discrepancy between its predicted bounding boxes and the ground truth annotations.Once it has been trained, YOLOv5 can be applied to carry out ship detection within SAR images. Given an input SAR image, the model processes it through the network and outputs bounding box predictions and class probabilities for ships. It is appropriate for a variety of object detection applications, including SAR ship detection, thanks to its modular architecture and effective implementation.

3.2. YOLOv8

Broadly speaking, the YOLOv8 model typically includes a deep convolutional neural network (CNN) as its backbone, responsible for capturing high-level features from SAR images [24]. The backbone could be a variant of popular architectures like Darknet or CSPDarknet, as seen in previous YOLO versions. To train YOLOv8 for SAR ship detection, a dataset of SAR images with annotated ship instances would be required. The model would be trained using supervised learning, where it learns to detect ships by minimizing the discrepancy between its predicted bounding boxes and the ground truth annotations.

During the training process, additional techniques specific to SAR ship detection may be employed. For example, data augmentation methods can be used to simulate different SAR imaging conditions, account for ship variations, and improve the model's robustness. Additionally, transfer learning could be applied, initializing the YOLOv8 model with weights pretrained on a large-scale natural image dataset, which can help in improving the model's generalization capabilities. Upon successful training, the YOLOv8 model becomes proficient at detecting ships in SAR images by processing the input image through the network, subsequently producing bounding box predictions along with associated class probabilities.

3.3. Detectron2

Detectron2 is an advanced object detection and segmentation framework created by Facebook AI Research [25]. It serves as a flexible and modular platform for constructing computer vision models. Although it doesn't have built-in support for SAR ship detection, Detectron2 can be used to develop SAR ship detection models. In order to utilize Detectron2 for ship detection with SAR , customizing the framework is essential to accommodate SAR images and ship annotations effectively. This involves preparing a dataset of SAR images with ship bounding boxes or segmentation masks.

Detectron2 supports various annotation formats, including COCO, Pascal VOC, and custom formats. In the training process, Detectron2 combines supervised learning with optimization techniques to acquire the capability to detect ships in SAR images. After the training phase, the Detectron2 model can be deployed to identify ships within new SAR images. By processing an input SAR image through the network, the model generates predictions for ship bounding boxes or segmentation masks.

Detectron2 provides comprehensive evaluation and visualization tools to assess the performance of your SAR ship detection model. The model's performance and accuracy will depend on the quality and diversity of the training data, network architecture, and optimization strategies employed during training.

3.4. YOLOv3

YOLOv3 is a widely used object detection model known for its real-time detection capabilities. While not initially designed for SAR ship detection, it can be adapted and trained for this purpose using the PyTorch framework [24]. For the task of detecting ships in SAR images, need a SAR dataset images that includes annotations for ship bounding boxes.

The dataset should contain SAR images along with their corresponding ship bounding box coordinates. Using PyTorch, the YOLOv3 model can be implemented and trained for SAR ship detection. The backbone network, typically based on Darknet or Darknet-53, extracts features from the SAR images to make predictions. Training YOLOv3 for SAR ship detection involves optimizing the model's parameters through supervised learning.

Once trained, the YOLOv3 model can be applied to SAR images for ship detection. By inputting an SAR image into the network, the model generates predictions for ship bounding boxes and their associated class probabilities. It's important to note that using YOLOv3 for SAR ship detection necessitates adapting the model to SAR data and carefully designing the training process. Factors like data preprocessing, hyperparameter tuning, and optimization techniques significantly impact the accuracy of ship detection.

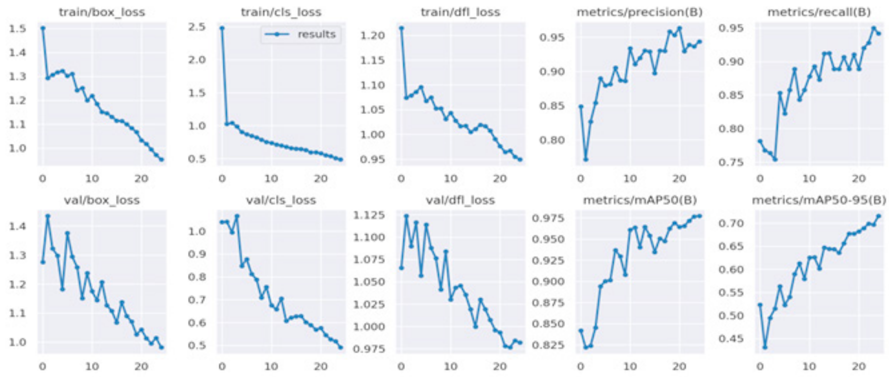


Fig. 3. YOLOv8 analysis.

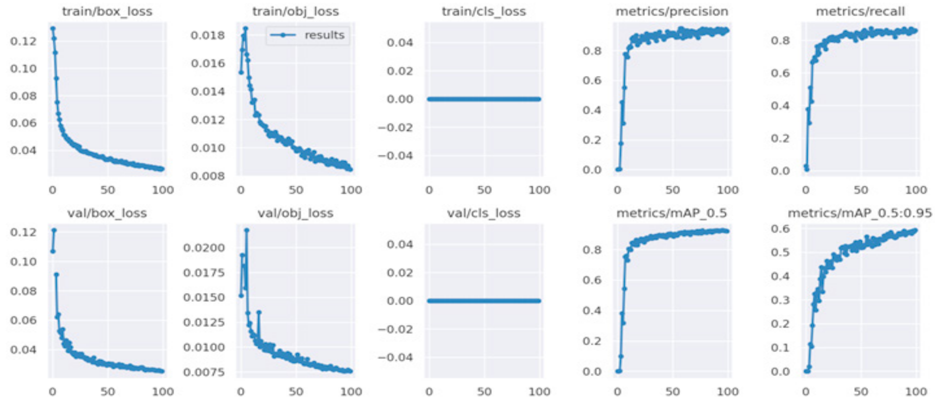


Fig. 4. YOLOv5 analysis.

3.5. TensorFlow2

TensorFlow2 is a widely-used deep learning framework that provides a range of tools and libraries for building and training machine learning models [26]. Although there isn't a specific pre-built SAR ship detection model in TensorFlow2, it can be leveraged to develop a custom ship detection model. To create a TensorFlow2 model for SAR ship detection, a dataset comprising SAR images and ship bounding box annotations is needed as the training data.

Using TensorFlow2, the model's architecture can be designed by constructing a convolutional neural network (CNN) backbone for feature extraction, along with additional layers for predicting ship bounding boxes and class probabilities. Training the TensorFlow2 model for SAR ship detection involves optimizing its parameters through supervised learning.

Once trained, the TensorFlow2 model can be utilized to detect ships in SAR images. By inputting an SAR image into the model, it generates predictions for ship bounding boxes and associated class probabilities. It's crucial to note that constructing a TensorFlow2 model for SAR ship detection necessitates customizing the architecture, training process, and post-processing techniques to suit SAR data characteristics.

3.6. YOLOv5 Oriented Bounding Boxes

YOLOv5 is a popular object detection model that focuses on bounding box predictions. Gather a dataset of SAR images annotated with oriented bounding boxes that accurately represent the ships' orientations [27]. The annotations should include the coordinates of the bounding boxes and the corresponding orientations. Modify the YOLOv5 model architecture to incorporate support for oriented bounding boxes.

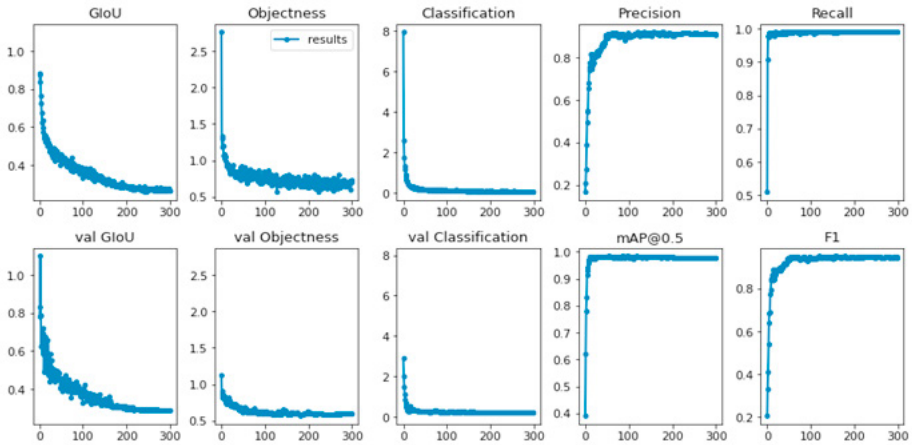
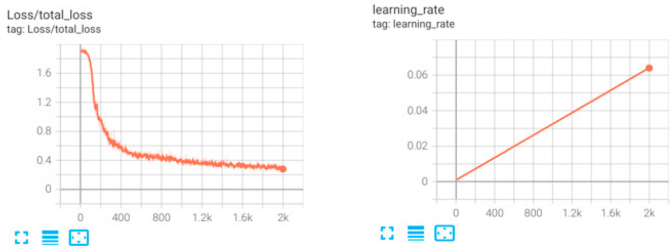


Fig. 5. YOLOv3 analysis.



Total Loss vs No. Of Epochs

Learning Rate vs No. Of Epochs

Fig. 6. TensorFlow2 analysis.

This may involve altering the bounding box prediction layers to include additional parameters for orientation estimation or replacing the bounding box regression with a different mechanism that can handle oriented bounding boxes. Formulate an appropriate loss function that considers disparities in both the position and orientation of the predicted bounding boxes in comparison to the ground truth bounding boxes. This loss function should guide the model to accurately predict both the position and orientation of the ships in SAR images.

Train the adapted YOLOv5 model using the annotated SAR ship dataset. This involves optimizing the model's parameters to minimize the defined loss function. Additionally, appropriate data augmentation techniques specific to SAR images, such as rotation or skewing, may be necessary to enhance the model's ability to handle oriented bounding boxes. Evaluate the performance of the trained model using appropriate evaluation metrics for oriented bounding box detection.

Furthermore, incorporate post-processing methods, such as non-maximum suppression, to enhance the precision of the ultimate ship detection outcomes. It's essential to emphasize that employing YOLOv5 for SAR ship detection using oriented bounding boxes demands a proficiency in both computer vision and deep learning methodologies.

4. Experimental Results and Analysis

After deploying the deep learning models across all six selected variants, we observed the training progress through plots generated over 300 epochs for each model. The training duration for each model was reasonable, and post-training, we witnessed noticeable enhancements in performance. Remarkably, YOLOv8 showcased the most impressive outcome, achieving a peak accuracy of 98.7%, which stands out as the highest among all the tested models. Our intention is to further refine these results by continuing the training process. It's important to note that employing just a deep learning model with a limited dataset for training could lead to suboptimal results. However, through the in-

S.No	Model Name	No of Epochs(Training)	Precison	Recall	mAP(mean avg precision)
1	YOLOv5	100	93.5	85.9	92.2
2	YOLOv8	50	94.4	94.1	98.7
3	Detectron2	200	91.2	89.3	90.3
4	YOLOv3 Pytorch	300	90.7	99.0	97.8
5	YOLOv5 Oriented Bounding Boxes	50	40	49	45.9
6	Tensorflow2	100	18(Local Loss)	29(Total Loss)	57(Learning Rate)

Table 1. Performance measures of various models.

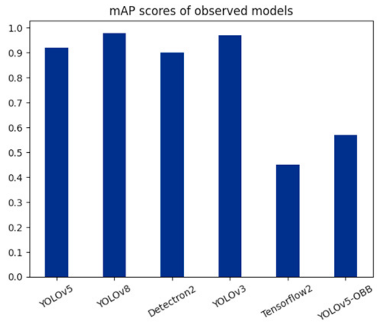


Fig. 7. Model Accuracy for SelectKBest

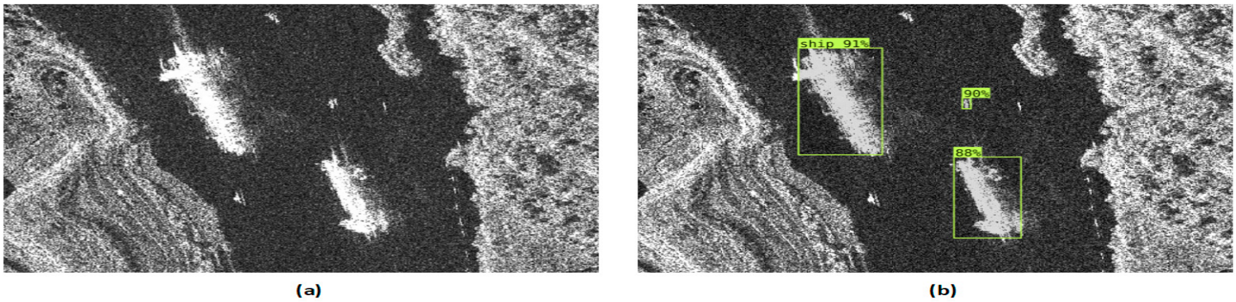


Fig. 8. (a) Input Image (b) Object detection using YOLOv8

corporation of masked layering techniques in this research, we aim to provide substantial evidence that deep learning can significantly enhance various models. With the YOLOv8 exhibiting the highest accuracy, our upcoming efforts will involve comparing each model's performance against YOLOv8.

4.1. Dataset Experimented

The dataset selected for this study contains 1160 SAR pictures with a 500 by 350 pixel size. There are 2358 ship occurrences in this particular dataset. SAR images have a spatial resolution of 1 to 15 metres per pixel. From Sentinel-1, TerraSAR-X, and RadarSat-2, these 1160 pictures were collected. The 1160 photos above are all in the.jpeg format and have a 24-bit colour depth. Images in the dataset are polarised in a mixture of HH, HV, VV, and VH. Three different types of annotational information are offered in the latest SSDD version: boundary box that is horizontal. Bounding box rotation. segmentation based on pixels.

4.2. Experimental Results

The experimentation was conducted on all the models as follows

- YOLOv8: After training for 300 epochs, the accuracy reaches 98.7% (refer to Fig. 3). However, if we extend the number of epochs and training duration, the accuracy improves in contrast to other object detection models.
- YOLOv5: After undergoing 300 epochs of training, the accuracy reaches 92.2% (see Fig. 4). Nonetheless, by extending the number of training epochs and prolonging the training duration, an increase in accuracy is observed, outperforming other object detection models
- YOLOv3: After being trained for 300 epochs, the accuracy reaches 97.8% (refer to Fig. 5). Through the augmentation of the number of training epochs and the extension of the training duration, there is a noticeable enhancement in accuracy when contrasted with other object detection models.

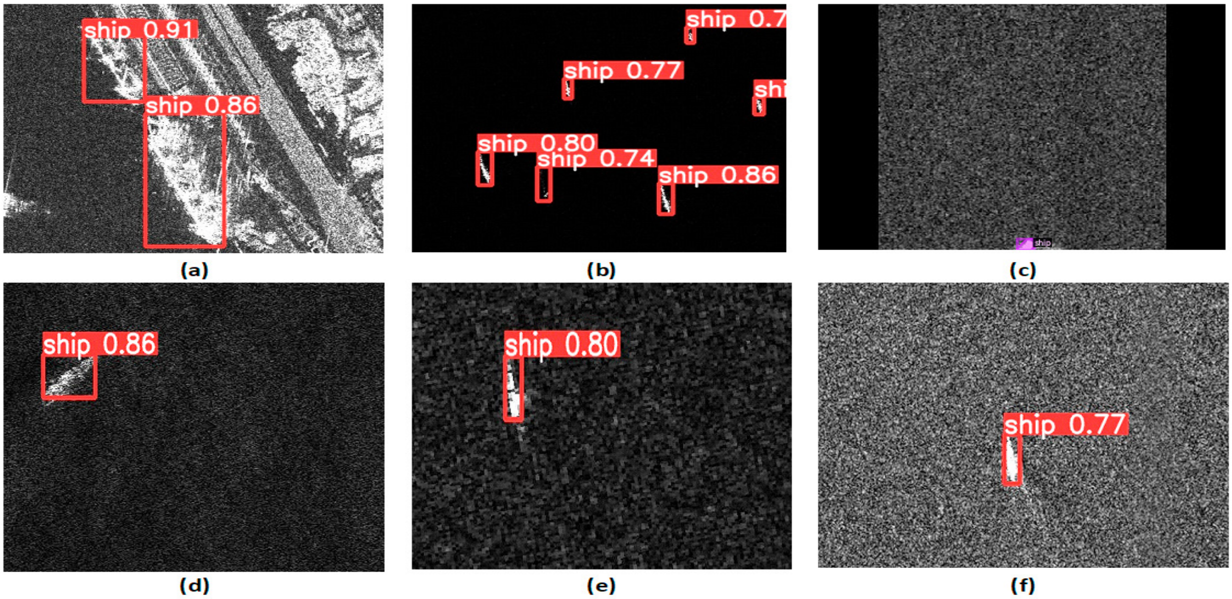


Fig. 9. Object detection with (a) YOLOv8 (b) YOLOv5 (c) Detectron2 (d) YOLOv3 (e) TensorFlow2 (f) YOLOv5-OBB

- TensorFlow2: After completing 300 epochs of training, the learning rate reaches 57% (depicted in Fig. 6). However, with the augmentation of epochs and extended training duration, the accuracy demonstrates enhancement in comparison to alternative object detection models.
- YOLOv5 Oriented Bounding Boxes Model: For 300 epochs of training the accuracy is 45.9% but if we increase the no of epochs and training time, the accuracy increases compared to other object detection models.

The mAP scores for various models is given in Table 1 and Fig. 7. The highest score is observed for the YOLOv8 model followed by YOLOv5. The least score is given by the TensorFlow2 model as YOLO is using a pre-trained model for object detection. Various performance measures are compared for the models and is given in Table 1. YOLOv8 model gives the highest performance in terms of precision (94.5), recall (94.1) and mAP score (98.7). Whereas the least perfromance is given by the TensorFlow2 model. However YOLOv5 also gives a comparable performance.

Therefore, ship detection in SAR images is best given by the YOLOv8 model as shown in Fig. 8. YOLOv8 gives more than 90% accuracy for the ship detection. The object detection of ship, a comparative analysis on various models is shown in Fig.9.

5. Conclusion and Future Scope

The proposed work observed an overall of six object detection models to study the different ship instances of SSDD-21 Data set. Utilized object detection models in deep learning to select a best model for the SAR Ship Instance prediction. Extracted sufficient domain features from the dataset, a custom dataset was created that contains three times the number of instances in the original training set. This custom data set utilized for training all the models utilized. The object detection models we build and observed are YOLOv5, YOLOv8, Detectron2, YOLOv3-Pytorch, TensorFlow2 and YOLOv5-Oriented Bounding Boxes. Out of all the models built and tested, the YOLOv8 model performed best on detecting the ships in SAR images. YOLOv8 gave an accuracy of 98.7% which outperformed all the other object detection models observed.

For future works, we plan to extend this SAR Ship Classification by developing the models to get the number of vessels in an instance given, dimensions of the vessels detected, by using computer vision we are willing to detect the vessels in large scale global complex SAR imagery. Upon further developments of the model, this can be used as a base line algorithm for detecting the illegal vessels or dark vessels in international waters

References

[1] Alberto Moreira, Pau Prats-Iraola, Marwan Younis, Gerhard Krieger, Irena Hajnsek, and Konstantinos P. Papathanassiou. A tutorial on synthetic aperture radar. *IEEE Geoscience and Remote Sensing Magazine*, 1(1):6–43, 2013.

[2] Andreas Reigber, Rolf Scheiber, Marc Jager, Pau Prats-Iraola, Irena Hajnsek, Thomas Jagdhuber, Konstantinos P. Papathanassiou, Matteo Nannini, Esteban Aguilera, Stefan Baumgartner, Ralf Horn, Anton Nottensteiner, and Alberto Moreira. Very-high-resolution airborne synthetic aperture radar imaging: Signal processing and applications. *Proceedings of the IEEE*, 101(3):759–783, 2013.

[3] Qingpeng Li, Lichao Mou, Qizhi Xu, Yun Zhang, and Xiao Zhu. R^3-net: A deep network for multioriented vehicle detection in aerial images and videos. *IEEE Transactions on Geoscience and Remote Sensing*, PP:1–15, 02 2019.

[4] Heng-Chao Li, Wen Hong, Yi-Rong Wu, and Ping-Zhi Fan. An efficient and flexible statistical model based on generalized gamma distribution for amplitude sar images. *IEEE Transactions on Geoscience and Remote Sensing*, 48(6):2711–2722, 2010.

[5] Ji-Wei Zhu, Xiao-Lan Qiu, Zong-Xu Pan, Yue-Ting Zhang, and Bin Lei. An improved shape contexts based ship classification in sar images. *Remote Sensing*, 9(2), 2017.

[6] Xianxiang Qin, Yanning Zhang, Ying Li, Yinglei Cheng, Wangsheng Yu, Peng Wang, and Huanxin Zou. Distance measures of polarimetric sar image data: A survey. *Remote Sensing*, 14(22), 2022.

[7] Hongwei Zhao, Weishan Zhang, Haoyun Sun, and Bing Xue. Embedded deep learning for ship detection and recognition. *Future Internet*, 11(2), 2019.

[8] Yanxia Wu, Ye Yuan, Jian Guan, Libo Yin, Jinyong Chen, Ge Zhang, and Pengming Feng. Joint convolutional neural network for small-scale ship classification in sar images. In *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, pages 2619–2622, 2019.

[9] Andrey A. Kurekin, Benjamin R. Loveday, Oliver Clements, Graham D. Quartly, Peter I. Miller, George Wiafe, and Kwame Adu Agyekum. Operational monitoring of illegal fishing in ghana through exploitation of satellite earth observation and ais data. *Remote Sensing*, 11(3), 2019.

[10] Rekha R. Nair and Tripty Singh. An optimal registration on shearlet domain with novel weighted energy fusion for multi-modal medical images. *Optik*, 225:165742, 2021.

[11] Tina Babu, Deepa Gupta, Tripty Singh, Shahin Hameed, Mohammed Zakariah, and Yousef Alotaibi. Robust magnification independent colon biopsy grading system over multiple data sources. *Computers, Materials Continua*, 69:99–128, 01 2021.

[12] Rekha R. Nair. Multi-sensor medical image fusion using pyramid-based dwt: a multi-resolution approach. *IET Image Processing*, 13:1447–1459(12), July 2019.

[13] Tina Babu, Tripty Singh, Deepa Gupta, and Shahin Hameed. Colon cancer prediction on histological images using deep learning features and bayesian optimized svm. *Journal of Intelligent Fuzzy Systems*, 41:1–12, 03 2021.

[14] Rekha R. Nair, Tina Babu, and Tripty Singh. Multiresolution approach on medical image fusion by modified local energy. *Signal, Image and Video Processing*, 2023.

[15] Gholamreza Akbarizadeh and Zeinab Tirandaz. Segmentation parameter estimation algorithm based on curvelet transform coefficients energy for feature extraction and texture description of sar images. In *2015 7th Conference on Information and Knowledge Technology (IKT)*, pages 1–4, 2015.

[16] Guang'an Yang and Haitao Lang. Semisupervised heterogeneous domain adaptation via dynamic joint correlation alignment network for ship classification in sar imagery. *IEEE Geoscience and Remote Sensing Letters*, 19:1–5, 2022.

[17] Ruchan Dong, Dazhuan Xu, Jin Zhao, Licheng Jiao, and Jungang An. Sig-nms-based faster r-cnn combining transfer learning for small target detection in vhr optical remote sensing imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 57(11):8534–8545, 2019.

[18] Zongyong Cui, Qi Li, Zongjie Cao, and Nengyuan Liu. Dense attention pyramid networks for multi-scale ship detection in sar images. *IEEE Transactions on Geoscience and Remote Sensing*, 57(11):8983–8997, 2019.

[19] Xiaoya Wang, Zongyong Cui, Zongjie Cao, and Sihang Dang. Dense docked ship detection via spatial group-wise enhance attention in sar images. In *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, pages 1244–1247, 2020.

[20] Yun Feng, Jie Chen, Zhixiang Huang, Huiyao Wan, Runfan Xia, Bocai Wu, Long Sun, and Mengdao Xing. A lightweight position-enhanced anchor-free algorithm for sar ship detection. *Remote Sensing*, 14(8), 2022.

[21] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C. Berg. SSD: Single shot MultiBox detector. In *Computer Vision – ECCV 2016*, pages 21–37. Springer International Publishing, 2016.

[22] M. Ma, J. Chen, W. Liu, and W. Yang. Ship classification and detection based on cnn using gf-3 sar images. *Remote Sensing*, 10(12), December 2018.

[23] M. Karthi, V Muthulakshmi, R Priscilla, P Praveen, and K Vanisri. Evolution of yolo-v5 algorithm for object detection: Automated detection of library books and performace validation of dataset. In *2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*, pages 1–6, 2021.

[24] Muhammad Hussain. Yolo-v1 to yolo-v8, the rise of yolo and its complementary nature toward digital manufacturing and industrial defect detection. *Machines*, 11(7), 2023.

[25] Ritik Singh, Shubham Shetty, Gaurav Patil, and Pramod J. Bide. Helmet detection using detectron2 and efficientdet. In *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pages 1–5, 2021.

[26] Yellamma Pachipala, M Harika, B Aakanksha, and M Kavitha. Object detection using tensorflow. In *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, pages 1611–1619, 2022.

[27] Qing HU, Runsheng Li, Chaofan Pan, and Ouyang Gao. Remote sensing image object detection based on oriented bounding box and yolov5. In *2022 IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, volume 10, pages 657–661, 2022.