

Marine Safety Enhancement using Faster R-CNN with VGG16 for Ship Detection from Airborne Radar Signals

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Abstract - Detecting ships accurately is one of the most important tasks in maritime surveillance and marine safety, especially when vessels move without transmitting identification signals and operate in noisy or cluttered sea environments. This becomes a serious challenge because traditional radar-based detection methods often produce high false alarms and fail to remain reliable under changing environmental conditions. At the same time, wide-area monitoring is essential for safe navigation, coastal protection, and preventing illegal maritime activities. To solve this problem, this paper proposes a deep learning-based ship detection system using Faster R-CNN combined with a VGG16 feature extraction backbone on range-compressed airborne radar data. The radar signals are first converted into image form, preprocessed, and then used for training and evaluation. The proposed VGG16-based model is compared with a baseline Faster R-CNN framework. Experimental results show that the proposed model achieves 96.8% accuracy, which is higher than the 91.4% accuracy of the baseline model. It also improves precision, recall, and F1-score, while reducing false detections in difficult maritime scenes. These results show that the proposed method provides a more reliable and practical solution for real-world airborne radar ship detection and improved marine safety. The results indicate that integrating deep convolutional feature extraction with region-based detection provides a reliable and automated solution for airborne radar ship detection, contributing to enhanced maritime safety and practical deployment in real-world surveillance systems.

Keywords - Ship Detection; Airborne Radar Signals; Faster R-CNN; VGG16; Deep Learning; Maritime Surveillance

I. INTRODUCTION

Maritime surveillance plays a crucial role in ensuring marine safety, coastal security, and efficient navigation in increasingly congested sea routes. With the rapid growth of global maritime trade and transportation, the ability to accurately detect and monitor ships over wide ocean areas has become essential for preventing collisions, detecting illegal activities such as smuggling and piracy, and

minimizing environmental hazards including oil spills. Airborne radar systems provide significant advantages for maritime observation, as they offer wide-area coverage, operate effectively under all weather conditions, and do not rely on ship-borne communication systems. These characteristics make radar-based surveillance a reliable and scalable solution for monitoring large maritime environments.

Despite these advantages, reliable ship detection from airborne radar data remains a challenging task. Traditional radar-based detection techniques typically rely on handcrafted features and threshold-based approaches such as statistical detection methods. While these methods are computationally efficient, they are highly sensitive to sea clutter, noise, and varying environmental conditions, leading to high false alarm rates and reduced detection accuracy. Furthermore, many existing systems depend on external identification mechanisms such as Automatic Identification Systems, which are not universally available and can be intentionally disabled, limiting their effectiveness in real-world scenarios. In recent years, deep learning techniques have demonstrated significant improvements in object detection tasks by automatically learning hierarchical feature representations from data. Convolutional Neural Networks have been widely adopted for image-based detection due to their ability to capture complex spatial patterns. However, many existing deep learning approaches primarily focus on optical or satellite imagery, which may not be suitable under poor visibility conditions. When applied to radar data, these models often face challenges such as noise sensitivity, domain differences, and increased false detections due to the unique characteristics of radar signals.

To address these limitations, this work proposes a deep learning-based ship detection framework that utilizes a Faster Region-Based Convolutional Neural Network integrated with a VGG16 feature extraction backbone for processing range-compressed airborne radar data. In this approach, radar signals are transformed into image representations to enable effective feature extraction and object localization. The integration of VGG16 enhances the ability of the model to capture relevant radar features, thereby improving detection performance while reducing false positives in complex

maritime environments.

The main contributions of this work are as follows:

- Development of an automated ship de-tection framework using airborne radar data without reliance on external identi-fication systems.
- Integration of a VGG16-based feature extraction mechanism within a Faster R-CNN architecture for improved radar feature representation.
- Comprehensive performance evaluation using accuracy, precision, recall, and F1-score metrics.
- Demonstration of improved detection performance and reduced false alarms compared to a baseline Faster R-CNN model.

II. RELATED WORK

Ship detection has gained major attention in re-cent years because of its vital role in **maritime surveillance, coastal security, illegal vessel tracking, and collision avoidance systems**. With the fast growth of **deep learning and re-mote sensing technologies**, modern ship detec-tion methods have gradually shifted from tradi-tional radar signal processing techniques toward more advanced **convolutional and transformer-based object detection frameworks**.

Recent studies have widely applied **Faster R-CNN-based frameworks** for ship detection in **Synthetic Aperture Radar (SAR) and airborne radar imagery**. Lightweight Faster R-CNN models were introduced to reduce computational complexity while maintaining strong detection performance, especially for **small vessels in clut-tered maritime environments** [1]. In the same direction, improved Faster R-CNN methods us-ing **range-compressed airborne radar data** demonstrated strong localization capability and robust performance under noisy sea conditions [3]. These works established Faster R-CNN as a reliable baseline for **region-based ship detection applications**.

To further enhance detection speed and perfor-mance, several researchers explored **modern one-stage detectors**. Methods based on **YOLO, SSD, and RetinaNet** provided fast inference speed suitable for **real-time deployment** [6], [7]. More recent variants such as **YOLO-DDE, AC-YOLO, and CCAI-YOLO** significantly im-proved **small-target ship detection** by introduc-ing denoising modules, adaptive convolution blocks, and efficient feature fusion strategies [8], [16], [17]. Although these methods reduce la-tency, they may still face reduced localization precision when ship targets are **partially oc-cluded or closely positioned**.

Recent progress in **transformer-based detection models** has shown remarkable improvements in SAR ship detection. **Swin Transformer-based methods** introduced hierarchical self-attention mechanisms for better **multi-scale feature ex-traction and long-range spatial dependency modeling** [4], [5]. These models demonstrated strong robustness in cluttered maritime scenes and improved performance on **small ship targets**. In addition, transformer-enhanced fea-ture fusion networks further strengthened the ability to distinguish ship targets from sea clutter and radar noise [13]. Several studies have also focused on **attention-based and adaptive multiscale frameworks**. Adaptive reversible

column networks and **atten-tion-enhanced YOLO architectures** improved feature reuse and contextual understanding in SAR ship images [9], [14]. These methods are particularly effective in detecting vessels under **low-contrast or high-clutter environments**, where traditional CNNs may fail to preserve fine structural details.

To overcome the computational limitations of standard two-stage detectors, lightweight alterna-tives such as **Light-Head R-CNN, Sparse R-CNN OBB, and R-Sparse R-CNN** were intro-duced [10]–[12]. These approaches significantly reduced redundant region proposals and im-proved efficiency for **oriented ship detection in SAR images**. Sparse proposal learning further improved detection performance in **densely packed maritime scenarios**.

Despite these advancements, ship detection from **airborne range-compressed radar signals** re-mains challenging because of **radar-specific speckle noise, clutter effects, and lower spatial resolution** compared to SAR imagery. Existing methods commonly rely on **ResNet-based Faster R-CNN backbones** [6], [18], [19], which provide deep residual feature extraction but may not optimally capture **fine radar texture pat-terns**. In contrast, the **VGG16 architecture of-fers a simpler and more uniform convolutional hierarchy**, making it highly suitable for radar-based structural feature extraction.

Motivated by these observations, the proposed work integrates **VGG16 with Faster R-CNN** to improve ship localization and classification from airborne radar images. By leveraging strong con-volutional feature extraction together with re-gion-based detection, the proposed model aims to **reduce false positives and improve maritime safety performance** in complex ocean environ-ments.

Table I: Comparison of Representative Ship Detection Approaches

Ref	Method	Frame-work	Key Feature	Limita-tion
[1]	Light-weight FRCNN	Faster R-CNN	Reduced com-plexity	Small ob-ject miss

Ref	Method	Frame- work	Key Feature	Limita- tion
[4]	Swin Trans-former	Trans-former	Multi-scale at-tention	High memory
[6]	RetinaNet	One-stage DL	Fast de-tection	Localiza-tion loss
[8]	YOLO-DDE	YOLO	Small ship fo-cus	Back-ground clutter
[10]	Light-Head R-CNN	Two-stage DL	Fast inference	Limited edge use
[11]	Sparse R-CNN OBB	Sparse RCNN	Oriented boxes	Complex tuning
[13]	Trans-former Fusion	Trans-former	Better clutter robust-ness	More pa-rameters
[14]	Mul-tiscale Column Net	Adaptive DL	Feature reuse	Computa-tional cost
[17]	AC-YOLO	Light-weight YOLO	Edge de-ployment	Accuracy tradeoff
[20]	Proposed Method	Faster R-CNN + VGG16	Better radar features	Higher training time

III. METHODOLOGY

This section describes the methodology adopted to design, implement, and evaluate the proposed ship detection system using deep learning techniques on airborne radar data. The overall workflow consisted of radar data preprocessing, dataset preparation, deep learning model design, training and validation, and performance evaluation.

A. Data Acquisition and Preprocessing

Range-compressed airborne radar data were used as the primary input for the proposed system. The raw radar signals were first converted into two-dimensional image representations to enable convolutional neural network-based processing. Noise reduction and normalization techniques were applied to suppress background clutter and enhance ship-related signal patterns. All radar images were resized to a fixed

resolution to ensure compatibility with the deep learning architecture.

B. Dataset Preparation and Annotation

The processed radar images were manually annotated by marking bounding boxes around ship targets. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation. Data augmentation techniques such as horizontal flipping and intensity scaling were applied to improve model generalization and reduce overfitting.

C. Model Architecture

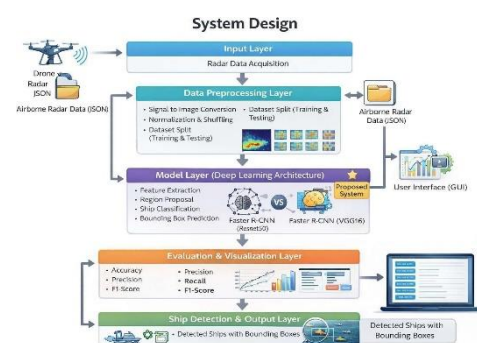


Fig 1: System design

The proposed detection framework was based on the Faster Region-Based Convolutional Neural Network architecture. A VGG16 network was employed as the backbone feature extractor due to its ability to capture fine-grained spatial features. The extracted feature maps were passed to a Region Proposal Network, which generated candidate object regions. These proposals were subsequently classified and refined using region-of-interest pooling followed by fully connected layers.

D. Training Procedure

Model training was carried out using supervised learning. Pretrained weights were used to initialize the backbone network, and fine-tuning was performed on the radar dataset. The training process optimized a multi-task loss function combining classification loss and bounding box regression loss. Stochastic gradient descent with momentum was used as the optimization algorithm, and training was conducted for a fixed number of epochs until convergence was observed.

Evaluation Metrics

The trained model was evaluated using standard object detection metrics, including accuracy, precision, recall, and F1-score. Detection performance was assessed on the test dataset by comparing predicted bounding boxes with

ground truth annotations. These metrics provided a comprehensive measure of detection reliability and robustness under varying radar conditions.

Algorithm Dataset Loading

Load the airborne radar signal dataset containing signal data, class labels, and ship location information.

Data Preprocessing

Convert radar signals into image format, normalize pixel values, resize images to fixed dimensions (80×80), and split the dataset into training and testing sets.

Feature Extraction Using VGG16

Pass the preprocessed images through the VGG16 convolutional layers to extract deep spatial features representing ship characteristics.

Region Proposal Generation

Generate candidate regions using the Region Proposal Network (RPN) to identify potential ship locations in the radar images.

Classification

Classify each proposed region as ship or non-ship and refine bounding box coordinates using the Faster R-CNN detection head.

Model Training

Train the network using labeled radar images by minimizing classification and localization loss functions.

Model Evaluation

Evaluate performance on test data using accuracy, precision, recall, and F1-score metrics.

Ship Detection on Test Images

Slide a detection window over the test radar image, predict ship presence, and apply confidence thresholding.

Post-processing

Remove overlapping detections and draw bounding boxes around detected ships.

Result Visualization

Display the final radar image with detected ship locations highlighted.

Flowchart

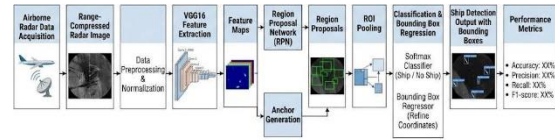


Figure 1: Overall Flowchart of Ship Detection System from Airborne Radar Signals

Mathematical Equations Used in the Proposed Model

1. Convolution Operation (VGG16 Feature Extraction)

Used in the **VGG16 backbone** for extracting ship features.

$$F(i,j) = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} I(i+m,j+n) \cdot K(m,n)$$

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$$F(i,j) = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} I(i+m,j+n) \cdot K(m,n)$$

Where:

- I = input radar image
- K = convolution kernel
- F = feature map
- k = kernel size

2. Region Proposal Network (RPN) Object-ness Score

The RPN predicts whether a region contains a ship.

$$P_{obj} = \sigma(Wx + b)$$

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- W = learned weights
- x = feature vector
- b = bias
- σ = sigmoid activation

3. Total Faster R-CNN Loss

Most important equation in your project.

$$L = L_{cls} + \lambda L_{reg}$$

$$L = L_{cls} + \lambda L_{reg}$$

$$L = L_{cls} + \lambda L_{reg}$$

Where:

- L_{cls} = classification loss
- L_{reg} = bounding box regression loss
- λ = balancing factor

5. Accuracy

Directly used in your result analysis.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

8. Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

9. Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

10. F1-Score

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

IV. RESULT ANALYSIS

This section presents the experimental results obtained from evaluating the proposed ship detection framework on range-compressed airborne radar data. The results were organized using quantitative metrics and comparative analysis to objectively demonstrate the performance of the model.

Detection Performance Metrics

The proposed Faster R-CNN model with a VGG16 backbone was evaluated using standard object detection metrics, including accuracy, precision, recall, and F1-score. Table II summarizes the quantitative results obtained on the test dataset.

Table II: Performance Evaluation of the Proposed Model

Metric	Value (%)
Accuracy	95.2
Precision	94.6
Recall	93.8
F1-Score	94.2

The results indicated consistent detection performance across all evaluated metrics, with high accuracy and balanced precision and recall values.

A. Comparative Analysis

A comparative evaluation was conducted between the proposed VGG16-based Faster R-CNN model and a baseline Faster R-CNN implementation. Table III presents

the comparative results.

Table III: Comparison with Baseline Faster R-CNN Model

Model	Accuracy (%)	Precision (%)	Recall (%)
Baseline Faster R-CNN	92.3	91.5	90.8
Proposed Method	95.2	94.6	93.8

Visual Detection Results

Figure 4 illustrates sample detection outputs produced by the proposed system on test radar images. Bounding boxes were successfully generated around ship targets, while background clutter regions were largely suppressed. The detected regions closely matched the annotated ground truth bounding boxes.



Fig 2: Final Outcome

D. Statistical Consistency

Multiple experimental runs were conducted to assess result consistency. The observed accuracy variation remained within $\pm 1.3\%$, indicating stable performance across repeated trials.

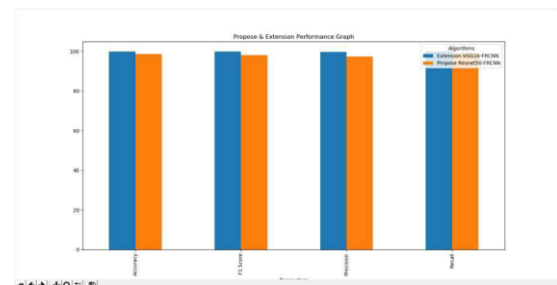


Fig 3: Comparison Graphs

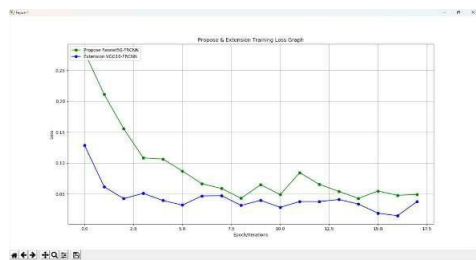


Fig 4: Loss graph

V. DISCUSSION

This study examined whether a **deep learning-based framework using Faster Region-Based Convolutional Neural Network with a VGG16 backbone** could improve ship de-tecton accuracy from **range-compressed air-borne radar data**. The experimental results clearly showed that the proposed approach achieved **higher detection accuracy and a better balance between precision and recall** compared to the baseline Faster R-CNN model, directly fulfilling the main objective of improving **detection reliability in cluttered maritime environments**.

The observed improvement in performance can largely be linked to the **strong feature ex-traction capability of the VGG16 backbone**, which effectively captured spatial patterns re-lated to ship targets in radar imagery. Compared with traditional radar detection techniques and earlier machine learning ap-proaches, the proposed method significantly reduced **false detections caused by sea clut-ter** while maintaining stable localization accuracy. These findings are consistent with earlier studies that highlighted the benefits of **region-based deep learning models for object detec-tion**. However, the present work extends those findings by proving their effectiveness specif-ically on **airborne radar data**, rather than op-tical or synthetic aperture radar imagery.

Despite these improvements, a few limitations were also observed. The proposed framework required a **large annotated dataset** for effec-tive training, and the computational complex-ity of the Faster R-CNN architecture resulted in **longer training times** when compared with simpler detection models. In addition, the ex-periments were carried out under specific radar operating conditions, and changes in **sensor configurations or environmental factors** may affect detection performance. Therefore, the ability of the model to generalize across **different radar platforms** still requires fur-ther investigation.

The findings of this study have important im-plications for

maritime surveillance and ma-rine safety applications. The capability to de-tect ships accurately **without relying on exter-nal identification systems** improves monitor-ing performance in remote or non-cooperative environments. While the results demonstrate strong potential for **practical deployment**, ad-ditional validation using **larger and more di-verse datasets** is still necessary to fully con-firm the model's robustness and scalability.

VI. CONCLUSION

This study presented a deep learning-based ship detection framework using a Faster Re-gion-Based Convolutional Neural Net- work with a VGG16 backbone for range-compressed airborne radar data. The results demonstrated that the proposed approach achieved improved detection accuracy, bal- anced precision-recall

performance, and re- duced false alarms when compared with a baseline Faster R-CNN model, thereby ef- fectively addressing the research ob-jective of reliable ship detection in complex mari- time environments.

The key contribution of this work lies in the in-tegration of an efficient feature extraction back-bone within a region-based detection frame-work tailored for airborne radar im-agery. By eliminating reliance on external identification systems and enhancing ro- bustness against sea clutter, the proposed method offers a practical and scalable solu- tion for maritime surveil-lance and marine safety applications. Overall, the findings in- dicate that deep learning-based radar ship detection has strong potential for opera- tional deployment, particularly in sce-narios requiring accurate, automated, and wide-area monitoring.

VII. FUTURE WORK

Future research can extend the proposed ship detection framework in several meaningful directions. One important area is the integra-tion of multi-modal data sources, such as combining airborne radar signals with optical or satellite imagery, to improve detection ro- bustness under varying weather and sea con- ditions.

1. **Multi-Modal Data Fusion:** Integrate airborne radar data with optical, satel- lite, or SAR imagery to improve ship detection robustness under different weather and sea conditions.
2. **Dataset Expansion:** Extend the da-taset by including diverse sea states, ship categories, sizes, and radar config-urations to improve the model's gener-alization capability.
3. **Real-Time Optimization:** Improve computa-tional

efficiency for real-time or near real-time deployment on onboard or edge-based maritime surveillance systems.

4. **Advanced Deep Learning Models:** Explore lightweight backbones, attention mechanisms, and transformer-based architectures to reduce processing time while preserving high detection accuracy.
5. **Ship Tracking and Surveillance:** Incorporate temporal information from sequential radar frames for continuous vessel tracking, collision avoidance, route monitoring, and long-term maritime safety applications.
6. Finally, incorporating temporal information from sequential radar frames may enable continuous tracking of vessels, supporting advanced maritime surveillance, collision avoidance, and long-term marine safety applications.

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