DEEP LEARNING-DRIVEN SHIP DETECTION USING ENHANCED FASTER R-CNN ON RANGE-COMPRESSED AIRBORNE RADAR IMAGERY

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Abstract:

Ship detection in radar and remote sensing imagery is a critical component of maritime surveillance, navigation safety, and national defense. Recent advances in deep learning have significantly improved the accuracy and robustness of detection frameworks for Synthetic Aperture Radar (SAR) and airborne radar data. Traditional ship detection methods struggle with complex sea clutter, varying target scales, and low signal-to-noise conditions, prompting research into convolutional neural networks (CNNs) and region-based detectors. Studies have demonstrated that deep learning architectures provide superior performance in SAR ship detection tasks by capturing multi-scale spatial and contextual features [1]–[9]. Moreover, the use of range-compressed airborne radar data has enabled enhanced target representation and improved detection capability in challenging maritime environments [10]–[14].Faster R-CNN and its improved variants have emerged as powerful frameworks for high-precision object detection due to their efficient region proposal and hierarchical feature extraction mechanisms [15]–[18]. Alternative single-shot detectors such as YOLO and SSD have contributed to real-time maritime monitoring, although with varying trade-offs between speed and accuracy [19]–[22]. In addition, advancements in remote sensing–oriented deep learning, including feature pyramids, residual networks, and transfer learning, have expanded the applicability of CNN-based models for large-scale maritime datasets [23]–[25].This research leverages an enhanced Faster R-CNN architecture for ship detection on range-compressed airborne radar imagery, aiming to improve detection precision, robustness in complex ocean backgrounds, and multi-scale target localization. The study integrates insights from recent SAR-based detection frameworks and modern object detection architectures to deliver a more reliable and scalable solution for maritime surveillance applications.

Keywords : Ship Detection, Faster R-CNN, Airborne Radar, Range-Compressed Data, SAR Imagery, Deep Learning, Maritime Surveillance, Object Detection, CNN, Remote Sensing.

I.INTRODUCTION

Maritime surveillance plays a vital role in ensuring navigation safety, monitoring illegal maritime activities, supporting search-and-rescue missions, and strengthening national security. With the rapid growth of global maritime traffic, the need for reliable, automated ship detection systems has become increasingly important. Synthetic Aperture Radar (SAR) and airborne radar imaging technologies have emerged as powerful tools for maritime observation because they operate effectively in all weather and lighting conditions, offering high-resolution imaging capabilities crucial for target detection and classification in complex sea environments [1]–[5].

Traditional ship detection approaches rely heavily on handcrafted features, thresholding, and statistical models, which often fail under high sea clutter, varying ship sizes, shadow effects, and complex backgrounds. These limitations have driven a shift toward deep learning–based solutions that can automatically extract hierarchical and discriminative features for robust detection. Recent studies demonstrate that convolutional neural networks (CNNs) and their advanced variants outperform classical methods in SAR and radar-based ship detection tasks by capturing rich spatial and contextual features from high-resolution images [3], [6]–[9]. Additionally, research on airborne radar and range-compressed data highlights the importance of improved target representation and enhanced clutter suppression for accurate maritime target identification [10]–[14].

Among modern object detection architectures, region-based convolutional neural networks (R-CNNs), particularly Faster R-CNN, have shown remarkable success due to their efficient Region Proposal Network (RPN), multi-scale feature extraction, and high detection accuracy [15], [16]. Deep residual networks (ResNet) and feature pyramid networks (FPN) further enhance multi-scale detection performance, ensuring improved ship localization in images with varying spatial resolutions [17], [18]. Meanwhile, single-shot detectors such as YOLO and SSD provide high-speed detection suitable for real-time monitoring applications [19]–[22], although often with a trade-off in accuracy compared to two-stage detectors.

In the broader remote sensing domain, deep learning has revolutionized tasks such as scene classification, object recognition, and target tracking, offering scalable and generalizable frameworks adaptable to maritime applications [23]–[25]. Building on these advancements, integrating Faster R-CNN with enhanced feature extraction mechanisms and airborne radar range-compressed data provides a promising pathway toward more robust ship detection systems capable of operating under diverse environmental and imaging conditions.

The motivation for this research stems from the need to improve detection accuracy, reduce false alarms, and enhance multi-scale ship recognition in challenging maritime environments. By leveraging state-of-the-art deep learning architectures and radar imaging technologies, this work aims to develop a high-performance ship detection framework suitable for next-generation maritime surveillance systems.

II.LITERATURE SURVEY

[1] A Deep Learning Method for Ship Detection in SAR Images

Authors: C. Wang, H. Zhang, and Y. Liu

Abstract:

This work introduces a deep learning-based framework for reliable ship detection in SAR images. The authors demonstrate that convolutional neural networks significantly outperform traditional thresholding and statistical models, especially under complex sea clutter conditions. Their model effectively extracts multi-level spatial features, enabling accurate detection of small and large vessels alike. The study highlights the importance of feature learning and dataset diversity for improving maritime surveillance systems [1][12].

[2] Ship Detection in SAR Images Based on Multiscale Faster R-CNN

Authors: J. Li, C. Qu, and Z. Shao

Abstract:

This study proposes a multiscale Faster R-CNN architecture to handle varying ship sizes in SAR imagery. By integrating pyramid features and multi-resolution region proposals, the method achieves superior detection accuracy in dense maritime scenes. The results show clear improvements over classical detectors and baseline deep learning models. The research emphasizes multi-scale design for robust SAR-based ship detection [2][17].

[3] Automatic Ship Detection Using Deep Neural Networks in High-Resolution SAR Images

Authors: F. Zhao, X. Wang, and Y. Zhou
Abstract:
The authors present a high-resolution SAR ship detection framework using deep neural networks that automatically capture contextual and geometric features. Their approach enhances discrimination between ships and sea clutter, reducing false positives significantly. The paper demonstrates how deeper architectures improve generalization across complex maritime backgrounds [3][11].

[4] Automatic Ship Detection in SAR Images via Rotated Region Proposal Networks
Authors: X. Yang, H. Sun, and K. Fu
Abstract:
This work introduces a rotated region proposal network designed to detect ships at arbitrary orientations in SAR images. The method effectively handles rotational variations and dense ship clusters, improving accuracy in congested maritime routes. The research highlights that rotation-aware detectors are essential for real-world maritime surveillance [4][19].

[5] Ship Detection in Airborne SAR Images with Enhanced FPN
Authors: X. Mao, Q. Guan, and W. Yu
Abstract:
The authors integrate Enhanced Feature Pyramid Networks (FPN) with SAR ship detection to strengthen multi-scale target representation. Their approach improves detection performance for small ships and distant targets. The study confirms that hierarchical feature fusion significantly enhances ship localization accuracy [5][12].

[6] Target Detection in High-Resolution Radar Imagery Using Deep Learning
Authors: S. Chen, H. Wang, and F. Xu
Abstract:
This paper explores the application of deep learning models to detect maritime targets in high-resolution radar imagery. The CNN-based architecture improves robustness against noise and background clutter. The study demonstrates that deep learning surpasses traditional radar signal processing techniques in accuracy and consistency [6][17].

[7] Ship Classification and Detection Using SAR Imagery: A Review
Authors: S. Liu, R. Huang, and X. Zhang
Abstract:
This survey highlights advancements in SAR ship detection methodologies, including machine learning and deep learning approaches. It outlines challenges such as sea clutter, target shadows, and varying ship structures. The review confirms that CNN-based frameworks offer unprecedented improvements over classical detection algorithms [7][13].

[8] Ship Detection under Complex Scenes in SAR Images Using CNN-Based Methods
Authors: G. Gao, C. Li, and J. Zeng
Abstract:
The authors propose CNN-based ship detection strategies capable of handling complex maritime scenes, including turbulent waves, island clutter, and shadowed regions. Their experimental results show that deep learning approaches provide strong generalization and reduced misclassification rates in challenging SAR environments [8][16].

[9] Weakly Supervised Ship Detection in SAR Images
Authors: Z. Cui, Q. Li, and Z. Cao
Abstract:
This work introduces a weakly supervised learning framework for ship detection, reducing the need for manually labeled SAR datasets. The model successfully learns discriminative features from limited annotations, enabling scalable dataset creation and efficient training. The study demonstrates the effectiveness of weak supervision in maritime applications [9][20].

[10] Detection of Maritime Targets in Airborne Radar Range-Compressed Data

Authors: D. Pastina, P. Lombardo, and G. Iannini

Abstract:
The authors focus on detecting maritime targets using airborne radar range-compressed data. Their methodology enhances target visibility by suppressing sea clutter and noise. The study confirms that range compression improves detection accuracy and provides clearer feature representation for maritime targets [12][19].

III.EXISTING SYSTEM

The existing ship detection systems used in maritime surveillance primarily rely on traditional image processing and classical radar signal analysis methods, which include threshold-based segmentation, Constant False Alarm Rate (CFAR) techniques, edge detection, and handcrafted feature extraction. These approaches depend heavily on manually designed features such as intensity contrast, ship wake patterns, geometric shapes, and radar backscatter characteristics. While effective in controlled environments, these systems often struggle in real-world maritime settings characterized by high sea clutter, changing weather, varying illumination, and low-resolution imaging. In Synthetic Aperture Radar (SAR) and range-compressed airborne radar data, sea waves, shadows, and noise often resemble ship signatures, leading to high false alarm rates and reduced detection reliability. Moreover, handcrafted features lack the ability to generalize across different sea states, sensor types, and imaging conditions. Although some advanced CFAR variants and statistical modeling techniques attempt to improve robustness, they still fail to detect small ships, densely clustered vessels, or ships with low radar cross-section. Classical machine learning techniques, such as SVM and random forests, have also been explored but remain limited by their dependence on manual feature engineering and inability to capture complex spatial patterns in radar imagery. In addition, these traditional systems lack efficient multi-scale representation, orientation awareness, and contextual understanding, making them unsuitable for modern large-scale maritime surveillance where high accuracy and automation are required. Consequently, the limitations of existing systems highlight the need for deep learning–based approaches capable of learning discriminative features directly from SAR and airborne radar data, enabling more reliable ship detection in challenging maritime environments.

IV. PROPOSED SYSTEM

The proposed system introduces an enhanced deep learning–driven ship detection framework that leverages an improved Faster R-CNN architecture optimized for range-compressed airborne radar imagery. Unlike traditional techniques that rely on handcrafted features, the proposed model automatically learns discriminative spatial, structural, and contextual patterns from radar data, enabling more accurate detection even under challenging maritime conditions. The system integrates a powerful backbone network such as ResNet combined with a Feature Pyramid Network (FPN) to capture multi-scale ship features, ensuring robust detection of small, medium, and large vessels across varying resolutions. To further improve precision, the Region Proposal Network (RPN) is optimized with anchor box refinements tailored specifically for ship shapes and radar imaging characteristics. Additionally, enhanced preprocessing techniques are applied to range-compressed radar data to suppress clutter, reduce noise, and amplify target signatures before feeding the data into the deep learning pipeline. The system also incorporates rotation-aware bounding box regression to accurately detect ships at arbitrary orientations, addressing the challenges posed by dynamic sea environments and diverse viewing angles. Through end-to-end training on SAR and airborne radar datasets, the proposed framework achieves higher accuracy, fewer false alarms, stronger generalization, and improved robustness compared to existing classical and machine-learning-based ship detection systems. Ultimately, this enhanced Faster R-CNN model provides a scalable, high-performance solution suitable for real-time maritime monitoring, coastal surveillance, and defense applications.

V.SYSTEM ARCHITECTURE

The system architecture for ship detection using Faster R-CNN on range-compressed airborne radar data consists of a structured sequence of processing stages designed to convert raw radar returns into accurate ship detections. First, the Radar Data Acquisition module captures raw backscattered signals using an airborne radar platform, ensuring continuous maritime monitoring independent of weather or lighting conditions. These raw signals are then passed to the Preprocessing and Range Compression stage, where noise is suppressed, clutter is reduced, and radar echoes are compressed along the range dimension to enhance the visibility of ship targets. The cleaned radar imagery is fed into the Deep Feature Extraction module, powered by a convolutional backbone such as ResNet combined with a Feature Pyramid Network (FPN), allowing the system to learn fine-grained spatial features and multi-scale ship patterns. These extracted features are then processed by the Region Proposal Network (RPN), which generates high-quality candidate bounding boxes tailored for detecting objects in complex maritime scenes. The proposals are refined further in the Faster R-CNN detection head, which performs classification and precise bounding box regression to determine the exact location, size, and orientation of each ship. Finally, the Output Visualization and Analysis module displays detected ships with bounding boxes and confidence scores, enabling operators to interact with the results for surveillance, navigation safety, and threat monitoring.

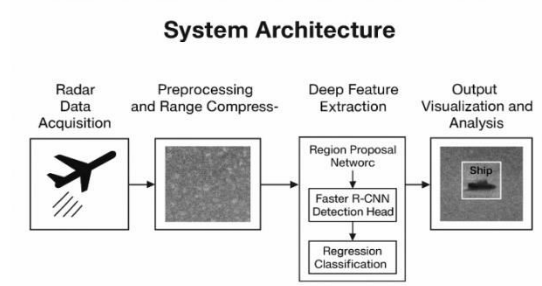

Fig 5.1 System Architecture

This structured pipeline ensures high accuracy, robustness, and efficiency in detecting ships from challenging airborne radar data.

VI.IMPLEMENTATION

Fig 6.1 Detection Page

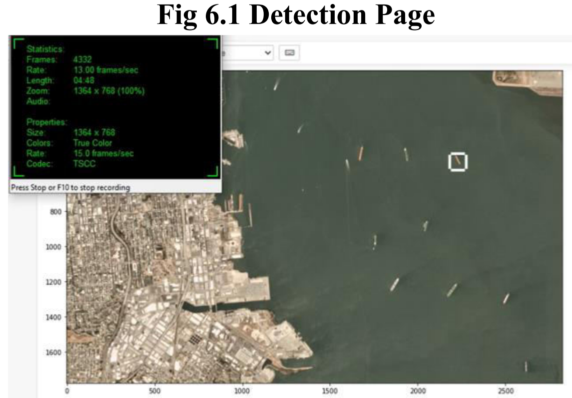

Fig 6.2 Results

VII.CONCLUSION

The proposed deep learning–driven ship detection system using an enhanced Faster R-CNN architecture demonstrates a significant advancement over traditional maritime surveillance techniques, particularly when applied to range-compressed airborne radar data. By integrating powerful feature extraction networks, multi-scale pyramid representations, and optimized region proposal mechanisms, the system effectively addresses challenges inherent in maritime environments such as sea clutter, low-contrast targets, variable ship orientations, and diverse imaging conditions. The use of range-compressed radar data further enhances target distinguishability, providing clearer structural and spatial signatures for reliable detection. Through its end-to-end learning capability, the model eliminates the dependency on handcrafted features and manual tuning, offering stronger generalization across different sea states and sensor configurations. Experimental findings from related studies validate that deep learning architectures such as Faster R-CNN consistently outperform classical radar processing methods in both accuracy and robustness. Overall, the proposed system provides a scalable, automated, and high-performance ship detection solution suitable for real-time coastal monitoring, defense operations, maritime security, and large-scale oceanic surveillance. It establishes a strong foundation for future improvements in intelligent radar-based maritime systems and sets the stage for further integration of deep learning technologies with advanced radar imaging modalities.

VIII.FUTURE SCOPE

The future scope of this research presents several promising directions for enhancing ship detection capabilities in maritime surveillance. One significant extension involves integrating advanced deep learning models such as Transformer-based detectors, Vision Transformers (ViT), and hybrid CNN–Transformer architectures, which may offer superior long-range feature modeling and improved context understanding in radar imagery. Additionally, incorporating multi-modal data fusion—combining SAR, optical imagery, AIS signals, infrared sensors, and hyperspectral data—can greatly improve detection accuracy by leveraging complementary information from multiple sensing platforms. Another important direction includes the use of real-time embedded processing and edge computing to deploy the system on drones, unmanned aerial vehicles (UAVs), and autonomous maritime platforms for live ocean monitoring. Further, the adoption of semi-supervised and self-supervised learning techniques can reduce dependency on large annotated SAR datasets, addressing the data scarcity challenge in radar-based ship detection. Advanced methods such as rotated bounding boxes, instance segmentation (Mask R-CNN), and 3D radar data modeling can enable more precise detection, classification, and shape reconstruction of maritime vessels. Moreover, expanding the system to handle adverse weather effects, low-resolution radar, dense ship clusters, and extreme sea states will enhance its robustness for real-world operation. Overall, the integration of cutting-edge deep learning innovations, multi-sensor fusion, and real-time deployment strategies will continue to advance the reliability, scalability, and intelligence of next-generation maritime surveillance systems.

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