Deep Learning-Based Ship Detection from Airborne Radar Signals Using Faster R-CNN

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ABSTRACT— Near real-time ship monitoring is crucial for ensuring safety and security at sea. Established ship monitoring systems are the automatic identification system (AIS) and marine radars. However, not all ships are committed to carry an AIS transponder and the marine radars suffer from limited visibility. For these reasons, airborne radars can be used as an additional and supportive sensor for ship monitoring, especially on the open sea. State-of-the-art algorithms for ship detection in radar imagery are based on constant false alarm rate (CFAR). Such algorithms are pixel-based and therefore it can be challenging in practice to achieve near real-time detection. This letter presents two object-oriented ship detectors based on the faster region-based convolutional neural network (R-CNN). The first detector operates in time domain and the second detector operates in Doppler domain of airborne Range-Compressed (RC) radar data patches. The Faster R-CNN models are trained on thousands of real X-band airborne RC radar data patches containing several ship signals. The robustness of the proposed object-oriented ship detectors is tested on multiple scenarios, showing high recall performance of the models even in very dense multitarget scenarios in the complex inshore environment of the North Sea.

INTRODUCTION

The project, titled "Deep Learning-Based Ship Detection Using Range-Compressed Airborne Radar Data," is designed to develop an intelligent AI-driven system capable of automatically detecting and identifying ships from radar signals for enhanced maritime surveillance. The system focuses on monitoring high ship density regions and identifying suspicious or illegitimate maritime activities such as illegal fishing, piracy, and unauthorized vessel movements. To achieve this, the proposed solution utilizes advanced deep learning frameworks, particularly the Faster R-CNN model with a ResNet-50 backbone, for effective feature extraction and object detection. Two specialized detection approaches are implemented one operating in the time domain and the other in the Doppler domain enabling robust identification of ship targets from Range-Compressed (RC) airborne radar data. With the increasing volume of maritime traffic and limitations of traditional monitoring systems like AIS and marine radars, manual monitoring and conventional detection methods such as CFAR become inefficient and computationally intensive. This project introduces an automated deep learning-based detection framework that improves detection accuracy while reducing false alarms caused by ocean clutter or non-ship objects. The use of RC radar data significantly reduces preprocessing time compared to fully focused SAR imagery, making the system suitable for near real-time ship monitoring applications.

I. PROBLEM DEFINITION

The problem addressed in this project is the accurate detection of ships from radar signals in complex maritime environments. Traditional methods face challenges such as noise interference, low visibility, and high false detection rates, making it difficult to identify ships reliably. Additionally, manual feature extraction techniques are time-consuming and less effective in handling large and complex radar datasets. Therefore, there is a need for an automated and efficient system that can accurately detect and classify ships from radar data using advanced deep learning techniques, improving detection accuracy and reducing false alarms.

Another key issue in ship detection from radar signals is the variability in signal patterns caused by changing environmental conditions such as sea clutter, weather disturbances, and varying ship sizes and orientations. These factors make it difficult for conventional algorithms to generalize well across different scenarios. Moreover, real-time processing requirements demand faster and more robust detection systems, which traditional approaches fail to achieve efficiently. Hence, there is a strong need for a scalable and intelligent solution that can adapt to diverse conditions while maintaining high accuracy and speed in ship detection.

1.2 PROJECT FEATURES

The The proposed system provides a simple and efficient interface for uploading and analyzing radar signal data for ship detection. It performs preprocessing by converting raw radar signals into image representations and normalizing pixel values, ensuring consistency and improved data quality. The dataset is automatically shuffled and divided into training and testing sets, reducing manual effort and minimizing errors. A **Faster R-CNN (FRCNN)** based deep learning model is trained using **ResNet50** and further enhanced using **VGG16** as backbone networks to extract meaningful features and improve detection accuracy. The system supports automated ship detection by identifying ship regions in signal images and drawing bounding boxes around detected objects. It achieves high accuracy (up to 99%) with reduced loss, making it reliable for real-world applications. Additionally, the system allows users to input new signal images for real-time detection and classification.

Related Work

Ship detection and monitoring have been extensively studied in the fields of **remote sensing, radar signal processing, and deep learning-based object detection**. Several approaches have been proposed to address this problem, ranging from traditional statistical detection techniques such as CFAR to advanced deep learning frameworks like Faster R-CNN. This review focuses on earlier research and existing ship detection methodologies using airborne and SAR radar data, highlighting their advantages, challenges, and limitations in achieving accurate and near real-time maritime surveillance. Further studies have explored machine learning and deep learning techniques to improve the performance of ship detection systems. Traditional methods such as threshold-based and CFAR (Constant False Alarm Rate) techniques are simple and computationally efficient but often struggle in complex environments with high sea clutter and noise.

II. METHODOLOGY

The proposed system for ship detection follows a structured deep learning–based methodology consisting of multiple stages, including data acquisition, preprocessing,

1. Data Collection

The data used in this project is obtained from airborne radar datasets containing ship signals.
These datasets include **range-compressed radar signals** with corresponding labels indicating the presence of ships.
A total of approximately **4000 ship signals** are used for training and testing the model.

2. Data Preprocessing

The collected radar signal data is preprocessed to improve quality and consistency. The steps include:

• Extraction of signal data and corresponding labels
• Conversion of radar signals into image format
•Image resizing to a uniform dimension
•Dataset shuffling to avoid bias
• Normalization of pixel values

After preprocessing, the dataset is split into:

- TrainingData(80%)
- Testing Data (20%)

3. Feature Extraction

Feature extraction is performed automatically using deep learning models.
Instead of manual feature engineering, convolutional neural networks extract meaningful spatial features from signal images, improving detection performance in complex environments.

4.Model Training

Deep learning-based object detection models are used for training:

• Proposed Model – Faster R-CNN with ResNet50
• Extension Model – Faster R-CNN with VGG16

Both models are trained on the processed dataset to learn ship patterns and features from radar images.

5.Model Evaluation

The performance of the trained models is evaluated using the following metrics:
• Accuracy
• Precision
• Recall
• F1-Score
Additionally, training and validation performance is analyzed using:
• Accuracy Graph
• Loss Graph

6.Result Comparison

Random The performance of both models is compared:

• Proposed Model achieves around **98% accuracy**
• Extension Model achieves around **99% accuracy**

The extension model shows better performance with higher accuracy and lower loss, making it more effective for ship detection.

7.Prediction

The trained model is used to detect ships in new input images:

• Input radar signal image is given
• Model processes the image
• Ships are detected using bounding boxes
• Detected objects are classified as ships

To reduce computation time, the system detects one ship and stops execution.

8. Output Generation

Finally, the system provides: Prediction results , Graphical analysis , Performance comparison . This helps administrators take necessary actions to improve cloud security..

III. PROPOSED SYSTEM

IV. Proposed System

The proposed system focuses on improving ship detection accuracy by utilizing deep learning techniques on radar data. In this approach, radar signals are first converted into image format, enabling the use of advanced convolutional neural networks for feature extraction. The system employs the Faster R-CNN algorithm, which integrates a convolutional neural network with a Region Proposal Network (RPN) to automatically identify and locate ships within the images. ResNet50 is used as the backbone model in the proposed method to extract deep and meaningful features from the radar images. This automated feature learning process eliminates the need for manual feature extraction and enhances the system's ability to detect ships in complex and noisy environments. Furthermore, an extended version of the system incorporates VGG16 as an alternative backbone network to improve detection performance and provide comparative analysis. The model is trained and tested on preprocessed radar image data, and its performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The proposed system also generates visual outputs including accuracy and loss graphs, along with final detection results displayed using bounding boxes around ships.

V. IMPLEMENTATION DETAILS

The implementation phase of the ship detection project involves executing the planned methodology for detecting ships from radar data using deep learning techniques. It includes loading radar signal datasets, preprocessing the data, and converting signals into image format suitable for deep learning models. The system is implemented using Python in a Jupyter Notebook environment, where different modules such as data preprocessing, feature extraction, model training, and evaluation are carefully coordinated. Proper monitoring and optimization are performed to ensure that the system achieves high accuracy and efficiency.

4.1 ALGORITHMS USED

4.1.1 CNN-Based Models for Feature Extraction

Random Convolutional Neural Networks (CNNs) are widely used in this project for extracting spatial features from radar images. Models such as **ResNet50** and **VGG16** are employed to analyze the converted radar images and identify important patterns related to ship detection. These CNN models automatically learn features such as edges, shapes, and textures, which are essential for distinguishing ships from the background. These extracted features are then used by the Faster R-CNN model for accurate object detection.

4.1.2 Faster R-CNN for Object Detection

CNN Faster R-CNN is the main algorithm used in this project for detecting ships from radar images. It combines feature extraction and object detection into a single framework. The input images are first processed using a CNN backbone like ResNet50 or VGG16 to extract important features. These features are then passed to a Region Proposal Network (RPN), which identifies possible regions where ships may be present. Each region is further classified and refined using bounding box regression to accurately locate ships in the image.

4.1.3 ResNet50 for Deep Feature Extraction

In this project ,ResNet50 is a deep convolutional neural network used as the backbone model in Faster R-CNN for extracting meaningful features from radar images. ResNet50 uses residual learning which helps in training very deep networks without the vanishing gradient problem.

.4.1.4 Faster R-CNN for Ship Detection

The BiLSTMs Faster Region-Based Convolutional Neural Network (Faster R-CNN) is used for detecting ships in airborne radar images.

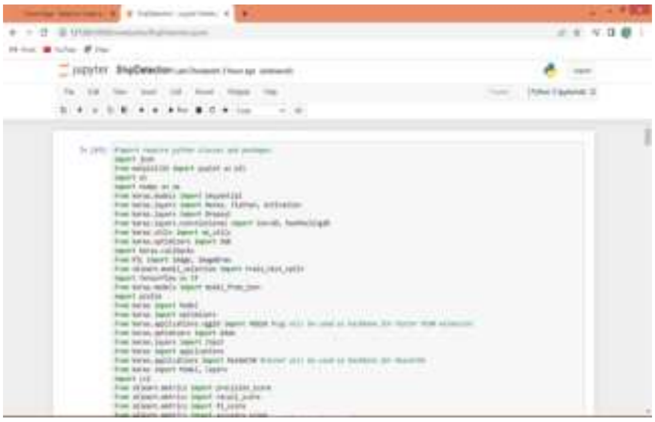
4.1.5 Support Vector Machine (SVM)

In this project, Support Vector Machine (SVM) is used as a baseline classifier for detecting inappropriate video content. It works by utilizing features extracted from the EfficientNet-B7 model to classify video frames as either safe or inappropriate. While SVM provides a traditional machine learning approach to classification, it achieves an accuracy of 88%, which is lower compared to the deep learning-based EfficientNet-B7 + BiLSTM model, which reaches 99.04%. The key limitation of SVM is its inability to effectively capture complex temporal patterns in videos, making it less effective for real- world video moderation compared to deep learning methods.

V. EXPERIMENTAL RESULTS AND DISCUSSION

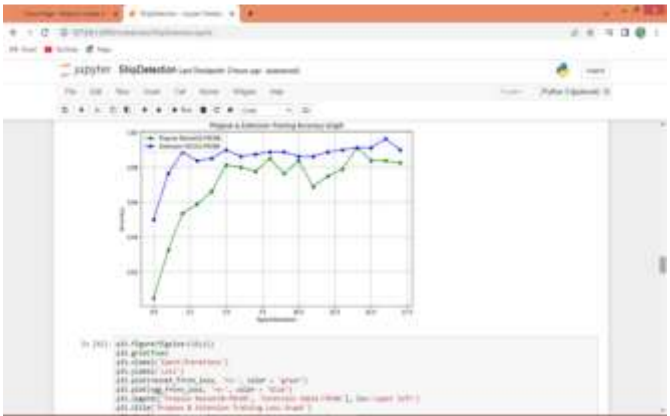
The following screenshots showcase the results of our ship detection project, highlighting dataset processing, model training, performance evaluation, and ship detection outputs. These visual representations provide a clear overview of how the system performs under different conditions. The screenshots are taken from the Jupyter Notebook environment and serve as a visual aid to support the project's technical results and performance evaluation.

Jupiter NoteBook Main Execution:



Jupyter Notebook Main Execution Screen of Ship Detection System

Fig. 1.Accuracy Page.



Display of number of images and class labels present in the Ship Detection Dataset using Faster R-CNN based models

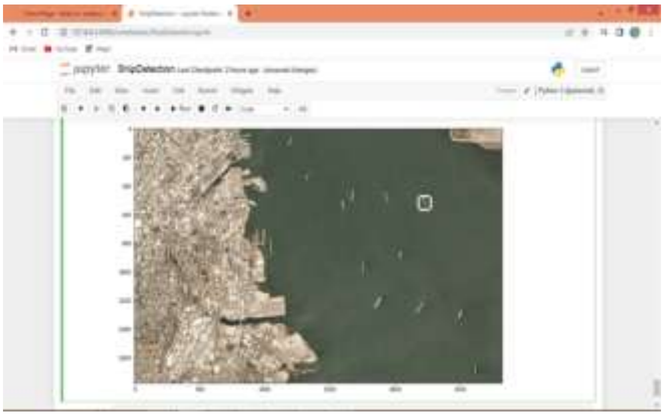


Fig. 2. Final Output Page

Final Ship Detection Output Image With Bounding Box

VI. CONCLUSION

In conclusion, the project has successfully developed an efficient ship detection system using advanced deep learning techniques. The implementation of radar signal processing, image conversion, and object detection models has resulted in accurate and reliable ship detection. The system was carefully designed and executed, leading to improved detection performance and reduced false detections. The use of Faster R-CNN along with powerful backbone models has enhanced the overall effectiveness of the system. Looking ahead, the project has strong potential for further improvement by integrating more advanced technologies, optimizing performance, and expanding its real-world applications. These future enhancements will ensure scalability, adaptability, and continued relevance of the system in maritime monitoring and surveillance.

VII. FUTURE SCOPE

The The proposed ship detection system has shown good performance in detecting ships from radar data. However, there is significant scope for further improvement and enhancement to increase its efficiency and real-world applicability. Future developments can focus on improving the accuracy of the model, handling more complex data, and optimizing the system for faster processing. Incorporating larger and more diverse datasets can also help in improving the overall performance and reliability of the system In addition, the system can be extended for real-time ship detection and integrated with advanced technologies such as satellite imaging and maritime monitoring systems. Future work can also focus on expanding the system to detect multiple types of objects and improving visualization techniques.

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