Dual Polarized SAR Imaging Techniques for Ship Classification

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ABSTRACT

Classifying ships in synthetic aperture radar (SAR) imagery is a challenging task because the targets are often small and the differences between ship categories are subtle. Traditional deep learning methods frequently disregard the polarimetric characteristics of SAR data, which becomes a limitation when working with dual-polarized images. The model was tested on a comprehensive dataset that included both three-class and six-class ship categories. Several deep learning architectures were evaluated, such as ConvNext, ConvNext with attention, VGG16, VGG19, InceptionV3, ResNet, and InceptionResNetV2. For ship detection tasks, different variants of the YOLO architecture were employed, including YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n.Among the classification methods, the ensemble of Xception and NasNet achieved the highest accuracy, demonstrating its effectiveness in distinguishing between ship types in dual-polarized SAR imagery. On the other hand, the YOLO-based models proved to be highly efficient for real-time detection, highlighting their potential for maritime surveillance and monitoring applications.

KEYWORDS

Synthetic Aperture Radar (SAR), Dual-Polarized SAR, Ship Classification, SAR Image Analysis, Polarimetric SAR, Ship Detection.

INTRODUCTION

Synthetic Aperture Radar (SAR) is a powerful imaging technology that creates high-resolution images regardless of lighting or weather conditions, making it an essential tool for Earth observation. A key application of SAR is in maritime environments, where it is used for ship identification and classification. This capability plays a critical role in vessel monitoring, maritime rescue operations, navigation safety, and transport management. SAR-based ship classification involves analyzing features such as radar backscatter intensity, shape, reflectivity, and dimensional characteristics to distinguish between different vessel types.

Over time, a variety of techniques have been developed for SAR ship classification, with deep learning (DL) approaches showing remarkable success due to their ability to extract complex and meaningful features from raw images. Early work used basic convolutional neural networks (CNNs), while later models introduced more sophisticated architectures. For instance, triple-branch networks with triple loss improved feature learning, and attention-based multiscale models helped suppress background noise. Research has also focused on enhancing model efficiency, such as integrating squeeze-and-excitation modules into lightweight networks like ShuffleNet V2, or using spiking neural networks in Siamese structures. To address limited labeled data, techniques like geometric transfer metric learning and ensemble approaches such as MetaBoost have been introduced, further advancing the state-of-the-art in SAR-based ship classification.

OBJECTIVES

This project aims to develop a novel Dual-Branch Deep Network (DBDN) for classifying ships in dual-polarized SAR imagery by leveraging unique polarimetric features to improve recognition accuracy across vessel types. Alongside the proposed model, various deep learning methods are evaluated for both classification and detection, offering a comparative analysis to advance maritime surveillance.

Identifying ships in dual-polarized SAR is challenging due to their small size and subtle class differences. Current deep learning models often ignore polarimetric features, limiting accuracy and impacting critical areas like defense, trade, and maritime safety. Ineffective classification can also compromise sea security by weakening surveillance and ship tracking capabilities.

METHODOLOGY

Dataset Acquisition

The proposed system presents a Dual-Branch Deep Network (DBDN) for effective ship classification and detection in dual-polarized SAR images. It leverages the unique polarimetric features of SAR data to improve accuracy, especially for visually similar ship types.

Model Architecture

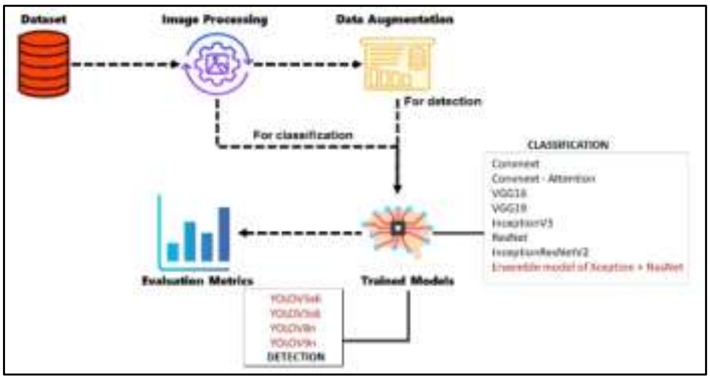


Fig. 1: System Architecture

Key Components:

- Classification Models:

Includes ConvNext, ConvNext-Attention, VGG16, VGG19, ResNet, InceptionV3, InceptionResNetV2, and an ensemble of Xception + NasNet to extract rich spatial and semantic features for high-accuracy classification across 3-class and 6-class datasets.

- Detection Models:

Utilizes YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n for real-time ship detection with strong performance on small and complex targets.

Dataset & Pre-Processing:

- Uses dual-polarized SAR images with annotated bounding boxes.
- Applies normalization, resizing, and augmentation (e.g., flipping, rotation) for both classification and detection tasks.
- Detection pipeline includes blob conversion, RGB transformation, masking, and YOLO-specific formatting.

Algorithms Used:

Classification:

ConvNext is a convolutional neural network built to balance simplicity with strong performance. In this project, it is applied to categorize different ship types in dual-polarized SAR images, offering both faster processing and reliable classification results.

ConvNext with Attention integrates attention layers into the base ConvNext model, allowing the network to highlight the most important regions of an image. This enhancement improves the ability to capture critical features in SAR images, leading to more accurate ship recognition.

VGG16 is a classic deep CNN that uses small filters across multiple layers to capture fine-grained details. In this work, it is employed to effectively classify various vessel categories from dual-polarized SAR datasets.

VGG19, an extension of VGG16 with three additional layers, enables deeper learning and extraction of complex image features. Its increased depth allows the model to better identify subtle ship patterns within SAR imagery.

InceptionV3 processes multiple filter sizes in parallel within its layers, enabling it to detect a wide range of visual cues. For this study, it helps strengthen ship classification by analyzing diverse feature sets present in SAR images.

ResNet (Residual Network) introduces skip connections that address the vanishing gradient problem, allowing the development of very deep models. Here, ResNet is applied to ensure stable and accurate identification of ship categories in SAR images.

InceptionResNetV2 combines Inception modules with residual connections, improving both training efficiency and accuracy. It is included in this project to enhance feature extraction for better ship classification performance.

Ensemble of Xception and NasNet brings together the strengths of both models. Xception leverages depthwise separable convolutions, while NasNet provides optimized feature extraction. Their combination aims to deliver higher accuracy and robustness in classifying ships from dual-polarized SAR imagery.

Detection:

YOLOv5x6 is an advanced variant of YOLOv5 built to process larger image sizes, which boosts detection accuracy. In this project, it is applied for real-time ship detection in dual-polarized SAR images, ensuring both speed and precision in identifying vessels.

YOLOv5s6 is a lightweight and efficient version of YOLOv5, designed for scenarios with restricted computational resources. It enables faster detection while maintaining reliable accuracy, making it suitable for ship recognition in SAR datasets.

YOLOv8n represents a newer generation of the YOLO family, offering improved speed and accuracy compared to earlier versions. It is used in this study to enhance real-time ship detection capabilities within SAR imagery.

YOLOv9n, the most recent YOLO release, provides even higher efficiency and detection precision. This model is integrated into the project to deliver cutting-edge results in identifying different ship types from dual-polarized SAR data.

RESULTS

Evaluation Metrics :

Accuracy: Measures the overall correctness of the model

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} (1)$$

Precision: Proportion of correctly predicted positives out of all predicted positives.

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)$$

Recall: Proportion of correctly predicted positives out of all actual positives.

$$Recall = \frac{TP}{TP + FN} (3)$$

F1-Score: Harmonic mean of precision and recall, balancing both.

$$F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100(4)$$

mAP (Mean Average Precision): Evaluates detection performance by averaging precision across recall levels and classes.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

Table.1 Classification Table

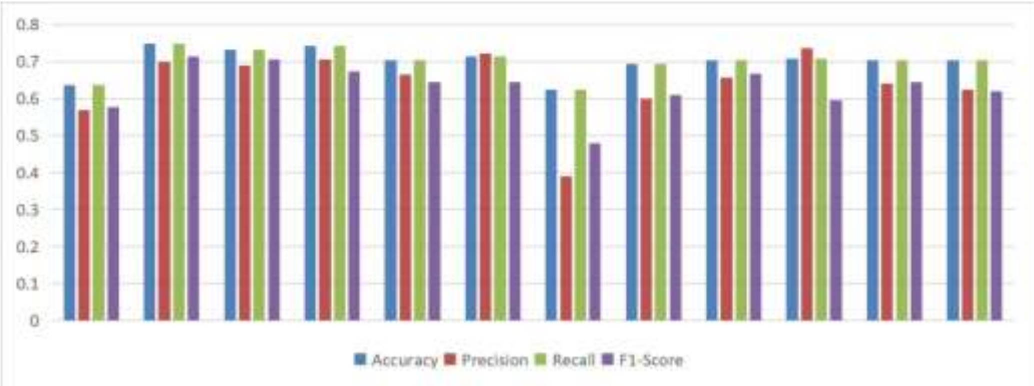
ML Model	Accuracy	Precision	Recall	F1_score
SwinTransformerV2 - With Attention	0.868	0.850	0.868	0.858
MAXViT	0.926	0.897	0.926	0.910
ResNet18	0.973	0.976	0.973	0.968
ConvNext/DCNN	0.966	0.943	0.966	0.954
WideResNet	0.885	0.848	0.885	0.852
VGG16	0.878	0.842	0.878	0.846
VGG19	0.953	0.926	0.953	0.939
DenseNet	0.959	0.935	0.959	0.947
EfficientNetV2	0.946	0.925	0.946	0.935
InceptionV3	0.973	0.949	0.973	0.960
InceptionResNetV2	0.946	0.945	0.946	0.938

Ensemble	0.953	0.933	0.953	0.943

Table.2 Detection Table

ML Model	Precision	Recall	mAP
YOLOv5s6	0.722	0.506	0.597
YOLOv5x6	0.519	0.534	0.550
YOLOv8	0.737	0.608	0.669
YOLOv9	0.603	0.595	0.643

Graph.1 Classification Graph

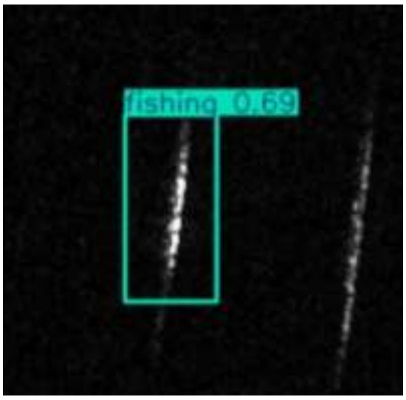


Graph.2 Detection Graph

OUTPUT SCREENS

Fig. 2: Dashboard

Fig. 3: Result for Classification



CONCLUSION

This project introduces a Dual-Branch Deep Network (DBDN) for classifying ships in dual-polarized SAR imagery, leveraging polarimetric features to improve accuracy in distinguishing small and visually similar vessels. An ensemble of Xception and NasNet models achieved superior classification performance, while YOLO-based detectors showed strong potential for real-time ship monitoring, enhancing maritime safety and defense applications.The proposed framework significantly advances SAR-based maritime surveillance by improving both classification and detection. Future work will explore transformer-based models, graph neural networks, attention mechanisms, and advanced data augmentation to further boost performance and generalization across diverse ship categories.

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