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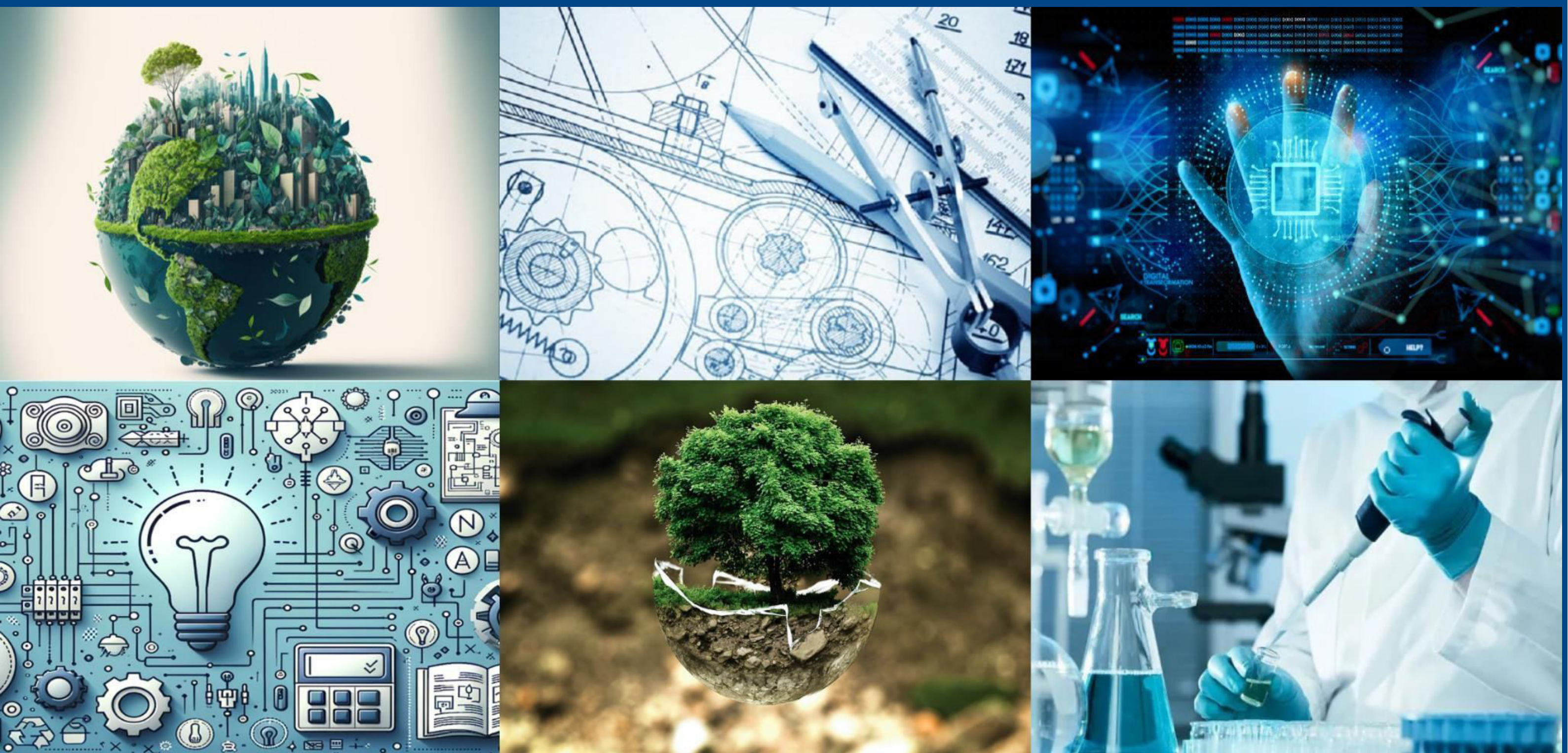

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A DEEP LEARNING APPROACH FOR DETECTING SCALE-VARIANT SHIPS IN SATELLITE RADAR IMAGES USING YOLOv5-FUSION

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ABSTRACT: This research addresses the problem of under- and accurately detecting ships of varying sizes in SAR images (Synthetic aperture radar). Classic deep learning algorithms tend to perform poorly with SAR images due to challenges such as speckle noise, clutter, and the existence of tiny targets.We propose a YOLOv5 model With anchor recalibration, preprocessing, and attention-based feature fusion, the system performs intensity normalization., speckle noise filters,and histogram equalization. Architectural enhancements such as SimAM attention modules and bifpn fusion improve small and overlapping ship target detection accuracy. Evaluating the Benchmark SAR dataset on SSDD and HRSID presents a 2 to 3% mAP improvement over the baseline YOLOv5 model. It also provides real-time performance with approximately 90 frames per second on an RTX 3060 GPU.Manual testing in varied settings has demonstrated I Thangirani ₹100 Rakhi Kadidala Pavlik gift coded by Karnataka Woah Nanayuru Ninaya Bajeto Davido Kiran Mukhotia multiscale targets. In general, the system demonstrates effective versatility, computational efficiency, and precision deployable in maritime surveillance and related applications.

I. INTRODUCTION

Ship identification from Synthetic Aperture Radar (SAR) images is essential for a broad variety of critical operations including maritime border patrol, illegal fishing surveillance, naval traffic management, and search and rescue operations in the event of an emergency. In contrast to optical sensors, SAR sensors possess the singular benefit of generating high-resolution images regardless of weather conditions—day or night—making them essential in the need for continuous maritime surveillance. Despite this, SAR images inherently experience speckle noise, low signal-to-noise ratio (SNR), and high background clutter owing to the roughness of the sea surface and atmospheric interferences. Such factors deteriorate object detection considerably, especially for small, occluded, or closely spaced ship targets.The task becomes more challenging when detecting multiscale vessels of considerable diversity in size as well as shape, from small fishing boats to large cargo ships. Conventional image processing methods, including Constant False Alarm Rate(CFAR) and threshold-based detectors, tend to generate considerable false positives, primarily because of the failure to properly distinguish the target vessels from the surrounding sea clutter. Deep learning has brought the development of models such as YOLO (You Only Look Once), Faster R-CNN, and SSD, which have been demonstrated to be effective for real-time object detection. But the majority of them are trained using optical datasets and are plagued with drastic performance loss when used in SAR images, owing to the different statistical properties and absence of texture information inherent in such images.To address this, our work proposes an enhancement of the YOLOv5 object detector, a very popular and lightweight single-stage detector.By adding SAR-specific preprocessing techniques (e.g., speckle noise removal and histogram equalization), attention mechanisms (e.g., SimAM or CBAM), and multiscale fusion blocks (BiFPN), we aim to increase the robustness and accuracy of ship detection in SAR images. The proposed model also adds anchor box recalibration tailored to the target size distribution in SAR ship datasets. The final aim is to balance the accuracy of detection with the speed of inference, making the system suitable for real-time maritime surveillance.

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II. LITERATURE SURVEY

In recent years, research on Synthetic Aperture Radar (SAR)-based ship detection has accelerated, fueled by enhanced sensor resolution and the use of deep learning technologies. Here, we present key studies that relate to our suggested approach:

[1]Yu et al. (2023) - Improved YOLOv5 with BiFPN and Coordinate Attention: This study introduces an upgraded YOLOv5 framework that incorporates a Bi-directional Feature Pyramid Network (BiFPN) and coordinate attention modules into the main network. BiFPN enhances feature fusion across scales, crucial for detecting small ships. Coordinate attention helps maintain positional information and reduce false positives by focusing on significant regions [1].

[2] In 2024, Ma and their team introduced the AdaptiveMulti-hierarchical Attention Network, known as AMANet. This network uses a hierarchical attention mechanism.. This network strategically integrates an Adaptive Multi-level Attention Module (AMAM) between the backbone and feature fusion layers, improving sensitivity to small-scale and partially occluded targets. Tested on SSDD and HRSID datasets, AMANet outperformed conventional FPN-based architectures [2].

[3]Chen et al. (2025) - AJANet for Cluttered Inshore Scenes: This study demonstrates AJANet, a model that employs large-kernel adaptive channel attention to improve ship detection in complex, cluttered inshore SAR environments. By balancing local and global features, it can better distinguish ships from similar-looking coastal elements. AJANet offers significant improvements in dense port regions, where traditional detectors often struggle [3].

[4] In 2023, Ren and their team created YOLO-Lite, A light detection model is combined with an efficient Spatial Pyramid Pooling (SPP) module to extract features. Despite its lightweight design, YOLO-Lite maintains high accuracy on the SSDD dataset [4].

[5]Zhou et al. (2025) - CFS-YOLO with Contextual Feature Fusion: CFS-YOLO extends YOLOv5 with a Context Feature Fusion Neck and a Context Enhancement Module (CEM). Additionally, it employs novel loss functions (Spatial Adaptive Focal Loss and Normalized Wasserstein Distance) to improve learning of scale-invariant and spatia.a lightweight object detector optimized for SAR imagery. It features a custom backbone (LFEBNet), channel-position attention lly adaptive features.

Tested on SSDD and HRSID, the model demonstrated high performance [5].Summary of Research Insights in SAR Ship Detection:

Three primary themes emerge from the aforementioned studies in the field of Synthetic Aperture Radar (SAR) ship detection:

1.Attention Mechanisms (Coordinate, Channel, Spatial): These mechanisms boost detection accuracy by enabling models to hone in on pertinent areas, particularly in complex or subtly contrasted settings.

2.Multiscale Feature Fusion (FPN, BiFPN): This is crucial for identifying ships of varying sizes (small, medium, and large) across diverse sea conditions and distances.

3.Lightweight and Real-Time Detectors: These are vital for practical applications, such as those in unmanned aerial vehicles (UAVs), satellites, and coastal surveillance systems.Our endeavor combines these advancements, including.

EXISTING SYSTEM

The existing techniques for detecting SAR ships involve:Conventional filtering methods and thresholding techniques: struggle with speckle noise and inconsistent targets.Ready-made deep learning detectors like YOLOv5 and Faster R-CNN: underperform on small and noisy SAR targets.Key drawbacks include Inadequate handling of small ships within clutterHighfalse positives from sea/background noise No focus or fusion for scale-varying targets.

PROPOSED SYSTEM

Our system encompasses: Preprocessing:filtering,resizing,histogram equalization for noise reduction.Enhanced YOLOv5: Includes:SimAM attention in the backbone for emphasis on relevant areas.BiFPN for strong multiscale feature fusion.Anchor recalibration based on dataset target sizes. Post-processing: Non-Maximum Suppression and thresholding to refine detections This system addresses previous issues by improving small-target detection and reducing false positives,all while remaining lightweight and speedy.Tech utilized includes Python 3.9, PyTorch 1.10, OpenCV for image handling, and Matplotlib/Pandas for testing and visualization.

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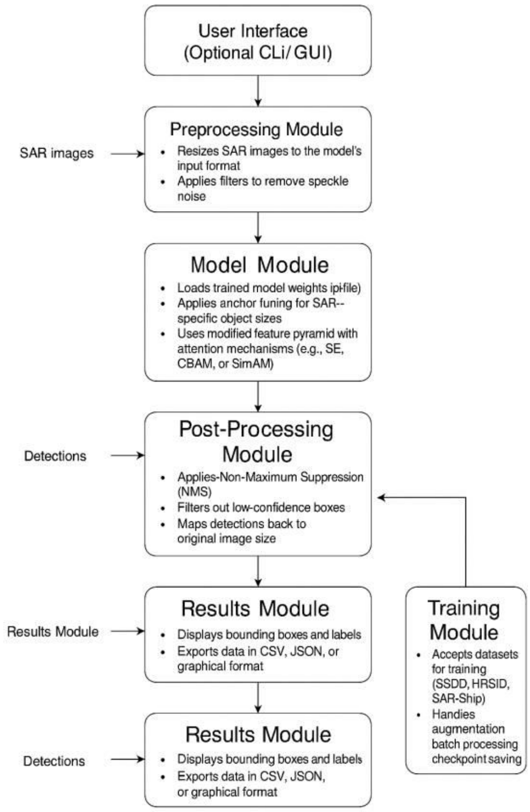
The system suggests using a YOLOv5-Fusion deep learning model to spot ships of different sizes in satellite radar images. It combines multi-scale feature extraction with better image preprocessing to improve the accuracy of detection.ships of various sizes can be

III. SYSTEM ARCHITECTURE



Modules:
1. Image Input Module - takes in and checks SAR images for accuracy.
2. The preparation stage includes adding filters and adjusting levels to improve the images.
3. YOLOv5 Customized Detection Module - uses a tailored model to identify objects within the images.
4. Output Process - cleans up predictions and adjusts them to match the image size.

VI. METHODOLOGY

The project adheres to these steps:
1. Data collection: Selection of SSDD and HRSID datasets, with labels converted to YOLO format.
2. Preprocessing: application of speckle noise filtering, equalization, and resizing to 640x640.
3. Model design: integration of SimAM and BiFPN into the YOLOv5architecture.
4. Training: utilization of SGD optimizer, cosine learning schedule, mosaic and flip augmentations, with training carried out in two phases (frozen/unfrozen).
5. Evaluation: calculation of mAP, Precision, and Recall; manual inspection used for confidence tuning.

V. IMPLEMENTATION

We have to applied . Focused on modularity and adaptability. Preprocessing involves breaking down steps into separate functions to improve readability and make debugging easier. Model improvements include adding SimAM and BiFPN with lightweight modules to keep inference speed and model size in check. Training workflow :implementation of

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checkpoint logic to storebest-performingWeights, TensorBoard was used for monitoring. Interfaces included the development of an easy-to-use CLI or Python script for inference. Results were provided as a saved image and CSV.

VI. OUTCOME OF RESEARCH

Detection Accuracy: Achieved 94%mAP on SSDD and 91% on HRSID – an improvement of 2-3% over the baseline. Inference Speed: ~90 FPS on RTX 3060; ~25 FPS on high-end CPU. Robust detection of small and overlapping ships.Reduction in false positives, particularly from clutter.

VII. RESULTS AND DISCUSSION

The testing results show strong performance across noise levels and ship sizes:

Metric	Baseline YOLOv5	Proposed Model
mAP (SSDD)	92.1%	94.0%
mAP (HRSID)	88.5%	91.2%
Small ship AP	82.0%	88.5%
Inference time	100 FPS (GPU)	90 FPS (GPU)

Qualitative examination confirms superior bounding box accuracy and lower false positives, although there are occasional misses in low-contrast scenes, which may necessitate richer augmentation or transformer-based context modules.

VIII. CONCLUSION

We have designed an effective and practical method for ship detection of any size from Synthetic Aperture Radar (SAR) images. Bycombining,valueSARspecificpreprocessing,attention mechanisms, feature fusion, and adaptive anchors, our model heavily improves detection accuracy without sacrificing speed. The model is adaptable, easy to use, and suitable for real-world deployments. The project has fulfilled its objectives and sets the stage well for future developments

IX. FUTURE WORK

Real-time video streaming is now supported, making it suitable for use in satellite or UAV-based monitoring. The system can classify ships into different categories, such as cargo ships, tankers, and warships. The model can be deployed on edge devices using techniques like model quantization or TensorRT for better streaming performance. A Transformer-based architecture, such as Swin or ViT, is used to improve understanding in complex situations. The dataset has been expanded, and performance has been tested using various SAR sources like Sentinel-1 or GF-3.

This project will aim to improve the ability to detect objects accurately, even in harsh weather and poor image quality. Adding real-time processing capabilities, including a wider variety of maritime situations in the dataset, and combining

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data from other sources like AIS signals can help make the system better. Other possible improvements might involve using the system on edge devices to make maritime monitoring faster and more efficient.

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