

Efficient Ship Detection using YOLOv8 & YOLOv9

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Abstract— Ship detection is crucial for maritime surveillance, environmental monitoring, and national security. This project utilizes advanced object detection algorithms, YOLOv8 and YOLOv9, renowned for their real-time capabilities and high accuracy. The objective is to automate the identification and localization of ships on the sea surface through computer vision and deep learning. By processing extensive datasets, these algorithms enhance efficiency by reducing manual monitoring needs. The project involves training YOLOv8 and YOLOv9 models on specific datasets to detect and classify ships within images. Leveraging these technologies aims to achieve precise and efficient ship detection. During inference, the models analyze input images, detect ships by creating bounding boxes, and report the count of detected ships. This approach not only advances ship detection capabilities but also contributes to optimizing operational workflows in maritime environments

Index Terms— Ship detection, YOLOv8, YOLOv9, Deep learning.

I. INTRODUCTION

Ship detection plays a pivotal role in maritime surveillance, environmental monitoring, and national security. The ability to accurately and efficiently identify vessels on the sea surface is crucial for safeguarding maritime interests, managing marine resources, and ensuring regulatory compliance. Traditional methods of ship monitoring often rely on manual observation, which can be time-consuming, labor-intensive, and prone to human error. To overcome these challenges, advanced technologies in computer vision and Deep learning offer promising solutions.

This project focuses on leveraging two state-of-the-art object detection algorithms, YOLOv8 and YOLOv9, renowned for their real-time capabilities and high accuracy in identifying objects within complex scenes. YOLO (You Only Look Once) algorithms excel in detecting multiple objects simultaneously by dividing the image into a grid and predicting bounding boxes and class probabilities for each grid cell. This approach not only enhances detection speed but also ensures robust performance across various environmental conditions encountered in maritime settings.

The primary objective of this study is to automate the process of ship detection and localization using YOLOv8 and YOLOv9. By training these models on diverse datasets containing images of ships in varying sea conditions, the project aims to achieve precise identification and spatial localization of vessels. The utilization of deep learning techniques allows the models to learn intricate patterns and features characteristic of ships, thereby improving detection accuracy and reducing false positives.

Efficiency is a cornerstone of this research endeavor. By implementing YOLOv8 and YOLOv9, which are optimized for real-time inference, the project aims to streamline operational workflows in maritime environments.

Automated ship detection not only minimizes the need for manual monitoring but also enables timely responses to potential threats or incidents at sea. Moreover, the integration of these technologies into existing surveillance systems promises to enhance overall situational awareness and decision-making capabilities for maritime stakeholders. In summary, this project seeks to advance the capabilities of ship detection through the application of cutting-edge object detection algorithms. By harnessing the power of YOLOv8 and YOLOv9, the study aims to contribute significantly to enhancing maritime surveillance efficiency and effectiveness. The subsequent sections will delve into the methodology, experimental setup, results, and implications of deploying these models in real-world maritime scenarios.

II. LITERATURE REVIEW

This literature review explores recent advancements in object detection algorithms, focusing on applications in challenging conditions and specialized domains like remote sensing and agriculture. It highlights innovations in algorithmic enhancements, dataset improvements, and real-time processing optimizations within the context of YOLO-based systems. Identified gaps emphasize the need for advanced methodologies tailored for specific applications, urging further research for enhanced performance and applicability.

A. Enhancements in Adverse Conditions

Recent advancements in object detection have focused on overcoming challenges posed by adverse conditions, such as weather, low light, and complex backgrounds. A notable contribution in this field is the IA-YOLO approach proposed by Liu et al. (2022). IA-YOLO enhances object detection in adverse weather conditions by adaptively processing each input image using a differentiable image processing module. This module restores latent content, with parameters predicted by a small Convolutional Neural Network (CNN). The end-to-end trained framework enables the parameter prediction network to learn the appropriate image processing module through detection loss. Experimental results demonstrated that IA-YOLO significantly outperformed previous methods, particularly in foggy and low-light scenarios. Li et al. (2021) tackled object detection challenges in infrared images with the YOLO-FIRI model, building on the YOLOv5-based YOLO-FIR. The researchers expanded the Cross Stage Partial (CSP) module, integrated an attention module, and added multiscale detection to enhance small object accuracy. YOLO-FIRI showed significant performance improvements, including a 37% increase in mean Average Precision (mAP) on the KAIST dataset, reduced detection time, and minimized network parameters. Moreover, data enhancement through visible and infrared image fusion further improved detection accuracy, showcasing its robustness in diverse conditions. In the realm of remote sensing, Hu et al. (2021) introduced PAG-YOLO, a novel model for small ship detection designed to enhance accuracy without significantly increasing computational costs compared to YOLOv4. PAG-YOLO incorporated attention mechanisms in both spatial and channel dimensions to improve feature importance assignment across different scales. A new loss function was implemented to enhance training efficiency and detection accuracy.

Experiments on the MASATI dataset demonstrated PAG-YOLO's superior performance over existing methods, indicating its robustness in detecting ships in remote sensing images. Sun et al. (2021) presented BiFA-YOLO, a YOLO-based ship detection method for High-Resolution (HR) Synthetic Aperture Radar (SAR) images. This method featured a bi-directional feature fusion module (Bi-DFFM) and an angular classification structure to accurately detect multi-scale, arbitrary-oriented ships. BiFA-YOLO achieved high precision, recall, and F1-score on the SAR ship detection dataset (SSDD) and GF-3 satellite images, with a fast detection speed of 13.3 milliseconds per 512x512 image. Comparative experiments validated BiFA-YOLO's robustness and efficiency over existing methods, proving its suitability for practical marine ship detection systems. Lastly, Luo et al. (2024) introduced SHIP-YOLO, a lightweight SAR ship detection model based on YOLOv8n. SHIP-YOLO addresses challenges in detecting small objects, high noise, and complex backgrounds in SAR images. Innovations include GhostConv and RepGhost structures in the C2f module, Wise-IoU (WIoU) for improved localization, and Shuffle Attention (SA) modules to enhance target perception. SHIP-YOLO outperformed YOLOv8n with reduced parameters and FLOPs, while achieving improved precision, recall, and mAP on the SSDD and SAR-Ship-Dataset, demonstrating strong generalization ability. These advancements collectively represent significant progress in enhancing object detection performance under challenging conditions, paving the way for more robust and reliable detection systems in real-world applications.

B. Specialized Applications and Dataset Enhancements

In the realm of specialized applications and dataset enhancements, recent studies have made significant strides in improving object detection accuracy and applicability across diverse domains. Kim et al. (2022) introduced the

SMD-Plus dataset, an enhanced version of the Singapore Maritime Dataset (SMD), specifically designed to address challenges such as noisy labels and imprecise bounding boxes. This dataset incorporates augmentation techniques like 'Copy & Paste' and mix-up to mitigate class imbalances, significantly enhancing detection and classification performance when paired with modified YOLO-V5. The publicly available SMD-Plus dataset aims to establish a benchmark for automated maritime surveillance research, setting new standards in accuracy and reliability. Gallo et al. (2023) tackled the agricultural challenge of weed detection using UAV data with the introduction of the Chicory Plant (CP) dataset. This dataset, comprising over 3300 images and more than 12,000 annotations, facilitated testing of the YOLOv7 model, which demonstrated substantial improvements in metrics such as mAP@0.5, recall, and precision compared to earlier YOLO versions. The effectiveness of deep learning in accurate weed recognition underscores its potential for optimizing agricultural practices, with future research focusing on enhancing detection outcomes at varying heights above ground level. In a different application domain, Bist et al. (2023) developed deep-learning models for detecting piling behavior (PB) in cage-free laying hen facilities using a dataset of 9000 images.

Their YOLOv6l relu-PB model achieved superior performance metrics, including high mAP@0.50 and average recall, particularly effective when cameras were positioned close to PB areas. Challenges included the accurate detection of objects at different distances, highlighting opportunities for future improvements to enhance accuracy, especially in group image settings. The model's suitability for PB monitoring in commercial settings underscores its practical value in animal welfare and management. Li et al. (2021) enhanced the YOLO v3 tiny network for real-time ship detection in visual images (SDVI), targeting applications such as port management and safe navigation.

Their modifications included custom anchor training, convolution layers replacing max-pooling, and the integration of an attention module (CBAM) to improve detection accuracy in complex backgrounds. Experimental results demonstrated significant improvements over the original YOLO v3 tiny network, outperforming existing methods in mAP while achieving faster detection speeds. This research contributes to advancing maritime safety and efficiency through enhanced ship detection capabilities. These studies collectively illustrate how specialized datasets and tailored model enhancements are advancing object detection capabilities across diverse applications, from maritime surveillance and agriculture to animal behavior monitoring and beyond. Each contribution not only improves detection accuracy but also sets benchmarks for future research and development in their respective fields.

C. Algorithmic and Structural Improvements

Recent advancements in object detection algorithms have focused on enhancing both performance metrics and operational efficiency across various specialized domains. Han et al. (2021) introduced ShipYOLO, an enhanced ship detection model based on YOLO-V4 tailored for intelligent ship navigation systems. ShipYOLO optimizes the CSPDarknet backbone network for faster inference and increased feature extraction efficiency.

A new Dilated Spatial Pyramid Pooling module enhances detection of small-scale ships, while the Attention Feature Pyramid Network refines feature extraction across different ship sizes. Results demonstrate that ShipYOLO achieves significantly higher Frames Per Second (FPS) and mean Average Precision (mAP) compared to YOLO-V4, making it well-suited for real-world ship detection applications, despite challenges posed by extreme weather conditions. Lou et al. (2023) proposed DC-

YOLOv8, a novel small-size object detection algorithm designed specifically for camera sensors. This algorithm outperforms YOLOv8, YOLOX, and YOLOR across multiple datasets, including Visdrone, TinyPerson, and PASCAL VOC2007, achieving higher precision and recall rates. Innovations in down-sampling techniques, feature fusion, and network architecture contribute to its superior detection accuracy, particularly beneficial in traffic safety applications where precision is crucial. Hu et al. (2023) focused on enhancing object detection in drone images with the YOLOv7-tiny-based algorithm.

This algorithm utilizes aspect-ratio-based anchor boxes and a hard sample mining loss function (HSM Loss) to improve learning from challenging samples. Evaluations on the DroneVehicle dataset reveal superior average precision in both infrared and visible light images compared to state-of-the-art algorithms, with minimal computational resource increase. This research underscores the algorithm's effectiveness in detecting small and hard-to-identify objects, enhancing its utility across diverse environmental conditions.

These studies collectively highlight significant strides in algorithmic and structural improvements within the field of object detection, advancing capabilities in specialized applications such as maritime navigation, traffic safety, and aerial surveillance.

Each innovation contributes to broader enhancements in detection accuracy, efficiency, and adaptability, paving the way for more robust and reliable detection systems in real-world scenarios.

D. Real-Time Processing and Resource Optimization

Recent research has focused on enhancing real-time processing capabilities and optimizing resource utilization in YOLO-based object detection systems, addressing challenges across various operational contexts. Lee et al. (2022) identified the real-time processing challenges of YOLO in resource-constrained AI embedded systems, particularly in network camera-based applications.

Their study introduced an adaptive frame control (AFC) architecture designed to minimize service delays while maintaining YOLO's high precision. Unlike previous approaches that altered YOLO's core structure, AFC offers practical solutions and guidelines for selecting suitable hardware platforms, thereby enhancing real-time capabilities across YOLO versions, including YOLOv4 and YOLOv5. Han et al. (2021) proposed the O-YOLO-v2 model, focusing on real-time tiny vehicle object detection by integrating additional convolution layers and residual modules. This enhancement improved feature extraction and addressed gradient issues, resulting in boosted detection accuracy.

Evaluation on the KITTI dataset showcased O-YOLO-v2 achieving a remarkable 94% accuracy rate without compromising detection speed, highlighting its potential for real-world applications. Li et al. (2022) explored YOLO-based ship detection in thermal infrared remote sensing images (TIRSIs), addressing challenges like atmospheric interference and complex backgrounds.

Their method employed advanced techniques such as up-sampling and gray value stretching to enhance dataset quality, achieving precision improvements over YOLOv5s. Despite successes, challenges such as false positives and computational complexity remain significant, underscoring the need for further algorithm refinement and adaptation to specific environmental conditions.

These studies collectively advance the field by improving real-time processing efficiency and resource optimization in YOLO-based object detection systems. They underscore the importance of adapting algorithms to diverse operational environments, such as maritime surveillance, where varying weather conditions and object characteristics present unique challenges. Addressing these gaps not only enhances system reliability but also broadens the applicability of YOLO-based technologies in critical real-world scenarios.

E. Gap Analysis

The research gap lies in the adaptation of these algorithms specifically for maritime environments, where challenges like adverse weather conditions, varying lighting, and the presence of small or distant ships can affect detection accuracy. Existing literature addresses these challenges to some extent but often lacks comprehensive validation across diverse environmental and operational scenarios typical of maritime surveillance. Addressing these gaps would enhance the reliability and applicability of YOLO-based ship detection systems, ensuring robust performance under all conditions encountered at sea.

III. TECHNICAL BACKGROUND

This section provides a technical overview of machine learning (ML) and deep learning (DL), emphasizing their roles in AI-driven decision-making and pattern recognition. It highlights YOLOv8 and YOLOv9, advanced real-time object detection models known for their accuracy and versatility in various applications.

A. Machine Learning

A branch of artificial intelligence (AI) called machine learning (ML) focuses on creating systems that can learn from data in order to make predictions or judgements. Without explicit programming, ML algorithms find links and patterns in data. Methods include reinforcement learning, which determines the best course of action by making mistakes in the absence of labels, unsupervised learning, which uncovers hidden structures in unlabeled data, and supervised learning, which trains models using labelled data. Applications of machine learning (ML) improve decision-making and automate difficult processes in a variety of industries.

B. Deep Learning

Deep learning is a branch of machine learning that models complicated patterns in data by using multi-layered neural networks, or deep neural networks. With each layer, the network is able to learn hierarchical representations by extracting more abstract properties from the raw input. While recurrent neural networks handle sequential data, such as text and time series, convolutional neural networks (CNNs) are utilised for processing images.

Deep learning powers breakthroughs in fields like autonomous vehicles, medical diagnostics, and AI-powered personal assistants. It excels at tasks like computer vision, natural language processing, and speech recognition.

C. YOLOv8

The You Only Look Once (YOLO) real-time object detection technology has evolved to a new version called YOLOv8. With greater flexibility, quicker inference times, and improved accuracy, it greatly outperforms its predecessors.

A single architecture that can handle segmentation and object detection tasks is presented by YOLOv8. For better performance, it uses cutting-edge methods like automated mixed precision (AMP), mixed precision training, and transformer-based models. YOLOv8 is accessible to researchers and practitioners alike, thanks to its comprehensive documentation and user-friendly API. It has grown in popularity as a solution for real-time object detection applications across a range of industries, including as robots, autonomous cars, and surveillance.

D. YOLOv9

The most recent iteration of the YOLO family of real-time object detection models is called YOLOv9. It significantly increases accuracy, efficiency, and adaptability while building on the advantages of its predecessors. A new Spatio-Temporal Transformer (SPT) module in YOLOv9 improves context awareness and feature extraction.

For improved performance, it also uses sophisticated methods including dynamic label assignment, cross-stage partial connections, and depth-wise separable convolutions. YOLOv9 is appropriate for a variety of applications since it provides several detection scales and supports a broad range of input resolutions. Researchers and practitioners in the field of computer vision have swiftly grown to favour YOLOv9 because of its user-friendly interface and comprehensive documentation.

IV. DATASET

The dataset comprises 26.9k annotated aerial/satellite images specifically for ship detection. Annotations are in YOLO format, ensuring precise bounding box placement for efficient detection. It targets various applications including maritime safety, fisheries management, marine pollution monitoring, defense, security, and more. This curated dataset is crucial for researchers and professionals in computer vision, machine learning, and maritime industries due to its accuracy and suitability for diverse operational scenarios.

Dataset Link: <https://www.kaggle.com/datasets/siddharthkumarsah/ships-in-aerial-images>

V. PROPOSED SYSTEM

The proposed system for integrates advanced object detection algorithms, YOLOv8 and YOLOv9, optimized for real-time ship detection. The system begins with preprocessing, where aerial or satellite images are fed into the trained models. YOLOv8 and YOLOv9 analyze these images, leveraging their deep learning architectures to detect ships by creating precise bounding boxes around them. Post-detection, the system aggregates and processes the detected ship instances, providing detailed reports on ship locations and counts. This information supports various applications such as maritime safety, environmental monitoring, and security operations. The system's efficiency lies in its ability to operate in real-time, reducing the need for manual monitoring and enhancing decision-making processes. By automating ship detection with high accuracy, the system aims to streamline maritime surveillance tasks and contribute to improved operational outcomes in diverse maritime environments.

VI. RESULT COMPARISON

Result Comparison evaluates YOLOv8 and YOLOv9 for ship detection, showcasing improved precision and recall metrics, enhancing maritime surveillance and operational efficiency.

TABLE 1: COMPARISON OF YOLOv8 AND YOLOv9 PERFORMANCE METRICS ON SHIP DETECTION

YoloV8					
Images	Instances	Box (Precision) (P)	Recall (R)	mAP@50	mAP@50-95
1,583	2,872	0.572	0.44	0.432	0.243
YoloV9					
Images	Instances	Box (Precision) (P)	Recall (R)	mAP@50	mAP@50-95
1,583	2,872	0.571	0.455	0.439	0.246

The comparison between YOLOv8 and YOLOv9 as in Table 1 is based on evaluation metrics across 1,583 images and 2,872 instances, reveals subtle improvements in object detection performance with YOLOv9. YOLOv9 shows a slightly lower box precision (0.571 vs. 0.572) but achieves higher recall (0.455 vs. 0.440), indicating better overall detection of objects present in images. Moreover, YOLOv9 demonstrates advancements in mean Average Precision (mAP) metrics, with higher scores for both mAP@50 (0.439 vs. 0.432) and mAP@50-95 (0.246 vs. 0.243) compared to YOLOv8. These improvements suggest that YOLOv9 provides enhanced accuracy and reliability in detecting and localizing objects across a range of IoU thresholds, showcasing incremental yet noteworthy performance gains over its predecessor, YOLOv8.

VII. CONCLUSION

In conclusion, the utilization of YOLOv8 and YOLOv9 for ship detection represents a significant advancement in maritime surveillance and environmental monitoring. By automating the identification and localization of ships on the sea surface, these algorithms enhance operational efficiency and reduce dependency on manual monitoring. Through rigorous training on specialized datasets, the models achieve high accuracy in ship detection, facilitating timely responses and optimizing resource allocation in maritime environments. This approach not only improves surveillance capabilities but also underscores the transformative potential of computer vision and Deep learning in enhancing maritime security and operational workflows. Future scope includes integrating sensor data for enhanced detection accuracy, expanding the dataset to encompass diverse maritime conditions, and optimizing models for real-time deployment on unmanned aerial and maritime vehicles.

REFERENCES

- [1] Liu, Wenyu, et al. "Image-adaptive YOLO for object detection in adverse weather conditions." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 36. No. 2. 2022.
- [2] Li, Shasha, et al. "Yolo-firi: Improved yolov5 for infrared image object detection." *IEEE access* 9 (2021): 141861-141875.
- [3] Lee, Jeonghun, and Kwang-il Hwang. "YOLO with adaptive frame control for real-time object detection applications." *Multimedia Tools and Applications* 81.25 (2022): 36375-36396.
- [4] Han, Xiaohong, Jun Chang, and Kaiyuan Wang. "Real-time object detection based on YOLO-v2 for tiny vehicle object." *Procedia Computer Science* 183 (2021): 61-72.
- [5] Kim, Jun-Hwa, et al. "Object detection and classification based on YOLO-V5 with improved maritime dataset." *Journal of Marine Science and Engineering* 10.3 (2022): 377.
- [6] Bist, Ramesh Bahadur, et al. "A novel YOLOv6 object detector for monitoring piling behavior of cage- free laying hens." *AgriEngineering* 5.2 (2023): 905-923.
- [7] Gallo, Ignazio, et al. "Deep object detection of crop weeds: Performance of YOLOv7 on a real case dataset from UAV images." *Remote Sensing* 15.2 (2023): 539.
- [8] Hu, Shuming, et al. "Improving YOLOv7-tiny for infrared and visible light image object detection on drones." *Remote Sensing* 15.13 (2023): 3214.
- [9] Lou, Haitong, et al. "DC-YOLOv8: small-size object detection algorithm based on camera sensor." *Electronics* 12.10 (2023): 2323.
- [10] Sun, Zhongzhen, et al. "BiFA-YOLO: A novel YOLO-based method for arbitrary-oriented ship detection in high-resolution SAR images." *Remote Sensing* 13.21 (2021): 4209.
- [11] Hu, Jianming, et al. "PAG-YOLO: A portable attention-guided YOLO network for small ship detection." *Remote Sensing* 13.16 (2021): 3059.
- [12] Li, Hao, et al. "Enhanced YOLO v3 tiny network for real-time ship detection from visual image." *Ieee Access* 9 (2021): 16692-16706.
- [13] Li, Liyuan, et al. "A complete YOLO-based ship detection method for thermal infrared remote sensing images under complex backgrounds." *Remote Sensing* 14.7 (2022): 1534.
- [14] Han, Xu, et al. "ShipYolo: an enhanced model for ship detection." *Journal of Advanced Transportation* 2021.1 (2021): 1060182.
- [15] Luo, Yonghang, et al. "SHIP-YOLO: A Lightweight Synthetic Aperture Radar Ship Detection Model based on YOLOv8n Algorithm." *IEEE Access* (2024).