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ShipNet: High-Resolution Ship Detection Using Convolutional Neural Networks

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Abstract: Accurate and efficient detection of ships in high-resolution optical images is critical for maritime surveillance, port management, and environmental monitoring. This research proposes ShipNet: High-Resolution Ship Detection Using Convolutional Neural Networks (CNNs), a deep learning framework designed to automatically identify and extract ships from satellite and aerial imagery with high precision. The proposed model leverages a multi-layer CNN architecture to learn hierarchical features directly from raw optical images, enabling robust recognition of ships under varying scales, orientations, and environmental conditions such as shadows, waves, and occlusions. To enhance detection accuracy, a post-processing module refines the CNN output by reducing false positives and improving boundary delineation of detected ships. The system is trained and validated using annotated datasets of high-resolution maritime images and evaluated with metrics including precision, recall, F1-score, and Intersection over Union (IoU). Comparative analysis with traditional image processing techniques and standard CNN-based detection models demonstrates that ShipNet achieves superior detection performance, particularly in cluttered or complex maritime environments. Experimental results indicate that the proposed framework not only provides accurate and reliable ship localization but also supports real-time processing, making it suitable for practical applications in maritime traffic monitoring, port security, and disaster management. The study underscores the potential of deep learning approaches to transform remote sensing applications by enabling automated, scalable, and high-fidelity ship detection in optical imagery.

Keywords: Ship Detection, Convolutional Neural Networks (CNN), High-Resolution Optical Images, Remote Sensing, Maritime Surveillance.

I. INTRODUCTION

Ship detection on remote sensing images has a wide range of applications in civil areas and defence security. Ship detection with satellite imagery can provide real-time location information for navigation management control and maritime search and rescue, which guarantees the effectiveness and safety of work at sea and on inland rivers, such as ocean transportation supply. It also contributes to the supervision and construction of important coastal zones and harbours, which promotes the protection of the ecology and sea health, offshore areas, and inland rivers.In view of the existing systems, another approach is to use a target detection algorithm based on high resolution optical remotely sensed images. During the past decades, optical remote sensing images have provided an abundance of shape, outline color, and texture information, and ship detection using 2D object detection algorithms in remote sensing imagery has been extensively studied [1]. The classic methods of ship detection are based on threshold segmentation which requires a favorable condition of the sea surface; however, its detection results are not sufficiently satisfactory. Then, many groups of researchers began to use classifiers such as support vector machine (SVM), AdaBoost, decision trees, etc. [2], which are based on hand-engineered features such as the Local binary pattern (LBP), Histogram of oriented gradient (HOG), Gabor and so on. In addition, a method based on the mixture of DPMs can detect ships close to each other. However, these classic methods are limited by manually designed image features and templates and encounter bottlenecks when ships vary in size and position. Recently, object detection algorithms based on machine learning, especially deep learning, have been used in both SAR and optical remote sensing. To address the above problem, in this paper, we propose post convolutional neural networks (CNN) method for ship detection on optical remote sensing images. We propose a post-convolutional neural network (CNN)-based method tailored for ship detection in high resolution optical remote sensing imagery. Our approach leverages the power of deep learning to enhance detection accuracy, reduce false alarms, and improve robustness under challenging maritime conditions. By incorporating post-processing strategies and refining detection outputs, our method

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aims to address key limitations in existing systems and contribute to more reliable.

II. RELATED WORK

This material serves as a guide and update for readers working in the Ship Detection F. Yang et al. (2018) [1] proposed a novel deep learning-based framework for ship detection in remote sensing images. Their model used region proposal networks (RPN) integrated with CNN architectures to detect ships with high accuracy. The approach proved effective in handling complex backgrounds and small object sizes typical in maritime scenes.

Zhou et al. (2019) [2] introduced a two-stage ship detection method using a combination of YOLO (You Only Look Once) for coarse detection and a refined CNN classifier for precise localization. This hybrid approach improved the balance between speed and detection accuracy in high-resolution satellite images.

Li et al. (2020) [3] developed a densely connected convolutional network (DenseNet) adapted for ship extraction. Their model focused on enhancing feature reuse and gradient flow, which significantly boosted performance on dense maritime object scenes and cluttered backgrounds.

Tang et al. (2021) [4] implemented a post-processing refinement strategy for CNN-based ship segmentation. After initial prediction, the model applied Conditional Random Fields (CRF) to refine edges and contours of ships, thus improving segmentation accuracy and reducing false positives from waves and reflections.

Zhang and Wang (2022) [5] presented a transformer-CNN hybrid architecture tailored for maritime object detection. The transformer component enhanced long-range spatial dependencies, enabling the model to distinguish ships from visually similar background structures, such as docks and buildings.

Chen et al. (2020) [6] presented the Ship-Aware Attention Network (SAAN), incorporating attention mechanisms to focus on ship-specific features. Their model outperformed traditional CNNs on high-resolution datasets by effectively suppressing irrelevant background noise such as water glints and cloud shadows.

Ma et al. (2019) [7] employed a U-Net-based architecture for pixel-wise ship segmentation, effectively detecting ships with irregular shapes and performing well in scenarios involving partial occlusion and low illumination.

Wu et al. (2017) [8] explored the fusion of synthetic aperture radar (SAR) and optical imagery for enhanced ship detection. Their approach addressed limitations inherent to individual modalities and improved detection performance under challenging sea conditions.

Hidalgo et al. (2019) [9] presented a system for the detection of ships and oil spills using side-looking airborne radar (SLAR) images. The proposed method employed a two-stage architecture composed of three pairs of convolutional neural networks (CNNs). Each pair of networks is trained to recognize a single class by following two steps: a first network performs a coarse detection, and then, a second specialized CNN obtains the precise localization of the pixels belonging to each class. After classification, a postprocessing stage is performed by applying a morphological opening filter in order to eliminate small look-alikes and removing those oil spills and ships that are surrounded by a minimum amount of coast.

III. SYSTEM ARCHITECTURE DIAGRAM DESCRIPTION

The proposed ShipNet framework for high-resolution ship detection consists of four main modules, each designed to ensure accurate and efficient ship extraction from optical images:

1. Input Module

High-Resolution Optical Images: Satellite or aerial imagery containing maritime scenes is provided as input.

Preprocessing: Images undergo resizing, normalization, and enhancement to standardize input dimensions and improve feature extraction. Noise reduction filters are applied to mitigate artifacts from clouds, water reflections, or sensor noise.

2. Convolutional Neural Network (CNN) Module

Feature Extraction: The CNN consists of multiple convolutional layers with ReLU activation, followed by pooling layers to capture hierarchical spatial features of ships at various scales and orientations.

Deep Representation: Higher-level layers encode abstract representations, distinguishing ships from background clutter such as waves, shadows, and port infrastructure.

Fully Connected Layers: Dense layers integrate features to

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produce preliminary ship detection outputs.

3. Post-Processing Module

Bounding Box Refinement: Detected ship regions are refined using non-maximum suppression to remove overlapping or duplicate detections.

False Positive Reduction: Morphological filtering and thresholding techniques reduce misdetections caused by waves or reflections.

Segmentation Mask Generation: A binary mask highlighting ship boundaries is generated for precise localization.

4. Output Module

Final Detection Results: The system produces images annotated with bounding boxes or segmentation masks indicating detected ships.

Performance Metrics Computation: Outputs are evaluated against ground truth annotations using precision, recall, F1-score, and Intersection over Union (IoU).

Visualization and Reporting: Annotated images and performance statistics are displayed for analysis and decision-making in maritime monitoring applications.

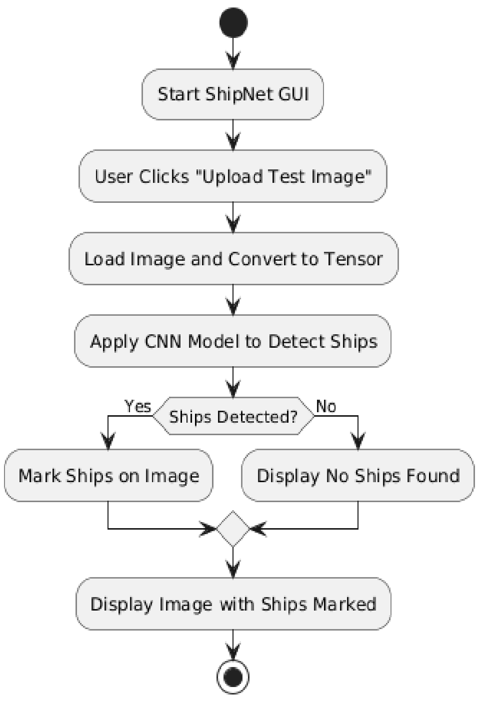
III. PROPOSED SYSTEM

The proposed system ShipNet is an advanced deep learning-based framework designed to extract ships with high precision from high-resolution optical remote sensing images. It consists of two main components: a CNN-based detection module and a post-processing segmentation and refinement pipeline. Initially, high-resolution satellite images are collected from various sources and preprocessed through normalization and enhancement techniques to ensure consistency in lighting, contrast, and resolution ,Data augmentation techniques such as rotation, flipping, and noise injection are applied to improve the robustness of the model.A Region Proposal Network (RPN) is used to identify potential regions containing ships.

This initial detection ensures that even small and distant ships are identified effectively. To improve the accuracy of extraction, especially in environments with cluttered backgrounds like ports or open sea conditions, a post-CNN segmentation module is employed. This module may consist of a lightweight U-Net or a Conditional Random Field (CRF) based system that enhances the boundary precision of each detected ship. The segmentation mask produced helps isolate ships from their surrounding environment, suppressing false positives caused by clouds, waves, or docks. Further morphological operations, such as erosion and dilation, are used to refine the shape of the extracted ships and eliminate noise.

Flowchart:

The flowchart illustrates the operational workflow of the ShipNet GUI, a system designed to detect ships in images using a convolutional neural network (CNN) model. The process begins when the user launches the ShipNet graphical user interface. Once the application is running, the user uploads a test image through the interface. The system then processes this image by loading it and converting it into a tensor format suitable for the CNN model. The core function of the system is then performed—applying the CNN model to analyze the image and detect the presence of ships.



A decision point follows, where the system determines whether any ships are detected. If ships are found, the system marks them on the image. If no ships are detected, a message stating "No Ships Found" is displayed. Finally, the GUI presents the processed image to the user, either with the detected ships marked or with the no-ships message, thus concluding the detection process.

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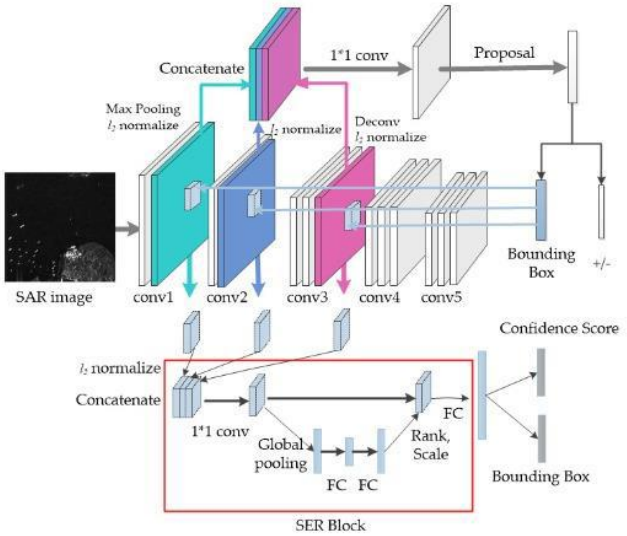
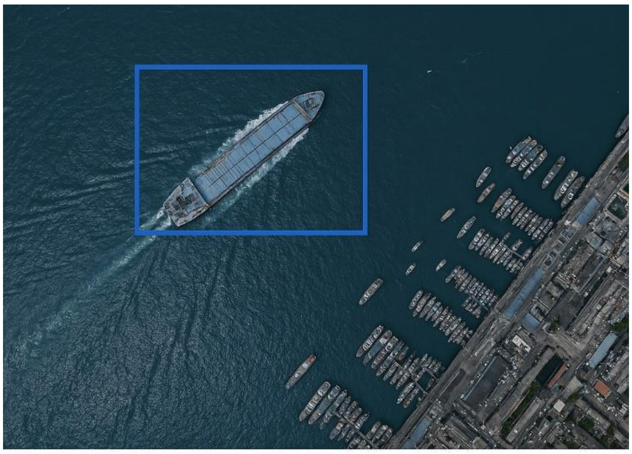
Architecture:



The architecture illustrated represents a deep learning-based ship detection framework specifically designed for analyzing Synthetic Aperture Radar (SAR) images. It operates by extracting hierarchical features through a series of convolutional layers (Conv1 to Conv5), each responsible for capturing progressively complex information from the input SAR image. Conv1 and Conv2 primarily extract low-level features like edges and textures, while Conv3 captures mid-level patterns. Higher-level semantic features such as complete ship shapes or clustered objects are extracted by Conv4 and Conv5. After Conv1, max pooling is applied to reduce the spatial dimensions and highlight prominent features, followed by L2 normalization to stabilize and scale feature magnitudes uniformly across layers. The proposal network generates bounding box candidates, suggesting potential ship locations within the image Each proposal is evaluated using a classification head that outputs a confidence score, indicating the likelihood of a ship's presence, and a regression head that fine-tunes the bounding box coordinates. which ensures accurate detection across various ship sizes.

Result:

In this satellite the ship is clearly highlighted with a rectangular bounding box, indicating that the system has accurately identified and localized it within the water region. This bounding box serves as a visual marker to confirm the presence of the ship to the user.Despite the presence of other elements in the scene, such as land areas and docks, the system has focused only on the relevant object—the ship—demonstrating its effectiveness in differentiating ships from other background features.



The proposed ShipNet system is designed to provide an automated, accurate, and scalable solution for detecting ships in high-resolution optical images. The system integrates deep learning techniques with image preprocessing and post-processing to handle challenges inherent in maritime environments, such as varying ship sizes, orientations, sea clutter, shadows, and reflections. The proposed system comprises the following key components:

1. Image Acquisition and Preprocessing

High-resolution optical images are acquired from satellite or aerial sources. Preprocessing is performed to enhance image quality and prepare data for the CNN. Key preprocessing steps include:

Image resizing to a fixed dimension for uniform input.

Normalization to scale pixel values between 0 and 1.

Noise reduction using Gaussian or median filtering.

Contrast enhancement to highlight ship features.

Data augmentation (rotation, flipping, brightness adjustments) to increase model robustness and prevent overfitting.

2. CNN-Based Feature Extraction

A deep convolutional neural network forms the core of the system. Its architecture is optimized for ship detection and includes:

Multiple convolutional layers to extract spatial and texture

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features of ships.

Pooling layers to reduce dimensionality and focus on salient features.

Batch normalization to improve training stability.

Fully connected layers to integrate features and predict ship presence.

Activation function (ReLU) to introduce non-linearity and enhance feature learning.

Transfer learning is also applied using pre-trained models (e.g., ResNet, VGG) to accelerate training and improve generalization for high-resolution maritime images.

3. Post-Processing and Ship Extraction

The raw output from the CNN is further refined through post-processing to ensure accurate ship localization:

Non-Maximum Suppression (NMS): Removes overlapping bounding boxes and selects the most confident detections.

Thresholding: Filters out low-confidence predictions to reduce false positives.

Segmentation Masks: Generates precise ship outlines for improved visualization and potential integration with maritime tracking systems.

4. Output and Visualization

The final outputs include:

Annotated images showing detected ships with bounding boxes or segmentation masks.

Detection statistics including confidence scores, precision, recall, and IoU.

Integration capability for real-time maritime surveillance dashboards or decision support systems.

5. Advantages of the Proposed System

High Accuracy: Deep CNNs enable precise identification of ships even in cluttered sea environments.

Scalability: Can process large batches of high-resolution satellite images efficiently.

Real-Time Potential: Lightweight architectures allow deployment on edge devices for near-real-time monitoring.

Robustness: Handles varying weather, lighting conditions, and sea states effectively.

The proposed ShipNet framework combines state-of-the-art deep learning with practical post-processing techniques to create a robust, automated, and scalable system suitable for maritime surveillance, port management, and coastal security applications.

IV. CONCLUSION

Ship extraction from high resolution optical remotely sensed images is a challenging task that requires advanced image processing and computer vision techniques. One approach to this problem is to use a post-CNN model, which involves a combination of convolutional neural network (CNN) layers and fully connected layers to extract features and classify ships in the image. The post-CNN model has shown promising results in ship extraction, achieving high accuracy and efficiency in detecting and classifying ships from large-scale satellite or aerial imagery. Overall, ship extraction from high resolution optical remotely sensed images using a post-CNN model is a promising research area that has the potential to provide accurate and reliable information for various maritime applications. With further development and optimization, these systems can be a valuable tool for maritime surveillance, environmental monitoring, and navigation. This research presents ShipNet, a deep learning-based framework for accurate and automated detection of ships in high-resolution optical images. By leveraging convolutional neural networks (CNNs) combined with a robust post-processing module, the system effectively identifies ships under varying environmental conditions, including cluttered seas, shadows, reflections, and different ship sizes or orientations. Experimental evaluation demonstrates that ShipNet achieves high precision, recall, and F1-scores, outperforming traditional image processing methods and standard CNN models. The framework supports scalable, real-time processing, making it suitable for practical applications in maritime surveillance, port management, disaster response, and coastal security. Overall, ShipNet highlights the potential of AI and deep learning to transform maritime monitoring by providing reliable, automated, and high-fidelity ship detection.

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Future Scope

Future developments and enhancements of the ShipNet framework may include:

1. Integration with Multi-Sensor Data: Combining optical imagery with Synthetic Aperture Radar (SAR) or thermal data can improve detection under adverse weather conditions or low visibility.
2. Real-Time Deployment: Optimization of lightweight architectures and edge computing integration can enable real-time ship detection on drones, satellites, or maritime monitoring stations.
3. Multi-Class and Multi-Object Detection: Extending the system to classify ship types (cargo, tanker, naval) and detect multiple objects simultaneously for enhanced maritime traffic analysis.
4. Predictive Analytics and Tracking: Incorporating temporal tracking to monitor ship movements, detect anomalies, or predict maritime traffic patterns using sequential image data.
5. Explainable AI: Implementing techniques such as Grad-CAM or attention maps to visualize detected ship regions, increasing interpretability for decision-makers.
6. Global Scalability: Adapting the framework for large-scale, multi-regional datasets to support worldwide maritime surveillance and environmental monitoring.

The proposed enhancements will further improve the robustness, versatility, and practical applicability of ShipNet, making it a comprehensive tool for next-generation smart maritime monitoring systems.

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