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Shipnet Post CNN Ship Extraction from High Resolution Optical Images

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Abstract: This project describes the concept to detect ships from sea images taken from satellites and these images are called as 'Synthetic aperture radar (SAR)'. Ships can be detected from SAR images using Post CNN Algorithm. It will be trained with ship images from VGG ImageNet Network, while training it extract features from images using its height, width and image colour channel. CNN filter train images features map from multiple layers of convolution neural network. All object detection from image will be maintained in train vector with value 1 and other background features marked as 0. Whenever new SAR test image uploaded then proposed algorithm will apply train vector on SAR test image to detect objects with ships features.

Keywords: Convolutional Neural Network, Image classification and Recognition, CNN, SAR.

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 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.

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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. 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.

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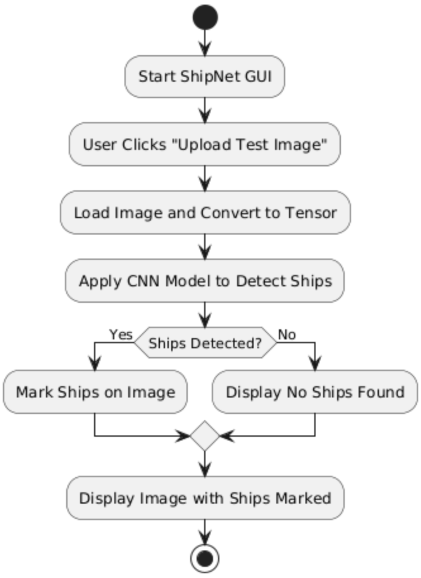
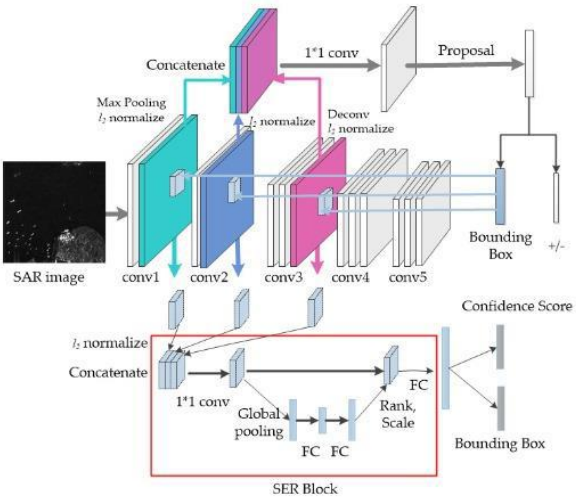


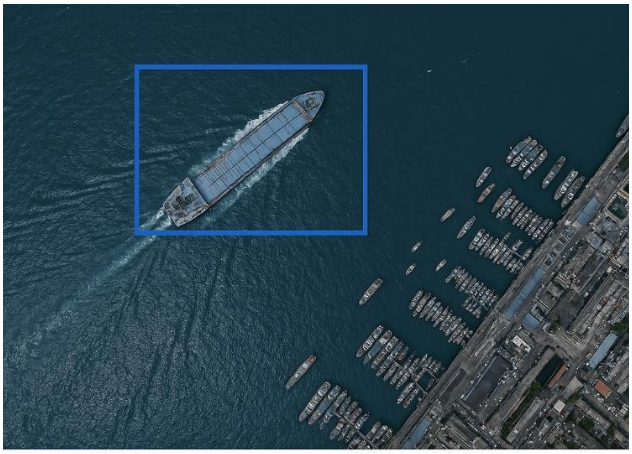
A decision point follows, where the system determines whether any ships are detected. If ships are found, the system marks them on the image. If no ships are detected, a message stating "No Ships Found" is displayed. Finally, the GUI presents the processed image to the user, either with the detected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

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.

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

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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.

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