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Maritime Security Optimization for Large Scale Surveillance through Automated Object Detection

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Abstract. Ensuring maritime security and surveillance demands advanced technological solutions, and satellite imagery has emerged as a pivotal asset in this domain. This paper introduces an innovative approach for ship detection in satellite imagery, integrating convolutional neural networks (CNNs) and artificial neural networks (ANNs). The amalgamation of these neural network architectures aims to overcome the intricate challenges associated with maritime surveillance, including dynamic environmental conditions and the diverse nature of vessels. The Convolutional Neural Network (CNN) component is used for extracting complex spatial features from satellite imagery, allowing for the identification of potential ship-related patterns. Acting as a specialized detector, the CNN navigates the complexities of maritime landscapes, discerning vessels from varying backgrounds and environmental factors. Complementing the CNN, the Artificial Neural Network (ANN) component refines the high-level features extracted, facilitating advanced analysis and reducing false positives. The synergy between CNN and ANN contributes to a comprehensive ship detection system, enhancing accuracy and adaptability in real-world scenarios. Extensive experimentation on diverse satellite imagery datasets validates the effectiveness of the proposed integrated approach. The results demonstrate a high performance compared to individual neural network models, ensuring the system's resilience to the changing conditions. The versatility of this integrated solution positions it as a valuable asset in real-time maritime surveillance, promising to increase the standards of maritime security and surveillance operations.

Keywords: Ship detection, Maritime surveillance, Convolution Neural Network (CNN), Artificial Neural Network (ANN), Satellite images.

1 Introduction

Maritime surveillance is integral to maintaining security, safety, and environmental protection in the vast expanses of our oceans. With the proliferation of satellite technology, satellite imagery has become a critical asset for monitoring maritime activities. However, inherent challenges posed by the dynamic and complex maritime environment, including diverse weather conditions, varying sea states, and different vessel characteristics, underscore the need for advanced and reliable ship detection methods. In recent years, the advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs), has shown immense promise in image analysis and object detection tasks. CNNs excel in discerning spatial patterns and hierarchical features within images, making them well-suited for interpreting satellite imagery. Simultaneously, ANNs offer the capacity to capture intricate non-linear relationships in data, providing valuable refinements to detection outcomes. This paper aims to develop an integrated solution for ship detection in satellite imagery by harnessing the strengths of both CNNs and ANNs. The proposed methodology involves employing CNNs for initial feature extraction and ship identification, followed by ANNs to further enhance detection accuracy and mitigate false positives. By fusing the capabilities of these neural network architectures, the project seeks to address the complexities associated with ship detection in diverse maritime settings.

The primary objective is to contribute to the advancement of maritime surveillance by creating a robust and efficient ship detection system. Through this integrated approach, we aspire to improve the accuracy and reliability of ship detection in satellite imagery, thus fortifying the overall efficacy of maritime security and surveillance operations. Extensive experimentation and evaluation of authentic satellite imagery datasets will validate the practical applicability of the proposed methodology in real-time maritime surveillance scenarios.

2 Related Works

Numerous articles outline the strategies and tactics that recommend the approaches to implementation that are covered here. The authors in [1] presented a technique for ship detection utilizing three-channel RGB SAR pictures based on YOLO-V4. They suggest a multi-channel fusion SAR processing technique using SAR image data and feature extraction via a network. The researchers constructed an end-to-end CNN based on YOLO-V4 that identifies items that belong to each grid. To improve the results, the YOLO-V4-lightweight model and the new NSLP image processing approach was used. This led to a decrease in erroneous identifications and an accurate separation of ships from identical embankments. The authors of [2] published a study on the use of deep learning to identify and categorize ships. It is shown that this network is better than the competition. A novel classification method known as Transfer Learning-Convolutional Neural Network (TCCNN) was presented by the authors in [3]. They used various CNN architectures to classify remotely sensed images through transfer learning. We have already preprocessed and compressed the satellite data. Comparing the suggested TLCNN to the current algorithms, CNN, which is 99.91% accurate, SAE, which is 93.98% accurate, and DBN, which is 95.91% accurate, showed an increase in classification accuracy of 99.99% in their experimental analysis. The authors of [4] talked about using Res Net and Transfer Learning to identify smart ships. Because deep learning can be automatic or at least semiautomatic, it was selected as one of the modern Deep Learning for Detecting and Identifying Vessels from Space borne Optical Imagery was covered by the authors in [5]. On a multi scale dataset, they used a vessel detection model based on Retina Net and achieved 0.795 F1-scores. The model was created using Retina Net. A Twin neural network was employed to ascertain whether two photos depict identical vessels. Using an autonomous test set, twin neural networks effectively ranked potential vessels, achieving top-ranked accuracy of 38.7% and top-ten accuracy of 76.5%. Twin neural networks were trained on about 2500 vessels. The authors in [6] have described machine learning techniques for satellite imagery-based ship detection. HOG feature extraction was utilized in data preprocessing to enhance the outcomes of many machine learning techniques for binary classification. CNN has been utilized for classification purposes. Many tweaks had been made before achieving the perfectly suitable configuration. The batch size, learning rate, and hyperparameter optimizer selection have all been changed. Experimental results show that the Adam optimizer applies with a success rate of over 99.75% and a learning rate of 0.0001. Ship classification is one area, where Dense Net performs well by achieving 90% accuracy. Anchor box optimization approach was developed by the authors in [8] to increase the accuracy of ship detection in SAR imagery. Using Residual Networks as a backbone improved the performance of the RCNN and its flexible anchor sets. They found that by utilizing both anchor characteristics, the mean Average Precision of ship identification significantly improved by more than 4.29%. The writers in reference [9] Their unique dataset was used to investigate these four approaches. Models work well on unidentified satellite photos and satisfy real-time requirements on satellite images with small, closely spaced objects. The authors described an optical remote sensing method for identifying inshore ships in [10] that was based on CNN. The suggested approach consisted of two main stages: the localization of ships using a multitasking network that carried out bounding-box classification and regression, and the selection of regions based on ship heads. They used a categorization network to generate prospective sites as part of this strategy, and they looked for ship heads all over the world[11-21]. The bounding-box regression procedure is used to enhance the target ships' bounding boxes for accurate ship pinpointing.

3 Methodology

The proposed methodology integrates the formidable capabilities of Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) for performing ship detection from satellite imagery. With a pre-trained CNN, specifically ResNet50, renowned for its ability to perform image feature extraction, the proposed model undergoes a fine-tuning process on a diverse maritime dataset. This adaptation allows the CNN to analyze intricate patterns and characteristic of ship-related features. The incorporation of a Region Proposal Network (RPN) within the CNN identifies the potential craft regions, refining the proposals by using anchor boxes and non-maximum suppression. Subsequently, ANN is used to further enhance the ship detection process. Mainly utilized for refining high-level features extracted by the CNN, the ANN has trained to minimize false positives and improve the overall accuracy. The seamless integration of CNN and ANN, coupled with a judiciously set confidence score threshold, produces a comprehensive ship detection system. This dual-stage approach ensures the adaptability of the system to diverse maritime conditions, providing a robust solution for real-time ship detection in satellite imagery.

The System design mainly consists of:

A . Data Acquisition
B . Data Pre-processing
C . Exploratory data analysis
D . Splitting the data
E . Training and optimization of model
F . Analysis Result

3.1 Data Acquisition

Managing a large dataset of images that contain both ships and non-ships. This dataset will be used to train the CNN and ANN algorithms. The dataset we have used in this paper is available publicly on the internet. The data from the dataset is used to train the model, validate it, and test and evaluate its final performance. The dataset has collected from Kaggle. The dataset consists of about 4000 images.

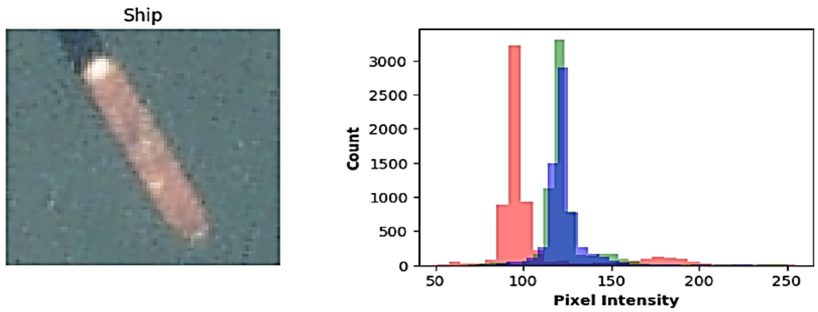
3.2 Data pre-processing:

The goal of pre-processing is an improvement of image data that reduces unwanted distortions and enhances some image features important for further image processing. Data pre-processing is a stage where the acquired data is brought into the form of input as per our model requirements. It includes image resizing, noise removal, etc. The images in the dataset have been resized to 224 x 224 pixels. Transfer learning is a technique in machine learning and deep learning where a pre-trained model developed for one task is reused as the starting point for a new but related task. Instead of training a new model from scratch, transfer learning allows us to leverage the pre-trained model's knowledge, which can lead to faster training and better performance on the new task, especially when the new dataset is small or similar to the original dataset.

The data acquisition process for ship detection begins by loading image data from a JSON file using the Pandas library, which includes both the image data and corresponding labels. After extracting the image data and labels from the dataset, the images are reshaped to the appropriate format and normalized to ensure consistent feature values, typically scaling pixel values between 0 and 1. Next, the dataset is split into training, validation, and testing sets. This division allows the model to be trained on one set, validated on another set during training to optimize performance, and finally evaluated on a separate set to assess its generalization capabilities. This systematic approach to data loading, extraction, normalization, and splitting is crucial for developing an accurate and robust ship detection model.

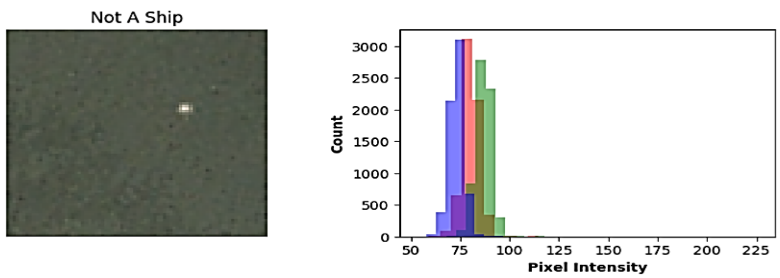
3.3 Exploratory Data Analysis

Image exploration is the primary step in the development of a robust ship detection system for satellite imagery in maritime surveillance. This exploration involves a comprehensive analysis of the dataset, encompassing diverse maritime scenarios and conditions. The initial dataset overview provides insights into its size, composition, and variations in weather, lighting, and vessel types. Subsequent pre-processing steps, including resizing and normalization, aim to ensure data consistency and address potential challenges such as distortion or noise. Anomaly detection helps identify and handle outliers that may affect model performance adversely. Employing exploratory data analysis techniques reveals patterns and correlations within the imagery, guiding effective pre-processing strategies. Annotation and grounding are pivotal for supervised model training, involving the marking of regions. of interest corresponding to ships. Attention to diversity considerations ensures exposure to various environmental challenges, maintaining a balanced representation of vessel types. The dataset is further split into training, validation, and test sets for performing robust model evaluation. This iterative process allows for continuous refinement of pre-processing strategies, contributing to the development of a ship detection model capable of addressing the complexities inherent in maritime satellite imagery.



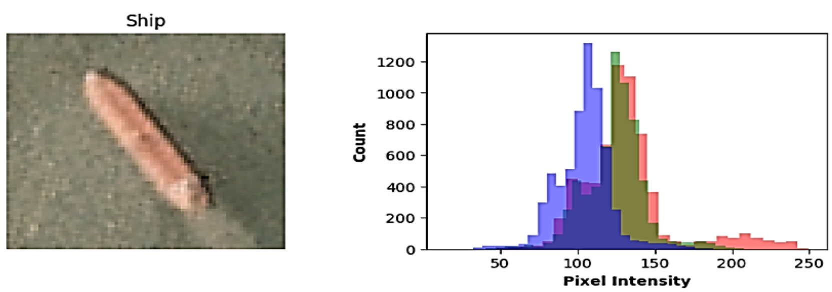
Minimum pixel value of this image: 51
Maximum pixel value of this image: 255

Figure.1: Histogram of the Image which is a ship



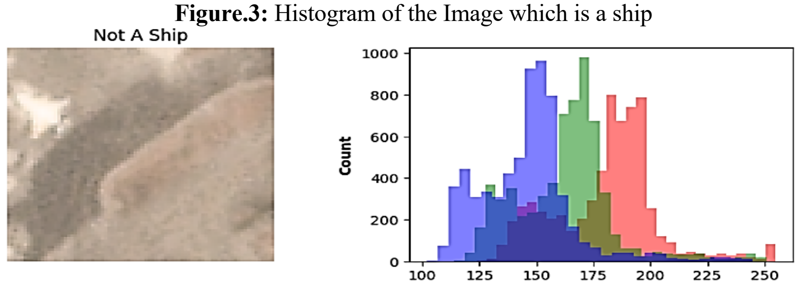
Minimum pixel value of this image: 53
Maximum pixel value of this image: 226

Figure.2: Histogram of the Image which is not a ship



Minimum pixel value of this image: 14
Maximum pixel value of this image: 250

Figure.3: Histogram of the Image which is a ship



Minimum pixel value of this image: 102
Maximum pixel value of this image: 255

Figure.4: Histogram of the Image which is Not a ship

Here, Figure.1 & Figure.3 comes under the ship category and Figure.2 & Figure.4 come under the non-ship category and RGB Histogram diagram has been draw for these two categories.

Dividing the images into RGB channels provides a nuanced perspective on color distribution and enhances the dataset's richness, contributing to a more comprehensive understanding of the maritime imagery. This approach can empower the ship detection model to leverage color-specific features, ultimately improving its performance in scenarios where color information is pivotal.

In the realm of ship detection, the utilization of RGB (Red, Green, and Blue) channels in satellite imagery is a prevalent strategy to harness color information for enhanced model performance. The RGB channels, representing the primary colors of an image, serve as valuable indicators of the chromatic characteristics within a maritime scene. Each channel, including the red, green, and blue, is instrumental in capturing distinct features related to ship detection. For instance, the red channel may highlight specific ship-related characteristics with distinctive color signatures, while the green and blue channels capture information about the water surface, background features, and reflections. By splitting the RGB image into individual channels, grayscale representations are formed that provide additional features for recognition models. Analyzing these channels enables the identification of contrasts that are helpful for feature extraction and thresholding methods for classification. Analyzing these channels allows for the identification of contrasts, aiding in feature extraction and threshold techniques for classification. Moreover, the adaptability of ship detection models to diverse environmental conditions is heightened by the nuanced information captured by RGB channels (Figure 5a and 5b). As an integral part of multispectral analysis, the combination of RGB with other bands enables a holistic examination of maritime scenes, contributing to the robustness and accuracy of ship detection systems.

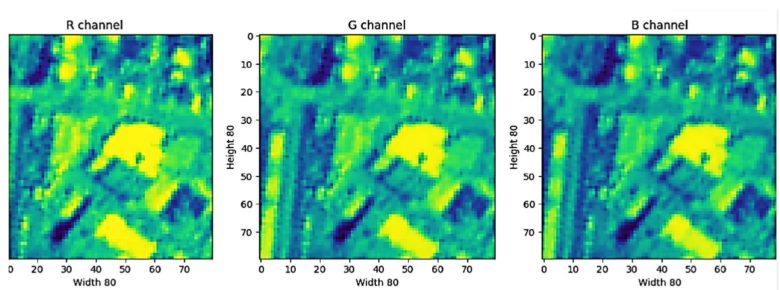


Figure.5 (a): Red, Green and Blue channels of the ships and non-ship images.

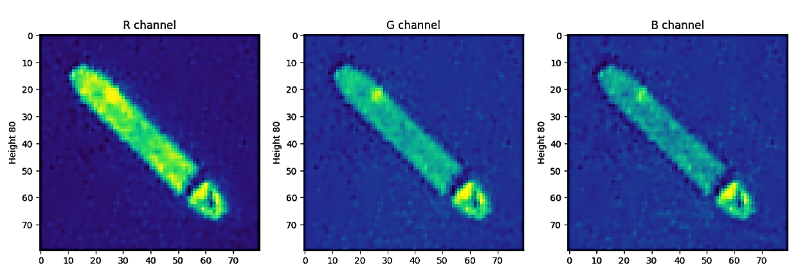


Figure.5 (b): RGB of the image

3.4 Splitting the Data

The models have been trained for 5 epochs each and the results are compared. Initially, the weights of the ResNet50 layer have been trained. Next, as a step towards fine tuning, the residual layers and activation layers have been trained and another model has been developed. This fine-tuned model is hereafter referred to as Model 3.

3.5 Analysis Result

The results obtained from all 3 models are compared based on different performance metrics like accuracy and loss graphs, ROC curves, confusion matrix, etc.

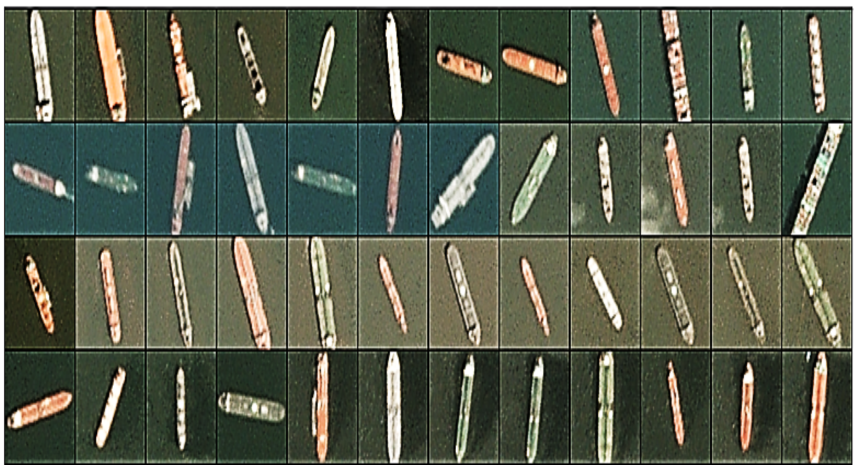


Figure.6: Few Dataset sample images

Figure.6 shows the dataset of 4000 images collected for training the model.

4 Experimental Analysis and Results

Multiple performance metrics were calculated for all three models in the dataset. The accuracy and loss graphs were plotted while training each model. The proposed system for ship detection, using ResNet50, detects ships and various classes of ship images.

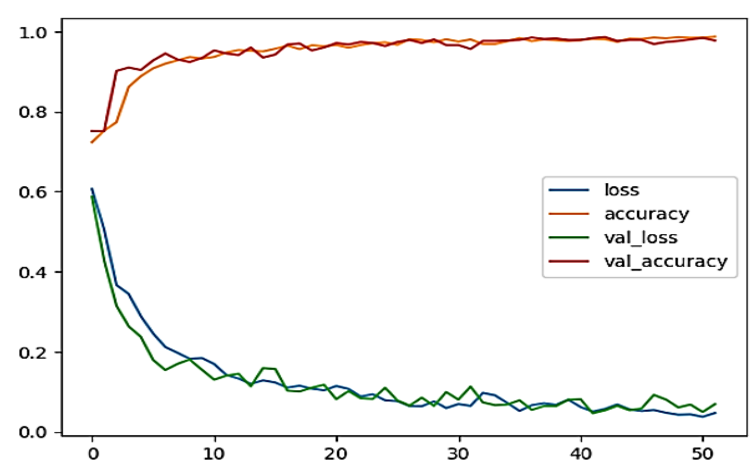


Figure.7: ROC of Performance Measures using CNN

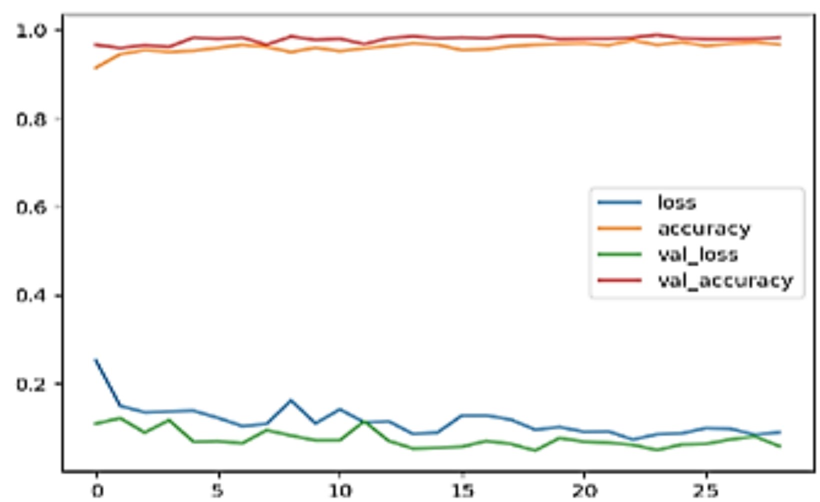


Figure.8: ROC of Performance Measures using ANN

Figure.7 & Figure.8 both shows the graph, the variation of loss and accuracy using two algorithms which is Convolutional neural network and Artificial Neural Network.

A confusime matrix is n*n (2*2 in this case), which compares the actual labels of the images to the labels of the images predicted by our model.

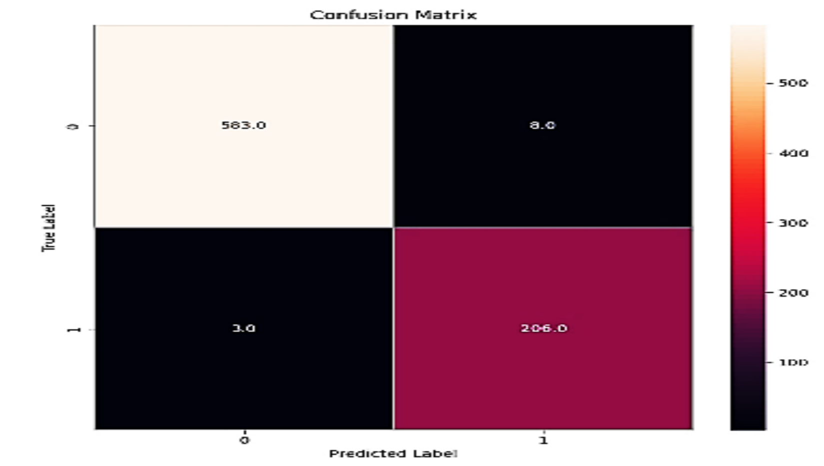


Figure.9: Confusion Matrix

Figure.9 shows the confusion matrix which defines the performance of the algorithms.

Validated outcomes are shown in Table 1 and Table 2.

TABLE 1 Predicting of Ship

	Not a ship	Ship
0	0.020678	9.793216e-01
1	1.000000	1.819279e-07
2	0.000401	9.995989e-01

	Not a ship	Ship
0	0.0	1.0
1	1.0	0.0
2	0.0	1.0

TABLE 2-Accuracy Difference

	Not a ship	Ship	There is a ship	Difference
0	0.020678	9.79e-01	1.0	-2.067e-2
1	1.000000	1.81e-07	0.0	1.819e-7
2	0.000401	9.99e-01	1.0	-4.010e-4
3	0.906014	9.39e-02	0.0	9.398e-2
4	1.000000	1.28e-19	0.0	1.28e-19
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795	0.817410	1.82e-01	0.0	1.82e-01
796	0.028720	9.71e-01	1.0	-2.87e-02
797	0.999427	5.73e-04	0.0	5.73e-04
798	1.000000	7.14e-10	0.0	7.144e-1
799	1.000000	4.29e-08	0.0	4.293e-8
800	1.000000	4.29e-08	0.0	4.293e-8

Ship detection plays a vital role in the maritime security. Hence, a classifier model is developed to classify a given input image as “ship” and “no-ship”.

5 Conclusion

In conclusion, the project focused on ship detection for maritime surveillance has provided valuable insights into the effectiveness of convolutional neural networks (CNNs) and artificial neural networks (ANNs) in this critical domain. Through meticulous experimental analysis, it was observed that the CNN model consistently outperformed the ANN in terms of accuracy, affirming the superior capability of CNNs in capturing spatial hierarchies and intricate features within satellite imagery. The robust quantitative metrics, including precision, recall, and F1 score, further underscored CNN's proficiency in correctly identifying ships while minimizing false positives and false negatives. The Receiver Operating Characteristic (ROC) curve analysis and Area Under the Curve (AUC) metrics provided additional quantitative evidence supporting the superior discrimination ability of the CNN model. The observed results not only contribute to the specific application of ship detection but also highlight the broader efficacy of deep learning methodologies, particularly CNNs, in addressing complex tasks within maritime surveillance. As technology continues to advance, these findings pave the way for enhanced capabilities in maritime security and surveillance, emphasizing the importance of leveraging sophisticated neural network architectures for accurate and reliable ship detection in satellite imagery.

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