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SAR (Synthetic Aperture Radar) Image Study and Analysis for Object Recognition in Surveillance

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Abstract: A summary of the many techniques used for this comprehensive review study aims to classify and detect synthetic aperture radar (SAR) images. SAR images have become more well-liked as a result of their adaptability and use in remote sensing activities such as planning, surveillance, and search and rescue regardless of the weather. The conversion of radar scatter returns to images and subsequent analysis for composition determination make it difficult to interpret these images efficiently. SAR images have been effectively categorized in the past for a variety of uses, with the possibility for further expansion across other SAR image types. In particular, feature extraction and SAR image categorization using Convolutional Neural Networks (CNNs) show potential.

Keywords: *detection, feature extraction, classification, ship type, SAR images*

1. Introduction

SAR, a sophisticated microwave imaging radar, makes it easier to continuously identify and locate important objects [1]. SAR produces images with exceptional resolution regardless of the weather or lighting. The detection and categorization of ground targets, notably ships, have significantly improved because to this technology. Diverse methods Techniques for target recognition in SAR imagery have been developed as a result of ongoing developments in SAR technology. The Constant False Alarm Rate (CFAR) segmentation method is one of the methodologies that researchers have carefully investigated for SAR target segmentation techniques [2].

Nevertheless, difficulties like speckle noise and misleading target signals make manual analysis of SAR images time-consuming. Studies focusing on recognizing and detecting maritime targets have received more attention in the field of remote sensing. The need for maritime surveillance is expanding across a number of businesses, including the shipping and military sectors, which is why there is a surge in interest.

The variety of applications in this field have Due to the dearth of real samples for categorizing marine objects, earlier research frequently used simulated SAR images.

However, reliable ship identification using remote sensing data is essential for important tasks including traffic monitoring, stopping illegal smuggling, and improving effective fisheries management.

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1.1 Background

The application of SAR imaging for object recognition and surveillance has clearly gained attention lately. The introduction of spaceborne SAR satellites like TerraSAR-X, RadarSat-2, and GF-3 has sparked an increase in interest in this area. These satellites deliver SAR images with different resolutions covering various geographical areas. There is a need to more thoroughly examine the characteristics of a wider range of targets, even though the current research in SAR-based marine target classification has mainly concentrated on prominent vessels like oil tankers, cargo ships, and container ships, each of which exhibit distinctive characteristics as described in previous investigations [3]. The distinctive scattering characteristics of different types of ships have been successfully used in earlier investigations [4] Support vector machines (SVM) and sparse representation classifiers have proven to be adept at attaining accurate categorization [5]. In addition, thorough investigations have shown that classification accuracy can be as high as 97.5% when three different ship classes are differentiated using methods like dictionary learning and histograms of oriented gradients (HOG) [6] Numerous studies have focused on combining the benefits provided by traditional machine learning (ML) classifiers, realizing the need of carefully constructing features [7].

1.2 Stimulation

Because SAR images have so many uses across so many different industries, research and analysis into object detection in surveillance have become more and more important, including defense, border security, and disaster management. With the ability to see through objects like walls, dust, and clouds, SAR images are preferable to optical images because they can be used in all types of weather. The speckle noise, complex scattering mechanisms, and low contrast in SAR images do, however, also provide some unique challenges. For effective object detection algorithms specifically designed for SAR images, a thorough understanding of these topics is essential. Effective SAR object detection algorithms may lead to better threat identification, better situational awareness, and improved disaster response.

1.3 Ship detection and SAR technology

SAR imaging has a wide range of applications due to its high precision capabilities, including mine detection, oceanography, and terrain categorization [8]. Additionally, it works well for finding concealed things and monitoring oil pollution on the ocean's surface.

A SAR image, which typically has a resolution of 0.2 to 100 meters, provides a 2-dimensional depiction of the reflectance of microwaves in the region being photographed.

SAR sensors are used, and they offer certain characteristics not seen in optical sensors, such as:

- SAR is an active imaging technology that can function without the need for sunlight.
- SAR makes use of microwave frequencies, which can pass through a variety of barriers, like addressing the soil, snow, vegetation, and clouds.
- By utilizing polarization to improve imaging, SAR can learn more about the structures of the things being shot.
- SAR interferometry can be used since SAR is a coherent imaging technique. On the other hand, the presence of speckles makes it challenging to interpret SAR images [9].

At the moment, image creation and decision-making are separated during the SAR processing process.

SAR simulation systems come in two varieties:

1. To build an image, raw data on the rate of absorption from systems that replicate SAR imaging systems must be processed [10].
2. SAR image simulation systems.

Due to its all-weather capabilities, SAR has proven to be extremely useful for monitoring huge maritime areas, giving it a unique advantage over competing technologies like visible light, infrared, and multi-/hyperspectral photography. The successful application of SAR-based maritime monitoring depends greatly on ship classification, which has recently attracted a lot of attention.

1.4 Objectives

- Researching and examining SAR images in relation for surveillance, object detection.
- To evaluate current approaches and research the variables that contribute to successful or unsuccessful SAR image identification of moving objects.
- Examine the potential uses of SAR imaging for surveillance and security activities.
- Examine several image processing methods to enhance the quality of SAR images and advance object detection for surveillance.

1.5 Scope of the review

SAR is a crucial technology with numerous uses in both the military and the civilian worlds, which stands for SAR. In military settings, SAR is frequently employed for tasks including target identification, combat monitoring, and precise targeting. In contrast, SAR is mostly utilized in civilian applications to monitor the Earth's surface, issue catastrophe warnings, and assess the maritime environment [11]. SAR technology developments have continually improved the detection and identification of ground targets, such as cars, ships, and specialized structures, which are of great importance. With several potential applications in emergency management, security, and military operations, ongoing research on SAR imaging processing for object recognition and surveillance remains active. It is expected that more developments in this area will take place as more complex algorithms and methods for the interpretation of SAR data emerge, taking advantage of the expanding accessibility of SAR imagery.

2. Detecting ship from SAR images

Although earlier research on SAR-based ship identification has provided useful insights, it has mostly focused on ship localisation in Open Ocean as opposed to coastal areas. Unique difficulties arise from the complex task of locating and recognizing ships in ports and coastal waterways. Complexity is increased by the wide variety of ship types, each with unique size, design, and navigational characteristics, especially when AIS transponder-less ships are present. Given the complicated and busy ship traffic in these areas, the creation of novel approaches is essential to effectively handle these complexity [12].

For ship detection in SAR images, a number of algorithms have been developed, Target identification has been done using a variety of methodologies, including CNN-based techniques, feature-oriented methods, and CFAR-based ones [13] [14] [15][16],. approaches Statistical models for maritime clutter, such as the Rayleigh distribution [17], Gamma distribution [18], and K-distribution, are employed in CFAR-based approaches, making it simple to calculate detection thresholds [13] Following sea-land segmentation, these techniques are typically employed to lessen false alarms brought on by land-based items like roads and houses. CFAR-based systems can suffer in low contrast environments even when they lack classification layers for target discrimination. In contrast, feature-based methods, as described in [14] offer a powerful substitute that makes use of gradient data coupled with Haar-like traits and the Radon transform. The first sea-land segmentation's impact can be reduced by excluding land pixels.

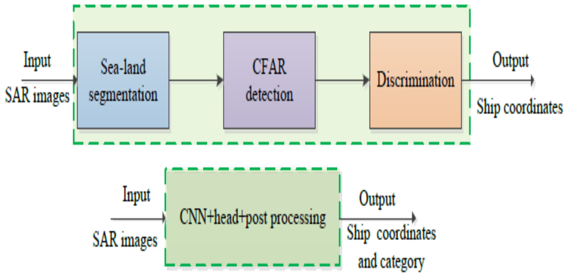

Fig 1. shows the architecture of a CFAR- and deep-learning-based detector.

2.1 Overview of algorithms to detect ship

In terms of ship detection studies, SAR photography is in the forefront [19] Hu et al. [20] first presented the Cumulative Projection Curve (CPC) technique in their quest to improve detection close to coastal areas. This method helps to identify smaller vessels close to port coasts by quantifying the degree of intersection between several categories. By creating a hierarchical approach that performs the dual functions of diagnosing and segmenting color images containing ships, Hong et al. [21] improved the discipline. Their method includes using Bayes classification, Principal Component Analysis (PCA) to categorize floating objects, and wavelet-based approaches for noise reduction. However, other studies has cast doubt on the effectiveness of statistically based techniques like PCA [22]. In addition, the use of SAR images for ship identification has been investigated in a number of studies, with some of them making use of the wavelet domain [23] .In light of this, RGB camera images are not covered. Dao-Duc et al. [24] described a method that makes use of a deep learning architecture similar to Alex-Net. To train the network, more than 130,000 real images of ships from 35 different categories were used. According to reports, the accuracy scores for both the Top1 and Top5 were between 80% and 95%. Fast-RCNN was suggested as a ship detection method by Japhet et al. [25] [26]. Fast RCNN uses a CNN architecture and is distinguished by its quick training and testing procedure [27]. 400 images were used in the study for both testing and training, and an outstanding overall accuracy rate of 87% was attained. Huang and team [28] introduced the BvSB-ADN technique, which combines deep learning with active learning. With little training data, this novel method delivers high detection accuracy. It is possible to choose the best deep network training samples using this approach. RBM, or Restricted Boltzmann Machine, was a feature of the network used in this study.

2.2 Features of the detection method are extracted

2.1.1 Intensity-Based Features*:* In their study, by [29] proposes the LSMDRK (Local Saliency Map with Dual-channel Radar Knowledge) ship identification method, which obtains an impressive overall accuracy rate of 87%.There are two main steps to the strategy. First, the system's descriptive capabilities are enhanced by polarimetric target breakdown during the feature extraction phase. Second, during the detection step, a saliency map is produced using a saliency detection approach. Then, local maximum detection is applied to this saliency map. Ultimately, the optimum detection outcomes are intended to be achieved via an adaptive threshold technique. The experimental outcomes indicate that the proposed approach outperforms conventional detection methods in accurately identifying subtle objects and minimizing false alarms. Using a dataset provided from RADARSAT-2, the effectiveness of the suggested technique is assessed.

2.1.2 Shape-Based Feature: **Using two cascades—**one based on automatically obtained data and the other on form—the authors of the article article [29], propose a method for detecting ships. A deep neural network autoencoder is used in the technique to automatically extract crucial information. In addition to Yandex and Google Maps, the researchers also used a tiny portion of images downloaded from the internet for algorithm testing and training. A UAV (unmanned aerial vehicle) can identify good ships with recall and precision of 0.95 and 0.94, respectively, when shape- and feature-based cascades are used in conjunction.The proposed strategy performs roughly as well as or slightly better than current state-of-the-art methods, according to the experiment findings.

2.1.3 Features Based on Texture*:* The researchers present a novel approach to ship detection in their work [30]that tackles the shortcomings of current approaches while taking into account large and challenging terrain. The suggested method improves performance under challenging circumstances with significant inshore background interference and varied object imaging features by including a scattering-keypoint-guided network. Dealing with the problem of imaging variability is the main objective of this method. Researchers created the GaoFen-3 ship detection dataset to assess the detector's adaptability and robustness. They used a SAR ship detection dataset that was openly accessible as well to illustrate how well the suggested improvements worked. The results of the experiments conducted on these two datasets demonstrate that the proposed approach is in line with the state-of-the-art in ship detection.

2.1.4 Features of Polarimetric: In their work [31], The researchers carefully evaluate the drawbacks of the current network designs for target identification, focusing on the ineffective use of polarimetric data, the ineffective recognition of small-scale targets, and the laborious sea-land segmentation techniques that increase the likelihood of false alarms. To solve these issues, the researchers provide a number of options. Their strategy begins by creating a skilled single low-level path aggregation network, intended to overcome the complexities involved in locating small targets. Through a semantic augmentation module, the network combines sophisticated single-scale feature mappings for detection, effectively reducing false alarms at the feature level. In addition, an adaptive dual-polarimetric feature fusion method is presented, which carefully selects multichannel features from dual-polarimetric decomposition to maximize effectiveness and reduce redundancy. A segmentation layer is seamlessly incorporated into the architecture to increase the network's effectiveness and reduce false alarms brought on by ground interference. A crucial step in establishing shared learning between the detection and segmentation layers is the incorporation of a unified loss function for the thorough training of both the feature extraction and feature fusion modules. Researchers have curated a special dataset for polarimetric SAR detection and segmentation to demonstrate the effectiveness of their suggested method. The dataset incorporates annotations from LS-SSDDv1 Null, covering areas like small vessel identification and sea-land separation. Through experiments on this dataset, the researchers validate the superiority of their suggested method over traditional techniques.

2.1.5 Hybrid Features: A hybrid model for ship recognition is presented in the study by [32] and incorporates classification, location, and segmentation tasks. An original boundary-box localization method makes use of an improved Intersection over Union (IoU) metric. This novel method not only links the training and evaluation phases, but also improves object positioning accuracy. To assess the effectiveness of the suggested hybrid model, a specially curated Synthetic Aperture Radar (SAR) dataset specialized to ship detection is used. Each ship sample in this collection has a resolution of 256 pixels in the range and azimuth dimensions, and it has been painstakingly annotated by skilled SAR analysts. Based on actual data, the proposed hybrid model significantly improves ship recognition accuracy, especially in difficult situations. Its vital role in reducing false alarms and boosting overall ship detection efficacy is further demonstrated by its significantly lower false positive rate when compared to competing models.

2.1.6 Statistical Features: In order to improve the portrayal of small targets in SAR images, a unique strategy is presented in [33] In order to partition the SAR images, this method uses a split convolution block (SCB). The network's ability to detect and represent these smaller targets is enhanced by using the smaller sub-images that are created as inputs. To preserve spatial information throughout the dimensionality reduction process, the feature pyramid network (FPN) combines a spatial attention block (SAB). The efficiency of evaluating multi-resolution SAR images, particularly in complex backdrops, is investigated in this work using datasets from Sentinel-1 and GaoFen-3. The outcomes show that the detection of small targets in these datasets is effectively improved by the SCB and SAB approaches. Together, these two modules produce a notable 1% improvement in mean Average Precision (mAP) and a significant 0.0216 improvement in the F1 score, resulting in a notable improvement in overall performance. A comparison with modern one-stage and two-stage object identification systems is also included in the study. The recommended approach outperforms SSD, YOLOv3, and Faster R-CNN in terms of mAP values, highlighting its benefits, particularly in enhancing the detection of small targets inside SAR images.

2.1.7 Scale-Variant Features: The goal of SARFNet, a novel learning strategy presented in [34], is to detect objects in SAR images. It uses adaptive feature selection to efficiently capture significant object properties at various scales. The paper assesses the efficacy of SARFNet through thorough examinations of publically available datasets particularly created for SAR object recognition. The results show that SARFNet performs better in terms of detection accuracy than the other approaches. SARFNet outperforms other cutting-edge methods in terms of quantitative performance indicators, which is particularly clear in its performance on the HRSID dataset, where it attained a remarkable average accuracy (AP) of 64.1%. These results demonstrate SARFNet's superiority over earlier approaches and demonstrate how well it can improve object detection accuracy in SAR images. The inclusion of an adaptive feature selection procedure by SARFNet, which makes it possible to more efficiently gather scale-related information, is credited with improving detection performance.

***2.1.8 Deep Learning-Based Features*:** According to the research by reference [35], the SARFNet (Scale-Aware Pyramid Network) has been developed as a cutting-edge learning methodology for object detection within SAR images. Through the use of an adaptive feature selection process, SARFNet successfully captures distinctive and practical properties of objects at various scales. Using publicly available datasets created expressly for SAR object detection, comparative experiments are conducted to assess SARFNet's performance. The results clearly demonstrate that SARFNet outperforms other techniques in terms of detection accuracy. When it comes to quantitative evaluations, SARFNet comes out on top, displaying remarkable performance, especially on the HRSID dataset, where it achieved an astounding average accuracy (AP) of 64.1%. These results demonstrate SARFNet's superiority to earlier approaches, enhancing the accuracy of object detection in SAR imagery. The proposed strategy is thoroughly compared to proven methods that are already in use to determine its viability. The experimental findings clearly show the suggested method's superior performance in both offshore and inshore settings, underscoring its adaptability and strength in a variety of difficult circumstances. A promising method for spotting ships in SAR images is introduced by the deep learning network suggested in reference [35] The accuracy and robustness of ship detection are improved by this method, which combines data from the spatial and frequency domains.

2.3 Classification methods

2.3.1 *Thresholding*: In their article, [36] introduces a straightforward framework with two approaches for quick recognition in SAR images. The simple setup described in [36] provides a workable option for quick identification inside SAR images.This network's introduction is essential for identifying possible targets because it reduces false alarms and significantly improves overall performance. The SSDD offshore dataset and the FUSAR-Ship-Detection dataset, both free to use, are used to assess the system's effectiveness. The comparative analysis evaluates the suggested framework's performance and computational complexity in comparison to the Multi-CFAR approach and YOLO-v4. The framework significantly outperforms Multi-CFAR, as evidenced by improvements of 14.43% on the SSDD offshore dataset and 7.36% on the FUSAR-Ship-Detection dataset. The promise of the framework for real-time SAR image processing applications is demonstrated by the integration of threshold and false alarm rejection neural networks, which improves accuracy and efficiency.

2.3.2 *Clustering*: In reference by [37] a brand-new ship identification method known as M-DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was presented. To improve ship detection, this technique makes use of the SEPD (Spatial Enhanced Pixel Descriptor) format. The effectiveness of M-DBSCAN is thoroughly assessed and contrasted to more established intensity-based clustering techniques like fuzzy c-means and k-means. The comparison uses the common intensity threshold-based detector with a constant false alert rate. The study covers a wide range of challenging situations, such as sidelobes, identifying small or faint targets, and moving objects. To record these events, high-resolution imaging is frequently used. The outcomes constantly show that the method outlined in reference [37] demonstrates remarkable performance under a variety of circumstances, highlighting its suitability for ship detecting tasks. The substantial improvement that can be seen when using both M-DBSCAN and the SEPD format for pixel clustering is particularly noteworthy. The method uses a density-based clustering algorithm that combines spatial information to handle complex circumstances and improve detection accuracy. Beyond the effectiveness of threshold-based approaches and current intensity-based clustering algorithms, the thorough investigation described in [37] suggests a viable route for ship detection, particularly in complicated scenarios intrinsic to high-resolution SAR data. The combination of M-DBSCAN and the SEPD representation is an example of how this strategy can significantly improve ship identification.

2.3.3 Template matching: The technique described in [35]. which aids in accurate ship detection, consists of three basic components. Initially, hierarchical spatial characteristics are acquired using the Feature Pyramid Network (FPN). In order to provide exact spatial multiscale features for ship targets and successfully capture their spatial characteristics, the FPN uses a top-down design. The emphasis then changes to pinpointing the rotation-invariant characteristics that SAR ship targets possess inside the frequency domain. This uses a polar Fourier transform, which is skilled at capturing the frequency characteristics of these objects, is used to do this. Then, a brand-new network is presented to combine spatial frequency properties. To effectively acquire compact feature representations spanning many domains, this innovative network constantly modifies the configurations of sub-networks. This method's invention significantly improves ship detection accuracy by the thoughtful application of multidimensional domain data. The efficiency of the suggested methodology is thoroughly evaluated using the well-established SAR ship detection dataset (SSDD) [35]. The experimental results support the suggested approach's superiority to popular CNN-based algorithms. This benefit is especially noticeable when detecting ship targets with varied sizes and rotations, even in complex backdrop settings. In order to produce accurate ship detection results, the methodology described in [35] skillfully blends hierarchical spatial attributes, rotation-invariant frequency features, and spatial frequency characteristics. Notably, the SSDD dataset evaluation of the suggested technique indicates its superior performance than earlier CNN-based algorithms. This is clear even in difficult situations with ship targets that have complicated backgrounds and differing sizes and rotations.

2.3.4 Support Vector Machine: The research discussed in [38] suggests a technique for ship detection based on block division. Using this method, the image is divided into tiny chunks that accurately represent ship and non-ship locations. This block-based method, as opposed to pixel-based ones, enhances region characterisation and is efficient in terms of processing. The blocks are categorized using Support Vector Machine (SVM), a supervised learning method, based on color and texture data. Color features capture the chromatic characteristics of the regions, while texture features capture the subtleties of the spatial pixel distribution. Blocks that were incorrectly categorised are then corrected, and a recovery procedure is started to recover the ships that were found. With a classification accuracy of up to 96.98%, the combination of color and texture features provides outstanding precision in separating ship blocks from non-ship components. Furthermore, the approach's accuracy reaches a remarkable 98.14% during the last stage of ship detection.

2.3.5 Machine Learning: The research described in [39] incorporates a wide range of AI and machine learning techniques [40], including Random Forest, Decision Tree, Naive Bayes, and CNN, in the aim of developing a reliable ship recognition model. The experiment's two main goals are to investigate efficient detection techniques and provide solutions for the difficulties involved in ship detection. Empirical results clearly demonstrate Random Forest's accuracy advantage over all other evaluated models. Random Forest performs better than Decision Tree and Naive Bayes, which is an important point of distinction. Its accuracy rates for RGB and HSV are 97.20% and 98.90%, respectively, in contrast to the statistics for Decision Tree and Naive Bayes, which are 92.43% and 96.30% for RGB and HSV, respectively. CNN also gets accuracy ratings of 90.45% for RGB and 98.45% for HSV. In the end, the Random Forest model's outstanding effectiveness is revealed, producing amazing results with accuracy scores of 97.20 for RGB and 98.90 for HSV. The relevance of the method put out in [39] reverberates in the field of artificial intelligence and offers a fresh viewpoint on ship detection. The goal of the project is to develop a reliable ship recognition model by the thorough integration of AI and machine learning techniques like CNN, Decision Tree, Naive Bayes, and Random Forest. The research achieves its main objectives by methodically examining efficient detection strategies and tactical responses to innate detection difficulties. The empirical findings highlight Random Forest's superior accuracy performance compared to the other models under consideration. Random Forest outperforms Decision Tree and Naive Bayes, achieving accuracy rates of 97.20% for RGB and 98.90% for HSV, vs 92.43% for RGB and 96.30% for HSV, respectively, and 96.82% for RGB and 97.18% for HSV. CNN also receives accuracy ratings of 90.45% for RGB and 98.45% for HSV. The Random Forest model ultimately proves to be the most effective, offering outstanding precision with accuracy scores of 97.20 for RGB and 98.90 for HSV. The method put forth in [39] is of utmost importance in the field of artificial intelligence since it offers a novel viewpoint on ship identification techniques.

2.4 Evaluation metrics

The suggested method [3] uses the Faster-RCNN [24] and SSD [41] models to show the improvements in ship detection. The evaluation findings, shown in Table 2, highlight the MR-SSD method's exceptional performance in areas including recall, precision, and the F1 score. Comparing the suggested technique to SSD, which only caused 8 false alerts, reveals a substantial decrease in false alarms. Faster-RCNN recognizes targets less accurately than the indicated method, but it still produces the same amount of false alarms, lowering its F1 rating. The proposed method outperforms existing approaches for precise localization of a range of maritime targets in large-scale SAR images.

TABLE I. RESULTS OF LARGE-SCALE SAR IMAGE DETECTION USING SEVERAL CNN MODELS ARE PRESENTED IN [3].

Method	Tf	Td	Tg	F1 (%)	Recall (%)	Precision (%)
MR-SSD	8	122	128	94.57	95.31	93.85
SSD	22	121	128	89.30	94.53	84.62
Faster-RCNN	8	119	128	93.33	92.97	93.70

TABLE II. DIFFERENT ALGORITHMS' AVERAGE PRECISION ACROSS DIFFERENT TARGETS (%) [3]

Method	Windmill (%)	Tower	mAP	Platform	Tanker	Cargo	Container
SSD	86.34	74.55	85.62	89.96	86.46	89.37	87.08
Faster-RCNN	78.19	68.79	82.09	89.61	86.70	89.47	79.78
MR-SSD	88.04	80.07	87.38	90.43	87.28	89.77	88.69

TABLE III. DETECTOR PERFORMANCE DEVELOPMENT ON THE SSDD DATASET

Reference	Year	Average Precision	Time	Reference	Year	Average Precision	Time
[42]	2017	78.8 %	173 ms	[43]	2020	90.7 %	13.6 ms 74 FPS
[44]	2019	89.76%	10.938ms	[45]	2020	94.6 %	258 FPS 3.9 ms
[46]	2019	90.16%	21ms				

3. Classification of a ship in SAR images

Historical research has primarily focused on using image processing and computer vision techniques to extract relevant information from visible spectrum images. This project becomes challenging, especially when it comes to categorizing ships in aerial images. The features collected are then used as inputs for supervised classifiers.

The two primary categories of ship classification are coarse-grained classification and fine-grained classification. Ships are categorized into bigger groups like military and commercial vessels in coarse-grained categorization. This classification is further aided by the subcategorization of ships into classes including fishing vessels, container vessels, sailing vessels, and coast guard vessels [47] [48], as well as the distinction between moving and stationary ships [47]. To evaluate the effectiveness of coarse-grained ship classification algorithms, the BCCT200 dataset, a common benchmark, is widely used. Classes like as barge, cargo, container, and tanker are included in this dataset [49]. The experiment [50] focused on categorizing ship fleets using satellite images with a spatial resolution of 10 meters is an exception to the rule that most of these algorithms are designed for images with spatial resolutions greater than 4 meters. Images with spatial resolutions greater than 2 meters are frequently used for ship categorization at a finer scale[51] [52].

Conventional methods for coarse-grained ship classification initially mainly involved comparing the collected ship features to an existing database. Gabor filters and multi-scale finished local binary patterns have gained popularity as major feature descriptors since the BCCT200 dataset was introduced. This combination makes it easier to extract both specific and general features [53] [54]Convolutional neural networks (CNNs) have been a popular method for accurate categorization of various ship types in the context of fine-grained ship classification [55]

3.1 Overview of methods for ship classification

The standard method in [56] called for the classification of ships using artificial or medium-resolution SAR images. The researchers in [57] used polarimetric SAR (PolSAR) and polarimetric interferometric SAR (PolInSAR) as a primary tool to investigate ship categorisation. It should be noted that the study by Touzi et al. [57] pioneered the use of coherent target decompositions, allowing the characterization of ships using PolSAR data. Additionally, by using PolInSAR data, the authors of [58], classified ships based on their 3D geometry representation and extrapolated height data. Although PolSAR and PolInSAR show encouraging findings, their practical application is accompanied by technological difficulties caused by particular system requirements that are frequently unorthodox for satellite sensors. Single polarimetric imagery-based ship categorization emerges as a practical solution to these problems as a result. Even though there has been some preliminary research [59] into exploiting high-resolution TerraSAR-X images, this investigation was confined to a limited number of extensively classified targets.

In recent years, a number of studies have created various ship detection and categorization systems. Zhu et al.'s [60] extraction of several high-dimensional local features from potential ship targets is classified using SVM. Two of these features are texture and shape. Bi et al. [61] presented a hierarchical salient-region-based technique that finds regions and captures properties in order to create a specific SVM classifier for ship detection. Similar to this, Xia et al. [62] suggested a method for ship detection that, after segmenting sea and land regions, combines Local Binary Patterns (LBP) features with an SVM classifier. By utilizing numerous factors and classifiers, these techniques have shown promising results in ship detection and classification. There are, however, few studies that have looked at both coarse- and fine-grained ship classification. Notably, a major barrier to ship classification continues to be the lack of a consistent annotation structure for ship categories.

3.2 Feature extraction techniques

SVM has become a popular approach in recent studies for examining ship classification and identification. For example, Zhu et al. [60] developed a ship categorization technique based on high-dimensional local data retrieved from possible ship targets, which included characteristics like shape and texture. The hierarchical salient-region analysis-based technique to ship detection developed by Bi et al. . [63] integrates SVM and characteristics from particular regions. In order to discriminate between sea and land and identify ships, Xia et al. [62] used Local Binary Patterns (LBP) features and an SVM classifier. Yang et al.'s approach 's [64] combined estimated features from extracted regions to choose potential ships by utilizing sea surface homogeneity analysis and a linear function. Last but not least, Marques et al. [65] presented a method for locating vessels in aerial image sequences that makes use of a UAV-mounted sensor. This method used blob extraction in conjunction with spatial and temporal feature analysis to categorize regions as being linked with ships or not.

However, conventional CNNs struggle to extract features, particularly in the confined parameter space of shallow layers. This could result in low resolution and few features for small targets. When faced with densely clustered small targets, conventional multi-scale target detection algorithms find it difficult to get satisfactory results. For the network to perform better at detection under these difficult conditions, feature extraction capabilities must be improved.

Yang et al. [65] proposed an inventive visual search engine-based ship detecting technique in a later study. They used a global contrast approach to highlight important details using local consistencies and geometric properties. An SVM was then used to classify these discovered regions. Another unique method used by Tang et al. [63] combined non-convolutional deep neural networks, the Extreme Learning Machine, and deep learning algorithms with wavelet coefficients from the JPEG2000 compressed domain. The raw image underwent initial preprocessing that laid the groundwork for ship location, including techniques like image augmentation and sea-land segmentation based on wavelet coefficients. A region proposal network (RPN) was used in recent work [66] to locate exact ship locations after CNNs were used for characteristic extraction and characteristic extraction. Zhao et al. suggested a specific coupled CNN in their study [67] that was designed for SAR ship detection in limited and crowded conditions. In terms of both detection accuracy and processing speed, our method performed better than the traditional CFAR detection algorithm. The suggested detectors worked at various scales and took into account different target sizes by using feature maps from various CNN layers. The CNN's thinner layers concentrated on gathering fine-grained data, improving the detection precision of tiny targets. On the other hand, bigger targets profited from the lower layers' extraction of more abstract elements, which made it easier to recognize them [68].

3.3 Classification methods

TABLE IV. VARIOUS SAR IMAGE CLASSIFICATION METHODS PROPOSED BY VARIOUS AUTHORS

Data on Ship Trajectory Research	Methodology	Advantages	Limitations
Marine Traffic Pattern Mining[69]	Analyzing the movement patterns of ships for navigation and route planning	Improves navigation and route planning for commercial and military vessels	Limited application to specific industries
Maritime Anomaly Detection[70]	Detecting abnormal behaviour in ship trajectory data	Helps identify potential threats to national security and prevent illegal activities	Limited application to security and surveillance industries
Ship Classification[71]	Classifying ships based on trajectory data	Can satisfy the requirement of identifying hazy types of objects in historical trajectory data	Limited accuracy in regions where ship types are not distinguishable
Creating a Classification System for Fishing Boats and Cargo Ships [72]	Putting out a system for separating fishing vessels from cargo ships using actual AIS data	Satisfies the demand for targets of unclear types in historical trajectory data	Limited to fishing boats and cargo ships
Compressed Trajectories and Kernel-Based Ship Classification[73]	Compressing trajectories and using kernel methods for ship classification	Retains stop and move information and can be used for ship classification	Unsuitable for ships travelling at a high rate of freedom in a large area of the sea
Polynomial Fitting and Adaptive Neuropathy-Fuzzy Inference System[74]	Ship classification using polynomial fitting and ANFIS based on trajectory features	Uses the inherent form features of trajectories to avoid the influence of geography	Discards temporal dimension and requires proper trajectory partitioning, which may be difficult for large datasets or long durations.

TABLE V. ACCURACY RATES (%) ACHIEVED BY VARIOUS EXISTING METHODS FOR CLASSIFICATION [3]

Ship types	ConvNet [75]	KNN	CNN-ML [76]	CNN-NB[77]	SVM	MT-CNN
Container	77.78	60.61	79.83	75.93	38.89	94.44

Tower	94.44	61.69	95.83	86.11	61.11	100.0
Tanker	65.79	65.37	73.68	63.16	75.00	88.16
Windmill	92.55	95.39	93.62	74.47	97.87	98.94
Boat	83.65	89.45	91.35	88.46	79.81	94.23
Average	82.27	70.58	90.41	80.96	71.80	95.20
Cage	97.47	68.06	98.73	98.73	68.09	100.0
Platform	87.27	62.76	92.73	83.64	45.45	90.91
Cargo	69.48	54.26	92.21	77.92	70.13	94.16

3.4 Evaluation metrics

The key performance indicators in Table 6 include precision, recall, F1 score, classification accuracy, and validation accuracy. These measurements are used to carefully assess how many units are present in the completely connected layers and their impact. According to the results, the difference in the number of units has a negligible effect on the classification performance measures including training accuracy, validation accuracy, and F1 score. Following the process of fine-tuning, additional refinement is used to improve the ship categorization model. The McNemar test is carried out to thoroughly evaluate the models' efficacy [78][79]. The computed p-value is greater than 0.05, indicating that there are no statistically significant differences between the models. The deployment of the model with the fewest embedded neural units (32) reduces overfitting and streamlines network complexity.

TABLE VI. ILLUSTRATION OF THE UTILIZATION OF VARYING UNIT QUANTITIES WITHIN THE FULLY CONNECTED LAYERS TO ASSESS THE SHIP CLASSIFICATION MODEL, WHICH IS CONSTRUCTED UPON THE VGG16 ARCHITECTURE [80]

The Number of Units	Average Precision (%)	Average F1 Score	Validation Accuracy (%)	Training Accuracy (%)	Average Recall
128	96.24	0.9628	96.09	100	0.9632
256	97.81	0.9778	97.92	100	0.9774
64	97.81	0.9778	97.79	100	0.9774
4096	97.00	0.9705	97.01	100	0.9710
32	97.85	0.9779	97.66	100	0.9774

TABLE VII. AIS-BASED SHIP MOVEMENT CLASSIFICATION USING CNN [81]:

Size of Batch	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC
64	71.51	93.57	64.72	76.34	81.20
32	77.66	92.35	61.96	76.38	81.15
16	70.25	91.48	62.00	76.35	81.08

The demand for skilled algorithms capable of classifying a ship's AIS data into distinct movement categories, including static, routine navigation, and maneuvering, has increased as a result of the expanding use of AIS data in marine transportation. As a result, numerous research projects have developed approaches that use labeled features for classification [74].

4. Latest progress In Sar-Based Ship Detection and Classification

The application of traditional statistical pattern recognition algorithms founded in Bayesian Theory stands out as a highly favored technique in the context of decoding SAR images, presenting the potential for optimal solutions [82]. The successful integration of these methods into the interpretation of SAR images depends on the careful selection of an appropriate statistical distribution to describe the SAR image data [83]. As a result, scholarly interest in statistical modeling of SAR images has increased over the past ten years, making it a lively and actively researched field [80]. The success of SAR image applications is significantly impacted by this statistical modeling project. It first improves our understanding of the fundamental ideas of terrain dispersion.

Additionally, it expands on insightful ideas that are useful in a variety of contexts, such as target recognition and identification [41], edge detection [84], segmentation [85], classification [86], and the lowering of speckle noise in SAR data. Its ability to combine statistical models with Inverse Synthetic Aperture Radar (ISAR) target databases to produce various SAR images with distinctive aspects including aspect, terrain composition, geographic placement, and Signal-to-Clutter Ratio (SCR) is a noteworthy accomplishment. Incorporating statistical modeling and ISAR databases allows for the production of sizable datasets, which aids in the building of trustworthy algorithms for SAR image interpretation [87]. The use of traditional statistical pattern recognition algorithms based on Bayesian Theory is currently a prominent method for interpreting SAR images, ensuring the promise of optimal results [82]. The key to these methods' success is the careful selection of an appropriate statistical distribution for modeling SAR image data [83]. Evidently, the statistical modeling of SAR images has seen a rise in scholarly attention over the past ten years, making this area of research both active and dynamic [80]. Applications of SAR images are significantly impacted by statistical modeling. It improves our understanding of the basic ideas behind terrain dispersion and broadens the applicability of its advantages. Target recognition and identification [41], edge detection [84], segmentation [85], classification [86], and the reduction of speckle noise in SAR images are all included in this.

While the classification of ships using optical vision has gotten comparably little attention [84], the field of SAR ship classification has recently undergone substantial exploration and evaluation [82] [88]. However, improvements in optical sensors have effectively overcome some of the drawbacks of SAR-based techniques. The primary objective of this study is to improve classification precision in order to meet the real-time requirements of ship monitoring. The incorporation of a transformer in CRTransSar [89], a ground-breaking method designed for ship detection in SAR images, is an important development in this area. On the Ship Detection Dataset (SSDD), this technique has earned a stunning 97% Average Precision (AP), demonstrating its extraordinary accuracy. Transformers are ready to become a crucial study area in this field, displaying their enormous potential, thanks to the revolutionary advances shown in the context of SAR ship identification. This method demonstrated its extraordinary accuracy with a stunning 97% Average Precision (AP) on the Ship Detection Dataset (SSDD). Transformers are in a prime position to have a big impact on the course of this domain's future thanks to their outstanding performance in SAR ship identification.

4.1 CFAR (Constant False Alarm Rate) Based advancement

The widely used CFAR approach modifies the threshold value by taking into account the statistical characteristics of the nearby clutter in order to maintain a constant false alarm rate. To describe marine clutter, many CFAR-based strategies have used theoretical models such the Gaussian, Rayleigh, and K distributions. However, the variation of the distribution of maritime clutter under real-world circumstances is a serious issue for CFAR and cannot be properly simulated with a fixed function. This issue has been addressed by the use of adaptive CFAR methods.

The adaptive CFAR strategy uses a variety of techniques, including the analysis of data in focused geographic areas, Making probability density curves and setting pixel segmentation thresholds in accordance with the desired false alarm rate are also steps in the procedure. Occasionally, background noise in SAR images can be reduced by using the Rayleigh distribution model. The fact that some clutter backgrounds might contain non-Rayleigh elements could limit the method's applicability. The author of [90] suggests a two-parameter CFAR detection method that provides increased versatility to get over this restriction.

The most widely used method for target segmentation in SAR image processing is adaptive threshold or CFAR detector [91], which finds high-value pixels by comparing pixel values with the nearby background. Several techniques, including CFAR segmentation, have been looked at and discussed for SAR target segmentation [92].

The Beamlet-based SAR image target detection methodology, the CFAR algorithm, and the use of two-dimensional principal component analysis for feature extraction have all been thoroughly investigated in the field of target detection in SAR imaging. Within the context of SAR image identification tasks, these approaches have produced encouraging results in obtaining robust target segmentation and detection rates results [93]. CFAR stands out as a notable and well-known algorithm among these methods. Its origins can be traced back to ship target detection testing carried out at the Ottawa Defence Tests Centre, which were first presented by Wackerman C. et al. in 2001 [90]. The CFAR method creates a distribution model using data from focused areas, builds a probability density curve based on this model, and then establishes a pixel segmentation threshold in line with a predefined false alarm rate. The application of this criterion demonstrates effectiveness in precisely identifying targets in SAR images with elevated grey values.

However, the majority of the recent work on SAR image target detection has been directed toward enhancing recognition rates and creating fundamental algorithms. There hasn't been enough focus on target recognition methods for SAR images that can adapt to complex backgrounds and take into account target distortion during detection. To adequately address these issues, further in-depth practical examination and research are required.

4.2 Fusion of images of multiple sensors

Multiple sensors working together should improve the precision of ship identification and classification in SAR images, it has been hypothesized. Using the complementary strengths of both sensors, the pairing of optical and SAR imagery, for instance, enhances ship recognition and classification. SAR imaging contains data on ship shape and size, whereas optical photography only provides exact information on color and texture [94] [95] [27]. Diverse sensors, including the Automatic Identification System (AIS) and Long-Range Identification and Tracking (LRIT), have been synergistically linked with SAR technology in an effort to improve ship detection and classification capabilities. This fusion of sensor data reduces false alarms while simultaneously improving the accuracy of ship type identification. The challenging task of aligning and registering data from disparate sensors as well as the requirement for advanced data fusion and analysis algorithms present difficulties in this sensor fusion technique. Despite these difficulties, research into the integration of numerous sensors to improve SAR-based ship identification and classification is still ongoing [96]. Researchers are actively working on developing answers to these issues, improving the fusion processes in the process to ultimately increase the overall effectiveness of ship detection and classification systems.

4.3 Automatic target recognition

With several applications in surveillance, homeland security, and military operations, automatic target recognition (ATR) is a well-known and developing subject of study [97]. The direction of current research is clearly toward the effectiveness and dependability of radar ATR through the use of SAR images. A wide range of variables, including shadowing effects, environmental interactions, and the projection of a three-dimensional image onto an inclined plane, play a crucial role in this realm, with the target's aspect playing a key role. Radar cross sections (RCS) are a particularly sensitive element of SAR images because of this aspect-dependent aspect dependent [98]. Additionally, the ability to recognize and distinguish between targets in SAR imaging exhibits a large fluctuation depending on the target's aspect.

Due to its quick execution and capability for global optimization, the Genetic Algorithm (GA) has acquired a lot of momentum as a preferred method for addressing the difficulty of target detection in SAR images [99]. The work of Lin and Bhanu Bhanu [100], who developed a novel feature selection method based on the GA paradigm, provides an example of this application. This algorithm expertly chooses the best features for target discrimination in SAR images by utilizing the inherent benefits of GA.

ATR algorithms that are dependable and effective for SAR imaging are constantly being developed. To improve target discrimination effectiveness and heighten the precision of ATR systems based on SAR technology, researchers are carefully investigating a variety of approaches, including genetic algorithms among others.

4.4 Unsupervised / Deep learning approaches

The development of deep learning-based object detection methods in computer vision has had a substantial impact on SAR researchers who previously had trouble accessing SAR images [101][40]. The resurgence of deep learning is the result of three key developments: increasing processing power, easy access to vast amounts of data, and algorithmic improvements. The first publicly available Standardised Ship Detection Dataset (SSDD) in 2017 helped researchers overcome the limitations of conventional algorithms by providing them with standardised data and evaluation standards. This innovation addressed the field's issues with comparability and data scarcity. Because deep learning-based procedures outperform more conventional CFAR-based ones, they have become more popular among researchers. The active and collaborative attitude of the computer vision community has further accelerated the progress in this domain. The launch of SSDD signaled the start of the deep learning era for SAR ship identification, presenting new opportunities and igniting research in the field.

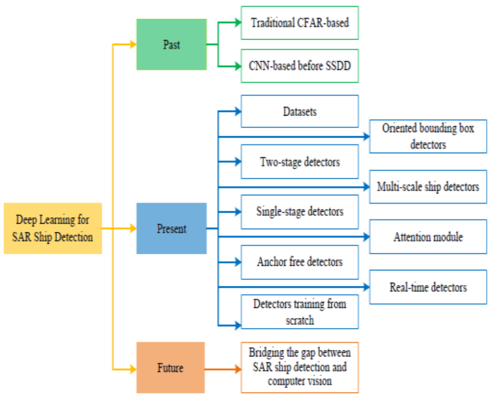

Fig 2. The lifespan of Deep learning method in SAR image detection and classification [102].

By incorporating a restricted Boltzmann machine into neural networks, Hinton [103], who is credited with the invention of deep learning, brought about a paradigm change. This innovative idea contributed to considerable improvements in computer vision tasks including object detection, segmentation, and categorization, which primarily use RGB images [104]. Deep learning models' range of use recently expanded to include SAR imagery as well [105]. Nogueira et al. [105] developed three methods using well-liked Convolutional Neural Networks (ConvNets) on optical and multispectral datasets, demonstrating the efficacy of combining finely-tuned features with an SVM classifier. This tendency was demonstrated by them. In a different investigation, Bentes et al. [77] assessed the use of CNNs for ship classification using TerraSAR-X images. Deep learning's ability to automatically extract distinguishing characteristics from SAR images eliminates the need for manual feature extraction, selection, and classifier optimization, which is its main advantage. Deep learning is a viable option for processing SAR images because this automated approach saves time and requires less human involvement.

5. SAR-BASED SHIP DETECTION AND CLASSIFICATION APPLICATIONS

The Search for Unidentified Maritime Objects (SUMO) algorithm is a dedicated method designed to precisely detect ships in satellite SAR images. Developed over a 15-year span, this technique utilizes an extensive dataset of SAR images captured by diverse L-, C-, and X-band satellites. Rigorous benchmark assessments have verified SUMO's robust performance across a spectrum of SAR image modalities, encompassing Spotlight to ScanSAR, and resolutions spanning 1 to 100 meters. SUMO excels in ship detection of varying sizes and types, demonstrating a keen understanding of radar imaging limitations [106].

The effectiveness of CNNs and other deep neural networks in ship recognition and categorization tasks has recently been demonstrated by solid evidence. Notably, Zou and Shi [107] developed the SVD network, a new architecture that combines a three-layer CNN and two layers for feature extraction. Ship pixels are represented by a probability map within a separate layer of the CNN, which is then subjected to a linear SVM classifier. Scenes acquired by the VRSS-1 and GaoFen-1 satellites were used to demonstrate the effectiveness of this method, with equally distributed training data from each satellite. Lin et al.'s [108] customised application of the ResNet architecture is another important addition. This modification focuses especially on the difficulties associated with identifying and localizing inshore ships in crowded harbor environments. Targets are positioned closer together in this scenario. Using information from Google Earth and GaoFen-2 satellite photography, the proposed technique underwent a thorough review.

SAR, an effective remote sensing technique, is capable of detecting and classifying ships even under unfavorable weather and lighting circumstances. SAR-based ship detection and classification has several applications in both the civilian and military domains. The following are the main applications of SAR-based ship detection and classification:

1. Maritime surveillance and security: SAR technology may be used to effectively monitor sea traffic, identify potential risks to national security early on, and follow illegal activities like smuggling and piracy.
2. SAR's ability to quickly identify missing or troubled ships helps search and rescue operations, enabling quick and effective rescue missions.
3. Environmental awareness: Using SAR helps with the constant monitoring of ecological threats including marine pollution, oil spills, and other ecological calamities. Rapid responses and mitigation measures are accelerated as a result.
4. Effective fisheries management: SAR's capabilities can be used to identify and continuously monitor fishing vessels in order to enforce fishing laws and prevent illicit fishing activities.
5. Improved navigation and route plotting: Commercial and military ships can make use of SAR's real-time information on ship trajectories and sea dynamics to optimize navigation and route choices.
6. SAR tracking can improve risk assessment and mitigation for insurance underwriting.
7. Scientific investigation: SAR technology is invaluable for understanding surface winds, ocean currents, and various oceanographic events. As a result, it provides crucial information for scientific research.

6. Challenges and Future Directions

The Chinese GaoFen-3 (GF-3) satellite's development of high-resolution SAR imaging has revolutionized maritime surveillance and made it possible to track marine organisms. Conventional methods, however, have trouble gathering the necessary information for precise differentiation and identification of various maritime subjects within SAR images. We suggest using a CNN model as a solution to solve these problems. This method, which focuses on locating maritime targets at the patch level, uses a complex system to find marine items among huge SAR datasets. By utilizing the strength of deep learning and CNNs, our suggested method intends to improve the accuracy and efficacy of classifying and detecting marine targets in SAR imagery.

In the study by [3], detailed feature analysis and the development of test datasets resulted in the discovery of eight different types of marine targets within GF-3 SAR images. A specific CNN model is created to meet this classification difficulty[16]. The method makes use of a network design with three pooling layers, six convolutional layers, and two fully connected layers for patch-level classification. Single Shot Multi-box Detector with Multi-Resolution Input (MR-SSD), a novel technique for locating maritime targets, is presented. Stages including sea-land segmentation, multi-resolution cropping, MR-SSD-based detection, coordinate mapping, and projected box consolidation are part of the methodology that has been developed. The efficiency of these strategies in reliably categorizing and recognizing marine targets, effectively addressing issues raised by SAR imaging, has been validated by experimental evaluations on the GF-3 dataset [3].

The research [3] divides marine targets into eight separate classifications using feature analysis and test datasets. A special CNN model is created for the job of patch-level classification, consisting of six convolutional layers, three pooling layers, and two fully linked layers. For the purpose of finding marine targets, the Single Shot Multi-box Detector with Multi-Resolution Input (MR-SSD) is also being developed. The study [3] is able to classify maritime targets into eight classes using methods such overlapping cropping, sea-land segmentation, and MR-SSD-based detection. The suggested CNN model is tailored for patch-level classification and has six convolutional layers, three pooling layers, and two fully connected layers.

Deep learning approaches have the ability to address the issues described before, according to research by Cheng and Han [109]. By promoting the adoption of deep learning-based solutions in this domain, our study is in line with this trajectory. New developments are necessary as we advance. This involves creating new types of data and increasing the number of examples in the training dataset. In addition, we intend to explore optimization techniques through field experiments targeted at ship categorization.

6.1 Limitations of current methods

The processing of SAR images for object recognition in surveillance applications has advanced significantly, however existing approaches still have a number of drawbacks.

The lack of established techniques for the analysis and interpretation of SAR data is a significant limitation. The complexity of SAR data frequently makes it difficult to understand, and analysts may use a variety of processing methods and analytical frameworks. As a result, there may be discrepancies and errors in the identification and classification of objects.

The difficulty of distinguishing indistinguishable objects in SAR images is another persistent problem. For instance, it can be difficult to reliably discriminate between certain items in SAR imaging due to their similar radar signatures, such as trucks and tanks.

Another disadvantage is the dependency of the current SAR object recognition and categorization methods on human ability and expertise. Many existing systems require manual categorization and object identification in SAR images, which can be time-consuming and biased.

In the end, a variety of environmental factors including weather, geography, and air interferences can affect how effective SAR object detection and categorization systems are. These factors have the potential to skew the SAR signal, which would reduce the accuracy of item identification and categorization.

Current technologies face two major difficulties when it comes to the identifying and categorization of ships using optical spaceborne imaging. They are subject to meteorological factors including cloud cover and oceanic disturbances, unlike infrared and SAR images. Additionally, the processing and analysis of optical images become increasingly complex due to their higher resolution and the significant amount of data they produce. Meanwhile, finding the optimal balance between performance and complexity is still a challenge [63].

TABLE VIII. CHALLENGES INHERENT IN NUMEROUS APPROACHES SUGGESTED FOR SHIP CLASSIFICATION USING SAR IMAGES

Model used	Findings	Research gap	Accuracy	Dataset (Year)
Efficient phase filtering algorithm [110]	Method's effectiveness in reducing phase noise, preserving fringes, and decreasing computation time.	The proposed approach lacks a comparison with other existing noise-filtering methods	95%	(2011)
Sparse representation classification (SRC) in feature space [111]	Emphasis is placed on extracting meaningful data and employing dimensionality reduction methods to enhance ship characterization and reduce dictionary dimensions in SRC. This approach enhances algorithm efficiency and elevates ship recognition	Extraction of more features to define the ships, experimentation on a huge data collection in various scenarios, and optimisation algorithms of the sparse representation	92%	TerraSAR-X SAR ship (2013)

	accuracy			
Single-pol SAR images [56]	Address the absence of a viable solution and achieve precise ship classification using a solitary SAR channel	Additional tests are required since value is indeterminate	70 %	(2015)
TEXTURE-BASED VESSEL CLASSIFIER [112]	Minimizing noise and background interference to optimize the influence of vessel information	Addressing cases of low classification certainty and enhancing classification outcomes through a more advanced decision-level classification approach	85.64%	Electro-optical satellite image (2015)
A novel Gabor feature-based CNN [113]	Demonstrates superior performance compared to CNN results and certain other conventional object recognition techniques	Future advancements are expected to introduce exceptional models, with a focus on simplification rather than further complexity	81.53%	ImageNet10 (2016)

6.2 Future research directions

SAR image processing has been transformed by deep learning applications in classification and segmentation [114]. While the majority of recent research focuses on ship detection, distinguishing between non-ship objects such icebergs that mimic ships receives less attention [115]. Future research aims to enhance SAR target detection algorithms by utilizing advanced deep learning models and techniques to effectively differentiate between icebergs and ships. This effort seeks to overcome the challenge posed by distinguishing these objects.

Our forthcoming endeavors encompass the integration of geographic attributes into our classification system to advance our research. This integration aims to refine ship positioning accuracy in optical aerial images. By incorporating positional data, we anticipate enhancing the spatial understanding and localization capabilities of our classification system, leading to more precise ship placement identification. The implications span various applications, including maritime traffic management, navigation, and surveillance systems. Furthermore, exploring alternative sensors like SAR holds potential for scenarios where visible spectrum photography is unfeasible, such as nighttime operations. Investigating numerous sensor combinations in a multimodal context is also on the agenda. Apart from ship identification, our objective is to extract precise ship locations using saliency estimation techniques. We also intend to expand the MASATI dataset by contributing additional images, bolstering its size and augmenting model performance. To expedite this process, we contemplate the utilization of semi-supervised approaches [116].

6.3 Rising patterns and technological advancements

The field of SAR image analysis for object detection in surveillance applications is rapidly evolving alongside emerging trends and technologies. A recent advancement involves the utilization of ML and AI algorithms to analyze SAR images. Through pattern recognition in SAR images, these algorithms enhance object detection accuracy. Furthermore, enhanced SAR imaging techniques, such as polarimetric SAR (PolSAR) and interferometric SAR (InSAR), have gained prominence. PolSAR aids in identifying object size, shape, and orientation, while InSAR provides height information.

Considerable research is underway in the realm of new SAR platforms and sensors. For instance, unmanned aerial vehicles (UAVs) or drones equipped with SAR sensors provide high-resolution images for identifying objects and conducting surveillance in challenging environments. Additionally, an emerging trend involves the fusion of SAR data with other data types like optical or thermal images. This integration enhances scene depiction, object identification, and classification accuracy.

The ship detector, also known as SUMO [107], is a collection of software-implemented algorithms that may locate ships using either fully automatic or semi-automatic approaches in satellite radar imagery. Its primary objective is to minimize operator involvement while facilitating the utilization of satellite radar images for marine surveillance. The Vessel Detection System (VDS), which employs satellite images to enhance the fisheries management system's self-reporting capabilities, was initially created with a fisheries control purpose [117]. Now part of the

SUMO application areas is maritime security and safety. The SUMO program includes a broad range of algorithms that address the various ship identification process sub-tasks. The Interactive Data Language (IDL) was used to implement earlier versions of SUMO, however the majority of the current versions are created in Java. Additionally, test versions have been created using MATLAB.

This review's goal is to categorize and evaluate several methodologies that are targeted primarily towards SAR image categorization. We try to determine the best suggested approaches in this subject of research by reviewing similar research fields.

TABLE IX. RECENTLY USED DATASETS IN THE DETECTION AND CLASSIFICATION OF SAR IMAGES 'S [64]

Author	Dataset	Description
[118]	NWPU VHR-10	The first publicly accessible dataset made to evaluate how well objects can be found in remote sensing images
[119]	Airbus Ship Detection	The Kaggle-hosted satellite image challenge of ship detection.
[120]	Fine-Grained Ship Detection (FGSD)	The most comprehensive labelled dataset for ship recognition and classification in remote sensing images will soon be released.

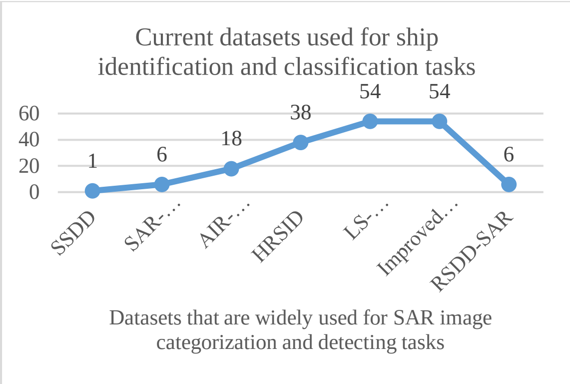

Fig 3. The datasets used most recently for categorizing and recognizing ships in SAR images, as well as the accuracy of their tasks.

7. Conclusion

This article briefly outlines the current obstacles and constraints associated with object detection and classification in SAR images for surveillance applications. While there has been substantial research on SAR classification algorithms, there remains potential for enhancing system quality. In order to perform object detection and classification in SAR images for surveillance purposes, there are currently a number of challenges and limitations that must be overcome. There is no consistent structure for data extraction from different radar frames in the current SAR categorization methods. These algorithms' dependencies on domain-specific data, which are essential for improving categorization in specific use cases, contribute to their complexity. It is difficult to modify them for diverse SAR images. To establish a dependable system for SAR object detection and surveillance, further research is necessary to enhance the precision and effectiveness of SAR categorization algorithms.

7.1 Key findings summary

The results of the tests done on the papers under review corroborate the findings of this study. These observations lead to some important conclusions, including the following:

- Earlier studies have shown a distinction between the decision-making process and SAR image processing.
- Depending on the precise requirements of the instrument built for its intended use, multiple methods can be used to distinguish targets from problematic objects.
- The enhancement of the SAR object categorization system's efficacy can be achieved through the synergistic integration of logical multi-approach and multi-concept training methods. This strategy optimally leverages diverse concepts and approaches, resulting in improved classification and search outcomes.
- In SAR image categorization, CNNs have demonstrated appreciable improvements in object

identification models for a variety of objects. CNNs are the method of choice for identifying SAR images because to their higher accuracy compared to competing techniques.

7.2 Implications for future research

- One noteworthy technique that deserves special attention is the Anchor-Free Detector.
- The Benefits of Starting Detector Training from Scratch.
- Detector necessitates a number of additional activities.
- Finding little ships is really intriguing.
- Create a simplified detection network with this objective in mind.

7.3 The value of SAR-based ship detection and classification

1. SAR-based ship detection and classification offers a quick, affordable way to keep track of marine activity and protect maritime security.
2. Piratery, smuggling, and illicit fishing are just a few of the illegal activities that can be identified and stopped with the aid of SAR-based ship detection and classification systems.
3. In urgent search and rescue operations, ship identification and classification using SAR procedures is essential.
4. SAR technology's ability to detect and classify ships precisely and accurately has the potential to greatly improve maritime security and safety measures around the world.

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