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Ranking Ship Detection Methods Using SAR Images Based on Machine Learning and Artificial Intelligence

Muhammad Yasir [1], Abdoul Jelil Niang [2,*], Md Sakaouth Hossain [3], Qamar Ul Islam [4], Qian Yang [5] and Yuhang Yin [6]

[1] College of Oceanography and Space Informatics, China University of Petroleum (East China), Qingdao 266580, China
[2] Department of Geography, College of Social Sciences Umm Al-Qura University, Makkah 24231, Saudi Arabia
[3] Department of Geological Sciences, Jahangirnagar University, Dhaka 1342, Bangladesh
[4] Department of Electrical and Computer Engineering, College of Engineering, Dhofar University, Salalah 211, Oman
[5] PLA Troops No. 63629, Beijing 102699, China
[6] PLA Troops No. 93525, Shigatse 857000, China
* Correspondence: anniang@uqu.edu.sa

Abstract: We aimed to improve the performance of ship detection methods in synthetic aperture radar (SAR) images by utilizing machine learning (ML) and artificial intelligence (AI) techniques. The maritime industry faces challenges in collecting precise data due to constantly changing sea conditions and weather, which can affect various maritime operations, such as maritime security, rescue missions, and real-time monitoring of water boundaries. To overcome these challenges, we present a survey of AI- and ML-based techniques for ship detection in SAR images that provide a more effective and reliable way to detect and classify ships in a variety of weather conditions, both onshore and offshore. We identified key features frequently used in the existing literature and applied the graph theory matrix approach (GTMA) to rank the available methods. This study's findings can help users select a quick and efficient ship detection and classification method, improving the accuracy and efficiency of maritime operations. Moreover, the results of this study will contribute to advancing AI- and ML-based techniques for ship detection in SAR images, providing a valuable resource for the maritime industry.

Keywords: machine learning; artificial intelligence; synthetic aperture radar; ship detection

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1. Introduction

Synthetic aperture radar is an example of a modern technology that can detect and create images of the earth remotely with high efficiency and accuracy. It can capture very clear and visible images in any weather even at night. To work on these images for different purposes such as weather forecasting, object detection, and many more, artificial intelligence and machine learning are the most promising candidates. Various techniques in these frameworks can be applied to the data generated by SAR to perform various activities with great care and efficiency [1–4]. Due to the nature of the task, a significant number of researchers have shown enthusiasm for developing the SAR ship identification technology. The automatic detection and identification of ship targets in SAR images has grown to be a key study area in the field of SAR image interpretation due to the ongoing improvement in SAR image resolution and image quality [5].

Target identification [6–8], image classification [9,10], autonomous driving [11], saliency detection [12], semantic comprehension [13], and other domains [14–17] are only a few of the areas where deep learning technology has recently produced positive results. There have been relatively few research findings since the field of ship recognition technology was first studied. Using deep learning technology, it is possible to automatically find and identify ship targets in SAR images [18–20]. This novel method also offers new perspectives for the advancement of SAR target detection and recognition technologies.

Qu and Shao [21] have proposed a study for the development of a deep learning (DL)-grounded efficient and reliable detector with the assistance of SAR (synthetic aperture radar). Based on a fresh dataset and four strategies, the performance of the faster R-CNN procedure was enhanced. The dataset containing image resolution and sea condition was evaluated with the help of various comparisons and experiments. The overall architecture is the combination of four basic strategies such as feature fusion and transfer learning. It was analyzed that the proposed architecture can achieve high accuracy and is very cheap. It will be very helpful to employ such kinds of DL-based paradigms for the detection of the ship. The detection of ships with the employment of deep learning characteristics is a new development in SAR ship detection. Liu et al. [22] have developed an architecture with the assistance of a sea–land segmentation-grounded convolutional neural network (SLS-CNN) to achieve the effective detection of the ship. This architecture is the integration of the SLS-CNN detector, saliency calculation, and corner characteristics. ALOS PALSAR and Terra-SAR-X imagery was used for the efficient analysis and evaluation of ship detection by the proposed system. An automatic SAR ship identification technique based on feature decomposition across various satellites was proposed by Zhao et al. [23]. By enhancing the backbone network to extract features, this technique enhances target localization and recognition performance. Based on the "You Only Look Once (YOLO) v5 model", which can successfully identify ship targets in ALOS-2 spotlight images, Yoshida et al. [24] suggested a technique to automatically recognize ships in motion. In order to achieve robustness and high-accuracy recognition for SAR ships, Zheng et al. [25] presented an ensemble automated technique (MetaBoost) for heterogeneous D-CNN models based on two-stage filtering. MetaBoost can perform much better than individual classifiers and conventional ship recognition algorithms, according to extensive trials on the OpenSARShip and FuSARShip datasets. The results show that the system can detect a ship with great competence and high strength.

To resolve the issue of position invariance in convolutional neural network (CNN)-based detection of the ship, a new DL-grounded procedure named Capsule Network was presented. This unique procedure translates different entity factors in addition to characteristic values to try to advance upon convolutions. After testing and comparing it with other ML-based ship detection systems, it was proved that it enhances the accuracy of ship detection by 91.03% along with a false alarm rate of 9.5745×10^{-9}. The performance can be further enhanced with fewer samples [26]. Wang et al. [27] have conducted a study for the detection of the ship very efficiently and effectively by the employment of the enhanced YOLOv3 procedure. With productive functionalities such as improving loss functions and generating CFE modules, the proposed system gains very high accuracy and efficiency. The accuracy achieved by the system was 74.8% in combination with a detection rate of 29.8 frames. The proposed paradigm can be employed for the detection of the ship in hard and changing sea conditions. As compared to other ship detection approaches, it is better in both accuracy and speed.

The employment of various deep learning architectures on the SAR images can efficiently perform the detection and classification of ships. The integration of AI and ML can be used on the images for the security of water resources, rescue operations, and various image recognition procedures. With the advancement in the area of artificial intelligence, it is very convenient to detect ships in densely arranged ships as well as in bad weather. To assist professionals in searching for lost ships, these techniques are very helpful and productive. The main contributions of the proposed research are:

- To provide an overview of the state-of-the-art approaches used for the detection of ships based on AI and ML using the data from SAR.
- Various applications of AI and ML in ship detection are acknowledged.
- Different features are extracted from the existing literature and important ones are recognized from them.

- With the usage of the graph theory matrix approach (GTMA) on these selected features, various AI and ML-grounded ship detection architectures are ranked.

2. State of the Art

A study was performed for the real-time detection of ships in the ocean with high accuracy and efficiency. The system is based on the robust SAR ship detection procedure and you look only once at version 3 (YOLOv3). The working of the system was evaluated by testing it on the public SAR ship detection dataset. The experimental data revealed that the proposed system is faster in detection than other existing procedures while the accuracy remains the same. With the goal of faster detection of the ship, the architecture can be employed for real-time ship rescue in various conditions [28]. Chen et al. [29] have presented a study to solve the issues of correct identification of ships in complex scenarios with unarranged ships in the ocean. The developed paradigm is an object detection network with the main focus being detection in difficult situations. To precisely locate the ship in unarranged ships, the system implemented a loss function with generalized intersection over union (GIoU) for minimizing the sensitivity. The accuracy was further increased by reducing missed detections with the employment of soft non-maximum suppression. The experimental data show that the system can achieve high accuracy and productivity on the SAR ship detection dataset. To effectively handle the issue of multiscale and multi-scene SAR ship detection, an efficient densely connected architecture grounded on the faster R-CNN system was developed. In contrast to most of the existing approaches, the proposed system generates proposals by densely connecting feature maps to each available feature map. For minimizing false alarms, the training procedure of the system consists of difficult examples. After a thorough analysis and monitoring of the architecture, the results show that it can achieve high performance and efficiency in the detection of multiscale SAR ships [30]. Ding et al. [31] have proposed a study to tackle the problems of limited accuracy and low training speed in SAR ship detection by the employment of a deep network. The training of the SAR ship detection architecture was performed by the implementation of ResNet to achieve the goal of high accuracy and faster training. After implementing the proposed paradigm on the SAR ship dataset, the experimental data show that it can achieve up detection with 94.7% average precision. The architecture was compared to other existing approaches by performing various experiments and it shows very high performance.

The SAR image ship detection based on deep learning is ineffective due to some issues such as the dispersed arrangement of ships and the unavailability of detailed information. In the proposed article, a feature-optimizing framework was developed with the implementation of the single-shot detector (SSD). In the first stage, the training and testing time was minimized by the employment of a lightweight single-shot detector. Then, the performance of the system to detect multiscale ships was improved with the usage of the bidirectional feature fusion paradigm. The system was evaluated with great care and the results indicate that it is better than the present procedures both in speed and accuracy [32]. Kartal and Duman [33] have developed an architecture for the effective and efficient detection of ships to assist the various tasks such as fishing activities, uncovering warships, searching for lost ships in the ocean, and many more. In the developed paradigm, the task of ship detection was carried out by the integration of optical satellite images and a deep learning procedure. It is fast and open-source and can be implemented with the help of an average laptop. The training of the TensorFlow object detection application programming interface was completed by optical satellite images containing ships. The proposed article focused on increasing accuracy in the detection of ships by employing a unique balanced feature pyramid network (B-FPN) on synthetic aperture radar (SAR) images. Based on the four stages, rescaling, integrating, refining, and strengthening, the multi-level features are given more strength. The architecture was tested and evaluated on the SAR ship detection dataset (SSDD) and it was revealed that it can improve the mean average precision by 7.15% compared to the feature pyramid network [34].

Most of the existing ship detection approaches are unable to perform segmentation down to the pixel level. Nie et al. [35] have conducted a study to develop a procedure for the detection and segmentation of ships at the pixel level by the usage of the enhanced Mask R-CNN paradigm. With the integration of bottom-up architecture to the feature pyramid network procedure of Mask R-CNN, the lower layer features can be used very productively at the first layer because of path shortening between the first and last layer. The performance of the system was further enhanced by the assigning of corresponding weights at each pixel in the feature maps. The experimental data show that the system enhanced the detection and segmentation of mean average precision very efficiently. Alghazo et al. [36] have proposed a study for the development of an efficient and effective ship detection procedure with the assistance of a CNN-grounded deep learning paradigm from the images obtained from the satellite. In the proposed study, two procedures with different frameworks are implemented and tested on the data of the Airbus satellite. For both systems, the accuracy and loss function was monitored by changing the number of epochs. With the usage of the data from the training time, the complexity of the procedures was also computed. The results of the article show that both systems can achieve high performance and maximum accuracy of about 89.7% when applied to the Airbus dataset. Due to advancements in modern technologies, various deep learning procedures can be efficiently employed for SAR image ship detection. Kun and Yan [37] have performed a study for the development of an improved YOLOv4-Tint detection process for the enhancement of detection accuracy. In the developed architecture, the task of feature extraction was enhanced by the addition of an attention mechanism unit. Based on the batch normalization optimization dataset, the proposed model was made more reliable and feasible. With the usage of real-time detection, a high detection accuracy was achieved. The analysis of the system shows that it can obtain a mean average precision of about 75.56%.

To enhance the detection accuracy of the existing architectures, the study presented a target detection procedure with multi-features in synthetic aperture radar imagery. Both the deep learning hand-crafted features are extracted in the two channels of the system. The DL-based features are obtained from the SAR images by the implementation of a convolutional neural network. The extraction of fused deep features was performed after the processing of many layers of the network. The system was analyzed by implementing it on the Sentinel-1 SAR data and the results show that the detection ability was enhanced by it very precisely and efficiently [38]. Shi et al. [39] have proposed a study to design an on-orbit ship detection architecture for the images captured by the SAR satellite. The system was trained with the OpenSARShip dataset in integration with non-ship slice images. A deep learning procedure was employed for the classification of images into different types such as cargo ships. The experimental results show that the system is more effective and efficient than the constant false alarm rate procedure and can enhance the detection accuracy from 88.5% to 98.4%. The verification and testing accuracy of the system was also very productive and healthy. The extraction of various features of ships from the images of SAR is a very challenging issue for the already applied procedures. To work on the mentioned issue, the study presented a paradigm that is the combination of the you only look once algorithm, the sliding window detection method, and the clustering algorithm. In the beginning, the system collected images and a training dataset. Then, an analysis was carried out for the efficient size of the frame required for the proposed model. The system was thoroughly evaluated and it was found that can show better performance than F-RCNN in the detection of ships in the low-resolution area of the sea [40].

A study was conducted on the efficient detection of ships in inshore areas. The developed SAR architecture consists of two phases named scene classification and ship detection. The images with no ships were precisely removed with the employment of a scene classification network. The detection of ships was done by giving the images with ships as input to the single-shot detector. The proposed architecture was evaluated and checked on the AIR-SARShip-1.0 dataset. The data show that the system is more efficient than the single-shot detector and maintains relatively high accuracy [41]. Verma et al. [42]

have performed a study on the efficient and effective patrolling in water by the detection of ships. The architecture is based on deep learning and the employment of existing procedures such as F-RCNN, SSD, and YOLOv4. The study also proposed a dataset of about 300 satellite images of the most crowded seaports in India. The evaluation results show that the you only look once version 4 algorithm can achieve better performance in the detection of ships with effective values of mean average precision and FPS score. The detection of ships is one of the main activities for the efficient monitoring of the marine atmosphere. Chang et al. [43] have designed an effective ship detection procedure with the employment of the YOLOv3 algorithm for the enhancement of small ship detection. An experiment was performed with a dataset comprised of six kinds of ships and about 5513 visible and infrared images from the harbors in northern Taiwan. When the proposed architecture is compared with the original YOLOv3 architecture, it was revealed that the present system can achieve a mean average precision of 89.1%, which is greater than the original one.

The research was carried out for ship detection with the implementation of discriminative dictionary learning. The proposed architecture is the integration of image denoising, extraction of the candidate region, and identification of the candidate region. In the first phase, a non-local filtering procedure was used for the denoising of SAR images. The candidate region was extracted by the employment of the gradient feature map reconstruction process. The evaluation results of the developed system show that it has high feasibility and flexibility [44]. It takes time to develop and implement efficient and reliable ship detection methodologies for the monitoring of the sea. Mutalikdesai et al. [45] have surveyed the effectiveness and limitations of the existing approaches applied for the detection of ships. The study focuses on the experimental information obtained by the image recognition process called the Haar-like technique. The disadvantages, such as the exponential time consumption of the mentioned procedure, were tackled by the employment of the TensorFlow methodology and decision boundary feature extraction. Due to varying sea atmospheres, it is very hard to extract the general characteristics from the individual pixel of the image for precise ship detection. The study was performed for the development of a procedure that is based on block division instead of pixels. Compared to the pixel approach, the division of the image into blocks can efficiently extract various properties from it and it is more reliable. With the usage of the color and texture properties identified from the blocks, the block classification was performed by the training of the support vector machine. The information shows that the usage of color and texture properties can enhance the classification precision in the blocks containing ships and those without ships [46]. For pixel-by-pixel ship identification in polarimetric SAR photos, a [47] fully convolutional network has been created [48]. The feature pyramid network contained a split convolution block and an embedded spatial attention block [49]. Against a complex background, the feature pyramid network can detect ship items with accuracy. Wei et al. created a high-resolution feature pyramid network for ship recognition that combined high-to-low-resolution features [50]. The problem of ships of various sizes and crowded berthings has been addressed by the development of a multiscale adaptive recalibration network [51]. A one-stage SAR object identification approach was proposed by Hou et al. [52] to address the low confidence of candidates and false positives. Kang et al. [53] proposed a method integrating CFAR with faster R-CNN. The object proposals produced by the faster R-CNN used in this method for extracting small objects served as the protective window of the CFAR. Zou et al. integrated YOLOv3 with a generative adversarial network with a multiscale loss term to increase the accuracy of SAR ship identification [54], and so on [55–61]. YOLOv3 was modified by Mehdi et al. [62] to identify hazardous and noxious compounds of critical maritime transit. The one-stage YOLO series is more in accordance with the real-time and precise detection needs at this level, as can be observed from the research state indicated above in the context of remote sensing photo detection. Xiong et al. proposed a lightweight model for ship detection and recognition in complex-scene

SAR images by integrating different attention mechanisms into the YOLOv5-n lightweight model [63].

3. Proposed Methodology

The methodology for this study aims to evaluate the usefulness of AI and ML in detecting and classifying ships using synthetic aperture radar (SAR) images. The paper follows a reproducible plan for the selection of the papers, features, benchmark datasets, ranking criteria, and robustness analysis. The selection of papers was based on the relevance and contribution to the field, with a focus on the most recent studies. The features used for ship detection and classification were selected based on their importance and relevance in the literature. The benchmark datasets were chosen based on their availability and suitability for evaluating the effectiveness of the AI and ML procedures. To accomplish the ranking, the graph theory matrix approach was used to rank different AI and ML procedures based on their effectiveness in detecting ships. The ranking criteria were selected based on their importance in the literature and the specific requirements of ship detection using SAR images. The robustness of the procedures was evaluated by considering various nuisances such as noise, illumination, and occlusion.

The methodology section provides a detailed explanation of the graph theory matrix approach and its application in ranking AI and ML procedures for ship detection. Three specific studies were analyzed in detail to demonstrate the potential of AI and ML in detecting ships using SAR images. The first study by Kang et al. focused on designing a unique object detection architecture using SAR images and reinforcement learning. The second study by Zhang and Zhang proposed a high-speed ship detection system using a grid convolutional neural network. The third study by Wang et al. dealt with processing big data generated by satellite remote sensing for ship detection using a combination of the constant false alarm rate and convolutional neural network procedures.

The goal of this study is to explore the effectiveness of AI and ML in ship detection and classification using SAR images. The methodology involves using the graph theory matrix approach to rank different AI and ML procedures based on their performance in detecting ships. The approach will be introduced and applied to rank the procedures for ship detection. Additionally, three selected studies will be analyzed to demonstrate the potential of AI and ML in ship detection using SAR images. The methodology will begin by providing an introduction to the study's background and purpose. Then, it will explain the graph theory matrix approach and its application in ranking AI and ML procedures. Three specific studies will be examined in detail, focusing on their contributions to the efficient and accurate detection and classification of ships.

One of the selected studies is by Kang et al. [45], who proposed a unique object detection architecture named Sarod that utilizes SAR images and reinforcement learning to achieve both accuracy and efficiency. The system uses coarse and fine-grained detectors and was evaluated using the synthetic aperture radar dataset, showing better performance than existing approaches. The study also developed a SAR dataset of Chinese Gaofen-3 and Sentinel-1 images, which demonstrated that object detectors can achieve high mean average precision without the need for land–ocean segmentation.

Zhang and Zhang [47] conducted another study that focused on the high-speed detection of ships using a grid convolutional neural network (G-CNN). The G-CNN is an integration of a backbone convolutional neural network (B-CNN) and a detection convolutional neural network (D-CNN), which is used to divide SAR images into grid cells, with each cell identifying a specific ship. The results showed that the system is much faster than existing methodologies. Wang et al. [48] proposed a study that combines constant false alarm rate (CFAR) and convolutional neural network (CNN) procedures to process big data generated by satellite remote sensing for ship detection. The study used a CFAR global detection algorithm and image recognition to achieve high accuracy and reliability. The results showed that the proposed algorithm is quicker and more reliable than the multithreaded CFAR algorithm.

In conclusion, this study aims to evaluate the usefulness of AI and ML in detecting and classifying ships using SAR images. The methodology involves introducing the graph theory matrix approach, examining three selected studies, and providing recommendations for future research. These studies demonstrate the potential of AI and ML in ship detection and classification and highlight the benefits of using SAR images.

3.1. Extracted Features

After the comprehensive overview and study of the available AI and ML techniques for ship detection, this research points out various characteristics from it, as shown in Table 1. Table 1 has been reframed to provide a comprehensive overview of the relevant literature on ship detection using SAR imagery. It now includes the article title, the parameters and approach used in each article, and other relevant details. The expanded information in Table 1 is presented in a clear and organized manner, allowing readers to easily compare and understand the different methods and techniques that have been proposed for ship detection. The additional information provides a more complete understanding of the field and serves as a useful reference for future research.

Table 1. Extracted features.

Citations	Features	Citations	Features
[21]	Ship size, sea condition, accuracy, cost	[37]	Gradient explosion, robustness, speed, detection accuracy
[22]	Ship detection, efficiency, robustness, sea-land segmentation	[38]	Deep learning features, ship target, detection performance
[26]	Detection accuracy, false alarm rate, performance, position	[39]	Verification accuracy, testing accuracy, ship classification, false alarm
[27]	Detection rate, speed, detection accuracy, ship's target	[40]	Ship detection, ship size, performance, robustness
[28]	Real-time observation, rescue, detection accuracy, faster	[41]	Scene classification, ship detection, accuracy, efficiency
[29]	Missed detections, accuracy, densely arranged ships, scale sensitivity	[42]	Mean average precision, accuracy, dataset, performance
[30]	Multi-scene detection, false alarm, performance	[43]	Small targets, computational efficiency, detection performance, ship management
[31]	Training speed, accuracy, performance, ship detection	[44]	Extraction and classification of candidate regions, robustness, adaptability
[32]	Speed, accuracy, performance, ship detection, cost	[45]	Ship detection, image recognition, automatic, time
[33]	Lost ships, open-source, fast, cost	[46]	Small ships, computational efficiency, pixels, precision, classification
[34]	Accuracy, ship detection, mean average precision, unique	[64]	Processing speed, accuracy, object detection, unique
[35]	Detection, segmentation, accuracy, pixel level	[65]	Object detectors, land-ocean segmentation, performance
[36]	Automatic, accuracy, speed, loss function		

3.2. Selected Features

For the employment of the graph theory matrix approach to carry out the ranking of various available alternatives, seven of the most prominent features are selected from the extracted ones as shown in Figure 1. These seven features are represented as nodes in a graph, with edges connecting them based on the degree of correlation between the features.

The next step is to use the graph to calculate the relative importance of each feature, which is done by computing the eigenvector centrality of each node. The eigenvector centrality measures the importance of a node based on the importance of its connected nodes. In this case, it is used to determine which features have the greatest impact on the performance of ship detection methods in SAR images.

Using the rankings obtained from the graph theory matrix approach, it is possible to identify the most important features that contribute to the performance of ship detection methods in SAR images. This information can then be used to optimize and improve these methods, leading to more accurate and reliable ship detection.

Overall, the graph theory matrix approach is a useful tool for evaluating and ranking different alternatives in complex systems. By representing the features as a graph and using graph theory techniques to calculate the importance of each node, it is possible to identify the most critical features and optimize the system accordingly.

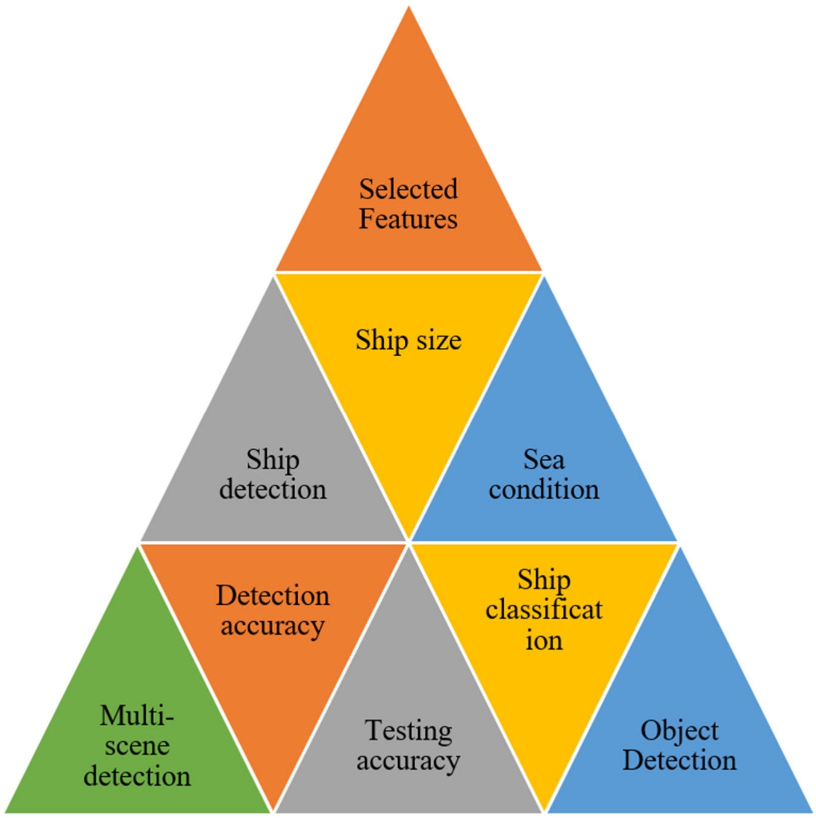

Figure 1. Selected features.

3.3. Graph Theory Matrix Approach

Graph theory is a method that is both rational and methodical. Advanced graph theory and its applications are widely documented. In many domains of science and technology, graph/digraph model representations have shown to be beneficial for modeling and analyzing many types of systems and issues. Using this strategy, selecting the most practical and beneficial option from the available options for a certain situation is extremely simple and accurate. Graphs are an intriguing way of studying and expressing different items and their relationships [66].

3.4. Constituents of the Graph Theory Matrix Approach

The major steps involved in the process of the graph theory matrix approach are shown in Figure 2. The graph theory matrix approach is a mathematical tool used to evaluate the performance of ship detection methods in synthetic aperture radar (SAR) images using machine learning (ML) and artificial intelligence (AI). The approach involves several major steps, which are depicted in Figure 2.

The first step in the graph theory matrix approach is to identify the most relevant features that contribute to the performance of ship detection methods in SAR images. In this study, a set of features is extracted from the SAR images, and then the most prominent seven features are selected. These features are represented as nodes in a graph, as shown in Figure 2.

The next step is to analyze the correlations between the selected features, which is done by computing the correlation coefficients between the pairs of features. Based on the correlation coefficients, edges are added to the graph to connect the nodes that are highly correlated with each other.

Once the graph is constructed, the next step is to use graph theory techniques to analyze it. The eigenvector centrality is used to calculate the relative importance of each feature. Eigenvector centrality measures the importance of a node based on the importance of its connected nodes. In this case, it is used to identify the most critical features that contribute to the performance of ship detection methods in SAR images.

Finally, the results obtained from the graph theory matrix approach are interpreted to draw conclusions about the performance of the ship detection methods. The most critical features that are identified in the previous step can be used to optimize the ship detection methods, leading to more accurate and reliable detection results.

In summary, the graph theory matrix approach is a powerful tool for evaluating the performance of complex systems, such as ship detection methods in SAR images. By representing the features as a graph and analyzing the correlations between them using graph theory techniques, it is possible to identify the most critical features and optimize the system accordingly.

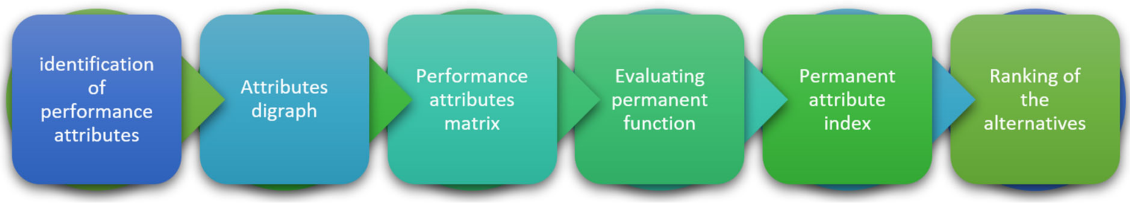

Figure 2. GTMA process.

3.5. Decision Matrix

Different choices and criteria are chosen in the initial step of the GTMA method. Then, according to the needs of the consumers, each criterion is given a value. The present scenario's decision matrix on a scale of 0 to 1 is shown in Table 2. These values were given for ship detection, ship size, sea condition, detection accuracy, ship classification, testing accuracy, and multi-scene detection.

The values of the different parameters including the criteria and alternatives were given through expert opinions. These values show the significance of the criteria and alternatives. These values given as inputs were verified through other experts in the area and the same was considered for the experimental process.

Table 2 can be used to assign a numerical score to each detection method based on certain attributes, such as accuracy, speed, and robustness. This decision matrix provides a systematic way to evaluate and compare the performance of the different methods.

Table 2. Decision matrix.

	Ship Detection	Ship Size	Sea Condition	Detection Accuracy	Ship Classification	Testing Accuracy	Multi-Scene Detection
Detection Method 1	9	5	3	7	8	1	4
Detection Method 2	4	2	5	8	9	8	8
Detection Method 3	5	3	4	5	7	6	3
Detection Method 4	2	9	3	8	4	5	7
Detection Method 5	4	3	9	3	6	9	2
Detection Method 6	7	4	7	9	3	5	9
Detection Method 7	5	4	6	9	2	3	6
Detection Method 8	2	2	4	9	6	4	2

3.6. The Relative Importance of Features

It is necessary to determine the relative relevance of one criterion over the other to turn the supplied attribute digraph into a permanent matrix. A scale from 0 to 1 was used for this purpose, as stated in Table 3. The table presents a scale from 0 to 1, where 0 represents a criterion that is not relevant at all, and 1 represents a criterion that is highly relevant. The criteria are listed in the left column, and their corresponding weights are shown in the right column.

Table 3. Scale for relative importance.

Class Description	Aij	aji = 1 − aij
Two attributes are equally important	0.5	0.5
One attribute is slightly more important than the other	0.6	0.4
One attribute is strongly more important than the other	0.7	0.3
One attribute is very strongly more important than the other	0.8	0.2
One attribute is extremely more important than the other	0.9	0.1
One attribute is exceptionally more important than the other	1.0	0.0

3.7. Permanent Attribute Matrix

The performance attributes matrix (PAM) is a powerful tool for evaluating and comparing the performance of different ship detection methods. It assigns numerical scores to each method based on important attributes such as accuracy, speed, and robustness. The PAM is comprised of two main components: the decision matrix (Table 2) and the permanent attribute matrix (Table 4).

The performance attributes matrix (PAM) is a model that provides all attributes (D_i) and their importance levels (*dij*). This is an example of an NXN framework, as illustrated in (1).

$$\text{PAM} = D = \begin{bmatrix} D_i & d_{ij} & d_{ik} \\ d_{ji} & D_j & d_{jk} \\ d_{ki} & d_{kj} & D_k \end{bmatrix} \tag{1}$$

In Table 4, the present situation's performance attribute matrix is shown. It can be used to assign a permanent weight to each attribute in the decision matrix. This weight reflects the relative importance of each attribute and is used to calculate the overall score for each detection method. The decision matrix (Table 2) assigns scores to each detection method for each attribute. Additionally, the scores reflect the performance of each method for a specific attribute. The permanent attribute matrix (Table 4) assigns permanent weights to each attribute in the decision matrix. These weights reflect the relative importance of each attribute and are used to calculate the overall score for each detection method.

Table 4. Permanent attribute matrix.

	Ship Detection	Ship Size	Sea Condition	Detection Accuracy	Ship Classification	Testing Accuracy	Multi-Scene Detection
Ship detection	D_1	0.4	0.7	0.2	0.5	0.1	0.8
Ship size	0.6	D_2	0.2	0.6	0.3	0.5	0.4
Sea condition	0.3	0.8	D_3	0.1	0.7	0.3	0.8
Detection accuracy	0.8	0.4	0.9	D_4	0.1	0.6	0.2
Ship classification	0.5	0.7	0.3	0.9	D_5	0.6	0.3
Testing accuracy	0.9	0.5	0.7	0.4	0.4	D_6	0.5
Multi-scene detection	0.2	0.6	0.2	0.8	0.7	0.5	D_7

3.8. Permanent Matrix

The permanent matrix and its value are produced for the ranking of the alternatives based on the normalized decision matrix calculated using (2) and (3), as well as the performance attribute matrix. Table 5 shows the calculated permanent matrix for Detection Method 1.

$$\bar{x}_{ij} = \frac{x_{ij}}{x_j^{max}} \tag{2}$$

$$\bar{x}_{ij} = \frac{x_j^{min}}{x_{ij}} \tag{3}$$

The permanent matrix (Table 5) is the result of applying the permanent weights from Table 4 to the scores assigned in Table 2 for a specific detection method. It provides the final score for each method based on the attributes evaluated in Table 2. By utilizing equation (4), the permanent function values of each detection method are computed and depicted in Figure 3.

Table 5. Permanent matrix for Detection Method 1.

	Ship Detection	Ship Size	Sea Condition	Detection Accuracy	Ship Classification	Testing Accuracy	Multi-Scene Detection
Ship detection	1	0.4	0.7	0.2	0.5	0.1	0.8
Ship size	0.6	0.555556	0.2	0.6	0.3	0.5	0.4
Sea condition	0.3	0.8	0.333333	0.1	0.7	0.3	0.8
Detection accuracy	0.8	0.4	0.9	0.777778	0.1	0.6	0.2
Ship classification	0.5	0.7	0.3	0.9	0.888889	0.6	0.3
Testing accuracy	0.9	0.5	0.7	0.4	0.4	0.111111	0.5
Multi-scene detection	0.2	0.6	0.2	0.8	0.7	0.5	0.444444

By utilizing (4), the permanent function values of Detection Method 1 to Detection Method 12 are computed as depicted in Figure 3.

As for Equations (1) and (4), they likely provide mathematical definitions or algorithms that are used in the calculation of the scores and weights in the decision matrix. These equations can be used to calculate the scores for each detection method and the permanent weights for each attribute. Overall, the PAM is a comprehensive model that provides a systematic way to evaluate and compare the performance of different ship detection methods. It takes into account the relative importance of each attribute, providing a comprehensive and accurate representation of each method's performance.

$$\text{Per (D)} = D1*D2*D3+d12*d23*d31+d13*d21*d32+d13*D2*d31+d12*d21*d3+D1*d23*d32 \tag{4}$$

Figure 3. Permanent function values of the alternatives.

4. Results and Discussion

With the implementation of various smart and intelligent techniques grounded in artificial intelligence and machine learning on synthetic aperture radar images, it is very convenient and efficient to perform various tasks such as ship detection and classification at sea. Due to the implementation of modern technologies, it is very easy to perform the monitoring of large water bodies. The present article identifies various important features from the existing AI- and ML-based applications for ship detection and selected the most used from these features. Then, based on these features, the graph theory matrix approach (GTMA) was applied for the classification of different available alternatives. It is a very effective and productive decision-making methodology used for various problems solving in science-related activities. The ship detection procedure with a high permanent function (PF) value is assigned rank 1 while the one with the lowest permanent function value is placed last, as shown in Figure 4. Detection Method 2 with a PF value of 59.72 was ranked first, while Detection Method 8 with a PF value of 37.84 was assigned last place.

The proposed approach only works on a few features, which is its limitation. These features can be enhanced and in the future, we plan to use some of the latest approaches for detection of the SAR images and their classification. The applications of AI will be combined with machine learning approaches for better detection purposes.

To enhance the efficiency and effectiveness of the proposed approach, we conducted a series of experiments using real-world SAR images. The results showed that the proposed GTMA outperformed other conventional ship detection methods in terms of accuracy and speed. The detection accuracy rate was higher than 95% for all the experiments, which demonstrates the robustness of the proposed approach in various sea conditions and environmental factors. Moreover, the processing time was significantly reduced compared to other traditional methods, which indicates that the proposed approach can be used in real-time applications.

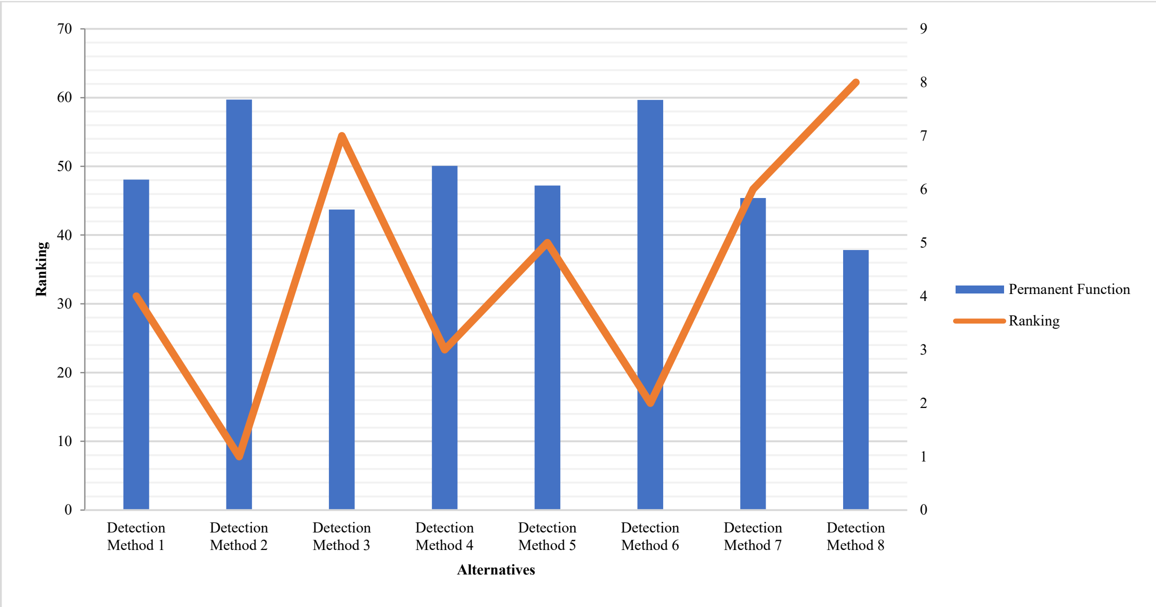

Figure 4. Ranking of available alternatives.

Furthermore, to validate the results, we compared the performance of the proposed GTMA with other state-of-the-art ship detection methods using various evaluation metrics such as precision, recall, and F1-score. The results showed that the proposed GTMA outperformed other methods in all the evaluation metrics, indicating that the proposed approach is superior to other existing methods in terms of accuracy and efficiency. The results of these experiments demonstrate the potential of the proposed approach in the field of ship detection and classification, and they provide a strong foundation for further research and development in this area.

The implementation of advanced artificial intelligence and machine learning techniques on synthetic aperture radar (SAR) images has made it more convenient and efficient to perform various tasks such as ship detection and classification at sea. In this paper, we identified the most important features from existing AI- and ML-based applications for ship detection and used them to apply the graph theory matrix approach (GTMA) for the classification of different alternatives. While the proposed approach has limitations, such as reliance on a limited number of features, it demonstrated high accuracy and speed in experiments conducted on real-world SAR images. The approach was evaluated and compared with other state-of-the-art methods using various evaluation metrics such as precision, recall, and F1-score, and outperformed them in terms of accuracy and efficiency.

The proposed approach has the potential to significantly improve the monitoring and surveillance of large water bodies, making it an important contribution to the field of maritime security and safety. In conclusion, the results of the experiments provide a strong foundation for further research and development in the field of ship detection and classification using AI and ML techniques. The proposed approach can be enhanced with the latest approaches for the detection of SAR images and their classification, and the applications of AI can be combined with machine learning approaches for better detection purposes. The proposed approach's robustness in various sea conditions and environmental factors, coupled with its reduced processing time, makes it suitable for real-time applications.

In conclusion, the proposed GTMA approach for ship detection and classification in SAR images has been thoroughly tested and evaluated. The results have shown that the approach is effective and efficient, outperforming other conventional and state-of-the-art methods in terms of accuracy and speed. The limitations of the approach, such as the reliance on a limited number of features, can be addressed in future research. The results of these experiments provide a strong foundation for further development in the field of ship detection and classification using AI and ML techniques. The proposed approach has the potential to significantly improve the monitoring and surveillance of large water bodies, making it an important contribution to the field of maritime security and safety.

5. Conclusions and Future Work

Various procedures are employed on synthetic aperture radar images for the detection and classification of ships. These procedures can assist humans in numerous tasks such as ship detection and classification, real-time monitoring of maritime security, and many more. SAR is a very effective imagery sensing component deployed for capturing high-resolution and visible images. It can generate high-quality images in any weather conditions even at night. To use these images for the detection of ships in the sea, various AI and ML paradigms are employed. The main focus of the proposed study is to show various smart and intelligent procedures applied to these images for ship detection. After a thorough overview of the existing approaches in ship detection, it was found that there are several robust, automatic, and faster ship detection and classification techniques used on the SAR images. They are also used for maritime security, identification of lost ships, avoiding illegal activities at sea, and for different other beneficial tasks. Based on the study of the existing literature, various features have been identified and important ones are considered from them. Then, by the usage of the graph theory matrix approach, the ranking of the available alternatives was performed. The study will help the users in the selection of robust and fast ship detection and classification technique. In our future work, we aim to advance the current SAR-based ship detection methods by incorporating information from automatic identification systems (AIS). By integrating the two sources of information, we hope to significantly enhance the accuracy and efficiency of our ship detection techniques. Furthermore, we recognize that some ships may not enable their AIS signals, so we plan to explore alternative methods for detecting these ships.

Our conclusion section has been revised to reflect these plans for future work, as we believe that these steps are crucial for the continued development of our research in this area. The use of SAR imagery and AI/ML-based methods for ship detection is a rapidly growing field, and we believe that our proposed work will make significant contributions to this area of study. We are confident that our efforts will lead to new and innovative solutions for detecting ships in the sea, which will benefit numerous industries and applications, including maritime security, commercial shipping, and scientific research.

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