SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I6P107

Volume 12 Issue 6, 90-100, June 2025

Original Article

Robust Multi Scale Multi Polarization and Multi Orientation Fused Maritime Target Recognition in SAR Images

M Mary Rosaline[1*], S Arivazhagan[1], Santhana Raj[1], Phillip Livingston[1], Stewart Phillip[1], K Alaguraja[1]

[1]*Departmen of ECE, Mepco Schlenk Engineering College, India.*

[*]*Corresponding Author : maryrosaline@mepcoeng.ac.in*

Received: 04 April 2025 Revised: 05 May 2025 Accepted: 06 June 2025 Published: 27 June 2025

Abstract *- A robust Multi Scale Multi Polarization and Multi Orientation CNN are proposed for feature extraction and classification in SAR-based Ship recognition, which exploits feature fusion across multiple scales, polarizations and looks. Data augmentation techniques are incorporated to mitigate data imbalance and increase the robustness of the model. The ablation studies are performed for 10 class classification problems of SAR ship classification varying the number of scales, orientations and polarizations with different learning algorithms and activation functions. The proposed model is validated on the OpenSARShip dataset to classify ships in SAR images. The proposed model achieved the highest accuracy of 97.1% for the task of ship classification. The proposed CNN model is better than the state-of-the-art conventional methods in terms of accuracy. The proposed model attained the said accuracy with only 328M network parameters. The proposed CNN is a beneficial model for identifying the different types of ships in SAR images and assisting maritime surveillance. The comparison of the experimental results with pre-trained and custom deep learning models available in the literature validates the reliability of the proposed deep CNN model.*

Keywords *- Multi scale multi polarization and multi orientation CNN, Ship classification, Synthetic Aperture Radar.*

1. Introduction

SAR ATR has three stages: target detection, target discrimination and classification. In SAR images covered in large portions of the ocean, Ship detection is performed to extract Regions of Interest (ROIs), possibly containing the ships. The ROIs are then processed by ship discrimination to reject the clutter of false alarms. Finally, the detected ship regions are processed in the classification stage to determine the ship class labels. Deep learning techniques have shown remarkable success in SAR image classification and target recognition in recent years. Among the deep learning approaches, CNNs have been widely used due to their excellent performance in image feature extraction. After the release of the OpenSARShip dataset for different ship classes in 2018, deep learning was employed for SAR ship classification. For ship recognition, though CNN is popularly used, it is essential to design the depth of the network rationally [1]. Nowadays, to improve recognition accuracy, the depth of the network is blindly increased, ignoring the network parameters. Due to this, recognition models often become too large, making real-time recognition a great challenge. As recognition models become large, training time also increases. Hence, the impact of the network parameters should be carefully considered when designing the network. Hence, a lightweight network for SAR image-based ship recognition is the need of the hour. Considering both the recognition accuracy and the amount of network model parameters becomes inevitable [2]. For accurate classification of a ship in SAR images, extraction of discriminative features of SAR images highlights the similarity in ships of the same classes and the dissimilarity in ships of different classes.

Two factors that limit the extraction of discriminative features are the insufficient number of SAR ship training samples for certain ship classes, which limits the learning of CNN, and the limited information that SAR images can provide compared to optical images.

Different ship classes, like cargo ships and bulk carriers, are different in size, and they also differ across different radar frequencies, angles of incidence, etc. Exploiting the differing sizes across radar frequency, angle of incidence, etc., can improve the robustness of Ship recognition. Owing to the rapid advancements in Synthetic Aperture Radar (SAR) and signal processing, with the help of target multi-frequency and polarization scattering information, SAR target recognition performance can be significantly improved.

Hence, SAR target recognition combines different SAR bands, namely C, L, and X -bands, different polarizations, namely HH, HV, and VV, and different incidence angles will be explored. This paper employs Multi Scale, Multi Polarization and Multi Orientation CNN for feature extraction and classification in SAR based ship recognition. Additionally, speckle noising and pose synthesis based data augmentation techniques are incorporated to mitigate data imbalance and increase the robustness of the model.

2. Literature Survey

Statistical features used for SAR based Automatic Target Recognition (ATR) include first order statistical features like mean, standard deviation, histogram, variance, skewness and kurtosis. The Second order statistics include Energy, Homogeneity, Correlation, Contrast, and Entropy derived from Gray Level Co-occurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM) and Gray Level Size Zone Matrix (GLSZM). Transform domain features are also often employed for Target Recognition. Jean-Philippe et al. [3] performed a multi-dimensional wavelet transform for SAR target recognition. Huan & Yang [4] employed Markov Random Field based target segmentation and Gabor Wavelet based feature extraction for SAR based target recognition.

Wang et al. [5] extracted Local features from Gabor filter output using Local binary pattern extraction and classified using Extreme Learning Machine. Yu-Long et al. [6] employed Graph Fourier transform-based feature extraction, 2D Principal Component Analysis-based feature compression and Metasample-based Sparse Representation Classifier (MSRC) for feature classification.

In the previous syudy, the author employed Quaternionic Wavelet Transform (QWT) for feature extraction, PCA-based feature reduction and SVM classifier for Target recognition. They also compared the performance of replacing QWT with Ridgelet transform, Log Gabor transform, and Speeded Up Robust Features (SURF) based features.

In model-based methods, the matching is done between the features extracted from the target and features extracted from the CAD target model. Due to advancements in the field of Electromagnetic Models and CAD models, 3D Scattering models can be easily developed. Bhalla & Ling [7] extracted the three-dimensional scattering-center model of a target from its geometrical CAD model employing the Shooting and Bouncing Ray (SBR) method in which the three-dimensional ISAR image of the target is generated employing ray tracing and three-dimensional position and strength of the scattering centers is extracted employing image-processing algorithm.

Jianxiong et al. [8] reconstructed the 2D / 3D scattering center models based on the target measurements at all angles. 1D / 2D / 3D Scatterer Map (OTSM) is designed and 1D scattering center projections are obtained. They employed Hough transform and the least squares method to filter out the stable scattering centers and their corresponding scattering coefficients. In Ding [9], Multi-level Dominant Scattering Areas (DSAs) are generated to describe the target region and scattering centres distribution from coarse to fine, and matching is performed at each level using the morphological erosion operation and Euclidean distance transform.

Xu et al. [10] proposed SARNet, and Li et al. [11] proposed DeepSAR-Net for target recognition. Zhao et al. [12] employed multi-stream CNN where multiple views of the same target are given as input. Lang et al. [13] presented a four-layer CNN model combined with hinge loss called LW-CMDANet for the 10-class problem of the MSTAR dataset. Zhai et al. [14] proposed MF-SARNet consisting of eighteen convolutional layers, eight fire modules and two fully connected layers with the data augmentation, increasing the dataset by 360 times.

Shi et al. [15] presented a deep residual shrinkage network with an attention module with less parameters and more accuracy. Zhang et al. [16] used a lightweight and effective spatial and channel attention module for SAR ATR with less data. Su et al. [17] proposed a 2D discrete cosine transformation-based frequency channel attention network for target recognition in the presence of noise. Wang et al. [18] presented a multi-view attention network with LSTM to learn features with spatial attention from different aspects. Ren et al. [19] proposed a new capsule network with multiple dilated convolutions for multi-sized feature extraction.

Shao et al. [20] proposed a lightweight CNN model employing channel-wise and spatial attention mechanisms to improve the representational power of the network and a new WDM loss function to solve the data imbalance problem in the data set. The authors achieved 81% accuracy for 3 class classifications.

Tianwen & Xiaoling [21] introduced HOG-ShipCLSNet, which combines traditional hand-crafted HOG features and modern abstract CNN features to improve recognition accuracy and achieved an accuracy of 78.16% for 3-class classification. Tianwen & Xiaoling [21] further introduced PFGFE-Net, which fuses dual polarization features, geometric features and polarization coherence features to improve accuracy and achieved an accuracy of 79.84% for 3 class classifications and 56.83% for 6 class classifications.

Zhan & Cui [22] employed RetinaNet as the backbone network followed by the Squeeze-and-Excitation (SE) module to take into account the high similarities among various SAR ship classes by increasing the inter-class feature distance features while also decreasing the intra-class feature distance. Finally, the Central Focal Loss (CEFL), based on depth feature aggregation, is constructed to reduce the intra-class feature distance and solve the problem of class imbalance in ship target recognition. They achieved an accuracy of 91.7% for 3 class classifications. Wang et al. [23] devised a SAR ship recognition method via multi-scale feature attention and adaptive-weighted classifier to enhance features in each scale. They achieved an accuracy of 79.97% for 3 class classification and 59.16% for the 6-class classification.

SAR image forms a graph with each pixel acting as a vertex of the graph, pixel value acting as the vertex attribute, and a non-attributed edge connecting every pair of neighbor pixels. Researchers performed experiments to evaluate the effect of data augmentation, L2 regularization term and dropout on AlexNet and ResNet performance for the MSTAR dataset. Due to the scarcity of SAR images, in the case of small datasets, data augmentation is performed to satisfy the requirements of deep-learning models. Researchers also compared the performance of SAR ATR, varying the amount of training data.

3. Materials and Methods

The proposed methodology for SAR ship classification is provided in Figure 1. The proposed Multi Scale Multi Polarization Multi Orientation CNN has two parallel Multi Scale Multi Orientation CNN networks working on HH and VV polarizations. Each Multi Scale Multi Orientation CNN network is comprised of CNN networks in parallel. SAR ship images at different scales and orientations are fed into the parallel branches of the Multi Scale Multi Orientation CNN network.

The input layer is the very first layer of the convolutional neural network. The input layer feeds the input data into the neural network for training and testing. It has three parameters, namely input size, name and value. Among the multiple layers in deep CNN, the convolutional layer plays a vital role in the extraction of the features. In the convolutional layer, a fixed-size window runs over the image with some stride, and the pixels under the window are given input to the neurons for feature extraction. The sparse connectivity, with less number of connections between two adjacent layers and weight sharing, with the same set of weights operating on one and all pixels, significantly reduces the computational complexity.

The pooling layer is used to reduce the spatial size of the image, indirectly reducing the number of parameters and computations in the neural network. Techniques like max pooling, min pooling, average pooling, tree pooling and gated pooling are available. Max pooling is used to sub-sample between different convolutional layers. The pooling layer extracts the relevancy and location of the features. In each feature map, the pooling layer operates independently. It is used to summarize the features present in the feature map produced by the convolutional layer. Thus, it makes the model more powerful in terms of variations in the presence of input image features.

The activation layer, aside from deciding whether to fire a neuron, ensures nonlinear mapping between the input and output. The activation layer boosts the ability of the network to learn complicated relationships between input and output. The popular activation functions include sigmoid, tanh, ReLU, leaky ReLU and parametric ReLU. The activation layer ensures that the robust image features, resistant to rotation, translation and other changes, are learned.

The fully connected layer collects all the input data from the previous layer and compiles the extracted data to form the final output. The main objective of the fully connected layer is to take the previous results and use them to classify the images into their class labels.

This is passed to the output layer to represent the classification label. Out of the various loss functions, including the cross-entropy loss function, Hinge loss function and Euclidean loss function, the cross-entropy loss function is popular for multi-class classification. It applies softmax activation to generate the probability of the input belonging to a particular class. In other words, the final hidden layer output is flattened and given to the fully connected layer to predict the classification label. The classification layer employs the cross entropy loss for classification and weighted classification loss. The output of the fully connected layer is given as the input to the classification layer to classify each image.

The Proposed Multi Scale Multi Polarization and Multi Orientation (MS-MP-MO) CNN has the following features:

- Features from different scales, polarizations and orientations are extracted with the help of Multi Scale Multi Polarization and Multi Orientation (MS-MP-MO) CNN.
- Augmentation is performed by despeckling followed by speckling, where speckle noise is added at different parameters
- SAR images of multiple orientations are obtained by the linear combination of two images of the target at two nearby angles
- It achieves accuracy as high as 97.1% and performs better than conventional methods for SAR Ship classification.

The OpenSARShip dataset has a huge imbalance of data owing to the small amount of data for some classes of ships. To avoid data imbalance, data augmentation techniques like Speckle noising and pose synthesis (Jun *et al.* 2016) are employed, as shown in Figure 2. In speckle noising, the images are despeckled employing median filtering, followed by the addition of exponentially distributed speckle noise of varying distribution parameters.

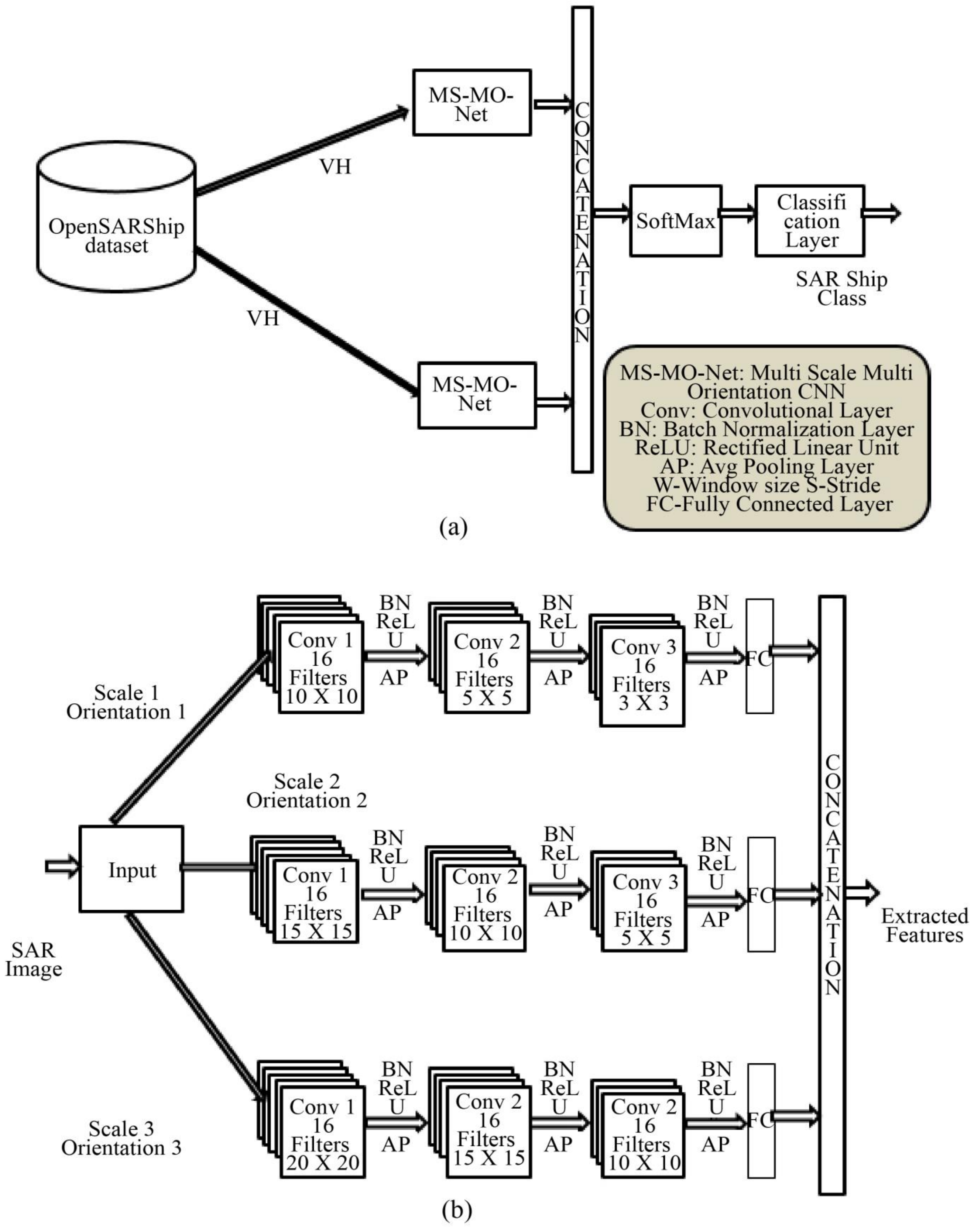

Fig. 1(a) Proposed methodology for multi scale multi polarization and multi orientation CNN based SAR ship recognition, and (b) MS – MO net architecture.

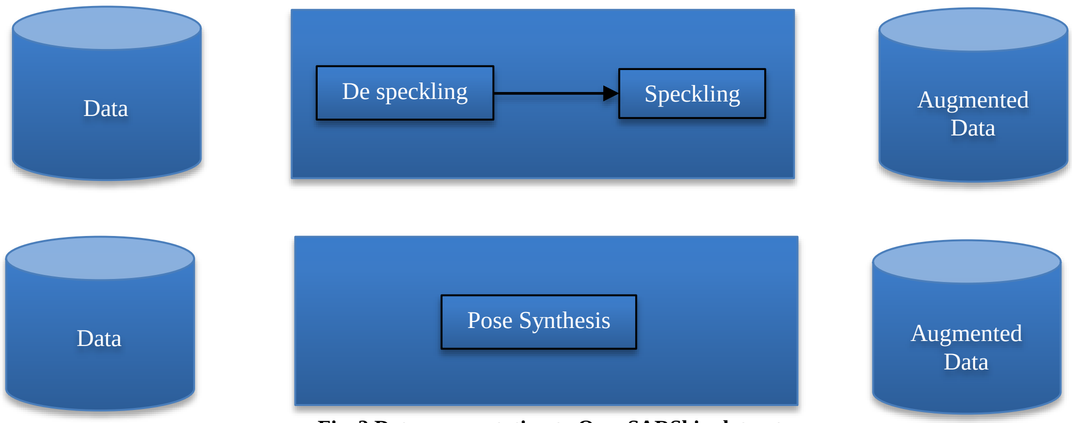

Fig. 2 Data augmentation to OpenSARShip dataset

In pose synthesis, the image of the target at an unknown angle is synthesized by the linear combination of two images of the target at known angles. Pose synthesis is performed by rotating the SAR images to two nearby angles and then obtaining the linear combination of them. Data augmentation techniques can make deep learning models more robust by generating variations that the model may face in the real world. The following are some of the advantages of data augmentation: expanding the algorithms' training dataset, preventing data scarcity for better models, reducing data overfitting (i.e. a statistical error that implies a function matches too closely to a restricted collection of data values) and generating variability in data. It improves the algorithms' capacity for generalization, assists in the resolution of problems with classification's class inequality, reduces data collection and marking costs, allows for the forecast of unusual events, and prevents data security issues.

4. Results and Discussion

The experiments are designed and performed to evaluate the proposed Multi Scale Multi Polarization and Multi Orientation CNN using the OpenSARShip dataset. The important objective of the proposed Multi Scale Multi Polarization and Multi Orientation CNN is to classify between different classes of ship SAR images. The Deep Learning models are tested for 20 hours on a DELL Workstation with a 2.4 GHz Intel Core (TM) i7-M520 CPU, MATLAB R2021a 64-bit, and 80 GB RAM running Windows 10. The implemented model was tested using Matlab 2021a in a DELL workstation with a 64-bit processor and 80 GB RAM. The settings for training the network include 30 number of epochs and an initial learning rate of 0.0001.

4.1. Dataset

OpenSARShip dataset is used for the experimentation. A split configuration of 70%, 20% and 10% are used as the training, validation and testing sets. 21000 SAR ship image chips from the OpenSARShip dataset are used for training. 6000 SAR ship image chips from the dataset are used for validation. 3000 SAR ship image chips from the dataset are used for testing. It is ensured that an equal number of ships are present for all classes in the training set.

4.2. Experimental Setup for Ablation Studies on Multi Scale Multi Polarization and Multi Orientation CNN

The idea behind an ablation study is that specific network components are modified or removed to better understand the behavior of the network. The ablation study aims to acquire a clear understanding of the model's performance by analyzing the consequences of altering some network components, such as hyper-parameters, number of layers, different kinds of activation and loss functions, learning rate, optimizers, filter sizes, and filter numbers. In this work, an ablation study is performed on the proposed Multi scale Multi Polarization and Multi Orientation CNN by altering the number of scales, number of orientations and number of polarizations and also varying the learning algorithm and pooling algorithm. OpenSARShip dataset is considered to have 10 classes of ship SAR images, each class having 3000 images. Out of this, 2100 images are considered for training, and 600 and 300 images in each class are considered for validation and testing, respectively.

4.3. Ablation Studies for Multi Scale Multi Polarization and Multi Orientation CNN Varying Number of Scales

The Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN for SAR-based ship recognition varying scales for different activation functions and learning algorithms. Table 1 provides the results of ablation studies done for multi-scale CNN-based ship recognition, varying the number of scales. It can be inferred that the performance of multi-scale CNN increases with an increase in the number of scales. In all the experiments at all scales, activation function ReLU gave the best results, followed by Tanh, which in turn performed better than Sigmoid. In all the experiments at all scales, the learning algorithm SGDM gave the best results, followed by RMSProp, which performed better than Adam.

Table 1. Performance of ship recognition for different numbers of scales

Number of Scales	Activation Functions	Learning Algorithms	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
3	Relu	SGDM	97.1	2.9	97.1	2.9
3	Relu	RMSProp	93	7	93	7
3	Relu	Adam	92.3	7.7	92.2	7.8
3	Tanh	SGDM	91.4	8.6	91.4	8.6
3	Tanh	RMSProp	87.9	12.1	87.9	12.1
3	Tanh	Adam	87.87	12.13	87.87	12.13
3	Sigmoid	SGDM	84.6	15.4	84.7	15.3
3	Sigmoid	RMSProp	80.4	19.6	80.4	19.6
3	Sigmoid	Adam	80.4	19.6	80.4	19.6
2	Relu	SGDM	95.6	4.4	95.7	4.3
2	Relu	RMSProp	91.3	8.7	91.3	8.7
2	Relu	Adam	89.8	10.2	89.8	10.2
2	Tanh	SGDM	89.1	10.9	89.4	10.6
2	Tanh	RMSProp	83.3	16.7	83.7	16.3
2	Tanh	Adam	84.7	15.3	84.6	15.4
2	Sigmoid	SGDM	83.4	16.6	83.5	16.5
2	Sigmoid	RMSProp	76.2	23.8	76.3	23.7
2	Sigmoid	Adam	78.7	21.3	78.9	21.1
1	Relu	SGDM	93	7	93	7
1	Relu	RMSProp	85.3	14.7	85.5	14.5
1	Relu	Adam	87.6	12.4	87.4	12.6
1	Tanh	SGDM	87.5	12.5	87.5	12.5
1	Tanh	RMSProp	80.7	19.3	80.6	19.4
1	Tanh	Adam	82.3	17.7	82.4	17.6
1	Sigmoid	SGDM	82	18	82	18
1	Sigmoid	RMSProp	71.4	18.6	71.5	18.5
1	Sigmoid	Adam	76.5	13.5	76.4	13.6

Table 2. Performance of ship recognition for different numbers of orientations

Number of Orientation	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
1	93.8	6.2	93.8	6.2
2	94.2	5.8	94.2	5.8
3	97.1	2.9	97.1	2.9

4.4. Ablation Studies for Multi Scale Multi Polarization and Multi Orientation CNN Varying Number of Orientations

The Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN for SAR based ship recognition varying the number of orientations. The number of scales is considered 3, with ReLU as an activation function and SGDM as a learning algorithm. The number of polarizations is considered as 2.

Table 2 provides the results of ablation studies done for Multi Scale Multi Polarization and Multi Orientation CNN-based ship recognition, varying the number of orientations. It can be inferred that the performance of Multi Scale Multi Polarization and Multi Orientation CNN increases with an increase in the number of orientations.

4.5. Ablation Studies for Multi Scale Multi Polarization and Multi Orientation CNN Varying Number of Polarizations

The Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN for SAR based ship recognition varying the number of polarizations. The number of scales is considered as 3 with ReLU as an activation function and SGDM as a learning algorithm. The number of orientations is considered as 3. Table 3 provides the results of ablation studies done for Multi Scale Multi Polarization and Multi Orientation CNN-based ship recognition, varying the number of polarizations. It can be inferred that the highest performance of Multi Scale Multi Polarization and Multi Orientation CNN is obtained for the combination of VV – VH polarization compared to VV or VH polarization. The Ablation studies were performed for Multi Scale Multi

Polarization and Multi Orientation CNN for SAR based ship recognition varying the number of polarizations. The number of scales is considered as 3 with ReLU as an activation function and SGDM as a learning algorithm. The number of orientations is considered as 3. Table 3 provides the results of ablation studies done for Multi Scale Multi Polarization and Multi Orientation CNN-based ship recognition, varying the number of polarizations. It can be inferred that the highest performance of Multi Scale Multi Polarization and Multi Orientation CNN is obtained for the combination of VV – VH polarization compared to VV or VH polarization.

Table 3. Performance of ship recognition for different numbers of polarizations

Polarization	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
VV-VV	95.1	4.9	95.1	4.9
VH -VH	94.6	6.4	94.5	6.5
VV - VH	97.1	2.9	97.1	2.9

Table 4. Performance of ship recognition for different learning algorithms

Learning Algorithm	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
SGDM	97.1	2.9	97.1	2.9
RMSProp	93	7	93	7
Adam	92.3	7.7	92.2	7.8

Table 5. Performance of ship recognition for different pooling algorithms

Pooling Algorithm	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
Max Pooling	97.1	2.9	97.1	2.9
Average Pooling	92.5	7.5	92.5	7.5

Table 6. Ablation studies for multi-scale multi-polarization and multi-orientation CNN

Experiment	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
MS-MO	92.3	7.7	92.2	7.8
MS-MP	95.1	4.9	95.1	4.9
MP-MO	95.6	4.4	95.7	4.3
MS-MP-MO	97.1	2.9	97.1	2.9

4.6. Ablation Studies for Multi Scale Multi Polarization and Multi Orientation CNN for Different Learning Algorithms

Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN for different learning algorithms. Table 4 provides the results of ablation studies done for Multi Scale Multi Polarization and Multi Orientation CNN-based ship recognition, varying the learning algorithms. It can be inferred that the performance of Multi Scale Multi Polarization and Multi Orientation CNN is the highest for SGDM compared to RMSProp and ADAM.

4.7. Ablation Studies for Multi Scale Multi Polarization and Multi Orientation CNN for Different Pooling Algorithms Subheadings

The Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN for different pooling algorithms. Table 5 provides the results of ablation studies done for Multi Scale Multi Polarization and Multi Orientation CNN-based ship recognition, varying the pooling algorithms. It can be inferred that the performance of Multi Scale Multi Polarization and Multi Orientation CNN is better for Max pooling compared to Average pooling.

4.8. Ablation Studies for Multi-Scale Multi-Polarization and Multi-Orientation CNN

The Ablation studies were performed for Multi Scale Multi Polarization and Multi Orientation CNN, removing one aspect at a time (Multi Scale, Multi Polarization or Multi Orientation). The results obtained are provided in Table 6. It can be inferred that having multiple polarizations has a huge impact on performance compared to other aspects.

4.9. Computational Complexity of Multi Scale Multi Polarization and Multi Orientation CNN with Data Augmentation

Multi Scale Multi Polarization and Multi Orientation CNN are implemented for different network parameters and scales 1, 2 and 3, as given in Tables 7, 8 and 9.

Table 7. Network parameters and input output dimension at scale 1

Name	Network Parameters		Input Output dimension	
	Layers	Kernel @ Stride	Input image dimension	Output image dimension
Stage-1	Convolution	15 x 15 x 1 @ 1	80 x 80	66 x 66
Stage-2	Max Pooling	5 x 5 @ 1	66 x 66	62 x 62
	Convolution	10 x 10 x 32 @ 1	62 x 62	53 x 53
Stage-3	Max Pooling	5 x 5 @ 1	53 x 53	49 x 49
	Convolution	5 x 5 x 64 @ 1	49 x 49	45 x 45

Table 8. Network parameters and input output dimension at scale 2

Name	Network Parameters		Input Output dimension	
	Layers	Kernel @ Stride	Input image dimension	Output image dimension
Stage-1	Convolution	10 x 10 x 1 @ 1	80 x 80	71 x 71
Stage-2	Max Pooling	5 x 5 @ 1	71 x 71	67 x 67
	Convolution	5 x 5 x 32 @ 1	67 x 67	63 x 63
Stage-3	Max Pooling	5 x 5 @ 1	63 x 63	59 x 59
	Convolution	3 x 3 x 64 @ 1	59 x 59	57 x 57

Table 9. Network parameters and input output dimension at scale 3

Name	Network Parameters		Input Output dimension	
	Layers	Kernel @ Stride	Input image dimension	Output image dimension
Stage-1	Convolution	20 x 20 x 1 @ 1	80 x 80	61 x 61
Stage-2	Max Pooling	5 x 5 @ 1	61 x 61	57 x 57
	Convolution	15 x 15 x 32 @ 1	57 x 57	43 x 43
Stage-3	Max Pooling	5 x 5 @ 1	43 x 43	39 x 39
	Convolution	10 x 10 x 64 @ 1	39 x 39	30 x 30

Table 10. Performance of proposed ship recognition methodology

Ship Class	Probability of Detection	Probability of Miss	Probability of Correct Detection	Probability of False Alarm
Cargo	91.7	8.3	95.3	4.7
Diving	100	0	100	0
Dredging	96.1	3.9	97.3	2.7
Fishing	98.3	1.7	95	5
Law	98.4	1.6	99.7	0.3
Passenger	98.3	1.7	98.3	1.7
Pilot	100	0	99	1
Porttrender	99.7	0.3	99	1
Tanker	95.1	4.9	90	10
Tug	93.9	6.1	97.3	2.7
Overall	97.15	2.85	97.09	2.91

The performance of the proposed CNN is given in Table 10 in terms of Probability of Detection, Probability of Miss, Probability of Correct Detection and Probability of False Alarm.

A confusion matrix is given in Figure 3. The largest recognition error is between tanker and cargo, both large in size used for carrying goods. 25 cargo vessels out of 300 vessels are misclassified as tankers, while 14 tanker vessels out of 300 vessels are misclassified as cargo.

The 10 Tug vessels out of 300 vessels are misclassified as fishing vessels, while 3 Fishing vessels out of 300 vessels are misclassified as Tug vessels. For all other ship classes, the classification accuracy is greater than 99%, as evident in Figure 3.

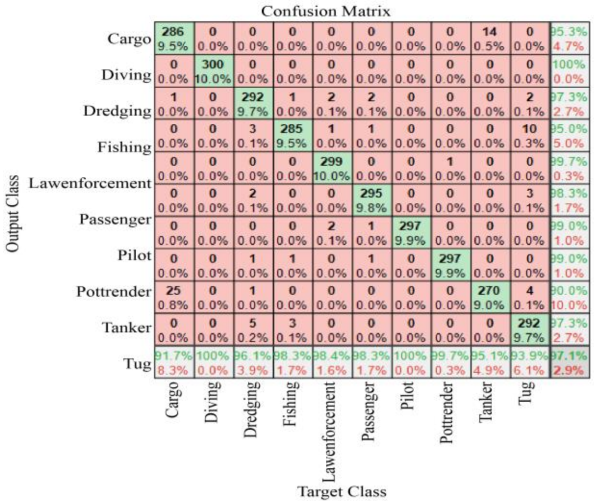

Fig. 3 Confusion matrix for SAR ship recognition

4.10. Comparison of the Proposed CNN Model with State of the Art Machine Learning Techniques

The proposed model is compared with state-of-the-art classification algorithms. The traditional features are extracted from the OpenSARShip dataset and fed to different state-of-the-art classifiers. Since the features are automatically learned in CNN, the manual effort needed for feature design and extraction is eliminated.

Table 11. Comparison of the proposed CNN model with the conventional features and SVM classifier

Traditional Features	Accuracy (%)
Mean	68
Variance	64
ASM	66
Contrast	59
Dissimilarity	60
Entropy	66
Homogeneity	62
HOG	58.2
LBP	79.3
GLCM	75.6
GLCP	79.8
Proposed (MSMPMO CNN)	97.15

Table 11 provides a comparison of the performance of the proposed CNN model with traditional features. The performance of the features with the SVM Classifier is provided.

The proposed CNN Model's performance is superior to traditional features for Ship recognition in SAR images. The performance of the GLCP with different classifiers, provided in Table 12 also implies the superiority of the proposed model.

Table 12. Comparison of the proposed CNN model with the GLCM and different classifiers

Traditional Classifiers	Accuracy (%)
Naïve Bayes	76.2
KNN	71.2
Decision Trees	69.2
Random Forest	74.9
SVM	79.8
Proposed (MSMPMO CNN)	97.15

4.11. Comparison of the Proposed CNN Model with Existing Deep Learning Methods

Table 13 presents the comparison of the proposed model with the existing state-of-the-art pre-trained deep-learning models for Ship recognition in SAR images using the OpenSARShip dataset. As inferred from Table 13, the proposed model performs better than state-of-the-art pretrained deep learning models.

Table 13. Comparison of the proposed CNN model with the state-of-the-art deep learning models

Deep learning Model	Accuracy
GoogleNet	51.6
SqueezeNet	50.03
ShuffleNet	51.03
MobileNetV2	54.5
AlexNet	74.53
ResNet18	55.10
DarkNet19	81.7
Vgg-16	79.43
Proposed (MSMPMO CNN)	97.15

Table 14. Comparison of the computational complexity of the proposed CNN model with the state-of-the-art deep learning models

Model name	Training time of an epoch (hours)	Prediction time per image (seconds)	Parameter quantity (M – million)	Memory consumption (MB – megabyte)
AlexNet	0.01	0.025	62.3 M	144.516 MB
SqueezeNet	0.01	0.002	1.2 M	67.5 MB
Vgg-16	0.37	0.02	138 M	488.227 MB
ResNet18	0.012	0.0027	11.51 M	58.5 MB
GoogleNet	0.04	0.018	5 M	8.255 MB
MobileNetV2	0.13	0.0038	3.5 M	8.393 MB
ShuffleNet	0.08	0.023	5.3 M	8.29 MB
DarkNet19	0.01	0.02	62.2 M	197 MB
Proposed (MSMPMO CNN)	0.2	0.007	328 M	1190 MB

Table 14 compares the proposed CNN's computational complexity with the other state-of-the-art deep learning models. The proposed CNN model performs better than the state-of-the-art deep learning models in terms of ship recognition accuracy.

Table 15. Comparison of performance of proposed CNN model with existing works

Authors	Methodology	Accuracy
Shao et al [20]	CNN with visual attention	83.5
Tianwen et al. [21]	Multi-Scale + Self Attention + HOG feature	78.16
Zhan & Cui [22]	Retinanet + Squeeze and Excitation Module	91.7
Wang et al. [23]	Multi-Scale Feature Attention and Adaptive-Weighed Classifier	79.97
Yu et al. [21]	Improved ResNet	81.4
Arivazhagan et al.	Proposed (MSMPMO CNN)	97.15

Table 15 provides a comparison of the performance of the proposed CNN model with the ship recognition models available in the literature. The proposed CNN model performs better than the existing works in terms of ship recognition accuracy.

5. Conclusion

In this paper, Multi Scale Multi Polarization and Multi Orientation CNN are proposed for feature extraction and classification in SAR-based Ship recognition. Data augmentation techniques are incorporated to mitigate data imbalance and increase the robustness of the model. The ablation studies are performed for 10 class classification problems of SAR ship classification varying the number of scales, orientations and polarizations with different learning algorithms and activation functions. The accuracy of the proposed methodology is better than that of the state-of-the-art algorithms available for SAR ship recognition.

Acknowledgments

The authors would like to thank the Principal and the Management of Mepco Schlenk Engineering College for providing facilities to carry out the research.

References

[1] Zhongzhen Sun et al., "Ship Recognition for Complex SAR Images via Dual-Branch Transformer Fusion Network," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] T. Saleh et al., "Ship Detection in COSMO-SkyMed SAR Imagery Using A Novel CNN-based Detector: A Case Study from the Suez Canal," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 10, pp. 715-722, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] O. Jean-Philippe et al., "Analysis of SAR Images by Multidimensional Wavelet Transform," *IEE proceedings of Radar, Sonar and Navigation*, vol. 150, no. 4, pp. 234-241, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[4] Huan Ruohong, and Yang Ruliang, "SAR Target Recognition Based on MRF and Gabor Wavelet Feature Extraction," *Proceedings of IEEE International Geoscience and Remote Sensing Symposium*, Boston, MA, USA, pp. 907-910, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[5] Wang Lu et al., "A Method of SAR Target Recognition Based on Gabor Filter and Local Texture Feature Extraction," *Journal of Radars*, vol. 4, no. 6, pp. 658-665, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] Yu Qiao, Yue Zhao, and Xiaoyong Men, "Target Recognition in SAR Images via Graph Wavelet Transform and 2DPCA," *Proceedings of the 2nd International Conference on Image and Graphics Processing*, Singapore Singapore, pp. 3-7, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] R. Bhalla, and Hao Ling, "Three-Dimensional Scattering Center Extraction using the Shooting and Bouncing Ray Technique," *IEEE Transactions on Antennas and Propagation*, vol. 44, no. 11, pp. 1445-1453, 1996. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jianxiong Zhou, Zhiguang Shi, and Qiang Fu, "A Novel Scheme for Global Scattering Center Modeling of Radar Targets," *Frontiers of Electrical and Electronic Engineering in China*, vol. 3, pp. 176-182, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[9] Baiyuan Ding, Ao Zhang, and Rui Li, "A 3-D Scattering Centre Model-Based SAR Target Recognition Method Using Multi-Level Region Matching," *Remote Sensing Letters*, vol. 15, no. 3, pp. 215-223, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Ying Xu et al., "SAR Automatic Target Recognition Based on Deep Convolutional Neural Network," *Image and Graphics, 9th International Conference, ICIG 2017*, Shanghai, China, vol. 10668, pp. 656-667, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Yang Li et al., "DeepSAR-Net: Deep Convolutional Neural Networks for SAR Target Recognition," *2017 IEEE 2nd International Conference on Big Data Analysis*, Beijing, China, pp. 740-743, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] Pengfei Zhao et al., "Multi-Stream Convolutional Neural Network for SAR Automatic Target Recognition," *Remote Sensing*, vol. 10, no. 9, pp. 1-22, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ping Lang et al., "LW-CMDANet: A Novel Attention Network for SAR Automatic Target Recognition," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 6615-6630, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Yikui Zhai et al., "MF-SarNet: Effective CNN with Data Augmentation for SAR Automatic Target Recognition," *The Journal of Engineering*, vol. 2019, no. 19, pp. 5813-5818, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Baodai Shi et al., "Synthetic Aperture Radar SAR Image Target Recognition Algorithm based on Attention Mechanism," *IEEE Access*, vol. 9, pp. 140512-140524, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ming Zhang et al., "Convolutional Neural Network with Attention Mechanism for SAR Automatic Target Recognition," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Bo Su et al., "CFCANet: A Complete Frequency Channel Attention Network for SAR Image Scene Classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 11750-11763, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Chenwei Wang et al., "Multiview Attention CNN-LSTM Network for SAR Automatic Target Recognition," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 12504-12513, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Haohao Ren et al., "Extended Convolutional Capsule Network with Application on SAR Automatic Target Recognition," *Signal Processing*, vol. 183, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Jiaqi Shao et al., "A Lightweight Convolutional Neural Network Based on Visual Attention for SAR Image Target Classification," *Sensors*, vol. 18, no. 9, pp. 1-21, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[21] Tianwen Zhang, and Xiaoling Zhang, "A Polarization Fusion Network with Geometric Feature Embedding for SAR Ship Classification," *Pattern Recognition*, vol. 123, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Ronghui Zhan, and Zongyong Cui, "Ship Recognition for SAR Scene Images under Imbalance Data," *Remote Sensing*, vol. 14, no. 24, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] Chenwei Wang et al., "SAR Ship Target Recognition via Multiscale Feature Attention and Adaptive-Weighed Classifier," *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Lei Yu et al., "Recognition Method of Ship Target in Complex SAR Image based on Improved ResNet Network," *Systems Engineering and Electronics*, vol. 44, no. 12, pp. 3652-3660, 2022. [CrossRef] [Google Scholar] [Publisher Link]