Multi-Scale Dense Networks for Ship Classification Using Dual-Polarization SAR Images

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***Abstract*—As one of crucial remote sensing applications, ship classification using synthetic aperture radar (SAR) images has increasingly been studied in modern maritime surveillance. Nowadays, the prevailing classification paradigm for SAR ship targets is to utilize the deep network models, which presents superior performance over the traditional handcrafted feature driven methods. Of which the SAR ship classification method using densely connected convolutional neural networks (CNNs) is among the state-of-the-art. However, the general CNNs cannot fully explore the SAR ship feature representations, which limits its potentials for better classification performance. In this paper, we propose a novel multi-scale framework for the CNNs to further improve the ship classification performance with dual-polarization SAR images. Particularly, the convolutional feature maps from different spatial scales are fused to acquire multi-scale global representations of the dual-polarization SAR images, which are finally integrated by the group bilinear pooling operation in the classification layer and will further be processed by multiple classifiers for better network training. Extensive experiments have proved that the proposed method can improve the robustness and classification performance against the state-of-the-art algorithms on the OpenSARShip datasets.**

***Keywords*—Dense convolutional networks, dual-polarization synthetic aperture radar (SAR) images, group bilinear pooling, multi-scale representations, SAR ship classification**

I. Introduction

With the rapid development of remote sensing systems and intelligent techniques, ship classification using synthetic aperture radar (SAR) images has been of great significance to realize advanced maritime surveillance [1]. For example, due to the powerful advantages of working day-and-night and weather-independence, shipping traffic, fishery management, and coastal monitoring are all practical applications by recognizing the ship types of particular interests in the satellite SAR images [2], [3]. Accordingly, automatic ship classification method has attracted more and more attention in the SAR remote sensing community [4]-[6].

Most of the early SAR ship classification methods resort to the handcrafted designed features, which present clear physical meaning [7]-[10]. For instance, the length, width and length to width ratio of geometric features, the mean radar cross section (RCS) values for different sections of the ship signature, as well as the texture and momentum invariant features are the most commonly used traditional handcrafted features [7]-[10]. The abovementioned features should be carefully designed by the expert experiences. And the extraction process is kind of a trivial problem, which is a little of time-consuming. Moreover, there usually exists feature redundancy and mismatch between the handcrafted features and the selected classifier [11]. Therefore, more effective SAR ship feature extraction methods and novel classification scheme should be particularly developed.

Motivated by the groundbreaking achievements of the deep learning methods, more and more researchers of the SAR remote sensing community started to apply the deep neural network models, especially the convolutional neural networks (CNNs) [12], to improve the SAR ship classification performance. Many of the researchers proposed to construct customized deep network models based on the characteristics of SAR ship images. For example, Bentes *et al*. [13] proposed a multiple input resolution CNN model to improve the SAR ship representation ability. Wang *et al*. [14] and Li *et al*. [15], respectively, developed deep learning methods to cope with the small sample and unbalanced dataset of SAR ship classification issues. He *et al*. [16] and Dong *et al*. [17] proposed to develop modified domain-specific CNN models from the advanced dense convolutional network (DenseNet) [18] and residual network (ResNet) [19] to perform ship classification in high resolution (HR) and medium resolution (MR) SAR images respectively, which are among the state-of-the-art methods. Additionally, Zhang *et al*. [20] developed a lightweight CNN model to cope

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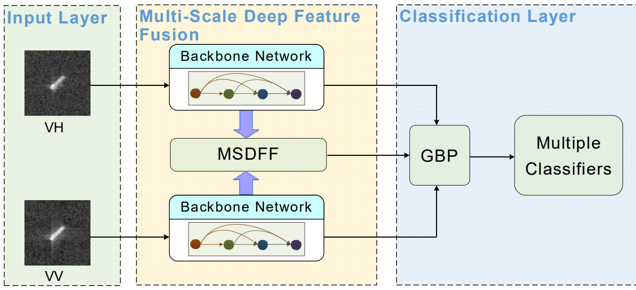

Fig. 1. Overall framework of the proposed MS-GBCNN model. MSDFF indicates the multi-scale deep feature fusion module. GBP indicates the group bilinear pooling module [23].

with the imbalanced high-resolution SAR ship recognition problem, and Anil Raj *et al*. [21] proposed to use hybrid Siamese network to deal with the more challenging one-shot learning SAR ship classification issue.

To further improve the SAR ship classification performance by using the deep learning methods, a lot of works proposed to utilize the polarization property of SAR images for better SAR ship representations [22]-[26]. He *et al*. [22], [23] first proposed to apply the bilinear pooling [27] to the convolutional feature maps derived from the VH and VV polarization SAR images, and further proposed the group bilinear pooling CNN (GBCNN) model to achieve superior classification performance. Xi *et al.* [24] designed a fusion loss imposed on the proposed feature-loss double fusion Siamese network (DFSN) for dual-polarized SAR ship classification. Likewise, Zeng *et al.* [25] also developed a hybrid channel feature loss (HCFL) for deep CNN features to jointly utilize the information contained in the dual-polarized SAR images. Additionally, Zhang and Zhang [26] proposed a squeeze-and-excitation Laplacian pyramid network with dual-polarization feature fusion (SE-LPN-DPFF) to promote the SAR ship classification.

Considering the abovementioned deep neural network models for SAR ship classification, one can find that most of them exploited the simple convolutional network framework or the modified advanced CNN models directly to the single/dual-polarized SAR ship images, which cannot adequately explore the deep SAR ship representations restricted by the plain processing framework of the CNNs. One promising way to improve the representation ability of deep features is to employ the multi-scale deep features fusion strategy, as the multi-scale CNN (MS-CNN) model did in [28]. However, the MS-CNN model is specifically designed for the single polarization SAR images, which has limited performance. Therefore, for superior performance consideration, this paper is dedicated to develop a novel multi-scale deep feature fusion (MSDFF) scheme based on our pre-proposed GBCNN model [23] for dual-polarized SAR ship representations. We call it the MS-GBCNN model. Then, the multi-scale SAR ship deep features, as well as the last convolutional feature maps, are individually integrated by the group bilinear pooling (GBP) module [23] for the dual-polarized SAR images, which are then separately sent to the Softmax classifier [16] for the final prediction.

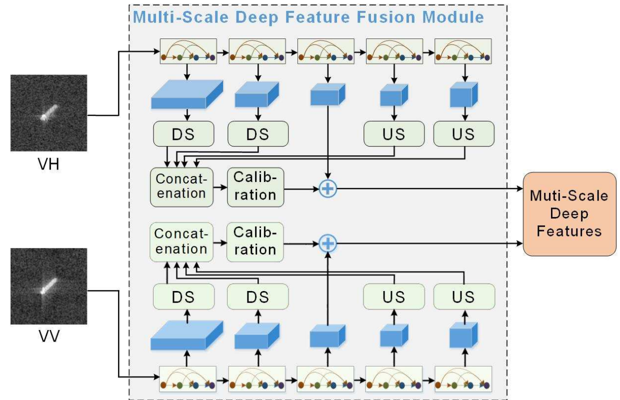

Fig. 2. Schematic structure of the MSDFF operated on the DB3. DS means the downsampling operation and US means the upsampling operation.

II. Proposed Methodology

A. *Overiew of the Proposed Methodology*

As Fig. 1 shows, the proposed MS-GBCNN model is mainly comprised of three parts, i.e., the dual-polarized SAR images input layer, the multi-scale deep features fusion layer, and the classification layer consisting of the GBP and the multiple classifiers. The paired VH and VV polarization SAR images are first separately sent to two structure-equal densely connected CNNs to derive the multi-level deep features, which are then processed by the MSDFF module. Finally, the multi-scale deep features and the last convolutional feature maps are separately integrated by the GBP module. Thus, the global representations of different spatial scales are obtained, which will be transformed by the multiple classifiers to the final predictions.

B. *Multi-Scale Deep Feature Fusion*

Similar to our previous works [16], [23], the modified DenseNets, particularly the SAR-DenseNet-v1 model [23], is still utilized as our backbone network to derive deep SAR ship representations. One can refer to [16], [23] for more details. In order to acquire coarse-and-fine deep features, this paper proposes the MSDFF scheme to enhance the SAR ship representations. As shown in Fig. 2, taking the scale of the third dense block (DB3) for example, the feature maps from other scales are fused to the specified scale. That is to say, the feature maps from the DB1 and DB2 are down-sampled to the size of the DB3 by the average pooling [18], and the feature maps from the DB4 and DB5 are up-sampled to the size of the DB3 by the transposed convolution [29]. Then, the transformed feature maps are concatenated and calibrated to the channel number of DB3 by an 1×1 convolution layer. Inspired by the ResNet [19], the calibrated feature maps are added to that of the DB3 by a residual connection to further improve the feature representation. The above operations are equally applied to the other scales. Hence, the enhanced multi-scale deep features are obtained for the dual-polarized SAR ship images, which will be integrated through the GBP module. Please note that, to reduce the computational burden and interferences of the fine scales, the multi-scale operation is applied only to the DB3 and DB4, respectively.

TABLE I

STATISTICS OF THE PAIRWISE EXPERIMENTAL DATASET [16]

Category	Tanker	Container ship	Bulk carrier	Cargo	General cargo
Training	280	167	632	707	91
Test	80	50	170	270	30
Total	360	217	802	977	121

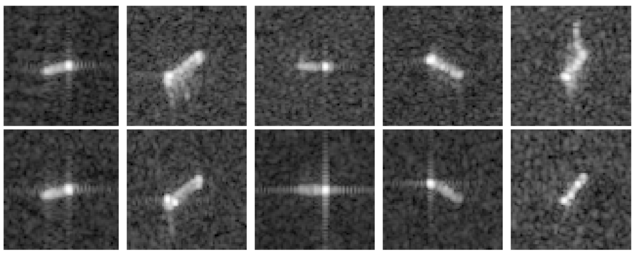

Fig. 3. Examples of the five category ship targets [23]. The first and second rows are, respectively, the VH and VV polarization SAR ship samples. From left to right: tanker, container ship, bulk carrier, cargo, and general cargo.

C. Training Scheme With Multiple Classifiers

After obtaining the multi-scale deep features of the paired dual-polarized SAR ship images, we employ the GBP method [23] to integrate them. The core operation is given as follows

$$\boldsymbol{z}^{G} = \left[\boldsymbol{B}(\boldsymbol{F}_{\mathrm{VH}}^{i}, \boldsymbol{F}_{\mathrm{VV}}^{j}) \right]_{\substack{1 \le i \le G \\ i \le j \le G}} \tag{1}$$

where the multi-scale feature maps $\boldsymbol{F}$ are divided into G groups with each containing d sub-feature maps, i.e., $\boldsymbol{F} = \{\boldsymbol{F}^{i} \mid \boldsymbol{F}^{i} \in \mathbb{R}^{H\times W\times d},\ i = 1, 2, ..., G\}$. H and W are respectively the height and width of the feature maps. $\boldsymbol{B}(\cdot,\cdot)$ represents the bilinear pooling [27], and $[\ \cdot\ ]$ refers to the concatenation of the vectorized bilinear vectors [23]. The last convolutional feature maps are processed the same as that in [23] by the GBP to derive the multi-polarization fusion loss (MPFL).

To deeply supervise the learning process of the network, we propose to introduce the multiple classifiers scheme to compute the final loss function and predictions. In addition to the MPFL loss, the multi-scale global bilinear vectors are also fed into the cross entropy loss [16], [23] function as follows

$$L_{\mathrm{DB}_j} = -\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{y}_i^{T} \log(\boldsymbol{S}_{\mathrm{DB}_j}(\boldsymbol{x}_i^{\mathrm{VH}}, \boldsymbol{x}_i^{\mathrm{VV}})) \tag{2}$$

where $\boldsymbol{y}_i$ is a one-hot vector representing the ground-truth class labels, N is the total number of training samples, and $\boldsymbol{S}_{\mathrm{DB}_j}(\boldsymbol{x}_i^{\mathrm{VH}}, \boldsymbol{x}_i^{\mathrm{VV}})$, j = 1, 2, 3, 4, 5, is the output of the softmax function for the multi-scale global bilinear vectors of the paired VH and VV polarization SAR images. As noted in Section II-B, the multi-scale losses are only computed for DB3 and DB4. Therefore, the final loss function to train the networks are defined as follows

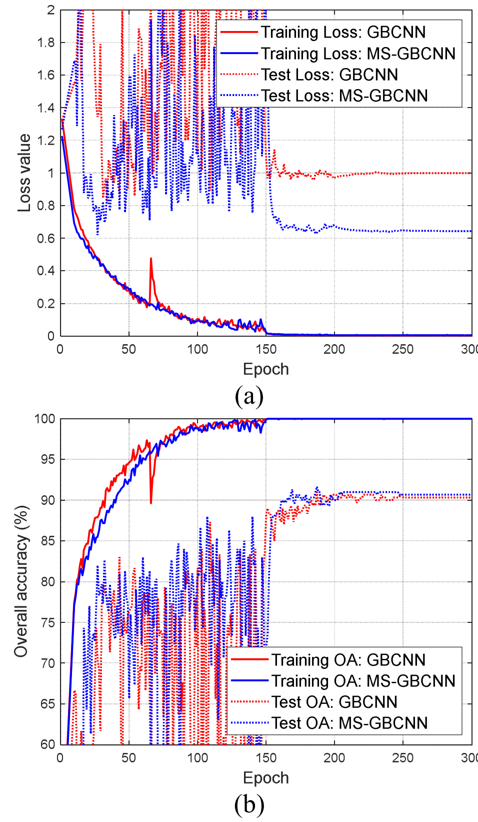

Fig. 4. Evaluation of the MSDFF scheme by the (a) loss value and (b) overall accuracy for the training and test sets with the best performance.

$$L = \mu(L_{\mathrm{DB}_3}/S + L_{\mathrm{DB}_4}/S) + (1-\mu)L_{\mathrm{MPFL}} \tag{3}$$

where μ is a hyperparameter to balance the importance between the multi-scale and MPFL loss terms, and S is the number of scales which equals to 2 here. In our experiments, μ is set as 0.5 to equally balance the two loss terms, which works well in practice. For inference, similar to the method in [23], the predictions from the multiple Softmax classifiers are averaged for final ship categorization.

III. EXPERIMENTS AND ANALYSIS

A. Experimental Setup and Evaluation Metrics

All the experiments are conducted on a PC workstation with the NVIDIA GeForce RTX 2080 Ti GPU (11 GB) and a 32-GB CPU memory. The network training and testing are conducted using the TensorFlow deep learning library.

Similar to the previous works [14]-[16], [22]-[26], [28], the three- and five-category SAR ship datasets developed in [16] from the OpenSARShip database [5] are used for algorithm evaluation. The paired VH and VV ground range detected (GRD) amplitude data, including the training and test sets splitting according to [16], [22], [23], are shown in Table I. The first three types served for the three category classification task. Some examples of the five category ship targets that are easily to be misclassified [23] are shown in Fig. 3. In line with [16], [22],

TABLE II

COMPARISON WITH STATE-OF-THE-ART METHODS ON THE THREE-CATEGORY TEST SET (%)

Method	Metrics (mean ± std.)			
	R	P	F_1	OA
DFSN	82.73 ± 1.35	86.41 ± 2.86	84.51 ± 1.89	86.80 ± 1.32
HCFL	83.08 ± 1.70	85.08 ± 0.79	84.06 ± 1.02	86.60 ± 0.86
SE-LPN-DPFF	69.51 ± 1.84	62.38 ± 1.33	65.76 ± 1.56	63.87 ± 1.30
GBCNN	85.25 ± 2.04	88.04 ± 2.04	86.61 ± 1.77	88.80 ± 1.15
MS-CNN	76.67 ± 2.52	74.07 ± 1.84	73.71 ± 2.21	77.67 ± 1.06
MS-GBCNN	**85.34 ± 1.75**	**87.78 ± 1.97**	**86.54 ± 1.55**	**88.93 ± 1.09**

TABLE III

COMPARISON WITH STATE-OF-THE-ART METHODS ON THE FIVE-CATEGORY TEST SET (%)

Method	Metrics (mean ± std.)			
	R	P	F_1	OA
DFSN	55.07 ± 2.51	56.11 ± 2.22	55.57 ± 2.07	64.53± 1.88
HCFL	56.05 ± 1.86	54.51 ± 2.69	55.25 ± 2.02	64.00 ± 2.26
SE-LPN-DPFF	38.56 ± 1.49	32.99 ± 1.12	35.55 ± 1.15	33.20 ± 1.30
GBCNN	57.79 ± 2.03	57.33 ± 1.93	57.54 ± 1.66	66.90 ± 1.20
MS-CNN	59.55 ± 3.76	51.03 ± 1.55	52.95 ± 1.60	55.34 ± 1.55
MS-GBCNN	**57.65 ± 1.43**	**58.14 ± 1.84**	**57.89 ± 1.57**	**67.03± 1.06**

[23], the results are reported by the mean and standard deviation of the five splits randomly applied to the curated datasets. The data preprocessing, augmentation, and training details are all in accordance with that in [16], [22], [23].

According to the evaluation metrics in [13], [14], [23], [26], we also select the overall accuracy (OA), being defined as the ratio of the number of the correctly classified ship samples to that of the total samples in the test set, the precision (P), recall (R), and F1 measure for comprehensive evaluation. The computation methods for the last three metrics conform with that in [23].

B. *Evaluation of the MSDFF Scheme*

Above of all, based on the benchmarking GBCNN model [23], we evaluate the robustness and convergence performance of the proposed MS-GBCNN method. Similar to [23], we plot the varying curves of the OA and the final cross entropy loss values of (3) for the GBCNN and MS-GBCNN models, which are shown in Fig. 4. The evaluation values are recorded from the experiment with the best performance in terms of OA. As indicated in Fig. 4, compared to the GBCNN model, one can find that the training process of the MS-GBCNN model is much more robust and has lower loss values, which indicates that the MS-GBCNN model has more powerful ability of deep feature representation. And the generalization ability of the MS-GBCNN model is much better. Therefore, the proposed method is superior in the robustness and convergence performance.

C. *Comparision With the State-of-the-Art Methods*

To comprehensively evaluate the proposed method, extensive experiments are conducted to compare the proposed method with the state-of-the-art algorithms. Aiming at the dual-

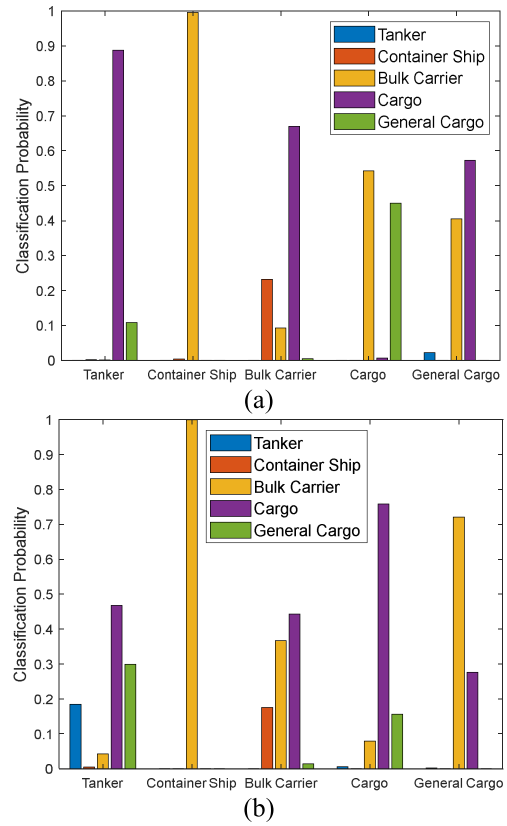

Fig. 5. The predicted results of the five ship targets presented in Fig. 3 are obtained by the (a) GBCNN and the (b) MS-GBCNN, respectively. The ship types of the horizontal axis are the ground-truth classes, and the classification probability values of the vertical axis are the predicted values of the GBCNN and MS-GBCNN coresponding to each category, respectively.

polarized SAR ship classification task, the GBCNN [23], the DFSN [24], the HCFL [25], and the SE-LPN-DPFF [26] are selected as the comparing methods. The implementation details and experimental results are consistent with that in [23]. In addition, we also make comparation with the MS-CNN model [28] in which the multi-scale scheme is applied to the CNNs by simply integrating the logits from different scales. Since the MS-CNN model is applied to the single-polarization SAR images, we extend it to the dual-polarized conditions by performing the MS-CNN on the paired VH and VV SAR ship images and then adding the logits of the two branches, which are finally sent to the Softmax classifier. The experimental results for the three- and five-category SAR ship datasets are listed in Tables II and III, respectively.

Observing the results of the Tables II and III, we can conclude that the proposed MS-GBCNN model can achieve more robust and superior performance compared with the state-of-the-art algorithms. Specifically, most of the evaluation metrics of the MS-GBCNN have much larger margins than the DFSN, the HCFL, the SE-LPN-DPFF and the MS-CNN methods. The overall performance of the MS-GBCNN is slightly better than that of GBCNN. By comparison with the GBCNN, the MS-GBCNN can decrease the classification error to 11.07% and 32.97% for the three- and five-category SAR ship datasets, respectively. Especially for the five-category SAR ship

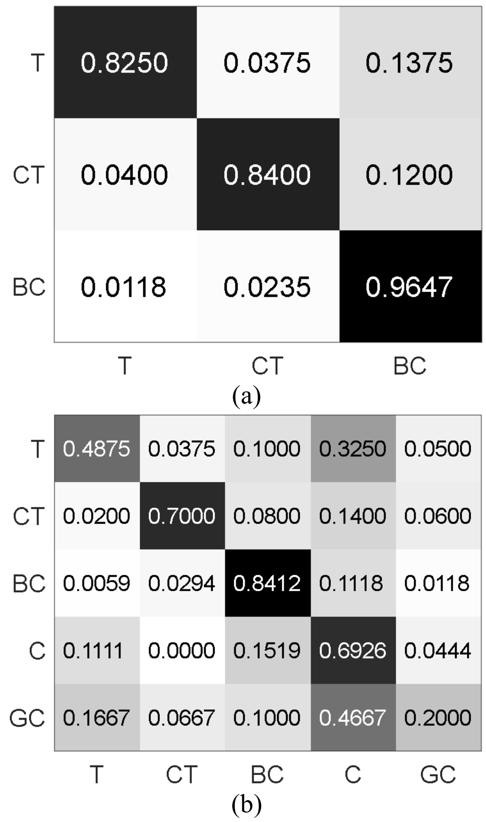

Fig. 6. Confusion matrices of the best performant results obtained via MS-GBCNN for the (a) three- and (b) five-category classification tasks, respectively.

dataset, the MS-GBCNN model has much better performance in terms of the precision and F1 measure metrics, which indicates the great potential of the MS-GBCNN to deal with more ship types under complex conditions. All these benefit from the powerful deep feature representation ability of the proposed multi-scale scheme, as the MS-GBCNN model can capture the coarse and fine deep feature representations via an integrating framework. However, due to the heavy computation cost of the original DenseNet, the proposed method is being critical of the time consumption to some extent. Hence, we will seek more efficient network architecture to further improve the comprehensive performance of the MS-GBCNN model.

D. Extensive Evaluation for the MS-GBCNN

We further validate the advantageous performance of the MS-GBCNN on the five-category SAR ship dataset. Based on the GBCNN and the proposed MS-GBCNN, the classification probabilities of the five ship targets shown in Fig. 3 are illustrated in Fig. 5. From Fig. 5(a), one can find that the predicted results of the GBCNN are all misclassified into either the cargo or the bulk carrier that have relatively sufficient samples. However, in Fig. 5(b), the misclassified cases for the five ship targets are alleviated by the proposed MS-GBCNN model, and the cargo ship is correctly classified. Therefore, the proposed MS-GBCNN model is superior to the GBCNN model.

In addition, as shown in Fig. 6, we present the confusion matrices for the three- and five-category classification tasks similar to that in Fig. 4. For simplicity, we denote the five ship types of the tanker, container ship, bulk carrier, cargo, and general cargo as T, CT, BC, C, and GC, respectively. From the Fig. 6, we can conclude that the proposed method can achieve a quite balanced performance for each of the SAR ship types. For example, in the three-category classification task, even the container ship has the fewest samples, the MS-GBCNN model can still acquire comparable or better performance to other two ship types. And the MS-GBCNN model can also generalize well for the five-category classification task.

IV. Conclusion

To realize the joint representation of multi-level deep features for the dual-polarized SAR ship images, this paper proposes a multi-scale dense convolutional neural network (DenseNet) model combined with the group bilinear pooling (GBP) integrating strategy, which is referred to as MS-GBCNN model. The MS-GBCNN first utilize two structure-equal DenseNets to extract the feature maps of different spatial scales. Then, the multi-scale deep feature fusion (MSDFF) module is applied to these deep features in a residual connection style. In this way, the improved multi-scale deep feature representations for the dual-polarized SAR ship images are acquired, which are finally integrated by the GBP technique. The overall framework is trained end-to-end by the multiple classifiers computed from the resulting global bilinear vectors. The MS-GBCNN model achieves the new state-of-the-art performance on the three- and five-category SAR ship datasets of the OpenSARShip database. As future work, the adaptive weighting scheme of the multiple classifiers will be studied to improve the flexibility of the MS-GBCNN. And we will also test the robustness and generalization ability of the proposed MS-GBCNN model using higher resolution SAR ship data, such as the data resources from the Cosmo-SkyMed, TerraSAR-X, TanDEM-X and RADARSAT-2 satellites under different sea state conditions.

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