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Synthetic Aperture Radar Automatic Target Recognition Based on a Simple Attention Mechanism

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Abstract

A simple but effective channel attention module is proposed for Synthetic Aperture Radar (SAR) Automatic Target Recognition (ATR). The channel attention technique has shown recent success in improving Deep Convolutional Neural Networks (CNN). The resolution of SAR images does not surpass optical images thus information flow of SAR images becomes relatively poor when the network depth is raised blindly leading to a serious gradients explosion/vanishing. To resolve the issue of SAR image recognition efficiency and ambiguity trade-off, we proposed a simple Channel Attention module into the ResNet Architecture as our network backbone, which utilizes few parameters yet results in a performance gain. Our simple attention module, which follows the implementation of Efficient Channel Attention, shows that avoiding dimensionality reduction is essential for learning as well as an appropriate cross-channel interaction can preserve performance and decrease model complexity. We also explored the One Policy Learning Rate on the ResNet-50 architecture and compared it with the proposed attention based ResNet-50 architecture. A thorough analysis of the MSTAR Dataset demonstrates the efficacy of the suggested strategy over the most recent findings. With the Attention-based model and the One Policy Learning Rate-based architecture, we were able to obtain recognition rate of 100% and 99.8%, respectively.

Keywords

Attention Mechanism, Automatic Target Recognition, Deep Convolutional Neural Network, Synthetic Aperture Radar.

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I. Introduction

Images of the Earth's surface taken by employing Synthetic Aperture Radar (SAR) systems, an observation tool, regardless of the weather condition, is referred to as SAR images. The SAR Automatic Target Recognition (ATR), which is an essential part of SAR image interpretation, is one long-term research complex problem for researchers across the globe since it is generally applied in not only the military field but also in the civilian ones mainly since it is usable in any weather and time of the day. Contrary to the optical images with colors considered rich, SAR images can be distinguished by the possession of solid grayscale pixels with regions that have high intensities representing the targets. SAR image classification, which tags per pixel in accordance with one or more retrieved characteristics, is crucial to SAR image comprehension. In a broad sense, SAR image analysis might be used widely in a variety of fields, including monitoring of the environment and natural resources [1], hydrological and agribusiness modeling [2], and urban planning [3]. The architecture of SAR ATR which is basic is composed of three components which are detection and discrimination, alongside classification [4]. In the first component – detection, target regions or areas are extracted by a detector named Constant False Alarm Rate (CFAR) detector [5]. In the second component – discrimination, the application of the discriminator is for the identification of the candidate areas that are located by the targets with respect to the output of stage one. The third component – classification makes use of a classifier to identify the category of every target type.

Convolutional Neural networks (CNN) that are deep learning-based have been seen as one of the approaches that are extensive enough to both classify and detect SAR images. Nevertheless, with the limitation in available data for SAR images [6], employing the convolutional neural network for the SAR ATR task results in overfitting (when a model fits exactly against its training data, resulting in a poor performance against unseen data, defeating its purpose). There were three rudimentary steps taken to address this complication. The first option we call the transfer learning [7] mechanism. Here, a CNN is pre-trained using huge and extensive data before calibrating the model again for precise SAR recognition problems. However, the disparity between SAR and optical images causes low-performance accuracy in SAR Images. On the other hand, a number of unmarked SAR images

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could be a good replacement for optical ones. The third option is image enhancement [8]. However, this method is not usually considered in most studies. Furthermore, the performance of the outcome of the studies employing image enhancements via CNNs models was not promising. This can be explained by the need to substantially strengthen the CNN Algorithm employed in these studies.

The master plan for refinement regarding the architecture of CNN generally consists of the expansion of the network's deepness and breadth. However, when the deepness is further stretched, there is a greater possibility of the network running into the challenge of vanishing/exploding gradients [9][10]. To resolve this challenge, ResNet [11] was proposed by Kaiming et al., which is composed of many residual modules that are superimposed. After the fusion of two layers, each dynamic ranges the value of the input and that of the output. Applying the principle of similarity projection makes the optimization of the variables' weighting on the network levels more rational. Additionally, this aids in stopping the problem of contours that dissipate or explode when the range is increased. For instance, in the recognition challenge utilizing the ImageNet data, the loss observed was decreased to roughly 3.57% when a deeper ResNet is made of tiers that exceed 100 [11]. Although it is known that the expansion of the depth of the network does not go on without bounds since one that is too deep is most likely to lead to overfitting. The other possible expansion is in the width of the architecture leading to the extraction of more features which is an advantage but may lead to generating more parameters and increasing the computational requirement as well as leading to overfitting.

This paper introduces a new attention-based ResNet architecture appropriate for the SAR recognition task to address this problem. This architecture focused more on extracting features because of the fewer representatives obtained from images of SAR. We summarize our key contributions as follows.

- We propose a simple channel attention mechanism for SAR ATR involving only a handful of parameters while attaining clear performance gains by eliminating discretization and using the right cross-channel interaction.
- We also explore the use of one policy learning rate in the ResNet backbone for SAR ATR.
- Finally, tests were done to see how well the proposed simple channel attention and the one policy learning rate worked on the ResNet-50 architecture for SAR ATR.

The following is how this document is organized: Section II reviews the theory of SAR ATR and attention mechanism for image recognition and classification, followed by the proposed integration of the Simple Channel Attention module in ResNet-50 architecture in Section III. Section IV provides the dataset and data preprocessing while the experimental results and analysis are seen in Section V. We concluded in Section VI.

II. Related Works

A. Introduction

Present-day major methods of classifying SAR-ATR are commonly subdivided into three methods which are template-based [12], model-based [13], and pattern-based [14]. The classic system of SAR-ATR that is template-based puts the least Mean Square Error (MSE) criteria to get the type of the target from a stored database used as a reference for the target images or templates [15]. The system that is model-based examines the detail of every image and finds out the contribution of every part of its recognition [16]. Weighed against the other two methods, the strategy that is based on the principle of pattern recognition devoted an outstanding contribution to the task of image classification in the years past. The architecture that is pattern-based is designed for the extraction of features by initiating extractors of features which transforms the raw image to feature vectors with low dimensions. The output vectors are then categorized into groups by the classifier. A couple of ATR algorithms have seen a wide application for the classification of SAR images as well as their recognition, Artificial Neural Networks (ANN) being an example [17] with Support Vector Machine (SVM) [18] and Convolutional Neural Networks (CNN) [19] being other examples.

Not very long ago a significant surge was ignited in the field of pattern recognition by deep learning algorithms which transcended with high recognition in the interpretation of images in remoting sensing [20]. This includes recognition of SAR targets where deep learning models, such as autoencoder and CNN, have found successful applications. Knag et al. [21] used a stacked autoencoder which they developed to achieve feature fusion by applying that to SAR target classification. The utmost often used deep learning technique for SAR image classification and recognition is the CNN, with several high-content articles employing different training methods and architectures. CNN was first employed and verified by Morgan [22] for SAR Target classification. The structure of All-Convolution Networks (A-ConvNets) was proposed by this author for SAR target classification. We saw the use of CNN architecture which experimented with the MSTAR dataset for SAR target recognition in another research work [19]. The results demonstrate that the recognition rate may be considerably improved using CNN. When the convolutional layer is employed in another study [23], instead of the fully connected layer in CNN, the over-fitting concern is amazingly minimized, the parameter count is reduced, and the recognition rate is subsequently increased. Due to small samples of MSTAR datasets and overfitting, Li et al. [24] used an autoencoder to prepare the network beforehand, and the SAR images used by Jun et al. [8] were modified to enhance the sample size. Some researchers improved the network structure to improve CNN recognition performance. Zhuangzhuang [25] increased the class differentiating the performance of CNN, employed SVM for information classification, and added the class conditional independence measurement to the error cost function.

Other strategies, such as inception [26][27] and Xception [28], were put out to enhance the CNN model performance and further address the problem. The inception/X-caption techniques do not only expand the width but also split the number of channels into independent sections. The sections having varying configurations are the concatenation fusion of the feature extraction obtained from various scales so that there can be enough features acquired and work at preventing computational complexity. A network architecture that is a combination of inception module and ResNet called Inception-ResNet was proposed recently with the aim of considering both the depth and width simultaneously. Even though these techniques have been shown to improve performance for the classification of optical images, they are not applied in the field of SAR images yet. Moreover, the attributes of the images from SAR differ from those of optical images. Thus, it is theorized that it is not suitable to use methods that perform well in optical images directly for the SAR-ATR field, as such there is a need for improvements.

To further improve CNN's recognition rate and adaptability for SAR ATR, this study offers integration of simple channel attention in the ResNet-50 architecture. The simple channel attention achieves better performance by applying dimensionality reduction during learning and an appropriate cross-channel interaction to decrease model complexity. Our findings provide further evidence that our method can raise classification accuracy for the MSTAR database.

B. Attention Mechanism

A conceptual system that resembles brain activity is called the Attention Mechanism (AM) [29]. AM primarily emphasizes the important aspects while suppressing irrelevant details. With minimal cost, the AM may be added to the CNN architecture and trained alongside the CNN [30]. Attention modules vary according to their implementation ideas, such as the Convolutional Block Attention Module (CBAM) [31] which paves the path for diverse feature maps to automatically learn pixel relationships and Channel Attention Modules which create a weight matrix to assess each channel's significance. In addition to channel attention, the spatial attention module, which accumulates the weight matrix of characteristics in a spatial context, focuses on "where" relevant information might be obtained.

This study focused on the channel attention mechanism, improving deep Convolutional Neural Networks (CNNs). Nevertheless, most current approaches are intended to build more advanced modules of attention for improving performance, thereby increasing the complexity of the model. This paper proposed Simple Channel Attention (SCA) which simply requires a few arguments while attaining apparent performance gain on SAR ATR.

III. Proposed Architecture

Considering that SAR image is substantially less vulnerable to reflection circumstances, overfitting is prone to happen while training CNN using SAR raw data. Since CNN is made up of huge parameters, there is severe overfitting because there aren't enough training data. By using an attention technique, this article streamlines the utilization of ResNet topology. Top-down convolutional layers gain the feature maps from the ResNet backbone network. An attention mechanism is then used to process each feature map. The results obtained using the attention mechanism are then passed through a fully connected layer that gives through the feature vectors. The final feature map is then passed through our classifier, and the classification results are acquired at the end.

A. Proposed Simple Attention Mechanism

The Channel Attention mechanism demonstrated high-performance results in improving deep CNNs. SE-Net [32] provides us with a useful method to examine channel attention and exhibits encouraging results. Therefore, the attention-module design may be classified in two ways: (1) improved feature aggregation; (2) pairing the channel and spatial attention. The proposed attention mechanism concerns the efficient convolutions designed for lightweight CNNs. Our simple channel attentions focus on the neighborhood interconnected interaction, similar to channel local attention [33] and channel-wise convolution [34]. In contrast, our approach probes a 1D convolution with adjustable Gaussian kernel size to replace fully connected layers in the channel attention module. Following the parameters of channels attention in SE Block, we assume

$$y = g(X), f_{\{w_1,w_2\}} \text{ takes the form } f_{\{w_1,w_2\}}(y) = W_2 ReLU(W_1 y) \quad (1)$$

Where $g(X) = \frac{1}{W\,H}\sum_{i=1,\ j=1}^{W,\ H} X_{i,j}$ denotes channel-wise global average pooling (GAP) and ReLU activation function [35]. We set the sizes of w_1 and w_2 to $C * \left(\frac{C}{r}\right)$ and $\left(\frac{C}{r}\right) * C$ to prevent high model complexity. As much as Eq. (1), reducing dimensionality can minimize the model computational cost. It disrupts the weights' and the channel's straight relationship.

Both the efficiency and effectiveness of our simple channel attention mechanism can be guaranteed by using the band matrix w_k of efficient channel attention to getting the interaction of the local cross-channels. We defend the band matrix w_k thus;

$$\begin{bmatrix} w^{1,1} & \cdots & w^{1,k} & 0 & 0 & \cdots & \cdots & 0 \\ 0 & w^{2,2} & \cdots & w^{2,k+1} & 0 & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & w^{C,C-k+1} & \cdots & w^{C,C} \end{bmatrix} \quad (2)$$

Where w_k in Eq. (2) involves $k * C$ parameters and the weight of y_i is computed by solely taking into account the association between k neighbors of y_i thus

$$w_i = \sigma\left(\sum_{j=1}^{k} w_i^j\, y_i^j\right), y_i^j \in \Omega_i^k \quad (3)$$

Where Ω_i^k explains k adjacent channels of y_i in sets. To distribute a constant learning rate per channel, Eq. (3) can be rewritten as follows:

$$w_i = \sigma\left(\sum_{j=1}^{k} w^j\, y_i^j\right), y_i^j \in \Omega_i^k \quad (4)$$

Which can only be executed by a fast $1D$ convolution with k kernel. Since our attention module is directed at capturing local cross-channel interaction, the $1D$ convolution kernel size k needs to be computed; thus, we adopt the below equation [5];

$$k = \psi(C) = \left|\frac{log_2(C)}{\gamma} + \frac{b}{\gamma}\right|_{odd} \quad (5)$$

Where $|t|_{odd}$ denotes the nearest odd number of t. Note: we set γ and b to 3 and 1 respectively according to our experiments. Fig. 3 illustrates the implemented attention mechanism.

B. One Policy Learning Rate

The learning rate is a hyper-parameter that determines how far our network's weights are adjusted in response to the loss gradient. Conventionally, we begin training the model by gradually raising the learning rate from low to high, halting when the loss becomes uncontrollable. As a result, getting it correctly might not be easy, as shown in Fig. 1. Mathematically we have:

$$\theta_1 := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_1) \quad (6)$$

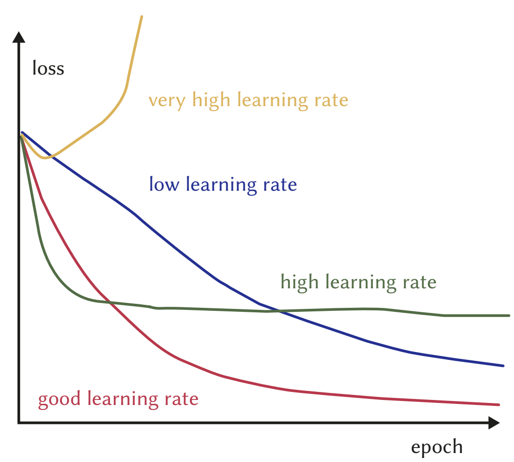


Fig. 1. Convergence effects of illustration of learning rates.

Gradient descent can be sluggish if it is too small or might overshoot the minimum if it is too great. It might either fail to converge or diverge right. Smith [36] stated that one might estimate a reasonable learning rate by first training a model with a low learning rate and then raising it (either gradually or rapidly) during every iteration, a process she called one policy learning rate. A learning rate scheduler approach enables (1) quicker network training and (2) a better understanding of the ideal learning rate. Several parameters are held constant during the experimentation, and the best learning rate is determined as the training advances. Weight decay, maximum learning rate, optimizer, and initial learning rate are examples of such parameters, with weight decay updating the learning rate by a critical factor in each epoch.

C. Backbone Network

This paper used a lightweight deep learning network (ResNet50[11]) as its proposed model backbone, a deep convolutional neural network with a light design. It has 50 layers that, instead of learning unattributed functions, redefine as residual functions using the layer inputs. A stack of similar or "residual" blocks makes up the ResNet architecture. This block functions as a convolutional layer stack. A block's output is also related to its input through an identity mapping mechanism. The feature mapping is continually down-sampled via depthwise convolution and the expansion in channel depth to retain the computational complexity per layer. To enable a lower computational workload while computing the 3x3 convolutions in the ResNet50 model, we have a three-layer bottleneck block that employs three convolutions to reduce and restore channel depth. We denote the flow chat diagram of our proposed architecture in Fig. 2.

D. Proposed Architecture Summary

Investigating how well the squeeze-and-excitation network (SENet) performs is the suggested model's main objective, which is the learning of channel attention to every convolution block and results in noticeable performance gains for various deep CNN architectures [37]-[40]. Although SeNet obtains higher precision, it frequently results in higher computational costs and a heavier computational complexity [11]. This paper concentrated on only three convolutional blocks while avoiding dimension reduction and accurately preserving cross-channel interaction as seen in Fig 4.

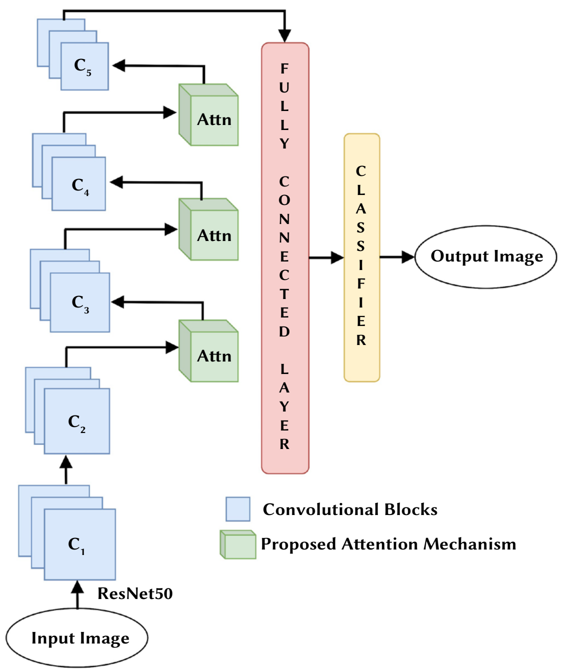


Fig. 2. Flowchart of the proposed architecture.

IV. Experiment

A. Dataset and Data Pre-Processing

We used the MSTAR data for our experiment and evaluations. It was created using stationary SAR and target measurements that were released by the MSTAR research and funded by the Air Force Research Laboratory (AFRL) and the Defense Advanced Research Project Agency (DARPA) [41]. It comprises ten types of tactical ground targets, as depicted in Fig. 5. The images at a 17° angle of depression were used for training while using the images at a 15° angle of depression for testing, as seen in Table I. In contrast, Table II illustrates the actual target model vs. the number of images. We used the original preprocessed data [41] in our experiment as a preprocessing technique. Before feeding to our network, all image is resized to a fixed size of 224 x 224 after some data augmentation such as random rotation and normalizing.

TABLE I. MSTAR Dataset Partition

	Angle	Total Number
Training Set	17°	2,752
Testing Set	15°	2,425

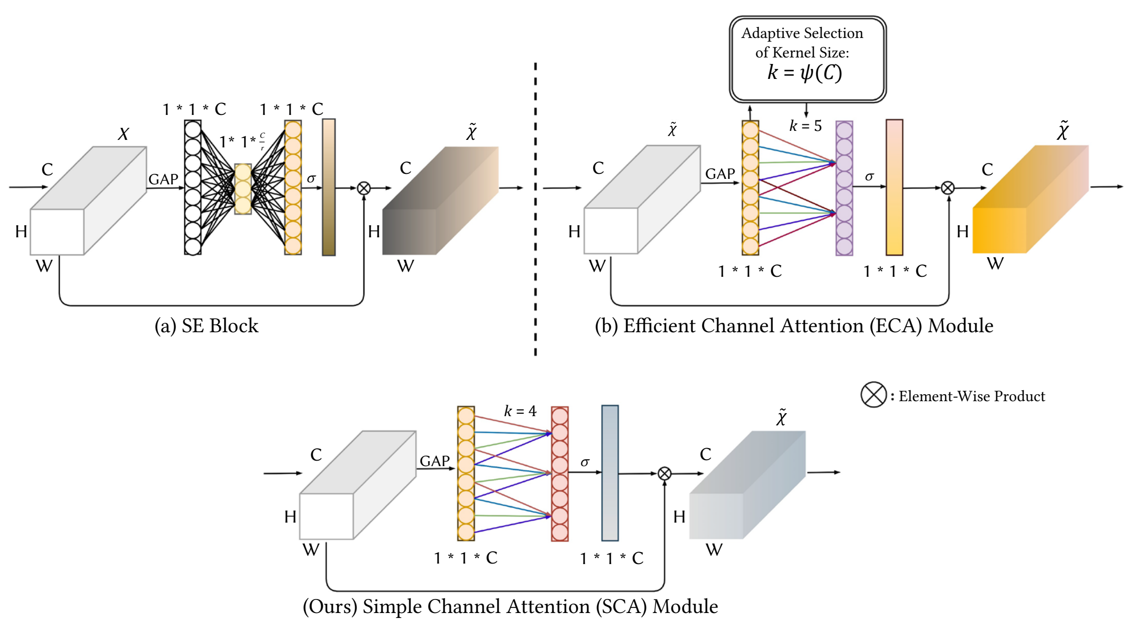


Fig. 3. An illustrative diagram of the Channel Attention Module from the SE Block to the ECA Module (The basis of our proposed SCA).

TABLE II. Target Description of MSTAR Database. There Are Three Types of Classes Thus the Artillery Class, Truck Class and the Tank Class

Target Model	θ	Artillery Class		Truck Class						Tank Class	
		2S1	ZSU_23_4	BRDM_2	BTR_60	SN_132	SN_9563	D7	ZIL131	T62	SN_C71
Training Set	17	300	299	299	257	233	233	300	299	299	233
Test Set	15	274	274	274	195	196	195	274	274	273	196

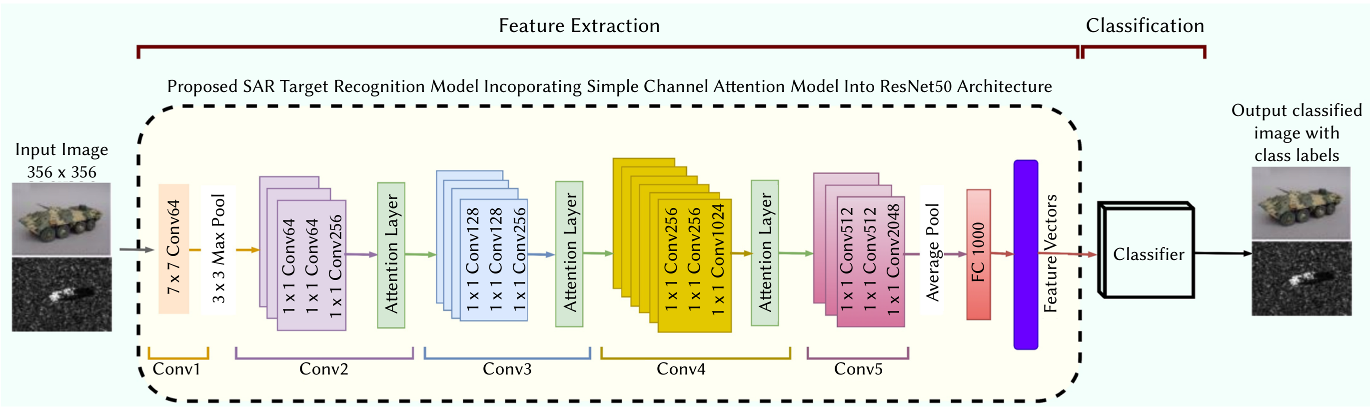


Fig. 4. Incorporating the proposed simple channel attention into the ResNet50 architecture. The proposed attention mechanism is incorporated into the second, third and fourth convolutional block to avoid the higher computational cost and computational complexity.

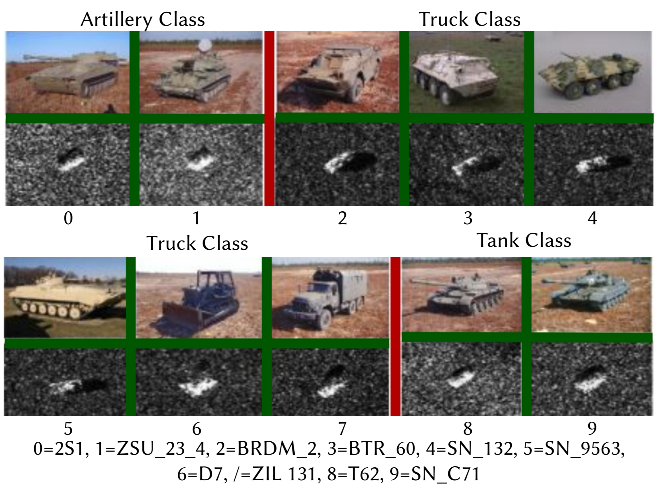


Fig. 5. Pictorial representation of the MSTAR Dataset.

B. Evaluation Metrics

General evaluation matrices including Classification Accuracy, Precision, Recall, F_1 Score, and IoU are applied in this paper. The percentage of accurately classified SAR imaging samples to all samples is used to calculate the classification accuracy. A higher percentage of correctly classified samples indicates a better classification performance. Mathematically we can express the classification accuracy as:

$$Acc = \frac{TP+FP}{TP+FP+TN+FN} \tag{7}$$

Where TP= True Positives, TN= True Negatives, FP= False Positives and FN= False Negatives.

The precision value equals ground truth SAR imagery pixels in the projected SAR imagery area divided by the number of predicted SAR Imagery pixels. The recall value is the percentage of detected SAR imagery pixels over the ground truth region. Mathematically, we express the Precision and Recall as:

$$Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN} \tag{8}$$

The F-score indicates the average overall performance as computed by precision and recall. This is how the F-Measure score is calculated mathematically:

$$F_1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{9}$$

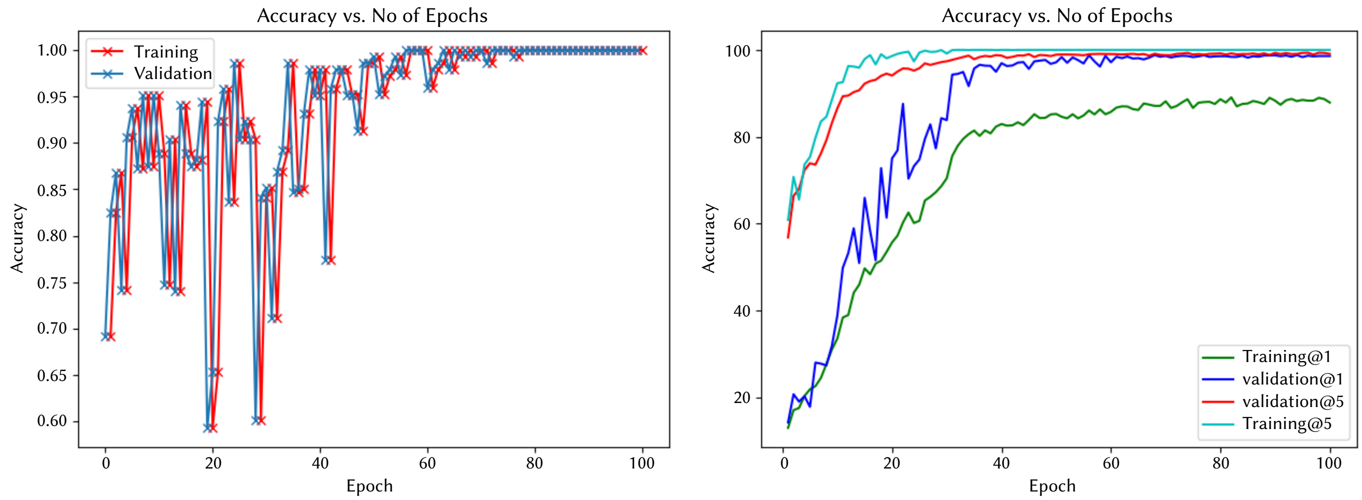
Analyzing the classification results and the loss value much further, we used the confusion matrix to envision them. It highlights the errors the classifier makes when handling multi-class situations. The predicted category is represented on the horizontal axis, while the vertical represents the correct category. Hence diagonal elements are the correctly classified SAR images Each SAR class's classification performance is represented by its lateral elements in the standardized confusion matrix. The following illustrates how to compute the Minimum Error using the loss and variance of the ground truth and the forecasted value [42]:

$$J = -\frac{1}{N}\sum_{n=1}^{N}[y_n log(\hat{y}_n) + (1-y_n) log(1-\hat{y}_n)] \tag{10}$$

Where $\hat{y}_n$ = predicted values, y_n = the ground truth, and N = number of samples. In direct contrast to Accuracy, the lower the loss value, the better the model performance.

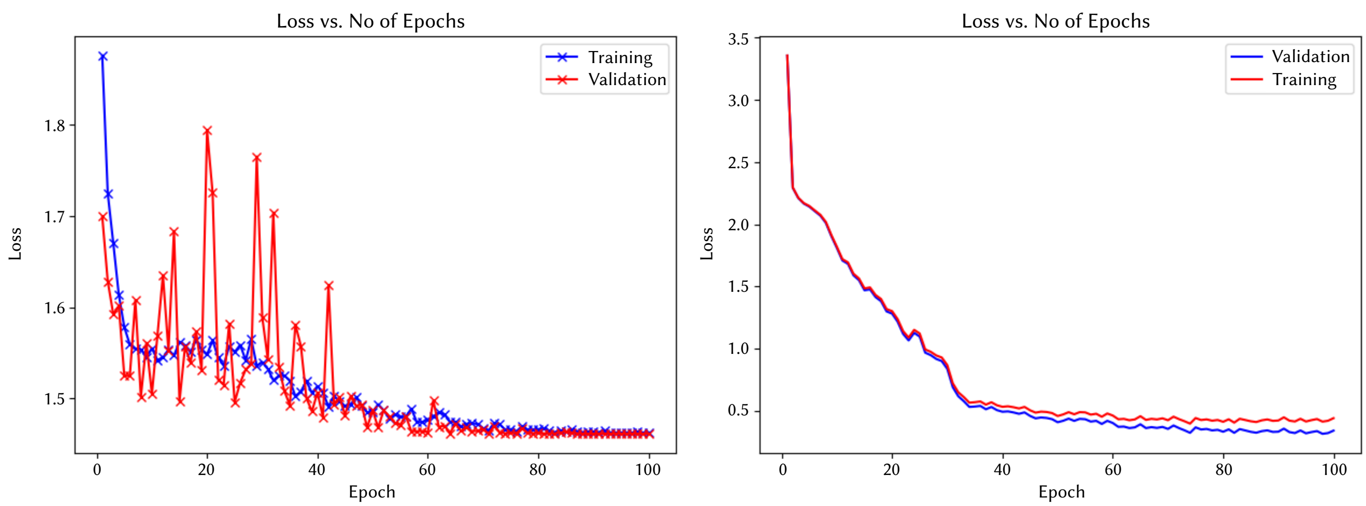
C. Implementation Details

We carried out our experiment on a windows OS computer based on the python environment, with 2.30GHz CPU Intel(R) Core (TM) i5-8300H and NVIDIA GeForce GTX 1050 Ti GPU (4g memory). We established the network using the open-source Pytorch deep learning framework, which we found to be an amazing resource. To increase our training performance, we used distributed processing relying on the CUDA 8.0 and CUDNN 5.1 prerequisites. The MSTAR dataset was used for evaluating our model. Fig. 1 displays samples of SAR images together with matching optical views. The input photos are randomly rotated horizontally and resized to 224 × 224. The training hyperparameters include 1e-4 weight decay, 0.9 momenta, 256 mini-batch, SGD optimizer, the initial learning rate of 0.1 and a reduction in learning rate of 10 per 30 epochs, 100 iterations.



(a) Model Without Att. Mechanism (b) The model with the Proposed Simple Channel Att

Fig. 6. Graphical representation of the training and validation Accuracy vs. Epochs. (a) shows the effects of the one policy learning rate. The models select random numbers as the learning rate until it finds a suitable range for the number for the training, which was around 60 epochs. (b) we show the training and validation accuracy at IoU 5 and 1. The model performs much better at the IoU at 5.



(a) Model Without Att. Mechanism (b) The model with the Proposed Simple Channel Att

Fig. 7. Graphical representation of the training and validation Loss vs. epochs. (a) Due to the random Learning rate selection, our model losses increased until the appropriate learning rate was determined, and the loss decreased. (b) shows that the attention mechanism performs very well by choosing the correct pixels of each input for classification.

V. Experimental Results and Analysis

A. Recognition Performance Result

The proposed method is validated and discussed in this section using experimental results. First, the training and validation graph of the two proposed models is illustrated in Fig. 6, whereas Fig. 7 illustrates the training and validation loss graph. Table III. represents results from our two-model setup for the ten categories of targets. We realized that the ReNet-50 architecture based on the simple channel attention recognition rate is 100%, whereas we had a recognition rate of 99.8% in the ResNet-50 setup with one policy learning rate. As shown in Fig. 8 and Table III for the attention-based model, we obtained only 0.01 classification error in the SN_132 and SN_9563 class under precision, SN_9563, and SN_C71 class under precision-Recall and finally SN_9563 category under f1-score. Regardless of the similarities of some images in some categories, with the help of simple attention, our model could recognize the appropriate class for the test datasets.

Fig. 8 illustrates the visual performance of the proposed model against the one-policy learning rate architecture. We test using just one image from each of the MSTAR three classifications. (Artillery Class, Truck Class and the Tank Class). The first and second row depicts the simple attention mechanism and the one policy learning rate visual performance result respectively. We further undertook an empirical comparison with a few recent state-of-the-rat results to validate the claims that the proposed model uses few model parameters compared to the previous work, thus attaining better results, as seen in Table IV. These CNN models have broader and deeper frameworks, and their findings are all lifted directly from the original articles. The findings above show that our proposed model outperforms benchmarked models while having substantially lower computational complexity. It is important to note that our simple attention can remarkably increase the performance of the comparable CNN models.

TABLE III. Classification Accuracies of the Ten Classes of the Target for the Attention-Based Model Vs. the One Policy Learning Rate-Based Model

Class	Ours (Model based on an Attention Module)				Ours (Model based on One Policy Learning rate)			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
2S1	1.00	1.00	1.00	274	0.99	1.00	1.00	274
BRDM_2	1.00	1.00	1.00	274	1.00	0.99	0.99	274
BTR_60	1.00	1.00	1.00	195	1.00	0.94	0.97	195
D7	1.00	1.00	1.00	274	0.99	1.00	0.99	274
SN_132	0.99	1.00	1.00	196	0.97	0.99	0.98	196
SN_9563	0.99	0.99	0.99	195	0.95	0.97	0.96	195
SN_C71	1.00	0.99	1.00	196	0.98	0.99	0.98	196
T62	1.00	1.00	1.00	273	1.00	1.00	1.00	273
ZIL131	1.00	1.00	1.00	274	0.99	1.00	0.99	274
ZSU_23_4	1.00	1.00	1.00	274	1.00	1.00	1.00	274
Accuracy			1.00	2425			0.99	2425
Macro Avg	1.00	1.00	1.00	2425	0.99	0.99	0.99	2425
Weighted Avg	1.00	1.00	1.00	2425	0.99	0.99	0.99	2425

TABLE IV. Model Parameter Contrast Between the Proposed Model Vs. Recent State-of-the-Art Models

REF	#. Param.	FLOPs	IoU@0.5	IoU@1
Ref [46]	74.45M	14.10G	-	98.18
Ref [60]	25.90M	5.36G	-	99.54
Ref [46]	46.66M	7.53G	-	98.52
Ref [42]	31.79M	5.52G	-	99.12
Ref [50]	27.35M	7.34G	-	99.18
Ref [46]	42.49M	7.35G	-	98.35
Ours	**24.37M**	**3.86G**	**1.00**	**0.994**

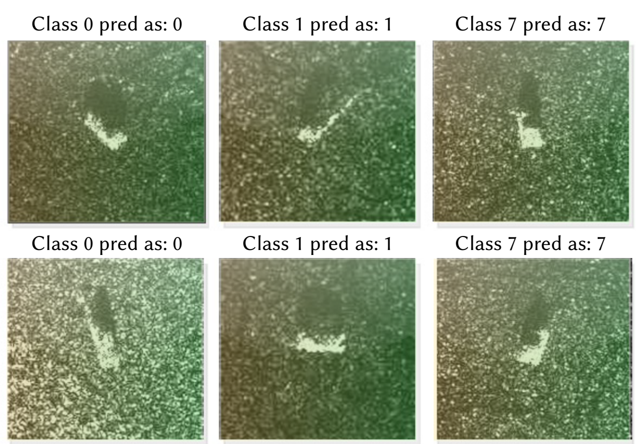


Fig. 8. Visual representation of the prediction outcome of the attention-based model vs. the One policy learning rate model.

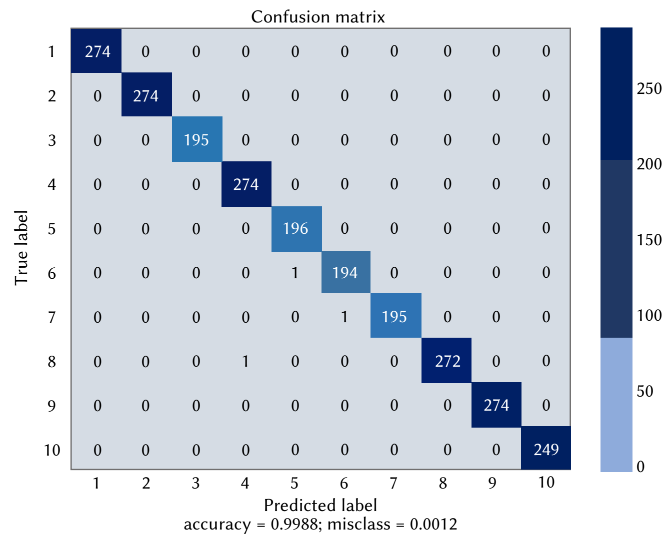


Fig. 9. Attention-Based Model Confusion Matrix of MSTAR Dataset. The accuracy of the test set is 100%.

Table III and Fig. 10 show that our one policy learning rate-based model had many misclassified samples due to similarities of the images among some classes against the attention-based model shown in Fig. 9. For the Precision, we had a misclassification rate between 0.01% - 0.05% in the 2S1, SN_132, D7, SN_9563, ZIL131 and C71 classes. For the Recall, the misclassification rate is between 0.01% - 0.06% in the BTR_60, BRDM_2, SN_9563, SN_132 and C71 classes. The F1-score had a misclassification rate between 0.01% - 0.04% in the BTR_60, BRDM_2, SN_132, D7, C71, ZIL131 and SN_9563 classes. The misclassifications result from the similarities between images in some of the classes.

B. Result Comparison and Discussion

As indicated in Eq. (4), our simple attention module involves a 1D convolution Kernel size denoted with K. When K is kept constant in the selected convolution blocks, our model records its best performance at k=9, which was obtained by an adaptive method using Eq. (5); thus, we fixed k=9 all through the experiment. Furthermore, the findings reveal that different deep CNNs have their best k, thus indicating that k had a positive influence on the proposed model performance. Moreover, we noted that the fluctuation of the accuracy performance between the proposed model and the one policy learning rate model was much for the one policy learning rate; thus, we concluded that deeper networks are more responsive to constant kernel size than shallower networks. Finally, substituting the SE Blocks with the primary proposed attention network with different amounts of k consistently produced superior results, demonstrating that avoiding dimension reduction and local cross-channel communication has a favorable influence on learning channel attention.

Furthermore, the proposed technique's performance is evaluated alongside 25 excellent state-of-the-art results from 2014 up to date using the same MSTAR Dataset. We pointed out the architectures used by each author in their work. We noted that our work is the

TABLE V. IoU Classification Comparison With the State-of-the-Art Methods

Author	Year	Authors Focus	IoU@0.5	IoU@1
Furukawa [43]	2018	End-To-End ATR of SAR Images Using Deep Learning	-	0.923
Ours (One Policy Learning Rate Based)	2021	Synthetic Aperture Radar Automatic Target Recognition Based on Attention Mechanism	-	0.998
Ours (Attention Based)	2021		**1.00**	0.994

TABLE VI. State-of-the-Art Result Comparison. The Performance of the Two Implemented Models Beats That of the State-of-the-Art Models. We Analyzed the Year, the Author's Focus and Their Approaches and the Results Obtained for the Recognition Task of SAR MSTAR Images

Author	Year	Authors Focus	Model	Accuracy
O'Sullivan et al. [44]	2001	Performance of SAR ATR with a Conditionally Gaussian Framework	Gond Gauss	97%
Srinivas et al. [45]	2014	Using Discriminative Graphical Models for SAR ATR	SVM	88%
Dong et al. [46]	2014	Using Sparse Encoding of a Single Gene Signal for ATR of SAR Images	Sparse Representation of a Monogenic Signal	93.66%
Dong et al. [47]	2015	Using Sparse Joint Encoding of a Single Gene Signal for ATR of SAR Images	Encoding of A Single - Gene Signal in Joint Sparse	93.41%
Tian et al. [25]	2016	CNN for ATR of SAR	CNN	93.76%
Zhao et al. [19]	2016	CNN-Based Patch Level SAR Image Classification	CNN	-
Chen et al. [23]	2016	Using Deep CNN for SAR Images Identification	A-ConvNet	99.13%
Gorovyi et al. [48]	2017	Effective SAR Images Recognition and Classification	Azimuth and Range Target Profiles Fusion	90.7%
David et al. [49]	2017	TL from Synthetic Data to Improve SAR ATR Models	Convnet Model	-
Furukawa [43]	2017	Deep Learning for SAR Image Classification Using Invariance and Data Enhancement	CNN With Data Enhancement	99.6%
Chang et al. [50]	2017	SAR Images ATR Based on Metadata Representations	Metadata Representation	94.88
Lin et al. [6]	2017	SAR Target Classification Using Deep CNN With Highway Block and Few Labeled Training Set	Deep CNN With Highway Block	99.09%
Huang et al. [7]	2017	TL with Deep CNN For SAR Target Recognition with Few Labeled Data	CNN-Transfer Learning	99.09%
Furukawa [51]	2018	End-To-End ATR of SAR Images Using Deep Learning	VersNet	99.55%
Wang et al. [52]	2018	CNN-Based SAR Image Target Recognition and Identification	CNN SVM	96.4% 93.85%
Gao et al. [53]	2018	An Improved Deep CNN Novel Algorithm for SAR Image Target Identification	DCNN + ICF + SVM	99%
Dong et al. [54]	2018	SAR Target Recognition Using a Salient Detail Localized Classifier Framework	Keypoint-Based Local Descriptor	-
Zhang et al. [55]	2019	Adaptive Region CNN for SAR Image Classification	Adaptive Neighborhood-Based CNN	-
Xie et al. [56]	2019	A New CNN for SAR Target Recognition	Umbrella	99.54%
Xinyan et al. [57]	2019	SAR Image Target Recognition with CNN	CNN	99.18%
Dong et al. [58]	2019	Target Recognition in SAR Images Via Dimension Reduction in The Frequency Domain	Bandwidth Modeling Approach for Sparse Signals	-
Zhang et al. [55]	2019	SAR Image Classification Using Adaptive Neighborhood-Based Convolutional Neural Network	Adaptive Neighborhood-Based CNN	-
Wu et al. [59]	2020	SAR Images ATR Based on CNN + SVM	AlexNet AlexNet + SVM Hybrid CNN Hybrid CNN +SVM	98.52% 98.35% 99.05% 99.18%
Wang et al. [60]	2020	SAR Target Recognition Using Recouped Non-Negative Matrix Induction and Meta-Learning	Depreciation and Amortization Non-Negative Matrix Deduction and Meta-Learning	97.9%
Lie et al. [61]	2021	Discrete Wavelet Transforms for Slight Discoloration in SAR Images	Contourlet-CNN	-
Miao et al. [62]	2021	Azimuth and Elevation Lower Bound Reconstruction for SAR Images	Adaptive Restoration with Azimuthal Sensitivity Restrictions	99.12%
Ours	2021	Synthetic Aperture Radar Automatic Target Recognition Based on Attention Mechanism	ResNet with Simple Attention Mechanism ResNet With One-Policy Learning Rate	100% 99.8%

first to implement an attention mechanism for the ATR SAR image recognition task; thus, we have established a new interest in research for further studies. Although the identified architectures demonstrate outstanding performance in the SAR images, as illustrated in Table V and Table VI, it is seen that the proposed architecture outperforms all the methods for SAR ATR and classification.

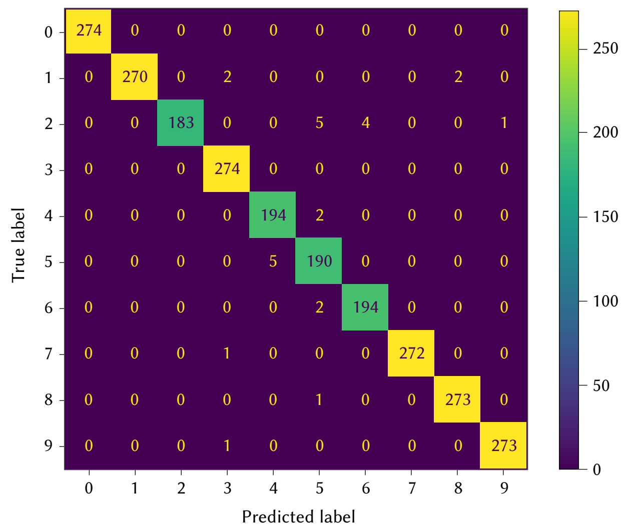


Fig. 10. One Policy Learning Rate-Based Model Confusion matrix of MSTAR Dataset. The test set yielded 99.8% accuracy.

VI. Conclusion

This article presents a new approach via an attention mechanism to tackle the limitation of SAR image ATR. Specifically, the channel attention mechanism is reviewed. We then proposed a simple channel attention mechanism that uses a few parameters. Yet, it yields good performance, avoids reducing dimensionality during learning, maintains cross-channel interaction performance, and decreases the complexity of the model. We fussed our simple attention module into the ResNet Architecture as our network backbone. We also examined the one policy learning rate to weigh up the potential of the attention mechanism on the ResNet-50 architecture. The total identification accuracy of the ten different MSTAR SAR images is 99.8% using the one policy-based architecture and 100% using the simple attention-based architecture. Therefore, we can say that the attention-based module we created is promising to be used as a standard for SAR target identification systems.

Conflicts of Interest

There are no conflicts of interest, according to the authors.

Acknowledgment

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References

[1] E. M. Ampe et al., "Impact of Urban Land-Cover Classification on Groundwater Recharge Uncertainty," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 5, no. 6, pp. 1859–1867, Dec. 2012, doi: 10.1109/jstars.2012.2206573.

[2] E. P. W. Attema, G. Duchossois, and G. Kohlhammer, "ERS-1/2 SAR land applications: overview and main results," IGARSS '98. Sensing and Managing the Environment. 1998 IEEE International Geoscience and Remote Sensing. Symposium Proceedings. (Cat. No.98CH36174), 1998, doi: 10.1109/igarss.1998.703655.

[3] P. Gamba and M. Aldrighi, "SAR Data Classification of Urban Areas by Means of Segmentation Techniques and Ancillary Optical Data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 5, no. 4, pp. 1140–1148, Aug. 2012, doi: 10.1109/jstars.2012.2195774.

[4] D.E. Dudgeon and R.T. Lacoss. "An overview of automatic target recognition," Te Lincoln Laboratory Journal, vol. 6, no. 1, pp. 3–10, 1993.

[5] Y. Cui, G. Zhou, J. Yang, and Y. Yamaguchi. "On the iterative censoring for target detection in SAR images," IEEE Geoscience and Remote Sensing Letters, vol. 8, no. 4, pp. 641–645, 2011.

[6] Z. Lin, K. Ji, M. Kang, X. Leng, and H. Zou. "Deep convolutional highway unit network for SAR target classification with limited labeled training data," IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 7, pp. 1091–1095, 2017.

[7] Z. Huang, Z. Pan, and B. Lei . "Transfer learning with deep convolutional neural network for SAR target classification with limited labeled data," Remote Sensing, vol. 9, no. 9, p. 907, 2017.

[8] J. Ding, B. Chen, H. Liu, and M. Huang. "Convolutional neural network with data augmentation for SAR target recognition," IEEE Geoscience and Remote Sensing Letters, vol. 13, no. 3, pp. 364–368, 2016.

[9] Y. Bengio, P. Simard, and P. Frasconi. "Learning long-term dependencies with gradient descent are difficult," IEEE Transactions on Neural Networks and Learning Systems, vol. 5, no. 2, pp. 157–166, 1994.

[10] X. Glorot and Y. Bengio. "Understanding the difficulty of training deep feedforward neural networks," Journal of Machine Learning Research, vol. 9, pp. 249–256, 2010.

[11] H. Kaiming, X. Zhang, S. Ren, and J. Sun. "Deep residual learning for image recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR' 16), pp. 770– 778, 2015.

[12] L.M. Kaplan "Analysis of multiplicative speckle models for template-based SAR ATR," IEEE Transactions on Aerospace and Electronic Systems, vol. 37, no. 4, pp. 1424–1432, 2001.

[13] Z. Hussein Arif et al., "Adaptive Deep Learning Detection Model for Multi-Foggy Images," International Journal of Interactive Multimedia and Artificial Intelligence, vol. 7, no. 7, pp. 26-37, 2022, doi: 10.9781/ijimai.2022.11.008.

[14] H. Ma, J. C. Chan, T. K. Saha and C. Ekanayake. "Pattern recognition techniques and their applications for automatic classification of artificial partial discharge sources," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 20, no. 2, pp. 468–478, 2013.

[15] G. J. Owirka, S. M. Verbout and L. M. Novak. "Template-based SAR ATR performance using different image enhancement techniques," vol. 3721 of Proceedings of SPlE, pp. 302–319, April 1999.

[16] Y. Kuno, K. Ikeuchi and T. Kanade. "Model-based vision by cooperative processing of evidence and hypotheses using configuration spaces," vol. 938 of Proceedings of SPlE, 444 pages, Orlando, Fl, USA, 1988.

[17] S. Singha, J. T. Bellerbyand O. Trieschmann. "Detection and classification of oil spill and look-alike spots from SAR imagery using an artificial neural network," in Proceedings of the 2012 32nd IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2012, pp. 5630–5633, Germany, July 2012

[18] C. Yuan and D. Casasent. "MSTAR 10-Class classification and confuser and clutter rejection using SVRDM," in Proceedings of the Defense and Security Symposium XVII, pp. 624501–624513.

[19] J. Zhao, W. Guo, S. Cui, Z. Zhang and W. Yu. "Convolutional neural network for SAR image classification at the patch level," in Proceedings of the 36th IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2016, pp. 945–948, July 2016.

[20] X. X. Zhu, D. Tuia, L. Mou, G. S. Xia, L. Zhang, F. Xu and F. Fraundorfer. "Deep learning in remote sensing: a comprehensive review and list of resources," IEEE Geoscience and Remote Sensing Magazine, vol. 5, no. 4, pp. 8–36, 2017.

[21] M. Kang, K. Ji, X. Leng, X. Xing, and H. Zou "Synthetic aperture radar target recognition with feature fusion based on a stacked autoencoder," Sensors, vol. 17, no. 1, p. 192, 2017.

[22] D. A. E. Morgan. “Deep convolutional neural networks for ATR from SAR imagery,” in Proceedings of the SPIE, pp. 1–13, Baltimore, MD, USA, July 2015.

[23] S. Chen, H. Wang, F. Xu and Y. Q. Jin. “Target classification using the deep convolutional networks for SAR images,” IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 6, pp. 1685–1697, 2016.

[24] X. Li, C. Li, P. Wang, Z. Men and H. Xu. SAR ATR based on dividing CNN into CAE and SNN. 5th Asia Pacific Conference on Synthetic Aperture Radar (APSAR), Singapore, 2015:676–679.

[25] T. Zhuangzhuang, Z. Ronghui, H. Jiemin and Z. Jun. "SAR ATR Based on Convolutional Neural Network," Journal of Radars, vol. 5, no. 3, pp. 320–325, 2016.

[26] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich. “Going deeper with convolutions,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR’ 15), pp. 1–9, IEEE, Boston, Mass, USA, June 2015.

[27] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna. “Rethinking the inception architecture for computer vision,” in Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, pp. 2818–2826, July 2016.

[28] F. Chollet, “Xception: deep learning with depthwise separable convolutions,” in Proceedings of the 30th IEEE Conference on Computer Vision and Pattern Recognition, pp. 1800–1807, 2016.

[29] V. Mnih, N. Heess, A. Graves and K. Kavukcuoglu. Recurrent Models of visual attention. In Proceedings of the Neural Information Processing Systems (NIPS), Montreal, QC, Canada, 13 December 2014; pp. 2204–2212.

[30] P. Wu, Z. Cui, Z. Gan and F. Liu. "Residual group channel and space attention network for hyperspectral image classification," Remote Sensing, vol. 12, no. 12, pp. 2035, 2020.

[31] S. Woo, J. Park, J.Y. Lee and I. S. Kweon. CBAM: Convolutional block attention module. In Proceedings of the European Conference on Computer Vision (ECCV), Munich, Germany, 8–14 September 2018; pp. 3–19.

[32] X. Cheng, X. Li, J. Yang and Y. Tai. SESR: Single image super-resolution with a recursive squeeze and excitation networks. In 2018 24th International Conference on Pattern Recognition (ICPR) (pp. 147-152). IEEE.

[33] D.-Q. Zhang, “clcNet: Improving the Efficiency of Convolutional Neural Network Using Channel Local Convolutions,” 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Jun. 2018, doi: 10.1109/cvpr.2018.00825.

[34] H. Gao, Z. Wang, L. Cai, and S. Ji, “ChannelNets: Compact and Efficient Convolutional Neural Networks via Channel-Wise Convolutions,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 8, pp. 2570-2581, 2021, doi: 10.1109/TPAMI.2020.2975796.

[35] Q. Wang, B. Wu, P. Zhu, P. Li, W. Zuo, and Q. Hu, “ECA-Net: Efficient Channel Attention for Deep Convolutional Neural Networks,” 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Jun. 2020, doi: 10.1109/cvpr42600.2020.01155.

[36] L. N. Smith. Cyclical Learning Rates for Training Neural Networks. Proceedings - 2017 IEEE Winter Conference on Applications of Computer Vision, WACV 2017 pages 464 -472.

[37] J. Hu, L. Shen, and G. Sun, “Squeeze-and-Excitation Networks,” 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Jun. 2018, doi: 10.1109/cvpr.2018.00745.

[38] J. Hu, L. Shen, S. Albanie, G. Sun, and A. Vedaldi Gather-excite: Exploiting feature context in convolutional neural networks. In NeurIPS, 2018.

[39] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, “CBAM: Convolutional Block Attention Module,” Lecture Notes in Computer Science, pp. 3–19, 2018, doi: 10.1007/978-3-030-01234-2_1.

[40] J. Fu et al., “Dual Attention Network for Scene Segmentation,” 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Jun. 2019, doi: 10.1109/cvpr.2019.00326.

[41] E. R. Keydel, S. W. Lee and J. T. Moore, “MSTAR extended operating conditions: a tutorial,” in Proceedings of the Algorithms for Synthetic Aperture Radar Imagery III, vol. 2527, pp. 228–242, April 1996.

[42] K. P. Murphy, “Machine learning: a probabilistic perspective,” MIT, 2012.

[43] H. Furukawa. Deep learning for target classification from SAR imagery: Data augmentation and translation invariance. arXiv preprint arXiv:1708.07920. 2017 Aug 26.

[44] J. A. O’Sullivan, M.D DeVore, V. Kedia and M.I Miller, “SAR ATR performance using a conditionally Gaussian model,” IEEE Transactions on Aerospace and Electronic Systems, vol. 37, no. 1, pp. 91-108, 2001.

[45] U. Srinivas, V. Monga and G. R Raghu, “SAR automatic target recognition using discriminative graphical models,” IEEE transactions on aerospace and electronic systems, vol. 50, no. 1, pp. 591-606, 2014.

[46] G. Dong, N. Wang, and G. Kuang. “Sparse representation of monogenic signal: with application to target recognition in SAR images,” IEEE Signal Processing Letters, vol. 21, no. 8, pp. 952– 956, 2014.

[47] G. Dong, G. Kuang, N. Wang, L. Zhao and J. Lu “SAR target recognition via sparse joint representation of a monogenic signal,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 7, pp. 3316–3328, 2015.

[48] I. M. Gorovyi and D. S. Sharapov. Efficient object classification and recognition in SAR imagery. In 2017 18th International Radar Symposium (IRS) 2017 Jun 28 (pp. 1-7). IEEE.

[49] D. Malmgren-Hansen, A. Kusk, J. Dall, A. A. Nielsen, R. Engholm and H. Skriver, “Improving SAR automatic target recognition models with transfer learning from simulated data,” IEEE Geoscience and remote sensing Letters, vol. 14, no. 9, pp. 1484-8, 2017.

[50] M. Chang and X. You, “Target recognition in SAR images based on information-decoupled representation,” Remote Sensing, vol. 10, no. 1, pp. 138, 2018.

[51] H. Furukawa. Deep learning for end-to-end automatic target recognition from synthetic aperture radar imagery. arXiv preprint arXiv:1801.08558. 2018 Jan 25.

[52] Y. Wang, Y. Zhang, H. Qu and Q. Tian. Target detection and recognition based on convolutional neural network for SAR image. In 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI) 2018 Oct 13 (pp. 1-5). IEEE.

[53] F. Gao, T. Huang, J. Sun, J. Wang, A. Hussain and E. Yang, “A new SAR image target recognition algorithm based on an improved deep convolutional neural network,” Cognitive Computation, vol. 11, no. 6, pp. 809-24, 2019.

[54] G. Dong and J. Chanussot. Target Recognition in SAR Image via Keypoint-based Local Descriptor—Foundation. Preprints 2018, 2018050116 (DOI: 10.20944/preprints201805.0116.v1).

[55] A. Zhang, X. Yang, L. Jia, J. Ai, and Z. Dong, “SAR image classification using adaptive neighborhood-based convolutional neural network,” European Journal of Remote Sensing, vol. 52, no. 1, pp. 178–193, Jan. 2019, doi: 10.1080/22797254.2019.1579616.

[56] Y. Xie, W. Dai, Z. Hu, Y. Liu, C. Li, and X. Pu, “A Novel Convolutional Neural Network Architecture for SAR Target Recognition,” Journal of Sensors, vol. 2019, pp. 1–9, May 2019, doi: 10.1155/2019/1246548.

[57] F. Xinyan and Z. Weigang, “Research on SAR Image Target Recognition Based on Convolutional Neural Network,” Journal of Physics: Conference Series, vol. 1213, no. 4, p. 042019, Jun. 2019, doi: 10.1088/1742-6596/1213/4/042019.

[58] G. Dong, H. Liu, G. Kuang, and J. Chanussot, “Target recognition in SAR images via sparse representation in the frequency domain,” Pattern Recognition, vol. 96, p. 106972, Dec. 2019, doi: 10.1016/j.patcog.2019.106972.

[59] T.-D. Wu, Y. Yen, J. H. Wang, R. J. Huang, H.-W. Lee, and H.-F. Wang, “Automatic Target Recognition in SAR Images Based on a Combination of CNN and SVM,” 2020 International Workshop on Electromagnetics: Applications and Student Innovation Competition (iWEM), Aug. 2020, doi: 10.1109/iwem49354.2020.9237422.

[60] K. Wang and G. Zhang, “SAR Target Recognition via Meta-Learning and Amortized Variational Inference,” Sensors, vol. 20, no. 20, p. 5966, Oct. 2020, doi: 10.3390/s20205966.

[61] G. Liu, H. Kang, Q. Wang, Y. Tian, and B. Wan, “Contourlet-CNN for SAR Image Despeckling,” Remote Sensing, vol. 13, no. 4, p. 764, Feb. 2021, doi: 10.3390/rs13040764.

[62] X. Miao and Y. Liu, “Target Recognition of SAR Images Based on Azimuthal Constraint Reconstruction,” Scientific Programming, vol. 2021, pp. 1–10, Apr. 2021, doi: 10.1155/2021/9974723.

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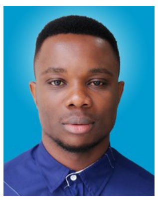

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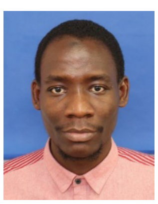

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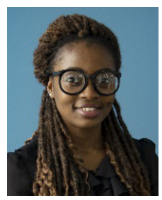

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