Multi-view Deep CNN for Automated Target Recognition and Classification of Synthetic Aperture Radar Image

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Abstract—**Demand towards the recognition of a target with a specific spatial signature by using remotely sensed images, the process of discovering the location, pose, and class that belongs to a particular kind of object is referred to as identification of the target. The progression of applying software and hardware to identify or recognize a goal from images of Synthetic Aperture Radar (SAR) outside the scope or within human availability is known as Automatic Target Recognition (ATR). The archaic architecture of ATR for SAR consists of three stages: recognition, distinctive, classification, and recognition. As1the time progresses many Deep1convolutional Neural Networks (DCNN) have been proposed and used for ATR-SAR and have obtained a state of the art results in many computer vision tasks, additionally shows subsequent result along the time, but most of them sort target from target chips found from SAR imagery, and used as a third stage (classification) of ATR-SAR archaic architecture. Also due to limited training images in ATR-SAR, DCNN yielded over-fitting when1directly applied to ATR-SAR. On the other hand, to make full use of SAR imagery, this paper presents Multi-View DCNN (MV-DCNN) for an end to end ATR-SAR which uses multiple views of SAR images. MV-DCNN takes1several views of a similar target. The proposed MV-DCNN proposed to instruct by the Moving1and Stationary Target Acquisition and1Recognition (MSTAR) benchmark dataset and to output scores of 10 number of classes.**

Index Terms—**automated target recognition, synthetic aperture radar, multi-view deep CNN, MSTAR**

I. Introduction

During 1903, Christian Hulsmeyer of Germany was the first person who granted the license from detecting objects by using radio waves to identify the presence of metallic objects but his invention called “Telemobiloscope” [1]. After few years around 1920s development of radar for ship and radar detection was started [2]. Before World War II, specialists in nations, for example, France, Britain, Germany, and Japan worked confidentially on creating advances that prompted the current-day version of radar.

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In 1940 the term RADAR was strike by the United States Navy as shortenings for Radio Detection and Ranging [3].

The relevant some major types of representation on radars are, the globular assessment Plan Position Indicator (PPI) images and the Side Looking images. The Army, Navy, Air Force, and NASA are prime users of imaging radars.

The use of PPI is restricted to observing air and maritime traffic. Remote distinguishing claims utilize the Side Looking images which are separated into three sorts – Real Aperture Radar also called Side Looking Airborne Radar (SLAR) or Side Looking Radar (SLR).

Synthetic Aperture Radar (SAR) is radar technology working in a microwave band that produces cognizant 2-dimensional imagery or 3-dimensional reconstruction of objects, of a target area by utilizing microwaves reflected from objects, under all climate. This radar is utilized on a flying machine or satellite and generally, its antenna beam is placed perpendicular to its bearing of movement. SAR has great properties and offers unmistakable dynamic remote detecting capacities for both military and regular citizen applications with the ground-breaking potential is commonly used by the navy, army, air force, and NASA. Since SAR is an active sensor, which gives its illumination, it can accordingly work day or night; ready to illuminate with a variable look point and can choose wide territory inclusion [4].

Detection, discrimination, and classification are the three distinct stages in standard architecture or processing flow of ATR-SAR handling. ATR recognizes a needed area of SAR image employing a Constant False Alarm Rate (CFAR) detector during the detection phase [4], [5]. Discrimination (otherwise called a Low-Level Classifier, LLC) is the second phase of ATR-SAR which segregates whether a Region of Interest (ROI) is a target or non-target region, and yields the separated ROI as a target chip and Classification (otherwise called a High-Level Classifier, HLC) is the third phase of ATR-SAR classifies target1classes from a target chip as it incorporates Classification, Recognition, and Identification. The initial two phases 2 together are ordinarily known as the meeting point-of-detecting module [6].

The ATR-SAR deals with the sequence analysis output from one or more sensor(s) aimed at a broad view of interest. The real-world empirical targets utilize on detected imagery. It generally1refers to the classification of into various perceptual classes and it standouts amongst the most testing algorithmic component of radar frameworks [7].

The SAR image provided as an input in Fig. 1 due to its high decree makes a high computational, the presence of different objects and clutter types. Its load is diminished as the data passes all through the ATR-SAR processing chain. The classifier stage-manages data that has a lower computational load. If the features and the classifiers ought to be cautiously designed the chance of having a good classification performance is very high [8].

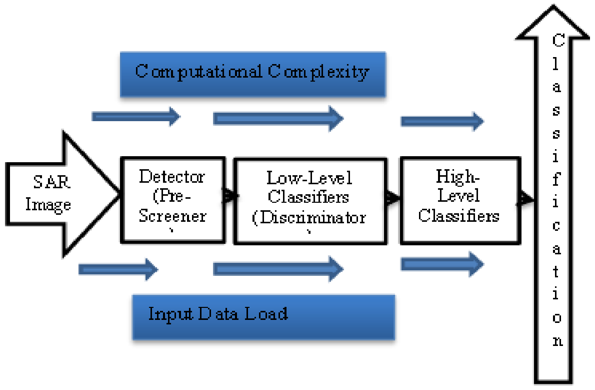

Figure 1. The general structure for an end-to-end ATR-SAR system.

Controlling unmanned flying vehicles during a fight is one of ATR's military uses [9]. A reliable onboard ATR accomplishes this by selecting and providing only target information back to the operator of the Unmanned Aerial Vehicle (UAV) instead of the entire scene across the flight path from which the operator must extract the target [10]. Ma *et al.* offer a patch level model for marine target classification. A convolutional neural network was used to create this image (CNN). It's also an all-encompassing system for detecting maritime targets in large-scale SAR photos.

This study proposed a new Deep Convolutional Neural Network (DCNN) called an end to end Multi-view DCNN (MV-DCNN), which is used to overcome the problems related to the recognition of objects of the previously designed ATR systems through separating the connection between images and classes in the learning model consisting different layers, for example, multitier convolution layer and others. To efficiently identify the objective classes, the model is trained on SAR pictures from several perspectives of identical targets.

A. *Evaluation Criteria*

The extensive comparative analysis below the Extended Operating Condition (EOC) and Standard Operating Condition (SOC) has been made to evaluate proposed network instances [11]. SOC utilizes the training and testing dataset with target types and similar image configurations, according to the evaluation, target classes are the same but with different aspects and depression angles. In EOC test scenarios, large differences between the training and test sets, including substantial variations in depression angle, target articulation, and version variants are observed.

II. Literature Review

In study, it proposes the DCNN and super-resolution generative adversarial networks [12]. It may be used to eliminate the ability of low-resolution SAR images to have poor feature categorization and acquire strong generalization performance.

Artificial training data generated by elastic distortion and affine transformations which represent examples of image errors in [13]. Using these examples, the classifier trained and it should be invariant. These artificial training data incorporate prior knowledge to the classifier. Support vector machine and convolutional neural network combined to design an efficient ATR system.

Ma *et al.* [14] offer a patch level model for marine target classification. A convolutional neural network was used to create this image (CNN). It's also an all-encompassing system for detecting maritime targets in large-scale SAR photos.

Data limitation and great variations of SAR image is identified in [15] as the major problems in ATR-SAR applications and proposed Multi-Stream CNN (MS-CNN) model to overcome the challenge in utilizing SAR images from multiple views which then allows for the whole usage of partial SAR image data and identify the target classes effectively.

Wan *et al*. [16] developed a model for the spectrogram feature using a two-dimensional CNN model.

Tian *et al*. [17] proposed a weighted kernel CNN method. This method incorporates a weighted kernel module with the common architecture of CNN.

A novel CNN named Group Squeeze and Excitation Sparsely Connected CNNs is devised in [18]. It overcomes the problems of normal CNNs of the negligence of channel-wise information flow due to fully connected structure and redundant parameters.

III. Methodology

Basically due to the inherent associations of the plentiful perspectives on similar target, to utilize limited rare SAR facts, and mine integral structures from multiple views of SAR images for progressively instructive SAR image illustrations, Multi-view Convolutional Layer was proposed. This technique can sufficiently extract multi-view features and decreases the number of factors to a great extent and improvement exercise proficiency and improves the recognition execution and fits the ATR-SAR jobs well.

Together with the multiple-view convolutional layer, a characteristic of the fusion layer introduced into the learning design as depicted in Fig. 2. The upper outputs produce the specifications of multi-dimensional views, and then builds robust complete representations. In the relation of practical value, MV-CNN can be simply and rapidly worked in actual ATR-SAR scenarios.

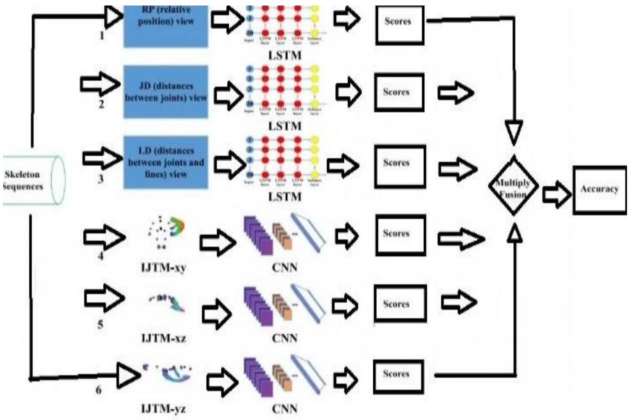

Figure 2. Structure of the proposed MV-CNN.

After the convolutional operation, the batch normalization operation is used, followed by the Rectified Linear Unit (ReLU) activation function, which is a non-linear function. For labelled SAR data, ReLU performs better without any unsupervised training and reduces training time.

The formula of Rectified Linear Unit (ReLU) activation function is expressed by Equation (1).

$$R(z) = \max(0, z) \tag{1}$$

The max-pooling operator is utilized. The cross-entropy cost function is used as an error function using Equation (2). It shows the separation between what the model believes the output distribution ought to be.

$$L(W, b) = -\sum_{i=1}^{K} y_i logp(y_i | q^L; W, b) \tag{2}$$

where *yi* is the original label of the ith class, *b* and *W* are sets of bias and weight of all the layers in MV-DCNN, and *yi* is the original label of the ith class.

Softmax will be applied after the final layer of the network to convert the output into what is essentially a probability distribution. The formula of softmax function expressed by Equation (3):

$$f(yy_i | q^{(L)}) = \frac{\exp(q_i^{(L)})}{\sum_{j=1}^{K} \exp\,(q_j^{(L)})} \tag{3}$$

where *yi* is predicted label of the ith class, *q*(*L*) is inputs to the softmax layer, is the weight sum of the ith node, *L* and *K* are the number of the layer and class respectively.

MV-DCNN has a multi-stream convolutional layer, which is more efficient but has fewer parameters. This multiple-input structure effectively and efficiently pulls information from several views on the same targets.

A. Dataset

The Sandia National Laboratory SAR sensor platform provided MSTAR publicly released benchmark dataset.

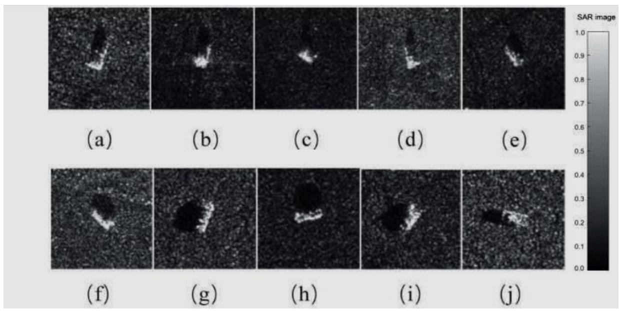

Figure 3. SAR images for each category in MSTAR. (a) 2S1. (b) BMP-2. (c)BRDM-2. (d) BTR70. (e) BTR60. (f) D7. (g) T-72. (h) T-62. (i) ZIL-131. (j) ZSU-234 [19].

It consists of ten types of targets, including the 2S1 rocket launcher; BMP-2, BRDM-2, BTR-70, and BTR-60 armoured personnel carrier; D7 bulldozer; T-72, T-62 tank; truck: ZIL-131; and ZSU-234 air defence unit. The suggested model will be trained and tested using 10 classes acquired by an X-band SAR sensor in a 0.3m×0.3m resolution spotlight mode. Fig. 3 depicts SAR images for each category.

IV. Evaluvation Results

A. Evaluation under SOC

The model is evaluated on ten dilemma classes in the SOC experimental setup. The experiment's SAR image dataset includes class types ZSU23/4, ZIL131, BMP2, BRDM2, BTR60, BTR70, D7, T62, T72, and 2S1. The same version and setup are used in the experiment for training and test datasets with various depression angles. To generate the multi-view SAR images for training and testing the neural networks, raw SAR images with a depression angle of 17° and 150 are selected from the MSTAR dataset for training and testing, respectively. Table I shows the class kinds, number of training and test samples, and depression angle for each class type.

TABLE I. The Number of Samples Selected of each Class Type from MSTAR Dataset for Training and Testing in Experiments under SOC

S.No.	Class	Training		Testing	
		Samples	Depression	Samples	Depression
1	ZSU23/4	299	17°	274	15°
2	ZIL131	299		274	
3	T62	299		273	
4	T72 sn- 132	232		196	
5	D7	299		274	
6	BTR60	256		195	
7	BTR70	233		196	
8	BRDM2	298		274	
9	BMP2sn- 9563	233		195	
10	2S1	299		274	

The confusion matrix is extensively used to evaluate the classification performance in the ATR-SAR literature. The columns show the predicted target and rows represent the actual class of the target. Table II presents the confusion matrix for three input views by applying proposed MV-DCNN under SOC. Table II shows that the lowest and highest accuracy (Acc) achieved are 97.9% and 100%, respectively, and that the overall accuracy is 98.91 percent. The confusion matrix for four input views by applying proposed MV-DCNN under SOC is depicted in Table III. It is observed that the minimum and maximum accuracy achieved are 98.4% and 100% respectively and the overall accuracy is 99.27%. Further, Table IV presents the confusion matrix for five input views by applying proposed MV-DCNN under SOC. The result shows the minimum and maximum accuracy achieved are 98.4% and 100% respectively and the overall accuracy is 99.54%.

TABLE II. The Confusion Matrix for Three-View by Applying Proposed MV-DCNN under SOC

Class	**ZSU23/ 4**	**ZIL131**	**T62**	**T72 sn-132**	**D7**	**BTR60**	**BTR70**	**BRDM2**	**BMP2sn-9563**	**2S1**	**Acc (%)**
ZSU23/4	272	0	1	0	0	0	0	0	0	1	99.2
ZIL131	1	271	1	0	1	0	0	0	0	0	98.9
T62	0	1	270	1	0	0	0	1	0	0	98.9
T72sn-132	0	0	0	196	0	0	0	0	0	0	100.0
D7	0	1	0	0	273	0	0	0	0	0	99.6
BTR60	0	0	0	0	0	192	0	2	0	1	98.4
BTR70	0	0	0	0	0	2	193	0	0	1	98.5
BRDM2	0	1	0	0	0	0	0	272	1	0	99.2
BMP2sn- 9563	0	0	2	0	0	0	0	1	191	1	97.9
2S1	0	2	0	1	0	1	0	0	0	270	98.5
Overall											98.91

TABLE III. THE CONFUSION MATRIX FOR FOUR-VIEW BY APPLYING PROPOSED MV-DCNN UNDER SOC

Class	ZSU23/4	ZIL131	T62	T72 sn-132	D7	BTR60	BTR70	BRDM2	BMP2 sn-9563	2S1	Acc(%)
ZSU23/4	274	0	0	0	0	0	0	0	0	0	100
ZIL131	0	274	0	0	0	0	0	0	0	0	100
T62	0	1	270	1	0	0	0	1	0	0	98.9
T72sn-132	0	0	1	193	0	0	0	0	1	1	98.4
D7	0	0	0	0	274	0	0	0	0	0	100
BTR60	0	0	0	0	0	193	1	0	0	1	98.5
BTR70	0	0	0	0	0	0	196	0	0	0	100
BRDM2	0	0	0	0	0	0	0	273	1	0	99.6
BMP2sn-9563	0	0	0	2	0	0	0	0	192	1	98.4
2S1	0	0	0	0	0	1	1	1	0	271	98.9
Overall											99.27

TABLE IV. THE CONFUSION MATRIX FOR FIVE-VIEW BY APPLYING PROPOSED MV-DCNN UNDER SOC

Class	ZSU23/4	ZIL131	T62	T72 sn-132	D7	BTR60	BTR70	BRDM2	BMP2sn-9563	2S1	Acc(%)
ZSU23/4	274	0	0	0	0	0	0	0	0	0	100
ZIL131	0	274	0	0	0	0	0	0	0	0	100
T62	0	1	270	1	0	0	0	1	0	0	98.9
T72sn-132	0	0	0	196	0	0	0	0	0	0	100
D7	0	0	0	0	274	0	0	0	0	0	100
BTR60	0	0	0	0	0	192	0	2	0	1	98.4
BTR70	0	0	0	0	0	0	196	0	0	0	100
BRDM2	0	0	0	0	0	0	0	274	0	0	100
BMP2sn-9563	0	0	0	1	0	0	0	0	193	1	98.9
2S1	0	1	0	0	0	1	0	0	0	272	99.2
Overall											99.54

B. *Evaluation under EOC*

Regarding recognition performance tests under EOCs, three comparative, progressive, and complex test scenarios experiments such as configuration variance, version variance, and depression angle variance, were conducted.

Configuration Variance: For configuration variance in the experimental setup for training the network, four classes of targets—T72, BTR70, BRDM2, and BMP2 as raw SAR pictures with a depression angle of 17°—are chosen. Table V shows the selected class, the number of raw SAR image samples for each class, and the depression angle. To test the network, two classes of targets, BMP2 and T72, were chosen, each having two and five different configuration changes as raw SAR images with depression angles of 15° and 17°, respectively. Table VI shows the selected classes with various configuration variants, the number of raw SAR image samples for each class, and the depression angle.

TABLE V. THE CLASS, NUMBER OF SAMPLES OF RAW SAR IMAGES, AND DEPRESSION ANGLE FOR TRAINING UNDER EOC WITH CONFIGURATION AND VERSION VARIANCES

Class	Samples	Depression
T72 sn-132	232	17°
BTR70	298	
BRDM2	299	
BMP2sn-9563	299	

TABLE VI. THE CLASS, NUMBER OF SAMPLES OF RAW SAR IMAGES, DEPRESSION ANGLE FOR TESTING UNDER EOC WITH CONFIGURATION VARIANCE

Class	Serial number	Samples	Depression
BMP2	sn-c21	429	15° and 17°
	sn-9566	428	
T72	sn-812	426	
	A04	573	
	A05	573	
	A07	573	
	A10	567	

TABLE VII. THE MV-DCNN CONFUSION MATRIX UNDER EOC WITH CONFIGURATION VARIANCE

Views	Class	BMP2	BTR70	T72	BRDM2	Acc (%)	Total
3-views	BMP2sn-c21	417	3	8	1	97.20	**95.19**
	BMP2sn-9566	404	4	18	2	94.39	
	Z72 sn-812	10	8	408	0	95.77	
	T72 A10	12	6	549	0	96.82	
	T72 A07	23	16	521	13	90.92	
	T72 A05	5	0	568	0	99.12	
	T72 A04	24	12	528	9	92.14	
4-views	BMP2sn-c21	409	1	15	4	95.33	**95.23**
	BMP2sn-9566	401	7	20	0	93.69	
	Z72 sn-812	8	6	412	0	96.71	
	T72 A10	15	10	540	2	95.23	
	T72 A07	22	15	531	5	92.67	
	T72 A05	7	0	565	1	98.60	
	T72 A04	18	9	541	5	94.41	
5-views	BMP2sn-c21	414	1	12	2	96.50	**95.62**
	BMP2sn-9566	397	8	22	1	92.75	
	Z72 sn-812	3	2	421	0	98.82	
	T72 A10	11	9	546	1	96.29	
	T72 A07	18	14	539	2	94.06	
	T72 A05	4	0	569	0	99.30	
	T72 A04	21	15	525	12	91.62	

The confusion matrices for EOC with Configuration Variance with three, four, and five input-view instances are summarized in Table VII.

Version Variance: In the experimental setting for training, the training dataset for EOC with version variance is the same as shown in Table V. To test the network, the target T72 was chosen with five different configuration changes as raw SAR images with depression angles of 15° and 17°. Table VIII shows the selected class with various configuration variants, the amount of raw SAR image samples for each class, and the depression angle.

TABLE VIII. THE CLASS, NUMBER OF SAMPLES OF RAW SAR IMAGES, AND DEPRESSION ANGLE FOR TESTING UNDER EOC WITH VERSION VARIANCES

Class	Serial number	Samples	Depression
T72	sn-s7	419	15° and 17°
	A64	573	
	A63	573	
	A62	573	
	A32	572	

The confusion matrices for EOC with version variance with three, four, and five input-view instances are summarized in Table IX.

Depression Angle Variance: In the experimental setting for training the network, four classes of vehicle targets—2S1, BRDM2, T72-A64, and ZSU23/4—are picked as raw SAR images with a depression angle of 17°. To produce testing combinations, raw SAR images with a 30° depression angle are used. Table X shows the chosen class, the quantity of raw SAR image samples for each class, and the training and testing depression angles.

TABLE IX. THE MS-CNN CONFUSION MATRIX BELOW EOC WITH VERSION VARIANCE

Views	Class	BMP2	BTR70	T72	BRDM2	Acc (%)	Total
3-views	Z72 sn-s7	20	6	391	2	93.31	**93.91**
	T72 A64	29	19	516	9	90.05	
	T72 A63	22	12	533	6	93.01	
	T72 A62	17	14	538	4	93.89	
	T72 A32	4	0	568	0	99.30	
4-views	Z72 sn-s7	21	4	394	0	94.01	**95.18**
	T72 A64	19	16	537	1	93.71	
	T72 A63	25	10	530	8	92.49	
	T72 A62	11	5	556	1	97.03	
	T72 A32	5	0	567	0	99.12	
5-views	Z72 sn-s7	17	3	398	1	94.98	**95.67**
	T72 A64	19	18	534	2	93.19	
	T72 A63	20	9	538	6	93.89	
	T72 A62	9	7	555	2	96.85	
	T72 A32	3	0	569	0	99.47	

TABLE X. TRAINING AND TESTING UNDER EOC WITH DEPRESSION ANGLE VARIANCE

Training			Testing		
Class	Samples	Depression	Class	Samples	Depression
2S1	299	17°	2S1	288	30°
BRDM2	298		BRDM2	287	
T72 sn- 132	232		T72-A64	288	
ZSU23/4	299		ZSU23/4	288	

TABLE XI. THE MS-CNN CONFUSION MATRIX UNDER EOC WITH LDA (LARGE DEPRESSION ANGLE)

Views	Class	2S1	BRDM2	T72-A64	ZSU23/4	Acc (%)	Total
3-views	2S1	268	11	9	0	93.05	**94.52**
	BRDM2	4	278	5	0	96.86	
	T72 sn-132	12	5	265	6	92.01	
	ZSU23/4	4	0	7	277	96.18	
4-views	2S1	272	6	10	0	94.44	**95.30**
	BRDM2	4	276	5	1	96.16	
	T72 sn-132	7	8	268	5	93.05	
	ZSU23/4	0	1	6	281	97.56	
5-views	2S1	270	14	4	0	93.75	**95.65**
	BRDM2	3	277	7	0	96.51	
	T72 sn-132	0	0	272	16	94.44	
	ZSU23/4	6	0	0	282	97.91	

Tables XI summarise the confusion matrices for EOC with depression-angle-variance with three, four, and five input-view occurrences.

V. ANALYSIS

Tables II-IV show that the proposed MV-DCNNs with three, four, and five input views have average accuracy of 98.91 percent, 99.27 percent, and 99.54 percent for ten target classes under SOC, respectively. Under SOC, five input views outperform the other two in terms of accuracy. In the experiment of EOC with configuration variance from Table VII, the suggested MV-DCNNs with three, four, and five input views have accuracy of 95.19 percent, 95.23 percent, and 95.62 percent, respectively. In the experiment of EOC with version variation from Table XI, the accuracy of the suggested MV-DCNNs with three, four, and five input views is 93.91 percent, 95.18 percent, and 95.67 percent, respectively.

In the experiment of EOC with depression angle variance, the accuracy of the suggested MV-DCNNs with three, four, and five input views is 94.52 percent, 95.30 percent, and 95.65 percent, respectively, according to Table XI. The accuracy is greater than 94 percent in all cases, and the proposed networks' peak recognition rate can exceed 95.5 percent. It's also worth noting that as the number of input views grows, so does the recognition rate.

A. *Result and Analysis of other Related Work*

The recital comparison among the proposed MV-DCNN and other seven ATR-SAR approaches as—Support Vector Machine (SVM), Extensive Maximum Average Correlation Height (EMACH) filter, Iterative Graph Thickening (IGT), Adaptive Boosting (AdaBoost), DCNNs, All-Convolutional Networks (A-ConNets), and two view DCNN (2-VDCNN) [6,47,48] was carried out. These approaches were selected for comparisons because these approaches outperformed in ATR-SAR and recently used in the literature and are based on diverse principles. The comparison of selected approaches and proposed MV-DCNN is based on several raw samples and accuracy (%). The number of raw samples and accuracy (%) of each approach under SOC and EOC with depression angle and version variance are depicted in Table XII. The results of other seven ATR-SAR approaches for comparison are cited from [5], [20]. The proposed MV-DCNN with three, four and five views are represented as MV-DCNN (3-view), MV-DCNN (4-view) and MV-DCNN (5-view) respectively. It can be seen from Table XII that the accuracy of all the approaches is more than 88% under SOC, but it differs greatly in EOC. The proposed MV-DCNN outperformed the other seven approaches in accuracy in both SOC and EOC with a lesser number of raw SAR images than the other seven approaches. Therefore, the experimental results strongly indicate that proposed MV-DCNN has achieved better recognition accuracy in both SOC and EOC over the other six approaches but A-ConNets.

TABLE XII. EOC1 RECOGNITION ACCURACY COMPARISON

	Traditional CNN	A-Convnet	SENet	ESENet
Accuracy (%)	88.44	88.95	91.01	94.10

BotEOC1 and EOC2, i.e., the enormous dejection variation dataset and variations dataset, are included in the EOC dataset. In EOC1, there are four target categories: 2S1, aBRDM-2, aT-72, and ZSU1-234. Images with a depression angle of 117 degrees are used as training examples, whereas images with a depression angle of 130 degrees are used as test samples, as indicated in Table XII. Configuration variants and version variants are the two target categories in EOC2. The alignment variations' training samples comprise BMP2, BRDM-2, BTR-70, and T-72, whilst the test samples only comprise T72 alternatives. The training samples contain BMP-2, BRDM-2, BTR-70, and T-72, while the test samples include variations of T72 and BMP-2.

Following that, the aforementioned technical specifications are used to assess ESENet's performance under large depression angle1 change. Table XIII shows that the ESENet outperforms the traditional CNN, the SENet, the A-convnet, and the ESENet in terms of recognition accuracy, with 88.44 percent, 88.44 percent, 94.10 percent, and 91.01 percent, respectively, demonstrating that the ESENet overtakes the others under EOC1. The EOC1 experiment, on the other hand, has a lower accuracy than the SOC experiment. For the reason that the SAR image is penetrating to fluctuations in inspecting angles, the substantial gap between the training and test samples has an impact on recognition accuracy. The targets for training and1testing have different components such as extra fuel tanks under the target configuration variation (EOC-C) test, while the version variation (EOC-V) test includes some structure transformation among the training and testing targets, such as the rotation of the tank turret and so on. All of these conditions will add difficulties to accurate recognition but could be encountered in real applications.

TABLE XIII. THE MV-CNN AND OTHER METHODS RECOGNITION ACCURACY COMPARISON

Methods	SOC		EOC-depression variants		EOC-version variants	
	inputs	Acc (%)	inputs	Acc (%)	inputs	Acc (%)
SVM [20]	3670	90.00	1129	81.00	1593	75.00
EMACH [20]	3670	88.00	1129	77.00	1593	68.00
IGT [20]	3670	95.00	1129	85.00	1593	80.00
AdaBoost [20]	3670	92.00	1129	82.00	1593	78.00
DCNN	2747	94.56	-	-	-	-
A-ConNets [5]	2747	99.13	698	96.12	698	98.93
2-VDCNN	2754	97.81	1130	93.29	998	93.75
MV-DCNN (3-view)	2747	98.91	1128	94.52	1128	93.91
MV-DCNN (4-view)	2747	99.27	1128	95.30	1128	95.18
MV-DCNN (5-view)	2747	99.54	1128	95.65	1128	95.67

VI. CONCLUSION

This research proposes the multiple-view deep convolutional neural network (MV-DCNN) as a new convolutional learning structure design for ATR-SAR. A multiple-stream convolutional layer, a fully coupled layer, a feature fusion layer, and a SoftMax layer are among the layers in this collection. The model extensively uses selective space-changing topographies and significantly expand detection rates. After the multi-stream convolutional layer, a unique fusion structure is added, which efficiently extracts and fuses the characteristics of multi-view SAR images to provide a strong visualization, establishing the extremely nonlinear connection between SAR images and their related classes.

CONFLICT OF INTEREST

We declare that authors do not have any conflict of interest.

AUTHOR CONTRIBUTIONS

Sudeshna Chakraborty (SC) reviewed the literature. The idea and methodology designed by Amrit a(AM). Tanupriya Choudhury (TC) idealizes the research and helps to design the methodology and collate all the changes. Paper formatting, References, and citing are all in proper order and whole review response comments are incorporated by Roohi Sille (RS), and also SAR data work is done by RS. Chiranjit Dutta (CD) and Bhupesh Kumar Dewangan (BKD) re-designed the diagrams up to 300 dpi and all the tables also designed by them.

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REFERENCES

[1] D. Pritchard, *The Radar War: Germany's Pioneering Achievement 1904-45*, Harpercollins, 1989.

[2] M. Skolnik, "Introduction to radar systems," *IEEE Aerospace and Electronic Systems Magazine*, vol. 16, no. 10, p. 19, 2001.
[3] K. El-Darymli, E. W. Gill, P. Mcguire, D. Power, and C. Moloney, "Automatic target recognition in synthetic aperture radar imagery: A state-of-the-art review," *IEEE Access*, vol. 4, pp. 6014-6058, 2016.
[4] R. Sivaranjani, S. M. M. Roomi, and M. Mareeswari, "An overview of Automatic Target Detection (ATD) algorithms in SAR image," *Computational Methods, Communication Techniques and Informatics*, vol. 415, 2017.
[5] 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. 54, no. 8, pp. 4806-4817, 2016.
[6] K. El-Darymli, P. McGuire, D. Power, and C. R. Moloney, "Target detection in synthetic aperture radar imagery: A state-of-the-art survey," *Journal of Applied Remote Sensing*, vol. 7, no. 1, p. 071598, 2013.
[7] N. Kumar and K. Niwaria, "An overview of automatic target recognition systems for underwater mine classification," 2012.
[8] 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.
[9] A. K. A. Raj, and B. Radhakrishnan, "A comparative study on target detection in military field using various digital image processing techniques," *International Journal of Computer Science and Network*, vol. 5, no. 1, pp. 181-185, 2016.
[10] J. A. Ratches, "Review of current aided/automatic target acquisition technology for military target acquisition tasks," *Optical Engineering*, vol. 50, no. 7, p. 072001, 2011.
[11] L. Wang, X. Bai, and F. Zhou, "SAR ATR of ground vehicles based on ESENet," *Remote Sensing*, vol. 11, no. 11, p. 1316, 2019.
[12] X. Shi, F. Zhou, S. Yang, Z. Zhang, and T. Su, "Automatic target recognition for synthetic aperture radar images based on super-resolution generative adversarial network and deep convolutional neural network," *Remote Sensing*, vol. 11, no. 2, p. 135, 2019.
[13] S. A. Wagner, "SAR ATR by a combination of convolutional neural network and support vector machines," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 52, no. 6, pp. 2861-2872, 2016.
[14] M. Ma, J. Chen, W. Liu, and W. Yang, "Ship classification and detection based on CNN using GF-3 SAR images," *Remote Sensing*, vol. 10, no. 12, p. 2043, 2018.
[15] P. Zhao, K. Liu, H. Zou, and X. Zhen, "Multi-stream convolutional neural network for SAR automatic target recognition," *Remote Sensing*, vol. 10, no. 9, p. 1473, 2018.
[16] J. Wan, B. Chen, B. Xu, H. Liu, and L. Jin, "Convolutional neural networks for radar HRRP target recognition and rejection," *EURASIP Journal on Advances in Signal Processing*, vol. 2019, no. 1, pp. 1-17, 2019.
[17] Z. Tian, L. Wang, R. Zhan, J. Hu, and J. Zhang, "Classification via weighted kernel CNN: Application to SAR target recognition," *International Journal of Remote Sensing*, vol. 39, no. 23, pp. 9249-9268, 2018.
[18] G. Huang, X. Liu, J. Hui, Z. Wang, and Z. Zhang, "A novel group squeeze excitation sparsely connected convolutional networks for SAR target classification," *International Journal of Remote Sensing*, vol. 40, no. 11, pp. 4346-4360, 2019.
[19] M. Ma, J. Chen, W. Liu, and W. Yang, "Ship classification and detection based on CNN using GF-3 SAR images," *Remote Sensing*, vol. 10, no. 12, p. 2043, 2018.
[20] J. Pei, W. Huo, C. Wang, Y. Huang, Y. Zhang, J. Wu, and J. Yang, "Multiview deep feature learning network for SAR automatic target recognition," *Remote Sensing*, vol. 13, no. 8, p. 1455, 2021.

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