Volume 66, Issue 4, 2022

Journal of Scientific Research

of

The Banaras Hindu University

Multi-Class Dual- Stream Convolutional Neural Network for Synthetic Aperture Radar Automatic Target Recognition of Ground Military Vehicle

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Abstract: Synthetic Aperture Radar (SAR) target classification is one of the largest branches of SAR image analysis. Despite the remarkable achievements of deep learning-based SAR target prediction algorithms, current object recognition algorithms are limited in terms of military applications. Acquisition and labeling of SAR target images are time-consuming and cumbersome. Obtaining adequate training data is also challenging in many cases. Deep learning-based models are always susceptible to overfitting because of insufficient training data. This limitation prevents them from being widely used to classify SAR targets. To overcome the problem of insufficient sampling and to learn more accurate representations for SAR image recognition, we propose a two-way input of SAR images into a dual stream of DCNN. Concatenating two input SAR images representations was done using the restricted raw SAR data in order to extract the integral features from the 2 input SAR images representations for classification. The proposed methodology addressed the problem of insufficient sample in SAR target classification and improved classification accuracy without overfitting. Experimental results confirmed that the proposed method is effective in addressing the problem of insufficient sample in SAR target classification. This technique can be integrated into any SAR classification model based on convolutional neural networks (CNNs). The model MCDS-CNN results in a 99.1% recognition accuracy. Despite the limited availability of SAR image data from MSTAR, this approach provides good recognition results.

Index Terms: **Automatic Target Recognition, Convolutional Neural Network, Ground Military Vehicle, Dual-Stream, Synthetic Aperture Radar**

1. INTRODUCTION

The recognition and classification of a target involves identifying the location, pose, and class of a target with a specific spatial stamp by using remotely captured images of a particular kind of object. The use of a computer-based techniques to identify a target from aerial images with or without human intervention is referred to as ATR (Kalkidan, & Sudeshna, 2019). The standard architecture of ATR consists of into three stages namely detection, discrimination, classification or recognition (Kalkidan, & Sudeshna, 2019). The ability to identify and recognize ground targets quickly and accurately enables an army to dominate battlefields and recognize the movements and intention of enemies (Yoo& Kim, 2021). Accurate detection, recognition, and classification of military vehicles as a target in a theatre of operation from an unmanned aerial vehicle is an essential strategy used by contemporary armies to minimize casualties and increase military intelligence (Goztepe, 2013). Hence, system is required to minimize the role of humans in target detection, recognition and classification, in order to implement a real-time and reliable system with high performance accuracy (Goztepe, 2013). SAR systems have been used in many civil and military applications, including terrain mapping, geological exploration, marine observation, atmospheric and environmental investigation, and automatic target recognition (Wang et al., 2018).

Numerous studies have been done using ATR from SAR for the categorization and recognition of military vehicles using different machine-learning approaches, including support vector machines, deep learning, and CNN. Using the MSTAR benchmark dataset, numerous studies in this field have been conducted. In both military and civilian applications, target classification for SAR images is a popular and difficult study subject. Without competent analysis, the image is useless since the analysis step draws knowledge from the data in the image (Hassan et al. 2019). The growth of machine learning has led to the application of several feature-based SAR ATR algorithms. The two steps of feature-based approaches are typically feature extraction and classification (Tian et al., 2018). The science of artificial intelligence is being driven by deep learning, a new subfield of machine learning (Zhang et al., 2018; Sun et al., 2018). It has recently experienced tremendous development and an increase in applications across many industries and fields of study. Deep learning is a neural network structure with numerous hidden layers, to put it simply. Deep learning, in contrast to typical neural networks, is an unsupervised feature learning technique that can automatically extract target features and avoid problems brought on by manually selecting features (Zhang et al., 2020).

The proposed multi-class dual-stream convolutional neural network model, which leverages on inherent associations of numerous perspectives on similar target to utilize restricted raw SAR data and extract integral features from two -input of SAR images representations. This technique can sufficiently extract image features, and to a large extent reduce the number of parameters. This increases the training accuracy, while improving the recognition process, of the SAR ATR. The proposed model uses a batch normalization operation after the convolutional operation. This is followed by the application of a nonlinear function called ReLU activation function. ReLU performs better without unsupervised training for labeled SAR data and decreases the training time. The max-pooling operator is also utilized to enhance the capability of the model.

Most of the recent studies on SAR ATR used the moving and stationary target acquisition and recognition (MSTAR) dataset for the implementation, design and testing of their target recognition algorithms (Yoo & Kim, 2021). Many of the SAR images used for military ATR are highly restricted and not available to the public. All academic researches on ATR to date used limited samples (small) of MSTAR Radar images dataset. The MSTAR dataset comprises of target SAR images acquired and delivered by the United States (US) Defense Advanced Research Project Agency and the US Air Force Research Laboratory (AFRL) MSTAR program as the only publicly available dataset for a ground military target recognition (Yoo & Kim, 2021).

The reasons for insufficient sample in the MSTAR dataset according to Liu et al. (2020) are as follows. Firstly, valid SAR target images are not easy to collect due to the effect of extraneous signals such as speckle noise. Secondly, the annotation of the SAR target is difficult and time-consuming. Thirdly, it is hard to collect sufficient examples for some scarce targets.

Consequently, these aforementioned difficulties prompted the following research questions on the use of deep learning for SAR image recognition: (i) Is it possible to avoid overfitting in models with limited data using dual-stream CNN? (ii) Can the dual stream improve the recognition accuracy of the model?

This study uses the MSTAR dataset to propose a multi-class dual-stream convolutional neural network for the categorization of SAR pictures of ground military vehicles.

The rest of this research work is divided into the following section: Section 2 recaps the review of related literature and Section 3 describes the research methodology adopted in this study and brief description of the dataset used. Section 4 outlines the discussion of results obtained from the experiment and the classification algorithms, which are compared with some other recent state-of-the-art models. Finally, the conclusion and future work are expressed in Section 5.

2. RELATED WORKS

In order to extract the features of the image for classification, a CNN and an automated encoder were combined in a multi-based integrated network structure technique (Zhang et al. 2020). In order to enhance the CNN model's prototype nature, the method first pre-trains the convolution kernel with a sparse auto-encoder by expanding the network branch. The next step was to input and process image data at various scales in order to extract features individually. Using various scale filters and sample times for each channel, a multi-channel structure was built. The ground feature map, which was obtained by a number of channels after the image size was down sampled, serves as an input to every fully connected layer and is ultimately utilized to classify ground features. Experimental outcomes showed the highest recognition rate of 98.5%.

An improved method for ATR of SAR images is based on a super-resolution generative adversarial network (SRGAN) and deep convolution neural network (DCNN) (Shi et al, 2019). The approach utilized threshold segmentation to eliminate the SAR image background clutter and speckle noise and accurately extract the target area of interest. The study further enhanced the low-resolution SAR images using SRGAN in other to ameliorate low visual resolution and poor feature characterization of the target in the SAR image. Automatic classification and recognition for SAR images are realized by using DCNN with good generalization performance. Performance evaluation based on the benchmark open dataset, MSTAR, shows that the method has a recognition accuracy of approximately 99.31% under standard operating conditions (SOC). An accuracy of 99.05% was obtained under extended operating conditions (EOC), which verify the effectiveness, robustness, and good generalization performance of the method. Similarly, to create a powerful ATR system, Wagner (2016) suggested combining CNN and support vector machines (SVM). The study went on to do another training using a different methodology while using the classifier's knowledge. This was designed to be able to deal with target variations and imaging faults. As a result, elastic distortion and affine transformations can be used to create synthetic training data for the models. A 99 percent categorization accuracy rate was attained. In a similar vein, Ma et al. (2018) provided an overall strategy for marine target detection in large-scale SAR pictures as well as a CNN model for marine target categorization at the patch level. In this study, eight different categories of marine targets from GF-3 SAR images are chosen and identified based on feature analysis. These targets include cargo ship, container ship, iron tower, tanker ship, windmill, boat, platform, and cargo. Six convolutions, three pooling layers, and two fully connected layers made up the proposed marine target convolution neural network (MT-CNN) CNN model. This method, which extracted characteristics at various levels, outperformed existing CNN models in classification accuracy.

According to Lu et al, (2019), convolutional neural networks were effective in classifying and recognizing power network icing images. The authors proposed a hybrid classification model that combined convolutional neural networks with support vector machines. Based on their simulations, they were able to classify the detected ice-covered power grids using convolution neural networks. They compared their model with the original CNN and found that their model performed better on image classification. A classification accuracy of 93.2% was achieved by the model. Additionally, it might be extremely difficult to detect and analyze huge scene SAR images due to the speckle noise and inappropriate connections between these processes. Cui et al. (2018) provides a method to combine detection and recognition of large-scale SAR images based on non-maximum suppression between regions (NMSR) as a solution to this issue. In comparison to other methods like constant false alarm rate (CFAR)+SVM, visual attention+SVM, and sliding-region based convolutional neural network, experiments on 1476 1784 simulated MSTAR images of simple scene and complex scene demonstrated that the proposed method can recognize all targets more quickly and accurately (RCNN). The performance evaluation of this model revealed a 95.67% accuracy rate.

Therefore, this work tried to explore the potentiality of two parallel stream of neural network called Multi-class Dual Stream CNN (MCDS-CNN) to tackle the problem of insufficient data sample and eliminate overfitting problem by improving recognition accuracy.

3 METHODOLOGY

This section outlines the thorough tests and evaluation procedures carried out to determine the viability of the suggested model. The experiment used synthetic aperture radar images to categorize military ground vehicles. The CNN model was developed and tested using the open-source Python deep learning framework with a tensor flow backend. A typical PC with a 20Gb RAM HP Proliant DL380p Gen8 server served as the platform for all studies. The flow of methodology adopted in this work is represented in Figure 1.

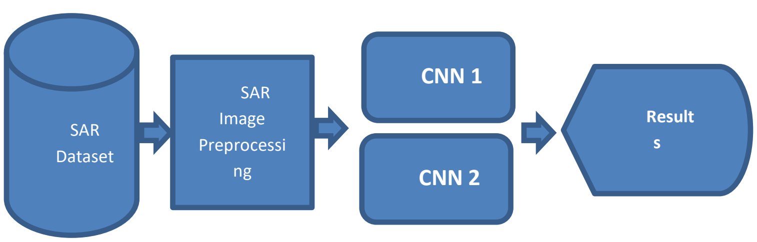

Figure 1: Methodology Flow

3.1 Data Collection

The MSTAR dataset of SAR images, which is openly accessible, is used in this work. The public was given access to the collection by the US Air Force for scholarly reasons. This program's public release has given researchers a rare chance to evaluate their progress in the field of SAR ATR. This radar data set is a collection of SAR images of military equipment generated by the former Soviet Union. The Sandia National Laboratory (SNL) SAR sensor platform obtained the MSTAR dataset at Redstone Arsenol in Huntsville, Alabama. SNL employed an X-band SAR sensor in spotlight mode with a one-foot resolution. The images are captured from a 360-degree view, which includes several different target orientations. Ten kinds of military targets make up our experimental dataset: the BMP2 (armored personnel carrier), T72 (primary battle tank), BTR60, BTR70, T62 (tank), 2S1 (cannon), D7 (bulldozer), BRDM2 (truck), SLICY (stationary structure), and ZIL131 (truck), as illustrated in Figure 2, while table1 shows the dataset distribution.

Figure 2: Images of targets from public release dataset collections

Table1: Dataset distribution

		No. of Images	Depression
1	**Training Set**	2746	17°
2	**Test Set**	1035	15°

3.2 Multi-Class Dual Stream CNN for SAR Ground Military Vehicle

The multi – class dual stream CNN -based deep neural network contains four building blocks as shown in Figure 3, i.e., the data input block, the feature extraction block, fusion of extracted features block and the output processing block. The data input processing block contains two data input layers. The two data input are fed separately into each of the two well-structured parallel CNN stream. At this point the discriminant features extracted in each of the CNN streams are concatenated at the fusion block layer. The outputs from the two dual-CNN layers are combined at the fusion layer using the simple fusion concatenation method rather than Max and multiplication, and it is the element sum of both. This is adopted to ensure generalization ability and computation efficiency, because cooperation and complementary of the two-network stream is required. The concatenated features can expressed as follows: Given that Z and X are the features extracted from the two parallel subnetworks, we have $Z = \{z^{(1)}, z^{(2)}, z^{(3)} \dots \dots \dots \dots . z^{(D)}\}$ $and\ X = \{x^{(1)}, x^{(2)}, x^{(3)} \dots \dots \dots \dots . x^{(D)}\}$ are suitable features that are automatically extracted via the two CNN with the network parameters W which will then be fed into a classifier to predict the corresponding labels C = $\{c^{(1)}, c^{(2)}, c^{(3)} \dots \dots \dots \dots . c^{(D)}\}, c^{(i)} \epsilon \{0,1\}^S$. At the end of each of the streams the features were flattened in other to create a single long feature. That means we unstacks all the tensor values into a 1-D tensor, so that it can be used as input for a Dense layer for classification. Two DCNN were assembled in other to learn complimentary features and thus form a wider network to extract more accurate image representation for effective and efficient recognition. It is worth to note that the two parallel streams have the same parameter numbers and receptive field size. Therefore, the model contained the same subnetwork

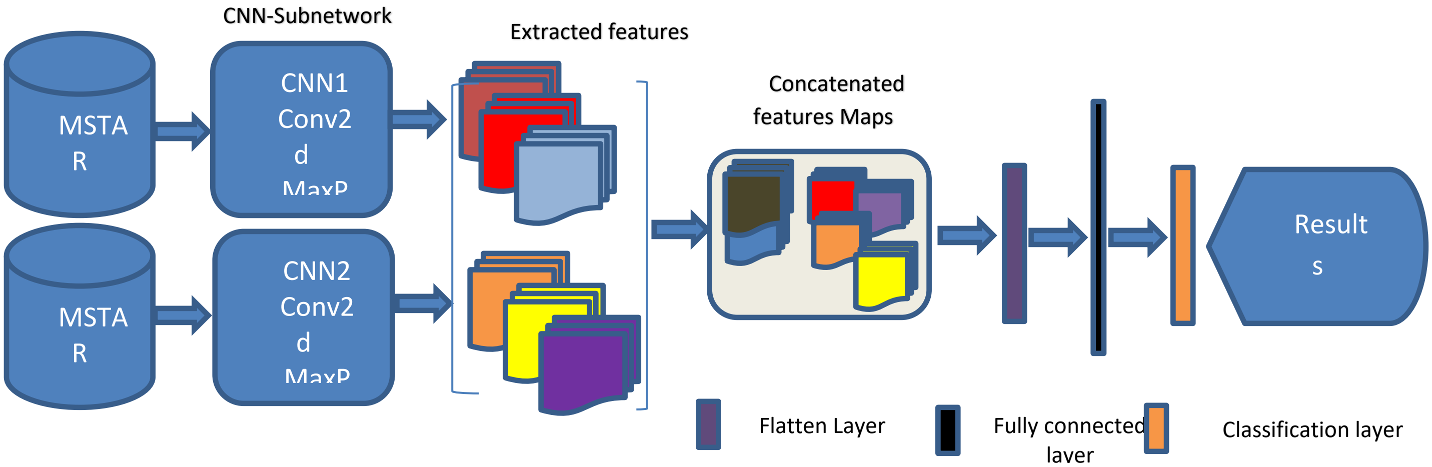

Figure 3: Multi-Class Dual-Stream Convolution Neural Network Architecture

3.2.1 *Pooling Layer*

Each convolutional layer is followed by a max-pooling layer, which performs feature selection and filtering on the result.

3.2.2. Merge Layer (Concatenation fusion)

The outputs of three parts of the 2D CNN architecture are concatenated into a 1D vector, which represents the combined spatial features learned from the SAR image. The concatenation function can be expressed as $y^{cat} = f^{cat}(x^a + x^b)$ stacks the two feature maps at the same spatial locations i, j across the feature channels d: $y^{cat}_{i,j,2d} = x^a_{i,j,d}$, $y^{cat}_{i,j,2d-1} = x^b_{i,j,d}$ where $y \in \mathbb{R}^{H\ x\ W\ x\ 2D}$ Concatenation does not define a correspondence, but leaves this to subsequent layers to define (by learning suitable filters that weight the layers)

3.2.3. Fully Connected Layer

The vector obtained from the merged layer serves as an input into the fully connected layer. The units are fully connected to the units in the previous layer. Feature combination is carried out and complex nonlinear relationships are created in this layer. Due to the limited number of samples of MSTAR data, few fully connected layers are sufficient for the model. In this experiment, we used one hidden layer.

3.2.5. Output Layer

The model outputs real numbers, constituting the probability that a sample belongs to a given classification category. The softmax functions shown in equation (1), is used for calculating the probability of each category:

$$\sigma(z)_x = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} \qquad (1)$$

where $\sigma\ is\ the\ softmax$, z is input vector, e^{zj} standard exponential function for input vector, K is number of classes in the multi-class classifier, and e^{zk}standard exponential function for output vector.

4 RESULT AND DISCUSSION

4.1 Model network parameter performance

Padding is used in the model convolution and as such, it preserves the size of the feature map and prevents it from shrinking at each layer. There is no change in the height and width of the feature map, while only the depth changed as shown in figure 4. Furthermore, we performed multiple convolutions on an input, with each of them using different filter and resulting in a distinct feature map. All these feature maps are combined to produce the final output of the convolution layer. The figure displays 16 feature maps of the military vehicles from SAR image in layer3.

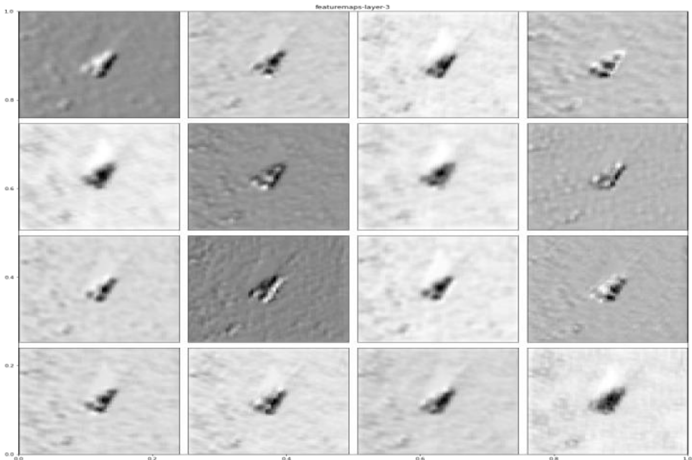

Figure 4: Feature Map obtained from layer 3 of the DCDSCNN

Figure 5 illustrates the prediction accuracy of the model where the MSTAR dataset classes are displayed as requested

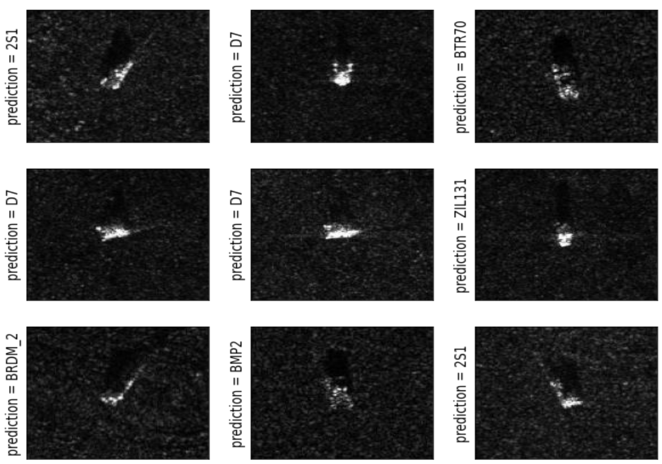

Figure 5: Predicted classes of the MSTAR dataset by the DCDSCNN model

4.2 Performance Accuracy

For a proper measure of the performance of this model, it is important to understand the performance and not just the end result. As shown in Figure 6 and 7, the training accuracy significantly increased, while training dataset loss decreased over time. This graph shows that the model was configured for the correct number of training iterations for classification. It is also very clear that the validation loss reduced while the accuracy increased. The validation results are similar to the actual test results and confirmed that the model did not over fit during training.

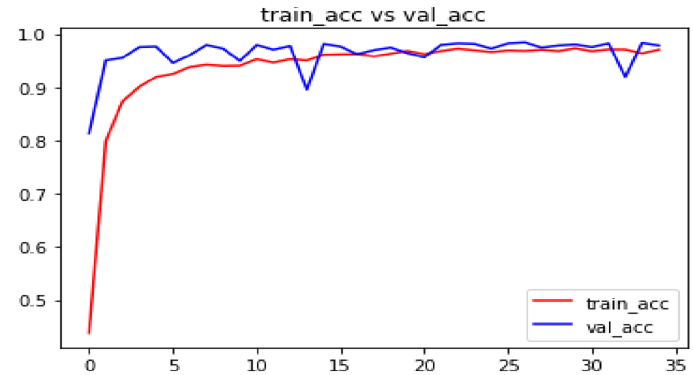

Figure 6: Train Accuracy versus Validation Accuracy

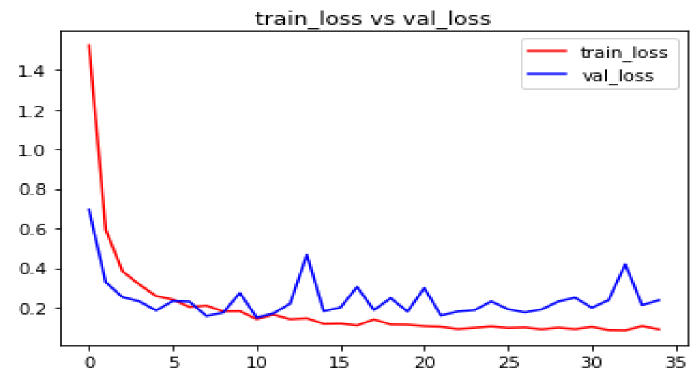

Figure 7: Train loss versus Validation Loss

4.3 Model Result Accuracy

Table2 shows that the overall validation accuracy is 99.1%. The table also shows the various degrees of accuracy in terms of precision, recall and f1-score. Table 2 reveals the performance of the model in each of the target class prediction in confusion matrix form. Figure8 is the graphical representation of Table2.

Table 2: Results Accuracy

	Precision	recall	f1-score	support
Class 0 (2S1)	1.00	0.99	1.00	129
Class 1 (BMP2)	0.95	0.95	0.95	85
Class 2 (BRDM_2)	0.99	0.99	0.99	118
Class 3 (BTR60)	0.98	0.99	0.98	83
Class 4 (BTR70)	0.99	0.98	0.98	87
Class 5 (D7)	0.97	0.99	0.98	113
Class 6 (T62)	0.99	1.00	1.00	103
Class 7 (T72)	0.99	0.92	0.96	92
Class 8 (ZIL131)	0.96	0.97	0.96	121
Class 9 (ZSU_23_4)	1.00	1.00	0.99	104
Accuracy			0.99	1035
macro avg	0.99	0.99	0.99	1035
weighted avg	0.99	0.99	0.99	1035

From table 2, the average precision for each target class is 0.98. This measures the total numbers of observations our model predicted over the number of correct and incorrect predictions as shown in Figure 7.

Precisions is calculated by using the formula

$$\text{Precision} = \frac{TP}{TP+FP} \quad (7)$$

where TP is True Positive while FP *means False Positives*

However, average recall accuracy is also 0.98, which is the measu re of numbers of observations
our model correctly predicted over the total amount of observatio ns.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{8}$$

where TP is the True Positive and FN means False Negative

Table 3: Confusion Matrix

Confusion matrix without normalization

```
[128   0   0   0   0   0   0   0   1   0]
[  0  81   1   0   0   1   1   0   0   1]
[  0   0 116   2   0   0   0   0   0   0]
[  0   0   0  82   1   0   0   0   0   0]
[  0   0   0   0  85   2   0   0   0   0]
[  0   0   0   0   0 112   0   0   1   0]
[  0   0   0   0   0   0 103   0   0   0]
[  0   4   0   0   0   0   0  85   3   0]
[  0   0   0   0   0   0   0   1 117   3]
[  0   0   0   0   0   0   0   0   0 104]
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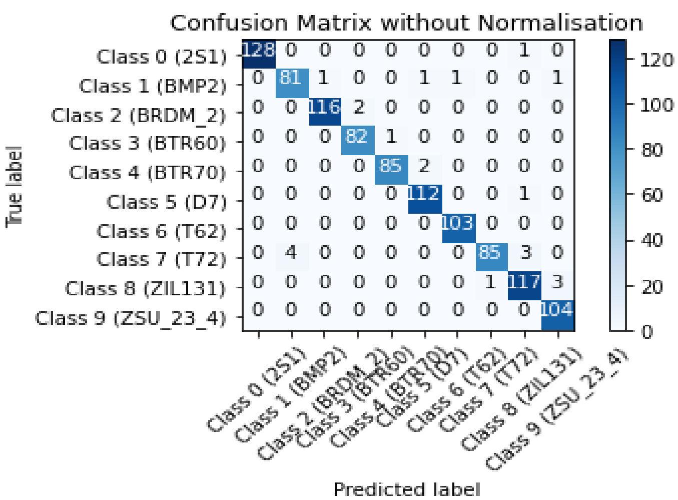

Figure 8: Confusion Matrix obtained from the classification of SAR ATR using MSTAR data

The confusion matrix in Figure 8 shows that our model has high performance accuracy. The model classified target ZSU_23 and T62 accurately without any wrong classification or false positive. Similarly, target 2S1, BTR60and D7 were also classified correctly except that each of them has only one wrongly classified target.

The goal is to assess the effectiveness of the proposed model. The proposed model possesses an overall performance accuracy of 98.4% and outperforms the state-of-the-art techniques.

4.4 Result comparison with other State-of-the-art algorithms

To evaluate the effectiveness of our proposed network, we compare our proposed network to the state-of-the-art models. Table 4 presents a comparison between the proposed model and other state-of-the-art algorithms.

5 CONCLUSION AND FUTURE WORK

Based on facts gathered from the literature, it was established that it is difficult to train DCNN -based models with limited data in SAR target classification without model overfitting. To address this problem, this paper proposed Multi-class Dual-stream convolutional neural network that is capable of improving feature discriminability of SAR image feature resulting in good recognition accuracy. The results of the experiments in the study shows that despite the limited data for training DCNN, a well-structured dual parallel neural network with two data input is able to learn the discriminant and dominant features from each SAR image. However, the concatenation of the two streams represent the aggregate of the two convolution result while the dense represent the output of the final result using the Softmax function. This results in an increase in the accuracy of the proposed model. The MCDS-CNN model is able to train limited data images of MSTAR and produce good recognition accuracy of 99.1%.

The proposed method can as well improve the classification accuracy when the training data is sufficient. Our simple and effective model can be integrated into any CNN based SAR classification models without the utilizing the use of transfer learning framework and data augmentation. Experimental results confirmed that the proposed method is able to address the problem of insufficient sample in SAR target classification and improve classification accuracy without overfitting.

A future work should focus on a multi-channel multi-stream CNN based on higher numbers of input and multiple CNN streams in order to achieve improved classification accuracy.

Table 4: Result comparison with other state-of-the-art algorithms

Author	Title	Methodology	Results
Ma et al., (2018)	Ship Classification and Detection Based on CNN Using GF-3 SAR Images	DCNN	95.2%
Cui et al., (2018)	SAR Target Recognition in Large Scene Images via Region-Based Convolutional Neural Networks	DCNN (RCNN)	94.67%
Chen. et al., (2019)	Convolutional factor analysis model with application to radar automatic target recognition	CNN Convolutional factor analysis	83.01%
Wang et al., (2018)	Ground Target Classification in Noisy SAR Images Using Convolutional Neural Networks	CNN	82.19%
Zhang et al., (2020)	Image Target Recognition Model of Multi-Channel Structure	DCNN	98.5%

	Convolutional Neural Network Training Automatic Encoder		
Wang et al., (2019)	SAR ATR of ground Vehicles on ESENET	CNN	97.32%
Proposed (Awujoola et al., (2021)	Multi- class Dual-stream convolutional neural network for automatic target recognition of ground military vehicle	MCDS-CNN	99.1%

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