Optimizing the classification ability of CNN for SAR fully polarized radar data based on DCGAN

ZeCong Bu¹,a*, Yue Zhang²,b, AnMai Zheng³,c
¹College of Geomatics and Geoinformation, Guilin university of technology, Guilin, Guangxi, China
²email: 76948059@qq.com, bemail: 2512919923@qq.com
³email: nirigothrough@gmail.com
*Corresponding author’s e-mail: chxy@glut.edu.cn

Abstract. In recent years, the deep learning network is widely used. In the field of remote sensing images, due to the high cost of image acquisition, there are still too few training samples, which greatly limits the application of deep learning in SAR data classification. This paper proposes a method that is generating simulated SAR image by generative adversarial network, and uses the image as the training data of convolutional neural network. Aiming at the impact of the simulated images generated by DCGAN’s generator on the classification of convolutional neural networks. The results show that DCGAN can fully extract the main features of the image, and the convolution model based on DCGAN can make CNN have better classification ability and get rid of the dependence on the sample size. CNN can also make full use of simulation data. Whether it is test data set or random dataset, its F1 score can obviously surpass the classification ability without DCGAN’s simulated data. In experiments with different sample numbers, the highest F1 score is 93.6479 in the dataset with DCGAN’s simulated data. In another experiment, its F1 Score reached 87.32, higher than the dataset without DCGAN’s simulated data.

1. Introduction
In recent years, with the popularization of social informatization, deep learning has made a breakthroughs in many applications, such as computer vision[1], image processing[2], speech recognition and so on[3]. High accuracy and high-speed processing performance make it possible to design a model to imitate the function of human brain. On this basis, we can achieve the following tasks: automatic image classification, and automatic image generation[4].

SAR radar data classification technology is a very important technology of data acquisition in the field of remote sensing in recent years. SAR radar technology has many irreplaceable advantages, making it widely used in forestry, urban planning and construction, power system monitoring and disaster relief[5]. After years of research, researchers have proposed a large number methods of SAR data classification.

In recent years, with the continuous development of image acquisition technology, more and more methods of image classification can classify images efficiently and accurately. Generative adversarial network is a generative model proposed by Goodfellow[6] in 2014, which can not only discriminate data, but also generate samples similar to the discriminated data. The relationship between generative network and discriminant network is antagonistic.
With the rapid development of deep learning, the effect of image classification using the depth model is getting better and better. However, the training process of the depth model needs a large number of training samples. In the field of remote sensing images, due to the high cost of image acquisition, there are too few training samples, which greatly limits the application of deep learning in SAR data classification. In recent years, the deep learning network is widely used. As a new generative model, the most direct application of GAN is data generation[7]. Aiming at this problem, this paper proposes a method that is generating simulated SAR image by generative adversarial network, and then uses the image generated by the generative adversarial network as the training data of convolutional neural network[8] and classification, to further improve the classification accuracy.

2. Materials and Methods

2.1. Experimental process

As shown is the technical route in Figure 1. Firstly, the SAR radar image is preprocessed, cropped and segmented. And then the original dataset is trained by DCGAN. The simulated SAR image data is generated by DCGAN generator. Only the best images are selected to be cropped. The virtual dataset is integrated into the original dataset to get a new dataset. The convolution neural network is used to train the model, and the test dataset is used to test the quality of the trained model. Finally, the original SAR image is classified, and the precision, recall and F1 score of the final result are calculated.
2.2. Experimental data
In this study, the European Space Agency's sentinel-1 radar satellite data is selected as the experimental data. They are IW SLC image pairs in Shanghai and August 22, 2019. They are full polarization. The ground resolution is 20 meters. The true color map of the data and the spatial distribution of various samples are shown in Figure 2.

According to different color labels (Middle Green, Bottle green, Pale green, White), the original image can be divided into four parts (the figure below has only three parts, the white area image is not shown), and then the effective area in the image is cut, and stored in different folders as training data, with a total number of 870 samples. Among them, 70% of the data set is used as training data (609 samples), and 30% as test data (261 samples). As shown in Figure 3, it is based on the image after cutting with the color label.

2.3. Experiment design
2.3.1. Train the DCGAN to generate analog images
The original DCGAN is modified to suit the characteristics of SAR data. The generator network consists of three layers of anti-convolution layer, using 4×4 convolutional cores. The first two layers of the network are using the activation function of ReLU, and the choice of BN to improve the gradient of the neural network, the last layer of output selection using the activation function of mean 0 Tanh. The discriminator uses 3 layers of stepping convolution, the first two layers choose to use LeakyReLU, which compresses the continuous real values entered, as the activation function. Select images from a certain training dataset until all types of pictures are trained. The generator is then used to generate simulated image data, pick out the best simulated data, and crop it.
2.3.2. Training and classification with DCGAN’s images
The original training data set and the generated simulation training data set are stored as tags respectively, which are used as CNN training data for training, and then the test data set is used to evaluate the accuracy of CNN training model. In this experiment, 214 samples are selected from the generated simulation data, and the total number of samples in the final training data set is 823. In the experiment, 500, 600, 700 and 823 samples are randomly selected as training samples for network training. There are no simulation samples in the training set of 500 and 600, 91 simulation samples in the training set of 700, and all simulation samples in the training set of 823. The remaining samples of each number of train sets are all taken as test set samples. After the network training, the remaining test samples are used to evaluate the final classification performance of the network model.

At the end, a 200 × 200 SAR image is cut by 20 × 20, from left to right, from top to bottom, each moving a pixel. It produces 40000 small pictures. The 40000 images are input into CNN’s model in order for discrimination, and four color pixel blocks of middle green, bottle green, pale green and white are generated according to the discrimination results. The blocks are re-integrated in order, and the resulting image is used as the classification object of CNN’s model for classification. Finally, the method of ahash is used to Evaluate the classification.

3. Results & Discussion

3.1. Result of CNN training the test dataset
The comparison table of classification accuracy of CNN training model for test dataset classification results under different sample numbers is shown in Table 1. The classification accuracy of the different datasets in the table can be concluded that because the experimental in this paper adds the simulated sample, that is, the SAR data generated by the GAN generator, the generalization ability of the trained classification model is stronger. The performance on the test datasets with different number proves the feasibility of the classification proposed in this paper, and the classification accuracy is greatly improved. From the classification results, it can be seen that the method of classifying based on the generative adversarial network proposed in this paper has the brilliant performance of classification in the case of limited training samples. By the addition of the simulated sample set, the F1 score of the classification results increased significantly, with 0.9696 and 2.613, respectively. The image of the simulated samples is shown in Figure 4.

|                  | 500         | 600         | 700         | 823         |
|------------------|-------------|-------------|-------------|-------------|
| accuracy (%)     | 87.44±1.17  | 88.93±2.01  | 91.09±1.54  | 93.21±1.38  |
| recall (%)       | 89.45±1.27  | 91.23±1.87  | 90.98±1.87  | 94.09±1.79  |
| F1 Score×100     | 88.4335     | 90.0653     | 91.0349     | 93.6479     |

Figure 4. Simulated SAR data generated by the DCGAN

3.2. Result of the model classification
The model of 600 and the model of 823 are used to discriminate 40000 small images after cutting. According to the discrimination results, four color pixel blocks of middle green, bottle green, pale
green and white are generated, and then these pixel blocks are re-integrated in order. The reconstructed results are shown in the figure 5.

The reconstructed image is transformed into a grayscale image, and then into the floating-point image for DCT transformation. Finally, the fitting degree between the reconstructed image and the original image is calculated by a hash algorithm. The performance of the models is shown in Figure 6. The experimental results show that the CNN model based on DCGAN has better ability of classification. The F1 score of the model is 0.0744 larger than the model without simulated samples, which shows that less training data can achieve higher classification accuracy and improve the problem of low classification accuracy caused by insufficient training samples of SAR data.

![Image](image1)

Figure 5. A image reconstructed by 40000 pieces of small images

|                  | Precision | Recall | F1 Score |
|------------------|-----------|--------|----------|
| Based on the few-sample convolution classification results | 80.15%    | 79.63% | 0.7988   |
| Based on the GAN convolution classification results    | 87.62%    | 87.04% | 0.8732   |

![Image](image2)

Figure 6. The Precision, Recall, F1 score of two results

4. Conclusions
The training process of the deep learning needs a large number of training samples. In the field of remote sensing images, due to the high cost of image acquisition, there are too few training samples, which greatly limits the application of deep learning in SAR data classification. As a new generative model, the most direct application of GAN is data generation. Aiming at this problem, this paper proposes this method that is generating simulated SAR image by generative adversarial network, and then uses the image generated by the generative adversarial network as the training data of
A convolutional neural network, to further improve the classification accuracy. The generated simulated sample data can be used not only in the CNN, but also in the training of most artificial intelligence models, such as Computer vision, machine learning, natural language processing, robotics, Biometric technology and so on.

This paper focuses on the impact of the simulated images generated by the generator trained by DCGAN on the classification effect of the convolutional neural network. The results show that DCGAN can fully extract the main features of the image, and the convolution model based on DCGAN can make CNN have better classification ability and get rid of the dependence on the sample size. CNN can also make full use of simulation data. Whether it is test data set or random dataset, its F1 score can obviously surpass the classification ability without DCGAN’s simulated data.

In order to give full play to the ability of Gan, the next work will further study the image generation ability of BigbigGAN, and how to make better use of the generated simulation data in semi supervised classification and unsupervised classification to help guide human daily life or work.

Acknowledgments
Thank Mr. Zhou, Mr. Zhang and Mr. Zheng for their help and encouragement in my work and life. Without their help, I could not complete part of the work of this paper. Finally, thank the reviewers. I wish you good health, smooth sailing and happy.

References
[1] Szegedy C, Liu W, Jia Y, et al. Going Deeper with Convolutions[C]. IEEE Conference on Computer Vision and Pattern Recognition. Boston, USA, 2015: 1-9.
[2] Ross Girshick, Jeff Donahue, Trevor Darrell, et al. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation[C]. IEEE Conference on Computer Vision and Pattern Recognition. Columbus, USA, 2014: 23-28.
[3] Yunji Chen, Tao Luo, Shaoli Liu, et al. DaDianNao: A Machine-Learning Supercomputer[C]. ACM International Symposium on Microarchitecture. Cambridge, UK, 2014: 13-17.
[4] Sutskever I, Vinyals O, Le Q V. Sequence to sequence learning with neural networks[C]. Proceedings of the 2014 Conference on Advances in Neural Information Processing Systems 27. Montreal, Canada, 2014: 3104–3112.
[5] Lodha S K, Kreps E J, Helmbold D P, et al. Aerial LiDAR data classification using Support Vector Machines[J]. IEEE 3rd International Symposium on 3D Data Processing, Visualization and Transmission. 2006, 13(2): 43-51.
[6] Goodfellow I J, Pouget-abadie J, Mirza M, et al. Generative adversarial nets[C]. International Conference on Neural Information Processing Systems. Siem Reap, Cambodia, 2014: 2672-2680.
[7] J. Liu, W. Sun and M. Li. Recurrent Conditional Generative Adversarial Network for Image Deblurring[J]. IEEE Access, 2019, 7(10): 6186-6193.
[8] Ren S, He K, Girshick R, et al. Faster r-cnn: Towards real-time object detection with region proposal networks[J]. Advances in neural information processing systems, 2015, 28: 91-99.