Improving radar target recognition based on generative adversarial network

Nguyen Van Tra[1*], Vu Chi Thanh[1], Doan Van Sang[2]

[1]Institute of Radar, Academy of Military Science and Technology, Cau Giay, Hanoi, Vietnam;
[2]Faculty of Communication and Radar, Vietnam Naval Academy, Nha Trang city, Khanh Hoa, Vietnam.
[*]Email: sinhvienaolinh2000@gmail.com
Received 30 Mar. 2023; Revised 12 Jan. 2024; Accepted 05 Feb. 2024; Published 25 Feb. 2024.
DOI: https://doi.org/10.54939/1859-1043.j.mst.93.2024.12-18

ABSTRACT

In this article, we propose a generative model based on the adversarial network structure to enhance images for the RAD-DAR multi-target dataset. The results of comparisons and evaluations indicate that the images generated by the proposed method exhibit a high degree of similarity to the original images. The experimental process also demonstrates that a deep neural network model trained on the augmented dataset achieves higher accuracy in multi-target recognition compared to a model trained on the original dataset. The proposed data generation model serves as an effective solution to address the data scarcity issue in multi-target datasets.

Keywords: Radar dataset; Radar Target Recognition; GAN; Deep Learning; Data Augmentation.

1. INTRODUCTION

Deep neural networks (DNNs) have made significant strides in various application domains, particularly in the realm of object classification within images. In the field of radar applications, scientists and researchers have increasingly turned their attention to DNNs, specifically for the task of target recognition. DNNs excel in automatically extracting features from radar images, thereby enhancing the accuracy of target recognition. However, it is crucial to note that the efficacy of deep learning models in discerning features is contingent upon a substantial volume of labeled radar data. The process of labeling radar targets is intricate, involving manual execution by radar operators or automated methods through a sensor system seamlessly integrated with radar technology and specialized software [1]. Unfortunately, this labeling procedure is resource-intensive, time-consuming, and costly due to its reliance on manual efforts or sophisticated systems. Additionally, the scarcity of radars equipped to output radar images and integrate effective target labeling tools further constrains this process.

Presently, the labeled radar datasets available primarily consist of small-range, civil radar datasets, often employed in automotive driving assistance systems [2, 3]. The limited availability of radar datasets poses a significant hindrance to the effective application of artificial intelligence technology in addressing radar signal processing challenges [4]. A viable strategy to overcome this limitation is through the implementation of data augmentation [5], a technique designed to enlarge the training set by generating diverse modified data from the existing dataset. This approach proves instrumental in mitigating the scarcity of labeled radar datasets, thereby enhancing the robustness and effectiveness of artificial intelligence models in radar signal processing applications.

Numerous algorithms can be considered for radar data generation, including methods such as flipping along the azimuth axis, translation along the distance or azimuth axis [4], the random selection cutting method [6], adjustment of noise intensity [7], and alteration of the intensity of all pixels [7]. Notably, the utilization of a Generative Adversarial Network (GAN) [8] stands out as an effective strategy for augmenting training data in the context of deep learning models tasked with automated radar target recognition. This approach has proven instrumental in substantially enhancing model accuracy [1], [9-11].

In this article, we propose a novel data generation model based on the GAN structure, aiming to generate radar target images within the range-Doppler domain of the RAD-DAR dataset. A comprehensive comparison and evaluation of the proposed method's effectiveness are subsequently conducted. The rest of paper is organized as follows: Section 2 described the structure of the proposed model utilized for data augmentation. The process of comparing and evaluating the effectiveness of our method is detailed in section 3. Finally, section 4 concludes the research results and outlines potential future directions for this research.

2. PROPOSED MODEL FOR RANGE-DOPPLER RADAR TARGET DATA AUGMENTATION

2.1. Model's structure

In this article, we propose an image generation model based on the adversarial generative network structure (named RDGenGAN) to enhance Range-Doppler images of the RAD_DAR dataset. The model consists of two main components: the generator and the discriminator. The generator is responsible for generating fake output data similar to real data to trick the discriminator. After each training cycle, the process of updating the model weights makes the output image of the generated model more similar to the real image. The discriminator learns to distinguish between fake data generated from the generator and real data. The discriminator acts like a grading teacher, informing the generator whether the way it generates data is sophisticated enough to pass the discriminator and if not, the generator needs to continue learning to create a more realistic image. Simultaneously, the discriminator must also improve its discrimination ability because the image quality created by the generator becomes increasingly realistic. Throughout the training process, both the generator and the discriminator enhance their abilities. Figure 1 illustrates the general structure and training process of the GAN model.

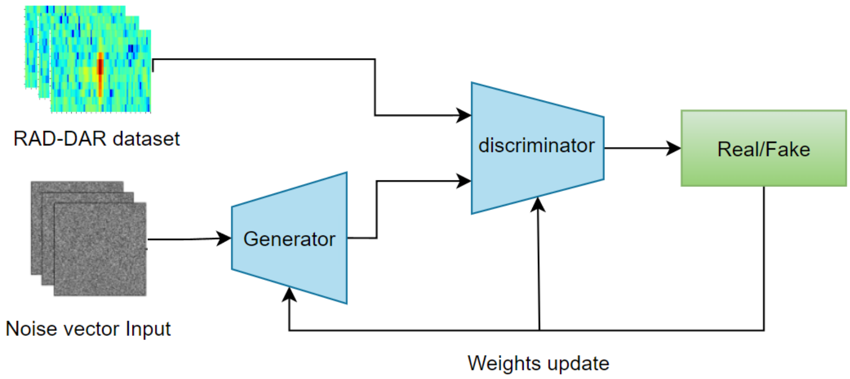

Figure 1. *General structure and training process of the GAN model.*

The generator receives a random vector of a fixed length and generates a fake radar target image. This vector is randomly generated from the Gaussian distribution and is utilized to initialize the generation process. Once the generator is trained, the points in this multidimensional vector space will align with the points from the real data, conforming to the natural data distribution. The generator of the proposed RDGenGAN model has a general structure comprising three main components: an input block, a convolution block, and an output block, as depicted in figure 2.

The discriminator is responsible for determining whether the input image is real or fake. The output of the detector will be classified as real if the input image is taken from the training sample set and as fake if it is derived from the output of the generator. Essentially, this is an ordinary binary classification model. Figure 3 illustrates the architecture of the discriminator in the proposed RDGenGAN model. In terms of structure and function, the discriminator is similar to a CNN (Convolutional Neural Network) model that classifies two different objects. The structure of the discriminator includes three main blocks: an input block, a feature extraction block, and an output block.

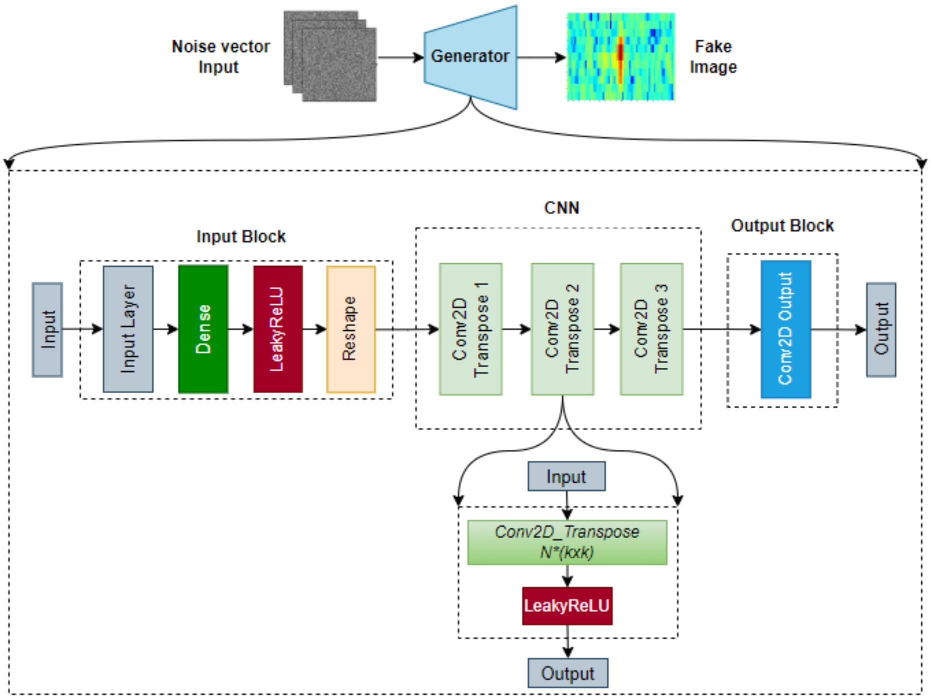

Figure 2. *The genenator structure of the proposed RDGenGAN model.*

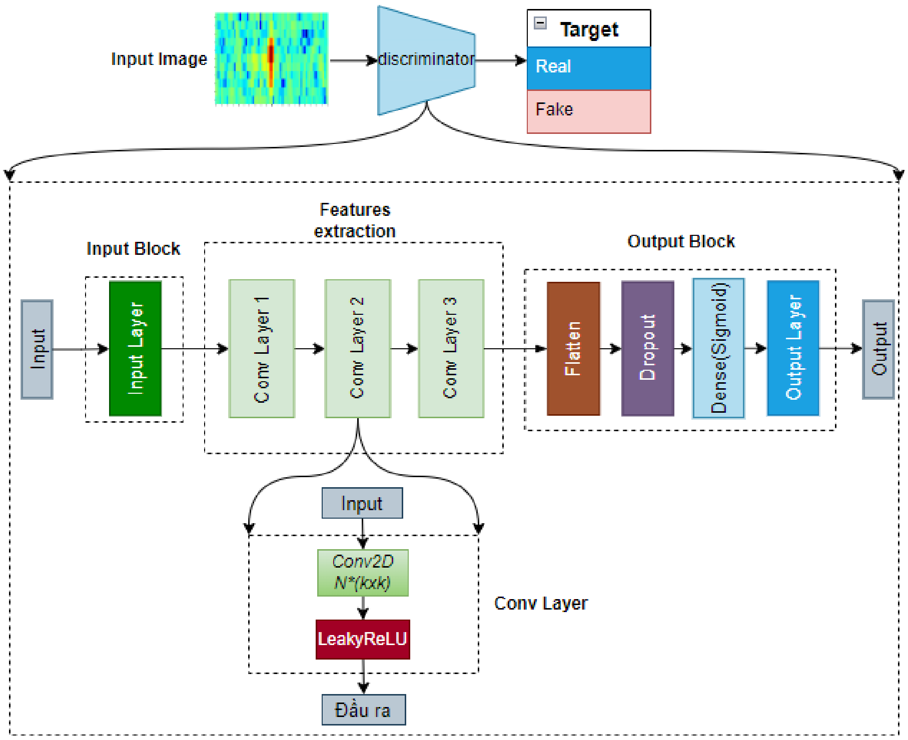

Figure 3. *The discriminator structure of the proposed RDGenGAN model.*

2.2. Loss Functions

The symbol *z* is the input noise of the generating model, *x* is the real data from the dataset.. The generator symbol is *G*, the discriminator is *D*. *G(z)* is the image generated from the generator. *D(x)* is the prediction value of the discriminator whether image *x* is real or not, *D(G(z))* is the prediction value whether the image generated from the generator is real or not. The GAN model includes two components (generator and discriminator) with different tasks, so the loss function for the GAN model also includes two components for the generator and discriminator, respectively.

The discriminator's loss function wants to maximize the value *D(x)* and minimize the value *D(G(z))*. The minimum value *D(G(z))* is equivalent to the maximum value *(1 – D(G(z)))*. Therefore, the loss function of the discriminator is described in formula (1).

$$\max V(D) = \mathrm{E}_{x\sim p_{data}(x)}[\log \mathrm{D(x)}] + \mathrm{E}_{z\sim p_z(z)}[\log(1-\mathrm{D(G(z))})] \qquad (1)$$

During training, the generator will learn to fool the discriminator that the output image it generates is a real image, or that *D(G(z))* approaches the value 1. Or the loss function wants the value *D(G(z))* to be the largest, which means the value *(1 – D(G(z)))* is the smallest. Equation (2) describes the loss function of the generator.

$$\min V(\mathrm{G}) = \mathrm{E}_{z\sim p_z(z)}[\log(1-\mathrm{D(G(z))})] \qquad (2)$$

The loss function of the GAN model is a function that simultaneously combines the loss function of the discriminator and the generator as described in formula (3). From the loss function of the GAN model, it can be seen that the training of the generator and the detector are opposite, while *D* tries to maximize the loss value, *G* executes to maximize the loss value. minimize this value. The GAN network training process ends when the model reaches the equilibrium state of the two generators and detectors.

$$\min_G \max_D V(D,G) = \mathrm{E}_{x\sim p_{data}(x)}[\log \mathrm{D(x)}] + \mathrm{E}_{z\sim p_z(z)}[\log(1-\mathrm{D(G(z))})] \qquad (3)$$

3. TESTING AND EVALUATION

3.1. Evaluation methods

To objectively evaluate the effectiveness of the proposed method, the article evaluates three different datasets: the original RAD-DAR dataset, the dataset enhanced with images generated by the image processing method (combination of 3 methods: image flipping, light intensity adjustment, background noise level adjustment) and the dataset is enhanced by the proposed RDGenGAN model. Despite great strides in the theoretical advancement of data image generation algorithms, evaluating and comparing the generated image sets with the original images is still a difficult task [12]. In this study, the augmented data are evaluated by using image comparison indices and experiment results.

3.2. Evaluation is based on image comparison indices

The article uses Frechet Inception Distance (FID) [12] and the Nearest Neighbor (NN) index to evaluate the similarity and overlap of the original image set and the generated samples as the authors in the study [13] proposed. Table 1 shows the FID and NN indices calculated from the original dataset with different generated imagesets. The image sets for comparison all have the same number of 1200 images. In particular, the image set generated by the image processing algorithm created from images in the original image set includes 400 images created by image flipping, 400 images created According to brightness adjustment, 400 images are created after adding noise to the original image. Two sets of images are generated from the RDGenGAN model with training cycles 20 and 25 repectively. A set of 1200 images randomly select from the

RAD-DAR dataset is used as the basis for evaluating the quality of the augmented images.

The results in table 1 show that the image created by the image processing algorithm has the lowest value of 0.23 that means this image set has the highest similarity compared to the original dataset. However, the NN index of this image set has a value of 1.24, relatively close to the value 1, showing that this image set is too similar and is copied from the original dataset. With the image set created by the RDGenGAN model, the FID and NN indices are quite close to the indices when comparing two image sets in the same RAD-DAR dataset. This proves that the image set generated from the RDGenGAN model is not a copy but is created based on the characteristics of the original image set. In particular, the image set of the RDGenGAN model with a number of epochs of 20 gives the most similar FID and NN values of 0.763 and 5.95, respectively.

Table 1. *The results of evaluation measure on augmented datasets.*

Dataset	FID	NN
1200 images RAD-DAR	0.626	6.18
1200 images generated by the image processing algorithm	0.237	1.24
1200 images generated by RDGenGAN 20 Epochs	**0.763**	**5.95**
1200 images generated by RDGenGAN 25 Epochs	0.884	8.71

3.3. Experimental results

The article installs the deep learning neural network model RINet [14] and trains the model with the original RAD_DAR data sets, the data set is increased by the image processing algorithm and by the RDGenGAN image generation model. Table 2 shows the results of evaluating the radar target recognition accuracy of the RINet neural network model on the corresponding data set. Those results indicate that the target recognition accuracy of the RInet model is improved when the training data is augmented with simulated target images. When using a dataset enhanced by image processing algorithms (flipping, adjusting light intensity, adding noise), the quality of target recognition is improved compared to when using the original dataset. Specifically, accuracy increased by 2.18%, loss decreased by 6.38%. Using data augmented by the proposed RDGenGAN model get the best result compared to using original data and data augmentation by image processing methods. Specifically, the accuracy is 97.56% increased by 3.2%, the loss is 6.16% decreased by 10.52% compared to result when using original data.

Table 2. *The Comparison the target recognition results of the RINet model.*

Dataset	Accuracy (%)	Loss (%)
RAD_DAR	94.36	16.68
RAD_DAR + tập ảnh theo thuật toán xử lý ảnh	96.54	10.3
RAD_DAR + RDGenGAN	**97.56%**	**6.16%**

Figure 4 and figure 5 are the results of the accuracy and loss during training and testing of the RINet model on the original dataset and the dataset augmented by the proposed RDGenGAN model. The RINet model stops training at 16 and 30 epochs for the two dataets, respectively. It shows that applying the RDGenGAN model to data augmentation will help the RINet model increase the number of training cycles before encountering the Overfitting problem. The increased number of training cycles is responsible for improving the model's target recognition accuracy.

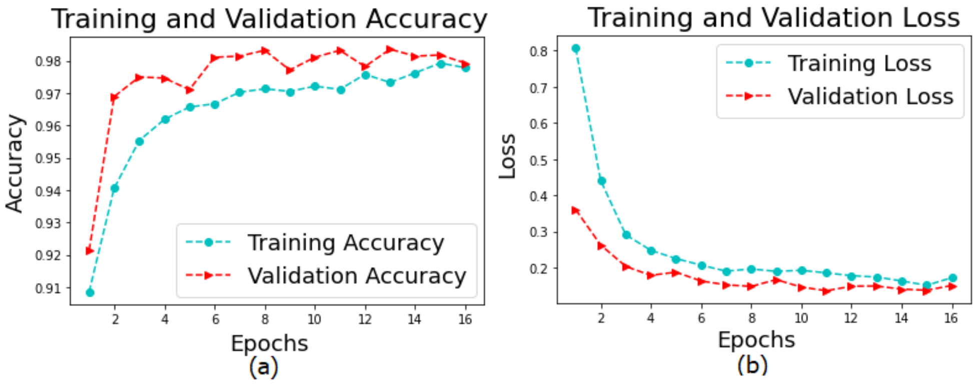

Figure 4. *Illustration of results the of RINet model on the RAD_DAR dataset. (a) Accuracy, (b) Loss.*

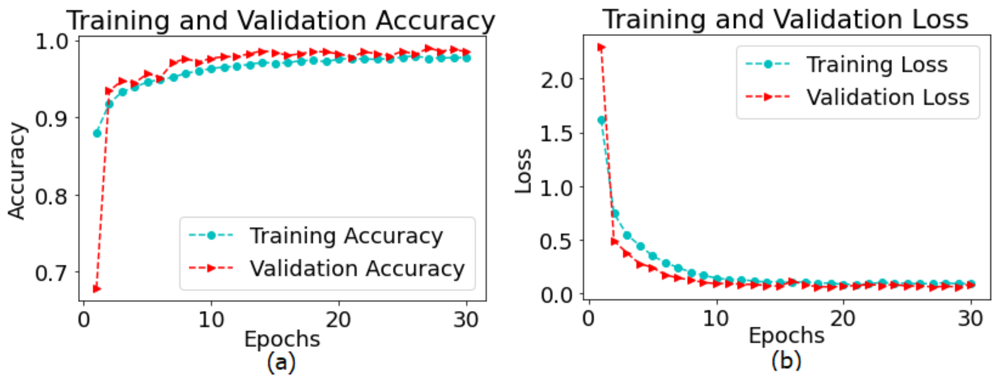

Figure 5. . *Illustration of results the of RINet model on the RAD_DAR dataset augmented by the RDGenGAN. (a) Accuracy, (b) Loss.*

4. CONCLUSIONS

Overall, in this article we propose a model for radar target image generation based on the GAN structure. Various radar target image sets, including the original RAD_DAR image set, an image set enhanced by image processing algorithms, and an image set improved by the proposed model, are evaluated and compared using image comparison indices and experimental processes. The comparison results reveal that the images generated by the RDGenGAN model proposed in this study exhibit a high degree of similarity to the original images. Training the neural network model on the augmented dataset significantly enhances the accuracy of radar target recognition. Our future work involves comparing GAN models with different CNN structures to identify the most suitable architecture for the image generation model.

REFERENCES

[1]. Marcio L. Lima de Oliveira and Marco J. G. Bekooij. *"Generating Synthetic Short-Range FMCW RangeDoppler Maps Using Generative Adversarial Networks and Deep Convolutional Autoencoders"*. In: 2020 IEEE Radar Conference (RadarConf20). pp. 1–6, (2020). DOI: 10.1109/RadarConf 2043947.2020.9266348.

[2]. Arthur Ouaknine, Alasdair Newson, Julien Rebuty, Florence Tupin and Patrick Perez. *"CARRADA Dataset: Camera and Automotive Radar with Range-Angle-Doppler Annotations"*. 2020 25th International Conference on Pattern Recognition (ICPR) Milan, Italy, Jan 10-15, (2021).

[3]. Yizhou Wang, Zhongyu JiangYudong Li, Jenq-Neng Hwang *"RODNet: A Real-Time Radar Object Detection Network Cross-Supervised by Camera-Radar Fused Object 3D Localization"*. arXiv:2102.05150v1 [cs.CV] (2021).

[4]. Xiangyu Gao, Guanbin Xing, Sumit Roy, and Hui Liu *"RAMP-CNN: A Novel Neural Network for Enhanced Automotive Radar Object Recognition"*. arXiv technical report (arXiv 2011.08981).

[5]. Ali, S., Ghatwary, N., Braden, B., Lamarque, D., Bailey, A., Realdon, S., Cannizzaro, R., Rittscher, J., Daul, C., & East, J., *"Endoscopy disease detection challenge 2020"*. ArXiv Preprint ArXiv:2003.03376, (2020).

[6]. Hidetoshi Furukawa *"Deep Learning for Target Classification from SAR Imagery: Data Augmentation and Translation Invariance"*. https://arxiv.org/abs/1708.07920.

[7]. Marcel Sheeny , Andrew Wallace and Sen Wang *"RADIO: Parameterized Generative Radar Data Augmentation for Small Datasets"*. Appl. Sci., 10, 3861, (2020); doi:10.3390.

[8]. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y., *"Generative adversarial nets"*. Advances in Neural Information Processing Systems, 27, (2014).

[9]. Ibrahim Alnujaim, Youngwook Kim *"Augmentation of Doppler Radar Data Using Generative Adversarial Network for Human Motion Analysis"*. Healthc Inform Res; 25(4):344-349, pISSN 2093-3681, eISSN 2093-369X, (2019).

[10]. Thomas Truong, Svetlana Yanushkevich, *"Generative Adversarial Network for Radar Signal Generation"*. arXiv:2008.03346v1 [eess.IV], (2020).

[11]. R. C. Tewari, P. Palo, J. Maiti and A. Routray, *"GAN-based Radar Micro-Doppler Augmentation for High Accuracy Fall Detection System,"* IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society, Brussels, Belgium, pp. 1-6, (2022), doi:10.1109/IECON49645.2022.9968957.

[12]. G. Huang, Y. Yuan, Q. Xu, C. Guo, Y. Sun, F. Wu, K. Weinberger, *"An empirical study on evaluation metrics of generative adversarial networks"*, International Conference on Learning RepresentationsRejected, (2018). URL https://openreview.net/forum?id=Sy1f0e-R-

[13]. Eduardo C. Fidelis, Fabio Reway, Herick Y. S. Ribeiro, Pietro L. Campos, Werner Huber Christian Icking, Lester A. Faria, Torsten Schon. *"Generation of Realistic Synthetic Raw Radar Data for Automated Driving Applications using Generative Adversarial Networks"*. arXiv:2308.02632v2 [cs.CV], (2023).

[14]. Nguyễn Văn Trà, Vũ Chí Thanh, Đoàn Văn Sáng, *"Giải pháp nâng cao xác suất nhận dạng đúng mục tiêu UAV ứng dụng trí tuệ nhân tạo"*, Tạp chí Khoa học và Công nghệ quân sự, số Đặc san FEE, (2023) (in Vietnamese).

TÓM TẮT

Nâng cao chất lượng nhận dạng mục tiêu ra đa dựa vào mạng sinh đối nghịch GAN

Trong bài báo này, chúng tôi đề xuất một mô hình sinh ảnh theo cấu trúc mạng sinh đối nghịch nhằm tăng cường ảnh cho tập dữ liệu mục tiêu ra đa RAD-DAR. Kết quả của các phép so sánh, đánh giá chỉ ra rằng các ảnh được tạo ra bởi phương pháp đề xuất có sự tương đồng cao so với ảnh gốc. Quá trình thực nghiệm cũng cho thấy mô hình mạng nơ-ron học sâu huấn luyện trên tập dữ liệu tăng cường có độ chính xác nhận dạng mục tiêu ra đa cao hơn so với mô hình huấn luyện trên tập dữ liệu gốc. Mô hình sinh dữ liệu bài báo đề xuất là một giải pháp hiệu quả để khắc phục tình trạng thiếu hụt dữ liệu trong các tập dữ liệu mục tiêu ra đa.

Từ khóa: Tập dữ liệu; Nhận dạng mục tiêu; Mạng sinh đối nghịch; Học sâu; Tăng cường dữ liệu.