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Comprehensive Survey of Deep Learning in Radar Signal Processing: Opportunities and Challenges

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Abstract:

As of the most important branches of artificial intelligence, deep learning (DL) has developed rapidly in recent years, and has been successfully used in many research fields. Although the DL-based algorithms offer a great opportunity for researchers to finally conquer the bottleneck problems in the field of radar signal processing, they also bring about brand-new technical challenges. In this paper, comprehensive review of the applications of DL methods is proposed, including low probability of interception and passive radar waveform recognition, automatic target recognition, radar jamming/clutter recognition and suppression, and radar waveform and antenna array design. Recently, the proposed DL-based radar waveform recognition and SAR automatic target recognition methods are summarized and analyzed in detail. The major factors limiting the performance of the DL algorithms are also examined. This work aims to provide valuable information to the scholars in this promising field of research.

Keywords:

Deep learning
Waveform recognition
Automatic target recognition (ATR)
Low probability of intercept

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1. Introduction

In recent years, with the development and popularization of Graphics Processing Units (GPUs), deep learning algorithms represented by Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have achieved remarkable successes in various fields such as image recognition, speech recognition, and autonomous driving. In the field of radar signal processing, more researchers are attempting to utilize deep learning algorithms to address related issues [1], such as waveform recognition [2,3], automatic target recognition [4], identification and suppression of interference and clutter signals [5], as well as bottleneck problems in areas like radar waveform and array design [6]. These efforts have yielded a series of research achievements with significant theoretical importance and practical value [7].

The following is a categorized overview:

(1) Radar waveform recognition

To address the issue of traditional radar's high-power emission signals being easily intercepted by enemy reconnaissance equipment, scholars worldwide have been dedicated to developing Low Probability of Intercept (LPI) waveforms with superior radio frequency stealth characteristics. Deep learning algorithms provide new insights for solving the problem of fast and accurate recognition of complex LPI waveforms, enhancing the capabilities of electronic warfare systems, anti-radiation missiles, and electronic support systems to intercept LPI signals [2]. On the other hand, passive radar technology, which utilizes external emitters such as TV/cell phone base stations, has also developed rapidly. Compared to active radars, passive radars not only offer better anti-intercept performance but can also be used for long-term monitoring of large detection areas without consuming additional energy or spectrum resources. However, the transmitted signals of passive radars are unknown to the radar receiver, making matched filtering impossible. To overcome this challenge, some scholars have proposed using deep learning algorithms to estimate external emitter signals, achieving a series of valuable preliminary results [8,9]. Although deep learning algorithms show great potential in radar waveform recognition, numerous studies have demonstrated that targeted adversarial attacks (AAs) can lead to a drastic decrease in the classification accuracy of these algorithms [10].

(2) Automatic target recognition

Radar automatic target recognition technology based on deep learning can be mainly divided into the following categories: (a) Automatic Target Recognition (ATR) based on SAR images [11]; (b) Target recognition based on high-resolution range profiles, primarily including recognition of aircraft [12], ground vehicles [13], and ship targets [14]; (c) Target recognition based on micro-Doppler features, mainly comprising human target action recognition [15,16] and discrimination between drones and birds [17,18]; (d) Automatic target recognition based on other information, such as target radar cross-section area [19]. Among the relevant papers published in this field in the past five years, the direction of Synthetic Aperture Radar ATR (SAR-ATR) accounts for the highest proportion. This technology, with its significant engineering practical value, distinct dual-use characteristics for military and civilian applications, and wide range of application scenarios, is the focus of this article. Although theoretical research on SAR-ATR has yielded abundant results, providing new insights for addressing the efficient and accurate interpretation of SAR images, its engineering application still faces challenges such as limited quantity and diversity of training samples and poor robustness under adversarial attack conditions. Closely related to this research direction are automatic target detection and recognition relying on SAR images [20,21] and video SAR [22], with typical problems including ground vehicle detection in large scenes [23] and ship target detection and classification in port areas [21].

(3) Identification and suppression of interference and clutter signals

With the continuous advancement of deceptive active interference technology, traditional anti-interference techniques such as sidelobe blanking and sidelobe cancellation can no longer ensure the normal operation of military radars under enemy electronic interference conditions. In view of this, scholars at home and abroad have carried out a series of electronic counter-countermeasures research based on deep learning, mainly including interference signal recognition [23,24], target recognition under interference conditions [25], and optimization of adaptive anti-interference strategies [26]. Meanwhile, deep learning algorithms provide technical support for further improving the suppression capability of modern radars against sea and ground clutter. Related research includes target detection in sea clutter [27,28] and ground clutter environments [29].

(4) Radar waveform and array design

In radar waveform and array design, deep learning is mainly used for: (a) Transmission power spectrum design for spectrum sharing. The most representative achievement in this area is the non-interfering spectrum interval discrimination and adaptive radar waveform adjustment technology developed by the US Army DEVCOM Laboratory [30]; (b) Multiple-Input Multiple-Output (MIMO) radar transmission waveform design and optimization [6]; (c) Antenna array design, with the main research direction being MIMO radar subarray design and optimization [31].

It should be noted that the technical route of deep learning-based interference and clutter signal recognition methods is the same as that of radar waveform recognition, while the target detection problem in interference and clutter has a certain degree of overlap with the target detection and recognition problem based on SAR images. Meanwhile, in the field of MIMO radar waveform and array design, existing research is mainly based on simulation experiment results using MATLAB, and there is relatively little field experimental data, which is not yet sufficient to demonstrate the absolute advantage of deep learning over classical algorithms. Therefore, due to space limitations, this article focuses on analyzing the application of deep learning in the field of radar waveform recognition and SAR-ATR and does not discuss other research directions in detail.

2. Low probability of intercept and passive radar waveform recognition

With the rapid development of LPI and passive radar technologies, radar waveform recognition techniques based on deep learning have become a hot spot of attention for researchers both domestically and internationally. Commonly used neural network models in this field primarily include CNNs [32], autoencoders [33], and RNNs combined with attention mechanisms [34] (see **Figure 1**). Numerous research results indicate that radar waveform recognition technology based on deep learning significantly outperforms traditional algorithms in areas such as LPI waveform recognition and passive radar external emitter signal estimation.

Currently, LPI waveform recognition is primarily achieved through time-frequency analysis methods such as Short-Time Fourier Transform (STFT) [35], Wigner-Ville Distribution (WVD) [2,36], and Choi-Williams Distribution (CWD) [37]. Among these, STFT belongs to linear time-frequency representation, while WVD and CWD belong to quadratic time-frequency representation. Compared to traditional WVD, CWD can effectively filter out cross-terms by selecting appropriate exponential weighted kernel function parameters, making it the most widely used. In 2020, researchers from Fraunhofer FKIE in Germany first performed time-frequency analysis on LPI waveforms using CWD and then achieved a recognition accuracy rate of over 99% under small sample conditions through transfer learning, utilizing five high-performance pre-trained CNN neural network models: VGG16, ResNet50, Inception-ResNetV2, DenseNet, and MobileNetV2 [37]. Given the high computational complexity of CWD, researchers from Beijing Institute of Technology, Nanjing University of Science and Technology, University of Electronic Science and Technology of China, and a branch of Islamic Azad University in Iran have respectively used pseudo-WVD [2], Fourier Synchrosqueezed Transform (FSST) [38], and STFT [39] for time-frequency analysis of LPI waveforms, effectively reducing computational time costs. Numerous studies have shown that CNN neural network models can accurately and efficiently analyze and extract features from time-frequency images, and their waveform recognition accuracy is significantly better than that of RNN networks such as Long Short-Term Memory (LSTM). It is worth noting that time-frequency processing is not the only technical approach for waveform recognition. For example, in 2020, Yildirim *et al.* (2020) from Qatar University proposed an adaptive one-dimensional CNN with four hidden layers and two dense layers for the classification of continuous and pulse waves [39].

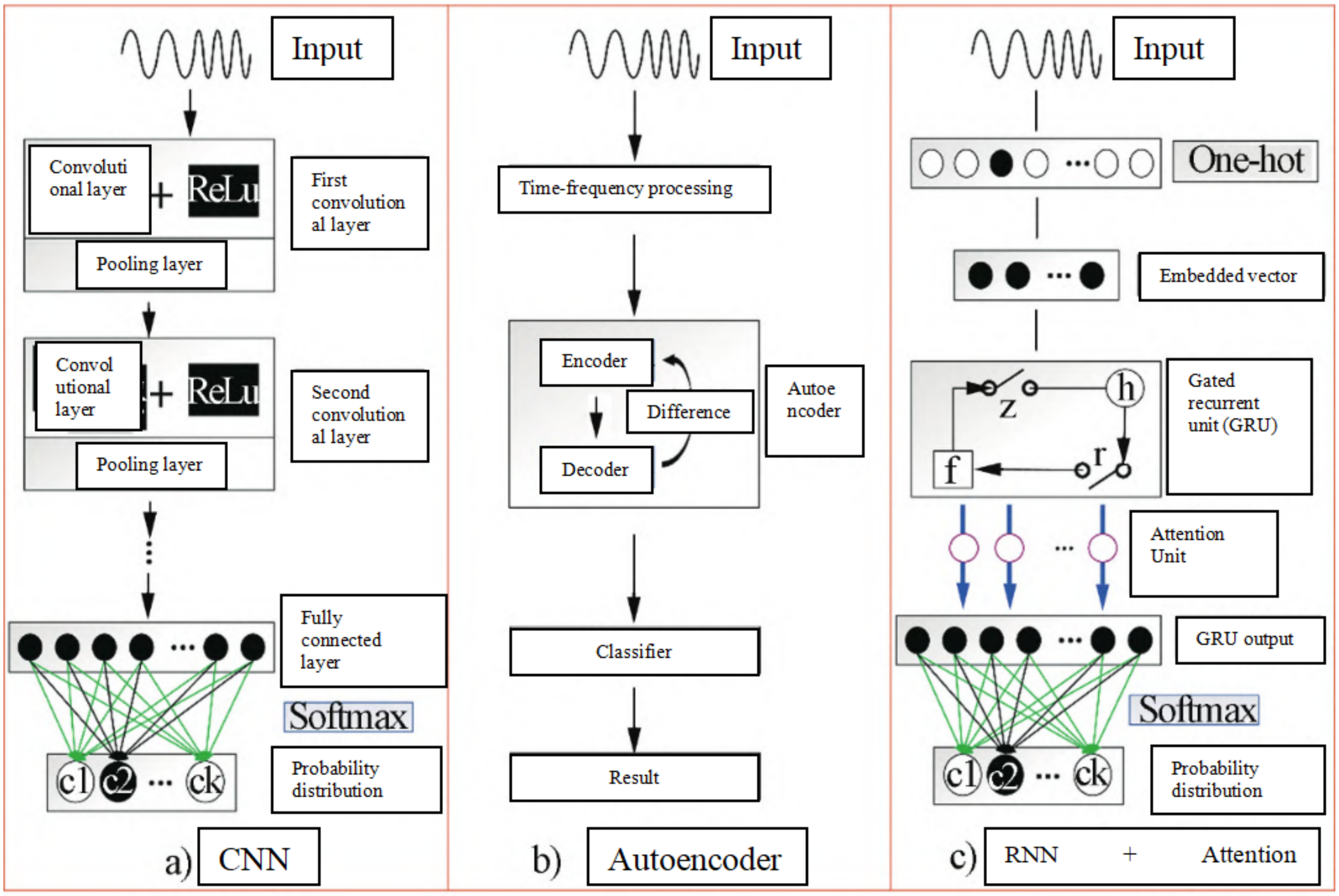

Figure 1. CNN, Autoencoder, and RNN combined with attention mechanism.

Passive radars utilize existing external emitters' radio waves for target detection, eliminating the need for dedicated radar transmitters and spectrum resources, thus resulting in lower costs. Commonly used external emitters include [40]: (1) analog communication systems; (2) digital communication systems; (3) satellite-based communication systems; and (4) ground-based positioning systems. Among them, passive radars that use digital television and mobile phone base stations as external emitters have been a hot research topic in recent years [41]. Television and mobile phone base stations are widely distributed across the country, with coverage areas increasing year by year. Radio waves were transmitted around the clock, uninterrupted, enabling long-term monitoring of specified detection areas without consuming additional energy. On the other hand, with the development of wireless communication technology and the popularity of mobile phones and televisions, the spectrum resources required by communication systems are expected to increase year by year. Building passive radars can help achieve spectrum sharing between radar and communication systems, thereby promoting the efficient use of scarce spectrum resources. Although passive radars have broad development prospects, their detection performance is often inferior to active radars because the waveforms of external emitter signals are usually not conducive to target detection and localization. These signals need to be estimated from the direct signals received from the external emitters through the receiver's reference channel. Currently, some scholars at home and abroad have conducted preliminary explorations on the estimation of external emitter signals based on deep learning. The most representative achievements in this field include a deep RNN designed by researchers at Rensselaer Polytechnic Institute in the United States for precise estimation of passive radar waveform parameters and high-quality reconstruction of SAR images [7], as well as a new neural network architecture and transfer learning mechanism composed of a dual-channel CNN and bidirectional LSTM, designed by researchers at Tianjin University [42].

Numerous studies have shown that the classification accuracy of radar and communication system transmit waveform recognition algorithms based on deep neural network models can significantly decrease under adversarial attack (AA) conditions. Depending on the attacker's level of knowledge about the structure and specific parameters of the neural network model, AAs can be classified as white-box, gray-box, and black-box attacks. In real-world confrontation scenarios, AA perpetrators generally do not have complete knowledge of the specific structure and parameters of their targets, so they often adopt the "black-box" attack approach. However, researchers and engineers often assume a "white-box" attack scenario when conducting AA risk assessments of waveform recognition algorithms based on deep learning, where the enemy is assumed to have full knowledge of our neural network model's specifics. In less sensitive application areas, developers sometimes voluntarily disclose model parameters and invite researchers in related fields to attack them in the form of contests with prizes. In 2019, researchers from Lulea University of Technology in Sweden pointed out that even if AA perpetrators do not know their target model's parameters, they can still significantly reduce the classification accuracy of the attacked neural network model by designing universal adversarial perturbations [10]. With the continuous development of AA technology, various AA detection and adversarial training (AT) methods have emerged, effectively improving the robustness of neural network models under AA conditions [43]. As the application of deep learning algorithms in the field of waveform recognition increases, AA and anti-AA technologies are expected to promote and restrict each other for a considerable period.

3. Automatic target recognition based on SAR images

Currently, relevant research conducted by scholars at home and abroad in this field mainly relies on the MSTAR dataset, which was collected by the Defense Advanced Research Projects Agency (DARPA) and the US Air Force Research Laboratory (AFRL) between 1995 and 1997. This dataset contains high-resolution SAR images of ground military targets such as tanks and armored vehicles.

In terms of developing SAR-ATI algorithms based on deep learning, the ten-class target classification problem under Standard Operating Conditions (SOC) has been solved for the MSTAR dataset. However, there is still considerable room for improvement in target classification accuracy under Extended Operating Conditions (EOC) [44]. The target observation parameters under these two conditions are shown in **Table 1**. Meanwhile, existing algorithms primarily utilize the MSTAR dataset to evaluate classification accuracy, lacking a systematic and in-depth analysis of the potential impact of confounders (i.e., targets present in the test set but not encountered during training) and clutter backgrounds in real-world engineering applications, as well as the inherent mechanisms of deep neural network models for extracting target feature maps.

In 2016, researchers from Wright State University in the United States and AFRL proposed AFILeNet [45]. When the training and testing sets contained targets of the same and similar categories, the classification accuracy of MSTAR's ten categories of targets was

Table 1. Target observation parameters for Standard and Extended Operating Conditions

Parameter name	Standard Operating Conditions (SOC)	Extended Operating Conditions (EOC)
Signal-to-noise ratio	/	Additional noise -10dB < SNR < +10dB
Depression angle	15° (Test), 17° (Training)	17° (Test), 30°/45° (Training)
Resolution	0.3×0.3 (m^2)	0.3×0.3 - 0.7×0.7 (m^2)
Sub-model	/	T72, BTR60, T62, BMP2
Target occlusion	/	Occlusion rate generally 10%–50%

99.4% and 93%, respectively. In 2019, Kechagias-stamatis *et al.* (2019) from Cranfield University in the UK proposed the l1-2-CCNN algorithm based on deep learning and sparse representation [46]. They used observation samples at a pitch angle of 15° as training data and observation samples at pitch angles of 30° and 45° as testing data, achieving classification accuracies of 99.61% and 70.87%, respectively. In the same year, Inkawhich *et al.* (2021) from Duke University in the United States conducted tests on representative small, medium, and large CNN networks and various loss functions to further improve the classification accuracy of the SAR-ATI system under 100% simulated training sample conditions [47]. Inkawhich *et al.* (2021) found that although large CNNs with depths exceeding 100 layers and containing tens of millions of neurons demonstrate unparalleled superiority over small and medium-sized networks in optical image recognition tasks, they do not have a significant advantage over medium-sized networks in low-resolution SAR image classification, which is dominated by grayscale images [48]. In 2021, they used SAR images of ships obtained by GF-3 and Sentinel-1 satellites to train neural networks for confusion detection, achieving good results.

Several other studies have conducted extensive and in-depth research on SAR target recognition [49–54]. Among them, Chen *et al.* (2016) propose a novel deep convolutional neural network called A-ConvNets, which achieves classification accuracies of 99.1%, 96.1%, and 98.9% under SOC, EOC-1, and EOC-2 working conditions, respectively [49]. Zhang *et al.* (2021) present an FEC algorithm based on electromagnetic scattering and deep CNN features, achieving an average classification accuracy higher than 98% for five variants of T72 in the EOC-2 scene [50]. Feng *et al.* (2021) propose to organically combine target component models with deep learning algorithms [51]. Firstly, it extracts the local features of the target using a bidirectional convolutional recurrent network based on the ASC model of target components. Then, it extracts the global features of the target using a fully convolutional network. Finally, it makes decisions on target categories by fusing local and global features. The recognition accuracy of this network is higher than 99% for both EOC-1 and EOC-2. Li *et al.* (2022) introduce a multi-scale CNN based on component analysis [52]. It first divides the SAR target into multiple parts according to its geometric structure by extracting ASC information from the target echo. Then, it judges the target category by synthesizing the global information extracted from the entire image by a shallow network and the local detail information extracted from each component by a deep network, ultimately achieving a SOC recognition accuracy higher than 98%. It should be noted that the aforementioned near-100% accuracy rates are all evaluated using data related to standard target morphologies at a 30° pitch angle. When tested using data at a 45° pitch angle and rigid target deformation, the classification accuracy is only 76.32%.

Table 2 and **Table 3** summarize the typical SAR-ATI algorithms developed by foreign and domestic researchers relying on the MSTAR dataset since 2016, respectively. Among them, SOC refers to the standard

Table 2. Overview of typical SAR target recognition algorithms based on deep learning (foreign)

DNN	Main features	Training/testing conditions	Number
AFRLeNet	LeNet Add dropout layer to the network	SOC	1-1
		EOC (different training/testing targets)	1-2
AlexNet	Fusion of deep learning and sparse representation	EOC (17° training, 30° testing)	2-1
		EOC (17° training, 45° testing)	2-2
LeNet (SMPL) ResNet18 (RN18) Wide-RN18 (WRN18)	Data augmentation, model construction, loss function selection	SOC	3-1
Improved ResNet18	ResNet18 + dropout layer, data augmentation, introduction of abnormal samples during training	SOC	4-1

Table 3. Overview of typical SAR target recognition algorithms based on deep learning (domestic)

DNN	Main features	Training/testing conditions	Number
A-Conv Nets	Remove the fully connected layer of a typical CNN, multi-level network + multi-layer feature fusion	SOC	5-1
		EOC-1 (17° training, 30° testing);	5-2
		EOC-2 (configuration, model variants)	5-3
MBCRN + A-Conv Nets	Local/global feature fusion for decision-making	EOC-1 (17° training, 30° testing)	6-1
		EOC-2 (configuration variants)	6-2
		EOC-2 (model variants)	6-3
CA-MCNN	Local/global feature fusion for decision-making	SOC	7-1
Improved VGGNet	Target ASC feature extraction + clustering + ASC and CNN feature fusion	EOC-2 (T72 model variants, including SN132, SN812, A04, A05, A07, A10)	8-1

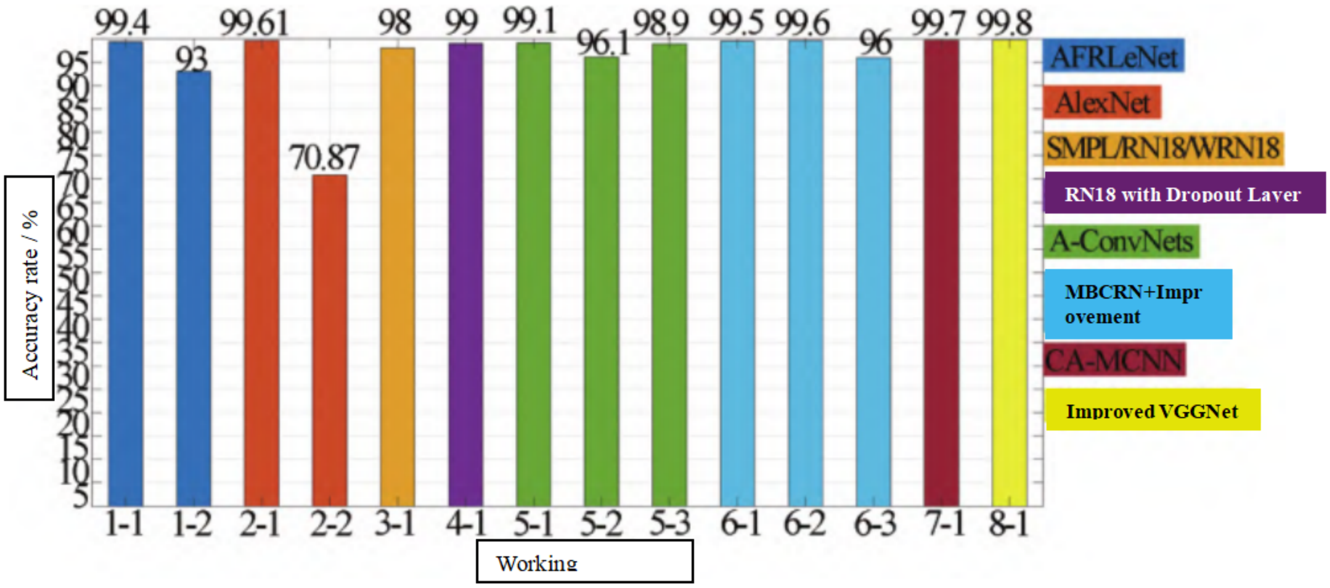

Figure 2. Performance comparison of existing deep learning networks under different operating conditions.

operating condition where data at a 17° pitch angle is used for training, and data at a 15° pitch angle is used for testing. The target recognition accuracies of various algorithms under SOC and different EOC conditions are shown in **Figure 2**.

Although deep learning-based target recognition technology provides a breakthrough for efficient and accurate interpretation of SAR images, the engineering application of this technology still faces the following two challenges:

(1) Limited number and variety of SAR image training samples

The number of labeled, measured SAR image samples available for neural network training is severely insufficient, and the backgrounds of training and testing samples are highly correlated. The use of simulation software based on ray tracing methods and finely adjusted target computer-aided design (CAD) models can generate high-quality simulated SAR images, but the computational cost is huge. At the same time, classic optical image augmentation techniques such as image rotation and stretching, as well as simulation SAR image synthesis techniques based on Generative Adversarial Networks (GANs), can rapidly expand the SAR image training set. However, they do not fully consider the electromagnetic scattering characteristics of SAR targets and cannot adaptively handle significant changes in SAR image morphology caused by changes in radar system parameters and observation scenes. Compared with the above techniques, dataset construction and expansion techniques based on the physical imaging mechanism of SAR images have better physical interpretability but higher computational complexity.

On the other hand, existing deep learning algorithms heavily rely on the correlation of clutter backgrounds between training and testing data when classifying targets in the MSTAR dataset, rather than focusing on the characteristics of the targets themselves. This leads to some deep learning algorithms still being able to correctly classify samples based on SAR image background clutter or shadows when the target area in the SAR image sample is 100% occluded. Simultaneously, most neural networks currently used for SAR image recognition are based on the assumption that the target types and poses of the SAR images in the training and testing sets are the same and that the statistical characteristics of the clutter background are consistent. They do not adequately consider the impact of variations in similar target types, rigid target deformations, confusing objects, statistical characteristics of clutter, and changes in clutter-to-noise ratio. Additionally, the physical interpretability of the specific decisions made by neural networks is not strong. Therefore, building a large, high-quality SAR image database with diverse target poses and clutter backgrounds is essential for achieving leapfrog development in deep learning-based SAR-ATI technology.

(2) Poor robustness of existing deep learning algorithms under AA conditions

AA refers to inducing deep learning algorithms to misclassify targets by altering the local details of the target images. As mentioned earlier, AA can be classified into white-box, gray-box, and black-box attacks based on whether the attacker has access to the structure and specific parameters of the target neural network. AA can also be divided into targeted attacks and generalized attacks based on whether there are specific requirements for misclassification categories. Furthermore, AA can be categorized into gradient-based attacks (such as I-FGSM, ILCM, etc.), score-based attacks, and decision-based attacks according to the specific means of attack. In 2020, researchers from Guangzhou University used three classic AA algorithms to attack neural networks: I-FGSM, ILCM, and DBA. Experimental results showed that under I-FGSM generalized black-box attack conditions, the target recognition rate of VGGNet and ResNet dropped from 95% to 7%. Under ILCM-targeted white-box attacks, the confidence of ResNet in the true class label decreased from 99% to 61.4%. Under DBA-targeted black-box attacks, the confidence of AlexNet, VGGNet, and ResNet in the true class label dropped to 22.4%, 15.9%, and 23.2%, respectively.

Although techniques such as adversarial training, adversarial detection, and gradient masking can improve the robustness of deep neural networks against adversarial samples, mainstream neural network models still need to enhance their resistance to adversarial attacks as AA technology continues to evolve. The challenges faced by existing deep learning-based SAR ATI technology are illustrated in **Figure 3**.

4. Conclusion

This article systematically reviews the research trends of deep learning algorithms in the field of radar signal processing. It briefly introduces the research overview and development trends of deep learning in areas such as LPI and passive radar waveform recognition, automatic target recognition, identification and suppression of interference and clutter signals, as well as radar waveform and array design. The article provides a detailed analysis

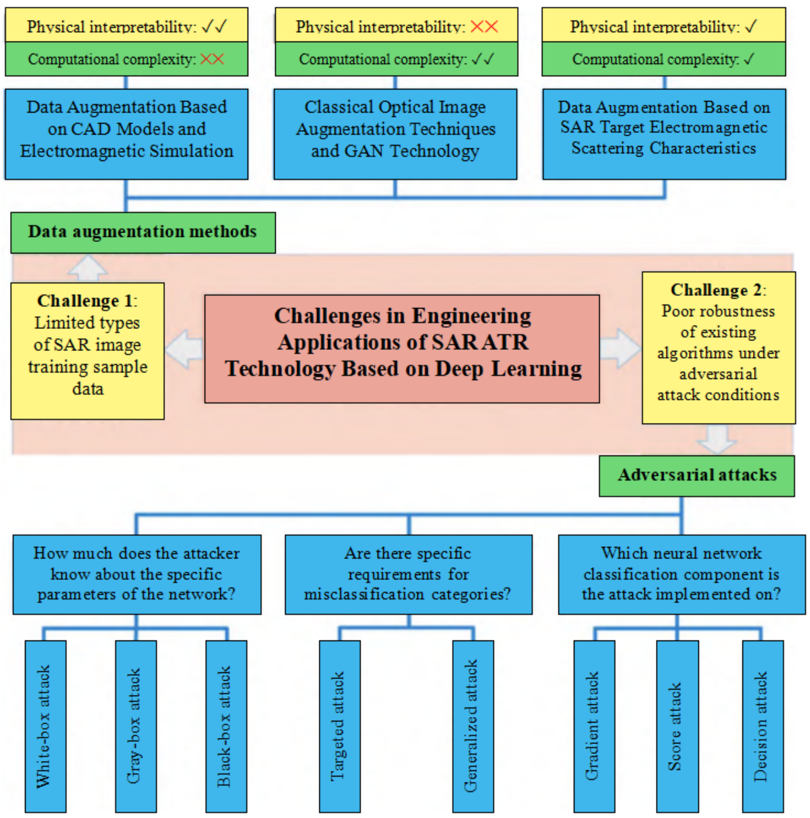

Figure 3. Challenges faced by deep learning-based SAR ATI technology.

of the extraordinary potential and urgent bottlenecks exhibited by typical deep neural network models such as CNN, RNN, autoencoders, and techniques like transfer learning in radar waveform recognition and SAR-ATI domains. The aim of this article is to present a comprehensive picture of the current research status in this field, providing references for researchers to explore potential research topics with significant scientific and engineering implications, and to carry out subsequent studies with significant theoretical and practical value.

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References

[1] Peng G, Zhu S, 2022, Opportunities and Challenges for the Development of Deep Learning Radar Recognition Methods. Modern Radar, 44(4): 95–96.

[2] Pan ZS, Wang SF, Zhu MT, et al., 2020, Automatic Waveform Recognition of Overlapping LPI Radar Signals Based on Multi-Instance Multi-Label Learning. IEEE Signal Processing Letters, 27: 1275–1279.

[3] Geng Z, Wang BN, Yan H, et al., 2021, Moving Target Detection and Tracking with Multi-Platform Radar Network (MIN). IET Radar, Sonar & Navigation, 16(5): 815–824.

[4] Zhu XX, Devis T, Mou LC, et al., 2017, Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. IEEE Geoscience and Remote Sensing Magazine, 5(4): 8–36.

[5] Xiao YH, Zhou JY, Yu YZ, et al., 2021, Active Jamming Recognition Based on Bilinear EfficientNet and Attention Mechanism. IET Radar, Sonar & Navigation, 15(9): 957–968.

[6] Hu JF, Wei ZY, Li YZ, et al., 2021, Designing Unimodular Waveform(s) for MIMO Radar by Deep Learning Method. IEEE Transactions on Aerospace and Electronic Systems, 57(2): 1184–1196.

[7] Mason E, Yonel B, Yazici B, 2017, Deep Learning for Radar. IEEE Radar Conference, IEEE Press, Seattle, 2017: 1703–1708.

[8] Yonel B, Mason E, Yazici B, 2018, Deep Learning for Waveform Estimation in Passive Synthetic Aperture Radar. IEEE Radar Conference, Orlando, FL: IEEE Press, 2018: 1395–1400.

[9] Wang Q, Du PF, Yang JY, et al., 2018, Transferred Deep Learning Based Waveform Recognition for Cognitive Passive Radar. Signal Processing, 155: 259–267.

[10] Sadeghi M, Larsson EG, 2019, Adversarial Attacks on Deep-Learning Based Radio Signal Classification. IEEE Wireless Communications Letters, 8(1): 213–216.

[11] Belloni C, Balleri A, Aouf N, et al., 2020, Explainability of Deep SARI through Feature Analysis. IEEE Transactions on Aerospace and Electronic Systems, 57(1): 659–673.

[12] Pan M, Jiang J, Kong QP, et al., 2017, Radar HRRP Target Recognition Based on t-SNE Segmentation and Discriminant Deep Belief Network. IEEE Geoscience and Remote Sensing Letters, 14(9): 1609–1613.

[13] Zhang L, Li Y, Wang YH, et al., 2021, Polarimetric HRRP Recognition Based on ConvLSTM with Self-Attention. IEEE Sensors Journal, 21(6): 7884–7898.

[14] Guo C, He Y, Wang HP, et al., 2019, Radar HRRP Target Recognition Based on Deep One-Dimensional Residual-Inception Network. IEEE Access, 7: 9191–9204.

[15] Dadon YD, Yamin S, Feintuch S, et al., 2021, Moving Target Classification Based on Micro-Doppler Signatures via Deep Learning. IEEE Radar Conference, IEEE Press, Atlanta, 2021: 1–6.

[16] Yang Y, Hou CP, Lang Y, et al., 2020, Omnidirectional Motion Classification with Monostatic Radar System Using Micro-Doppler Signatures. IEEE Transactions on Geoscience and Remote Sensing, 58(5): 1–14.

[17] Kim BK, Kang HS, Park SO, 2017, Drone Classification Using Convolutional Neural Networks with Merged Doppler Images. IEEE Geoscience and Remote Sensing Letters, 14(1): 38–42.

[18] Rahman S, Robertson D, 2020, Classification of Drones and Birds Using Convolutional Neural Networks Applied to Radar Micro-Doppler Spectrogram Images. IET Radar, Sonar & Navigation, 14(5): 653–661.

[19] Wengrowski E, Purrii M, Dana K, et al., 2019, Deep CNNs as a Method to Classify Rotating Objects Based on Monostatic RCS. IET Radar, Sonar & Navigation, 13(7): 1092–1100.

[20] Fu JM, Sun X, Wang ZR, et al., 2020, An Anchor-Free Method Based on Feature Balancing and Refinement Network for Multiscale Ship Detection in SAR Images. IEEE Transactions on Geoscience and Remote Sensing, 59(2): 1331–1344.

[21] Huang LQ, Liu B, Li BY, et al., 2018, OpenSARShip: A Dataset Dedicated to Sentinel-1 Ship Interpretation. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(1): 195–208.

[22] Ding JS, Wen LW, Zhong C, et al., 2020, Video SAR Moving Target Indication Using Deep Neural Network. IEEE Transactions on Geoscience and Remote Sensing, 58: 7194–7204.

[23] Wang ZC, Du L, Mao JS, et al., 2019, SAR Target Detection Based on SSD with Data Augmentation and Transfer Learning. IEEE Geoscience Remote Sensing Letters, 16(1): 150–154.

[24] Shao GQ, Chen YS, Wei YS, 2020, Convolutional Neural Network-Based Radar Jamming Signal Classification with Sufficient and Limited Samples. IEEE Access, 8: 80588–80598.

[25] Wang WY, Wei Y, Zhen XX, et al., 2019, Classifying Aircraft Based on Sparse Recovery and Deep-Learning. The Journal of Engineering, 2019(21): 7464–7468.

[26] Li K, Jiu B, Wang PH, et al., 2021, Radar Active Antagonism Through Deep Reinforcement Learning: A Way to Address the Challenge of Mainlobe Jamming. Signal Processing, 186(9): 1–15.

[27] Chen X, Su NY, Huang Y, et al., 2021, False-Alarm-Controllable Radar Detection for Marine Target Based on Multi-Features Fusion via CNNs. IEEE Sensors Journal, 21(7): 9099–9111.

[28] Ma LW, Wu JL, Zhang JP, et al., 2019, Research on Sea Clutter Reflectivity Using Deep Learning Model in Industry 4.0. IEEE Transactions on Industrial Informatics, 16(9): 5929–5937.

[29] Lepetit P, Ly C, Barthes L, et al., 2021, Using Deep Learning for Restoration of Precipitation Echoes in Radar Data. IEEE Transactions on Geoscience and Remote Sensing, 60: 1–14.

[30] Devcom USA, Affairs ARLP, Tech V, 2020, Army Fast-Tracks Adaptable Radars for Congested Environments. Army Communicator, 6: 1–6.

[31] Elbir AM, Mishali KV, Eldar YC, 2019, Cognitive Radar Antenna Selection via Deep Learning. IET Radar, Sonar & Navigation, 13(6): 871–880.

[32] Zhou RL, Liu FG, Gravelle CW, 2020, Deep Learning for Modulation Recognition: A Survey with a Demonstration. IEEE Access, 8: 67366–67376.

[33] Qu ZY, Wang WY, Hou CB, et al., 2019, Radar Signal Intra-Pulse Modulation Recognition Based on Convolutional Denoising Autoencoder and Deep Convolutional Neural Network. IEEE Access, 7: 112339–112347.

[34] Liu ZM, Yu PS, 2019, Classification, Denoising, and Deinterleaving of Pulse Streams with Recurrent Neural Networks. IEEE Transactions on Aerospace and Electronic Systems, 55(4): 1624–1639.

[35] Ghadimi G, Norouzi Y, Bayderkhani R, et al., 2020, Deep Learning-Based Approach for Low Probability of Intercept Radar Signal Detection and Classification. Journal of Communications Technology and Electronics, 65(10): 1179–1191.

[36] Wang C, Wang J, Zhang XD, 2017, Automatic Radar Waveform Recognition Based on Time-Frequency Analysis and Convolutional Neural Network. 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE Press, Los Angeles, 2017: 2437–2441.

[37] Lay B, Charlish A, 2020, Classifying LPI Signals with Transfer Learning on CNN Architectures. 2020 Sensor Signal Processing for Defence Conference (SSPD), IEEE Press, Edinburgh, 2020: 1–5.

[38] Ni X, Wang HL, Meng F, et al., 2021, LPI Radar Waveform Recognition Based on Multi-Resolution Deep Feature Fusion. IEEE Access, 9: 26138–26146.

[39] Yildirim A, Kilanyaz S, 2020, 1D Convolutional Neural Networks Versus Automatic Classifiers for Known LPI Radar Signals Under White Gaussian Noise. IEEE Access, 8: 180534–180543.

[40] Deng H, Geng Z, 2020, Radar Networks. CRC Press, Boca Raton.

[41] Geng Z, Xu RH, Deng H, 2020, LTE-Based Multistatic Passive Radar System for UAV Detection. IET Radar, Sonar & Navigation, 14(7): 1088–1097.

[42] Ma ZY, Huang Z, Lin AN, et al., 2020, LPI Radar Waveform Recognition Based on Features from Multiple Images. Sensors, 20(2): 526–552.

[43] Kokalj-Filipovic S, Miller R, Chang N, et al., 2019, Mitigation of Adversarial Examples in RF Deep Classifiers Utilizing Autoencoder Pre-Training. 2019 International Conference on Military Communications and Information Systems (ICMCIS), IEEE Press, Montenegro, 2019: 1–6.

[44] Kechagias-Stamatis O, Aouf N, 2021, Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey.

IEEE Aerospace and Electronic Systems Magazine, 36(3): 56–81.

[45] Profeta A, Rodriguez A, Clouse HS, 2016, Convolutional Neural Networks for Synthetic Aperture Radar Classification. SPIE Defense and Security, IEEE Press, Maryland, 2016: 185–194.

[46] Kechagias-Stamatis O, Aouf N, 2019, Fusing Deep Learning and Sparse Coding for SAR ATI. IEEE Transactions on Aerospace and Electronic Systems, 55(2): 785–797.

[47] Inkawich NA, Inkawich MJ, Davis EK, et al., 2021, Bridging a Gap in SAR-ATI: Training on Fully Synthetic and Testing on Measured Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14: 2942–2955.

[48] Inkawich NA, Davis EK, Inkawich MJ, et al., 2021, Training SAR-ATI Models for Reliable Operation in Open-World Environments. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14: 3954–3966.

[49] Chen SZ, Wang HP, Xu F, et al., 2016, Target Classification Using the Deep Convolutional Networks for SAR Images. IEEE Transactions on Geoscience and Remote Sensing, 54(8): 4806–4817.

[50] Zhang JS, Xing MD, Xie YY, 2021, FEC: A Feature Fusion Framework for SAR Target Recognition Based on Electromagnetic Scattering Features and Deep CNN Features. IEEE Transactions on Geoscience and Remote Sensing, 59(3): 2174–2187.

[51] Feng SJ, Ji KF, Zhang LB, et al., 2021, SAR Target Classification Based on Integration of ASC Parts Model and Deep Learning Algorithm. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14: 10213–10225.

[52] Li Y, Du L, Wei D, 2022, Multiscale CNN Based on Component Analysis for SAR ATI. IEEE Transactions on Geoscience and Remote Sensing, 60: 1–12.

[53] Wang C, Shi J, Zhou YY, et al., 2021, Semisupervised Learning-Based SAR ATI via Self-Consistent Augmentation. IEEE Transactions on Geoscience and Remote Sensing, 59(6): 4862–4873.

[54] Wang K, Zhang G, Xu YB, et al., 2021, SAR Target Recognition Based on Probabilistic Meta-Learning. IEEE Geoscience and Remote Sensing Letters, 18(4): 682–686.