remote sensing

MDPI

Review

Radar Target Characterization and Deep Learning in Radar Automatic Target Recognition: A Review

Wen Jiang, Yanping Wang *, Yang Li, Yun Lin and Wenjie Shen

Radar Monitoring Technology Laboratory, School of Information Science and Technology, North China University of Technology, Beijing 100144, China; jiangwen@ncut.edu.cn (W.J.)
* Correspondence: wangyp@ncut.edu.cn

Abstract: Radar automatic target recognition (RATR) technology is fundamental but complicated system engineering that combines sensor, target, environment, and signal processing technology, etc. It plays a significant role in improving the level and capabilities of military and civilian automation. Although RATR has been successfully applied in some aspects, the complete theoretical system has not been established. At present, deep learning algorithms have received a lot of attention and have emerged as potential and feasible solutions in RATR. This paper mainly reviews related articles published between 2010 and 2022, which corresponds to the period when deep learning methods were introduced into RATR research. In this paper, the current research status of radar target characteristics is summarized, including motion, micro-motion, one-dimensional, and two-dimensional characteristics, etc. This paper reviews the progress of deep learning methods in the feature extraction and recognition of radar target characteristics in recent years, including space, air, ground, sea-surface targets, etc. Due to more and more attention and research results published in the past few years, it is hoped that this review can provide potential guidance for future research and application of deep learning in fields related to RATR.

Keywords: radar automatic target recognition; radar target characteristics; deep learning; artificial intelligence; radar signal processing

Citation: Jiang, W.; Wang, Y.; Li, Y.; Lin, Y.; Shen, W. Radar Target Characterization and Deep Learning in Radar Automatic Target Recognition: A Review. *Remote Sens.* **2023**, *15*, 3742. https://doi.org/10.3390/rs15153742

Academic Editor: Andrzej Stateczny

Received: 23 June 2023
Revised: 13 July 2023
Accepted: 22 July 2023
Published: 27 July 2023

1. Introduction

Due to the rapid development of devices and the great progress of radar signal processing and data processing technology, the function of radars has been developed from the traditional single-scale information measurement to the fine feature information measurement, so as to provide more abundant feature information for radar automatic target recognition (RATR) [1,2]. RATR technology extracts the stable target characteristics from the radar echo signal and then further discriminates the target attribute or category [3]. Currently, this technology involves the field of the recognition of space, air, ground, and sea-surface targets, etc., which plays a significant role in improving the command automation level, attack and defense capability, territorial air defense, and early-warning capability and will become an inevitable and indispensable function for the next generation of radar systems [4].

The research of radar target characteristics is the foundation and a crucial part of RATR, which mainly refer to the electromagnetic scattering characteristics of the observed target under electromagnetic wave irradiation. The common radar target characteristics highlight the great significance of signals for radar target recognition, such as micro-Doppler spectrums [5], high-resolution range profiles (HRRPs) [6], synthetic aperture radar (SAR) images [7,8], and inverse synthetic aperture radar (ISAR) images [9]. According to the characteristics of different radar data, relevant algorithms based on machine learning, such as support vector machine (SVM) [10], K-Nearest Neighbors (KNN) [11], and statistical recognition [12] have been used for RATR. Theoretical research mainly focuses on target fine feature analysis and the application of advanced machine learning algorithms in RATR.

However, with the rapid progress and application of target control technology and false target digital synthesis technology, various false targets and decoys have been able to accurately imitate the real target's trajectory, radar cross section (RCS), geometric structure, surface material, and other features [13]. RATR based on traditional feature information, especially diverse non-cooperative target recognition, has become difficult or even ineffective. In addition, due to the complex electromagnetic environment with multiple jamming and noise signals, it is an extremely challenging task to recognize targets in a complex environment, and therefore, developing robust and reliable RATR algorithms is of great significance [14]. Moreover, classical features are mostly applicable to specific scenarios; in unknown scenarios, the optimal feature vector is difficult to determine, which will lead to the weak generalization of the recognition system [15].

As a branch of machine learning, deep learning technology utilizes statistics to create mathematical models describing the relationship between inputs and outputs and to automatically extract features from large-scale raw data [16]. The next generation of advanced radar systems will be equipped with deep learning technology, so as to identify targets and make the correct decisions [17,18]. An increasing number of deep neural networks have been successfully applied to RATR, such as deep belief networks (DBNs), convolutional neural networks (CNNs), and recursive neural networks (RNNs) [19–22], which can learn features automatically instead of using a complex feature extraction process. Jokanovic et al. [23] introduced a fall detection and recognition method based on deep learning using range-Doppler radars. In [24], a radar target recognition method based on an RNN was proposed using micro-Doppler signatures as the input. Kim et al. [25] discussed a human activity recognition algorithm based on micro-Dopplers utilizing a CNN. Fu et al. [26] designed a maritime ship target recognition algorithm with deep learning. The application of deep-learning-based methods in RATR is presented in Figure 1.

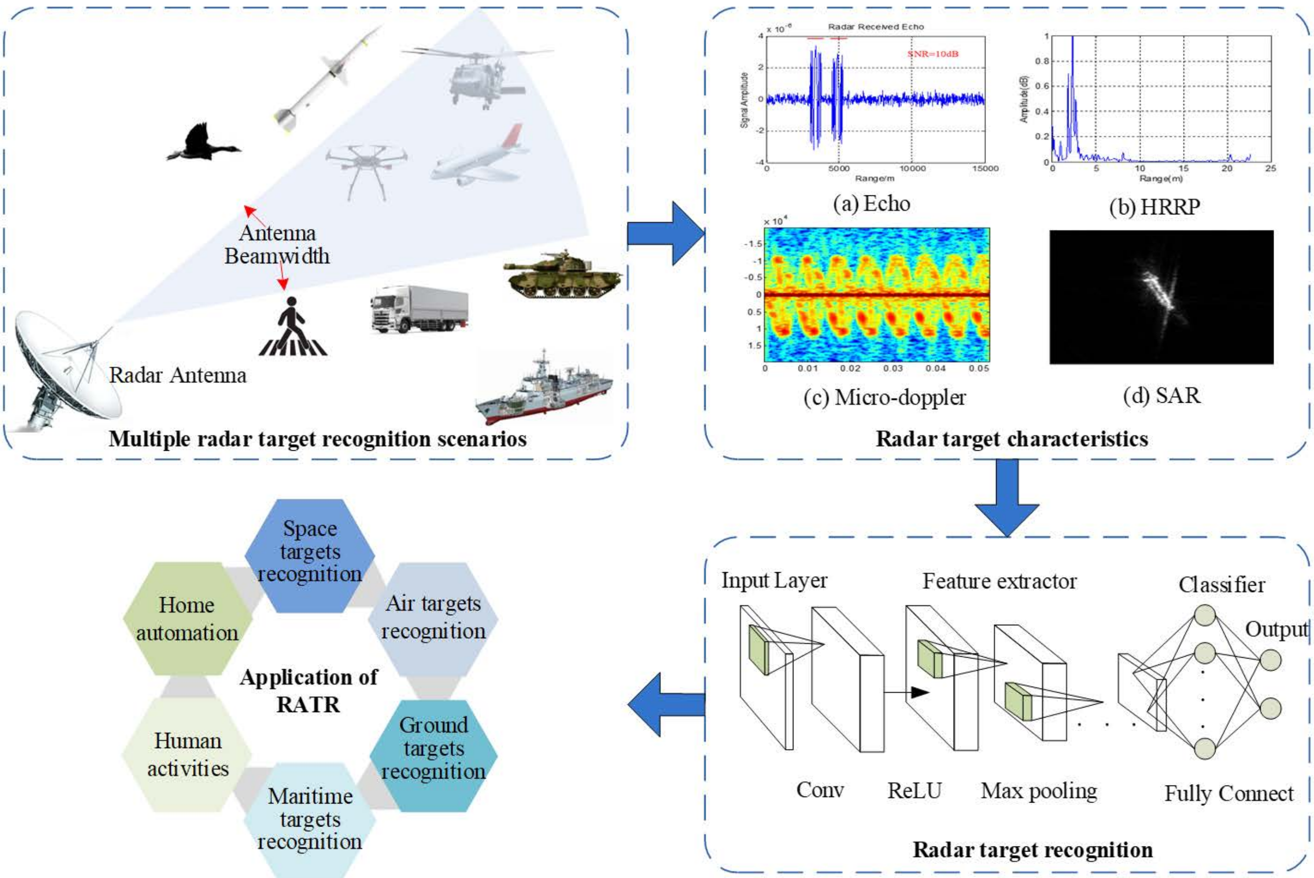


Figure 1. Application of deep learning for RATR.

Although deep learning technology has been widely applied to some aspects of RATR, the complete theoretical system of RATR has not been established. In addition, due to the diversity of radar systems, target types, and the extreme complexity of the environment, existing RATR systems are still functionally limited. In fact, most research on intelligent RATR is still in the theoretical stage. In summary, the latest advances in RATR study include (1) the research progress of the radar target characteristics and mechanism, mainly the electromagnetic scattering characteristics of targets, and (2) the progress of radar target characteristic acquisition technology, modern signal processing technology, and artificial intelligence technology which are widely used in target recognition, which provides a new solution for RATR.

Most of the existing research on RATR focuses on a special technology, but related review research is rare. Due to the limited target recognition methods, the early research and investigation mainly focus on the description of some recognition techniques or simply list the target recognition methods. With the rapid development of RATR and deep learning techniques, increasing systematic recognition methods have emerged with high recognition performance. This paper reviews the radar target characterizations and applications of deep-learning-based methods in RATR, discusses several kinds of radar target characteristics, as well as different deep learning frameworks for radar target recognition that are successful in theoretical research and application, and analyzes the possible solutions to the problem and the potential limitations in this field.

This paper mainly reviews articles in IEEExplore, IET, Springer Link, Elsevier, MDPI, and other online databases. Recent articles presented in the leading journals and international conferences of radar signal processing or artificial intelligence are highlighted. Most of them were published between 2010 and 2022, which coincides with the period when deep learning techniques were introduced into RATR research, and these articles represented a wide range of (1) methods from the theoretical research of radar target characteristics to the application research of RATR, (2) recognition targets from space targets to human activity, (3) deep learning networks for RATR, (4) data forms from radar signals to two-dimensional (2D) images, and (5) method improvements from algorithm optimization to real application.

The rest of this paper is organized as follows: In Section 2, related work on radar target characteristics is introduced. In Section 3, recent RATR approaches based on deep learning are reviewed and discussed. Section 4 describes some of the related open datasets for RATR, and the potential challenges and research opportunities are summarized in Section 5. Finally, conclusions are presented in Section 6.

2. Related Work on RATR

2.1. Radar Target Characteristics

The research of radar target characteristics is the most basic and crucial step of RATR. The main research directions of RATR are low-resolution target characteristics based on narrowband radar and high-resolution target recognition based on wideband radars. Because the wideband and the narrowband information of the target are highly complementary, it is of great benefit to adopt the multi-feature information of the radar simultaneously.

2.1.1. Narrowband Target Characteristics of Low-Resolution Radar

Although target recognition based on high-resolution radars is the main development trend at present, the role of narrowband radars cannot be ignored. Compared with wideband RATR, narrowband radars also have some advantages: they require fewer resources for signal processing, and their real-time performance is better than that of wideband radars under the condition of limited signal resources. Narrowband radars are low-cost and can make use of the narrowband features of targets for rough classification and auxiliary classification, providing prior information, so as to obtain more detailed target features. According to recent research status, the target characteristics of low-resolution narrowband radars can be divided into roughly six aspects as follows.

(1) Motion characteristics

The kinematic parameters of the target, such as the trajectory, speed, maneuverability, and spatial coordinate information of the target, reveal the changing characteristics of the different spatial positions and motion states of the target over time, which can effectively represent the target motion performance and have a certain ability to distinguish different targets [27]. Different types of flight targets, such as propeller planes, helicopters, and fighter jets show different motion characteristics, such as motion trajectory, flight altitude, cruising speed, acceleration performance, climb rate, etc. By using the target motion characteristics data, the "rough" discrimination of the target type can be realized.

(2) Echo characteristics

The global information of the target such as size can be reflected in the narrowband waveform to some extent, and the features extracted based on the narrowband echo can be used for the "rough" classification of target type or number. The amplitude and phase of radar echo signals can reflect the comprehensive information of the target, and the frequency, time width, bandwidth, and signal form of the echo reflect the type of radiation source [28].

For air targets, which can be regarded as point targets for low-resolution radars, the amplitude and phase of the target echo will vary with the relative attitude of the target to the radar during its movement. According to the changing process of the echo amplitude and phase, the shape of the target can be determined, and the movement of the target can be further determined by analyzing complex information [29].

(3) RCS characteristics

Early research on radar target characteristics focuses on the RCS of the target. The statistical characteristics of the RCS can reflect the backscattering ability of the target to a certain degree, which is related to the size, shape, and material of the target and the frequency band of the radar [30]. Generally, the position, dispersion, distribution, and transformation features are extracted from the RCS sequence.

RCSs with different times, frequencies, polarization, and angles contain different target information [31]. For instance, the attitudes of space targets moving along the orbit change constantly with respect to the radar's line of sight (LOS), and the RCS value changing with the LOS is obtained, in which the change rule will reflect the physical and structural characteristics of targets. The RCS characteristics of the target that can be extracted mainly include the RCS sequence, RCS mean value, variance, extreme value, and statistical distribution, which can be used for "rough" size differentiation and attitude stability discrimination.

(4) Modulation spectrum characteristics

The periodic motion of dynamic targets, such as the propellers of aircraft, the rotating blades of jet engines, the rotors of helicopters, and other rotating parts, will produce periodic modulation of the radar echo. The periodic modulation spectrum of different targets varies greatly, so taking full advantage of this property is beneficial to target recognition. The motion modulation characteristics of the rotating component have nothing to do with the attitude of the target and the working state of the radar, which are stable characteristics for recognition. Bell et al. [32] analyzed the phenomenon of jet engine modulation (JEM) in detail and established corresponding mathematical models, which lays a theoretical foundation for RATR using JEM features.

The micro-motions caused by the local motion of the target can be studied in two ways, namely micro-RCS and micro-Doppler. Among them, the micro-RCS indicates micro-motion characteristics through changes in the RCS, while micro-Doppler indicates micro-motion characteristics through changes in Doppler frequency. Victor Chen has made outstanding contributions to the micro-Doppler characteristics of radars and defined the concept of micro-Doppler occurring on the target or any structural components on the target under micro-motion dynamics for the first time [33]. He introduced the micro-Doppler phenomenon from Lidar to microwave radars and further constructed the micro-Doppler model which was induced by the rotation motion of the target and micro-Doppler modulations on the radar echo signals. For simple micro-motions such as rotation, its motion form in the direction of the radar LOS is simple harmonic motion, and the micro-Doppler frequency under ideal conditions can be modeled as (1):

$$f_{m-D}(t) = \frac{2}{\lambda}[\boldsymbol{\omega} \times \boldsymbol{r}(t)]^T \cdot \boldsymbol{n} = \frac{2A_0\omega_0}{\lambda}\cos(\omega_0 t + \varphi_0) \quad (1)$$

where λ represents the wavelength of the radar transmitting signal, $\boldsymbol{\omega}$ is the rotating angular velocity vector, $\boldsymbol{r}(t)$ represents the rotation radius vector at time t, $\boldsymbol{n}$ represents the direction of the LOS, A_0 is the radial micro-motion amplitude, ω_0 is the target micro-motion frequency, and φ_0 represents the initial phase of simple harmonic motion.

(5) Target pole distribution characteristics

The natural resonant frequency of the target is known as the target poles; the "pole" and "scattering center" are the basic concepts established in the resonant region and optical region, respectively. The target pole distribution is only determined by the target shape or structure and inherent characteristics and has nothing to do with the radar observation direction (target attitude) and the radar polarization mode, which brings great convenience to target recognition.

The concept of target poles emerged in 1971. In 1975, Blarium et al. [34] first proposed the Prony method to extract target poles directly from a series of transient response time-domain data, which can be adopted as target features for recognition. Since the 1980s, the research of target poles mainly focuses on how to increase the anti-noise ability and estimation accuracy of the algorithm itself [35,36]. In order to avoid extracting pole distribution information directly from noisy target scattering data, the target recognition method based on waveform synthesis technology has been widely considered [37].

(6) Target polarization characteristics

Polarization characteristics are some of the basic properties of radar target scattering, which describes the vector characteristics of an electromagnetic wave. The polarization characteristic is closely related to the shape of the target. Any target has a specific polarization transformation effect on the irradiated electromagnetic wave, and the transformation relationship is decided by the shape, structure, size, and orientation of the target. In addition, the variable polarization responses of different targets to various polarized waves can be measured to form a feature space, which can be used to identify targets.

Many methods of target recognition using polarization information have appeared in the past twenty years. Cameron et al. [38] used the polarization scattering matrix to recognize targets with relatively simple structures. Chamberlain et al. [39] combined polarization information with impulse response and proposed target transient polarization response for target recognition. In addition, the polarization reconstruction of target shape and combination with imaging technology [40] are also common target recognition methods.

2.1.2. Wideband Target Characteristics of High-Resolution Radar

High-resolution wideband radars can provide fine structural information which is helpful for target recognition. Generally, the characteristics of the target that can be used for recognition include high-resolution one-dimensional images (HRRPs), 2D images (e.g., ISAR and SAR), and various image sequences.

(1) HRRP characteristics

The HRRP of a target is one of the important characteristics of RATR, which is the coherent summation of complex echoes of the target scattering centers in each range unit, reflecting the distribution of strong scatters in the direction of the radar LOS. The illustration of an HRRP is shown in Figure 2. It has a close correspondence with the actual shape of the target, which can be used as the basis for RATR. At the same time, the target micro-motion, such as precession, nutation, and roll, will also cause the projection of each scattering center position on the radar LOS to change, resulting in the target HRRP sequence changes according to a certain rule [41]. Therefore, the size features, micro-motion features, and shape features of the target can be extracted from the HRRP for target recognition. Generally, the higher the bandwidth, the finer the features of the target will be reflected. Compared with ISAR and SAR images, HRRPs are easier to obtain and more efficient to process.

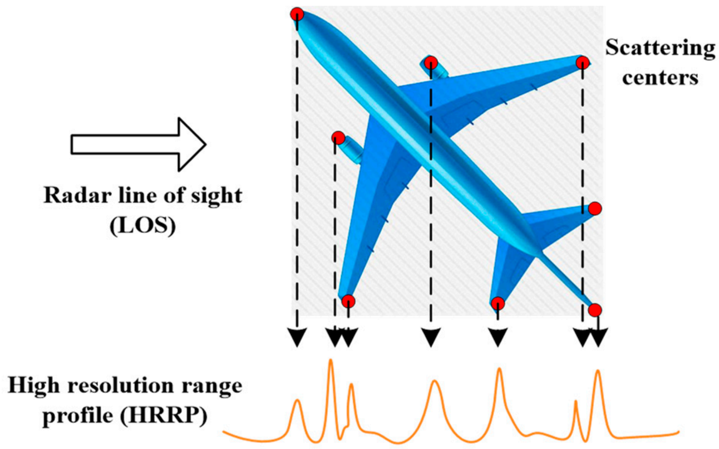


Figure 2. Illustration of the HRRP of a plane target.

It is generally believed that an HRRP can be obtained by the matched filtering processing of the radar echo signal. Assuming that the length of the echo signal is N_k, the HRRP can be expressed discretely as (2):

$$\begin{aligned} x_r(n_k) &= x(n_k)^H * (H(n_k) * x(n_k)) \\ &= \sum_{l=1}^{L} \frac{T_p a_l}{2} sinc[\frac{T_p b}{2}(n_k - \tau_l)] \exp(-j2\pi f_d n_k), n_k = 1, 2, \ldots, N_k \end{aligned} \tag{2}$$

where $x(n_k)^H$ represents the conjugate transpose of the echo signal, $H(n_k)$ is the response function, T_p represents pulse width, a_l represents the amplitude of the lth scattering point, b represents the slope of frequency modulation, τ_l is the time delay of the lth scattering point, and f_d is the Doppler frequency.

HRRPs are sensitive to the aspect angle, the distance of the target in space, and the gain of the radar receiver. Therefore, in the process of target recognition, it is necessary to consider the sensitivity of the amplitude scale, target aspect, and time shift of the HRRP. Generally, in order to obtain stable features, the sensitivity of the amplitude scale can be treated by normalizing the amplitude. The sensitivity of the target aspect can be reduced to some extent by incoherent or coherent averaging methods. As for the time-shift sensitivity, Li et al. [42] discussed a sliding correlation matching method based on the HRRP as the feature for target recognition, so the recognition results were not affected by the time shift.

Extracting low-dimensional and high-divisible features that can represent the essential characteristics of targets from the HRRP can not only reduce the dimensionality of high-dimensional HRRP data, thus reducing the storage requirements of the algorithm, but can also increase the accuracy and speed of the target recognition algorithm. In addition to the common Fourier transform, bispectrum transform, and other methods, various transformation solutions have been adopted to reduce the dimension of the HRRP to obtain features with good intra-class aggregation and strong inter-class separability [43].

(2) SAR and ISAR image characteristics

Compared with one-dimensional images, 2D images of high-resolution radars (e.g., SAR and ISAR) contain more information about the shape and structure of targets and are therefore more beneficial to target recognition.

By using the relative motion of the radar and target, SARs synthesize several smaller real antenna apertures into radars with equivalent antenna apertures by means of data processing. They have high-resolution, all-day, all-weather, and large-width characteristics, which can effectively identify camouflage and penetrate coverings, and have high application value in both military and civilian fields. They can generate 2D images in the range and azimuth, which can reflect not only the electromagnetic and geometric characteristics but also the backscattering intensity of the electromagnetic wave. Consequently, image recognition technology can be used for SAR-ATR, which is the most intuitive method in the field of target recognition, but how to obtain high-quality 2D images of the target is the first problem to be solved.

Due to the scattering mechanism and speckle noises in SAR imagery, it is not as straightforward as in optical images whose edges are easy to detect. In SAR-ATR technology, target image features that are widely used include a target peak feature, shadow feature, wavelet low-frequency feature, and scattering center feature [44]. In addition, due to the similarity between SAR images and optical images, texture features can also be used for target recognition. Texture is the variation and repetition of the image gray level in space. Texture, color, shape, and other features are all low-level visual features. The semantic feature is a more abstract high-level feature representation formed by the combination of low-level texture features, including scene semantic features, behavior semantic features, emotion semantic features in images, etc. Many features for target recognition have been developed, such as the gray-level co-occurrence matrix [45], which is considered to be the best classification algorithm in traditional texture statistical analysis. In addition, scale-invariant feature transform [46] and histograms of oriented gradients [47] are traditional methods to generate image feature descriptions.

The ISAR imaging of moving targets in the range-Doppler domain is usually represented by the sparse distribution of scattering centers. Because the target is non-cooperative, the translation component can easily cause range ambiguity, while the micro-motion component can easily lead to azimuth ambiguity. In addition, the special characteristics of moving targets, such as a high speed and complex motion form (often accompanied by spin, precession, maneuver, etc.), will also lead to imaging processing difficulties. Therefore, the imaging conditions of ISARs are harsh, and the requirement for radar operating parameters is also high.

Besides the high dimension, ISAR images as the target recognition feature also have problems of translation, rotation, scale change, etc. Therefore, feature extraction, such as moment features and area features, can be carried out to distinguish different targets [48].

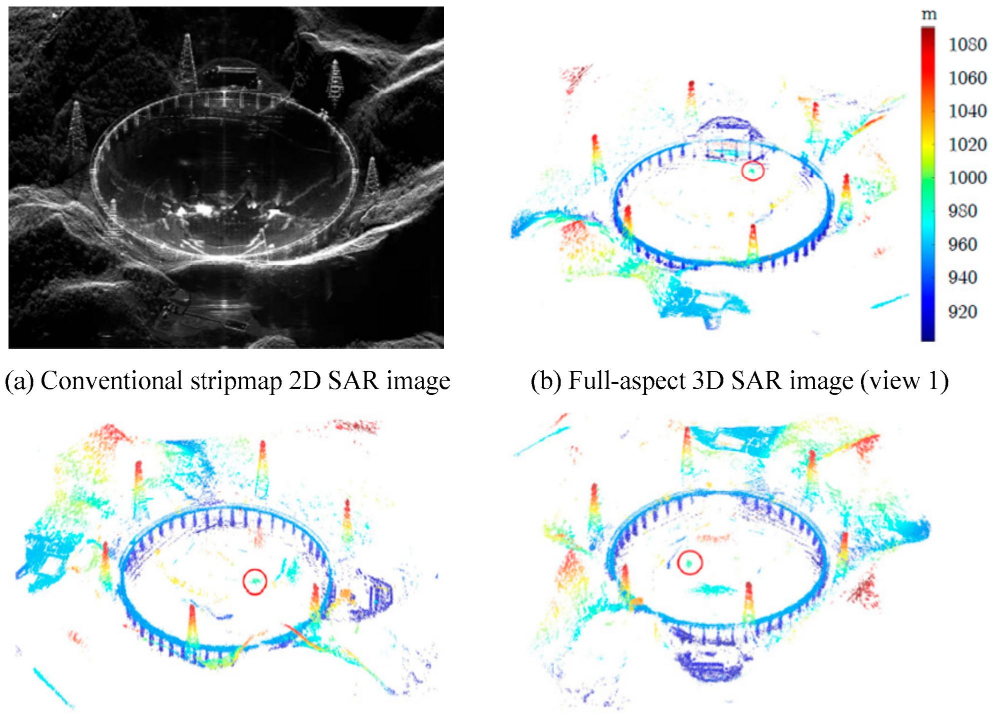
(3) Tomographic SAR and Interferometric SAR image characteristics

Traditional SARs can only perform 2D imaging. However, interpretations based on conventional SAR images have two main difficulties: (1) Two-dimensional SAR images have difficulty accurately reflecting the real three-dimensional (3D) structural characteristics of targets due to the geometric deformation phenomena such as overlay, masking, top-to-bottom inversion, and perspective expansion [49]. In complex environments, the deformation phenomena will cause the target to be indistinct. (2) Target scattering characteristics are very sensitive to the observation angle, and therefore, the SAR image features are greatly affected by the observation angle, and the target information obtained is incomplete [50].

Three-dimensional SAR imaging is an important development direction of traditional 2D SAR imaging in the field of fine information acquisition and perception, which can obtain high-resolution 3D information of the range, azimuth, and elevation of targets and can distinguish multiple targets overlapping in the same pixel of 2D SAR images.

By extending the synthetic aperture principle of SARs to the elevation direction of 3D imaging, tomographic SAR (TomoSAR) imaging can reconstruct the 3D information of scatters and invert the elevation profile, which can effectively solve the overlay effect in 2D SAR imaging [51]. Compared with interferometric SARs (InSARs), TomoSAR imaging technology can not only acquire the elevation information of target scatters but can also get the distribution of scatters in the elevation direction, which can fully restore the real 3D scene [52]. Based on these advantages, the TomoSAR has become one of the most popular and promising 3D imaging methods.

The 3D SAR imaging of complex structures is a significant but extremely challenging task in the field of SAR imaging. Currently, the common 3D SAR imaging technology relies on multiple channels or multiple flights in the direction of elevation, which has high requirements on radar systems and data collection systems [53]. Circular SARs extend the observation dimension of conventional SARs to the aspect dimension, which makes the obtained target information significantly richer [54]. Firstly, circular SARs have the capability of resolving overlay, so the signal contains 3D structure information about the target. Moreover, circular SARs can obtain more complete target scattering characteristics by complementing scattering information from different angles [55]. Lin et al. [56] combined the advantages of the high-precision altitude measurement of InSARs with the advantages of the full-aspect observation of circular SARs to mine the 3D imaging capability of complex structural targets. By adopting the method proposed in [56], the 3D SAR images of the FAST radio telescope with a full aspect were obtained for the first time, and the comparison between a conventional stripmap 2D SAR image and a full-aspect 3D SAR image is presented in Figure 3. Therefore, the full-aspect 3D imaging of circular SARs can effectively solve the problems of image overlay and angle sensitivity in RATR application and enrich the ability of SARs to acquire fine features of targets without increasing the complexity of the system.



(a) Conventional stripmap 2D SAR image (b) Full-aspect 3D SAR image (view 1)

(c) Full-aspect 3D SAR image (view 2) (d) Full-aspect 3D SAR image (view 3)

Figure 3. Comparison of 2D SAR image and full-aspect 3D SAR image [56].

2.1.3. Radar Target Characteristics for Recognition

The information describing target attributes mainly includes physical characteristics, motion characteristics, micro-motion characteristics, and radiation characteristics. Radars cannot directly obtain the above information but use echoes to inverse information. Radar echoes include the amplitude, phase, Doppler shift, frequency, and polarization information of the signal. (1) The amplitude fluctuation can reflect the structure, shape, and micro-motion of a target or its components. (2) The accumulation of phase changes can be used for 2D imaging and Doppler feature estimation. (3) The Doppler shift can describe the motion and micro-motion characteristics of the target. (4) The polarization information includes the structure, shape, material, and rotation of the target. Through the above introduction of radar target characteristics, the features available for RATR are summarized in Table 1.

Table 1. Radar target characteristic classification and common robust features.

Target Attribute		Commonly Used Robust Features
Motion characteristics		Target altitude, velocity, acceleration, ballistic coefficient, regional features
Micro-motion characteristics		Micro-motion period, spectrum distribution width, waveform entropy, instantaneous frequency, polarization scattering matrix, depolarization coefficient, maximum polarization direction angle, moment feature
Physical characteristics	structural feature	Target size, radial length, scatter intensity, strong scattering centers, number of peaks, width of crest, high-order central moment, scattering center distribution, radial energy
	image feature	Target contour, area graph, peak feature, shadow feature, wavelet low-frequency feature, scattering center feature, texture feature, and semantic feature

2.2. Traditional Methods for RATR

The classification techniques used in pattern recognition can be adopted as RATR methods after specific transformation. According to different feature extraction methods, RATR approaches can be divided into traditional approaches and deep-learning-based approaches.

Traditional RATR approaches first process the obtained target information and extract features manually, then compare and measure the known target feature parameters in the database, and finally use linear discriminant analysis, SVM, and other classifiers to achieve the purpose of target recognition. The processing flowchart of the traditional RATR approach is presented in Figure 4. The algorithm of RATR typically consists of a feature extractor and a trainable classifier. The feature extractor is usually designed manually to transform the raw data into a representation with domain knowledge, which has a great influence on recognition accuracy. Therefore, the key step of this kind of method is the feature extraction of the target, and the quality of feature extraction directly determines the recognition performance. Over the past few years, multiple architectures have been designed for RATR, which can automatically learn features or representations from data, rather than making features manually.

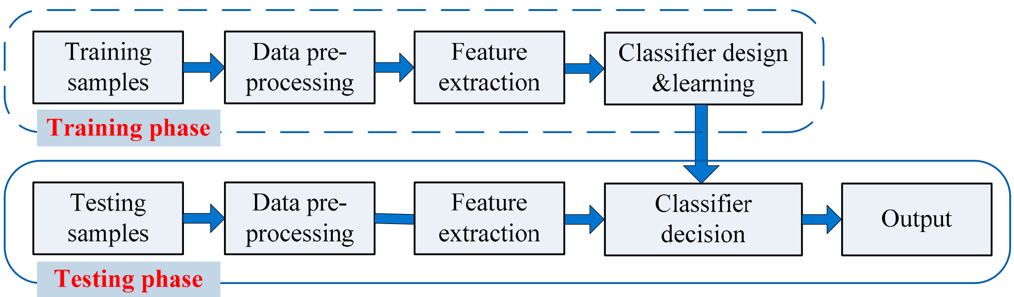


Figure 4. The flowchart of traditional RATR method.

2.3. Deficiencies and Challenges of Traditional RATR Methods

To sum up, traditional RATR approaches perform well in some specific scenarios; however, it is still a rather complex issue in practical application, with many deficiencies and challenges. At present, the difficulties of RATR still mainly lie in the aspects of radar data preprocessing, target feature extraction performance, classifier design, etc. [57].

In traditional methods, classical features are mostly obtained from the analysis and calculation of measurement data and are mostly related to radar parameters, application scenarios, and observation angles. (1) However, in some complex or unknown scenarios, for example, the recognition of non-cooperative targets, the detection range is relatively far, and the surrounding environment is complex and changeable, so the SNR of the echo signals is very low, which will make it more difficult to pre-process data and thus greatly reduce the recognition performance. (2) In addition, a feature is the representation of target characteristics in different dimensions, which reflects the depth and credibility of feature mining and determines the separability of different targets to a certain extent. According to the above analysis of radar target characteristics, target features are manually extracted and straightforward, but for non-cooperative targets or unknown targets, there must be deep recessive features that are helpful for recognition. Therefore, how to extract robust features of the non-cooperative target is an urgent issue to be solved in the study of RATR. (3) Most importantly, most of these traditional approaches can only learn features that can be represented linearly, while it is difficult to represent complex nonlinear data. Therefore, how to design more robust classifiers is in real demand.

3. Application of Deep Learning Technology in RATR

The applicable scenarios and recognition tasks supported by the above radar target characteristics or features are different. Therefore, when the application scenario of RATR changes, the generalization ability of each feature needs to be improved. So far, advanced machine learning methods represented by deep learning have made remarkable progress in civil optical image processing, speech recognition, and some other fields [58,59]. With the accumulation of massive equipment-measured data and the continuous optimization of high-precision electromagnetic simulation software, the application of deep learning networks for RATR becomes feasible. In this section, classical deep learning network architectures for RATR will be introduced first, and then related work on micro-motion-characteristic-based RATR, HRRP-RATR, SAR-ATR, etc., will be reviewed.

3.1. Typical Deep Learning Network Architecture in RATR

The goal of feature self-learning based on deep learning is to improve the generalization ability of networks and features, mine the context association relationship of time-sequential information, and realize the association and transfer of multi-modal features. The typical deep learning networks commonly used for RATR are described as follows.

(1) Convolutional neural network

The dimension of traditional target feature representation and extraction is limited, while the special structure of a CNN enables it to learn the hierarchical features of the target automatically. Taking the recognition of an aircraft target as an instance, the common method is to transform the one-dimensional echo sequence into a time–frequency 2D space through time–frequency analysis to picturize radar features; then, the visual feature extraction mechanism of the CNN is used, and the structure of the CNN is optimized to realize the deep extraction of target radar characteristics. In other words, the nodes with a strong response to motion are strengthened, while the nodes with a strong response to clutter and noise are weakened, and in this way, the self-learning of target features is realized, and the generalization ability of features is also improved. The basic structure of the CNN adopted is presented in Figure 5, including convolutional layers, pooling layers, fully connected layers, and an output layer. The three properties of the CNN, namely local connection, weight sharing, and convergence, make it invariant to translation, scaling, and rotation. In addition, regularization and other techniques can be utilized to effectively alleviate the problem of overfitting in neural network training, and data augmentation techniques can also be adopted to deal with the problem of insufficient data samples [17,20].

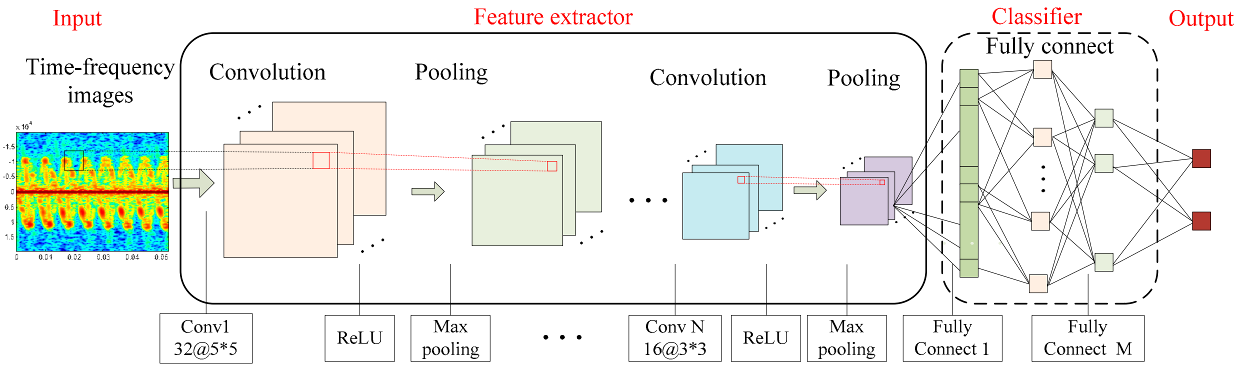


Figure 5. A typical CNN structure for RATR with micro-Doppler time–frequency images [18].

(2) Deep belief network

A DBN is a kind of probabilistic generation model that can establish the joint distribution relationship between labels and observed values, and it is well-suited for solving problems of target recognition. The DBN consists of a stack of restricted Boltzmann machines (RBMs), in which each RBM includes a visible layer and a hidden layer [21]. Figure 6 presents the typical DBN structure, where each RBM is trained using the hidden layer of the previous RBM as input and its output as input to the next RBM. In addition, the most common method for training an RBM is to adopt the contrastive divergence algorithm based on Gibbs sampling, which is applied to compute weight updates during the gradient descent procedure [60].

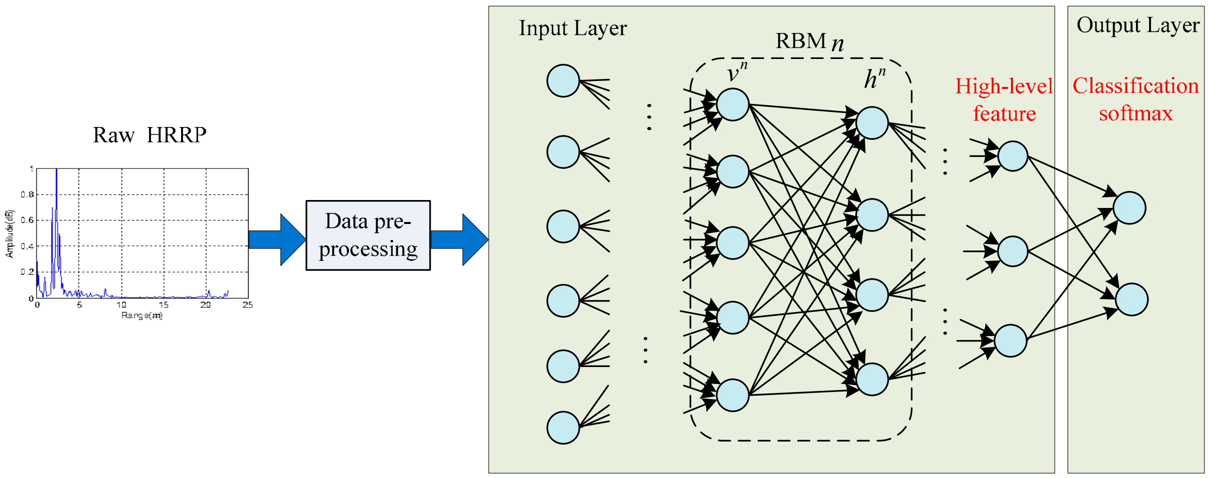


Figure 6. A typical DBN structure for RATR with HRRP.

(3) Recurrent neural network

The characteristic representation of radar target changes with time during the observation time; for example, the warhead target often presents a stable posture, while the projectile body target appears to roll in disorder. The RNN can process time series data of arbitrary length by using neurons with self-feedback and is more suitable for mining the association relationship of context. The structure of the RNN is shown in Figure 7. It is worth mentioning that long short-term memory (LSTM) is a typical variant of this model, which is suitable for solving the trade-off problem of historical information in different recognition tasks [61].

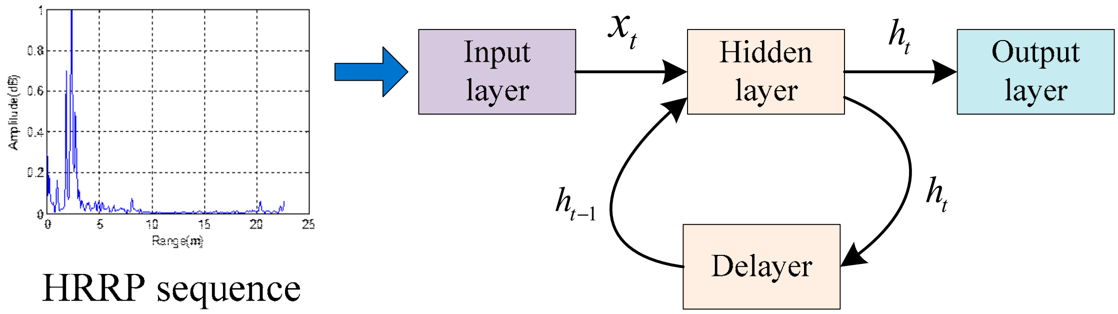


Figure 7. An RNN structure for RATR with HRRP sequence.

(4) Autoencoder

An autoencoder is a kind of neural network based on unsupervised learning, which aims to construct a neural network capable of reconstructing dimensionally compressed input samples and performing feature expression by constantly adjusting parameters [60]. It is similar to the structure of the RBMs, but the difference is that the autoencoder needs to define an error function to make the error of the input sample and the reconstruction result converge to the minimum by adjusting the parameters. The mapping between the input layer and the middle layer is called encoding, and the mapping between the middle layer and the output layer is called decoding. The compressed vector is obtained through encoding and then reconstructed through encoding.

The network structure of the denoising autoencoder (DAE) is the same as that of the normal autoencoder, but the training method is improved [62]. Random noise is added to the training sample, and the new obtained sample is input to the input layer. The DAE can better extract features that reflect the properties of the sample and eliminate the noise contained in the input sample while keeping the input sample unchanged. The overall structure is presented in Figure 8.

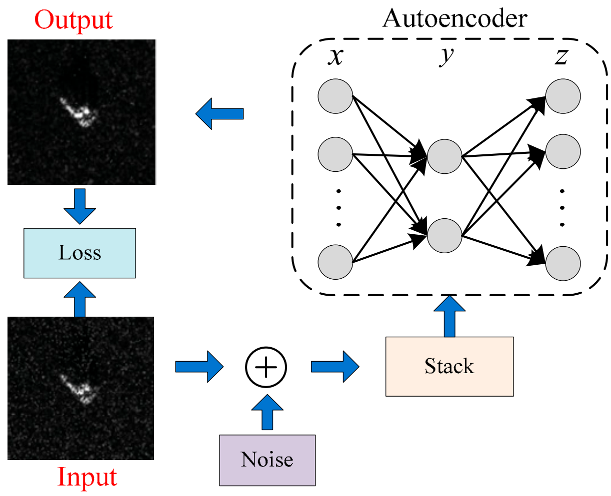


Figure 8. A denoising autoencoder structure for RATR.

(5) Multi-head attention mechanism

The complementarity of the characteristic representation dimensions of different features can support the association, transfer, and joint representation of different features. Taking the cooperative association between the HRRP feature and the micro-motion feature as an example, the HRRP feature can represent the structural characteristics of the target, while the micro-motion feature can represent the local motion characteristics of the target. The combination of the two features is helpful to improve the precision of recognition. A multi-head attention mechanism model is used for parallel computation, which integrates the self-attention of radar feature data of different dimensions, focuses on multiple aspects of different tasks, and covers multiple types of semantic information. It allows the network to extract interrelated feature information in different representation subspaces. At the same time, by reducing the dimension of feature data, the consumption of overall computing resources can be reduced, and the global dependencies among features can be captured more effectively. The specific calculation formula is shown in (3).

$$\begin{aligned} MultiHead(Q, V, R) &= Concat(head_1, head_2, \ldots, head_h)\boldsymbol{W}^O \\ head_i &= Attention(Q\boldsymbol{W}_i^Q, K\boldsymbol{W}_i^K, V\boldsymbol{W}_i^V) \end{aligned} \tag{3}$$

where Q, V, and K are the attention parameters, $\boldsymbol{W}$ is the linear transformation parameter of Q, V, and K, representing the self-attention calculation formula, and $Concat$ represents the combined formula of multi-head attention.

3.2. Deep Learning for RATR Based on Micro-Motion Characteristics

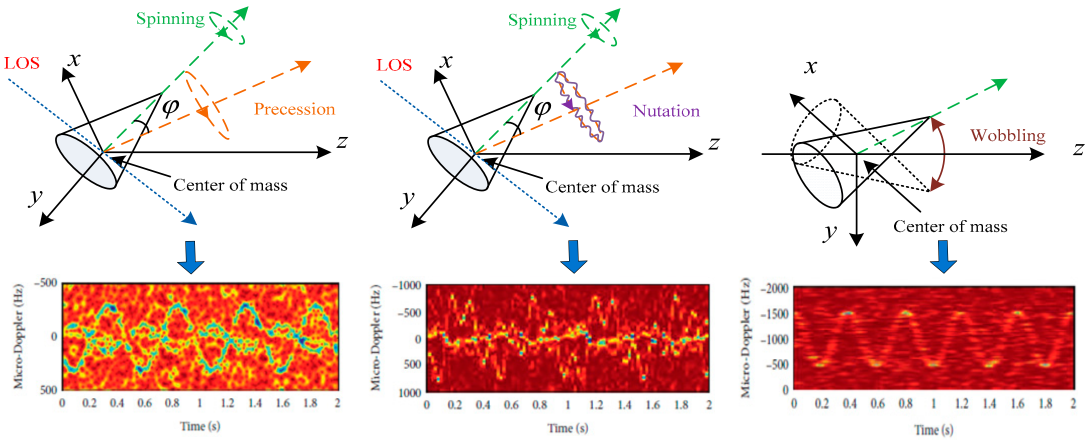
Any coherent Doppler radar can be adopted for collecting micro-motion echoes of the target, such as continuous wave (CW) radars, frequency-modulated continuous wave (FMCW) radars, or pulse-Doppler radars. Recently, more advanced deep-learning-based methods for RATR using micro-Doppler signatures have been studied, including space targets (e.g., tactical ballistic missiles), air targets (e.g., drones, flying birds), ground targets (e.g., vehicles), sea-surface ship targets, and human activities (e.g., gestures, vital signs). Table 2 lists the deep learning algorithms employed in various works on micro-Doppler signatures for target recognition.

Table 2. Summary of recognition approaches, target classes, and radar types for micro-motion characteristic-based RATR.

Areas of Application	Target Classes	Methods	Radar	Acc.	Ref.	Year
Space targets	Ballistic targets	AlexNet and SqueezeNet	——	97.5%	[63]	2019
	Warhead and decoy	LSTM	Pulse-Doppler	99%	[64]	2020
Air targets	Drones	CNN	FMCW	96.86%	[65]	2022
	Three commercial small drones	Light CNN	FMCW	97.14%	[66]	2020
	Drones and birds	CNN	FMCW	94.4%	[67]	2020
	Fixed-wing aircraft and hexacopter	MobileNetV2	FMCW	99%	[68]	2021
	Drones	CNN	——	93%	[69]	2018
	Helicopters with 3,4,6,8 propeller blades	CNN	——	95.8%	[70]	2022
Ground targets	Car, single and multiple people, and bicycle	DNNs	FMCW	98.33%	[71]	2018
	Pedestrians and vehicles	SVM-CNN	FMCW	95%	[72]	2020
	Pedestrians, wheeled and tracked vehicles	LeNet5	CW	95%	[73]	2021
	Pedestrians, wheeled and tracked vehicles	DCDE + residual network	CW	>90%	[74]	2022
Human activities	Hand gestures	CNN	FMCW	95.2%	[75]	2021
	Hand gestures	LSTM	FMCW	85.7%	[76]	2022
	6 human motions	LSTM	CW	92.65%	[77]	2019
	6 human motions	CNN + Sparse Autoencoder	SFCW	96.42%	[78]	2021
	6 human motions	CNN + Transfer learning	Pulse-Doppler	96.7%	[79]	2021
	6 suspicious actions	CNNs	CW	98%	[80]	2022

(1) Recognition of space targets

Due to the short reaction time and high cost of intercepting, it is crucial to distinguish tactical ballistic missiles (TBMs) from other confusing space targets. It is worth mentioning that various micro-motions (e.g., precession, nutation, spinning, and wobbling) of space targets, such as TBMs, exhibit unique micro-Doppler characteristics [81]. Generally, the warhead of a TBM presents precession and nutation motions, while the decoy exhibits wobbling motion. Therefore, their individual micro-Doppler signatures highlight this difference and can be used to distinguish TBMs from decoys. In addition, micro-motion parameters, such as the precession rate, nutation angle, spin rate, and inertia ratio, can be obtained and estimated from micro-Doppler signatures, and all of these parameters are helpful for RATR [82]. The micro-Doppler signatures derived from the precession, nutation, and wobble motion of space targets are shown in Figure 9.



(a) Precession (b) Nutation (c) Wobble

Figure 9. The micro-Doppler signatures from micro-motion of space targets [82].

Related deep learning algorithms for the micro-Doppler-based recognition of space targets include the CNN and the RNN. Wang et al. [63] used two deep CNN-based models to classify space micro-motion targets with spinning, precession, and nutation. Transfer learning was adopted to train AlexNet and SqueezeNet, making the training process faster and easier. The micro-Doppler representation of three kinds of micro-motions was analyzed, and the time–frequency spectrograms of echo signals were generated as the training dataset. It demonstrated that the designed CNN-based algorithm can realize the high-precision recognition of space micro-motion targets, in which the recognition accuracy of spinning targets was the highest while the main misrecognition came from the confusion between precession and nutation. Han et al. [64] introduced a network architecture for the recognition of warheads and decoys, which consists of time–frequency transformation, a one-dimensional parallel structure for feature learning, an LSTM structure for extracting global information, and a softmax function for classification, and the proposed diagram is presented in Figure 10. The recognition accuracy of the proposed network was evaluated under different SNR. The recognition performance of the designed network was better than that of traditional networks by comparison.

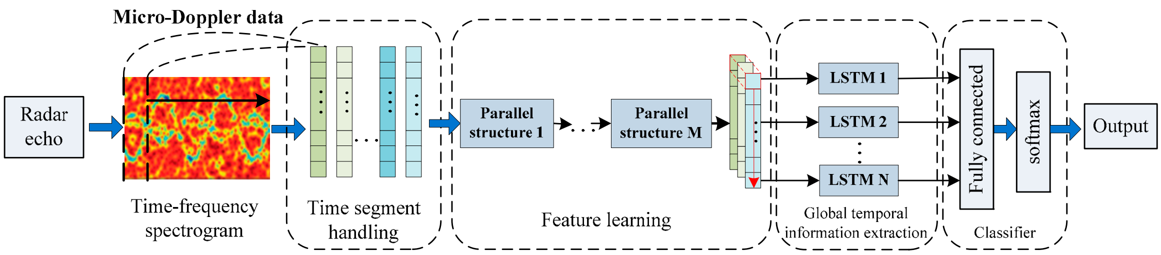


Figure 10. Diagram of the one-dimensional parallel network [64].

(2) Recognition of air targets

Air targets with rotating parts have secondary moving components which can induce an additional Doppler shift. The micro-Doppler effects of these rotating parts are peculiar to different bodies, such as the rotation of the propellers of fixed-wing aircraft, blades of helicopters, turbofan of jet engines, and rotor blades of drones, etc., which are shown in Figure 11. Therefore, the micro-Doppler effects of rotating components can be utilized for air target recognition [83]. In addition to fixed-wing aircraft, helicopters, drones, and other flying targets, flapping birds are another common air target, in which the birds' micro-Doppler signatures come from the flapping, sweeping, and twisting motions of their wings. Thus, making full use of the quite different micro-Doppler signals can be utilized to distinguish flying birds from other air targets. Studies [84,85] also studied the micro-motion features of birds, established the echo modulation model caused by the flapping of the wings of the bird target during flight, and analyzed the micro-motion features generated. The micro-Doppler signatures of a bird with flapping wings are presented in Figure 12.

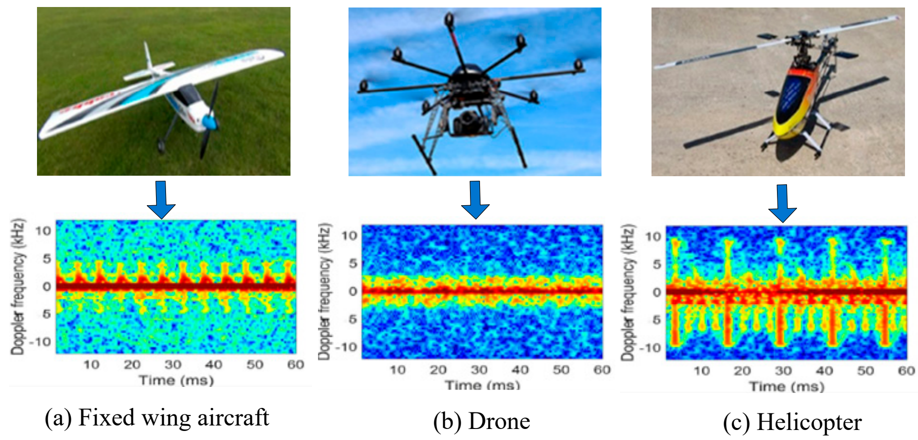


Figure 11. Micro-Doppler signatures of (**a**) fixed-wing aircraft, (**b**) drone, and (**c**) helicopter [83].

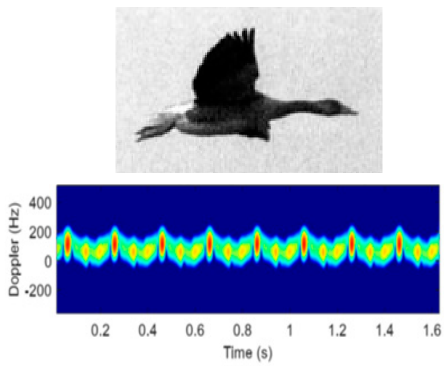


Figure 12. Micro-Doppler signature of birds' flapping wings [85].

In recent years, deep learning approaches for air target recognition based on micro-Doppler signatures have been studied extensively [65]. A great deal of research work has been carried out based on real outdoor experimental environments to distinguish different types of drones or to differentiate birds from drones. Park et al. [66] proposed a micro-Doppler signature extraction approach and a lightweight CNN structure for the recognition of three commercial drones, namely, DJI Inspire 1, DJI Inspire 2, and the DJI Spark series. Experimental results proved that the combination of the proposed method is effective for the fast and accurate recognition of small drones, which was 10% better than that of the conventional method. Rahman et al. [67] developed series CNN networks for drone (e.g., DJI Phantom Standard 3, DJI Inspire 1, DJI S900) and bird (e.g., Owl, Eagle, Hawk) recognition and compared them with GoogLeNet. Compared to the series CNN network, GoogLeNet performed better on the dataset but was more time-consuming, proving that it can be used in practical scenarios. Hanif et al. [68] adopted an AWR 1843 FMCW radar sensor to collect the returned signal from a fixed-wing aircraft and a hexacopter, and then the MobileNetV2 CNN was utilized for target recognition based on micro-Doppler signature images.

At the same time, a simulated dataset is also used for air target recognition. Choi et al. [69] investigated a CNN-based structure to classify drones based on micro-Doppler images which were simulated by changing the speed of rotors, the number of rotors, and the direction. Vanek et al. [70] adopted a CNN to discriminate the number of propeller blades of helicopters from a simulated micro-Doppler signature dataset.

(3) Recognition of ground targets

Discriminating ground targets such as vehicles, humans, and animals is of great significance to safety monitoring, intelligent transportation, surveillance, etc. At present, ground vehicle recognition based on micro-Doppler characteristics, such as tracked or wheeled vehicles, has been successfully applied to ground surveillance systems [86]. Deep learning methods are utilized to recognize the micro-Doppler characteristics of different ground targets, which usually adopted the time–frequency images as the input.

Angelov et al. [71] considered three different types of DNNs, including the CNN, the residual network, and the combination of the CNN and the RNN, for four classes of ground target recognition, and these methods were verified on experimental data. Aiming at the problem of the class-imbalance of pedestrian and vehicle recognition with limited experimental data, Wu et al. [72] introduced a hybrid SVM-CNN method; in the first stage, a modified SVM was utilized to identify vehicle targets and adjust the imbalance between pedestrians and vehicles in the limited data, while the second stage was performed using a CNN to classify the residual unclassified targets. Experimental results illustrate that the proposed architecture can promote the performance of class-imbalance recognition on the algorithm level.

Similarly, for the typical ground targets of pedestrians and tracked and wheeled vehicles, Zhu et al. [73] considered the micro-Doppler characteristics and designed a multi-level target recognition network based on the CNN and transfer learning, in which the first-level structure was adopted to discriminate pedestrians and tracked and wheeled vehicles, while the second-level method was designed to distinguish the conditions of the jogging, walking, and stepping of pedestrians; the designed method was proven to be effective by experiments. In 2022, in order to improve the recognition accuracy under the condition of low SNR, they [74] further designed a deep convolutional denoising encoder (DCDE) structure to remove noise without affecting micro-Doppler features effectively and designed a special residual network to extract micro-Doppler features, reducing the training burden and achieving higher learning efficiency. The designed structure is presented in Figure 13. The experimental results indicate that the combination approach has high recognition accuracy even with low SNR.

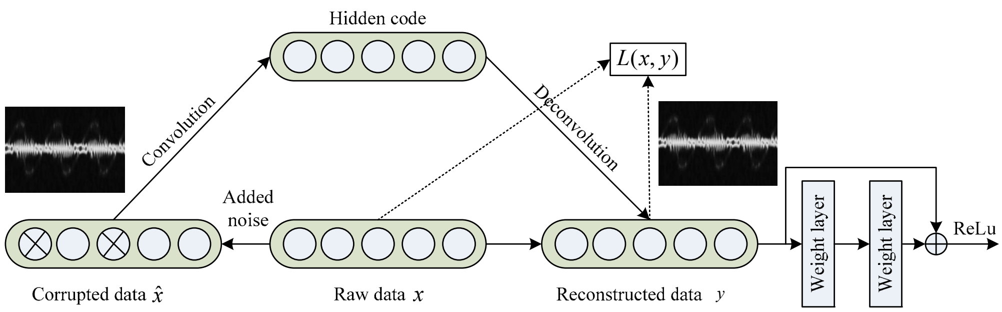


Figure 13. Structure of combining DCDE with residual network for ground target recognition [74].

(4) Recognition of sea-surface ship targets

The attitude of the ship target on the sea-surface changes with the fluctuation of the sea water, which can be manifested as three-dimensional rotation (pitch, roll, and yaw) simultaneously. Therefore, the micro-Doppler theory provides an effective solution for the detection and recognition of sea-surface targets.

It has been proven that sea-surface targets possess specific micro-motions, which are affected by the sea state. In order to describe the refined micro-Doppler signatures of sea-surface targets, Chen et al. [87] established the sea-surface micro-motion target echo model under the condition of multiple scenes and verified the correctness of the theoretical analysis through the measured data. They further adopted real radar data to analyze the micro-motion characteristics of sea-surface targets which were different from sea clutter [88].

In the whole radar echo, the sea clutter signal is often stronger than the useful target scattering signal, which brings great difficulties to the acquisition and processing of the target micro-Doppler signal and has a serious impact on the recognition of sea-surface targets. Therefore, it is necessary to deeply study the relation between the target motion state and echo characteristics and then design the corresponding algorithm to improve the signal-to-clutter ratio and enhance the ability of radars for sea detection.

(5) Recognition of human activities

Human targets are the current research focus in the field of micro-motion feature extraction and recognition. Relevant research studies mainly include the identification of the human body from other living/non-living organisms [89,90], human gait recognition [91,92], and the detection of human vital features (breathing, heartbeat, etc.) [93,94]. Many of these mature theories have been applied in medical diagnosis, safety monitoring, and automatic driving and achieved good results.

Due to the complex changes in human motion states (such as stationary, marching, stepping, creeping, etc.) and the obvious differences in attributes (such as gender, age, height, weight, etc.), the micro-motion forms (body marching, heart beating, chest fluctuating, hand and leg swinging, etc.) are diverse. However, the echo modeling of human targets is a very complicated problem, and so far, there is no ideal solution. Human activity recognition based on micro-Doppler signatures has significantly promoted the development of smart homes, security surveillance, health care, and other application fields.

Gesture recognition, which is an increasingly considered application in the field of no-contact human–computer interaction, can also be realized by using micro-Doppler characteristics. Jiang et al. [75] designed a dynamic gesture recognition system based on an mm-wave FMCW radar, which adopted the CNN to recognize six kinds of dynamic gestures, and the recognition accuracy reached 95.2%. Kong et al. [76] introduced an ultrasonic FMCW radar gesture recognition system, which utilized a specially designed Conv-LSTM to mine timing features between gesture movements.

In addition, analysis of the micro-Doppler features of diverse human motions, such as periodic movements (e.g., walking, jogging, crawling, boxing, jumping, throwing, etc.) and non-periodic movements (e.g., kneeling, falling, etc.) can be used for safety monitoring. Wang et al. [77] proposed a stacked RNN structure with multiple LSTM layers to identify the six human motions according to the micro-Doppler signatures. Jia et al. [78] introduced a network that combined multiple CNNs and sparse autoencoders (sAEs) to extract and fuse human motion features from micro-Doppler spectral graphs and range maps. For human motion recognition with insufficient training data, Li et al. [79] designed a CNN structure as the backbone of transfer learning, which was composed of three interrelated and necessary parts: data pre-training, data selection of the correlated source, and an adaptive collaborative fine-tuning algorithm.

In [80], an X-band CW radar was employed to collect data of various human suspicious behaviors, including crawling, boxing, marching, jogging, jumping with guns, grenade throwing, etc. Six pre-trained CNNs were adopted for the recognition of human suspicious actions, and the experimental results showed that the overall recognition accuracy of VGG19 using transfer learning outperforms other CNNs, reaching 98%.

3.3. Deep Learning for HRRP-RATR

RATR based on an HRRP has attracted a lot of attention in recent years, which is a hot branch of current research. Many researchers argued that nonlinear deep networks can achieve excellent performance in a variety of practical problems, including HRRP-based RATR. Compared with the shallow network algorithm, the deep network can extract the local and global features of targets from the HRRP, and the deep features are more robust and more separable. Many "deep" networks, such as CNN-based, AE-based, RNN-based, and other improved deep-learning-based approaches, have been applied to HRRP-RATR to improve target recognition accuracy. In addition, it is worth noting that several inherent issues in HRRP-RATR, such as amplitude-scale reduction and target-aspect and time-shift sensitivity, need to be preprocessed or embedded in these deep networks.

(1) CNN-based methods for HRRP-RATR

It is difficult for the classical shallow-model-based algorithms to extract the complete information or features of the HRRP of the radar target from different angles, while the deep CNN can automatically extract features from the HRRPs. In 2016, Lundén and Koivunen [95] established a CNN model for target recognition in multi-static radars, which can automatically extract high-order features from the HRRP of radar targets from different angles. The dataset was derived from the simulation calculation of multiple aircraft models, and the HRRP was augmented by adding Gaussian white noise. Experimental results of the classifiers from different monostatic and bistatic radars were fused and further compared with the chosen threshold to identify the target type. It demonstrated that the method has highly reliable recognition results even at low SNRs.

However, problems such as gradient disappearance, gradient explosion, and overfitting may occur during the training process, which will lead to poor generalization performance of the model. Moreover, if the model parameters of the neural network are initialized randomly, the model training may fall into a local optimum. Thus, it is difficult to improve the recognition performance of the whole system effectively only by deepening the depth of the network.

Inception networks come into being under such circumstances. Guo et al. [96] combined a residual network and an Inception network and proposed a cosine central loss function to decrease intra-class distance but increase inter-class distance, which is shown in Figure 14. The dataset was derived from the simulation calculations and data augmentation of seven ship models. Compared with the CNN and other network structures, the recognition accuracy of this proposed structure is significantly improved under the condition of fewer training parameters. Based on the same dataset, the research team also proposed an HRRP recognition algorithm that is based on a deep multi-scale one-dimensional CNN structure [97] and an HRRP recognition algorithm that is based on a feature pyramid fusion lightweight CNN [98]. In these two algorithms, a multi-scale convolution kernel was used to extract the shallow and deep HRRP features, respectively, to ensure that features can contain the global and local information of the target, so as to effectively enhance the robustness of the features.

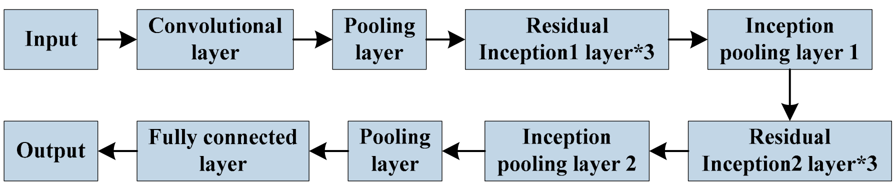


Figure 14. A structure that combines residual network and Inception network.

In addition, for the issue of target-aspect sensitivity, some research teams have also carried out targeted study. In 2018, Liao et al. [99] constructed an HRRP-RATR method based on concatenated DNNs by extending and cascading the hidden layers of several shallow neural networks. The raw HRRP samples and the features extracted from the previous subnetwork were fused as the input of the next subnetwork, so that the problems of gradient disappearance, gradient explosion, or overfitting that may occur during the training process can be solved. The dataset was simulated and measured data of four types of aircraft, and a secondary-label coding method was carried out to decrease the intra-class differences between features and increase the inter-class differences, thus solving the issue of aspect angle sensitivity. The multi-evidence fusion strategy was adopted to further improve the recognition performance of the system.

Although various research teams have implemented a lot of study work on CNN-based HRRP-RATR by using the acquired dataset, the emphasis is different, including analyzing the influence of different CNN structures, activation functions, learning rates, and other hyperparameters on target recognition accuracy, analyzing the recognition accuracy of HRRPs at different target-aspect angles or SNR, and analyzing the improvement of accuracy by fusing recognition results of multi-sensor HRRP data. Compared with other conventional algorithms, such as the SVM, KNN, multilayer perceptron (MLP), and principal component analysis (PCA), HRRP-RATR methods based on CNNs present recognition performance.

(2) AE-based methods for HRRP-RATR

Traditional deep learning networks process each HRRP sample independently, which ignores the structural similarity and amplitude fluctuation characteristics of the targets in HRRPs. Therefore, deep networks represented by stack autoencoders (SAEs) are widely used in HRRP-RATR.

In 2016, Pan et al. [100] designed a novel radar HRRP recognition approach based on a discriminative deep stack sparse autoencoder (SsAE), which could extract high-level features reflecting the physical structure characteristics of the target and train HRRP data globally with limited training data. The framework of the SsAE is presented in Figure 15. In 2017, Feng and Chen et al. [101] established the stack corrective autoencoder (ScAE) to learn the stable structure information and correlation of targets from HRRPs. According to the Mahalanobis distance criterion, the correction term was obtained from the average contour of each HRRP sample whose covariance matrix was considered as the loss function. The dataset was derived from the measurements of three types of aircraft, and the data were preprocessed by centroid alignment and L2 normalization. The experimental results of comparing the recognition results of the ScAE of different layers with the DAE, linear discriminate analysis (LDA), DBN [102], and other traditional approaches demonstrated that the average HRRP contour performs in a smoother and more concise way, and the proposed method can extract more abstract and useful hierarchical features, which not only effectively solves the problems of the speckle effect and outliers but also has better generalization performance.

As above, the SAE uses data to learn features and can obtain feature expression at different data levels. However, due to the deep structure of the network, it is difficult to obtain excellent generalization ability under the condition of fast learning. The extreme learning machine (ELM) has attracted wide attention for its great generalization ability and fast training speed. Therefore, taking full advantage of the SAE and ELM can help improve classification performance. In 2018, Zhao et al. [103] introduced an HRRP-RATR algorithm integrating the SAE and ELM, and the network structure is presented in Figure 16, in which the SAE was adopted to extract deep features of each hidden layer, and the ELM was used as the classifier instead of softmax regression, which can enhance the generalization performance and learning speed. Experimental results demonstrated that compared with other models, this method has higher recognition ability and shorter training time, and it also had a good recognition ability under the condition of small training samples. In the next stage, combing the SAE and ELM was considered as a solution to improve the robustness of the model to noise. In terms of RATR based on the ELM, Zhao et al. [104] further analyzed the effect of the introduction of Dropout on the ELM RATR ability. They showed that Dropout can not only solve the overfitting problem of neural networks but also enhance the generalization performance of the model effectively.

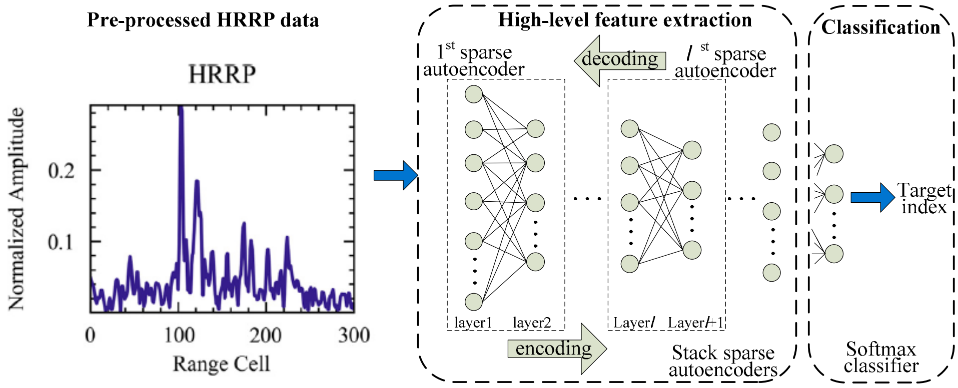


Figure 15. Framework of deep stack sparse autoencoder [100].

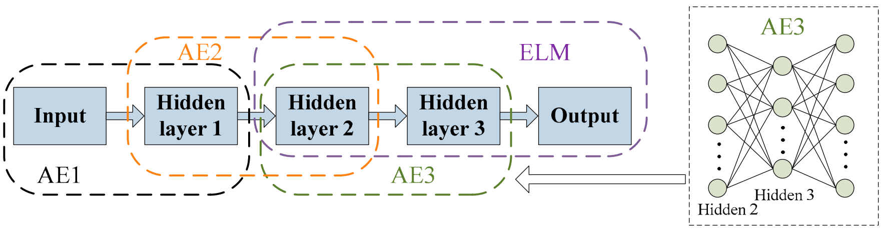


Figure 16. The structure of SAE-ELM network [103].

The combination of the sparse autoencoder (sAE) and convolutional autoencoder (CAE) also provides a way to improve RATR performance. Yu et al. [105] introduced a sparse convolutional autoencoder (sCAE) network to classify and identify the full-space and half-space HRRP samples of three vehicle target models. The dataset was derived from the simulation of electromagnetic computing software. The RATR process of this model was essentially the same as that of the CNN, which was mainly composed of three parts: preprocessing, feature extraction, and classification. The preprocessing of the data was the L2 normalization of amplitude and time-shift compensation based on centroid alignment. Compared with the traditional LDA, PCA, SVM, DBN, and other model results, the recognition ability was greatly improved.

As discussed above, HRRP target recognition based on different AE structures has been widely studied, mainly focusing on analyzing the improvement of recognition accuracy by extending and improving AE structures and the influence of AE structures with different depths on recognition accuracy. Compared with the combination of different AE structures, the introduction of convolution operation improves the accuracy of RATR more obviously, and the recognition results are better than those of traditional methods.

(3) RNN-based methods for HRRP-RATR

From the above work, it can be seen that deep learning networks can be widely applied to radar HRRP-RATR. However, the above deep learning networks do not explore the time dependence between range units. Some studies have proposed methods to describe the time dependence of HRRPs. In 2013, the RNN was first used for RATR. It is a kind of neural network with interconnected hidden layers that enables the model to represent dynamic sequential behavior in the input samples and can achieve advanced performance for the sequential data of different tasks.

RNNs are often combined with the attention mechanism to achieve superior recognition performance that is more robust to time-shift sensitivity than traditional approaches.

In 2016, Xu et al. [106] designed an RNN-based method for radar HRRP target recognition utilizing time-domain features. Firstly, the proposed structure adopted attention-based RNN encoding time-domain features to reveal the correlation within the target. Secondly, the model assigned weights to each part and summed up hidden features with each weight for RATR. The dataset was the measured flight data of three types of aircraft. Experimental results showed that the RNN algorithm based on the attention mechanism is very effective in improving the performance of HRRP-RATR. In 2018, they further developed the target-aware recurrent attentional network [107] for HRRP-RATR, taking advantage of the time dependence to explore the informative regions in HRRPs. Specifically, a specific designed RNN was utilized to mine the sequence correlation in the range units of the HRRP, and then each time step in the hidden layers was weighted according to the attention mechanism to find the target region that is more informative and discriminative. Considering the temporal correlation between range units in HRRP samples, Xu et al. [108] studied a bidirectional LSTM network for HRRP-RATR, combined with a softmax classifier and voting strategy for classification, and the target recognition performance was improved, which was proven to be able to overcome the translation sensitivity of the HRRP well.

(4) Improved deep learning methods for HRRP-RATR

The above CNN, autoencoder, and RNN methods presented strong representational capacity and obtained superior recognition performance than conventional algorithms. There are also some other variants based on improved deep learning networks that integrate different network structures with good performance and make improvements according to the characteristics of the HRRP. While creating a more complex network structure, the improved network overcomes the shortcomings of gradient disappearance or explosion in the process of learning. Compared with the simple deep learning network, the improved network has faster convergence and higher recognition accuracy.

(a) Attention mechanism

The HRRP typically contains a large number of non-target regions, where the information is unhelpful or even counterproductive for target recognition. However, conventional feature extraction approaches often ignore the fact that the information contained in different regions of the HRRP is of different importance. The attention mechanism, derived from research in the field of computer vision, can selectively focus on related information while ignoring others that are less relevant. Considering that HRRP data contain non-target information, the attention mechanism is applied to HRRP-RATR to pick out the discriminative feature of the target region.

In order to obtain more useful information and discriminative features from the HRRP, Du et al. [109] introduced a region-factorized RNN for HRRP-RATR, which can not only take full advantage of the temporal dependence between HRRP samples through the RNN structure but can also automatically find the target region in the HRRP through clustering. The attention mechanism was adopted to weight the recognition contribution rates of different hidden layers in each time step, which is presented in Figure 17. Besides the competitive recognition accuracy of RATR, the proposed method also possessed a promising interpretability by comparing it with other conventional approaches.

Chen et al. [110] designed a target-attentional CNN structure combining the attention mechanism and CNN for HRRP-RATR, which is presented in Figure 18. In the first step, a one-dimensional CNN was adopted as the feature extractor to exploit the structural features of HRRP data. Secondly, the attention mechanism was implemented through the bidirectional gated recurrent unit structure to enhance the model's interest in the useful target information region, which fully considered the sequential relationship between the features of different regions in the HRRP, so as to locate the target region.

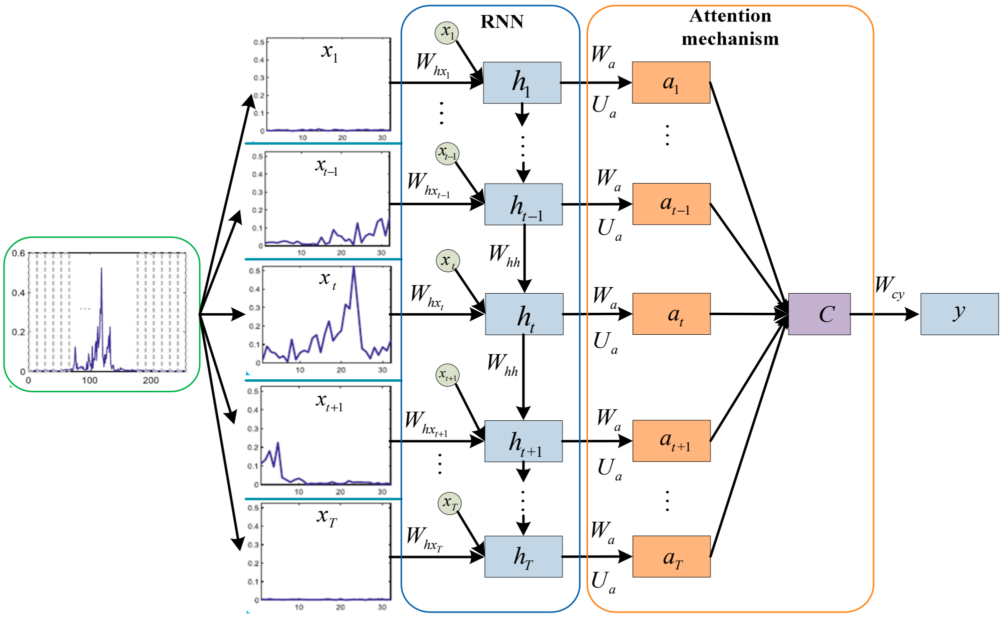


Figure 17. An RNN structure for HRRP-RATR based on attention mechanism [109].

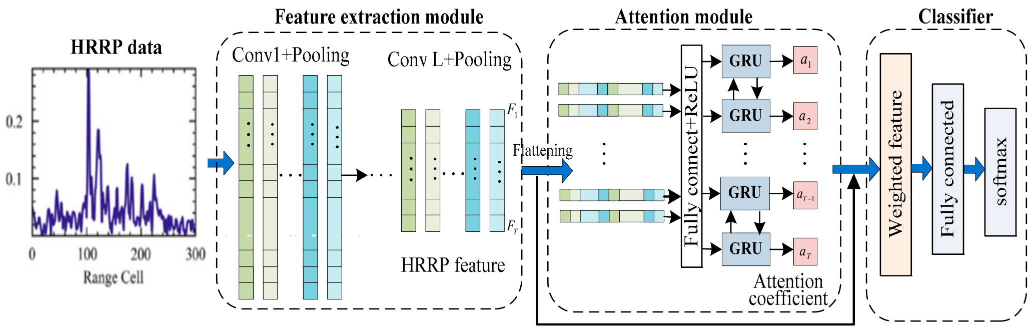


Figure 18. A CNN structure for HRRP-RATR based on attention mechanism [110].

Considering the target-aspect sensitivity of the HRRP, especially in a complex environment with non-cooperative targets, the target-aspect sensitivity has a great impact on the performance of HRRP-RATR. Song et al. [111] introduced a generative adversarial network (GAN) with aspect-directed attention, which could not only generate multi-view HRRP samples but could also exploit the internal feature of the HRRP through a cascade of self-attention layers. Although most of the aspect information of the non-cooperative target is missing, experimental results showed that the generated HRRP can still be categorized correctly, and the recall rate of HRRP-RATR is improved by more than 40%.

(b) Network fusion methods

The improved HRRP-RATR methods integrate different networks with superior performance and make improvements according to the HRRP characteristics. In addition to creating a more complex network structure, the shortcomings of gradient disappearance or explosion during the training process are overcome. Compared with the simple structure of deep learning networks, the improved fused network presents faster convergence and higher recognition accuracy.

Zhang et al. [112] designed a deep network structure by fusing CNN and LSTM network structures and concatenated the one-dimensional features extracted from signal time–frequency graphs with the original HRRP samples using a multi-layer CNN, which acted as the input of the LSTM network for RATR. The fused method is presented in Figure 19. The dataset was constructed by simulating the X-band calculation of four simple targets, namely a cone cylinder, a cylinder, and two different sizes of cones. The changes in target recognition accuracy under different SNR conditions have also been considered. RNNs are powerful network structures that specialize in processing sequential data. A wavelet AE network combined with the RNN was designed for HRRP-RATR in [113], which can exploit the spectrum features and fully consider the dependency and correlation between range cells in HRRP samples; therefore, the proposed fusion model achieves superior recognition accuracy than the sole RNN model.

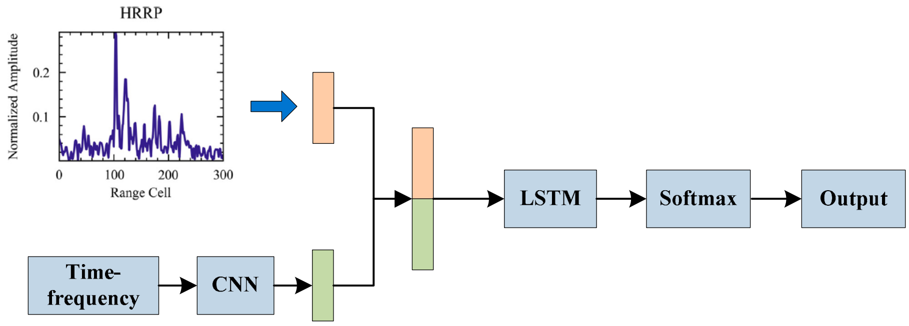


Figure 19. A network structure integrating CNN and LSTM [112].

(c) Imbalanced and open-ended data distribution

At present, most research on deep-learning-based RATR algorithms is conducted under the assumption of balanced samples and a close dataset, in which the "balanced samples" means that the number of samples of each class is approximately equal, and the "close dataset" means that the classes of training are the same as the classes of testing. However, samples are often imbalanced and open-ended in practical application [114]. Zhang et al. [115] designed a dual self-attention neural network combing a memory mechanism for HRRP-RATR on an imbalanced and open dataset, in which an Arc-loss function was introduced as a classifier to improve the inter-class difference and intra-class similarity in one integrated model. Compared with other existing methods, the discriminative feature representation of the proposed approach was more obvious, and the recognition rate was improved, indicating that it would have a good application prospect in imbalanced and open HRRP-RATR.

Currently, there is no typical public dataset for the research of deep-learning-based HRRP-RATR. Most of the datasets for HRRP target recognition come from model simulation calculations or anechoic chamber measurements carried out by different research teams themselves. However, different studies have also shown that deep-learning-based HRRP-RATR is a promising approach with higher recognition performance than most traditional recognition approaches.

3.4. Deep Learning for SAR-ATR

The scattering imaging mechanism of the SAR and the existence of background noise or clutter make SAR image interpretation very different from that of optical images. In traditional target recognition and classification algorithms, feature extraction is achieved by manual selection, which only uses the texture features of SAR images and does not exploit the more valuable semantic features. In addition, manually selected features are often incomplete and may fail under noisy conditions. Different from traditional RATR technology, deep learning networks, especially CNNs, can automatically learn and select the target's hierarchical features and perform target recognition, which not only improves the recognition accuracy but also reduces the computational pressure. At present, for SAR-ATR based on deep learning, researchers mostly conduct studies from four research aspects. The specific recognition approaches and effects based on deep learning are presented in Table 3.

Table 3. Some deep-learning-based methods and effects on SAR-ATR in recent literature.

Method Improvement	Specific Methods	Main Contributions	Dataset	Acc.	Ref.	Year
Semantic feature extraction and optimization	Sparse autoencoder + CNN	Using a single layer of CNN to extract features.	MSTAR	84.7%	[116]	2015
	CNN without fully connected layers	Using sparsely connected convolution architecture to reduce overfitting.	MSTAR	99%	[117]	2016
	Multi-scale CNN	Extracting robust multi-scale and hierarchical features of built-up areas.	TerraSAR-X	92.86%	[118]	2016
	CNN + SVM	Using SVM to classify the feature map and introducing class separability measure into the loss function.	MSTAR	93.76%	[119]	2016
	CNN + SVM	Feature maps extracted by CNN are classified by SVM.	MSTAR	99.5%	[120]	2016
	CNN + autoencoder	Combining CNN and autoencoder to extract features of military vehicles.	MSTAR	93%	[121]	2017
	CNN + autoencoder	Splitting CNN into SNN and CAE to greatly reduce the learning time.	MSTAR	98.02%	[122]	2015
	Shallow CNN	Designing a light-level shallow CNN to classify targets.	MSTAR	99.47%	[123]	2017
Multi-aspect	CNN	Using pseudo-color image as input to reduce the difference between targets at different azimuth angles.	MSTAR	98.49%	[124]	2018
	CNN + parallel network topology	Sufficient multi-aspect SAR images are generated and features are extracted using parallel CNN.	MSTAR	98.52%	[125]	2018
	Bidirectional LSTM	A bidirectional LSTM structure is used to explore the spacing-varying scattering feature of different aspects.	MSTAR	99.9%	[126]	2017
	Multi-stream CNN	Multi-stream CNN is used to extract the multi-view features and then combine them by the Fourier feature fusion.	MSTAR	99.92%	[127]	2018
	EfficientNet + BiGRU + island loss	Combining EfficientNet, BiGRU, and island loss to reduce azimuth sensitivity of SAR targets.	MSTAR	100%	[128]	2021
Small-sample dataset	Data augmentation	Extending the training data by central clipping and using ResNet to extract features.	MSTAR	99.56%	[129]	2017
		Three domain-specific data augmentation operations are performed on SAR images utilizing CNN.	MSTAR	93.16%	[130]	2016
		Constructing simulated SAR images based on CAD models to fill the data gap.	——	——	[131]	2016
	GAN	Using GAN to generate SAR target slice images.	MSTAR	——	[132]	2018
		Combining semi-supervised CNN and dynamic multi-discriminator GAN.	MSTAR	97.81%	[133]	2019
	Transfer learning	Transferring the pre-trained CNN model from the 3-class target recognition task to the 10-class target recognition task.	MSTAR	99.13%	[134]	2018
		Transfer learning combined with VGG16.	MSTAR	94.4%	[135]	2020
		Transferring a CReLU-based model from simulated dataset to MSTAR dataset.	MSTAR	99.78%	[136]	2020
		Transferring a CNN-based model pre-trained with MSTAR to OpenSARShip.	MSTAR, OpenSARShip	90.75%	[137]	2020
	Metric learning	The convolutional highway unit network is adopted for training with limited SAR data.	MSTAR	99%	[138]	2017
		A Siamese CNN based on deep learning and metric learning is adopted to evaluate the similarity between data.	MSTAR, OpenSARShip	94.77%	[139]	2019
		The Siamese network is introduced to evaluate the probability of similarity between two samples.	MSTAR	93.2%	[140]	2019
Multi-feature fusion	CNN	Using intensity and edge information jointly.	Self-built	93.64%	[141]	2017
	Canny-WTD-CNN	The edge features extracted by Canny operator fused with the wavelet features extracted by wavelet threshold denoising method as the input of CNN.	MSTAR	99.14%	[142]	2020

(1) Semantic feature extraction and optimization methods of SAR images

The key question of SAR-ATR research is how to learn the most representative target features in SAR images. A semantic feature is an abstract high-level feature representation formed by the combination of low-level texture features, which has a high discrimination ability for images and targets. How to learn high-level semantic features from SAR images is also a complicated issue in image interpretation.

In 2015, Chen et al. [116] initially adopted single-level CNN to automatically extract representative features for SAR-ATR. The classification accuracy of 90.1% and 84.7% was achieved by using the learned morphological features in the Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset with 3 and 10 classes of targets, respectively. Later, in 2016, a novel full CNN composed only of sparsely connected layers was designed to cut down the number of model parameters and avoid the problem of overfitting [117]. The network structure is composed of five convolutional layers and three sub-sampling layers. The training results on the MSTAR dataset demonstrated that the classification performance of the proposed approach is significantly superior to the traditional approaches, and the classification accuracy of the 10 classes of targets can reach 99%, which reflects the advantages of CNN-based approaches in SAR-ATR.

In the CNN, convolutional and pooling layers are alternately connected to learn hierarchical target features. Although the traditional CNN has a certain robustness, small changes in the input image size will still lead to big differences in the final recognition results [143]. It is difficult to extract enough semantic features using s single-scale CNN, so a multi-scale CNN has been applied to SAR-ATR. Li et al. [118] designed a multi-scale CNN structure to learn multi-scale training features directly from the image patch sizes of 14×14, 42×42, and 84×84, which is shown in Figure 20. By connecting three convolutional layers and three pooling layers alternately, the structure extracts the hierarchical features of the target, and eventually, the target is recognized through feature fusion. In the task of RATR in urban construction areas, the training results on the TerraSAR-X dataset obtained a classification accuracy of 92.86%, which is better than that of the single-scale CNN (89.64%) and the gray co-occurrence matrix algorithm (88.78%).

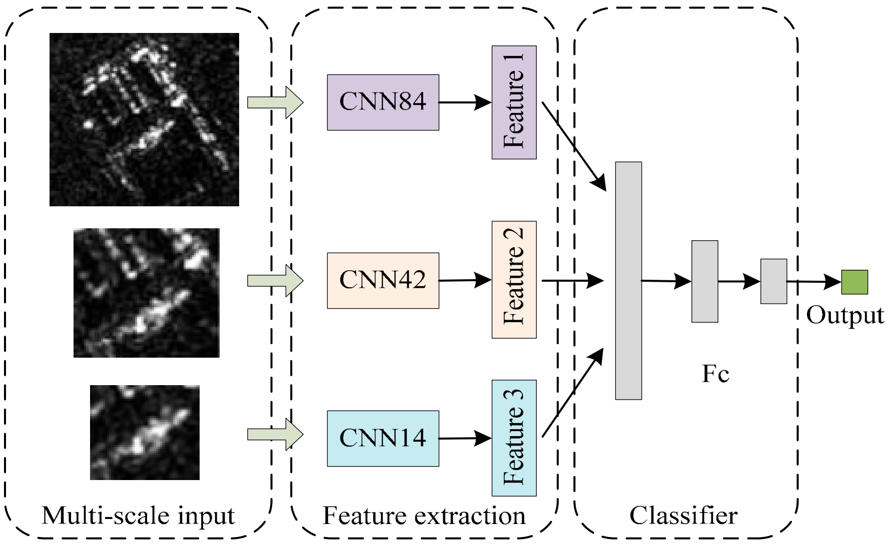


Figure 20. Architecture of multi-scale CNNs [118].

In traditional CNN models, a softmax regression model is usually used as a classifier, but its single-layer fully connected method is not effective in solving nonlinear classification problems. Meanwhile, the SVM can map nonlinear classification to the high-dimensional feature space through the kernel function, which converts the nonlinear classification issue into linear classification, and performs well in solving the high-dimensional pattern recognition problem. In 2016, Tian et al. [119] adopted the SVM to classify the feature map extracted by the CNN and brought in the class separability measure into the loss function, thus improving this network's ability to distinguish between categories. Experimental results on the MSTAR image data demonstrated that without manual feature extraction, the proposed method achieves 95.90% recognition accuracy in the 3-class target classification dataset, while the average recognition accuracy in the 10-class dataset is still as high as 93.76%. Wagner et al. [120] designed a SAR-ATR approach based on the combination of the SVM and the CNN, in which the representative feature is achieved by utilizing the CNN, and then it is input to the SVM classifier for discrimination. The combination structure presented in Figure 21 can enhance the generalization ability of the classifier while keeping the computation time low and has a more accurate recognition rate and better robustness. In 2017, Housseini [121] proposed a recognition method combining the CNN and the convolutional autoencoder, first extracting the trained filter from convolutional autoencoders and then applying them to the CNN. This scheme significantly reduces the time complexity of the algorithm without reducing the recognition accuracy.

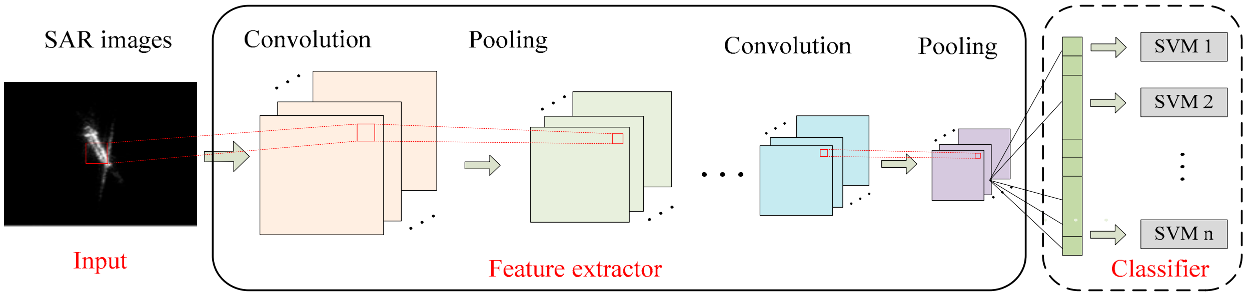


Figure 21. A SAR-ATR architecture combining CNN and SVM [120].

In order to enhance the recognition performance of the deep-learning-based SAR-ATR algorithm, including accuracy and speed, generally, one must modify the network structure and optimize the network algorithm to improve the network recognition accuracy while reducing the network complexity and effectively reduce the time consumption of training. For example, the small-batch momentum gradient descent algorithm is usually adopted to speed up the learning process, reduce the oscillation, and seek the optimal parameters faster. Li et al. [122] designed a fast recognition structure to extract high-level features through unsupervised training, utilizing convolutional layers and pooling layers as convolutional autoencoders, while other fully connected layers were treated as classifiers for target recognition. It demonstrated that the modified approach can greatly shorten the model training time. He et al. [123] presented a light-level CNN and proposed an unsupervised detection method, which first adopted the MSTAR dataset to train a shallow CNN for classification, then extracted the outputs of the convolutional layers, and achieved fast target recognition and detection through maximum sampling and clustering processing.

(2) Multi-aspect SAR-ATR methods

The same target in the SAR image will be very different from different aspects, so it is greatly sensitive to the aspect of the targets. In other words, different imaging angles will make a difference to the recognition results of SAR-ATR, and only utilizing the single-azimuth observation image of the target cannot take full advantage of the rich information of SAR images. Therefore, more robust and reliable multi-aspect SAR-ATR approaches are needed, and currently, the issue of multi-aspect SAR-ATR has gradually become the research focus in the field of RATR. In addition, the MSTAR dataset also provides a 2D SAR image target with different aspects.

Since the SAR images presented by the same target in different aspects will be greatly different, multi-aspect images are used jointly for SAR-ATR, as illustrated in Figure 22. Zou et al. [124] introduced a multi-aspect SAR-ATR approach based on the CNN structure, which inputs SAR image data of three azimuth angles into the network for processing as

RGB images of three channels of color images, effectively reducing the difference between targets at different azimuth angles and improving the recognition effect. Pei et al. [125] further improved the generation method of multi-aspect SAR data to ensure sufficient network training input with limited original SAR images. The structure of CNNs with a multi-input parallel topology is presented in Figure 23. Hierarchical learning and multi-layer fusion were adopted to obtain excellent recognition performance and reduce the demand for the number of raw SAR images. Aiming at the issue of the aspect sensitivity of SAR targets, Wu et al. [144] established an improved pooling CNN model, which can improve the recognition performance of the CNN at different azimuth angles without increasing the algorithm complexity.

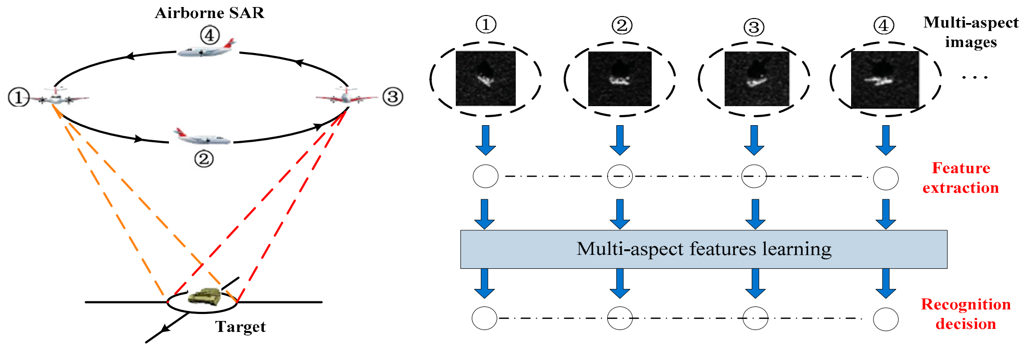


Figure 22. The diagram of a multi-aspect method for SAR-ATR.

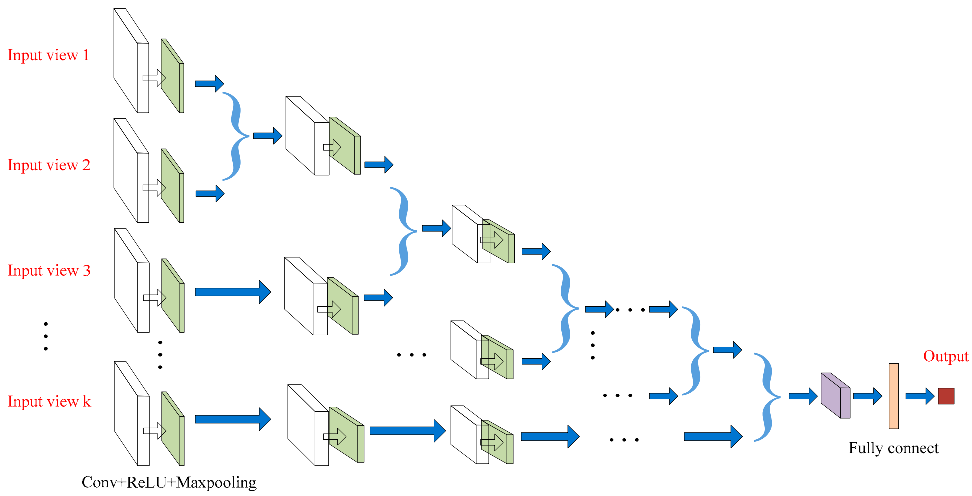


Figure 23. The basic structure of a multi-view CNN for SAR-ATR [125].

In addition to the CNN, the RNN is also widely used in multi-aspect SAR-ATR. In order to learn a wide range of contextual features at the same time, Zhang et al. [126] explored a bidirectional LSTM network for SAR-ATR based on a multi-aspect-aware mechanism, which is presented in Figure 24. Firstly, the multi-aspect spatial changing image sequences were constructed by selecting SAR images from different aspects. Subsequently, the feature extraction of multi-aspect spatial scattering information was realized by employing the three-patch local binary pattern and Gabor filter methods. Then, the feature dimension is reduced by adopting the fully connected layers. It demonstrated that the classification accuracy can reach 99.9% on the MSTAR dataset, and compared with other traditional algorithms based on deep learning, the proposed architecture presented superior anti-confusion and anti-noise performance. Zhao et al. [127] also designed a multi-stream structure based on the CNN to fuse the multi-view features of the same SAR target. Then, they further introduced a multi-aspect SAR-ATR model based on EfficientNet and BiGRU. A set of EfficientNet networks with shared weights were used first to learn the spatial features of each image in the image sequence, and then after dimension transformation, the BiGRU network was further employed to learn the sequence information of multi-aspect SAR images [128]. The results demonstrated that the recognition accuracy of the proposed algorithm on the MSTAR dataset can reach 100%, which is superior to other more advanced SAR-ATR approaches on the same MSTAR dataset and has a certain degree of robustness.

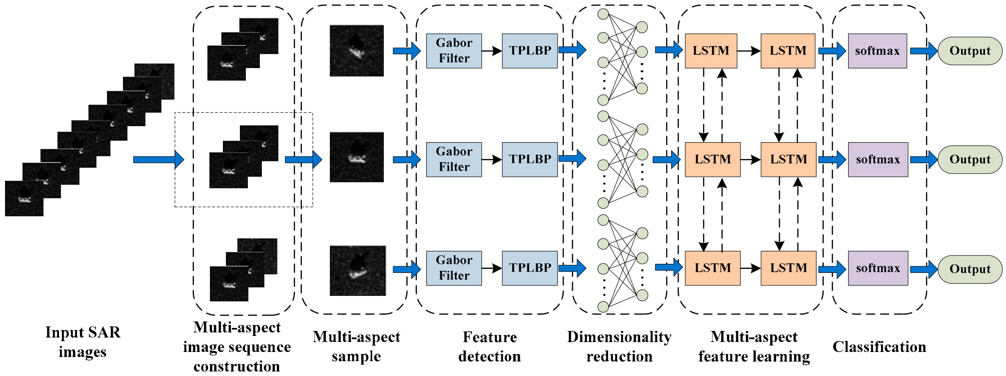


Figure 24. The diagram of a multi-aspect-aware bidirectional LSTM network for SAR-ATR [126].

(3) SAR-ATR methods based on small-sample dataset

Sufficient training samples are needed in the learning process of deep learning networks. However, in the actual SAR-ATR application, because of its unique imaging mode, the acquisition cost of SAR images is high, and the data that can be used as a training set are very limited. Especially in military applications, the high requirement of real-time information leads to the limited SAR image data of specific targets, and the lack of a training set easily leads to the over-extraction of features and overfitting of models, which make it difficult for the network to be effectively trained. Therefore, the small-sample problem is always a prominent challenge in the field of SAR-ATR. The current SAR-ATR approaches based on small-sample data are summarized as follows:

(a) Data augmentation

In the process of deep learning model design and training, data augmentation methods are often adopted to expand the sample data to prevent the model overfitting problem. The main principle of data augmentation is to take full advantage of the existing dataset and increase the amount of data by changing part of the data structure or constructing a new way of data combinations. SAR images after data augmentation are shown in Figure 25, such as flipping, shifting, rescaling, rotating, and adding noise to the data, etc., so as to generate sufficient data and enhance the generalization and learning performance of the model.

Data augmentation technology can change the position of image pixels and the size of the image and make the image undergo geometric transformation, but the characteristics of the image will not change accordingly, so that the "new" image can be obtained and the training dataset can be expanded.

Furukawa et al. [129] extended the training data by central clipping and other data augmentation methods and trained a deep residual network with 18 convolutional layers by referring to the idea of the residual network. The CNN with extended training data achieved a recognition accuracy of 99.56%, which fully reflects the effectiveness of extended training data in improving classification accuracy. Ding et al. [130] utilized a data augmentation algorithm to synthesize SAR images with specific angles from images with known azimuth angles. After the attitude is synthesized, the image is processed with noise to obtain a larger training dataset. Experimental results on MSTAR demonstrated that expanding the dataset through data augmentation technology can significantly enhance the recognition accuracy of DCNN. Before data augmentation, the recognition accuracy of the CNN was 89.14%, while after data augmentation, the recognition accuracy of the CNN increased to 93.16%.

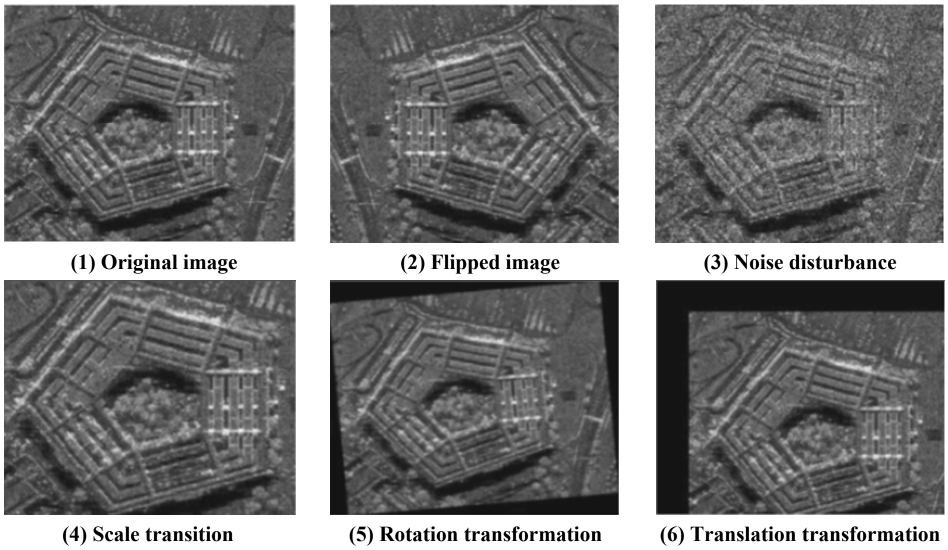


Figure 25. Common data augmentation techniques [129].

In addition, generating simulated data through simulation experiments is also a very effective method to solve this problem. Odegaard et al. [131] used CAD to generate simulated images, and the experiment demonstrated that the usage of simulated data was an effective way to improve the recognition results of SAR images by the CNN.

(b) Generative adversarial network

In recent years, GANs have also been applied in the field of SAR-ATR. To some extent, the GAN can learn new image samples with a similar distribution through model learning. The general structure of the GAN for SAR-ATR is presented in Figure 26. The GAN can be applied to SAR image processing and data augmentation, using the GAN to generate SAR target slice images and SAR images with specific azimuth, which can realize the augmentation of the SAR image dataset [132]. In 2019, Zheng et al. [133] proposed a semi-supervised SAR-ATR approach combining the CNN and GAN, adopting the GAN to generate unlabeled images, which together with the original labeled images serve as the input of the CNN; thus, effective training and recognition can be achieved with limited training samples. Experiments on the MASTR database indicated that this method can improve the recognition accuracy and robustness of the SAR-ATR system. At the same time, the GAN presents a superior application potential in the fields of SAR image denoising and SAR image super-resolution reconstruction.

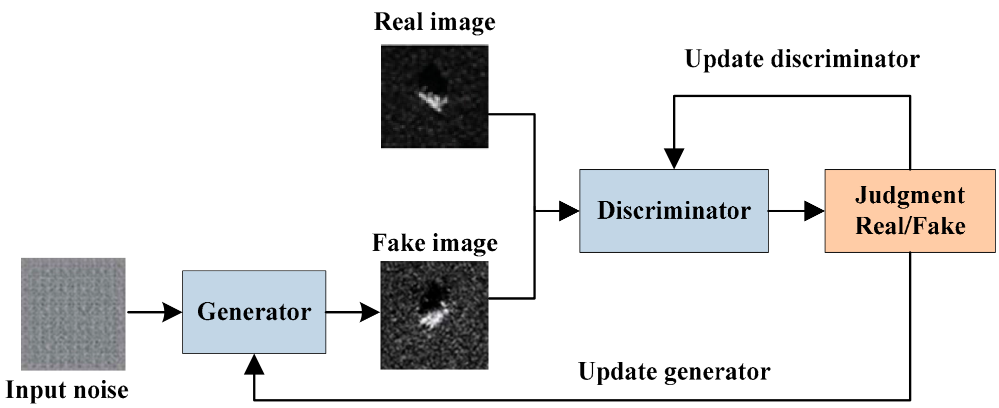


Figure 26. The structure of GAN for SAR-ATR.

(c) Transfer-learning-based methods

The main idea of transfer learning is to transfer the parameters of a pre-trained model or weighted samples to new models to help construct new models with stronger generalization performance, which has been widely applied to the field of SAR-ATR with small SAR image samples. The framework of transfer learning is shown in Figure 27, for a given source domain Ds and its corresponding source task Ts and a target domain Dt and its corresponding target task Tt; transfer learning obtains the target prediction function $f(g)$ of the target domain Dt by learning the corresponding knowledge from the given source domain Ds and source task Ts.

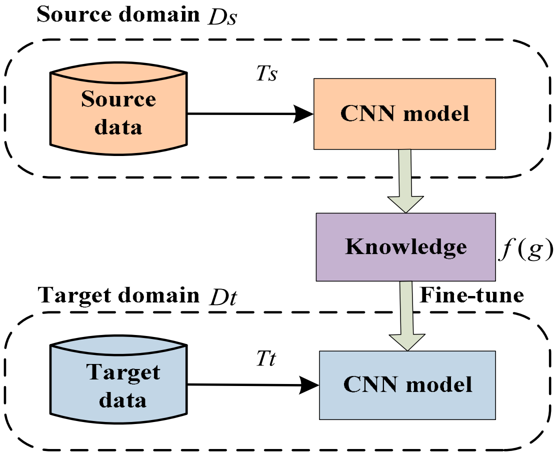


Figure 27. The framework of transfer learning.

For the MSTAR dataset, Chen et al. [134] took three types of target data as the training samples of the source domain first, and the CNN model was pre-trained for the three-class target recognition task. Then, by constructing the same CNN architecture as the pre-trained model as the target task in the target domain and taking the pre-trained model as the initial parameter, the model of 10-class target data was fine-tuned and trained, and the recognition accuracy reached 99.13%. Ren et al. [135] designed a SAR-ATR approach combining transfer learning with VGG16. The target features were extracted by fine-tuning the pre-trained model of transferring VGG16 for the target recognition on the MSTAR dataset; the recognition accuracy was improved to 94.4%, which verified the feasibility of the application of transfer learning in SAR-ATR. Another method is to transfer the pre-trained model learned from sufficient simulated SAR images to the real SAR images, which can effectively solve the problem of overfitting caused by insufficient SAR images [136].

The essential problems of transfer learning applied to SAR-ATR are usually discussed from three aspects: (1) which source tasks and network models are more suitable for transferring to SAR image targets; (2) the transferred features of which layers are more general to SAR targets; and (3) how to carry out transfer learning in SAR-ATR tasks effectively [137]. To solve the above issues, Huang et al. [137] presented a novel domain adaptive transitive transfer learning algorithm based on multi-source data, which could reduce the difference between the source data and target data of SAR images. Experimental results on the MSTAR and OpenSARShip datasets validated that the domain adaptive learning mechanism can enhance the performance of SAR-ATR.

(d) Metric learning

Metric learning is a branch of machine learning and is commonly used in the field of classification, which can learn the metric distance function from data for different tasks independently, thereby enhancing the performance of similarity-based algorithms. By measuring the similarity between two samples, sample data can be classified into categories with greater similarity. In addition, metric learning is one of the approaches to solve the issue of small-sample classification, which is generally realized by the Siamese neural network (SNN). Compared with the classical networks, the SNN model mainly judges the similarity of the input samples without knowing the category of each label. It obtains a similarity measure through data learning and compares the similarity of the new samples.

Taking the SAR image target as an example, the structure of the SNN is presented in Figure 28. First, the two SAR image target samples X_1 and X_2 are taken as the input of the SNN, and the low-dimensional features $G_W(X_1)$ and $G_W(X_2)$ are obtained through the feature extraction of the SNN. Then, the distance of the two input vectors is calculated by some distance measure, and the similarity E_W of the two input SAR image targets is judged.

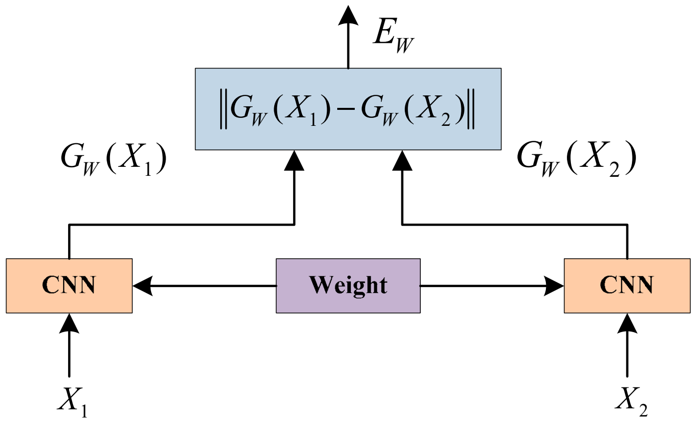


Figure 28. The diagram of Siamese neural network.

Lin et al. [138] took two SAR image target samples as the input of the SNN and obtained low-dimensional features through the feature extraction of the SNN; then, the distance of two input vectors was calculated by some distance metric methods, and the similarity of the two input SAR image targets was evaluated. Aiming at the small-sample problem of SAR-ATR, Wang et al. [139] used the strategy of constructing positive and negative sample pairs to expand the dataset and designed a metric-learning-based Siamese CNN to calculate the similarity between the training sample and the testing sample. Then, a weighted voting mechanism was adopted to identify specific types of targets in the Siamese CNN. Experiments on the MSTAR and OpenSARShip datasets demonstrated the effectiveness of the proposed algorithm. Pan et al. [140] also adopted the SNN method for small-sample SAR-ATR, in which features were extracted through the SNN first, and then the output of a single branch of the SNN was employed as the input of an additional classification network, which could avoid calculating the similarity between two samples. Experiments on the MSTAR dataset with 10 classes of targets showed that the similarity between the same type of targets decreased while the between-class distance increased, thereby, improving the performance of the classifier under small-sample conditions.

(4) SAR-ATR methods based on multi-feature fusion

Different sensors can capture different statistical characteristics of the same target, and combining different characteristics is helpful to enhance the performance of SAR-ATR. Wang et al. [141] proposed a SAR-ATR algorithm based on multi-feature fusion, which fused the intensity feature and gradient amplitude feature into the classification network, and demonstrated the high efficiency of the method through experiments. Because of the complementary properties of the radar image and optical image, target recognition based on a SAR and an optical sensor has been paid more and more attention. For the change detection of SAR images and optical images, Liu et al. [145] introduced a symmetric convolutional coupling network that can extract feature maps by convolving and pooling optical images and SAR images in different periods, and then the feature maps were directly compared and analyzed to achieve the pixels that have changed in the image, and the change detection of the whole image was further carried out pixel by pixel. Wang et al. [142] presented an optimization approach of SAR-ATR utilizing multi-feature and the CNN, namely Canny-WTD-CNN. The edge features extracted by the Canny operator were adaptively fused with the wavelet features extracted by the wavelet threshold denoising method as the input of the CNN. Experimental results on the MSTAR database with three-class targets verified the efficiency and feasibility of the fusion algorithm, and the recognition accuracy reached 99.14%.

3.5. Deep Learning for Other Radar-Target-Characteristic-Based RATR

For other narrowband radar target characteristics such as echo characteristics, the application of deep learning for RATR is relatively rare. Inspired by the huge success of deep learning techniques in the field of SAR-ATR and computer vision, Fan et al. [146] designed a five-layer CNN for typical cube, tetrahedron, and triangular prism recognition utilizing raw radar signals with different angles, which could avoid complex signal processing such as matched filtering. Iqbal et al. [147] discussed an algorithm to predict the forward motion and backward motion of the target by applying a CNN framework on echo signals. The direction of target motion is directly reflected by the variation in echo amplitude and frequency. It was concluded that deep learning methods based on raw echoes can be applied in target recognition, especially for targets with simple shapes or basic motions, which have distinct echo characteristics.

As the basic property of a radar target, RCS characteristics are a vital narrowband recognition feature for RATR in low-resolution radars. For simple-shape targets, a CNN model was proposed to classify corner reflectors based on the RCS characteristics of corner reflectors [148]. For rotating targets, Wengrowski et al. [149] generated RCS signals and adopted an 18-layer residual network to classify cone, cylinder, plate, and spheroid targets, which only produced a 2% recognition error on self-generated datasets. It demonstrated that deep learning methods can perform well on RCS signals. According to the analysis in [150], there are significant differences in RCS characteristics between aircraft targets of various sizes, materials, and shapes, and therefore these characteristics can be applied to RATR. Considering the large variance of the RCS of different targets and the effect of micro-motion factors on RCS time series, Yang et al. [151] analyzed the statistical RCS characteristics and adopted multilayer CNNs and RNNs to classify targets based on RCS time series, respectively, confirming that deep learning methods have the capability of target recognition based on RCS series, especially with micro-motion difference. The depth of the model has a vital effect on the accuracy of recognition, and RNN models are slightly inferior to CNN models. However, the statistical models and machine learning classifiers for one-dimensional RCS data have been proven to be able to obtain superior recognition performance than deep learning approaches in low-SNR scenarios [152]. Finally, it is worth mentioning that the RCS dataset used for the above work was obtained through simulation modeling and calculation.

3.6. Summary of Deep Learning Methods for RATR

From the above existing studies, it is obvious that deep-learning-based RATR approaches mainly use the amplitude, phase, frequency, and other information of the target echo signal, while the polarization and target pole information of the target is relatively limited. On the one hand, for low-resolution radars, it is difficult to obtain stable and clear polarization and pole characteristics from the radar echo directly; on the other hand, it is limited by the accurate measurement technology of the polarization scattering matrix and pole distribution. The development of high-resolution radar technology and advanced signal processing technology makes it possible to obtain stable and definite target characteristics in radar echoes.

Deep learning techniques turned out to be qualified and remarkable in RATR, which could be designed for RATR tasks with different radar target characteristics. Among them, RATR based on the wideband target characteristics of high-resolution radars is the most mature application, especially based on 2D images. For HRRP-RATR, different preprocessing methods or embedding deep networks are required to mitigate the sensitivity of the amplitude scale, target aspect, and time shift. As a kind of narrowband characteristic, micro-motion characteristics used for RATR can be developed well because of signal processing technology. Therefore, various radar signal processing methods can be considered as preprocessing means, which could help to extract features effectively and promote recognition ability.

4. Datasets for RATR

The application of deep learning algorithms relies heavily on large-scale, measurable, standardized, and accurate training samples. Therefore, the availability of training data with labels is considered to be the first prerequisite for promoting the progress of deep learning approaches in RATR. Although there have been many successful research studies and applications of current deep learning methods in radar target characteristics and RATR, most studies still use self-built datasets or simulated datasets. In general, there are few publicly released datasets for HRRP-RATR or micro-motion RATR, except for SAR-ATR. In this section, we focus on the datasets of MSTAR, OpenSARShip, and FUSAR_Ship that are relatively widely used in SAR-ATR.

4.1. Dataset Descriptions

(1) MSTAR dataset

The MSTAR dataset [153], sponsored by the Defense Advanced Research Projects Agency and the Air Force Research Laboratory and released by the Sandia National Laboratory, consists of images of military targets utilizing an X-band SAR sensor in a one-foot resolution spotlight mode. It is the main data source of SAR-ATR research, which promotes the development of SAR-ATR.

In the MSTAR dataset, the range and azimuth resolution of each SAR image is 0.3 m $\times$ 0.3 m, the pixel size of most target images is 128 $\times$ 128, and the polarization mode is HH. The dataset is mainly composed of different types of stationary ground vehicle targets (e.g., 2S1, BMP2, BRDM2, BTR60, BTR70, D7, T62, T72, ZIL131, ZSU234) from full aspect angles (0~360°) and different depression angles, which could facilitate the study of the influence of different imaging angles on the recognition algorithm. Among them, the data with depression angles of 15° and 17° have been adopted by most researchers. Table 4 presents the number of 10 types of target slices under these two groups of depression angles. In addition, MSTAR also contains a small number of environmental scenarios, including rural and urban scenarios.

Table 4. Sample numbers of different types under different depression angles in MSTAR dataset.

Depression Angles (°)	2S1	BMP2	BRDM2	BTR60	BTR70	D7	T62	T72	ZIL131	ZSU234
15	274	195	274	195	196	274	273	196	274	274
17	299	233	298	255	233	299	299	232	299	299

(2) OpenSARShip dataset

The OpenSARShip dataset [154], constructed and released by Shanghai Jiao Tong University in 2017 (OpenSARShip) and 2019 (OpenSARShip2.0), is specifically for ship target recognition in SAR images. Its data were acquired from the Sentinel-1 satellite, and the polarization modes are VH and VV, which provides 11346 SAR ship images integrated with automatic recognition system information, including cargo, dredging, fishing, passenger, pilot vessel, port tender, and other types which make up a total of 17 ship targets [155,156].

(3) FUSAR_Ship dataset

FUSAR_Ship dataset [157] is a SAR-AIS open counterpoint dataset of the Gaofen-3 (GF-3) satellite supported by Fudan University. GF-3 is the first civilian C-band fully polarized spaceborne SAR of China, which is mainly used for marine remote sensing and ocean monitoring.

The high-resolution FUSAR_Ship dataset contains 15 major ship classes (including cargo, tankers, fishing, and so on), 98 subclasses, and many marine targets that are not ship targets. The data slices were taken from 126 original Gaofen-3 remote sensing images. The polarization mode included DH and DV, and the imaging mode was UFS, covering various sea, land, coast, river, and island scenes. There are 16144 slices in this dataset, including 6252 ships with matched AIS information, 2045 strong false alarms such as bright spots which are similar to ships, 1461 bridges and coastlines, 1010 coastal areas and islands, 1967 complex sea clutter types, 1785 sea surfaces, and 1624 land types. It is suitable for ship recognition and detection on complex sea surfaces. Table 5 presents the comparison information of the above three SAR-ATR datasets.

Table 5. Information comparison between three SAR-ATR datasets.

Dataset	Release Time and Nation	Gathering Satellites	Resolution	Number of Images	Size of Images
MSTAR	1996, USA	——	0.3 m × 0.3 m	5950	128 × 128
OpenSARShip	2017/2019, China	Sentinel-1A	20 m × 22 m (2.7 m~3.5 m) × 22 m	11,346 (V1) 34,528 (V2)	——
FUSAR_Ship	2020, China	GF-3	(1.7 m~1.754 m) × 1.124 m	6252	512 × 512

4.2. Summary of Datasets for RATR

The research of RATR methods based on echo, RCS, and HRRP characteristics highly depends on datasets. However, due to the specificity of RATR tasks, there is no typical public actual radar time-series dataset for deep-learning-based research except SAR datasets. Most of the datasets for RATR come from electromagnetic simulation, model calculation, or anechoic chamber measurement carried out by different research teams themselves. Since the acquisition cost of radar target characteristics is high, and the measurement process is very challenging, it is well worth studying transferring the existing model based on simulation data to real data.

5. Challenges and Opportunities

Over the past few decades, RATR has accumulated plenty of significant theoretical and technical achievements in the process of development for different targets. However, it is worth noting that deep learning approaches for RATR still face challenges in practical applications, and for now, they are mainly tested in laboratory settings. In terms of radar target characteristic analysis, deep-learning-based RATR algorithms, and dataset construction, etc., they still cannot fully meet the requirements of actual application.

(1) Radar target characteristic analysis

Static and dynamic measurement in the external field is a necessary means to obtain the real electromagnetic scattering characteristics of the target, but there are many problems in the implementation process, such as a high experimental cost and difficulty working on non-cooperative targets, etc. [158]. In the study of radar target characteristics, it is necessary to reflect the target scattering characteristics more accurately and comprehensively. Electromagnetic simulation can quantitatively reflect the real target scattering characteristics [159]. However, it is an urgent problem to boost the fidelity of electromagnetic simulation, especially the simulation accuracy of wideband target characteristics. In addition, the speed of electromagnetic simulation should be increased as much as possible under the condition of meeting the requirements of simulation accuracy. Moreover, it is necessary to expand the range of simulation targets, such as the scattering characteristics of some subtle parts of the target (e.g., inlet, rotor, antenna, etc.) and different media, especially various coating materials.

(2) RATR methods based on deep learning

Based on the research of radar target characteristics, features are extracted according to the characteristics of different targets. In order to meet the requirements of target recognition in various application environments, especially in a complex jamming environment, it is inevitable to increase the robustness and effectiveness of feature extraction [160]. How to implement explainable RATR, secure and trusted RATR, and real-time on-board RATR methods is an urgent problem to be solved in the future [161]. Thus, there is still a lot of room for the exploration of diversified deep learning approaches in RATR. In addition, on the premise of further mining the fine features of the target, the efficiency of recognition can be improved through multi-feature fusion [162,163]. Multi-feature fusion technology processes data from multiple sensors at different levels and in various directions, thus generating novel, practical, and valuable information that cannot be obtained by any single sensor [164]. Obtaining complete information about the target depends on the synthesis of data from all aspects. However, how to extract higher-level information for RATR is an urgent problem that multi-sensor data fusion needs to solve.

(3) Insufficient RATR Dataset

One of the current bottlenecks in applying deep-learning-based algorithms to RATR is that there are not enough publicly available training samples, except for 2D image datasets. Different from other application fields, radar application is relatively special, and the cost of collecting real-world data is high. Hence, simulation modeling is an alternative scheme to solve this problem, but how to ensure the fidelity of simulation data and obtain completely alternative data is an extremely challenging problem. In order to further advance the deep-learning-based RATR research with limited actual radar samples, some learning strategies should be emphasized, such as the following: (1) data augmentation, which has been adopted in [129–131]; (2) the GAN [132,133], which has been proven to be robust to the issue of insufficient training data; (3) various learning strategies such as transfer learning [134–137], metric learning [138–140], and meta learning [165,166] which can break through the limitation of data insufficiency; and (4) establishing more advanced learning-based methods for RATR which seems to be a solution [167].

6. Conclusions

This paper reviews the research progress of radar target characterization and deep-learning-based approaches applied to RATR, focusing on the wideband and narrowband target characteristics of radars and various architectures of deep learning networks in different application scenarios; inevitably, some might be missed. The general results show that the deep learning methods present good applicability and feasibility in RATR, especially in some specific scenarios. At present, although some great achievements have been made, the research of deep learning in RATR is still in the theoretical stage, primarily tested in laboratory settings, and there are still many challenges and possible limitations in the application, such as the fidelity of electromagnetic modeling, the robustness of the model, dataset deficiency, etc. However, there is no denying that deep learning technology will make a great contribution and improvement in RATR. Therefore, it is advisable to acknowledge the ongoing challenges and future directions in the field. In addition, it is hoped that this review will provide readers with new prospects to explore suitable deep-learning-based techniques for RATR applications.

Author Contributions: Conceptualization, W.J. and Y.W.; methodology, W.J. and Y.W.; investigation, W.J. and Y.W.; resources, Y.L. (Yang Li), Y.L. (Yun Lin) and W.S.; writing—original draft preparation, W.J.; writing—review and editing, W.J.; supervision, Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the Beijing Natural Science Foundation under Grant 4234082, in part by the Natural Science Foundation of China (Key Program) under Grants 62131001, in part by the Natural Science Foundation of China (General Program) under Grants 61971456 and

61571421, in part by the Research Start-up Foundation of North China University of Technology under Grant 110051360023XN224-2, and in part by the Innovation Team Building Support Program of Beijing Municipal Education Commission (No. IDHT20190501).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Skolnik, M.I. *Introduction to Radar Systems*; McGraw-Hill: New York, NY, USA, 1980.
2. Bhanu, B. Automatic Target Recognition: State of the Art Survey. *IEEE Trans. Aerosp. Electron. Syst.* **1986**, *22*, 364–379. [CrossRef]
3. Cohen, M.N. Survey of Radar-based Target Recognition Techniques. *Int. Soc. Opt. Photonics* **1991**, *1470*, 233–242.
4. Tait, P. *Introduction to Radar Target Recognition*; Institution of Electrical Engineers: New York, NY, USA, 2005; p. 432.
5. Chen, V.C. *The Micro-Doppler Effect in Radar (Artech House Radar Series)*, 2nd ed.; Artech House: Norwood, MA, USA, 2019.
6. Jacobs, S.P.; O'Sullivan, J.A. Automatic Target Recognition Using Sequences of High-resolution Radar Range Profiles. *IEEE Trans. Aerosp. Electron. Syst.* **2000**, *36*, 364–381. [CrossRef]
7. El-Darymli, K.; Gill, E.; McGuire, P.; Poewr, D.; Moloney, C. Automatic Target Recognition in Synthetic Aperture Radar Imagery: A State-of-the-Art Review. *IEEE Access* **2016**, *4*, 6014–6058. [CrossRef]
8. Pei, J.F.; Huang, Y.L.; Sun, Z.C.; Zhang, Y.; Yang, J.Y.; Yeo, T. Multiview Synthetic Aperture Radar Automatic Target Recognition Optimization: Modeling and Implementation. *IEEE Trans. Geosci. Remote Sens.* **2018**, *56*, 6425–6439. [CrossRef]
9. Pastina, D.; Spina, C. Multi-feature Based Automatic Recognition of Ship Targets in ISAR. In Proceedings of the IEEE Radar Conference, Oklahoma City, OK, USA, 23–27 April 2018; IEEE Press: Rome, Italy, 2008.
10. Zhang, R.; Xia, J.; Tao, X. A Novel Proximal Support Vector Machine and Its Application in Radar Target Recognition. In Proceedings of the Chinese Control Conference, Zhangjiajie, China, 26–31 July 2007; pp. 513–515.
11. Yu, X.; Wang, X. Kernel Uncorrelated Neighborhood Discriminative Embedding for Radar Target Recognition. *Electron. Lett.* **2008**, *44*, 154–155. [CrossRef]
12. Du, L.; Liu, H.; Bao, Z. Radar HRRP Statistical Recognition: Parametric Model and Model Selection. *IEEE Trans. Signal Process.* **2008**, *56*, 1931–1944. [CrossRef]
13. Byi, M.F.; Demers, J.T.; Rietman, E.A. Using a Kernel Adatron for Object Classification with RCS Data. *arXiv* **2010**, arXiv:1005.5337.
14. Long, T.; Liang, Z.; Liu, Q. Advanced Technology of High-Resolution Radar: Target Detection, Tracking, Imaging, and Recognition. *Sci. China Inf. Sci.* **2019**, *62*, 40301. [CrossRef]
15. Haykin, S. Cognitive Radar: A Way of the Future. *IEEE Signal Process. Mag.* **2006**, *23*, 30–40. [CrossRef]
16. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef]
17. Mason, E.; Yonel, B.; Yazici, B. Deep Learning for Radar. In Proceedings of the IEEE Radar Conference, Seattle, WA, USA, 8–12 May 2017. [CrossRef]
18. Jiang, W.; Ren, Y.; Liu, Y.; Leng, J. Artificial Neural Networks and Deep Learning Techniques Applied to Radar Target Detection A Review. *Electronics* **2022**, *11*, 156. [CrossRef]
19. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; The MIT Press: Cambridge, UK, 2016.
20. Mustaqeem; Ishaq, M.; Kwon, S. A CNN-Assisted deep echo state network using multiple Time-Scale dynamic learning reservoirs for generating Short-Term solar energy forecasting. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102275. [CrossRef]
21. Hinton, G.E.; Osindero, S.; The, Y.W. A Fast Learning Algorithm for Deep Belief Nets. *Neural Comput.* **2006**, *18*, 1527–1554. [CrossRef]
22. Ricci, R.; Balleri, A. Recognition of Humans Based on Radar Micro-Doppler Shape Spectrum Features. *IET Radar Sonar Navig.* **2015**, *9*, 1216–1223. [CrossRef]
23. Jokanovic, B.; Amin, M. Fall Detection using Deep Learning in Range-Doppler Radars. *IEEE Trans Trans. Aerosp. Electron. Syst.* **2018**, *54*, 180–189. [CrossRef]
24. Tang, T.; Wang, C.; Gao, M. Radar Target Recognition Based on Micro-Doppler Signatures Using Recurrent Neural Network. In Proceedings of the IEEE 4th International Conference on Electronics Technology, Chengdu, China, 7–10 May 2021. [CrossRef]
25. Kim, Y.; Moon, T. Human Detection and Activity Classification based on Micro-Dopplers using Deep Convolutional of Neural Networks. *IEEE Geosci. Remote Sens. Lett.* **2016**, *13*, 2–8. [CrossRef]
26. Fu, H.X.; Li, Y.; Wang, Y.C.; Peng, L. Maritime Ship Targets Recognition with Deep Learning. In Proceedings of the 37th Chinese Control Conference, Wuhan, China, 25–27 July 2018.
27. Arabshahi, P.; Tillman, M. Development and Performance Analysis of a Class of Intelligent Target Recognition Algorithms. In Proceedings of the 15th IEEE International Conference on Fuzzy Systems, New Orleans, LA, USA, 11 October 1996.
28. Han, J.; He, M.; Mao, Y. A New Method for Recognition for Recognizing Radar Radiating Source. In Proceedings of the International Conference on Wavelet Analysis and Pattern Recognition, Beijing, China, 2–4 November 2007.
29. Zyweck, A.; Bogner, R.E. Radar Target Classification of Commercial Aircraft. *IEEE Trans. Aerosp. Electron. Syst.* **1996**, *32*, 598–606. [CrossRef]
30. Lee, K.; Wang, L.; Ou, J. An Efficient Algorithm for the Radar Recognition of Ships on the Sea Surface. In Proceedings of the 2007 International Symposium of MTS/IEEE Oceans, Vancouver, BC, Canada, 29 September–4 October 2007; pp. 1–6.

31. Shuley, N.; Lui, H. Sampling Procedures for Resonance Based Radar Target Identification. *IEEE Trans. Antenna Propag.* **2008**, *5*, 1487–1491.
32. Bell, M.; Grubbs, R. JEM modeling and measurement for radar target identification. *IEEE Trans. Aerosp. Electron. Syst.* **1993**, *29*, 73–87. [CrossRef]
33. Chen, V.; Li, F.; Ho, S. Micro-Doppler Effect in Radar Phenomenon, Model and Simulation Study. *IEEE Trans. Aerosp. Electron. Syst.* **2006**, *42*, 2–21. [CrossRef]
34. Blaricum, M.L.; Mittra, R.A. Technique for Extracting the Poles and Residues of a System Directly from Its Transient Response. *IEEE Trans. Antennas Propag.* **1975**, *23*, 777–781. [CrossRef]
35. Jain, V.K.; Sarkar, T.; Weiner, D. Rational modeling by Pencil-of-Function Method. *IEEE Trans. Acoust. Speech Signal Process.* **1983**, *31*, 564–573. [CrossRef]
36. Hua, Y.B.; Sarkar, T.K. Generalized Pencil-of-Function Method for Extracting Poles of an EM System from Its Transient Response. *IEEE Trans. Antennas Propag.* **1989**, *37*, 229–234. [CrossRef]
37. Chen, K.M. Radar Wave Synthesis Method: A New Radar Detection Scheme. *IEEE Trans. Antennas Propag.* **1981**, *29*, 55–565.
38. Cameron, W.L.; Leung, L.K. Feature Motivated Polarization Scattering Matrix Decomposition. In Proceedings of the IEEE International Radar Conference, Arlington, VA, USA, 7–10 May 1990; pp. 549–557.
39. Chamberlain, N.F. Syntactic Classification of Radar Targets Using Polarimetric Signatures. In Proceedings of the IEEE International Conference on Systems Engineering, Pittsburgh, PA, USA, 9–11 August 1990.
40. Xiao, J.; Nehorai, A. Polarization Optimization for Scattering Estimation in Heavy Clutter. In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, Las Vegas, NV, USA, 31 March–4 April 2008; pp. 1473–1476.
41. Gao, Q.; Liu, J.; Wu, R. Novel Method for Automatic Target Recognition Based on High Resolution Range Profiles. *J. Civ. Aviat. Univ. China* **2002**, *20*, 1–4.
42. Li, H.J.; Yang, S.H. Using Range Profiles as Feature Vectors to Identify Aerospace Objects. *IEEE Trans. Antennas Propag.* **1993**, *41*, 261–268. [CrossRef]
43. Turnbaugh, M.A.; Bauer, K.W.; Oxley, M.E.; Miller, J.O. HRR Signature Classification Using Syntactic Pattern Recognition. In Proceedings of the IEEE Aerospace Conference, Big Sky, MT, USA, 1–8 March 2008; pp. 1–9.
44. Mishra, A.K.; Mulgrew, B. Bistatic SAR ATR. *IET Radar Sonar Navig.* **2007**, *6*, 459–469. [CrossRef]
45. Yang, W.; Zou, T.Y.; Dai, D.X. Supervised Land-cover Classification of TerraSAR-X Imagery over Urban Areas using Extremely Randomized Clustering Forests. In Proceedings of the 2009 Joint Urban Remote Sensing Event, Shanghai, China, 20–22 May 2009.
46. Lowe, D.G. Object Recognition from Local Scale-invariant Features. In Proceedings of the Seventh IEEE International Conference on Computer Vision, Kerkyra, Greece, 20–27 September 1999.
47. Dalal, N.; Triggs, B. Histograms of Oriented Gradients for Human Detection. In Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR05), San Diego, CA, USA, 20–25 June 2005; pp. 886–893.
48. Saidi, M.; Hoeltzener, D.; Toumi, A. Automatic Recognition of ISAR Images: Target Shapes Features Extraction. In Proceedings of the 3rd International Conference on Information and Communication Technologies: From Theory to Applications, Damascus, Syria, 7–11 April 2008; pp. 1–6.
49. Feng, S.; Lin, Y.; Wang, Y.; Teng, F.; Hong, W. 3D Point Cloud Reconstruction Using Inversely Mapping and Voting from Single Pass CSAR Images. *Remote Sens.* **2021**, *13*, 3534. [CrossRef]
50. Li, Y.; Yin, Q.; Lin, Y.; Hong, W. Anisotropy Scattering Detection from Multiaspect Signatures of Circular Polarimetric SAR. *IEEE Geosci. Remote Sens. Lett.* **2018**, *15*, 1575–1579. [CrossRef]
51. Lin, Y.; Liu, Y.; Wang, Y.; Ye, S.; Zhang, Y.; Li, Y.; Li, W.; Qu, H.; Hong, W. Frequency Domain Panoramic Imaging Algorithm for Ground-Based ArcSAR. *Sensors* **2020**, *20*, 7027. [CrossRef]
52. Wang, Y.; Song, Y.; Lin, Y.; Li, Y.; Hong, W. Interferometric DEM-Assisted High Precision Imaging Method for ArcSAR. *Sensors* **2019**, *19*, 2921. [CrossRef]
53. Zhang, H.; Lin, Y.; Teng, F.; Hong, W. A Probabilistic Approach for Stereo 3D Point Cloud Reconstruction from Airborne Single-Channel Multi-Aspect SAR Image Sequences. *Remote Sens.* **2022**, *14*, 5715. [CrossRef]
54. Wang, Y.; Zhang, Q.; Lin, Y.; Zhao, Z.; Li, Y. Multi-phase-center Sidelobe Suppression Method for Circular GBSAR Based on Sparse Spectrum. *IEEE Access* **2020**, *8*, 133802–133816. [CrossRef]
55. Teng, F.; Lin, Y.; Wang, Y.; Hong, W. An Anisotropic Scattering Analysis Method Based on the Statistical Properties of Multi-Angular SAR Images. *Remote Sens.* **2020**, *12*, 2152. [CrossRef]
56. Lin, Y.; Zhang, L.; Wei, L.; Zhang, H.; Feng, S.; Wang, Y.; Hong, W. Research on Full-aspect Three-dimensional SAR Imaging Method for Complex Structural Facilities without Prior Model. *J. Radars* **2022**, *11*, 909–919.
57. Zhou, J.; Zhao, H. Global Scattering Center Model Extraction of Radar Targets Based on Wideband Measurements. *IEEE Trans. Antennas Propag.* **2008**, *56*, 2051–2060. [CrossRef]
58. Haykin, S. *Neural Networks and Learning Machines*; Pearson Education Inc.: Upper Saddle River, NJ, USA, 2009.
59. Bi, F.; Hou, J.; Wang, Y.; Chen, J.; Wang, Y. Land Cover Classification of Multispectral Remote Sensing Images Based on Time-Spectrum Association Features and Multikernel Boosting Incremental Learning. *J. Appl. Remote Sens.* **2019**, *13*, 044510. [CrossRef]
60. Hinton, G.E.; Salakhutdinov, R.R. Reducing the Dimensionality of Data with Neural Networks. *Science* **2006**, *313*, 504–507. [CrossRef] [PubMed]

61. Mikolov, T.; Karafiat, M.; Burget, L.; Cernock, J.; Khudanpur, S. Recurrent Neural Network Based Language Model. In Proceedings of the International Speech Communication Association, Makuhari, Chiba, Japan, 6–10 September 2015.
62. Vincent, P.; Larochelle, H.; Bengio, Y.; Manzago, P.A. Extracting and Composing Robust Features with Denoising Autoencoders. In Proceedings of the International Conference on Machine Learning (ICML), Helsinki, Finland, 5–9 July 2008; pp. 1096–1103.
63. Wang, Y.; Feng, C.; Zhang, Y.; Ge, Q. Classification of Space Targets with Micro-motion Based on Deep CNN. In Proceedings of the IEEE 2nd International Conference on Electronic Information and Communication Technology (ICEICT), Harbin, China, 20–22 January 2019; pp. 557–561.
64. Han, L.; Feng, C. Micro-Doppler-based Space Target Recognition with a One-Dimensional Parallel Network. *Int. J. Antennas Propag.* **2020**, *2020*, 8013802. [CrossRef]
65. Garcia, A.J.; Aouto, A.; Lee, J.; Kim, D. CNN-32DC: An Improved Radar-based Drone Recognition System Based on Convolutional Neural Network. *ICT Express* **2022**, *8*, 606–610. [CrossRef]
66. Park, J.; Park, J.-S.; Park, S.-O. Small Drone Classification with Light CNN and New Micro-Doppler Signature Extraction Method Based on A-SPC Technique. *arXiv* **2020**, arXiv:2009.14422. [CrossRef]
67. Rahman, S.; Robertson, D.A. Classification of Drones and Birds Using Convolutional Neural Networks Applied to Radar Micro-Doppler Spectrogram Images. *IET Radar Sonar Navig.* **2020**, *14*, 653–661. [CrossRef]
68. Hanif, A.; Muaz, M. Deep Learning Based Radar Target Classification Using Micro-Doppler Features. In Proceedings of the 17th International Conference on Aerospace and Engineering (ICASE), Las Palmas de Gran Canaria, Spain, 17–22 February 2018. [CrossRef]
69. Choi, B.; Oh, D. Classification of Drone Type Using Deep Convolutional Neural Networks Based on Micro-Doppler Simulation. In Proceedings of the International Symposium on Antennas and Propagation (ISAP), Busan, Republic of Korea, 23–26 October 2018; pp. 1–2.
70. Vanek, S.; Gotthans, J.; Gotthans, T. Micro-Doppler Effect and Determination of Rotor Blades by Deep Neural Networks. In Proceedings of the 32nd International Conference Radio Elektronika, Kosice, Slovakia, 21–22 April 2022. [CrossRef]
71. Angelov, A.; Robertson, A. Murray-Smith R, and Fioranelli F, Practical Classification of Different Moving Targets Using Automotive Radar and Deep Neural Networks. *IET Radar Sonar Navig.* **2018**, *12*, 1082–1089. [CrossRef]
72. Wu, Q.; Gao, T.; Lai, Z.; Li, D. Hybrid SVM-CNN Classification Technique for Human-vehicle Targets in an Automotive LFMCW Radar. *Sensors* **2020**, *20*, 3504. [CrossRef]
73. Zhu, L.; Zhang, S.; Wang, X.; Chen, S.; Zhao, H.; Wei, D. Multilevel Recognition of UAV-to-Ground Targets Based on Micro-Doppler Signatures and Transfer Learning of Deep Convolutional Neural Networks. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 2503111. [CrossRef]
74. Zhu, L.; Zhang, S.; Chen, K.; Chen, S.; Wang, X.; Wei, D.; Zhao, H. Low-SNR Recognition of UAV-to-Ground Targets Based on Micro-Doppler Signatures Using Deep Convolutional Denoising Encoders and Deep Residual Learning. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 5106913. [CrossRef]
75. Jiang, W.; Ren, Y.; Liu, Y.; Wang, Z.; Wang, X. Recognition of Dynamic Hand Gesture Based on Mm-wave FMCW Radar Micro-doppler Signatures. In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toronto, ON, Canada, 6–11 June 2021. [CrossRef]
76. Kong, F.; Deng, J.; Fan, Z. Gesture Recognition System Based on Ultrasonic FMCW and ConvLSTM model. *Measurement* **2022**, *190*, 110743. [CrossRef]
77. Wang, M.; Zhang, Y.; Cui, G. Human Motion Recognition Exploiting Radar with Stacked Recurrent Neural Network. *Digit. Signal Process.* **2019**, *87*, 125–131. [CrossRef]
78. Jia, Y.; Guo, Y.; Wang, G.; Song, R.; Cui, G.; Zhong, X. Multi-frequency and Multi-domain Human Activity Recognition Based on SFCW Radar using Deep Learning. *Neurocomputing* **2021**, *444*, 274–287. [CrossRef]
79. Li, X.; He, Y.; Fioranelli, F.; Jing, X.; Yarovoy, A.; Yang, Y. Human Motion Recognition with Limited Radar Micro-Doppler Signatures. *IEEE Trans. Geosci. Remote Sens.* **2021**, *59*, 6586–6599. [CrossRef]
80. Chakraborty, M.; Kumawat, H.C.; Dhavale, S.V. Application of DNN for Radar Micro-Doppler Signature-based Human Suspicious Activity Recognition. *Pattern Recognit. Lett.* **2022**, *162*, 1–6. [CrossRef]
81. Persico, A.R.; Clemente, C.; Gaglione, D. On Model, Algorithms, and Experiment for Micro-Doppler-based Recognition of Ballistic Targets. *IEEE Trans. Aerosp. Electron. Syst.* **2017**, *53*, 1088–1108. [CrossRef]
82. Gao, H.; Xie, L.; Wen, S.; Kuang, Y. Micro-Doppler Signature Extraction from Ballistic Target with Micro-motions. *IEEE Trans. Aerosp. Electron. Syst.* **2010**, *46*, 1969–1982. [CrossRef]
83. Huizing, A.; Heiligers, M.; Dekker, B.; Wit, J.; Cifola, L.; Harmanny, R. Deep Learning for Classification of Mini-UAVs Using Micro-Doppler Spectrograms in Cognitive Radar. *IEEE Aerosp. Electron. Syst. Mag.* **2019**, *34*, 46–56. [CrossRef]
84. Zhang, Q.; Zeng, Y.; He, Y.; Luo, Y. Avian Detection and Identification with High-resolution radar. In Proceedings of the 2008 IEEE Radar Conference, Rome, Italy, 26–30 May 2008; pp. 1–6.
85. Zhu, F.; Luo, Y.; Zhang, Q.; Feng, Y.; Bai, Y. ISAR Imaging for Avian Species Identification with Frequency-stepped Chirp Signals. *IEEE Geosci. Remote Sens. Lett.* **2010**, *7*, 151–155. [CrossRef]
86. Amiri, R.; Shahzadi, A. Micro-Doppler Based Target Classification in Ground Surveillance Radar Systems. *Digit. Signal Process.* **2020**, *101*, 102702. [CrossRef]

87. Chen, X.; Dong, Y.; Li, X.; Guan, J. Modeling of Micromotion and Analysis of Properties of Rigid Marine Targets. *J. Radars* **2015**, *4*, 630–638.
88. Chen, X.; Guan, J.; Zhao, Z.; Ding, H. Micro-Doppler Signatures of Sea Surface Targets and Applications to Radar Detection. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016. [CrossRef]
89. Damarla, T.; Bradley, M.; Mehmood, A.; Sabatier, J. Classification of Animals and People Ultrasonic Signatures. *IEEE Sens. J.* **2013**, *13*, 1464–1472. [CrossRef]
90. Shi, X.R.; Zhou, F.; Liu, L.; Bo, Z.; Zhang, Z. Textural Feature Extraction Based on Time-frequency Spectrograms of Humans and Vehicles. *IET Radar Sonar Navig.* **2015**, *9*, 1251–1259. [CrossRef]
91. Amin, M.G.; Ahmad, F.; Zhang, Y.D.; Boashash, B. Human Gait Recognition with Cane Assistive Device Using Quadratic Time Frequency Distributions. *IET Radar Sonar Navig.* **2015**, *9*, 1224–1230. [CrossRef]
92. Saho, K.; Fujimoto, M.; Masugi, M.; Chou, L.S. Gait Classification of Young Adults, Elderly Non-fallers, and Elderly Fallers Using Micro-Doppler Radar Signals: Simulation Study. *IEEE Sens. J.* **2017**, *17*, 2320–2321. [CrossRef]
93. Mikhelson, I.V.; Bakhtiari, S.; Elmer, T.W., II; Sahakian, A.V. Remote Sensing of Heart Rate and Patterns of Respiration on a Stationary Subject Using 94-GHz Millimeter-wave Interferometry. *IEEE Trans. Biomed. Eng.* **2011**, *58*, 1671–1677. [CrossRef] [PubMed]
94. Xu, Z.W.; Wu, Y.J.; Lu, X.Q. Time-frequency Analysis of Terahertz Radar Signal for Vital Signs Sensing Based on Radar Sensor. *Int. J. Sens. Netw.* **2013**, *13*, 241–253. [CrossRef]
95. Lunden, J.; Koivunen, V. Deep Learning for HRRP-based Target Recognition in Multi-static Radar System. In Proceedings of the 2016 IEEE Radar Conference, Philadelphia, PA, USA, 2–6 May 2016; pp. 1–6.
96. Guo, C.; He, Y.; Wang, H.P.; Jian, T.; Sun, S. Radar HRRP Target Recognition Based on Deep One-Dimensional Residual-Inception Network. *IEEE Access* **2019**, *7*, 9191–9204. [CrossRef]
97. Guo, C.; Jian, T.; Xu, C.; He, Y.; Sun, S. Radar HRRP Target Recognition Based on Deep Multi-Scale 1D Convolutional Neural Network. *J. Electron. Inf. Technol.* **2019**, *41*, 1302–1309.
98. Guo, C.; Wang, H.P.; Jian, T.; He, Y.; Zhang, X. Radar Target Recognition Based on Feature Pyramid Fusion Lightweight CNN. *IEEE Access* **2019**, *7*, 51140–51149. [CrossRef]
99. Liao, K.; Si, J.; Zhu, F.; He, X. Radar HRRP Target Recognition Based on Concatenated Deep Neural Networks. *IEEE Access* **2018**, *6*, 29211–29218. [CrossRef]
100. Pan, M.; Jiang, J.; Li, Z.; Cao, J.; Zhou, T. Radar HRRP recognition Based on Discriminant Deep Autoencoders with Small Training Data Size. *Electron. Lett.* **2016**, *52*, 1725–1727.
101. Feng, B.; Chen, B.; Liu, H.W. Radar HRRP Target Recognition with Deep Networks. *Pattern Recognit.* **2017**, *61*, 379–393. [CrossRef]
102. Pan, M.; Jiang, J.; Kong, Q.; Shi, J.; Zhou, T. Radar HRRP Target Recognition Based on t-SNE Segmentation and Discriminant Deep Belief Network. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 1609–1613. [CrossRef]
103. Zhao, F.; Liu, Y.; Huo, K.; Zhang, S.; Zhang, Z. Radar HRRP Target Recognition Based on Stacked Autoencoder and Extreme Learning Machine. *Sensors* **2018**, *18*, 173–187. [CrossRef] [PubMed]
104. Zhao, F.; Liu, Y.; Huo, K. A Radar Target Classification Algorithm Based on Dropout Constrained Deep Extreme Learning Machine. *J. Radars* **2018**, *7*, 613–621.
105. Yu, S.H.; Xie, Y.J. Application of a Convolutional Autoencoder to Half Space Radar HRRP Recognition. In Proceedings of the 2018 International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR), Chengdu, China, 15–18 July 2018.
106. Xu, B.; Chen, B.; Liu, H.; Jin, L. Attention-Based Recurrent Neural Network Model for Radar High-Resolution Range Profile Target Recognition. *J. Electron. Inf. Technol.* **2016**, *38*, 2988–2995.
107. Xu, B.; Chen, B.; Wan, J.W.; Liu, H.; Lin, P. Target-Aware Recurrent Attentional Network for Radar HRRP Target Recognition. *Signal Process.* **2018**, *155*, 268–280. [CrossRef]
108. Xu, B.; Chen, B.; Liu, J. Radar HRRP Target Recognition by the Bidirectional LSTM Model. *J. Xidian Univ. Nat. Sci.* **2019**, *46*, 29–34.
109. Du, C.; Tian, L.; Chen, B.; Zhang, L.; Chen, W.; Liu, H. Region-factorized Recurrent Attentional Network with Deep Clustering for Radar HRRP Target Recognition. *Signal Process.* **2021**, *183*, 108010. [CrossRef]
110. Chen, J.; Du, L.; Guo, G.; Yin, L.; Wei, D. Target-attentional CNN for Radar Automatic Target Recognition with HRRP. *Signal Process.* **2022**, *196*, 108497. [CrossRef]
111. Song, Y.; Zhou, Q.; Yang, W.; Wang, Y.; Hu, C.; Hu, X. Multi-View HRRP Generation with Aspect-Directed Attention GAN. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2022**, *15*, 7643–7656. [CrossRef]
112. Zhang, Y.; Wu, Z.; Wei, S.; Zhang, Y. Spatial Target Recognition Based on CNN and LSTM. In Proceedings of the 12th National Academic Conference on Signal and Intelligent Information Processing and Application, Hangzhou, China, 20–22 October 2018; pp. 1–4.
113. Zhang, M.; Chen, B. Wavelet Autoencoder for Radar HRRP Target Recognition with Recurrent Neural Network. In Proceedings of the International Conference on Intelligence Science and Big Data Engineering, LNCS, Lanzhou, China, 18–19 August 2018; pp. 262–275.
114. Liu, Z.; Miao, Z.; Zhan, X.; Wang, J.; Gong, B.; Yu, S. Large-scale Long-tailed Recognition in an Open World. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 15–20 June 2019.

115. Zhang, X.; Wang, W.; Zheng, X.; Wei, Y. A Novel Radar Target Recognition Method for Open and Imbalanced High-resolution Range Profile. *Digit. Signal Process.* **2021**, *118*, 103212. [CrossRef]
116. Chen, S.; Wang, H. SAR Target Recognition based on Deep Learning. In Proceedings of the IEEE International Conference on Data Science & Advanced Analytics, Shanghai, China, 30 October–1 November 2014.
117. Chen, S.; Wang, H.; Xu, F.; Jin, Y.Q. Target Classification Using the Deep Convolutional Networks for SAR Images. *IEEE Trans. Geosci. Remote Sens.* **2016**, *54*, 4806–4817. [CrossRef]
118. Li, J.; Zhang, R.; Li, Y. Multiscale Convolutional Neural Network for the Detection of Built-up Areas in High Resolution SAR Images. In Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; pp. 910–913.
119. Tian, Z.; Zhan, R.; Hu, J.; Zhang, J. Research on SAR Image Target Recognition Based on Convolutional Neural Network. *J. Radars* **2016**, *5*, 320–325.
120. Wagner, S.A. SAR ATR by a Combination of Convolutional Neural Network and Support Vector Machines. *IEEE Trans. Aerosp. Electron. Syst.* **2016**, *52*, 2861–2872. [CrossRef]
121. Housseini, A.E.; Toumi, A.; Khenchaf, A. Deep Learning for Target Recognition from SAR Images. In Proceedings of the Detection Systems Architectures & Technologies, Algiers, Algeria, 20–22 February 2017.
122. Li, X.; Li, C.; Wang, P.; Men, Z.; Xu, H. SAR ATR Based on Dividing CNN into CAE and SNN. In Proceedings of the 2015 IEEE 5th Asia-Pacific Conference on Synthetic Aperture Radar (APSAR), Singapore, 1–4 September 2015; pp. 676–679.
123. He, H.; Wang, S.; Yang, D.; Wang, S. SAR Target Recognition and Unsupervised Detection Based on Convolutional Neural Network. In Proceedings of the 2017 Chinese Automation Congress (CAC), Jinan, China, 20–22 October 2017; pp. 435–438.
124. Zou, H.; Lin, Y.; Hong, W. Research on Multi-azimuth SAR Image Target Recognition using Deep Learning. *Signal Process.* **2018**, *34*, 513–522.
125. Pei, J.; Huang, Y.; Huo, W.; Zhang, Y.; Yang, J.; Yeo, T. SAR Automatic Target Recognition based on Multi-view Deep Learning Framework. *IEEE Trans. Geosci. Remote Sens.* **2018**, *56*, 2196–2210. [CrossRef]
126. Zhang, F.; Hu, C.; Yin, Q.; Li, W.; Li, H.; Hong, W. Multi-aspect-aware Bidirectional LSTM Networks for Synthetic Aperture Radar Target Recognition. *IEEE Access* **2017**, *5*, 26880–26891. [CrossRef]
127. Zhao, P.; Liu, K.; Zou, H.; Zhen, X. Multi-stream Convolutional Neural Network for SAR Automatic Target Recognition. *Remote Sens.* **2018**, *10*, 1473. [CrossRef]
128. Zhao, P.; Huang, L. Target Recognition Method for Multi-aspect Synthetic Aperature Radar Images Based on EfficientNet and BiGRU. *J. Radars* **2021**, *10*, 859–904.
129. Furukawa, H. Deep Learning for Target Classification from SAR Imagery: Data Augmentation and Translation Invariance. *IEICE Tech. Rep.* **2017**, *117*, 13–17.
130. Ding, J.; Chen, B.; Liu, H.; Huang, M. Convolutional Neural Network with Data Augmentation for SAR Target Recognition. *IEEE Geosci. Remote Sens. Lett.* **2016**, *13*, 364–368. [CrossRef]
131. Odegaard, N.; Knapskog, A.O.; Cochin, C.; Louvigne, J. Classification of Ships using Real and Simulated Data in a Convolutional Neural Network. In Proceedings of the 2016 IEEE Radar Conference, Philadelphia, PA, USA, 2–6 May 2016.
132. Zhang, M.; Cui, Z.; Wang, X.; Cao, Z. Data Augmentation Method of SAR Image Dataset. In Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, 22–27 July 2018.
133. Zheng, C.; Jiang, X.; Liu, X. Semi-Supervised SAR ATR via Multi-Discriminator Generative Adversarial Network. *IEEE Sens. J.* **2019**, *99*, 7525–7533. [CrossRef]
134. Chen, L.; Wu, H.; Cui, X.; Guo, Z.; Jia, Z. Convolution Neural Network SAR Image Target Recognition Based on Transfer Learning. *Chin. Space Sci. Technol.* **2018**, *38*, 45–51.
135. Ren, S.; Suo, J.; Zhang, L. SAR Target Recognition Based on Convolution Neural Network and Transfer Learning. *Electron. Opt. Control* **2020**, *27*, 37–41.
136. Wang, Z.L.; Xu, X.H.; Zhang, L. Automatic Target Recognition Based on Deep Transfer Learning of Simulated SAR Image. *J. Univ. Chin. Acad. Sci.* **2020**, *37*, 516–524.
137. Huang, Z.; Pan, Z.; Lei, B. What, where, and how to transfer in SAR target recognition based on deep CNNs. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 2324–2336. [CrossRef]
138. Lin, Z.; Ji, K.; Kang, M.; Leng, X.; Zou, H. Deep Convolutional Highway Unit Network for SAR Target Classification with Limited Labeled Training Data. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 1091–1095. [CrossRef]
139. Wang, B.; Pan, Z.; Hu, Y.; Ma, W. SAR Target Recognition Based on Siamese CNN with Small Scale Dataset. *Radar Sci. Technol.* **2019**, *17*, 603–609.
140. Pan, Z.X.; Bao, X.J.; Zhang, Y.T.; Wang, B.; Lei, B. Siamese Network Based Metric Learning for SAR Target Classification. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 28 July–2 August 2019; pp. 1342–1345.
141. Wang, N.; Wang, Y.; Liu, H.; Zuo, Q.; He, J. Feature-Fused SAR Target Discrimination Using Multiple Convolutional Neural Networks. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 1695–1699. [CrossRef]
142. Wang, Y.L.; Xu, T.; Du, D.W. SAR Image Classification Method Based on Multi-Features and Convolutional Neural Network. *Math. Pract. Knowl.* **2020**, *50*, 140–147.

143. Zhang, W.; Xu, Y.; Ni, J.; Shi, H. Image Target Recognition Method based on Multi-scale Block Convolutional Neural Network. *J. Comput. Appl.* **2016**, *36*, 1033–1038.
144. Wu, Y. *Research on SAR Target Recognition Algorithm Based on CNN*; University of Electronic Science and Technology of China: Chengdu, China, 2020.
145. Liu, J.; Gong, M.; Qin, K.; Zhang, P. A Deep Convolutional Coupling Network for Change Detection Based on Heterogeneous Optical and Radar Images. *IEEE Trans. Neural Netw. Learn. Syst.* **2016**, *29*, 545–559. [CrossRef] [PubMed]
146. Fan, T.; Liu, C.; Cui, T.J. Deep Learning of Raw Radar Echoes for Target Recognition. In Proceedings of the International Conference on Computational Electromagnetics, Chengdu, China, 26–28 March 2018.
147. Iqbal, S.; Iqbal, U.; Hassan, S.A.; Saleem, S. Indoor Motion Classification Using Passive RF Sensing Incorporating Deep Learning. In Proceedings of the IEEE Vehicular Technology Conference, Porto, Portugal, 3–6 June 2018.
148. Hang, H.; Meng, X.; Shen, J. RCS Recognition Method of Corner Reflectors Based on 1D-CNN. In Proceedings of the 2021 International Applied Computational Electromagnetics Society (ACES-China) Symposium, Chengdu, China, 28–31 July 2021.
149. Wengrowski, E.; Purri, M.; Dana, K.; Huston, A. Deep CNNs as a Method to Classify Rotating Objects Based on Monostatic RCS. *IET Radar Sonar Navig.* **2019**, *13*, 1092–1100. [CrossRef]
150. Cao, X.; Yi, J.; Gong, Z.; Wan, X. Preliminary Study on Bistatic RCS of Measured Targets for Automatic Target Recognition. In Proceedings of the 13th International Symposium on Antennas, Propagation and EM Theory, Zhuhai, China, 1–4 December 2021.
151. Yang, J.; Zhang, Z.; Mao, W. Identification and Micro-motion Parameter Estimation of Non-cooperative UAV Targets. *Phys. Commun.* **2021**, *46*, 101314. [CrossRef]
152. Ezuma, M.; Anjinappa, C.; Semkin, V.; Guvenc, I. Comparative Analysis of Radar-Cross-Section-Based UAV Recognition Techniques. *IEEE Sens. J.* **2022**, *22*, 17932–17949. [CrossRef]
153. The Sensor Data Management System, MSTAR Public Dataset [EB/OL]. Available online: https://www.sdms.afrl.af.mil/index.php?collection=mstar (accessed on 4 April 2009).
154. Available online: https://opensar.sjtu.edu.cn/ (accessed on 30 May 2017).
155. Huang, L.; Liu, B.; Li, B.; Guo, W.; Yu, W.; Zhang, Z.; Yu, W. OpenSARShip: A Dataset Dedicated to Sentinel-1 Ship Interpretation. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2018**, *11*, 195–208. [CrossRef]
156. Li, B.; Liu, B.; Huang, L.; Guo, W.; Zhang, Z.; Yu, W. OpenSARShip 2.0: A large volume dataset for deeper interpretation of ship targets in Sentinel-1 imagery. In Proceedings of the SAR in Big Data Era: Models, Methods and Applications (BIGSARDATA), Beijing, China, 13–14 November 2017.
157. Hou, X.; Wei, A.; Song, Q.; Lai, J.; Wang, H.; Feng, X. FUSAR-Ship: Building a High-Resolution SAR-AIS Matchup Dataset of Gaofen-3 for Ship Detection and Recognition. *Sci. China* **2020**, *63*, 36–54. [CrossRef]
158. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Rabinovich, A. Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, 20–25 June 2009; pp. 1–9.
159. Chen, J.; Du, L.; He, H.; Guo, Y. Convolutional Factor Analysis Model with Application to Radar Automatic Target Recognition. *Pattern Recognit.* **2019**, *87*, 140–156. [CrossRef]
160. Qosja, D.; Wagner, S.; Brüggenwirth, S. Benchmarking Convolutional Neural Network Backbones for Target Classification in SAR. In Proceedings of the IEEE Radar Conference, San Antonio, TX, USA, 1–5 May 2023.
161. Copsey, K.; Webb, A. Bayesian Gamma Mixture Model Approach to Radar Target Recognition. *IEEE Trans. Aerosp. Electron. Syst.* **2003**, *39*, 1201–1217. [CrossRef]
162. Nebabin, V.G. Data Fusion: A Promising Way of Solving Radar Target Recognition Problems. *JED* **1996**, *19*, 78–80.
163. Jiang, W.; Liu, Y.; Wei, Q.; Wang, W.; Ren, Y.; Wang, C. A High-resolution Radar Automatic Target Recognition Method for Small UAVs Based on Multi-feature Fusion. In Proceedings of the 2022 IEEE 25th International Conference on Computer Supported Cooperative Work in Design, Hangzhou, China, 4–6 May 2022.
164. Li, Z.; Papson, S.; Narayanan, R.M. Data-Level Fusion of Multi-look Inverse Synthetic Aperture Radar Images. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 1394–1406.
165. Hospedales, T.; Antoniou, A.; Micaelli, P.; Storkey, A. Meta-Learning in Neural Networks: A Survey. *arXiv* **2004**, arXiv:2004.05439v1. [CrossRef] [PubMed]
166. Tian, L.; Chen, B.; Chen, W.; Xu, Y.; Liu, H. Domain-aware Meta Network for Radar HRRP Target Recognition with Missing Aspects. *Signal Process.* **2021**, *187*, 108167. [CrossRef]
167. Yu, X.; Liu, S.; Ren, H.; Zou, L.; Zhou, Y.; Wang, X. Transductive Prototypical Attention Network for Few-shot SAR Target Recognition. In Proceedings of the IEEE Radar Conference, San Antonio, TX, USA, 1–5 May 2023.