

(iii) Systematicness: We provide a systematic taxonomy of core challenges in SAR ATR, clearly delineating which have been adequately addressed and which remain open, thereby offering

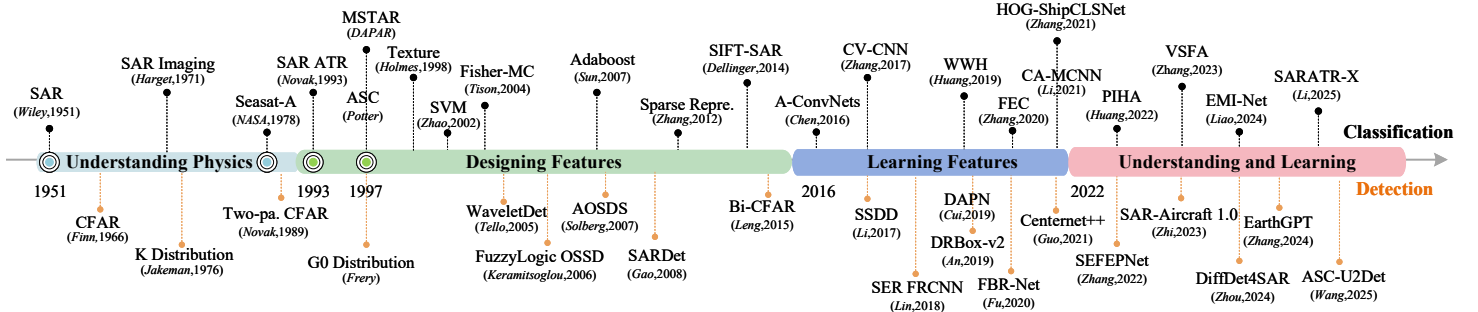


Fig. 2. Timeline milestone of SAR automatic target recognition evolution, including two core tasks of classification and detection, from understanding physics, designing features, learning features to understanding and learning features. **(Classification:** SAR [20], SAR Imaging [21], SAR ATR [22], MSTAR [23], ASC [24], Texture [25], SVM [26], Fisher-MC [27], Adaboost [28], Sparse Representation [29], SIFT-SAR [30], A-ConvNets [31], CV-CNN [32], WWH [33], FEC [34], HOG-ShipCLSNet [35], CA-MCNN [36], PIHA [37], VSFA [38], EMI-Net [39], SARATR-X [40]. **Detection:** CFAR [41], K Distribution [42], Two pa.CFAR [43], Go Distribution [44], WaveletDet [45], FuzzyLogic OSSD [46], AOSDS [47], SARDet [48, 49], Bi-CFAR [50], SSDD [51], SER FRCNN [52], DAPN [53], DBBox-v2 [54], FBR-Net [55], Centernet++ [56], SEFEPNet [57], SAR-AIRCRAFT 1.0 [58], DiffDet4SAR [59], EarthGPT [60], ASC-U2Det [61].)

a clear agenda for future research.

(iv) **Openness:** We provide a comprehensive compilation of open-source datasets and code repositories, complete with direct links to facilitate reproducibility and support rapid prototyping.

(v) **Future-oriented:** Building on historical context, we distill key emerging research directions to offer a forward-looking roadmap for the field.

1.3 Scope and Organization

Given the enormous work on SAR ATR shown in Fig. 1 (b), exhaustive coverage within a single article is impractical. Therefore, this survey focuses on:

(i) **Literature source:** peer-reviewed papers from high-impact top journals and conferences relate remote sensing, as well as research with pioneering significance.

(ii) **Temporal span:** Nearly five decades from 1978 (the launch of the first spaceborne SAR satellite, Seasat-A) to the present.

(iii) **Task scope:** target detection and classification in single-channel, static SAR images.

For topics such as moving target detection, SAR video target recognition, and polarimetric SAR, this paper lists them as independent research directions in the future.

The remainder of this paper is structured as follows. Problem definition, core challenges, and datasets of SAR ATR are summarized in Section 2. In Section 3, we review the history of SAR ATR. Section 4 and 5 provide a comprehensive survey of the evolution of SAR target detection and classification. A taxonomy of SAR target detection and classification methods is illustrated in Fig. 3. Section 6 covers recent advances of SAR ATR. In Section 7, we conclude the paper and discuss the possible promising future research directions.

2 PROBLEM OF SAR ATR

2.1 Definition

SAR ATR system was first proposed by Lincoln Laboratory in 1993 [22, 74, 75], with its classical architecture consisting of three progressively advanced stages: pre-screening, discrimination, and classification. In the prescreening stage, the system performs rapid processing on large-scene SAR images to eliminate background regions that obviously do not contain targets and outputs a number of Regions of Interest (ROIs) that may contain targets. The discrimination stage then conducts more refined analysis on these candidate regions to distinguish real targets from false alarms caused by natural clutter. In the classification stage, the

Evolution of SAR ATR

Evolution of SAR Target Detection (Section 4)

- Traditional Methods (Section 4.1)
 - Statistical Feature-based Methods
 - Non-Statistical Feature-based Methods
- Deep Learning-based Methods (Section 4.2)
 - Anchor-based SAR Target Detection
 - Two-stage Methods
 - One-stage Methods
 - Anchor-free SAR Target Detection

Evolution of SAR Target Classification (Section 5)

- Traditional Methods (Section 5.1)
 - Intensity-based Methods
 - Texture-based Methods
 - Scattering Modeling-based Methods
 - Structural Modeling-based Methods
- Deep Learning-based Methods (Section 5.2)
 - Intensity Statistical Feature-based Methods
 - Structural Feature-based Methods
 - Electromagnetic Scattering Feature-based Methods

Fig. 3. The taxonomy of representative methods in SAR ATR.

system extracts discriminative features (e.g., scattering center distribution, contour moments) from the regions confirmed to be targets so as to realize the determination of specific categories, models and even identities (for example, distinguishing Boeing 737 from A330 aircraft).

Over the more than two decades of SAR ATR development, the terminology and scope of this task have undergone significant evolutions. In early literature, *detection* often referred only to the prescreening stage [48, 66, 68]. With the improvement of methods integration, *detection* has gradually covered both the prescreening and discrimination stages [71]. To ensure the consistency and clarity of the discussion, this paper uniformly refers to both the process of extracting and screening candidate target regions as *detection*, and the subsequent process of category inference as *classification*. In conclusion, the SAR ATR task discussed in this paper refers to detecting the positions of potential targets in large-scene, single-channel, and static SAR images and then classifying their categories, as shown in Fig. 4 (a).

Based on the aforementioned task definitions, the core objective of SAR ATR can be further summarized as achieving efficient and reliable target detection and classification in complex, dynamic, and potentially interfering real-world scenarios, specifically reflected in the following four dimensions:

(i) **High accuracy:** Achieve superior precision and classification accuracy while optimally balancing precision-recall trade-offs.

TABLE 1

Summary and comparison of the primary surveys in the fields of SAR ATR. **T** and **D** of **Scope** column denote the methods covered by the surveys as **Traditional** and **Deep learning-based** methods, respectively.

Ref	Year	Topic	Scope	Contributions	Limitations
[23]	1996	vehicle features	T	Emphasizes the model-driven method in ATR and provides a detailed description of MSTAR EOCs on SAR target features.	Lacks a summary of other targets and detection methods.
[65]	2004	ship detection	T	Discusses the imaging mechanism and theoretical basis, as well as implementation details and application effects in actual SAR images.	Lacks a summary of SAR target classification, challenges, and relevant problems.
[48]	2008	detection	T	Focuses on traditional SAR target detection methods in the past 20 years based on contrast differences, other features of the image, and complex features.	Lacks a summary of SAR target classification, challenges, and relevant problems.
[49]	2009	discrimination	T	Focuses on traditional discrimination methods in the past 20 years from feature extraction, knowledge, scattering characteristics, and the differences in the variation characteristics of the observation angle between the target and clutter.	Lacks a summary of SAR target classification, challenges, and relevant problems, and separates detection and discrimination.
[62]	2013	CFAR detection	T	Categorizes SAR detection approaches into single-feature-based, multifeature-based, and expert-system-oriented methods.	Lacks a summary of target classification, challenges, and relevant problems.
[66]	2016	holistic SAR ATR system perspective	T	Discusses from a holistic end-to-end perspective and proposes a two-fold benchmarking scheme for evaluating existing SAR ATR systems and motivating new system designs.	Uses MSTAR dataset on simple backgrounds for analyses, without complex urban clutter and multi-target scenes.
[67]	2018	vehicle classification	T	Reviews SAR target classification from the perspective of the autoencoder and its 7 variants.	Lacks a summary of other targets and detection methods.
[68]	2020	detection	T+D	Surveys single-channel SAR target detection and identification methods in complex scenes in the past decade.	Lacks a summary of target classification, challenges, and relevant problems.
[69]	2021	classification on MSTAR	T+D	Summarizes SAR target classification based on reflectance attribute and transformation.	Lacks a summary of challenges, relevant problems, datasets.
[70]	2022	ship detection	T+D	Reviews 177 articles on SAR ship detection from deep learning method frameworks and the required deployment.	Lacks a summary of challenges, relevant problems, datasets and performance.
[63]	2023	ship detection	D	Summarizes 81 articles on deep learning-based ship detection from 2016 to 2022, focusing on the network architecture.	Lacks a summary of the challenges and future direction in-depth.
[64]	2023	aircraft detection and classification	D	Delivers a comprehensive survey covering target characteristics, key challenges, algorithmic evolution, datasets, performance metrics and future trends	Lacks a summary of other targets and relevant problems, and comprehensive open-source datasets.
[71]	2023	detection and classification	D	Reviews 197 papers from small sample, class imbalance, real-time, polarimetric and complex SAR, and others.	Lacks comprehensive open-source datasets.
[72]	2025	detection and classification	D	Reviews 171 articles based on the datasets, classification, and detection of different types of targets.	Lacks comprehensive open-source datasets.
[73]	2025	dual perspective for detection and classification	T+D	Reviews detection and classification methods from dual perspectives of tradition and deep learning, and emphasizes practical applications from real-time, lightweight and on-device constraints.	Lacks analysis of connection between traditional and deep learning-based methods, and comprehensive open-source datasets.
Ours	2025	fifty evolution of SAR ATR	T+D	Provides the first comprehensive review of fifty years of SAR ATR development.	-

(ii) **High agility:** Demonstrate robust generalization capabilities and rapid adaptability to novel target categories, imaging scenarios, and sensors, while retaining high effectiveness under few-shot or zero-shot conditions.

(iii) **Strong robustness:** Maintain fault tolerance to target pose variations, geometric deformations, background clutter, noise perturbations, and adversarial attacks to ensure stable and reliable performance.

(iv) **Resource efficiency:** Operate within strict computational/power constraints of space/airborne edge platforms and enable real-time processing in mission-critical scenarios.

2.2 Core Challenges

Despite fifty years of development, most SAR ATR methods have not been capable of meeting real-world requirements due to various challenges. As illustrated in Fig. 5, to systematically present the challenges in SAR ATR, we classify the main difficulties as data-related and technique-related challenges.

1) **Data-related Challenges:** SAR data faces inherent difficulties in acquisition, quality, and annotation, which severely constrain the training and generalization of recognition models.

First, image quality degradations obstruct robust feature extraction. Beyond inherent coherent speckle noise, SAR images suffer from artifacts caused by geometric distortions (e.g., multipath effects, layover deformation) and radio frequency (RF) interference, as shown in Fig. 4 (b). Sidelobe spillover of strong

scatterers motion induced defocus and target wakes further corrupt imagery and distort target signatures.

Second, extreme variability in target appearance is pivotal. Fig. 4 (b) shows that signatures are jointly dominated by target attributes (geometry, material, state), environmental factors (occlusion, clutter, multipath), and sensor parameters (geometry, resolution). These interactions inflate intra class divergence and blur inter class boundaries, while electromagnetic coupling among crowded targets further impedes accurate recognition.

Third, SAR acquisition and labeling are prohibitively costly and quality unstable. Data collection is far more expensive than optical imaging, and sparse target distributions yield small, class-imbalanced, long-tailed corpora. Manual annotation is error-prone because occlusions, shadows, and weak scatterers induce omissions while similar or fine-grained objects trigger mislabels, and geometric distortions preclude precise boundary delineation.

Moreover, the conflict between large-scale scenes and small or weak targets is prominent, as shown in Fig. 4 (b). SAR images span vast regions yet targets such as vehicles or ships occupy only a minute pixel fraction, producing an ultra low target-to-background ratio that escalates computation and suppresses subtle signatures beneath clutter.

2) **Technique-related Challenges:** Beyond data challenges, the algorithm models themselves face numerous technical bottlenecks that impede their robust and efficient deployment in

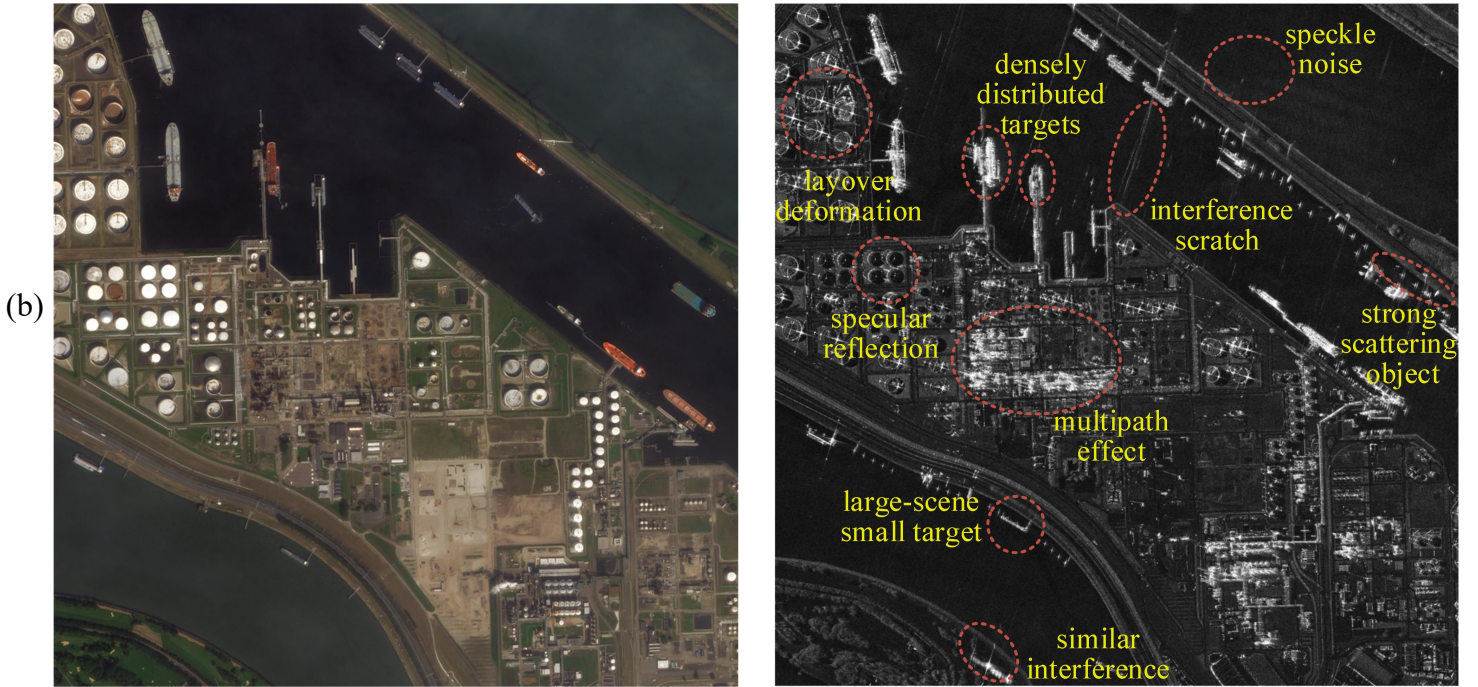
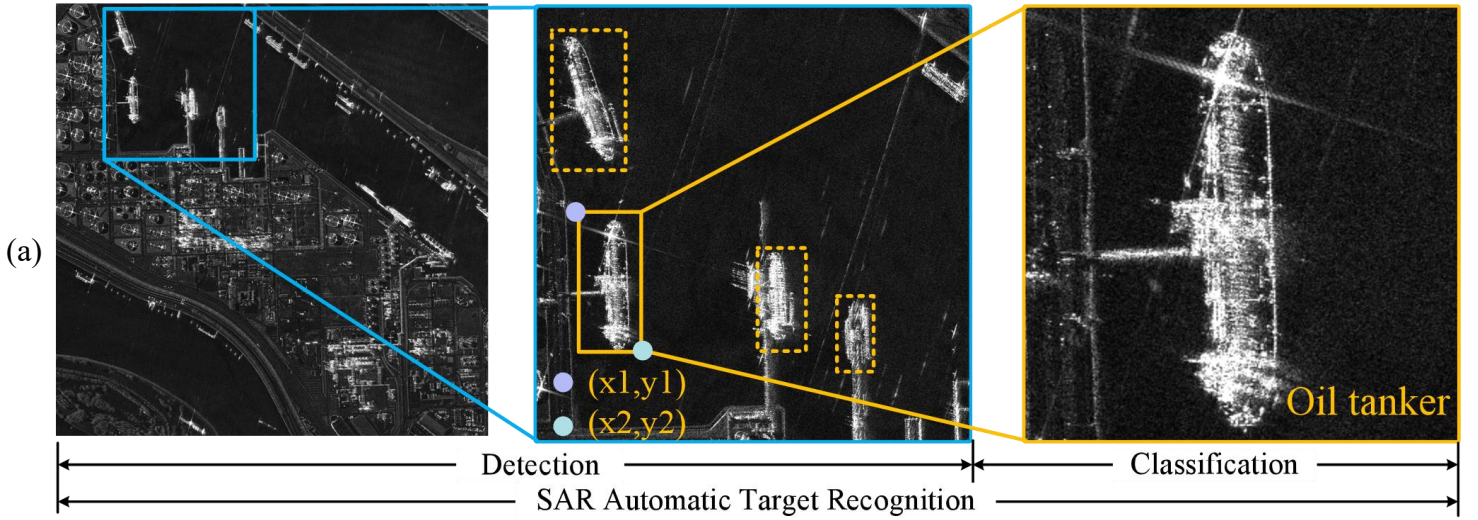


Fig. 4. (a) Definition of SAR ATR. It encompasses two key stages: **detection**, which locates potential target regions within a large-scale SAR image, and **classification**, which classifies the specific category (exemplified by the oil tanker ship) of the detected target. (b) Difference between optical and SAR images, and some challenging instances during SAR target recognition.

practical systems.

First, current technologies heavily rely on large-scale high-quality annotated data for supervised training. However, SAR labeling demands domain expertise in electromagnetic scattering and incurs prohibitive expense. This impedes models to rapid adaptation to new targets and scenarios, ultimately thwarting high agility.

Second, model generalization remains limited. Networks trained under controlled conditions tend to collapse when imaging parameters, environments, or target variants deviate. The underlying cause is their inability to capture intrinsic scattering physics, as they instead rely on superficial statistical cues.

Third, edge deployment faces severe efficiency constraints. Many advanced models impose heavy computational and memory footprints, making it difficult to meet real-time processing requirements on resource-constrained edge platforms (e.g., spaceborne, airborne). Therefore, achieving model lightweighting and inference acceleration while maintaining accuracy remains a critical engineering challenge for efficient deployment.

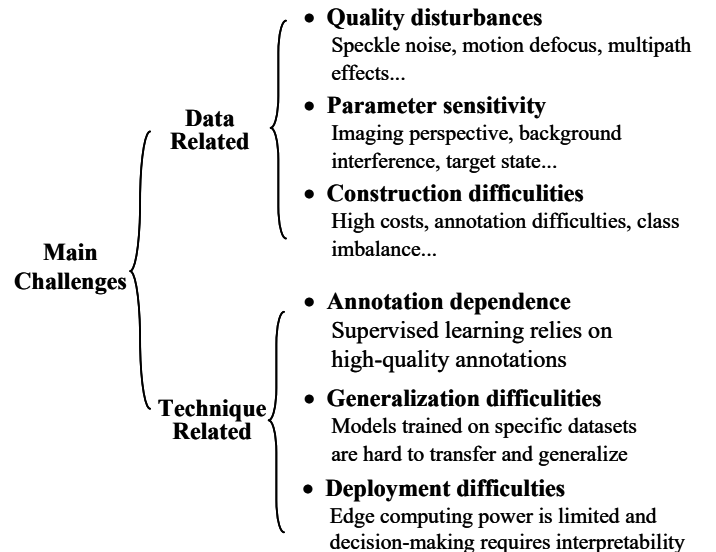


Fig. 5. Main Challenges of SAR ATR.

TABLE 2

Summary of OPEN-SOURCE SAR target CLASSIFICATION datasets from the 1990s to the 2020s. (Cls.: Number of target classes. Types: Number of target types. Img.: Number of images. Res.: Resolution. Pol.: Polarization. GF-3: Gaofen-3, S-1: Sentinel-1.)

Dataset	Year	Link	Country	Target	Source	Band	Pol.	Cls.	Types	Res.(m)	Img. Size	Img.
MSTAR [76]	1995	link	USA	vehicle	airborne	X	single	8	10	0.3	128-193	14,557
CV Domes [77]	2010	link	USA	vehicle	3D simulation	X	quad	3	10	0.3	-	-
Gotcha [78]	2012	link	USA	vehicle	3D airborne	X	-	7	13	0.3	-	-
SARSIM [79]	2017	link	Denmark	vehicle	simulation CAD	X	-	7	14	0.1	139	21,168
OpenSARShip [80]	2018	link	China	ship	S-1	C	dual	16	-	2.7-22	9-445	26,679
SAMPLE [81]	2019	link	USA	vehicle	simulation	X	single	7	10	0.3	128	2,690
FUSAR-Ship [82]	2020	link	China	ship	GF-3	C	dual	98	-	1.1-1.7	512	5,243
MATD [83]	2022	link	China	aircraft	airborne	Ku	-	2	2	-	128	144
SAR-ACD [84]	2022	link	China	aircraft	GF-3	C	single	2	6	1	32-200	3,032
ATRNNet-STAR [85]	2025	link	China	vehicle	airborne	X, Ku	quad	21	40	0.12-0.15	128	194,324

TABLE 3

Summary of OPEN-SOURCE SAR target DETECTION datasets from the 1990s to the 2020s. (Cls.: Number of target classes. Img.: Number of images. Ins.: Number of instances. Res.: Resolution. Pol.: Polarization. GF-3: Gaofen-3, S-1: Sentinel-1. * and ◇ represent horizontal and oriented target detection.)

Dataset	Year	Link	Country	Target	Source	Band	Pol.	Cls.	Res.(m)	Img. Size	Img.	Ins.	Ins./Img.
*miniSAR [86]	2005	link	USA	vehicle	airborne	Ku	-	1	0.1	1638*2510	20	-	-
*FARADSAR [87, 88]	2015	link	USA	vehicle	airborne	Ka,X	-	1	0.1	1300*580 -1700*1850	412	-	-
*SSDD [51]	2017	link	China	ship	S-1,RadarSat-2 TerraSAR-X	C/X	HH,VV, VH,HV	1	1-15	160-668	1,160	2,456	2.12
*AIR-SARSHIP1.0 [89]	2019	link	China	ship	GF-3	C	Single	1	1, 3	3000	31	461	14.87
*AIR-SARSHIP2.0 [89]	2019	link	China	ship	GF-3	C	Single	1	1, 3	1000	300	2,040	6.8
*SAR-SHIP-DATASET [90]	2019	link	China	ship	S-1,GF-3	C	Single, Dual, Full	1	3-25	256	39,729	47,416	1.2
*LS-SSDD-v1.0 [91]	2020	link	China	ship	S-1	C	VV,VH	1	5-20	800	9000	6015	0.67
*HRSID [92]	2020	link	China	ship	S-1B,TerraSAR-X, TanDEM-X	C/X	HH,HV,VV	1	0.5-3	800	5,604	16,951	3.02
◇ SRSDDD-v1.0 [93]	2021	link	China	ship	GF-3	C	HH,VV	1 (6 sub)	1	1024	666	2,884	4.33
◇ *Official SSDD [94]	2021	link	China	ship	S-1,RadarSat-2 TerraSAR-X	C/X	HH,VV, VH,HV	1	1-15	160-668	1,160	2,456	2.12
◇ *DSSDD [95]	2021	link	China	ship	S-1	C	VV,VH	1	9,14	256	1,236	3,540	2.86
◇ RSDD-SAR [96]	2022	link	China	ship	GF-3, TerraSAR-X	C/X	HH,HV	1	2-20	512	7,000	10,263	14.66
*SADD [97]	2022	link	China	aircraft	TerraSAR-X	X	HH	1	0.5-3	224	2,966	7,835	2.64
*MSAR [98]	2022	link	China	aircraft, ship, bridge, oil tank	HISEA-1	C	HH,HV VH,VV	4	1	256-2048	28,449	60,396	2.12
*SAR-AIRCRAFT1.0 [58]	2023	link	China	aircraft	GF-3	C	Uni-polar	1 (7 sub)	1	800-1500	4,368	16,463	3.77
*SIVED [99]	2023	link	China	vehicle	airborne	Ka,Ku,X	VV/HH	1	0.1, 0.3	512	1,044	12,013	11.51
◇ *OGSOD [100]	2023	link	China	bridge, oil tank, harbour	GF-3	C	VV/VH	3	3	256	18,331	48,589	2.65
*SARDet-100k [101]	2024	link	China	aircraft, ship, bridge, oil tank, vehicle, harbour	TerraSAR-X,TanDEM-X RadarSat-2,Airborne HISEA-1,GF-3,S-1B	Ka,Ku, X,C	HH,HV, VH,HV	6	0.1-25	512	116,598	245,653	2.11
◇ FAIR-CSAR [102]	2024	link	China	aircraft, ship, bridge, oil tank, tower crane	GF-3	C	HH,HV, VH,HV	5 (22 sub)	1-5	1024	106,672	349,002	3.27
◇ RSAR [103]	2025	link	China	aircraft, ship, bridge, tank, car, harbour	TerraSAR-X,TanDEM-X RadarSat-2,Airborne HISEA-1,GF-3,S-1B	Ka,Ku, X,C	HH,HV, VH,HV	6	0.1-25	512	95,842	183,534	1.91

2.3 Datasets and Evaluation

1) Datasets: Constructing larger datasets with smaller biases is crucial for developing advanced detection and recognition algorithms. Over the past five decades, the development history of SAR ATR datasets has itself been a technical history that drives the evolution of paradigms in this field. TABLE 2 and TABLE 3 present the currently available open-source classification and detection datasets, along with official download links.

2) Evaluation Metrics: How do we evaluate the accuracy of SAR ATR systems? The answer to this question may vary over time. In the early research on detection, there were no widely accepted metrics for evaluating detection accuracy. For example, in early studies on ATR systems [22], Novak used the probability of detection for uncloaked and camouflaged targets and confusion matrices to assess the classification accuracy of the system. Later, ATR methods typically categorized detection results into correct detections (where targets are correctly identified) and false alarms (where non-target objects are mistakenly classified as targets). The key performance indicators for these methods include the probability of detection (PD) and the probability

of false alarm (PFA). Particularly in Constant False Alarm Rate (CFAR) detectors [104, 105, 105], maintaining a constant false alarm rate under various conditions is crucial.

In recent years, the most commonly used detection evaluation metrics are accuracy and AP. AP is defined as the average detection precision across different recall rates, usually in a class-specific manner [106]. The mean AP (mAP) across all classes is typically used as the final performance indicator. More details are summarized in TABLE 4, and further details are provided in Reference [106] and [73].

3) Performance: For a long time, the classical MSTAR [23] and SSDD [51, 94] datasets have served as fundamental benchmarks in the field of SAR target classification and detection, greatly promoting the development of related methods. However, as illustrated in Fig. 6 (a) and (b), the performance of existing methods on these datasets has gradually approached saturation. This phenomenon reflects the limitations of such traditional datasets in scale, diversity, and scene complexity, which can no longer pose effective challenges to next-generation methods. Meanwhile, some existing public datasets generally suffer from

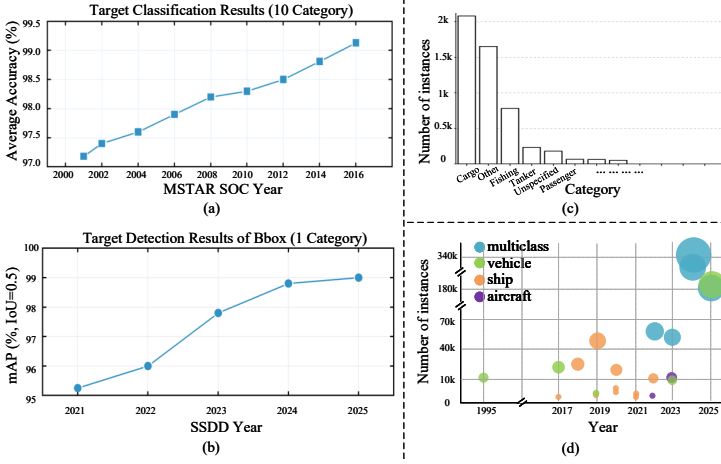


Fig. 6. Development status and challenges of SAR ATR datasets. (a) Annual average classification accuracy on the MSTAR dataset [23] under SOC. (b) Annual variation of mAP on Bbox SSDD dataset [51, 94]. (c) Instances count distribution across different categories in FuSAR-Ship dataset [82], presenting a significant long-tailed phenomenon. (d) Scale (instances) and category coverage of released SAR ATR datasets in recent years, reflecting the trend of datasets developing toward larger scales and more categories.

TABLE 4
Summary of commonly used metrics for evaluating SAR ATR methods.

Metric	Meaning	Definition and Description
TP	True Positive	A true positive detection.
FP	False Positive	A false positive detection.
FN	False Negative	A false negative detection.
TN	True Negative	A true negative detection.
Acc	Accuracy Rate	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$.
FAR	False Alarm Rate	$FAR = \frac{FP}{TN+FP}$.
F1	F1-score	$F1\text{-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$.
mAP	mean Average Precision	• AP: mAP averaged over ten IOUs: {0.5 : 0.05 : 0.95}; • $AP^{IOU=0.5}$: mAP at IOU=0.50; • $AP^{IOU=0.75}$: mAP at IOU=0.75 (strict metric);
mAR	Average Recall	The maximum recall given a fixed number of detections per image, averaged over all categories and IOU thresholds.

obvious long-tailed distribution and inter-class imbalance issues (Fig. 6 (c)), which restrict the generalization capability of models in real-world scenarios. Nevertheless, the research community has grown increasingly focused on dataset development. In recent years, several new datasets with larger scales, richer categories, and more detailed annotations have been successively proposed (Fig. 6 (d)). These efforts indicate that constructing next-generation SAR datasets with large scales, multi-scene coverage, and high challenge levels has become a critical prerequisite for advancing SAR ATR technology toward practical applications.

3 HISTORY OF SAR ATR

Over the past 50 years, the development of SAR ATR has consistently centered on the core issue of representing target features, accompanied by a continuous succession of research paradigms and expansion of target domains. This evolutionary context is concentratedly reflected in the SAR ATR method evolutionary tree shown in Fig. 7. The tree takes target types as branches (including ships, vehicles, aircraft, and others) and uses method nodes and connection relationships to embody the inheritance, innovation, and generalization trends of technologies. Branch density variations reveal distinct developmental maturity across target domains while demonstrating a clear

transition from specialized models toward unified perceptual frameworks. This fifty-year progression is categorized into four dominant stages based on feature representation methodologies and driving paradigms, as depicted in Fig. 2.

3.1 Understanding Physics: Theoretical Foundations and Statistical Modeling (1970s–1990s)

Early research centered on physical mechanism modeling and statistical theory, aiming to establishing the theoretical foundations of SAR imaging and target scattering. In 1951, Carl Wiley proposed the Doppler Beam Sharpening (DBS) principle and presented the frequency-domain formation conditions for synthetic aperture imaging [20]. Rihaczek established the first theoretical connection between electromagnetic target properties and recognition feasibility [107]. Harger standardized imaging geometric models, creating reproducible analytical workflows [21]. After the launch of Seasat-A in 1978, extensive measured images drove the statistical modeling of speckle noise, including the speckle model [108], K-distribution [42], product model [109], and texture analysis [110, 111]. Concurrently, Cell-Averaging Constant False Alarm Rate (CA-CFAR) [41, 112] converted the Neyman-Pearson criterion into an adaptive threshold algorithm, realizing automatic detection under a constant false alarm rate. Novak *et al.* (1989) [43] further integrated clutter covariance estimation with multi-polarization channel fusion, providing foundational solutions for automatic target detection in cluttered environments.

3.2 Designing Features: Handcraft Feature Engineering (1990s–2010s)

This phase witnessed SAR ATR research expand from target detection toward finer-grained recognition and classification, driven by the refinement of the theoretical framework, the creation of benchmark datasets and systematic research on feature representation. In 1993, Lincoln Laboratory established the three-stage processing pipeline [22, 74], laying a systematic algorithmic framework for SAR target recognition. Meanwhile, researchers have fully explored and characterized the target properties from multiple dimensions. Physical features, represented by Attributed Scattering Center (ASC) parameters [24], directly reflected the electromagnetic scattering mechanisms of targets. Statistical features described the statistical properties of regional scattering based on model parameters such as the G_0 distribution [44] and Fisher distribution [27]. structural features like wavelet transform [45], and Gray-Level Co-occurrence Matrix (GLCM) [25] were widely used to characterize the geometric morphology and texture structure of targets.

The 1996 release of the MSTAR dataset and subsequent SOC/EOC evaluation protocols [113] provided standardized benchmarks for SAR target recognition research. Machine learning methods such as SVM [26], AdaBoost [28], sparse representation [29], and SIFT-SAR [30] were introduced to optimize handcrafted features. For detection, CFAR algorithms evolved continuously [50, 114], while methods including Radon transform [115], morphological filtering [116], edge detection [117], and Markov Random Field (MRF) [118] advanced detection tasks from pixel-level threshold judgment to structural semantic understanding. The core paradigm manifested itself in physically meaningful features designed by domain experts combined with traditional machine learning classifiers.

3.3 Learning Features: Data-Driven End-to-End Learning (2010s–2020s)

This stage is marked by the comprehensive introduction of deep learning techniques [119], whose core lies in leveraging deep neural networks to directly learn hierarchical feature representations from raw SAR images, thereby reducing reliance on expert-designed handcrafted features. Early works [31, 120] validated the effectiveness of CNNs on the MSTAR dataset. The Complex-Valued CNN (CV-CNN) [32] incorporated the phase information of SAR complex data into the end-to-end learning framework, enhancing feature representation completeness. By 2020, the FEC framework fused electromagnetic scattering center features with CNN deep features through discriminant correlation analysis [34], demonstrating the complementarity between physical models and data-driven methods. For target detection, with the release of datasets like SSDD [51], general detectors such as Faster R-CNN [121] were adapted to SAR characteristics, spawning specialized architectures including attention mechanisms [53], rotated anchor designs [54], and multi-scale feature fusion [122]. This stage demonstrated the effectiveness of deep learning and initially explored effective paths for embedding physical priors into networks. However, reliance on large-scale labeled data and poor model interpretability of deep learning also gradually emerged in practice.

3.4 Understanding and Learning: Physics-Data Dual-Driven Fusion (2020s–Present)

The current SAR ATR field is evolving by deep integration of physics guidance and data-driven approaches. For data, the construction of large-scale, multi-task SAR datasets [102, 103] provide a crucial foundation for training generalized models. For model architectures, Vision Transformer and state space models [123] have been introduced into SAR ATR, enhancing feature representation capabilities. Meanwhile, physics-prior attention mechanisms [36, 37] and diffusion models [59, 123] embed electromagnetic scattering principles into network structures or loss functions. Regarding learning paradigms, self-supervised learning [124] and cross-domain pre-training [40] leverage massive unlabeled data to learn universal representations, significantly reducing dependency on annotations while improving few-shot and zero-shot generalization. Nowadays, tasks such as detection, recognition, and segmentation can be flexibly adapted on unified SAR foundation models [60, 125], demonstrating strong task scalability and scenario adaptability. SAR ATR has thus progressed from physics-driven to data-driven approaches and now toward physics-data dual-driven fusion, advancing powerful recognition systems with high performance, interpretability, and operational robustness.

4 EVOLUTION OF SAR TARGET DETECTION

The development of SAR target detection technology constitutes an evolutionary history, progressing from “model-driven” exploration of physical priors to “data-driven” representation learning. **Its core challenge has always been to stably and accurately separate targets of interest from strong speckle noise and complex, variable terrain backgrounds while controlling false alarms.**

4.1 Traditional Methods for SAR Target Detection

1) *Statistical Feature-based Methods*: Traditional SAR target detection formulates the task as a statistical hypothesis test, and

the constant false alarm rate (CFAR) detector family is the most widely adopted implementation of this principle [127, 128, 129]. CFAR partitions the local background with a sliding window and adaptively sets the detection threshold from the clutter distribution. This strategy maintains a constant false alarm rate in complex and time-varying electromagnetic environments, as shown in Fig. 8 (a). This physics-driven parametric modeling approach translates inherent SAR phenomena such as multiplicative speckle and non-stationary clutter into quantifiable statistical distributions, including Rayleigh, Weibull, K, and generalized gamma. CFAR detectors are consequently categorized into window setting-based parametric CFAR and background distribution modeling schemes.

(i) *Window Setting-based Parametric CFAR*: Originating from cell averaging CFAR (CA-CFAR) [41, 112, 130], the parameterized branch has produced OS-CFAR [131], SO-CFAR [132], GO-CFAR [104], TM-CFAR [105] and others [133]. Each variant applies a distinct nonlinear transformation to the background window to survive nonhomogeneous scenes. SO-CFAR [132] minimizes the power estimate between leading and lagging windows to resolve closely spaced targets. GO-CFAR [104] takes the maximum estimate to reduce masking from interfering targets. OS-CFAR [131] replaces the sample mean with a ranked statistic, which yields robustness near the clutter edges. TM-CFAR [105] symmetrically censors extreme samples, trading a slight loss in signal-to-noise ratio for significantly improved adaptability to environmental transitions. However, these detectors face an intrinsic trade-off in selecting the size of the background window. A large window tends to straddle heterogeneous regions and introduces contaminated samples, biasing the clutter model. A small window provides insufficient samples, inflating the variance of the estimated parameters and causing erratic thresholds. Although Ratio-CFAR [134] reduces false alarms induced by speckle and BLUE-CFAR [135] employs a Weibull-Gumbel transform to account for self-shadowing of extended targets, such refinements do not overcome the fundamental limitations imposed by model mismatch and poor scene adaptability.

(ii) *Clutter Estimation-based CFAR*: To cope with non Gaussian and spatially inhomogeneous clutter, refined CFAR schemes have been introduced that assume specific complex distributions [136]. K-CFAR [137] models spiky sea clutter by a K distribution and employs a guard band reference window to reduce target leakage into the background estimate. GFD-CFAR [138] derives a closed-form threshold for high-resolution sea clutter by replacing the conventional distribution with the generalized Gamma distribution. Similar strategies adopt the generalised gamma [139] or other flexible distributions [50, 140] to capture the complex scenarios encountered in ground and sea regions. Yet the core difficulty remains that a single parametric form cannot accommodate the abrupt statistical transitions present at urban edges, within densely packed harbors, or across mountainous terrain, and the resulting model mismatch continues to degrade detection performance in complex scenes.

(iii) *Others*: Beyond pixel-level grayscale statistics like CFAR, some works transform SAR images into multiscale or wavelet domains, leveraging differences in high-frequency energy, co-efficient distribution, or correlation between targets and backgrounds to achieve detection. Tello *et al.* [45] leveraged discrete wavelet transforms to enhance multiscale discontinuity features based on statistical distribution disparities between ships and surrounding sea surfaces. Mercier *et al.* [141] modeled the wavelet coefficients of normal sea conditions as a zero-mean Gaussian mixture, combining wavelet-domain features

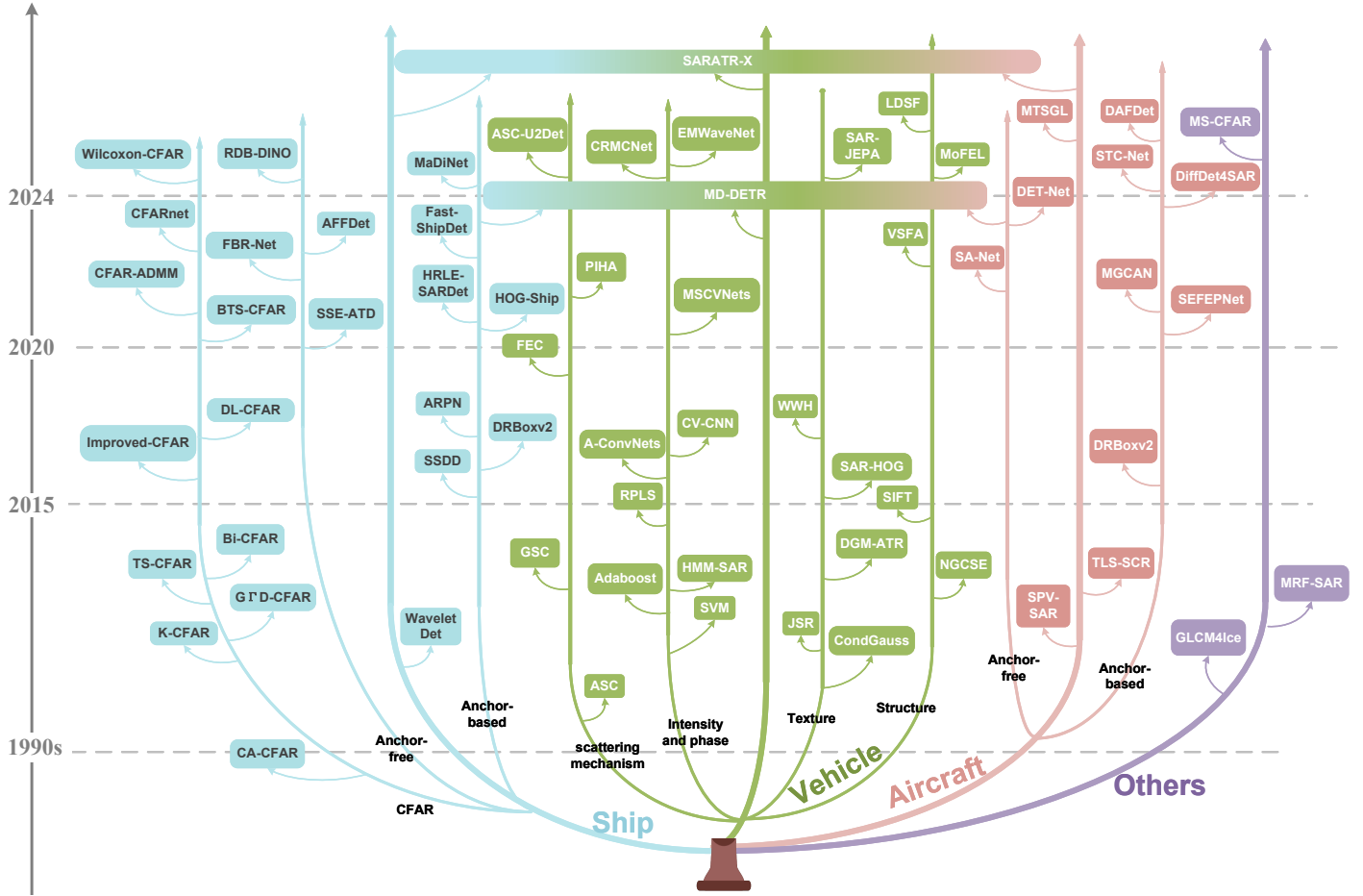


Fig. 7. An evolutionary tree of SAR ATR technology from the 1990s to present, organized into four primary branches based on target types: ships, vehicles, aircraft, and other targets. Branch nodes represent landmark methodologies, connecting lines indicate technological inheritance and innovation, while cross-branch linkages signal the emergence of generalizable models. (1) Early approaches (pre-2015) predominantly employed handcrafted features and statistical modeling, exemplified by CFAR variants focused on ship detection. The post-2015 period saw deep learning becoming mainstream through architectures like A-ConvNets [31] and CV-CNN [32], though most remained target-specific. Since 2020, generalist models such as MD-DETR [126] and SARATR-X [40] have demonstrated cross-target generalization capabilities. (2) Branch analysis highlights distinctive development patterns. Ship detection exhibits the densest node distribution, reflecting research maturity and methodological diversity. Vehicle targets show accelerated growth despite later emergence. Aircraft recognition relies heavily on structural and scattering feature modeling. (3) Three key trends define the evolution of SAR ATR. A clear transition from reliance on handcrafted features to adoption of data-driven learning paradigms. A shift from specialization in single-target detection to development of multi-target generalization capabilities. Growing convergence of physics-inspired approaches with data fusion and model-driven frameworks. Considering the rapid development of SAR ATR, we share the source file of research in this free and encourage readers to make incremental updates at <https://github.com/JoyeZLearning/SAR-ATR-From-Beginning-to-Present>.

with kernel functions for oil spill detection amid small-scale slicks and strong sea clutter. These methods remain severely constrained by background distribution priors and parameter estimation accuracy. Moreover, most are designed specifically for sea-surface ships, requiring domain adaptation or re-engineering when migrating to complex terrestrial contexts.

(iv) *Discussion:* Despite the aforementioned limitations, as a classic framework for SAR target detection, CFAR has continued to evolve through integration with emerging technical paradigms such as deep learning [142, 143, 144]. For instance, CFARnet [145] embeds CFAR constraints into the neural network architecture, enabling the model to learn a detector that complies with CFAR principles from data. CFAR-DP-FW [146] converts CFAR decisions into attention maps that are concatenated with the input of a convolutional network, enabling end to end training with a semantic loss. Other studies have applied CFAR to detection preprocessing [147] or clutter noise modeling [148] to improve the generalization performance of detection systems in complex scenarios. This trend indicates that traditional statistics-driven methods and modern data-driven paradigms are gradually moving toward deep integration, which also provides new solutions for addressing target detection challenges in complex

environments.

2) Non-Statistical Feature-based Methods: Beyond statistical methods, researchers leverage visual saliency, complex-domain physical features, or shallow learners for detection to circumvent clutter distribution priors. Wang *et al.* [149] used Bayesian saliency maps to preserve complete structures of targets and strong clutter, then employed morphological saliency maps combined with vehicle size priors to suppress natural and man-made strong clutter. Souyris *et al.* [150] and Ouchi *et al.* [151] exploited coherence time differences between targets and clutter by dividing single-look complex imagery into sub-apertures along azimuth, enhancing weak scatterers via unnormalized Hermitian inner product or multi-look cross-correlation. Filipidis *et al.* [4] employed feedforward neural texture blocks for coarse target/non-target classification, fusing texture confidence, background discrimination, and size priors with fuzzy rules for airport aircraft detection. These approaches achieve robust detection in unknown or non-uniform clutter with lower computational costs than deep networks. These methods demand manual parameter tuning and specialization for specific scenes, requiring adaptive mechanisms or cascading with statistical features for complex terrestrial environments.

Traditional methods

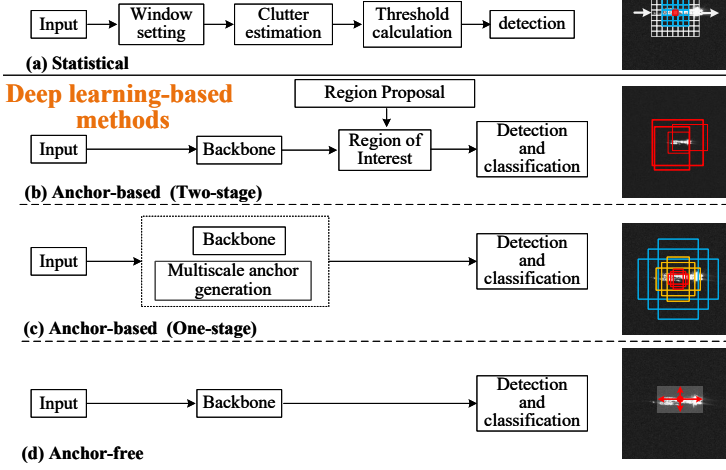


Fig. 8. Overview of key steps between traditional and deep learning-based methods for SAR target detection. (a) Statistical methods. (b) Anchor-based (two-stage) methods. (c) Anchor-based (one-stage) methods. (d) Anchor-free methods.

4.2 Deep Learning-based SAR Target Detection

This section, focusing on deep learning-based SAR target detection tasks, summarizes existing methods classified into anchor-based and anchor-free categories on their detection frameworks. The methods are categorized based on their attributes and core innovations, concluding with the key concerns discussion.

1) Anchor-based SAR target detection: In SAR target detection, anchor-based methods provide prior references for target localization and classification by predefining a set of candidate bounding boxes with varying scales, aspect ratios, and angles on the image. Based on differences in their detection pipelines, they can be categorized into two-stage and one-stage methods, as shown in Fig. 8 (b) and (c), each with distinct focuses on detection accuracy and inference speed.

(i) Two-stage methods: Two-stage methods first generate candidate target regions via a Region Proposal Network (RPN), followed by fine-grained classification and location regression for each candidate region [106]. Improved Faster R-CNN [51] addresses the issues of multi-scale and dense distribution of ship targets by adopting multi-feature fusion to enhance target representation capability, as shown in Fig. 9 (a). SER Faster R-CNN [52] incorporates the Squeeze-and-Excitation channel attention mechanism and a score correction strategy to improve the model's ability to screen key scattering features. ARPNet [167] utilizes a multi-branch convolutional structure to extract multi-scale features, aiming to tackle the problem of significant target size variations in SAR images. In recent years, emerging architectures such as transformers and diffusion models have also been integrated into the two-stage framework. FastShipDet [147] applied the progressive detection process of global-regional-target to very large scenes, as shown in Fig. 9 (b). DiffDet4SAR [59] redefines the detection task as a bounding box denoising process, avoiding heuristic anchor box design. MaDiNet [123] builds on this by introducing a Gamma diffusion process to model the implicit association between the target position and scattering points and captures long-range dependencies with the help of a state-space model, as shown in Fig. 9 (c). This design improves the detection performance of structural targets in large scenes. This category of methods typically achieves high detection accuracy but also incurs relatively high computational complexity.

(ii) One-stage methods: One-stage methods eliminate the region proposal step and directly perform target localization and

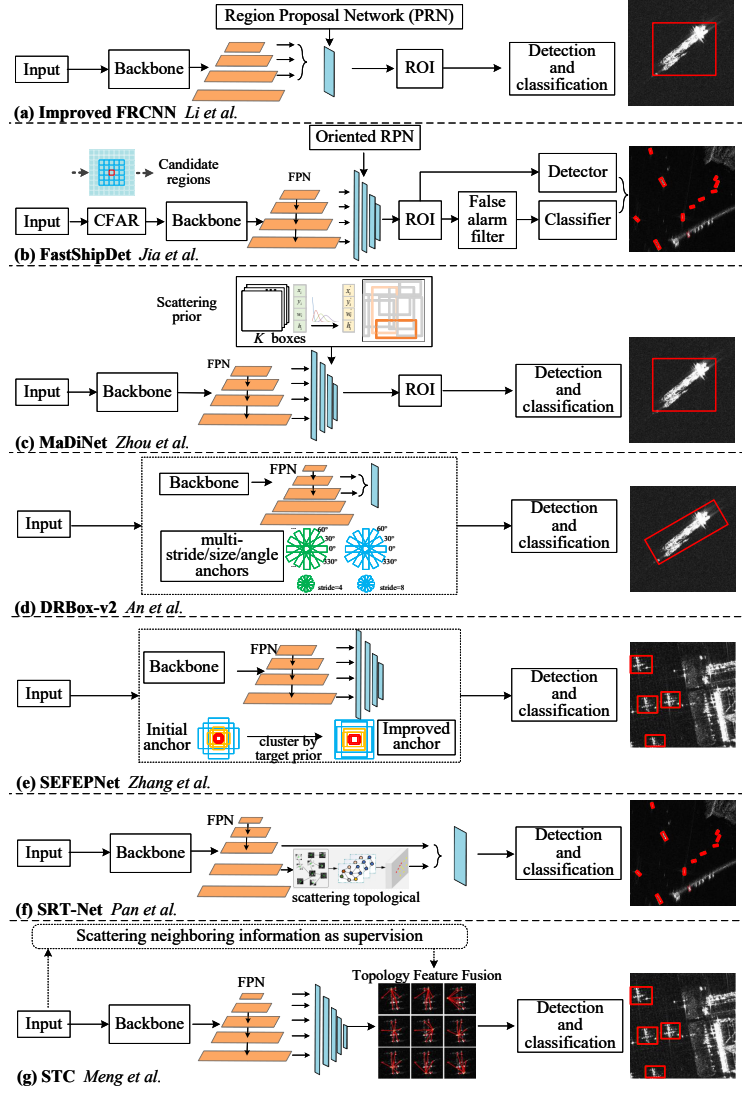


Fig. 9. Overview of representative deep learning-based methods for SAR target detection. (a)-(c) are anchor-based (two-stage) methods. (d) and (e) are anchor-based (one-stage) methods. (f) and (g) are anchor-free methods. ((a) Improved FRCNN [51], (b) FastShipDet [147], (c) MaDiNet [123], (d) DRBox-v2 [54], (e) SEFEPNet [57], (f) SRT-Net [152], (g) STC [153])

classification simultaneously within the network [154, 168]. As a result, they typically exhibit faster inference speed and are more suitable for real-time detection tasks. This category of methods achieves coverage of targets with varying sizes and orientations through dense anchor sampling and prediction across multiple feature levels. For instance, DRBoxv2 [54] proposes an improved rotated box encoding strategy and a multi-level prior box generation mechanism, as shown in Fig. 9 (d). It significantly enhances the detection accuracy for orientation-sensitive targets such as ships and aircraft. SEFEPNet [57], on the other hand, redesigns anchor sizes based on prior knowledge of the scattering point distribution of aircraft targets, thereby improving the accuracy of target localization regression, as shown in Fig. 9 (e). Simultaneously, novel architectures continue to advance single-stage methodologies. MGCAN [169] constructed a geospatial self-attention mechanism to enhance modeling of contextual semantic relationships between targets and their surroundings. Additionally, lightweight designs are gaining traction. HRLE-SARDet [155] achieved high-precision multi-class detection with extremely low parameters. DAFDet [157] introduced a dynamic inference mechanism that adaptively

TABLE 5
Performance of representative SAR target detection methods on six mainstream datasets.
(SSDD [51], SAR-Ship-Dataset [90], HRSID [92], SAR-Aircraft-1.0 [58], SADD [97], MSAR [98].)

Taxonomy	Year	Methods	Open-source	Backbone	Performance (mAP50,%)					
					SSDD	SAR-Shipdataset	HRSID	SAR-Aircraft1.0	SADD	MSAR
anchor-based	2017	Improved FRCNN [51]	-	ZIF-Net	78.8	-	-	-	-	-
	2019	DRBoxv2 [54]	Code	VGG16	92.8	-	-	-	-	-
	2019	YOLOv2-reduced [154]	-	Darknet-19	90.0	-	-	-	-	-
	2022	SEFEPNet [97]	Code	Darknet-53	-	-	-	-	93.4	-
	2023	HRLE-SARDet [155]	-	EfficientNet	98.4	-	92.5	-	-	88.4
	2024	ShipDetector [156]	-	CSPNet	97.6	91.2	93.6	-	-	-
	2024	DiffDet4SAR [59]	Code	Res50+FPN	96.9	95.1	-	88.4	-	-
	2024	MSFA [101]	Code	VAN	97.9	-	83.7	-	-	-
	2025	DAFDet [157]	-	Hybrid	98.1	<u>96.5</u>	-	-	-	97.2
	2025	SARDet-CL [158]	-	Res50	-	-	-	86.8	<u>87.7</u>	73.8
	2025	PGD-YOLOv5 [159]	Code	Res50	-	-	-	<u>90.4</u>	-	-
	2025	MaDiNet	Code	Hybrid	<u>99.0</u>	97.6	-	90.8	-	-
anchor-free	2020	SSE-ATD [160]	-	DLA	-	94.7	-	-	-	-
	2021	FBR-Net [55]	-	Res50	94.1	-	-	-	-	-
	2021	CP-FCOS [161]	-	Res50	-	-	<u>96.0</u>	-	-	-
	2021	Centernet++ [56]	-	DLA	95.1	95.4	-	-	-	-
	2023	SA-Net [58]	-	Res50	-	-	-	80.4	-	-
	2024	3SD-Net [162]	-	Res50	90.5	91.6	-	-	-	-
	2025	PFARN [163]	-	Res50	98.1	-	94.8	-	-	-
	2024	MD-DETR [126]	-	Swin-T+Res50	98.9	-	-	-	-	-
	2024	PVT [164]	-	ViT	96.8	-	-	-	-	-
	2024	SFS-CNet [165]	Code	CSPDarkNet	99.6	-	96.2	89.7	-	-
	2025	STC-Net [153]	-	Res50+FPN	-	-	-	89.0	-	-
	2025	RDB-DINO [166]	-	DINO	98.3	-	92.8	-	-	-
	2025	PGD-YOLOv8 [159]	Code	Res50	-	-	-	90.7	-	-

* The data are extracted from the original papers. We use “-” to mark the dataset without reporting in the original papers. The **best** results are **bold** and underlined, while the second-best are underlined only.

adjusts computational paths based on image content, effectively balancing detection efficiency and accuracy.

(iii) *Discussion*: Although significant progress has been achieved by anchor-based methods in SAR target detection, they still face several common challenges. First, the size, aspect ratio, and angle of anchors need to be preset based on specific tasks, resulting in limited generalization ability across different scenarios. Second, while dense anchor strategies can improve recall, they also incur high computational and memory overheads. Third, in extremely inhomogeneous scenarios, mismatch imbalance tends to occur between anchors and real targets. Consequently, future research could explore adaptive anchor mechanisms, lightweight designs, and embedding physical knowledge to address these limitations.

2) *Anchor-free SAR target detection*: Anchor-free methods eliminate the predefined anchor mechanism and achieve more flexible detection through keypoint detection, center point localization, or pixel-level prediction [163, 170], as shown in Fig. 8 (d). SSE-CenterNet [160] integrates attention mechanisms in both channel and spatial dimensions to enhance semantic features. FBR-Net [55] directly learns bounding box encoding to avoid the impact of anchor box bias. CP-FCOS [161] proposes generating guidance vectors from the classification branch to optimize the accuracy of localization regression. DenoDet [171] integrates the transform-domain denoising concept from traditional image processing into the deep learning framework. By leveraging attention mechanisms to perform dynamic soft-thresholding in the frequency domain, it significantly enhances target detection accuracy and robustness in SAR imagery. To address the common issue of discontinuous target contours in SAR images, AFFDet [170] adopts geometric projection to replace angle parameters. SRT-Net [152] extracts scattering points of aircraft targets via Harris corner detection and K-means clustering and constructs a graph structure to capture global information, as shown in Fig. 9 (f). SA-Net [58] utilizes key scattering points for auxiliary localization, improving the detection reliability of aircraft targets. STC-Net [153] incorporates scattering topology cues into SAR

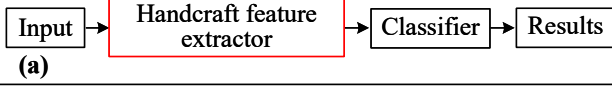
aircraft detection and leverages their structural relationships to enhance robustness in complex scenarios, as shown in Fig. 9 (g). In recent years, DETR-based detection architectures have also made progress in the SAR field. For example, MD-DETR [126] introduces a triple denoising strategy to achieve high-precision detection across multiple target categories. DET-Net [172] first unifies denoising, dynamic range compression, and channel combination into a single detection-based enhancement framework. RDB-DINO [166] explicitly constructs sample and noise queries during the decoding stage. This design reduces the complexity of Hungarian matching and the missed detection of small targets, thereby optimizing matching efficiency and training stability. However, these anchor-free methods still face their own challenges. They have higher requirements for feature alignment and regression consistency, making training more difficult and prone to unstable convergence.

3) Summary

i) *Performance comparison*: This section systematically benchmarks mainstream SAR target detection methods. To ensure equitable comparison despite implementation variances (e.g., backbone architectures, feature fusion strategies, training protocols), we adopt mAP50 (%) from six widely used public datasets (SSDD [51], SAR-Ship-Dataset [90], HRSID [92], SAR-Aircraft-1.0 [58], SADD [97], MSAR [98]) as the primary metric. The specific performance is presented in TABLE 5. To fully demonstrate the characteristics of each method, TABLE 5 provides their specific taxonomy and backbones. We have also provided codes of open-source methods for reproduction.

From the performance results, SFS-CNet [165] achieved the best performance on the SSDD dataset with 99.6%, followed closely by MaDiNet (99.0%) [123]. On the SAR-Shipdataset, MaDiNet took the lead with 97.6%, with DAFDet [157] trailing behind at 96.5%. For the HRSID ship detection dataset, PFARN [163] delivered excellent performance at 94.8%, while CP-FCOS [161] also reached 96.0%. On the aircraft target datasets SAR-Aircraft1.0 and SADD, SEFNet [57] and PGD-YOLOv8 [159] achieved 93.4% and 90.7% respectively, demonstrating their

Traditional methods



Deep learning-based methods

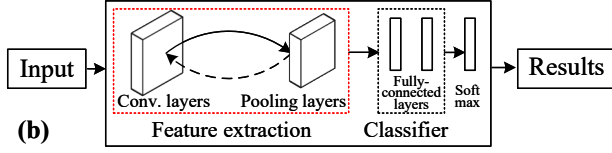


Fig. 10. Overview of key steps between traditional and deep learning-based methods for SAR target classification. (a) Traditional methods. (b) Deep learning-based methods.

good generalization ability on specific target categories. As a multi-target scenario dataset, MSAR saw DAFDet [157] perform the best at 97.2%, reflecting its outstanding cross-category detection capability.

ii) Main issues and facts: First, the evaluation framework still relies on a single metric such as mAP50, which does not adequately reflect the overall performance of the model in aspects such as missed detection, false detection, localization accuracy, and small target performance. Second, inconsistencies in experimental conditions and implementation details (e.g., data augmentation, hyperparameter configuration, and backbone selection) limit the credibility of comparisons. More importantly, most methods have not released their code, which seriously undermines reproducibility and subsequent research. Finally, there is a clear gap between current detection setups and practical application scenarios. The generalizability of the models under real-world conditions, such as complex environments, extreme weather, target occlusion, and deformation, still needs systematic verification.

5 EVOLUTION OF SAR TARGET CLASSIFICATION

The core of SAR ATR lies in extracting highly discriminative, effective and robust features. As shown in Fig. 10 (a), traditional methods rely on handcrafted features and combine them with shallow classifiers. Deep learning methods automatically optimize feature representation through end-to-end learning, as shown in Fig. 10 (b). Despite differences in their paradigms, their core essence is to extract features that can effectively distinguish targets. From the perspective of feature representation, this section conducts a unified classification and review of traditional and deep learning methods, with each subsection concluding with a discussion of key issues.

5.1 Traditional Methods

We summarize existing methods classified into intensity-based, texture-based, scattering modeling-based, and structural-based categories, noting some overlap across these domains. The methods are categorized based on the main feature utilized.

1) Intensity-based Methods: These methods directly take the pixel intensity values of target region images as the source of features and high computational efficiency. Their fundamental assumption holds that targets with different structures and materials exhibit unique and stable backscattering statistical patterns under different azimuth angles [173, 174, 175]. A typical practice involves extracting statistical metrics—such as mean, variance, histogram distribution, or moment features—from image slices [176], which are then input into traditional classifiers (e.g., SVM [26] or AdaBoost [28]) for classification. For example, Enderli *et*

al. [5] proposed a SAR target classification method based on the weighted deflection criterion. By computing third-order pseudo-Zernike moments, the method used a quadratic filter to approximate the optimal likelihood ratio classifier. However, these methods are sensitive to noise and attitude variations, neglect phase and contextual information, have limited discriminative ability, and easily lead to confusion between different targets at specific angles.

2) Texture-based Methods: Texture features leverage the spatial distribution patterns of pixel intensity in SAR images, with typical examples including the Gray-Level Co-occurrence Matrix (GLCM) and its derived metrics such as contrast, entropy, and correlation [110, 177, 178]. These features are used to characterize the roughness and uniformity of targets. Specifically, GLCM4Ice [25] has been successfully applied to sea ice type discrimination, while MRF-SAR [179, 180] systematically compared different texture modeling methods and analyzed the impact of window size on feature stability. However, the performance of texture-based methods is severely affected by speckle noise and exhibits poor robustness to target pose variations, which limits their application in complex scenarios.

3) Scattering Modeling-based Methods: Based on the physical mechanism of electromagnetic scattering, this category of methods models target responses as a set of parameterized scattering centers, such as the Attributed Scattering Center (ASC) model based on the Geometric Theory of Diffraction (GTD) [24, 181]. By fitting and extracting attributes including scattering point type, frequency, and azimuth-dependent factors, these methods form physically interpretable feature vectors, thereby elevating SAR image interpretation from the pixel level to the physical structure level. For such approaches, MSTAR-EOC [23] and GSC [182] systematically established evaluation criteria and a global scattering center model, respectively. This category of methods has laid a physical foundation for SAR target recognition and provided semantic priors for subsequent physics-guided deep learning. However, it suffers from limited ability to describe complex targets, high complexity of template matching, and a high degree of dependence on data quality.

4) Structural Modeling-based Methods: Structural features focus on describing the macroscopic morphology and local invariant structures of targets. For instance, they can involve extracting contour regions through morphological operations [182], or adopting SIFT descriptors [30, 183] from the optical field to extract rotation and scale-invariant features. NCCSE-ATR [184] proposes a feature representation method based on neighborhood geometric centers, which improves the performance of sample clustering. However, structural features in SAR images are susceptible to noise interference and relatively sensitive to local deformations and occlusions.

5) Discussion: Despite these advances, traditional methods remain constrained by inherent limitations of handcrafted feature engineering. They heavily depend on expert prior knowledge, restricting generalization capabilities. Handcrafted features also suffer significant information loss, impairing their ability to characterize intra-class variations or complex target structures. Furthermore, the modular separation of detection, feature extraction, and classification prevents end-to-end collaborative optimization. These bottlenecks become especially prominent in complex scenarios, ultimately driving the shift toward data-driven, end-to-end deep learning solutions.

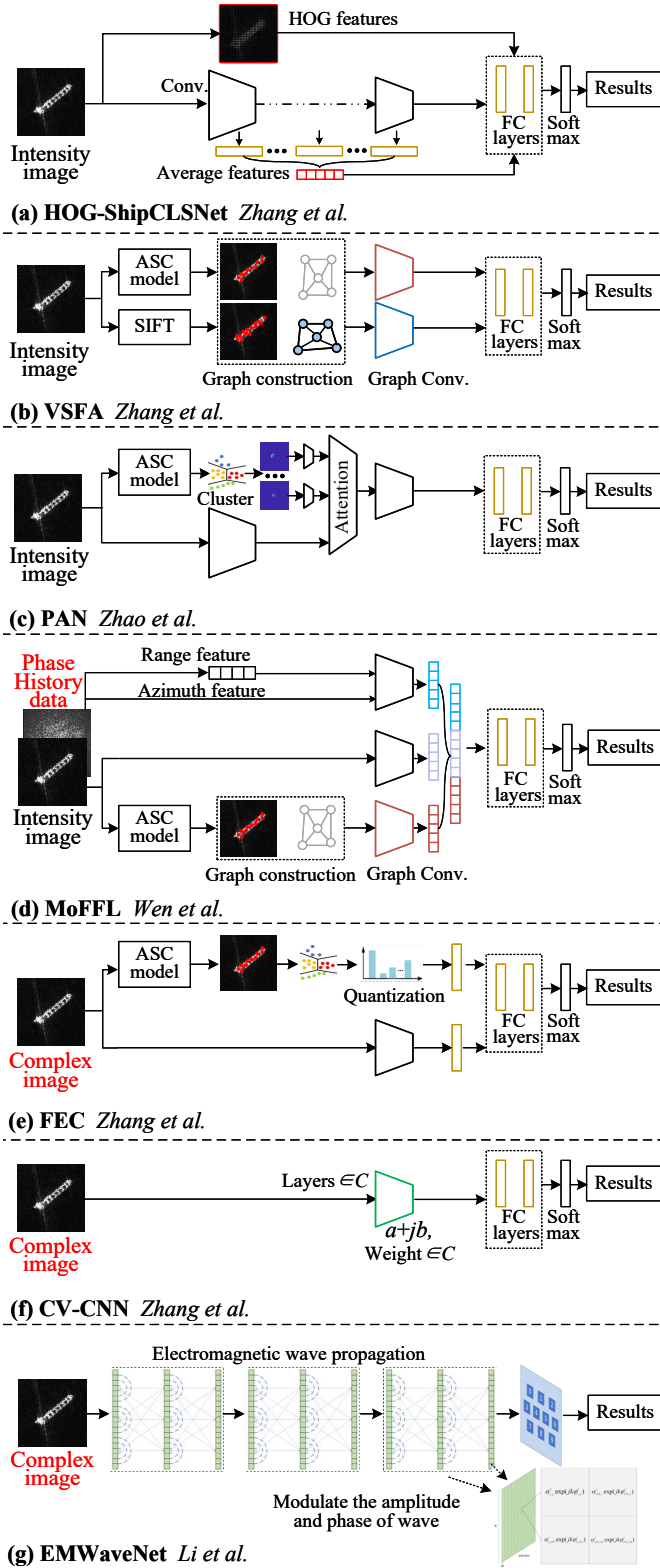


Fig. 11. Overview of representative deep learning-based methods for SAR target classification. (a) and (b) are intensity statistical feature-based methods. (c) and (d) are structural feature-based methods, and (e)-(g) are electromagnetic scattering feature-based methods. ((a) HOG-ShipCLSNet [35]. (b) VSFA [38]. (c) PAN [185]. (d) MoFFL [186]. (e) FEC [34]. (f) CV-CNN [32]. (g) EMWaveNet [187].)

5.2 Deep Representation Learning For SAR classification

Existing methods can be categorized into three categories according to the main types of information features used: intensity statistical feature-based, structural feature-based, and electromagnetic scattering feature-based methods.

1) Intensity Statistical Feature-based Methods: This category

of methods mainly extracts apparent statistical features and deep texture features from SAR intensity images. HOG-ShipCLSNet [35] fused traditional HOG features with deep features extracted by convolutional networks, as shown in Fig. 11 (a). This fusion enhanced the representation capability of ship targets. VSFA [38] modeled the ASC and SIFT key points into graph structures, as shown in Fig. 11 (b). It also utilized Graph Neural Network (GNN) to fuse local scattering and spatial structure information. SAR-JEPA [124] replaced pixel reconstruction with gradient prediction and effectively overcame the interference of speckle noise on self-supervised learning. MIGA-Net [188] used multi-view intensity images to model azimuth information in SAR sequences and improved angular robustness. Moreover, MJT-Net [189] utilized the multi-head attention mechanism of Transformer to alleviate the feature inconsistency caused by uncertain view intervals. This category of methods primarily focuses on feature enhancement and view modeling at the intensity image level. It demonstrates strong applicability for scenarios involving complex target structures and variable imaging angles, while exhibiting robust engineering adaptability.

2) Structural Feature-based Methods: This category of methods focuses on modeling spatial topological relationships within targets or between target components. It is particularly suitable for targets with explicit structural characteristics, such as vehicles and aircraft. As shown in Fig. 11 (c), PAN [185] clustered ASC and introduced attention mechanisms, achieving component-level semantic and structural correlation. MoFFL [186] proposed a hierarchical graph aggregation mechanism to gradually construct target structural features from individual components to the entire target, as shown in Fig. 11 (d). LDSF [190] introduced graph topological loss to enhance intra-class aggregation capability. MTSGL [191] incorporated structural templates and geometric transformations in aircraft classification, reducing reliance on pixel-level annotations. These methods explicitly utilize the spatial layout of targets and enhance robustness against structural variations and occlusions.

3) Electromagnetic Scattering Feature-based Methods: This category of methods deeply explores the electromagnetic physical essence of SAR data, and can be further divided into complex domain modeling and physical mechanism embedding.

i) Physical Mechanism Embedding: These methods bridge interpretability and data-driven capabilities. FEC [34] quantized ASC features and fused them with CNN deep features, as shown in Fig. 11 (e), enhancing target representation. CA-MCNN [36] integrates the ASC model into multi-scale CNNs, boosting robustness against occlusion and limited samples. PIHA [37] leverages high-level physical semantics to guide local feature learning. Recent advances like EMI-Net [39] and ASC-U2Det [61] further incorporate physical knowledge as supervisory signals, enforcing electromagnetic consistency across detection and classification tasks. This subcategory excels in operational scenarios demanding reliability and generalization, establishing a critical pathway for future SAR target classification.

ii) Complex Domain Modeling: These methods construct complex neural networks to explore the complex characteristics of SAR data, thus improving the discrimination and robustness of target classification. CV-CNN [32] first proposed the complex-valued convolutional neural network to process both amplitude and phase information simultaneously, as shown in Fig. 11 (f). Subsequently, CV-FCNN [192] and MSCVNs [193] further expanded the complex-valued convolutional structure by introducing fully convolutional and multi-scale mechanisms. In recent years, CV-SAR-Det [194] proposed complex-valued

TABLE 6

Performance of representative SAR target classification methods on
MSTAR SOC [23].

Taxonomy	Year	Methods	Open-source	Performance
				(Acc,%)
Tradition	2001	SVM [26]	-	90.00
	2001	Cond Gauss [198]	-	97.18
	2007	AdaBoost [28]	-	92.00
	2014	IGT [199]	-	95.00
	2014	MSRC [200]	-	93.60
Deep learning	2015	MSS [201]	-	96.60
	2016	A-ConvNets [31]	Code	99.13
	2017	VDCNN [202]	-	98.52
	2020	FEC [34]	-	99.59
	2022	SDFNet [203]	-	99.58
	2023	HDANet [204]	Code	99.64
	2025	MMFF [205]	-	99.95

* The data are extracted from the original papers. Given that most existing literature employed inconsistent experimental setups and evaluation metrics, we prioritized methods that use the same training and test sets for comparison. The **best** results are **bold** and underlined, while the second-best are underlined only.

loss functions and data augmentation strategies. FDC-TA-DSN [195] designed four-dimensional dynamic weights to improve anti-noise performance. EMWaveNet [187] constructs an interpretable complex-valued network completely based on physical propagation formulas to promote the development of complex-valued networks toward physical interpretability, as shown in Fig. 11 (g). CRMC-Net [196] and DAF-Net [197] optimized the complex-valued network structure from activation functions and view fusion, respectively. These methods optimize approaches by adapting to distinct target characteristics, emphasizing the intrinsic properties of SAR data at the signal level. It excels in tasks requiring sensitivity to electromagnetic attributes, offering robust theoretical foundations and strong framework extensibility.

4) *Performance and Summary*: We conduct a systematic summary and comparison of the performance of mainstream SAR target classification methods on the classic MSTAR SOC dataset, as shown in TABLE 6. Deep learning methods show distinct overall advantages, with MMFF [205] in particular achieving near-limit classification accuracy. Nevertheless, critical challenges persist: evaluation systems excessively rely on singular accuracy metrics, failing to comprehensively assess model generalization and stability. Inconsistent experimental setups and data processing standards compromise result comparability. And limited code availability severely hinders reproducibility and collective progress. Reported high accuracies primarily reflect dataset-specific optimization rather than practical performance in complex operational environments. Future research should focus on constructing high-quality, multi-scenario, and highly challenging datasets to advance SAR target recognition toward practical applications.

6 RECENT ADVANCES IN SAR ATR

Over the past three years, SAR ATR has experienced remarkable progress, driven primarily by three key aspects: foundation models, limited data and domain adaptation.

6.1 Foundation models

Foundation models [3, 206, 207, 208], pre-trained on extensive data in a task-agnostic manner (generally through self-supervised learning), can be flexibly adapted to a wide range of downstream tasks. Current research for SAR foundation models can be categorized into three aspects distinguished by pretraining strategies and prior embedding mechanisms. In

data-driven general representation learning, SARViT [209] first validated ViT architecture and Masked Autoencoder paradigm in SAR images, adjusting the masking ratio to adapt to the low SAR signal-to-noise ratio (SNR) characteristics. SARATR-X [40] constructed the first foundation model for SAR ATR tasks, using two-stage self-supervised pretraining to suppress speckle noise and enhance structural feature learning. In terms of physical interpretability, Wang *et al.* [210] proposed a complex-valued SAR foundation model embedding Yamaguchi decomposition during pretraining for deep electromagnetic scattering modeling. SUMMIT [211] explicitly embedded denoising, edge reconstruction, and scatterer detection as auxiliary tasks via multi-task self-supervised learning to augment scattering understanding. In multimodal cooperative pretraining, SkySense++ [2] constructed a 21 million sample multimodal remote sensing dataset with representation and semantic enhancement, enabling unified modeling of optical/SAR/multi-temporal data. These works signal SAR ATR's paradigm shift from task-specific models toward foundation model adaptation. However, fundamental challenges persist. First, model architectures remain derivatives of transformers, lacking SAR-specialized backbones. Second, the scale and diversity of pre-training data are still limited. Third, physics integration relies on heuristic designs rather than end-to-end differentiable modeling. In addition, Standardized benchmarks for cross-domain generalization, noise robustness, and interpretability are nascent.

6.2 Limited data

In practical SAR ATR applications, limited data are a key challenge constraining the generalization ability of models. Based on different practical constraints, this problem can be further divided into three interrelated sub-directions: limited quantity, limited category, and limited distribution.

1) *Limited Quantity*: Due to high acquisition costs and lengthy labeling cycles, scarce annotated SAR data severely restricts training sample volume. Compounded by inherent speckle noise, multi-view variations, and polarimetric diversity, this scarcity amplifies intra-class ambiguity and inter-class subtlety, heightening classification difficulty [212]. To address this challenge, Mada-SGD [213] unified weight factors, update factors, and update directions as learnable parameters in the meta-learning framework to improve optimization adaptability. DCBES [214] leveraged density clustering to select representative samples, alleviating the problem of skewed sample distribution. MBEN-BC [215] performed image-level and descriptor-level classification based on Euclidean distance prototypes, as well as local second-order relationships and global distribution divergence, respectively. Moreover, SAR-INR [216] draws on the idea of Neural Radiance Fields (NeRF), combines SAR imaging geometry to implicitly model 3D scattering characteristics, and enhances classification generalization by generating continuous-view images.

2) *Limited Categories*: In real-world scenarios where target categories continuously expand, the traditional closed-world assumption becomes inadequate, necessitating systematic approaches to address the dual challenges of limited known-class adaptation and unknown-class identification. Research in this area can be further divided into class-incremental learning and Open-Set Recognition (OSR).

i) *Class-Incremental Learning*: This direction focuses on the gradual expansion of known categories. Wang *et al.* [217] proposed a pseudo-incremental training strategy and a hybrid distance metric mechanism to alleviate feature confusion between

old and new classes. ACRM [218] achieved continuous learning in the azimuth domain of SAR targets to tackle distribution shifts caused by azimuth angle variations. Kong *et al.* [219] imposed feature orthogonality constraints via the Frobenius norm to reserve embedding space for newly added categories. Li *et al.* [220] further extended incremental learning to detection and fine-grained recognition tasks, introducing scene priors to mitigate the distribution bias of replay samples.

ii) Open-Set Recognition: This direction primarily addresses the discrimination of unseen unknown classes that are not encountered during training [221]. Xiao *et al.* [222] introduced the reciprocal points mechanism, explicitly constructing an unknown space by increasing the distance between known classes and reciprocal points. Gao *et al.* [223] proposed a density estimation method based on neuron activation coverage, avoiding manual threshold setting. GLGE [224] fused ASC and Gabor texture features, estimating joint likelihood via a flow model to reduce misjudgment of targets with similar scattering characteristics. Additionally, Xiao *et al.* [225] proposed an online open-set detection method suitable for airborne SAR, which realizes life-long open-set recognition by maintaining a category prototype queue and adopting cosine margin contrastive learning.

3) Limited Distribution: The predominance of majority-class samples leads to poor model fitting for minority classes and decision boundary bias toward dominant categories [226]. Zhang *et al.* [227] proposed a variance-weighted information entropy loss, which integrates class quantity penalty and image difficulty penalty to alleviate inter-class and intra-class imbalance in long-tail scenarios. Liu *et al.* [228] introduced evidence learning into the detection head, using uncertainty to guide hard sample mining, and proposed tri-cluster contrastive learning to optimize intra-class distribution. SCDQ [229] formulated the imbalanced recognition problem as a Markov decision process and optimized the classifier through an enhanced Q-learning paradigm.

4) Discussion: Research on limited quantity focuses on unlocking data potential through meta-learning and generative augmentation. Limited category studies aim to balance known-class retention and unknown-class discovery in open-world settings, while limited distribution research centers on decision boundary rectification in long-tail scenarios. Despite distinct challenges across these subdomains, they share a unified objective for enhancing model generalization, robustness, and scalability under constrained annotation resources.

6.3 Domain Adaptation

Cross-domain SAR-ATR aims to overcome distribution shifts caused by differences in imaging parameters, sensor configurations, or modalities, while maintaining stable mapping of discriminative features. Traditional methods assume that training and test data are independent and identically distributed, yet the statistical characteristics of SAR images are highly susceptible to perturbations from factors including sensor heterogeneity, simulation-real gap, dynamic changes in resolution and viewing angle, and cross-modal differences. These challenges make global feature alignment difficult, lead to the loss of domain-specific information, and amplify inter-class similarity. Early works relied on discriminators or gradient reversal layers to force feature distribution alignment between the source and target domains [230, 231, 232]. Subsequent researchers decomposed domain differences into interpretable sub-problems, such as scattering topology [233], rotation angle [234], and sub-aperture decomposition [235], and achieved differential compensation through gated fusion [233] or dynamic convolution

[236]. In terms of single-domain generalization, SAFA-MAO [237] adopted multi-gradient descent optimization to endow the model with meta-adaptability to changes in imaging conditions, with its loss function explicitly balancing task performance and domain invariance. CDFS-SAR [238] leveraged pre-trained natural image models and measures foreground-background separation via Brownian Distance Covariance to achieve zero-shot SAR knowledge transfer.

7 CONCLUSION AND OUTLOOKS

In this paper, we present a comprehensive and systemic survey of SAR ATR, covering its background and significance, problem definition, core challenges, general schemes, relations with related problems, datasets, evaluation protocols, and metrics. We focused on the classification and object detection tasks in SAR ATR, summarized the relevant works, analyzed their performance, and summarized the main issues and facts faced by SAR ATR. Its research focus is shifting from single-task, static models and closed environments to intelligent perception systems under multi-modal, multi-platform, multi-task, and open dynamic environments. We attempt to offer valuable insights and discuss potential directions, which are mainly divided into three aspects: ecosystem, methods, and applications.

7.1 Ecosystem: Open-Source Unification

The open-source ecosystem serves as the core foundation for the large-scale development of SAR ATR technology, aiming to address the bottlenecks in current research, including data-sharing barriers, lack of unified evaluation standards, and insufficient reproducibility. This direction focuses on two core tasks: first, constructing high-quality open-source datasets covering multi-scenario and multi-target types, which encompass real-world conditions such as complex terrain, extreme weather, and diverse target morphologies. Second, establishing unified and comprehensive performance evaluation criteria that break free from the limitation of single metrics and integrate multi-dimensional evaluation metrics like miss detection rate, localization accuracy, and small-target adaptability. This ecosystem development significantly reduces research barriers, improves methodological comparability and reproducibility, and accelerates cross-disciplinary innovation between academia and industry for accelerated technology deployment.

7.2 Methods: General Intelligent Perception

1) Universal Representation and Multimodal Fusion

i) Building General Foundation Models: Efforts are focused on breaking the limitations of current domain-specific models tailored for single scenarios (*e.g.*, land, maritime, and aerial domains) to develop cross-domain general foundation models. By integrating multi-domain data features via distributed architectures, these models enable knowledge sharing and transferability, enhancing adaptability to diverse targets. Herein, federated learning, as a key supporting technology, enables multi-institution collaborative model training while protecting data privacy. It avoids the security risks associated with centralized data storage and provides a compliant and efficient pathway for the development of foundation models.

ii) Fine-Grained Recognition: Efforts aim to break through the limitations of traditional coarse-grained classification, achieving accurate recognition of target subtypes and operational states. This requires integrating high-resolution SAR image data, extracting subtle target features via advanced model architectures,

and fusing image processing techniques to enhance the capability of detail representation.

iii) Text-Aided Multimodal Fusion: Efforts focus on constructing multimodal foundation models integrating general and domain-specific knowledge, which combine textual information with SAR images, radar signals, and other data types. Textual semantics, such as target names and type descriptions, can serve as prior knowledge to assist the model in understanding target attributes and contextual relationships in images, enriching the dimensions of feature expression. Meanwhile, textual information can facilitate the generation of intuitive recognition result reports, lowering the decision-making threshold and enhancing the practicality and operability in field deployments.

2) High Trustworthiness and Strong Generalization

i) Triple-Driven Interpretability with Mechanism, Data, and Knowledge: This paradigm embeds the prior knowledge, including SAR imaging principles, target electromagnetic scattering properties, and geometric configurations, into model design and training processes. Physical mechanisms guide feature extraction, reasoning, and decision-making, generating feature representations with clear physical meanings. This thereby ensures a traceable, transparent, and trustworthy decision-making chain.

ii) Complex Scenario Adaptation: Future SAR ATR systems must address the dual challenges of adapting to complex terrains and adversarial environments. In terms of terrain adaptation, they need to accommodate complex scenarios such as dense urban building clusters, forest vegetation occlusion, and strong desert clutter. In terms of adversarial resilience, they must counter malicious attacks including target camouflage, active jamming, and signal spoofing. Research focuses on three key aspects: adversarial robustness enhancement, uncertainty-aware evaluation, and cyber-physical security frameworks.

iii) Unsupervised and Self-Supervised Learning: By designing learning objectives driven by the intrinsic structure of data (e.g., contrastive learning, masked reconstruction), models autonomously mine feature patterns and regularities from raw data, significantly reducing dependence on expert knowledge and annotated datasets. This approach not only lowers development costs but also enhances operational adaptability to novel data distributions and unknown scenarios. However, designing SAR-specific self-supervised tasks that address unique characteristics (e.g., speckle noise, strong sparsity) remains a persistent challenge.

iv) Dynamic Open-World Adaptation: To address the challenges of moving targets, scene dynamics, and unknown categories in real-world environments, systems with dynamic tracking and continuous learning capabilities are being developed. By incorporating technologies such as online learning and incremental learning, models dynamically update target states (e.g., pose, position) while adapting to novel scenes and unidentified targets. Such functionality meets operational demands in dynamic scenarios, including traffic flow monitoring and border surveillance, ensuring sustained high recognition performance in evolving open-world settings.

7.3 Application: Diverse Cooperation and Lightweight Deployment

1) All-Domain Perceptual Collaboration

i) Multi-Payload Collaborative Perception: Centered on SAR as the primary modality, this approach synergizes heterogeneous sensors (e.g., optical, infrared) to overcome inherent limitations of single-payload systems. For instance, texture and color information from optical images can compensate for the lack of detail

in SAR images, while the thermal radiation detection capability of infrared payloads supplements target features in nighttime or low-visibility environments. By merging multimodal data and adopting a decoupling strategy, the unique value of the information from each payload is preserved, and efficient integration of global features is achieved, significantly improving target recognition accuracy in complex environments.

ii) Multi-Platform Collaboration: Integrating SAR sensors deployed across multiple platforms, including space-based satellites, air-based aircraft, and unmanned aerial vehicles (UAVs), forms a collaborative system enabling macro coverage and fine-grained observation. Space-based SAR leverages its advantages of wide coverage and terrain independence to quickly locate potential target areas, while air-based SAR delivers high-resolution and flexible fine-grained imaging and recognition of targets. This collaborative model not only improves target detection efficiency but also ensures that when one platform is interfered with or malfunctions, others can seamlessly take over—guaranteeing mission continuity and stability.

2) Lightweight Edge Deployment

Traditional cloud computing models suffer from high data transmission latency and heavy bandwidth dependence, rendering them inadequate for real-time-critical scenarios (e.g., satellite-ground collaborative detection, UAV emergency response). Edge computing addresses these limitations by offloading partial computing tasks to edge devices such as satellites and UAVs, enabling local data processing and rapid response. Key research includes designing lightweight model architectures, developing efficient inference algorithms and specialized SAR chips, and exploring on-satellite edge computing modes. Moreover, the lightweight architectures are tailored to the limited computing resources of edge devices, while the efficient algorithms and specialized SAR chips help boost processing speed. For on-satellite edge computing, preliminary target detection and screening are completed on satellites, which significantly reduces downlink data volume and enhances system autonomy.

3) Diverse Application Expansion

Building on traditional applications such as target recognition, this initiative deeply explores civilian potentials. In environmental monitoring, it can be used for deforestation tracking, marine pollution monitoring, and glacier change analysis, providing data support for resource management. In disaster assessment, it is capable of quickly identifying the scope of building damage and flood-affected areas, assisting in disaster relief decision-making. In addition, it can be extended to scenarios including traffic monitoring, smart agriculture, and urban planning. With technological advancement and cost reduction, it will provide broader safeguards for social development and livelihood security.

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