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Advancements in Radar Performance through Generative AI: A Sector-Wide Survey

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Abstract – This article presents a comprehensive survey on the integration of Generative Artificial Intelligence (AI) technologies in radar applications, with a focus on enhancing radar data processing and system capabilities. Generative AI techniques, particularly Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), are explored for their potential to address persistent challenges in radar technology such as noise management, data augmentation, and target classification. The study investigates how GANs can generate synthetic radar datasets, aiding in model training when actual data is scarce, and how VAEs contribute to signal processing by denoising and reconstructing accurate radar signals. The analysis includes case studies on clutter suppression, radar data augmentation, beam blockage correction, and data fusion, highlighting the transformative impact of Generative AI on radar systems. This paper aims to provide insights into the current advancements and future directions of Generative AI applications in radar, suggesting that these technologies hold significant promise for improving the accuracy and efficiency of radar systems in diverse and dynamic environments.

Keywords – Radar, GAN, VAE, SAR, ATR, Clutter Suppression, Denoising, Beam Blockage

I. INTRODUCTION

The main purpose of radar (Radio Detection and Ranging) technology, which has become an indispensable tool in various fields such as aviation, maritime, weather forecasting, and defense, is to identify the distance and properties of distant objects [1]. This technology, which works by transmitting electromagnetic energy and interpreting the echoes that bounce back from objects, facilitates the detection of the locations, movements, and even material compositions of objects. Despite its extensive applications and ongoing advancements, it constantly faces challenges such as coping with noisy environments and clutter and accurately classifying targets under changing conditions [2]. These challenges are compounded by the need for radars to adapt their functionalities dynamically to complex environments and diverse application requirements.

Generative AI is a branch of AI that enables computers to synthesize realistic images, text, and other media. Generative AI focuses on mimicking real content and getting a sense of the real datasets. Thus, generally, rich and quality datasets are needed for Generative AI models to work efficiently. In the following two paragraphs, the two most well-known models, GANs and VAEs, are explained briefly.

In 2014, Goodfellow et al. [3] introduced a Generative AI model that consists of two networks that work adversarially in their process, namely GANs. These networks, generator and discriminator, try to generate synthetic data gaining inspiration of the given dataset. The aim of the generator is to generate most realistic data that the discriminator indiscriminate between the generated data between sample dataset. In every iteration, the generator gets feedback from the discriminator, and tries to enhance its work.

Another model of Generative AI is VAE. In this model, VAEs encode data into a lower-dimensional latent space representing a probability distribution from which new data points can be generated. This encoding process involves transforming the high-dimensional data into a lower-dimensional but meaningful latent representation. The decoder part of a VAE then works to reconstruct the input data from this latent space, ensuring that the output closely mimics the original input. Unlike GANs, VAEs focus on reconstructing data and ensuring the smoothness of the latent space, which allows for the generation of diverse and realistic outputs [4].

By improving data analysis and simulation capabilities, Generative AI can significantly improve Radar applications. For instance, GANs can be employed to generate synthetic radar data, which is particularly useful for training machine learning models when actual radar data is scarce or too costly to obtain. Like GAN models, the studies that get help from VAEs in Radar applications also analyzed in this paper. For example, VAEs can be used for radar signal processing, where they help in denoising and reconstructing signals from noisy radar data, thus enhancing the clarity and reliability of the detection systems. Thus, this paper analyses previous studies about Clutter Suppression, Radar Data Augmentation, Denoising and Beam Blockage Correction, Data Fusion and Recognition in *Related Work* section, and suggests that Generative AI could improve radar applications.

II. PREVIOUS WORK

Generative AI, particularly GANs, has emerged as a transformative solution to the challenges faced by traditional radar methods in managing and analyzing complex data [5]. These challenges include difficulties in understanding large and noisy datasets, hampering processes such as recognition, clutter suppression, and classification of objects. In the dynamic and unpredictable radar environment, these limitations significantly impact system accuracy and effectiveness [6]. However, with generative AI, including GANs, there's a newfound capability for data augmentation, clutter suppression, and image resolution enhancement. These advancements are not merely theoretical concepts; they address critical needs in navigation, weather forecasting, and defense applications.

This section aims to delve into the diverse methods employed, the contexts of their application, and their resultant outcomes. By exploring the innovative applications of Generative AI in extracting enhanced value from radar signals, improvements in detection and classification tasks are evident. Moreover, these advancements lay the groundwork for future exploration, indicating potential directions for radar technology. Through this discussion, we aim to elucidate the current state-of-the-art in Generative AI for radar applications, shedding light on existing methodologies and their prospects for refinement.

A. Clutter Suppression and Classification

The subcategory *Clutter Suppression and Classification* plays a crucial role in the improvement of target detection accuracy. The effective distinction between the targets and foreign reflections is achieved by the reduction of unwanted inference.

Zhang, X. *et al* [7]., aimed to improve the sea-land clutter classification in OTHR systems. In the article, a GAN-based approach was used with some modifications. The authors decided to use a Weighted Loss Semi-Supervised GAN (WL-SSGAN) to improve the classification performance through the effective usage of unlabeled data as well as labeled data. The results of the article show that WL-SSGAN has provided a better classification for a dataset with 1200 labeled and 2100 unlabeled data with an accuracy of 98.90%. The approach makes better use of unlabeled data with a comparison of other classification methods, such as k-nearest neighbors (KNNs) or supply vector machine (SVMs), and represents a future use for a similar problem with highly unlabeled data.

With a similar aim Pei, J. *et al.* [8] proposed a cycleGAN-based method to improve clutter suppression and target detection performance for marine surveillance radars. Researchers decided to use GAN with a machine-learning-based approach to improve the training process and adaptability of the model. The results show that the performance of the radar was increased with a higher σ (15.52) and structural similarity index measure (SSIM) (0.63) values than a cycleGAN (σ= 12.7 and SSIM = 0.37) without a machine-learning approach. The article enlightens the clutter suppression and classification problem for future works with a novel approach.

Another study by Wu, Y. *et al.* [9] with a complex-valued self-attention model named CV-SAGAN. Generative AI was used to improve the processing of complex radar signals and clutter suppression. The model is self-attention to be able to accurately detect -especially low-intensity- targets. It was stated in the article that the model has a higher detection rate (by 3%) and a lower false alarm rate (FAR) (about 50% of RV-SAGAN), which shows a more successful result than RV-SAGAN (real-valued SAGAN) models. The model is also applicable to over-the-horizon radar (OTHR) systems and contains valuable information for future applications.

Lastly, Mou, X. *et al.* [10] use Generative AI for its ability to learn the complexity of the clutter and the potential to produce clear images. The proposed method is SCS-GAN (sea-clutter suppression GAN), with a residual attention generator and a sea-clutter discriminator. It is used for clutter suppression in PPI (plan-position indicator) and improving the visibility of targets. The results of the article show that SCS-GAN can have fast decluttering and strong generalization ability with a higher CSR (clutter suppression ratio). Generalization ability is quite important for the model to work in various sea states. Therefore, it is thought that this study may inspire future studies on sea clutter suppression and PPI image improvements.

All articles have used Generative AI for clutter suppression and classification but with varying proposed methods. However, the use of GANs is a common theme. An obvious fact is that every algorithm has its advantages and limitations, which can be seen in Table 1.

Table 1. The Advantages and Limitations of the Proposed Methods for Clutter Suppression and Classification

Method	Advantages	Limitations
WL-SSGAN	Effective use of unlabeled data	Complexity of computation and the need for more test data in real-world scenarios
cycleGAN	Increment in potential target detection	The constraints of machine-learning structure and model not being tested on different sea-states
CV-SAGAN	Innovative approach for complex-valued radar signals	Complexity of computational cost and the need for more test data for real-world scenarios
SCS-GAN	Fast decluttering with generalization ability	Complexity of the structure

From Table 1, it can be seen that the limitations across these studies often involve computational complexity and adaptability to real-world scenarios. Therefore, future research can focus on improving the adaptability of these methods, considering the unpredictable nature of radar environments.

B. Radar Data Augmentation

Radar Data Augmentation and its applications enables radar technology to be used effectively in a wider range of different applications by augmenting radar data. This data can be used in specific contexts later, which helps the radar produce more information, reduce noise, and increase data augmentation.

The research by Scholz, D. *et al.* [11] aims to solve the problem of insufficient radar data for applications. The paper learns radar data using a VAE and shows the impact of increasing the dataset by generating new and realistic examples from this data. The results show that VAE can provide effective data augmentation by improving the generalization ability of classifiers. However, the accuracy of the model depends on the dataset but remains above 90% for the Infineon Gestures dataset and for the Soli dataset at 88.09% which authors suggest is because the set has fewer samples and more classes.

In another research, Fidelis, E. *et al.* [12] aim to generate synthetic radar data using GANs for autonomous driving applications, which is different than every other article's field mentioned in this paper. The proposed GAN method aims to improve driverless vehicle technologies by making it easier to generate radar data that is difficult or dangerous in the real world. The Fréchet inception distance (FID) score between the generated data and the test data is 0.51, which is close to the score between the training and test data. These values suggest that the generated data is realistic and not copied from the training data. In the future, this method could help improve driver-assistance systems in different fields, including military applications.

Park, S. *et al*. [13] introduced an AI-assisted method to augment radar data to improve Unmanned Aerial Vehicle (UAV) classification. This study produces synthetic Range-Doppler (RD) maps using cGAN. These synthetic maps increase the performance of UAV classification by increasing the training data of the deep convolutional neural network (CNN) classifier. The results show that using synthetic RD map data improves the classification performance of the trained classifier with the best accuracy of 90.91%. In addition to providing an effective solution to the problem of data insufficiency in radar applications, it has potential for other areas of radar technologies with similar data limitations.

Kim, Y. and Hong, S. [14] present a CGAN-based model for very short-term rainfall prediction using ground radar observations. The method aims to enhance rainfall forecasting from 10 minutes to 4 hours, utilizing the Korea Meteorological Administration's CAPPI data for training and validation. The model demonstrates promising results, with high statistical scores indicating effective rainfall prediction, which could complement existing forecasting systems. This approach represents a novel application of CGAN in radar meteorology, showcasing potential improvements in short-term rainfall prediction accuracy and offering a valuable tool for real-time weather monitoring and disaster prevention. For a prediction time of 1 hour, the Probability of Detection (POD) is 0.8442, the FAR is 0.2913, and the Critical Success Index (CSI) is 0.6268. These results suggest that the CGAN model is effective in predicting short-term rainfall with considerable accuracy, demonstrating its potential utility for enhancing existing meteorological forecasting systems.

Similarly to the preceding subcategory, the methodologies within this category exhibit their respective advantages and limitations, as delineated in Table 2.

Table 2. The Advantages and Limitations of the Proposed Methods for Radar Data Augmentation

Method	Advantages	Limitations
VAE	Generation of realistic data	Effectiveness depends on the quality of learned latent space
GAN	Efficient generation of diverse radar data in safety-critical scenarios	Effectiveness depends on the quality of training data
cGAN for Range-Doppler Map	Augmentation for a limited dataset	Effectiveness depends on the quality of training data
cGAN for Rainfall Prediction	Demonstrates high accuracy in short-term forecasts with potential to complement existing systems.	Prediction effectiveness may diminish beyond the very short-term range due to inherent model and data limitations.

As presented in Table 2, the efficacy of data augmentation methodologies is intrinsically dependent to the quality of the training datasets. A sensible selection of high-quality data is pivotal to optimizing the performance of these augmentation techniques, particularly in scenarios where accessing data is limited.

C. Denoising and Beam Blockage Correction

This subcategory establishes a critical component that improves the performance and accuracy of radar systems. It enables radar signals and radar data to be more reliable and precise. This is particularly critical for accurate target detection and identification.

For the discussed purpose Tan., S. *et al.* [15] used a cGAN-based method to remove beam occluding in weather radar data. The challenges of data limitations and poor quality in radar observations made this paper necessary. The proposed method has the potential to increase the reliability of radar data for meteorological studies and weather forecasts. The results show that, over the traditional methods, the CGAN restores precipitation observations more consistently for two different datasets, KDAX and KFSW. Also, the radar data has been accurately recovered with high True Positive (TP), False Negative (FN), True Negative (TN), and low False Positive (FP) rates, while the Mean Absolute Error (MAE) remains significantly low, indicating that the method's predictions closely match the ground truth. Therefore, it has great potential for application in the future to improve and increase the reliability of weather radar data in complex terrain regions.

With a similar purpose, Armanious, K. *et al.*, [16] the GAN method is proposed for noise removal to clean radar micro-Doppler (μ-D) signatures. This work stands out because it uses GANs to overcome the limitations of traditional cleaning methods. The results obtained show that the GAN-based approach is more effective than traditional methods and plays an important role in radar-based human activity recognition with SSIM = 0.7231 surpasses other methods, indicating superior image structure preservation post-denoising and Peak Signal-to-Noise Ratio (PSNR) of 10.54 dB, it offers higher signal reconstruction quality.

As the last research in this area, Kumar, A. S. and Kalyani, S. [17] introduce a two-stage neural network that enhances radar sensing capabilities under noisy conditions using orthogonal time frequency space signaling. The methodology employs a CNN to classify noise levels followed by a GAN for denoising, achieving significant reductions in mean absolute error even at low signal-to-noise ratio (SNR) values, thereby addressing a critical challenge in practical radar applications. The approach demonstrates a MAE of 0.68 in the Delay Doppler domain, achieving impressive clarity in signals with an SNR as low as -20 dB. This novel approach underscores the adaptability of Generative AI in optimizing radar signal processing and paves the way for improved detection and surveillance operations.

The limitations and advantages of the methods used in various studies can be seen in Table 3.

Table 3. The Advantages and Limitations of the Proposed Methods for Denoising and Beam Blockage Correction

Method	Advantages	Limitations
cGAN for correcting blockage	Effective restoration of blocked radar data	Quality of restoration depends on the training data
cGAN for μ-D signatures	Adaptive and generalizable approach to denoising	Effectiveness depends on the quality of training data
GAN for denoising	Effective denoising in low SNR environments and accurate noise level classification	Effectiveness depends on tthe quality of training data

Table 3 presents a summary of GAN methods for radar data restoration and noise reduction. It highlights cGAN's effective restoration of blocked radar data, the adaptability of cGAN for micro-Doppler signatures, and the efficiency of GAN in denoising signals in low SNR conditions. A common limitation across these methods is their dependency on the quality of the training data, which is a determining factor for their performance.

D. Data Fusion and Recognition

Data fusion and recognition in radar systems represent the cutting-edge intersection of signal processing and artificial intelligence. This segment explores the synthesis of data from multiple sensors to achieve more accurate and comprehensive environmental recognition.

Ebel, P. *et al.*, [18] focused on overcoming the challenge of cloud cover in optical satellite images and for this reason, they suggested a multi-sensor data fusion approach using a cycle-consistent GAN. The main goal is to develop a cloud removal method to clear areas covered by clouds and use these clear images in many applications, such as environmental monitoring, agriculture, urban planning, and disaster response. By integrating synthetic aperture radar (SAR) data into optical data, the model improves image quality while effectively removing clouds using the SEN12MS-CR dataset and can be used in a variety of applications in the future.

Another study published by Guo, Y. *et al.* [19] suggest GAN for SAR automatic target recognition (ATR). It offers an advanced approach to noise removal for ATR. This research aims to improve noise robustness in SAR ATR and contributes to potential applications for accurate target recognition in high-noise environments. On the MSTAR dataset, the proposed method achieves the highest accuracy of 91.38% and the lowest accuracy of 78.05%. On the Gotcha dataset, the proposed method achieves the highest accuracy of 99.17% and the lowest accuracy of 94.17%.

The research [20] by Xiong, H. *et al.* aims to deal with the limited number of instances of ground penetrating radar (GPR) error data by using GANs. The proposed method will be used for GPR data generation. This study aims to generate and improve GPR error data in a challenging field due to limited samples. GPR-GAN is a method that can generate complex GPR error data using an adaptive network structure. The method helps enable training with small datasets and also improves error detection performance. This technique has great potential in applications where precise GPR data is difficult to obtain, such as non-structural testing and similar areas for military or surveillance purposes.

Lastly, Zheng, C. *et al.* [21] introduce a semi-supervised approach for SAR ATR, similar to the article Robust SAR Automatic Target Recognition Via Adversarial Learning. The approach is a bit different since it is using a multi-discriminator GAN (MGAN). The primary goal is to improve the recognition performance of CNN in SAR ATR. The method is particularly useful when dealing with limited labeled sample images. The results of the article show significant improvements in recognition accuracy. This approach has potential in both military and civilian fields, especially in scenarios where collecting extensive labeled SAR data is challenging.

Every method mentioned under this subcategory is constructed into Table 4 for a better understanding of their advantages and limitations in the field.

Table 4. The Advantages and Limitations of the Proposed Methods for Denoising and Beam Blockage Correction

Method	Advantages	Limitations
cycle-consistent GAN	Effective in removing clouds from optical imagery	Effectiveness depends on the quality of SAR data
GAN for ATR	Offers an adaptive and effective solution for denoising in SAR ATR	Effectiveness depends on the quality of training data
GPR-GAN	Tailored for GPR data generation and adaptable to various GPR tasks	Effectiveness depends on the quality of training data
MGAN for Semi-Supervised SAR Target Recognition	Improved recognition accuracy in SAR ATR	Effectiveness depends on the quality of training data

Table 4 shows a range of GAN methods used for radar data processing challenges. It features the cycle-consistent GAN for removing cloud obstructions, a GAN designed for denoising in SAR ATR, and GPR-GAN, which is customized for generating GPR data. Additionally, MGAN is spotlighted for its enhanced recognition accuracy in semi-supervised SAR ATR tasks. A recurrent theme is the dependency of these methods' effectiveness on the quality of the training data provided.

III. METHODOLOGY

The methodology section of our paper will outline the strategic framework applied to evaluate the efficiency and applications of Generative AI techniques in radar systems. The roadmap in Fig. 1 encapsulates the logical flow of the paper, from reviewing Generative AI technologies to observing their strengths and unique attributes. Subsequent sections will delve into the constraints and considerations of these techniques, setting the stage for analyzing their performance outcomes.

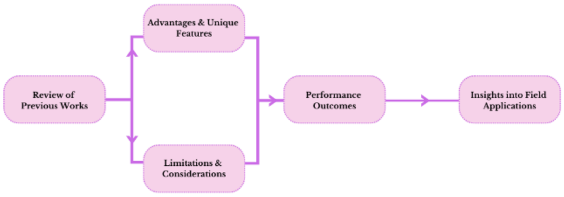

Fig. 1 A criteria flowchart for comparative analysis.

The flowchart above in Fig. 1 illustrates our approach to our analysis, beginning with a thorough review of existing Generative AI Technologies by their core strengths and features for greater insight into their potential. At the same time, however, it's essential to acknowledge any limitations or practical concerns with proposed methods; finally, the paper will transition into offering insight into field applications that connect Generative AI's capabilities directly with its real-world consequences as part of an exhaustive analysis.

IV. RESULTS

In this section, the trends arising from Generative AI methods applied to radar technology will be analyzed and interpreted. With respect to our methodology, the findings from reviews of previous works will be synthesized with highlighted limitations of the methods. Therefore, the adaptability of these methods to overcome blockages and improve data augmentations will be discussed. Our discussion also extends beyond the general trends and their limitations. Within each category, insights to fill the current gaps will be offered.

A. Clutter Suppression and Classification

Trending Methods in Current Studies: Recent studies in clutter classification and suppression demonstrate an increasing use of GANs. Notably, Zhang, X. et al. [7] utilized WL-SSGAN to improve sea-land clutter classification for OTHR systems while Pei, J. et al. [8] implemented cycleGAN-based techniques for marine surveillance radars to increase clutter suppression and target detection capabilities. Wu, Y. et al. [9] created CV-SAGAN to process complex radar signals more efficiently so they could improve clutter suppression, while Mou X.et al [10] used SCS-GAN equipped with Residual Attention Generator and Sea-Clutter Discriminator for sea clutter suppression within PPI radar images.

Conflicts and Limitations of Methods: While the advantages of methods were evident and outshone traditional approaches, there were also limitations and conflicts to take into account. Complex GAN models with their high computational costs as well as the need for large and quality datasets highlighted some points to keep in mind when applying these methodologies to real-life situations. These considerations must be kept in mind in order to make these approaches as useful as possible in real-life settings.

Gaps and Future Directions: As previously discussed, radar clutter suppression with Generative AI methods reveals gaps in terms of computational efficiency and model complexity, so addressing them in current studies is critical for improving clutter suppression and classification techniques. Future research directions could involve creating GANs with reduced computational needs as well as enhanced adaptability to different operational conditions so they can more reliably and conveniently be used in real-world applications.

B. Radar Data Augmentation

Trending Methods in Current Studies: Trending methods used for radar data augmentation include GANs, as well as VAEs and Conditional GANs. Techniques such as these being implemented by researchers like Scholz D *et al.* [11] and Park S. *et al.* [13] are being utilized to enhance data sets to enhance accuracy and functionality across applications from gesture recognition to UAV classification.

Conflicts and Limitations of Methods: One major limitation to AI models lies in their reliance on quality training data, as evidenced in various studies such as [12] and [14]. Another drawback concerns how well these models generalize to new, unexpected scenarios; emphasis should be placed on providing realistic, diverse, and robust datasets as input to these models.

Gaps and Future Directions: In terms of future directions for radar data augmentation, it will involve improving computational efficiencies and creating high-fidelity training datasets. Addressing any existing gaps could allow for wider application and adaptability across real world situations, potentially revolutionizing areas such as meteorology and autonomous vehicle technology.

C. Denoising and Beam Blockage Correction

Trending Methods in Current Studies: Radar signal processing has increasingly relied on cGAN-based techniques to improve data accuracy and reliability. Studies by Tan, S. *et al.* [15], Armanious K *et al.* [16], Kumar AS and Kalyani S [17] among others have used such approaches to remove beam blockage/noise, improve radar data under noisy conditions or enhance it during times of low signal/noise conditions. These studies demonstrate an increasing reliance on GANs to address specific challenges related to clarity and precision issues with radar signals.

Conflicts and Limitations: Across these studies, one common limitation has been their dependence on training data quality. While cGANs can significantly enhance radar data processing, their performance can often be limited by available and diverse training datasets they are provided with.

Gaps and Future Directions: Future research should seek to reduce the data dependency of current models through unsupervised learning or advanced data augmentation techniques, creating more robust operational environments as well as handling any scarcity issues in the field. Bridging these gaps may result in models capable of handling both.

D. Data Fusion and Recognition.

Trending Methods in Current Studies: Recent advancements in radar data processing reveal an emerging trend toward using GANs for data fusion. Researches [18], [19], [20], and [21] have documented this development, showing it as cycle-consistent GANs for atmospheric interference removal and multi-discriminator GANs for improved SAR ATR accuracy being adopted to enhance image resolution and contrast within radar systems.

Conflicts and Limitations of Methods: Although GANs offer significant advantages in radar imaging, their implementation poses unique obstacles. Computational requirements and the need for high-quality training data often impede their scalability and efficiency; further contributing to an imbalance between their potential use in wide scale deployment.

Gaps and Future Directions: GANs have proven an ideal platform for radar data fusion, yet gaps remain when applied to technologies. Computational efficiency improvement as well as adaptability improvements will play a pivotal role in further advancement. Innovative solutions which bridge these gaps offer great promise to expanding both reliability and application scope of radar imaging technologies.

V. DISCUSSION

The introduction of Generative AI to radar technology has revolutionized the way we analyze and interpret signals. Our investigation has shown a shift away from traditional approaches towards AI-driven methods, using GANs in particular. GAN models are able to meet the high accuracy and fidelity requirements of complex radar environments.

Generative AI implementation in radar systems has yielded tangible advantages, such as reduced false alarms and enhanced detection accuracy, as well as improved performance under low SNR conditions. But even though Generative AI has proven its worth, there remain challenges - for instance when data are difficult or scarce, relying on high-quality training data may present difficulties; additionally, training and deployment of complex models places significant computational demands on real-time applications.

Future success of Generative AI applications depends on meeting these challenges head-on. Research should aim at increasing efficiency and accessibility while refining existing techniques; furthermore, efforts should explore methods for reducing computational burden by expanding generalization with limited data or using unsupervised training methods that do not depend on large labeled databases; new approaches will likely emerge as radar technology advances which may become standard practices or help expand Generative AI further to unlock its full potential, innovation and collaboration are key.

VI. CONCLUSION

GANs have revolutionized radar technology. By applying Generative AI models - especially GANs - these advancements have outshone traditional approaches, successfully overcoming challenges associated with clutter suppression, data augmentation, and data fusion applications. Though their success depends on the availability of quality training data, Generative AI applications show promise as future research solutions in radar. The field stands ready to improve the efficiency and applicability of AI models for further research purposes.

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