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Generative Adversarial Networks in Medical Imaging: A Review of Emerging Trends and Insights

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Abstract*—Generative Adversarial Networks (GANs) are increasingly applied in biomedical imaging for realistic image synthesis, enhancement, and modality translation. Despite rapid progress, challenges persist in preserving anatomical accuracy, standardizing evaluation, and achieving reliable clinical integration. This review examines recent GAN-based studies, identifying their architectures, applications, datasets, evaluation methods, strengths, and limitations. The main contribution is a comprehensive synthesis of GAN models across biomedical domains, outlining trends, performance metrics, and research gaps for future exploration. A structured literature review was conducted, analyzing peer-reviewed studies that met predefined inclusion criteria. From the screened records, 66 articles satisfied the eligibility criteria for final inclusion. Data extraction covered GAN types, biomedical applications, dataset characteristics, evaluation metrics, strengths, and limitations. Applications were categorized, and architectures compared to identify thematic and performance patterns. Results indicate research concentration in Medical Physics & Reconstruction and Cancer Imaging & Diagnosis. Advanced models such as StyleGAN, PGGAN, and CycleGAN deliver superior image realism and enhance downstream performance. Frequently used datasets include CBIS-DDSM, ChestX-ray14, BraTS, and OAI. Evaluation relies on SSIM, PSNR, and FID, complemented by clinical metrics such as Dice and AUC. Strengths include improved image quality, diagnostic accuracy gains via augmentation, and adaptability to diverse imaging modalities. Limitations involve dataset dependency, anatomical inaccuracies, training instability, high computational demands, and insufficient clinical validation. In conclusion, GANs show strong potential for biomedical imaging, but advancements are needed to enhance anatomical fidelity, create standardized evaluation protocols, and address ethical considerations to ensure safe clinical deployment.

***Keywords*—GANs; Biomedical Imaging; Image Synthesis; Deep Learning; Medical Image Analysis**

I. INTRODUCTION

The rapid advancements in medical imaging have significantly transformed diagnostic practices, enabling the precise and early detection of a wide array of diseases [1]. Despite the impressive capabilities of conventional imaging techniques, significant challenges remain in achieving high accuracy and reliability, particularly when distinguishing subtle patterns in complex medical data [2]. These challenges are further exacerbated by the limitations of available datasets, high variability in image quality, and the need for specialized models that can handle diverse imaging formats [3]. For example, in fields like oncology, radiology, and neurology, traditional imaging techniques often struggle with issues such as incorrect identifications, low resolution, and challenges in recognizing early-stage abnormalities [4]. These issues underscore the need for innovative methods that improve the analysis of medical images, particularly in automating interpretation and enhancing diagnostic accuracy [5]. GANs have emerged as a potentially effective approach to these challenges, particularly in the realm of medical imaging. With their unique architecture, comprising a generator and a discriminator, GANs have shown significant potential in generating realistic medical images, augmenting datasets, and improving image quality [6]. The key strength of GANs rests in their capacity to generate high-quality artificially generated visuals that closely resemble real medical data, offering a valuable solution in situations where access to large annotated datasets is limited [7]. GANs have been applied to a variety of applications including enhancing image resolution, reducing noise, partitioning images, and translating across imaging modalities, all of which contribute to enhancing the accuracy and robustness of diagnostic systems [8].

Over the past few years, the incorporation of GANs within the medical imaging domain has received considerable attention, with numerous studies demonstrating their ability to improve diagnostic outcomes across various applications [9]. One of the most notable contributions has been in the detection of cancer, where GAN-enhanced types of imaging techniques including mammograms, CT scans, and MRI scans have shown substantial improvements in classification accuracy [10]. GANs have also been effectively applied in dermatology, where they help generate synthetic images for skin cancer detection, as well as in radiology and histopathology, where they have enhanced the quality of diagnostic images allowing for better feature extraction and more accurate detection of abnormalities [11]. These successes underscore the versatility and potential of GANs in diverse medical fields. The contribution of this review aims to deliver an in-depth examination of the emerging trends in

GANs for medical imaging, with a particular emphasis on their applications, benefits, along with challenges. This review will examine various GAN architectures, such as DCGAN, CycleGAN, and StyleGAN, and their applications in medical imaging, including data augmentation, image reconstruction, and modality translation. We will also discuss the evaluation metrics frequently applied within GAN-based clinical imaging research, such as SSIM, PSNR, and FID, and how these indicators serve to evaluate the quality and applicability of generated visual outputs in clinical settings.

Furthermore, this review will highlight the novel contributions of GAN-based techniques in overcoming the limitations of traditional medical imaging approaches. Specifically, we will discuss how GANs can produce artificial datasets of superior quality, offering a remedy for the challenge of limited data availability in healthcare imaging. Additionally, we will explore the potential for GANs to handle various imaging modalities and the possibility of creating generalized models that can be applied across different medical disciplines. Through this analysis, we seek to provide a detailed understanding of the present forefront of GAN applications in clinical imaging, with emphasis on obstacles, advancements, and forthcoming directions in this rapidly evolving field.

II. METHODOLOGY

A. Eligibility Criteria

To ensure a focused and comprehensive review of the latest developments, this study adopted a clearly defined set of eligibility criteria for selecting relevant literature. Articles were sourced exclusively from the ScienceDirect, IEEE Xplore, SpringerLink, and Wiley databases, which were chosen for its extensive and reliable coverage of peer-reviewed publications in the fields of medical technology and artificial intelligence. The search strategy was based on the use of specific keywords related to GANs and their applications in medical imaging. These keywords included terms such as “Generative Adversarial Network”, “GAN”, “medical imaging”, and additional terms like “trends”, “applications”, and “current insights” to target publications focused on the use of GANs in medical imaging contexts. The search was restricted to publications from the past three years (2022–2024) to ensure the inclusion of recent advancements and emerging trends in the field.

Additional inclusion criteria required that articles be available in full text, written in English, and directly related to the biomedical applications of GANs in imaging modalities such as radiology, histopathology, or other diagnostic domains. This review included only original research articles that presented technical implementations, methodological advancements, or clinical implications of GAN-based approaches in medical imaging. Review articles, editorials, conference abstracts, and non-peer-reviewed materials were excluded. Studies were also excluded if they focused on non-medical domains, did not employ GAN-based techniques, or lacked sufficient methodological or experimental detail. This rigorous filtering process was intended to ensure that the final set of included studies provided robust empirical evidence and meaningful insights into the evolving role of GANs in medical imaging.

B. Information Sources

The ScienceDirect, IEEE Xplore, SpringerLink, and Wiley databases were electronically searched for eligible studies. The search was conducted for publications published between January 2022 and December 2024, focusing on articles that utilized specific keywords related to GANs and their applications in medical imaging.

C. Search Strategy

The search for relevant studies was conducted using a carefully crafted search query to ensure the identification of comprehensive and up-to-date literature. The query employed was ("Generative Adversarial Network" OR "GAN") AND ("medical imaging") AND ("trends" OR "applications" OR "current insights"). This search string was specifically designed to capture a wide array of research articles that focus on the use of Generative Adversarial Networks (GANs) within the domain of medical imaging. The terms "Generative Adversarial Network" and "GAN" were included to ensure that the search encompassed all publications related to GAN technologies, including those using the abbreviation “GAN”. By incorporating the keyword "medical imaging", the search was further refined to focus on studies that apply GANs in various diagnostic imaging techniques, such as radiology, histopathology, and other medical imaging fields.

To ensure the query captured the most current and relevant studies, additional keywords like “trends”, “applications”, and “current insights” were used. These terms were specifically chosen to target publications that explore the evolving and cutting-edge uses of GANs, ensuring that only studies that present current advancements, emerging applications, and state-of-the-art insights in GAN-based medical imaging were included. This strategic approach in the search query helped narrow down the articles to those that not only employed GANs in medical imaging but also discussed new trends and innovations within the field, ensuring the inclusion of the most relevant and recent research on the topic.

D. Study Selection and Quality Assessment

The procedure for selecting studies incorporated in this review followed a structured approach to guarantee that only pertinent and rigorous research was taken into account. The first stage involved assessing the title of each identified article. Articles were screened for their relevance to the topic of GANs within clinical imaging. If the title clearly indicated a focus on the application, methodology, or impact of GANs within clinical imaging, it proceeded to the next step in the selection process. If the title appeared unrelated to the subject or lacked clarity regarding the use of GANs, the article was excluded from further consideration.

Following the title assessment, the next step was to review the abstract and keywords of each article. The abstract provided an initial overview of the study's objectives, methods, and conclusions. During this phase, particular attention was given to ensuring that the study specifically addressed the application of GANs in medical imaging. Articles whose abstracts mentioned GANs applied to imaging modalities such as radiology, histopathology, or other diagnostic imaging fields were included. Keywords were also evaluated to confirm that they were aligned with the scope of the review, focusing on relevant terms such as "GAN", "medical imaging", "applications", and "trends". If the abstract and keywords suggested a mismatch with the review's scope, the article was excluded.

The final phase in the study selection involved analyzing the full text of the articles that passed the previous stages. This step was critical to assess the depth of the study's methodology, experimental design, and overall relevance. Only original research articles that employed GAN-based methods and provided sufficient empirical data were included in the review. Articles were evaluated for their methodological rigor, including the clarity of the study design, the reliability of the findings, and the soundness of the evaluation. Studies lacking detailed methodology, statistical analysis, or those not contributing substantial insights into the uses of GANs within clinical imaging were excluded at this stage. By thoroughly analyzing the full text, the review ensured that only studies with a strong scientific foundation and relevance to the research question were selected to be incorporated.

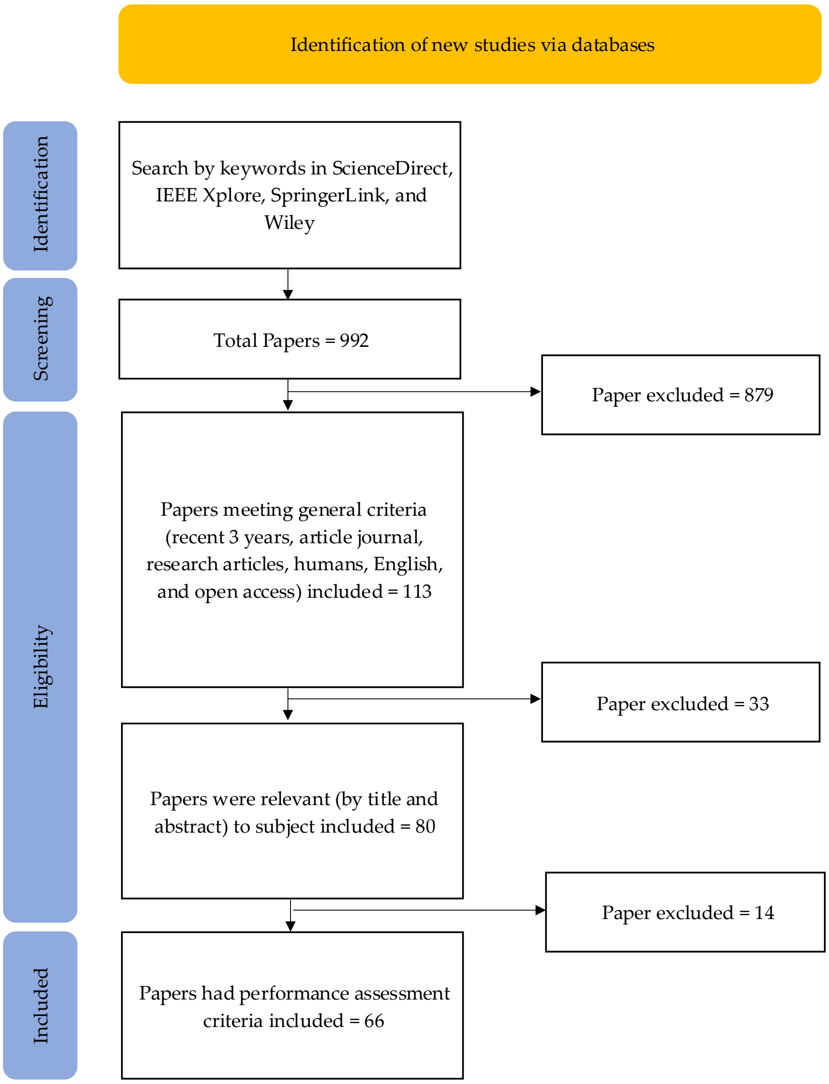

Fig. 1. PRISMA flow diagram of study selection.

TABLE I. SELECTED PAPERS ACCORDING TO THE SPECIFIED CRITERIA

Ref	Author & Year	GAN Type	Biomedical Application	Dataset	Evaluation Method
[12]	Yamazaki et al., 2022	CR-GAN	Mammogram Synthesis, Breast Cancer	CBIS-DDSM, INBreast, CMMD	PSNR, SSIM, FID, MS-SSIM, Cos_sim
[13]	Karar et al., 2022	Semi-Supervised GAN, AC-GAN	COVID-19 Diagnosis (Ultrasound)	Public Lung US POCUS Dataset	Accuracy, Precision, Recall, Specificity, F1-score
[14]	Zhang et al., 2022	SOUP-GAN	MRI Super-resolution	T1 MRI, T2-FLAIR MRI, CT	PSNR, SSIM, RMSE, FID, Perceptual Loss
[15]	Toda et al., 2022	StyleGAN	Lung Cancer, Tumor Imaging	CT (private)	PSNR, SSIM, FID, LPIPS
[16]	Liu et al., 2022	SSGAN	Chest X-ray, Histopathology	ChestX-ray14, BreakHis	Accuracy, F1-Score, AUC, Sensitivity, Specificity
[17]	Ali et al., 2022	3D CycleGAN	Skeletal Muscle Contraction Dynamics	Simulated + Experimental	DBhat, Correlation, SSIM, Temporal Consistency

Ref	Author & Year	GAN Type	Biomedical Application	Dataset	Evaluation Method
[18]	Khaled et al., 2022	Multi-stage GAN	Brain Segmentation	MICCAI iSEG, MRBrainS 2013	Dice Coefficient, Computational Time, Accuracy
[19]	Guo et al., 2022	Physics-assisted GAN	X-ray Tomography	Synthetic CircuitFaker	BER, SSIM, MSE, FID
[20]	Qu et al., 2022	cGAN	Collaborative Learning, Federated Learning	Diabetic Retinopathy, Bone Age	Accuracy, AUC, MAE, Dice
[21]	Sun et al., 2022	HA-GAN	3D Image Synthesis (CT, MRI)	COPDGene, GSP	FID, MMD, IS, t-test, R^2
[22]	Gan et al., 2022	HieGAN	Knee Imaging, Osteoarthritis	OAI dataset	AM Score, Mode Score, MAE, WD, FID, IS
[23]	Liang et al., 2022	Ad CycleGAN	COVID-19 X-ray Image Synthesis	Kaggle COVID-19	MSE, RMSE, PSNR, FID, UIQI, VIF, Accuracy
[24]	Shah et al., 2022	cGAN	Forearm Vein Segmentation	NIR dataset	Sensitivity, Specificity, Accuracy, Dice, AUC
[25]	Salvia et al., 2022	DCGAN	Skin Cancer Diagnosis (Hyperspectral)	Hyperspectral Skin Cancer Dataset	FID, Accuracy, Precision, Recall, F1
[26]	Waqas et al., 2022	PGGAN	Knee MR Imaging, Data Augmentation	OAI dataset	AM Score, Mode Score, Dice
[27]	Salini et al., 2022	CycleGAN	Retinal Fundus Image Generation	DRIVE	F1, SSIM, AUC, Accuracy, Precision
[28]	Tai et al., 2022	rAC-GAN	Lung Cancer, Pulmonary Embolism	Yunnan & Chongqing datasets	AUC, Sensitivity, Specificity, Accuracy, F1
[29]	Rahman et al., 2022	cGAN	Dose Mapping, Proton Therapy	Custom (Geant4/GATE simulations)	MRE, δD, δR
[30]	Singla et al., 2022	cGAN	Pleural Effusion Diagnosis	MIMIC-CXR	CV, FID, Classifier Consistency
[31]	Velzen et al., 2022	CycleGAN	Cardiac Calcium Scoring	RTP CT, NLST	ICC, CAC pseudo-mass, Agatston score
[32]	Alrashedy et al., 2022	DCGAN	Brain Tumor Detection	Kaggle Brain Tumor Dataset	Accuracy, Precision, Recall, AUC, Loss
[33]	Campello et al., 2022	cGAN	Cardiac MRI Aging	UK Biobank	MAE, FID, PSNR
[34]	Kelkar et al., 2023	StyleGAN2	Medical Image Synthesis	Simulated datasets	FID, JS Divergence, PCA
[35]	Chaudhury et al., 2023	Progressive GAN	Breast Cancer (Ultrasound)	BUSI Dataset	Accuracy, Precision, Recall, F1, AUC
[36]	Li et al., 2023	cGAN	OCT Super-Resolution	Coronary, Fish Corneal, Rat Retina	PSNR, SSIM, SFD, EPI
[37]	Phienphanich et al., 2023	FGAN	Stroke Screening (Facial Weakness)	Real Subjects dataset	AUC, Sensitivity, Specificity, F1, Confusion Matrix
[38]	Magalhães et al., 2023	DCGAN, cGAN	Endoscopy, Gastric Cancer	Public endoscopic images	Accuracy, Sensitivity, Specificity, F1, AUC
[39]	AlTakrouri et al., 2023	ISRGAN	Image Super-Resolution (Diagnostics)	CIFAR-10	PSNR, SSIM, MAE, MSE, FID
[40]	Cackowski et al., 2023	VAE-GAN	MRI Image Harmonization	ABIDE, OASIS, SRPBS	SSIM, AUC, t-SNE, Confusion Matrix
[41]	Kou et al., 2023	MPGAN	DOF Extension, Image Fusion	Multi-focus dataset	PSNR, SSIM, MTF, Perceptual Loss
[42]	Campos et al., 2023	cGAN	Food Safety (Poultry Defect Detection)	Private (SWIR)	Precision, Recall, F1, BACC; Visual inspection
[43]	Tolpadi et al., 2023	PatchGAN	Rheumatoid Arthritis Imaging	27 Rheumatoid Arthritis Patients dataset	nRMSE, PSNR, SSIM, Occlusion Maps
[44]	Ikuta et al., 2023	TextureWGAN	CT Reconstruction, Denoising, Super-Resolution	LIDC/IDRI	PSNR, SSIM, Texture Analysis
[45]	Kalantar et al., 2023	Cycle-GAN	COVID-19 Pneumonia (CT)	NCCID	AUC, Sensitivity, Specificity, FPR, Fleiss' Kappa
[46]	Buczek et al., 2023	cGAN	Chest X-ray, Colorectal Cancer Imaging	CXR, NCT-CRC-HE-100K	Accuracy, Precision, Recall, F1
[47]	Luong et al., 2024	DCGAN	Breast Cancer Classification (Ultrasound)	BUSI Dataset	Accuracy, Precision, Recall, F1
[48]	Kumaar et al., 2024	Style-based GAN	Brain Tumor Classification	T1 MRI dataset	Accuracy, Precision, Recall, F1, ROC-AUC, Confusion Matrix
[49]	Mohammed et al., 2024	cGAN	Fabric Defect Detection	AITEX Fabric Dataset	Accuracy, Precision, Recall, F1, Loss, ROC-AUC
[50]	Lerch et al., 2024	cGAN	Breast Ultrasound	BUSI Dataset	Balanced Accuracy, ECE, CNR, gCNR
[51]	Alqushaibi et al., 2024	cGAN	Colon Cancer Segmentation	Kvasir-SEG	Dice, IoU, F-beta, SSIM, MAE
[52]	Di Giammarco et al., 2024	DCGAN	Ophthalmology (Retinal Fundus)	MedMNIST	Accuracy, Precision, Recall, F1, AUC, Loss

Ref	Author & Year	GAN Type	Biomedical Application	Dataset	Evaluation Method
[53]	Al-Adwan, 2024	DCGAN	Brain Tumor MRI	Brain Tumor MRI Dataset	PSNR, MSE, SSIM, Accuracy, Precision, Recall, F1
[54]	Rakhmetulayeva et al., 2024	CycleGAN	Echocardiography	EchoNet	PSNR, SSIM, FID, User Study
[55]	Elmourabit et al., 2024	CycleGAN	COVID-19 CT-Scan	Mosmed, Coronacases, Radiopedia	Dice, Sensitivity, Specificity
[56]	Yamaguchi et al., 2024	CycleGAN	Neuroimaging (Schizophrenia)	COBRE, ABIDE	VBM, Age Prediction, Dice
[57]	Galande et al., 2024	HDGAN	Holographic Microscopy	Cervical cells, RBCs, ISBI 2014	SSIM, MSE, Phase-SNR, Visual Inspection
[58]	Zhou et al., 2024	ProGAN	Signal Detection, Imaging Systems Optimization	Lumpy Object Model, ADNI MRI	ROC, AUC, PSNR, Phase-SNR
[59]	Dey et al., 2024	cGAN	Polarimetric Imaging (Target Detection)	Polarimetric Dataset	PSNR, SSIM, Precision, Recall, mAP, F1
[60]	Hémon et al., 2024	cGAN	Radiotherapy (Multimodal Registration)	Prostate Cancer Dataset	Dice, MAE
[61]	Xu et al., 2024	SR-GAN	Infrared Imaging, Super-Resolution	Custom infrared dataset	PSNR, SSIM, FID
[62]	Zhang et al., 2024	WGAN-GP	Low-Dose CT Denoising	AAPM-Mayo LDCT	PSNR, SSIM, FID, L1 loss
[63]	Hamghalam et al., 2024	cGAN	Brain Tumor Segmentation	BraTS'13, BraTS'18	Dice, Sensitivity, PPV, Hausdorff, p-values
[64]	Irtaza et al., 2024	DCGAN	Lung Disease Classification	NIH Chest X-ray 14	Precision, Recall, F1, Binary Accuracy, AUC
[65]	Freitas et al., 2024	cGAN	Bladder Cancer Segmentation	Private WLC video	mAP, mAP50, mAP75, Precision, Recall
[66]	Thandiackal et al., 2024	cGAN	Histopathology Classification	K-16, K-19, CRC-TP	F1, mAP, mAP50, mAP75
[67]	Rai et al., 2024	StyleGAN3	Breast Cancer Detection (Ultrasound)	BrEaST, BUSI, Thammasat, HMSS	Accuracy, Precision, Recall, F1, T-Test, Wilcoxon
[68]	Han et al., 2024	RCGAN	Pneumonia Diagnosis (CXR)	Guangzhou CXR dataset	Accuracy, Precision, Sensitivity, Specificity, F1, AUC
[69]	Moazami et al., 2024	cGAN	Brain Extraction (MRI)	NFBS, CC359, LPBA, IBSR	Dice, Sensitivity, PPV, VR
[70]	Oliveira et al., 2024	StyleGAN2-ADA	Retinal Imaging (AMD Detection)	iChallenge-AMD, ODIR-2019, RIADD, STARE	FID, Sensitivity, Specificity, Accuracy, Expert Eval
[71]	Long et al., 2024	cGAN	Ultrasound CT, Breast Cancer Imaging	Synthetic & Phantom datasets	PSNR, SSIM, nRMSE
[72]	Kokomoto et al., 2024	StyleGAN-XL	Pediatric Dentistry (Growth Prediction)	8,092 panoramic radiographs	FID, Visual inspection, Latent analysis
[73]	Ahmadkhani et al., 2024	TopoSinGAN	Dental Growth Prediction	8,092 panoramic radiographs	FID, Visual inspection, Latent analysis
[74]	Cui et al., 2024	cGAN	MRI Segmentation	BUS2017, DDTI, LiTS, ATLAS, BRATS 2015	Dice, IoU, Precision, Recall
[75]	Song et al., 2024	cGAN	Thyroid Disease (Ultrasound Elastography)	Shanghai Sixth People's Hospital dataset	PSNR, SSIM, MSE, Rago Score, Perceptual Study
[76]	Yang et al., 2024	SCGAN	Fundus Imaging, Ophthalmology	Custom & Public datasets	BRISQUE, PIQE, SSIM, PSNR, u-score, F1, Sensitivity, Specificity, AUC
[77]	Li et al., 2024	CycleGAN	CT Radiology, Distribution Shift	IMR & YA-CT images	SSIM, MS-SSIM, T-SNE, Segmentation accuracy

III. RESULTS AND DISCUSSIONS

A. *Generative Adversarial Networks in Medical Imaging*

In recent years, GANs have become an integral part of medical imaging workflows, addressing challenges such as limited datasets, variability in image acquisition, and the need for high-quality, realistic data. Within the domain of data generation, GAN variants have been applied to produce clinically relevant synthetic images across a wide range of modalities and applications. Examples include CR-GAN for mammogram synthesis in breast cancer screening [12], StyleGAN and its derivatives such as StyleGAN2, StyleGAN3, ADA, and XL for lesion-specific image synthesis and developmental growth modeling in ultrasound, CT, and panoramic radiographs [15,34,67,70-72], and PGGAN or ProGAN for progressively refined image detail [26,58]. High-resolution designs such as HDGAN [57] and MPGAN [41] have been used for specialized imaging tasks, while 3D and hierarchical attention architectures such as HA-GAN [21] and HieGAN [22] have generated volumetric data with improved structural realism for CT, MRI, and knee osteoarthritis imaging. Cycle-consistent approaches have enabled unpaired image-to-image translation for retinal fundus images [27], cardiac CT calcium scoring [31], COVID-19 chest CT adaptation [45,55], echocardiography enhancement [54], and schizophrenia neuroimaging harmonization [56]. More recently, domain shift robustness has been explicitly tested in CT radiology to ensure model generalization beyond the training environment [77].

A significant proportion of research focuses on reconstruction, super-resolution, and denoising, moving beyond perceptual quality toward diagnostic sufficiency. MRI super-resolution has been advanced with SOUP-GAN [14], which incorporates perceptual constraints, while OCT imaging has benefited from cGAN designs with edge-sensitive metrics [36]. Super-resolution in diagnostic imaging has been addressed by ISRGAN [39] and SR-GAN [61], while low-dose CT denoising has achieved stability and high fidelity through WGAN-GP with L1 loss regularization [62]. Texture preservation, a key diagnostic requirement often overlooked by conventional perceptual metrics, has been addressed with TextureWGAN [44]. Physics-assisted GANs [19] integrate acquisition priors into the generative process for X-ray tomography, and ProGAN has been used for optimizing detectability in imaging systems [58], representing a shift toward physics-informed, application-aware image synthesis.

In segmentation, registration, and quantitative mapping, GAN-based frameworks have improved spatial delineation and cross-modality alignment. Multi-stage GANs have been used for infant brain MR segmentation [18], while NIR forearm vein segmentation [24], colon cancer segmentation [51], and bladder cancer detection in cystoscopic video [65] have leveraged conditional GANs for precise boundary detection. Brain tumor segmentation using BraTS datasets has been improved with cGAN architectures [63], and prostate radiotherapy workflows have incorporated GAN-based multimodal registration [60]. CycleGAN has supported domain adaptation in calcium scoring [31], COVID-19 CT harmonization [55], echocardiography enhancement with expert-validated outputs [54], and neuroimaging adaptation for schizophrenia research [56]. These studies illustrate that GANs are not merely image generators but also facilitators of accurate clinical measurements, improving indices such as Agatston scores and Dice coefficients even when labeled data is scarce.

For classification, GANs have been embedded into pipelines to balance class distributions and improve performance in data-constrained scenarios. SSGAN has enhanced chest X-ray and histopathology classification [16], cGAN-based augmentation has supported pleural effusion detection [30], and DCGAN or RCGAN augmentation has improved lung disease [64] and pneumonia detection [68]. StyleGAN and DCGAN have been applied to breast ultrasound classification [35,47,50,67] and brain tumor MRI classification [48,53], with some studies incorporating deployment-oriented metrics such as Expected Calibration Error (ECE) and contrast-to-noise ratio (CNR/gCNR) [50]. Applications extend beyond traditional medical tasks to include gastric cancer detection in endoscopy [38] and defect detection in safety-critical contexts such as fabric inspection [49] and polarimetric imaging [59], demonstrating the methodological adaptability of GAN frameworks.

From a methodological standpoint, the reviewed works span multiple GAN families, such as conditional GANs (cGAN, cWGAN) for label-guided synthesis and mapping, cycle-consistent GANs (2D, 3D, and 3D-patch) for unpaired domain translation, style-based architectures for high-resolution and latent-space manipulation, progressive growth strategies for stability and detail, and texture/attention/hierarchical approaches to protect fine anatomical structures [12-77]. Increasingly, volumetric fidelity is addressed through 3D synthesis and patch-based processing [17,21,45], and privacy-preserving federated training is explored to address multi-site heterogeneity [20]. These developments signal a transition from purely data-driven generative modeling toward clinically robust, generalizable architectures.

The dataset ecosystem reflects both diversity and clinical relevance, encompassing mammography (CBIS-DDSM, INBreast, CMMD) [12], chest radiography (ChestX-ray14, NIH CXR14, NCCID, MosMed) [16,45,55,64,68], large-scale multi-site MRI and CT cohorts (ABIDE, OASIS, SRPBS, LIDC/IDRI, AAPM-Mayo) [40,44,62], ultrasound datasets such as BUSI and multi-center breast image collections [35,47,50,67], ophthalmic datasets including DRIVE, iChallenge-AMD, ODIR, and RIADD [27,69,75], osteoarthritis OAI knees [22,26], cardiac UK Biobank and EchoNet [33,54], and specialized collections for radiotherapy, urology, and elastography [50,60,65,75]. Private or simulated datasets are also common in domains where annotated data is scarce, such as CT tumors, proton dose mapping, infrared, and polarimetric imaging [15,29,39,58,61], underscoring persistent challenges in open data availability.

Evaluation practices have evolved into multi-objective frameworks that combine fidelity, perceptual, and clinical task metrics [12-77]. Common measures include PSNR and SSIM (with variants like MS-SSIM, UIQI, and VIF), perceptual scores such as FID and LPIPS, and statistical distribution tests like MMD or PCA divergence. Task-specific performance is evaluated using Dice, IoU, and Hausdorff distance for segmentation and registration, and AUC, sensitivity, specificity, and F1-score for classification. Texture and phase-sensitive metrics such as Phase-SNR, texture analysis, and EPI/SFD are used where structural detail is critical [36,44,57,58]. Importantly, some studies incorporate expert reader studies or clinical user evaluations [54,69,74], and a few report calibration metrics such as ECE [50], reflecting a growing focus on deployment readiness.

Across 2022-2024, the research trend moves decisively from data augmentation toward deployment-oriented generative pipelines. Key developments include federated learning for privacy and cross-site robustness [20], harmonization of multi-site MRI data [40], explicit distribution shift evaluation [77], texture-preserving SR and denoising [44,62], and the integration of physics-based priors [19,29,58]. Persistent gaps remain, including limited external validation across diverse healthcare settings, underreporting of calibration and uncertainty, reliance on non-public datasets, and occasional misalignment between perceptual and clinical outcome metrics. Promising directions involve scaling 3D generative modeling for whole-organ and temporal analysis [17,21,45], leveraging style-space control for longitudinal predictions and developmental studies [71,72], refining physics-informed architectures for safety-critical tasks [19,58,62], and developing end-to-end evaluation pipelines that link image quality directly to clinical decision performance [31,40,50,77]. Taken together, these studies illustrate how GANs have matured from tools for synthetic data generation into clinically relevant, integrated components of medical imaging systems, enhancing reconstruction, super-resolution, segmentation, and classification while moving toward the rigor and reliability required for real-world healthcare applications.

B. GAN Type

GANs are a category of advanced learning algorithms designed to produce artificial information that closely mirrors actual-world examples in statistical terms [78]. The architecture is built upon two neural network components: the Generator (G), which produces fabricated information, and the Discriminator (D), which assesses the genuineness of the provided input. These two models are trained in an adversarial framework where the Generator attempts to generate results that imitate the distribution of actual data, while the Discriminator acquires the ability to differentiate authentic samples from artificially created counterparts [79]. Different variants of GANs have been developed and tailored to meet specific clinical objectives, ranging from super-resolution and denoising to segmentation, synthesis, and classification support. The selection of a GAN framework is frequently influenced by the type of imaging technique, the intended clinical use, and the preferred trade-off between accuracy and processing efficiency [80]. The following presents the distribution of GAN types most frequently employed in biomedical contexts, with a particular focus on medical imaging.

TABLE II. DISTRIBUTION OF GAN TYPES

GAN Type	Frequency	References
Conditional GAN (cGAN)	25	[13], [20], [24], [28], [29], [30], [33], [36], [38], [42], [43], [46], [49], [50], [51], [59], [60], [63], [65], [66], [68], [69], [71], [74], [75]
CycleGAN	7	[27], [31], [45], [54], [55], [56], [77]
StyleGAN	6	[15], [34], [48], [67], [70], [72]
DCGAN	7	[25], [32], [38], [47], [52], [53], [64]
Wasserstein GAN (WGAN)	2	[44], [62]
Modified GAN	20	[12], [14], [16], [17], [18], [19], [21], [22], [23], [26], [35], [37], [39], [40], [41], [57], [58], [61], [73], [76]

The distribution of GAN types in medical imaging research [12-77] shows a clear preference for Conditional GANs (cGANs), which account for 25 studies. This dominance reflects the versatility of cGANs in incorporating label or attribute information during training, enabling more targeted synthesis, domain translation, and data augmentation for supervised and semi-supervised tasks. Their frequent use in applications such as segmentation, classification, and modality translation underlines their adaptability across diverse imaging modalities and clinical objectives.

The second most frequent group is Modified GANs, appearing in 20 studies. This category includes various architecture adaptations, such as physics-assisted GANs, hierarchical attention GANs, multi-stage GANs, and texture-preserving GANs. The high number indicates a strong trend toward tailoring baseline GAN architectures to meet the specific demands of medical imaging, whether by integrating domain knowledge (e.g., physics-based constraints) or optimizing for volumetric data and high-resolution outputs. This also highlights that researchers often find it necessary to go beyond standard architectures to achieve clinically acceptable results.

CycleGANs appear in 7 studies, reflecting their established utility in unpaired image-to-image translation. Their ability to align domains without paired datasets is particularly valuable in medical imaging, where paired multi-modal or cross-vendor data are rare. Applications include domain adaptation between imaging modalities and harmonization across scanners or institutions. StyleGANs are used in 6 studies, mainly for high-quality, high-resolution synthesis and latent-space manipulation. Their generative control and visual fidelity make them attractive for tasks requiring fine anatomical detail preservation, such as lesion synthesis or developmental modeling. While StyleGAN's adoption is lower than cGAN, its unique strengths are increasingly recognized for specialized tasks.

DCGANs are found in 7 studies, mostly as a baseline architecture for data augmentation and classification support. Although DCGAN is one of the earliest GAN variants, its simplicity and relative ease of training still make it useful for straightforward augmentation scenarios or as a foundation for hybrid designs. Finally, Wasserstein GANs (WGANs), including WGAN-GP, appear in only 2 studies. This low frequency may be due to their more specialized use cases, such as improving training stability in super-resolution and denoising tasks. While WGANs offer theoretical advantages in training dynamics, they are often embedded within broader, more specialized architectures rather than used in their pure form.

C. Biomedical Application

GANs have emerged as a transformative technology in biomedical imaging, enabling innovations in image synthesis, enhancement, and analysis across diverse medical domains [81]. By leveraging their ability to generate high-fidelity, realistic images, GANs address long-standing challenges such as limited annotated datasets, variations in imaging protocols, and the need for modality translation [82]. Their applications span from improving image quality in low-dose or time-constrained acquisitions to supporting disease diagnosis through synthetic data augmentation and cross-domain adaptation. Table 3 summarizes the distribution of GAN applications across various biomedical imaging categories, highlighting both well-established use cases and emerging research areas.

TABLE III. GAN IN BIOMEDICAL APPLICATIONS

Biomedical Application Category	Frequency	References
Cancer Imaging & Diagnosis	16	[12], [15], [25], [28], [32], [35], [38], [46], [47], [48],

Biomedical Application Category	Frequency	References
		[51], [53], [63], [65], [67], [71]
Cardiac Imaging	3	[31], [33], [54]
Neurological Imaging	4	[18], [37], [56], [69]
Ophthalmology	4	[27], [52], [70], [76]
Musculoskeletal	4	[17], [22], [26], [43]
Pulmonary & Thoracic Imaging	4	[16], [45], [64], [68]
Vascular Imaging	1	[24]
Dental	2	[72], [73]
Medical Physics & Reconstruction	17	[14], [21], [29], [36], [39], [40], [41], [42], [44], [49], [55], [58], [59], [61], [62], [74], [77]
Infectious Diseases	2	[13], [23]
Histopathology	1	[66]
Other Biomedical Applications	8	[19], [20], [30], [34], [50], [57], [60], [75]

Based on Table 3, the utilization of GANs in biomedical imaging can be grouped into several major categories, each reflecting distinct clinical and research priorities. The highest representation is found in Medical Physics & Reconstruction (17 studies), where GANs are employed to enhance image quality through super-resolution, denoising, image harmonization, and reconstruction. This dominant share indicates that improving the fidelity and diagnostic utility of medical images is one of the most impactful contributions of GANs. These applications are critical in scenarios with low-quality or noisy data, such as low-dose CT scans, MRI harmonization across different scanners, and multimodal image registration. GAN-based approaches in this category help reduce acquisition time, minimize radiation exposure, and improve interoperability between imaging systems.

Cancer Imaging & Diagnosis (16 studies) forms the second-largest category, demonstrating GANs' crucial role in oncological applications. Their use spans data augmentation for training classifiers, tumor segmentation, and synthesis of realistic cancer-related imaging for modalities such as mammography, CT, MRI, ultrasound, and endoscopy. These applications are essential in addressing class imbalance, increasing dataset diversity, and improving the robustness of AI diagnostic tools across various cancer types, including breast, lung, brain, skin, gastric, colorectal, and bladder cancers. A moderate level of research activity is observed in Neurological Imaging (4 studies), Ophthalmology (4 studies), Musculoskeletal (4 studies), and Pulmonary & Thoracic Imaging (4 studies). In neurological applications, GANs support brain segmentation, lesion detection, and neuroimaging harmonization, while in ophthalmology they facilitate retinal image synthesis, enhancement, and disease detection such as age-related macular degeneration (AMD). Musculoskeletal uses include knee osteoarthritis imaging and skeletal muscle modeling, whereas pulmonary applications involve chest X-ray enhancement, lung disease classification, and pneumonia diagnosis.

Other specific categories show lower frequencies but notable potential. Cardiac Imaging (3 studies) employs GANs for calcium scoring, MRI analysis, and echocardiography enhancement. Dental applications (2 studies) involve pediatric growth prediction and dental morphology modeling. Vascular Imaging (1 study) focuses on vein segmentation in near-infrared (NIR) imaging. Infectious Diseases (2 studies) target COVID-19 diagnosis and domain adaptation for related modalities. Histopathology (1 study) highlights the underexplored but highly relevant area of applying GANs for pathology slide classification and augmentation. Other Biomedical Applications (8 studies) capture diverse but less common use cases, including signal detection optimization, polarimetric imaging, and safety-critical inspection tasks (e.g., fabric defect detection in biomedical manufacturing contexts).

The distribution indicates that GAN research in biomedical imaging is currently concentrated in two main domains, image quality enhancement (Medical Physics & Reconstruction) and cancer-related applications. This focus reflects both the immediate clinical impact and the feasibility of GAN integration into these areas due to available datasets and well-defined evaluation metrics. However, lower representation in areas like histopathology, vascular imaging, and infectious diseases suggests significant research gaps and opportunities for innovation. Expanding GAN applications into these underexplored domains could help address emerging clinical challenges, especially where data scarcity, cross-domain variability, or the need for high precision is critical. Furthermore, the balance between diagnostic accuracy, image realism, and clinical interpretability will remain central to GAN adoption in healthcare settings.

D. Dataset

The datasets used across the reviewed studies on GANs in biomedical imaging demonstrate a combination of widely recognized public repositories and institution-specific private collections. Public datasets such as CBIS-DDSM, INBreast, and CMMD are frequently used for breast cancer mammography synthesis due to their standardized imaging protocols and rich annotation quality, which make them ideal for evaluating GAN-based image generation. Similarly, large-scale open datasets like ChestX-ray14, NIH Chest X-ray 14, and MIMIC-CXR provide diverse chest radiographs for training GAN models in pulmonary and thoracic imaging tasks, such as pneumonia detection and lung disease classification. These repositories offer the advantage of size and variety, but often require careful preprocessing due to heterogeneous quality and labeling standards.

In the neuroimaging domain, datasets such as MICCAI iSEG, MRBrainS 2013, BraTS (2013 and 2018 editions), OASIS, and ABIDE are used extensively for segmentation, tumor classification, and MRI harmonization tasks. These datasets are valuable for their multi-modal imaging formats (e.g., T1, T2, FLAIR) and standardized challenges, which allow for objective benchmarking of GAN architectures. Moreover, studies focusing on cross-modality synthesis or harmonization often use combinations of MRI and CT datasets, such as COPDGene and GSP, to evaluate the ability of GANs to maintain anatomical fidelity while translating between modalities. Ophthalmology applications frequently utilize datasets like DRIVE, MedMNIST, ODIR-2019, iChallenge-AMD, and STARE for retinal fundus image generation, enhancement, and disease detection. The relatively high quality and specific disease annotations in these datasets make them suitable for GAN-driven diagnostic support, particularly for age-related macular degeneration (AMD) and diabetic retinopathy. Likewise, gastrointestinal cancer detection and segmentation often rely on datasets such as NCT-CRC-HE-100K and Kvasir-SEG, which provide histopathology or endoscopic images with pixel-level annotations.

A notable proportion of studies rely on private or proprietary datasets, particularly in cases where public data are scarce or the imaging modality is highly specialized. Examples include near-infrared (NIR) forearm vein segmentation datasets, synthetic and phantom datasets for ultrasound CT imaging, and institution-specific collections for dental growth prediction, thyroid elastography, and bladder cancer segmentation. While private datasets offer highly controlled imaging conditions, they may limit reproducibility and cross-institutional validation unless shared through collaborative agreements. Finally, synthetic datasets and simulated environments also play a role, particularly in physics-based GAN applications and imaging systems optimization. Simulated data generated from platforms like Geant4/GATE or synthetic phantoms allow researchers to explore GAN performance in controlled scenarios without patient privacy concerns. However, translating results from synthetic to real-world clinical data remains a challenge due to differences in texture, noise patterns, and anatomical variability.

TABLE IV. DATASET GROUPING

Ref	Dataset	Category
[12]	CBIS-DDSM, INBreast, CMMD	Public Dataset
[13]	Public Lung US POCUS Dataset	Public Dataset
[14]	T1 MRI, T2-FLAIR MRI, CT	Public Dataset
[15]	CT (private)	Private Dataset
[16]	ChestX-ray14, BreakHis	Public Dataset
[17]	Simulated + Experimental	Synthetic / Simulated Dataset
[18]	MICCAI iSEG, MRBrainS 2013	Public Dataset
[19]	Synthetic CircuitFaker	Synthetic / Simulated Dataset
[20]	Diabetic Retinopathy, Bone Age	Public Dataset
[21]	COPDGene, GSP	Public Dataset
[22], [26]	OAI dataset	Public Dataset
[23]	Kaggle COVID-19	Public Dataset
[24]	NIR dataset	Public Dataset
[25]	Hyperspectral Skin Cancer Dataset	Public Dataset
[27]	DRIVE	Public Dataset
[28]	Yunnan & Chongqing datasets	Public Dataset
[29]	Custom (Geant4/GATE simulations)	Synthetic / Simulated Dataset
[30]	MIMIC-CXR	Public Dataset
[31]	RTP CT, NLST	Public Dataset
[32]	Kaggle Brain Tumor Dataset	Public Dataset
[33]	UK Biobank	Public Dataset
[34]	Simulated datasets	Synthetic / Simulated Dataset
[35], [47], [50]	BUSI Dataset	Public Dataset
[36]	Coronary, Fish Corneal, Rat Retina	Public Dataset
[37]	Real Subjects dataset	Public Dataset
[38]	Public endoscopic images	Public Dataset
[39]	CIFAR-10	Public Dataset
[40]	ABIDE, OASIS, SRPBS	Public Dataset
[41]	Multi-focus dataset	Public Dataset
[42]	Private (SWIR)	Private Dataset
[43]	27 Rheumatoid Arthritis Patients dataset	Public Dataset
[44]	LIDC/IDRI	Public Dataset
[45]	NCCID	Public Dataset
[46]	CXR, NCT-CRC-HE-100K	Public Dataset
[48]	T1 MRI dataset	Public Dataset
[49]	AITEX Fabric Dataset	Public Dataset
[51]	Kvasir-SEG	Public Dataset
[52]	MedMNIST	Public Dataset
[53]	Brain Tumor MRI Dataset	Public Dataset
[54]	EchoNet	Public Dataset
[55]	Mosmed, Coronacases, Radiopedia	Public Dataset
[56]	COBRE, ABIDE	Public Dataset
[57]	Cervical cells, RBCs, ISBI 2014	Public Dataset
[58]	Lumpy Object Model, ADNI MRI	Synthetic / Simulated Dataset
[59]	Polarimetric Dataset	Public Dataset
[60]	Prostate Cancer Dataset	Public Dataset
[61]	Custom infrared dataset	Private Dataset
[62]	AAPM-Mayo LDCT	Public Dataset
[63]	BraTS'13, BraTS'18	Public Dataset
[64]	NIH Chest X-ray 14	Public Dataset
[65]	Private WLC video	Private Dataset
[66]	K-16, K-19, CRC-TP	Public Dataset
[67]	BrEaST, BUSI, Thammasat, HMSS	Public Dataset
[68]	Guangzhou CXR dataset	Public Dataset
[69]	NFBS, CC359, LPBA, IBSR	Public Dataset
[70]	iChallenge-AMD, ODIR-2019, RIADD, STARE	Public Dataset
[71]	Synthetic & Phantom datasets	Synthetic / Simulated Dataset
[72], [73]	8,092 panoramic radiographs	Public Dataset
[74]	BUS2017, DDTI, LiTS, ATLAS, BRATS 2015	Public Dataset
[75]	Shanghai Sixth People's Hospital dataset	Private Dataset
[76]	Custom & Public datasets	Private Dataset
[77]	IMR & YA-CT images	Public Dataset

E. Evaluation Method

The evaluation methods used in GAN-based biomedical imaging studies reflect a combination of quantitative image quality metrics, task-specific performance measures, and, in some cases, qualitative or expert-based assessments. Among the most frequently used metrics are PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), which serve as standard indicators of image reconstruction quality and structural fidelity. PSNR evaluates pixel-level differences between generated and reference images, making it a useful benchmark for super-resolution, denoising, and image harmonization tasks. SSIM complements PSNR by assessing perceived image quality based on luminance, contrast, and structural similarity, which is particularly important in medical imaging where structural integrity is critical for diagnosis. Studies often report both metrics together to provide a more comprehensive evaluation of generative performance.

In diagnostic and classification-oriented applications, evaluation methods frequently include Accuracy, Precision, Recall, Specificity, F1-score, and AUC (Area Under the ROC Curve). These metrics are crucial when GANs are used for tasks such as disease detection, tumor classification, or segmentation, as they quantify the balance between detecting true positive cases and avoiding false positives. For segmentation-specific studies, overlap-based metrics like the Dice Coefficient and Intersection over Union (IoU) are widely used, as they directly measure the degree of correspondence between predicted and ground truth regions. Some studies also incorporate Hausdorff distance to capture spatial discrepancies between segmentation boundaries, which is important in applications like tumor or organ delineation where boundary accuracy can impact treatment planning. Beyond these common metrics, advanced generative evaluation techniques such as FID (Fréchet Inception Distance), LPIPS (Learned Perceptual Image Patch Similarity), and IS (Inception Score) are used to assess the realism and diversity of GAN-generated images. FID, in particular, is popular in recent studies because it measures the distance between the feature distributions of real and generated images, offering a robust indicator of visual quality. LPIPS focuses on perceptual similarity, which better aligns with human judgment, while IS estimates the diversity and quality of generated samples, albeit with certain limitations in medical domains where class distributions are highly imbalanced.

Some specialized applications integrate domain-specific evaluation methods. For example, in radiotherapy dose mapping, Mean Relative Error (MRE) and dose-specific deviation metrics are used. In elastography studies, Rago scores and perceptual evaluation by clinicians are included to assess diagnostic relevance. Similarly, multimodal registration tasks employ registration accuracy measures such as mean absolute error (MAE) in spatial alignment. In rare cases, user studies and expert grading are used alongside quantitative metrics, especially when evaluating subtle visual improvements that are difficult to capture numerically. Overall, the evaluation strategies reflect the dual need to assess both image realism and task performance. Image-level metrics like PSNR, SSIM, and FID ensure that generated images maintain visual and structural fidelity, while task-specific metrics like Dice, AUC, and sensitivity confirm that these images are clinically useful. This multi-metric approach is essential in medical imaging, where visual plausibility alone is insufficient, outputs must also meet rigorous clinical accuracy standards before they can be adopted in real-world diagnostic or therapeutic workflows.

TABLE V. EVALUATION METRICS MAPPING

Evaluation Metric	Primary Purpose	Description
PSNR (Peak Signal-to-Noise Ratio)	Image Quality	Measures pixel-level similarity where higher values indicate a closer match to reference images
SSIM (Structural Similarity Index)	Image Quality	Assesses luminance, contrast, and structure similarity which aligns with perceived image quality
FID (Fréchet Inception Distance)	Image Quality / Perceptual	Measures distribution similarity between generated and real images in feature space
LPIPS (Learned Perceptual Image Patch Similarity)	Perceptual Quality	Estimates perceptual similarity based on deep network features and aligns with human judgment
IS (Inception Score)	Image Quality / Diversity	Evaluates both the quality and diversity of generated images
Accuracy	Classification / Detection	Proportion of correctly classified samples over all samples
Precision	Classification / Detection	Proportion of predicted positives that are actually positive
Recall (Sensitivity)	Classification / Detection	Proportion of actual positives that are correctly identified
Specificity	Classification / Detection	Proportion of actual negatives that are correctly identified
F1-score	Classification / Detection	Harmonic mean of precision and recall to balance false positives and false negatives
AUC (Area Under the ROC Curve)	Classification / Detection	Measures the ability to distinguish between classes across thresholds
Dice Coefficient	Segmentation	Measures the overlap between predicted and ground truth segmentation masks
Intersection over Union (IoU)	Segmentation	Ratio of intersection area to union area between predicted and reference regions
Hausdorff Distance	Segmentation	Measures the maximum distance between segmentation boundaries
MAE (Mean Absolute Error)	Regression / Spatial Alignment	Average absolute difference between predicted and true values or positions
MSE (Mean Squared Error)	Image Quality / Regression	Average squared difference between predicted and reference pixel values
RMSE (Root Mean Squared Error)	Image Quality / Regression	Square root of MSE which retains the unit scale of the data
nRMSE (Normalized Root Mean Squared Error)	Image Quality / Regression	RMSE normalized by the range or mean of the data
Rago Score	Clinical Assessment	Expert grading for thyroid elastography based on stiffness patterns
Confusion Matrix	Classification / Detection	Table showing true positives false positives true negatives and false negatives
mAP (Mean Average Precision)	Detection / Segmentation	Average precision over multiple IoU thresholds often used in object detection tasks
mAP50 / mAP75	Detection / Segmentation	Average precision at fixed IoU thresholds of 50 percent and 75 percent
Visual Inspection	Perceptual Assessment	Expert-based qualitative evaluation of generated images
Perceptual Study	Perceptual Assessment	Human observer study to assess visual realism or diagnostic acceptability
t-SNE	Feature Analysis	Visualizes similarity in feature embeddings between generated and real data
Mode Score	Generative Diversity	Measures coverage and quality of generated samples relative to the dataset distribution
AM Score	Generative Diversity	Evaluates realism and diversity as an adaptation of IS for medical data
BER (Bit Error Rate)	Signal Analysis	Measures data accuracy in signal reconstruction tasks
MTF (Modulation Transfer Function)	Image Quality (Optics)	Quantifies the system's ability to reproduce contrast at different spatial resolutions
Cos_sim (Cosine Similarity)	Feature Similarity	Measures similarity between feature vectors of generated and reference images
VBM (Voxel-Based Morphometry)	Neuroimaging Analysis	Statistical analysis of brain anatomy differences between groups

IV. Strengths and Limitations

A. Strengths

One of the most notable strengths across the studies is the ability of GAN-based models to generate high-fidelity and realistic medical images. Many works, such as those using StyleGAN, PGGAN, and StyleGAN3 architectures, demonstrate exceptional visual quality with high SSIM, PSNR, and low FID scores. This capability is particularly valuable for tasks like mammogram synthesis [12], retinal fundus image generation [27], and 3D image synthesis [21], where realistic representation is critical for clinical interpretability. By producing synthetic images that closely mimic real data, these models provide effective solutions to data scarcity and facilitate training of robust diagnostic systems without overfitting.

Another recurring strength is the improvement in downstream diagnostic and segmentation performance through data augmentation and domain adaptation. Several studies employing cGANs and CycleGANs have demonstrated significant boosts in classification accuracy, F1-scores, and AUC values when synthetic data are incorporated into the training process. For instance, lung cancer and pulmonary embolism detection [28] and brain tumor segmentation [63] benefited from augmented datasets, which enhanced model generalizability to diverse patient populations and imaging conditions. Additionally, the unpaired image-to-image translation capabilities of CycleGANs allow models to adapt to different imaging domains, such as cross-scanner harmonization in MRI [40] or distribution shift correction in CT imaging [77], without the need for paired datasets, a major advantage in real-world medical settings.

Many studies also highlight the capacity of GAN-based approaches to enhance image quality for improved clinical utility. In Medical Physics & Reconstruction tasks, such as low-dose CT denoising [62], MRI super-resolution [14], and multimodal image fusion [41], GANs consistently outperformed conventional reconstruction methods. The integration of perceptual loss functions, texture-preserving modules (e.g., TextureWGAN [44]), and physics-informed designs (e.g., Physics-assisted GAN [19]) has led to sharper, noise-free images that preserve diagnostically relevant features. This not only aids human interpretation but also improves the performance of automated AI pipelines in detection and segmentation.

A further strength lies in the architectural flexibility of GANs, enabling tailored solutions for specific medical imaging challenges. Modified architectures like HA-GAN [21] for high-resolution volumetric synthesis, HieGAN [22] for multi-scale representation, and SCGAN [76] for structure-constrained enhancement address domain-specific constraints. For example, HA-GAN successfully generates 3D CT and MRI volumes with improved structural fidelity, while SCGAN optimizes ophthalmic fundus imaging by integrating quality assessment metrics into the training loop. These custom adaptations demonstrate the versatility of GAN frameworks in accommodating diverse biomedical imaging needs. Finally, the robustness of GAN models in handling limited or imbalanced datasets stands out as a consistent advantage. Semi-supervised approaches like AC-GAN [13] and rAC-GAN [28] leverage both labeled and unlabeled data, effectively mitigating annotation costs while still delivering competitive performance. This is particularly beneficial in clinical contexts where expert-annotated data are scarce or expensive to obtain. Moreover, federated and collaborative GAN learning strategies [20] allow various organizations to jointly develop models collaboratively without exchanging unprocessed patient information, ensuring compliance with privacy regulations while expanding data diversity.

B. Limitations

A repeated constraint observed in numerous investigations is the dependency of GAN performance on the caliber and heterogeneity of the training dataset. While GANs are effective in generating realistic images, their outputs can degrade when trained on small, homogeneous, or biased datasets. Several studies, particularly those in niche medical domains such as holographic microscopy [57], fabric defect detection [49], and certain ultrasound applications [71], highlight that limited sample size led to overfitting, reduced generalizability, and artifacts in synthetic images. In low-data scenarios, models such as DCGAN and early cGAN implementations struggled to maintain structural fidelity, producing outputs that may not be clinically reliable.

Another significant limitation is the risk of generating anatomically inaccurate or clinically misleading features, especially in tasks requiring precise structural preservation, such as tumor segmentation [63, 65] or multimodal registration [60]. Even when visual metrics like SSIM and PSNR are high, subtle anatomical distortions or hallucinated features may occur. These errors are particularly critical in diagnostic workflows, as they could lead to misinterpretation by radiologists or degrade the performance of AI-assisted diagnosis tools. For example, texture inconsistencies in TextureWGAN outputs [44] and boundary inaccuracies in CycleGAN-based segmentation tasks [55, 74] illustrate this challenge.

Training instability and high computational requirements also appear as common drawbacks. GAN models, especially high-capacity architectures like StyleGAN2-ADA [70], StyleGAN-XL [72], and PGGAN [26], require extensive tuning of hyperparameters, careful balance between generator and discriminator updates, and powerful GPU resources. Several studies reported mode collapse or unstable convergence during training, necessitating the use of advanced regularization techniques such as gradient penalty (WGAN-GP [62]) or adaptive discriminator augmentation. These complexities can hinder reproducibility and limit the accessibility of GAN-based methods in clinical research environments with constrained computational resources.

A further limitation lies in the lack of standardized evaluation protocols across studies. While metrics like SSIM, PSNR, and FID are widely used, they primarily assess visual similarity rather than clinical validity. Only a subset of works, such as those in ophthalmology [70, 76] and cardiac imaging [31], incorporated domain-specific or expert-based evaluations. The absence of clinically grounded benchmarks makes it difficult to compare results across studies and raises concerns about the real-world diagnostic impact of GAN-generated outputs. Finally, regulatory and ethical challenges remain underexplored in most papers. Although some studies address privacy concerns through federated learning [20] or data anonymization, very few consider the downstream implications of deploying GAN-generated images in clinical decision-making. The potential for misuse, such as generating realistic but synthetic patient images that could be mistaken for real data, presents ethical risks that require formal guidelines and verification processes before clinical adoption.

V. CONCLUSION

In conclusion, the systematic review of GAN-based approaches in biomedical imaging demonstrates that these architectures (ranging from foundational models like DCGAN and cGAN to advanced variants such as StyleGAN, PGGAN, WGAN-GP, and specialized modified GANs) have significantly advanced capabilities in image synthesis, enhancement, and cross-domain adaptation. Their applications span a broad spectrum of biomedical domains, with the highest concentration in Medical Physics & Reconstruction and Cancer Imaging & Diagnosis, supported by datasets both public and proprietary, including CBIS-DDSM, ChestX-ray14, BraTS, OAI, and ABIDE. Evaluation commonly relies on quantitative image quality metrics such as SSIM, PSNR, and FID, supplemented by task-specific measures like Dice, AUC, and expert visual assessment. The key strengths of these methods lie in their ability to generate realistic high-quality images, improve diagnostic performance through data augmentation, enhance imaging in low-quality or low-dose conditions, and adapt flexibly to diverse clinical tasks, even with limited labeled data. Nonetheless, limitations persist, including dependency on high-quality and diverse datasets, risks of anatomical inaccuracy, training instability, high computational demands, non-standardized evaluation protocols, and underexplored ethical and regulatory considerations.

VI. FUTURE DIRECTIONS

Future research on GANs in biomedical imaging should focus on bridging the gap between technical advancements and clinical translation. Priority should be given to developing architectures that not only generate visually realistic outputs but also preserve fine-grained anatomical accuracy, ensuring clinical safety and trustworthiness. Integrating domain knowledge, such as physics-informed constraints and pathology-specific priors, could further enhance the interpretability and reliability of generated images. Standardized, clinically relevant evaluation protocols, combining quantitative metrics with expert-driven assessments, are needed to allow fair benchmarking across studies and modalities. Additionally, expanding research into underexplored domains such as histopathology, vascular imaging, infectious diseases, and pediatric imaging could unlock new diagnostic opportunities. Addressing computational efficiency and training stability will be crucial for enabling deployment in resource-limited healthcare settings, while privacy-preserving approaches like federated GAN learning should be advanced to support multi-institutional collaboration without compromising patient confidentiality. Finally, ethical and regulatory frameworks must evolve in parallel with technical innovation to mitigate risks of misuse and to define clear guidelines for the safe integration of GAN-generated content into clinical workflows.

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