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# Cardiac Magnetic Resonance Imaging Focus Generative Adversarial Network Segmentation

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**ABSTRACT**

Cardiovascular function analysis is crucial for illness diagnosis, risk assessment, and therapy selection in clinical cardiology. Doctors may identify cardiac disorders such as right ventricular failure, hypertrophic cardiomyopathy, and dilated cardiomyopathy using a variety of imaging modalities that allow them to spot pathological alterations. The optimum course of therapy may be chosen more quickly thanks to accurate automation of the relevant duties. Artificial neural networks and deep learning are the foundation of generative adversarial networks (GANs), which are methods for creating synthetic pictures. The potential capacity of the GANs to solve problems has attracted interest in addition to their inherent flexibility and the adaptability of deep learning, on which they are founded. This survey aims to examine the significance of medical imaging in the study and diagnosis of cardiac disease. Demonstrate the widespread adoption of GAN Network approaches in the field of magnetic resonance imaging (MRI) medical image analysis; Explain the recent segmentation application of generative adversarial networks. GANs in cardiovascular imaging additionally Identify the hurdles to the effective application of the GAN Network to medical imaging tasks and highlight particular contributions that address or get around these problems.

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## 1. INTRODUCTION

Image data that could save lives is frequently collected in the medical imaging area [1]. These imaging techniques can produce images that show anatomical views of various human bodily organs. As a consequence of the advancement of the biomedical imaging disciplines, the data are currently given by positron emission tomography (PET), computed tomography (CT), magnetic resonance imaging(MRI), and a few more modalities including microscopy and digital pathology. However, using the available imaging data, radiologists have difficulty locating lesions with accuracy. Similar to MRI imaging, CT scanning provides extensive anatomical information and assists in accurate diagnosis.[2].

All methods of lesion tissue segmentation ask for slice-to-slice analysis on 2D format image data because these image data are given in 3D format. Slice-to-slice image data in 2D format was needed for all lesion tissue segmentation techniques. However, it will take roughly fifteen minutes per image to manually annotate medical imaging data by a radiologist or annotation specialist. The hand annotation technique is costly, time-consuming, and difficult to scale.

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The leading cause of death globally is cardiovascular disease [3]. Clinical AI applications have been developed to assess cardiac function and improve image quality. AI is presently revolutionizing the advancement of cardiac imaging technology and its medicinal use. [4]. Recent advances in deep learning have made it possible to use different convolution neural networks) CNN (models to solve many medical imaging problems, including image segmentation [5]. For difficult medical imaging, decision-making, deep learning models are famous for their outstanding performance [6]. These deep networks use a variety of involving transformations to abstract data at different layers, which they combine to anticipate outcomes. Deep neural networks are fully capable and necessary to create a complex link between input and predicted outcomes and possess the capacity to completely comprehend the hidden characteristics [7]. GANs, which have made remarkable strides in deep networks and have a wide variety of applications in medical imaging, have only lately attracted the interest of the research community. A subclass of deep neural networks called GANs trains two networks simultaneously. The use of GAN in medical imaging has been covered in a few studies and review papers [8]- [11]. These articles take a broad view of the study issues, which is advantageous to novice GAN scholars. However, how to use GAN for the biomedical segmentation task was not completely covered. Our study aims to comprehensively summarize the applications of GANs in segmenting biomedical images. To collect data, we used "Google Scholar" a search engine for articles with certain titles. (GANs, "Generative Adversarial Network," "GANs Segments," "GANs Medical Image Segmentation").

Most of the papers were obtained from reputable journals like "IEEE, Springer, Elsevier, and some papers from linked conferences," among others. From" arXiv" e-Print, articles with strong citations are also taken into consideration. We carefully examined each article before excluding any that did not have any bearing on biomedical imaging or GANs. We want to comprehensively summarize how AI heart imaging, including CT and MRI, has developed. First, we gave a narrative overview of the technical advancements in AI and presented the GAN approach's adaptive framework. The adaptive generative adversarial network (AGAN) is proposed to be composed of three elements: a selection generator, a discriminator, and a feature harvester. The feature extractor's function extracts pertinent features from the input data, which benefit the generative model. These features may be extracted using various methods, such as convolutional neural networks or auto encoders. The generator then employs the extracted features to generate a new set of data points. We then display the findings of a thorough literature review of current studies and discuss the clinical applications of AI and their prospects for clinical practice.

## 2. HEART'S ANATOMY FUNCTIONS

Two atria (top chambers) and two ventricles, totaling four compartments, make up the human heart (as shown in Fig. 1). Cardio vertebral node there is a membrane between the two heart chambers. The two sides do not immediately communicate unless there is a septal abnormality, but they do [12], [13]. The two primary types of circulatory channels that travel through the heart are the pulmonary circuit and the systemic circuit. The pulmonary circuit carries deoxygenated blood to the right atrium or half of the heart. the circulation then goes on to the lungs, where oxygen is taken in. The oxygenated blood is subsequently returned to the left ventricle via the pulmonary duct. The second pathway, commonly referred to as the systemic circuit, is used by the left ventricle (LV) to send oxygenated blood into the artery and arterial circulation. The atria and ventricles are separated by the bicuspid (mitral) and tricuspid atrioventricular (AV) valves. The cusps of the AV valves are linked to the papillary muscles, which are ventricular muscular expansions. The four phases of a healthy heart contraction are as follows. In early diastole, the heart is initially at rest. The atrium closes during the atrial systole phase, forcing blood into the ventricles. Third, the ventricles constrict until they are fully emptied while maintaining a consistent volume. In the last phase, they stop tightening, unwind, and restart the cycle. [14].

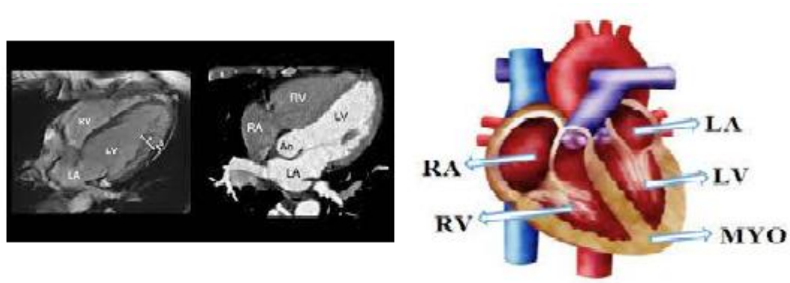


**Fig.1. Human heart anatomy (atria and ventricles).**

## 3. CARDIAC MAGNETIC RESONANCE IMAGING

Measurements of ventricular capacity and mass are needed to evaluate cardiovascular illnesses. The go-to imaging method for quantitative research is often cardiac magnetic resonance (CMR) [15], [16]. Medical image analysis commonly uses motion SSFP, first-pass stress perfusion images, and late gadolinium enhancement (LEG) images in CMR image modules. Cine The initial criteria for rating image quality were established, among the factors limiting the quality of CMR images are well-known frequent picture artifacts Applying certain criteria to each sort of image series, such as the CMR image modules listed above, can yield a numerical score that represents the overall picture quality of the CMR research and its three modules.

## 4. CMR IMAGE QUALITY ASSESSMENT CHALLENGES

CMR imaging offers a non-invasive approach to cardiac anatomy and function for population imaging research [17]. To assess cardiovascular diseases, it is essential to quantify ventricular anatomy and function using patient cohorts from lengthy clinical large-scale imaging studies or trials. Tools for image analysis and automatic image quality evaluation are needed for this quantification. The development of reliable and accurate image analysis tools for quantitative assessment is needed due to the technological constraints of imaging systems. For such systems to be used in clinical diagnosis, precise predictive performance, accessibility, and interpretability are also requirements

### *4.1. CMR imaging anomalies with a defined boundary*

There are not many clinical or non-clinical guidelines that specify what constitutes an excellent medical picture and CMR investigation [18].

### *4.2. Methods for limited quality evaluation in video editing*

For automatically determining the quality of photos, a substantial corpus is available. Several techniques for video processing can identify visual distortions in frequently occurring multimedia interactions [19] [20].

### *4.3. Recognizing connections in cross-modality imaging data*

When evaluating image clarity in medical image analysis, it may be advantageous or even vital to infer a picture from one modality from an image from another. The difficulty of CMR slice posture prediction arises from the disparity of data sources.

## 5. CARDIOVASCULAR IMAGING METHOD

The application of AI in cardiac imaging has been explained using two different strategies. To anticipate diagnostic or prognostic outcomes utilizing multiple clinical and pre-computed image attributes, large datasets have been employed to train traditional ML algorithms. Images from the actual world have been diagnosed using deep learning (DL) techniques, a more sophisticated kind of AI. DL does not, in contrast to conventional intelligence techniques. Direct image interrogation is utilized for tasks like image segmentation or result projection instead of "feature engineering," which computes and extracts "custom-tailored" imaging variables. Examples of huge, complex datasets with a range of properties that are good candidates for DL are imaging and genomics datasets. The underlying concept of:

**Classical AI** is that by automatically and repeatedly changing the appropriate weighting. It is possible to combine several weak basic classifiers to create a single potent classifier. Each iteration results in a new weighting distribution and basic classifier predictions. These projections are then used to create the weighted majority voting-based ML hazard rating, which represents a continuing assessment of the potential threat and runs from 0 to 1. Automatic feature selection using Logit Boost model construction information gain ranking and 10-fold cross-validation were all done using machine learning an ML score for risk integrating clinical and CTA evaluation is superior to accepted risk indices and visual CTA evaluation. The area under the curve (AUC) for the prediction of mortality (ML AUC = 0.79) revealed much more information. [21]. The best data on all-cause mortality after age was found in the percentage of segments with cemented and no calcified plaque. [22]. In the MESA ("Multi-Ethnic Study of Atherosclerosis") study, artificial intelligence (AI) outperformed coronary calcium scoring (CCS) in forecasting negative cardiovascular outcomes in more than 6,800 asymptomatic participants. [23]. A coronary composite risk number ('ML AUC = 0.83 vs. CTA Stenosis = 0.66') has been demonstrated to considerably increase the ability of 13N-ammonia positron emission tomography to detect decreased myocardial flow reserve. [24]. The prediction of ischemia specific to individual lesions has also been done using AI. Using CT angiography, the NXT research, in which 254 patients had CTA before invasive coronary angiography with fractional flow reserve, it was discovered that an assessment of plaque features improved the differentiation of lesion-specific ischemia. (FFR) [25]. A related research looked at the viability of using AI to forecast lesion-specific ischemia while incorporating clinical information and precise assessments of stenosis and plaque from CTA, this combination produced a higher AUC for predicting ischemia when compared to the pre-test likelihood of coronary artery disease or quantitative CTA metrics. ("ML AUC = 0.84 vs. best clinical score = 0.63, CTA stenosis = 0.76, low-density no calcified plaque volume = 0.77; p 0.006") Software applications can incorporate these machine learning risk scores to improve patient risk assessment. The clarity of CTA images has also been evaluated using the random forest method, and the findings are similar to those of expert visual assessment [26]. The groundbreaking study by Krizhevsky and Hinton [27] .1.3 million images containing more than 1,000 distinct objects were automatically classified using Deep learning. The result of DL could be an interpretation, forecasting, diagnosis, or (more frequently) a changed photograph, such as the dataset's anatomical labels or a higher-quality image.

**Deep learning (DL)** has been suggested for several medicinal diagnostic applications. DL's outstanding accomplishment in computer vision, together with advancement over the last two years. Two factors that have contributed to this growth are recent advancements in reasonably priced graphics processing units ("created for the computer gaming business") and a range of DL toolkits that are open-source and accessible to all academics. The performance of fully automated segmentation, identification, and categorization of organs or lesions utilizing DL algorithms has been much enhanced compared to traditional methods. Pathology image analysis has been the most widespread application, however, numerous techniques for analyzing cardiac images have lately been put forth (as shown in Fig. 2). Cardiologists have employed DL to determine the coronary centerline. LV image segmentation, CCS from CMR, CT, and sonar images, and [28], [29]. The availability of freely available training image datasets made the research possible. More for CMR, where a sizable open archive has already been created. The 2016 Kaggle CMR competition's winning teams calculated the LV volumes using a DL technique Researchers employed complete automation to measure LV volumes. In one documented instance of this research, 1,340 subjects underwent training and validation. [30].

An automatic DL algorithm's training and evaluation for identifying a severe angiographic disease from SPECT MPI by Betancur et al. [31] utilizing the most current registry (" 1,638 SPECT MPIs from the REFINE SPECT") Use of SPECT cameras is advised for patients with possible coronary artery dysfunction. [32]. To control memory and processing effectiveness, instead of using complete 3D image datasets, they used displays for automatically produced 2D polar maps as the convolutional neural network's initial input. Each vascular territory's obstructive condition was trained into the DL network. This technique (which distinguished between training and test data using cross-validation) beat the industry standard for quantifying these images. Despite not having the specialized graphics card used for system instruction, the pre-trained model assessed a brand-new patient in less than one second.

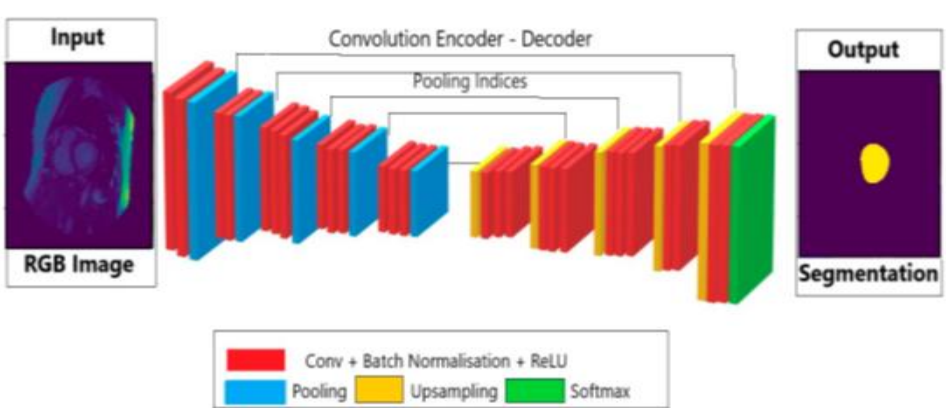


**Fig. 2. Example of context-enabled Encoder-Decoder segmentation [33].**

## 6. CARDIAC MR IMAGE SEGMENTATION

Heart image segmentation is crucial for obtaining accurate diagnosis of heart disorders and for giving information that will be helpful during clinical therapy and surgery. MRI is the modality most frequently used to produce cardiac pictures (as shown in Fig. 3). Segmentation is a helpful technique for examining the quantitative function and perfusion of cardiac MR images. By tracking left ventricular volume (LVV) over the cardiac cycle, as well as associated indices including ejection percent, wall thickness during the cardiac cycle, and left ventricular myocardium mass (LVMM), it provides an accurate and quick diagnostic of the heart.

The analysis and interpretation of CMR images are often time-consuming. Cardiac features like the left ventricular wall can significantly decrease the automated segmentation of the time required for image processing. To automate this process, several techniques have been suggested. These techniques can be classified as deep learning or non-deep learning techniques. An overview of the steps required to divide heart pictures into the following categories: Multi-Chamber, Left Ventricle, Right Ventricle, Aortic Valve, Left Atrium, and Right Atrium.

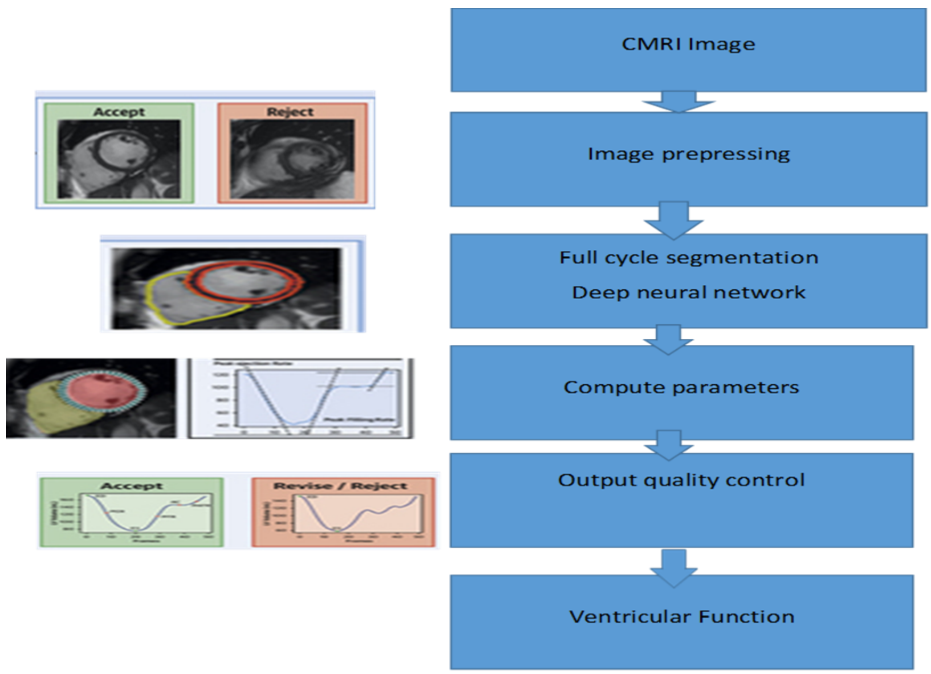


**Fig. 3. An overview of the tasks involved in segmenting heart images.**

## 7. GAN APPLICATION IN CARDIAC IMAGING

The applications of the GAN model in different biomedical imaging methods are discussed in this section (as shown in Table 1). Heart diseases, clinical monitoring, and therapy planning all stand to benefit greatly from cardiovascular segmentation in medical imaging. Because it contains information on premedication and surgical procedures, the information given by cardiac magnetic resonance imaging (CMRI) helps, evaluate all possible therapies. However, echocardiogram encounters some challenges, including poor spatial precision, deformable appearance, and a lack of readily available annotation images.

## 8. GAN-based derivative models

Since (Goodfellow et al). [34] proposed a GAN in 2014There have been several GAN-based derivative models presented. These models combine cutting-edge theoretical advancement, model construction, and application principles. Semi-GAN was suggested by Odena et al. [35], who improved the training of the discriminator D with knowledge from real data annotation. [36] Another suggestion was to employ the conditional GAN ("CGAN") by incorporating y, which may be labels or other supplementary data, into the model. Traditional GANs create a generative model to connect the distribution of the data from the hidden layer with that of the real data and other data. (As shown in Fig. 4).

In this particular version, the input to generator G is split into z and c, where z is identical to the input to the GAN and c denotes the implicit connection between a given semantic and a set of hidden structural variables. $pG(x) = pG(x \mid c)$ in a GAN. However, there is a significant connection between c and the outcome of G. The output of the generator is shown by the equation G (z, c). Given that a GAN cannot construct a discrete space distribution and can only produce a continuous real number distribution, [37]"Browne et al." Our proposed SeqGAN enhances GNs with the RL-based generator to handle the issue of sequence creation, where the discriminator sends a reward signal after each sequence. Monte Carlo technique. Table 2 lists the GAN model's advantages and disadvantages.

**Table 1. The articles for cardiac segmentation using GAN models are summarized.**

| Reference | Type GAN | Method description |
|---|---|---|
| [53] | Automap-GAN | Our approach is based on the newly created Automap reconstruction technique, which uses deep learning to directly recreate high quality MR images from k-space. |
| [54] | Network CCGAN | Suggest a technique for bi-ventricle segmentation that is automatic and concurrent. First, we select the area of interest (ROI) from the initial cardiac image at various sizes. The captured ROI is then fed into the conditional convolution generative adversarial network (CCGAN), which creates a segmentation overlay. |
| [55] | Unet-GAN | Proposed a comprehensive architecture to solve this issue, consisting of (1) a vendor adaption GAN for unpaired GANs and (2) object segmentation GANs. The Unet-GAN concept that is being suggested calls for GAN to obtain feature data from Unet at the feature level. However, we choose cardiac cine MRI as the example, with three significant manufacturers functioning as three zones (Philips, Siemens, and GE). The method may be used to extensively segment medical pictures. |
| [56] | SDNet (U-Net and GAN) | A cycle-consistency-based approach to latent space decomposition is suggested. Consider the implementation of cardiac MR segmentation, where data about the myocardium is separated from imaging-related characteristics and auxiliary substructures. |
| [57] | conditional GANs | Dividing the myocardial of individuals with congenital heart disease using a chain of conditional GANs for semantic segmentation |
| [58] | CGAN(VoxelAtlasGAN.) | Utilized in 3-D echocardiography to divide the LV. This network combines map into a framework augmentation from start to finish and is built using voxel-to-voxel-based cGAN. The findings highlight how crucial the suggested paradigm is for clinical applications. |
| [59] | VAE-GAN | For the implementation of cine-MR image cardiac segmentation, we suggest a Variation Auto encoder (VAE) - Generative Adversarial Net-works (GAN) model can generate highly realistic MRI along with its pixel exact ground truth. |
| [60] | CGAN U-Net | To capture these interactions, suggest a machine learning technique that uses a conditional Generative Adversarial Network (cGAN) to predict cardiac deformation from individual cardiac magnetic resonance (CMR) frames and learns a deterministic mapping between end-diastolic (ED) and end-systolic (ES) CMR short-axis frames. |
| [61] | AAE | For both discrete and continuous hidden variables in probabilistic autoencoders, the GAN framework has been presented as a variational inference method. On the real-valued MNIST and Toronto Face datasets, the adversarial autoencoder (AAE) approach we use creates rival test likelihoods. |
| [62] | GAN-based (U2S network) | A few-shot GAN Transfer Learning for Interactive Echocardiography Translation was suggested in the article. Both the U2S Parent Network and the S2U Parent Network have been previously developed and retrained. |
| [63] | GANs (PSCGAN) | Progressive sequence causal GANs (PSCGAN) are suggested in this paper. This is the first comprehensive CA-free IHD approach that can simultaneously create an LGE-equivalent image from cine MR images and segment tissues crucial for diagnosis (such as scars, healthy myocardium, blood pools, and other pixels). |
| [64] | Unet-GAN | In the suggested Unet-GAN design, GAN picks up segmentation-specific feature information from Unet at the feature level. The technique can be applied to the segmentation of medical pictures generally, However, we chose cardiac cine MRI as the illustration, with three important manufacturers (Philips, Siemens, and GE) acting as three areas |
| [65] | progressive sequential causal GANs ) | (1) Generating a crude tissue overlay in advance with GAN.<br>(2) LGE analogous picture synthesis GAN condition.<br>(3) GAN with precise segmentation. |
| [66] | (MuTGAN) | Complementarity between segmentation and measurement (A1): joint feature learning network for multitask learning (A2): spatiotemporal feature extraction network by 3D sequential convolution; kinematic abnormalities and LV morphology (A1): combined feature learning network for multitask learning; The (B) discriminator (B1) is the task-relatedness network, which uses task-relatedness patterns as an innate structure between occupations. |
| [67] | (R2Unet-GAN) | The R2U-Net serves as the generating network and the FCN operates as the discriminative network in the network design, which is based on a conventional architecture known as a conditional generative adversarial network (cGAN). |
| [68] | DT-GAN | To decrease the number of pictures needed for training while keeping high segmentation accuracy, we therefore present a semi-supervised semantic segmentation method. |
| [69] | (DAN) model | A novel deep adversarial network (DAN) model is proposed to achieve reliably effective segmentation results on both annotated and unannotated pictures in the field of biomedical imaging. |

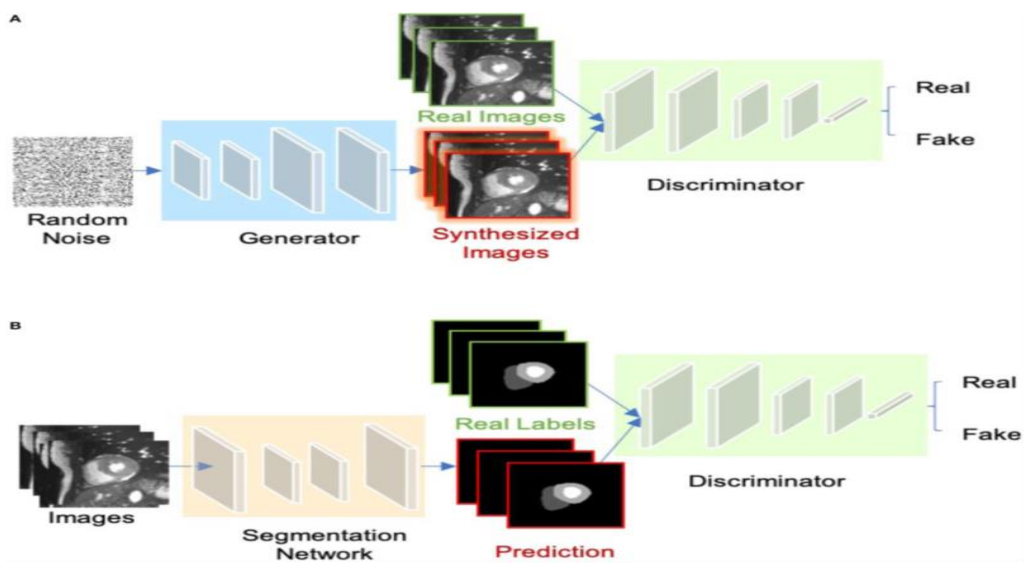


**Fig. 4. (A) GAN for image synthesis overview. (B) A description of antagonistic training for segmenting images. [38]**

**Table 2. Some previous studies of the GANs network in terms of the advantages and disadvantages**

| Model | Advantage | Disadvantage |
|---|---|---|
| DCGAN[39] | Model stability and picture processing suitability | Model bursts, gradient vanishes, and it's uncontrollable |
| CGAN[40] | Controllable training | Gradient vanishes, model erupts |
| WGAN[41] | can stop the eruption of gradient disappearance; more stable | Selecting a weight-cutting range can be challenging. |
| INFOGAN [42],[ 43] | comprehensible example features | Gradient vanishes, model erupts |
| BEGAN[44] | The model is simpler to train and the generated sample diversity is superior | Model bursts, the gradient vanishes, and it's uncontrollable |
| CycleGAN[45] | Training rounds don't need to be paired | substantial use of processing resources |
| SRGAN[46] | Low-resolution photos are scaled up by 4x to create high-resolution images. | There is some disturbance and not enough realistic texture information |
| ACGAN[47] | For each division, accuracy can be evaluated | Overlooks the damage that class labels do when a label is missing from a particular training picture. |
| LAPGAN[48] | training independently for each pyramid stage | No convergence and mode collapse |
| SAGAN[49] | Recent studies have shown that generator conditioning affects GAN performance, and improves training dynamics. | Focus is not Expanded |
| GRAN[50] | Sequential generation of images | Samples break down after extensive training |
| AAE [51] | Balanced approximation is superior to vibrational autoencoders and can be expanded to semi-supervised learning | Examples produced are fuzzed and smoothed |
| Pix2Pix[52] | The generation of realistic pictures and parameter reduction | Images must be paired one to one. |

## 9. CHALLENGES

Despite their ability to generate data, GANs have associated disadvantages that may prohibit them from accepting data synthesis software. The following list includes some of these restrictions:

1. Dynamics Instruction. The training process with GANs is unstable and unpredictable due to their adversarial structure. Mode collapse, where GAN's generator only learns to create a subset of a reference dataset, limits the trained model's usefulness.
2. Another problem is the long training times for advanced GAN models; even modern graphics processing units take weeks of training.
3. Model Evaluation. Since it is challenging to objectively assess Uncertainty exists regarding model convergence and the quality of the generated pictures, and dynamics instruction is made more difficult.

4. Medical Clinicians must exercise caution when implementing new tools because their choices influence their patients' health. Because they fall under the category of "black-box" probabilistic models, the behaviour of the neural networks that constitute the core elements of GANs is not completely understood [70].
5. Additionally, the intricate features of an organ or pathology may not be fully captured in GAN images. These issues need to be fixed for GANs to be accepted as reliable therapeutic tools.
6. Data Ethics and Rules. Because it is so closely related to a person's health details, medical data is extremely sensitive. In light of this, it is still unclear whether data laws and regulations protect Synthetic data generated by GANs trained on actual patient data.
7. GANs have the potential to amplify the biases inherent in the original datasets, which poses ethical questions about the use of GAN-generated data as a trustworthy source of information

## 10. DATA AVAILABILITY

| Dataset /References | Link |
|---|---|
| York10[71] | http://www.cse.yorku.ca/~mridataset |
| Sunnybrook [72] | http://www.cardiacatlas.org/studies/sunnybrook-cardiac-data/ |
| LVSC:[73] | http://www.cardiacatlas.org/challenges/lvsegmentation-challenge/ |
| RVSC [74] | http://www.litislab.fr/?projet=1rvsc |
| cDEMRIS:[75] | https://www.doc.ic.ac.uk/~rkarim/la_lv_framework/fibrosis |
| LVIC:[76] | https://www.doc.ic.ac.uk/~rkarim/la_lv_framework/lv_infarct |
| LASC'13:[77] | www.cardiacatlas.org/challenges/left-atriumsegmentation-challenge/ |
| HVSMR:[78] | http://segchd.csail.mit.edu/ |
| ACDC:[79] | https://acdc.creatis.insa-lyon.fr/ |
| LASC'18:[80] | http://atriaseg2018.cardiacatlas.org/data/ |
| MM-WHS:[81] | http://www.sdspeople.fudan.edu.cn/zhuangxiahai/0/mmwhs17/ |
| CAT08:[82] | http://coronary.bigr.nl/centerlines/ |
| CLS12:[83] | http://coronary.bigr.nl/stenoses |
| CETUS:[84] | https://www.creatis.insa-lyon.fr/Challenge/CETUS |
| CAMUS:[85] | https://www.creatis.insa-lyon.fr/Challenge/camus. |

## 11. CONCLUSION

This article summarized a thorough analysis of cardiac magnetic resonance imaging and GAN including their fundamental concepts, GAN variants, cardiac MR image segmentation by GAN, and their visual perception-related computational uses. A comparison between biological and computer vision is made to better comprehend the development of neural networks and the background of computer vision. This poll offers a thorough comparison of recent and previous surveys. This study in-depth examines GAN's uses in cardiac MR image segmentation. It has been demonstrated that GAN can address the issue of insufficient data and enhance picture generation quality. The experimental results are discussed to examine the capabilities of GAN model variations. The benefits, disadvantages, and network designs of several GAN models are explained. Cardiac MR Image Segmentation and GAN applications are also addressed, both of which have made significant progress in many computer vision applications. The possibilities and difficulties in all the emerging areas are covered in depth in this article. One of the potential directions for future study is to modify GAN in this manner.

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