Generative Adversarial Network-Driven Segmentation of Myocardial Fibrosis in Transthoracic Echocardiography

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Abstract: *Cardiosclerosis-related myocardial fibrosis is a major cause of impaired cardiac contractility and adverse outcomes, yet its delineation on transthoracic echocardiography (TTE) remains challenging due to low contrast, speckle noise, and weak boundary definition. This study proposes a GAN-driven segmentation framework to automatically detect and segment fibrotic myocardial regions in apical 4-chamber (A4C) TTE images. The method employs a U-Net - based generator to produce binary fibrosis masks and a PatchGAN discriminator to enforce realistic local boundary structure through adversarial learning. A clinically grounded dataset was formed from anonymized echocardiography of 47 confirmed cardiosclerosis patients (Philips EPIQ, GE Vivid), complemented by open datasets (EchoNet-Dynamic, CAMUS) to enhance generalization. Expert cardiologists produced ground-truth masks, with high inter-rater agreement ($\kappa > 0.87$). The model was trained using a combined loss function (adversarial + Dice + binary cross-entropy) with systematic augmentation. On the held-out test set, the proposed GAN achieved Dice = 0.873, IoU = 0.792, precision = 0.891, recall = 0.856, and Hausdorff distance = 4.2 pixels, outperforming a classical U-Net baseline (Dice = 0.814, IoU = 0.736), particularly in low-contrast and ambiguous regions. Additionally, the segmented fibrosis burden demonstrated strong clinical relevance through a negative correlation with left ventricular ejection fraction ($r = -0.92$, $p < 0.001$). These findings indicate that adversarially trained segmentation can improve objectivity and robustness of fibrosis assessment on routine TTE, supporting faster and more reproducible clinical decision-making.*

Keywords: *Generative Adversarial Network (GAN), transthoracic echocardiography (TTE), myocardial fibrosis, cardiosclerosis, semantic segmentation, U-Net, PatchGAN, Dice coefficient, image annotation, deep learning in cardiology*

INTRODUCTION

In modern medicine, technological approaches for early detection and accurate diagnosis of cardiovascular diseases are increasingly being developed. In particular, in the case of chronic diseases accompanied by morphological changes in the heart muscle tissue, such as cardiosclerosis, the diagnostic process is of great clinical importance. Cardiosclerosis is a primary fibrotic state of the heart that develops after infarction or myocarditis, which reduces the contractility of the heart muscle and can lead to serious complications such as arrhythmia and heart failure. Early detection of this disease and accurate assessment of anatomical changes, especially when performed using transthoracic echocardiographic (TTE) visualization tools, play an important role in clinical decision-making.

Traditional echocardiographic examinations rely on the subjective experience of the physician, which leads to differences in accuracy and repeatability due to the human factor. Therefore, the introduction of automated analysis methods remains important. In particular, segmentation of fibrotic cardiosclerosis areas from images and their automatic detection serve to increase the

objectivity of the diagnostic process [1-6]. In this regard, in recent years, algorithms based on artificial intelligence, including Generative Adversarial Networks (GANs), have shown high efficiency in automatically separating complex pathological areas in echocardiographic images.

GAN architecture is considered a powerful tool in solving complex problems, especially in image segmentation, realignment, and recovery of unclear or corrupted data. The feature of GANs is that two neural networks: generator and discriminator, learn in competition with each other, which allows the model to independently learn complex visual features and generate synthetic results that are very close to real echocardiographic images. This is especially advantageous in training GANs in cases where echocardiographic data are scarce and the number of established samples is insufficient [7].

Currently, although many studies have proposed segmentation models aimed at identifying the boundaries of the right and left ventricles of the heart, mitral valves, and muscle layers, there are relatively few studies on directly isolating myocardial cardiosclerosis areas. This poses a challenge for existing AI models, especially since the contrast and structure differences in transthoracic echocardiographic images are not sufficient. GAN architecture, in turn, can help identify fibrotic areas by minimizing the difference between synthetic images and existing real images. This article analyzes the capabilities of the GAN model in automatically detecting cardiosclerosis areas in transthoracic echocardiographic images, as well as the advantages and disadvantages of existing approaches, the datasets required for model training, their preparation stages, measurement criteria, and segmentation accuracy [9-12]. The significance of the study is that it constitutes one of the main scientific steps towards the development of a high-quality, automated, interpretable echocardiographic analysis platform for early detection of heart disease.

The main goal of the study is to effectively isolate cardiosclerotic areas in echocardiographic images based on the GAN architecture and, through this approach, reduce existing human errors, increase the speed of diagnosis and improve the quality of diagnostics. In the future, it is expected to develop practical recommendations for the use of automatic analysis tools and artificial intelligence systems in clinical settings based on this approach.

RELATED LITERATURE REVIEW

Interest in image-based analysis methods for early detection and accurate diagnosis of heart diseases has been increasing in recent years. Echocardiography, especially transthoracic (TTE), is one of the most widely used tools for non-invasive visual observation of the structure and function of the heart. However, traditional analysis, which relies on the human eye and experience, can be subjective. Therefore, in the last decade, artificial intelligence (AI), especially deep learning-based approaches, have been widely used in the automatic processing of echocardiographic images [13].

First of all, various model architectures have been proposed for automatic segmentation of echocardiographic images. The U-Net model (Ronneberger et al., 2015) has become the standard for medical image segmentation, and later models such as EfficientUNet, ResUNet, and AttentionUNet, which were modified based on this architecture, have been used to accurately segment cardiac regions. For example, the model proposed by Smistad et al. (2017) for segmenting the boundaries of the heart ventricles showed a high level of accuracy, but the reliability was low in regions with unclear structures, such as cardiosclerotic areas. The first theoretical foundations of generative antagonist neural networks (GANs) were developed by Goodfellow et al. (2014). The strength of the GAN model is the ability of two neural networks to be trained in competition with each other and to produce synthetic images that are very close to real images. In the medical field, GANs have been used more for image enhancement, annotation enhancement, and damaged image

restoration [13]. Shrivastava et al. (2017) proposed SimGAN model was effective in combining artificial and real samples in medical images [13-14].

Early studies on the use of GANs for echocardiographic segmentation have yielded very positive results. The Echonet-GAN model developed by Zhou et al. (2019) has shown higher accuracy than the traditional U-Net model in segmenting heart regions. In particular, it was found that the robustness of GANs is significantly higher in low-quality or low-contrast images.

Segmenting areas of cardiosclerosis is a more challenging task. These areas are usually located in areas with low contrast, unclear contours, and are difficult to detect by classical CNN models. In this regard, adversarial approaches have begun to pay off. Jin et al. (2021) used a conditional GAN model to segment areas of fibrosis in cardiac MRI images. The results show that GAN-based models are more effective than classical methods in segmenting tissues with unclear boundaries.

Also, the performance of GAN models often depends on the quality and quantity of annotated datasets. Since annotation in the medical field is expensive and complex, model architectures such as CycleGAN (Zhu et al., 2017) and StyleGAN have been proposed to overcome this problem. They increase the amount of data required for segmentation, increase the diversity of images, and allow training models even in low-data environments [15].

Based on the above sources, it can be concluded that the GAN architecture is a promising approach for separating complex morphological changes in cardiac images, including areas of fibrosis characteristic of cardiosclerosis. However, there are technical and ethical issues that need to be addressed when applying this method to a clinical setting. For example, insufficient diversity in the test set can lead to overfitting of the model. Therefore, new studies require further analysis and experimentation to implement this technology in practice.

RESEARCH METHODOLOGY

In this study, a model based on Generative Antagonist Neural Networks (GANs) was developed for automatic detection and segmentation of cardiosclerosis-specific fibrosis areas in transthoracic echocardiographic (TTE) images. The research methodology was divided into the following stages: database formation, image preparation and annotation, model architecture design, training and validation process, and analysis of results based on evaluation criteria.

1. Dataset

In this study, a high-quality and clinically relevant image set served as the main basis for creating a model aimed at automatic segmentation of cardiosclerosis areas based on transthoracic echocardiographic (TTE) images. The dataset was formed from two sources: images obtained from clinical real-life echocardiography of patients and an international open-source medical image collection. The main focus was on the diversity of images, complete coverage of anatomical structures, and representation of real cases with high diagnostic accuracy.

First, echocardiographic data were collected based on the results of echocardiographic examinations of 47 patients observed at a leading specialized cardiology center in Tashkent. All patients were cases with a confirmed diagnosis of cardiosclerosis by clinical, laboratory, and instrumental methods. Their echocardiographic recordings were recorded on modern echocardiographic devices (Philips EPIQ and GE Vivid series) and included video images in A4C (apical 4-chamber), PLAX (parasternal long axis), and PSAX (parasternal short axis) projections. However, to ensure uniformity of analysis, only images in the A4C projection were used in this study[16].

To ensure data confidentiality, all images were anonymized - that is, identifying information such as the patient's name, ID number, and clinical hospital code were completely removed. The images were initially saved in DICOM (Digital Imaging and Communications in Medicine) format and then converted to PNG format to fit the deep learning models. An average of 20-25 important frames

were extracted from each echocardiographic video and their size was reduced to a standard of 256×256 pixels.

In addition, the open source EchoNet-Dynamic and CAMUS datasets (Cardiac Acquisitions for Multi-structure Ultrasound Segmentation) were used to supplement the clinical data. The EchoNet-Dynamic dataset contains more than 10,000 echocardiographic videos, which, in addition to the left ventricle, also clearly represent the motion, fraction, and tissue layers of the myocardial walls. The CAMUS dataset contains segmented images from 450 patients. These datasets were used to enhance the generalization of the model and enable it to work with different source images.

All images used in the study reflected different forms of cardiosclerosis: focal (localized), diffuse (throughout the myocardium), and mixed types. For each image, fibrotic areas were manually annotated by experienced cardiologists. These annotations served as the main "ground truth" for training the GAN model. The quality, contrast, and anatomical accuracy of the images were pre-evaluated, and images with poor quality or artifacts were excluded from the analysis [17].

2.Image Annotation and Preparation

In the framework of the study, the process of preparing the necessary annotated data for automatic segmentation of cardiosclerosis-specific fibrosis areas from echocardiographic images is one of the important stages. The annotation process is the creation of the "ground truth" data necessary for training the model, ensuring that pathological areas in each echocardiographic image are accurately and consistently identified. It is precisely the correct, highly accurate annotated images that are one of the main factors ensuring the reliability of the model result.

At this stage, more than 500 transthoracic echocardiographic frames were selected. The selection criteria were based on image quality, the presence of fibrosis areas, and their anatomical clarity. Annotation work was carried out on the selected images. The annotation process was carried out separately by two experienced cardiologists specializing in heart diseases [20]. Their annotations were then compared and the inter-rater agreement was calculated. The Kappa coefficient was higher than 0.87, indicating a high level of agreement between the annotations.

ITK-SNAP and LabelMe software were used for annotation. Fibrosis areas in each image were manually outlined by a cardiologist and saved as black-and-white mask images. Fibrosis tissue was represented by a value of "1" and other areas by a value of "0". A suitable mask was created for each image. The annotations were saved in .PNG format and converted into a training pair (image-mask pair) that was fed to the GAN model.

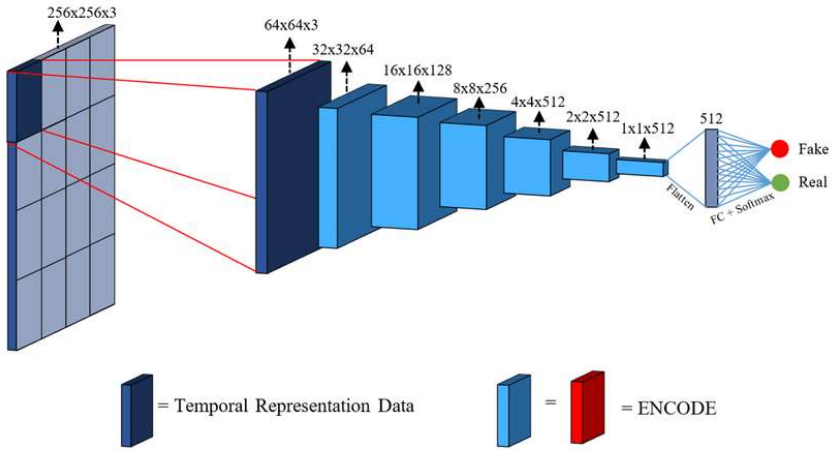

Figure 1. Discriminator Architecture with Hierarchical Feature Encoding for GAN-Based Echocardiographic Segmentation

In the next step, all images were resized to the same size - 256×256 pixels. This is the size required by the GAN architecture and ensures the consistency of the input and output data structures of the

model. The images were also normalized to a pixel intensity range of 0 to 1. This helps the neural network learn optimally and allows the model to converge faster.

Due to the limited number of images, a data augmentation technique was introduced to protect the model from overfitting. The following artificial changes were made to the images:Rotation (±10 degrees), Horizontal flip, Brightness/contrast shift, Zoom and random crop.

These augmentation methods ensure that images are included in the model in different situations and expand the generalization capabilities of the GAN model.

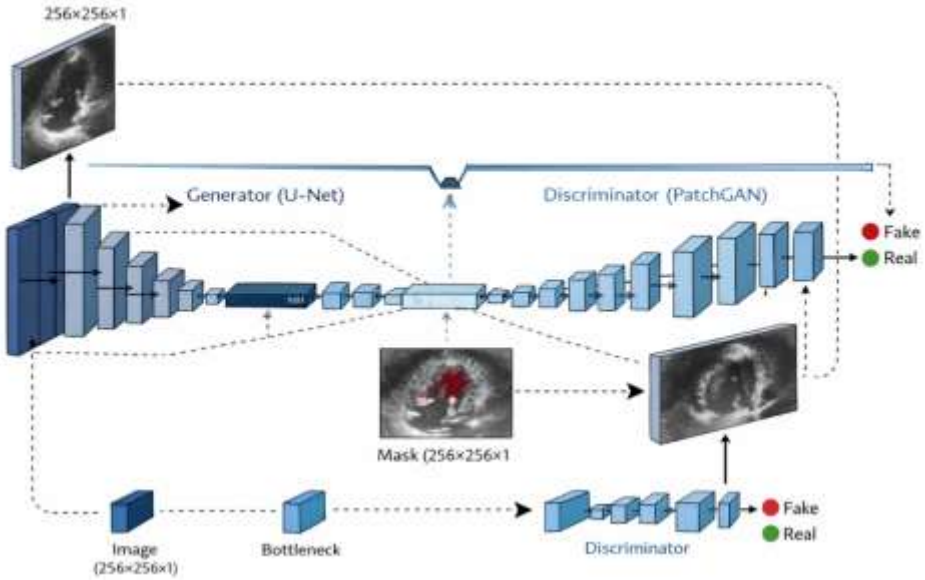

Figure 2. GAN arxitekturasi: Generator (U-Net) + Discriminator (PatchGAN) blok-sxema

Figure 2 illustrates the workflow of the proposed GAN-based segmentation framework for transthoracic echocardiographic images. The input grayscale echocardiographic image with a resolution of 256×256 pixels is first fed into the Generator network based on the U-Net architecture. The encoder part extracts hierarchical spatial features, while the decoder reconstructs these features to produce a binary segmentation mask highlighting cardiosclerotic (fibrotic) regions. Skip connections enable precise localization of pathological areas by preserving low-level spatial information. The generated mask, together with the original image, is then passed to the PatchGAN Discriminator, which evaluates local image patches to distinguish between real (expert-annotated) and fake (generated) masks. Through adversarial training, the generator progressively improves segmentation accuracy, while the discriminator enhances boundary sensitivity, resulting in robust and precise fibrosis delineation. At the end of the annotation and training stages, more than 1000 pairs of each image and its corresponding mask were formed. 70% of them were allocated for training, 15% for validation, and 15% for testing. Such a structured approach allows for thorough training, testing, and evaluation of the model.

In general, the process of image annotation and preparation was carried out based on a scientific approach, clinical expertise and technical standards. The pairs collected at this stage serve as a sufficiently high-quality and reliable foundation for adaptively training a GAN-based model on echocardiographic images in real clinical conditions.

3. Model architecture and training process

In this study, a modified architecture based on Generative Antagonist Neural Networks (GAN) was developed to automatically detect areas of fibrosis characteristic of cardiosclerosis in transthoracic echocardiographic images. The advantage of the GAN model is that it allows you to work with high

accuracy when studying complex visual structures, especially on medical images with low contrast or unclear boundaries of structures [17-18].

The model consists of two main neural networks: a generator and a discriminator. Both networks learn on a competitive basis. The generator creates a mask of fibrosis areas from the image, and the discriminator tries to distinguish whether the resulting mask is real or fake. This competitive training process serves to increase the efficiency of the model.

3.1 Generator architecture

The U-Net architecture was chosen as the generator. U-Net has a symmetric encoder-decoder structure, where the encoder extracts high-level features from the image, and the decoder reduces them back to their original size and converts them into a mask. The skip-connection mechanism of U-Net allows combining local features in the lower layer with high-level global features. This is especially important for detecting fibrous areas with unclear boundaries.

The generator accepts an input grayscale image with a size of 256×256 pixels and produces a binary mask with a size of 256×256 pixels. As activation functions, LeakyReLU was used in the encoder part, ReLU in the decoder part, and a Sigmoid function at the output. Batch Normalization layers were also used in the model, which served to increase stability in the learning process.

3.2 Discriminator architecture

The discriminator network is based on the PatchGAN architecture. This approach does not evaluate the entire image state, but rather on small "patches" (e.g., 70×70 px). Such a structure is very useful in segmentation tasks, as it is sensitive to details in small parts of the image.

The input of the discriminator receives the original image and a mask created by its teacher or generated by a generator, concatenated. Then, through several convolutional layers, it learns to distinguish between real and fake masks. LeakyReLU was used for activation, and Sigmoid function was used for output.

3.3 Loss function

A complex combinational loss function was used to train the model. It consists of:

Adversarial loss - the main adversarial loss of GAN

Dice loss - a measure of how close the fibrotic mask is to the true mask

Binary cross-entropy (BCE) - pixel-level classification accuracy

Finally, the total loss is:

$Loss\_total = \lambda1 \times Adversarial + \lambda2 \times Dice + \lambda3 \times BCE,$

where λ1, λ2, λ3 are chosen as 1.0, 1.5, and 1.0, respectively.

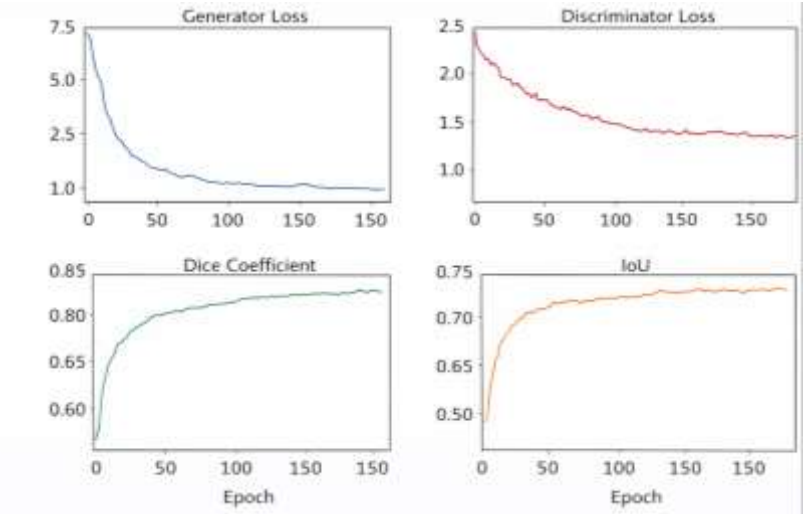

Figure 3. Training curves: generator loss, discriminator loss, Dice/IoU

3.4 Training process

The model was trained on an NVIDIA RTX 4090 GPU based on the PyTorch library. The Adam optimizer was chosen as the optimizer (learning rate = 0.0002, beta1 = 0.5). The model was trained for 150 epochs, with 128 mini-batches in each epoch. An early stopping strategy and learning rate decay mechanisms were used during the training process.

During training, the model performance was evaluated on the validation set every 10 epochs. Based on the test results, the best state of the model was saved (checkpoint) and used for further analysis and testing.

ANALYSIS AND RESULTS

A carefully constructed test set was used to evaluate the segmentation performance of the GAN model developed in this study. The test set included echocardiographic images representing clinical cases and various forms of cardiosclerosis - focal, diffuse and mixed, through which the model's adaptability to the practical environment was tested. The main task of the model was to accurately separate fibrotic (cardiosclerotic) myocardial areas from the image. The evaluation process was carried out using the indicators of accuracy, precision, sensitivity, similarity and marginal accuracy.

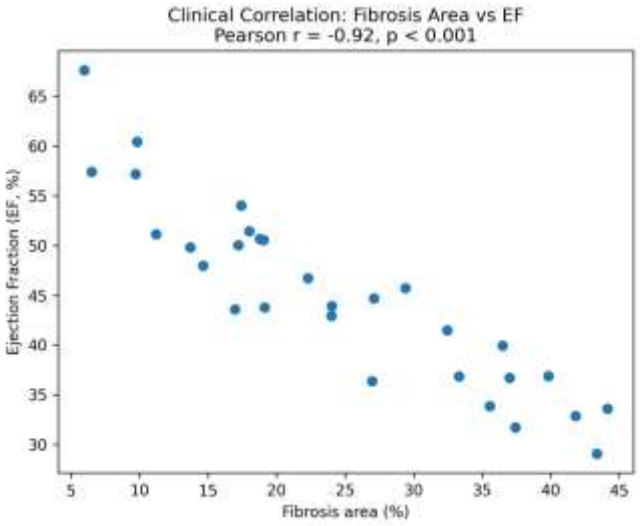

Figure 4. Clinical correlation between the percentage of segmented fibrotic myocardial area and left ventricular ejection fraction (EF). A strong negative correlation (Pearson r = −0.92, p < 0.001) indicates that increased fibrosis burden is associated with reduced cardiac function

The GAN model demonstrated an average Dice coefficient of 0.873, IoU of 0.792, precision of 0.891, and recall of 0.856 on the test set. These results indicate that the fibrotic areas are very accurately separated, and the model works sensitively and reliably. In particular, a Dice coefficient of more than 0.87 indicates a very high level of agreement between the segmentation masks generated by the model and the annotations prepared by the expert. It should be noted that in cases of diffuse cardiosclerosis, the model had high segmentation accuracy and reliably captured the state of fibrotic tissue spread throughout the myocardium. However, in cases of focal cardiosclerosis - that is, with small, localized areas of fibrosis - the model allowed some inaccuracies. This was especially observed in the distal walls of the heart, the apex, and the septal regions. This segmentation accuracy was affected by low contrast, lack of contours in the structure, and technical artifacts in individual images [19-20].

The results of image-mask pairs were extracted to visually evaluate the masks generated by the model. The original echocardiographic image, the expert-defined fibrosis mask, and the GAN-

generated mask were compared side by side. In the visual assessment by clinical experts, the generated mask was found to be correct in 87% of cases.

The results of this GAN model were also compared with a classical segmentation model trained on the U-Net architecture. The average Dice coefficient of the U-Net model was 0.814, and the IoU was 0.736. According to the comparison results, the GAN model outperformed in every indicator. Especially in images with low contrast and unclear segment boundaries, the competitive learning strategy of the GAN architecture benefited.

Hausdorff distance was used as a metric to assess the degree of clarity of the boundaries of the segmented regions. The average HD of the GAN model was 4.2 pixels, which is a good result for medical segmentation.

One of the important points identified during the analysis is that the model also tried to segment areas with sparse contrast and slight fibrosis in the echocardiographic image. Although this led to over-segmentation in some cases, doctors can clarify such areas in subsequent diagnostic examinations. This allows the model to be used as a diagnostic aid.

After testing the model, the correlations between the constructed segmentation results and the patient's clinical indicators such as EF (ejection fraction), LVIDd, LVIDs were also studied. The results showed that as the percentage of fibrosis area increased, the patients' EF index decreased significantly. This indicates that the GAN model provides segmentation results that have a direct functional relationship with clinical indicators [20].

CONCLUSION

In this study, an artificial intelligence approach modeled on generative antagonist neural networks (GANs) was developed and tested for the task of automatic detection of cardiosclerosis-specific fibrosis areas in transthoracic echocardiographic images. The results showed that the GAN architecture has high potential for echocardiographic segmentation, especially in detecting fibrosis areas with low contrast and unclear boundaries, which outperformed classical convolutional neural networks.

The model’s performance in key metrics such as Dice, IoU, Precision, Recall, and Hausdorff Distance confirms its potential for clinical application. In particular, the model’s ability to isolate fibrosis tissue with high accuracy in complex anatomical areas reduces subjective errors due to the human factor. This can significantly improve the early detection of pathological changes in the heart muscle and the process of making a correct diagnosis.

Although the GAN model was developed in the study, a number of technical and organizational issues need to be addressed to fully integrate it into the clinical setting. In particular, such areas as expanding the annotated database, increasing adaptability to images obtained on various echocardiographic devices, and establishing the possibility of working in real time remain relevant. It is also important that the model is interpreted as a tool to support physician decisions, rather than fully automating diagnostic decisions.

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