*Informatics and Technology in Clinical Care and Public Health*
*J. Mantas et al. (Eds.)*

*doi:10.3233/SHTI210910*

# Artificial Intelligence Models for Heart Chambers Segmentation from 2D Echocardiographic Images: A Scoping Review

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**Abstract.** Echocardiography (echo) is a non-invasive, safe, widely available imaging modality that is frequently used to assess the heart structure and function. Accurate heart chamber segmentation is an essential step to quantify certain parameters, including heart chamber volumes. In clinical practice, this task is manually done by echo experts, where it consumes considerable time and is subjective to both errors as well as intra-operator variability.. Artificial intelligence (AI) models have been used to automatically segment heart chambers. We conducted a scoping review to provide an overview of the AI models used for this task. Three bibliographic databases; PubMed, Embase, and Google Scholar were explored. Out of 640 initially retrieved studies, 36 studies were included. Multiple AI models used for echo images segmentation were identified, which can be broadly categorized into five methods: low-level image processing, deformable-based, statistical techniques, machine learning (ML), and deep learning-based (DL) techniques. The initial three categories were relatively simple and required less computational complexity compared to the ML and DL models. The convolutional neural network was the most widely used DL-based technique in most-recent publications. Generalizability of the models is a major concern that needs to be addressed in the future. Well-annotated larger 2D echo image datasets would be required to mitigate the challenges to some extent.

**Keywords.** Artificial intelligence; Deep learning; 2D echocardiography; segmentation

## 1. Introduction

Cardiovascular disease (CVD) is the leading cause of death worldwide [1]. Several imaging modalities are used for diagnosing this disorder, including echocardiography (echo), computed tomography (CT), cardiac magnetic resonance imaging (CMR), and cardiac nuclear imaging. Echo is a non-invasive, safe, and most widely-used imaging modality that plays a crucial role in the diagnosis and management of CVD. In 2D echo

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studies, heart chambers images (left ventricle (LV), right ventricle (RV), left atrium (LA), right atrium (RA)) are acquired from multiple views, as well as during contraction (systole) and relaxation (diastole). The four basic views in echo are Apical two chambers (A2C), apical four chambers (A4C), parasternal long axis (PLAX) and parasternal short axis view (PSAX) [2]. The main drawbacks of echo, compared to other imaging modalities, are inconsistency and high inter- and intra-observer variation in image acquisition, analysis, and interpretation [3]. Heart chambers segmentation is done by manual boundary delineation, which is a time-consuming, subjective to errors task that depends on interpreter experience [4,5]. Therefore, it is critically importance to find methods to improve interpretation efficiency and reduce reporting time. Artificial intelligence (AI) models have been leveraged to execute tasks that are usually manually performed by echo experts (i.e., image segmentation and measurements of cardiac structural and functional indices) [6]. This review aims to explore different and the most recently used AI models for 2D echo images segmentation.

## 2. Methods

The review was conducted following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines [7]. A systematic search was conducted using three electronic databases, PubMed, Google Scholar, and EMBASE. The search terms were selected based on population, intervention, and outcome. We searched for terms related to 2D echo images and all AI segmentation models used for heart chambers segmentation. There were no age, gender, or health status restrictions. The search focused on the most recently-developed AI models; therefore, studies published from January 2010 to date were included. Because the Google Scholar search resulted in a large number of studies, only the first 100 studies were included. In addition, backward reference searching of the included studies and any relevant reviews was conducted. The titles and abstracts of all possible studies were reviewed, then full-text reading was conducted to identify the eligible studies. The data from the final list of included studies were extracted into an Excel sheet. Lastly, the data from the included studies were synthesized in a narrative approach.

## 3. Results

As shown in the PRISMA chart in Appendix 1, 36 studies satisfied the eligibility criteria and were included in this review from the initial 640 studies retrieved from the databases search. The included studies are listed in Appendix 2. The methods used for segmentation fell into five main categories: low level image processing (n=4), deformable-based (n=7), statistical techniques (n=6), machine learning (ML) (n=4) and deep learning (DL)-based (n=15) techniques [8]. The CNN U-net model was incorporated as the backbone architecture in 5 studies. Most of the studies (n=24) used AI models for LV segmentation, while only one publication discussed RV segmentation alone. Two studies provided a framework for comprehensive automated echo images analysis and interpretation and used algorithms to segment all heart chambers (LV, LA RV, and RA). One study included a dataset of children's echo images, while five studies used fetal images. The remaining studies included adult echo images (n=30). The characteristics of the included studies can be found in Appendix 3.

The AI models used in the low-level processing-based category include the watershed algorithm, thresholding, morphological appearance model, and the level-set algorithm. Active contouring was widely used for the deformable-based category; pSnakes, B-Spline, K-means clustering algorithms were used for this model. Other deformable-based models included phase-based level-set evolution and constrained level-set. The third category was based on statistical methods. An active appearance model was used for fetal heart segmentation. Two studies utilized an active shape model (ASM), while two others combined ASM with Random Forest. Classification algorithms were mainly used in ML approaches. The models used in this category included the shape regression machine model, Bayesian probability maps, and adaptive group sparse representation model. Another ML approach used a sparse matrix transform model combined with a level-set model. However, most echo image segmentation studies published in recent years focused on DL models. The majority of these models (n=14) are based on a convolutional neural network (CNN). Furthermore, many approaches were followed to design derivatives to CNNs for better segmentation performance such as encoder-decoder model, bilateral segmentation network and dynamic CNN. ML and DL models datasets included large data sets that ranged from 350 to 1500 echo images.

## 4. Discussion

### *4.1 Principal Findings*

The objective of this scoping review is to summarize AI techniques used for 2D echo image segmentation. From the included 36 studies, we identified many AI models that had been experimented with. As LV parameters carry the most clinical importance, most studies focused on this chamber segmentation [3]. AI segmentation models fall into five main categories. One of the initial methods was low-level processing models. The performance of these techniques are acceptable and are not computationally exhaustive. But these techniques perform poorly in low-quality images. Deformable models require higher computational power and are sensitive to the initial contours. Segmentation accuracy was enhanced by statistical techniques compared to low-level processing and deformable models, but they were found to be sensitive to the presence of variations in shape or appearance. Conventional ML and DL methods have been extensively studied recently. These models require large, well-annotated datasets. U-Net has been incorporated as the backbone architecture in many studies for various medical imaging segmentation. In our review, we identified studies that either used U-Net architecture (n=5) or compared the performance of their proposed model to U-Net. The modifications in the U-Net achieved better performance than the vanilla U-Net.

Moreover, DL models can be designed to perform tasks related to image interpretation apart from segmentation alone. Zhang et al. [9] and Arafati et al. [10] proposed a framework that included all the four heart chambers segmentation while also measuring other important parameters. The model by Arafati et al. designed a fully convolutional neural network combined with adversarial training and post-processing optimization, which was compared to other DL models. Results showed superior performance of this model. Over the past decade, an overall trend to improve AI models' performance based on 2D echo image segmentation has been observed.

### 4.2 Practical Implications

The majority of AI models utilized for heart chamber segmentation based on 2D echo image are not only comparable to experts' manual performance, but also requiree lower execution time. Utilizing such AI-based frameworks in clinical setups would reduce the burden on clinicians and improve the diagnosis plan. We recommend that researchers focus on improving existing DL models. Despite the presence of few online public echo image datasets, there is still a need for larger and well-annotated datasets to achieve generalizable AI models.

## 5. Conclusions

In this study, we highlighted the AI-based techniques that are used for 2D echo image segmentation. DL-based techniques are the most recent and highly accurate methods to perform this task. Availability of large and well-annotated echo image datasets may help the community to improve existing DL models.

Appendix files are available at GitHub: https://github.com/DawdAlKindi/Appendix .

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